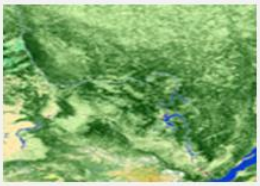
SOURCEBOOK

UNCBD COP 13




A SOURCEBOOK OF METHODS AND PROCEDURES FOR MONITORING ESSENTIAL BIODIVERSITY VARIABLES IN TROPICAL FORESTS WITH REMOTE SENSING

GOFC-GOLD
Global Observation of Forest and Land Cover Dynamics

GEO BON
Group on Earth Observations
Biodiversity Observation Network

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1 INTRODUCTION

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1.1 BACKGROUND, THE ROAD TO COORDINATED BIODIVERSITY MONITORING SYSTEMS

Effective, timely and informed conservation and sustainable development decisions require consistently produced and trustworthy biodiversity data, derived from in-situ and remotely sensed sources and scalable from the local to global. Producing such data requires clear monitoring objectives driven by user needs and a coordinated approach to allow for the integration of biodiversity data from multiple sources and scales.

The past several decades have seen a growing demand for biodiversity data to inform development decisions at the local to national scale for underpinning sub-global and global assessments. The Ramsar Convention on Wetlands of International Importance, that came into force in 1975, was the first global Multilateral Environmental Agreement (MEA) on biodiversity protection. In 1992, 172 governments participated in the first Earth Summit held in Rio de Janeiro under the aegis of the United Nations, to define the first global plan of actions for the World's sustainable development. This Rio Conference, officially called the United Nations Conference on Environment and Development (UNCED), resulted in the adoption of the three Rio Conventions, namely the Convention on Biological Diversity (CBD), known as the Biodiversity Convention, which entered into force in 1993, the UN Framework Convention on Climate Change (UNFCCC) in 1994, and the UN Convention to Combat Desertification (UNCCD) in 1996. During that period many scientists, civil servants, decision makers and politicians involved in the work of these conventions recognized that the data and observations required for global, regional and even national biodiversity assessments were largely lacking.

Until recently, biodiversity assessments were largely uncoordinated and usually conducted on an individual basis by small groups of scientists. Unlike the Intergovernmental Panel on Climate Change (IPCC), established in 1988 to produce scientifically sound global assessments to support the work of the United Nations Framework Convention on Climate Change (UNFCCC), there were no similar mechanisms to support global biodiversity assessment. Moreover, biodiversity research findings were not easily integrated into policy making and appeared to be poorly reflected in policy discussions on biodiversity conservation and the contribution of ecosystems to human well-being. In 1998, Watson (1998) called for a more integrative assessment of scientific issues at a global level especially on the interlinkages between climate, biodiversity, desertification, and deforestation. The Millennium Ecosystem Assessment (MA), initiated in 2001, was the first global assessment of the consequences of ecosystem changes on human welfare and also the first scientific basis for coordinated actions needed to enhance the conservation and sustainable use of ecosystems. The MA report, which was formally presented in 2005, involving the work of more than 1,300 scientific experts worldwide, provided the first scientific evidence on the changes made to ecosystems and on the risk of irreversible loss of biodiversity. Although the gains in human well-being and economic development were recognized by the MA, these gains were being achieved at the cost of a massive degradation of many ecosystems and of the services they

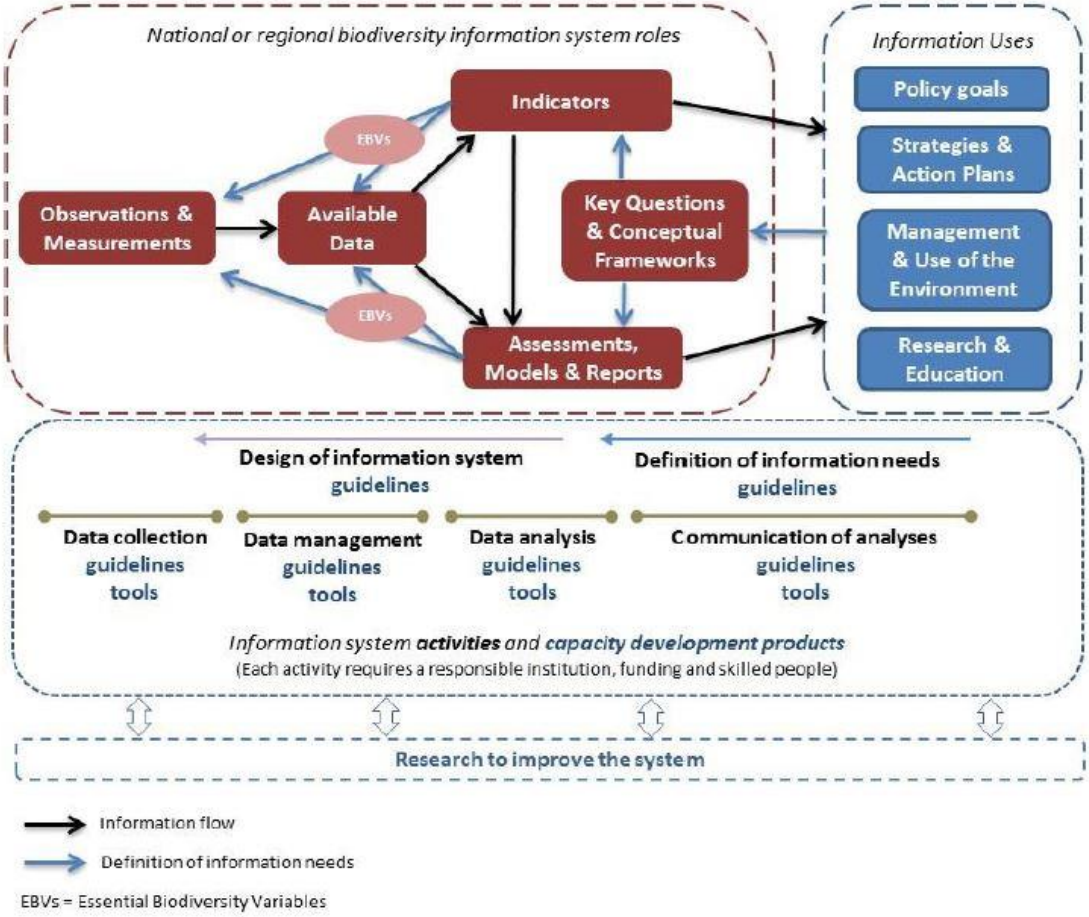
provide, which could become a barrier to achieving the Millennium Development Goals. The MA also showed that, with appropriate coordinated and global actions, it is possible to reverse the degradation of many ecosystems and restore their services over the next 50 years. The MA findings were endorsed by the Conference of Parties (COP) of the CBD and UNCCD and by the standing committee of the Ramsar convention. Only in 2012, the Intergovernmental Platform for Biodiversity and Ecosystem Services (IPBES)[1] was founded to play a similar role as IPCC for all biodiversity related conventions. This independent international body will strengthen the links between scientists and policy makers on the conservation of biodiversity and ecosystem services and hence support biodiversity-related policy formulation and implementation. The principal mandate of IPBES is to provide regular scientific assessments of the state of biodiversity and ecosystem services and their interlinkages, at both global and regional scales, as well as for thematic issues. Another function of IPBES is to prioritize the information that is needed for policy decision on appropriate scales and to catalyse efforts to collect the necessary observations and generate new knowledge. Although IPBES plays an important role in biodiversity knowledge building, the panel does not have the mandate to coordinate global data provision for biodiversity and ecosystem service assessment.

Until the beginning of this century, monitoring biodiversity was mainly an issue of research institutes, museums, national agencies, individual researchers and interest groups. Species richness and ecosystem diversity were monitored where the ecologists or interested researchers were located. The best monitored taxa were birds, as they are attractive and easy to follow. Some research groups and conservation agencies were carrying out systematic surveillances of other species and ecosystems in some countries and national parks, but they were not generally applied and certainly not globally coordinated. The consequence is that the way biodiversity surveillance and monitoring was done, until recently, was not standardised at global or regional levels. This scarce cooperation between biodiversity observers was, in part, due to the barriers in global communication, only recently removed with the advent of the Internet. This lack of communication and cooperation, and therefore of harmonisation, was clearly reflected in the data that were used by countries in their policy reporting, as seen in the reporting by the member states of the European Union on the Habitats Directive, which was insufficient for some habitat types and species to obtain meaningful and comparable assessments. This is also illustrated in the results of an analysis of the CBD 4th National Reports, where only 36% of the reports included evidenced based policy indicators (Bubb et al. 2011).

The Global Biodiversity Information Facility (GBIF)[2] and more recently the Group on Earth Observations - Biodiversity Observation Network (GEO BON)[3] launched in 2008 under the Group on Earth Observations (GEO)[4] initiative have been instrumental in stimulating the first global coordinated efforts to harmonise biodiversity observations and to better link in-situ and remotely-sensed information. GEO BON's mission is to improve the acquisition, coordination and delivery of biodiversity observations and related services to users, including decision makers and the scientific community. The ultimate goal of GEO-BON is to promote the development of robust and interoperable observation networks that can, together, contribute to effective and scientifically-sound biodiversity conservation, and ultimately to mitigation and adaptation policy decisions regarding the world's ecosystems, the biodiversity they support, and the services they provide. GEO BON activities are supported by the Group on Remote Sensing for Biodiversity and Conservation[5] of the Committee on Earth Observation Satellites (CEOS) whose aim is to identify Earth Observation (EO) needs and shortcomings for

[1] http://www.ipbes.net/
[2] http://www.gbif.org/
[3] http://www.geobon.org/
[4] https://www.earthobservations.org/
[5] http://remote-sensing-biodiversity.org/networks/ceos-biodiversity/

biodiversity and conservation, improve the data exchange and the coordination between the space-based Earth Observation community and the ecologists, and facilitate access to remotely-sensed EO data and software for biodiversity and conservation activities. The Global Observation of Forest Cover and Land Dynamics[6] (GOFC-GOLD) is another international group of EO experts, which provides complementary assets facilitating the interactions between space agencies, the scientific community and users of Earth Observation data and products, developing and promoting standards. These international and overarching initiatives collaborate closely with GEO-BON and, through these collective efforts, greatly increase the value of observations by allowing more biodiversity-related information to become available covering larger areas and longer time series. At the species level, this is slowly improving mainly through national initiatives in various countries and through their links with GBIF. The coordination of global efforts in ecosystems and habitats monitoring is still largely to be accomplished and the use of EO information in this context is still insufficiently exploited. Considering this, GEO BON is focusing on partnerships with national governments such as Colombia France, and China, international, regionalbodies such as the Asia-Pacific BON and Conservation of Arctic Flora and Fauna (CAFF) and thematic BONs, such as marine and wetlands[7]). to build interoperable biodiversity observation systems that underpin reporting requirements for MEAs (e.g. the CBD) and allow for the integration and scaling of biodiversity observations from the sub-national to the global level and for the disaggregation of global datasets to inform national reporting. This effort is being structured around a conceptual approach for a biodiversity observation and information system (Figure 1).



[6] http://www.gofcgold.wur.nl/index.php
[7] http://geobon.org/become-a-bon/become-a-bon/

Figure 1: Conceptual Framework for a National or Regional Biodiversity Observation System. Philip Bubb, UNEP WCMC (2015).

Yoccoz et al (2001) stated already in 2001 that many monitoring programs for biological diversity suffer from design deficiencies, because they appear to be developed without enough attention to the basic questions: why monitor? what should be monitored? and how should monitoring be carried out? Biodiversity monitoring should not only serve knowledge development and site management. Policy decision-making and reporting on biodiversity trends are also important. This implies a different way to conduct biodiversity monitoring since it also requires a basic set of observations targeted for policy making. Biodiversity surveillance and monitoring must therefore evolve from purely scientific research driven activities to globally coordinated monitoring activities, as is already the case for climate, demographic, economic and health information. This also means that biodiversity science has to contribute to the development of globally connected information services that can serve decision-making and policy reporting. Applied research in biodiversity must therefore also be driven by policy and user needs, and consequently requires long-term continuity and global coverage of adequate observations. Such observations if repeated in time and in space allow the assessment of the effectiveness of policy implementation, if national management practices effectively fulfil legal obligations such as those of national legislations or those of legally-binding resolutions from international environmental agreements.

At the 10th Conference of the Parties (COP-10) of the CBD held in Nagoya, Japan, in October 2010, the Contracting Parties to the Convention adopted a revised and updated Strategic Plan for Biodiversity 2011-2020[8]. This plan provides a new overarching international framework for the CBD and all its Contracting Parties, but also for other biodiversity-related conventions and for all scientists, conservation agencies, national governments engaged in biodiversity management and policy development. The CBD Contracting Parties, which means all countries that have ratified the Convention, also agreed to translate this new Strategic Plan into National Biodiversity Strategies and Action Plans (NBSAP). The new Strategic Plan for Biodiversity contains a coherent overarching framework to assess progress toward twenty ambitious but achievable targets, collectively known as the 2020 Aichi Biodiversity Targets. These targets are organized under five strategic goals. Strategic Goal A and its four targets address the drivers of biodiversity changes. Goal B contains five targets related to the state of biodiversity. Goal C contains three targets that look at the effectiveness of actions taken to protect biodiversity. Goal D contains three somewhat diverse targets relating to the benefits derived from biodiversity. Goal E contains four targets that largely relate to the CBD mechanisms. In order to monitor progress towards the five Goal B targets on the state of biodiversity, global-scale observations are needed by the CBD and above all by the IPBES, the leading intergovernmental body that has the mandate to assess the state of planet's biodiversity. Large-scale observations are also required by the national governments of the CBD Contracting Parties, for the implementation of their NBSAPs and hence for their national biodiversity monitoring and assessment. There are known major deficiencies in the evenness and adequacy of global observations for assessing progress towards these targets on the state of and pressure on biodiversity. Many existing observations are too narrow in scope and their data quality insufficient. Target 14 (ecosystem services) of Strategic Goal D is another target that does not have yet a globally adequate observation system. Target 15 seeks to relate biodiversity and climate change in both directions and can benefit from the observations conducted by the climate change community. Overall, the observations needed to monitor progress towards many of the 2020 Aichi Biodiversity Targets are achievable only if there is a concerted international effort to harmonise biodiversity data collection, management and reporting. To assess progress towards the Aichi Biodiversity Targets and the nationally

[8] www.cbd.int/doc/meetings/cop/cop-10/information/cop-10-inf-12-rev1-en.pdf

developed NBSAP targets, experts also need consistent global and national indicators. At its 11th Conference of the Parties (COP-11) in Hyderabad, India in October 2012, the CBD adopted an indicator framework for the Biodiversity Strategic Plan and notably for the Aichi Biodiversity Targets. This framework contains a list of 98 provisional indicators, which provides to the CBD and to the Parties a flexible basis to assess progress towards the Aichi Targets. The adoption of global and national indicators is fundamental since they allow conveying simple and clear messages to policy makers. The reporting and decision making process implies sharing knowledge with the world outside of scientific circles, such as the politicians and the society in general. When communicating with society, graphs on probabilities of species population changes with uncertainties do not always have the right impact. Policy makers want information on what goes well and what goes wrong and where and why it is happening. Then they can make a decision to respond. Indicators are required to provide rather simple information on complex processes, which can be understood by decision makers. A clear and unambiguous definition of indicators also facilitates the development of biodiversity monitoring systems since these can be tailored to the derivation of the required policy indicators. The CBD has mandated the Biodiversity Indicators Partnership (BIP)[9] to promote and coordinate the development of biodiversity indicators in support to the Convention and to the monitoring of the 2020 Aichi Biodiversity Targets. The BIP is an international partnership that brings together more than 40 international organisations on the development of a global indicator framework and on the production of guidelines for helping countries defining their NBSAP indicators. The biodiversity indicators defined by the BIP provide the elements for a consistent monitoring and assessment of the state of biodiversity, the conditions of the ecosystems, the benefits provided by the ecosystems and the drivers of changes. They serve both the IPBES in its global, regional and thematic assessments, as well as the countries when developing their national biodiversity indicators. The adoption of biodiversity indicators provides also a framework for identifying the essential observations that are necessary to be collected in a consistent way for an efficient and reliable biodiversity monitoring and assessment. To do so the Essential Biodiversity Variables (EBVs) have been proposed as a concept to provide a consistent framework for biodiversity observations that allows for integration, via modelling, to produce the desired indicators (Pereira et al 2013). The EBVs have been mapped to the Aichi Targets and key indicators to exhibit this relationship (Secades et al (2014), Geijzendorffer et al. 2015).

This means that biodiversity monitoring activities need to be of high quality, reliable and with assurance of continuity and consistency. They should cover the major elements of biodiversity value and the collected information must be exchangeable between conservation agencies, governments and non-governmental organisations. Cooperation is essential for obvious reasons of cost-effectiveness, but also to efficiently integrate all observations into a comprehensive knowledge of the state of biodiversity and of the levels of ecosystem services provision, in particular in support to the global biodiversity assessments performed by the IPBES for the multilateral environmental agreements, but also to support national scale conservation and sustainable development decisions. This means that there is a need for a global framework in which countries agree on what to measure, how to measure it and at which frequency. A conceptual and theoretical basis for monitoring biodiversity was given already in 1990 by Noss (1990). In his hierarchical characterisation of biodiversity, he emphasises that biodiversity is not just a number of genes, species and ecosystems, but that it should also include its most important structural, functional and compositional aspects. If biodiversity monitoring has to deliver data for policy makers, then sensitive and essential elements of biodiversity should be measured and translated into relevant indicators. Measurable and significant proxies should be used if it is too costly or too difficult to measure

[9] http://www.bipindicators.net

these essential biodiversity variables themselves. We have to know what the species stand for and what changes in their abundance and distribution mean in terms of ecosystem health and ecosystem service provision. For the same reasons, we also need to measure status and trends in the extent, structure and function of ecosystems.

The Essential Biodiversity Variables (EBVs) have been developed upon the request of the CBD and represent the minimum set of essential measurements that are required to be collected globally and regularly for studying, reporting, and managing changes to biodiversity. They have been defined to capture the major dimensions of biodiversity changes and to provide the first level of abstraction between the primary observations and the high-level biodiversity indicators defined by the Biodiversity Indicators Partnership. In their EBV conceptual paper published in Science, Pereira et al (2013) recognized that there is, at present, no global and harmonized observation system that can deliver regular and timely data on biodiversity changes. Despite some clear progress in the digital mobilization of biodiversity records and data standards, the main obstacle is the lack of consensus about which parameters to monitor. They screened dozens of biodiversity variables to identify a minimum set of essential variables that fulfil criteria on scalability, feasibility, and relevance. The EBVs are proposed to be based both on remotely sensed observations that can be measured continuously across space by satellites and on field observations from local sampling schemes that can be integrated into large-scale generalisations. The EBVs were then grouped in six major classes of EBVs: genetic composition, species population, species traits, community composition, ecosystem structure and ecosystem function. The concept of EBVs has started to stimulate high interest in the biodiversity community and to catalyse investment in targeted and harmonized approaches to biodiversity observations.

The EBVs can only become a reality if ecologists and remote sensing experts join their efforts in defining together a global monitoring strategy for biodiversity. This is the appeal by Skidmore et al, calling for an agreement on the biodiversity metrics that need to be tracked from Space (Skidmore et al., 2015). They stressed that satellite remote sensing is crucial to getting long-term and global coverage of some of the essential biodiversity variables, for a wide range of scales and in a consistent, borderless and repeatable manner. To stimulate discussions, they proposed ten variables that capture biodiversity changes and can be monitored from Space. The main reasons why researchers were previously unable to define a set of biodiversity variables to be monitored from satellites were an inadequate access to satellite data, uncertainties in the continuity of observations and temporal and spatial limitations of satellite imagery. Another main bottleneck to the development of Earth Observation approaches in biodiversity monitoring has been the lack of communication between the conservation and remote-sensing communities. Most of the ecologists are ill equipped to effective utilize EO technologies. This requires cooperation to further promote EO technologies in biodiversity teaching and research, especially on the integration of EO and in-situ information for species and ecosystem monitoring. It also requires the development of tools that can facilitate the easy uptake and use of continually emerging EO technologies. A better use of Earth Observations by ecologists would reduce the lack of biodiversity information and improve their capacity to conduct proper data analysis, and accuracy assessment. The importance of remote sensing for biodiversity monitoring was also recognized in 2014 by Secades et al (2014) in their review of current EO approaches and future opportunities for tracking progress towards the Aichi Biodiversity Targets. This detailed review of the possibilities that remotely sensed data provide to biodiversity monitoring, has assessed the adequacy of Earth Observations to monitor progress towards each of the Aichi Biodiversity Targets. The review also explored the main obstacles and identified opportunities for a greater use of Earth Observation in biodiversity monitoring. There were many barriers to developing EO capacity amongst the biodiversity community such as the restrictive data access policies, the cost of data, the lack of EO derived products easy to use by ecologists, the absence of dense time series of observations and the uncertainties in the long term

continuity of observations. In developing countries, there are additional barriers such as education, internet bandwidth and data access. As a conclusion, the review called for some consensus building between EO experts, biodiversity scientists and policy users to better manage the potential that EO data provide to biodiversity monitoring.

During the last decade, the Space Agencies have tried to adequately respond to these obstacles. In 2008, the US Geological Survey (USGS) opened its Landsat archive at no charge over the Internet, giving free and open access to four decades of Earth Observations, with the direct impact that the use of satellite observations in biodiversity and conservation increased dramatically and that novel and innovative monitoring methods were developed. Others, including the Brazilean Space Agency INPE has made its archives accessible. The European Copernicus initiative and the Sentinels, jointly implemented by the European Commission and the European Space Agency (ESA), and the NASA's Sustainable Land Imaging program will offer an unprecedented ensemble of satellite observations with a long-term continuity and a free and open data access policy. Advanced sensors to be launched within a decade will provide increasingly accurate information on species traits and ecosystem extent, function and condition. As a whole, the Space Agencies offer a large and growing variety of Earth Observation satellite sensors with free and open data policies, to efficiently monitor a number of remotely sensed parameters. Combined with in-situ observations and appropriate modelling, this will offer improved insights into the ecological processes and the disturbances that influence biodiversity.

Reliability of measurements and accuracy estimates are also critical aspects to consider when dealing with biodiversity data. In the field of remotely sensed data, international collaborative initiatives such as the Calibration and Validation Working Group[10] of CEOS aim to coordinate the quantitative validation of satellite-derived products. The GOFC-GOLD is also engaged in defining and promoting robust validation practices of land cover and land cover change products at the global scale (Strahler et al., 2006, Herold et al., 2008, Stehman et al., 2012, Olofsson et al., 2012, Olofsson et al, 2013), but also at local and national scales like the Reducing Emissions from Deforestation and forest Degradation (REDD+) activities (GOFC-GOLD, 2014). These best practices in satellite data quality assessment and product validation are essential to be adopted when dealing with the integration of satellite-derived products in biodiversity conservation and monitoring.

The development and production of remote sensing-based EBVs for tropical forest environments can benefit from these collaborative efforts of the biodiversity and EO communities to build a comprehensive and global monitoring of the state of and changes to biodiversity. It can also benefit from related activities conducted in the framework of other Environmental Conventions such as those of the UNFCCC in Reducing Emissions from Deforestation and Forest Degradation and in promoting conservation and sustainable management of forests and enhancement of forest carbon stocks (REDD+). Of particular interest is the Warsaw framework of UNFCCC COP 19, which recommended that countries should promote and support social and environmental safeguards for REDD+ (UNFCCC Decision 12/CP.19[11]). Concomitantly, at its 11th Conference of the Parties in Hyderabad in 2012, the CBD has issued a decision that provides information on how safeguards relevant to biodiversity can be implemented by REDD+ participating countries (CBD Decision XI/19[12]). The development of REDD+ environmental safeguards in the context of the conservation of forest biodiversity implies that a synergetic approach to forest biodiversity monitoring and REDD+ activities is a policy necessity. The importance of promoting synergies between biodiversity monitoring and REDD+ activities were already recommended by complementary

[10] http://ceos.org/ourwork/workinggroups/wgcv/

[11] http://unfccc.int/land_use_and_climate_change/redd/items/8180.php

[12] http://www.cbd.int/decision/cop/default.shtml?id=13180

initiatives such as the ZSL-GIZ sourcebook, the GOFC-GOLD REDD sourcebook (GOFC-GOLD, 2014), and the Method and Guidance Document (GFOI, 2013) from the Global Forest Observation Initiative (GFOI[13]) of the Group on Earth Observation. See section 8 for synergies between biodiversity monitoring and REDD+.

The conditions to develop a coherent, standardised and global biodiversity knowledge system are favourable now with the reinforcement of international environmental agreements such as the UNFCCC, UNCCD, CBD and the Ramsar convention. The overarching collaborative initiatives in the collection of biodiversity and conservation data (e.g. GEO-BON), the establishment of international platforms that facilitate the dialogue between scientists and policy makers (e.g. IPBES) show the sense of common purpose in informing and promoting sustainable development practices. This has also been demonstrated by the recent adoption of the United Nations Sustainable Development Goals (SDGs), the active involvement of both conservation and remote sensing communities to determine the essential biodiversity variables that can be monitored systematically and globally, and the commitment of Space Agencies to provide continuity of key observations of the Earth system on the long term and with a free and open data policy. Considering the global importance of tropical forests and the biodiversity they contain, the increasing development pressures on these systems and the increasing opportunities for improved and sustained Earth observation due to continually improving technologies, the *Sourcebook for biodiversity monitoring in tropical forests with remote sensing* comes at the right time to synthesize, in a unique book, the best case practices in the monitoring of tropical forest biodiversity using remote sensing.

1.2 PURPOSE AND SCOPE OF THE SOURCEBOOK

Standardised and harmonised biodiversity data and monitoring methods are required in order to assess how tropical forest biodiversity is evolving at the global scale, and what the drivers of change are. Collaborative efforts towards the development of such harmonised monitoring methods are carried out by national and regional forest agencies, the scientific and research community, and NGOs. These standardisation efforts are supported by the Essential Biodiversity Variables (EBV) concept that is currently developed by GEO-BON, and by Space Agencies and the Earth Observation research community at large. This sourcebook is developed by a wide group of forest researchers and practitioners, to promote the best operational monitoring practices based on scientific literature, and consensus. Since there is a continuous evolution of national and international policy frameworks, of the available datasets, and of the monitoring methods, the *Sourcebook for biodiversity monitoring in tropical forests with remote sensing* is intended to be a living document that will be updated on a regular basis. The focus, however, on the EBV concept, allows for harmonized approaches to monitoring tropical forests that can be independent of the current policy demands. The intention is to share best approaches and find ways to harmonise the existing forest cover and habitat classification systems, and the methods that are used to interpret and process Earth Observation data without being overly prescriptive. The Sourcebook presents also how remote sensing data can be used jointly with in-situ data and knowledge.

To date, GEO BON is continuing to refine and develop the EBVs with the scientific community in relation to the policy drivers such as the biodiversity indicators that are also under development. Among the current list of candidate EBVs[14], the authors of the sourcebook selected five EBVs that are relevant to tropical forests and that can be monitored with remote

[13] http://www.gfoi.org

[14] http://geobon.org/essential-biodiversity-variables/ebv-classes-2/

sensing data: Vegetation phenology, Net primary productivity, Ecosystem extent and fragmentation, Habitat structure, and Disturbance regime. This list of EBVs may change following the on-going international policy discussions and scientific developments.

The Sourcebook is composed of 8 sections with the following content:

- Section 1 is the present introduction. It provides the overall framework in which the *Sourcebook for biodiversity monitoring in tropical forests with remote sensing* is developed.
- Section 2 of the sourcebook presents how the six selected EBVs can inform on the magnitude, velocity and direction of changes, for the essential dimensions of tropical forest biodiversity.
- Section 3 presents how remote sensing can help provide indicators to characterise drivers of biodiversity loss (proximate and underlying).
- Section 4 presents operational methods based on remote sensing data coupled with field observations to produce the six selected EBVs. It presents the available datasets and their adequacy for each EBV, but also the best practices in map accuracy assessments as recommended by the literature.
- Section 5 presents upcoming Earth Observation satellite missions, and some emerging technologies that are relevant to tropical forest monitoring (e.g., unmanned aerial systems, hyperspectral technologies).
- Section 6 presents the value and opportunities of community- and citizen-based approaches to tropical forest biodiversity monitoring through different successful experiences in developing countries. Guidelines for setting up a community or citizen-based project are provided.
- Section 7 reports on existing regional biodiversity networks in the pan-tropical region, and provides guidelines on how to develop new networks.
- Section 8 discusses how synergies between biodiversity monitoring and REDD+ can be made, both at the institutional and technical levels. The assets of coordinated actions are presented. Potential adverse effects discussed in the literature are reported also. Finally, opportunities for synergies in the field of Research and Development are introduced.

The target audience of this sourcebook is composed of project managers and technical level practitioners in national and sub-national governmental forest agencies, academic institutions, NGOs involved in operational activities, or in capacity development initiatives, and large certified logging operators. We assume the audience to have a background on remote sensing and biodiversity observation techniques. By focusing on remote sensing-based methods in relation to the development of EBVs relevant to tropical forests, this sourcebook is complementary to the sourcebook for biodiversity monitoring for REDD+ developed in 2014 by the Zoological Society of London (ZSL) in collaboration with the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) (Latham et al., 2014). The ZSL-GIZ sourcebook considers project managers as the target audience, and aims to define a cross-scale framework to help setting up a monitoring system in the context of REDD+ activities.

1.3 FOREST DEFINITIONS

The general forest types that are being covered in the sourcebook comprise the general tropical rainforest biome:

- **Lowland equatorial evergreen rain forests** are forests that receive high rainfall (more than 2000 mm, annually) throughout the year. These forests occur in a belt around the equator, with the largest areas in the Amazon basin and the Mata Atlantica of South America, Central America, the Congo Basin of Central Africa, Indonesia, Southern India and Sri Lanka, Malaysia, and New Guinea. All lowland rain forests have a comparable forest structure with at least two tree layers, but the Latin American, the African and the Asian forests differ in characteristic tree species and species richness. The Latin American forests are, due to their long isolation, the most species rich with about 93,500 plant species, followed by the Asian rainforests with about 61,700 plant species and African rainforests with about 20,000 plants species. The African forests are much dryer than the other rain forests. The Asian forests are in general characterised by Dipterocarp species. The rain forests of New Guinea and Australia have Asian related species, but are different with many Marsipulami species. Finally, the Madagascar rain forests are different in composition from all other rain forests (Primark and Corlett, 2005).
- **Moist deciduous and semi-evergreen seasonal forests** are tropical forests that receive overall some high rainfall with a warm summer wet season and a cooler winter dry season. Their trees drop some or all of their leaves during the winter dry season. These forests are found in parts of South America, in Central America and around the Caribbean, in coastal West Africa, in parts of the Indian subcontinent such as the Ghats (Ramesh and Gurrukal, 2007), and across much of Indochina.
- **Montane rain forests and cloud forests**, are found in the gradients between the lowland rainforests and the higher mountain areas (Bruijnzeel et al., 2010). The trees in these forests do not reach the height of those in the lowland rain forests, but are very rich in species. Depending on latitude, the lower limit of montane rainforests is generally between 400m and 2500m while the upper limit is about 3500m. These forests are found in Central and South America from northern Argentina to middle range mountains along the Andes, in the Caribbean islands, in Central Africa east and west of the rain forest, and the largest extension is found in southern Asia, Malaysia, Indonesia and New Guiney.
- **Flooded forests**, Philips et al. (1994) recognized several types of flooded forests that can be distinguished in permanently waterlogged forests, swamp forests, seasonally flooded swamp forests and floodplain forests that can be frequently or rarely flooded. The wetland forests are often very open and dynamic while the floodplain forests are more narrow, dense and related to river dynamics.
-

Next to these there are

- **Dry forests** (steppe forest, chaco, cerrado, Boswellia forests, miombo). The tropical dry forest biome is found around the tropical rain forest biome. In the Americas it is found in large parts of Mexico, in Latin America east of the Amazon forest, in the Cerrado and Caatinga and in the south in the Chaco. In Africa, dry forests are found in the Sahel zone from Mauretania to Ethiopia and Somalia, along the east coast in the zone of the Great Rift Valley (Boswellia forests and plantations), in southern Africa from Angola and Namibia to Mozambique (Miombo) (Campbell, 1996) and remnants on the west coast of Madagascar. In Asia its greatest distribution is in India, Myanmar and Thailand. Also in northern Australia there are extensive dry tropical forests

dominated by Acacia and Cycas species. The climate is here more extreme than in the rain forest biome. Especially the precipitation has an extreme distribution between very wet and very dry seasons. In all these forests fire is a characteristic feature and most trees have adaptations to regular fires. Many of these forests generally occur on geologically old, nutrient-poor soils. Cerrado forests have the same kind of tree species diversity as the rain forests and are rich in fruits (Bridgewater, 2004). The shrub layer is variable in density and composition. The ground cover varies from a dense coarse grass growth to a sparse cover of herbs and small grasses. They transcend to shrub and steppe grasslands in the dryer regions.

- **Mangrove forest**: Mangrove forests occur in all tropical and subtropical tidal areas of the world. They are extensive in Asia where they occur from Taiwan to Sri Lanka including all the ASEAN countries, Bangladesh, India and Pakistan. There are extensive mangroves on the shores of the Arabian peninsula and along the Red Sea, In Africa they are found on the Kenyan and Madagascar coasts and along the coast from Mauretania to Cameroon. In the Americas they occur in Florida and along the west coast of Mexico in the north, in the whole of the Caribbean, along the Brazilian northern coast and in the Pacific coast of Colombia. In Australian region they occur in New Guinea on the eastern and northern coast as well as on many of the islands in the Pacific Ocean. Following the Indian Ocean tsunami of 2004, the protective role of mangroves from natural disasters have become more widely realized (Giri et al., 2015). Mangroves are vulnerable, however, as they are linear vegetation zones between a dynamic ocean and land. In the last decades there is a yearly loss of about 2% of the Mangrove forests (Valiela et al., 2001).

Monitoring changes in these different tropical forest types requires different approaches as these forest types differ in characteristics such as height, density, greenness, patchiness, shape, species diversity, and spectral responses. All these aspects should be taken into account when developing methods to observe status and monitor changes in these forests. As an example, while patchiness can be considered as an inherent characteristic of dry forests, it can be considered as an expression of negative impact when it occurs in mangrove forests. Similarly, changes in extensive rain forests will be expressed in different ways from changes in cloud forests. The monitoring methods described in the source book will be differentiated depending on the different tropical forest types described above.

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2 MONITORING KEY EBVS WITH REMOTE SENSING

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2.1 INTRODUCTION – ESSENTIAL BIODIVERSITY VARIABLES

The Tropics, are estimated to contain half of the world's species while undergoing rapid and accelerating rates of development resulting in widespread documented declines on species population abundances (e.g. the tropical Living Planet Index shows a decline of 56 percent between 1970 and 2010; WWF 2014). Although the assumption of extensive losses across tropical areas has been widely cited, recent studies indicate that biodiversity change is much more complex (Dornelas et al. 2014; Vellend et al. 2013), with positive trends in some regions, driven by interacting and cumulative drivers making it difficult to accurately forecast and therefore respond to biodiversity change at the local scale (Beaudrot et al. 2016). Considering the complex nature of biodiversity change and that biodiversity declines are most often best addressed through local conservation actions, it is imperative that effective, interoperable and scalable monitoring systems are implemented that can track biodiversity change to inform local development decisions to global assessments.

In virtually all regions of the planet, biodiversity information is spatially and temporally limited, is not integrated due to widely varying methodologies and standards, and most existing observation systems are poorly funded and not well connected to policy needs. Furthermore, most funding mechanisms for biodiversity observation and research are not easily accessible to long-term monitoring projects, instead favouring projects that focus on producing new knowledge via experimentation. As a result, many observation systems do not make full use of existing data and knowledge, preferring instead to develop new monitoring efforts rather than to first build upon and advance current efforts. This limits our ability to make informed conservation decisions and, ironically, further undermines support for investing in much-needed long term biodiversity observation programs.

However, the answer is not simply to produce more biodiversity data. More data alone will not lead to an improved understanding of biodiversity change that informs effective policy, conservation actions and forecasting. Existing efforts at the global and regional scale to integrate biodiversity data are often hampered by differences in methods, schemas, standards and protocols and in many cases, existing data is not easily accessed or translated. Considering the limited resources available for biodiversity observation and research, it is critical that monitoring efforts are not only integrated but also strategic in regards to the intended target. With all of this in mind, a harmonized framework for biodiversity observation and forecasting systems is required that facilitates integration, outputs and communication. In response, the Group on Earth Observations Biodiversity Observation Network (GEO BON) is developing the Essential Biodiversity Variables (Pereira et al. 2013).

The EBVs were inspired by the Essential Climate Variables (ECVs) which guide the implementation of the Global Climate Observing System in a structured and coordinated manner. Analogous to the ECVs, the EBVs identify the most important variables for capturing major dimensions of biodiversity change, complementary to one another and to other environmental change observation initiatives. EBVs can be used to help structure the relevant

observation and information systems but they also provide an intermediate layer between primary observations and indicators, thus isolating indicators from changes in observation methods and technology (see Figure 2.1.1).

Figure 2.1.1 EBV relationship to high level indicators

2.1.1 What are Essential Biodiversity Variables?

A key question that GEO BON addresses is how is biodiversity changing, i.e. what are the speed and direction (i.e. increasing or decreasing) of change across multiple spatial scales for the key dimensions of biodiversity? These quantities, based on *in-situ* or remotely sensed Earth observation measurements (EO), once harmonized, will allow us to work seamlessly with other disciplines. Once developed, EBVs have the potential to be integrated with other types of data to help us identify, evaluate and study the causal mechanisms of change in one or more dimensions of biodiversity, which in turn are necessary to, report, predict and manage biodiversity change from local to global scales.

However, this definition still leaves us with two problems: What do we consider as the key dimensions of biodiversity? And what are the spatio-temporal scales at which it makes sense to measure change at each of these dimensions? These are not simple questions and the answers may vary depending on the objectives and the audience. To conceptualize the key dimensions of biodiversity and the most appropriate spatial and temporal scales, we adopted a series of guiding concepts that allow us to refine, frame and direct the idea of Essential Biodiversity Variables. In general, it is well accepted that the key dimensions of biodiversity can be grouped into four flexible sometimes overlapping categories: genetic, taxonomic, functional, and structural diversity. These key dimensions of biodiversity can be measured at different spatial scales (e.g., global, regional and local scale), which can also be defined depending on what is the most dominant process (e.g., extinctions, speciation, migration, colonization, inter- and intra-specific species interactions) as well as consider different combinations of biological organization (e.g., genes, species, populations, ecosystems). These equally important categories leave us with a multidimensional matrix where each component and/or resulting combination has the potential to become an EBV.

Also, very important, is that EBVs should be independent from attribution. In other words, the reasons behind the change should not be part of the EBV metric per-se. For example, an EBV focused on trends in Net Primary Productivity should not also try to explain the causes behind the change.

With this framework, GEO BON, as a result of a consensus process among experts, proposes a list of EBV classes and EBV candidates (http://geobon.org/essential-biodiversity-variables/ebv-classes-2/) to provide a reference for the minimum set of essential measurements that can help capture the major dimensions of biodiversity change.

EBVs should align well with the general needs of policy and decision-making offering robust computations that can help populate the indicators to assess progress towards the 2020 Aichi Targets and contribute to other initiatives such as the IPBES Regional Assessments. However, policy can change over short periods of time and indicators that are tailored too precisely to meet the demands of policy can quickly become irrelevant. One advantage of EBVs is the distance in the degree of abstraction that separates them from indicators that shield them

from changes in policy, making them valuable over longer periods of time and flexible enough to populate a multitude of potential indicators and decision support tools operating at various scales (e.g. national and local scale indicators for decision-making, biodiversity scenario for supporting policy and management decisions). With this in mind, the EBV concept can be applied to structuring the approach for monitoring tropical biodiversity using remote sensing techniques.

2.1.2 Tracking EBVs Using Remote Sensing

The Strategic Plan for Biodiversity, 2011-2020 (https://www.cbd.int/sp/) outlines a series of targets for reducing the loss of biodiversity and addressing the underlying causes driving such loss. Whilst efforts are underway to better inform these targets through indicators, inadequacy of data limits our ability to confidently report on progress (or lack thereof). In some cases, remote sensing offers an opportunity to both achieve long-term global and continental scale coverage and indicate patterns in biodiversity loss, thereby facilitating effective conservation actions (Skidmore et al. 2015). Continual and rapid advances in sensor technology offer growing opportunities (e.g. monitoring individual tree species or animals using high spatial resolution imagery, or imaging spectroscopy for mapping plant function and structural attributes) for tracking biodiversity change, though *in-situ* (ground) data is needed to calibrate and validate the models and data products. However, a consistent approach is required to define and translate remotely sensed observation data into metrics (e.g. EBVs) relevant to biodiversity monitoring. For example, the definition used for a forest has direct implications in regard to how one measures and quantifies forest degradation (Skidmore et al. 2015).

EBV Class	Candidate RS-EBV
Species populations	Species distribution*
Species populations	Species abundance*
Species traits	Phenology (e.g., leaf-on and leaf-off dates; peak season)
Species traits	Plant traits (e.g., specific leaf area, leaf nitrogen content)
Community composition	Taxonomic diversity
Community composition	Functional diversity
Ecosystem function	Productivity (e.g., NPP, LAI, FAPAR)
Ecosystem function	Disturbance regime (e.g., fire and inundation)
Ecosystem structure	Habitat structure (e.g., height, crown cover and density)
Ecosystem structure	Ecosystem extent and fragmentation
Ecosystem structure	Ecosystem composition by functional type

Table 2.1.2.1 Candidate EBVs that can be measured by remote sensing. * Spaceborne RS is increasingly used to map the distribution and abundance of particular species

In this context, the following sections will introduce relevant EBVs for tracking biodiversity change in tropical forests and will explore how remote sensing techniques can be harnessed

to support the development of these EBVs. From a larger list of EBVs that can capture biodiversity change using remote sensing techniques (see Table 2.1.2.1), the following sections focus on five examples: Vegetation Phenology, Net Primary Productivity, Ecosystem Extent and Fragmentation, Habitat Structure and Disturbance Regime. Some examples of remote sensing derived EBVs that can directly track forest structure and function include leaf area index (LAI) important for estimating growth potential; foliar N and chlorophyll has a significant role in ecosystem processes and functional aspects of biodiversity as a primary regulator for many leaf physiological processes; species occurrence is an important EBV for wildlife habitat assessment and effective natural resource management; primary productivity is the synthesis of plant organic compounds from atmospheric CO2 and can be measured using remote sensing; and habitat fragmentation is the process by which continuous broad areas of tropical forest is reduced to discontinuous patches and can also be estimated and measured using a series of satellite images over time. More methodological and technical information, using case study examples, is found in Section 4 of the Sourcebook.

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2.2 VEGETATION PHENOLOGY

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2.2.1 Concepts of vegetation phenology

The International Biological Program defined phenology as "the study of the timing of recurrent biological events, the causes of their timing with regard to biotic and abiotic forces, and the interrelation among phases of the same or different species" (Lieth, 1974). Vegetation phenology refers to the periodic plant life cycle events controlled by biotic/abiotic factors (e.g., plant species, climate, hydrology, soil, etc.) (Rathcke and Lacey, 1985). Traditional definitions of vegetation phenometrics are related to the biological phenomena of specific organisms. These phenometrics usually refer to specific life cycle events such as budbreak, flowering, or leaf senescence using in-situ observations of individual plants or species. Comparing to the distinct phenophase transition of specific organisms from ground level observation, the process of observing land surface phenology (LSP) using remote sensing satellites is fundamentally different. There rarely have distinct phenophase transitions for satellite-derived phenometrics, such as the start-of-season (SOS) and end-of-season (EOS) which are two common phenometrics derived from remote sensing time-series data (Schwartz, 2013).

Many abiotic (i.e., environmental factors) and biotic (e.g., plant species, age) factors influence the vegetation phenology. Phenology and its trends vary by geographic locations (i.e., latitude, longitude and altitude), climatic zones, and vegetation type. Phenology cycles and its variations may primarily be influenced by the potentially interacting effects of multiple environmental factors including sunlight/radiation, temperature and precipitation. Because vegetation phenology are very sensitive to small variations in climate, especially to temperature, phenological records can be a useful proxy and tools for reflecting historical climate changes; therefore, vegetation phenology becomes one of the most important indices for climate change studies (Menzel et al. 2006a; Schwartze et al. 2006; Yu et al., 2010; Richardson et al., 2013; Yang et al., 2015). Shifts in vegetation phenology will also trigger the changes in ecosystem composition (e.g., biodiversity), structure (e.g., spatiotemporal pattern) and function (e.g., carbon uptake and net primary productivity), and thus alter the water, heat and carbon exchange among soil, vegetation and atmosphere systems (Piao et al., 2008; Richardson et al., 2010; Dragoni et al., 2011), which in turn affect regional and global climate system and augment climate change (Peñuelas et al., 2009). Therefore, vegetation phenology also becomes a critical parameter for modelling land surface processes and vegetation dynamics (Cleland et al., 2007; Chen and Wang, 2009).

2.2.2 Phenometrics

To accurately and effectively reflect the phenological changes, many satellite-derived phenometrics (phenological variables) have been developed to quantify and separate different phenology stages (i.e., phenophases) from satellite-derived vegetation index (VI) time-series data (Figure 2.2.2.1; Table 2.2.2.1). Generally, satellite-derived phenometrics cover a suite of phenopahses including SOS and EOS, length of season, seasonal amplitude, and time-integrated series in terms of various VIs. Phenometrics can be derived from satellite data in several ways. Some researchers use complex mathematical models. Others apply threshold-based approaches that use either relative or pre-defined (global) reference values at which vegetative activity is assumed to begin.

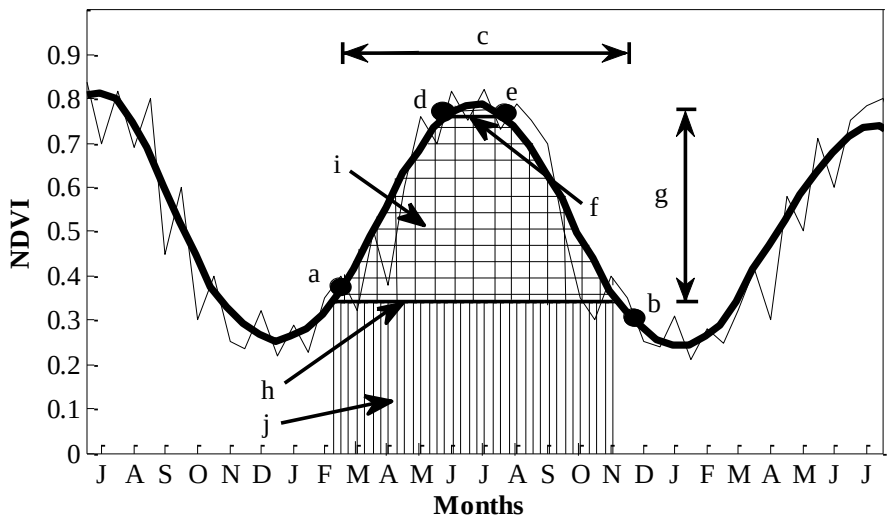


Figure 2.2.2.1 Example of phenometrics extracted from a seasonal normalized difference vegetation index (NDVI) curve. Redraw of (Jönsson & Eklundh, 2004; Wessels et al., 2011). (a) Start of season (SOS), (b) End of season (EOS), (c) Length of season (LENGTH), (d) Start of seasonal peak (SOP), (e) End of seasonal peak (EOP), (f) Top level (TOP), (g) Seasonal amplitude (AMP), (h) Base level (BASE) (i) Small seasonal integral (SI), (j) Large seasonal integral (LI). See Table 1 for details.

Table 2.2.2.1 Definitions of phenometrics shown in Figure 1, after (Jönsson & Eklundh, 2004; Wessels et al., 2011).

Phenology metrics	Productivity metrics
a. SOS –increase to 20% of seasonal amplitude as measured from the left minima of curve	f. Top level (TOP) – average between NDVI values of SOP and EOP
b. EOS – decrease to 20% of seasonal amplitude as measured from the right minima of curve	g. Seasonal amplitude (AMP) – difference between TOP and BASE
c. LENGTH – length of time from SOS to EOS	h. Base level (BASE) – average between NDVI values of SOS and EOS
d. SOP – increase to 90% of seasonal amplitude as measured from the left minima of curve	i. Small seasonal integral (SI) – integral of growing season calculated between the fitted function and the BASE
e. EOP – decrease to 90% of seasonal amplitude as measured from the right minima of curve	j. Large seasonal integral (LI) – integral of growing season calculated between the fitted function and the zero level

2.2.3 Methods for monitoring vegetation phenology

To date, vegetation phenology is observed by three typical approaches: in-situ observation, remote sensing monitoring and model simulation.

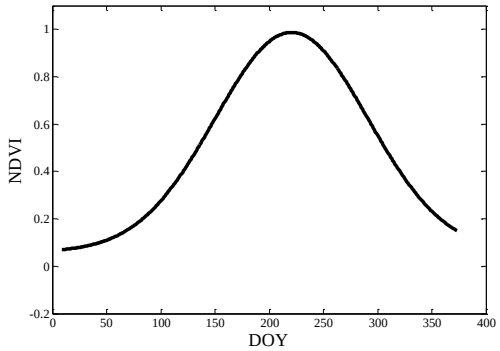
In-situ observation is a traditional approach to monitor vegetation phenology. It refers to the observations of individual plants or species at fixed positions; therefore, in-situ observation mainly reflects the growth rhythm on individual level. Since it is easily operated and can get precise phenometrics on single plant or in small region, in-situ observation is still the most popular method for studies on the seasonal community structure changes (PhenoAlp Team, 2010). However, in-situ observations can hardly reflect the spatial distribution of vegetation phenology in large scale (Menzel et al., 2006b) due to the uneven distribution of stations (Wei et al., 2003), the deficiency of widely distributed data (Schwartz et al., 2006) and the limitation of spatial coverage. In recent years, phenology observation based on flux tower and digital camera has been developed progressively (Zhu et al., 2012; Ahrends et al., 2009; Richardson et al., 2007), and has built an bridge between in-situ observation and remote sensing monitoring. See section 4.2 for more information on in-situ data.

Model simulation method can explore the temporal and spatial variation of vegetation phenology by building phenology model at individual and population level based on the physiological mechanisms of plant growth cycle. Phenology model quantitatively expounds the impacts of environmental factors (e.g., climate, hydrology, soil, etc.) on plant growth (Migliavacca et al., 2012), simulates vegetation phenology using these environmental factors, and further infers physiological mechanism of plants growth and environmental thresholds (Chuine et al., 2013; Chuine et al., 2004). Currently, the most often used phenology models can be divided into two categories: statistical and mechanism models. Statistical model is based on the statistical relation between phenophase and environmental factors; while mechanism model analyzes the causal relationship between biological process and environment factors using mathematical formulas and discovers the occurrence conditions of phenophase. Till now, all the available phenology models are built based on the ground-observed data and are rarely based on the satellite-derived phenometrics. Besides, most of these models simulate the phenology at plant species scale instead of community or ecosystem scales. See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

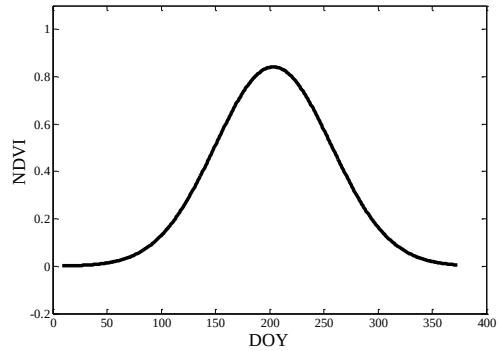
Using remote sensing to monitor vegetation phenology is mainly based on the sensor-recorded spectral information of object according to the principle that everything in nature

has its unique characteristic of emitted, reflected and absorbed electromagnetic radiation. Remote sensing method uses data gathered by satellite sensors that measure wavelengths of light absorbed and reflected by green plants. Certain pigments in plant leaf strongly absorb wavelengths of visible (red) light. The leaves themselves strongly reflect wavelengths of near-infrared light, which is invisible to human eyes. As a plant canopy changes from early spring growth to late-season maturity and senescence, these reflectance properties also change. Due to its ability to record large-scale information, satellite remote sensing can effectively represent the vegetation phenological patterns at regional, continental, even global scale (Reed and Brown, 2005). The satellite-derived phenometrics reflect the vegetation growing and seasonal changes of communities or ecosystems at pixel level, which is very different from ground-observed phenological events at single plant or species level (Dragoni et al., 2011; Chen and Wang, 2009). There are a large number of methods to identify vegetation phenology from satellite data, but none of them is applicable to all types of vegetation for all study regions. Each of them has its own advantages and disadvantages, and specifically aims to a particular condition (Chen and Wang, 2009; White et al., 2009). Therefore, the selection of remote sensing methods should be determined based on the specific study area, varied study periods, spatial resolution, satellite platform and atmospheric corrections, compositing schemes and vegetation types (White et al., 2009). In addition, the parameterization and localization of the selected method should be accompanied with ground-observed phenological data.

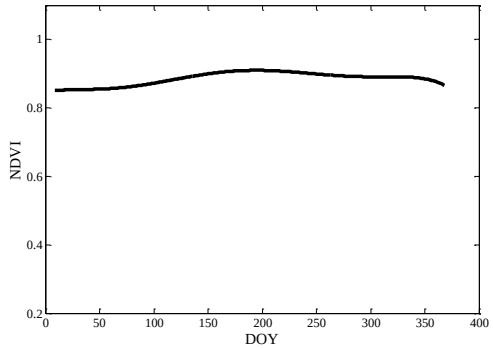
Based on remote sensing data properties, several vegetation indices (VIs) were created to quantify phenophases during past several decades, such as the NDVI, the ratio vegetation index (RVI), the enhanced vegetation index (EVI), etc. Among these indices, NDVI is one of the most widely used VIs. NDVI values range from +1.0 to -1.0. Areas of water, bare ground, or snow generally have very low NDVI values (usually < 0.1). Sparsely vegetated areas, such as woodlands, open-canopy shrublands and grasslands, generally have moderate NDVI values (0.1 - 0.5). High NDVI values (> 0.5) often imply denser vegetated areas, such as closed-canopy forests, shrublands, cropland and grassland. Figure 2.2.3.1 demonstrates the filtered NDVI curves of typical vegetation types. Major differences across these vegetation types in the base level, top level (average between left and right 90% of curve), seasonal amplitude and width can be identified. Specifically, evergreen broadleaf forests had the largest seasonal width with smaller variations within a year; crops which ripe once a year, deciduous broadleaf forests, grasses, mixed forests and shrubs generally have one growing season within one year; crops can ripe two or three times a year in some regions and thus have two or three growth cycles within one year. Satellite-based methods can take advantage of the characteristics of these curves of VI time series and quantify the vegetation phenometrics.



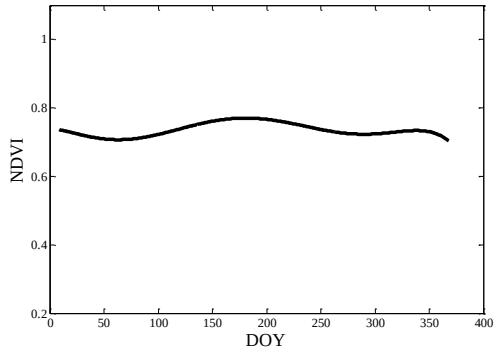
(a) Deciduous broadleaf forests



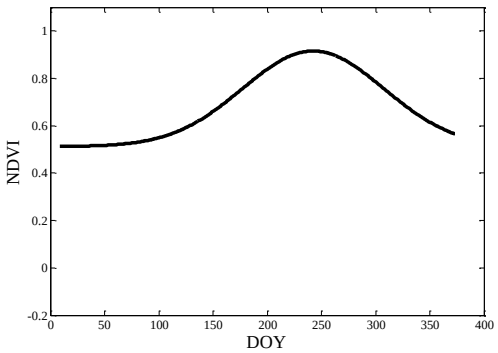
(b) Deciduous coniferous forests



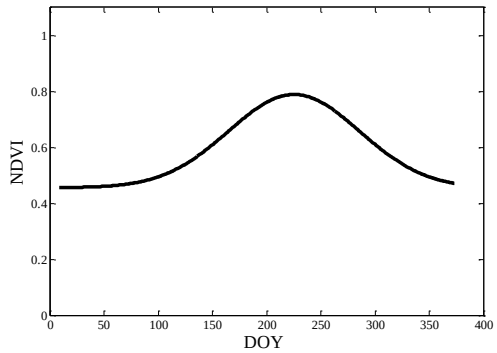
(c) Evergreen broadleaf forests (no or small seasonal variations)



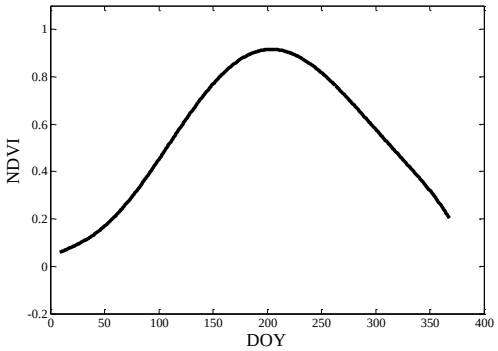
(c) Evergreen coniferous forests (no or small seasonal variations)



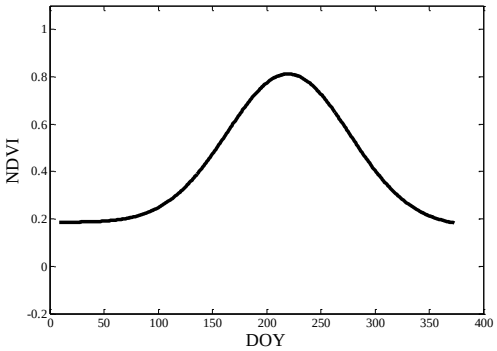
(e) Tropical dry evergreen broadleaf forests
(dry-wet season)



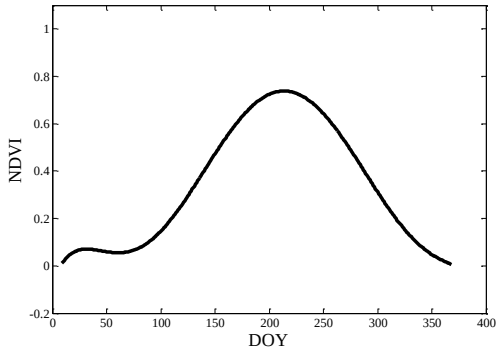
(f) Tropical dry evergreen coniferous forests (dry-wet season)



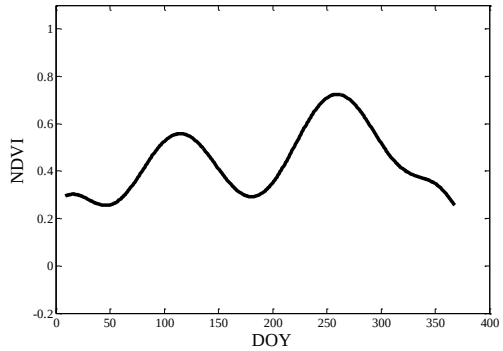
(g) Shrubs



(h) Grassland



(i) Crops (ripe once a year)



(j) Crops (ripe twice a year)

Figure 2.2.3.1 Phenological curves as represented by NDVI time series of typical vegetation types

The SOS and EOS are two most common phenometrics derived from remote sensing time-series data. The definition of SOS/EOS depends on the specific phenology extraction method (Table 2.2.3.1). For example, for the double logistic fitting method (Zhang et al., 2003), SOS is defined as the Julian day of year (DOY) when it reaches the maximum rate of change in curvature of the fitted logistic function based on the growth part of the satellite-derived VI annual time-series curve, while for the global threshold method (Myneni et al., 1997), SOS is defined as the DOY when it reaches a specific threshold (e.g., 20%, 30% and 50%) of the seasonal amplitude in the growth part of the annual VI time-series curve.

Table 2.2.3.1 Definitions of SOS/EOS for different phenology retrieving methods

Method		Definition of SOS/EOS		References
Threshold method	Global threshold method	SOS/EOS is defined as the DOY when NDVI curve crosses the threshold in an upward/downward phase.	A fixed threshold	Myneni et al., 1997; Lloyd, 1990
	Local threshold method		Threshold is determined by the shape of NDVI curve	Yu et al., 2010; White et al., 1997
Delayed moving average method		SOS is defined as the DOY when the NDVI curve crosses the delayed/advanced moving average time series in the upward phase		White et al., 2009; Reed et al., 1994
Function fitting method	HANTS-FFT	SOS is defined as the DOY with maximum increase on Fourier approximation of NDVI		White et al., 2009
	Asymmetric Gaussian function	SOS/EOS is defined as the DOY when the asymmetric Gaussian approximation of NDVI curve crosses the local threshold in an upward/downward phase		Jönsson and Eklundh, 2002
	Double Gaussian function	SOS/EOS is defined as the DOY when the Double Gaussian approximation of NDVI curve crosses the local threshold in an upward/downward phase		Fan et al., 2014

	Sixth-degree polynomial function	SOS/EOS is defined as the DOY when the sixth-degree polynomial approximation of NDVI curve crosses the local threshold in an upward/downward phase	Piao et al., 2006
	Double Logistic function	SOS/EOS is defined as the DOY when the double logistic approximation of NDVI curve crosses the local threshold in an upward/downward phase	Beck et al., 2006; Fisher et al., 2007
	Piecewise Logistic function	SOS/EOS is defined as the DOY when the maximum rate of change in curvature of the fitted logistic function based on the growth/senescence part of the satellite-derived VI annual time-series curve is gotten	Zhang et al., 2003

2.2.4 Opportunities for using remote sensing to monitor vegetation phenology

Existing remote sensing platforms

At present, there exist many satellite sensors (e.g., NOAA/AVHRR, SPOT-VGT, MODIS, MERIS, etc.) to observe vegetation characteristics and retrieve VIs (e.g., NDVI and EVI) time series at multiple temporal and spatial scales (Table 2.2.4.1). The original satellite images for many sensors are daily collected, but the VI products are usually composites of the best pixels from consecutive days and turn to 10-day/15-day/monthly VI products. The longest available VI time series data is NOAA/AVHRR GIMMS NDVI3g data (Jiang et al., 2013), which started from July 1981 to present. However, it shows a low spatial resolution (8 km) and thus has different vegetation types in one pixel. Therefore, it can represent the phenological changes on ecosystem level but difficult to interpret the physiological mechanisms of phenology changes. VI time series data derived from MODIS/MERIS have better spatial resolution of 250 m/300 m and are more suitable for monitoring phenological changes at population or community level, but they have relatively short time sequences, starting from February 2000 and May 2003, respectively. Besides the above datasets with moderate or low spatial resolutions, Landsat TM/ETM+/OLI has begun to be used in vegetation phenology monitoring due to its long time span and high spatial resolution (Melaas et al., 2013). However, these optical sensors are easily affected by the weather condition, such as cloud or rain, and generate low-quality data. Microwave remote sensing can overcome this shortcoming since it is not sensitive to bad weather, as Jones et al. (2011, 2012) successfully derived vegetation phenology using AMSR-E passive microwave data. See also sections 4.1 and 5.1 for complentary information on available and upcoming sensors.

Table 2.2.4.1 Overview of existing and potential remote sensing platforms for retrieving vegetation phenology

EO data type		Sensor	Method	Operational level	References
Optical	Hyper-spectral	Hyperion		Potential research value	
		Hyperspectral Imaging Radiometer (HIS)		Potential research value	
	VHSR	Landsat TM/ ETM+	Logistic function fitting	Study on the leaf sprout and senescence of forests in southern New England during 1984-2002	Fisher et al., 2006
		Landsat TM/ETM+	Logistic function fitting	Study on the SOS and EOS of deciduous broadleaf forest in southern New England during 1982-2011	Melaas et al., 2013
		Landsat TM	Logistic function fitting	Study on the vegetation phenology in Queensland, Australia during 2003-2008	Bhandari et al., 2012
	Moderate optical	MODIS	Double Logistic function fitting; Asymmetric Gaussian function fitting; Fourier analysis	Study on the vegetation dynamic changes (including phenology) in northern Scandinavia during 2000-2004	Beck et al., 2006
		MODIS	Logistic function fitting	Study on the SOS and EOS of vegetation in New	Zhang et al., 2003

				England during 2000-2001	
		MODIS	Harmonic analysis and threshold method	Study on the crop phenology in Japan in 2002	Sakamoto et al., 2005
		ENVISAT MERIS	Asymmetric Gaussian function fitting	Study on the growing season length of vegetation in southern England during 2003-2007	Boyda et al., 2011
		ENVISAT MERIS	Fourier analysis; Double Logistic function fitting; asymmetric Gaussian function fitting, Whittaker smoother	Study on the SOS of vegetation in Indian subcontinent during 2004-2006	Atkinson et al., 2012
	Moderate or coarse optical	SPOT-VGT	Dynamic threshold method	Study on the SOS of vegetation and its changing trend in northern Eurasia during 1982-2004	Delbart et al., 2006
		NOAA/AVHRR GIMMS	Threshold method based on the maximum NDVI ratio	Study on the SOS of temperate vegetation and its changing trend in northern hemisphere during 1982-2008	Jeong et al., 2011
		NOAA/AVHRR GIMMS	Threshold method based on the maximum NDVI ratio	Study on the SOS and EOS of temperate vegetation and their changing trend in China during 1982-1999	Piao et al., 2006
		NOAA/AVHRR GIMMS	Threshold method	Study on the phenometrics of vegetation in	White and Nemani, 2006

				eastern Canada during 1982-2003	
Synthetic Aperture RADAR	C-band	RADARSAT-2	BBCH-scale (*Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie*)	Study on the rice phenology in Serbia and southern Spain in 2009 and 2010	(Lopez-Sanchez et al., 2014)
	X-band	SAR Polarimetry	BCH-scale	Study on the he rice phenology in Serbia and southern Spain in 2009	(Lopez-Sanchez et al., 2012)
		AMSR-E	vegetation optical depth (VOD) parameter	Study on the SOS of vegetation in North America during 2004-2007	(Jones et al., 2012)

Existing methods for retrieving phenometrics

The satellite-derived VI time series can reflect the rhythm of plants growth, which makes it possible to identify the phenometrics using remote sensing data. Figure 2.2.4.1 demonstrates the progress of identifying the SOS for different vegetation types with two general processes: reconstructing high-quality VI time-series data through noise removal (e.g., using a sixth-degree polynomial function or a Double Gaussian function to fit the original VI time series) and computing the phenometrics from the reconstructed data (e.g., using a local threshold to retrieve SOS/EOS). More specifically, phenometrics are estimated with the following steps: firstly, obtaining points in the NDVI curve when the date fits the green-up and defoliation periods according to the in-situ observations; secondly, recognizing the characteristics of SOS and EOS by analyzing the NDVI value and position (timing) in the curve of selected points, such as the points with the largest changing rate in curvature; lastly, using the above characteristics to identify the SOS and EOS for the other pixels for the same vegetation type. The right panel in Figure 2.2.4.1 showed the processes for distinguishing the SOS of tropical dry forests from dry season forests, where the SOS represents the start of flourishing season rather than growing season.

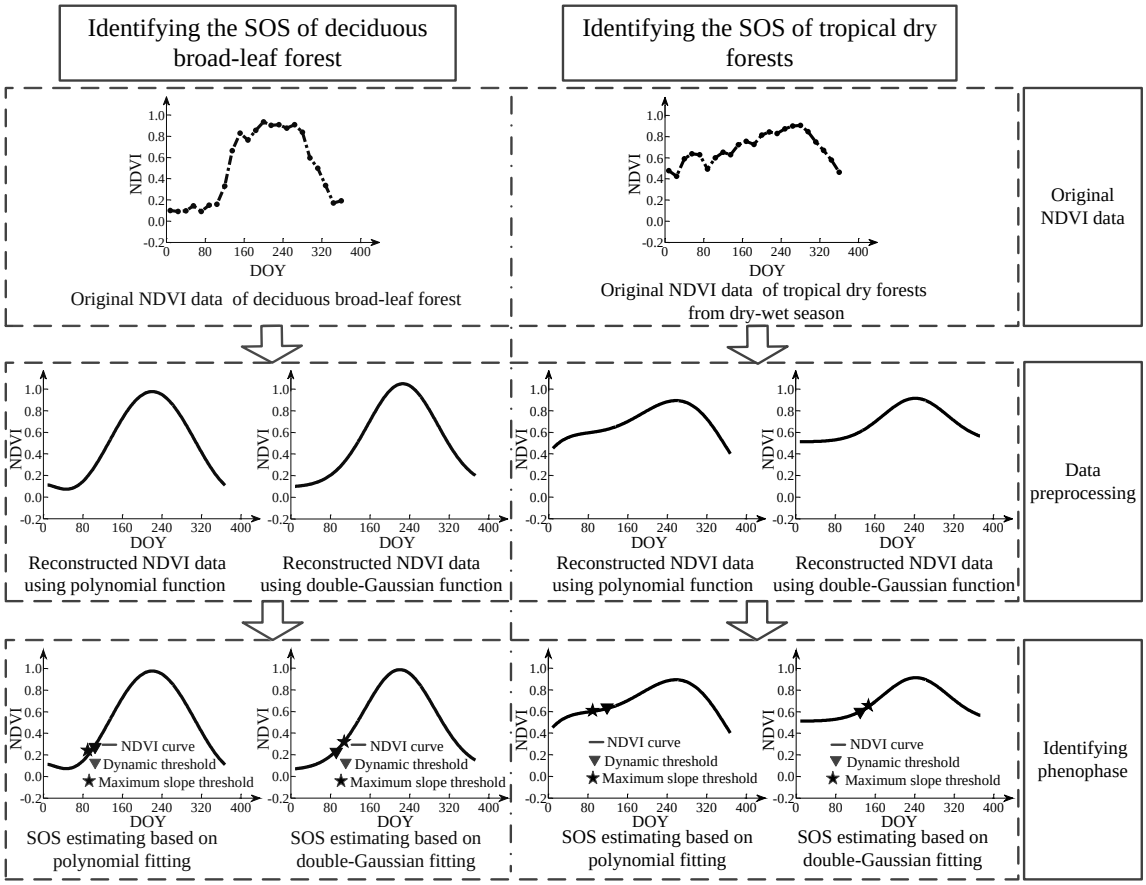


Figure 2.2.4.1 Schematic of retrieving phenometrics from remote sensing data

At present, a large number of methods have been developed to derive vegetation phenology using different VI time-series data. These methods can be summarized as threshold method, moving average method and function fitting method (Table 2.2.3.1).

Threshold method determines the SOS and EOS by setting a threshold value in the NDVI curve. This method is further divided into absolute threshold method (also called global threshold method) (Lloyd, 1990) and dynamic threshold method (also called local threshold method) (Jönsson and Eklundh, 2002). Global threshold uses a fixed threshold value regardless of its changes with time and region. For example, Lloyd (1990) used NOAA/AVHRR NDVI datasets and set 0.099 as the global threshold of SOS; Fischer (1994) derived the SOS and EOS using a pre-determined threshold as well. Global threshold method is effective in determining SOS and EOS at local scale, but not suitable for the regions with various soil and land cover types, while dynamic threshold method can overcome this limitation. The greenness of the vegetation is indexed by transforming the NDVI data into a NDVI ratio (range between 0 and 1) between the NDVI value at a given time and the minimum NDVI value in a certain time period, normalized by the total range of NDVI values during this period. For example, White et al. (2006) adopted the dynamic threshold method to identify the land surface phenology in the eastern Canada using the AVHRR NDVI data from 1982 to 2003 and predicted the short-term phenology changes. Delbart et al. (2006) used the dynamic threshold method along with the SPOT-VGT and NOAA/AVHRR NDVI data to study on the dates of vegetation green-up in northern Eurasia during 1982-2004.

Moving average method determines the vegetation phenometrics based on the intersections between the original VI curve and the moving averaged curve. Reed et al. (1994) first proposed the delayed moving average (DMA) method and extracted the phenometrics from

AVHRR NDVI datasets, such as the green-up, length of season and senescence of crops, forests and grassland. The results proved the strong consistency between derived phenometrics and in-situ observations for various vegetation types. Duchemin et al. (1999) used the moving average method to monitor the germination and defoliation period of temperate deciduous forest. Schwartz et al. (2002) adopted three methods (i.e., DMA method, seasonal NDVI mid-point method and surface phenology simulation method) to study the SOS of deciduous forests and mixed forests in the mainland of the United States during 1990-1993 and 1995-1999, respectively, and found that the DMA method performed better than the other two. The DMA method can help to obtain reliable and stable results from NDVI time series for the regions with one growing season in a year, but fails in those with multiple growing seasons in a year or strongly influenced by rainfall. Several potential risks should be noticed when using the DMA method. The first green-up stage may not be recognized for the region with multiple growing seasons if the time interval is set too short (Hudson and Keatley, 2010); moreover, the detected green-up dates might be advanced if the study region is influenced by snow melting in the spring (Wu et al., 2008); finally, this method is sensitive to the setting of the window size.

Function fitting method obtains the vegetation phenology based on the fitted VI time-series curve with S-shape functions, such as the polynomial function, logistic function, Fourier function and Gaussian function. Taking the logistic function as an example, NDVI time series is firstly fitted using the logistic function, and then the extreme curvature variation of the fitted curve can be defined as the phenophase transition (Zhang et al., 2003). Zhang et al. (2003) firstly proposed the logistic function fitting method and applied it to extract the date of green-up, maturation, senescence and dormancy of vegetation around the central New England. The logistic function fitting method reduces human interference since it needs no predefined threshold and data smoothing, but increases the risks of failure in fitting since the NDVI curves of different vegetation types are not all ideal regular S-curve, which leads to low detection precision (Cui, 2012). Harmonic analysis method uses Discrete Fourier Transform to approximate the NDVI time series by summation of harmonically periodic functions with various frequencies, and then extracts the land surface vegetation phenological information based on the harmonic characteristics (Zhang et al., 2004). Lin and Mo (2006) reconstructed NDVI timer series using the improved Fourier method and NOAA/AVHRR NDVI data in 1992, and utilized harmonic analysis to extract the phenometrics of various vegetation types in southern Hebei Province. Harmonic analysis has been proved to eliminate the noises in NDVI time series effectively, but the reconstructed curve is over-smoothed and deviates from the original curve, which will end in misrecognition of phenological characteristics (Liang et al., 2011). Moody et al. (2001) used discrete Fourier analysis method to calculate the phenometrics of vegetation in southern California. Jönssone et al. (2002) evaluated the SOS ad EOS of vegetation in Africa by using asymmetric Gaussian function method. Function fitting method may plunge a local extremum caused by inappropriate initialization and fail to get the global optimum value; meanwhile, parameter optimization is limited by numbers of points in VI series, which implies that the time resolution is an additional constraint for the precision of curve fitting (Hudson and Keatley, 2010).

In addition to the above-mentioned 3 types of method, the derivative method combines derivations of VI time-series curve with other conditions or methods to define SOS/EOS as the DOY when the curve reaches a maximum/minimum in an upward /downward phase (Balzter et al., 2007; White et al., 1997). For example, Moulin et al. (1997) used the derivative method and empirical coefficient to evaluate the SOS and EOS of global vegetation. To avoid the influence of NDVI increasing caused by snow melting on monitoring vegetation phenology, Yu et al. (2003) proposed a method using a combination of derivative and threshold methods. They limited the range of change slope using the given thresholds and estimated the vegetation green-up dates in the eastern Central Asia. Balzter et al. (2007) developed the "Camelback Phenology Algorithm", which is based on the combination of derivative method and moving average method, and derived the SOS and EOS in the central and eastern Siberi.

Sakamoto et al. (2005) defined vegetation green-up as the date at the point when MODIS EVI curve reaches the maximum and defined harvest time as the date at the point when the second derivative crosses zero and the first derivative turns from positive to negative. Maximum-slope method is effective for the crops ripping once a year, but the derived first harvest time will be delayed for the crops ripping twice a year. It is hard to judge whether the changes of derivation-derived vegetation phenology is significant or in a reasonable range, since the derivative method cannot analyze the errors. Meanwhile, the derivative method is appropriate to extract SOS and EOS when the VI curve has no sudden increase or decrease, especially when the datasets are contaminated by clouds (Hudson and Keatley, 2010).

Available remote sensing products for phenology studies

1) VI time series products

A. NOAA/AVHRR GIMMS NDVI3g data. This dataset starts from July 1981 to present. It has a spatial resolution of 1/12 (or 0.0083) degree and a 15-day interval. The data were provided by NASA and can be freely downloaded at the Ecological Forecasting Lab website (http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0/).
B. SPOT-VGT S10 NDVI data. This dataset starts from April 1998 to present with 1 km spatial resolution and a 10-day interval. The image quality and the calibration accuracy of the products are monitored by the Image Quality Monitoring Centre (QIV) at CNES (Toulouse, France) and the data can be freely downloaded from the Flemish Institute for Technological Research (VITO, http://free.vgt.vito.be/).
C. MODIS VI products (MOD13). This data can provide NDVI and EVI time series every 16 days at 250 m resolution from April 2000 to present. The data is processed by the Earth Resources Observation and Science (EROS) Center and can be downloaded at Reverb (http://reverb.echo.nasa.gov/).
D. eMODIS products. The data are produced only for the United States, including Continental United States and Alaska, at spatial resolutions of 250m/500m/1000m and 7-day intervals from 2000 to present. The output layers of the data are NDVI, surface reflectance bands, quality and acquisition date. They are produced by USGS EROS Center based on the MODIS datasets and have no compatibility issues (e.g., file format, production latency, reprojection, etc.) with the MODIS datasets. The data is available at https://lta.cr.usgs.gov/emodis.
E. ENVISAT-1 MERIS data. This data covers the period from March 2002 to April 2012. It has a spatial resolution of 300 m and a temporal resolution of 35 days. The data can be downloaded from the European Space Agency (https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat).

