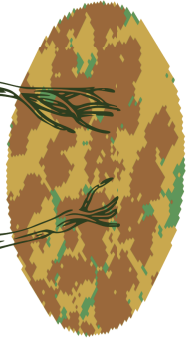




Emerging Technologies for Biodiversity Assessment of Changing Tropical Forests



Kalkidan Ayele Mulatu

Emerging Technologies for Biodiversity Assessment of Changing Tropical Forests

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Propositions

1. Integrating advanced monitoring techniques is required for reliable measurement and understanding of changing tropical forests.
(this thesis)
2. Substituting in-situ measurements with satellite remote sensing estimates, trades off accuracy for convenience.
(this thesis)
3. As long as science perceives nature objectively, it will fail to protect it.
4. Technology enables the process of turning fantasy into a reality.
5. Building on indigenous knowledge leads to sustainable solutions while imposed scientific knowledge leads to confusion.
6. Migration existed to connect humanity; now it has become a tool to frighten society.

Propositions belonging to the thesis, entitled

Emerging Technologies for Assessment of Biodiversity in
Changing Tropical Forests

Kalkidan Ayele Mulatu

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Emerging Technologies for Biodiversity Assessment of Changing Tropical Forests

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Emerging technologies for biodiversity assessment of changing tropical forests

Kalkidan Ayele Mulatu

Thesis

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Chapter 1

Introduction

1.1 Background

Tropical forest ecosystems host at least two-thirds of the Earth's terrestrial biodiversity and provide a wide range