2) Phenology products

A. MODIS Land Cover Dynamics (MCD12Q2) Product. This data provides phenophase transition dates at 500 m spatial resolution from 2001 to present. The product is developed from a time series of the Enhanced Vegetation Index (EVI) (Huete et al., 2002) calculated from the 8-day composited Normalized BRDF-Adjusted Reflectance data (MCD43A4). The phenometrics are derived according to the derivatives of piecewise logistic functions (Zhang et al., 2003, 2006). The dataset can be downloaded from Reverb (http://reverb.echo.nasa.gov/).
B. MODIS for NACP (North American Carbon Program) Products. These data include Gap-Filled-Smoothed (GFS) Product and Phenology (PHN) Product. This Product provides smoothed and gap-filled MODIS VI series using the TIMESAT software package (Jönsson and Eklundh, 2004) to fit the asymmetric Gaussian functions (Jönsson and Eklundh, 2002) from two different MODIS products: EVI/NDVI calculated from MOD09A2 and

MOD09Q2, while LAI/FPAR derived from MCD15A2 (Gao et al., 2008). MODIS-for-NACP PHN Product provides phenometrics estimated from MODIS VIs from the two different MODIS products (Tan et al., 2011). These datasets are available at http://accweb.nascom.nasa.gov/index.html

C. USFS ForWarn's Phenology Products. They are MODIS-based national phenology datasets. These data are available under ForWarn Project. ForWarn is a near-real-time tracking system of vegetation changes across the United States, and it relies on daily eMODIS and MODIS satellite datasets. The phenology products include phenology derived products and phenology parameter products. These products are available from 2003 to 2009 and can be downloaded from http://forwarn.forestthreats.org/

D. USGS Remote Sensing Phenology Products. These data are provided by the USGS Earth Resources Observation and Science (EROS) Center, including phenometrics like timing and NDVI value of start and end of season, the timing and NDVI value of the annual maximum, duration and amplitude of the growing season, and time-integrated NDVI. The products are derived from AVHRR and MODIS, respectively. These AVHRR phenometrics are the longest record available at 1 km from 1989 to present. These data are available at http://phenology.cr.usgs.gov/get_data_main.php

Existing international phenological observation networks

A. Chinese Phenological Observation Network (CPON), website: http://cpon.ac.cn/

B. European Phenology Network (EPN), website: http://www.dow.wau.nl/msa/epn/index.asp

C. The UK network, website: http://www.naturescalendar.org.uk/

D. USA National Phenology Network, website: https://www.usanpn.org/

2.2.5 Issues and Challenges

Remote sensing data quality and its pre-processing

Satellite-based monitoring of vegetation phenology has a requirement for both higher temporal and spatial resolutions. Satellites, such as NOAA/AVHRR, SPOT-VGT and MODIS, can provide daily or even half-day (Terra/Aqua MODIS) records, but they have lower spatial resolution. For example, the spatial resolutions of NOAA/AVHRR, SPOT-VGT and MODIS are 8 km, 1 km and 250 m, respectively. This results in difficulties in analyzing physiological mechanisms of phenology shifting when the study region contains various vegetation types. Remote sensing data with spatial resolution smaller than or equal to 30 m (such as Landsat data, IRS data, HJ data) have been widely used, but their revisiting periods are usually longer than 3 days (such as 3-5 days for HJ satellites, 16 days for Landsat series of satellite). Considering the impacts of bad weather, aerosol or other factors, numbers of high quality data within a year are extremely limited, which is hardly to meet the requirements of monitoring vegetation phenology. For the tropical region, the quality of remote sensing data based on optical sensors is challenged by the high moisture content and cloud cover, but microwave sensors can overcome these problems and show potential in monitoring vegetation phenology in this region.

The quality of remote sensing data is also hindered by the solar elevation angle, satellite observation angle, cloud condition, atmospheric aerosols and other factors. Therefore, the VI time series obtained from satellite always contains tons of noises, which leads to difficulties in extracting phenological information from remote sensing images (Yu and Zhuang, 2006). To reduce these contaminations, most of the existing datasets (e.g. NOAA/AVHRR GIMSS NDVI3g, SPOT-VGT NDVI and MODIS VI time series) have been preprocessed and composited by implementing the Maximum Value Composite (MVC) (Holben, 1986) or Constrained-View

Angle Maximum Value Composite (CVMVC), but lots of noises still remained (Huete et al., 2002). Cloud cover has the largest impact on VI products quality, especially under condition that all the dates for deriving remote sensing images are contaminated by cloud. Therefore, the noise-reduction should be conducted for these VI time series before the application.
Plenty of noise-reduction methods have been developed for VI time series, such as the asymmetric Gaussian method (Jönsson and Eklundh, 2004), changing-weight filter method (Zhu et al., 2012), but none of them performs well under all situations (Song et al., 2011, Zhang, 2015). Using a time series of daily EVI2 (two band enhanced vegetation index) from AVHRR long term data record (LTDR) (1982–1999), Zhang (2015) developed a hybrid piecewise logistic model (HPLM) to reconstruct a global dataset of spatially and temporally consistent and continuous daily VI. Verifications indicated that the HPLM algorithm is reliable and consistent and can be applied for the reconstruction of EVI/NDVI from AVHRR, MODIS and VIIRS data globally.

2.2.5.1 Uncertainties in retrieving methods

The satellite-derived vegetation phenometrics retrieved with different methods showed large discrepancies. White et al. (2009) compared 10 SOS extraction methods and concluded that the average difference and standard deviation among the methods is ±60 days and ±20 days, respectively; these extraction methods showed higher precision in the northern hemisphere at high latitudes than in the region with arid, tropical or Mediterranean climate. Mou et al. (2012) evaluated three kinds of widely used satellite-based methods (i.e., threshold method, moving average method and function fitting method) from two aspects: feasibility and accuracy, and drew conclusions that the dynamic threshold method performed best with the highest feasibility and accuracy; better performance was also observed for the first derivative method of the logistic fitting function; the global threshold method had the worst performance both in feasibility and accuracy. There are three reasons responsible for the large inconsistency among different methods. First, there is no obvious phenophase transitions in the phenometrics derived from remote sensor data, which is the aggregated result of phenological information from different plants; second, these retrieving methods are different in definitions and algorithms; third, most existing evaluations are based on the in-situ observed phenology, but there has no direct relationship between satellite-derived phenology (e.g., green-up, dormancy, etc.) and ground-observed phenology (e.g., plant spout, flowering, etc.).
Moreover, the following reasons increase the challenge of extracting phenological metrics from remote sensing data for tropical forests: firstly, tropical forests have higher biodiversity level, which results in more hybrid information of various plants in one pixel in remote sensing image; secondly, vegetation in tropical forests has higher biomass and shows higher VI value, even in dry seasons; therefore, the VI curve changes little throughout a year (e.g., low amplitude in VI curve) and it is hard to identify phenological characteristics; thirdly, the phenological characteristics are not significant for tropical forests.

2.2.5.2 Difficulties in validation

The validation of the satellite-derived vegetation phenology is a difficult issue. High temporal-resolution satellite data are always with relative low spatial resolution, and also along with the influences from data quality, data pre-processing and phenology retrieving methods, which ultimately lead to the incompatibility between satellite-derived phenometrics at pixel level and ground-observed phenological events at individual or species levels. Most of the existing studies adopt the in-situ observations to validate the satellite-derived phenometrics. Fisher et al. (2006) used in-situ observations to validate the phenometrics derived from Landsat and MODIS, and quantified the precision of the satellite-derived phenometrics at the high (i.e., Landsat) and low spatial resolution (i.e., MODIS). They discovered that the average

dates of satellite-derived phenology could reflect the statistical conversion from fine scale to coarse scale, and the spatial disparity caused by local micro-climate was the primary cause for the incompatibility between satellite-derived and ground-observed phenometrics; Yu et al. (2010) studied the spring vegetation phenology on Qinghai-Tibet Plateau by using NOAA/AVHRR NDVI data from 1982 to 2006. They evaluated the differences between ground-based observations and satellite-derived phenometrics according to two indicators: the mean absolute error (MAE) and the root mean square error (RMSE). In the absence of enough in-situ observations, Chang et al. (2014) used standard differences to indirectly validate the sensor-based growing season according to the daily average temperature data derived from meteorological stations; while Zhang et al. (2013) identified the green-up dates of vegetation in Qinghai-Tibet Plateau based on three sensor datasets (i.e., NOAA/AVHRR GIMMS, SPOT-VGT, MODIS) and validated the results by comparing the trends between satellite-derived and ground-observed phenology.

Actually, there is no direct relation between satellite-derived phenology (e.g., green-up, dormancy, etc.) and ground-observed phenology (e.g., plant spout, flowering, etc.) since their scales (a pixel on sensor image vs. a single plant) and the observed values (spectral responses of vegetation vs. phenological events) are completely different (Fisher et al., 2006, Schwartz et al., 2002). Therefore, the validation for the satellite-derived phenology should be based on the spatial-temporal trends rather than the specific dates between ground-observed phenological events and satellite-derived phenometrics. There needs to develop other methods to make a more explicit understanding of the linkages between remotely sensed phenology and ground-observed phenology. Liang et al. (2011) validated satellite phenology through intensive ground observation and landscape scaling in a mixed seasonal forest. Delbart et al. (2015) compared land surface phenology with leafing and flowering observations from the PlantWatch citizen network to explain the correlation with satellite-derived green-up.

2.2.6 Potentials and applications of phenology studies in tropical forests

The differences in phenometrics among tropical forests can be used to improve the classification of land cover types, biomes and bioclimatic zones. Tropical evergreen and deciduous (seasonal) forests have similar spectra in the wet seasons, but there is at least 20% difference at the near infrared band in the dry seasons (Schwartz, 2013). This difference has been attributed to the seasonal variations in leaf phenology of deciduous forest. A significant portion of forest area could not be identified by the remote sensing images if only those images from dry seasons are used or do not consider leaf phenological changes, even using the higher spatial resolution remote sensors (e.g., < 30 meters). For example, dry deciduous forests may be misinterpreted as pasture or croplands if the remote sensing images are obtained during the dry seasons. Leaf losses of dry deciduous forests during dry seasons make the spectral signal of forest the same as the pasture or croplands. Therefore, the tropical deciduous forests have often been overlooked by many previous remote sensing analyses (Arroyo-Mora, 2002).

Phenology can provide a new clue to monitor biological diversity in tropical forests because it can contribute to the identification of wet of dry forests. Two distinct seasons are divided to study phenology for tropical dry forests: dry season and wet season. In the northern hemisphere, dry season usually ranges from March to July, when 85-100% of the forest leaves may fall down. Soil moisture is the dominant factor for the timing of leaf onset and offset, while the combined effects of ecosystem composition, topography and forest age structure determine the degree of deciduousness (Piperno and Pearsall, 1998; Lüttge, 1997). In general, moist or wet forests have more species than Neotropical dry forests. Taking records in Costa Rica as an example, 430 species of woody plants have been documented in the wet forest of La Selva Biological Station (Hartshorn and Hammel, 1994), while only 160 species in dry forest of the Santa Rosa National Park (Kalacska et al., 2001). However, dry forests

have more structural diversity (e.g., wood specific gravity) and physiological diversity (e.g., growth seasonality) than wet forests (Medina, 1995).

Phenometrics are critical parameters of exploring the dynamics of ecological processes in tropical forests. Phenometrics can be used to parameterize the phenology model (Whitcraft et al., 2015). The phenological mechanism model parameterized with phenometrics can be further integrated with process-based models to study the impacts of climate change on ecosystem composition, structure and function (Tian et al., 2010; Weiss et al., 2014; Arora and Boer, 2005). The parameterized model can be also integrated with crop models to simulate crop growth process and forecast crop yields in tropics (Ruane et al., 2014; Kadiyala et al., 2015).

Phenology change has a cascade effect on tropical forest ecosystems. Change or disruption of vegetation phenology may be reflected in the changes in interaction between plant population and animal function. Biotic factors (e.g., competition for pollinators or pollinator attraction) have been regarded as vital adaptive forces for vegetation phenological patterns in tropical region (Sakai et al., 1999; Lobo et al., 2003). Delayed or advanced flowering may reflect the behavior and visitation rate of pollinators. If changes happen over time in the flowering pattern of the plants which share pollinators in the same guild (Fleming, 1988), competition will happen for the same pollinators, finally resulting in detrimental effects on the reproduction of plants and the ability of pollinators to obtain resources. For example, in the tropical dry forest of the Chamela-Cuixmala Biosphere Reserve in Mexico, trees in *Bombacaceae* family provided main resources to the nectarivorous bats Leptonycteris curasoae for eight months and Glossophaga soricina for six months. The two species of bats gathered on the same bombacaceous species every month (Stoner et al., 2003). These sequential utilizations of bombacaceuos species by the bats happen to be the flowering time of the tree species. Some research data suggest that changes in flowering time (e.g., reduction of flower production) caused by habitat destruction may result in increased interspecific competition between bat species and may ultimately end in local extinction, especially for the endemic species in this dry tropical forest. Intraspecific variations in the frequency, duration, amplitude and synchrony of individual flowering phenology has been considered as the main influencing factor for tropical plant populations in both reproduction and genetic structure in disturbed habitats (Nason and Hamrick, 1997; Doligez and Joly, 1997). The fruiting time and seed predation behavior may affect the ecosystem in tropical forests. Then the habitat reduction and phenological changes will end in the species reduction of reproductive plants, the increasing negative impacts caused by endogamy, the quantity decreasing and quality declining of pollen, and the genetic variability lowing of the progeny (Cascante et al., 2002). Over time, finally, this may disturb the viability and establishment of plant populations.

2.2.7 Activities of phenology monitoring in tropical forests

Vegetation phenology in tropical forests has aroused wide interests for researchers in recent years (Table 2.2.7.1). At the South American Continent, Cho et al. (2010) utilized NOAA/AVHRR NDVI and Sea Surface Temperature (SST) data to study the influences of Atlantic SST on the vegetation greenness in Amazon during 1981-2001. They discovered a strong correlation between NDVI and SST during 1980s and 1990s. Additionally, NDVI in rainy season (from December to next February) during 1981-2001 lagged behind SST with strong correlation and the lag phase was 14 months. Saleska et al. (2007) extracted the vegetation green-up dates using MODIS EVI data in 2005, and found that there was no significant drought-caused reduction in vegetation greenness as compared with the other years. Bradley et al. (2011) explored the relationship of vegetation phenology with surface radiation and precipitation in Amazon based on the MODIS EVI data from 2000 to 2006. Comparing with subtropical or tropical savannah, they found that Terra Firme forests showed weak but significant annual cycles, which mainly caused by the vegetation heterogeneity and

nonsynchronous phenological events. Moreover, the region with significant annual radiation cycle accounted for 86% of the study region while the region with significant annual precipitation cycle accounted for 90%, but the two types of regions showed different spatial patterns in vegetation phenology.

Table 2.2.7.1 Activities of phenology monitoring for tropical forests at different continents

Continents	Regions	RS Activities	Fieldwork activities	Reference
South America	Amazon	Study on the relationship between the greenness of vegetation and the sea surface temperature (SST) using NOAA/AVHRR NDVI and SST data during 1981-2001.	Combining with sea surface temperature data of Atlantic sea surface; No ground-based validation.	(Cho et al., 2010)
	Amazon	Study on the vegetation phenology based on MODIS EVI data in 2005.	Combining with precipitation data; No ground-based validation.	(Saleska et al., 2007)
	Amazon	Study on the relationship between vegetation phenology and the surface radiation and precipitation using MODIS EVI data during 2000-2006.	Combining with vegetation map, radiation and precipitation data; Validating the phenology using the ground-based observation data	(Bradley et al., 2011)
North America	Hawaiian Islands	Study on the relationship between the leaf sprout date of tropical ecosystem and the precipitation based on the MODIS NDVI/EVI data during 2000-2006	Combining with precipitation data; No ground-based validation.	(Park, 2010)
	Hawaiian Islands	Study on the dates of leaf sprout in tropical forests region of Hawaiian Islands and its asynchronous response to El Niño–driven drought using MODIS NDVI data during 2000-2009	Combining with precipitation and SST data; No ground-based validation.	(Pau et al., 2010)
	Oaxaca, Mexico	Study on the start dates and length of season of vegetation using	Combining with precipitation data;	(Gómez-Mendoza et al., 2008)

		NOAA/AVHRR NDVI during 1997-2003	No ground-based validation.	
Africa	savannas and woodlands	Study on the start dates of growing season in the savannah and woodland region using the MODIS datasets during 2000-2011	No ground-based validation.	(Guan et al., 2014)
Asia	Uttara Kannada of India	Study on the vegetation phenology and its response to climate change based on SPOT-VGT NDVI data during 1999-2007	Combining with temperature and precipitation data; No ground-based validation.	(Prabakaran et al., 2013)
	India	Study on the spatial pattern of phenology for 8 species of forest and its response to climate change using NOAA/AVHRR NDVI data during 1990-2000	Combining with precipitation data; No ground-based validation.	(Prasad et al., 2007)
	Indian sub-continent	Study on the start dates of growing season of vegetation in Indian subcontinent using ENVISAT MERIS data during 2003-2007	No ground-based validation.	(Atkinson et al., 2012)
	China	Study on the vegetation phenology and growing season of the forests using AVHRR NDVI data in 1995 and 1996	the satellite-derived phenometrics correlated significantly with the ground observations	(Luo et al., 2002)

At the North American Continent, Park (2010) analyzed the connection between leaf phenology and rainfall regimes in Hawaii tropical ecosystems by using MODIS NDVI/EVI data during 2000-2006, and concluded that the vegetation greenness kept fluctuating and the period of fluctuations showed a strong relationship with precipitation. They also made a comparison between leaf phenology and rainfall patterns and proved that the photosynthesis and seasonal rainfall cycle showed consistency in tropical ecosystems and inconsistency in humid forests. Pau et al. (2010) explored the response of leaf phenology to El Niño-driven drought in Hawaii tropical forests using MODIS NDVI data during 2000-2009, and discovered the asynchronous response of Hawaii forests (both tropical rain and dry seasonal forests) to El Niño-driven drought and found that NDVI in dry seasonal forests showed stronger correlation with precipitation than that in rain forests. Gómez-Mendoza et al. (2008) studied the relationship between NDVI and precipitation using NOAA/AVHRR NDVI data during 1997-2003 and discovered a significant variation in SOS and length-of-season among different years in Oaxaca, Mexico.

At the African Continent, Guan et al. (2014) explored the impacts of land surface hydrology on vegetation phenology of savannah and woodland in Africa based on MODIS data during 2000-2011. They stated that the rain season onset generally occurred before SOS and thus could be used to predict SOS in African savannah, while rain season onset occurred after SOS and leaf senescence period varied nonlinearly with tree fraction in African woodland.
At the Asian Continent, Prabakaran et al. (2013) used SPOT-VGT NDVI data to derive the vegetation phenology and analyzed the response of vegetation phenology to climate change in Uttara Kannada of India during 1999-2007. They found that the phenological events of evergreen forests were earlier than those of dry deciduous forests, and discovered a negative relationship between the highest air temperature and SOS, a positive relationship between the highest temperature and defoliation dates and a positive relationship between precipitation and SOS. Prasad et al. (2007) studied the spatial pattern of vegetation phenology of eight types of forests in India using NOAA/AVHRR NDVI during 1990-2000, and analyzed its relationship with climate. They found that the evergreen forests had larger range between SOS and EOS (around on day 270). Besides, the vegetation greenness of different vegetation types showed different responses to climate change, but the average monthly NDVI were negatively related to temperature and positively related to precipitation. Atkinson et al. (2012) used four different methods to extract SOS in the Indian subcontinent based on ENVISAT MERIS data in the period 2003-2007, and discovered that the study results were consistent between the southwestern and the northeastern India. Luo et al. (2002) studied the growing season change of forests in China during 1995-1996 based on the AVHRR NDVI datasets, and proved the effectiveness of PhenLAI model in predicting the maximum LAI for most forest types.

2.2.8 Key References for section 2.2

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2.3 NET PRIMARY PRODUCTIVITY

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2.3.1 Definition and relevance

Terrestrial net primary productivity (NPP) is an indicator of the energy flow through ecosystems. It can be described as the net production of biomass over a specific time period (e.g., year), and measures the amount of carbon that is taken up by vegetation during photosynthesis minus the carbon released during plant respiration. This can be written as:

$$NPP = GPP - R_a \qquad (2.1)$$

where GPP is the gross primary productivity and R_a is the autotrophic respiration rate. The GPP measures the entire photosynthetic production of organic compounds in an ecosystem, and the autotrophic respiration indicates how much of that production is used to meet the energy needs for growth and maintenance of plant tissues. NPP is usually expressed in grams of carbon per square meter per year ($gC/m^2/yr$).

NPP is an important parameter for biodiversity assessment; areas with higher NPP generally host more plant and animal species, although this effect is most clearly observed when considering larger spatial scales (Costanza *et al* 2007; Field *et al* 2009; Chase 2010). Although at a regional basis, peak biodiversity is sometimes found to correlate with intermediate productivity levels (Oindo and Skidmore 2002; Said 2003), most evidence and ecological theories seem to point to an overall positive relationships between NPP and species richness (Gillman *et al* 2015). Given that tropical forests are high NPP ecosystems hosting a multitude of animal and plant species, drastic reduction of NPP in ecosystems, for example through climatic shifts or land use change (Huston 2005; Higgins 2007), may negatively affect species diversity. Tropical forests are subject to various human-induced changes aimed at harvesting timber and woodfuel, and forest conversions for agricultural or mining purposes. Monitoring NPP (among other variables) through time for these regions would help to understand the impact of these changes on biodiversity.

2.3.2 Field measurements of net primary productivity

NPP field measurements are crucial to evaluate the accuracy of spatio-temporal NPP assessments from remote sensing or models. Nonetheless, NPP cannot be directly measured in tropical forests. Two main approaches exist for estimating NPP *in-situ*: (1) the measurement of biomass and its changes over time, and (2) the measurement of carbon fluxes (Pan *et al* 2014).

2.3.2.1 Biomass

Field quantification of NPP is possible following NPP's definition of the total new biomass produced over a given time interval. Nonetheless, the accurate quantification of new biomass in the field is cumbersome, because during the measurement interval transformations occur due to consumption (herbivory), decomposition, mortality, and leaching (Kloeppel *et al* 2007). To make this measurable, biomass needs to be split into various components, including aboveground and belowground biomass. For both components increments in live biomass and

biomass losses need to be added to obtain an accurate measure of NPP (Clark *et al* 2001a). For aboveground biomass, biomass increments include net increase of wood (stems/branches) as well as green biomass (foliage). Losses include fine litter (leaves, twigs, fruits, flowers), consumption by herbivores, and leaching/volatility of organic compounds. Belowground NPP is comprised of net root increments, and root losses due to mortality, herbivory, root exudates, and export of organics to symbionts. The root biomass is poorly understood, but varies widely depending on the ecosystems and species, varying between approximately 20-150% of the above ground biomass (Whittaker 1975; Albuquerque *et al* 2015). See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

A detailed description on how to measure or estimate each of these components can be found in Clark *et al* (2001a), Gower *et al* (1999), and Kloeppel *et al* (2007). Only very few studies have attempted to measure belowground biomass for forest ecosystems (for a review see: Tierney and Fahey 2007), and aboveground NPP (or ANPP) is mostly taken as the combination of aboveground biomass increment and fine litter only (Clark *et al* 2001b). In this section we focus on ANPP given that remote sensing can best contribute to this assessment. Two approaches exist for estimating ANPP: (1) area harvest, i.e. destructive sampling of all plant tissue, or (2) the use of allometric equations that relate wood volume to more easily-measurable parameters like stem diameter and tree height (Gower *et al* 1999), with the wood volume being converted into biomass based on wood density (note that many allometric equations for biomass increment are based on destructive sampling). Due to the relative small NPP increment with respect to standing biomass, approach (1) is challenging for forests, but some key tropical forest biomass allometric equations are nonetheless based on such painstaking work (e.g. Chambers *et al* 2001; Basuki *et al* 2009). Approach (2) is feasible when implemented using permanent plots: in this case stem diameter and top height increments provide an estimate of biomass increase, that is, if appropriate allometric equations for the species within the plot are available from literature or, ideally, from harvested trees in the vicinity of the plot. There are examples of biomass increment and NPP being estimated using temporary plots being repeatedly measured in an area.

In short, *in-situ* field estimates of NPP based on biomass measurements are challenging for tropical forests and large errors can remain if not all NPP components are accurately identified and measured. Field-based NPP estimates require rigorous sampling and measurements for different components and for at least two moments in time. Detailed studies at benchmark sites and a greater standardization of approaches is needed (Kloeppel *et al* 2007). Nonetheless, such techniques remain the 'gold standard' for validation and calibration of models based on flux tower or remote sensing measurements.

2.3.2.2 Flux tower measurements

Flux towers use the eddy covariance method to continuously measure the exchanges of CO_2, water vapor, and energy between terrestrial ecosystems and the atmosphere (Baldocchi 2003). Globally over 450 flux towers are actively operating, the majority of which are located in North America and Europe. These are organized in the FLUXNET network of regional networks (http://fluxnet.ornl.gov/) (Baldocchi *et al* 2001). Flux towers measure the vertical turbulent fluxes. The upwind area that is sampled ("seen") by eddy covariance measurements is called the flux footprint. Its size and shape varies with tower height, wind velocity, and canopy characteristics. Depending on these parameters, the typical contribution to the measured signal originates from few tens of meters up to several hundreds meters. The footprint can be described using the analytical model of Schuepp et al. (1990). CO_2 exchange can be accurately measured at hourly to annual intervals particularly over flat terrain, stable environmental conditions, and homogeneous vegetation cover for an extended distance upwind (Baldocchi 2003).

Although flux towers do not measure NPP, they can provide relevant and related quantities. In fact, the flux towers measure the net ecosystem exchange of CO_2 (NEE) that can be directly converted into the NEP (Net Ecosystem Production), which is related to NPP as follows:

$$NEP = GPP - R_e = GPP - R_a - R_h = NPP - R_h \qquad (2.2)$$

where R_e is the ecosystem respiration that is composed of the autotropic respiration (R_a) and the is the heterotrophic respiration (R_h). R_h is the microbial decomposition of organic matter into CO_2 by the soil and animals. Ecosystem respiration is largely modulated by meteorological conditions such as temperature and humidity. Night time flux measurements, representing R_e as no photosynthesis occurs at night, are used to develop models to estimate R_e as a function of the driving meteorological variables. Such models are in turn used to estimate GPP from NEP measurements during daylight (a process often referred to as partitioning; Reichstein *et al* 2005). In summary, although NPP cannot be directly estimated with flux measurements, GPP can be estimated and used as proxy (for instance using a fixed conversion factor compiled from literature review) when time consuming biometric measurements of NPP are not available.

2.3.3 Remote sensing for estimating NPP

Given that primary production can be partitioned into various space- and time-variant elements, a range of remote sensing techniques can potentially contribute to the assessment of NPP. The incorporation of remote sensing in light use efficiency models is the most widespread approach and forms the basis of an operational NPP product derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) (section 2.3.3.1). Another approach to estimate NPP is to construct direct empirical relationships between measured NPP and remote sensing-derived parameters like spectral vegetation indices (section 2.3.3.2). Finally we provide an overview of an alternative approach of multi-temporal biomass assessment (section 2.3.3.3). For completeness, we note that remote sensing has also been incorporated into ecosystem process models that simulate ecological processes like photosynthesis and respiration. Such models, often referred to as land surface models (LSMs) describe the main governing processes of the exchange of energy and carbon between terrestrial ecosystems and the atmosphere. LSMs rely on a number of hypotheses and require a large parametrization that is often taken from a limited number of observations gathered at different scales (from plant organs to canopy scale) gathered under specific environmental conditions. Application of such models to large areas where input data and parametrization are often uncertain, typically leads to large uncertainty in GPP and NPP estimates. The assimilation of remote sensing observation is increasingly used to reduce such uncertainties (see for example Liang 2004). These ecosystem process models (or LSMs) are not discussed here, but for more information we refer the reader to Turner *et al* (2004).

2.3.3.1 Light use efficiency models

Light use efficiency (LUE) models, also called production efficiency models (PEM) are based on Monteith (1972) who found that vegetation dry matter productivity under unstressed conditions linearly relates to the incoming photosynthetically-active radiation (PAR) that is absorbed by green leaves. Based on this observation, GPP (or NPP, depending on how ε_{max} is defined) can be expressed as:

$$P = \varepsilon_{max} \times fAPAR \times PAR \times f(E) \qquad (2.3)$$

where ε_{max} is the maximum conversion efficiency of light energy into vegetation biomass under optimal conditions, fAPAR is the fraction of incoming PAR absorbed by leaves and f(E)

are functions to describe the effect of environmental stress (such as water shortage and temperature limitation) on ε_{max}. This equation forms the theoretical basis for many satellite-based estimates of NPP. A detailed overview and discussion on how remote sensing has been used as input for LUE models is found in Hilker *et al* (2008). Of note is that the ε_{max} definition and consequently its estimated values can vary much among various models, depending on whether NPP or GPP is assessed, whether below-ground production is incorporated, whether total radiation or only PAR is considered, and moreover many models use ε_{max} as a calibration parameter (Song *et al* 2013). Hence ε_{max} values cannot readily be transferred between models. Despite this, because all LUE models capture the seasonal variation of fAPAR and meteorological variables, they all achieve a reasonably accurate assessment of productivity (Song *et al* 2013). Here we limit ourselves to describing briefly the operational MODIS NPP product (Running *et al* 2004) as an example of feeding satellite data into an LUE model. A more detailed description of the algorithm can be found in Heinsch *et al* (2003), although some changes to the product have been subsequently made.

The MODIS MOD17 datasets consist of an 8-daily GPP and annual NPP product. The GPP product (MOD17A2) precisely follows the definition of equation 2.3. The elements are assessed as follows:

- ε_{max} varies with vegetation type. Biome-specific values for ε_{max} are determined from the annual MODIS-based land cover product (MOD12Q1) and a biome parameter lookup table (BPLUT). The values in the BPLUT are first estimated from an ecosystem model, and then modified based on eddy flux measurements and NPP field measurements (Heinsch *et al* 2003).
- fAPAR: in many models fAPAR is an empirical linear function of the normalized difference vegetation index (NDVI), but such functions are scene- and sensor-dependent and also subject to saturation at high NDVI values. The current version of MOD17 takes fAPAR from the 1-km MOD15A2 fAPAR/LAI product (Zhao *et al* 2005), which is based on the biome-specific inversion of a canopy radiative transfer model using a look up table (Knyazikhin *et al* 1999).
- PAR is obtained from NASA's Data Assimilation Office (DAO). DAO combines surface weather observations with a global climate model to produce estimates of various parameters at a coarse resolution of 1° by 1.25°, including the incident shortwave solar radiation (Running *et al* 2004). The PAR fraction of this solar radiation is assumed to be 45 percent.
- f(E) is split into two components for MOD17, i.e. a temperature and a water stress part. Both stresses can reduce ε_{max}. While soil water stress is the most direct link to plant growth (Song *et al* 2013), the MODIS product approximates this using vapor pressure deficit (VPD). Both daily minimum temperature and VPD are obtained from the DAO (as above for PAR) and they are scaled as simple linear ramp functions between biome-specific minimum and maximum temperature and VPD values that allow reducing ε_{max} for sub-optimal conditions.

From the 8-daily GPP, the annual NPP is calculated as:

$$NPP = \sum(GPP - R_{lt}) - R_g - R_m \qquad (2.4)$$

where the autotrophic respiration terms relate to daily maintenance respiration of leaves and fine roots (R_{lt}), annual growth respiration to construct leaves, fine roots, and new woody tissues (R_g), and maintenance respiration of live cells in woody tissues (R_m) (Running *et al* 2004). Daily R_{lt} is estimated using LAI (from MOD15A2), average temperature from the DAO, and five biome-specific leaf parameters contained in the BPLUT. The annual respiration terms (R_g and R_m) are obtained by first calculating live woody tissue maintenance respiration, and then estimating growth respiration costs for leaves, fine roots, and woody tissue using biome-

specific parameters (BPLUT) values. This approach largely relies on empirical findings that relate the annual leaf growth to the annual growth of other plant tissues.

The principal validation source of the MOD17 product are flux tower measurements that are compared to a 7x7km^2 sample of the MODIS product located around each tower (Turner *et al* 2006; Friend *et al* 2007).

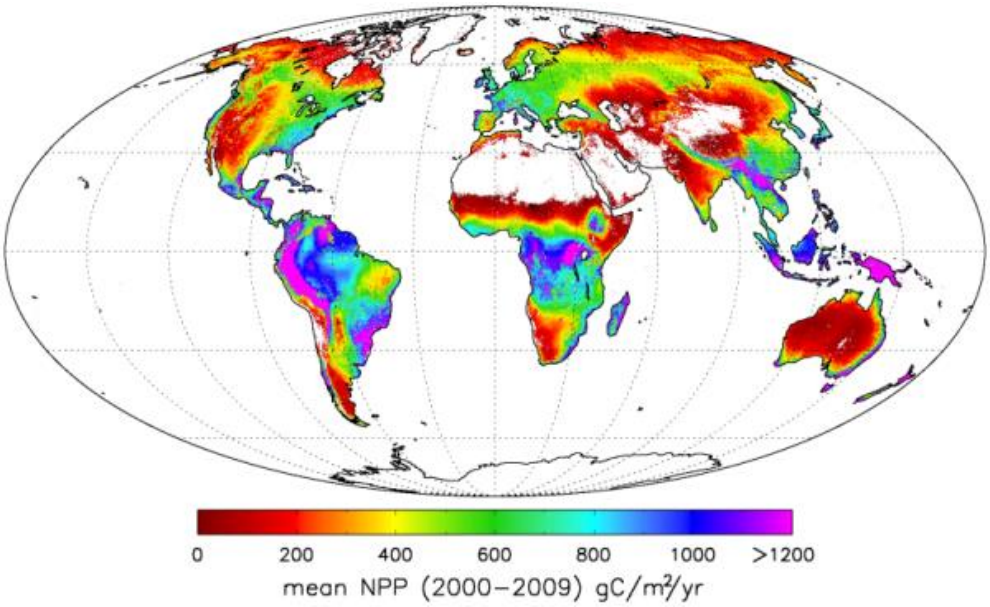

Figure 2.3.3.1.1: mean NPP of 2000-2009 from the MOD17 product (figure source: http://www.ntsg.umt.edu/project/modis)

2.3.3.2 Remote sensing-based proxies of NPP

The previous section shows that while the concept of LUE models is simple, the input data requirements and assumptions needed are nonetheless substantial and are based on coarse resolution (spatial and thematic) input parameters. For this reason, a large number of studies focussed on simpler proxies of primary productivity that require less modelling and input data; for example an approach that was piloted in the 1980s (Goward *et al* 1985). The majority of these use a growing season integration of spectral vegetation indices. Given the difficulty to estimate autotrophic respiration, and the fact that flux tower measurements give a more direct measure of GPP than NPP, the empirical relationships relating production to vegetation indices mostly focus on GPP rather than NPP. For example, Sims *et al* (2006) found good relationships with integrated MODIS EVI (enhanced vegetation index) and tower-based GPP. They later improved this relationship by incorporating MODIS land surface temperature to account for short-term GPP variation, which further improved accuracies especially for evergreen sites (Sims *et al* 2008). NPP could equally be derived from such an empirical approach as long as good field-estimates of NPP are available. Note that the assessment of the seasonal 'start' and 'end' is discussed in the remote-sensing based phenology assessment (section 2.2).

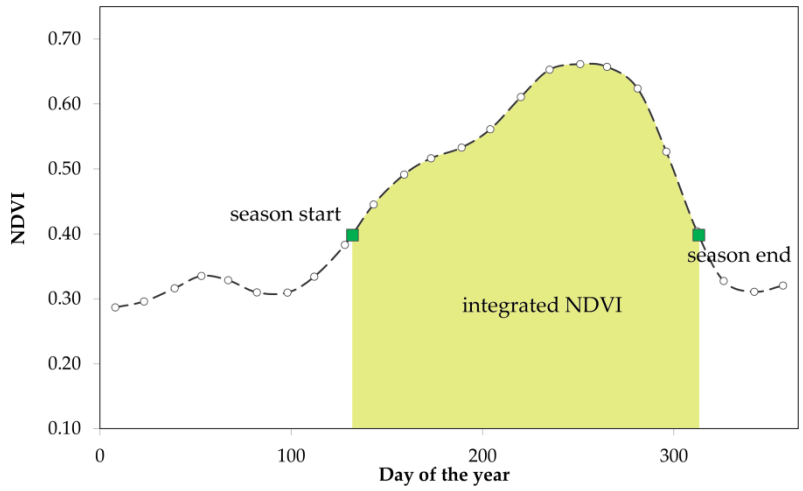

Figure 2.3.3.2.1: Illustration of seasonally-integrated spectral vegetation indices (here: NDVI) that is frequently used as proxy for primary production. Note that for moist tropical forests with limited seasonal variation the approach may not be effective.

2.3.3.3 Assessment of biomass and its changes

In addition to providing input to LUE models and seasonally-integrated vegetation indices, remote sensing has the capacity to provide relevant input to estimating NPP components (section 2.3.2.1). Even if not resulting in direct NPP estimates, biomass estimates are an important component of field-based NPP data. A variety of remote sensing techniques have been developed to accurately estimate biomass for tropical forests. In the past, international developments on the Reduced Emissions from Deforestation and Forest Degradation (REDD) have strengthened the need for such measurements as they require accurate estimates of forest carbon stocks and its changes (Gibbs *et al* 2007). For a detailed overview of this topic, we refer the reader to the REDD sourcebook by GOFC-GOLD, which is updated annually for each Conference of Parties of the UNFCCC (GOFC-GOLD 2016). Section 2.3 of the REDD sourcebook focuses on the estimation of forest carbon stocks, while section 2.10 reviews emerging remote sensing technologies for monitoring changes in forest area and carbon stocks. In addition the Remote Sensing Handbook contains a chapter summarizing recent progress in the estimations of above-ground biomass with remote sensing (Ni-Meister 2015).

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2.4 ECOSYSTEM EXTENT AND FRAGMENTATION

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One of the candidate essential biodiversity variable (EBV) groups described in the seminal paper by Pereira et al. (2014) concerns Ecosystem Structure. This EBV group is distinguished from another EBV group which encompasses aspects of Ecosystem Function. While the Ecosystem Function EBV treats ecosystem processes like nutrient cycling, primary production, trophic interactions, etc., the Ecosystem Structure EBV relates to the set of biophysical properties of ecosystems that create biophysical environmental context, confer biophysical structure, and occur geographically. The Ecosystem Extent and Fragmentation EBV is one of the EBVs in the Ecosystem Structure EBV group.

Ecosystems are understood to exist at multiple scales, from very large areas (macro-ecosystems) like the Arctic tundra, for example, to something as small as a tree in an Amazonian rain forest. As such, ecosystems occupy space and therefore can be mapped across any geography of interest, whether that area of interest be a site, a nation, a region, a continent, or the planet. One of the most obvious and seemingly straightforward EBVs is Ecosystem Extent and Fragmentation. Ecosystem extent refers to the location and geographic distribution of ecosystems across landscapes or in the oceans, while ecosystem fragmentation refers to the spatial pattern and connectivity of ecosystem occurrences on the landscape.

2.4.1 Ecosystems vs. Ecosystem Occurrences

The overall extent of an ecosystem is the area encompassed by all of the occurrences of the ecosystem. Ecosystems rarely exist as large, homogenous, single polygon entities; they are more often composed of patches (occurrences) of repeating areas on the ground or in the water with similar ecosystem properties. An ecosystem is usually composed of many repeating occurrences of variable shapes and sizes, and the area or extent of the ecosystem overall is the sum of all the areas for each of the individual ecosystem occurrences.

It is important to keep the distinction between area of occurrences and overall area of the ecosystem in mind when considering ecosystem extent and fragmentation. An analysis of any ecosystem property (size, condition, value, etc.) is usually derived from a geographic summation of the property across all of the ecosystem's occurrences. This occurrence-based approach is fundamental in both raster and vector spatial analytical frameworks. To calculate ecosystem extent, the analyst simply selects all the raster (cells) or vector (polygons) occurrences of the ecosystem and calculates the sum of these occurrences as the total extent, or area, of the ecosystem. It is a straightforward analysis in any GIS on any ecosystems-related layer to select all of the occurrences of an ecosystem class and calculate a summed area. But while the calculation of ecosystem extent for the ecosystem classes in an ecosystems-based GIS layer is straightforward, ecosystem maps are still relatively uncommon, and proxies for ecosystems are frequently used. Thus, prior to assessing ecosystem extent, it is imperative that there is an understanding of the definition of ecosystems, the distinction between different ecosystem types, and the use of proxies (e.g. land cover) for ecosystems.

2.4.2 Ecosystems as Distinct Physical Environments and Associated Biota

A terrestrial ecosystem (Figure 2.4.1) at any given point is a vertical integration of the atmospheric regime, the organisms, and the hydrogeomorphology of the surface and sub-surface environments (Bailey, 1996), and its current state may have been influenced by former states and evolutionary history.

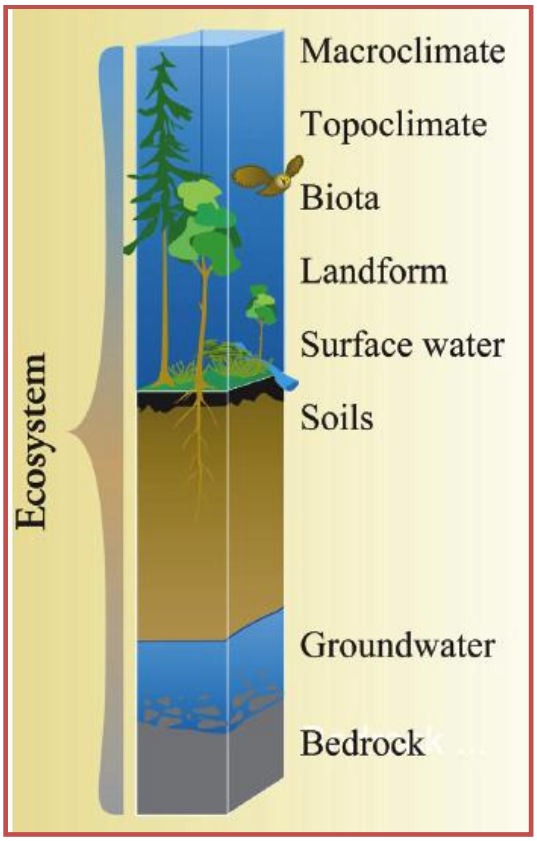

Figure 2.4.1 – The vertical arrangement of the biophysical elements of ecosystem structure (Bailey, 1996). Reproduced with permission from Robert G. Bailey.

By mapping and then spatially combining these structural elements of ecosystems, ecosystems can be geospatially delineated in a robust, standardized, and data-derived fashion. This is the principle behind the GEO (Group on Earth Observations – a consortium of nations working to advance Earth observation for societal benefit) Global Ecosystem Mapping Initiative, which has produced a global terrestrial ecosystems map (Sayre et al., 2014). The GEO Global Ecological Land Units resource is a standardized, raster-format, data-derived map of global terrestrial ecosystems at a 250 m spatial resolution. There are 3,639 ELUs and the global distribution and extent of any individual ecosystem type is easily queried in a GIS as the sum of the area of all the raster cells in that type. As such, the ecosystem extent of the GEO global terrestrial ecosystems is known. Figure 2.4.2 below depicts the method for mapping the ecosystems by first mapping, and then spatially integrating, the four principal elements of ecosystem structure (bioclimate, landforms, lithology, and land cover):

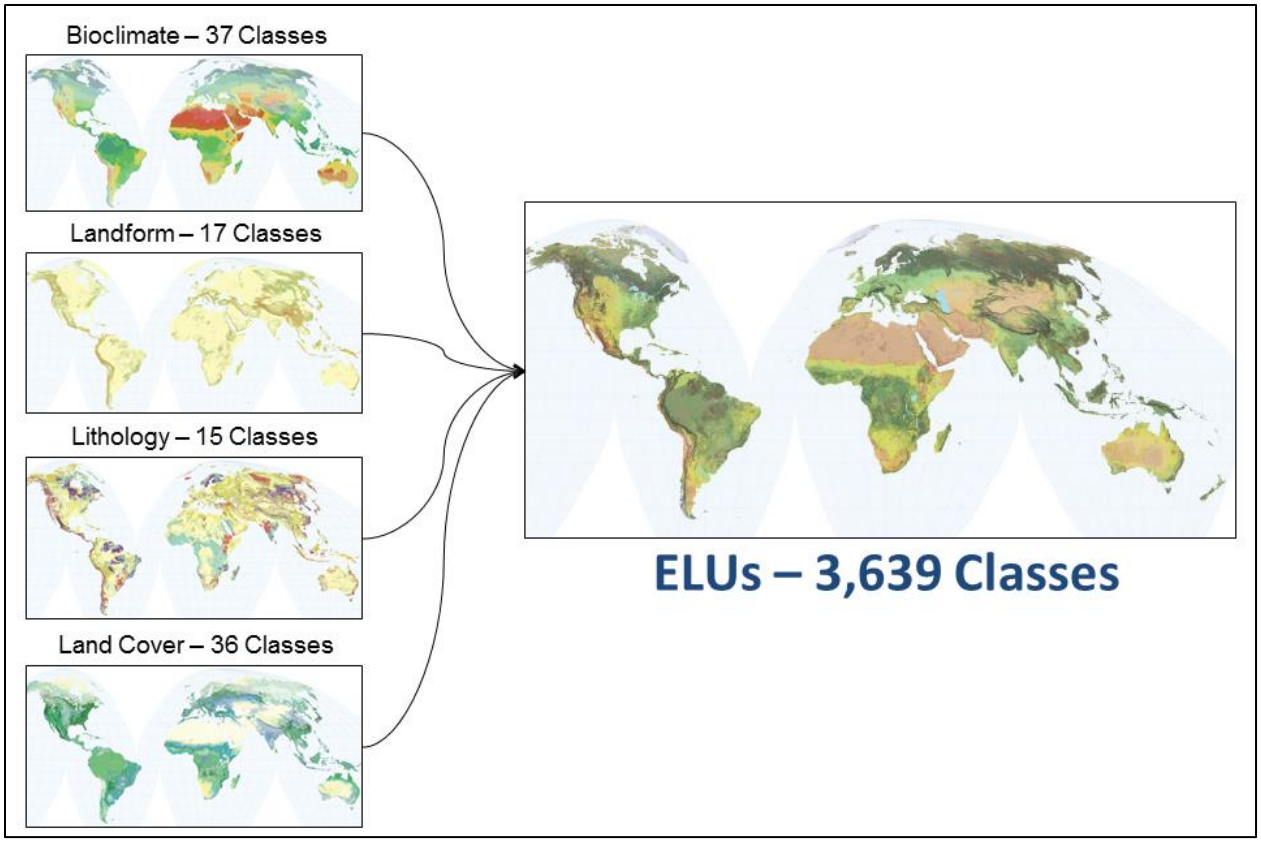

Figure 2.4.2 – Global Ecological Land Units (ELUs) as mapped from a spatial combination of four primary elements of ecosystem structure: bioclimate, landform, lithology, and land cover. A total of 3,639 global terrestrial ecosystems were mapped, of which 544 are tropical forest ecosystems.

For this particular ecosystem classification, which is globally comprehensive, and which exists at a relatively fine spatial resolution (250 m) for a global product, ecosystem extent is readily calculated in a simple GIS analysis. As such the global ELU represents a candidate datalayer for use in the EBV on ecosystem extent. However, the global ELUs are currently only available for one time period, the 2010 epoch. They represent, in essence, a baseline distribution of terrestrial ecosystems over a five year period centered on 2010. If the ELUs were developed for say 2000, 2005, 2010, and 2015, and were also modeled into the future for say 2020, 2025, 2030, etc., the change in ecosystem extent would be possible between different time periods. Change in ecosystem extent is the actual focus of the EBV, and in fact the emphasis on change in extent should be reflected in the title of the EBV as "Change in Ecosystem Extent". Since the global ELUs discussed above are not currently available as a time series, there are some constraints against their application for determining change in ecosystem extent.

2.4.3 Land Cover as a Proxy for Ecosystems

Due to a lack of availability of time series data on ecosystem extent, and also to the general lack of ecosystem maps in the first place, land cover is often used as a proxy for ecosystems. It is important to understand that land cover is an element of, rather than a proxy for,

ecosystems, as shown in Figure 2.4.2 above. In fact, in the GEO ecosystem concept, land cover is intended as a proxy for vegetation, and vegetation is subsequently intended as a proxy for all biota. However, practically, land cover is often used as a proxy for ecosystems. This can lead to a situation where land cover is equated with ecosystems, even though land cover data may carry little or no information on climate regime, geomorphology, and substrate chemistry, all important elements of ecosystem structure.

2.4.4 Land Cover Change – A Proxy Approach for Assessing Change in Ecosystem Extent

When land cover is equated with ecosystems, change in ecosystem extent can be inferred from change in land cover extent. Because land cover data is typically derived from remotely-sensed imagery, it is often available as a time series, and lends itself well to analyses of change in extent of land cover classes (again, which are typically presented as ecosystem types). Change detection in land cover classes between two or more points in time requires that the same set of classes have been interpreted and mapped from imagery at each time point. After calculating land cover extents for the different time points, it is possible to determine 1) what changed?, 2) from what?, 3) to what?, and 4) the magnitude of the change. If the classification units have changed across different epochs because of new sensors or image processing algorithms, the new land cover classes need to be "crosswalked" back to the original classes prior to calculating change in land cover extent.

2.4.5 Unspecified Change and Ecosystem Basemaps – A Proxy-Free Approach

Another approach to assessing change in ecosystem extent which does not require use of a land cover proxy is to obtain a change map derived from image analysis of two images at different dates. The images can be compared for changes in spectral properties, and without classifying the spectral signatures into land cover classes, a change map can be produced which indicates where, on the ground, changes have occurred. A change map produced from comparison of differences in spectral properties across different dates presents only areas of unspecified change. It is not known what changed, or from what to what, but only that change has occurred in some area. The resulting map is a map of polygon or raster footprints indicating that change has occurred. This change map can then be spatially combined with an ecosystem basemap, such as the ELUs map, and the ecosystems which have experienced change can then be identified. While this approach is excellent at identifying places on the ground and ecosystem types which are experiencing change, and can help with monitoring of ecosystem condition, there is no information provided on the "new" state. As such, simple calculation of change in ecosystem extent by differencing ecosystem extent at time t_0 and t_1, is precluded.

Advanced and accurate change detection approaches are now available for identifying change on the ground from analysis of spectral properties. One model, termed the Continuous Monitoring of Forest Disturbance Algorithm (CMFDA; Zhu et al., 2012), characterizes disturbance by flagging the number of times a pixel's spectral resolution changes through a sequence of temporal images. Many images can be included in the assessment, evolving traditional "change pair" approaches into a "change stack" or data cube framework. Another model, the Breaks for Additive Season and Trend approach (BFAST; Verbesselt et al., 2013) uses multiple images from an area to establish historical stability in variation of spectral properties, and then automates rapid identification of change in newly acquired imagery as significant departures from the historical baseline. These two approaches illustrate an increasing use of multi-temporal data cubes as the spatial data framework for detecting

change in imagery, now possible due to technological improvements that permit the storage and analysis of "big data" resources.

2.4.6 Ecosystem Fragmentation

Fragmentation refers to the changing spatial pattern of the distribution of the occurrences of ecosystems (or land cover classes as a proxy for ecosystems). There may be a tendency over time for larger occurrences of an ecosystem to "fragment" into increasingly smaller and more numerous occurrences. This change in the original spatial pattern of the occurrences can be caused by both human (e.g. land conversion) and natural (e.g. fire) disturbances, and usually results in an overall reduction in the historical distribution (range) of the ecosystem. There are a number of ecological questions relating to the number, size, and landscape context of ecosystem occurrences as they influence ecosystem integrity. A general conclusion from this line of work is that a considerable reduction in historical ecosystem range, and fewer, smaller, more dispersed, and less connected occurrences reflect a loss of ecosystem integrity. This reasoning has become the basis for the development of IUCN's recent program and effort to develop Ecosystem Red List Criteria (Keith et al., 2013).

The analysis of fragmentation patterns and trends lends geographic specificity to the changes in ecosystem extent that are occurring. Assessing the overall change (often reduction) in the original ecosystem extent is important, but it is also important to understand whether that change is mostly on the periphery of occurrences, or in the interior, or both. Several different kinds of fragmentation (e.g. interior, edge, perforated, transitional, patch, etc.) have been identified (Ritters et al., 2000) and fragmentation analysis algorithms have been developed. The location of fragmentation-based change is important because ecological processes (productivity, nutrient cycling, water flux, etc.) may not be uniformly distributed in the occurrence. In a global analysis of forest fragmentation, Ritters et al. (2016) reported that a substantial loss of global forest cover from 2000 to 2012 was also accompanied by a shift to a more fragmented condition, with important implications for managing ecological risk. See also sections 4.3 and 4.5 for more in-depth information and case studies on forest fragmentation and change monitoring.

2.4.7 Forest Cover Change Monitoring with Global Forest Watch Products[15]

As an important class of global ecosystems, and the ecosystem type upon which this sourcebook is focused, forest ecosystems have been increasingly studied with respect to carbon content and change in forest distributions from deforestation and reforestation. For the former, the GEO-commissioned Global Forest Observations Initiative (GFOI) has produced a rigorous set of best-practice monitoring, reporting, and verification (MRV) guidelines assessing forest carbon stocks and fluxes (GFOI Methods and Guidance Document (MGD) - https://www.reddcompass.org/download-the-mgd). Forests are also now being continuously monitored in an innovative global forest change initiative. Global Forest Watch (GFW - http://www.globalforestwatch.org/) is an interactive online resource delivering accurate forest monitoring information to the public in order to improve forest management and conservation. Information on global forest extent and change is required to establish trends, to study drivers, and to assess the impacts and effectiveness of land use policies. Transparency is key to advancing such understanding and is a core principal of GFW. Anyone can use GFW tools to create custom maps, analyze forest trends, subscribe to alerts, or

[15] Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government

download data for their local area or the entire world. GFW data serve governments, the private sector, NGOs, journalists, universities, and the general public. These and other stakeholders may assess and advance forest land use based on a common set of facts provided by GFW.

One of the principal data sets contributing to GFW's mission is generated by the University of Maryland's Global Land Analysis and Discovery research team. GLAD generates global-scale tree cover extent and change data using time-series Landsat inputs. Annual updates on forest loss are generated at a 30m spatial resolution as are interim forest disturbance alerts for selected countries. Current inputs consist of Landsat 7 and 8 imagery, totaling over 250,000 scenes per year. Landsat data from the United States Geological Survey are acquired globally, are available free of charge and feature robust geometric and radiometric pre-processing. Sentinel 2 data from the European Space Agency have similar data policies and processing, and will be streamed with Landsat in advancing GFW global forest monitoring products.

To implement global forest monitoring methods, knowledge of the regional variation of forest change dynamics is required, from forest types such as primary intact to secondary regrowth or woodlands, to causal factors such as mechanical clearing and fires, to scale of change such as large agro-industrial and smallholder clearings, to post-clearing land uses including agriculture and forestry. For example, mapping of the Brazilian Amazon is comparatively simple as the majority of clearing occurs within primary forests, consists of large scale clearings, and results in deforestation, i.e. forests are replaced with non-forest land uses. For most other regions in the tropics, the circumstances for monitoring differ. In the Congo Basin, forest loss consists of small-scale swidden agricultural and selective logging, with a majority of disturbances within secondary regrown forests. In Insular Southeast Asia, forests are cleared and replaced with timber plantations and palm estates, and the majority of change occurs within established forest land uses. GFW's methods and products aim to account for the complexity of these dynamics in providing a globally consistent, locally relevant record forest extent and change.

2.4.8 Ecosystem Extent and Fragmentation – Summary of Issues

1. The calculation of change in ecosystem extent or fragmentation is technologically straightforward as a software-based differencing of ecosystem extent at different time periods.
2. The spatial analytical units to be used in these assessments, however, is not straightforward, due to a general lack of ecosystem maps. When maps of ecosystem occurrences do exist, they may not exist in a time series format which allows calculation of change in extent by differencing between time periods.
3. Land cover is often used as a proxy for ecosystems as it is 1) derived from remotely-sensed imagery, and 2) is often available in a time series. However, it must be remembered that land cover is actually an element of, rather than a proxy for, ecosystems.
4. High resolution (250 m), data-derived, standardized global maps of ecosystem types (including tropical forest types) do exist as a 2010 epochal baseline, and can be used to monitor changes in global or local ecosystem extent for ~3600 ecosystem types.

See also sections 4.3 and 4.5 for more in-depth information and case studies on forest fragmentation and change monitoring.

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2.5 ECOSYSTEM STRUCTURE

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2.5.1 Background

In Skidmore et al. (2016) vegetation height is being mentioned as one of the remotely sensed (RS) EBV candidates (RS-EBVs) to support the measurement of the EBV 'Ecosystem structure', next to ecosystem distribution, fragmentation and land cover. While land cover is already provided as operational RS product since the eighties, vegetation height is currently the most challenging one, and subject of this chapter. Vegetation height can be measured directly or indirectly by specific RS sensors and could support the EBV 'Ecosystem structure' with very valuable information. Vegetation height is valuable information next to spectral information to identify specific ecosystem or vegetation types. Moreover, the regular mapping of vegetation height would help to identify processes such as shrub and tree encroachment. Noss (1990) describes a hierarchy concept for monitoring biodiversity. The different levels of information that can be considered for biodiversity and ecosystem studies are the compositional, structural and functional aspects at multiple levels of ecological complexity. Vegetation height is as such an important component of the structural aspect of ecological complexity. Bunce et al. (2013) emphasises the importance of habitat/vegetation structure in the development of biodiversity policies in their own right and also demonstrates that there are strong links between vegetation structure and occurrence of species. Only a very small part of all species can be monitored while vegetation structure or habitats, as a flagship for many species, are easier to be monitored. As mentioned before, vegetation height is an important aspect as well in the definition of an ecosystem or habitat type. For instance, measuring forest degradation from space requires an agreed definition of a forest. Without a clear definition it is hard to compare forest distribution across large areas or across time. In the 1990s, the Food and Agriculture Organization of the United Nations (FAO) defined forests as ecosystems with a minimum of 10% canopy cover of trees or bamboo associated with wild flora. That definition was updated in 2005 with a minimum height of 5 meters for trees. Such shifts influence perceptions of where forests are, as well as where they used to be (Skidmore et al. 2016).

To enable the measurement of vegetation height, remote sensing can play a crucial role and can become an important information source. Early applications pertained to the stereoscopic visual interpretation of aerial photography were a great step forward in vegetation monitoring. More recently, satellite imagery with a large range of spatial and temporal resolutions is available and enables applications for entire ecosystems. Traditional vegetation mapping methods that use visual interpretation of aerial photography and in combination with field surveys are, and have always been, working very well. But they are often also labour intensive and temporal frequencies are low, while policies are currently demanding higher temporal monitoring frequencies. Therefore, also terrain and nature managers are looking for alternatives that can support the mapping and monitoring of vegetation in more efficient ways.

New developments in remote sensing such as the use of very high resolution (VHR) satellite imagery (passive optical as well RADAR active sensors) and LiDAR (Light Detection And Ranging) techniques, next to the use of UAV platforms (Unmanned Aerial Vehicles), can help

to speed up the process of vegetation mapping and monitoring. Nevertheless, som e of these methods are all relatively new and requires ecologists and remote sensing experts to collaborate closely and review the newest methods and technologies. Therefore this chapter discusses the potential use of passive optical sensors, RADAR and LiDAR technology for measuring vegetation height to support the monitoring of the EBV 'ecosystem structure'. See also chapters 4.1 and 5.1 for more information on current and upcoming Earth observation missions, respectively.

2.5.2 Passive sensor technology

Several studies have employed passive satellite sensor data to estimate vegetation height. A wide variety of features have been extracted from passive sensors of spatial resolutions ranging from several centimetres to some tens of metres. For example, the panchromatic channel of Worldview-1 imagery with a 0.5 m spatial resolution has been used to estimate the height of pine forest stands (Mora et al. 2013). The stand median grey-level value and the 90% percentile of crown size distribution in combination with a *k*-nearest neighbour model provided the highest accuracies in terms of the coefficient of determination (R^2 = 0.69) among other predictors and models. Donoghue and Watt (2006) approximated mean vegetation height for plots of 0.02 ha using directly the mean reflectance values from spectral bands of Landsat Enhanced Thematic Mapper Plus (ETM+) and IKONOS images. In particular, a curvilinear regression model with a power function was used to model mean height as $y = ax^b$, where y represents the mean height in a plot, x the mean reflectance, and a and b are real values. They managed to estimate the height of Sitka spruce plantations with R^2 values up to 0.87. Spectral indices from Landsat images, i.e. the Normalized Difference Water Index (NDWI) and the Optimized Soil Adjusted Vegetation Index (OSAVI), have been used to estimate the height of soybean and corn (Anderson et al. 2004) using the biomass development of the crop as main variable. Ahmed et al. (2015) used Landsat time series to approximate the height of conifer and deciduous forest stands. A random forest approach proved more effective than a nonlinear multiple regression model, with Time Since Disturbance (TSD) being the most discriminatory predictor for young (< 30 years) stands and the Normalized Difference Vegetation Index (NDVI) and the Tasseled Cap transformation Angle (TCA) the best ones for mature (> 30 years) stands. In a recent study, Hansen et al. (2016) evaluated Landsat 7 and 8 data both individually and in synergy to estimate tree height in an extensive area in Sub-Saharan Africa. Spectral band reflectance and NDVI values from a large number of images from 2013 and 2014 were collected and sorted for each pixel. Values below the 10th and above the 90th percentiles, i.e. the 20% most extreme values, were discarded. The means for the remaining ranges of values for each image band as well as NDVI were used as predictors in a regression tree approach. Predictors from the integrated Landsat 7 and 8 datasets achieved the lowest Mean Absolute Error (MAE = 2.45 m) suggesting their combined used as well as the potential integration of Sentinel-2 data in future height estimation studies in case LiDAR information is not available or limited. Besides spectral information, texture features extracted from passive sensors have been correlated with vegetation height in several studies. Early studies used simple texture features for the estimation of coniferous tree height, such as the mean (Puhr and Donoghue 2000) and the standard deviation (Franklin et al. 1986) of reflectance values within a 3×3 pixel moving window. Similar features have been calculated from Satellite Pour l'Observation de la Terre 5 (SPOT-5) images and evaluated with different regression models in hardwood and coniferous forests (Wolter et al. 2009). In another study involving SPOT-5 data, a number of first-order and second-order texture features were used together with spectral ones in a tropical forest area (Castillo-Santiago et al. 2010). The variance of the near-infrared (NIR) band in a 9×9 pixel window and the reflectance values in NIR and mid-infrared (MIR) bands were selected as the best predictors by a multiple linear regression model (R^2 = 0.71). Similar second-order

grey-level co-occurrence matrix (GLCM) texture features from IKONOS imagery approximated the height of oak, beech, and spruce trees with accuracies up to R^2 = 0.76 (Kayitakire et al. 2006). Chen et al. (2011) used spectral and texture features as well as shadow fraction from a Quickbird image to compare pixel-based and object-based analysis under nonlinear regression. The experimental results from the object-based approach proved more accurate than the pixel-based ones. Instead of a regression problem, as in the previous approaches, vegetation height estimation has also been formulated as a classification problem. In an object-based approach, Petrou et al. (2015) calculated texture features based on local variance, entropy, and local binary patterns from WorldView-2 imagery. The features were used to classify heathland vegetation to six height classes appropriate for habitat studies, ranging from less than 5 cm to 40 m. Filter-based dimensionality reduction and a random forest classifier achieved classification accuracies over 90%, identifying the best performing subsets of features and decreasing the originally extracted features by around 97%.

2.5.3 RADAR technology

RADAR (Radio Detection And Ranging) is an important tool for detecting the structure and height of vegetation because of its ability to penetrate clouds, to provide a signal from the geometric properties of the vegetation and to generate images over large areas. The RADAR signal, backscatter and interferometric phase, depends on the physical structure and dielectric properties allowing an indirect measurement of vegetation structure. Short wavelength RADAR (X- and C-band; ~2 cm and ~6 cm wavelength) only partially penetrates the vegetation / forest canopy and mainly receives a signal from leaves and small branches. In contrast, long wavelength RADAR (L- and P-band; ~23 and ~60 cm wavelength) penetrates the vegetation / forest canopy and the signal is primarily caused by branches and trunks making it more suitable for mapping ecosystem structure and vegetation height (Ulaby et al. 1986; Woodhouse 2005). Since the early 1990s several studies have demonstrated the relationship between RADAR backscatter and vegetation structure and height (e.g. Dobson et al. 1995, Joshi et al., 2015). Interferometric SAR (InSAR) allows a more direct estimation of height and the vertical distribution of vegetation (Florian et al., 2006, Papathanassiou et al., 2008, Treuhaft and Sinqueira 2004). InSAR derives its sensitivity to vertical vegetation structure from the difference in signal of two RADAR receivers separated in space by a known distance, the so called "baseline". The difference between phases of the signal received at the two ends of the baseline can be translated into a topographic height. The topography measured from InSAR depends on the vegetation characteristics and the RADAR wavelength. Shorter wavelengths provide a signal relatively close to the canopy, while longer wavelength penetrate deeper into the canopy to the ground surface (Rosen et al., 2000). Varying InSAR methods exist to detect the forest height. Some studies compare InSAR height with independent measurements of the ground surface (e.g. national surface height maps) (Kellndorfer et al., 2004, Kellndorfer et al., 2006; Simard et al., 2006). A second approach, uses the difference in between multiple wavelengths (e.g. X-band and P-band) to measure interferometric heights at two frequencies. Height is calculated as the difference in elevation between the two measurements (Wheeler and Hensley, 2000, Sexton et al., 2009). More explorative studies make use of polarimetric InSAR (PolInSAR) technology and use both interferometric height and correlation, along with multiple baselines and/or polarizations in retrieving information on the vertical distribution directly (Cloude and Papathanassiou, 1998; Treuhaft and Siqueira, 2000, Kugler et al., 2007, Garestier et al., 2008, Khati & Singh, 2015). Garestier et al. (2008) used a random volume over ground (RVoG) model to detect forest height from single-pass X-and PolInSAR data set using HH and HV channels over a sparse pine forest. Recently, Khati & Singh (2015) successfully demonstrated the use of space-borne PolInSAR data acquired by TerraSAR-X/TandDEM-X for tree height inversion at a pine forest site. The observed RMSE of 7.6 m relates to an underestimation of the tree heights that is caused by the low penetration capabilities of X-band RADAR into to forest canopy. Garestier et al. (2008) and Wang et al. (2016) found that forest height inversion using short wavelength

RADAR (X- and C-band) strongly depends on the forest density. While forest height inversion has been demonstrated at sparse boreal forest, the applicability at dense tropical forest is very limited. Long wavelength PolInSAR (L- and P-band) is much lesser affected, however, current provision of long-wavelength PolInSAR data is limited (Wang et al., 2016).

2.5.4 LiDAR technology

The following subsections deal with LiDAR technology from different platforms that all have their own merits for surveying, they concern respectively, manned and unmanned airborne, spaceborne and terrestrial liDAR scanning.

2.5.4.1 Airborne LiDAR

The use of airborne laser scanning dates back to the 1970s. However, their commercial development is traced back to the mid-1990s only. From the perspective of ecological research, LiDAR can be therefore considered as a relatively new technology (Carson et al. 2004). LiDAR was originally introduced to generate more accurate digital elevation models (DEMs) (Evans et al. 2006) but has recently become an effective tool for natural resources applications (Akay et al. 2008). In the process of creating a DEM, only reflections from the ground level are used, and reflections from vegetation are considered redundant. Recent studies with LiDAR data have explored the possibilities to use these redundant vegetation reflections as a new source of geospatial data that can provide fine-grained information about the 3D physical structure of terrestrial and aquatic ecosystems (Geerling et al. 2007). This result can then be applied in forestry, ecological (habitat) mapping and vegetation monitoring (Hyde et al. 2005). Airborne LiDAR provided most of the applications so far, but Terrestrial LiDAR as well as spaceborne and UAV liDAR will provide more and more applications in the future, since they all have their own merits. Scopus[16] presents very well the steep increase in publications per year between 2000 and 2015, respectively from around 10 in 2000 to 400 publications in 2015 (search "LiDAR AND vegetation"). LiDAR is an active remote sensing technique that measures the properties of emitted scattered light to determine the 3D coordinates (x, y, z) and other properties of a distant target (St-Onge 2005; Mallet et al. 2009). To do so, the LiDAR instrument transmits laser pulses and calculates the distance from a target based on energy that is reflected from the target back to the instrument. The time for laser pulses to return back to the LiDAR sensor is used to calculate the distance to the target (Akay et al. 2008). LiDAR provides geometric data but also radiometric data, such as signal intensity, amplitude, and pulse angle (Hall et al. 2005; Evans et al. 2006). The laser camera measurements are combined with the platform's position and altitude data - measured by a differential global positioning system (GPS) and an inertial navigation unit (INU) - identifying the position and elevation of each collected point (Wehr et al. 1999).The "xy" accuracy of the pulse center is typically 0.05–0.5 m, depending on the flying height. The accuracy in "z" is usually better than 0.2 m. Values range from 0.2 m to 1.0 m for flying heights of 1–5 km (Korpela et al. 2009).

[16] www.scopus.com

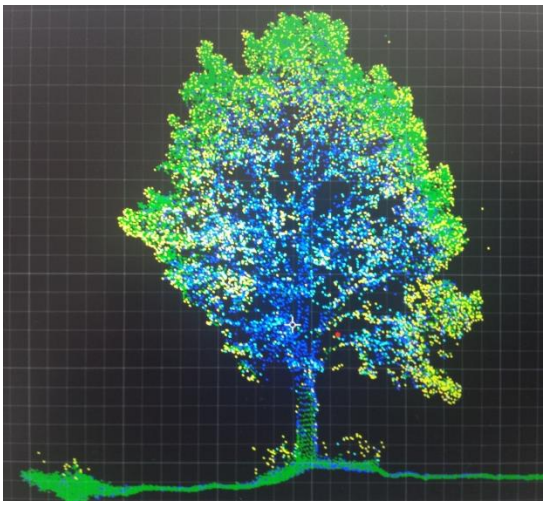

Figure 2.5.4.1.1 Example of a LiDAR point cloud of an individual tree, visualized in 3D, as taken by an UAV LiDAR camera (Acquired with VUX-SYS camera mounted on RiCopter). The colours represent the multiple returns. The first returns are indicated indicated in green and represent leaves or ground, while blues colours represent more the internal woody skeleton or branches of the tree.

So airborne LiDAR offers the possibility to collect structural information over larger spatial extents than could not be obtained by field surveys (Bradbury et al. 2005). LiDAR, in contrast to optical remote sensing techniques, can be expected to bridge the gap in 3D structural information, including canopy shape, number of vegetation layers and individual tree identification at the landscape scale (Graf et al. 2009).

2.5.4.2 UAV LiDAR (drones)

The use of unmanned airborne vehicles (UAVs) or so-called drones that can carry a LiDAR camera is a recent development. Recently, the use and adoption of UAVs as a flexible sensor platform for monitoring has evolved rapidly. Potential application domains are e.g. agriculture (phenotyping of individual plants), coastal monitoring, dikes, archaeology, corridor mapping (power lines, railway tracks, pipeline inspection), topography, geomorphology, and construction site monitoring (surveying urban environments), next to forestry and vegetation monitoring. Until recently it was not possible to have a LiDAR camera on a UAV since the cameras were too heavy to be carried by a UAV. Before, LiDAR measurements were made only from manned helicopters or airplanes. Attaching a LiDAR sensor to a moving UAV platform allows 3D mapping of larger surface areas. The big advantage of the use of a UAV is its flexibility to be used in space and time. The major limitation compared to manned airborne laser scanning is still limited in its areal coverage, not only due to the technological capabilities but also due to aviation regulations which does not allow in most cases to fly beyond line of sight. The use of unmanned LiDAR Scanning (ULS) has certainly advantages compared to the more static terrestrial laser scanning (TLS) or large-scale systems using manned platforms (Kooistra and Mücher, 2015, business plan prepared for evaluation within CAT Agrofood Program of Wageningen University and Research Centre):

1. In general, the flexible agile deployment is an important asset of UAV data collection especially compared to satellites and manned aircrafts: for example LiDAR observations can be combined with additional camera observation to characterize both the structure and bio-chemistry of 3D objects;

2. Compared to TLS, UAV based LiDAR scanning allows the coverage of a much larger areal extent allowing to investigate relevant processes at local to regional scale (up to 100 ha per day);
3. Compared to manned platforms, UAV based LiDAR scanning allows timing of data acquisition at critical moments and repeated measurements as part of monitoring experiments. The costs for manned platforms for monitoring is often too expensive.

However only a limited number of manufacturers can provide at the moment such integrated UAV-LiDAR systems (ULS).

2.5.4.3 Spaceborne LiDAR

NASA's GLAS instrument (Geoscience Laser Altimeter System) on the spaceborn ICESat platform (Ice, Cloud, and land Elevation satellite), launched on 12 January 2003, is a good example of the promising technique from space. Although the main objective of the GLAS instrument was to measure ice sheet elevations and changes in elevation through time, it was also very successful in measuring forest height. Amongst others Hayashia et al. (2013) showed that ICESat/GLAS data provides useful information on forest canopy height with an accuracy RMSE of 2.8 m. New advanced sensors to be launched in the next couple of years will provide increasingly accurate information on traits such as vegetation height and plant-species characteristics. These include the NASA Global Ecosystem Dynamics Investigation Lidar (GEDI). The scientific goal of the GEDI is to characterize the effects of changing climate and land use on ecosystem structure and dynamics to enable radically improved quantification and understanding of the Earth's carbon cycle and biodiversity. Focused on tropical and temperate forests from its vantage point on the International Space Station (ISS), GEDI uses LiDAR to provide the first global, high-resolution observations of forest vertical structure (http://science.nasa.gov/missions/gedi/).

2.5.4.4 Terrestrial LiDAR

Terrestrial LiDAR, also called terrestrial laser scanning (TLS), is a ground-based remote sensing system that can measure 3D vegetation structure (i.e. the size and location of canopy elements) to centimetre or even millimetre accuracy and precision. Broad scale mapping based on remote sensing (satellite) data rarely, if ever, record the type of forest structural and dynamic information we require directly. Various simplifying assumptions, models and ancillary data are typically required to extract such information. At the fine (sub-ha plot) scale, it has also been difficult to incorporate rapid and robust assessment of accurate ground reference data of 3D forest structure into existing surveying and mapping strategies. This is in part due to the relative newness of such detailed structural data and the consequent lack of consistent methods for processing and analyzing these data in conjunction with more traditional survey and monitoring methods (Calders et al, 2015a).

2.5.5 LiDAR applications supporting EBV ecosystem structure

In this section some examples of LiDAR applications in vegetation monitoring are given, related to the EBV ecosystem structure. The first three subsections are on forest parameters, vegetation structure, and habitat classification, all based on airborne LiDAR. Real LiDAR monitoring applications are so far mainly limited to Terrestrial LiDAR, and these are described in last subsection.

2.5.5.1 Forest structure

Vegetation vertical structure is defined as the bottom to top configuration of above-ground vegetation including for example, canopy cover, tree and canopy height, vegetation layers, and biomass or volume (Bergen et al. 2008). LiDAR remote sensing being capable of providing both horizontal and vertical information at high spatial resolutions and vertical accuracies,

allows forest attributes to be retrieved (Dubayah et al. 2000; Akay et al. 2008). Both discrete-return and full waveform devices have been used worldwide for characterizing forest structure (Lefsky et al. 2002a; Lim et al. 2003). These technologies have successfully been used to retrieve tree height (Jan 2005; Wang et al. 2008; Rosette et al. 2009; Heurich et al. 2008), above ground biomass and timber volumes (Calders et al., 2015;Means et al. 2000; Lefsky et al. 2002b; Zimble et al. 2003; Patenaude et al. 2004; Zhao et al. 2009) and leaf area (Roberts et al. 2005;) across various ecosystems such as temperate (Anderson et al. 2006) or tropical forest (Drake et al. 2002). The combination of airborne LiDAR data with other optical remote sensing data also shows promising results for the estimation of forest structural characteristics (Coops et al. 2004), often better that when LiDAR data were used alone (Hudak et al. 2002; Wulder et al. 2003). In some case the intensity recorded by the LiDAR sensors is also used to measure tree metrics and vegetation structure (Lovell et al. 2003; Hall et al. 2005; Evans et al. 2006; Weishampel et al. 2007).Those studies have demonstrated the ability of LiDAR techniques to measure vegetation height, and cover as well as more complex attributes of canopy structure. From those measurements, further analysis can be done related to the vegetation attributes and function.

2.5.5.2 Vegetation structure

Vegetation attributes and structure information generated from airborne LiDAR data have also applications beyond forestry and are of a great help for ecological functions understanding. These canopy metrics and structural data have been proven to be strong predictors of species richness for woodland birds in several studies (Vierling et al. 2008; Mason et al. 2003; Hill et al. 2005), even in difficult terrain (Hyde et al. 2005). Furthermore, the correlation between LiDAR-derived estimates of vegetation structure important to birds have been demonstrated in areas ranging from grasslands to forests (Bradbury et al. 2005; Hinsley et al. 2006). LiDAR have been also demonstrated to be able to identify differently structured habitat units and to quantify variation in vegetation structure within those units (Bradbury et al. 2005). LiDAR can also provide indication about territories and breeding success of several types of birds species (Bergen et al. 2008). Graf et al. (2009) concluded their study on the great potential offered by LiDAR for effective habitat monitoring and management of endangered species. In Korpela et al. (2009) the result obtained using LiDAR for the mire habitat classification accuracy were considered as surpassing earlier results with optical data. Some studies also highlighted that the result of habitat analysis obtained with LiDAR may be enhanced when used in combination with spectral data (Bergen et al. 2007; Clawges et al. 2008; Hyde et al. 2006). In view of those results, LiDAR remote sensing shows considerable efficacy for habitat mapping/characterization and wildlife management in fine detail across broad areas. It may replace many labour-intensive, field-based measurements, and can characterize habitat in novel ways (Vierling et al. 2008). Considering monitoring applications, the repeatable and high absolute "xyz" accuracy is advantageous since changes can be detected at submeter scales and the same measurement units can be monitored over time (Korpela et al. 2009). In that sense, LiDAR constitutes an efficient tool for short and long term monitoring of changes in surface structure and vegetation. For example, Wieshampel et al. (2007) used LiDAR measurements to monitor vegetation recovery after several disturbances and Calders et al (2015) used TLS for phenology monitoring.

2.5.5.3 Habitat classification

Studies conducted in order to classify vegetation or habitats using LiDAR showed that discrimination of some types was only possible based on vegetation height and density when they had similar spectral reflectances (Geerling et al. 2007; Geerling et al. 2009). LiDAR appeared to succeed as well in characterizing tree species with the canopy height as the strongest explanatory variables in the vegetation classification (Korpela et al. 2009; Geerling et al. 2007). The integration of spectral information coming from optical remote sensing data and canopy height data generated from LiDAR into the classification has been demonstrated

to produce an ecologically meaningful thematic product for a complex woodland environment (Hill et al. 2005). In most of the ecological studies based on LiDAR techniques, the intensity/amplitude is rarely used as it must be calibrated and corrected first (Mallet et al. 2009), even though it appears as a potential important factor for feature extraction or land cover classification. Antonarakis et al. (2008) demonstrate that the combination of intensity and elevation data from LiDAR point clouds can be enough to classify multiple land types using object-based classification method. Other studies using intensity values were conducted and their results imply that the intensity of the laser return signal can be used for classification purposes (Lim et al. 2003; Brennan et al. 2006; Korpela et al. 2009). A biodiversity observation system that is consistent and cost effective is desirable, but its development and implementation remains a significant challenge. Recent advances in Earth Observation (EO) allow inroads to the design of such a system (Mücher et al, 2015). Light Detection and Ranging (LiDAR) and Very High Resolution (VHR) multi-spectral sensors are increasingly becoming available. These images provide opportunities for land cover and habitat mapping with a very high spatial resolution of 1 or 2 meters (mapping scale ~ 1:4000) and a high thematic differentiation in such a way that the derived maps meet the demand of end-users such as terrain and nature conservation managers. The launch of the multi-spectral Worldview-2 (WV-2) sensor with eight spectral bands (including the coastal, yellow and red edge as well as a second (overlapping) NIR channel) and a spatial resolution of 2 meters provides new opportunities for discrimination of land covers/habitats, hence it is preferred for adoption with the EODHaM system (Lucas et al, 2015). A limitation of using optical imagery is that information on vegetation height cannot be retrieved with sufficient reliability unless relationships with, for example, textural measures are provided (Lucas et al, 2015). As such, LiDAR is complementary to optical EO data, since the technology allows for the measurement of vegetation structure (Mücher et al., 2013). LiDAR-derived canopy height models (CHM) represent the calculated height of the woody vegetation above the ground surface (in centimetres) for each individual grid cell. This is critical for the descriptions of woody life forms within the Food and Agricultural Organization (FAO) Land Cover Classification System (LCCS) taxonomy (di Gregorio and Jansen, 2005) and the General Habitat Category (GHC) system for habitat surveillance and monitoring (Bunce et al., 2008). Since vegetation physiognomy and structure are an important diagnostic criteria in the land cover as well as habitat classification system, we put a major emphasis on the exploitation of LiDAR data for CHM in combination with multi-temporal and multi-spectral VHR satellite imagery. The CHM is a result of the difference in height between the calculated Digital Surface Model (DSM), indicating the top of the vegetation, and the Digital Terrain Model (DTM), indicating the ground surface. EODHaM requires in general several satellite images distributed over the growing season (a pre-peak flush image, a peak flush image, and a post-peak flush image) which allows the calculation of a wider range of spectral indices with a sufficient spatial detail. The imagery needs to be acquired for periods that are phenological optimal for the discrimination of land cover and habitat classes (Lucas et al., 2015). An important additional input in the EODHAM system was the CHM with a spatial resolution of 1 by 1 meter and vegetation height indicated in centimetres, as derived from the LiDAR multiple return data. It shows that the combination of LiDAR with VHR satellite imagery is a powerful tool for the identification of plant life forms and associated land covers due to the generic possibilities that it provides in combination with the EODHAM system for any site across the globe. Even though the validation is not showing the highest accuracies (Mücher et al, 2015).

2.5.5.4 Forest Monitoring

The potential of TLS for forest monitoring was first demonstrated more than a decade ago, but has not yet reached its full potential, for the reasons outlined above. Newnham et al. (2015) & Anderson et al. (2015) provide a full review of the development of TLS as a forest measurement tool.

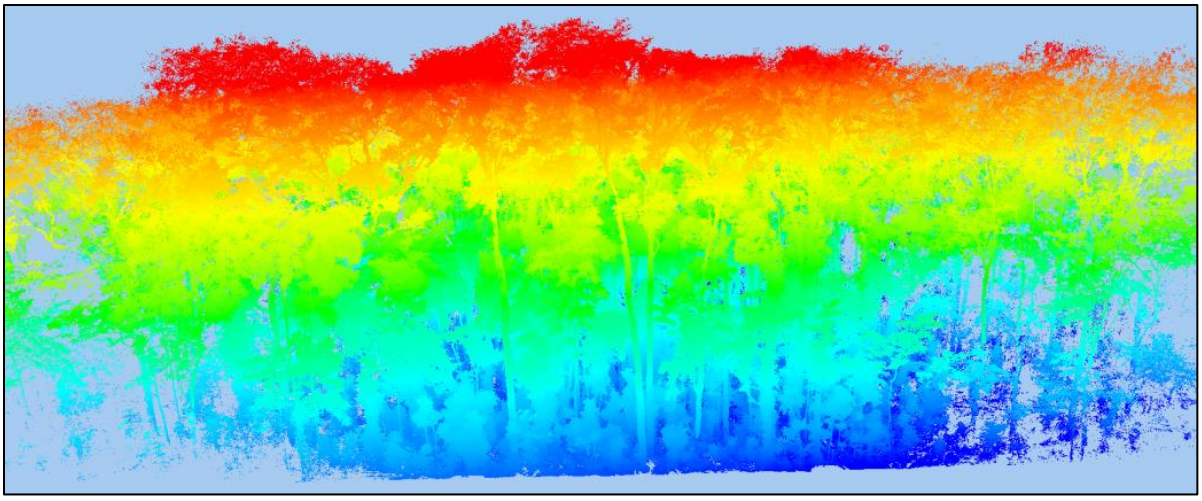

Figure 1.5.5.4.1: Illustration of a 3D terrestrial in-situ laser scanner point cloud of a Maranthaceae forest in Lopé National Park located in central Gabon. The data were collected with a RIEGL VZ-400 LiDAR camera from 7 different scan locations. Coloured by height (blue = 0 m; red = 45 m).

Terrestrial LiDAR sensors are usually tripod mounted and record single scans from a fixed location. As such, scans are affected by occlusion, i.e. the near objects in the forest can obscure objects further from the scanner. The effects of occlusion can be significantly reduced by obtaining data from multiple scan locations. Multiple single scans made at different locations can be co-registered (to within mm accuracy depending on instrument and environment) using high reflectivity targets that act as tie-points between different scans (see Figure 2.5.5.4.1). A range of scientific and commercial scanners are currently available. Whereas airborne LiDAR systems have been used in forest measurements since the mid-eighties (Nelson et al., 1984), the first commercial terrestrial laser scanners came to the market in the late 90s with instruments such as the RIEGL LMS Z210 and CYRAX 2200. The first TLS instruments used a time-of-flight ranging principle, with phase-shift based ranging instruments following soon after. The commercial instruments were (and still are) generally developed for precision mapping and survey applications where hard targets (i.e. structurally continuous surfaces) dominate e.g. urban areas and/or mineral and petrochemical exploration. This has implications for their use in forest applications, where many laser hits are partial, and/or from softer targets (i.e. structurally fragmented or dispersed surfaces) with anisotropic reflecting surfaces such as leaves or needles and bark. Of the scientific (i.e. non-commercial) scanners, the Echidna Validation Instrument (EVI) was one of the first laser scanners specifically designed to monitor vegetation (Strahler et al., 2008). Commonly used commercial instruments include the RIEGL VZ-series, Leica C10 and HDS7000, Optech ILRIS-HD and FARO Focus^{3D} X 330 and Trimble TX8. Newnham et al. (2012) provide a detailed independent comparison between some commercial scanners and evaluated their performance for measuring vegetation structure.

2.5.6 Status and outlook

Monitoring ecosystem structure can now be supported by a wide range of remote sensing techniques. The challenge to date is to support the biodiversity community with a global observing system that revolves around the monitoring of a set of agreed variables essential to the tracking of changes in biological diversity on Earth (Pettorelli, 2016), such as EBV ecosystem structure. To achieve this the remote sensing techniques available have to be exploited to a much wider range and should complement each other, so that large parts of the globe can be monitored in reality. LiDAR technique is a tremendously growing remote sensing technique that due to its absolute physical measurements of height and structure has an enormous potential for applications. As we have seen LiDAR instruments can be placed on many different platforms that all have their own merits, ranging from terrestrial to spaceborne LiDAR. Although the LiDAR instruments are still very expensive we see that prices are lowering due to its wide range of applications, and makes it also slowly affordable to mount on UAV platforms. For regular forest monitoring terrestrial LiDAR still has the best credits but will probably change with increasing use of UAV and spaceborne platforms. We have mainly focused on vegetation and more specifically on forest, but it should be stressed that the LiDAR technique has a wide range of applications from terrain, infrastructure and urban applications, to agriculture, archaeology, geology, bathometry, and many other domains. Spaceborne LiDAR is not yet well developed but planned satellite sensors as NASA's GEDI show that this will change. Passive sensor data can be used in certain cases as alternatives of LiDAR data for vegetation height estimation. Although not as accurate as LiDAR overall, satellite passive sensors have provided high precision approximations of height and have been proven particularly useful in cases where LiDAR information was unavailable due to high cost or limited coverage. Several types of predictors have been derived from passive sensor imagery, including reflectance values, spectral indices, texture features, or even temporal and semantic-based information (e.g. time-since-disturbance features in multi-temporal imagery). ESA's upcoming P-band RADAR 'BIOMASS' mission holds promises for accurate space-borne large-area estimation of vegetation structure and height. It is intended to derive vegetation structure and height using POLInSAR globally and at a spatial scale of 100-200 m (Scipal et al., 2010). Due to the long wavelength of ~60 cm a much reduced saturation and underestimation of forest height is expected when compared to results found for shorter wavelength RADAR (e.g. Garestier et al. 2008, Khati & Singh 2015), even over dense tropical forests. Such variety of features is essential in creating non-redundant information between active and passive sensor data and improve height estimation. Experiments involving synergies of LiDAR, RADAR, and passive multispectral data have shown that fusion of data from different sensors can provide increased performance compared with single-sensor data (Hyde et al. 2006). Furthermore, passive optical imagery can indirectly complement LiDAR data in height estimation by spectrally distinguishing vegetation from ground and remove noisy LiDAR measurements from the background that deteriorate accuracy (Riaño et al. 2007). Finally, widely and freely available RADAR and passive optical RS data, think of for example SENTINEL 1 and 2, should be used in synergy with limited but highly accurate LiDAR measurements to increase the spatial coverage of vegetation height measurements.

2.5.7 Acknowledgements

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2.6 DISTURBANCE REGIME

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2.6.1 Background and ecological concept

When disturbance occur in sequence over a long time period or be accumulative, they are defined as disturbance regime. GEOBON has pointed out their determinant roll on the ecosystem function, structure and composition. In this sense, disturbance regime belong to the ecosystem functioning variables classes in the EBV framework. It is important to precise that even if a disturbance occurs once (e.g. logging, fire) but others continue (e.g. livestock, plantations) and in consequence a new land cover/use is established, the set of disturbances can be seen like a chain reaction and be assessed as an entire disturbance regime instead of individual events.

In general, disturbance is any relative discrete event in time that disrupts ecosystem structure, changes resources availability and micro/macro habitat conditions. They are related to the spatial and temporal dimensions (Pickett and White 1985). For that reason, ecological disturbance regimes have to be observed according with their own spatial-temporal scale. Besides, they play an important roll in the ecosystem dynamics being a determining factor in the ecosystem maintaining and functioning (Turner et al. 2001). In this sense, disturbance creates a continuum dynamic that controls the establishment and rechange of individuals, as well as the succession dynamic of communities (Hobbs et al. 2007).

The ecosystem disturbance adaptation is based on their own resistance and resilience. The first one is the capacity to resist small alterations through time preserving structural and functional attributes under a stress regime, in other words it is the system capacity to resist displacement from its initial state. The second one refers to the recovery capability to return to an initial state after important disturbance.

Some ecosystems are very resilient but their resistance is low when facing certain disturbance. As an example, the boreal forest is no resistance to fire but recover completely after some years (Thompson 2011). On the other hand, the dry forest is very resistance to disturbance regime because it has evolved within these conditions; however their resilience capacity is low. Thereby, it is important to take into account that the disturbance response and the stress causing it vary among forest types. Besides, it has been observed that more complex systems have higher capacity to absorb extreme fluctuations even though they fluctuate more against environmental changes (Hernández *et al*. 2002).

When the ecosystem is adapted to the disturbance, it will be resilient and recover to its previous state. Complementary, new landscape patterns may be appeared that will also affect the disturbance respond. For example disturbance regime cause forest patchiness that lately facilitate or reduce the disturbance spread (Turner et al. 2001). On the other hand, when a disturbance occurs rarely or its magnitude or frequency increases, the changes could lead to a new ecosystem. Then, the ecosystem lost their resilience capacity and reaches an ecological tipping point or threshold, which drives to a new state with considerable, nonlinear, unpredictable and dramatic changes (Thompson 2011). Under this scenario, the species biodiversity is modified through chances in competitive interactions and successional trajectories (Noble & Slatyer 1980).

The causes of disturbance might be either natural or human made. Natural disturbance vary from frequent and small disturbance (e.g. falling trees) to large and very rare (e.g.

glaciations). Initially, natural disturbance were closely related to the climatic conditions, weather patterns and hydrological regimes of the zone, those determined their occurrence, frequency and magnitude. Nowadays, from local to large scale human activities have altered the natural disturbance regimes cycles. From a worldwide perspective hurricanes or the ENSO phenomenon regularity have changed as well as the magnitude and the periods of rain, wind and drought (Overpeck, et al., 1990, Dale et al., 2001). At local scale, anthropogenic disturbance effects might be punctual but cumulative in larger scales. Most of the anthropogenic disturbance have an analogue natural disturbance, but their frequency magnitude and extension vary radically (Walker & Walker 1991).

Three different phases can be considered for disturbance dynamics assessment. The first phase is related to pre-disturbance ecosystem state, which informs about the ecosystem conditions and antecedents that often are determinant factors on the disturbance effects (Figure 2.6.1). It could be seen like a base line but also contains the previous state of the system, including even slight recent changes that increase the ecosystem vulnerability. The second phase is the disturbance by itself; it should occur in short intervals of time (hours) usually when the origin is abiotic or longer periods of time (months, years) related to biotic causes like insects and disease outbreaks. In this way, monitoring programs and early warning systems make possible a well-timely disturbance detection. The last phase is post-disturbance which looks through the implications and synergies after the disturbance.

Examples of related topics are resilience, plant succession, patch dynamics and land use change; detailed information is in subsection 2.6.4.

Even though all disturbance assessment phases are included in Figure 2.6.1.1, the scope of this section is mainly the disturbance and post disturbance stages.

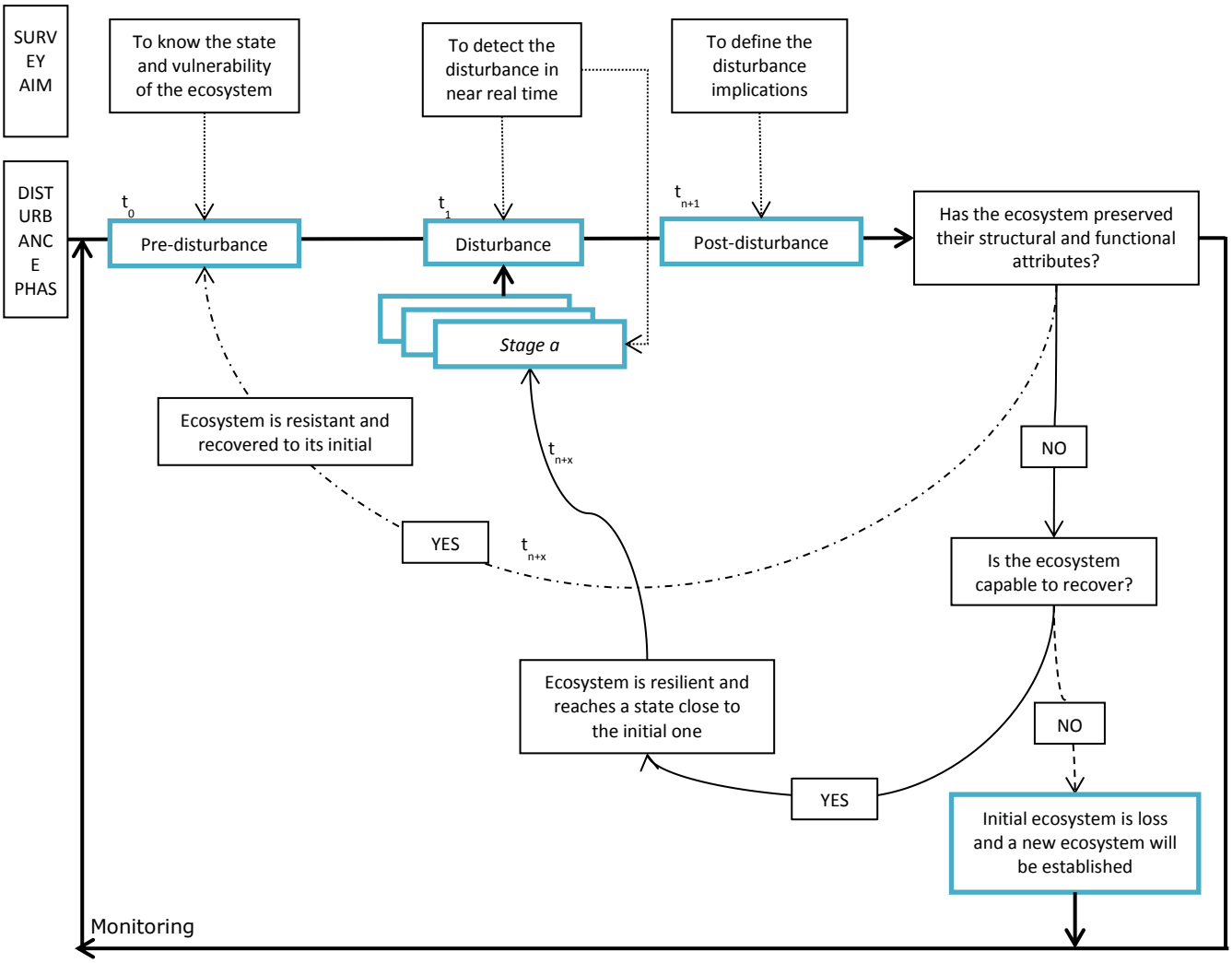

Figure 2.6.1.1 Remarks of pre-disturbance, disturbance and post-disturbance assessment phases. The thick solid line is the ideal disturbance assessment direction which could turn into a monitoring system. The round dotted line shows the aim of each phase. The dash dot line represent natural disturbance. The solid thin line is mainly a combination of natural and human made disturbance. The dash line shows strong disturbance usually anthropogenic that increase their impact in a climate change scenario. The blue boxes represent different ecosystem stages; the "*Stage a*" refers to a new stage close to the initial one. t_0= it is a specific time before disturbance, t_1=time of disturbance occurrence, t_{1+n}=time of assessment of disturbance implications, t_{n+x}=time required for an ecosystem to return to its initial state or close to it.

After the disturbance, the ecosystem trajectory may have different effects on time and space. On the first scenario the ecosystem is capable to recover because it is adapted or the alteration in the environment was punctual and likely associated to natural causes. Conversely, on the second scenario the disturbance is chronic, it maintains through time and space driving the system to collapse and preventing them to recover, usually their origin is anthropic (Ceccon 2013) (see section 2.6.3).

The observation and assessment of disturbance requires continuity in time. It may also be necessary to make observations at multiple spatial scales, i.e. to understand how certain phenomena observed on small scales may affects or could be observed in larger spatial scales,

where these processes have their own interactions and properties. Nevertheless, disturbances surveys from the ecology point of view, are manly planned at local scales. Additionally, large scale disturbances that occur rarely as volcanic eruption, large fire, flooding and storms, do not have proper dataset in time, then their ecological research is challenging and limited (Turner and Dale 1998).

A list of descriptors to characterize and study disturbance regimes (Table 2.6.1.1) from the ecological point of view was proposed by Pickett and White (1985). Some of these descriptors could be measured by remote sensing within certain space and time limitations; but others require ground data. For example, fire and flooding require high temporal resolution to get real time data and information of its frequency. While logging occurs once in long time period, then imagery to describe spatial features accurately like distribution and area is mostly used. Other descriptors as synergism and return interval demand more resources; monitoring programs or modelling.

Table 2.6.1.1 Definition of disturbance regime descriptors (Modified from Pickett and White 1985)

Descriptor	Definition	Remote sensing requirements	Disturbance stage
Distribution	Spatial distribution, including relationship to geographic, topographic, environmental and community gradients	Moderate/high spatial resolution	Disturbance or post disturbance
Frequency	Mean number of events per time period	Hyper temporal resolution	Disturbance detection
Area or size	Disturbed areas: this can be expressed as e.g. area per event, area per time period, among others	High / moderate spatial resolution	Post disturbance
Synergism	Effects on the occurrence of other disturbance	Monitoring program	Post disturbance
Return Interval	Mean time between disturbance	Monitoring program	All stages
Rotation Period	Mean time needed to disturbance an area equivalent to the study area. The study area varies and has to be explicitly defined by the researchers	Modelling	NA
Magnitude	a) Physical force of the event per area per time b) Impact on the organism, community, or ecosystem	It requires ground data	Disturbance or post disturbance

2.6.2 Disturbance regimes implications in tropical forest and remote sensing connotation

Natural disturbance regime occurring in tropical forest are fire, flooding, droughts and landslides, and they vary within different forest types, e.g. humid forest, dry forest, mangroves. In general, ecosystems are adapted to natural disturbance occurrence within a certain periodicity which allow them to return to their pre disturbance state or even do not been altered. Species develop strategies or specific ecomorphological structures as a result of environmental changes caused by that event. For example, tropical dry forest vegetation

exhibit leaves loss, stomatal aperture at night, thick trunks, seed dormancy, thorns, and so on, due to stational drought (Castillo 2003).

On flooded forested tropical areas, woody species have vegetative reproduction, high seed viability when are immersed in water, and radicular adaptations that make them resistant to this events (Piedade et al. 2010). It is important to highlight that swamp forest are water storage in the rainforest system, this condition make them host of biochemical process such as nitrogen turnover and methane emissions (Giafranco de Grandi et al 2000) which have to be considered on climate change research. The drainage of flooded forest or forested wetlands soils has serious implications as source of emissions that have to be incorporated as well as it is done with carbon stock loss (Brown et al 2008).

In tropical savannahs and dry forest, fire is a natural disturbance. Although, it is also one of the most used human mechanisms to create openings and establish a new land use in all forest types. Fires operates at multiple scales, causes changes in forest structure, biodiversity, reduces the aboveground and belowground carbon stocks altering the carbon cycling patterns, modifies the soil conditions and hydrological regimes (Page et al 2013).

All tropical forest types are vulnerable to the spread of exotic species, plagues and forest disease. Alike, they all are exposed to human disturbance promote by agriculture, logging, mining expansion, and hydrological alterations (e.g. roads, dams). Anthropogenic interventions take place in short time periods and reiteratively, being persistent and preventing the system to recover. Additionally, they are rapidly cumulative causing higher impacts. Table 2.6.2.1 contains a list of disturbance documented on the literature that occurred in tropical forest either by natural or anthropogenic causes.

Table 2.6.2.1 List of disturbance by tropical forest types. N: Natural disturbance, A: Anthropogenic disturbance

Disturbance	**Tropical forest type**				
	Dry Forest	**Humid forest in lowlands**	**Humid forest in highlands**	**Mangroves**	**Gallery forest in savannahs**
Droughts	N				N
Floods		N	N		N
Landslides	N	N	N	N	N
Wind		N		N	
Water level		N		N	N
Fire	N, A	N, A			
Plagues and forest disease	N				N
Exotic species	N, A	N, A	N, A	N, A	N, A
Agriculture	A	A	A	A	A
Livestock	A	A	A	A	A
Logging	A	A	A	A	A
Mining		A	A		
Hydrological alterations		A		A	

The assessment of disturbance regime through remote sensing has turned into new possibilities of observation and data availability. Generally, the possibility of carrying out a systematic field data collection in large regions was rare or extremely expensive. The data obtained from satellite imagery, especially low and medium spatial resolution have the advantage of systematic land observation in large spatial scales, and more frequently (several times per year). These allow to measure not only structural (biomass, logging) but also seasonal changes (drought, flood) or other aspects associated to the forest disturbance. Even though, they do not have the precision that characterizes the field data.

For that reason, the outcomes from remote sensing analysis have to be complemented with field data whenever possible. Ground data is a source of information to comprehend detailed local phenomena and allows a bottom-up scaling. Besides it is necessary to calibrate satellite data. In all cases, particularly for remote sensing, the results have to be understood within an ecological context providing guidelines for better management of natural and human disturbance, information required by stakeholders and decision making.

2.6.3 An overview of remote sensing concepts and parameters used to derive disturbance regime

In accordance to disturbance regimes attributes, particularly magnitude, frequency and persistence, it is possible to take advantage of different capacities of the remote sensors. For that, it is essential to take into consideration the concept of resolution, which means the sensor's sensitivity to detect objects or phenomena on the Earth's surface and intrinsically determine the data quality and amount of information that is captured. In this way, the spatial, temporal, spectral and radiometric resolutions, as well as the response from active and passive sensors, have to be carefully evaluated when a disturbance regime is going to be assessed. They are key features in order to select a specific tool to observe and measure an object or ecological process. Some descriptors useful to determine the level of detail in imagery are the size of the area affected, the recurrence of the disturbance and the level of detail required on the imagery (Table 2.6.1.1).

Usually, there is a trade-off between spatial and temporal resolution. Sensors that cover large areas with low spatial resolution have higher temporal resolution. Conversely, very high spatial resolution is scarce, expensive and hardily affordable for large area surveys. Figure 2.6.3.1 displays the number of sensors against spatial resolution, from coarse to very high.

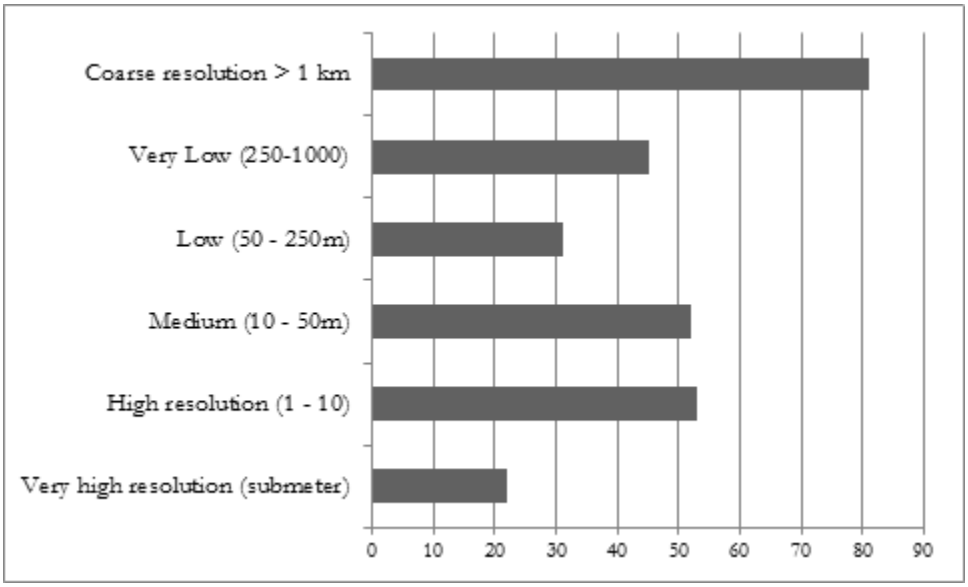

Figure 2.6.3.1 Number of satellite sensors against spatial resolution.

The spectral resolution also has an important role. It used to be that high spatial resolution sensors cover a limited range of the electromagnetic spectrum. In this sense, to gain spatial resolution data could imply less capacity of vegetation features detection that are observed in the infrared wavelengths range. However, this trend is changing with technology, nowadays launched or programmed satellites look up for higher spatial resolution with more convenient spectral capacities. Understanding the differences between resolution concepts and their implications, it is essential to properly select an adequate image type to identify a disturbance or design a successful monitoring program.

Additionally, the active sensors have to be considered. Active and passive sensors detect and highlight different features properties, but also their capacities and limitations vary. For that reason, it is necessary to take into consideration the sensors observation capabilities with respect to the survey necessities; starting for their potential to register spatial features in disturbance regimes, their topographic and environmental limitations. See chapters 4.1 and 5.1 for more information on current and upcoming Earth observation missions, respectively.

After thinking over the imagery and satellite properties, it is necessary to introduce some parameters used to assess disturbance regime. A general approach consists in discriminating biotic and abiotic parameters. Biotic parameters refer to direct measurements of vegetation. Two examples are vegetation indexes and forest biomass. The often analysed indexes are EVI and NDVI, but there are other methods that used a higher number of spectral bands and classification techniques to assess the photosynthetic green vegetation pre and post disturbance. Parameters related to biomass measurements are stem volume, basal area, leaves density and canopy openness. Biomass estimations could be derived from optical imagery analysis but mainly from radar or airborne datasets, and even single dates comparison allows detection of changes (Langner et al. 2012). These parameters are also used in forest degradation disturbance assessment (Miettnen et al., 2014).

Abiotic parameters are more related with the phenomena itself such as fire, water, or some implications in the land physical cover properties like temperature. Some abiotic parameters are soil and land surface temperature (LST), that have been demonstrated to be useful to assess forest loss due to their strong relation with vegetation. Wang et al. (2005) and Matricardi et al. (2010) found that the Modified Soil Adjusted Vegetation Index (MSAVI), which includes a soil factor, exposes the highest detection of deforestation and selective logging of very dense forest in Brazil. The MSAVI shown less saturation in dense forest, and has been well incorporated in linear mixture model to mark canopy fraction gaps. In the same way, Mildrexler et al. (2007) developed and tested a Disturbance Index (DI) that includes LST and EVI. The DI has been tested in Canada and US, but not in the tropics. Besides, features of the terrain also have effect on the disturbance intensity. Negron Juarez et al (2014) shown that wind speed and direction of tropical cyclones as well as the degree of exposure are altered by landforms calculated from the DEM.

Looking individually to disturbance, one of the most extensively monitored is fire. A review of Earth observation applications and programs related to fire is included in Secader et al (2014). Some of the most known programs are the MODIS Rapid Response System that provides information daily (https://earthdata.nasa.gov/data/near-real-time-data/rapid-response), the ATRS World Fire Atlas which produces monthly global fire maps (http://due.esrin.esa.int/page_wfa.php), the Global Fire Forest Watch (http://fires.globalforestwatch.org/) convened by the World Resource Institute and the Fire Monitoring Tool released by JRC in 2013 oriented to ecological implication of fire in natural parks (http://firetool.jrc.ec.europa.eu/).

Another disturbance regime commonly assessed is natural flooding which is associated to seasonality. Since 1990, the L-Band of JERS shows its capacity to penetrate through the canopy and generate a double-band return due to the sign interaction with the smooth water surface, trunks and branches (Hess et al. 1990, de Drandi et al. 2000). Similarly, the L-Band of Alos Palsar has been extensively used to detect and map swamp forest in the Amazons,

Africa and Asia. Hoekman et al. (2010) included a flooded forest class map in the Borneo detected by L-Bands. In the same way, Arnesen et al. (2013) reported the efficiency of Alos L- Band, HH polarized ScanSAR mode data, to determine flood extent for multiple periods of the hydrological cycle.

Disturbance like drought, plagues, diseases, exotic species spreads, selective logging and blow-downs, are used to be studied at studied at canopy, community and ecosystem level. Hence, they require high level of detail and are carried out at local scale. In these cases, high spatial resolution sensors are very suitable because they are capable to capture slight data differences with high spatial accuracy. For example, physiological trend and variance of vegetation and soil are identified by hyperspectral imagery, while LiDAR data generates structural profiles of the trees and relief features. In both cases, the detailed forest information improves the ecological understanding of the disturbance, and brings out keys and tools to its management. A few examples are below:

- Drought stress of deciduous tropical forest was assessed by Bohlman (2008) in Panama. Data from four dry season and one wet season was captured by hyperspectral airborne at 1 m pixel size. The outcomes show a good interpretation of the green vegetation and non-photosynthetic vegetation (NPV) through a mixture spectral analysis (MSA). But also it was observed that the NPV value is similar to the soil spectral response. Hence NPV can be easily misclassify driving to incorrect detection of forest gaps, pastures and similar land covers. In this sense, calculation of carbon uptake, evapotranspiration and rainfall must include information of disturbance such as drought to improve their accuracy and their relation with phenology and biodiversity. Further, this study shows how tropical forest it is not a "invariant high leaf density system".
- Deutscher et al. 2013 used Cosmo SkyMed X-Band imagery and the SRTM (90 m) to map forest disturbance in Cameroon and Republic of Congo. The high resolution SAR data highlight canopy disturbance, specifically natural or man-made gaps, logging roads and skid trail through. Two developed methods were tested; the Height Variance Approach and the SRTM Difference Approach for 3D mapping. They both reach an overall accuracy above 75%. Nevertheless the methods performed differently, while the first was independent from topography, the second had limitation on hilly areas being exclusive for flatlands.
- Blow-downs on tropical rainforest were documented by Espírito-Santo et al. (2014) in Brazil. They used data from airborne Lidar and medium spatial resolution imagery as well as forest growth simulator. It was found that small scale disturbance caused 98.6% of total carbon released in the Amazons, 1.1% is due to intermediate disturbance and 0.3% to large disturbance.

Indirect approaches to study disturbance are surveys made with other purposes but their results may provide important information. These happen with the illicit crops or ecosystem transformation assessment. They bring out data to identify main drivers of loss and disturbance regimes patterns or dynamics. As an example, the United Nations Office on Drugs and Crime has used successfully Landsat 7 and 8 imagery for the Colombian 2014 report; pansharpened images with the panchromatic band, and the implementation of decision trees algorithm were used to identify coca crops verified with overflights afterwards. Additionally, other plant cover types were classified by supervised methods (UNODC 2015). The outcomes of this survey can be used to assess patchiness in the landscape and land cover change. As well transformation studies remark the main drivers affecting the ecosystem at different stages. Etter et al. (2007) explain how clearing, cattle grazing, exotic pastures complemented with drug economy, migration and deforestation, among others, have caused forest loss in Colombia. To identify these drivers, their trends and occurrence will improve the

understanding of tropical forest risk and loss, and will help to create a more appropriate and pertinent monitoring programs.

Table 2.6.3.1 shows the hyperdata application from optical sensors according to Chamber et al. (2007). The specific relation to disturbance regime was included. Hyperdata is understood as high volume of data, some are related to high spatial or spectral detail, or high frequency This paper also explain the relevance from other sensors such as SAR and LiDAR datasets, and highlight the potential of fusion data and scaling methods to create a more complete view of the ecosystem.

Table 2.6.3.1 Hyperdata features from sensors used for disturbance regime assessment

	HYPER		
	Spectral	**Spatial**	**Temporal**
Other resolutions	High spatial Low frequency	Multispectral Low frequency	Moderate spatial resolution Multispectral
Study level	Crown/canopy level	Trees level and possible trees delineation	Regional to Global view
Properties assessed	Biochemical content (pigments, nitrogen) Moisture content Canopy nutrients	E.g. Green vegetation, no green vegetation (wood, litter), soil, shade.	Spectral indexes or spectral response changes
Disturbance assessed	Drought Diseases Plagues Invasive species	Drought Selective logging Fire Flooding	Logging Fire detection Fire recovering Greenness loss

2.6.4 Synergies and implications

Synergies of disturbances arise when the ecosystem is not adapted because they occur rarely or are not natural. Synergies are caused either by extreme natural events such as volcanoes eruption and landslides or have mostly an anthropogenic origin (logging, fire, roads). Additionally, cumulative disturbance generate strong synergies that diminishes the ecosystem recovery probability. In this case, tropical forests are drive to a new state with a new land cover and use.

Figure 2.6.4.1 shows some interactions of disturbances and synergies in tropical forests identified on the post disturbance stage. The core driver of biodiversity and forest loss is logging. After clearance, land is not recovered and has new purposes; agriculture, mining and

livestock. These activities demand infrastructure for extraction and products therefore transportation increase the pressure and the accumulation of disturbance. Other external variables also affect, population growth, cities expansion, demand new land and natural resources for urbanization, highways, dams, ports, among others.

The ecosystem affected by clearance present an alteration on their ecological process such as hydrological alterations, fragmentation and invasive species. For example, habitat fragmentation will have different implications on coming disturbance. Patchiness mosaic in the landscape is based on size, persistence, composition and location attributes through time. All these parameters fix the relationship between the patches and their surrounding areas determining how the disturbance moves. In cases where the disturbance spreads over specific species or cover types like a specific parasite, heterogeneity in the landscape retards the spread. In contrast, disturbance as fire are enhanced and facilitate by some patches attributes as edges and number of patches. Otherwise, landscape mosaic do not have any effect on thunderstorms, volcanic eruption, tornadoes among others (Turner et al. 2001).

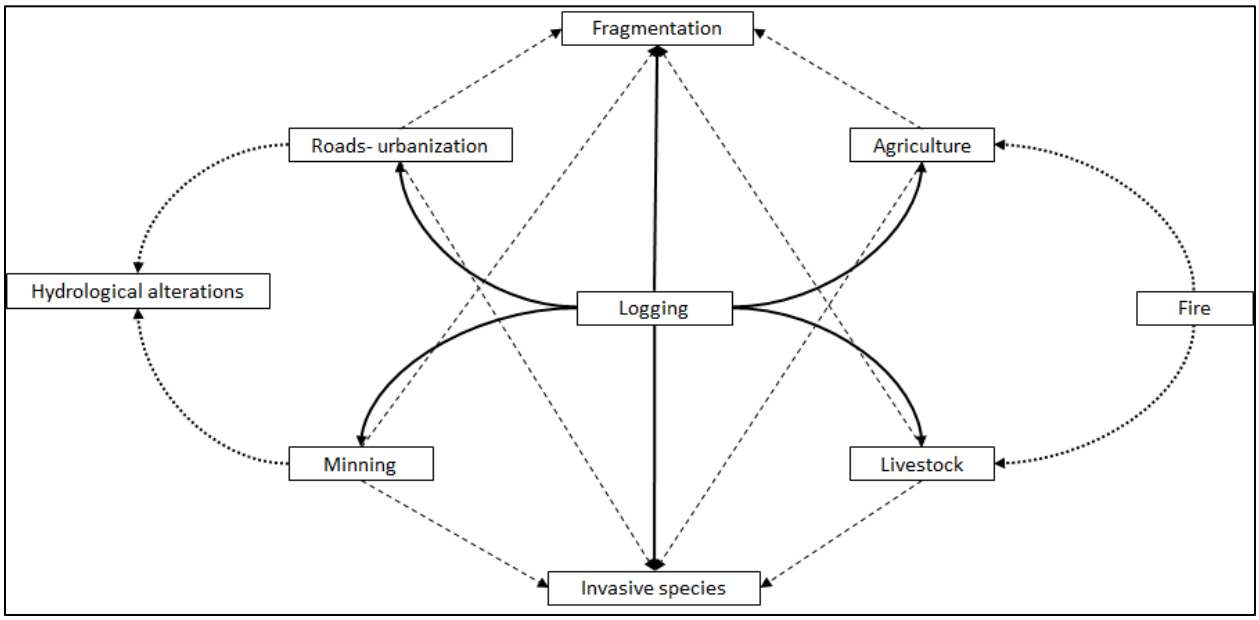

Figure 2.6.4.1 Disturbances synergies of tropical forest loss due to human interventions. Solid lines are direct relationships among disturbances. Dashed lines are likely relationships.

Another important synergy after a disturbance is the biological invasions. The exposed areas are more vulnerable to alien species invasion. Changes in vertical and horizontal structure, species composition and diversity are observed at community level reducing native species. Herein, the availability and distribution of resource vary facilitating seed dispersion, establishment and persistence of new competitors. There are only few species that tolerate extreme environmental conditions and higher disturbance frequency. For these reasons, the colonization and spread of foreign and invasive species is more favourable on those areas (Hobbs & Huenneke, 1992). See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

After the synergies are identified as well as the effect of cumulative disturbance, an analysis of the ecosystem state and trend will bring out a guide for further management. A study showing this interactions was made by Monzon-Alvarado et al. (2012) in Guatemala. They show how after wild fire tropical burned areas were converted to agricultural land. The process is explained not only by fire but for other factors like immigration, lack of governance, soils quality, proximity to roads, valuable timber and derived products.

Cumulative disturbance effects are intrinsically related to synergies and observed after logging and wild or human made fire at any scale. Monzon-Alvarado et al. (2012) described how after wild fire in Guatemala, tropical burned areas were converted to agricultural land when other variables are present. The process is explained not only by fire but for other factors like immigration and lack of governance besides soils quality, proximity to roads, valuable timber and derived products.

Complex synergies demands multiple approaches for an efficient disturbance regime assessment. They require to be evaluated at different spatial and temporal scales. On one hand, fragmentation, logging and fire are usually surveyed at landscape level with coarse spatial resolution imagery. On the other hand, other disturbance such as biological invasions, disease, selective logging required more detailed information and higher spatial resolution. The identification of the synergies at different scales on tropical forest are the clue for an appropriate selection of sensors and monitoring programs which must have a multi hierarchical approach.

2.6.5 Limitations and challenges of remote sensing applications in the tropics

In the tropics, moisture can reach high values mainly in areas located in the Intertropical Convergence Zone. The relief varies, from flat and lowlands to steep mountains with height greater than 4.000 m.a.s.l., these particular conditions constrain remote sensing applications. In this sense, optical satellite imagery in the tropics often presents high cloud cover and shadows, which limits their use mainly in the raining seasons and humid forest (Gibbs et al 2007, Deutscher et al. 2013). Therefore, the frequency time with which a satellite passes and captures an image is determinant for a correct selection of a sensor in the tropics.

In addition, commercial satellites (with high spatial resolution) have very low temporal resolution in a specific orbit, although nowadays is increasing the development of satellite constellations (e.g. Rapideye, Spot, Worldview).The main acquisition constrain is that they have to be booked and are restricted to the government or corporation's budget. As well, imagery is used to be captured on dry season that limits their application on ecosystems such as wetladns.

Imagery from sensors with medium spatial resolution are captured almost one or two per month which suggest enough continuity of data. In spite of this, the strong and long rainy season in the tropics and the complex topography (relief) in some areas implies that the frequency with which an image is captured it is not directly related with data availability in short and stables periods of time. Depending on the topography and the weather of specific regions, it is possible just to have one-two free cloud image every year or even less. Table 2.6.5.1shows the satellite passing time intervals for different spatial resolution sensors.

Table 2.6.5.1 and Figure 2.6.5.1 show the image availability for satellite programs with different spatial resolutions. Three different sites were checked; Colombia (COL; lat: -1.072, lon: -70.588), Congo (CON; lat: -0.165, lon: 21.481) and Indonesia (IND; lat:-1.556, lon: 144.115). The selected scenes have less than 10% cloud cover and the assessed time window is mainly between 2005 (Jan-1st) and 2015 (Dec-31st) although it varies for some programs based on their schedule specificities. It is observed how the number of images increase when the sensors have moderate or medium resolution as well as when composites are available. In the same way, an average of one scene is available for high resolution per year. Among the three sites, the table shows that the most challenging location for optical imagery surveys is Indonesia.

Table 2.6.5.1 Different sensors checked to assess imagery available with cloud cover less than 10% in the tropics.

Spatial resolution range	Sensor	Pixel size (m)	Time window	Global revisit time (days)
High and Very High (<10m)	Spot 6/7	1.5	2012-2015	26 (single date)
	Spot 6/7	2.5	2012-2015	26 (single date)
	Spot 6/7	6	2012-2015	26 (single date)
Medium (10-100m)	Spot 4/5	10	2005-2015	26 (single date)
	Spot 4/5	20	2005-2015	26 (single date)
	Landsat 7	30	2005-2015	16 (single date)
	Landsat 8*	30	2013-2015	16 (single date)
	Aster (L1A)	30	2005-2015-	16 (single date)
Low and very low (>100m)	Modis (MOD09A1)	500	2005-2015	Everyday (8 days composite)
	Spot Vegetation* 1/2 (S10)	1000	2005-2014	Everyday (10 days composite)

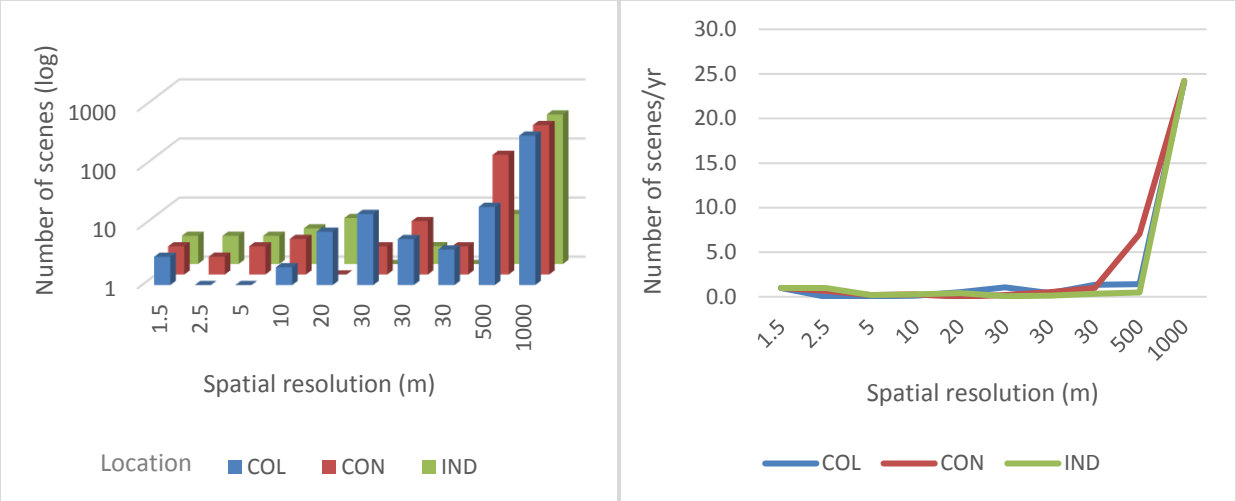

Figure 2.6.5.1 Imagery available with cloud cover less than 10% for Colombia (COL), Congo (CON) and Indonesia (IND). On the left it is the total number of scenes on the time window assessed at logarithmic scale. On the right it is the number of scenes normalized per year.

When disturbance demands frequent observation may be observed solely with medium or low spatial resolution imagery. Landsat satellites products are the most used on monitoring logging disturbance (e.g. Global Forest Watch, Hansen et al. 2013). Even though the satellites passes over the same path row every 16 days it is unlikely to obtain a quality image every 16 days. One alternative of some monitoring programs that work with 30 m resolution has been used to generate composites with good quality pixels.

The use of lower-moderate spatial resolution is also often. In the last years, MODIS program with 16 days composites have been broadly used to evaluate forest degradation, land use change and more. As well, specific events that are easily detectable like active fire and thermal anomalies can be measured with higher frequency programs like GOES and MODIS between 2 to 12 hours periods. Frequency of low spatial resolutions sensors is high, then the possibility to obtain a free cloud imagery is higher. All this suggest an implicit relationship between low spatial resolution and high temporal resolution, in other words is less likely to get a good quality image at high spatial resolution in the tropics when temporal resolution is low.

Otherwise, disturbance regime studies with active sensors have been limited. The acquisition, process and analysis of SAR data increase significantly the cost, this reduce its application in the tropics. In addition, a good quality DEM is required for a proper SAR calibration rarely available in tropical countries. However, this trend is changing, since Sentinel-1 is in orbit delivering C-band data free of charge and ALOS Palsar I imagery is also available for everyone. All these imply more opportunities to develop new SAR applications.

Finally, it is recommended to build up a framework including data of forest conditions and the disturbance features to choose properly a type of sensor for disturbance regime assessment. In this sense, Gibbs et al. (2007) proposed a stratification matrix for tropical carbon stocks that could be modified and applicable for disturbance regime surveys. The matrix include broad forest types, forest conditions like drainage, slope, and others (Annex 1). All this information create a more complete perspective and understanding of the forest, presenting the vulnerability level of the ecosystem and their exposure to different types of disturbance that have to be complemented with a budget assessment. At that point, it is necessary to evaluate cost, real availability, and other scientific and logistic aspects. The integration of these key factors will improve the selection of a specific sensor for disturbance regime monitoring highlighting the assessment priorities for each forest type into a well-planned program. See also chapters 4.1 and 5.1 for more information on current and upcoming Earth observation missions, respectively.

2.6.6 Existing resources and monitoring programs for disturbance regime assessment

Worldwide exist several resources for visualizing and obtaining satellite images and processed related to disturbance, some data are:

- **Forest**
  - Global Land Cover Facility (University of Maryland) (http://www.glcf.umd.edu)
  - Global Forest Watch (http://www.globalforestwatch.org/)
  - Global 1km Forest Canopy Height (Simard et al., 2011) http://webmap.ornl.gov/wcsdown/dataset.jsp?ds_id=10023

- **Towards in near real time**

  To obtain real-time data to support implementation of monitoring systems (near real time and long-term)

  Fires and smoke emissions:
  - Global Fire Forest Watch http://fires.globalforestwatch.org/
  - MODIS Rapid Response https://earthdata.nasa.gov/data/near-real-time-data/rapid-response
  - ESA - ATSR World Fire Atlas http://due.esrin.esa.int/page_wfa.php
  - JRC Fire Monitoring Tool http://firetool.jrc.ec.europa.eu/
    Flooding
  - Global Flood Detection System http://www.gdacs.org/flooddetection/

- **Terrain and climate**
  To get data for describe, analyze and model disturbance regimes across local to continental scale.

  - Shuttle Radar Topography Mission (http://www2.jpl.nasa.gov/srtm/)
  - Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) (http://topotools.cr.usgs.gov/gmted_viewer/)
  - 3D Land Mapping: Combining Lidar and Radar for Remote Sensing of Land Surfaces (http://lidarradar.jpl.nasa.gov)
  - WorldClim: Global climate data for modelling and GIS (Hijmans et al, 2005) http://www.worldclime.org.

2.6.7 Key references for section 2.6

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3 DRIVERS OF BIODIVERSITY LOSS

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3.1 INTRODUCTION

Drivers are induced factors, natural or human, that directly or indirectly bring about a change (Millenium-Ecosystem-Assessment 2003). There are several drivers of biodiversity loss, acting at different scales. Some are evident and occur at an alarming rate, such as the clearcutting of natural forest, or land cover change (Mukul and Herbohn 2016). There are also indirect drivers, such as economic trends and human population increase. Drivers are classified as proximate (direct) and underlying (indirect) (Geist and Lambin 2002; Kissinger et al. 2012). Some of the drivers listed in this section are considered only from a conceptual point of view, although it is not possible to track them directly using remote sensing (RS) data, they are important for understanding the disturbance regimes and assessing the vulnerability of ecosystems (Chuvieco et al. 2014; Pereira et al. 2013).

Despite the general agreement among the international community through the Convention on Biological Diversity (CBD) on the importance to preserve biodiversity, the extent of natural areas (including forests) is still decreasing (Keenan et al. 2015). Geist and Lambin (2002) classified the forces driving tropical deforestation into two types of drivers: proximate (agricultural expansion, wood extraction, infrastructure, mining and oil exploitation and settlement), and underlying (demographic, economic, technological, policy and institutional, and cultural factors). Proximate drivers are the "visible motivations", while underlying drivers belong to a higher causal order that determines the degree of pressure on the environment (Rademaekers et al. 2012).

The geography of life on Earth remains poorly documented (Jetz et al. 2012). In order to develop a biodiversity monitoring system, biodiversity must be defined in such a way that proper indicators can be developed for efficiently assessing the impact of the driver(s) or disturbance(s) occurring in the region of interest. However, robust monitoring designs remain scarce, with the result that the drivers of biodiversity loss are not fully understood (Bradshaw et al. 2015). Moreover, no standards for spatial analysis are applied to ecological studies, yet these are essential to enable valid cross-comparison (Wegmann et al. 2016).

This chapter presents concepts to develop baselines or reference scenarios for monitoring biodiversity and characterising drivers of biodiversity loss. Proximate drivers and disturbance regimes are concepts commonly used interchangeably. For information on disturbance regimes, please see section 2.6.

3.2 BASELINE OR REFERENCE SCENARIOS FOR BIODIVERSITY MONITORING

In order to monitor biodiversity, a clear definition of reference scenario or "baseline" is required; however, the definition often differs between the RS community and the conservation community. Fortunately, new publications that aim to improve communication between both communities are available, one of the publications is that by Buchanan et al. (2015). Both communities use similar terms when defining reference scenarios, the terms "ecosystem", "habitat" and "landscape" are used. An ecosystem is usually defined as a community of a biotic component interacting with an abiotic components (Smith and Smith 2012). The environment in which this interaction takes place may have specific spatial limits that fluctuate in time but are drawn for practical reasons. The ecosystem is used as the basic unit of analysis by scientists from various disciplines, including geographers, RS specialists and ecologists. The term is also commonly used by the land planning community and in the anthropocentric concept of ecosystem services (Strand et al. 2007). On the other hand, "habitat" is defined as the location where a particular organism can be found: the size of the habitat depends on the particular organism and its environmental requirements (McGarigal & Marks, 1995). For this reason, defining habitat instead of ecosystem may be more appropriate when defining reference scenarios for a particular organism. Noss (1983) considers that the identification of landscapes as patterns of habitat types or patterns of interacting ecosystems was required to support long-term management decisions, by favouring regional conservation above local conservation.

The extent of habitats or ecosystems is frequently determined from land cover maps derived from RS, as wetlands, savannas, agriculture and different forest types can be distinguished by their respective spectral characteristics and phenological patterns. Phenology has been used to discriminate different land cover types based on the interannual variation of vegetation reflectance, which has been especially helpful for characterising agricultural cycles (Anaya et al. 2015; Ganguly et al. 2010; Jeganathan et al. 2014; Leinenkugel et al. 2013). From such maps it is possible to derive an ecological interpretation based on spatial heterogeneity (McGarigal and Marks 1995). The capability of satellite data to cover large areas makes RS data an obvious choice for monitoring direct drivers, such as agriculture as a driver of wetlands loss (Chen and Liu 2015), the use of fire in savannas to maintain grassland for livestock production (Burrows et al. 1990; Palomino and Anaya 2012) and the pressure on natural forests that is brought about by the expansion of oil palm plantations (Fitzherbert et al. 2008).

There are also numerous types of RS-based products which can be used to increase the level of detail on these spatial units, such as tree height, tree density and vegetation structure. Different strategies derived from RS technology can be used to discriminate forest conditions. For example, active sensors such as LiDaR or RADAR are well known for their ability to penetrate the canopy and inform on forest vertical structure, while the spectral resolution of optical data is known for its ability to characterise biochemical components (chlorophyll, water, dry matter). Fusion of optical, RADAR and LiDaR data can also improve the ability to discriminate between forest types (Reiche et al. 2015; Tsui et al. 2012). See section 4.1 for information on available Earth observation data.

The choice of a monitoring technique needs to be based on the particularities of the forest type of interest and the nature of the disturbance(s). For example, monitoring dry forests remains challenging, since during the dry season the leaf area index (LAI) is low and most of the energy captured by the sensor comes from the underlying bare ground. In such a case, cloud-free images from the wet season are required to better assess these ecosystems (Strand et al. 2007). On the other hand, the natural vegetation of tropical rain forests is often considered to be homogeneous and difficult to classify or subdivide into further classes

because the differences between phenological patterns are subtle and the vegetation indices are saturated. Additionally, depending on the spatial resolution of the sensor, it may be difficult to identify forest margins and fragments, since the transition from pasture to forest is often gradual (Tomich et al. 2005). Souza et al. (2005) combined spectral and spatial information to detect canopy damage by using Landsat images and aerial videography. Note that this technique was developed in order to detect logging. In tropical regions, cloud cover is common and this significantly affects the monitoring capability of optical sensors (Anaya et al. 2015). Increasing the frequency of observations can improve the probability of obtaining cloud-free observations. The advent of the Sentinel-2 constellation will also improve the probability of obtaining forest canopy data in such regions with a revisit time of only five days.

3.3 DRIVERS OF BIODIVERSITY LOSS

3.3.1 Proximate drivers

The strongest impact on tropical forest biodiversity is from the expansion of agriculture (Newbold et al. 2014), and it occurs at different scales: first, large areas of traditional crops (e.g. soya, coffee, banana, sugar cane, rice), new crops for biofuels, commercial forest plantations and the creation of pasture for cattle ranching; and second, local subsistence, such as illegal cropping, self-sufficiency farming, fuelwood extraction and illegal logging. Some of these practices not only remove native vegetation but also establish exotic vegetation, which grows rapidly and has no natural competitors: agricultural and forestry activities are highly dependent on exotic species, which are considered to be an important threat to the abundance of native plant species and biodiversity in general (Jauni and Ramula 2015). Changes in biotic communities brought about by the introduction of invasive plant species affect the evolution of native species via, for example, competitive exclusion, and may lead to their extinction (Mooney & Cleland, 2001). Selective logging deserves particular attention, since in the context of tropical developing countries, these logged areas are at risk of undergoing permanent land use change (Asner et al. 2005; Berry et al. 2010). It is estimated that by the middle of this century, approximately 25 million kilometres of legal and illegal roads will have been built throughout the world (Laurance et al. 2016).

Among the important proximate drivers are those arising when implementing development projects, such as hydrocarbon exploration and production (Killeen 2007); oil extraction may also lead to contamination, from oil-spill (Hurtig and San Sebastián 2002). Other proximate drivers arise from the construction of hydroelectric power plants and energy grids (Killeen 2007). The contamination accompanying gold mining in high mountain ecosystems of the neotropics is especially harmful to fauna, since mercury and cyanide are used to separate gold from ore along water bodies. (Messerli et al. 1997; Preciado Jeronimo et al. 2015; Velásquez 2012). Most such projects have entailed road construction and have been followed by a process of human settlement (Southworth et al. 2011). Thus there is a need for effective algorithms to detect roads in different environments, including tropical forests in developing nations.

Also considered as proximate drivers are unintentional fires on cropland or pasture that spread to forest during land clearance or the burning of crop residues, and natural phenomena such as flooding, wildfires and blowdown. Spaceborne data has attracted particular interest because it makes possible the characterisation and monitoring of fire-related drivers, enabling the mapping of burned areas and the detection of active fires. The occurrence, intensity and size of fires are expected to increase because of the higher temperatures that will result from climate change (Anderson et al. 2011; Aragão et al. 2007; Le Page et al. 2008; Morton et al. 2013; Oliveras et al. 2014). Among the different RS datasets available, optical data is particularly suitable for wildfire monitoring, allowing the black land surfaces that usually

remain after fire to be detected from the changes in reflectance, especially in the Red and Near-Infrared (NIR) bands; this can be augmented by characterising the water content by using the Short-Wave Infra-Red (SWIR) band (Chuvieco et al. 2008; Oliva and Schroeder 2015; Roy et al. 2008). Active fires can also be detected by the sharp thermal contrast between hotspots and the background, which is more easily observed in the middle infrared (for instance, channel I4 for VIIRS or 21 for MODIS). Near real-time products based on these techniques are available online at Fire Information for Resource Management System FIRMS[17]. Regional networks like *Red Latino Americana de incendios forestales* RedLatIF[18], Southern African Fire Network SAFNET[3] and Southeast Asia Regional Research and Information Network SEARRIN contribute to the distribution and validation of such global-scale burned area products. More information on the characterisation of proximate drivers using RS can be found in section 2.6 Disturbance Regimes.

3.3.2 Underlying drivers

Unlike the majority of proximate drivers, most underlying drivers cannot be observed by using RS, as this technology cannot register or detect market trends and geopolitics (Killeen 2007), technological change (driving agricultural expansion) (Kissinger, et al., 2012) and aspects of ethics, such as the failure to account for the importance of biodiversity loss (Hooper et al. 2012). Social-political factors are also of great concern, including lack of environmental protection policy enforcement by authorities, uncertain property rights, poverty and all the aspects of human well-being (Crane 2006). However, RS can be used to monitor other important underlying drivers of biodiversity loss, such as human population increase and climate change.

The IPAT equation has been used to elucidate the forces driving environmental impacts (I) as a function of population (P), average consumption (A) and technology (T) (York et al. 2003). RS studies have demonstrated the usefulness of night-time optical data to determine the distribution of regional (Escobar et al. 2015) and global human settlements and their connectivity (Dobson et al. 2000; Keola et al. 2015; Zhou et al. 2014). Urbanised areas are important indicators of human population and their interaction with the environment (Patel et al. 2015). The highest accuracy from ten global urban maps was found for the MODIS 500 m based on the Enhanced Vegetation Index; these maps have been validated by using high resolution images from Google Earth and Landsat images (Potere et al. 2009). Recently, daytime optical data from a 40-year time series of Landsat data has also been used to derive urbanised areas (Patel et al. 2015). Urban maps and census information have been used as a modelling approach to generate a grid map of population density (Lung et al. 2013). Night-time light imagery has also been successfully used for estimating population and economic growth in different parts of the world (Archila Bustos et al. 2015; Zhang and Seto 2011).
The consequences of climate change, such as droughts (Vogt et al. 2016), extreme precipitation events and frequent major floods (Cavalcanti 2012; Hoyos et al. 2013) have the potential to become the most important drivers of biodiversity loss (Strand et al. 2007). For instance, recent climatic variability in the tropical Andes has exceeded previous records (Anderson et al. 2011), clearly signalling a trend towards extreme events (Cavalcanti 2012; Hoyos et al. 2013). It has also been reported that the intensification of the hydrological cycle in western Amazonia (Gloor et al. 2013) and also the impacts of extreme droughts in Amazonian forests are accelerating tree mortality and decreasing forest productivity (Feldpausch et al. 2016). RADAR and optical data techniques have been used to measure climatic variables at a global scale, such as precipitation (Mantas et al. 2015), temperature

[17] https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms
[18] http://www.redlatif.org/
[3] http://safnet.meraka.org.za/

(land surface and oceans) and composition of the atmosphere (carbon monoxide (Liu et al. 2005), carbon dioxide and ammonia (Buchwitz et al. 2015)). A list of satellite sensors contributing to the understanding of essential climate variables is available in Hollman et al. (2013).

3.4 CONCLUSIONS AND RECOMMENDATIONS

Population growth (the world population is expected to be more than 7 billion by 2015) and the growth of the market economy are important global drivers of biodiversity loss. In this context, the regional footprint has been found to be an important indicator of the level of consumption in a world that will become resource-constrained (Tukker et al. 2016). Higher demand from the human population for goods and services results in a chain of reactions, triggering multiple drivers, such as the intensification of agricultural practices, more tree plantations and increased fossil fuel consumption (Proença and Pereira 2015). These drivers result in more waste and pollution that intensify the impact on the health of ecosystems.

The difficulty of mitigating the impact of these drivers is reinforced further by uncertainty about land ownership (Naughton-Treves and Wendland 2014) and the failure to take account of the value of biodiversity and ecosystem services (Proença and Pereira 2015). All these negative impacts occur despite the implementation of policies and regulations and of measures such as the establishment of reserves, parks, or other types of protected areas in developing countries as part of conservation programmes (Combes et al. 2015). One good example of the use of high resolution RS for supporting policy application is the Brazilian programme CAR (www.car.gov.br/#/, last accessed March 2017) which regulates the country's land reform programme, will enable the enforcement of the law on illegal deforestation and supports the implementation and compliance monitoring of the forest code. Nowadays, most biomes are experiencing biodiversity loss (Proença and Pereira 2015) and efforts to curtail deforestation in the tropics have met with varying success (Pfaff et al. 2013).

The identification of underlying drivers is important in order to understand the dynamics of proximate drivers across time and space. However, RS data cannot provide all the information needed to identify all the drivers of the loss of forest or of biodiversity. Ground monitoring (e.g. through regional networks) is necessary, not only for the calibration and validation of monitoring procedures, but also to provide detailed information and to characterise the human activities occurring in the region of interest (e.g. deforestation due to selective logging, or fuelwood consumption by local populations). Section 4.2 presents approaches for field data collection, and section 5.3 presents emerging techniques for using RS data synergistically with field data for ecosystem monitoring. Section 2.6 provides further information on types of disturbances that can affect tropical forests.

The tremendous amount of free high and medium spatial resolution RS data (e.g. Landsat, Sentinel-1/2) provides an opportunity for large-scale monitoring of drivers of biodiversity loss[19]. Specifically, the Landsat archive allows the characterisation of the dynamics in forest cover over the past four decades. Hansen et al. (2013) used these data to map the area under trees throughout the world from 2000–2012, to reveal losses and gains in tree cover. This project is still actively releasing information every year. Furthermore, RS datasets are becoming easier to download and use[20]. The advent of the Sentinel constellations (1A/B, 2A/B in particular[21]) will further facilitate the establishment of dense time series of RS data, enhancing the capabilities for monitoring the impact of drivers in tropical regions affected by

[19] Google earth engine has data from Landsat, MODIS, Sentinel and other sensors

[20] http://glovis.usgs.gov/

[21] https://sentinel.esa.int/web/sentinel/home

cloud cover. See sections 4.1 and 5.1 for further information on available and upcoming Earth observation data. Recently, methods to monitor forest cover change at global and regional scales, based on dense time series, have been successfully applied (Hansen et al. 2014; Yan and Roy 2016). The Global Forest Watch tree cover change products[22] have been produced in response to monitoring requirements, particularly those of REDD+; they are available online for free and can be an asset for countries with low forest monitoring capacities. Initiatives such as the Global Observation of Forest Cover and Land Dynamics (GOFC-GOLD) and the Global Forest Observations Initiative (GFOI) provide recommendations on how best to use such datasets[23].

Determining the spatial distribution of biodiversity is important not only to assess the impacts of drivers and disturbance regimes but also to identify the vulnerability of biodiversity. Land cover maps derived from RS have been used as input in order to determine habitats and ecosystems. Here we have pointed out that the term "ecosystem" can be used as a common unit of analysis for biodiversity and we have stressed the importance of defining the practical limits of different ecosystems, in order to improve monitoring schemes. The concepts discussed in this chapter may help to bridge the gap identified by Buchanan et al. (2015) between the conservation community and the RS community that has arisen because some conservationists are not using the full potential of RS for biodiversity research and monitoring, and some RS specialists are not fully capturing the complexity of biological systems.

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4 GUIDANCE ON USING REMOTE SENSING DATA AND METHODS

4.1 AVAILABLE EARTH OBSERVATION DATA

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The possibility to observe the Earth from air and from space opened the doors to periodically observe natural resources over vast areas. From the launch of the first Earth observation satellite TIROS, (Television Infrared Observation Satellite*)* intended for meteorological studies in 1960 (NASA, 2015a) until present, space agencies worldwide have developed various programs to collect data and thus have helped us learn more about Earth-surface processes.

A wide variety of data are currently available, from various sensors including optical, radar, hyperspectral and Light Detection And Ranging (LiDAR). These data are captured from a wide range of platforms from in-situ collection to satellites, all with the same purpose of "Observing the Earth."

Recent changes have allowed access to Internet databases containing historical remotely-sensed data, which has been positive for scientific research. Also available now are new tools that will aid in understanding natural and anthropic processes, leading to improved natural resource management (ESA [no date]).

Note the use of Unmanned Aerial Vehicles (UAVs), also known as Unmanned Aerial Systems (UAS) or *drones*, for Earth observation is still at the research and development stage for tropical forest monitoring, however its use has been increasing over the past years (Colomina and Molina, 2014). Such platforms can carry different types of sensors such as optical, thermal, hyperspectral, SAR, and LiDAR sensors (Colomina and Molina, 2014). Based on the type of sensor onboard the UAV, such platforms can support the acquisition of data relevant for the six EBVs considered in this sourcebook (see Table 4.1.2.2). UAVs can be employed for sampling operations but also for wall-to-wall monitoring activities, within the local legal framework that regulates the employment of such systems. Examples of applications can be accessed for free online (Pajares Martinsanz, 2012; Lucieer et al., 2015).

4.1.1 Earth observation programs

In response to a recommendation from an expert panel on remote sensing from space, the Committee on Earth Observation Satellites (CEOS) was established in 1984, as an international forum whose function was to coordinate Earth observations from space, with the main objective of making it easier for the community to access and use data collected by satellites. It currently places special emphasis on the validation of data by external groups. This initiative promotes the exchange of information and inter-agency collaboration among various national and international space agencies which partner together to launch satellites. It has further contributed to the establishment and development of the Group on Earth Observations (GEO), currently with 31 members (space agencies of various countries) and 24 participating organizations, which are government agencies and organizations (CEOS [no date]; CEOS, 2013).

One major program designed to monitor the Earth's land surface and understand key components of its functions is NASA's Earth Observing System, a program established in the 1980s (NASA, 2015b). This program is still in operation and uses several satellites and sensors to accomplish its objectives. As an example, it operates three sensors which are a succession of systems for the study of the three main components of Earth's processes: atmosphere, ocean, and land. These sensors are: AVHRR (onboard NOAA satellites since 1978); MODIS (onboard satellites Terra and Aqua, launched in 1999 and 2002, respectively); and VIIRS (onboard the Suomi-NPP satellite, launched in 2011); VIIRS data are the successors to the former two. This means that historical data are available to generate time series.

Within this same program, perhaps the data with more spatial and temporal coverage available and used, are undoubtedly Landsat. The Landsat era started in 1972 with the launch of Landsat 1 (initially called the Earth Resources Technology Satellite) and continues until nowadays with Landsat 8 (NASA, 2015c). Its design allows doing long-term studies that provide information about natural resources since the 1970s.

Following Landsat, medium resolution data more widely available are SPOT (Satellites Pour l'Observation de la Terra) images, which are used in various applications, mainly in Europe. These were designed by the Centre National d´Etudes Spatiales (CNES) in France. The SPOT era started in 1986, with the launch of the first SPOT satellite. Between 1986 and 2015, seven satellites have been launched, each one mainly improving in terms of spatial resolution (CNES, 2015).

In Europe, Earth observation is one of the main activities of the European Space Agency (ESA). To fulfill this purpose, ESA established the European monitoring system Copernicus, previously known as GMES (Global Monitoring for Environment and Security). The mission of this program is to collect data from different sources, such as satellites and sensors in-situ, and make them available for use in the study of six themes: land, sea, atmosphere, climate change, safety, and emergency management (Copernicus, ND). A series of satellite constellations, known as Sentinels, has been designed, and the first satellites: Sentinel 1A, and Sentinel 2A, were launched in 2014 and 2015, respectively. At present, satellite data can be divided into two groups: data provided by the Sentinels, expressly developed to fulfil the objectives of Copernicus; and the Copernicus Contributing Missions, operated by national or international agencies. Among them, for example, we find ENVISAT, designed to support studies on atmosphere, land, ocean, and ice (Copernicus [no date]).

Within the framework of European collaboration, Belgium, France, Italy and Sweden, together with ESA, established the Vegetation Program with the satellites SPOT 4 and SPOT 5. This program, aimed at monitoring vegetation at a regional and global level, started in 1998 with SPOT 4, and was terminated in 2015 following the decommission of the SPOT 5 satellite sensor. The design of this sensor was based on users' proposals and requirements set on the first meeting of the International Users Committee held in Brussels, Belgium, in 1992. For 17 years, this program made available to users a wide variety of products which allowed them to analyze changes in vegetation and study the connection between biosphere and climate change (VITO NV, 2015).

A specific group of sensor types are imaging spectrometers, also known as hyperspectral sensors, which simultaneously acquire spatially co-registered images in many narrow spectrally-contiguous bands (Schaepman, 2007). This allows for physical-based measurement and modeling of key dynamic processes of the Earth's ecosystems by extracting geochemical, biochemical, and biophysical parameters (Ustin et al., 2009). Apart from more traditional fields of applications using imaging spectrometers (IS) such as in geology, the biodiversity community identified IS as a key technology to directly retrieve foliar information of plant

pigments linked to photosynthesis, and more detailed characterization of landscape measuring key surface pattern (Pettorelli et al., 2014).

The first operational sensor HYPERION on the EO-1 Platform of NASA's Jet Propulsion Laboratory (JPL) was designed as a one year experiment, launched in 2000. After 15 years of operation, this system is still running and provides long-term and free data from selected sites. In 2001, ESA's imaging spectrometer CHRIS on PROBA platform was launched and is also still operational. Special emphasis was put on BRDF measurement capability to analyse the influence of the viewing direction to surface characteristics. The Hyperspectral Imager for the Coastal Ocean (HICO) has been operating on the International Space Station since October 2009 and provided free data for wide range of applications. There are several instruments launched by China over the past three decades (Tong et al., 2014). However, data is not yet available at an operational basis for a wider user community.

Various space agencies worldwide (and the above-mentioned countries) have developed systems capable of generating useful data for the study of Earth, and forests specifically; among them, owing to the availability of spatial and temporal data: Germany, France, and Italy in Europe; Japan, India, and China in Asia; and the USA, Canada, Argentina, and Brazil in America.

4.1.2 Available Data sets

Table 4.1.2.1 describes the sensors according to the most important parameters, and lists the relevant EBVs they can contribute to. This sub-section discusses some key concepts that are important to understand regarding the suitability of the sensors for the different forest monitoring activities. The section will be updated on a yearly basis to report on the new missions. Note section 5.1 of the sourcebook lists sensors and associated datasets that will be available in a near future.

Table 4.1.2.1 classifies sensors in two broad types: passive and active. Passive sensors, are often referred to as "electro-optical" or simply "optical" sensors. They have the capability to acquire the reflected electromagnetic waves of the sunlight and/or the emitted infrared radiation from objects on the ground. Examples of such optical satellite systems include Sentinel-2, Landsat, and WorldView. Active sensors, refer to 1) RADAR sensors such as synthetic aperture radar (SAR), or LiDAR systems. Both can emit their own energy to illuminate a target or area of interest, and measure the reflected signal. Examples of active sensors are SAR satellites such as Sentinel-1, TerraSAR-X, TanDEM-X, and RADARSAT, and LiDAR satellites like ICESat.

Among other key parameters, spatial resolution is important to consider when choosing datasets for a given application. Table 4.1.2.1 provides the values of this parameter (expressed in meters) for each sensor, and spectral range when appropriate. Spatial resolution is an important parameter to consider with respect to the spatial scale of the derived EBVs. The spectral range and resolution regulate which EBV can be derived. As an example, the narrow band index such as NDLI (Normalized Difference Lignin Index) describing the lignin content of vegetation can only be derived using sensors with a high spectral resolution in the short wave infrared region (SWIR). Note sensors are described also in broad spatial resolution categories. In this sourcebook, the chosen categories are as follows: Very High: <=1m, High: <=10, Medium: <=30m, Low: <=300m, Coarse <=1,000m. Note the spatial resolution for LiDAR datasets is measured by the distance between the centres of consecutive beams, and between the scanning lines. The beam divergence affects also the spatial resolution.
Another key sensor characteristics is the temporal resolution. Parameters such as phenology and productivity are strongly linked to seasonal conditions and needs to be monitored

regularly. Since the availability of data from passive sensors systems are determined by cloud cover, low revisit times can impede the acquisition of appropriate time series to monitor a certain biophysical/biochemical parameter.

In Table 4.1.2.1, column "Relevance to EBVs" lists the EBVs relevant to tropical forest monitoring to which the sensors can contribute. Table 4.1.2.2 provides the coding number of the EBVs used in Table 4.1.2.1. For more information on the six EBVs covered by this sourcebook, please check: http://geobon.org/essential-biodiversity-variables/ebv-classes-2/

For further information on past and current observing systems please go online:

- CEOS EO HANDBOOK – CATALOGUE OF SATELLITE MISSIONS
  http://database.eohandbook.com/database/missiontable.aspx
- National Aeronautics and Space Administration (NASA, USA):
  http://eospso.nasa.gov/future-missions
- European Space Agency (ESA):
  https://earth.esa.int/web/guest/missions/esa-future-missions
- the German Aerospace Center (DLR) compiles information on (past, present and) future space-borne imaging spectroscopy missions:
  http://www.enmap.org/sites/default/files/pdf/Hyperspectral_EO_Missions_2015_06_22_FINAL.pdf
- Check the publication from Labrador et al. (2012) on "Satélites de teledetección para la gestión del territorio" (in Spanish).

Table 4.1.2.1 Data sets available

Platform/ Mission	Life span	Revisit time period	Spatial Resolution (m)	Swath (Km)	Wavelength	Availability	Relevance to EBVs	Reference
Passive sensors								
Hyperspectral								
Hyperion	2000 -	No continuous coverage	30	7.7	0.4-2.5 µm	Free	2	http://eo1.usgs.gov/sensors/hyperion
CHRIS PROBA	2001 -	No continuous coverage	18-36 m	14 km	0.4-1,1 µm	Free	2	https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/proba/instruments/chris
HICO	2008 -	No continuous coverage	90 m	90 km	0.4-1,1 µm	Free	2	http://hico.coas.oregonstate.edu/
Multispectral								
Airborne	1940's -	Varies					1, 2, 3, 5	
GeoEye	2008 -	3 days	PAN:0.41 MS: 1.64	15.2	PAN/VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/g/geoeye-1
Ikonos	1999 -	3–5 days	PAN: 0.82 MS: 3.28	11	PAN/VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/i/ikonos-2
RapidEye	2008 -	5.5 (at nadir)	MS: 6.5	77	VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eop

		Daily (off-nadir)						ortal/satellite-missions/r/rapideye
Quickbird	2001 - 2015	2–4 days	PAN: 0.61 MS: 2.5	16.5	PAN/VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/q/quickbird-2
Worldview 1,2,3	2007 -	1–3 days	PAN:<=0.5 MS:<2 SWIR: 3.7 CAVIS: 30	13.1-17.5	PAN/VIS/NIR/SWIR/CAVIS	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/v-w-x-y-z/worldview-3
AWIFS	2003 -	5 days	56	740	VIS/NIR/SWIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/i/irs-p6
Landsat 1,2,3,4,5, 7,8	1972 -	16 days	PAN: 15 MS: 30 TIR: 100	185	PAN/ VIS/NIR/SWIR	Free	1, 2, 3, 5	http://landsat.gsfc.nasa.gov/ http://earthnow.usgs.gov/
IRS P6 Resources at-1 LISS III, IV	2003 -	5-24 days	MS: 5.8-23.5	MS: 24-70-140	PAN/VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/i/irs-p6
IRS Resources at-2 LISS III, IV	2011 -	24 days	MS: 5.8-23.5	MS: 24-70-140	PAN/VIS/NIR	Commercial	1, 2, 3, 5	http://www.isro.gov.in/Spacecraft/resourcesat-2
SPOT 1,2,3,4,5, 6,7	1986 –	Daily (combined)	PAN: 1.5-2.5 MS: 6-10-20	60	PAN/ VIS/NIR/SWIR	Commercial	1, 2, 3, 5	http://www.cnes.fr/web/CNES-en/1415-spot.php http://www.geo-airbusds.com/en/14

								3-spot-satellite-imagery
Pleiades 1A/B	2011 -	26 days	PAN: 0.5 MS: 2	20	VIS/NIR	Commercial	1, 2, 3, 5	https://pleiades.cnes.fr/en/PLEIADES/GP_systeme.htm
Sentinel 2A/B	2015 – 2017-	5 days S2 A&B	10, 20, 60	290	VIS/NIR/SWIR	Free	1, 2, 3, 5	http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-2
AVHRR NOAA-6, 7,8, 9, 11, 12,14, 15, 16, 17, 18 19	1978 -	Daily	1100	2600	VIS/NIR/TIR	free	1, 2, 5	http://www.nsof.class.noaa.gov/release/data_available/avhrr/index.htm#4
MERIS	2002 - 2012	3 days	300	1150	VIS/NIR	Free	1, 2, 5	https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat/instruments/meris https://earth.esa.int/web/guest/-/how-to-apply-1375
MODIS	1999 -	1 day ,8-16-32 day composites	250 500 1000	2330	VIS/NIR/SWIR /MWIR/TIR	Free	1, 2, 5	http://modis.gsfc.nasa.gov/
SPOT VGT 1, 2	1998 - 2015	Daily Global coverage, 10 day composites	1000	2250	VIS/NIR/SWIR	Free/commercial	1, 2, 5	http://www.spot-vegetation.com/index.html http://www.spot-vegetation.com/userguide/userguide.htm

VIIRS	2011 -	Daily	375 750	3040	PAN/VIS/NIR/ MWIR/LWIR	Free	1, 2, 5	http://viirsland.gsfc.nasa.gov/index.html
Active sensors								
Synthetic Aperture Radar (SAR)								
Airborne	1950's	Varies					3, 4, 5	
ALOS-PALSAR 1,2	2006 -	14 days	Stripmap 3, 6, 10 ScanSAR 100 , 60	Stripmap 50, 40, 70, 30 ScanSAR 350, 490	L-band	Free	3, 4, 5	http://www.eorc.jaxa.jp/ALOS/en/about/palsar.htm http://www.eorc.jaxa.jp/ALOS-2/en/about/palsar2.html
JERS 1	1992 - 1998	44 days	18	75	L-band	Free	3, 4, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/j/jers-1
ERS 1, 2	1991 - 2011	3 - 35 days	30	100	C-band	Free	3, 4, 5	https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/ers/instruments/sar https://earth.esa.int/web/guest/-/how-to-apply-1375
ENVISAT - ASAR	2002 - 2012	35 days	30, 150, 1000	100 - 400	C-band	Free/commercial	3, 4, 5	https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat/instruments/asar https://earth.esa.int/web/guest/-/how-to-apply-1375

Sentinel 1A/B	2014 – 2016 -	6 days S1 A&B	5*5 5*20 25*100 5*20	80 250 400 20*20	C-band	Free	3, 4, 5	http://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus/Sentinel-1/Instrument https://earth.esa.int/web/guest/-/how-to-apply-1375 https://sentinel.esa.int/web/sentinel/sentinel-data-access
Radarsat 1, 2	1995 –	24 days	3 -100	50 -500	C-band	Commercial	3, 4, 5	http://www.asc-csa.gc.ca/eng/satellites/radarsat/radarsat-tableau.asp
TerraSAR-X	2007 –	11 days	1, 3, 16	10 - 100	X-band	Free for scientific applications / Commercial	3, 4, 5	http://www.dlr.de/dlr/en/desktopdefault.aspx/tabid-10377/565_read-436/#/gallery/350
TanDEM-X	2010 -	11 days	1, 3, 16	10 - 100	X-band	Commercial	3, 4, 5	http://www.dlr.de/dlr/en/desktopdefault.aspx/tabid-10378/566_read-426/#/gallery/345
Light Detection And Ranging (LiDAR)								
Airborne	1970's -	Varies				Commercial	1, 2, 3, 4, 5	
ICESat	2003 – 2010	9 -91 days	40 pulses / sec	70(footprint)	532 nm 1064 nm	Free	3, 4, 5	http://icesat.gsfc.nasa.gov/icesat/hdf5_products/index.php

Table 4.1.2.2. List of acronyms and coding numbers of EBVs used in table 4.1.2.1.

List of acronyms	Coding number of EBVs
CAVIS: Atmospheric Sensor IWS: Interferometric Wide Swath LWIR: Long Wave Infrared MS: Multi spectral MWIR: Medium Wave Infrared NIR: Near infrared Pan: Panchromatic SWIR: Short Wave Infrared TIR: Thermal infrared VIS: Visible	1- Vegetation phenology 2- Net primary productivity 3- Ecosystem extent and fragmentation 4- Habitat structure 5- Disturbance regime

4.1.3 Key References for section 4.1

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4.2 IN-SITU DATA: DEFINITIONS AND APPROACHES

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4.2.1 Introduction

Monitoring biodiversity is fundamental to nature conservation policy and originates from ornithology, biogeography, botany and phytosociology. Biogeography studies the distribution of species and ecosystems in space and time, while phytosociology deals with the composition of plant communities. Organisms and biological communities vary according to geographic gradients of latitude, elevation, isolation and soil types. Land can be characterised by identification of the species assemblages present, the habitats in which they occur and the landscapes in which the latter are present.

The use of Earth Observation (EO) tools requires ground validation based on in-situ observations, because for the interpretation of biodiversity value, the observed land cover units must be defined in more detail than can be observed from space. EO observations of land cover therefore need to be calibrated with observation of the actual vegetation and species present on the ground. The strength of EO is that large areas can be mapped relatively rapidly, whereas in contrast, in-situ data are expensive to collect and therefore can only be recorded in relatively few carefully selected samples. It has therefore been necessary to develop procedures to link EO with in-situ data. This requires a network of sites set up for recording in-situ observations to link the EO images with the real world on the ground. Evidence is required to determine which types of field observations are necessary for specific objectives, linked to the approaches that are now available. To allow for informed decisions on this topic, it is important that the different types of in-situ observations that have been identified e.g. species of canopy trees and epiphytes, are included. It is important to emphasize, that for the majority of tropical vegetation, and especially forests, there is still a lack of empirical baseline data concerning alpha and beta diversity, as well as on species dynamics and interactions within communities and habitats (Scholes et al. 2008). In this section, we will elaborate the role of in-situ data for the monitoring of changes in tropical forest biodiversity and make a link with the EO data that are described in sections 4.3 and 4.4.

There are several global and regional in-situ observation networks in tropical regions that provide data on the habitats present, as shown in Table 4.2.1.1. The restricted coverage shows that there are still relatively few empirical field observations at the necessary levels of detail. Even basic inventories of current biodiversity are incomplete (Phillips et al. 2003). There are several reasons for this but mainly because cooperation in biodiversity research and monitoring is a relatively recent phenomenon. Standardized procedures are not yet available, and protocols are not yet agreed or shared. Strategic sampling has not yet been widely considered and there is limited exchange of data between spatial scales. Such coordination is time intensive and expensive, but recent work on a biodiversity network within GEOBON (Scholes et al. 2012), in Africa (Jürgens et al. 2011) and Europe (Ichter et al. 2014), and the availability of a global bio-climatic classification (Metzger et al. 2013), could enable these problems to be overcome. Now is therefore the time to integrate concepts and approaches for the monitoring of tropical forests, and harmonize them, at and between, the multiple scales of species, habitats and landscapes needed to produce a coherent, realistic and practical system. Any monitoring procedure also needs to cope with the impacts of various drivers of global change in tropical forests.

Network	Coverage	Type of Observations	Number of sites

Name			
IBAs Birdlife	Global	Birds, habitats	11,700 sites
IWC	Global	Annual synchronised counts of water birds	>15,000 sites
RAINFOR	South America	Tropical forest	300+ sites, 8 countries
BIOTA Africa	Africa	Terrestrial species	46 observatories in 3 transects in south and west Africa
LTER China	China	Forest, grassland, wetland, desert, marine, agricultural and urban ecosystems	37
China BON	China	Mammals, birds, amphibians, and butterflies	500+ sites, with 8000+ line transects and point transects
AfriTRon	Africa	Tropical Forest	300+ sites, 14 Countries

Table 4.2.1.1 Examples of some major existing Observation Networks that include tropical forests and their characteristics.

In the tropics alpha and beta diversity in the forests is not only exceptional, but additionally, the habitats are the most complex in the world (Phillips et al. 2003, Bridgewater et al, 2004). Sampling such complexity therefore presents major challenges, including questions such as where to place field samples, how many sites need to be sampled and what is a time and cost efficient strategy?

Field inventories are most suitable for in-situ species identification, but have their limitations, such as there are few people who can identify tropical trees and animals. Moreover, tropical forests are extensive and, because of the many remote locations, site visits are therefore difficult, expensive and time consuming. Tree species recognition often requires tree-climbing, mostly by native experts with the necessary local knowledge. Approaches are being sought to overcome these problems especially in the time and cost optimization of a sampling strategy with identification of representative sampling sites, the recording of indicator species and the use of life form spectra to define a given forest site. The latter would not need the identification of individual species and could therefore be used as a first tier in describing a given forest by providing basic information linked to biodiversity, as tropical forests differ widely in their structure even within a region.

EO data are able to provide consistent and objective time series of land cover measurements and phenological change. Monitoring sites can be linked to locations of intensive observations e.g. Long Term Ecological Research (LTER) sites, to assess impacts of change and underlying processes, provided that such sites are representative, as described by Metzger et al (2010), for LTER sites in Europe. Synergies also need to be established between the existing infrastructures set up by Earth sciences for water and soil parameters and biodiversity observatories.

4.2.2 Habitat definitions and species relations

The term habitat can be defined as the spatial extent of a resource for a particular species (Bunce at al. 2013). Species with comparable ecological requirements can be considered to share the same or comparable habitats. Plant species assemblages comprise vegetation and form recognisable main divisions in the tropical forests. Species can be important in their own right e.g. teak (*Tectona grandis*) or because of their importance in vegetation structure e.g. strangling

figs (e.g. *Ficus altissima*). The tropical forest has been recognized as the most complex ecosystem in the world at many levels e.g. species diversity, structural variation and the range of variation between continents. Tropical forests on different continents share few species because they have diverged in isolation caused by the shifts of the land masses over very long periods of time. Tropical forests nevertheless share many ecological characteristics and have been described as biomes by the classical bio-geographers of the 19th Century e.g. Von Humboldt and Bonpland (1807), because they occur in comparable climates and edaphic conditions. The types of tropical forests are based on a combination of observed vegetation and climate and therefore constitute comparable ecosystems in different continents but with unique species combinations. The term biome has continued to be used at the global scale in bio-geographical studies and for modelling the impacts of land use and climate change on ecosystems across the world (Woodward, 1987).

Habitats are used in similar contexts in the literature but they are rarely defined. Reviews of the application of the term have been made e.g. by Hall et al. (1997). Definitions have also changed over time:

Place, living space, where an organism lives (Odum, 1963);
Habitat is a zone (area) comprising a set of resources, consumables and utilities, for the maintenance of an organism. The resources occur in union and/or intersect and may also be equivalent; links between resource outlets are established by individual searching movements of the organism (Dennis and Shreeve, 1996);
Place where a species normally lives, often described in terms of physical factors such as topography and soil moisture and by associated dominant forms (Calow, 1999);
An element of the land surface that can be consistently defined spatially in the field in order to define the principal environments in which organisms live (Bunce et al 2008).

In Europe several habitat classification systems are used for in-situ monitoring. The most generally applicable and standardized system is that of General Habitat Categories (GHC, Bunce et al 2013), developed in the EU-FP7 project EBONE[24] that is used for in-situ monitoring of habitats in several countries in Europe, in Western Australia and South Africa. The methodology enables exchange and cooperation between existing national systems such as the Swedish NILS system (Ståhl et al. 2011) and the GB Countryside Survey (Haines-Young et al. 2000). General Habitat Categories (GHCs) are based on the regression of Life Forms on the environment. They are defined in classic science, as defined by Raunkiaer (1934), and transcend species. For international comparisons, it is important that no biogeographical terms or local names are used and that there are explicit rules for definition and determination in the habitats in the field (Bunce et al 2008). The GHCs therefore enable integration between different national and project approaches because they transcend local and regional differences in species composition. GHCs have been used in several European research projects and it is exchangeable with the FAO Land Cover Classification System (FAO-LCCS, Kosmidou et al, 2014)[25]. The IUCN has developed a standard habitat classification scheme[26] belonging to its species Red List against which >50,000 species have been coded globally, but comparison with habitat categories such as FAO-LCCS or the GHC has not been undertaken. Because of the incomplete status and ambiguous classification of some species (e.g. bamboo species (*Bambusa* spp) may belong to several broadleaf categories. In addition, geographical terms are not fit for monitoring at a wide scale because they are rarely defined. For collecting in-situ information in observation sites, for comparing habitats across a continent and general statistics; the General Habitat Category (GHC) protocols are suitable as they have been designed for this purpose and already have appropriate life form qualifiers for tropical habitats e.g. palms and bamboos.

Assessing habitats for their biodiversity value is essential because, as the Convention on Biodiversity (CBD) emphasizes, habitats are not only an important indicator of biodiversity in their own right, but also serves as a proxy for identification of/diversity in plant species and faunal taxa (Bunce et al. 2013). There is a range of different relationships between species and habitats. For example, there are generalist species without relationships to specific habitats,

[24] http://www.ebone.wur.nl/
[25] http://www.fao.org/docrep/003/X0596E/X0596e00.htm
[26] http://www.iucnredlist.org/technical-documents/classification-schemes/habitats-classification-scheme-ver3

whereas other species can be associated with one specific habitat type, such as wetlands, whereas other species use contrasting habitats in different periods of their life cycle. Da Silva et al (2015) showed for the transition zone between the Amazon and Pantanal that habitats can be characterized by particular tree species assemblages. They concluded that 332 tree species from both biomes are present in this region, that the four major forest habitats had their own characteristic species, shared some common species, but that only 14 tree species are common to all four habitats. Species which are dependent on other biota for food can be predicted from the occurrence of that species, e.g. many bumble bees and butterflies depend on specific plants for pollen and nectar and continuity of flowering so that food supply will be a factor that may constrain population viability and hence actual species occurrence.

4.2.3 Existing in-situ sampling sites

Tropical ecological studies and forest conservation initiatives mainly focus on recording field data with an emphasis on floristic observations (Phillips et al 2003). Observations of faunal species are less developed, probably because it requires specific expert knowledge and a greater time investment. In practice, there are also major taxonomic, spatial and temporal gaps in available knowledge and information (Gilman et al 2011).

The oldest series of in-situ plot observations was set up by Alwin Gentry from the University of Missouri in 1971 (Gentry 1982). Gentry plots have not been used for the monitoring of changes in biodiversity, but for describing the variation within, and between, geographic areas predominantly in Latin America. Each plot is 0.1 ha and is composed of 10 subplots, each 2×50 m. He developed a sampling design for a rapid inventory of diversity in species rich tropical forests[27]. He placed 10 contiguous long, but rather narrow transects (about 2×50 m) in what were considered to be relatively homogeneous forests. The data consist of measurements of Diameter at Breast Height (DBH) of every individual tree in each transect. This system has later been adopted by the Instituto Nacional de Pesquisas Da Amazônia (ANPA) in a modified way in its monitoring system RAPELD, a Brazilian acronym for rapid monitoring in LTER systems (Magnusson et al. 2005). The system consists of making a long axis (250 m) of individual plots along the isocline, using different widths of plot for different taxa, and distributing the plots regularly across the landscape being sampled. The plots are being used in long-term ecological studies and therefore their location and access are carefully described. Other organisms, life stages and functional groups are measured in plots or subsamples narrower than those used for plants along the entire 250 m (Magnusson et al 2005).

The Amazon Forest Inventory Network (Rede Amazônica de Inventários Florestais, RAINFOR) has developed standards for establishing and monitoring forest plots, including soil and foliar sampling, which are used widely in the Amazon, Africa and Australia. Since 2001 RAINFOR has implemented a stratified ground-based forest monitoring network across Amazonia using *in-situ* and EO approaches to determine ecosystem service impacts of extreme drought (Phillips et al 1998). The African Tropical Rainforest Observation Network (AfriTRON) led by the University of Leeds, is developing a parallel initiative in Africa (Lewis et al, 2009). The Forest Plots portal hosts access to data from many individual researchers and networks including RAINFOR, AfriTRON, Biodiversity and Ecosystem Functioning in Degraded and Recovering Amazonian and Atlantic Forests (ECOFOR), The Brazilian Program for Biodiversity Research (PPBio), the Tropical Biomes in Transition project (TROBIT) and the Tropical Forests in the Changing Earth System project (T-FORCES)[28].

Subplot	Width (m)	Size (ha)
Understory	2	0.05

[27] http://www.mobot.org/MOBOT/research/gentry/transect.shtml
[28] http://www.forestplots.net/

Shrub/tree DBH > 1 cm	4	0.1
Shrub/tree DBH > 10 cm	20	0.5
Shrub/tree DBH> 30 cm	40	1

Table 4.2.3.1 ANPA-RAPELD subplot characteristics in the 250 m transects for measuring vegetation cover in a tropical forest.

The Chinese Forest Biodiversity Network (CForBio) was initiated in 2004 to study forest biodiversity in China. The CForBio sites have mainly focused on tree species and species interactions, biotic relationships and small-scale dispersal. Important suggestions for future research are the evaluation of the effects of climate change on forest composition and the application of new technologies, such as EO, to improve current monitoring of forest biodiversity change (Feng et al. 2016).

The China Biodiversity Observation Network (China BON) was initiated in 2011 and is supported by the Ministry of Environmental Protection of China. There are more than 500 sampling sites (counties, approximate 20% of the number of counties in China), with >8000 line transects and point transects. The objectives of China BON are to detect changes in species composition, distribution and population dynamics, assess threats to target species and to analyze conservation policy efficiency. The project is currently focused on the monitoring of species diversity of mammals, birds, amphibians, butterflies and plants. National standards and field protocols are being implemented within the network. Participants include more than 400 universities, research institutes, protected area staff and civil societies.

As shown above in the examples and the forest plots portal, networks are currently being developed by researchers, institutes, national agencies and international NGOs acting cooperatively at various spatial scales in order to achieve shared objectives. A monitoring network should include sufficient sampling sites to guarantee a statistically valid number of observations of each phenomenon (Steel et al. 2013). Sufficient, but not redundant replication, within an observation network makes it possible to draw statistical inferences from defined populations. However, some of the observations could be replaced by estimates from EO observations (Lang et al. 2015). When planning an observation network, it is important that the monitoring observations will be able to capture likely changes in habitat and species distributions in terms of potential alterations in ecological communities and ecosystems. Shifts in biome boundaries and between different climate change scenarios also need to be included.

There are also socio-economic and governance benefits related to in-situ observation networks. Observation networks need to be cost effective and reduce the variability of the data obtained. Through coordinated management activities, a well-designed network can optimize the use of limited resources for governance and secure funding mechanisms, staff training and capacity building. A consistent assessment of the costs of biodiversity measurement is essential in order to minimize the costs for a given level of information needed (Targetti et al. 2014). Given the uncertainties about future climate change and responses of ecosystems, there is a need to systematically monitor and study changes. Establishing ecosystem baselines and monitoring gradual changes through site networks, using standardized techniques, can enable the separation of site-based influences from global changes in order to provide a better understanding of ecosystem responses to global change. Alternative adaptation options also need to be included (Gilman et al. 2008).

4.2.4 Sampling bias and monitoring costs

The establishment of observatory networks in the tropical forests on Earth represents a major challenge. The Amazon basin alone covers about 7 million km^2. Therefore, even a sparse coverage, with one sample site per 10,000 km^2, would still require about 700 sampling sites (Magnusson et al 2005). Time and budget limitations restrict the potential number of sites and

investment at each site, but on the other hand an incomplete coverage of data makes the observations less valuable (Reddy & Dávalos 2003). It is therefore essential to have an objective sampling design that ensures that a minimal number of representative samples are obtained and that there is no duplication, as has been carried out in the long-term monitoring system of the Countryside Survey in Britain (Bunce et al. 1996). Metzger et al (2013) have produced a statistical classification of global bio-climates which could form an appropriate framework, especially if linked to altitudinal gradients because these are critical to determine different types of biodiversity in many tropical rain forest regions. This concept is further described at the end of this section.

The costs of installing the RAPELD plot system are rather high, but it is also possible to use the data for integrated studies. The costs for installation and surveys of flora, fauna, biomass, stocks and fluxes of the system in Reserva Ducke near Manaus is about US$ 300,000 (Magnusson, 2005) which leaves scope to search for a more time-efficient and cost-effective system.

It is important to realize that in practice, areas within easy-access and close proximity to populated places or busy travel routes, are likely to have higher sampling intensities because of reduced travel times. In addition to conveniently accessible areas, biodiversity recorders tend to favor areas that they presume will reward them with frequent sightings of novel species. Thus, well-sampled areas appear to be more species rich than poorly sampled areas; this may therefore generate a bias (Reddy and Dávalos 2003). This includes protected areas and those areas with high biodiversity. For instance, in Thailand, the three provinces with the highest plant collection density were those associated with national parks and mountains. Such places are better sampled because they are the preferred study areas of researchers in an otherwise transformed landscape (Parnell et al. 2003). The size of the plots used can also lead to the identification of false differences between forests. Thus, Phillips et al (2003) concluded that using sample units of 0.1 ha or 1.0 ha, can lead to differences in species quantity and diversity estimation. Effort is therefore needed to identify the ideal size for sample units.

Literature on monitoring activities reports a wide range of costs and effort for the measurement of different indicators with various results. Schmeller and Henle (2008) reported for Europe an average 17.6 person days per site for high precision biodiversity surveys of plant species, while Bisevac and Majer (2002) considered in an Australian study that 0.67 person days per site were sufficient for surveying vegetation in restored areas. Geijzendorffer et al (2016) also estimated the costs of monitoring farmland in the EU and provide a detailed breakdown of the costs between habitat monitoring, compared with various groups of species. The dominant cost and time components for monitoring in tropical forests depend primarily on the variability of travel time to sites. Even if sampling protocols and objectives are similar, there will be major differences in the time required to sample different ecosystems because of variations in terrain and habitat complexity. Thus, the time required for habitat mapping is mainly related to landscape diversity and the many associated habitat categories of partially modified tropical forest ecosystems, compared with highly modified habitats encountered in agricultural ecosystems.

Since in-situ monitoring efforts cannot realistically be extended across all taxa, choices have to be made as to which biodiversity components should be monitored, the number of sampling units to be taken and the spatial and temporal distribution of survey activities sampling to be determined (Yoccoz et al, 2001). A monitoring scheme that is able to detect changes and trends is based on three considerations (Couvet et al, 2011):

The extent of the site to be surveyed,
The density of sampling locations within the area,
The observation effort required per location.

The relative importance given to each of these three parameters within a monitoring scheme has major consequences on its ability to address various scientific questions. It is also important to consider the anticipated rate of change that can be detected. The observation effort must therefore be described in terms of the necessary resolution and frequency of sampling to achieve sensitivity to small, short-term changes or the detection of larger changes over longer periods. The latter has lower cost but although the information may be acceptable for policy development, it could be too infrequent to inform adaptive forest management for biodiversity.

Observations, focusing on individual sites can be very important for ecosystem ecology, e.g. by characterising the extent of nutrient release after deforestation (Ricklefs and Miller 2000). A site based, targeted monitoring approach can be used for discrimination between a priori hypotheses (Nichols and Williams 2006). For example, NEON[29], an in-situ monitoring system in the USA designed to observe ecosystem processes, defines 20 ecological domains with three sites per domain and additional re-locatable sites, in which different ecological variables are monitored (Pennisi, 2010).

An alternative system could consist of a high density of sites that allows for the detection of period fine-grained spatial variations of biodiversity in the context of general trends over a large territory and longer time. Since total observation efforts are limited, such schemes result in a coarse-grained resolution per site, due to the limited observation effort per site and are considered as extensive monitoring schemes. Climate monitoring and long-term data series, in general, illustrate the benefits of such a surveillance approach. With targeted scientific protocols, this approach can combine passive monitoring to address patterns, targeted monitoring to test hypotheses, and adaptive monitoring to evaluate the effects of various policies. They can deliver major information about the trends in biodiversity and specific species (Soldaat et al. 2007).

4.2.5 Habitat Data: linking in-situ and Remote Sensing

An in-situ habitat monitoring scheme should not be implemented in isolation, but should be complemented by additional targeted monitoring of specific trends, for instance a focus on endangered species, on biodiversity hotspots or sinks, use of remotely sensed information or the integration of biodiversity data from existing monitoring schemes (Geijzendorffer et al, 2016). There are several advantages in the use of in-situ monitoring of 'habitats' because they effectively integrate species and RS information:

Aerial photographs, especially infra-red, can be used to estimate habitat extent and its change over time e.g. Ståhl et al. (2011),
Remote sensing data from satellites can be linked to in-situ maps of habitats in larger units, (e.g. Van den Borre et al., 2011),
Relationships between habitats and species composition or particular taxa important to biodiversity can be used to link habitat records to other biodiversity indicators, such as species (e.g. Santo-Silva et al 2016),
Habitat records can be linked to landscape level changes over time and to vegetation species composition (e.g. Laurance et al 2011).

4.2.6 A possible structure for integration and harmonization

Monitoring biodiversity and ecosystems has to be organised in such a way that the data is sensitive to various aspects for any specific question regarding biodiversity change issues as well as that the data should be taken it into account in broader assessments (UNEP-WCMC 2009). To align with this diversity of knowledge demands in decision-making, organising the process of data gathering and analysis needs to be highly flexible, while at the same time employing core methodologies that ensure transparency, scientific rigor, independence and minimal bias. As elaborated further in chapter 4.4., an important criterion could be the use of strata as discrete and mutually exclusive subsets of the study regions in the sampling design. This allows for the analysis of subsets of the study regions that are of interest for the reporting and will also improve the precision of estimates. It also allows a larger sample size for smaller but important sub-regions that otherwise risk insufficient sampling if implementing a simple random or simple systematic design. A global stratification of bio-climates has been produced recently, as described by Metzger et al (2013) and is freely available through the GEO portal. A stratified monitoring system has been proposed with the following steps:

A framework for monitoring and analysis will be constructed from separate databases for South America, Africa, Asia and the Asian Islands including Australia. The underlying objective of separate analyses is that there are fundamental differences between the structure and species

[29] http://www.neonscience.org/

composition of tropical forests at a continental level because of movement of the land masses over geologic time. The outputs will be summary maps of tropical rain forests in each continent using available information.

The procedure will then be to analyze the strata that contain tropical forest as defined by the global bio-climate classification (Metzger et al, 2013, Figure 4.2.6.1).The objective will be to determine the major environmental subdivisions coherent within, and across, the continents. The outputs will be tables of frequencies and maps of the World Environmental Climate Classes for each continent.

Each climate stratum will then be divided into sub-divisions according to appropriate altitudinal ranges. The objective would be to capture the different types of tropical forests known to be present at contrasting elevations. The outputs will be descriptions of the altitude climate classes for each continent.

The procedure will then automatically map land cover classes using EO images within each of the sub-divisions. The objective is to introduce the first tier of information of direct relevance to biodiversity. Iso-clustering would then be used to reduce the complexity of each of the sub-divisions and to provide a sample framework. The outputs would be maps of the principal types of tropical rain forests in each continent.

The exact location of every existing in-situ sample will then be identified within the sample design constructed by steps 1-4. The objective is to identify the extent of the existing coverage and in particular, to determine where there are currently no samples. The outputs will be tables of the existing data sets according to the maps of stage 4. Note that none of the steps 1-5 require field visits.

Representative sample sites will then be located where in-situ observations are required for additional survey to fill the gaps identified in step 5 and to facilitate the collection of ground-truth data. The outputs will be tables of GIS locations of the required sites together with strategic maps.

The range of life forms will then be recorded in these sample sites, using existing standard protocols of plant life forms (Bunce et al 2013). This survey will not require species information, so the sites will be relatively rapid to record. The objective is to prepare a database for selection of a reduced number of sites for species surveys. The output will be a handbook for standardized recording of life forms in tropical forests.

Classify the range of life forms into relatively homogeneous groups using iso-clustering. These classes will provide a key measure of biodiversity at the habitat level. The objectives are to reduce the number of sites where species data need be recorded in the field and to produce habitat classifications that are comparable between continents. Existing data will also be analyzed at this level. The output will be a handbook for standardized recording of biodiversity in tropical forests, as described in step 7.

Carry out detailed field surveys of biota, such as plants and mammals, for the assessment of biodiversity within representative habitats using the monitoring systems described earlier. The objective is to produce integrated assessments of biodiversity. Different taxonomic groups can then be progressively surveyed by appropriate experts, because of the relatively small number of formally selected, representative sites. The outputs will be a detailed time and location specific database that can be used for ground-truth of EO images and for specification of observations in different regions.

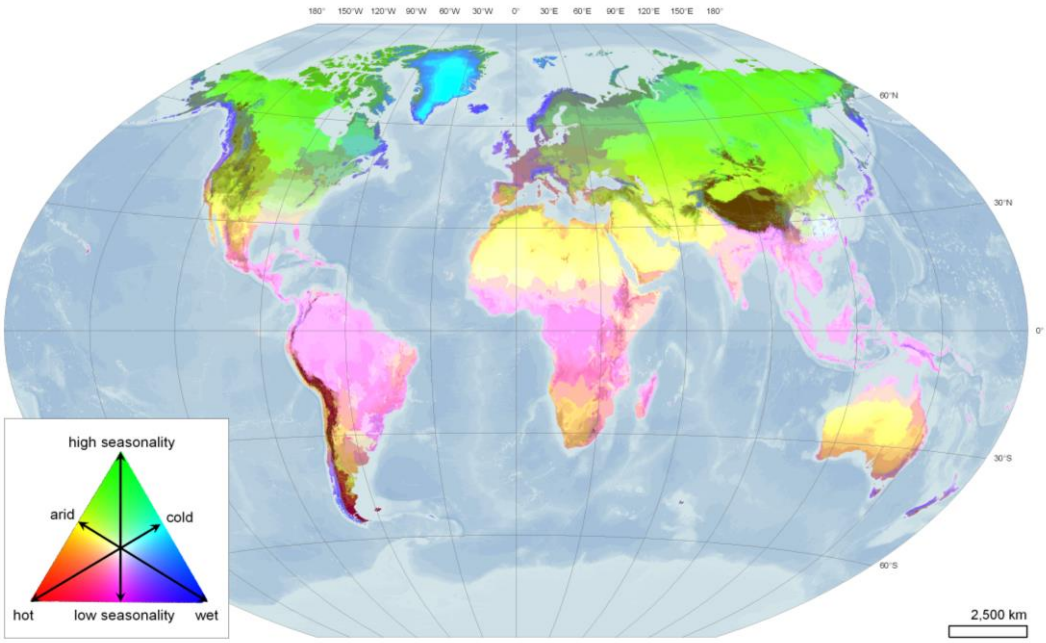

Figure 4.2.6.1. The global stratification in which 125 global strata are aggregated into 18 global environmental zones. The stratification has a 30 arc sec resolution (0.86 km^2 at the equator). The tropical environmental zone (extremely hot and moist) consists of ten global strata (Metzger et al 2013).

4.2.7 Key References for section 4.2

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4.3 MAPPING FOREST EXTENT AND CHANGES

4.3.1 Introduction

The past decades have seen a growing demand for accurate, reliable information on forest extent and change estimates. Such a request comes from different policy frameworks such as the UNFCCC, but also the UNCBD which the EBVs have been proposed to provide support to. Two out of the five selected EBVs for this sourcebook benefit directly from such estimates (Ecosystem extent and fragmentation, Disturbance regime), while the three other EBVs (Vegetation phenology, Net primary productivity (NPP), Ecosystem structure) benefit indirectly (e.g., forest boundaries, period of growth/ stability as a factor of NPP, and forest structure). This section presents some case studies that illustrate different forest monitoring options in terms of data and methods accross the pan-tropical region.

The first example of section 4.3 provides a simple, robust and cost-effective method for forest cover change detection in Central Africa. The case study demonstrates how to present change estimates compliant with IPCC reporting requirements. The second example takes place in Colombia with the use of MODIS data time-series. Inclusion of SAR data to improve result of land cover classification is tested. A third example in Southern India compares some forest cover change detection techniques and discusses the trade-off betweeen costs and overall accuracies. For more methods and datasets, we recommend to check section 5 on emerging approaches.

4.3.2 Forest cover change mapping in Gabon

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4.3.2.1 Country background

Gabon is an equatorial country located in the Congo-Ogoué basin region of Central Africa with total area, including land and water, of 267,667 km². Forests are mostly evergreen, dense-humid, equatorial forest with mangrove on the coast and swamp forests. Deforestation and degradation rates are expected to be small in Gabon, mainly because of the small human population (1;8 million inhabitants) mostly concentrated in urban settlements. Agriculture activities are sparse with subsistence agriculture mostly concentrated in the north of the country east of Equatorial Guinea and south of Cameroon around Oyem. However, limited industrial plantations have started to be developed in other parts of the country over the last few years. A new forest code and 13 national parks contribute since 2002 leading to establishing sustainable forest management plans in many forest concessions and protected areas, all of which contribute to preserving Gabon's forest cover.

Gabon has not yet adopted a national definition of forest. However, the UNFCCC (2006) defines forest as "a minimum area of land of 0.05–1.0 hectare (ha) with tree crown cover (or equivalent stocking level) of more than 10–30 per cent with trees with the potential to reach a minimum height of 2–5 meters at maturity in-situ." For purposes of assessing change, the largest values in the UNFCCC ranges were selected for defining forest land in Gabon: minimum area of 1 ha, tree crown cover of at least 30%, and minimum potential height at maturity of 5 m. Tree plantations are excluded from the forest definition, i.e., rubber or oil palm plantations are considered non-forest.

4.3.2.2 Objectives

The study included three main objectives:

(1) To assess the possibility of producing wall-to-wall forest cover maps based on available Remotely Sensed data archives with consideration given to persistent cloud cover and the lack of direct ground satellite reception in Gabon;
(2) To produce an accurate assessment of forest cover in Gabon for which there has been no detailed previous work;
(3) To develop a baseline for two reporting periods: 1990-2000 and 2000-2010.

4.3.2.3 Map construction

Forest/non-forest (F/NF) maps and forest change maps were constructed using Landsat and Terra ASTER data and the forest definition as previously described. Due to persistent cloud cover in Gabon, very little cloud-free imagery was available. Therefore, a compositing procedure was applied to individual classifications of selected images for each scene. Images were selected starting with the image closest to the reference year with cloud gaps filled gradually with data from other image scenes. Each selected image was classified using an unsupervised procedure with an interactive grouping of spectral classes in F/NF thematic classes. A minimum mapping unit of 1 ha was applied to ensure compliance with the forest definition, and classification artefacts were removed by visual assessment. An initial F/NF map was produced for 2000, and the same procedure was applied to 1990 and 2010 for selected image scenes, but using the 2000 F/NF map to provide context for predicting forest cover change. Thus, F/NF change maps were produced from the 2000 F/NF maps for 2000-1990 and 2000-2010 (Figure 4.3.1.3).

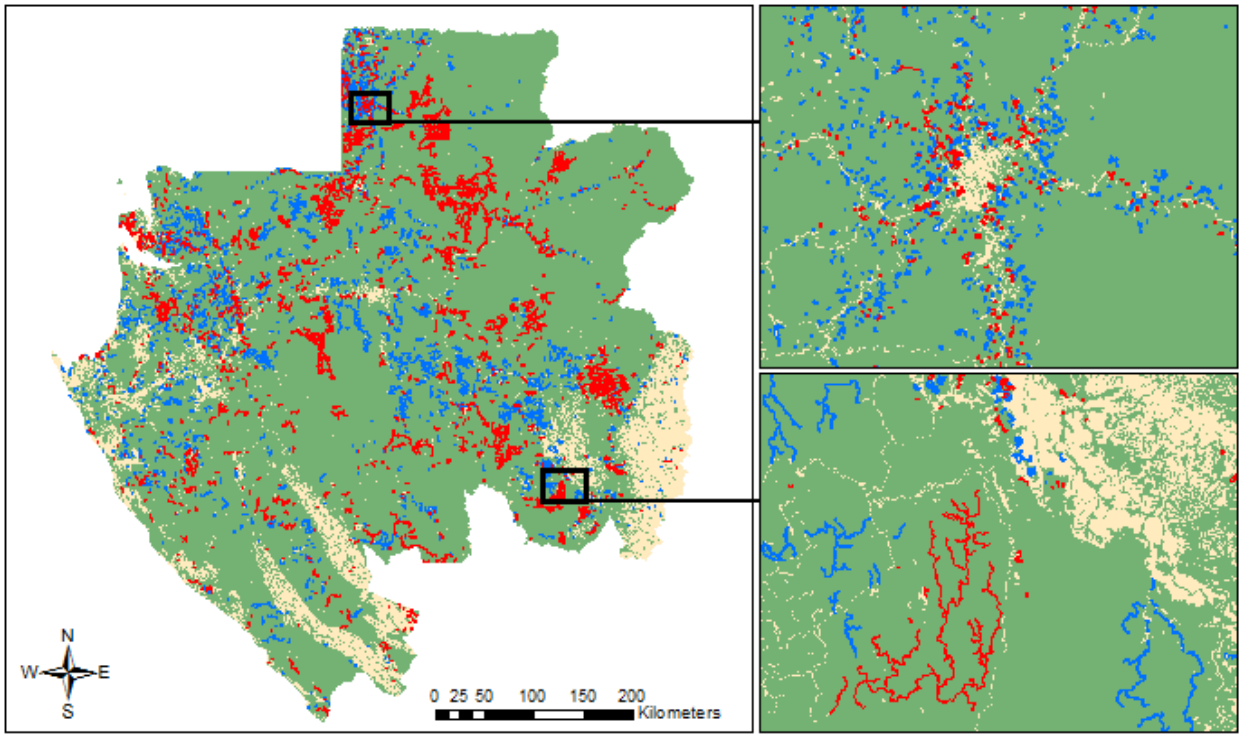

Figure 4.3.1.3. Forest cover change maps for 2000-2010 with locations of deforested areas highlighted in red and regenerated areas hihglighted in blue.

4.3.2.4 Reference data

The sources of reference data were primarily SPOT 5 with a 2.5m pixel size, ALOS PRISM & AVNIR-2, and RapidEye satellite imagery, all with finer spatial resolution than the imagery used for map construction. The reference data were initially categorical (F/NF), but were aggregated over blocks of contiguous pixels to produce block-level percentages of forest cover. The reference data were collected and processed by trained thematic experts independently from the map construction effort.

A probability sampling design with a systematic component was used to acquire the reference data. Gabon was tessellated into 20 x 20-km blocks, and one 2 x 2-km primary sample unit (PSU) was randomly selected from within each block. In this manner, 665 PSUs were selected for the whole country. This approach ensured that all areas of the country were sampled. Within each PSU, 50 secondary sample units (SSU) in the form of Landsat pixels were randomly selected for the purpose of assessing accuracy via error matrices.

4.3.2.5 Analyses

A model assisted, generalized regression (GREG) estimator as described in Sannier et al. (2014) was used with the combination of the map data and the PSU-level reference data. Designating the Reference sample as S_I, population means were estimated for the two response variables: (1) *proportion forest* for which $z_i = y_i^{ref,t}$ is the reference observation for i ε S_I for the tth year and $\hat{z}_i^{map,t}$ is the corresponding map prediction, (2) *net proportion deforestation* for which $z_i = y_i^{ref,t_2} - y_i^{ref,t_1}$ is the reference observation for i ε S_I for the interval t_1 to t_2. The GREG estimator takes the form,

$$\hat{\mu}_{GREG} = \frac{1}{M}\sum_{i=1}^{M}\hat{z}_i - \frac{1}{m}\sum_{i\varepsilon S_I}(\hat{z}_i - z_i),$$

with variance estimator,

$$\hat{Var}(\hat{\mu}_{GREG}) = \frac{1}{m(m-1)}\sum_{i\varepsilon S_I}(\varepsilon_i - \bar{\varepsilon})^2,$$

where $\varepsilon_i = \hat{z}_i - z_i$, $\bar{\varepsilon} = \frac{1}{m}\sum_{i\varepsilon S_I}\varepsilon_i$, m=665. In this manner, the area of forest cover for each of 1990, 2000, and 2010 and area of net deforestation for each of the two 10-year intervals were estimated by multiplying the proportions by the total area of Gabon.

4.3.2.6 Estimates

The resulting forest cover estimates for 1990, 2000 and 2010 and forest cover change estimates for 1990-2000 and 2000-2010 are reported in Table 4.3.1.5.

Table 4.3.1.5. Estimates*

Estimate	Area of forest cover (ha)			Area of net deforestation (ha)	
	2000	**1990**	**2010**	**1990-2000**	**2000-2010**
Map estimate	23,663,416	23,725,862	23,660,939	61,258	4,142
GREG estimate	23,652,023	23,739,451	23,633,596	86,240	20,092
95% CI width	70,396	66,360	69,647	27,655	25,072
*Total area=26,766,700 ha					

4.3.2.7 Discussions and conclusions

The Forest area and area change estimates were the first reliable national estimates of the extent and change of the Gabonese forest for which the uncertainty was estimated and minimized. It is worth noting that previously the area of forest in Gabon based on regional assessments was thought to represent around 85% of the territory which is around 1 million hectares less than the estimates from this study. In addition, this study provided direct input to drafting Gabon's national climate action plan for the forest sector and the development of a national land use plan.

The method developed is simple, robust and cost-effective. Subsequent to this study, the methodology has been transferred to the Gabonese Agency for Space Observations Studies (AGEOS) which is now capable of producing their own updates of the forest cover map. An update was effectively produced by AGEOS for 2015 and will be published soon.

Forest area and area change estimates could be produced from a sampling approach alone, but results show that the combination of sample data with a wall-to-wall map can reduce the number of sample units required to provide the same precision by a factor close to 60 to estimate forest area. In this case, this would mean increasing the sample size from 665 to almost 40,000. In addition, even though producing wall-to-wall maps of forest area and forest cover change is time-consuming and requires specialized staff and equipment, their use can be extended to other

purposes such as forest management, land use planning and near-real time national forest monitoring system to detect illegal logging.
The use of Earth Observation can contribute at two levels (i) for collecting sample data to produce a "ground truth" reference dataset based on the independent visual interpretation of satellite imagery, and (ii) for producing the wall-to-wall F/NF map. The availability of current satellite systems is compatible with a near-real time national forest monitoring system. Finally, the method was successfully applied in other Congo basin countries including Cameroon, Central African Republic and Republic of Congo as well as part of Bolivia for the Pando Departamiento.

4.3.2.8 References for section 4.3.1

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4.3.3 Forest cover mapping of Colombia using a multi-year data-integration approach

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The tropics are known for the significant cloud and fog cover affecting optical satellite image observations. Some areas have been described as being persistently (Helmer et al. 2010) or pervasively cloudy (Holden and Woodcock 2016). Additionally, fog occurrence is an important indicator to determine the habitat extent and richness of epiphytes, a climatic feature that has been described using MODIS night-time data (Obregon et al. 2014). However, in the context of optical satellite image classification of forest extent, fog and clouds considerably restrict the amount of useful observations. For this reason, cloud occurrence is very important when defining the quality of a pixel (Leinenkugel et al. 2013).
Two approaches are available to quantify forest cover in areas with persistent clouds: increase the temporal resolution of optical observations or see through the clouds with radar wavelengths. The capability of radar to map natural forest in regions affected by persistent clouds and other atmospheric effects (Saatchi et al. 2011; Thapa et al. 2014) is well known. Another approach to quantify forest extent in areas where consistent periodicity is difficult to achieve is the selection of the best observations from a time series (Broich et al. 2011). Integrating these datasets has also been found useful; for example when merging the high spectral resolution of optical sensors with the long wavelength of radar (Reiche et al. 2015).
A case study of land cover was developed in Colombia, a tropical country that is subject to cloud persistence, especially in the Pacific Coast where the humid currents from the ocean and the Andes Mountains promotes orographic cloud formation (Poveda et al. 2006). A multi-year data-integration approach was used by Anaya et al. (2015) in order to map land cover. Data for time series generation was based on 16-day vegetation index composite data (MOD13A1) from the Moderate Resolution Imaging Spectroradiometer (MODIS). TiSeG, a software that explores the MODIS data quality flags and provides indicators on spatial and temporal data availability (Colditz et al. 2011; Colditz et al. 2008), was used to remove low quality observations from a five-year period 2009-2013. Most removed pixels were contaminated by clouds. For the study area, on average, 50.4% of the observations from 2001 to 2013 where classified as invalid pixels. Given the large interval (usually months) between valid observations (Figure 4.3.2), an interpolation of the annual time series of 2011, which maintains typical or expected phenological characteristics, was not possible. Therefore invalid observations of 2011 were substituted by valid observations from adjacent years. In a second step this multi-year time series was used for an improved land cover classification. Ancillary variables such as the Phased Array L-band Synthetic Aperture Radar (PALSAR) were included to evaluate the impact on accuracy.

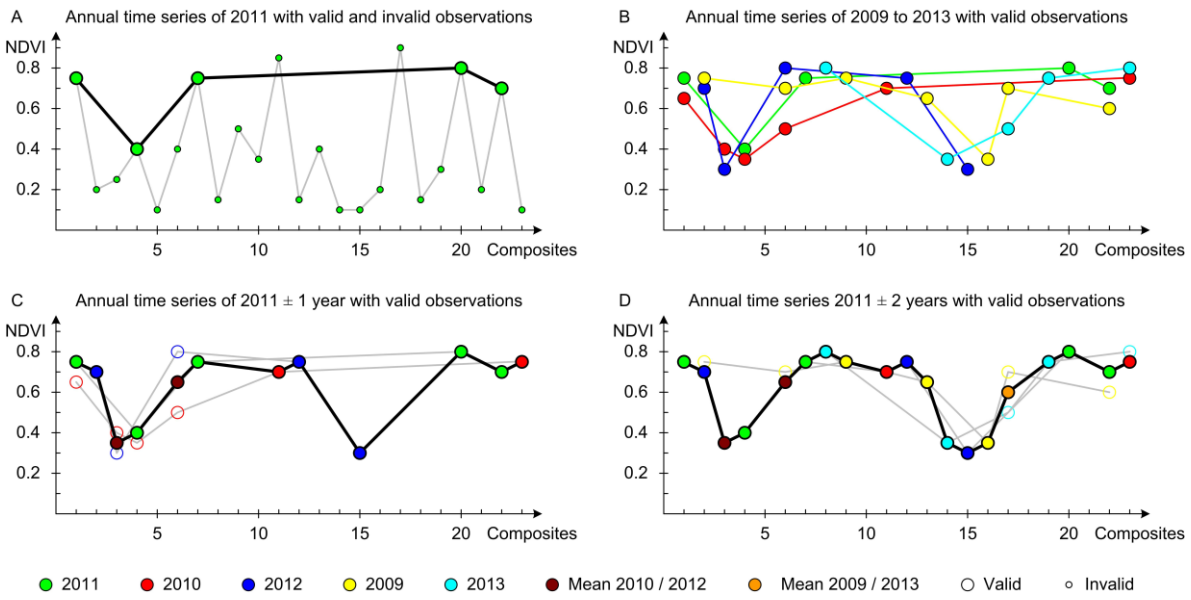

Figure 4.3.2. Multi-year data integration for time series generation. The hypothetical data should represent an annual time series with bi-modal characteristics, typical for agriculture with two growing seasons. (A) Time series of 2011 of valid (large circles) and invalid (small circles) observations connected by a grey line and linear temporal interpolation of valid data shown by a black line; (B) annual time series from valid observations of five years in different colors; (C) integrated time series from data of 2011 ± 1 year; and (D) integrated time series from 2011 ± 2 years, based on (C). Void circles and grey lines in (C) and (D) indicate valid data and linear interpolation of annual data from (B) (Anaya et al. 2015).

From this study a total area of 526,667 km^2 of broadleaf forests were estimated in Colombia, mostly located in the Amazon basin and the Pacific Coast. The data analysis for the above-mentioned years suggests that approximately 4% of the study area were under persistent cloud cover. The classification accuracy improved by 10% in comparison to simply eliminating invalid pixels, and by 3% when using MODIS data without quality analysis. Additional tests including ancillary information, such as elevation, increased the accuracy by another 1.5%. While radar imagery did not improve the classification accuracy in this case study, inclusion of micro-wave data is suggested for monitoring tropical forests, due to the persistence of clouds and capabilities to reveal information on forest structure. The time series approach builds upon two important assumptions: 1) no notable temporal shifts or differences in magnitude in vegetation growth between all years and 2) no land cover change during the multi-year period. Several extensions are possible, such as step-wise quality-dependent assimilation based on ranked indicators (Colditz et al. 2011), more advanced fitting functions (Chen et al. 2004; Jönsson and Eklundh 2004), or piece-wise approaches (Viovy et al. 1992). Alternatively reduced operating costs of low-flying unmanned vessels such as drones, kites, planes or helicopters may provide a cost-effective means to obtain site-specific data at nearly any time.

4.3.3.1 References for section 4.3.2

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4.3.4 Changes in tropical forest: assessing different detection techniques

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4.3.4.1 Introduction

The monitoring of forest ecosystem state involves the detection of changes which may have occurred in the specific area. The operational definition of ecosystem mapping and monitoring proposed by Maes et al.(2014) suggests that ecosystem changes can be quantified through Land Cover/Land Use (LC/LU) class changes. The detection of LC/LU class changes implies not only the identification of when and where they may have occurred, but also the definition of both the type and magnitude of target (e.g., forest) class transitions from time T_1 to time T_2, with $T1<T_2$, along with the quantification of class modifications. The changes thus detected can then be used to identify anthropic and other pressures acting on the area (Nagendra et al., 2014; Sorrano et al., 2014).
The present study compares the data obtained through the Cross-Correlation Analysis (CCA) technique, developed by the American company Earthsat, Inc., with those resulting from a traditional unsupervised technique in the detection of changes in tropical forest ecosystem.
The CCA technique has already been used by Koeln and Bissonnette, (2000) and Civco et al. (2002) to analyse High Resolution (HR) (e.g., Landsat TM) and Medium Resolution (MR) imagery (e.g., MERIS). More recently, Tarantino et al. (2016) have applied the CCA technique to Very High Resolution (VHR) data (e.g., WorldView-2) to detect grassland ecosystems changes.
Focusing on a protected area in Southern India, the present study investigates the advantages in terms of costs and Overall Accuracy (OA) of the CCA technique.
A brief description of materials and methods used will be followed by indications of the study area and input data. Thereafter, the accuracy of the results obtained and their discussion will provide support to the operational implementation of the CCA technique and its application to tropical forest monitoring.

4.3.4.2 Materials and methods

Study site and input data

The present study site is a 540 km^2 Tiger reserve located in the Western Ghats biodiversity hotspot in Southern India, named Biligiri Rangaswamy Temple Tiger Reserve (Figure 4.3.3.2.a). The area has a heterogeneous physiography, with hills running in the North-South direction, and elevation ranging from 600 to 1800m above sea level. This location and its physiography produce a unique climate regime, due to which the site receives rainfall in two different seasons. These biophysical conditions allow a distinctive ecosystem to thrive on the area with consequent high level of diversity in endemic flora and fauna. The vegetation of the region has been classified into ten different types, ranging from dry scrub forest to dense wet evergreen forests in the higher elevation areas. The evergreen forests are found in contiguous areas, and also in dense patches among a mosaic of high elevation grassland area. Such characteristics provide for a habitat known as 'sholas'.
The multiresolution image data set available for this area consists of: one recent VHR WorldView-2 (WV-2) image (Figure 4.3.3.2.c), provided by the ESA within the FP7-SPACE BIO_SOS project; two Landsat images and one recent Sentinel-2 data. An existing validated LC map (1:50000) dated 1998 (Figure 4.3.3.2.b), was used in our CCA experiments to extract the T_1 target class layer (i.e., evergreen forest) for the detection of changes. The existing data were compared according to the following scheme:

1. Change Detection (Map to Image comparison) at VHR by CCA with the WV-2 image (2m. spatial resolution), dated March 14, 2013, as T_2 image.
2. Change Detection (Map to Image comparison) at HR by CCA with the Sentinel-2 image (20m. spatial resolution), dated February 19, 2016, used as T_2 image.

3. Change Detection (Map to Image comparison) at HR by CCA with the recent Landsat 8 OLI (30m. spatial resolution), dated March 20, 2016 as T_2 image.
4. Unsupervised change detection at HR, by direct comparison of the NDVI indices from two Landsat images (Image to Image comparison) dated March 16, 1997 (Landsat 5 TM) and March 20, 2016, as T_1 and T_2 images, respectively.

The analysis carried out and the acronyms used are reported in **Table 4.3.3.2**.

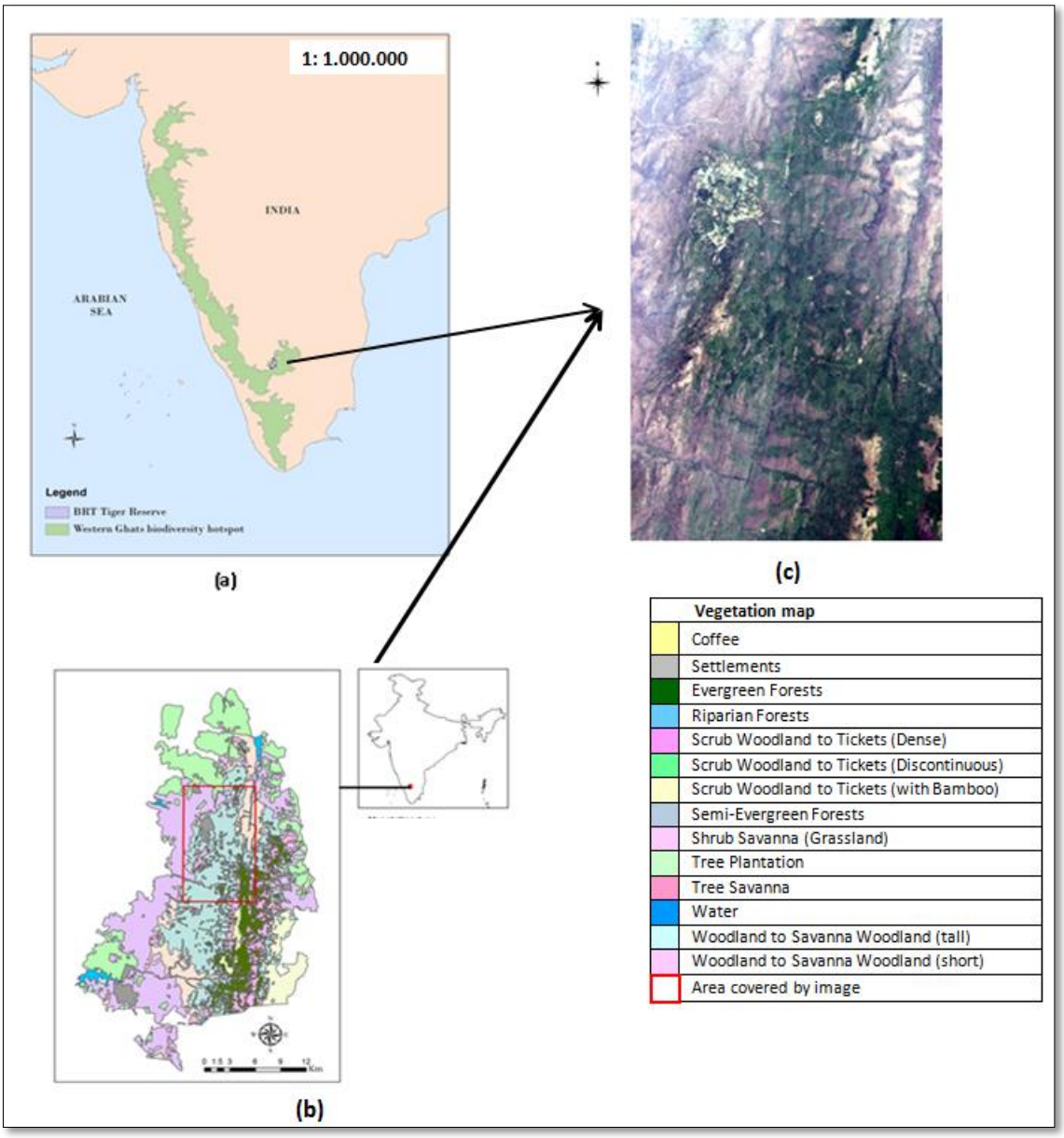

Figure 4.3.3.2. (a) Location of the Biligiri Rangaswamy Temple Tiger reserve, India. (b) Existing LC map dated 1998. The red rectangular area corresponds to the WorldView-2 image coverage. (c) Available WorldView-2 image, 2m resolution, March 14, 2013. True Color Composite: R=5, G=3, B=2.

Table 4.3.3.2. Set of experiments and acronyms used in the paper for Biligiri Rangaswamy Temple Tiger Reserve, India.

Exp.	**Input data at T_1**	**Time T_2**	**Change Method**	**Change Method Acronym**
1	Pre-existing Land Cover/Land Use Map used to extract the tropical evergreen forest target class of interest: 1998	Worldview-2 image: 14 March 2013	Cross Correlation Analysis	**CCA_VHR**
2		Sentinel-2: 19 February 2016		**CCA_HR_Sentinel-2**
3		Landsat 8 OLI image: 20 March 2016		**CCA_HR_Landsat**
4	Landsat 5 TM image: 16 March 1997	Landsat 8 OLI image: 20 March 2016	NDVI direct comparison by image differencing	**DIFF_NDVI_HR**

Techniques

When using Earth Observation (EO) data and remote sensing techniques to detect LC/LU changes in the monitoring process, the selection of automatic change detection techniques can be determined, on the one hand, by specific user requirements, on the other, by data availability and costs related to both data acquisition (if any) and data processing.

As reported in the literature (Koeln and Bissonnette, 2000 and Civco et al., 2002), the *C*CA technique can be applied to quantify differences between a specific target class layer (e.g., tropical forest) extracted from an existing LC/LU map (T_1) and a recent single-date image (T_2) with $T_1 < T_2$. All pixels of the T_2 image belonging to the selected thematic layer (target class) in the T_1 map must be analysed first to determine the expected reference class metrics in T_2 (i.e., class average spectral response and standard deviation). Then, a statistical measure, named Z-statistic, can be used to evaluate the distance between the specific pixel spectral signature at T_2 and the reference class metrics computed. Large values of Z-statistic measures reveal possible occurrence of class changes, whereas small Z-statistic values represent non observable changes. The Z-statistic results evidence the need of a threshold (TH) which can help to identify most of the significant changes. Once these changes are found, information about class transitions or modification at T_2 can be obtained by local in-field campaigns or visual inspection of VHR imagery (if available). The equations used by CCA are described in (Koeln and Bissonnette, 2000; Tarantino et al., 2016).

Accuracy assessment

A set of changed and unchanged forest reference polygonal area was selected to validate the output map, through visual inspection of the available WV-2 image. Stratified random sampling was applied. When the sampling intensities were found to differ for the considered classes (i.e. changed and unchanged areas), correct calculation of the overall accuracy (OA) would require weighing the within-class accuracies by the proportions of the study area characterising the map classes, otherwise, the OA cannot be calculated as the sum of diagonal counts divided by the total count, as generally done in the case of simple random sampling or systematic sampling design (Congalton & Kass, 2009). To overcome this problem, for each experiment, the change error matrix was produced in terms of sample counts. For a more accurate quantification of change overall accuracy, both the protocol described in Olofsson et al. (2013; 2014) and the recommendations reported in Section 4.4 of this text were adopted. The aforementioned protocol is based on a more informative presentation of the change error matrix, thus it offers the advantage that change accuracy and area estimates can be computed directly from it.

In accuracy assessment, when map categories are reported as rows (i) and the reference categories are the columns (j), A_{tot} represents the total area of the map (window), $A_{m,i}$ is the mapped area (ha) of category i in the map and $W_i = \frac{A_{m,i}}{A_{tot}}$ is the proportion of the mapped area as category i, $\hat{p}_{ij}$ is then:

$$\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i\cdot}} \qquad (2)$$

The unbiased stratified estimator of the area of category j can be obtained as:

$$A_j = A_{tot} \times \hat{p}_{\cdot j} = A_{tot} \sum_i W_i \frac{n_{ij}}{n_{i\cdot}} \qquad (3)$$

where $\hat{A}_j$ can be viewed as an "error-adjusted" estimator of the area because it includes the area of map error omission of category j and leaves out the area of map error commission.

The estimated standard error of the estimated proportion of area is:

$$S(\hat{p}_{\cdot j}) = \sqrt{\sum_{i=1}^{q} W_i^2 \frac{\frac{n_{ij}}{n_{i\cdot}}\left(1 - \frac{n_{ij}}{n_{i\cdot}}\right)}{n_{i\cdot} - 1}} \qquad (4)$$

The standard error of the stratified area estimate can then be expressed as:

$$S(\hat{A}_j) = A_{tot} \times S(\hat{p}_{\cdot j}) \qquad (5)$$

and the approximate 95% confidence interval for $\hat{A}_j$ is:

$$\hat{A}_j \pm 2 \times S(\hat{A}_j) \qquad (6)$$

4.3.4.3 Results and discussion

The quantitative results of the experiments carried out are summarized in Table 4.3.3.3. Figure 4.3.3.3. shows the changes detected by using the CCA technique. Specifically, CCA_VHR experiment results carried out by using WV-2 image, Sentinel-2 and Landsat OLI images as T_2 date are shown in Figure 4.3.3.3.f, Figure 4.3.3.3.g, Figure 4.3.3.3.h. whereas the result obtained through the DIFF_NDVI_HR the experiments are shown in Figure 4.3.3.3.i. Some close-up of the changed areas encircled in red and yellow in Figure 4.3.3.3 (f to i) are reported in Figure 4.3.3.4. and Figure 4.3.3.5., respectively.

With the threshold set as μ+1σ, the CCA technique at VHR provided both the largest OA (82,4%) and the smallest error in the stratified change area estimate (±2.55ha). The OA obtained is similar to the one obtained by CCA at HR (82,29%), with a Landsat OLI image, and the error in the stratified changed area was smaller (±2.55ha) than the one from Landsat OLI (±32.01ha). These findings are in line with those obtained in a previous paper by Tarantino et al. (2016) for grasslands ecosystems. Moreover, the results obtained with the Sentinel-2 image were lower in terms of overall accuracy (72.70%).

In consideration of the different techniques used, the direct comparison of NDVI image pairs provided the smallest OA (63.33%) with the largest stratified changed area estimate. This estimation takes into account omission errors due to the technique applied. As can be observed in the close-up areas from DIFF_NDVI_HR reported in Figures 4.3.3.4.i and 4.3.3.5.i, several changes appear not to be detected at all.

With regards to the scale of analysis, the close-up windows in Figure 4.3.3.4 can reveal how difficult it may be to detect changes in the density of the tropical forest cover at HR. As shown in Figure 4.3.3.4.f and 4.3.3.5.f, changes in forest density could be clearly detected at VHR by CCA. Forest fragmentation detected in 2013 by VHR can still be observed not only in the CCA images from both Sentinel-2 and Landsat OLI images dated 2016, but also in the DIFF_NDVI_HR output image, although the latter image seems not detect all forest coverage changes (Figure 4.3.3.5.i).

Table 4.3.3.3. Change detection matrix. Results from CCA at (VHR and HR) and DIFF_NDVI_HR. Producer's and overall accuracies are based on stratified estimation. TH refers to the threshold applied to the Z-statistic image in the CCA experiments. A_m is the mapped change area.

Change: transition from *Evergreen Forest* to *Other* – at different TH for an area of 911 ha (at T_1)									
Exp.	**Change Method Acronym**	**TH**	**Change User's Acc.%**	**Change Producer's Acc.%**	**No Change User's Acc.%**	**No Change Producer's Acc.%**	**Overall Acc.%**	**A_m (ha) change**	**Stratified changed area estimate with 95% conf. interv. (ha)**
1	**CCA_VHR**	**CCAμ+1σ**	69.96±0.26	43.96±0.19	84.56±0.16	94.20±0.14	**82.40±0.14**	**134.53**	**214.10±2.55**
		CCA>μ+2σ	85.35±0.33	10.95±0.13	72.60±0.17	99.21±0.04	73.09±0.16	34.60	296.76±2.93
		CCA>μ+3σ	95.93±0.30	2.54±0.05	67.80±0.17	99.95±0.01	68.04±0.17	7.90	298.53±3.01
2	**CCA_HR_ Sentinel-2**	**CCA>μ+1σ**	80.00±2.91	22.56±1.36	71.95±1.50	97.24±0.54	**72.70±1.38**	**86.68**	**307.36±25.89**
		CCA>μ+2σ	89.02±3.47	7.08±0.73	67.13±1.48	99.54±0.19	67.73±1.44	25.60	321.81±26.96
		CCA>μ+3σ	100.0±0.01	3.32±0.16	65.00±1.47	100.0±0.01	65.41±1.45	11.12	334.62±27.13
3	**CCA_HR_ Landsat**	**CCA>μ+1σ**	92.03±2.31	34.62±1.78	81.24±1.84	98.95±0.67	**82.29±1.67**	**93.24**	**247.86±32.01**
		CCA>μ+2σ	98.70±1.30	11.59±0.76	73.54±1.95	99.94±0.16	74.40±1.88	32. 49	276.65±36.02
		CCA>μ+3σ	100.0±0.01	4.66±0.29	68.91±1.98	100.0±0.01	69.37±1.95	14.31	307.36±37.24
4	**DIFF_NDVI_HR**	DIFF>0	44.29±5.98	9.68±1.88	65.26±2.09	93.31±0.62	**63.33±1.98**	**72.99**	**334.08±37.31**

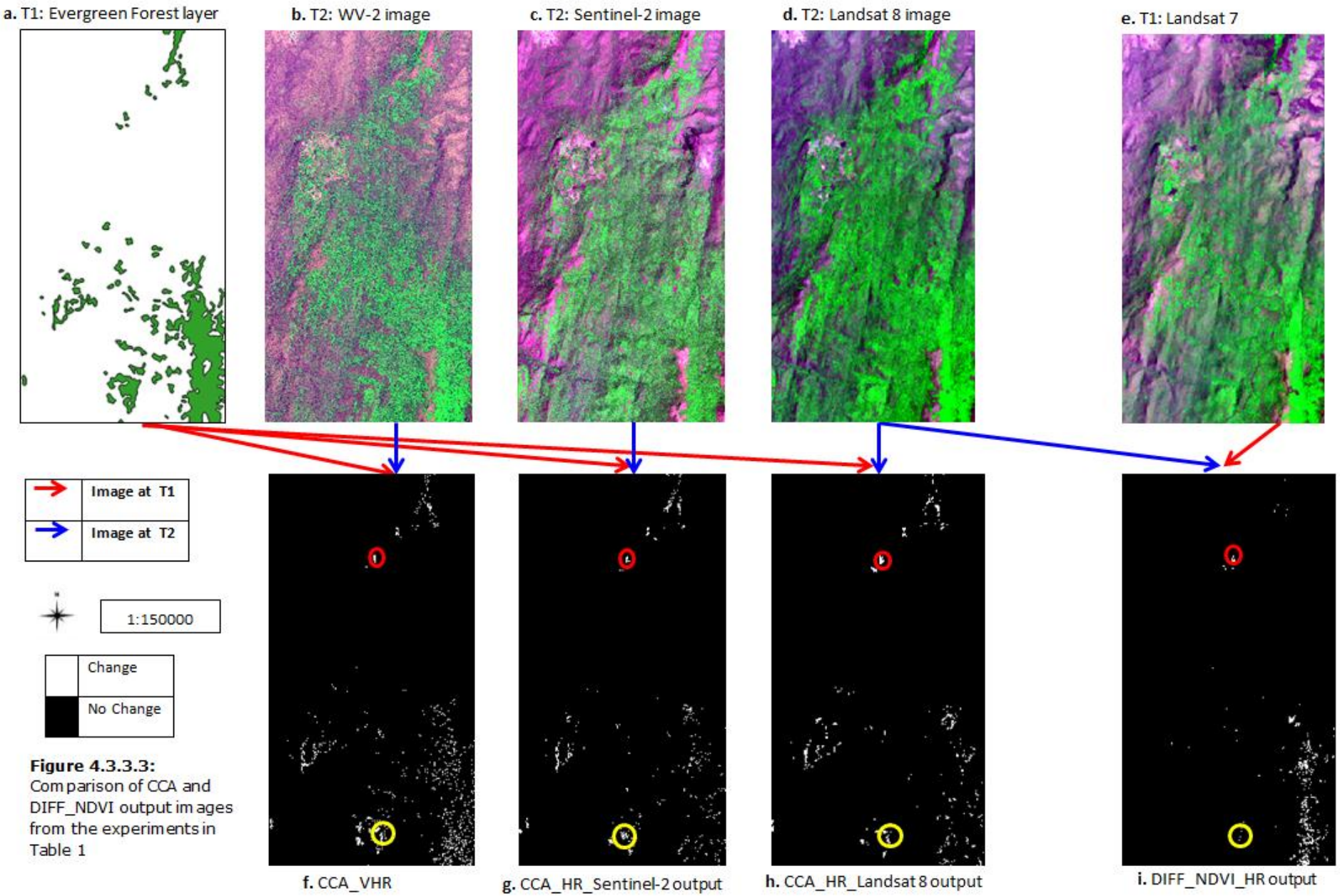

Figure 4.3.3.3: Comparison of CCA and DIFF_NDVI output images from the experiments in Table 1

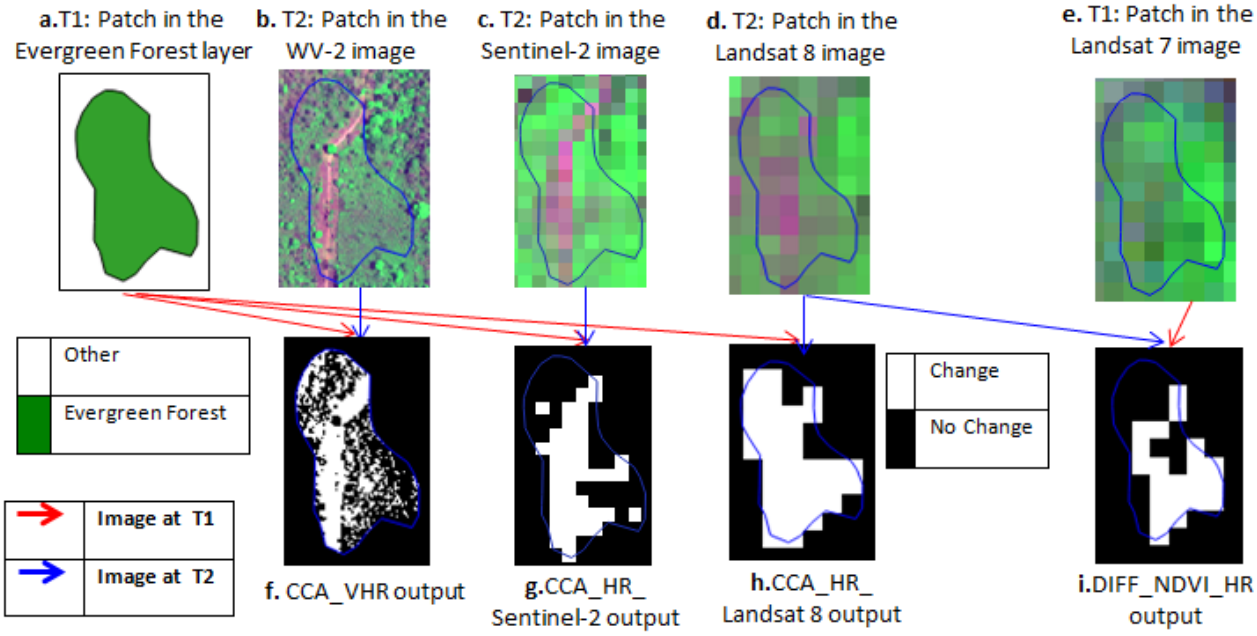

Figure 4.3.3.4. Close-up of the changes in the red circle of Figure2 for CCA and DIFF_NDVI

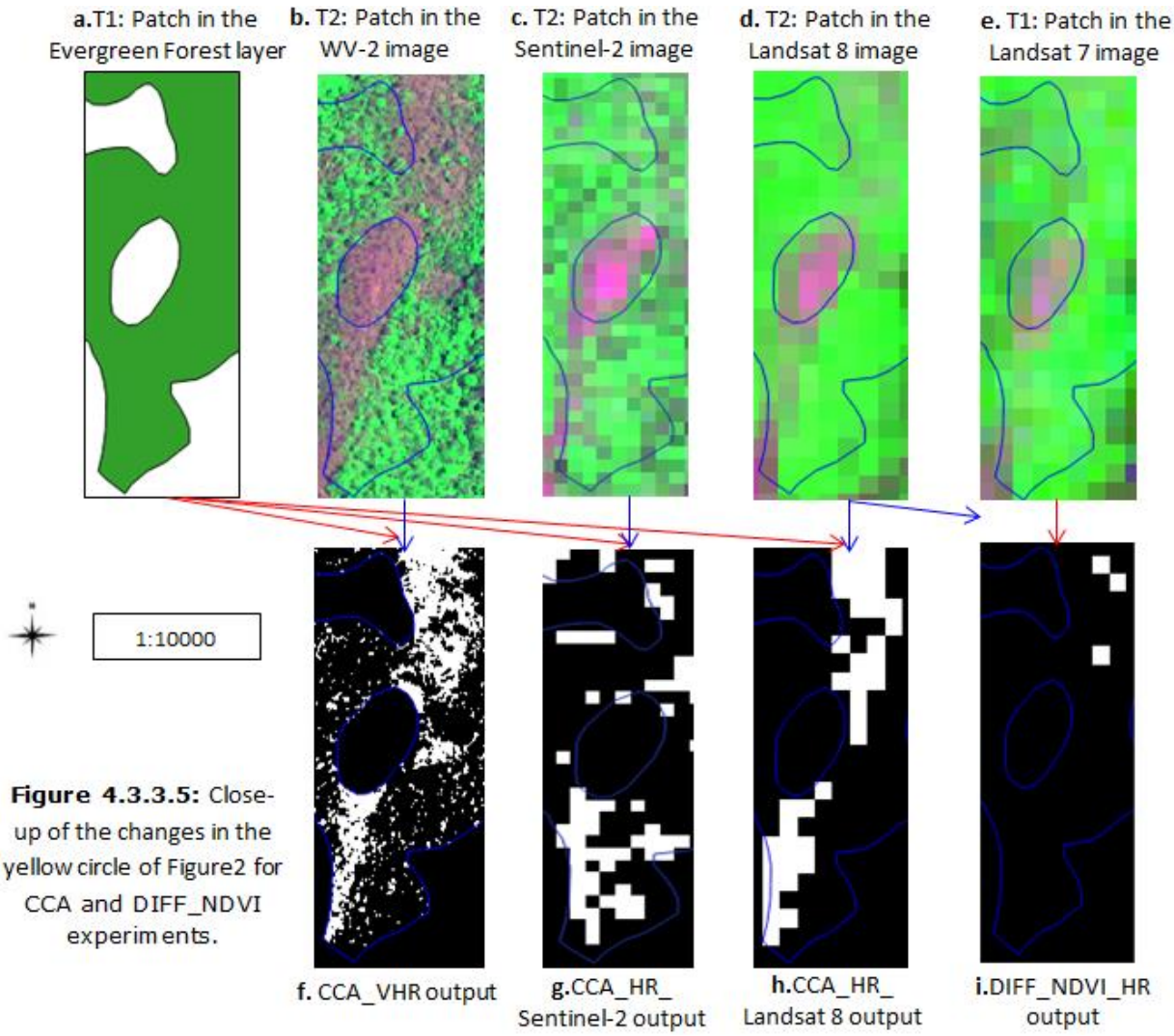

Figure 4.3.3.5: Close-up of the changes in the yellow circle of Figure2 for CCA and DIFF_NDVI experiments.

4.3.4.4 Conclusions

The findings reported in the present study underline the need of VHR data for detailed monitoring in support to conservation studies. Even though the DIFF_NDVI_HR technique can reveal changes in the forest ecosystem, the CCA technique can provide more significant results. The application of this technique can reduce costs of fine scale change detection when: a) the acquisition of several (multi-seasonal) VHR images at time T2 (e.g., within year), required to produce high quality LC/LU maps to be compared, is too expensive, and b) no archival VHR data are available at T_1 for direct image comparison with a new image tasked at T_2 with $T_1 < T_2$. Therefore, the comparison of the results, discussed, invites the conclusion that VHR data are needed in investigating tropical forest changes. As well known the present policies concerning VHR data require cost reduction in the monitoring and regular acquisition of data for endangered areas in support of conservation commitments of their management authorities.

4.3.4.5 Acknowledgements

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4.4 ACCURACY ASSESSMENT AND AREA ESTIMATION

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4.4.1 Rationale

The strength of remote sensing data is the provision of wall-to-wall coverage of the area of interest. Classification of the remote sensing data will yield a wall-to-wall map of the area that provides a spatially explicit representation of mapped features, such as land cover categories. The drawback with this approach is that classification errors are inevitable. Classification errors result in pixels (or whatever image objects that are analyzed) in the remote sensing data being assigned to incorrect map classes. This entails, in addition to an incorrect spatial representation, that the areas of the mapped classes are incorrect unless the errors of omission and commission cancel each other out which is unlikely. Omission errors of a map class *A* are pixels that were misclassified as belonging to something else than *A*; the analyst omitted or missed this instance of *A* (hence, an errors of *omission*). A commission error on the other hand of class *A* are pixels that were misclassified as belonging to *A*. The extent of these errors is estimated by implementation of an accuracy assessment. Central to the accuracy assessment is the use of a probability sample of reference observations that are of greater quality than the classification. Errors are identified by comparing the sample of reference observations to the classification. Using this information, it is possible to estimate measures of accuracy that provide information about the magnitude of the overall map error, and errors of omission and commission of individual map features. While accuracy measures provide important information on how to use and interpret the map, they do not provide an adjustment or correction for estimated bias in the areas of map classes. This requires construction of an unbiased area estimator that excludes the area committed and includes the area that was omitted in the classification. The information required to construct an area estimator is typically contained in the error matrix.

4.4.2 Designing the accuracy assessment

An important part of the assessment is the design of the sample of reference observations. If a reference sample does not exist for the study area, it needs to be created. In a design-based inference framework, the map units – for example, the pixels in the map – form the population from which the sample is selected. A critical recommendation is that the sampling design should be probability-based, which requires that randomization is incorporated in the sample selection protocol. Probability-based sampling is defined in terms of inclusion probabilities, where an inclusion probability relates the probability of a map unit being included in the sample (Stehman 2000). The inclusion probability must be known for each unit selected in the sample and must be greater than zero for all units in the population (Stehman 2001). There are several probability sampling designs are applicable to accuracy assessment, with the most commonly used designs being simple random, stratified random, and systematic (Stehman 2009; Stehman & Foody 2009). An important decision is whether to use strata, which are discrete and mutually exclusive subsets of the study area. Stratified sampling where the study area is partitioned into strata allows for analysis of subsets of the study area that are of interest for reporting results (e.g., reporting accuracy and area by land-cover class or geographic subregion), and it typically improves the precision of estimates. Another important advantage is the ability to increase the sample size for smaller but important subregions that risk insufficient sampling if implementing a simple random or simple systematic design (a common example of such regions are areas of deforestation or other land change processes which tend to be small compared to the total study area). For these reasons, stratified random sampling is a practical design that satisfies most accuracy assessment objectives and most

of the desirable design criteria (Olofsson et al. 2014). Further recommendations for determining total sample size and within-strata sample sizes are provided in Olofsson et al. (2014). A more detailed discussion of sample designs are provided in Stehman (2009).

4.4.3 Interpreting the sample

After a sample has been designed, reference observations need to be collected for each unit in the sample. Depending on the nature of the map, several sources of reference data are possible: satellite data, field plots, forest inventory data, crowdsourced data, etc. For a more exhaustive discussion on reference data sources and reference labeling protocol, see Olofsson et al. (2014, p. 47-51).

4.4.4 Analysis of accuracy and area

After reference data have been collected for each sample unit, an error matrix can be constructed by cross-tabulating the map and reference classes. The error matrix typically represents map labels in rows and reference labels as columns, with the matrix elements p_{ij} expressing the proportion of area for the population that has map class i and reference class j (Table 4.4.4.1). For Class 1, $p_{12} + p_{13}$ is the error of commission while $p_{21}+p_{31}$ is the error of omission.

Table 4.4.4.1. Example error matrix with tree classes.

		Reference			
		Class 1	**Class 2**	**Class 3**	**Total**
Map	Class 1	p_{11}	p_{12}	p_{13}	p_{1+}
	Class 2	p_{21}	p_{22}	p_{23}	p_{2+}
	Class 3	p_{31}	p_{32}	p_{33}	p_{3+}
	Total	p_{+1}	p_{+2}	p_{+3}	1

Unbiased area estimators can be created using the information in the error matrix. When the map classes are discrete, as is the case in Table 4.4.4.1, stratified estimation typically produces more precise estimates whereas the model-assisted regression estimator produces more precise estimates in the case of a continuous predictions (Stehman 2013). Stratified estimation – called post-stratified in the case of simple random or systematic sampling – is described by Cochran (1977) with further explanation in a remote sensing context provided by Olofsson et al. (2013). The model-assisted regression estimator is described in Särndal et al. (1992), with examples of its usage provided by (McRoberts 2011; McRoberts & Walters 2012). These references also contain the variance expressions required to construct confidence intervals around the area estimates. A confidence interval expresses the uncertainty of an estimate: an interval at a 95% confidence level implies that 95% of such intervals, one for each set of sample data, include the true value of the parameter. Hence, a smaller confidence interval of an estimate implies a higher precision. In addition to area estimates, it is recommended that three measures of accuracy are reported: overall, user's and producer's accuracy. Overall accuracy is the proportion of the area mapped correctly, whereas the user's and producer's accuracy are the complements of the probability of commission and omission errors of a specific map category, respectively. The estimators for calculating the accuracies must be consistent with the sampling design. Formulas for estimating accuracy with confidence intervals are provided by Olofsson et al. (2014) and Stehman & Foody (2009).

4.4.5 Guidance and implementation

More specific guidance on decisions pertaining to sampling design, estimators and the use of existing reference and map data is provided in the Methods & Guidance Document (MGD) of the Global Forest Observations Initiative (GFOI). The first version of the document (Penman et al. 2014, Section 3.7) contains two common examples. The upcoming second version to be released in spring 2016 will contain decision trees and additional guidance. Open-source software tools and hands on instructions for implementation are provided by the BEEODA suite (Boston Education in Earth Observation Analysis) which is free for download at http://beeoda.org and https://github.com/beeoda. The BEEODA material supports implementation of the good practices for accuracy assessment and area estimation outlined in Penman et al. (2014) and Olofsson et al. (2014). See section 4.3 for implementation examples within case studies.

4.4.6 Key References for section 4.4

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4.5 HABITAT, FRAGMENTATION, AND CONNECTIVITY

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4.5.1 Introduction

Global biodiversity, and the ecosystem functions it supports, is increasingly threatened by anthropogenic impacts, yet how ecological assemblages at different scales are responding to these pressures is less clear and even controversial (e.g. Newbold et al 2015; Vellend et al 2013; Cardinale et al. 2012). Inferring that ecosystem functions will decline due to biodiversity loss in the real world remains an untested assumption. Hence, several latest studies working with large global database of different nature, have been contesting that such loss is actually occurring in particular at local scales in nature (see Vellend et al 2013, Dornelas et al 2014; Elahi et al. 2015; Newbold et al 2015). Nevertheless, it is well known that different human pressures are traduced into land-use change that is recognized as the main driver of biodiversity degradation at global scale. Plant communities in particular can undergo declines (homogenization) or increases (differentiation) in β-diversity depending on the landscape configuration and on the spatial scale of analysis (e.g. Arroyo-Rodríguez et al 2009; 2013).
There are still substantial knowledge gaps in relation to conservation and sustainable use of biodiversity. These include gaps related to the state of biodiversity, drivers of loss and pressures on biodiversity, their impact now and in the future, and the effectiveness of policy responses. In many cases, the effect of habitat loss and fragmentation on species has been shown to be non-linear, reflecting a threshold value beyond which its negative impacts increase significantly (Swift & Hannon 2010).

Causes of recent changes in tropical forest dynamics remain unclear and the responses of tropical trees to environmental changes are still poorly understood. New research strategies with a new vision are needed, focusing on landscapes instead of single trees, on long term instead of short term changes in order to improve predictions of forests responses to global change. User surveys have identified the need for guidance documents and detailed information related to advanced monitoring systems including remote sensing (RS) data and methods for biodiversity monitoring in tropical forests, including good practices, in link with policy targets.
Analysing a large vegetation data base from a hierarchically nested sampling design in a rain forest in Mexico, Arroyo-Rodríguez et al. (2013) found that patterns of floristic homogenization and differentiation depend on the landscape configuration and on the spatial scale of analysis. Hence, a multi-scale approach, including space and time, seems to be needed to accurately assess the impact of land-use change on β-diversity and to have a better understanding of the mechanisms that contribute to the maintenance of species diversity in particular in fragmented landscapes (Harrison & Cornell 2008; Lôbo et al 2011).
In the past 100 years, the global forest coverage has decreased by 50%, an estimated loss of the size of the UK per year (FRA 2015). Here, the tropical forest ecosystems are under particular increasing threats due to excessive human development including mining, deforestation, conversion to agriculture, fires, and with 1.6 billion people (~ 25 % of the world population) directly depending on forests for their livelihood & subsistence (State of the World's Forests 2014). The vast majority of these activities are driven by economic interests only, are not sustainable, and have a significant impact on the environmental and social services provided by tropical forests. The ever-growing demand for new land and resources imposes a large risk in particular to tropical forests, known as a highly vulnerable ecosystem. For example, the Amazon rainforest is the largest remaining tropical forest on our planet, which is home to 1/3 of the world's species, 1/4 of the world's freshwater, 1/5 of the world's forests, 48 billion tons of carbon dioxide in its trees, and 200 indigenous and

traditional communities (The Nature Conservancy; Forest Peoples Program, 2012 (based on various sources). An overview on the global state of forests is summarized in the UNEP report on vital forests (http://www.unep.org/vitalforest/). The Forest futures survey report shows that developments in the agricultural sector have larger impacts on forest loss than reducing pressure from wood extraction on forest through an increased supply from planted forests. This report estimates cropland expansion as the main cause of forest loss and fragmentation at present and towards the horizon 2050, in particular for South America followed by Africa and Asia. To revert this situation policies with a strong implementation are needed to control and halt monocultures, in particular to preserve resilient tropical forests and its livelihood they maintain.

4.5.2 Forest fragmentation

Fragmentation is simply the disruption of continuity (Lord & Norton 1990). When defined in this manner, the concept of fragmentation can be applied to any domain in which continuity is important to the functioning of ecosystems. In a restricted way, fragmentation occurs when a large expanse of habitat is transformed into a number of smaller patches of smaller total area, isolated from each other by a matrix of habitats unlike the original (Wilcove *et al.*, 1986). The fragmentation of natural habitats is usually a result of the expansion of land use that accompanies human population growth. As fragmentation proceeds, average fragment size and total fragment area decreases and insularity of fragments increases (Moore 1962; Burgess & Sharpe 1981).

Habitat fragmentation and forest loss have been recognized as a major threat to ecosystems worldwide (Pacha et al 2007; Armenteras et al. 2003; Noss, 2001; Dale and Pearson, 1997; Iida & Nakashizuka, 1995). These two processes may have negative effects on biodiversity, by increasing isolation of habitats (Debinski & Holt, 2000), endangering species, and modifying species' population dynamics (Makari et al., 2002; Romero-Calcerrada & Luque 2006). Fragmentation may also have negative effects on species richness by reducing the probability of successful dispersal and establishment (Gigord et al., 1999; Luque et al., 1994; Luque 2000) as well as by reducing the capacity of a habitat patch to sustain a resident population (Iida & Nakashizuka, 1995). For example, fragmentation of the Maulino temperate forest in central Chile has affected the abundance of bird richness (Vergara & Simonetti, 2004) and regeneration of shade-tolerant species (Bustamante and Castor, 1998), while it also favoured the invasion of alien species (Bustamante et al., 2003). The ecological consequences of fragmentation can differ depending on the pattern or spatial configuration imposed on a landscape and how this varies both, temporally and spatially (e.g. Armenteras et al., 2003). Some studies have shown that the spatial configuration of the landscape and community structure may significantly affect species richness at different scales. Other authors emphasise the need to incorporate the spatial configuration and connectivity attributes at a landscape level in order to protect the ecological integrity of species assemblages (Herrmann et al., 2005; Piessens et al., 2005).

The dynamics of populations inhabiting terrestrial habitat fragments have received considerable research attention, including studies of birds, mammals, invertebrates, and plants (Herkert 1994; Johnston & Hagan 1992; Romero-Calcerrada & Luque 2006). Although there is general agreement on the fragmentation effects on breeding birds within forest habitats, the mechanisms that account for these trends are not clear (Lynch 1987, Martin 1988). There is a need for studies that provide a quantitative treatment of landscape pattern changes and dynamics to better understand the widespread population decline of several species in fragmented landscapes. We need to be able to compare different study sites and species information to better understand fragmentation and its impact as well as to target the many unresolved questions that exist within the subject, as has been pointed out by several authors (e.g. Fahrig 2003, Bissonette & Storch 2002). See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

4.5.3 Forest fragmentation in the tropics

An impressive amount of biodiversity has evolved within the dense and diversely forested landscape of tropical forests (see Section 2.5). For this reason, forest fragmentation is the primary driver of species loss in tropical forest. There are several mechanisms whereby forest fragmentation impacts species, including the direct effects of human disturbance during and following timber harvesting activities, reduction of species population size due to decreased habitat area, reduced immigration combined with introduction of exotic species, forest edge effects, and changes in community structure (Turner 1996). Many tropical forest species are intolerant to conditions outside their native habitat, making them especially susceptible to habitat fragmentation. Finally, fragmentation will reduce the connectivity between forest habitats and hence restrict the ability to navigate the landscape and to locate and settle in new forest habitats.

The different types of human activities act at different scales, from local (logging, slash and burn), to regional (oil palm plantations, soy and other industrial monocultures, fires, timber production), up to large scale landscape changes (mining, deforestation). Depending on their type, these activities may have different impacts on the previously intact forest cover, resulting in introducing perforations, degradation, segregation, up to complete removal of the forest cover. In the literature, the conversion of intact forest cover is often described with the terms degradation (Shimabukuro et al., 2014, Souza et al., 2015) and fragmentation.

In general, degradation is associated with a loss in biodiversity or species richness within existing forest coverage, for example as a result of a temporary forest loss. From a remote sensing point of view, the assessment of degradation requires the analysis of a long-term time series of comparable forest maps.

Fragmentation, in contrast, is a rather complex mix of several, different landscape aspects, addressing the number and typical shape, the inter-patch distance, pattern, connectivity, and patch configuration. In addition, fragmentation is typically perceived as a species-specific measure having a multitude of qualitative definitions (Bogaert et al., 2011; Rutledge, 2003; Forman, 1995), mostly describing the possibility of species movement. By definition, such concepts require a-priori knowledge of a given species and for the same landscape will result in high or low fragmentation, depending on the species under study. Other, geometric based concepts, try to measure and then combine the different spatial aspects or use very simple assessment schemes such as deviation from intact forest (Bucki et al, 2012), or focussing on a single aspect only, i.e., division by road networks (Jaeger, 2000). Generic, robust concepts were suggested by Riitters et al. (2000, 2002, 2012) and extended to normalised spatial indicators by Vogt (2015) using geometric assessment schemes based o complexity, entropy, and contagion. The advantage of those holistic models is the objective and simultaneous evaluation of the various spatial aspects associated with fragmentation, such as shape, amount, inter-patch distance, perforation, and configuration. By design, they allow for the detection of spatial hotspots, the quantitative assessment of changes in fragmentation over time, as well as the direct comparison of the degree of forest fragmentation when comparing different forest maps. For example, in GuidosToolbox (Vogt, 2017) the Contagion index is focussing on the foreground class (i.e. forest) only and for this reason will result in high values in areas of isolated trees or small forest remnants. The Entropy index has a different approach, addressing the duality in a binary forest mask: forest is fragmented by non-forest and vice versa. With this definition, fragmentation of a forest mask is complimentary to the one of the corresponding non-forest mask: low fragmentation values are found for isolated trees equally to core forest areas having isolated perforations; and highest values are found in areas of an equal intermix of small forest and non-forest areas.

These features are of prominent importance to assess and understand the resilience in complex ecosystems as in the case of tropical forests. Biodiversity monitoring via remote sensing is limited to the monitoring and assessment of the arrangement of forest patches. While it is not feasible to monitor individual species, the structure and spatial configuration of their habitats can be assessed and quantified by generic, scale independent forest fragmentation schemes. A generic framework of robust and consistent methodologies is

the onset for a reliable long-term monitoring scheme. The provision of such a system can be applied from local to continental level and will facilitate a common assessment base for countries using different data sources, reference years, thematic projects, or political directives.

Connectivity refers to the degree to which a landscape facilitates of impedes the movement of organisms between habitat patches, and is typically measured with reference to a particular species or group of species (Tischendorf & Fahrig 2000). For example, a small bird and a jaguar will have a different perception of connectivity on the same landscape. This owes to the spatial scale at which a species perceives its environment (at both, fine-scales – *grain*, and coarse-scales – *extent*), and its movement capabilities (Wiens et al. 1997). As previously mentioned, species inhabiting tropical forests are especially sensitive to fragmentation. Consequently, maintaining habitat connectivity involves conserving landscapes with vast and continuous tracts of mature tropical forest for many tropical species. In other environments, species have evolved to habituate much more fragmented landscapes, where primary habitat patches are interspersed within a matrix of non-habitat (Turner, Gardner, O'Neill 2001).
Methods for studying habitat fragmentation and connectivity have evolved over the last years, primarily in the field of landscape ecology (Turner 1989). Geographic Information Systems (GIS) combined with airborne and satellite remote sensing have been integral to these developments. Through remote sensing researchers can map landscape features (e.g., land use and land cover) with increasing detail. GIS has provided researchers with the tools needed to manage, process, and analyse fragmentation and connectivity.
In recent years, tools for quantifying and analysing habitat fragmentation and connectivity have become readily available to researchers through several initiatives. Many of these tools represent stand-alone software packages that incorporate functionality that can be applied to most popular GIS data structures. Here we highlight examples that are specially designed for studying habitat fragmentation and connectivity based in public available freeware.

4.5.4 Toolboxes

The monitoring and evaluation of landscape structure is often linked to describe the underlying processes in biodiversity. A typical strategy in Landscape Ecology has been the development and usage of landscape metrics. A comprehensive overview of metrics and their suitability to monitor biodiversity, address questions of nature protection, conservation and habitat modelling can be found in Waltz, 2011. While aggregated metrics may be sufficient for some thematic studies they have intrinsic limitations due to their nature as a single value indicator for an entire region. For example, an indicator such as average patch size may not represent an actually existing typical patch size nor will it be able to capture the spatial distribution of patch sizes or locate hotspots of highly fragmented areas. In a similar way, an index total forest area may be constant over time due to averaging out different geographic areas showing forest loss and forest gains. To overcome the indicator-intrinsic limitations more recent studies focus on spatial map analysis, a pre-requisite for the adequate assessment of pattern, fragmentation, connectivity, locating spatial changes and as such forming the base for landscape planning, conservation, and restoration policies.
The following provides a selection of tools targeted towards a better characterisation and understanding of fragmentation. These tools provide a graphical interface designed to facilitate the investigation and analysis of spatial data, extracting fragmentation relevant information in a user-friendly way, and providing solutions for landscape monitoring and planning.

IMPACT Toolbox:
A portable, browser-based, free and open-source application for typical processing tasks in image processing, visualization and mapping. This software links research projects on

monitoring forests in the tropical belt (TREES; FOROBS; ReCaREDD) with national forest services. It combines a variety of tools, including data extraction, layerstacking, radiometric calibration, normalization, mosaicking, automatic classification, segmentation, visual editing and map validation. The full processing chain from raw satellite imagery to the final product, a pixel-based classification land cover map, supports Landsat (30m) and RapidEye (5m) data, while support for additional satellite data sets (Sentinel2) is ongoing. Individual generic components such as segmentation and map editing may use any other satellite data like Skybox (2m), Spot5take5 (10m), or Sentinel (10m). The Toolbox is under constant development, a feature summary is provided in a flyer, and the latest version and further information on the software is available on the IMPACT Toolbox homepage.

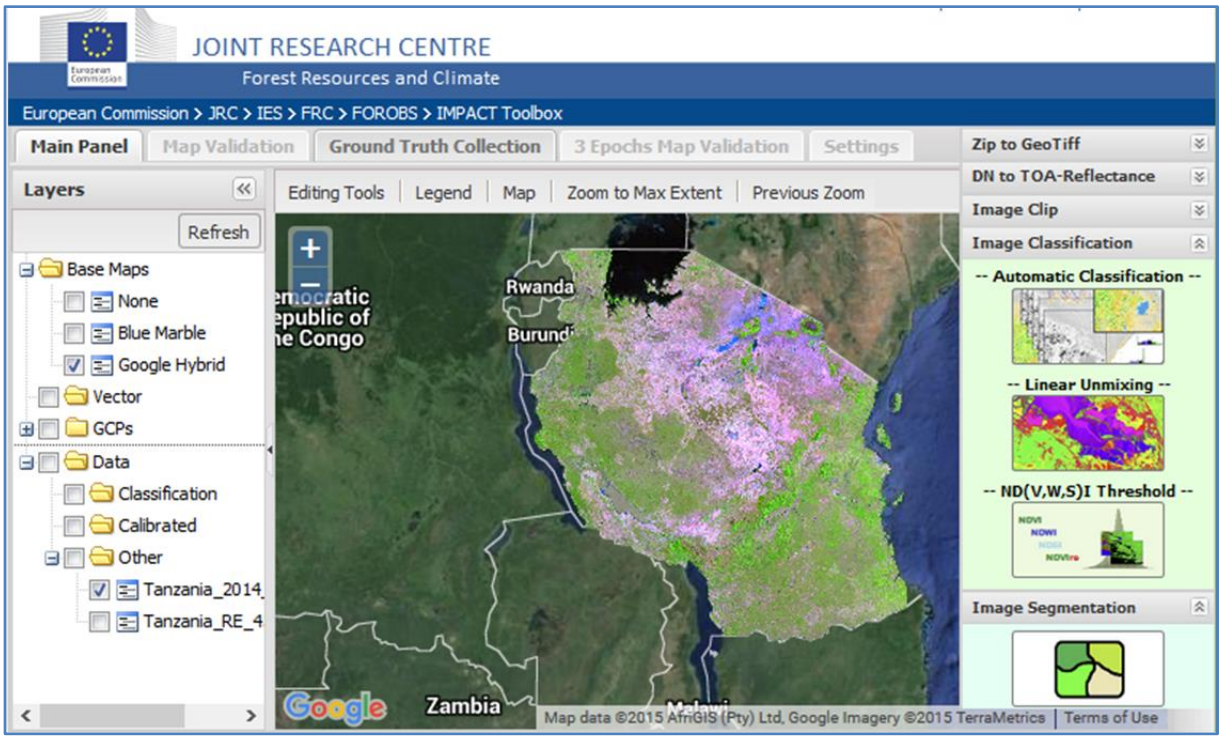

Figure 4.6.1. IMPACT Toolbox: Portable GIS toolbox for image processing and land cover mapping.

GuidosToolbox:
A free software collection of generic raster image processing routines aimed at the detection, description and measurement of essential image object attributes such as pattern, connectivity, fragmentation, distance, change and cost analysis. All methodologies are based on geometric concepts only and thus applicable to any kind of digital raster data and at any scale. Typical application fields include studies on deforestation, fragmentation, degradation, carbon stocks, natural hazards (fires/pests), landscape and restoration planning, and sustainable management of forests. The input data can be land cover or binary forest maps, which, after processing, can be saved as Geotiff for post-processing in any GIS environment or for web-publishing as GoogleEarth image overlays.

A key component of GuidosToolbox is MSPA (Morphological Spatial Pattern Analysis, Soille & Vogt, 2008) resulting in mutually exclusive geometric feature classes, including the automatic detection of connecting pathways. Over time, a wide variety of additional tools were added to the toolbox to address typical issues in landscape monitoring and planning, i.e. generic and normalised measures for maps of forest fragmentation via concepts of local contagion or spatial entropy (Vogt, 2015). Temporal changes may be assessed via a dedicated morphological change detection algorithm (Seebach et al., 2013), developed for and used in the FRA2015 assessment. The change detection now also includes the index

Elasticity (Riitters et al., 2015) to account for the severe damage to intact forest areas caused by the loss of interior forest. The latest add-on to the image analysis software collection is a morphological cost analysis deriving the least cost path as well as a cost map with user-driven cost zones, a product which should be useful to analyse as well as simulate the impact of land cover changes, including hazards, on species-specific movement patterns and habitat fragmentation and restoration maps alike.

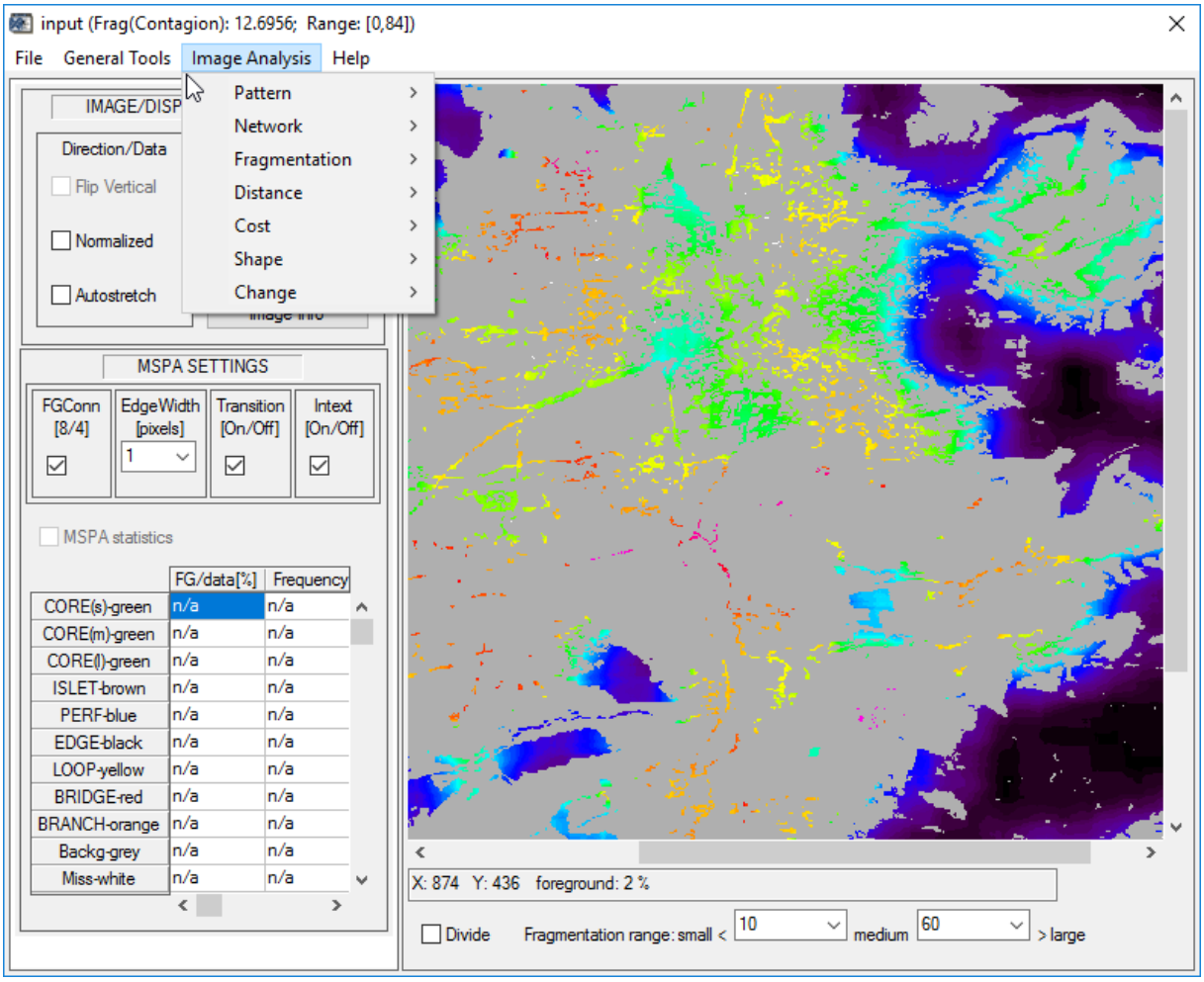

Figure 4.6.2. GuidosToolbox: example showing per-pixel fragmentation values ([0-100] %) and further potential processing options available in the Image Analysis menu.

GuidosToolbox is under constant development and available for free for the MacOS, Linux, and MS-Windows operating system from the GuidosToolbox homepage. A feature summary is provided in the flyer, and the optional workshop material with detailed further information can be installed from within the software.

Conefor:
Conefor (Saura & Torne 2009) is a free software package containing a series of functions for quantifying important habitat areas and links in the analysis of habitat connectivity. It also includes a set of new connectivity indices (integral of index of connectivity and probability of connectivity) which are suitable for many applications (e.g., Pascual-Hortal & Saura 2006, Saura & Rubio 2010). Typically, it is thought of as a decision support tool where it can be used to prioritize areas (specifically habitat patches, or corridors) which are integral to maintaining connectivity at the landscape scale. Conefor builds upon the graph-theory approach (Urban & Keitt 2001) for modelling habitat connectivity by considering how a series of habitat patches (nodes) are connected by corridors (links).

Conefor uses resistance surfaces to model the heterogenous environment in order to consider non-linear movement paths between patches. Through the use of resistance surfaces, barriers and/or highly impassable habitat types can be directly incorporated into connectivity models.
Conefor is available as a standalone graphical user interface (GUI) or command-line interface (http://www.conefor.org/), or as a plug-in to the GIS package Quantum GIS (www.qgis.org). It operates on the Windows operating system, and is distributed free-of charge for non-commercial uses. The GuidosToolbox also provides functionality for exporting files suitable for use with Conefor for integrated analysis workflows.

4.5.5 Study Cases – Corridors to improve protection & conservation

Protected areas have been the dominant strategy for tropical forest conservation, increasing substantially in area in recent decades (Jenkins and Joppa 2009). While protected areas have generally been effective at reducing deforestation inside; deforestation outside protected area boundaries has increased the isolation of forests within them. This generalized situation is negatively affecting related ecological processes and biodiversity. Better connected forest patches promote species persistence by allowing for recolonization after local extinctions and connected forests help species respond to climate shifts by allowing for dispersal as environmental conditions change (Noss 2001).

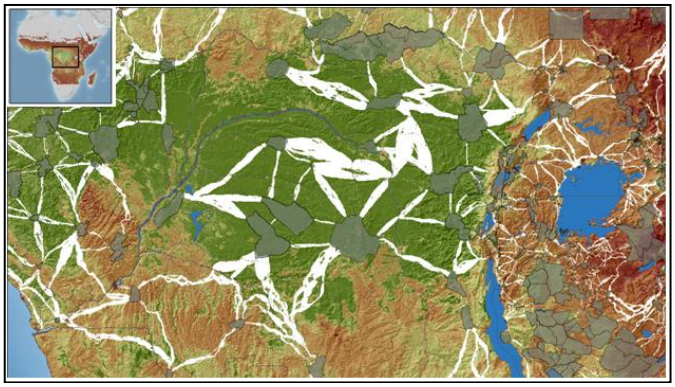

Figure 4.6.3. Corridors (white) between protected areas in central Africa (Jantz et al. 2014). Aboveground biomass (Baccini et al. 2012) is shown in green (high) to red (low) gradient in the background.

Recognizing the negative effects of forest fragmentation and loss of connectivity, the Convention on Biological Diversity (CBD) Aichi Biodiversity Targets aim to significantly reduce forest fragmentation by 2020 and the CBD Programme of Work on Protected Areas sets a goal of integrating "protected areas into broader land- and seascapes and sectors so as to maintain ecological structure and function" (CBD Programme of Work on Protected Areas Goal 1.2). The emergence of REDD+, a mechanism for reducing carbon emissions from deforestation, and the development of biodiversity safeguards to ensure sustainable REDD+ implementation, suggest an alignment of goals for forest carbon protection and protected area connectivity. More recently, the International Union for Conservation of Nature (IUCN) and the World Commission on Protected Areas (WCPA) drafted guidelines defining Areas of Connectivity Conservation (ACC) as a basis for assessing progress toward Target 11 of the Convention on Biological Diversity (Worboys et al. 2015). See section 8 for synergies between biodiversity monitoring and REDD+.

To address these types of priorities, Jantz et al. (2014) mapped corridors that traverse the highest biomass forests between tropical protected areas. The approach uses common GIS algorithms to identify forests where protection could help maintain protected area connectivity while preventing CO_2 emissions from deforestation (Fig. 4.6.3). Across a range of biomass densities, there were large numbers of corridors that were at least as dense as the protected areas they connect, suggesting opportunities for achieving multiple co-benefits via protection of high biomass forest corridors.

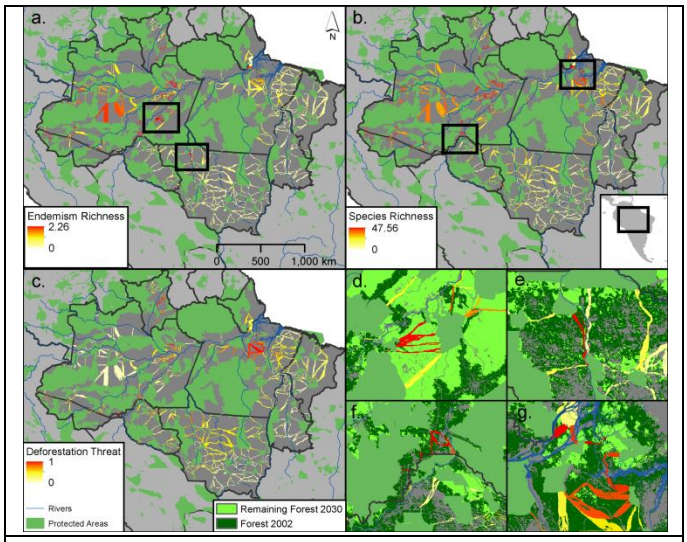

Figure 4.6.4. Multicriteria scoring of corridors with high deforestation risk, high biomass and high endemism richness (a) or high species richness (b). Deforestation risk shown in (c). Panels d-g show detail of a and b with spatial maps of deforestation risk in the background.

To illustrate a possible approach for prioritizing conservation investment among corridors, they used multicriteria analysis to identify corridors in the Brazilian Amazon with high biodiversity value (either overlapping with rare species ranges or a high number of species ranges), high deforestation risk, low economic opportunity cost and high biomass. As a whole our analysis showed significant potential across the tropics for co-benefits from REDD+ investments but with considerable geographical variability. For example, the southern portion of the Amazon had relatively low biodiversity scores and high economic opportunity cost due to soybean farming, yielding low conservation benefit per dollar invested in corridor protection relative to other regions (Fig. 4.6.4 a and b). Maps of priority connectivity areas created using consistent, high quality satellite imagery and GIS datasets can inform ongoing conservation efforts. For example, UN-REDD and GRASP (Great Apes Survival Project) developed a web application that allows users to overlay and summarize the corridors described above, protected areas and great ape habitat suitability layers, helping decision makers and other stakeholders achieve both climate mitigation and great ape habitat connectivity benefits (Fig. 4.6.5).
http://primatdbext.eva.mpg.de/redd/
http://www.un-grasp.org/new-web-tool-facilitates-joint-efforts-to-protect-great-apes-and-fight-climate-change/

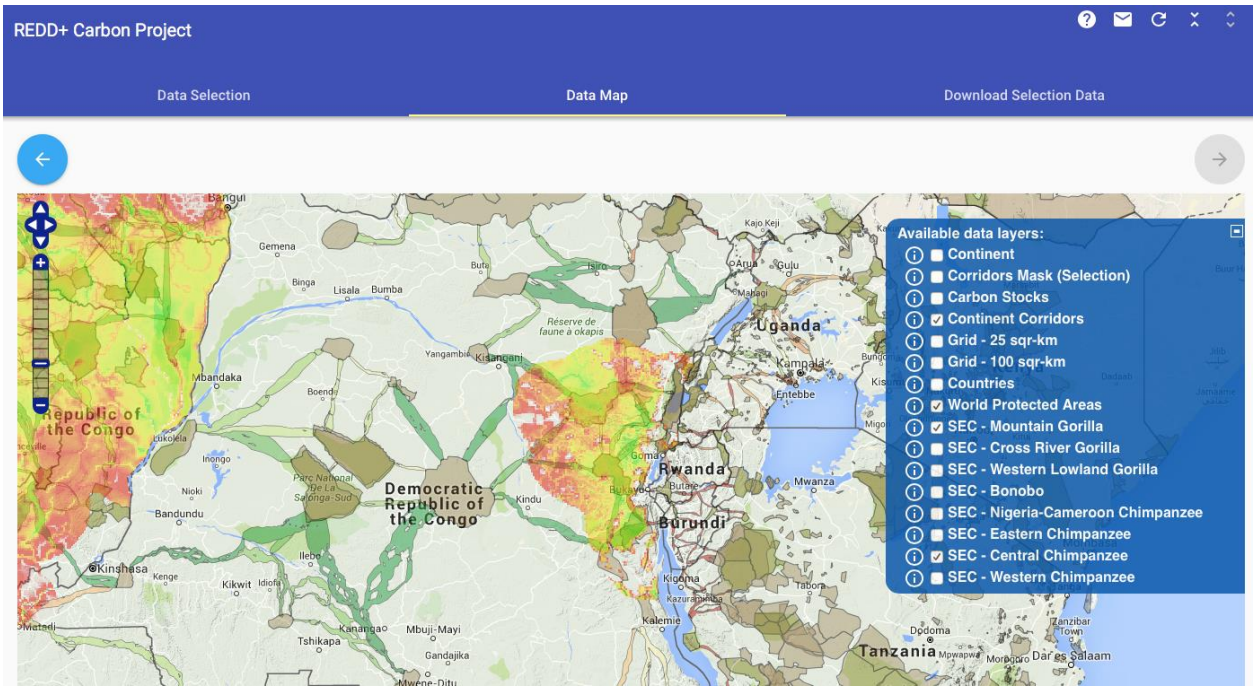

Figure 4.6.5. Screenshot of the UN-REDD/GRASP web tool showing vegetation carbon stock corridors (green polygons) overlaid with mountain gorilla habitat suitability layers (red to yellow gradient).

4.5.6 Conclusion

There is a need to develop management and planning options for a) landscapes that are already significantly altered and in need of either improved management or restoration, and b) for landscapes, which are still relatively altered, but which are under increasing human pressure. The provision of such options depends on an understanding of landscapes processes and the ability to use this understanding to develop strategies, which are effective in dealing with the biophysical problems while at the same time are socially and economically acceptable.

The ecological consequences of fragmentation can differ depending on the pattern or spatial configuration imposed on a landscape and how this varies both, temporally and spatially. Some studies have shown that the spatial configuration of the landscape and community structure may significantly affect species richness at different scales. Other authors emphasise the need to incorporate the spatial configuration and connectivity attributes at a landscape level in order to protect the ecological integrity of species assemblages. See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

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4.6 FOREST SPECIES MAPPING

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4.6.1 Introduction

Remote sensing has become increasingly important in vegetation mapping. Early applications pertained to aerial photography, but more recently satellite imagery with a huge range of spatial and temporal resolutions is in use that increases the applicability's from entire ecosystems to specific vegetation types. Some mapping projects apply remote sensing to segment the landscape into homogenous polygons to aid field surveyors, while others produce maps directly from imagery by combining imagery with other spatial data sets. The latter approach is gaining momentum in the light of major improvements in the technology. Using a mixture of remote sensing and field methods seems to deliver the best results.

In recent years advances working with different sensors at different resolutions are allowing to work not just at finer resolutions but also to work on areas where cloud cover was a problem. As an example, remote sensing images with high spatial and temporal resolutions are required to precisely identify land use at the field scale in agricultural areas covering more than a few hectares. An assessment, produced by Dusseux et al (2014), provided important insights on the ability of optical images, SAR (Synthetic Aperture Radar) images and the combination of both types of data to discriminate between grasslands and crops in agricultural areas where cloud cover is very high most of the time, which restricts the use of visible and near-infrared satellite data. They compared the performances of variables extracted from four optical and five SAR satellite images with high/very high spatial resolutions acquired during the growing season providing improved classification accuracy (Dusseux et al 2014). Hence, some critics argue that deriving information on biodiversity from space on a global level remains to be demonstrated. Because characterizing species traits or ecosystem structure requires data on diverse scales (spatial, temporal and spectral), data from multiple missions must be combined (Skidmore et al 2014). Nevertheless, satellite remote sensing is crucial to getting long-term global coverage. It can rapidly reveal where to reverse the loss of biological diversity on a wide range of scales in a consistent, borderless and repeatable manner (Turner 2014). The present chapter is divided in two sections, first tree species identification and mapping is presented, providing some insights on classification methods, general principles and recent advances. In the second section the role of remote sensing is considered in the light of: i) directly mapping forest species, ii) modelling their distribution, iii) accounting for uncertainty in mapping forest species, iv) applying continuous methods to solve mapping issues. In all, the chapter discusses open challenges and pitfalls regarding remote sensing for forest-related studies. Evidence to demonstrate the usefulness of remote sensing in directly mapping and modelling forest plant species, and the potential for RS to detect forest patterns is argued.

4.6.2 Direct tree species mapping

Tree species identification and mapping based on remotely sensed data is particularly challenging in tropical forests, due to several properties of these dense closed canopies. First of all, neighbouring crowns are not perfectly delineated and their boundaries overlap or mix with each other. Second, proper identification of tree species is directly dependent on the size of its crown and the pixel size defined by the instrumental characteristics of the sensor used to acquire imagery. Finally and most important, the number of species to

differentiate is extremely important, making confusion between species' spectral signatures inevitable. This very high biological diversity is tightly linked to leaf chemical diversity, which in turn directly influences the spectral diversity (Asner and Martin, 2009). However, many scaling challenges still exist to link leaf spectral signatures of species with their canopy counterpart: the variability of the leaf optical properties and the complexity of the canopy structure directly influence the measured signal, leading to strong difficulties when attempting to assign spectral or spatial patterns to a particular species at the canopy scale (Féret and Asner, 2011). Numerous open challenges remain to disentangle the relative contribution of the different chemical, structural and experimental factors to the signal acquired by airborne or space borne platforms. These questions are currently very actively investigated: researches involving physical modelling aim to better understand interaction between light and vegetation and help interpret vegetation properties for complex canopies (Morton et al., 2014). Complementary to these physically-based approaches, data-driven approaches based on statistical and mathematical tools consistently proved their ability for canopy species identification. The most successful and widespread approaches developed during the past decade are built on supervised classification algorithms applied to imaging spectroscopy (Baldeck et al., 2015; Clark et al., 2005; Féret and Asner, 2013). Identifying individual species reliably using satellite-based and aerial imagery is challenging due to the difficulties of choosing and detecting optimal spectral wavelengths to differentiate the target species from others (which may only be possible at certain times of year), and controlling for the effects of vegetation structural characteristics (Kempeneers et al., 2008; Zeng et al., 2009; Chopping, 2011; Pisek et al., 2011). In this section, we will propose a brief overview of the strategies that can be depicted from this field of research.

4.6.2.1 The "brute force strategy"

The most common strategy consists in performing one-step multi-class classification, based on prior definition of the species of interest. Supervised algorithms for multi-class classification problems are basic yet efficient tools for the hyperspectral remote sensing community. As for any classification task, the performances of these methods are strongly dependent on the data used to train the classifier: they needs to be representative enough of the population of each of the species to be discriminated and possibly well balanced. The classification model obtained after training can then be applied more or less successfully over an extended dataset, such as a full image, if its generalization properties are satisfying. The validation of tree species identification procedures is usually limited to study sites with moderate taxonomic diversity due to the financial and logistic costs associated with airborne and field data collection.

A large variety of classification algorithms is available in most of the softwares and programming languages, and one can cite among others: linear and regularized discriminant analysis (LDA, RDA), support vector machines (SVM), random forest (RF). The straightforwardness of this strategy is a strong advantage; however the many studies applying it highlight its limitations by restricting themselves to a limited number of species of interest. A limited pool of species was discriminated either in order to show a proof of concept, or because the biological diversity of the sites under investigation was reasonably low. The pioneering work of Clark et al. (2005) demonstrated that high spectral and spatial resolution imagery acquired over tropical rainforest canopy had strong potential for species discrimination: they selected seven tree species from Costa-Rican forest and performed supervised classification using several methods (LDA, spectral angle mapper, and maximum likelihood), several spectral configurations (selection of bands and spectral domains) and several data grouping strategies (pixel scale, crown scale, and object-based classification). The most successful configurations outreached 85% overall accuracy but the limited sample size would not allow generalization for operational mapping of tree species in hyper-diverse ecosystems.

Following this study, Clark and Roberts (2012) derived a large number of metrics from hyperspectral data (including spectral indices derivatives and absorption-based techniques, and spectral mixture analysis) and used them to train a RF classifier. They concluded in slightly lower performances of RF compared to LDA (Clark et al., 2005), but mentioned the possible bias and limitations of the comparison due to the sample size and different optimization strategies. The authors used hyperspectral metrics instead of the reflectance bands in an effort to interpret the spectral differences between species in terms of chemical and structural properties.

Féret and Asner (2013) compared different classification algorithms for tree species discrimination in the Nanawale rainforest (Hawaii, USA). They achieved about 73% overall accuracy for the discrimination of the 17 dominant species found in the study site, and concluded on the equivalent performances of LDA, RDA and SVM, although SVM showed better performances when limited number of training samples was used. This classifier was applied to a whole image in order to map species distribution, and validation showed good results; however this particular site of the Nanawale forest included moderate species diversity and available spectral information also showed moderate resolution.

These studies share a certain number of conclusions, including the added value of combining spectral and spatial information through object-oriented approaches, thus highlighting the importance of individual tree crown delineation. They also confirmed limitations of the brute-force strategy, consisting in using classification algorithms off the shelf without further refinement for operational mapping (for ecological conservation or industrial perspective) in forests encompassing high taxonomic diversity, as the chances of spectral confusion among species increases with the number of species to discriminate. Another strong limitation is the poor adaptability of standard classifiers to changing conditions, such as changes in illumination resulting from multiple geometries of acquisition, and integration of multi-source remotely sensed imagery. Alternative strategies have been recently explored in order to answer the needs of operational tree species mapping for conservation and management monitoring, and also in order to get the most from the increasing diversity of remote sensing data sources.

4.6.2.2 Operational tree species mapping: take home messages

Advanced classification strategies based on single species identification or species grouping

The exhaustive mapping of forest species in tropical environments may not be relevant due to the current limitations explained in the previous section. When facing high complexity, it may be wiser to take step backwards and reformulate the problem in order to decrease the complexity: ecologists and forests managers may actually be more interested in knowing the accurate spatial distribution of a limited number of tree species because of their ecological importance as keystone species, dominant species, endangered species, or species of commercial interest, rather than an exhaustive map of all tree species with high overall error rates. Maximizing the chances of successful species identification depends on two components: i) prior knowledge about the time period when target species discrimination is optimal, and ii) application of an efficient classification algorithm.

As aforementioned in the previous section, remote sensing is a powerful tool for the monitoring of plant species. In return, plant phenological stages such as flowering can strongly help to accurately map plant species using remote sensing. Sánchez-Azofeifa et al. (2011) illustrated this potential by mapping flowering *Tabebuia guayacan* trees at Barro Colorado Island (Panama) using Quickbird satellite imagery (spatial resolution: 2.4 m). Multi-temporal high spatial resolution images may therefore provide valuable information for species mapping. However two challenges arise: detection of flowering may not be discriminative enough in all situations and for proper detection of all species of interest,

and multi-seasonal acquisitions cannot be guaranteed in tropical ecosystems due to frequent cloud coverage. Imaging spectroscopy allows overcoming these two difficulties, as single acquisitions can potentially be used to accurately identify non-flowering tree species (Baldeck et al., 2015; Féret and Asner, 2012). Baldeck et al. (2015) developed a method for operational tree species mapping in a diverse tropical forest based on airborne imaging spectroscopy, and were able to accurately map three non-flowering focal species using binary SVM and biased SVM. Working on a selection of focal species allows increase in classification model performance and dramatically decreases the amount of data required to train the classifier. They also obtained effective multi-species classification models by combining single species classification models. Another possible option when it comes to simplifying over-complex classification problems is to group species by guilds or functional types (Vaglio Laurin et al., 2016).

Multimodal acquisitions and domain adaptation

All the studies cited earlier share the same weakness: the classification models are image specific and usually show poor performances when applied to other images acquired with the same sensor due to changes in illumination and geometry of acquisition. This being said, it is also impossible to directly apply such classification models to other data sources. This is a strong limitation, in light of the financial and logistical constraints associated with airborne imaging spectroscopy, and the increasing availability of satellite imagery compatible with tree species identification. New methodological innovations such as multimodal data processing are currently developed, in order to deal with the increasing volume, complexity and dimensionality of available remote sensing data. Some of these methods allow domain adaptation in order to combine heterogeneous data sources (Gomez-Chova et al., 2015; Tuia and Camps-Valls, 2016).

4.6.2.3 Plant phenology

Phenological studies are critical to understanding how species change and adapt their life cycles, especially in view of recent climate warming. In this vein, remote sensing has a great potential for directly tracking phenology for plants and indirectly determining temporal and spatial changes in habitat suitability for animals.

Different mapping methods have been developed to understand the nature of the structure of vegetation in relation to its spectral behaviour (see Forster et al., 2010; Nagai et al., 2010; Eastman et al., 2013). While the concept of a spectral library has been proven for spectrally homogeneous and stable features (e.g., geological formations at coarse spatial scale), the spectral response of plant species varies with phenology, stress, and environmental conditions (Kumar et al., 2001). This variation impairs the transferability of relations between vegetation and spectra and hence affects the use of spectral libraries (Feilhauer and Schmidtlein, 2011; Eastman et al., 2013). However, if the complete vegetation cycle can be included with measurements of field spectra, a relation between remote sensing imagery and a spectral library is possible for a given date of acquisition (Forster et al., 2010).

On the other hand, relying on time series data, phenological changes allow ecologists to gain better understanding of species life cycle events and seasonal dynamics of populations and assemblages of species. This is particularly true considering the development of dedicated programmes like the Copernicus Sentinel program (European Space Agency) or the well-known Landsat NASA programme.

Phenology also plays a significant role in detecting and mapping the spatial distribution of species in remote sensing applications (He et al., 2011). Multidate remotely sensed images have become very useful in forest studies. In particular, the unique phenology of some

species provides a sound basis for spectral differences between targeted species and co-occurring native vegetation (Singh and Glenn, 2009).

Phenology and other environmental attributes derived from remote sensing are crucial for both land cover/land use and habitat mapping using categorization schemes such as those developed by FAO in the forest land cover classification system (LCCS) (Di Gregorio and Jansen 1998) and by Bunce et al. (2011) in the General Habitat Categories (GHCs). Both are useful tools for the monitoring of habitat qualitative features from the perspective of vegetation dynamics induced by global warming coupled with anthropogenic disturbances (Franklin 2010). Habitat mapping thus conducted can be used to deduce species locations, assisting in RS-based direct mapping of species.

In the tropics, time series of space-borne Hyperion data have been used to study the dynamic changes and plant species in Hawaiian rainforests (Asner et al., 2006). The authors compared the structural, biochemical, and physiological characteristics of nitrogen-fixing trees like (*Myrica faya*) and (*Metrosideros polymorpha*) in humid montane forests. By using nine scenes of Earth Observing-1 Hyperion satellite data spanning a period from July 2004 to June 2005, including a transition from drier/warmer to wetter/cooler conditions, the authors successfully identified the basic biological mechanisms favouring the spread of tree species and provided a better understanding of how vegetation-climate interactions affect plant growth.

In general, most understory species are hard to detect and map by remote sensing since they are usually hidden by overstory canopy. As an example, in some cases, a temporal window may exist when a clear phenology difference exists between native overstory species and understory invaders (Somers and Asner, 2013a). Wilfong et al. (2009) effectively detected the distribution of an understory invasive shrub, Amur honeysuckle (*Lonicera maackii*), in the deciduous forests of southwestern Ohio, using phenological difference between Amur honeysuckle and co-occurring native tree species in the canopy. These authors conclude that the best phenological window for mapping this invasive shrub species is in early spring and late fall, when it retains leaf cover in comparison to the other native deciduous forest species, which are devoid of leaves.

An additional example is provided by Evangelista et al. (2009) mapping tamarisk invasion in Arkansas River in southwestern Colorado (USA). This study demonstrated the capacity of relatively simple yet well-timed multitemporal image analysis, if used during specific time frames in which the phenological attributes of a plant species were maximally differentiated, to discriminate invading tamarisk formations from other vegetation types.

From this point of view, the revisiting period of satellite imagery is crucial. As an example, the Sentinel-2 system (ESA, Copernicus program) guarantees 5 days revisit cloud free data, fully in line with vegetation changes.

4.6.2.4 Modelling the distribution of forest species

The potential of remote sensing in forest species mapping has a number of different facets of interest, from direct species mapping to forest mapping and uncertainty. Mapping the distribution of plant species becomes crucial for forest biodiversity estimates. Gillespie et al. (2008) report a number of case studies demonstrating the use of remote sensing for species mapping. As an example, Saatchi et al. (2008) demonstrated that the inclusion of remote sensing data when modelling the distribution of Amazonian tree species significantly improved model performance. The same trend is found when modeling the distribution of "hidden" species such as epiphyllous liverworts (Jiang et al. 2013; Vihervaara et al. 2015).

In some cases indicator species are used as a proxy of diversity over an area (Judith et al. 2013). This is not only related to rare species but also to common species which may be considered as the most important structural part of forest species communities (Gaston et al. 2008). Some recent research indicates that different scales of observation may be most appropriate for different taxa, depending on their size, mobility, and modes of dispersal. For instance, birds, plants and insects are most appropriately detected in Mediterranean landscapes using very high resolution remote sensing data at landscape, patch and plot levels respectively (Mairota et al. 2015 a).

Extending on Araujo and Rozenfeld (2014), given two species sp1 and sp2, the probability of co-occurrence (spatial overlap) is a function like f (p_{sp1} , p_{sp2}, I_{sp1sp2}) where p = probability of occurrence and I = interaction between species. In other terms the intersection of the probability of co-occurrence of species sp1 and sp2 is not merely related to the set containing all the individuals attaining at both species but to emergent properties rising from their interaction I.

Hence, such concept could be reliably used to detect sp1 relying on its interaction with and the spatial distribution of sp2. This phenomenon is also known as cross-taxon surrogacy. These concepts can be reliably applied to remote sensing detection as an indirect method to estimate the distribution of hidden species based on directly detectable species (Rocchini, 2013).

Furthermore, species distribution models for the occurrence of species of conservation concern can be improved by including remotely sensed predictors. For example, Parviainen et al. (2013) used unclassified, continuous remote sensing data to improve distribution models of 28 red-listed plant species in north-eastern Finland regions, including high latitude forests. They demonstrate that the inclusion of remote sensing variables in the generalized additive models improved both the explanatory power (on average 8.1% improvement) and cross-validation performance (2.5%of the models.)

Concerning spatial autocorrelation in species distribution models, as stressed by Miller (2012), while there are a number of different methods to account for functions and predictor interactions (Elith et al., 2006), it is impossible to find a single method which performs better than others in all situations. When dealing with spatial autocorrelation in species distribution modelling (see Kuhn and Dormann, 2007), distance decay processes appear to mainly drive the dispersal of species (Dormann, 2007). Further, since environmental variables are responsible for part of the species distribution pattern, the use of remotely sensed images as an additional proxy seems promising because of their explicit spatial character that may allow identifying spatial autocorrelation of a species over space based on its relationship with pixel reflectance (Carter et al., 2009).

In some cases, building land cover or vegetation maps from remote sensing data may be of use for depicting the spatial spread of a given plant species dominating a vegetation type (Hernandez-Stefanoni and PonceHernandez, 2004; Lechner et al., 2013). However, in most cases, digital vegetation mapping based on crisp classes may be unfeasible. In such cases, fuzzy sets provide a better approach to describe the continuous variation of a specific species over space (Figure 4.6.2.4) (Amici, 2011). The same applies when attempting to judge the accuracy of vegetation maps by common expert based methods. In this view, the use of fuzzy procedures for judging vegetation maps may represent a valuable tool (Franklin et al., 2001).

Moreover, the use of fuzzy sets may allow to explicitly depict the uncertainty of a species distribution model, relying on the so called maps of ignorance (Boggs, 1949) representing the bias or the uncertainty derived from species distribution modelling, alongside predictive maps (Rocchini et al., 2011). Uncertainty can derive from a number of input data sources, such as the definition or identification of a certain species, as well as location-based errors. In addition, maps derived from the overlap of different thematic layers, may lead to uncertainty related to the modelling procedure being adopted (Arbia et al., 1999). Hence

the spatial distribution of uncertainty should be explicitly shown on maps to avoid ignoring overall accuracy or model errors. Quoting Swanson et al. (2013) "including such estimates alongside mean projections gives a map of ignorance as called for by Rocchini et al. (2011), highlighting areas where knowledge is lacking and could be improved with additional sampling effort or the inclusion of additional covariates."

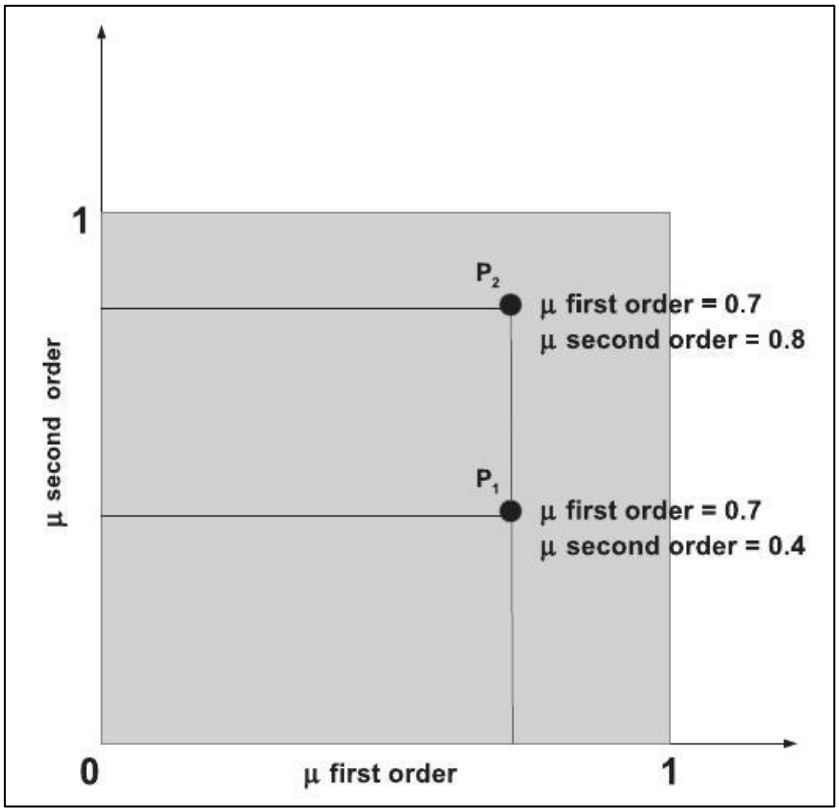

Figure 4.6.2.4. A statement describing a vague phenomenon must be necessarily vague. This has led to the possibility of assuming for each level of the fuzzy membership function (x axis) a fuzzy set membership (y axis). As an example both P1 (representing a pixel) and P2 show a high membership to a certain class (say classA, μ_I=0.7). However, P2 has also a higher value of second order membership (μ_II=0.8) to μ_I=0.7. In other words, P2 is more certain to belong to the classA than P1. Figure reproduced from Rocchini et al. (2013).

4.6.2.5 Uncertainty in mapping forest species

The accurate supervised classification of remotely sensed images requires appropriate ground reference data which are often derived from field training sites. There are many sources of uncertainty in the training stage of a supervised classification, such as class definitions, subjectivity of field data collection and the mixed pixel problem.

Since plant species represent the bulk of habitat structure (Chiarucci, 2007), training sites are often derived from plant sampling-based field surveys, for which one of the main problems lies in the definition of plant communities, an issue raised as early as 1926 by Gleason. Moreover, there is an intrinsic difficulty in judging survey completeness (Palmer et al., 2002). This is generally true for all observational sciences; geosciences are not free from such uncertainty as a result of a partial input (Henley, 2006).

There are a number of provoking papers dealing with problems in the discrimination of species in the field, including operator bias (Bacaro et al., 2009), taxonomic inflation

(Knapp et al., 2005) and more generally taxonomic uncertainty (Guilhaumon et al., 2008; Cayuela et al., 2011).

Evidence exists about the possibility that abrupt classification of vegetation types, especially at the species hierarchical level, can present misleading or even erroneous results (Schmidtlein and Sassin, 2004). This is due to the often continuous transition of vegetation assemblages due to changes in environmental gradients (e.g. moisture) and self-organization in vegetation. Alternative approaches like ordination methods aim to extract major floristic gradients describing the variation of the assemblages as metric variables, thus retaining the continuous character of the data (Trodd, 1996; Schmidtlein and Sassin, 2004). These gradients can be related to any sort of remote sensing data-set using regression approaches such as generalized linear models or partial least squares regression (Wold et al., 2001; Feilhauer et al., 2011).

A second major problem in input data sources for forest ecosystem mapping and its related uncertainty is the gap perceived between the scale of the field sampling, namely its grain (sensu Dungan et al., 2002), and the spatial resolution of the image being used, which appears to be a case of incompatible spatial data (sensu Gotway and Young, 2002). This is because in most cases field-collected data often are not designed for integration with remotely sensed data (Reinke et al., 2006). The structure of forest plant communities is spatially organized at different spatial scales (e.g. Osborne et al., 2007; Bacaro and Ricotta, 2007). When using coarse spatial resolution remotely sensed data, mixed pixels will occur, and will generally tend to smooth reflectance variability at a detailed scale thus leading to a scale mis-match with field data (Ricotta et al., 1999; Song and Woodcock, 2002; Lechner et al., 2009).

Finer spatial resolution data sets are not free from problems. For example, images such as those from IKONOS (1m to 4m spatial resolution) or QuickBird (0.61m to 2.88m spatial resolution) may show very high local spectral variability (e.g. due to shadows or tree cover gaps). This may lead to higher intra-class variation and noise rather than useful information, with an increase in the variability of signatures of pixels that cover the same individual plants/communities (Nagendra and Rocchini, 2008). Hence, there is the need to consider to what extent the training pixels represent their respective classes (Pal and Mather, 2004).

In this view, the use of hyperspectral, instead of hyperspatial, remote sensing data (e.g. HyMap, spatial resolution 5m, 128 bands, spectral resolution 440–2500 nm for local scales studies) has proven useful in better discriminating spectral signatures of different habitats, with the possibility of detecting single species across a range of ecosystem types (e.g. Oldeland et al., 2010, using Hymap). This is considerably important for a number of tasks like species invasion forecasting (He et al., 2011), biodiversity assessment (Oldeland et al., 2010), and single tree species mapping of tropical rain forests (Clark et al., 2005). Hyperspectral imagery is often coupled with field spectrometry to produce a structured number of training areas with known statistical properties in the spectral space. These spectral libraries are subsequently used to classify unknown field or pixel spectra relying on e.g. nearest-neighbour approaches (van der Meer, 2006). This is of particular interest considering the extensive investigation of the spectral signal by radiative transfer (Verhoef, 1984) and geometric optical models (Li and Strahler, 1986) and their combination for application in the estimation of vegetation properties. Different models have been developed to understand the nature of the geometry of vegetation in relation to the spectral behavior (among the others Schlerf et al., 2006; Kuusk et al., 2008; Förster et al., 2010). While the concept of a spectral library has been proven for spectrally homogeneous and stable features (e.g. geological formations), the spectral response of species varies with plant phenology, stress, and environmental conditions (Kumar et al., 2001). This variation impairs the transferability of relations between vegetation and spectra and hence affects the use of spectral libraries (Feilhauer and Schmidtlein, 2011). However, if the complete vegetation period can be covered with measurements of field spectra, a relation between remote sensing imagery and a spectral library is possible for a given date of acquisition

(Förster et al., 2011), assuming that environmental conditions and the occurrence of plant stress are homogeneous for the mapped area.

4.6.2.6 Fuzzy sets for forest mapping

The assessment of ecological complexity of forest landscapes relies largely on field monitoring (Ferretti and Chiarucci, 2003). Meanwhile, as previously stated, remote sensing offers the capability of obtaining a synoptic information over large areas in order to guide sampling design for improving their efficiency (Rocchini et al., 2005). In this view forest related maps are increasingly being used in landscape planning and management (see e.g. Romero-Calcerrada and Perry, 2004; Adra et al 2013;). But its use is very rare in tropical forests.

Noteworthy, one of the most pressing needs in landscape ecology is to take into account the uncertainty related to patterns in the landscape (Bolliger, 2005). Analyzing landscape patterns with a-priori defined thresholds and boundaries may lead to losses in the capability of catching their actual complexity, by hampering the ability to account for continuous landscape variability over space (Mairota et al., 2015 b; Redon et 2014).

Fuzzy set theory can aid in maintaining uncertainty information related to each class. The concept of fuzzy sets was first introduced by Zadeh (1965), and have been widely used in ecology dating back to 1980's (see as an example Feoli and Zuccarello, 1988; Roberts, 1996; Ricotta and Anand, 2006).

The principle behind fuzzy set theory is that the situation of one class being exactly right and all other classes being equally and exactly wrong often does not exist. Conversely, there is a gradual change with continuous values of membership, generally from 0 to 1 (Gopal and Woodcock, 1994).

Two major assumptions lead us to consider fuzzy sets as a powerful tool for maintaining uncertainty information when aiming at mapping and analysing landscape patterns: (i) membership of ecological entities to classes is not forced to occur within the integer range [0,1] as in Boolean logic, (ii) considering different classes [A,B,…,N] the sum of membership values does not equal 1 for each pixel or polygon. Thus, different classes may overlap to different degrees overcoming the traditional restriction on the mutually exclusive nature of map classes (Rocchini and Ricotta, 2007).

Strictly speaking, one pixel or polygon may show a high membership to broadleaf forests (e.g., =0.8) and to grassland (e.g., =0.7) as well. Noteworthy pixels should include several classes. The spectral signatures for these mixed pixels (Small, 2004) are due to a combination of classes (Gibson and Power, 2000). This may hardly be solved by a simple dominance criterion. Moreover, property (ii) aids in avoiding difficulties in building a-priori exhaustive hierarchical classification schemes.

However, crisp classification cannot be dismissed, overall considering a basic conceptual drawback related to fuzzy set theory. This is related to the deterministic relationship between each object and each class which is a paradox since in this case the description of uncertainty is made with class membership values that are a-priori suspected to be certain. In other words, a statement describing a vague phenomenon must be necessarily vague. This has led to the possibility of assuming for each level of the fuzzy membership function a fuzzy set membership . This is also known as type 2 fuzzy set, or second order vagueness which has been extended to higher order vagueness concept by Varzi (2003). Refer to Fisher et al. (2007) for applied examples of higher order vagueness and type 2 fuzzy sets to mountain peak and coastal dune detection, respectively.

This said, some papers have stressed the higher map accuracy reached by fuzzy classification with respect to a crisp one (see e.g. Shanmugam et al., 2006). In several

cases expert knowledge is advocated as fundamental components in deriving crisp land cover maps; although this presents a challenge of adequately quantifying the complexity of a landscape (Comber et al., 2005). Hence, habitats are typically expected to gently and continuously vary within a landscape rather than abruptly change. Thus, it is crucial that geographical maps and databases, which are rapidly created after the spread of GIS, account for uncertainty problems (Fisher, 2000; Baja et al., 2002).

4.6.2.7 Open Challenges

Nagendra and Rocchini (2008) have reviewed issues related to the resolution of remotely sensed data to study forest biodiversity (Figure 4.6.2.7). They also provide an extensive table with all the characteristics of such sensors (see Table 1 in Nagendra and Rocchini, 2008; see also section 4.1 of this sourcebook).

While most of the relevant research is focused on throughput of hyper-spatial resolution data, Nagendra and Rocchini (2008) found that 'the devil is in the detail'. In other words, they provided a number of examples where remote sensing data with a higher fragmentation of the electromagnetic spectrum (higher spectral resolution) may outperform high spatial resolution data in studies of species patterns over space and time. This is particularly true considering the high level of noise in the spectral signal deriving from shadows when using hyper-spatial data.

This work was further reinforced by He et al. (2011) who provided a number of useful examples of studies relying on hyperspectral remote sensing to detect invasive species in a number of different habitats and sites, from riparian forest vegetation in South California (Hamada et al., 2007) to terrestrial ecosystems in South Africa (Rouget et al. (2003).

As previously stated, in some cases, direct detection of invasive plant species may rely on the spectral signature of a given species in the electromagnetic space. As an example, Somers and Asner (2012) distinguished invasive and non-invasive tree types using spaceborne imaging spectroscopy to analyse the seasonal dynamics of the canopy hyperspectral reflectance properties.

Moreover, in some cases, the hyperspectral information has been supported by LiDAR-based Digital Elevation Models (DEM, Asner et al. 2010), proving the availability of a wide range of remote sensing products for forest species detection.

When dealing with forest species, remote sensing direct detection is one of the most valuable methods and is akin to niche based modelling techniques. This is true also when relying on multispectral sensors, i.e. when fewer spectral bands are available. As an example, Pouteau et al. (2011), modelling the distribution of *Miconia calvescens* in Tahiti tropical rain forests, demonstrated that relying on direct remote sensing may outperform niche based modelling techniques, by comparing Support Vector Machine classification of Quickbird images (spatial resolution 2.44m at nadir) versus the GARP (Genetic Algorithm for Rule set Production) developed by Stockwell and Peters (1999).

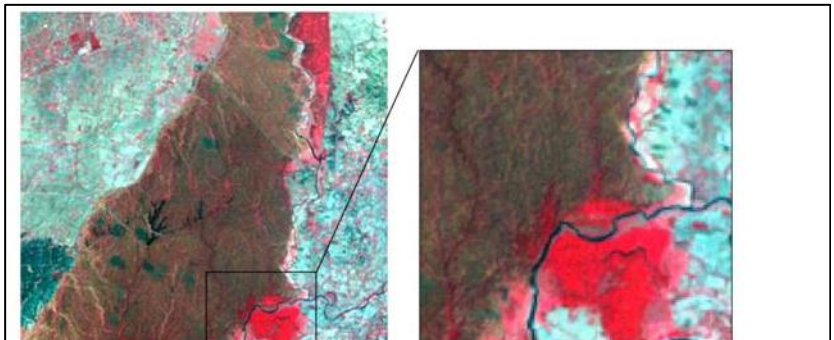

Figure 4.6.2.7. Mapping forest habitats might be straightforward if proper imagery is selected. This example represents a dry tropical forest area in the Chitwan district (Nepal), covered by (a) a Landsat ETM+ image of March 2000 and (b) an IKONOS image of October 2001. Figure reproduced from Nagendra and Rochcini (2008).

4.6.3 Concluding Remarks

Tree species identification of tropical forests based on remotely-sensed data raises particular interest among the ecology and forestry communities. Information about the presence and spatial distribution of key species contributes to biodiversity mapping, and detection of floristic gradients. Thus it helps in better understanding ecological processes occurring in these complex ecosystems and the influence of various factors, from hydrology to climate effects and direct human activity. The exact location of commercially interesting individuals may also decrease damages due to industrial forest exploitation, thus indirectly contributing to forest conservation on the long term.

We described the general principle and recent advances made by research in the domain of tree species identification in tropical ecosystems. We explained that the main classification algorithms which can be appropriately used for such tasks are currently implemented in any modern programming languages and image processing software. However, complex ecosystems such as dense tropical forests still require particular efforts and research for operational applications in the domain of tree species mapping at regional to local scale. Despite increasing data availability and ongoing algorithmic advances for domains such as multi-source data integration (including multi-temporal and multi-

resolution data) and uncertainty mapping, no operational method currently exist. These limitations are due to the technical expertise required to apply advanced methods including data fusion, image segmentation, as well as the cost induced by remote sensing data acquisition, and field data collection. Despite the increasing availability of satellite remote sensing images (such as the Copernicus Sentinel program), high potential data sources such as imaging spectroscopy still depend on costly airborne acquisitions, and their processing also require advanced skills in high dimensionality data processing. Field data also cost money and time, but are still necessary in order to perform a training stage required by supervised and semi-supervised classifications.

Finally, thematic expertise also needs to be tightly linked to any operational method designed for such applications: identifying the best candidates for species discrimination (based on ecological or commercial considerations), and understanding and integrating seasonal dynamics of species or groups of species often appear necessary when seeking for optimal performances in tree species mapping. Such prior knowledge helps in remote sensing data selection, field data collection, decision for methodological options, and reduction of financial costs.

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5 EMERGING APPROACHES

5.1 UPCOMING EARTH OBSERVATION MISSIONS

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5.1.1 General considerations

Section 5.1 aims to present upcoming missions and sensors relevant to tropical forest monitoring. Table 5.1.1.1 classifies sensors into two broad types: passive and active. Sensors are described according to the most important parameters (spatial resolution, spectral range and resolution, swath width and revisit time). The table lists the relevant EBVs each sensor is most likely to contribute to. Sub-section 5.1.2 presents upcoming navigations systems. The section will be updated on a yearly basis to report on the new EO missions. Note section 4.1 of the sourcebook lists sensors and associated datasets already available, and discusses further key parameters to best choose datasets.
Sensors are described also in broad spatial resolution categories. In this sourcebook, the chosen ground spatial resolution categories are as follows: Very High: <=1m, High: <=10, Medium: <=30m, Low: <=300m, Coarse <=1,000m. Note the spatial resolution for LiDAR datasets is measured by the distance between the centres of consecutive beams, and between the scanning lines. The beam divergence affects also the spatial resolution. This information that is not available yet for the LiDAR systems reported in Table 5.1.1.1, will be added in future releases of the sourcebook.
In Table 5.1.1.1, column "Expected relevance to EBVs" lists the EBVs relevant to tropical forest monitoring the sensors can contribute to. Table 5.1.1.2 provides the coding number of the EBVs used in Table 5.1.1.1. For more information on the six EBVs covered by this sourcebook, please check: http://geobon.org/essential-biodiversity-variables/ebv-classes-2/.

With the wider availability and free access of EO data, it is interesting to note virtual constellations (VC) for land and water characterization gain in importance, and are also strongly supported by the Committee on Earth Observation Satellites (CEOS) (Wulder et al., 2015). Per definition, a VC defines a virtual satellite constellation as a "set of space and ground segment capabilities that operate in a coordinated manner to meet a combined and common set of Earth Observation requirements" (Source: http://www.ceos.org/index.php?option=com_content&view=article&id=275).

The interoperability of sensors is a key feature to enlarge the temporal density of available data (Reiche et al., 2015). At the same time, analysis techniques have to deal with a change from pixels-based concepts towards scene based concepts, to explore the full potential of such VC.

For further information on upcoming observing systems please go online:

- National Aeronautics and Space Administration (NASA, USA):
http://eospso.nasa.gov/future-missions

- European Space Agency (ESA):
https://earth.esa.int/web/guest/missions/esa-future-missions

- the German Aerospace Center (DLR) compiles information on (past, present and) future space-borne imaging spectroscopy missions:

http://www.enmap.org/sites/default/files/pdf/Hyperspectral_EO_Missions_2015_06_22_FINAL.pdf

- Brazilian Space Agency – the planned missions up to 2021 (in Portuguese)

http://www.aeb.gov.br/wp-content/uploads/2013/01/PNAE-Portugues.pdf

Table 5.1.1.1: List of upcoming sensors and missions relevant to tropical forest monitoring

Platform/ Mission	Life span	Revisit time period	Spatial Resolution (m)	Swath (km)	Wavelength	Availability	Expected relevance to EBVs	Reference
Passive sensors								
Hyperspectral								
PRISMA	2016-2022	7 days	PAN 2.5-5 Hyp 20-30	30-60	PAN 0.4-0.7 µm VNIR 0.4–1.0 µm SWIR 0.9-2.5 µm	?	1, 2	http://www.asi.it/en/activity/observation-earth/prisma
EnMAP	2018-2022	≤ 4 days (± 30° off-nadir tilt) ≤ 21 days (± 5° off-nadir tilt)	30	30	VNIR 0.4-1 µm SWIR 0.9-2.4 µm	Free for scientific applications	1, 2, 5	www.enmap.org
HISUI/ ISS	2019-2021	60 days	20m (along track) 30m (across track)	20	VNIR 0.4-0.9 µm SWIR 0.9-2.5 µm	Currently discussed	1, 2, 3	http://www.grss-ieee.org/wp-content/uploads/2014/12/2014_07_ISIS_Session1_Mission/Matsunaga_HISUI_Status_07final.pdf
HYSPIRI	2020-2024	VSWIR 16–19 days TIR 5 days	VSWIR 30–60 TIR 60	VSWIR 150 TIR 600	VSWIR 0.3–2.5 µm TIR 3-12 µm	?	1, 2, 5	https://hyspiri.jpl.nasa.gov/

DESIS	2016-2020	~50 days	30	30	0.4-1 µm	Free for DLR & partners, Commercial	1, 2	http://www.dlr.de/os/desktopdefault.aspx/tabid-9294/16011_read-39367/
SHALOM	2019-2023	2 days	PAN 2.5 VNIR-SWIR 10	10	PAN 0.4-0.5 µm VNIR 0.4-1.0 µm SWIR 0.9-2.7 µm	Commercial	1, 2, 3, 4	http://space.gov.il/en/node/1144
HYPXIM	2020-2030	3 days (± 60° off-nadir tilt), or 19 days	PAN 2 VSWIR <8 TIR 100	16	VSWIR 0.4-2.5 µm TIR 8-12 µm	?	1, 2, 3, 5	http://www.researchgate.net/publication/228518155_HYPXIMA_hyperspectral_satellite_defined_for_science_security_and_defence_users
FLEX	2020-2023	19 days	300-500	105-150	0.5-0.7 µm	?	2, 5	http://www.esa.int/Our_Activities/Observing_the_Earth/The_Living_Planet_Programme/Earth_Explorers/Future_missions/Glowing_plants_a_sign_of_health
Multispectral								
WorldView 4 (GeoEye 2)	2016->2026	~ 3 days	PAN 0.31 MS 1.2	14.5	PAN/MS	Commercial	1, 2, 3, 5	http://investor.digitalglobe.com/phoenix.zhtml?c=70788&p=irol-newsArticle&ID=1953904
ALOS 3	2019-2026	?	0.8	50	PAN/VIS/NIR	Commercial	1, 2, 3, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/a/alos-3
CartoSAT-2C/2D/2E	2016-	?	PAN 0.62 MS <2	?	PAN/MS	?	1, 2, 3, 5	http://www.sac.gov.in/SACSITE/asac-ongoing-rsp.html
DMC3 / Beijing 2 constellation	2015-2021	1 day	PAN 1 MS 4	23	PAN/MS	?	1, 2, 3, 5	http://spacenews.com/indias-pslv-lofts-uk-built-earth-observation-satellites-leased-by-chinese-firm/
VENµS	2016-2018	2 days	5, 10	?	VIS/NIR	?	1, 2, 3, 5	http://missions-scientifiques.cnes.fr/VENUS/

Amazônia 1/1B	2016-	4 days	40	720	VIS/NIR	?	1, 2, 3, 4, 6	http://www.inpe.br/produtos_servicos/engenharia_satelites/amazonia1.php
Sentinel 3A/B	2017-2024	1-2 days S3 A&B	300	1300	VIS/NIR	Free	1, 2, 5	https://directory.eoportal.org/web/eoportal/satellite-missions/c-missions/copernicus-sentinel-3
GCOM C1/2/3 series	2016-2028	2-3 days	250-500-1000	1150-1400	VIS/NIR/TIR	?	1, 2, 5	http://global.jaxa.jp/projects/sat/gcom_c/
Active sensors								
Synthetic Aperture Radar (SAR)								
NISAR	2020-2022	?	multiple	multiple	L/S-dualB	?	3, 4, 5	http://nisar.jpl.nasa.gov/
NovaSAR S1/2/3 constellation	2016-2023	1 day	multiple	multiple	S-band	Commercial	3, 4, 5	http://www.sstl.co.uk/Blog/November-2013/NovaSAR-wins-an-Innovation-Award-from-the-IET
RADARSAT C1/2/3 Constellation	2018-	4 days	multiple	multiple	C-band	Commercial	3, 4, 5	http://www.asc-csa.gc.ca/eng/satellites/radarsat/default.asp
BIOMASS	2020-2025	≤25 days	200 50	?	P-band	Free	3, 4, 5	http://esamultimedia.esa.int/docs/EarthObservation/SP1324-1_BIOMASSr.pdf
Light Detection And Ranging (LiDAR)								
ICESat 2	2018-2022	?	?	?	532 nm	?	3, 4, 5	http://icesat.gsfc.nasa.gov/icesat2/index.php
GEDI	2019-	?	?	?	1064 nm	Free	3, 4, 5	http://science.nasa.gov/missions/gedi/

Table 5.1.1.2. List of acronyms and coding numbers of EBVs used in table 5.1.1.1.

List of acronyms	Coding number of EBVs
MS: Multi spectral NIR: Near infrared Pan: Panchromatic TIR: Thermal infrared VIS: Visible	1- Vegetation phenology 2- Net primary productivity 3- Ecosystem extent and fragmentation 4- Habitat structure 5- Disturbance regime

5.1.2 Navigation systems

Global navigation satellite systems (GNSS) are used as crucial data providers for many remote sensing applications ranging from determining an accurate position of the user on the surface of the Earth to land cover classification of remotely sensed imagery. The only two existing and globally operational systems are the Global Positioning System (GPS) backed by the United States of America and the GLObal NAvigation Satellite System (GLONASS) funded by the Russian Federation. However, recently several initiatives were either started existing regional system are being expanded to global coverage.

Table 5.1.2.1. Developing/upcoming global or large scale regional navigation satellite systems

System/Provider	Global scale	Open access maximum positional accuracy	First fully operational year	Operational satellite units (2015)	Final Number of satellite units
BeiDou/China	x	10m	2020	20	35
Gallileo/European Union	x	1m	2020	8	30
IRNSS/India		10m	2016	4	7
CYGNSS*/USA	x		2016	0	8
QZSS/Japan		7.5m	2023	1	7

Indian Regional Navigation Satellite System (**IRNSS**)
http://www.isro.gov.in/irnss-programme

Quasi-Zenith Satellite System
http://qzss.go.jp/en/technical/downloads/isos7j0000000bl4-att/qzss_pamphlet_201503.pdf
http://www.esa.int/Our_Activities/Navigation/The_future_-_Galileo/What_is_Galileo

CYGNSS (Cyclone Global Navigation Satellite System) – specialized positioning system not designed for direct positioning, rather to measure ocean surface wind speed using direct and reflected GPS signals
http://clasp-research.engin.umich.edu/missions/cygnss/

5.1.3 Key References for section 5.1

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5.2 AIRBORNE SENSORS

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5.2.1 Lidar

5.2.1.1 Background

Laser altimetry, more commonly known as LiDAR (light detection and ranging), is an active remote sensing technology that directly measures the three-dimensional structure of a scene. From these measurements can be derived highly accurate estimations of plant canopy height and structure, as well as subcanopy topography (Lefsky et al. 2002). Lidar metrics are shown to be highly correlated with crucial forest structural characteristics such as above ground biomass (AGB) (Drake et al. 2003). Lidar systems are effective at estimating AGB in high-biomass ecosystems where other remote sensing technologies, such as radar, may fail (Lefsky et al. 2002).

Airborne LiDAR systems send out individual laser pulses and determine the range from the sensor to the object by measuring the time it takes for a pulse to return. The three-dimensional position and angular attitude of the sensor is recorded using a Global Navigation Satellite System (GNSS) and an Inertial Navigation System (INS). These observations allow the LiDAR system to record precise, georeferenced positions of the LiDAR pulse returns. Contemporary small-footprint airborne LiDAR systems can send out up to 500,000 pulses per second.

Lidar sensors can be broadly classified into two types: large-footprint and small-footprint systems. The term "footprint" refers to the area of the ground that is covered by the laser beam. Large-footprint LiDAR (roughly 10 m – 100 m diameter footprint) can deliver decimeter-level vertical resolution and accuracy with roughly < 2 m horizontal accuracy, specifications which make it well suited for biomass estimation on the landscape scale (Omasa et al. 2007). Large-footprint systems record and analyze the full waveform of the return signal, allowing them to capture the vertical structure of multi-tiered canopy and the topography of the ground beneath (Blair et al. 1999). Airborne large-footprint LiDAR was developed largely as proof of concept for spaceborne systems. Currently there is no availability of airborne large-footprint LiDAR beyond NASA's Land, Vegetation, and Ice Sensor (LVIS). A spaceborne large-footprint LiDAR mission, ICESat-2, is set to launch in 2017, though its ability to measure forest characteristics remains to be seen.

Small-footprint systems (typically < 1 m diameter footprint) offer centimeter-level vertical resolution and meter-level horizontal and vertical accuracy. Because of the smaller footprint, these systems must record many more points per square meter to offer coverage similar to that obtained by large-footprint systems. Small-footprint systems typically record a single return or a small number of returns (Omasa et al. 2007) but newer systems allow for recording the full waveform of the return. In contrast to discrete return systems, in which a certain threshold of return energy must be detected to record a return, a full waveform system records the entire energy profile of the return laser pulses (Mallet and Bertar 2009). The number of discrete returns that the system records, or whether the system analyses the full

waveform, dictates how much information about the canopy and understory is recorded. The higher resolution data collected by small-footprint systems is apt for detecting individual trees and for the generation of high-resolution topographic models.

The vast majority of airborne LiDAR systems are scanning systems that measure swaths of points beneath the aircraft. There are also profiling LiDAR systems that record data along a single, narrow line beneath the aircraft, which is useful for a sampling approach.

5.2.1.2 Data processing overview

Discrete return LiDAR data is most often presented as a three-dimensional point cloud, where each point represents the location where the outgoing pulse was intercepted, and from where the individual return pulse originated. These points are georeferenced by the LiDAR data provider so that their locations are estimates of real-world position. A handful of methods of representing full waveform LiDAR data exist, many of which effectively discretize the full waveform into numerous individual points of interest (Drake et al. 2002, Reitberger et al. 2009). An emerging standard data exchange format for full waveform data, PulseWaves, is openly available and compatible with the existing LAS format for discrete return LiDAR point clouds (Isenburg 2012).

An essential step in processing LiDAR data is classifying the points as either ground or non-ground returns. Those points classified as ground are used to generate a bare Earth digital terrain model (DTM). The non-ground (i.e., vegetation) points can then be compared to the DTM, from which metrics such as canopy height and canopy cover can be derived. Many software packages, both proprietary and open-source, are capable of LiDAR point cloud processing, including FUSION, LAStools, and SAGA GIS to name but a few.

5.2.1.3 Lidar and habitat structure

Lidar metrics such as canopy height, canopy cover, and subcanopy topography have been shown consistently to be of equal or greater accuracy than field-based estimates and estimates made from high-resolution aerial photography. From these metrics, key characteristics can be modeled, including AGB, basal area, and canopy volume (Dubayah and Drake, 2000). These relationships between directly observed LiDAR metrics and forest characteristics are found through non-species specific allometric models, such as those proposed by Chave et al. (2005).

Drake et al. (2002 and 2003) tested the utility of the LVIS large-footprint airborne LiDAR system for estimating forest characteristics in a tropical wet forest. The study found LiDAR metrics to be highly correlated with field-based measurements of stem diameter, AGB, and basal area. Building upon the work of Chave et al. (2005), Asner et al. (2008) used small-footprint airborne LiDAR to better quantify AGB beyond the hectare scale, a nontrivial task in complex tropical forests. It is worth noting that Asner et al. found that airborne LiDAR could directly measure canopy height in the closed canopy conditions, whereas field measurements relied on species-specific allometric equations to derive tree height from stem diameter and wood density. Valgio Laurin et al. (2014) among others demonstrate an improvement of AGB estimates by merging hyperspectral features, which by themselves are relatively ineffective at predicting AGB, with small-footprint airborne LiDAR data.

These highly correlated relationships between LiDAR metrics and habitat structure variables, particularly AGB, are shown to outperform other remote sensing technologies such as radar and passive optical sensors, especially as the study area increases (Zolkos et al. 2013). The study also shows that merging LiDAR data with data from other sensor types to improve AGB models.

Canopy height and vertical structure has been shown to be an effective predictor of biodiversity of birds and insects, among other taxa (Bergen et al. 2009). Despite the predicting power of forest characteristics that can be estimated with LiDAR, only a handful of studies have quantitatively assessed relationships between LiDAR-derived metrics and wildlife habitat (Vierling et al. 2008). Directly measured LiDAR metrics (e.g. altitude and canopy height) can be used to derive proxy variables such as forest gaps, canopy density and climate-related variables to evaluate biodiversity of beetles at the landscape scale (Müller and Brandl, 2009).

Using various algorithms, individual trees can be detected and delineated from LiDAR data. This procedure has been better studied in boreal forests (Hyyppä et al. 2001, Koch et al. 2006, etc.), where the spatial density of both individual trees and species is much smaller than in tropical biomes. Individual tree segmentation can be useful for species classification and physiological stress response, among other applications, especially when the LiDAR data is composited with data from passive sensors such as hyperspectral (Dalponte et al. 2008) or thermal data (Omasa et al. 2007).

5.2.1.4 Designing and evaluating LiDAR surveys

An effective LiDAR survey must be conjoined with field measurements to establish local relationships between AGB, basal area, and other target parameters with LiDAR metrics, as these allometric models, though not always species-specific, tend to be confined to local forest types (Chave et al. 2005). Once an adequate number of field measurements are made to reach the desired statistical significance of the study, the LiDAR data, collected over a larger area, can be used to accurately predict biodiversity variables essential to habitat structure.

A key consideration when designing a LiDAR survey or evaluating the usefulness of an existing LiDAR dataset is the number of pulse returns per unit area, often referred to as pulse density or sampling density. For a small-footprint airborne system, a pulse density of >5 points m-2 is desirable to avoid underestimating canopy height. This phenomenon is due to an oversampling of tree crown shoulders and an undersampling of the local maxima of treetops (Omasa et al. 2007). Also, it has been demonstrated that the optimal pulse density for the generation of a DTM or digital surface model (DSM) should be greater than or equal to the desired spatial resolution of the DTM or DSM (Liu, 2008).

For a scanning LiDAR system, both the width of the beam swath and the size of the beam footprint are directly correlated with the aboveground height of the sensor. For a biomass sampling survey, a higher flying height is desirable, whereas a need for finer resolution data (e.g. individual tree detection) may require a lower flying height. These factors are also dependent upon the sampling rate (i.e. pulses per second) and other specifications of the sensor being used. A LiDAR data provider can easily control for pulse density, width of beam swath, proper accuracy assessment, and other considerations through proper mission planning.

Lidar data and have been shown to be effective in biomass estimation when applied both in a wall-to-wall manner (i.e., complete coverage of a study site) and in a conventional sampling-based manner, an approach in which swaths of LiDAR data, perhaps separated by many kilometers, are used to make estimates on habitat structure for a more expansive area of interest. For either approach, the area of the scanned site(s) is positively correlated to the accuracy of estimates of habitat structure such as AGB. This is due to the effects of trees just outside the boundaries of the study areas whose canopies, in a planimetric sense, extend into the study area. These edge effects can be mitigated by increasing the plot sizes.

5.2.1.5 Near-term developments in airborne LiDAR

A recent development is a commercially-available Geiger-mode LiDAR sensor capable of collecting higher-resolution data at a higher sampling rate than a conventional scanning LiDAR sensor. The improvements in both resolution and sampling rate are attributed to the system's shorter pulse duration and ability to record lower-energy returns, which allows for more precise detection of a pulse's time of flight and for more pulses to be emitted per second. This Geiger-mode LiDAR sensor also captures spatial data from multiple view angles, which produces a point cloud with fewer occlusions. These specifications allow for the collection of airborne LiDAR data from a higher elevation and a higher rate of flying speed, offering a cost-effective method for obtaining three-dimensional information of a forested area (Romano 2015).

Scanning LiDAR sensors, along with GNSSs and INSs, are becoming increasingly more lightweight and less expensive, allowing for the development of small Unmanned Aerial Systems (UAS) for airborne LiDAR surveying. These systems are limited to shorter flying times and a lower flying altitude than conventional aircraft, but are vastly less expensive and easier to deploy, making them well-suited for surveys at the landscape (< 1 km2) scale.

5.2.1.6 Data costs and availability

Costs for LiDAR data collection and processing are variable. A key consideration for an airborne LiDAR survey via conventional aircraft are fuel costs, which are affected by the distance between the study site and the aircraft's point of departure. Estimates can be as low as USD$1 per hectare, but required minimum flyover areas of hundreds to thousands of hectares are common. However, LiDAR data may be more cost effective than data from passive or radar sensors despite the large front-end cost of data acquisition. Due to the density and accuracy of LiDAR data compared to other remote sensing data and pure field sampling, far fewer field observations are needed for a study to achieve a particular precision (Næsset et al., 2011).

Requisition of airborne LiDAR data is available globally through commercial vendors, subject of course to national airspace jurisdictions. Some nations, such as Australia and the United States, make freely available those LiDAR data which are acquired for public use. Global coverage from the now-defunct spaceborne GLAS sensor are available via NASA.

5.2.2 High-resolution aerial imagery

5.2.2.1 Overview

A conventional aerial imagery system equips a manned aircraft with a still frame camera or video camera to capture images of the terrain at high spatial resolution (< 1 m2 per pixel). As the camera records images, its location and angular attitude are typically recorded using a global navigation satellite system (GNSS) and an inertial navigation system (INS). Without these data, aerial images would be of little use outside of qualitative interpretation of the terrain and its vegetation and other features. Knowing the position and orientation of each image (or video frame) allows for further image processing and quantitative interpretation via the science of photogrammetry.

If the images are captured in such a way that they provide stereo, overlapping coverage of the terrain (i.e., stereopairs of images overlap each other by 60% or more), it is possible to make precise and accurate three-dimensional measurements of the terrain in an absolute, real-world scale. These three-dimensional measurements are useful for generating digital terrain models (DTMs) (Wolf et al. 2014), measuring individual tree heights, delineating

individual tree crowns, and other key variables related to habitat structure (Brown et al. 2005). This real-world scale, three-dimensional reconstruction of the terrain is possible without GNSS and INS if there are a sufficient number of control points visible in the images, but the placing and geolocating of these control points presents issues, especially over inaccessible or densely vegetated terrain. It is worth noting that, because of the need for stereo coverage of terrain, dense or closed forest canopies can drastically inhibit the utility of an aerial image survey.

Another useful photogrammetric product is the orthophoto. A necessary condition of aerial images, by virtue of the camera being affixed to such a dynamic platform as an aircraft, is that camera is never facing exactly downward when recording images. Another necessary condition of any photograph is the effect of relief displacement, which makes objects appear to "lean outward" from the center of a photograph. Tall objects and objects further away from the center of an image exhibit greater relief displacement. The effects of tilt and relief displacement are corrected in a process called orthorectification. The product of orthorectification is the orthophoto, whose scale is uniform throughout, much like a conventional map (Wolf et al. 2014). Orthophotos can be used for two-dimensional mapping purposes such as coastline mapping and vegetation community mapping.

There are numerous photogrammetric software packages for both three-dimensional reconstruction and orthophoto generation, many of which are intended for use by trained photogrammetric specialists.

Conventional high-resolution aerial photography is not often utilized for monitoring biodiversity variables such as habitat structure, phenology, or species abundance. This could be due to overhead cost or the availability of more advanced aerial mapping technologies such as LiDAR. The emergence of small UAS allows for collection of high-resolution aerial imagery at a lower overhead cost, allowing for more widespread use for biodiversity monitoring. This development is discussed in detail in Section 4.2.2.

5.2.2.2 Data costs and availability

Aerial photography is available nearly worldwide at resolutions of > 1 m2 per pixel (GSD). Most wide-scale aerial image surveys are designed to efficiently cover large areas, and are therefore flown at higher altitudes, lowering the spatial resolution of the imagery. In nearly all cases, the photos have already been orthorectified, mosaicked, or otherwise processed, and individual photos are not typically available. This limits the use of the photography to two-dimensional mapping at a coarse scale. To obtain high-resolution imagery, one must go through a commercial vendor or an outfit with access to an aircraft.

The largest source of cost in an aerial image survey besides ground control is use of the aircraft itself. Though these costs can vary by vendor, airborne image collection can cost around USD$300 per hour of flying time. The number of person-hours needed to process and analyze the data can also be extensive, especially when working with stereopair photographs to make three-dimensional measurements (Brown et al. 2005).

5.2.2.3 Low-cost aerial photography

Professional aerial photography requires expensive equipment to stabilize and/or record roll, pitch, and yaw, and other equipment that can put this technique out of reach of many organizations interested in using remote sensing for tropical forest diversity monitoring. There have been several projects that have successfully used low-cost aerial photography techniques to map tree species in tropical forests. These techniques have used relatively low-cost cameras without gyroscopes or IMUs, thus resulting in photographs that are geometrically distorted. Non-photogrammetric cameras are pointed down from a rental plane

and are either mounted to the aircraft or held by a photographer leaning out of the airplane. Ground control points, such as Mylar balloons in the canopy (Gonzalez et al. 2010; Trichon et al. 2001, 2006) and/or registering and warping aerial images to match a high-resolution satellite image (Jansen and Bohlman 2008; Garzon-Lopez et al. 2013) allow placing individual crowns in the correct location not precisely, but with acceptable error for the application. Visual interpretation is then used to identify species with distinct vegetation or reproductive features. Because visual interpretation and color cameras are used, there is a limited number of tree species that can be identified out of the hundreds of species that occur in the canopy at each of these sites (Panama, Ecuador, Australia). However, the methodology, although time consuming to process the photos, is not expensive and can be used to map targeted species over wide areas for various applications (Caillaud et al. 2010; Garzon-Lopez et al. 2013, 2014, in press). See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping.

5.2.3 Unmanned Aerial Systems

5.2.3.1 Background

Small unmanned aerial systems (UAS) have found uses in many disciplines, and are expected to revolutionize data collection in a diverse array of fields such as forestry (Merino et al., 2012), agriculture (Zhang and Kovacs, 2012), civil infrastructure (Seibert et al., 2014), and mining (Liu et al., 2012). They have also garnered interest in spatial ecology, including mapping biodiversity (Anderson and Gaston, 2013). UAS are capable of rapidly collecting extremely high-resolution data, making them ideal for monitoring fine-scale changes in scene composition. Terms such as "unmanned aerial vehicle" (UAV) and "drone" are regularly used in literature, often with particular disciplines favoring one over the others. "UAS" is used here since it comprises more explicitly the vehicle (platform), onboard sensors, ground control station, and other support components needed to carry out aerial data acquisition, avoiding the trivialization of these important considerations. Because many call for surveillance and reconnaissance in areas potentially dangerous for manned missions, UAS have their beginnings in military applications (Eisenbeiss, 2004). Advances in technology and algorithms have led to widespread feasibility of small UAS in the civilian sector. Specifically, Global Navigation Satellite Systems (GNSS) receivers, Inertial Navigation Systems (INS), digital cameras, autonomous flight controllers (autopilots), and small high capacity batteries have made UAS possible. The fine-scale resolution data products provided by UAS enable them to capture parameters correlated with biodiversity metrics, such as small gaps in tree canopy, not obtainable from more conventional manned-airborne or satellite data (Getzin, et al., 2012).

5.2.3.2 General Characteristics

UAS can be split into three main components: the platform; the sensor-suite payload; and the ground-control station. The platform consists of usually either a fixed-wing, or vertical take-off and landing (VTOL) multirotor vehicle (although there are balloon-based systems) and a flight controller. A fixed-wing and VTOL UAS are shown in Figures 5.2.3.2.1 and 5.2.3.2.2, respectively. The flight controller steers the vehicle automatically based on input from sensors such as integrated INS and GNSS units. The sensor suite usually comprises at least a small digital RGB camera, although miniature multispectral, hyperspectral, thermal, and laser scanning sensors (among others) have been used. For UAS with higher payload capacities, multiple sensors can be mounted simultaneously. Sometimes the sensor suite also includes a GNSS receiver and/or INS distinct from, and more precise than, those on the flight controller. These are used for precision direct-georeferencing. Further, some systems carry discrete data storage units, sensor-controlling computers, and timing synchronization units

to correlate GNSS/INS data with sensor data. Scanning sensors, such as LiDAR and hyperspectral line imagers, require direct observation of position and orientation provided by GNSS/INS. The ground station comprises transmitters to relay instructions to the platform and to enable manual control if necessary, receivers to gather telemetered data from the platform and sensor suite, and a computer to process mission information. UAS are able to collect data in predefined areas-of-interest by navigating flight paths with precise horizontal and vertical parameters, practically impossible to navigate by manual control. Users plan flights based on desired coverage and data resolution, sensor characteristics, and battery capacity. The UAS platform then triggers the sensor continuously or at predetermined locations as it autonomously travels along the planned lines.

5.2.3.3 Price

There are a variety of commercially-available UAS ranging greatly in price and performance. A small multirotor UAS with a small action video camera that can stay aloft for 15-minutes can cost <$1000 USD. On the other hand, professional-grade systems with higher payload capacity and flight times can cost tens of thousands of dollars (USD). Payload sensors also have a wide range of prices. Off-the-shelf consumer grade cameras can be used for many applications, with mirrorless interchangeable-lens digital cameras preferred due to their light-weight and high-quality imagery. If users intend to integrate sensors on their own, care should be taken to select a camera that can communicate (via e.g. GigE) with the onboard computer to enable triggering, capture, storage, and correlation with the timing device. Miniature LiDAR scanners are priced in the range of about $1,000-$100,000 USD, and miniature hyperspectral scanners price can range from about $40,000-$90,000 USD. Sensor costs are correlated with capability, however they should be carefully selected based on the target application. GNSS/INS packages also have a wide range of prices. A small integrated GNSS/INS can cost from about $5,000-$60,000 USD. Similar to sensor selection, accuracy of these devices should also be carefully considered, since they may or may not be appropriate for the associated sensor suite.

Figure 5.2.3.2.1 MAP-M4 VTOL Multirotor UAS vehicle

(Courtesy of Micro Aerial Projects LLC).

Figure 5.2.3.2.2. Nova II Fixed-wing UAS vehicle (Courtesy of The University of Florida).

5.2.3.4 Sensors

Because onboard UAS sensors are normally scaled-down versions of those used in manned aerial platforms, the products are generally the same, but at different resolution. For example, miniature hyperspectral imagers may have a higher spatial resolution due to proximity of the sensor to scene, but lower radiometric resolution due to constraints stemming from miniaturization of the sensors. These trade-offs are unique to the sensor modalities, but some careful pre-analysis can reveal potential for specific applications relative to larger versions or distinctive capabilities. Pajeres (2015) provides an extensive overview of UAS applications including various associated sensors. Most common is the use of a frame camera operating in the visible spectrum, and there are numerous examples of applications employing these. UAS-mounted small multispectral (Kelcey and Lucieer, 2012) and hyperspectral sensors (Hruska, et al., 2012) have also become common for many applications. Note that although there are frame hyperspectral sensors for UAS (at the time of writing, two are known and reported in Bareth et al., 2015), typically, these sensors are line scanners. This necessitates direct georeferencing of each collected line, and thus a high-accuracy INS/GNSS unit is required to maintain spatial fidelity of the products. These additional components can be costly both monetarily and in weight required. Lightweight laser scanners are beginning to be used, with the first study involving a small UAS mounted with a laser scanner reported in 2010 (Jaakola et al., 2010). Laser scanners also require accurate INS/GNSS support units. More recently, researchers have combined light, low accuracy georeferencing hardware with supporting orientation data from computer vision methods applied to onboard videography to better utilize UAS laser scanners (Wallace et al. 2012, 2014a, 2014b). Other sensors that have been used on UAS include video cameras, thermal cameras, near-infrared cameras, and radar (Pajeres, 2015). UAS with higher payload capacities can carry multiple sensors concurrently and collect data simultaneously. It is advisable to plan for combined payloads that minimize across-senor data redundancy, and allow for synchronization of capture when appropriate to facilitate processing and registration.

5.2.3.5 Planning and Collection

The main considerations for flight planning are the sensors suite, the vehicle, take-off and landing locations, lines along which the vehicle flies, and the location of the base station. Sensors are selected based on the desired data type and coverage to be collected, with consideration for modular components such as lenses that influence resolution and collection time. The vehicle must be able to support the sensor and requisite auxiliary hardware to allow for sufficient flight time and therefore coverage. Here, weight restrictions and battery capacity are the limiting factors. The vehicle must also be able to be launched and land in the vicinity of the project area, preferably close to the base station. In densely forested areas, there is often not enough suitable terrain for launching and landing fixed-wing vehicles, although vehicles capable of water landing are available (Watts, et al., 2010), and VTOLs may be more appropriate. Getzin et al. (2014) recommend VTOLs due to their stability leading to better orthophoto quality. Planning of the flight lines must take into consideration the area to be covered and other mission-specific parameters such as flying height and overlap. Flying height must be chosen first and foremost such that vertical obstructions are avoided, and such that the desired ground sample distance (GSD), a component of the data resolution in addition to resolving power of the lens in the case of cameras, is sufficient for the application. There are also strict regulations in some countries that govern the allowable height above ground that a UAS can fly. In typical manned photogrammetric missions, it is common for endlap (along-track overlap) to be around 60%, with sidelap (across-track overlap) around 30% (Wolf et al. 2014). Due to the dynamic flight of small unmanned aircraft, these numbers are typically increased (to about 70%-80% and ~60%, respectively) to ensure full stereo coverage (and therefore three-dimensional reconstruction) in the case of frame photography. Flight lines are limited by battery capacity, and may sometimes need to be split into separate flights to obtain full coverage. Often, data must be georeferenced, and therefore some control must be introduced to the UAS. Ground control targets are preferred for frame sensors, although these can be problematic in forested areas since they may not be readily captured in the sensor data and surveying them can be a troublesome due to occlusion of GNSS signals by vegetation. Airborne control via GNSS/INS is a viable option (Turner et al., 2012), although some supplementary ground control is always advisable (Cramer et al., 2000). The base-station should be near the take-off and landing zone, and should allow visual line-of-sight to the aircraft at all times. It is also important to consider possible occlusion of telemetered data between the base-station and aircraft. Loss of communication may lead to contingency routine execution by the UAS, and users should be aware how the platform will behave under these circumstances. In anticipation of widespread "in-house" acquisition and use of UAS by individuals, thorough operation, safety, and regulatory training for ground crew personnel is highly advisable to reduce the occurrence of mishaps.

5.2.3.6 Data Products and Processing

Since many applications call for a photogrammetric products and they are less expensive compared to other payloads and therefore ubiquitous, this section focuses on data and processing associated with frame camera sensors. With a standard small digital camera, UAS can provide a variety of data. This includes raw aerial imagery, naïvely stitched mosaics (photomaps), orthorectified mosaics, point clouds, and digital elevation models (DEM). The first two can provide information for planning and reconnaissance in hard-to-visit areas, and the latter three can provide extremely accurate geospatial data used for modeling and analysis (Wolf et al., 2014). The amount of data that can be collected and area covered varies from platform to platform, and is dictated primarily on flight duration. Standard photogrammetric processing to produce orthophoto mosaics and 3D products can be achieved using one of a number of commercial and open-source options. These computer programs are often referred to as computer vision-based, however the algorithms they use to develop their high-accuracy products are based on photogrammetric models (Granshaw and Fraser, 2015). Although the workflow and theory behind the software suites are very similar, each has moderate

algorithmic variations and different capabilities. There are a several articles that compare software characteristics and capabilities of various packages (e.g. Gini et al., 2013; Sona et al., 2012; Turner et al., 2014).

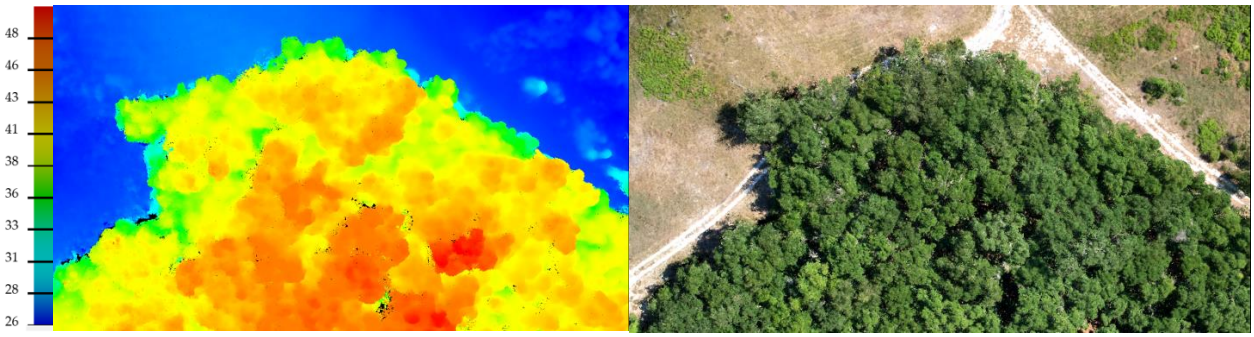

Figure 5.2.3.6.1. Dense point cloud generated from UAS-mounted camera imagery. The left portion is colored based on height (in metres), on the right is colored based on RGB imagery.

Workflow for frame imagery from UAS follows the following general steps:

1. Acquisition of imagery, navigation, and time-synchronization data

2. Image-matching to produce the spatial relative orientation of imagery

3. Absolute orientation of imagery relative to a mapping coordinate system using control via aerotriangulation, often with camera calibration parameters (such as focal length and lens distortion) resolved simultaneously

4. Three-dimensional model generation via a second round of image feature matching, producing a dense point cloud from which a raster digital surface model can be obtained

5. Orthophoto generation from imagery, orientation parameters, and digital surface model, essentially creating a spatially-accurate planimetric map

It is important to include camera calibration parameters in the workflow process during the refined absolute orientation step. Although pre-mission calibration and definition of these parameters is possible with most software suites, the parameters of commercial off-the-shelf cameras can change rapidly over time, necessitating re-calibration. Thus, performing the calibration for each mission is recommended. Time required for processing can be a major issue due to the extreme amount of data collected. A rule of thumb is that for each hour of collection from a consumer-grade camera, it will take 20 hours to process the data at the highest accuracy and resolution on a single high-end work-station. Less time is needed when processing at lower resolutions, and often a compromise is prudent.

5.2.3.7 UAS and Biodiversity Tropical Forests

UAS have been explored recently for evaluation of biodiversity in tropical forests, and are of much interest due their cost, mitigation of cloud effects associated with conventional remote sensing methods over tropical forests, and rapid repeatability of surveys (Anderson and Gaston, 2013). The studies mentioned here all used frame visible-spectrum digital cameras, although platforms were a mix of both fixed-wing and VTOL. Koh and Wich (2012) developed a low-cost fixed-wing UAS (<$2,000) and evaluated its performance in Indonesia. They developed georeferenced mosaics, which can be used as near real-time land use/cover maps, and transects of videography were shown to be able to capture individual trees, and large

mammals. They captured both a Sumatran orangutan and Sumatran elephant in UAS imagery, illustrating the potential of UAS imagery for wildlife surveys. They also observed that tree-species identification was possible due to the high resolution imagery's ability to capture canopy, fruit, and flower features. Garzon-Lopez et al. (2012) used high-resolution aerial photography to map tropical forest canopy tree species in Panama, and point towards UAS as a viable platform from which to obtain like data. Getzin et al. (2012) developed high-resolution orthophotos (7 cm GSD) from fixed-wing UAS imagery, using the data to enable detection and segmentation of small canopy gaps in temperate forest. These data were subsequently used to estimate understory floristic biodiversity. They suggest that canopy gap analysis from UAS can also be used in neotropical rainforests, since they impact plant composition due to correlation with microclimatalogical effects and ecological processes, and encourage future work therein. Further studies of gap pattern analyses in forests from UAS imagery (Getzin et al., 2014) showed that fine-scale gaps measurable in UAS data made up the majority of gaps in a temperate forest study site, and again point towards tropical forest biodiversity applications since understory vegetation in these environments are highly susceptible to light availability. Zahawi et al. (2015) created three-dimensional models of canopy in Costa Rica using imagery taken from an inexpensive (~$1,500) VTOL UAS. Canopy structure measurements extracted from the models (height, openness, roughness) were then used as predictors of frugivorous bird abundance. They found that UAS-derived point clouds were comparable to results from manned LiDAR measurements. Paneque-Gálvez et al. (2014) explored the use of small UAS for community-based forest monitoring, with potential benefit to biodiversity conservation in tropical forests. It is expected that UAS will find increased uses in biodiversity monitoring in tropical forests due to the unique fine-scale spatial and temporal data they offer, their versatility in tropical environments compared to conventional methods, and their relative affordability. This is especially likely since the hardware and associated algorithms will likely become smaller and more efficient.

5.2.4 Measurement of Tropical Forest Biodiversity using Airborne Hyperspectral Data

5.2.4.1 Overview

Airborne hyperspectral data shows great promise in mapping and understanding patterns of tropical forest biodiversity because of its high spatial resolution and high spectral resolution. Much recent work has shown that airborne hyperspectral can directly map species, functional group variation (e.g. lianas vs. trees), functional traits, and genetic variation. In addition to direct mapping of species and species properties, spectral variation can potentially be used as a proxy of diversity measures locally (alpha) and across the landscape (beta). However, in tropical forests, not all tree species can be identified, nor can animal diversity be directly measured. Hyperspectral data can be indirectly linked to diversity via understanding habitat characteristics linked to animal and plant biodiversity and habitat mapping.

5.2.4.2 Detection and Mapping of Tree Species

The remote detection and mapping of individual tree species (operational species mapping) in the tropics has been a driver of advances in tropical remote sensing. While great progress has been made in the understanding of the spectral uniqueness of tropical species, operational species mapping is still a major challenge. The key to separation of individual species with remote hyperspectral data is that spectral variation between species are greater than spectral variation within a species. At the leaf-level, these spectral patterns are dominated by variation in leaf biological and chemical compounds, including element and pigment composition, water content, and leaf thickness. Many studies have explored the uniqueness of species leaf

spectra, with the conclusion that some species are unique and therefore separable, while other species are not. These studies have been done for a handful of tropical tree species in Costa Rica (Castro-Esau et al. 2006, Zhang et al. 2006, Clark and Roberts 2012), in the Peruvian Andes and Amazon regions (Asner et al. 2014), and tropical wetland species in Jamaica (Prospere et al. 2014). While leaf-level separability can help inform the degree to which a species has a unique spectral signature, airborne hyperspectral data captures variation in crown properties, in addition to leaf chemical and biological properties. Factors such as leaf density, leaf angle, arrangement, and clumping, in addition to the amount of exposed wood all affect a species' spectral signature. Variation in crown properties may aid in spectral separability of species, driven by differences in reflectance of bark spectra (Clark and Roberts 2012), or other unique canopy traits such as leaf density, angle distribution, crown shape, and shading (Zhang et al. 2006). In a foundational paper for tropical tree species mapping, Clark et al. (2005) performed an automated species classification on crown spectra of seven emergent tropical tree species. Their results, which were further highlighted by Zhang et al. (2006) supported the need to consider the differences among crowns within a species. Despite advanced methods to suppress within-species variability (e.g+. Wavelet analysis), there are still some species that show little separability.

There are very few examples of the automated creation of a full-species map of a forested tropical landscape with an airborne hyperspectral image. The primary challenge of operational species mapping of a diversity canopy is inadequate field data of all species and automated classification algorithms to characterize the variability within and among species. This is an issue of confronting the inherent uniqueness, or lack thereof, in canopy spectra among a high number of species, in addition to a challenge in generating a sufficiently large set of data to build automated classification algorithms (Baldeck and Asner 2014a). One of the only tropical locations where a full species map of crowns has been develop is Hawaii, where 17 species were mapped with 73% accuracy (Féret and Asner 2012a). While mapping all species in a tropical forest is perhaps an infeasible goal, separating species of interest from a background of unknown species is also a large area of development and has been done successfully in Hawaii (Féret and Asner 2012b), and a temperate savanna ecosystem (Baldeck and Asner 2014b). The key to target species mapping is to ensure that the species being mapped have ecological relevance, and not just are those species that are spectrally unique, such as Dipterix panamensis in Costa Rica (Clark et al. 2005).

A second challenge involves the segmentation of a digital image into units that represent individual tree crown canopies. Generation of training data often involves manual segmentation of images (Clark et al. 2005, Féret and Asner 2012b). However, applying an automated classification also requires that the pixels in the image are divided into discrete units that represent a tree crown. The automated image classification is then applied to an entire crown unit, rather than individual pixels. Work in non-tropical ecosystems have used structural information from LiDAR data (light detection and ranging), which can help successfully resolve individual tree crowns (Strîmbu and Strîmbu 2015). Combined hyperspectral and LiDAR imaging systems, such as the platform used by the Carnegie Airborne Observatory (Asner et al. 2012), provide spectral data alongside canopy structural data. In tropical forests, where the canopy is more uniform relative to conifer forests or open savannas, the incorporation of spectral data with structural data may aid in automated crown delineation (Tochon et al. 2015). While often the focus of species mapping in the tropics, hyperspectral species applications are not limited to detection of individual tree species. Moderate resolution hyperspectral images (10-30 m pixel size) allow for the detection and mapping of single-species forest types, such as a tropical plantation (Fagan et al. 2015) or mangrove ecosystem (Kamal and Phinn 2011).

While the airborne data is available, the field-validated data and computer models are not yet at a place to achieve automated species mapping of a diverse topical forest canopy. To detect and map many (>10) individual species, other data forms may be necessary. These can include LiDAR data collected at the same time to get tree height and crown structure (Féret and Asner 2012b, Colgan et al. 2012), use of ancillary data of leaf and crown characteristics (Asner and Martin 2009), and high temporal imagery to look at phenology (Hesketh and Sánchez-Azofeifa 2012, Somers and Asner 2013). While operational species mapping in the species-rich tropics is still not achievable, great efforts have been made in recent years to understand other types of canopy diversity, primarily along the lines of foliar chemical and functional diversity.

5.2.4.3 Detection and mapping of other types of diversity characteristics (life forms, functional diversity, genetic diversity)

Understanding and predicting changes in an ecosystem may be best done by understanding the spatial and temporal patterns of plant functions, often grouping species into plant functional types. In tropical systems, remote mapping of plant functional types is advantageous because it reduces the high number of species into groups that have meaning for ecosystem dynamics and community assembly. The distinction between lianas and canopy tree species is one example of how remote sensing can be used to detect and map plant functional groups. Because of their increasing presence in neotropical tropical forests due to changes in climate conditions (Wright et al. 2004), remotely detecting the abundance and distribution of lianas could be useful to understanding ecosystem dynamics. It has been shown that in tropical dry ecosystems, leaves of liana species have higher water content and thinner leaves than their co-occurring tree species (Castro-Esau et al. 2004, Sánchez-Azofeifa et al. 2009, Ball et al. 2015). These differences are detected in the spectral reflectance of individual leaves (Castro-Esau et al. 2004, Kalacska et al. 2007), canopy spectra (Sánchez-Azofeifa and Castro-Esau 2006), and canopy spectra from airborne images (Kalacska et al. 2007).

In recent years, there has been a large effort to map functional traits of vegetation and tree canopies of tropical forests to understand how these ecosystems are changing (Asner et al. 2015). The common functional traits that are relevant to remote sensing applications foliar chemical and pigment concentrations, leaf dry matter and surface area (as Leaf Mass per Area or Specific Leaf Area, and leaf water content (Asner 2015). Relationships between functional diversity and spectral reflectance have been examined across tropical dry forest succession (Alvarez-Añorve et al. 2012), and in Amazon to Andean tropical forests (Asner et al. 2014).

Genetic diversity of tropical forests is also important. It was found that airborne hyerpsectral data (AVIRIS) can distinguish geonotypes of a highly-clonal temperate species (Populus tremuloides). While genotype detection may be infeasible for a species-rich tropical forest, it could play an important role in understanding diversity of monospecific forests (Hart 1990).

5.2.4.4 Mapping community species richness and diversity measures

In addition to discriminating and mapping individual tree species, airborne hyperspectral data has been successfully used to map local tree diversity (alpha diversity) as well as landscape turnover in tree species composition (beta diversity). The high spatial resolution of airborne data is advantageous because it captures the between-crown heterogeneity that should increase with higher diversity levels (see spectral diversity hypothesis below). High spectral resolution is advantageous because the small spectral bands and full spectrum coverage are more likely to pick up small chemical and compositional differences among tree species.

Many methods of detecting and mapping species diversity are purely statistical. Techniques such as Partial Least Squares Regression PLSR (Harris et al. 2015, Schmidtlein et al. 2007, 2012), nearest neighbor similarity (Thessler et al. 2005) or random forests (Laurin et al.

2014) are used develop relationships between hyperspectral data and floristic gradients based on species or plant functional type gradients, which are then predict continuous trends in floristic gradients and biodiversity.

Others methods are based on theoretical relationships between spectral reflectance and diversity. Vegetation indices such as Normalized Difference Vegetation Index (NDVI) have been used, mostly with satellite and multi-spectral sensors, to map diversity (Gillespie et al. 2005; 2009; Hernández-Stefanoni et al. 2012) based on the hypothesis that higher productivity is associated with greater diversity at least locally (Chisholm et al. 2012) which is the scale at which airborne systems operate. However, the main theoretical model applied to mapping species diversity for high spatial and spectral resolution images is the Spectral Variation Hypothesis (Palmer 2002; Rocchini et al. 2004, 2007, 2010, 2015; Medina et al. 2013) that posits that greater heterogeneity in pixel spectral values is correlated with greater heterogeneity in species composition. For alpha diversity, this means that areas with greater local diversity will have greater local spectral variation among pixels. For beta diversity, this means that two locations with few shared species (low species similarity) will have low spectral similarity.

Alternatively, based on the success of discriminating individual crowns mentioned previously, recent work has shown that a more direct calculation of species diversity using airborne hyperspectral data is possible. In these cases, species locations in an image are mapped using either supervised or unsupervised methods (Baldeck and Asner 2013; Feret and Asner 2014), then alpha and beta diversities measures are calculated from the pixel or crown representations of species locations.

Limitations to mapping biodiversity measures using airborne hyperspectral data include the requirement of field measurements of alpha or beta diversity, which are extremely time consuming in high diversity tropical forests. Using proxy taxa, such as ferns, instead of a complete inventory, has been used in some cases (Thessler et al. 2005). These methods do not address animal diversity, which cannot be directly detected from hyperspectral data, and must use indirect methods described in the following paragraphs. Finally, there have been no reports of how well these methods work in detecting changes in biodiversity through time. These types of studies will be an important test of what degree the hyperspectral data detects plant species themselves, or underlying environmental gradients.

5.2.4.5 Detection of biodiversity stressors from hyperspectral data

Hyperspectral imagery can predict the distribution of animals and plants that may not be directly detectable in aerial imagery by measuring fine-scale changes in habitat structure (Ghiyamat and Shafri 2010). One approach is to correlate spectral variability with biodiversity (Rocchini et al. 2010), assuming that spectral variability indicates diversity of canopy traits that translate into species richness (Carlson et al. 2007) or that increased spectral variability represents increased habitat heterogeneity that can host a greater number of species than homogenous habitats (Leutner et al. 2012). Another approach is to use hyperspectral data to produce a map of habitat suitability for the organisms of interest and then apply a species distribution model to the classified habitat (Eldegard et al. 2014). The latter approach may be particularly useful for cryptic plants and animals that are not directly detectable from aerial images. For example, high resolution aerial imagery can be applied to predict the distribution of coral-reef associated fishes (Simon J. Pittman and Anders Knudby 2014). Both approaches have caveats. The relationship between spectral diversity and canopy trait diversity may be complex and mediated by other sources of variability in remote sensors (Rocchini et al. 2010). Relating habitat heterogeneity to species abundance data via species distribution models is still an active topic of research in ecology (Merow et al. 2014), and presents challenges that are independent of the quality of habitat data from remote sensing. These challenges include

accounting for imperfect detection (Lahoz-Monfort et al. 2014) and spatial autocorrelation in abundance that is unrelated to habitat quality (Crase et al. 2014).

Hyperspectral data collected from aerial platforms can measure habitat degradation related to biodiversity loss. Invasive plant species represent a serious threat to native plant biodiversity (Pyšek et al. 2012) and can be detected using hyperspectral data (Ustin et al. 2002, Underwood et al. 2003, He et al. 2011). For example, hyperspectral data in conjunction with LiDAR data was used to detect invasive tree species in a Hawaiian rainforest with <7% error rates in detection at spatial scales of ~7 m2 (Asner et al. 2008b) and to show that, in Hawaii, invasive plants displace native species and fundamentally alter forest structure (Asner et al. 2008a). Hyperspectral imagery can also measure degradation in habitat structure, including soil degradation (Shrestha et al. 2005, Townsend et al. 2008) and fire damage (Robichaud et al. 2007). Because hyperspectral imagery reflects canopy chemical composition, plant stress that causes changes in leaf traits is also detectable with this data source. Plant stress related to pathogen damage can be measured in single species plantations (Delalieux et al. 2009), including oil palms (Shafri and Hamdan 2009). At the community level, changes in forest structure related to insect damage can also be measured using hyperspectral data (Pontius et al. 2008). Because herbivores and pathogens play critical roles in maintaining tropical forest biodiversity (Bagchi et al. 2010, Comita et al. 2010), it is anticipated that the ability to measure effects of these organisms in tree canopies and over large scales will provide an indispensable tool for understanding and managing tropical biodiversity.

5.2.4.6 Collection of hyperspectral images

Airborne hyperspectral sensors are typically mounted on airplanes, but sensors are being developed that can also be mounted on Unmanned Aerial Vehicles (UAVs). A major limitation of airborne hyperspectral images is their cost and availability. Airborne hyperspectral data is not routinely collected by government agencies as is satellite data. To operate one's own hyperspectral sensor is a significant investment, including purchasing a hyperspectral sensor (tens to hundreds of thousands of dollars), owning or renting an aircraft or drone, and learning to operate the sensor and platform. The cost of the sensor is affected by the spectral range that it covers. Sensors that cover the visible (VIS) and Near Infrared (NIR) only are less expensive than sensors that cover the VIS, NIR and short wave infrared (SWIR). Sensors with just VIS/NIR may be equally suited for measuring vegetation density, but the additional information in the SWIR bands can be important for analyzing biodiversity in highly diverse tropical forests. Some hyperspectral sensors used in hyperspectral analyses of tropical forest biodiversity in recent years include: Carnegie Airborne Observatory (Carnegie Institution-US; Asner et al. 2012); AISA Eagle (Specim-Finland; Laurin et al. 2014); Hymap (HyVista-Australia; HySpex VNIR-1600-Norway; Fagan et al. 2014)

5.2.4.7 Image processing

Analyzing hyperspectral data also poses some challenges. The images are much larger than multispectral data because each pixel contains so many values, thus processing can take a long time. There is a high degree of correlation between bands in hyperspectral data, such that using data reduction techniques that remove noise and redundancy, and target areas of the spectra relevant to ecological analysis, are often used. These include Miminum Noise Fraction (Underwood et al. 2003); band indices targeted at particular vegetation features such as water content or plant health (Roberts et al. 2011); or spectral mixture analysis (Gillespie and Adams 2006). Standard commercial remote sensing software packages, including ENVI, ERDAS Imagine, and MATLAB have many analysis tools specific to hyperspectral data, but are expensive. Free software that is designed specifically to handle hyperspectral images include: Python Hyperspectral Toolbox, Gerbil, Opticks, TNTmips Free and packages in R.

5.2.5 Airborne Active Microwave Remote sensing

5.2.5.1 Introduction

Airborne active microwave remote sensing, or more colloquially referred to as radar remote sensing, has been an active field of research since the early 1990's, with most technological development focused on the interpretation of synthetic aperture radar (SAR). Applications have encompassed land cover classification and various forest attributes such as canopy height, aboveground biomass, phenology, inundation, and forest disturbance. Before expanding upon the advantages and challenges encompassed with radar remote sensing, it is useful to review some key concepts relating to active microwave remote sensing of vegetation. Backscatter is the reflection of the transmitted microwaves, and brightness refers to the intensity of the backscatter. The backscatter response from vegetation differs across the radar bands. Generally, the longer wavelengths penetrate deeper into vegetated surfaces and are less affected by clouds or other atmospheric effects. For example, the P-band (lambda: 30-100 cm) can penetrate through canopies, woody biomass, and into soil, although it can reflect from tree trunks. L-band (lambda: 15-30 cm) can also penetrate canopies and into the biomass, but will register less signal from tree trunks. C-band (lambda: 3.75-7.5 cm) can penetrate partially into the canopy and even detect fine branch structure from deciduous trees, while the X-band (lambda: 2.4-3.75 cm) can only penetrate the canopy surface (Jones and Vaughan, 2010).

Radar remote sensing over forests has most often been utilized to generate polarimetric SAR (PolSAR) and interferometric SAR (InSAR) imagery to characterize canopy height, biomass, or deformation relating to forest disturbance. Unlike multi-spectral imagery from optical remote sensing, radar remote sensing is used to generate "multi-specular" images relating to the different polarization responses of the radar backscatter. The naming designation of polarized backscatter is described with polarization from the transmitter first, followed by the polarization received. For instance, if the transmitter emits horizontal polarized (H) waves, and the receiver is tuned to vertical (V) waves, the resulting backscatter is considered HV. A full polarimetric sensor will generate HH, HV, VH, and VV signals. The interaction of the microwave polarity with the surface (and atmosphere depending on the band) determines the degree to which the backscatter is depolarized. A smooth surface may reflect a high degree of the incoming polarity, whereas a Lambertian surface such as forest canopy will act to cross-polarize the incoming microwaves (HV and VH backscatter) (Jensen 2000).

Interferograms are generated from at least two SAR images from repeat passes or generated simultaneously. For example, the Shuttle Radar Topography Mission mapped the Earth's topography with two C-band radar antenna separated by a 60 m mast (Farr et al. 2007). While this design could produce high precision interferograms, the design is impractical for most airborne platforms because the distance between antennas was invariant. The Jet Propulsion Laboratory has developed a new platform, UAVSAR, that automates the flight path of the plane to be within 10 m of the prespecified route (Rosen et al. 2006). The exceptionally high spatial accuracy of multiple flight paths allows for interferograms to be generated that can map the surface, or that can show temporal change in structure when more than one flight has been made.

5.2.5.2 Advantages

There are distinct advantages that are unique to active radar remote sensing, as compared to optical airborne systems. Perhaps most importantly, radar systems can gather data irrespective of the time of day, and many radar bands useful to the remote sensing of vegetation are relatively less-affected by cloud cover or precipitation. Airborne SAR systems

can be flown at higher altitude and collect data over a larger range of angle of incidence than corresponding optical remote sensing. This allows for a swath width that can be roughly ten times larger than that of small foot-print LiDAR (Balzter et al 2007). For instance, NASA JPL's UAVSAR polarimetric L-band has a swath range of 16 km (Rosen et al. 2006), in comparison to the Carnegie Airborne Observatory LiDAR swath width of 1.5 km (Asner et al. 2013).

Next, the longer microwave bands can infer environmental properties that are generally indistinguishable for either active or passive optical remote sensing. The P and L bands can indicate the number of stems in a forest because trees greater than a given diameter will act as corner reflectors and emit a higher brightness. P and L bands can be used to infer soil moisture, or if there has been flooding that has been obscured from the canopy (Hess et al. 1995). Recently developed algorithms have even been able to simultaneously estimate tropical forest soil moisture with aboveground biomass with less than 4% and 15% relative error, respectively (Truong-Loi et al. 2015). Airborne radar may present another pertinent application relating to the degradation of forest, considering the expansion of petroleum industries into tropical forest regions (ex: Finer et al. 2008). SAR has been often been used with great effect to identify oil spills because the oil acts as a specular reflector on the water which reflects more diffusely. Research with UAVSAR data has indicated probable oil spills in areas of complex vegetation and sediment such as the Louisiana salt marshes north of the Deep Water Horizon oil spill (Ramsey et al. 2011).

5.2.5.3 Challenges and Future Opportunities

The processing, analysis, and interpretation required of raw radar data to extract useful environmental information are undoubtedly non-trivial. Even after imagery has been orthorectified, the end user must remain aware of the caveats associated with radar. For instance, airborne radar systems are most often side-looking so topography can create "shadowing" on surface areas with aspects opposite to that of the plane's flight path. Next, the accuracy for some environmental metrics, such as canopy height, is generally less than that of LiDAR systems. Polarized L-band radar exhibited much higher error than LiDAR when estimating aboveground biomass with linear regression models at biomass ranges of <30 Mg ha-1, but the size of this error decreased with increasing biomass per hectare (Tanase et al 2014). Even in a relatively homogenous managed pine plantation, L-band and X-band InSAR exhibited 50-100% higher RMSE than LiDAR derived estimates of stand height (Balzter et al. 2006). One of the largest hurdles for radar remote sensing to overcome for the past two decades has been that radar backscatter saturates with biomass, especially beyond 100 Mg ha-1 for even the P-band, while shorter wavelengths saturate at considerably lower levels of biomass (Imhoff, 1995). More recent analysis has used multiple polarimetric bands with InSAR data to begin overcoming this limitation, especially with regards to high biomass tropical forests (ex: Saatchi et al. 2011).

Various airborne SAR campaigns have been flown over the last two decades (eg: UAVSAR, TropiSAR), although the enthusiasm for biomass mapping via radar has perhaps been dampened because of the accelerated development of LiDAR capabilities to more accurately estimate canopy height. Despite the challenges of working with radar data, a number of new multi-sensor data-fusion approaches suggest a bright future for radar remote sensing, where SAR data is used in conjunction with LiDAR or passive optical sensors to improve the accuracy of forest biomass estimation (ex: Treuhaft et al. 2004; Sun et al. 2011; Banskota et al. 2011).

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5.3 TIME-SERIES ANALYSIS FOR FOREST COVER CHANGE

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5.3.1 Background

During the recent decade, forest monitoring methods using satellite image time series have been rapidly evolving. Many studies have demonstrated the utility of time series of medium resolution optical data for mapping and quantifying forest change ([1]–[5], and others). The opening of the Landsat archive to the global public in 2008 is arguably the most important factor in the development of these novel approaches, as this decision effectively removed substantial cost barriers faced by many users. Beginning in 2010, an effort to consolidate all historical Landsat imagery into one central repository has further facilitated historical forest change mapping and quantification [6]. This opening and consolidation of all Landsat data, paired with the centralized pre-processing and delivery of surface reflectance and cloud mask products [7], [8], has effectively brought about a paradigm shift in satellite-based forest monitoring.

While coarse resolution satellite data such as MODIS remain important resources for monitoring global dynamics, the availability of Landsat data to the public has triggered a shift from coarse resolution mapping of change to medium spatial resolution (30m), allowing for the monitoring at spatial scales often demanded by many ecological applications [9]. At this spatial resolution, methods have shifted from conventional bi-temporal change detection approaches [10], [11] to time series analysis [12], [13]. While many methods in which two images are compared have been shown to be robust, the timing of change is frequently misrepresented using bi-temporal change detection methods. Landsat time series, on the other hand, provide a synoptic view of forest changes in both time and space, allowing for wall-to-wall mapping of annual forest change [2] or near real-time forest change alerts [14].

Operational forest monitoring for such purposes as the Reducing Emissions from Deforestation and Degradation (REDD+) mechanism increasingly relies on annual Landsat time series data [4], [15], [16]. As biodiversity moves into the range of forest monitoring objectives, including theintegration of Essential Biodiversity Variables (EBV) into existing monitoring frameworks [17], [18], the question of whether such time series approaches adequately address forest monitoring objectives needs to be critically addressed. A recent study comparing bi-temporal, annual or "all-available" Landsat time series, for example, has suggested that only by using all available observations can gradual land surface changes be adequately captured [19], an insight with likely implications on biodiversity monitoring in forest ecosystems. Despite its limitations resulting from the spatial resolution of Landsat data (e.g. in dry tropical forests, where fine resolution imagery are required to quantify and forest cover change), the temporal depth and expected continuity of the Landsat archive positions it as one of the best tools for biodiversity monitoring in forest ecosystems.

Table 5.3.1.1: Selection of time series analysis methods for forest monitoring

LTS type	Method / Algorithm	Description	References	Availability
Annual imagery or composites	Vegetation Change Tracker (VCT)	Forest disturbance and regrowth monitoring using integrated forest z-scores (IFZ)	[3]	N/A
	LandTrendR	Analysis and segmentation of temporal trajectories to describe forest disturbance, regrowth and trends	[20]	http://landtrendr.forestry.oregonstate.edu/content/landtrendr-code-0
	National to global scale annual forest gain/loss	Bagged decision tree classification using temporal variables	[2], [15], [21]	N/A
	Best Available Pixel (BAP) methods	Generation of annual BAP image composite time series based on criteria related to day of year, proximity to clouds, etc.	[22]	N/A
All available data	Continuous Change Detection and Classification (CCDC)	Dynamic season-trend model fitting, break detection and dynamic land cover classification using all available data	[23][24]	https://github.com/prs021/ccdc
	Breaks For Additive Season and Trend (BFAST) Monitor	Season-trend model fitting, break detection and monitoring using structural change monitoring methods and all available data	[25]–[28]	http://github.com/dutri001/bfastSpatial http://bfast.r-forge.r-project.org/
	Forest probability time series	Time series of forest probability estimates using all available data	[29]	N/A

Two current aspects of forest change detection methods relevant to biodiversity monitoring using Landsat time series are described in this chapter. First, the use of all available Landsat data to understand forest dynamics beyond abrupt land cover changes is described in the context of post-disturbance regrowth (Chapter 1.1.1.2). Here, a statistical data-driven method is proposed to understand the fate of forests following disturbances. Second, combining time series of different sensors to compensate for the limitation of single sensor monitoring efforts is described in Chapter 1.1.1.3. Such data gaps can occur in optical time series due to persistent cloud cover in the tropics or unexpected failures experienced by certain systems (e.g. ALOS failure in 2011), and the integration of SAR with optical time series is proposed to address this limitation.

5.3.1.1 Example I: Disturbance-Regrowth Monitoring using Landsat Time Series

Objective statistical methods to monitor disturbances using dense remote sensing time series have recently been demonstrated using the Breaks For Additive Season and Trend (BFAST) Monitor method [28]. Recent research has demonstrated this method over a number of tropical forest sites, allowing for the monitoring of small-scale agriculture-driven disturbances in sub-Saharan Africa [25], disturbance monitoring in the dry tropics [26], or disturbance monitoring in data-limited areas [27]. These studies demonstrate the utility of BFAST Monitor as a robust data-driven tool for objective monitoring of forest disturbances, despite the challenges associated with forest monitoring in moist tropical regions.

The ability to monitor forest dynamics following a disturbance is critical to understanding impacts on biodiversity and opportunities for conservation and mitigation activities. To date, few methods have been demonstrated that can measure post-disturbance forest regrowth using dense Landsat time series. In a recent study, DeVries et al. (2015) demonstrate an approach for monitoring post-disturbance forest regrowth using statistical principles similar to those behind the BFAST Monitor method [30]. In short, this method monitors the moving sums (MOSUM) of residuals derived from a historical stable forest model. The moment that the MOSUM values return to a 'stable' state based on this historical period is labelled as 'regrowth'. Figure 5.3.1.1.1 demonstrates the use of MOSUM for monitoring post-disturbance growth for a time series of one Landsat pixel. This example is based on a time series of the Normalized Difference Moisture Index (NDMI) from Landsat 5 and Landsat 7, where NDMI is computed as (Band4 – Band5) / (Band4 + Band5). In this method, a stable history devoid of disturbances or significant noise is first identified. Then, a season model is fit to the stable history period and projected into the monitoring period. Just as in other BFAST-related methods [28], [31], the approach is flexible with regards to the type of model fit to the history period. After projecting the model, the MOSUM is computed, based on the residuals (expected minus actual observations) for every time point in the monitoring period. The moment after the initial disturbance at which the MOSUM crosses below the critical boundary, computed based on a statistical significance level, is interpreted as regrowth.

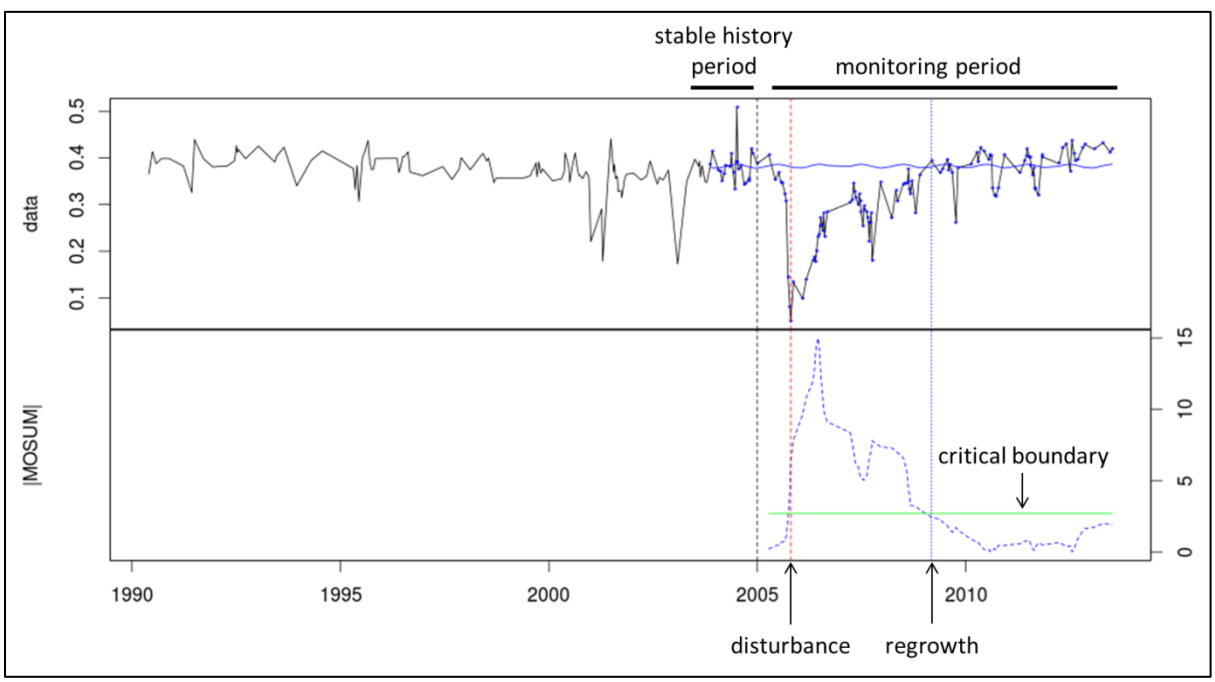

Figure 5.3.1.1.1: Demonstration of the use of a Moving Sum (MOSUM) parameter to monitor post-disturbance regrowth over a single Landsat pixel. The normalized difference moisture index (NDMI) is used as input data (top panel) in this example. The blue line in the top panel represents the model fitted to the history period and forecasted into the monitoring period.

A demonstration of this automated regrowth monitoring method over a study site in Madre de Dios, Peru showed that the algorithm can detect regrowth events with very high user's accuracy (i.e. low false positives), but with relatively lower producer's accuracy (i.e. higher false negatives). In other words, the method rarely confused forest regrowth with other phenomenon, but frequently missed actual regrowth events. The latter observation was found to be due to timing of the disturbances and limitations to the Landsat time series themselves: earlier disturbance events allowed for better monitoring of regrowth simply because there were more data in the time series following the event, whereas late disturbance events had fewer observations following them from which regrowth could be determined with certainty.

This method is freely available as the 'regrowth' package in R (http://github.com/bendv/rgrowth).

5.3.1.2 Example II: Combining Landsat and SAR time series for monitoring forest cover loss

The main limitation of optical-based time series methods in tropical regions in general is the restricted data availability due to frequent cloud cover resulting in sparsely sampled time series [32], [33]. In some regions, such as parts of the Amazon Basin or Central Africa, persistent cloud cover inhibits full optical coverage from Landsat-like sensors even when compositing is performed over a period of one to three years [32], [15], [34]. This results in late detection of changes and prohibits intra-annual monitoring. Efforts combining optical and Synthetic Aperture Radar (SAR) time series imagery have demonstrated their potential to improve forest cover loss monitoring in tropical regions, where cloud cover limits time series approaches relying on optical data only [27], [35]–[37].

For combining optical and SAR time series Reiche, Verbesselt, et al., (2015) recently introduced the pixel-based Multi-sensor Time series correlation and Fusion approach (MulTiFuse). Figure 5.3.1.2.1 illustrates the main steps of applying the MulTiFuse approach to fuse optical and SAR image time series. The MulTiFuse approach first models the relationship of two overlapping time series, using an optimized weighted correlation. The resulting optimized regression model is used to predict and fuse the two time series. A time series analysis method can subsequently be used to detect forest cover loss within the fused time series.

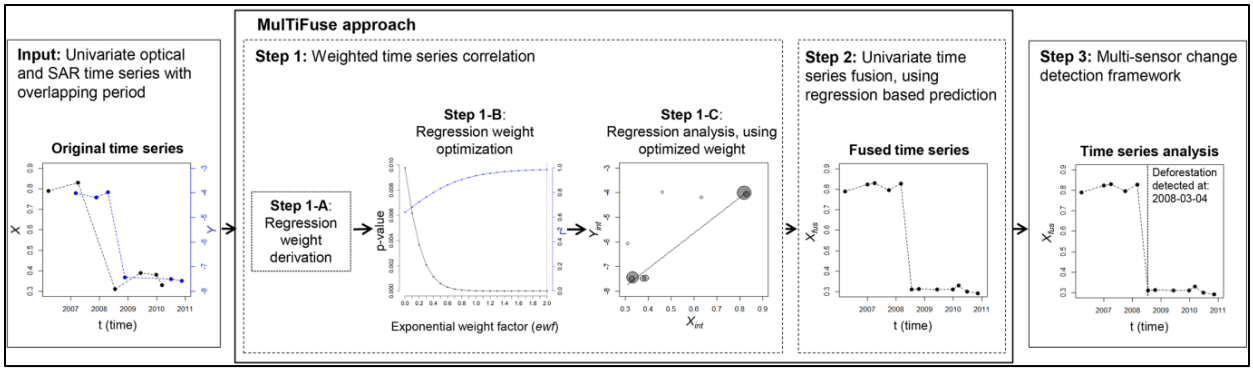

Figure 5.3.1.2.1: Schematic overview of MulTiFuse approach to fuse optical and SAR image time series.

The MulTiFuse approach was applied to fuse Landsat NDVI (~6.5 observations/year) and ALOS PALSAR backscatter (~2 observations/year) time series acquired at a managed evergreen tropical forest site in Fiji. To detect the forest cover loss due to managed logging activities, BFAST Monitor [28] was used for time series analysis. Three-monthly reference data (4 time steps per year) was utilized to validate and assess the spatial accuracy and the temporal accuracy (timing of the change) (Figure 5.3.1.2.2). The temporal accuracy is measured as the mean time lag of detected changes. For the fused Landsat-PALSAR time series the overall accuracy was 95.5% with a 1.59 month mean time lag of detected changes. The MulTiFuse approach showed good results when dealing with abrupt changes (deforestation), but needs to be tested and evolved for gradual changes such as forest degradation and when dealing with seasonal tropical forest.

The MulTiFuse approach is freely available as the 'multifuse' package in R (http://github.com/jreiche/multifuse).

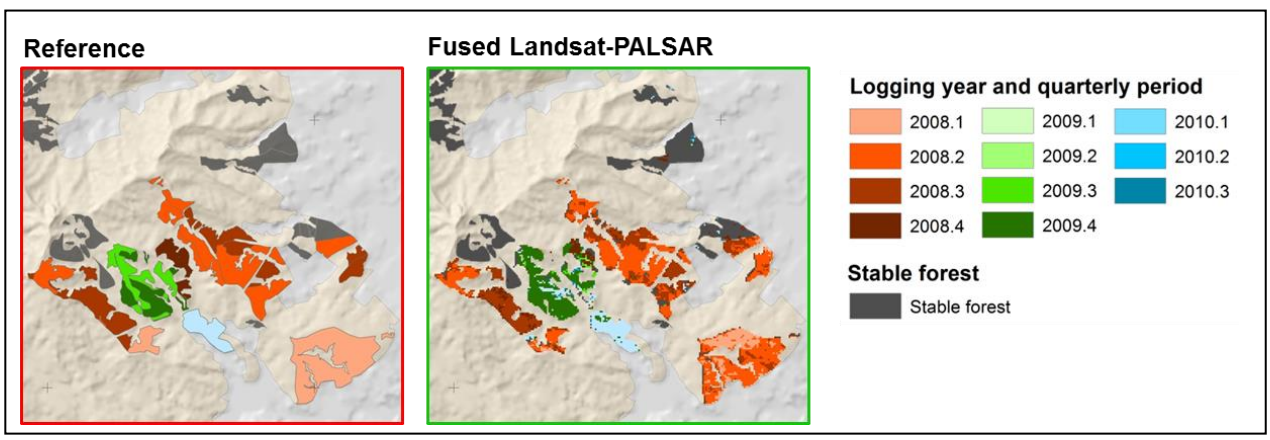

Figure 5.3.1.2.2: Map results showing detected deforestation between 01/2008 – 09/2010 for the fused Landsat-PALSAR case compared to the reference data for a subset of the managed evergreen tropical forest site in Fiji. The time stamp "2008.1" refers to the first quarterly period of 2008 (January – March).

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6 THE VALUE AND OPPORTUNITIES OF COMMUNITY- AND CITIZEN-BASED APPROACHES TO TROPICAL FOREST BIODIVERSITY MONITORING

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3. Durrell Wildlife Conservation Trust Madagascar, Antananarivo
4. Life Net Nature, Willcox, AZ, USA
5. Engineering and Innovation Department, The Open University, UK
6. FundAmazonia, Iquitos, Peru
7. University of Copenhagen and NORDECO, Denmark
8. Independent researcher
9. Earthwatch Europe, Oxford, UK
10. USA National Phenology Network, Tucson, AZ, USA
11. Nordic Foundation for Development and Ecology (NORDECO), Copenhagen, Denmark
12. Earthwatch Institute Brazil
13. Edinburgh Napier University, Edinburgh, Scotland
14. Dept Conservation Ecology & Entomology, Faculty of AgriSciences, University of Stellenbosch, Matieland, South Africa
15. Department of Geography, Royal Holloway University of London; United Kingdom
16. Wageningen University & Research, Wageningen, The Netherlands
17. Tropic Ventures Sustainable Forestry & Rainforest Enrichment Project, Las Casas de la Selva, Puerto Rico
18. NORDECO, Copenhagen, Denmark
19. University of Copenhagen, Denmark
20. Tropic Ventures Sustainable Forestry & Rainforest Enrichment Project, Las Casas de la Selva, Puerto Rico
21. National Polytechnic Institute, CIIDIR-Oaxaca, Mexico

6.1 INTRODUCTION

Earth Observation (EO) refers to the direct and indirect measurement of the Earth's surface that can be undertaken using satellites, aircraft, on the ground and underwater using active and passive sensors (O'Connor et al., 2015). EO provides a valuable source of information for biodiversity monitoring of tropical forests (chapter 2; Turner et al., 2003; Gillespie et al., 2008; O'Connor et al., 2015), in particular from space-based platforms due to their extensive spatial and temporal coverage. With data from the new Copernicus Sentinel satellites now coming online and the planned Biomass mission of the European Space Agency (ESA), biodiversity monitoring could greatly benefit from these higher spatial and temporal resolution measurements.

The Group on Earth Observations Biodiversity Observation Network (GEO BON) has proposed a set of 22 Essential Biodiversity Variables (EBVs) (Pereira et al., 2013a). These EBVs provide quantifiable measures that can be used to monitor targets, e.g. the Aichi biodiversity targets, or they can be employed within conservation monitoring and research more generally. O'Connor et al. (2015) have surveyed experts in EO and biodiversity in order to identify a subset of EBVs, referred to as RS-EBVs, which can be entirely or partially monitored by remote sensing (RS). O'Connor et al. (2015) have shown that these RS-EBVs can aid in the monitoring of 11 out of 20 Aichi targets.

Although remote sensing has clear advantages for monitoring in terms of spatial and temporal coverage as mentioned previously, field level data are still needed to complement remote sensing if conservation measures are to be monitored in a meaningful way (Stephenson et al., 2015). From a remote sensing perspective, field level data are needed for calibration and validation of products derived from EO but also for those EBVs where remote sensing cannot be used for monitoring.

To fill this information gap, the participation by community members in monitoring and science (Bonney et al., 2009b; Chandler et al. 2016b) shows considerable potential for helping to collect ground-based data, that together with analysis, could contribute to international environmental agendas (Danielsen et al., 2014c). Several important factors have led to a dramatic increase in citizen science projects as well as interest in greater leveraging of citizen science (Theobald et al., 2015). The recent creation of professional associations dedicated to the advancement of the field of citizen science is helping to develop best practices, standards and lessons learned that will improve both ends of the equation - namely valuable data collected and meaningful participant experience. For example, the Participatory Monitoring and Management Partnership (www.pmmpartenrship.com) has been created to promote the dialogue between communities involved in natural resource and biodiversity monitoring as well as to document and disseminate best practices in community-based monitoring.

Another important advancement in citizen involvement has been driven by recent advances in technology and the proliferation of mobile devices, allowing more citizens to contribute to environmental monitoring and conservation at both local to global scales. Citizen science is now seen as being able to fill the perceived gap between an increased demand for monitoring and decreasing funding for professional staffing that traditionally performed in-situ monitoring, for government natural resource agencies. Additionally, citizen science can help boost civic engagement with a promise of building social capital that can be used to better inform and support management and policy initiatives, and empower individuals and communities (Constantino et al., 2012; Crain et al., 2014).

There are many examples of successful citizen science biodiversity monitoring projects across multiple ecosystem types (e.g. see http://scistarter.com/; http://www.earthwatch.org)

including tropical forests. Many of these projects are focused on species occurrence and phenology, including invasive species. They range from very intensive projects (www.earthwatch.org), which require considerable training and commitment on the part of citizens, to easy-to-use mobile applications (e.g. iNaturalist)), or Do-It-Yourself (DIY) kits that anyone can download and use. GEO BON is also currently developing a BON in a BOX toolkit to support development of biodiversity observation systems at the country level, including tools for citizen science. The first region for the BON in a BOX toolkit will be Latin America hosted by Instituto Humbodt and GEO BON.

More recently, citizen science, in this case community-based forest monitoring, has been considered a viable approach in the framework of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) for the monitoring of carbon (Danielsen et al., 2011, 2014a) and many new schemes are starting (Danielsen et al., 2013). Integrating biodiversity monitoring within community-based forest monitoring initiatives could therefore provide a potential source of calibration and validation data for products derived from EO. See section 8 for synergies between biodiversity monitoring and REDD+.

This chapter presents case studies of successful projects that have involved the community and citizen scientists in the monitoring of different biodiversity indicators and variables. We start with an overview of the various terms that can be found in the literature to denote the involvement of local people in monitoring activities including citizen science. This is followed by an assessment of the needs of the biodiversity community in terms of the variables of interest for monitoring and scientific research, the role of remote sensing in measuring these variables and what calibration and validation data are needed from ground-based measurements. The case studies serve to highlight what types of data are currently being collected by communities, how these relate to the key variables of interest and what gaps in ground-based monitoring exist.

Although citizen and community-based monitoring have considerable potential in supporting data collection for EO, the creation and development of a citizen science program is not a trivial task. Attracting, training and maintaining sufficient numbers of citizen scientists to meet monitoring needs is a significant endeavour (Chandler et al., 2016). There are many examples of programs where the cost of running the programs outweighed the benefits in terms of data collected, and in terms of the quality of the experience for the participants - ultimately resulting in a lack of sustainability of the programs. One key outcome from reviews of programs to date is the need to find a balance between the data gathering needs for the monitoring programs with delivering tangible (direct) benefits to the community members participating and contributing their time and effort (Chandler et al., 2016; Shirk et al., 2012). Thus, the final part of this chapter addresses these types of issues by providing guidelines for setting up a community or citizen-based project for tropical biodiversity monitoring, drawing upon experiences from many different past and ongoing projects around the world.

6.2 TERMINOLOGY

The term citizen science is often conceived by its practitioners in the broadest sense - i.e. the participation by the non-scientific public in scientific research and monitoring; see the review of typologies in Bonney et al. (2009b), Wiggins and Crowston (2011) and Haklay (2015). The bulk of current projects labelled as environmental "citizen science" occur in temperate and western countries where many if not most participants engage in these projects as a hobby or in service of their "community" (Haklay, 2015). In practice and for the purpose of this

chapter, it is useful to differentiate community-based monitoring as a distinct subset of citizen science. In the tropics, much of the important monitoring engages local community members, where many participants are and remain active users of their natural environment (Danielsen et al., 2005a; Haklay, 2015).

Evans and Guariguata (2008) have provided a meta-review of existing literature on participatory monitoring in tropical forest management as well as the lessons learned from these projects. Although many of these initiatives have been aimed at sustainable management of tropical forests rather than biodiversity monitoring, there are examples of where monitoring has included variables of interest to the biodiversity community (Ojha et al., 2003; Lawrence et al., 2006). Because of the importance of these works in considering how best to engage local communities in forest monitoring, we provide Table 6.2.1 which outlines the terminology that appears in Evans and Guariguata (2008) along with their original cited sources; we have expanded this to include community-based monitoring more generally and monitoring by citizen science programs.

Table 6.2.1: Summary of terminology

Term	Definition	Source
Participatory monitoring	The systematic collection of information at regular intervals for initial assessment and for the monitoring of change. This collection is undertaken by locals in a community who do not have professional training. The term is often used in the context of monitoring forests for their sustainable management but can be extended to other ecosystem services.	Guijt (2007); Evans and Guariguata (2008). See also Wikipedia (2015)
Locally-based monitoring	This is similar to participatory monitoring but monitoring can also be undertaken by local staff from government authorities.	Danielsen et al. (2005a)
Collaborative monitoring	Local monitoring that is embedded within resource management decision-making and part of an iterative learning cycle. The monitoring processes are also heavily driven by the need to be locally relevant.	Guijt (2007)
Participatory Assessment, Monitoring and Evaluation of Biodiversity (PAMEB)	Biodiversity monitoring, evaluation and assessment by non-specialists. Similar to the aims of many citizen science programs but with a specific emphasis on biodiversity.	Lawrence and Ambrose-Oji (2001); Lawrence (2010)
Joint monitoring or multi-party monitoring	Monitoring by local people together with local government authorities where the emphasis appears to be on enforcement.	Andrianadrasana et al. (2005); Bagby et al. (2003)
Self-monitoring	The monitoring of activities by local people which are related to natural	Noss et al. (2005); Constantino et al.

Term	Definition	Source
	resource use, e.g. hunting or the harvesting of timber.	(2008)
Event monitoring	The monitoring of events (e.g. fires, invasive species) by local people when they occur or as part of a census or other planned activity.	Stuart-Hill et al. (2005)
Community-based ecosystem monitoring	Monitoring involving non-specialists that are organized by government or conservation organizations in developed countries.	Whitelaw et al. (2003)
Community-based monitoring	Monitoring of environmental resources via the engagement of local communities to provide accountability, transparency, sustainability and inclusion in decision-making. Used also in the context of the monitoring of health programs and other public services.	Constantino et al. (2008); Wikipedia (2013)
Citizen science monitoring programs	The involvement of citizens in scientific research from data collection (**contributory**) to analysis and design (collaborative) to co-creation, in which citizens are involved in all stages of the scientific process. Also referred to as public participation in scientific research.	Bonney et al. (2009a, 2009b)

For the sake of clarifying important differences in approaches, we will focus on two forms of engaging community members in the data collection needed for monitoring and field research - community-based monitoring and "citizen science". For the purpose of this chapter, we use ***community-based monitoring*** to denote the involvement of local community members in the data collection process, whether for the purpose of sustainable resource management, biodiversity monitoring or greater involvement in decision-making at the local level. We distinguish this from ***citizen science monitoring***, where participants participate in projects, often driven by external bodies, i.e. scientists, conservation bodies, etc., with participants both distant or local to the study area, often giving their time and resources by a shared passion for nature, or desire to help conserve nature in some way. It is important to state that there are many different approaches to citizen science, varying in the degrees to which participants lead, design or direct outcomes, and any generalisations will fail to capture the full variety of citizen science that exists.

A continuum exists in the degree of influence citizen science participants have in shaping the data collected, problem formulation, analysis and dissemination of results. Many community-based monitoring programs have some elements of being "co-created" or adapted to local circumstances (participatory sensing and civic/community science using Haklay (2015) terms), whereas many citizen science projects are "contributory" (sensu Bonney et al., 2009) where participants have little input to the creation of the programs or shaping of research or monitoring outcomes beyond data collection. Of course, there are many other kinds of

important educational or social outcomes which both community-based monitoring and citizen science monitoring programs regularly achieve. In fact these "peripheral" or secondary benefits may outweigh any benefits derived from increased data gathering from the community's perspective. See Funder et al. (2013) for a good example of where the heightened involvement by community members in monitoring their forests was deemed of very high value because it led to a greater demonstration of occupancy and sense of control over "their" lands.

There will always be trade-offs between the information needs of the tropical biodiversity monitoring community and the needs of communities on the ground, so it is important to understand where the main data gaps are and how communities can also directly benefit from their involvement in data collection efforts.

In the sections that follow, we will demonstrate that both community-based monitoring and citizen science monitoring projects can provide valuable data for the calibration and validation of EO-derived products.

6.3 INFORMATION OF VALUE FOR BIODIVERSITY MONITORING IN TROPICAL FORESTS

Table 6.3.1 presents the variables of interest for biodiversity monitoring, which include relevant Essential Biodiversity Classes (EBC) and EBVs as published previously by Pereira et al. (2013a) as well as other variables of interest to biodiversity monitoring. The table also summarizes how these variables are measured in-situ, what training is required for in-situ measurement by communities and citizens, and whether these variables can be measured using remote sensing, thereby serving as potential calibration and validation data. There are many different types of in-situ measurement technique listed in Table 6.3.1 including field observations/presence surveys for groups of species or single species; patrol records; transects; species lists; village group discussions; camera traps; hair traps; footprints protocols; mist-nets; pitfall traps; nested vegetation plots, among others. The reader is referred to field manuals (Buckland et al., 2004; Silvy, 2012; Magnusson et al., 2013) and a considerable literature on nested vegetation plots (Shmida, 1984; Stohlgren et al., 1999, 1998, 1997, 1995) for more detailed explanations of these in-situ methods. See also chapters 4.2.2, 4.6.2, and 5.2.4 for more information on species mapping. See section 4.2 for more information on in-situ data.

Table 6.3.1 is shaded green when variables are observable by remote sensing and red when ground-based data are the only way to measure these variables. This shading has been informed by the survey of O'Connor et al. (2015) but is more focused on tropical biodiversity monitoring and is not linked to specific Aichi targets. This characterization indicates that four out of five EBCs can use remote sensing for monitoring all constituent EBVs while only the EBC Species Traits has some EBVs that require ground-based data exclusively.

6.4 CASE STUDIES OF COMMUNITY-BASED AND CITIZEN SCIENCE MONITORING

This section provides a series of case studies from citizen science and community-based monitoring projects for biodiversity and/or forest management. These case studies were chosen based on direct knowledge of EarthWatch projects and other community-based monitoring initiatives in order to provide a good geographical representation. These case studies are not meant to be a comprehensive selection but rather they each bring different approaches and lessons learned to the table.

Evans and Guariguata (2008) have provided an excellent review and resource of many community-based forest monitoring programs. The selection provided in Table 6.4.1 is complementary to Evans and Guariguata (2008) in that there are good examples of community-based forest monitoring programs but these are more up to date than the previous review. However, in contrast to Evans and Guariguata (2008), the emphasis of the case studies presented here is more on biodiversity monitoring rather than community-based forest monitoring, and it also covers citizen science programs. These 14 cases are summarized in Table 6.4.1 and then outlined in more detail in the sections that follow. In particular the link is made between what EBCs are captured through in-situ monitoring across the diverse set of case studies presented here.

Although the focus is not always on tropical forests, the case studies are still useful to illustrate good practice and lessons learned, some of which can be transferred to a tropical forest environment.

Table 6.3.1: Variables of interest for biodiversity monitoring organized by EBC and EBV. Shading is partly based on the characterization of O'Connor et al. (2015) of RS-EBVs, i.e. green is totally or partially observable by remote sensing and red is not observable, requiring ground-based data.

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
Species populations **(SP)**	Species distribution	Field observations/ presence surveys for groups of species or single species; easy to monitor over an extensive network of sites with geographic representativeness. Via patrol records, transects, species lists, village group discussion, camera traps, hair traps, footprints protocols, mist-nets, pitfall traps	Training in patrol records, transects, species lists, village group discussion, species identification and training in protocols for collection of other animal/plant census data, collection of DNA samples for DNA barcoding, nested vegetation plots	Via aerial photos to count large mammals, reptiles or certain plants in less dense forests and woodlands. Potential role for incidental data from any spatial location. Via remote sensing imagery, including hyperspectral technology (Carlson et al. 2007). Native or invasive plant species classification and distributions (Gillespie et al 2008; Everitt et al., 2006). Potential role for incidental data from any spatial location.	Several case studies; see Giorgi et al. (2014). Examples of the use of: • patrol records (Brashares and Sam, 2005; Danielsen et al., 2010; Gray and Kalpers, 2005) • community-based transects (Andrianandrasana et al., 2005; Becker et al., 2005; Rovero et al., 2015) • community-based species lists (Bennun et al., 2005; Hockley et al., 2005; Roberts et al., 2005) • village group discussion (Poulsen and Luanglath, 2005; van Rijsoort and Jinfeng, 2005; Danielsen et al., 2014a)
	Population abundance	Population counts for groups of species; easy to monitor and/or	Training in patrol records, transects, species lists,	Via aerial photos to count large mammals, reptiles or	Many examples in the row above

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
		important for ecosystem services and habitat quality assessment, over an extensive network of sites with geographic representativeness. Via patrol records, transects, species lists (presence or absence of species on fixed-time lists incl. 1-day index of abundance), and village group discussion.	village group discussion and nested vegetation plots. Quadrats, point counts, camera trapping, mist nets, with individual identification techniques (bands, tags) review and analysis of imagery	certain plants animals in less dense forests. Via model inputs derived from remote sensing imagery, including hyperspectral remote sensing for native or invasive vegetation assessments and monitoring (Gillespie et al 2008; Carlson et al, 2007; Foody et al., 2005).	
	Population structure by age/size class	Quantity of individuals or biomass of a given demographic class of a given taxon or functional group at a given location, e.g. via forest vegetation plots for monitoring	Identification of size classes, dbh measurements, and from capture and release	Vegetation structure measurements via active remote sensing technology (e.g., LiDAR) and: Laser Vegetation Imaging Sensor (LVIS), an aircraft-mounted LiDAR sensor.	Examples of the use of community-based forest vegetation plots for monitoring forest biomass (Skutsch et al. 2011; Brofeldt et al. 2014; Torres & Skutsch 2015, Theilade et al. 2015) Examples of the use of community-based vegetation

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
		forest biomass and tree diversity			plots for monitoring tree diversity (Zhao et al. In review in PLoS ONE).
Species traits (ST)	Phenology	Record timing of periodic biological events for selected taxa/phenomena at defined locations. Examples include: timing of breeding, leaf coloration, flowering. Via patrol records, transects, and village group discussion	Identification of plant and animal species, their life cycles/stages; use common staging classification (e.g. NPN).	A range of remotely-sensed vegetation indicators can be used to determine phenology of some plant types, e.g. crops, annual plants, leaf-area index	Examples of the use of patrol records, community-based transects, and village group discussions provided above (row on species populations). Examples from temperate areas include: • National Phenology Network (section 6.4.8) (Kellermann et al., 2015) • Movebank (*www.movebank.org)*, • Project Budburst • Climatewatch.org • Phenocams (Crimmins and Crimmins, 2008) • try-db.org
	Body mass	Body mass (mean and variance) of selected species (e.g. under harvest pressure), at	Animal population field methods. Measurements from capture & release, and examination of	No	Case study in Majete Wildlife Reserve, Malawi (section 6.4.9); Constantino (2015)

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
		selected sites (e.g. exploitation sites).	harvested individuals		
	Natal dispersal distance	Record median/frequency distribution of dispersal distances of a sample of selected taxa.		No	Unaware of current examples
	Migratory behavior	Record presence, absence, destinations, pathways of migrant selected taxa, e.g. via patrol records and village group discussion	Train in the identification and field count methodologies for migratory raptors, butterflies	Use of radar imagery; satellite or radio tagging	An example of the use of patrol records and village group discussion for recording seasonal migration of ungulates include Topp-Jørgensen et al. (2005) Examples from temperate areas include: HawkWatch (hawkwatch.org); eBird (ebird.org); Movebank; Journey North (www.journeynorth.org)

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
	Demo-graphic traits	Effective reproductive rate (e.g. by age/size class) and survival rate (e.g. by age/size class) for selected taxa at selected locations	Measurements from capture and release studies	No	Case study in Majete Wildlife Reserve, Malawi (section 6.4.9); Freshwater turtle monitoring schemes in Zábalo, Ecuador, e.g. Townsend et al. (2005)
	Physiologic al traits	For instance, measurement of thermal tolerance or metabolic rate. Assess for selected taxa at selected locations expected to be affected by a specific driver.	Capture and rearing of insects for bio-chemical analyses (see Dyer et al. 2012)	No	See Dyer et al. (2012)
Community Compositio n **(CC)**	Taxonomic diversity	Multi-taxa surveys (including by morphospecies) and metagenomics at selected in-situ locations at consistent sampling scales over time, e.g. via patrol records,	Training in patrol records, community-based transects, species lists, and nested vegetation plots. Training in other survey techniques (mist	Hyper-spectral remote sensing over large ecosystems	Case study in Loma Alta, Ecuador (section 6.4.2); Pacaya Samiria, Peru (section 6.4.1) Examples of community-based tools used in practice (Bennun

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
		transects, species lists, and permanent forest vegetation plots	nets, camera traps, etc.)		et al. 2005; Danielsen et al. 2014a, Rovero et al. 2015; Zhao et al. 2016; Dyer et al. (2012)
	Species interactions	Studies of important interactions or interaction networks in selected communities, such as plant-bird seed dispersal systems or of threats operating at local or larger scales. Via patrol records, transects, and village group discussions	Species identification of focal species and disturbances using survey transects and capture & release	Combined with multi-spectral remote sensing data, LiDAR offers potential for parametrizing predictive organism-habitat association models.	Case study in Pacaya Samiria, Peru (section 6.4.1) Case study in Majete Wildlife Reserve, Malawi (section 6.4.9) See Dyer et al. (2012). See also examples above (in the row on species populations)
Ecosystem function (EF)	Net primary productivity	Validation of measurement of net productivity for selected groups. For forest trees via	Measure change in biomass in permanent forest vegetation plots and nested vegetation plots	Global mapping with modeling from remote sensing observations (fAPAR, ocean greenness) and selected in-situ locations (eddy covariance); calculated	Examples of the use of community-based forest vegetation plots for net primary productivity (Skutsch et al. 2011; Brofeldt et al. 2014; Torres & Skutsch 2015)

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
		permanent forest vegetation plots		from NDVI (normalized difference vegetation index); ocean colour	Case studies: San Pablo Elta; MX for carbon assessment; and community-based monitoring for REDD+ (section 6.4.3); Casas de la Selav (section 6.4.4)
	Secondary productivity	Measurement of secondary productivity for selected functional groups, using in-situ methods or methods combining in-situ, remote sensing, and models. Example of functional groups include: bush meat;, fisheries; livestock; krill; herbivorous birds. Via patrol records, transects, and village group discussion		See above	Case study in Pacaya Samiria, Peru (section 6.4.1) for hunted and fished species, and in Lake Aloatra, Madagascar (section 6.4.10) for fish productivity. Examples of community-based tools used for monitoring production of non-timber forest products, fish, and freshwater turtle eggs (Danielsen et al., 2000, 2007; Poulsen and Luanglath, 2005; Topp-Jørgensen et al., 2005; Townsend et al., 2005)

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
	Nutrient retention	Ratio of nutrient output from the system to nutrient input, measured at selected in-situ locations. Can be combined with models and remote sensing to extrapolate regionally.		Monitoring of crop cover to infer nutrient retention	Case study in Loma Alta, Ecuador on water capture (section 6.4.2)
	Disturbance regime (e.g. pest outbreak)	Type, seasonal timing, intensity and frequency of event-based external disruptions to ecosystem processes and structure. Flood regimes; fire frequency; windthrow; pests. Via patrol records, photo documentation, and village group discussions	Training in patrol records, photo documentation, and village group discussions. Species identification of key focal species and disturbances using survey transects and capture & release	Large and sudden changes might be identified through remote sensing (RS) but not smaller, slower outbreaks. Examples: sea surface temperature and salinity (RS); scatterometry for winds (RS); fire frequency (in-situ); burnt areas (RS); oil spills (RS); cultivation/ harvest (RS); monitor vegetation indices over time (RS)	Case study in Pacaya Samiria, Peru (section 6.4.1), Kafa, Ethipioa (section 6.4.13). Examples of the use of patrol records, community-based transects, and village group discussions for monitoring fire and other threats to forest ecosystems are listed above (the row on species populations). An example of the use of community-based photo documentation method to monitor threats is found in Danielsen et al. (2000)

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
Ecosystem Structure (ES)	Habitat structure	Via photo documentation, and forest vegetation plots. Data calibration of habitat structure (canopy height, habitat classification, etc.)	Training in photo documentation, and community-based forest vegetation plots and nested vegetation plots	Remote sensing measurements of cover (or biomass) by height (or depth) classes globally or regionally, to provide a 3-dimensional description of habitats. Different sensors can measure biomass globally or locally but this requires more calibration and validation data to improve the maps, especially globally.	Case study San Pablo Elta, Mexico (section 6.4.3) and Gazi Bay, Kenya (section 6.4.11). Examples of the use of photo documentation (Danielsen et al., 2000), community-based forest vegetation plots for monitoring forest biomass (Skutsch et al. 2011; Brofeldt et al. 2014; Torres & Skutsch 2015) and tree diversity: Zhao et al. 2016).
	Ecosystem extent and fragmentation	Local (aerial photo and in-situ monitoring). Some wetland areas can be identified using RS but remains problematic. Requires more calibration and validation data.	Mapping boundaries, e.g. of wetlands, and wetland identification	Global mapping (satellite observations) of natural/semi-natural forests, wetlands, free running rivers, etc.	Case study San Pablo Elta (section 6.4.3). Global map of wetland extent by Lehner & Döll (2004); new water occurrence product by JRC (Pekel et al., 2014)
	Ecosystem composition by	Functional types can be directly		Functional types can be inferred from remote	N/A

EBC Class/ Variable of interest	EBV	Measurement in-situ	Training for in-situ data collection by community members	Can it be measured remotely by professional scientists?	Examples of data repositories or tools
	functional type	inferred from morphology.		sensing (translated from land cover maps)	
OTHER	Land cover	Photo documentation	Knowledge of land cover definitions, protocols for collection, training in image interpretation	Land cover can be identified using automated and semi-automated classification methods but higher accuracies and higher temporal frequencies are needed. Requires more calibration and validation data.	See Halme and Bodmer (2006) for an example from Amazonian Peru
	Land use	Village group discussions. Photo documentation. Household surveys	Training in survey methods	Some land use types can be identified with RS but most are not discernible or require knowledge from the ground	Several examples of the use of village group discussions and photo documentation for monitoring land use can be found in Danielsen et al. (Danielsen et al., 2005b)
	Cultural and social heritage	Village group discussions	Training in participatory methods	RS could be used to identify change in an area but monitoring of cultural and social heritage requires ground-based data collection	Examples in Danielsen et al. (Danielsen et al., 2005b) Case study in Pacaya Samiria, Peru (section 6.4.1)

Table 6.4.1: Summary of case studies with relevance to Essential Biodiversity Classes

Section	Location	Types of participants	References	EBCs
6.4.1	Pacaya Samiria, Peru	Both	Bodmer et al. (2008; 2014)	SP, ST, CC
6.4.2	Loma Alta, Ecuador	Both	Becker et al. (2005)	SP, ST, CC, EF
6.4.3	San Pablo Etla, Mexico	Community-based		SP, EF, ES
6.4.4	Casas de la Selva, Puerto Rico	Citizen science monitors	Nelson et al. (2010; 2011)	SP, CC, EF, ES
6.4.5	Atlantic Forest, Brazil	Both	Giorgi et al. (2014)	SP, ST, CC
6.4.6	Project COBRA, Guyana	Community-based	Berardi et al. (2013); Mistry et al (2014)	SP, CC, ES
6.4.7	National Program for Biodiversity Monitoring, Brazil	Community-based	Pereira et al. (2013b); Nobre et al. (2014); Santos et al. (2015)	SP, ST, CC
6.4.8	National Phenology Network, North America	Both	Reports and scientific publications can be found at: https://www.usanpn.org	SP, ST
6.4.9	Majete Wildlife Reserve, Malawi	Both		SP, ST, CC, EF
6.4.10	Lake Aloatra, Madagascasar	Community-based	Andrianandrasana et al. (2005)	SP, ST, CC
6.4.11	Gazi Bay, southern Kenya	Both	Huxham et al. (2015)	SP, ST, CC, EF
6.4.12	REDD+ monitoring in China, Indonesia, Laos and Vietnam	Community-based	Brofeldt et al. (2014)	SP, ST, CC, EF
6.4.13	Kafa Biosphere Reserve, Ethiopia	Community-based	Pratihast et al. (2014: 2016)	SP, ST, CC, EF
6.4.14	Protected Areas, Philippines	Community-based	Danielsen et al. (2009)	SP, ST, CC

6.4.1 Pacaya-Samiria National Reserve, Peru

The Pacaya-Samiria National Reserve (PSNR) is one of the largest protected areas in Peru with an area of more than 20,000 km², situated between the confluence of the Marañon and Ucayali Rivers. The PSNR has around 20,000 people living within the reserve boundaries.

A biodiversity monitoring program was developed in 2001 for data gathering to be conducted by both local community members as well as international citizen scientists and students (e.g. Earthwatch volunteers, Operation Wallacea students). The current project is helping to conserve the biodiversity of the Amazon, and is working with local people to collectively better manage the rich resources from this region. The project is led by Richard Bodmer, a reader in Conservation Ecology at the Durrell Institute of Conservation and Ecology (DICE), UK, and also the president of FundAmazonia (www.fundamazonia.org).

The reserve was originally created in 1982 as an area with strict protection that largely excluded local people. This led to conflict between the reserve authorities and the local population who lost long-term interest in managing their traditional lands inside the reserve and reverted to overharvesting. The conflict escalated with the reserve authority battling to reduce harvesting and the local people taking as many natural resources as they could, as fast as they could. After violent confrontations, the Peruvian Protected Area Authority changed its management policy and in 1998, the local people actively participated in reserve management as a co-managed reserve. By 2006, the biodiversity monitoring program began to demonstrate that many animal populations along the Samiria River basin had recovered, e.g. woolly monkeys, black caiman, manatees, and turtle populations, after the change to include locals in management decision making (Bodmer et al., 2008). More recently, the project has been evaluating the impact of climate change events, especially severe droughts and extreme flooding on the biodiversity and local people, which have resulted in decreasing populations of resource use species. Bush meat species have largely disappeared as a result of the consistent extreme floods impacting the livelihoods of the local population (Bodmer et al., 2014).

Approaches Used and Data Collected

Over a number of years, the research team has developed rigorous protocols to train both local community members as well as international citizen scientists in collecting data on wildlife surveys using observational and capture and release techniques. Moreover, the project also trains local biologists in basic methodologies that provide essential support to the community-based monitors and international citizen scientists, and verification of data quality. Community-based observers and international citizen scientists are given a range of research tasks and responsibilities. These include carrying out censuses along transects for terrestrial mammals and game birds, point counts for macaws, capture and release studies of fish and caimans, aquatic transects of wading birds, river dolphins and turtles, and the setting and checking of camera traps to record large ground dwelling mammals, particularly carnivores, ungulates and edentates. A key to engaging local community members was the inclusion of species important for subsistence hunting and fishing since the beginning of the project, and species that provide economic benefits. Citizen scientists are interested in the project because of its broader implications for conservation of biodiversity in the Amazon and climate change.

The data collected during wildlife surveys involves field teams that are always composed of 1) local community members, 2) citizen scientists and 3) local biologists. Each type of person has a different role, which when combined, yields large verified data sets. The local community members are particularly adept at sighting animals in the physically complex forests. The citizen scientists are adept at data recording, measurements and data entry, and the local biologists are trained to verify data collected, including species identification, GPS locations, transect lengths, and measurements.

Adaptive management activities at the Samiria River basins are being incorporated as a result of the insights gained through Earthwatch and Operation Wallacea research. In 2007, a review of change occurring over the previous years found significant improvements for the wildlife, environment, and local people. Monitoring demonstrated increasing numbers of key species such as giant otters and primates and increased awareness of rare species using protected areas (e.g. manatees). The data have also helped to identify potential ecological interactions that may limit species response, e.g. increases in large-bodied

primates are correlated with decreases in small-bodied primates; increases in black caiman lead to a decrease in speckled caiman (Bodmer and Puertas, 2007).

Over the past 8 years the 'citizen science' monitoring program has shown how recent climate fluctuations are impacting biodiversity and the livelihoods of the local people. The historically high floods of 2009, 2011, 2012 and 2013 have resulted in population crashes of the ground dwelling species in the flooded forests, including white-lipped and collared peccary, red brocket deer, black agouti, paca, armadillos, giant anteater, among others. Many of these species were the favored bushmeat species of the Cocama indigenous people who can no longer rely on this subsistence resource (Bodmer et al., 2014). The monitoring data show that an estimated 2 million ground dwelling animals have died from the recent impacts of climate change in the northern Peruvian Amazon of Loreto. A co-benefit from engaging international citizen scientists is the first hand appreciation and increased awareness of the impact of carbon emissions and economic development on natural and human systems.

Successful Outcomes

Prior to establishing this model of protected areas, the regional government had taken the view that the PSNR was not functioning and had not looked to establish any more protected areas. However, monitoring by the "citizen science" program delivered quantitative results, demonstrating the success of the reserve (Bodmer et al., 2008). With the monitoring results in hand, the regional government was able to look at drafting new protected areas. Wildlife monitoring by the local community and international citizen scientists played an important role in helping to justify new protected areas in Loreto and increase the prevalence of community-based co-management systems.

The development of a biodiversity monitoring program for key wildlife species in and around the protected areas has been key to a more successful and comprehensive management program and helped create successful public-private partnerships with local people. The project has also led to increased economic input into the region with respect to the value of the reserve and its wildlife via international citizen science.

The impacts of climate change have been documented through the "citizen science" based program and present new challenges for the reserve and the local people living in the area. Threats are becoming obvious from the greater variations in water level, both in terms of droughts and intensive flooding. By working together, the reserve authority and local people are taking a collaborative and combined effort to overcome and adapt to the physical nature of climate change impacts.

6.4.2 Loma Alta, Ecuador

By 1994, most of the forest cover along the west coast of Ecuador had been cleared or selectively harvested, leaving less than 5% remaining (Becker, 1999). While looking at aerial photos, Dr. Dusti Becker was surprised and curious about large areas of forest remaining in the Colonche Hills near the community of Loma Alta. The land was communally owned, so tragedy of the commons should have made deforestation more likely. Why then were there thousands of hectares of fairly pristine intact cloud forest still there? In 1995, Becker put together a team of natural and social scientists from Indiana University, all influenced by the thinking of Dr. Elinor Ostrom a champion of the idea that local people can develop rules to sustain and manage natural resources independently of national government influence (and winner of the Nobel Prize in Economics in 2009 on this theme). With additional citizen scientists from Earthwatch, the Becker/Ostrom research team headed to Loma Alta to study the forest and interview community members to find out if the villagers had devised special rules or traditions to protect the forest.

The team discovered that the community had a strong system of local governance, but there were few rules explicitly in place to conserve the forest. The only rule that

significantly slowed deforestation was a ban on timber exploitation by large forestry companies – only local community members were permitted to harvest trees and make them into boards for sale. These local wood-cutters didn't have the capacity to clear the forest quickly. Most of the forested land had been allocated to families for eventual use, but people were too poor to develop it. The most distant communal land had been stolen and cleared by another ethnic group who had cleared and burned about 200 hectares to encourage grass for cattle. By the end of our study, it was painfully clear that eventually, the Loma Alta forest would go the way of the other 95% as ranchers, local wood cutters and farmers expanded slowly cleared away the incredibly diverse and lush tropical montane forest (Becker, 1999).

While standing on the edge of the forest one foggy day, our team noticed that it seemed to be raining inside the forest but was only foggy in the cleared pasture. The forest was muddy, while the pasture soil was dry. Becker knew what the next citizen science effort had to be. We had to measure fog capture, report results to the villagers and hope that they would use their good governance to protect the forest for its valuable ecosystem service of providing water for all the activities in the lowlands.

In May 1995, several Loma Alta villagers were trained to monitor through-fall from fog capture, which is the quantity of water dripping off trees and other plants during the fog season (Jun-Nov). This water originates from fog and mist (locally known as garua) that forms over the Pacific Ocean, where it is intercepted by vegetation, and particularly on windward slopes of coastal mountain ranges. Monitoring by the community and Earthwatch volunteers during 1995 revealed that 2.24 million liters of water were trapped by trees per hectare on the slopes of Loma Alta. Equivalent to an Olympic pool/per hectare, fog-capture by the forest doubles the amount of water provided by rain in the Loma Alta watershed. The importance of the ecosystem service is further shown by the fact that a neighboring community in an adjacent watershed cleared its forest, their land became a scrub desert and they began purchasing water from Loma Alta. Despite these realities is was not until the Becker team reported on fog capture that the community became very proactive about forest conservation.

The data on fog capture enhanced local awareness about ecosystem services, leading them to alter their land use from the slowly extractive (and destructive) to protective, as they officially made an ecological reserve. As a result of the monitoring program pertaining to the water provisioning services by the forest, the community allocated more than half of the community lands to be a forest reserve. Many of the families who had lost rights to expand agricultural fields and cut timber were looking for new ways of making income. The community and Earthwatch volunteers decided to monitor bird diversity, hoping that findings and publications would encourage bird watching and ecotourism in the future. In 2004, the bird monitoring led to the entire Loma Alta watershed being declared an international Important Bird Area (IBA), because the Earthwatch and community monitoring teams had discovered 78 endemic species, 15 endangered species, and striking aggregations of hummingbirds.

Local awareness about the value of biodiversity has been greatly enhanced from none to a keen enthusiasm for local birds and wildlife and pride from local development of ecotourism. A small hotel and visitor cottages were built just outside the reserve while two small camps for visitors and researchers who come to enjoy the natural area or study birds have been set up inside, providing extra income to the local community. The project has also developed new and strengthened existing social connections at local, regional, national and international levels, and there have been positive impacts on how local people perceive themselves.

Starting around 2008 the community received "Socio-bosque" funding from the Ecuadorian government as part of international carbon sequestration payments to developing nations. The money, which is on the order of $ 20,000 to $ 30,000 USD/year, is used for protecting the reserve and for community development needs. Community rangers patrol the 7,000

acres of native vegetation, about half of which is recovering to mature cloud forest, and there are now only very rare cases of cutting and subsistence hunting, primarily because the community does not depend on exploitation of the forest for survival and needs the water provided by the intact forest ecosystem. The system is likely to be sustainable long into the future because most leaders and decision-makers in the community have a more "total" economic value for the forest now than they had in 1994. Now, it is clear to most everyone that the indirect values of ecosystem services and the option value associated with tourism far outweigh direct values of timber harvesting and farming in the cloud forest.

Originally conceived and led by Dr. Dusti Becker of Life Net Nature, with help from Aves de Ecuador, and Earthwatch Institute, avian monitoring and community-based conservation efforts are continued by Eve Astudillo Sanchez-Breon from University Espiritu Santo in Guayaquil, Ecuador. Dovetailing local indigenous efforts with capable well-educated citizens is far more sustainable than projects that rely on foreign-based conservation organizations. More details of this case study can be found in Becker et al. (2005).

6.4.3 San Pablo Etla, Mexico

San Pablo Etla (SPE) is a municipality in the Etla Valley of Oaxaca, Mexico, approximately 20 km northeast of the state capital. SPE abuts the Sierra Norte mountain range of southern Mexico, and maintains a 3,000 hectare forest reserve that includes large stands of oak, pine and mixed oak/pine forest. The community elects a Commission of Communal Resources to manage, protect and resolve disputes regarding the community's reserve. Commission members donate their time as community service for three-year terms. Although the reserve contains large stands of high quality timber species, in the early 1990s, SPE became a "Community Voluntarily Committed to Conservation," an official designation by the National Commission on Protected Natural Areas (CONANP). The community has declared the land off-limits for timber harvesting, hunting, destruction of plant life, and instead manages the lands for the provision of ecosystem services, including water provision, carbon storage, biodiversity, and eco-tourism. While the community has obtained some public and private grants to cover some of the costs of conserving the reserve, its sustainability will ultimately depend on whether or not it can receive payments from the end beneficiaries of its eco-services such as water provision to the Oaxaca City metropolitan area and carbon off-sets for standing timber.

Approaches Used and Data Collected

In 2011, UC Davis researcher, John Williams, worked with community members to conduct a carbon inventory of the SPE forest reserve. Using established carbon market measurement protocols (Pearson et al., 2005), Williams and local forest reserve staff established a series of forest biomass plots where they measured standing woody biomass volume for each of the three major forest types of the reserve. The sampling data were then input into a carbon calculator (Winrock International, 2006) to generate an estimate of carbon stored in aboveground woody biomass within the reserve. Forest conservation and data-supported estimates of aboveground woody biomass for the forest reserve will hopefully lead to carbon offset payments in the future.

In addition to the carbon storage study, community members and visitors have initiated a number of additional projects including: an orthorectified, geographic information system (GIS) based community map to support additional management activities and scientific research; a thorough year-round inventory and monitoring of the bird species found in the forest; camera-trap monitoring of wildlife populations; a collaborative weather monitoring effort with the Mexican Water Commission (CONAGUA) and the National Research Institute for Forestry, Agriculture, and Livestock (INIFAP); reforestation of degraded lands in the lower-elevations of the reserve; an environmental demonstration and educational center "La Mesita," which includes a nursery for native plants and tree seed collection and

propagation, erosion control techniques, water capture and usage techniques, and a series of award-winning landscape architectural design projects conducted in collaboration with the Real Architecture Workshop (RAW), a U.S.–based educational organization engaging volunteer architecture students.

Successful Outcomes and Lessons Learned

Multi-year bird diversity monitoring and data collection is undertaken that is input into the open-access eBird database managed by Cornell University and is available to scientific researchers, conservation managers, and bird enthusiasts worldwide. There is local participation in ecological research and biodiversity monitoring, resulting in several university level theses on themes including medicinal plants and uses, oak propagation techniques, and flora and fauna inventories.

There has been systematic education in the conservation education center of SPE, which has resulted in greatly increased community awareness about the municipality's natural resources, species diversity, and the connection between forest protection and the benefits people receive from healthy ecosystems. There is also local pride about the reserve and the community's environmental image, as well as increased local involvement in related projects.

Success has also spread to neighboring communities, which have recognized and been inspired by SPE's natural resource management achievements and have been inspired to develop similar types of projects. There has also been an increased awareness and tourism by Oaxacan, Mexican and international visitors, as well as an increased interest by scientists to conduct ecological research in the reserve, providing more opportunities for locals and visitors to participate in citizen science projects.

Currently, researchers from the Mexican National Polytechnic Institute are conducting a number of studies in the Reserve, including an investigation of the effects of climate change on the distributions of trees, rodents and butterflies, and one using bioacoustic techniques to examine how closely-related bird species establish territories and partition resources.

Community commitment to conservation that enables continuous efforts over many years and across sequential governing administrations is essential to achieving cumulative conservation progress. Incremental development of small projects leads to a critical mass-type of momentum that leads to greater community support and additional awareness and opportunities. No single theme (e.g., ecotourism, carbon offsets) will meet all the community's natural resource expectations, but a broad-spectrum approach with a diverse set of projects can be effective for raising awareness of conservation benefits and for building community support. Community collaboration with a broad-range of public and private organizations is essential for resource mobilization.

6.4.4 Casas de la Selva, Puerto Rico

Las Casas de la Selva is an experimental sustainable forestry and rainforest enrichment project begun in 1983 in southeastern Puerto Rico in the Cordillera Mountains. The 409 ha forest is located on steep slopes, at an average elevation of 600 m (2000 ft), receiving an average annual rainfall of over 3000 mm and an average temperature of 22 deg. C. Most of the land was logged, converted to coffee plantations and then subsequently abandoned, resulting in areas of severe erosion and a secondary forest which now covers the property. The project is managed by Thrity Vakil and Andrés Rua, with assistance from Dr. Mark Nelson on scientific papers and Norman Greenhawk, a herpetologist currently working on a Master's degree.

The Las Casas de La Selva project, undertaken by Tropic Ventures Research and Education Foundation (Patillas, P.R.) with consulting by the Institute of Ecotechnics (U.K., U.S.) has three principal objectives:

1- Restore and conserve the secondary forest ecosystem.
2- Identify and test the forestry techniques that provide the best ecological and economic outcomes as viable alternatives to conversion of the forest for agricultural and other uses.
3- Monitor the forest and its trees, key indicator animal species and the resource use to understand the ecological and socio-economic impacts of the project.

Foresty enrichment with line-planted valuable timber species was chosen as a method of providing economic returns without destroying the secondary forest on the land. Between 1984 and 1990 some forty thousand tree seedlings were planted in lines in about 25% of the secondary forest. Ninety percent of the seedlings were mahogany (mainly *Swietenia macrophylla x S.mahagoni)* while the other 10% was primarily mahoe *(Hibiscus elatus).* Seventy-five percent of the land including the steeper slopes of the forest were left untouched to minimize erosion and to provide areas to study natural regeneration and ecological succession of the forest. On the areas previously converted to grazing, more than a thousand fast-growing *Pinus caribaea* (Caribbean pine) were planted to hold the soil and mahogany and mahoe interplanted once the pines had established.

The hypothesis was that the program of line-planting, since overall forest conditions are minimally disturbed, would result in only small changes in both forestry parameters and in faunal populations. Small impact on tree and amphibian diversity was demonstrated by research after twenty years of the program (Nelson et al., 2010).

There are also studies, begun in 2009, of the "liberation thinning" technique to improve growth of valuable native trees in secondary forests (Wadsworth and Zweede, 2006). These are the first tests in Puerto Rico to see whether eliminating competitor trees will accelerate the growth of native hardwood species. If so, it will provide better economic returns and rationales for valuing and protecting secondary forests which are rapidly expanding on the island due to the abandonment of farming land.

More details of this project and its results on growth of the line-planted trees and its minimal ecological diversity impacts can be found in Nelson et al. (2011, 2010) and www.eyeontherainforest.org.

Approaches Used and Data Collected

The project staff includes some people with advanced or university training and also others who have learned forest management skills over several years through operating the project and collaborating with a wide diversity of scientists who have helped collect data. The data collection has also been helped by cooperation with the Earthwatch Institute, which has sent groups (i.e. citizen science monitors) since 2000, and also university classes and other volunteers.

The types of data that have been collected include:

- Measurements of tree survival and growth in the line-planted areas (basal area (BA), diameter at breast height (dbh), canopy, height, commercial height) and measurements of trees and biodiversity in the secondary forest areas compared to line-planted areas, in randomized geo-located plots.
- Measurements of tree seedling numbers in both line-planted and secondary forest.
- Impact of thinning on the line-planted areas in random plots and impact of liberation thinning on plots in the secondary forest compared with control plots (with advice from Dr. Frank H. Wadsworth, the developer of liberation thinning).
- Planting and monitoring of critically endangered endemic tree species for recovery and habitat enhancement. A shade nursery has been established for

caring and sheltering of saplings of threatened endemic species until planting. The initial survival, growth rate, and success of the reintroduced material is monitored to ensure the best contribution to the recovery of the species.

With support from the USDA Forest service and the Puerto Rican Department of Natural Resources, Las Casas de la Selva has been conducting a Forest Products Assessment. This project has enabled Andrés Rúa, a member of the Las Casas management and a "citizen scientist" to visit sawmill owners all over the island, interview dozens of artisans who work with forest products, as well as large and small scale wood and product dealers. The project aims to investigate use of forest products in Puerto Rico; where the wood is coming from; what types of wood; who are the buyers; and what other forest products are in demand and use.

Herpetological studies have focused on identifying which species of reptiles and amphibians are present at Las Casas de la Selva in order to determine the population density, population fluctuations, microhabitat utilization, and the effects of forest management on the herpetofauna of the forest. Biodiversity and population studies of birds, vines and fungi have also been undertaken. Finally, basic meteorological data such as rainfall, temperature and relative humidity are recorded.

Successful Outcomes

The project would not have had the data to evaluate the overall program of forest enrichment nor its impact on natural biodiversity of the secondary forest without the extensive numbers and hours of research data collection. This has resulted in publication of several papers in forestry journals and helped project management evolve a program in response to the findings. In particular, it has quantified the success and rapid growth of the mahoe trees and other valuable native timber trees planted compared with the slower-growing mahogany.

The confirmation that the forest enrichment program has not significantly decreased tree or amphibian diversity has validated the project's main initial hypothesis and is helping make the project a model for sustainable forestry management on the island.

Coqui frogs are an important part of the forest food chain and were studied as key indicator species in the line-planted and untouched forest. Common coqui (*Eleutherodactylus coqui*) and melodious coqui (*E. wightmanae*) are the most commonly encountered frog species at Las Casas. Although relative abundance means were slightly greater in the undisturbed forest and during the wet season, there were no statistically significant differences which shows that line-planting did not significantly affect amphibian diversity (Nelson et al., 2010). In addition, several threatened and endangered frogs have been discovered in the property, extending their known range and anole lizards, another key part of the fauna have been unaffected by forest enrichment (Greenhawk, 2013, 2015).

Similarly, the line-planted areas had a slightly higher, but not statistically significant diversity, richness, and evenness of tree species than the control plots in the undisturbed forest. A multi-response permutation procedure (MRPP) showed statistically significant tree community composition differences between line-planting and control plots. But mean similarity among plots in both the line-planted and control plots was relatively low at less than 50% of shared species, indicating high diversity of vegetation in the overall forest area. Canopy cover by tree species greater than 3 cm in dbh was much higher in the undisturbed forest but as the young planted trees grow, this difference may be reduced. These data indicate that forest enrichment through line-planting of valuable timber species in secondary subtropical wet forest does not significantly affect tree diversity (Nelson et al., 2010).

Tree growth studied over 20 years since planting shows that mahoe had a BA increase over three times that of mahogany. In 57 years from planting, the mahoe trees will reach a

mean stand BA of 0.20 m²/tree, which correlates to a dbh 50 cm. The upper quartile of mahoe trees currently have a mean BA greater than 0.10 m²/tree and are already being selectively harvested and marketed as a thinning of the stands. The BA annual increment for mahogany indicates that it will take 175 years from planting to achieve a mean stand BA of 0.20 m²/tree for the best 25% of the mahogany trees. In trials with native species, Coccoloba pubescen, Calophyllum brasiliense and Cedrela odorata had the greatest percent increase in height with favorable survival rates, but longer term studies are needed to determine years to commercial size.

Because of the success, which has been validated by the enormous databases our citizen scientists have helped us collect, the project is also collaborating with a wide range of scientific institutions both in Puerto Rico (including the Institute of Tropical Forestry and the University of Puerto Rico at Rio Pedras) and elsewhere. It has also put Las Casas de la Selva in the forefront of a growing movement to promote a sustainable local timber/wood industry. Puerto Rico currently imports almost all of its commercial wood from the U.S. and Canada. Forest management for timber is still in its infancy despite the fact that the island has the greatest rate of secondary forest increase in the world. In another sign of the change of attitude towards its forests, the University of Puerto Rico has recently begun its first program in tropical forestry and silviculture.

6.4.5 Landscape Partnerships Project, Southern Brazil

The Brazilian Atlantic Forest (AF) is considered a major global biodiversity hotspot and is one of the most endangered ecosystems in the world (Myers et al., 1999; Mittermeier et al., 2004). The AF contains high biological diversity, including 1020 species of birds and 250 of mammals, with high numbers of endemic and threatened species. Additionally, the AF offers numerous ecosystem services to the Brazilian and global population, for example, providing drinking water for 60% of the Brazilian population and the sequestering of 2 billion tons of CO_2 (Calmon et al., 2011). The AF originally covered 16% of the Brazilian territory, but only 11.7% of the original forest cover is now left, where the majority of remnants are isolated patches embedded in a mosaic of secondary and anthropogenic forest tree plantations, pastures and agricultural crops (Ribeiro et al., 2009). These are subject to continued pressure from urbanization, agricultural expansion, and other threats associated with human presence, such as hunting and logging (Giorgi et al., 2014).

Ana Paula Giorgi and Thais Azevedo Vieira of the Earthwatch Institute in Brazil and Morena Mills of the University of Queensland in Australia lead the Landscapes Partnerships project. This project aims to map conservation opportunities with a focus on conducting restoration actions in the Southern AF based on recently changed Brazilian environmental legislation. It consists of a three-stage framework for conservation planning to conduct conservation and restoration actions. First, high resolution satellite imagery (0.5m) is used to analyze the impacts of Brazil's new Forest Code within the study region in order to identify areas at risk of deforestation and potential areas to be restored by mapping 15 watersheds (67,000 ha) throughout the Serra do Itajai National Park buffer zone. Second, interviews are conducted with local small-scale farmers to investigate motivations and barriers to participation in restoration initiatives, and to estimate the percentage of the population likely to adopt different programs and their adoption rate (Mills et al., submitted). Finally, biodiversity prioritization models are run to define priority areas for biodiversity conservation. The Landscape Partnerships opportunities map will be built by overlapping the results from these three stages. Mapping conservation opportunities offers an understanding of the factors that contribute directly to effective actions and improves identification of candidate areas where conservation initiatives can be implemented feasibly.

Approaches Used and Data Collected

Citizen science monitors have been involved in carrying out censuses along transects as well as the setting and checking of camera traps to record terrestrial mammals. This

research also includes the use of mist-nets, point counts for birds and bird banding. The citizen monitors help to check for footprints and set up the camera traps for mammal assessments, and for bird counts, they set up the mist-nets, and take the birds out of the nests to do biometric measurements. Since the start of the project in 2013, 180 small farmers/landowners have been interviewed regarding landscape perceptions and 67,000 ha have been mapped at a 1:3000 scale. In 2013, during only 17 days of field work for bird assessment and monitoring, the team of researchers and citizen scientists captured 485 birds from 94 species in the mist-nets. Of this number, 404 individuals were banded and released. When mist-nets and point count assessments were combined, the team identified a total of 199 species (18% of them are endemic to the AF) from 52 families living in one particular area of the study site. In 2014, while gathering bird data at a new site, citizen science monitors and researchers assessed 54 bird species, with 23 endemic to the AF and 45 listed in the IUCN Red List.

Two types of maps have been produced for the national park managers, the Brazilian Federal Government, and the Santa Catarina State Government for monitoring and enforcement: a map of priority areas for biodiversity; and an opportunities map showing where restoration and conservation actions should be focused.

Successful Outcomes

Detailed information on the mammal and bird communities throughout the National Park's buffer zone and surrounding water catchments has contributed to species population information. In addition, during the execution of the project, a potential Ecological Corridor, linking the two biggest protected areas of the Santa Catarina State, the Serra do Itajai National Park and the Serra do Tabuleiro State Park, was identified. The State Government invited the project coordinators to develop a proposal for such a corridor. Furthermore, a high number of birds are being banded, which will allow the team to include population dynamics and detailed ecological studies in the future, such as the effect of the fragmentation and different land-uses on the birds' movements and behavior. This will contribute to data on both species traits and collection of land use information.

6.4.6 Project COBRA, Guyana, South America

Jay Mistry of Royal Holloway University of London and Andrea Berardi of The Open University are key proponents of the COBRA project (Community Owned Best practice for sustainable Resource Adaptive management), which is funded by the European Commission's 7th Framework programme. The mission of COBRA is to "find ways to integrate community owned solutions within policies addressing escalating social, economic and environmental crises, through accessible information and communication technologies" in the Guiana Shield region of South America (see www.projectcobra.org). Starting in September 2011, the project has worked with various Indigenous communities in Guyana, Brazil, Suriname, Venezuela, French Guiana and Colombia (see http://projectcobra.org/communities for a description of each community). The aim of the project is to showcase Indigenous solutions for the management of natural resources and change development policies and projects so that they strengthen the position of Indigenous communities as stakeholders rather than undermine them, while inspiring other communities to take the initiative in facing up to global challenges.

Approaches Used and Data Collected

Project COBRA used accessible visual methods of Participatory Video (PV) and Participatory Photography (PP) to collect information about the social-ecological viability of Indigenous communities. Through a facilitated process, indigenous community members identified and recorded indicators that they perceived as allowing their community to survive in the face of a range of challenges. These were then documented through PV and PP where community researchers planned, filmed, screened and edited the indicator information into

films and photostories through an iterative process of consultation and evaluation with community members. Indicators included how communities valued land rights in order to secure access to key resources, but also the ability to use new technologies in order to adapt to the challenges of an increasingly globalised world. Information on the status of all the indicators was collected by community members and used to identify 'best practices', i.e. local solutions which have been most successful at allowing communities to survive and thrive (see Table 6.4.6.1). These best practices were then documented through the PV and PP process for sharing with other communities across the Guiana Shield and policymakers at national and international levels. More details are available in Berardi et al. (2013), Mistry et al. (2015) and Berardi et al. (2015).

Table 6.4.6.1: Themes of the community owned solutions, or 'best practices' identified by each community.

Communities	Local community owned solutions
North Rupununi, Guyana	Traditional fishing practices Traditional cultural transmission Community radio Traditional farming techniques Local civil society organization Self-help practices
Antecume Pata, French Guiana	Traditional fishing practices
Katoonarib, Guyana	Forest island management
Kavanayén, Venezuela	Tourism cooperative
Kwamalasamutu, Suriname	Two-farm traditional system
Laguna Colorada, Colombia	Traditional cultural transmission
Maturuca, Brazil	Cattle raising to assert land rights

It is important to note here that the actual indicators and associated data collected through the community-led process focused on issues and practices that were of concern to the communities themselves, rather than the interests of external biodiversity scientists or policy makers. Indigenous communities highlighted indicators pertaining to land-rights, and access to key forest and river resources as essential to their existence. They identified the ability to continue with traditional rotational farming practices and the maintenance of a diversity of crops as important characteristics for giving them flexibility in a highly variable and unpredictable environment. They showed that indicators of community cohesion and self-help practices allowed them to function ideally in a situation of resource scarcity. They highlighted how advanced information and communication technologies allowed them to adapt to changing environmental conditions. But they also illustrated a range of indicators on how maintaining traditional culture and identity allowed them to resist deleterious change. Finally, they showed how partnerships with a range of organizations have enabled them to strengthen their responses in a range of initiatives, including the management of endangered species, such as the *Arapaima gigas*, the largest scaled freshwater fish species in South America.

Although the indicator selection on data recording did not fit neatly into the criteria often required for biodiversity monitoring and management (e.g. there were no indicators that focused on species abundance and distribution), the approach strongly suggests that addressing the concerns of Indigenous communities for maintaining their traditional livelihoods will have an indirect impact of also maintaining the natural habitats and species that biodiversity monitoring experts are so concerned with counting and preserving.

Satellite data published on Global Forest Watch (Hansen et al., 2013) show almost intact forest cover and negligible deforestation over the 10 years within the immediate surroundings of the Indigenous communities with whom Project COBRA has worked. This is corroborated with other studies in the Amazon comparing Indigenous and non-Indigenous lands such as Nepstad et al. (2006) and Walker et al. (2014). The reasons why Indigenous territories seem to have higher levels of environmental protection are complex and may not always be linked to Indigenous cultures. For example, Indigenous territories tend to suffer from poor transport infrastructure, which makes the commercialisation and unsustainable exploitation of natural resources more difficult compared to better connected non-Indigenous areas. However, in our work, the overriding perception is that the identity and livelihoods of the Indigenous communities we engaged with were intimately linked with their local natural environment. As opposed to non-Indigenous people, community members felt that they had 'nowhere else to go' - if they unsustainably mismanaged their territories and were forced to leave, or 'sold out' to commercial interests, then they would lose everything: their livelihoods; their identity; their culture; and even their lives. Thus, identifying and sharing community owned solutions that strengthened the cohesiveness and cultures of Indigenous people more often than not has the indirect outcome of also protecting the local environment.

Successful Outcomes

Project COBRA has demonstrated that participatory approaches that allow local communities to identify, record and share what matters to them ought to be an essential component of effective natural resource management and biodiversity conservation. The participatory approaches used in Project COBRA not only engaged people directly in the research process, but also supported self-representation, encouraged reflection, collective involvement and empowered the individuals that are directly affected, and can react to habitat degradation and biodiversity loss. Supporting Indigenous communities in identifying and sharing their own solutions to conservation challenges constitutes one of the most ethically appropriate frameworks for research and interventions within Indigenous communities. Communities are becoming aware that the solutions to their challenges do not lie exclusively in the hands of professional experts, but also in people just like them.

6.4.7 National Program for Biodiversity Monitoring, Brazil

The Brazilian government, through the Ministry of Environment and the agency for biodiversity conservation and protected areas, Instituto Chico Mendes de Conservação da Biodiversidade (ICMBio), has recently launched the National Program for Biodiversity Monitoring in protected areas. The 320 federal protected areas were design to conserve biodiversity under the management responsibility of ICMBio, and are categorized as conservation units that allow the use of natural resources, mainly by local communities, and conservation units that are strictly for biodiversity protection.

To improve their management capacity, the agency has been implementing different monitoring schemes addressing land cover change and management effectiveness of protected areas. The third pillar of information to manage the areas, however, was lacking until 2012 when the Program for Biodiversity Monitoring was established.

The program was built during three years of cooperation with the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), the Gordon and Betty Moore Foundation and Instituto de Pesquisas Ecológicas, using the lessons learned from 10 years of previous pilot programs, local initiatives and attempts to implement government-led biodiversity monitoring. Two major frontlines compose the program: on the one hand, it intends to provide continuous and systematic biodiversity information to support the management of the National System of Protected Areas; on the other hand, it was structured to also provide biodiversity information to support decisions at the level of single protected areas.

To answer the request at the national scale, the program is based on the information of a few, simple-to-collect biological indicators of biodiversity that every protected area has to provide through a standardized methodology that is easy to implement. Here, the program considers the involvement of local people in data collection, after participating in capacity-building courses. Therefore, representatives of communities that live in protected areas are participating in a national government-led program that provides information to manage biodiversity.

At the level of single protected areas, the program is open to a more comprehensive and intense involvement of local communities. In each protected area participating in the Program, communities participated in the design of the whole monitoring scheme. Together with the local staff they decide on the component of biodiversity that should be monitored, provide information to support and validate the design of the monitoring methodologies, select communities and members that participate, and collect the data. As such, the information produced is relevant for the local management of biodiversity both for the government as well as for communities living in the protected areas. Moreover, the core methods developed in one protected area have the potential to be adopted in others allowing for regional analysis and decision-making at broader scales.

Approaches Used and Data Collected

Given the size of the country, the elevated number and extension of protected areas, and the relative lack of financial and human resources to monitor biodiversity, the program opted to simplify things as much as possible since its design.

The two approaches developed in the Program are complementary and based on the principles that monitoring should be feasible to implement, and therefore, able to involve as many people as possible, independent of the level of formal education (Pereira et al., 2013b). Hence, four biological indicators, which provide complementary information on biodiversity, were selected to be monitored in every protected area engaging in the program: medium and large mammals, large birds, arboreal plants, and frugivorous butterflies. Simple methods were developed that allow local people to collect data on the number of mammals, birds, and butterflies, and the size of plants (Nobre et al., 2014). These data are used to estimate parameters of population, community structure and function. The program also designed two additional modules for each indicator that generate more complex information that can be adopted in protected areas that have partners willing to contribute, such as universities and research NGOs.

The technology for monitoring is intended to be applicable to as wide a variety of contexts as possible. Therefore, the option, in the first phase, was to use paper and pencil to record data. The program developed supporting material to facilitate the adoption and use of data collection protocols. The guides of data collection and identification were designed to facilitate the manipulation of local people and the information in them was expressed in drawings and photographs, instead of using words. Videos were also made to show the technical details of the data collection. Whenever communities in the protected areas are willing to participate in this part of the program, there are also capacity-building courses oriented to this audience (Santos et al., 2014).

The local approach was built on a series of meetings and workshops with community leaders and other members to design the monitoring. Although there were differences in the process depending on the protected area, the general overview and guidelines were maintained. The selection of monitoring target was defined after defining a question relevant to the management of biodiversity at the scale of the protected area. Usually, communities and government staff prioritized those targets that were included in the formal management agreement instruments of the protected areas (i.e. the management plan, the management agreement between communities living in protected areas of sustainable use and the state, and the term of commitment of communities using resources in protected areas of strict protection). Currently, communities in protected areas work with the government to monitor the status and use of Brazil nut trees, game species,

peacock bass (tucunaré), and aquatic chelonians, as well as the effect of logging on large mammals and birds. Each monitoring target has specific methodologies, instruments, and technologies associated with it. Nevertheless, the methodological protocols were carefully developed to collect data with enough quality to support local management interventions with significant information. Moreover, a core group of data was defined for collection wherever these targets are monitored.

Successful Outcomes

The National Program for Biodiversity Monitoring is currently collecting data in 20 federal protected areas to provide information to manage the national system of protected areas. In addition, there are seven protected areas currently participating in the program, all in Amazonia, that are producing monitoring information for the local management of biodiversity. People living in communities in these protected areas participate in diverse ways and levels of engagement, being an essential part of the program. This program is a pioneer in recognizing local knowledge and promoting local engagement in a biodiversity monitoring program coordinated by a federal government to support local and national scale decision making. As it is now, the program is starting to provide nationwide continuous systematic information on trends of animal populations, and community structure and function.

Although the program is still in the first years of implementation, there is a strong effort to expand the activities. The Amazon Region Protected Areas Program of the Ministry of Environment is adopting the principles, including community involvement and the methodologies developed in the National Program for Biodiversity Monitoring. As a consequence, ICMBio is planning to include another 20 Amazonian protected areas in their program by the end of 2016. Moreover, state governments in Amazonia are interested in monitoring biodiversity in their protected areas according to these methodologies, and there is also interest in adapting the program for implementation in other indigenous lands across the country. In addition, ICMBio is expanding their network of collaborators to implement the more complex modules of biodiversity indicators in protected areas that already have the basic modules, and to develop a more traditional citizen science component.

6.4.8 Nature's Notebook: USA National Phenology Network

Nature's Notebook is led by the USA National Phenology Network (USA-NPN; www.usanpn.org), which was established in 2007 by the US Geological Survey in collaboration with other governmental and non-governmental organizations. The USA-NPN is a national-scale science and monitoring initiative focused on phenology – the study of seasonal life-cycle events such as leafing, flowering, reproduction, and migration – as a tool to understanding how plants, animals, and landscapes respond to environmental variation and change.

Formally launched in 2009, *Nature's Notebook* (www.nn.usanpn.org) is a ground-based, multi-taxa phenology observing program, which enables both professional and volunteer participants (typically contributory citizen science) across the USA to observe and record phenology of plants and animals according to standardized, published protocols via web or mobile applications.

The success of *Nature's Notebook* and the ability of USA-NPN to deliver a high-quality multi-taxa data resource hinges on the activity of the participants. Approximately half of the participants are volunteers. Therefore, without the efforts of the thousands of citizen scientists, it would be impossible to provide such a rich, deep phenology data resource.

Approaches Used and Data Collected

Participants in *Nature's Notebook* submit observations on the status of several phenological stages, or *phenophases*, during repeated visits over the course of a season (Denny et al.,

2014). Status monitoring involves evaluating phenophase status (e.g., the presence or absence of leaves, flowers, or fruits for plants, and mating, feeding, or movement for animals) during a series of repeated observations over the course of a season. Observations are expressed as the question, "Do you see [phenophase]?" to which the observer answers "yes", "no", or "uncertain" for the presence of each phenophase. In addition, observers may record the intensity or abundance of each phenophase (e.g., number of flowers present, percentage of flowers open, number of robins feeding, etc.). The use of status-based monitoring is particularly suitable for tropical and sub-tropical systems where there is little seasonality, or where seasonal drivers typically considered important in more temperate regions, such as accumulation of warmth during spring, are unknown or of less importance. Status-based monitoring captures repeated bouts of flowering or leaf-out over the course of the growing season, which is common in tropical and aseasonal systems.

The data collected via *Nature's Notebook* directly supports the "phenology" EBV, and is suitable for documenting changes in species phenology as well as in synchrony of states or events between or among species (e.g. plant-pollinator interactions). Although primarily focussed on temperate climates of the coterminous USA, this type of citizen-based monitoring approach could easily be transferred to tropical forests.

Successful Outcomes

Nearly 7 million records (as of early 2016) of plant and animal phenology have been contributed to *Nature's Notebook* since the launch of the program in 2009, representing hundreds of species of plants and animals at over 8000 unique locations across the USA. These data have resulted in 21 peer-reviewed publications to-date (http://www.usanpn.org/biblio/%20contemporary-data) with several more under development. For example, data from the network have been used to improve models that predict onset of seasonal activity of important tree species in the eastern United States (Jeong et al., 2013), which has implications for local activities and economies, such as maple syrup production, honey production, allergy seasons, bird migrations, cultural festivals and harvesting of native herbs. Other models using data from the network indicated that 2012 was the earliest spring since 1900 (Ault et al., 2013), and illustrated how such a "false spring" increased susceptibility of agricultural crops (such as apples and grapes in Michigan) to frost, and may have exacerbated impacts of summer drought on regional agricultural productivity.

6.4.9 Majete Wildlife Reserve, Malawi

The 70,000 ha Majete Wildlife Reserve (MWR), at the tail-end of the Rift valley in southern Malawi, provides a home for many of Africa's iconic species: leopards, elephants, water buffalo, black rhinos, sable antelopes, eland, lions, leopards, and hyenas, among others. MWR was originally established as a game reserve in the southern section of the Great Rift Valley in 1955, and poaching became rampant during the late 1980s and 1990s. In March 2003, a decision was made to rehabilitate MWR through the establishment of a public-private partnership, between the Government of Malawi (Department of National Parks & Wildlife) and African Parks PTY Ltd. Since then, millions of dollars have gone into developing the reserve's infrastructure, primarily for ecotourism purposes and building up its staff component, with a current total of 135 full time staff, all employed from the surrounding communities. Tourism has been steadily increasing since African Parks took over management of the reserve. A 142-kilometer (88-mile) electric fence now surrounds the reserve, protecting the original 2,554 animals of 14 different species that were reintroduced to the reserve, along with their new offspring. Almost 10 years later, the project is gradually moving from its inception and rehabilitation phase into a conservation, monitoring and habitat management phase, including the provision of water, fire and visitor management, control of alien and invasive species, continued re-introduction and monitoring and translocation of animals and managing the rare and endangered species.

Changes in animal numbers due to high breeding success rates and the predicted impact on vegetation brought about by the rehabilitation programme now require monitoring and measuring.

Dr Alison Leslie from the University of Stellenbosch (South Africa) and Earthwatch initiated a biodiversity research and monitoring program in 2013 to monitor key species and their ecological interactions in Majete Wildlife Reserve in Malawi.

Approaches Used, Data Collected and Successful Outcomes

Community-based monitoring and Earthwatch volunteers (i.e. citizen scientists) are being used to determine population trends of all 14 reintroduced species within the reserve. Fixed-point photography is used to monitor vegetation changes. Waterholes are monitored for the development of and an increase in the size of piospheres. Distance sampling monitoring, on foot and by vehicle, is undertaken for animal counts, camera trapping is conducted to determine presence/absence of species in different areas of the reserve and to determine species abundances and scat/dung is collected from herbivores and predators to determine the preferred seasonal diet of the various species.

The biodiversity observation monitoring program is providing data on key biodiversity indicators, including the status and trends of species, and identification of potential ecological interactions which may limit species response. The research team knew exactly how many individuals of what species were introduced (a rare situation) and are currently gaining a better understanding as to reproductive rates and population growth rates in general. All 14 reintroduced species are doing incredibly well (all species have reproduced since re-introduction) and using citizen scientists, Dr Leslie is studying actual rates of increase. Currently there are over 200,000 camera photographs of species presence/absence (habitat use) in areas of the reserve, which will use citizen scientists for identification. Thirty-two waterhole counts are carried out by citizen scientists per field season (June-December) totaling 384 hours. Fixed-point photography study is well underway with photographs taken every 3 months at 58 sites throughout the reserve, totaling 360 photographs per sampling session. Citizen scientists are responsible for sorting and collating all photographs. Additionally, citizen scientists undertake 512 hours of distance sampling, on foot and by vehicle per fielding season, contributing a huge amount of data to the research monitoring programme, which would otherwise be impossible to collect. The identification of potential ecological interactions which may limit species response include elephant impacts on habitat and habitat selection within the reserve, the development of piospheres around waterholes and the high number of wild fires. In the future, predator impact on herbivore populations will be studied.

The abundance, productivity and reproductive success of biological organisms can provide an indication of the overall health of an ecosystem. Monitoring of these variables provides key information for management decisions and will contribute to the overall success of one of Malawi's largest protected areas, and Malawi's only "Big 5" reserve. Monitoring has already indicated a higher number of elephants than expected and in late 2016, one of Africa's largest elephant relocation projects will be undertaken by African Parks. Results from this program will ultimately contribute towards a Management Plan for MWR, which will be provided to African Parks and the Department of National Parks and Wildlife, for implementation. This management plan may also assist other reserves within the country and further afield in the form of suitable monitoring protocols for a large number of re-introduced species of both predators and their prey. Additional outcomes of the research program include the training of numerous post-graduate students (including Malawian citizens), peer reviewed publications and ultimately the protection of some of the last remnants of Africa's eastern Miombo woodland.

6.4.10 Participatory Ecological Monitoring in Madagascar: The Case of Lake Alaotra New Protected Area

The Island of Madagascar (58.7 million hectares) is a biodiversity hotspot due to its exceptional rate of endemism and current environmental threats. All 103 species of primates (Mittermeier et al., 2006), 98% of amphibians (Glaw and Vences, 2007), 91% of reptiles, 52% of birds (Morris and Hawkins, 1998), and 80% of plants are endemic to the country. However, since the arrival of humans around 2,350 years ago, Madagascar has lost more than 90% of its original forest with a high annual rate of deforestation of 1.95%/year from 1990 to 2000 and 1.28%/year from 2000 to 2005 (Harper et al., 2007). Moreover, with a high multidimensional poverty index of 0.41 (Alkire et al., 2013), about 80% of people live in rural areas (INSTAT, 2010) and rely importantly on natural resources to survive. The main pressures on natural resources are slash-and-burn agriculture, tree felling for firewood and charcoal and illegal timber exploitation, causing loss and destruction of natural habitats. Due to lack of resources, the government has difficulty in controlling illegal timber exploitation. Therefore, many of the species are under serious threat of extinction.

Participatory ecological monitoring has been deployed by many conservation NGOs to help save Madagascar's wildlife. Lake Alaotra (17°02'-18°10'S, 48°00'-48°40'), where the Durrell Wildlife Conservation Trust introduced a participatory ecological monitoring approach for the first time in 2000, has been a key pioneering site. With a surface area of 20,000 hectares, and surrounded by a further 23,000 hectares of reed beds, Lake Alaotra was designated as a Ramsar site in 2003, and after receiving temporary protected area status in 2007, it was awarded an official permanent decree of protection n° 2015-756 on 23 July 2015

The main goals for the Lake Alaotra Protected Area are to conserve the lake and marsh area, their biodiversity including the Alaotran gentle Lemur *Hapalemur alaotrensis*, the carnivore *Salanoia durrelli* and indigenous fish and waterbirds, and to maintain the provisioning of ecosystem services to sustainably improve human well-being.

Approaches Used and Data Collected

Participatory ecological monitoring takes place yearly every rainy season when Lemurs and water birds are more active and the water level is high enough for travel by canoe (Andrianandrasana et al., 2005). The fieldwork lasts for 3-5 days per village. Monitoring teams at each site consist of up to 15 people: 8 villagers, 2 government representatives, 3 qualified Durrell Wildlife staff (all have university degrees) and 2 local technicians who have a secondary school education. Following a preparatory visit, participants are chosen at an initial meeting to which all members of the community are invited. Selection criteria include detailed knowledge of the marshes, interest in conservation, and literacy. Monitoring indicators were chosen with the local community through public village meetings. They include key species such as the Alaotran gentle lemur, the 50 species of water bird (Langrand, 1995), indigenous fish; the key habitat such as the reed beds and lake; and the main threats such as marsh fires, invasion of water hyacinth and snake-head fish, illegal fishing and rice farming. Indicators also cover some key environmental services such as fish productivity and hunting. Field data forms based on those indicators were developed with local monitors, authorities and government officials to make sure everyone understands the procedures of data collection and reporting. Participants who volunteer are paid around $3/person/day, less than the average income from fishing. Since 2002, participating villagers, most of whom have had primary school education, have been given training in data collection.

The monitoring teams are divided into 5 subgroups. Each subgroup has the specific objective to observe lemurs and water birds along fixed canoe transects, and map out burned marsh areas using base maps and GPS. The subgroups that look at biodiversity and threats follow the existing tracks within the marsh area to record the name and number of mammals, reptiles and water bird species. They also visit the lake to check whether the

selected no fishing zones already fenced with phragmites are respected. The group that is in charge of the fish productivity survey stays at the port to record the time spent by each fisherman and measure and identify the fish caught. They also record the type of fishing materials used by each fisherman. At the end of the annual participatory ecological monitoring, a big public meeting attended by government officials, local authorities and local associations is then organised in each village to discuss results of the observation. After some public speeches given by the authorities and government representatives that reminds the local people about the laws and the importance of natural resources for sustainable development, the monitoring teams give feedback about the results of their observation and discuss publicly the illegal activities. These review meetings are often animated by public quizzes and traditional dancing.

Between 2011 and 2016, Durrell has received financial support from the MacArthur Foundation, the Helmsley Charitable Trust, the Tusk Trust, the JOAC (Jersey Overseas Aid Commission), and the GEF UNDP MRPA (Managed Resources Protected Areas) to expand and reinforce participatory ecological monitoring in five sites including Lake Alaotra, Menabe dry forests, Lake Ambondrobe, Nosivolo River and Manombo rainy forest. The Ministry of the Environment and Forests approved the training of 468 local monitors, 96 of them in Alaotra, as well as the provision of uniforms and equipment including mobile phones and simple cameras.

Since April 2011, these local monitors have carried out patrols on a weekly basis to observe key species, their habitats and illegal activities within their local management area. Overall, the monitoring has provided useful data for decision making and started the process of building local pride in the environment as well as the ability to analyze the monitoring data locally.

The monitoring has supported wetland management by guiding amendments to, and increasing respect for, a regional fishing convention; by catalysing the transfer of marsh management to communities, by stimulating collaboration and good governance; and by raising awareness. Monitoring has revealed trends in natural resource management over time (e.g., changes in the extent and frequency of devastating annual marsh fires) and provided valuable fishery data. Surveys have also provided information on the levels of hunting of water birds and lemurs and the areas of lemur occupancy.

Data collected through participatory ecological monitoring has indicated stability in fish productivity from 0.23 kg/person/hour in 2002 to 0.25 kg/person/hour in 2005. That could be an impact of the reduction of marsh burning from 7,300 hectares in 2000 to 2,500 hectares in 2003 (Andrianandrasana et al., 2005). That stability was followed by a significant decrease in fish productivity until 0.09kg/person/hour in 2009, which has been confirmed by the massive decline in fish production from 2000 tonnes/year in 2004 to around 800 in 2011 (DRPRH, 2013)(DRPRH, 2013). Fish production and marsh burning may depend not only on overfishing and illegal rice farming but also on quantity of rainfall, climate change, and immigration and water quality issues. In addition to the lack of control of the use of illegal fishing gear, it seems that some of the more than 10,000 mosquito nets distributed in the area between 2010 and 2012 for reduction of malaria control have been used for fishing. At night, according to local monitors' reports, at least 10 seine fishing nets are still operated on the lake. Due to lack of resources and personnel, it is difficult to apply the national fishing regulations and the local fishing convention known as 'dinan'ny jono', which bans fishing of Tilapia less than 13cm length, *Ciprinus carpio* less than 15cm and eels less than 45cm. Furthermore, enforcement of the annual closed fishing season (15 November to 15 January) is often difficult especially if this coincides with political campaigning activity.

Successful Outcomes

The data collected through participatory ecological monitoring and local patrols are robust and have contributed to an understanding of the changes that have occurred across all the sites including Lake Alaotra. Contributions have been made to data on species populations

and species traits as well as ecosystem structure through habitat monitoring. The data have also helped to develop management plans at each site and facilitated discussions during the process of developing management structures. The monitoring approach has contributed to achieving the government's objectives to expand the size of protected areas from 1.7 million hectares to six million hectares, most of which are under IUCN category V and VI that require the involvement of the local community in their management. In particular, Lake Alaotra, Menabe dry forest and Nosivolo River, and Lake Ambondrobe have become part of the official New Protected Areas, and have substantially succeeded in involving local people in their management.

The approach has worked well both in terms of involving villagers in the process of conserving biodiversity and improving collaboration between the communities and the local authorities responsible for sustainable management of natural resources. Although local monitors report on illegal activities, law enforcement is lacking and there is a little evidence of follow-through on these reports. This has had a negative effect on the reputation of the local monitors and dampened their enthusiasm for the hard work required to collect the data. The lack of law enforcement has also meant that there has been insufficient evidence to demonstrate the effectiveness of the participatory ecological monitoring approach at times although some positive changes of local people's attitudes are still evident. Overall, determining how best to monitor the effectiveness of the participatory approach remains an ongoing issue.

6.4.11 Community-led mangrove conservation and restoration in Gazi Bay, southern Kenya

For many coastal communities, such as those living around Gazi Bay in Kenya, mangrove ecosystems provide key services such as firewood and building poles, nursery provision for fish, coastal protection and opportunities for tourism. The forests also generate regional and global benefits, by protecting neighboring ecosystems such as coral reefs and through their exceptional ability to trap and sequester carbon, mitigating climate change. Whilst the mangroves of Gazi Bay have supported people for millennia, current patterns of use are unsustainable, with projections based on business as usual, suggesting that more than 40% of mangrove forests in southern Kenya will be lost in the next twenty years (Huxham et al., 2015).

A community-led mangrove conservation, restoration and research project is being led by Professor Mark Huxham of Edinburgh Napier University in partnership with Earthwatch Institute, James Kairo of the Kenya Marine and Fisheries Research Institute, Dr Martin Skov of Bangor University and the Kenya Forest Service. The aim of the project is to help sustain the supply of mangrove goods and services by linking mangrove management with direct community benefit. In particular, the project is pioneering the use of carbon credits as a new way to fund mangrove conservation and social development in the area, and has used scientific research conducted by international and local scientists and volunteers to underpin this work. Participants in the project include local stakeholders, students and early career scientists from Africa and Asia, corporate employees from major international companies, and self-funded volunteers recruited by Earthwatch. The engagement of a wide range of people and the building of trust over many years has proved critical to long term project success.

Approaches Used and Data Collected

In 2003, work began to research techniques to restore mangroves and associated marine ecosystems and to evaluate the carbon stocks they hold. In collaboration with Earthwatch, 253 individuals from 48 countries have taken part in the research and conservation activities. Tasks have included:

- planting trees as part of experimental studies and for general conservation and restoration purposes - over twenty thousand mangrove trees have been planted and measured over 20 years;
- monitoring established experimental stands to measure how trees are growing and surviving and which species combinations are best suited for restoration; and
- measuring the amounts of carbon accumulated above and below ground by different species of trees.

These data have led to a greater understanding of mangrove forests and their management – including effective restoration. The work has helped to clarify the role of mangroves in storing carbon and has used experiments to measure carbon losses arising from deforestation. The Mikoko Pamoja initiative ('Mangroves Together' in Kiswahili) was launched in 2009 to apply this research and use payments for ecosystem services (specifically, payments for carbon credits) to safeguard conservation gains and improve the quality of life of the local community. This research has led to the development of the first community mangrove conservation project to be funded by the voluntary carbon market, after gaining formal accreditation to sell carbon credits through the charity Plan Vivo. This project involves collaboration between local, national and international bodies:

- The Mikoko Pamoja Community Organization is run by nominated community representatives from Gazi Bay; all expenditure of project funds on local projects is determined following full community consultation.
- The Mikoko Pamoja Steering Group provides technical support and consists of staff from the Kenya Marine and Fisheries Research Institute, the Kenya Forest Service, the Tidal Forests of Kenya Project, Edinburgh Napier University and Earthwatch.
- The Association for Coastal Ecosystem Services is a charity registered in Scotland that facilitates the transfer of international funds, organises charitable fundraising and education and reports to the Plan Vivo Foundation (the organization that grants official accreditation of carbon credits).

Successful Outcomes

Specific project outcomes include: generation of new scientific knowledge in the form of 15 peer reviewed publications; increased technical skills and income to local people employed to assist with carrying out project functions; enriched opportunities for women through their representation within the village committee; training to 30 local school students and four master's students each year; investment in 12 future conservation leaders from developing countries each year through immersive training programmes and mentoring; improving sustainability of local fuel and timber sources through the planting of woodlots (which will also provide timber for sale to raise funds for community projects); enhancing ecosystem services through the protection of ~120 hectares of mangrove forests; locking away 2500 tonnes CO_2 per year, derived from avoided deforestation, prevented forest degradation and new planting; providing an income of ~£8000 each year from carbon credit sales, which is used to run the project and support community development; investing in community-led local livelihood projects such as beekeeping and tourism.

This pioneering carbon project is a triple win for community livelihoods, biodiversity conservation and climate change mitigation. More generally, the project at Gazi Bay has provided a greater understanding of sustainable mangrove utilization, and demonstrated the opportunities for community-based conservation of mangrove forests supported in-part by carbon credits. There is huge potential (and interest in) this model in Kenya and elsewhere, and the intention is to act as a catalyst and support for similar projects. The project has established a regional expert network to disseminate knowledge and help support similar initiatives: the East African Forum for Payments for Ecosystem Services, www.eafpes.org. Expansion at both the current site and other sites along the coastline will

help to generate security in the face of fluctuating carbon markets, and bring benefits for local livelihoods, biodiversity and climate change mitigation.

6.4.12 Community-based Monitoring of Carbon Stocks for REDD+, Asian countries

Climate change has been identified as one of the biggest threats to society and our environment as a whole. Reducing CO_2 emissions can mitigate the threat of climate change. REDD+ is a proposed financial mechanism that can provide incentives to developing countries to reduce CO_2 emissions and increase CO_2 removal from the atmosphere by forests (Ghazoul et al., 2010). A "Monitoring and Measurement, Reporting and Verification" (MRV) system is needed for REDD+. Monitoring of forest carbon stocks can involve both remote sensing and in-situ measurement. The United Nations Framework Convention on Climate Change recognises that REDD+ may, in some cases, harm biodiversity and local livelihoods and has asked for safeguards to be implemented to ensure that REDD+ is consistent with the conservation of natural forests and biological diversity (Gardner et al., 2012). The Convention for Biological Diversity (CBD) is likewise calling for countries to identify potential indicators and monitoring mechanisms for assessing the biodiversity impacts of REDD+.

According to the REDD+ monitoring and implementation requirements, it is important to involve local community groups and societies to carry out forest monitoring, in particular, if there is any prospect of payment and credits for environmental services. There are several reasons why local communities should be involved in monitoring forest carbon stocks and biodiversity for REDD+ (Larrazábal et al., 2012; Boissière et al., 2014). Firstly, it is just and fair that local communities are informed of, and invited to participate in, activities pertaining to the forest areas that are central to their livelihoods (Skutsch et al., 2011; Danielsen et al., 2013; Butt et al., 2015). Secondly, it can help to address the concerns of local people that their existing forest use rights and benefits will not be undermined by top-down REDD+ implementation (Burgess et al., 2010). Thirdly, the participation of local communities can help link the monitoring to decision-making and this can lead to increased local forest management capacities (Gibson et al., 2005; Danielsen et al., 2007; Pratihast et al., 2013).

The role of community monitoring for REDD+ has been explored in several projects, including K:TGAL (Kyoto: Think Global, Act Local[30]; Skutsch, 2011), Land use and climate change interactions in Central Vietnam (LUCCi) and I-REDD+ (Impacts of Reducing Emissions from Deforestation and Forest Degradation and Enhancing Carbon Stocks) projects. This case study describes the approaches used by the I-REDD+ project, which was funded by the EU and led by the University of Copenhagen, NORDECO and partner organisations during 2010-2014[31]. One component of this project compared community-based and professional forest monitoring of forest biomass and biodiversity in forested landscapes in six field sites in China, Indonesia, Laos and Vietnam (Brofeldt et al., 2014).

Approaches Used and Data Collected

The I-REDD+ project worked with local partner organisations which, in the spirit of Free, Prior and Informed Consent (United Nations, 2008), contacted local communities living close to the forest and dependent upon forest resources for their livelihood. Communities choosing to become involved in the project participated in mapping and zoning of the local

[30] http://www.communitycarbonforestry.org

[31] http://www.i-redd.eu; www.monitoringmatters.org

[3] http://www.lucci-vietnam.info/

forest and proposed a stratification that reflected forest type and tree density (Brofeldt et al., 2014). A network of permanent circular plots for structured random sampling was established within each stratum. After a short training session, the community members established plots and measured all trees with diameter at breast height (dbh) > 10 cm within those plots. Some of the participating communities agreed to try to identify the species of all the measured trees. Carbon estimates were calculated using the dbh measurements and appropriate allometric equations. Professional foresters measured the same trees and the results of community monitors and professional foresters were compared.

Successful Outcomes

The I-REDD+ project built, to a large extent, on the lessons learned in the K:TGAL project, which had shown that local communities using hand-held computers could monitor forest carbon stocks in relatively simple-structured forests (Peters-Guarin and McCall, 2011). The I-REDD+ project took this a step further by excluding the use of computers in the field and assessing carbon stocks of complex, species-rich old-growth forests (Danielsen et al., 2011, 2013). The rationale was that reliance on the use of hand-held computers (Peters-Guarin and McCall, 2011; Pratihast et al., 2012) may represent a constraint to community involvement and the broad-scale implementation of local community monitoring of forest condition because capacity is limited in some communities (Howell, 2012). Employing low-tech field approaches, such as recording of data using pen and paper, measuring using ropes marked at relevant points, and utilizing other feasible protocols for local communities, may greatly enhance the application of the local approach to monitoring forest condition. The results showed that members of rural communities can monitor and measure levels of carbon stock even in complex, old-growth forests without the use of electronic devices (Brofeldt et al., 2014; Torres and Skutsch, 2015). An overview of who is involved in community-based monitoring of forests and where they are working is provided on the Forest COMPASS website[32] .

Combining REDD+ and Biodiversity Monitoring

There has been limited attention on how local communities can become involved in monitoring the biodiversity impacts of REDD+ (Gardner, 2010; Gardner et al., 2012; Swan, 2012; Enright, 2014; Hawthorne and Boissière, 2014; Latham et al., 2014; McCall et al., 2014). A central question is whether data on biodiversity can be collected while community members are already gathering carbon stock data. We know of three examples of this. Firstly, community members that meet regularly to discuss forest-related issues such as REDD+, the use of forest products and forest management can be encouraged to discuss trends in biodiversity, using the Focus Group Discussion method. Focus groups have the potential to provide results that are similar to results obtained from monitoring by professional scientist (Danielsen et al., 2014b). Focus groups are particularly useful in providing early warnings of changes in biodiversity. Secondly, community members can be encouraged to take notes on any encounter with selected rare but easily recognisable species (howling gibbons, hornbills heard flying above the canopy, calling pheasants, bear markings on trees, etc.; Padmanaba et al., 2013). Thirdly, permanent plots for monitoring carbon stocks, as done by community members in the K:TGAL and the I-REDD+ projects, can also be used to provide valuable biodiversity information. They can be used to provide data on forest type and structure (density and size of trees) (Theilade et al., 2015) and, in some cases, even on tree species diversity (Zhao et al, 2016). If funding permits, additional biodiversity monitoring activities can be undertaken, similar to the activities described in other sections of this chapter. See section 8 for synergies between biodiversity monitoring and REDD+.

[32] http://forestcompass.org

6.4.13 Community-based Monitoring of Activity Data for REDD+, Kafa Biosphere Reserve, Ethiopia

The Kafa Biosphere Reserve is located in the south western part of Ethiopia. Expanding around 700K ha in size, the reserve achieved UNESCO recognition in 2011. This area contains some of the last remaining forests in Ethiopia, which are comprised of large areas of mountainous afromontane cloud forest (Pratihast et al., 2014). Kafa Biosphere Reserve is very important from an ecosystem service point of view as the wild coffee Arabica originates in this area. Wild coffee, as well as high value spices and honey, obtained from these forests are important for the livelihoods of the local communities. However, increasing pressure from the expanding Small-holder agriculture continues to threaten the forest (Pratihast et al., 2014) while, at the same time, climate change could drastically reduce the areas where wild coffee can grow in the future (Davis et al., 2012).

Community-based forest monitoring in the context of REDD+ is one mechanism for safeguarding local livelihoods, especially if this activity is linked to an incentive scheme such as payments or credits (Pratihast et al., 2013). Community-based monitoring can also play an important role in contributing to national-level forest monitoring systems (NFMS) for MRV as outlined in the previous case study (section 6.4.12), which focused on carbon stock data. This case study considers activity data referring to forest area change (generally measured in hectares) for MRV purposes. This is normally undertaken using remote sensing in combination with field measurements by professional surveyors. The main concern with community involvement in MRV is the lack of confidence in data collection procedures and unknown quality of such data set for their integration in the NFMS. To this aim, Arun Pratihast (and colleagues) at Wageningen University & Research, Mesfin Tekle of the Nature and Biodiversity Conservation Union in Ethiopia and community members made an approach to combine the use of high-resolution satellite imagery and forestry expert measurements to assess the accuracy and consistency of community monitoring data in Kafa Biosphere Reserves, Ethiopia in terms of spatial, temporal and thematic category. The results of the study shows that the local communities were capable of describing processes of change associated with deforestation, forest degradation and clearly demonstrated the value of community involvement in forest monitoring of activity data. Full details of the study can be found in Pratihast et al. (2014).

Approaches Used and Data Collected

The data collection task was undertaken by 30 community members. These community members were recruited within the frame of the project entitled "Climate Protection and Primary Forest Preservation—A Management Model using the Wild Coffee Forests in Ethiopia as an Example". All selected community members were educated personnel, to a minimum of secondary level high school, and some fundamental understanding on forest management and conservation in the Kafa Biosphere Reserve. These community members were concurrently involved in activities such as the development of ecotourism, education and reforestation activities, and therefore had some basic experience of forest management. By ensuring that recruitment was geographically balanced across the 10 administrative districts in the area, a strong community representation was created.

Two mechanisms for data collection were employed: paper-based forms with separate GPS devices to capture location; and mobile phones using a survey-style app built from the open source ODK (Open Data Kit) Collect. Community members were trained through events that took place before and during the forest monitoring activities, and user-friendly training materials were provided. The community members collected data from 755 locations between January 2012 to December 2013; paper forms were used in 2012 while a shift to mobile phone data collection occurred in 2013.

Unlike other examples of community-based REDD+ projects (Danielsen et al., 2011, 2013; Shrestha et al., 2014), which have focused on measuring carbon stocks, the data collection here was centred on the monitoring of forest change processes. Three main categories of data were collected:

- Spatial category: Three aspects of the spatial category of the local experts' data were collected, including categorical location information, GPS location information and the estimated size of forest change. The deforestation areas were mapped on the ground while the central location and area affected were recorded for degradation.
- Temporal category: The time of forest change (day, month and year) was acquired under this category.
- Thematic category: The type of change (deforestation, degradation, reforestation), drivers of change (agricultural expansion, settlement expansion, charcoal and firewood extraction, intensive coffee cultivation, timber harvesting and natural disasters), with documentation consisting of photographs taken in four cardinal directions, were collected in this category.

As mentioned previously, a key component of this study was the assessment of data quality, in particular for MRV purposes and for potential scaling up to national level reporting. An accuracy assessment was performed across all categories of community acquired data sets. Field reference data were collected by a team of local and regional experts who revisited 140 randomly chosen sites at the end of 2013. A time series of high resolution imagery between 2005 and 2013 (including pan-sharpened SPOT and RapidEye images) were used to manually digitize areas and to identify the time of forest change.

Outcomes

In general, the results of the study show that community members were able to document forest change processes, where accuracy varied depending on the category of data collected. The spatial accuracy varied between 71 to 92% for different spatial categorizations of change (Administrative units, Distance to nearest village, Distance to nearest road and Distance to core forest). The positional accuracy (GPS errors) reported by community members compared with those reported in the reference data showed a slight systematic error on the order of 0.65 m.

For large change areas, i.e. greater than 2 ha, the community members systematically underestimated the size of the change. For the time of change, 33% of deforestation events were accurately reported when compared to the remote sensing analysis while 45% was reported 1 to 2 years later than indicated by remote sensing. Forest degradation, on the other hand, was reported earlier than remote sensing for 54% of degradation occurrences, reflecting the advantage of a ground-based approach over remote sensing. Finally, recognition of the type of change and the presence/absence of forest were documented with high overall accuracy (83 to 94%) while drivers of forest change, which were more complex to assess, were still documented to a reasonable accuracy of 69%, assuming that the experts monitoring represented the "truth".

Relevance for Earth Observation

The data collected through community-based monitoring represents a complementary data stream to remote sensing observation, where the latter will continue to have a clear role to play in forest change monitoring and detection. Remote sensing requires ground-based data for calibration and validation; community-based monitoring represents a cost effective way to acquire in-situ data on both forest cover and change over time. However, it can also provide additional information on drivers of change and other land use information that is beyond the capabilities of remote sensing. In addition to land cover and land use (Table 6.3.1), this study documented drivers of change, which partly addresses the EBV of disturbance regime within the broader class of ecosystem function. It might also be possible to extend the types of data collected to other environmental monitoring variables such as biodiversity, plant species type and phenology. Thus, the integration of other environmental monitoring variables may have potential for including community-based monitoring in monitoring and benefit-sharing systems in REDD+ projects (Visseren-Hamakers et al., 2012).

6.4.14 Community-Based Monitoring of Philippine Protected Areas

Until the 1990s, the most protected areas in the Philippines existed only on paper. In 1992, a new protected area act, the National Integrated Protected Areas System Act (DENR, 1992), allowed for community participation in management of protected areas. In 1996, the World Bank and Danish aid (DANIDA) agreed to assist the Philippine government to operationalize the new act, and for three years they worked together to develop a simple scheme for monitoring protected areas based on observations undertaken and interpreted by community-members and protected area rangers.

Representatives of the local communities in each community helped the government select community participants on the basis of their interest in and experience with forest resources. The community participants included some of the most experienced collectors of forest products in each community. Most of the community participants had attended only primary school and had a limited ability to read and write; however, in each community there was at least one literate participant.

The scheme was intended to identify trends in important biodiversity assets and to use these trends to guide management action in protected areas. It was also intended to enhance participation of protected-area communities in management of the protected area.

The scheme was developed by the government's Biodiversity Management Bureau in cooperation with Nordic Foundation for Development and Ecology (NORDECO). It is a category 4 Collaborative Monitoring Scheme with Local Data Interpretation (*sensu* Danielsen et al., 2009). Foreign support to the scheme ceased in 2001 but the scheme continues at most of the sites where it was established.

Approaches Used and Data Collected

Data were collected by government rangers and volunteer community members. The aim of this monitoring system is to ensure better management and the involvement of local people rather than data-based falsification of scientific hypotheses concerning variation in biodiversity values. By allowing park staff to carry out the field assessments, this monitoring encourages them out of their offices and into the field and improves their understanding of park issues and thus their capacity for park management (Danielsen et al., 2000). In each park, monitoring focused on a list of 10–15 taxa and 5–10 signs of resource use (usually large terrestrial mammals, easily identifiable birds, crocodiles, marine turtles, fish and shellfish). The targets of the monitoring were selected by local community members together with protected area staff. Data were collected every 3 months. Data interpretation was undertaken locally by the protected-area staff and community members, and a small report was presented every quarter to the Management Council of each protected area. The report included the data set, a list of important observations of changes in species and resource use, and a list of proposed management interventions with a description of the issue identified, the location, and the proposed action to be taken by the protected-area council (Danielsen et al., 2005b).

Successful Outcomes

Before this monitoring scheme was established, there was little collaboration between local people and park authorities, and park monitoring was restricted to assessments of the quantity of extracted timber (Danielsen et al., 2005b, 2007). As a result of 2.5 years of operation of the scheme by 97 rangers and 350 community volunteers, 156 interventions were undertaken in terrestrial, marine, and freshwater ecosystems across 1.1 million ha of 8 protected areas in the Philippines (Danielsen et al., 2005b). The majority of these interventions were meaningful and justified, 47% targeted the 3 most serious threats to biodiversity at the site, and 90% were implemented without external support. By "the most serious threats", we mean the human activities with the most negative impact on the areas'

conservation values. Based on existing information on each park from other sources, the three most serious threats of each site were identified as industrial and road development (four sites), logging and timber poaching (four sites), small-scale agriculture (four sites), large-scale agriculture (three sites), and commercial marine fishing (three sites), along with gathering of non-timber forest and wetland products, grazing, wildlife hunting, and quarrying (one site each).

Many of the interventions were jointly undertaken by community members and the management authorities or consisted of local bylaws in support of park management. As a result of monitoring, schemes to regulate indigenous resource use were reestablished with government recognition in several parks. Monitoring led to more-diversified management responses on the part of the authorities, including a more socially acceptable and effective approach to enforcement. The findings by the community members closely correspond with findings by professional scientists (Danielsen et al., 2014a). The government has promoted the scheme as a standard management tool in protected areas, and it has spread to new sites. In 2012, there were 435 community member participants in the scheme (Jensen *in litt.*, 2013; Danielsen, 2016).

6.5 LESSONS LEARNED FROM COMMUNITY- AND CITIZEN-BASED MONITORING PROJECTS

One of the common themes found in the case studies, and certainly expressed in current reviews of citizen science (Azavea and SciStarter, 2014; Theobald et al., 2015) revolves around balancing the objectives of:

- increasing contributions to answering research questions pertaining to status and trends of key EBVs through accessible regional databases,
- enabling the application of management decisions based on sound monitoring, while
- maintaining relevance to key local partners and participants through the flexible and responsive development of projects that reflect local interests and perspectives.

Achieving potentially divergent goals (i.e. collecting standardized data for top down directed goals vs. meeting the identified needs of participants through bottom up project design) is, however, possible, as these case studies, and others demonstrate. One key approach that is common to most successful projects is that leaders of the monitoring program have sought to identify and incorporate benefits or local relevance for the different participants with whom they were working. Leveraging communication tools that allow for discovery, use or value generation by the participants is clearly a rich avenue to explore in fostering benefits for the participants. See, e.g., case studies Project COBRA (section 6.4.6), and the Natural Phenology Network (section 6.4.8) for communication tools for community-based monitors and citizen monitors, respectively.

Many of the case studies illustrate the power of building field research monitoring programs that leverage three distinct groups of participants: local community members, citizen science monitors (often away from their "homes"), and the field research team (scientists, resource managers (e.g. rangers) and often biology students) (see Figure 6.5.1).

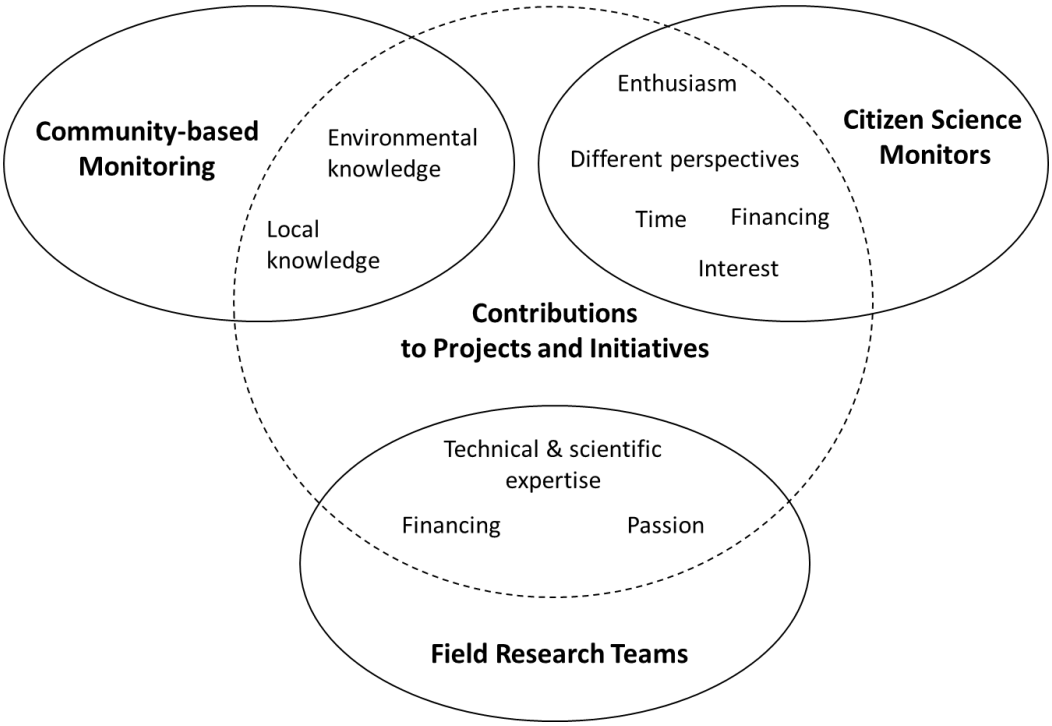

Figure 6.5.1: Synergies between groups of participants in contributing to projects and initiatives

Each of these groups brings important contributions to a successful monitoring program. For example, local community members bring knowledge about the environment derived from experience that is not otherwise available to the other two groups; citizen science monitors can bring additional resources (time, experiences, financing, interest) that extend the monitoring, and the research team brings technical expertise, and other resources, usually not found in the other two groups. It should be mentioned that there is at least one other avenue of support to biodiversity monitoring programs, i.e. the engagement of the public from their homes, who lend their time and online resources to make observations, review images, detect patterns, etc. that otherwise would overwhelm the limited number of highly trained monitoring staff (e.g. Ellwood et al., 2015). Zooniverse is one of the best examples of such programs.

Many of the outcomes identified through the case studies can be attributed to optimizing the synergies between community-based monitoring, citizen scientists and the research field team. For example, in the Pacaya-Samiria case study in Peru (section 6.4.1), the local community brought local knowledge and legitimacy, foreign citizen scientists (e.g. Earthwatch volunteers, Operation Wallacea students) brought additional hands in the field, enthusiasm, interest and financing, and the field research team (including trained Peruvian university students) brought technical know-how, helping to train and direct the monitoring programs. Each group contributed unique resources, but also derived important values from each of the other groups. In this case, the interest, energy and enthusiasm of the citizen scientists enhanced the commitment and attention to the monitoring program by the other two groups, as evidenced on teams where the citizen scientists were absent. Secondary benefits can emerge from such blended projects. In the Community-Based Monitoring project of Philippine Protected Areas (section 6.4.14), the blending of both park rangers and local community members not only increased the capacity of both groups in field surveys but enabled the development of a closer working relationship between the two groups which had heretofore not existed.

Successful use of community members or citizen scientists does not require the whole blending of these approaches, and most start with one group and then evolve over time. For example, in both the Loma Alta (Ecuador) (section 6.4.2) and the Pacaya Samiria (Peru) (section 6.4.1) case studies, the projects started by assessing characteristics that were of high value to the local community (water in Ecuador, hunted mammals in Peru) and then blended in other habitat and biodiversity monitoring subsequently.

The rest of this section considers a number of key issues relevant to citizen science projects and community-based monitoring, including setting up a project; considerations around recruitment, training and sustainability; the management and sharing of the data collected by the communities and citizen volunteers; the quality of the data, which continues to be a key issue within citizen science (Nature, 2015), and mechanisms for communication and feedback. Guidance on these issues from the published and grey literature are provided along with relevant lessons learned from both the case studies and author experiences.

6.5.1 Setting up a project

A significant number of resources exist for developing citizen science projects, whether to start a project of your own or building on what others have done. The same basic standards and principles apply to engaging citizens in biodiversity monitoring. Resources for developing projects can be found at:

- http://www.birds.cornell.edu/citscitoolkit/toolkit/manual
- http://www.ceh.ac.uk/products/publications/documents/citizenscienceguide.pdf
- http://www.birds.cornell.edu/citscitoolkit/publications/CAISE-PPSR-report-2009.pdf/view

A large number of model projects are available from:

- http://scistarter.com/
- http://earthwatch.org/expeditions
- http://www.birds.cornell.edu/citscitoolkit/projects

Furthermore, http://www.citsci.org has a platform for developing citizen science projects that includes standardized templates and support for data collection, storage and mapping, among other features.

One important consideration when setting up a citizen science project is the desired scale of the project. Haklay (2015) reviewed citizen science projects in Europe and found the infrastructure needed to scale up from local to regional is significant and often beyond the means of many smaller scale organizations.

6.5.2 Recruiting, training and maintaining participants

Key aspects for successful project development include:

- identifying the needs, e.g. the numbers, time commitment needed (both total amount of hours but also when), the kind of data to be collected, etc.;
- who the participants will likely be (local community members, visitors, etc.);
- what the likely motivation for participating is; and,
- why the research or monitoring goals of the program might be relevant to the participants.

Identifying the appropriate communication "tools", processes and feedback systems is of particular importance to keeping the alliance between "project leads" and the participants, be they communities or citizen scientists "external" to the region being studied. The use of cameras or videos for monitoring can be extended by community members to include indicators of specific interest to the monitoring project as well as others that may also be of principal interest to the participants (e.g. see the case study on Project COBRA in section 6.4.6).

Projects that focus on ***community-based (ecosystem) monitoring*** often emphasize sustainable resource management, biodiversity monitoring and greater involvement in decision-making at the local level (e.g. community forest reserves, Pacaya Samiria and Loma Alta case studies in sections 6.4.1 and 6.4.2). Evans and Guariguata (2008) have reviewed many examples of approaches taken in the creation of successful community-based monitoring of forests. Many if not most rural community members adjacent to tropical forests will likely have little formal education, and have little time or financial wealth to dedicate to hobbies. Here we assume that the primary motivational factors for community participation are clear benefits to them in terms of improved management of key resources that they will benefit from - in terms of sustainability and access to these resources, jobs, etc., or valuable co-benefits including improved overall surveillance of their community lands with the potential of warding off other detrimental incursions on their lands. Typically, community-based monitoring initiatives are only successful if they are co-designed together with key community members to ensure that the language, goals, and end products of the program are internally consistent with the community as well as the end users of the data.

Projects that focus on ***citizen science monitoring*** typically include participants that are both local and distant to the study area and share an enthusiasm for being outdoors (see e.g. the Natural Phenology Network case study in section 6.4.8). These projects are directed by external institutions, i.e. scientists, government agencies, etc. The main driver for those who are leading these projects is the need for data collection to assess status and trends of natural resources of interest, with secondary goals being greater education or engagement of the general public. Many (if not most) participants to these contributory citizen science projects have above average income (or their parents do) and formal education, and dedicate time and resources to nature-based hobbies (e.g. birding, hikers, etc.). Typically participants do not directly depend on the biodiversity observed for their livelihoods (e.g. Cornell's Lab of Ornithology Backyard Birds), and their primary motivation is to help some management authority or science institution to better understand the state of the environment and thereby enable better decision making in a way that is consistent with their beliefs. Reflecting the diversity of potential citizen science participants is a diversity of motivations including just getting out into nature, having fun, meeting other like-minded people, contributing to science, helping monitor the state of the planet, etc.

Capacity building is often an essential need that enables the transfer of methodologies and communication across audiences and key stakeholders in such programs. A number of organizations are developing modules to train field leaders of citizen science projects. Earthwatch Institute trains senior field scientists and staff to successfully lead teams of public participants to ensure that project leads get the data they need, and participants have a meaningful and safe experience. Building capacity is essential to ensuring that both project leads but also the participants have the capability and confidence to carry out the tasks to the level needed for a successful project. The Citizen Science Academy trains educators to lead citizen science projects on a number of different kinds of projects (citizenscienceacademy.org) including phenology through project Budbust (www.budburst.org).

Finally, a clear understanding of the resources that are needed and available is essential. This includes any financial, technological, personnel, and infrastructure resources that

would enable the project to succeed. Developing and sustaining citizen science projects requires a non-trivial amount of resources to succeed.

6.5.3 Data collection: management and sharing

The data management plan for programs, which include community and citizen participants, needs to emphasize several key components. Several useful resources for data management and sharing include:

- Data Policies for Public Participation in Scientific Research: A Primer, DataONE Public Participation in Scientific Research Working Group, August 2013 http://www.dataone.org/sites/all/documents/DataPolicyGuide.pdf

- Data Management Guide for Public Participation in Scientific Research, DataONE Public Participation in Scientific Research Working Group, February 2013 http://www.dataone.org/sites/all/documents/DataONE-PPSR-DataManagementGuide.pdf

- Primer on Data Management: What you always wanted to know but were afraid to ask, Carly Strasser, Robert Cook, William Michener, Amber Budden http://www.dataone.org/sites/all/documents/DataONE_BP_Primer_020212.pdf

- Citsci.org, which is an example of a useful data collection, storage and sharing platform. See Azavea and Scistarter's 2014 publication, which summarizes a review of platforms at: http://www.azavea.com/index.php/download_file/view/1368/

The purposeful sharing of data is a key criterion to be decided early on in the creation of a project. For example, will participants have access to their data, to the data of others, and how accessible will the data be to partners? What sort of attribution needs to be made to the data collectors when data are used and aggregated into other databases?

It is often thought that the motivation and maintenance of participants in citizen science projects can be tied to the relevance they see in the data that they collect. Visualizing their own data or the data that citizen scientists collect in some sort of summary format against monitoring questions of interest can help keep participants engaged. See Sheppard et al. (2014) to see some of the solutions for tagging volunteer-collected data as it migrates through databases.

6.5.4 Quality assurance

Participants can be trained to reliably collect a wide variety of data, covering most of the EBVs. Earthwatch supports many projects where scientists are able to train citizen scientists to collect trustworthy data on many variables (www.earthwatch.org). Danielsen et al. (2014a) studied the similarity in data on status and trends of tropical forests collected by both community members and scientists across 34 tropical forest sites and 4 countries (Madagascar, Nicaragua, Tanzania). In general they found high correlations for species counts as well as 5 types of resource use. Their findings concurred with their review of previous studies that suggested that community members can in fact report the same data as "scientists". Discrepancies only occurred when there was a notable separation in where samples were collected or if there was a significant time lag between data collection efforts. Similar positive correlations between community collected data and professional foresters on forest carbon stocks was reported by Brofeldt et al. (2014), who looked at 289 plots across four countries in South-East Asia.

The ability for non-specialists to collect reliable data depends greatly on the amount of training, and the kind of oversight and support that is provided. One key factor is the degree of confidence that the data collector has in their abilities (Buesching et al., 2014). There are several papers which discuss general approaches to training and motivation that enhance the quality and consistency of the data collected. See Newman et al. (2003); Wiggins et al. (2011); and Buesching et al. (2014) for examples of approaches.

Initially, citizen science monitoring projects may expect to invest more heavily in having "experts" to review the data collected by participants, verifying both outliers and novel observations, but also "normal" observations. This initial phase serves to identify problem points, enhance training and clarity of data collection tools, as well as building towards the next phase, which may include a more automated data quality reviewing process. This second phase often takes the shape of post data collection screening tools, whereby set criteria are used to identify potential anomalous data points, which can be reviewed by experts; atypical observations can then be verified or removed. This second stage should be less intensive on the time of the "experts".

A third stage for more developed programs (e.g. eBird) leverages models that are built to predict future observations against which new observations can be assessed.

Given that many citizen science programs remain in the first phase of data screening, setting appropriate expectations on the investment needed for "experts" to review and verify the data is important. This is one positive attribute of large scale programs such as iNaturalist and iSpot, which have developed a very large community of reliable observers to verify the observations.

6.5.5 Use of technological tools to enhance data collection.

There are several technology-enabled tools to facilitate the collection and sharing of biological observations. By combining mobile observation systems with communities of experts, the ability to greatly increase observations by the public is potentially unleashed. Given the increase in capable software programmers, ease of web hosting and the need for technology-enhanced data collection, storage and sharing, it is not surprising that many apps and websites exist to support field data collection, interpretation and sharing. It is beyond the scope of this chapter to review the strengths and weaknesses of the different programs. Instead, we share information about a small number that are well established globally in order to illustrate the potential.

*iNat (*www.iNat.org*) and iSpot (*www.ispotnature.org*)* are two examples of web and app enabled platforms that can be used across much of the globe to record observations that have established communities of "experts" who can identify or verify observations. Once verified, these observations are uploaded into the Global Biodiversity Information Facility (GBIF) where national inventories can access them for their reporting purposes. Whereas iNat and iSpot are open to all species, other platforms such as *eBird* are very much focused on specific taxa. In fact, *eBird* leverages the passion and enthusiasm of birders globally and is the single largest contributor of biodiversity observations to GBIF (http://ebird.org/content/ebird/news/gbif/). These established platforms have significant communities that support them. Their use is further refined by an ability to create one's own projects that help focus on specific regions of interest, including species lists, etc. Furthermore, some of these programs can be enhanced by creating versions in local languages and tailored to local interests (see http://naturalista.conabio.gob.mx/ for a Mexican version of iNaturalist).

These technological tools are further enhanced by cross-linking to other web programs such as the Encyclopedia of Life (http://www.eol.org), which themselves are further

repositories of information relating to species. For example, EoL has created Traitbank, which is a repository of traits associated with species, many of which are EBVs (http://eol.org/info/516), and GloBI, which provides access to biotic interaction datasets. Finally, there are other platforms that operate at scale or support the development of programs that seek scale. For example, there are many country-based platforms such as the National Biodiversity Network in the UK and the India Biodiversity Portal among many others, taxa-based platforms such as eBird or platforms that clearly contribute to a particular EBV such as Nature's Notebook and Project BudBurst, which focus on phenology.

Moreover, there are platforms that seek to support the development of local initiatives by providing common tools, database standards and interfaces. By creating common standards, programs such as citsci.org enable local efforts to share their data more widely and increase the value of these varied contributions. Most of these platforms remain, however, in English and are only accessible to users with smartphones or other expensive communication devices. The digital divide remains a real barrier to access.

Several new approaches are evolving to enable programs with fewer resources or in more remote areas to develop apps that are much more tailored to local audiences. Two examples of such approaches are OpenDataKit (ODK - http://www.opendatakit.org) at the University of Washington, and Sapelli (https://www.ucl.ac.uk/excites/software/sapelli), which is built on top of ODK, at the Extreme Citizen Science (ExCiteS) lab at University College London (http://www.ucl.ac.uk/excites). The list of example deployments for ODK is extensive, with several looking at supporting the monitoring of forests, agricultural fields and water sources among other (https://opendatakit.org/about/deployments/). The goal behind ODK is to provide relatively straightforward do-it-yourself kits to building data collection and sharing tools for local projects. ExCiteS has exciting new programs looking at building local apps for forest monitoring using the icon-based interface of Sapelli, which can serve both the local community needs, but also the needs of governments and corporations as well.

6.5.6 Communication and feedback

As emphasized by many of the case examples, communication is key to building and maintaining a monitoring program that is relevant to its contributors and users, whether they be community members or participants that live external to the location. Identifying the appropriate media, the content and the messaging that best engages the different audiences can be a challenge given the potential for multiple languages, interests, and varying access to different media. As such, this is a vigorous area of research in the field of citizen science to identify best practices and provide guidelines.

The Project COBRA case study (section 6.4.6) explores some interesting approaches to creating stories and feedback that enhance the value of the program to local communities. For more information, see the Project COBRA Handbook entitled: How to Find and Share Community Owned Solutions at: http://projectcobra.org/how-to-find-and-share-community-owned-solutions. This Handbook, available in English, Spanish, Portuguese and French, specifically shows how to engage community members in identifying their own indicators of social-ecological viability using participatory visual techniques. Examples of participatory films and photostories can be found on the MediaGate: http://projectcobra.org/media-gate.

Creating mechanisms to solicit feedback from key users, and demonstrating to users that the program is listening to them is one obvious means of engagement that can be very powerful. This requires dedicated investment in communication and feedback, and time and resources should not be underestimated. Ultimately the building of a supportive community is essential to the long term success of any citizen science project.

6.6 SUMMARY

This chapter illustrates a small number of approaches that can be undertaken to meaningfully engage the broader public in data collection activities that complement and contribute to Earth Observations. Many of the examples demonstrate the potential for citizen science projects to complement EO, especially around the Essential Biodiversity Classes of Species Populations and Species Traits. This is especially true for species occurrence and species trait data (e.g. tree dbh), and certain species with well-developed methodologies and interest groups (e.g. birds, butterflies, large mammals) or species of value to local communities (e.g. hunted or fished species). The spatial and temporal distribution of the power of the many people is especially effective and perhaps even essential to cover the large landscapes at the resolution necessary to corroborate data collected by EO. Programs such as eBird and iNaturalist are already the greatest contributors to GBIF observations for many species.

A number of citizen science programs are developed to cover large scales (e.g. Brazil's National Biodiversity Monitoring Program (section 6.4.7) and the National Phenology Network - section 6.4.8), as are the website-enabled programs using apps (e.g. iNaturalist; eBird, Naturalista). Moreover, there are large country-wide assessments of species occurrence for a number of taxa, particularly in Europe (http://butterfly-conservation.org/; http://www.ukbms.org/; Pocock et al., 2015). A large country-wide citizen science study of decomposition rates coordinated by university scientists was found to yield valuable data and was one-quarter the cost of doing the project with paid staff.

Nevertheless the great majority of citizen science projects are focused on a more narrow spatial and temporal scale and do require significant investment to be successful. The scaling up of citizen science to contribute to national level programs will require several key factors. First, careful attention to the needs and interests of the participants (in effect co-design for both top down (i.e. data needs) and bottom up (i.e. participant needs) benefits is essential to the development of sustained and successful programs. Projects that successfully blend different kinds of participants (e.g. community members, citizen science monitors, technical monitors and experts) will yield secondary benefits. Investment in the professional development or capacity building of key stakeholders across regions is essential to ensure standardization of data collection efforts. Careful design of data management including data interoperability and the sharing of data across the system and users is important to demonstrate the usefulness and value of the programs. Finally, citizen science is a social process. Programs that integrate regular gatherings and attentive communication with all users can build an army of support and contributors that can pay off multi-fold.

Citizen science and community-based monitoring can be considered as essential inputs to the collection of tropical biodiversity data, complementing EO and other tools. Emerging techniques and protocols are being developed that should increase the effectiveness and reliability of citizen science programs, and we look forward in particular to developments that leverage citizen science community-based monitors at scale.

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7 REGIONAL BIODIVERSITY NETWORKS

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7.1 INTRODUCTION

In all regions of the planet, biodiversity change is often driven by multiple and interacting drivers occurring at a variety of scales (Pereira et al. 2013; WWF 2014). Similarly, the dimensions of biodiversity (e.g. genes, species, and ecosystems) often occur at scales beyond the geographic mandate of an individual organization (Scholes et al. 2011). Detecting biodiversity change is challenging, due to the significant natural variation, in both space and time, found in most biotic variables. This complexity, variation and scale demands an adequate and sustained sampling effort in order to have the power to detect biodiversity trends (Legg and Nagy 2006; Yoccoz et al. 2001)) and this sampling effort must be coupled with intensive experimental research in order to identify the underlying drivers of change (Krebs 1991; Nichols and Williams 2006). Without this statistical power and understanding of the drivers of change, policy and management responses are blind, unable to effectively respond to an unwanted trend. Such an intensive and extensive sampling effort can rarely be achieved by a single organization therefore requiring a coordinated, collaborative, long-term and scaled effort to detect and understand biodiversity change (Kickert et al. 1997; Craine et al. 2007; Scholes et al. 2008).

Recognizing these challenges, a number of global and 'regional' (defined as involving more than one country) biodiversity monitoring networks have been established in different parts of the world (Craine et al. 2007). These networks seek to maximize and scale the efficiency and power of individual research and monitoring efforts by connecting them into a coordinated system to increase their power and value. This includes tropical regions where a number of regional and trans-continental networks have recently been established to produce interoperable, harmonized in-situ biodiversity observation data (for examples of outputs from tropical regional networks see: Beaudrot et al. 2016; Shin-ichi Nakano et al. 2012). Beyond the direct benefits of harmonized and scaled in-situ research and monitoring, the outputs of these coordinated efforts can also be integrated with remotely sensed data allowing for validation and calibration of remotely sensed data and the interpolation and extrapolation of biodiversity change across multiple scales (Pettorelli et al. 2014). See section 4.2 for more information on in-situ data.

The following sections profile several existing examples of tropical and sub-tropical regional biodiversity observation networks (Section 7.1) and provide guidance on the key attributes required for a sustainable and user-driven biodiversity observation network, drawing upon examples and experiences of successful biodiversity observation networks from around the world.

7.2 EXISTING NETWORKS

The following profiles some existing regional networks operating in tropical and subtropical areas that can be seen as excellent examples of integrated, biodiversity observation networks. One from the Asia-Pacific region, one from the Africa continent and one that spans Latin America, Africa and Asia were chosen to be highlighted. Beyond their direct value, these networks can also serve as ground validation and calibration sites for remotely sensed biodiversity observation data thereby providing complementary methods to produce a richer source of information for applications such as spatial modelling and scaling plot based measures to regional analyses (Muchoney 2008; Scholes et al. 2011;

Stephenson et al. 2015). In some cases, these networks are already actively integrating in-situ data with remotely sensed data to infer biodiversity change.

Asia-Pacific Biodiversity Observation Network

The Asia-Pacific Biodiversity Observation Network (AP-BON) was established in 2009 as a regional network of the Group on Earth Observations – Biodiversity Observation Network (GEO BON). It involves most countries[33] of the Asia-Pacific region and is supported by a Secretariat at the Biodiversity Center of Japan in the Nature Conservation Bureau of the Ministry of Environment with in-kind and direct support also coming from agencies found within each country of the network. . It covers all levels of biodiversity and ecosystems and employs both remote sensing techniques, and in-situ observations and includes ecological process, ecosystem service, and targeted species and genetics research.

The vision of AP-BON is (1) to establish a coordinated Asia-Pacific network that gathers and shares information on biodiversity and ecosystem services, (2) to develop regional BON in a Box (GEO BON global toolkit) applications, and (3) to contribute to improving ecosystem management, sustainable use of biodiversity, and human well-being. Since 2009, AP-BON has had six workshops and published two books on biodiversity and ecosystems in the Asia-Pacific region. Further, AP-BON has contributed to the annual GEOSS-Asia Pacific symposia to tighten linkages with GEO activities in other social benefit areas. The goal is for regionally coordinated biodiversity research and monitoring using harmonized approaches, tools and data management to answer key questions, predict future scenarios and assemble data to inform regional and national assessments.

AP-BON's governance includes an international steering committee and five working groups (Genetics/phylogenetic diversity, terrestrial species monitoring, terrestrial ecosystem change, freshwater ecosystem change, and marine ecosystem change). Each working group is designing specific monitoring plans for their component. The steering committee provides overall governance and oversight and sets the strategic direction for the network while the working groups coordinate, at a technical level, the research and monitoring activities under five themes.

AP-BON's work to date includes facilitating the establishment of national biodiversity observation networks in each of the countries found within the network to support required reporting on the status and trends of biodiversity as per the requirements from the Convention on Biological Diversity. To date, three national BONs have been established (Japan, Korea and China) and other countries in the network are on their way towards developing national BONs. It also includes developing integrated observation and assessment approaches for the region, development of a shared database using common data standards (e.g. Darwin Core) and capacity building including supporting the implementation and use of new technologies (e.g. e-DNA) and standard tools (e.g. distribution modelling). More detailed information on this network can be found at: http://www.esabii.biodic.go.jp/ap-bon/index.html

Tropical Ecology Assessment and Monitoring Network

The Tropical Ecology Assessment and Monitoring Network (TEAM) monitors long-term trends in biodiversity, land cover change, climate and ecosystem services in tropical forests with a particular focus on understanding the impact of climate change on ecosystem health.

[33] Australia, Bangladesh, Brunei Darussalam, Cambodia, China, Chinese Taipei, Fiji, India, Indonesia, Japan, Kazakhstan, Republic of Korea, Lao, Malaysia, Mongolia, Myanmar, Nepal, Palau, Papua New Guinea, Philippines, Samoa, Singapore, Thailand and Vietnam.

Operating in 14 countries[34], it focuses on measuring and comparing plants, terrestrial mammals, ground-dwelling birds and climate using globally standard methodology in a range of tropical forests, from relatively pristine places to those most affected by people. TEAM conducts integrated research and monitoring in sixteen tropical forest sites across Africa, Asia and Latin America supporting a network of scientists committed to standardized methods of data collection to quantify how plants and animals respond to pressures such as climate change and human encroachment. A key feature of TEAM is its widespread deployment and use of camera traps to monitor terrestrial mammals and ground-dwelling birds. To date, it has collected over 2.6 million images and has developed the Wildlife Picture Index as a tool for analysing and tracking vertebrate trends using consistent methodology within and across its sites. TEAM makes all of the network data publicly available as it is collected, in near real time, which allows TEAM to operate as an early warning system for tropical ecosystems.

TEAM has a coordinating unit located at Conversation International's headquarters in Washington, DC that provides the overall day to day administrative and technical management of the network. The network has 297 members consisting largely of data collectors at the individual sites found within the 14 countries of the network. As well, a nine member Science Advisory Board provides overall strategic direction and oversight for the network. More detailed information on this network can be found at: http://www.teamnetwork.org/

Southern African Service Center for Climate Change and Adaptive Land Management

The Southern African Service Center for Climate Change and Adaptive Land Management (SASSCAL) is a joint initiative of Angola, Botswana, Namibia, South Africa, Zambia, and Germany, responding to the challenges of global change. The establishment of SASSCAL was set up to complement the existing research and capacity development infrastructures and research initiatives in the region. Its mission is to conduct problem-oriented research in the area of adaptation to climate change and sustainable land management and provide evidence-based advice for all decision-makers and stakeholders to improve the livelihoods of people in the region and to contribute to the creation of an African knowledge-based society. Its research themes include climate, water, agriculture, forestry, and biodiversity. Its approach is to support sustainable development and land-use/resource management decision-making and climate change risk mitigation and adaptation through the integration of research on land and resource management and climate change, and through compiling, analysing and disseminating best practices and developing and demonstrating the feasibility of adapted land management systems and strategies.

SASSCAL's core activities include integrated research on climate change and land management, capacity building activities that support national, regional and local institutions and service providers to develop relevant skills, and regional advisory and information services and products which includes a series of interlinked data centers. Specific biodiversity related research and monitoring to date include detailed inventories, monitoring and assessments of animals in Angola and the assembly of plant and vegetation databases in Namibia. More detailed information on this network can be found at: http://www.sasscal.org/index.php

[34] Costa Rica, Panama, Ecuador, Peru, Brazil, Suriname, Cameroon, the Republic of Congo, Rwanda, Tanzania, Madagascar, Lao, Malaysia and Indonesia.

Table 7.1 Summarizing the Key Attributes of Existing Tropical Biodiversity Observation Networks

Network	Countries Involved	Start Year	Realms Covered	EBV Classes Covered	Lead Organization and Contact Information
AP-BON	Australia, Bangladesh, Brunei Darussalam, Cambodia, China, Chinese Taipei, Fiji, India, Indonesia, Japan, Kazakhstan, Republic of Korea, Lao, Malaysia, Mongolia, Myanmar, Nepal, Palau, Papua New Guinea, Phillipines, Samoa, Singapore, Thailand, and Vietnam	2009	Marine, Freshwater, Terrestrial	Genetic composition, Species populations, Species traits, Community composition, Ecosystem Structure, Ecosystem function	AP-BON Secretariat: webmaster@biodic.go.jp http://www.esabii.biodic.go.jp/ap-bon/aboutus/index.html
TEAM	Costa Rica, Panama, Ecuador, Peru, Brazil, Suriname, Cameroon, the Republic of Congo, Rwanda, Tanzania, Madagascar, Lao, Malaysia and Indonesia	2002	Terrestrial	Species populations, species traits, community composition, ecosystem structure, ecosystem function	Conservation International, help@teamnetwork.org; www.teamnetwork.org/contact
SASSCAL	Angola, Botswana, Namibia, South Africa, and Zambia		Terrestrial, Freshwater	Genetic composition, Species populations, Species traits, Community composition, Ecosystem Structure, Ecosystem function	SASSCAL, Norbert.juergens@t-online.de; http://www.sasscalobservationnet.org/

7.3 **Developing new networks: guidance**

Developing a national or regional Biodiversity Observation Network (BON) that is sustainable, efficient, powerful and well connected to policy needs requires a systematic, open and inclusive process for successful development and implementation (Gill 2015). As well, it is important that a BON does not develop and operate in isolation, but rather draws from and contributes to broader regional and global biodiversity observation efforts while, at the same time, allows flexibility and customization to respond to national and sub-national needs. In this regard, the GEO BONis focused on working with national and regional organizations to help facilitate effective and efficient biodiversity observation networks that, first and foremost, respond to and serve user needs at the national and sub-national level (e.g. policy and decision-makers) (Scholes et al. 2011). While also contributing to the development of a global, interoperable network for biodiversity observations that improve our overall ability to detect, track and understand global and regional biodiversity trends (Scholes et al. 2008; see www.geobon.org).

Key Attributes of a Successful and Sustainable Biodiversity Observation Network
In many instances, biodiversity observation programs are established through the good-will, interest and enthusiasm of a group of individuals whether its in the academic, government or NGO realm. However, these programs are often not sustained as they are missing some key attributes, particularly regarding direct connections to policy-making and/or clear monitoring objectives (Yoccoz et al. 2001). Considering the considerable and varied challenges facing biodiversity conservation, it is critical that biodiversity observation programs and networks are well thought in their design to ensure they are efficient and effectively serving conservation and sustainable development decision-making (Legg and Nagy 2006). If they fail to achieve this, they can end up misinforming conservation efforts and/or unnecessarily use up limited resources available for conservation. Below, eleven key attributes are listed that define a successful and sustainable biodiversity observation network or program:

1. Clear authorizing environment for the BON, direct connections to decision and policy-making and clearly defined user needs and objectives;

In order for a network to be sustained over the long-term, the network needs to have clearly defined user needs, should be formally recognized to respond to these needs, and is clearly and effectively serving the needs of decision and policy makers. While regional networks often begin via the dedicated efforts and enthusiasm of a set of scientists volunteering their time who see the value in integration and coordination of biodiversity observations, it is critical that the network quickly establishes clear links to decision-making mandates and designs itself to produce data relevant to serve those mandates. This typically involves a co-development process where decision-makers and scientists work together to identify the key goals and objectives of the observation network. Clearly defined and articulated objectives and questions provide a clear purpose and roadmap for the development and operation of the BON (Yoccoz et al. 2001; Craine et al. 2007). In many cases, observation networks have developed with only a vague understanding or articulation of their core objectives. Without this being specifically stated and defined, the network risks both drifting over time (aka 'mission-drift') resulting in the failure to establish long-term datasets and/or not being successful in mobilizing sustained funding support.

In the case of all biodiversity observation networks, the most important needs and objectives are typically those that serve domestic information needs such as for land-use and conservation planning, species-at-risk recovery, and environmental impact assessment. Additionally, however, all tropical nations are signatories to the Convention on Biological Diversity (CBD). This provides a common need and platform for monitoring

and reporting on the status and trends in biodiversity and thus, can serve as a mechanism for organizing the regional biodiversity observation focus and approach. Other multi-lateral environmental agreements such as the Ramsar Convention or the Convention on Migratory Species and related global or regional strategies (e.g. the Global Strategy for Plant Conservation) can serve in a similar fashion by providing a common purpose and objective for the regional observation network. Outputs from these networks should directly support national reporting obligations as signatories to these multi-lateral environmental agreements. An example of this is the Wildlife Picture Index, an output from the TEAM network, which can be used to assess progress towards the CBD Aichi Target 12 (By 2020, the extinction of known threatened species has been prevented and their conservation status, particularly of those most in decline, has been improved and sustained).

2. Early, targetted, relevant, credible and frequent outputs that showcase the value-added of an integrated effort for:

    - Scientists;
    - Policy and decision-makers; and,
    - Public (regular and frequent information on the state of biodiversity and ecosystem services)

While there are clear reasons and benefits for establishing regionally coordinated biodiversity observation networks, it is equally important to clearly and effectively demonstrate this value to both the participants in the network (e.g. scientists) and the recipients of the outputs (i.e. decision-support for the public and policy makers). With regard to policy makers, the most effective way to demonstrate value is through the early and repeated production of relevant policy support tools and information that directly support and/or inform decisions that could not be made without the integration of data across regional scales (e.g. see above with regard to the Wildlife Picture Index and Aichi Target 12). In the case of maintaining scientist involvement, scientists are typically overwhelmed by their own day to day demands and responsibilities, thereby requiring the regional network to clearly indicate the value-added for a scientist to engage and contribute to the network. This is typically done through allowing for clear opportunities to access and share data, tools and funding, and improve the opportunity for the development of publications, models, assessments and indicators. It can also be seen as an avenue by which an individual scientist's work can directly or indirectly influence policy-decision making. For the public, this involves regular and frequent infromation on the state of biodiversity and ecosystem services and the need for sustained observations and monitoring to inform effective policy to preserve both. In all cases, careful thought must be put into the design of products to ensure that they are user friendly and effectively target the relevant user groups and address their priority information needs.

3. A network of diverse and active contributors;

Regional networks are fundamentally reliant on the people that comprise the network. In most cases, regional networks are envisioned and built by a small group of visionary and motivated people who see the value of their establishment. However, the transition from design and implementation to sustained operation can be difficult if not specifically accounted and planned for. Since the inherent value of a BON is, in part, due to its longevity (i.e. its production of long-term data), succession plans and continual recruitment are key. A network comprised and solely led by late-stage career scientists becomes vulnerable to the loss of a small number of participants. A network is also at risk if it is soley comprised of scientists with little local expert involvement. To enhance the resilience of a network, it is important to involve and continually recruite young scientists and where relevant citizen scientists, and allow them opportunities to grow into leadership roles. It is also important to include, where feasible, user groups in the network to ensure a continual close connection with user needs to maintain the relevance of the network.

In many cases, particulary in tropical regions, successful observation systems and networks are ones that directly involve local participation. This both lowers the cost of operation (e.g. more cost-effective sampling) but also helps to ensure that the outputs of the observation system are locally relevant and understandable by local citizens who fundamentally rely on the information to make decisions (Danielsen et al. 2003).

In order to keep the network active, it is essential that remote communication (emails, skype) are not the only means of communication. As humans are social animals, regular face to face meetings create the environment for sustained connections based on friendship, belonging, peer pressure, mutual interest and trust. While on a day to day basis remote communication is key, it alone cannot establish this. While face to face meetings are costly, they are essential and help ensure that the collective commitments of the network participants are met. The trick is to minimize these costs to the extent possible so that the benefits of network function outweight them. In many cases, meeting costs can be mitigated by scheduling them to co-occur during other regional or international meetings, conferences and workshops.

4. Start small and build on existing monitoring/observation capacity and information using simple and cost-effective methods;

Another important consideration is to avoid the temptation to grow the network too quickly thereby challenging its very sustainability (Danielsen et al. 2003). Sustained networks tend to start out small, stay focused on their core objectives and carefully expand if the benefits outweigh the costs. As well, biodiversity observation activities are typically expensive and logistically challenging. There is great benefit in designing the sampling framework for the network to take advantage of and support existing infrastructure, data and observation capacities and to utilize simple and cost-effective data collection methods (Danielsen et al. 2003; Dias 2015). In too many cases, networks forget this and fall to the temptation of designing new sampling systems that ignore existing capacity and data (Gill 2015). This results in lost opportunities to repatriate and rescue historical and even paleo data and creates a network that is hard to sustain.

5. Maintain focus on key variables and prioritize new observation efforts;

Related to the previous attribute, a successful biodiversity observation network tends to stay true to its core variables and only expands observation efforts after careful analysis that identifies the most optimal areas to expand observation efforts. Again, the greatest value for a BON is its ability to produce consistent, scientifically credible long-term data sets that are relevant to decision and policy-makers. The challenge for long-term networks is to maintain their discipline to focus on their core variables when demands from funding mechanisms continually change. A successful network tends to be good at securing new funding through their ability to creatively and flexibly meet multiple needs whilst maintaining support for their core program.

6. Simple, efficient internal governance with team member roles clearly defined reflecting the political nature of the region in question;

A formal governance structure is important for clearly defining roles and responsibilities within the network and ensuring a balance of power that reflects the political nature of the region in question. It is equally important that the governance structure is simple and efficient, thereby lowering the overhead costs for maintaining it (e.g. holding regular face to face meetings, etc.). As well, the network's operational costs must be less than the benefits accrued from working in an integrated, networked manner (Costello et al. 2014). In some cases, a regional political body can provide the formal mechanism and mandate for the needed ongoing engagement of scientists, local experts and research and monitoring networks found within each nation (e.g. the Arctic Council provided this for the

Circumpolar Biodiversity Monitoring Program). In many cases, however, no such regional body exists and thus, the governance must be developed from the beginning. For small networks, one team comprised of a mix of technical experts and decision-makers may be sufficient. In other cases, involving larger regions that must taken into account complex mandates, two bodies may be needed with clearly differentiated roles. The first body is comprised of decision-makers and 'users' of the outputs of the observation network with the responsibility of setting the overall objectives and monitoring the progress of the network to fulfill them. The second body consists of technical experts that focus on the technical details of design and implementation of the biodiversity observation network.

7. Data management, analysis, communication and reporting built into the original design and budgeted for;

Observation networks need to account and budget for not only the design and implementation of the observation effort but also for the effective management, analysis, communication and reporting of the subsequent data produced. These are critical ingredients for a successful regional biodiversity observation network that are often an afterthought. Ignoring these needs risks stranding the data through the limitation of the network to convert it into useful products. Without equal care and attention given to data management, analysis and reporting, a network is unlikely to be sustained by funders.

8. Utilization of common or comparable standards, collection protocols and tools;

A fundamental principle of a regional biodiversity observation network is to promote and support harmonized approaches to biodiversity observations thereby, producing interoperable data that can be easily aggregated and disaggregated to inform a variety of needs.

9. Core, secretariat operations supported and diverse and leveraged funding sources;

It is rare for one single and sustained source of funding to be available to support a regional biodiversity observation network over the long-term. In most cases, the reality is that one must seek multiple sources of funding that, in many cases, don't directly support the core operations of the network but rather focus on related research projects that are of a short-term nature. It is important, therefore, for the network to use its members to creatively produce a diverse and networked set of funds. The more funding sources, the more likely that the network can sustain itself over the long-term.

10. People of influence ('champions') within national governments and funding sources in the program's governance structure;

Where possible, selecting not only subject matter experts but also representatives positioned well within national governments and/or have strong connections to funding sources can greatly increase sustained funding opportunities for the networks.

11. Ensure sampling effort to maintain adequate statistical power to confidently detect change.

Biotic variables tend to vary greatly in both space and time, requiring significant sampling efforts to produce adequate statistical power. In many programmes, power analysis of the parameters measured has not been conducted and in many cases, the parameters chosen require sampling efforts orders of magnitude greater than what can be technically or financially achieved. In the design and implementation of a biodiversity observation program, care must be taken to choose realistic parameters for measurement and, during the implementation phase, power analysis should be conducted on preliminary and existing data (if available) to measure variation to allow for power analysis. Without this analysis,

an observation network's outputs can be misleading and lead to the waste of limited resources that could have been used for other purposes (Legg and Nagy 2006; Yoccoz et al. 2001).

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8 SYNERGIES BETWEEN BIODIVERSITY MONITORING AND REDD+

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8.1 INTRODUCTION

Deforestation has been identified as a major driver of both biodiversity loss and climate change (Baillie et al., 2014; Smith et al., 2014). The agriculture, forests and other land use (AFOLU) sector represented 24% of global net anthropogenic greenhouse gas (GHG) emissions in 2010 (Smith et al., 2014). During the 2000s, annual carbon emissions from deforestation and forest degradation in tropical forests represented about 10% of the total anthropogenic emissions of GHGs (Smith et al., 2014; Le Quere et al. 2015). To help mitigate GHG emissions from the AFOLU sector, the Paris Agreement signed in December 2015 by the Parties of the United Nations Framework Convention on Climate Change (UNFCCC), referred explicitly to the Reducing Emissions from Deforestation and forest Degradation (REDD+) framework (UNFCCC, 2015). The REDD+ mechanism is composed of the five following activities: a) Reduced emissions from deforestation, b) Reduced emissions from forest degradation, c) Conservation of forest carbon stocks, d) Sustainable management of forests, e) Enhancement of forest carbon stocks.

All scenarios of the Millennium Ecosystem Assessment have forecasted with high certainty the loss of habitat and local species in tropical forests and tropical woodlands due to anthropogenic activities (Millennium Ecosystem Assessment, 2005). To address these threats, the Convention on Biological Diversity's (CBD) Decision XI/19 "urges Parties, other Governments, and relevant organizations to fully implement the relevant provisions and decisions of the Convention on Biological Diversity and the United Nations Framework Convention on Climate Change in a coherent and mutually supportive way" (UNCBD, 2012). The Parties of the CBD also adopted a Strategic Plan to protect biodiversity for the period 2011-2020, which comprises a series of 20 targets known as the Aichi Biodiversity Targets[35]. A number of these targets are important for forest ecosystems, for example Target 5 aims to at least halve the rate of loss of all natural habitats, including forests, by 2020. The CBD Strategic Plan is implemented primarily at the national level through activities that consider local circumstances as outlined in National Biodiversity Strategies and Action Plans (NBSAPs).

Possible synergies between biodiversity monitoring and REDD+ activities are summarised by Latham et al. 2014 (Table 3). Synergies include co-benefits of forest conservation that support the achievement of REDD+ objectives related to GHG emissions reductions, while also providing essential habitat and related biodiversity monitoring activities undertaken as part of REDD+.

Five options that can facilitate synergies between REDD+ and NBSAP initiatives were identified by Miles et al. (2013): 1) inter-sectoral coordination between CBD and REDD+ focal points and implementing agencies, 2) development of approaches that consider all existing processes and guidelines on forests at the national level, 3) consideration of NBSAP commitments in REDD+ activities, 4) identification of potential contributions and trade-offs from REDD+ in NBSAP activities, and 5) communication of such information to REDD+ decision makers to support the Cancun safeguards (UNFCCC, 2011). Possibilities to include REDD+ activities in existing biodiversity monitoring systems have also been presented (Dickson and Kapos, 2012; Latham et al., 2014). Venter et al. (2009) discuss the possibility of significantly increasing the biodiversity benefits of REDD+ by incorporating biodiversity values in REDD+ planning.

[35] https://www.cbd.int/sp/targets/

Decision 4/CP.15 of the Conference of Parties to the UNFCCC requested developing country Parties engaged in REDD+ to consider, according to national circumstances, the use remote sensing data in combination with ground data to establish National Forest Monitoring Systems (UNFCCC, 2010). Several publications present and discuss such techniques (e.g., GOFC-GOLD, 2014; GFOI, 2014; Goetz et al. 2015; Romijn et al. 2015). To help progress towards the Aichi Targets, the Group on Earth Observations, Biodiversity Observation Network (GEO BON) proposed a first set of 22 Essential Biodiversity Variables[36] (EBVs) that could be used as a global-scale basis for biodiversity monitoring. Pereira et al. (2013) define EBVs as "a measurement required for study, reporting, and management of biodiversity change", fostering the use of remote sensing data to enable large-scale generalization. Some of these EBVs can be developed and monitored with the use of remote sensing data (Secades et al., 2014). However, for tropical forests, the development of reliable indicators and baselines that can be monitored remotely is still lacking or not entirely agreed upon (Skidmore et al., 2015).

This sourcebook helps to address the potential for remote sensing of EBVs by presenting techniques that are suitable five EBVs relevant to tropical forest environments (Vegetation phenology, Net primary productivity, Ecosystem extent and fragmentation, Habitat structure, and Disturbance regime). See Chapter 2 of this sourcebook for more information on the concept of EBVs. This section presents options identified in the literature to synergize efforts aimed at conserving biodiversity and mitigating climate change.

8.2 INSTITUTIONAL ARRANGEMENTS & OUTCOMES

A joint Zoological Society of London (ZSL) and Deutsche Gesellschaft fur Internationale Zusammenarbeit (GIZ) sourcebook on biodiversity monitoring for REDD+ proposes a framework aimed at supporting countries efforts to develop integrated biodiversity and REDD+ monitoring activities (Latham et al., 2014). The sourcebook provides guidance on how to develop monitoring systems at different spatial scales that are capable of supporting requirements for both climate and biodiversity conventions, illustrated by individual country framework scenarios. Analysis of a series of country cases (Cameroon, Uganda, Columbia, Vietnam, Philippines) indicates that these countries recognize potential synergies between NBSAPs and REDD+ (CBD, 2014). Most of these countries have developed inter-ministerial communication and complementary actions to meet objectives of both initiatives (e.g. management of protected areas). However, coordination between initiatives varies substantially from one country to another. Information on how to determine the best institutional arrangements for forest monitoring, based on local circumstances and tailored objectives, has been well documented in literature on REDD+ (Mora et al., 2012, Gupta, et al., 2013, GOFC-GOLD, 2014) and biodiversity monitoring more generally (Christophersen and Stahl, 2011, Dickson and Kapos, 2012, Gardner et al., 2012).

In order to address concerns related to biodiversity safeguards for REDD+ activities, a stepwise approach has been proposed by Gardner et al. (2012). The three-tiered approach mirrors that of existing IPCC architecture for assessing carbon emission, with a monitoring framework that gradually increases in complexity: starting with globally available datasets (e.g., coarse-scale estimates of forest types and levels of disturbance), then moving to national data (e.g., national forest monitoring data, remote sensing-based data), and finally incorporating newly collected field data to measure changes in biodiversity. The framework also discusses possible institutional arrangements for the coordination and implementation of the monitoring activities. The overall approach can be compared with the one proposed by Herold et al. (2012) for developing REDD+ reference levels by countries.

Synergies in objectives, activities and monitoring can not only be developed between biodiversity and carbon emission reduction programmes, but also with those considering

[36] https://www.earthobservations.org/geobon_ebv.shtml

other initiatives aimed at mitigating illegal deforestation. For example, the 2003 European Union's Action Plan on Forest Law Enforcement, Governance and Trade (FLEGT) focuses on combating trade from illegal timber via Voluntary Partnership Agreements (VPAs) (European commission, 2003). Tegegne and Lindner (2014) demonstrate how synergetic linkages between REDD+ and FLEGT can be developed, stressing the need to strengthen knowledge and information sharing among the different institutions in charge of REDD+ and related monitoring initiatives (e.g. Ministries etc.). They note the respective Secretariats of REDD+ and FLEGT should identify crosscutting issues, common interests, and be supported by sustained political incentive with dedicated resources. There is also need for an integrated donors approach to encourage and support both regimes in their efforts to develop such a framework. Coordination should also be developed at the technical level (e.g. fieldwork, mapping activities). For example, the Copernicus Sentinel-1/-2 constellations provide a wealth of free, open access, optical high spatial resolution Earth observation data that enable a high revisit time period, further strengthened when combined with Landsat data. Such data can improve the monitoring capabilities for REDD+, while also enabling the early detection of illegal harvesting activities (e.g. outside concession areas), thus facilitating the implementation of FLEGT VPAs.

Outcomes of positive synergies between REDD+ and conservation initiatives have been reported in Indonesia, with 25% of ongoing REDD+ activities spatially overlapping protected areas (Murray et al. 2015). The additional source of funding provided by REDD+ programs in such protected areas can be beneficial, since at least 11% of the protected areas in Indonesia are threatened by medium to high deforestation rates (Murray et al., 2015). Jantz et al. (2014) propose multi-criteria approaches to identify 'carbon corridors' that allow the connection between different protected areas, in South America, Africa and South East Asia. Such corridors have the potential to improve habitat connectivity while avoiding deforestation and forest degradation. The approach can be adapted to local circumstances and priorities, taking into account local population livelihoods and land ownership. Feeley and Rehm (2014) argue that the design of such corridors should consider edge effects and the specific needs of migrating species, ensuring that connected habitats have consistent characteristics.

8.3 POTENTIAL ISSUES AND ADVERSE EFFECTS

Efforts aimed at conserving forest biomass globally can be significantly beneficial to biodiversity, and vice-versa, even though the benefits may be unevenly distributed. Strassburg et al. (2010) note biodiversity-rich regions with low carbon value could experience greater human pressure due to REDD+ activities being implemented nearby. Expanding on this issue, another global study by Di Marco et al. (2015) concludes that expanding protected areas where the potential loss of aggregate species' suitable habitat is highest, could contribute to safeguarding about 30% more carbon stocks than expanding protected areas where deforestation rates are highest. The authors point out potential conflicts between solutions to biodiversity loss, stressing the necessity to adopt a strategic framework considering the entire set of Aichi targets, and other relevant policy requirements. A stepwise approach could be considered following the recommendations of Panfil and Harvey (2015), by developing adaptive monitoring systems that allow the integration of new information on biodiversity and other impacts as knowledge and techniques evolve.

Five policy approaches to biodiversity co-benefit approaches of REDD+ policies, have been proposed by Phelps et al. (2012). They discuss respective strengths and limitations of each approach and note that prioritizing win-win circumstances (e.g. forests of high carbon density and species richness) may also accommodate setting aside forests of lower carbon density but of high biodiversity value. They also discuss possible negative impacts of having non-coordinated REDD+ and biodiversity activities happening in the same region, including the possibility of generating competition between activities and thereby also driving up financial costs. As always, costs are a particularly important issue that requires optimizing

efficiencies of activities and monitoring. Biodiversity monitoring can be resource intensive so countries must undertake monitoring in the context of emissions reductions efforts, which is justified by the co-benefits of forest conservation related to avoiding deforestation and forest degradation. Venter et al. (2013) indicate the best way to combine conservation and REDD+ activities requires first letting REDD+ projects protect the relevant forests for REDD+, and then use biodiversity funds to protect the remaining forests in a given region. This recommendation is underpinned by the assumption that REDD+ activities will provide high collateral benefits to the targets of biodiversity action plans. Such actions can then focus on areas not sufficiently protected by REDD+ activities. This approach can be applied in other tropical regions with similar context, i.e. with high rates of deforestation and presence of iconic species. However, the authors indicate that such a recommendation would make the success of biodiversity aims dependent upon the success of the REDD+ activities, thus sharing experience and conducting collaborative planning can help reduce costs.

8.4 COORDINATION OF R&D AND CAPACITY DEVELOPMENT ACTIVITIES

As described above, significant advances have been made in recent years quantifying relationships between carbon dynamics and biodiversity in mature tropical forests, but substantial additional research is needed both within and beyond the tropics (Talbot, 2010). For example, Murray et al. (2015) could not identify a clear correlation in Indonesia between forest carbon stocks and biodiversity measurements, such as species richness or the number of threatened species. Rather they found negative correlations at the national scale and weak positive correlations within islands. Similar findings have been reported elsewhere, such as in Madagascar (Wendland et al., 2010), and South Africa (Egoh et al., 2009). These findings may be related to the "defaunization" of forests (Redford, 1992), but the authors also highlight the impact that choice of biodiversity metrics has on resulting spatial patterns, with any particular taxa differing from the overall species richness when used as a measure of biodiversity.

Related, a review of 80 REDD+ projects that address biodiversity issues following Climate, Community and Biodiversity (CCB) Standards, distributed over 34 countries, reveals most projects did not sufficiently define biodiversity conservation goals (Panfil and Harvey, 2015). Projects often do not provide quantitative targets for their biodiversity conservation objectives. Some projects did not provide methodological details (e.g. sampling design) or baseline reference scenarios of the project. Finally, some projects lacked alignment between the objectives, and clarity on how threats (or drivers of biodiversity loss) could be addressed to reduce pressure on intact forests. This reveals, among other issues, a lack of awareness related to providing and implementing methodologically robust approaches to forest monitoring systems in tropical regions. This was also highlighted in a recent study assessing national forest monitoring capacities in tropical countries, although there has been progress in monitoring capacities over the past decade (Romijn et al., 2015). Clearly broader capacity building activities are needed and must be coordinated to the extent possible for consistency across countries.

8.5 CONCLUSION

Discussions to reach internationally agreed upon policy frameworks to simultaneously tackle the issue of biodiversity loss and climate change mitigation are still ongoing. Agreement regarding which bio-indicators are the most relevant still needs to be reached. To help with this, GEO BON is advancing establishment of a "best set" of EBVs. This effort has already identified some modalities to synergise activities, and lessons can be learned from early experience. The literature we have briefly summarized here provides substantial

guidance on how to determine institutional arrangements for both biodiversity and carbon emission reduction programmes, based on the local circumstances and objectives. In particular, the ZSL-GIZ Sourcebook provides a framework to support countries in developing integrated biodiversity and REDD+ monitoring activities (Latham et al, 2014).
For example, improved coordination between R&D institutes, and also national Space Agencies via the Committee on Earth Observation Satellites (CEOS), would enable faster progress in scientific and technical knowledge that is needed to bring some monitoring methods to an operational level. The relevant Tasks and Initiatives from GEO, such as the BON and GFOI (which foster coordination of research within their own field), could also improve information sharing to improve cross-coordination of their activities. Several capacity development initiatives exist, providing sourcebooks and training materials, and organizing training sessions (GOFC-GOLD, 2014, 2015; FCPF-UNREDD, 2015, GFOI 2016).
Better coordination of parallel and sometimes redundant initiatives has been initiated within the GHG emission mitigation community, with the help of the GFOI Secretariat. Such coordination considers other key partners such as GOFC-GOLD, the UN-REDD Programme, the World Bank Forest Carbon Partnership Facility (FCPF), and the USA's multi-agency SilvaCarbon Programme.
Within the REDD+ framework, the Cancun safeguards encourage decision makers to find synergies between GHG emission reduction activities and biodiversity conservation, among other key issues such as indigenous rights and local community livelihoods. If properly considered, such safeguards will contribute towards achieving the CBD's Aichi Biodiversity Targets. Potential adverse effects of insufficient biodiversity loss mitigation programmes have also been identified, as described above. This emphasizes not only a need for more research on such issues, but also more guidance to countries on how to best coordinate activities, particularly at the institutional level.
This sourcebook, which belongs to the BON-in-a-Box toolkit series[37], is complementary to the other existing materials providing guidance on how EBVs relevant to tropical forests can be effectively and consistently monitored. This living document will be updated annually to incorporate policy and methodological developments, notably on the progress made by various communities to better synergise their R&D and capacity development activities, ultimately for the benefit of improved forest monitoring and biodiversity conservation in tropical regions.

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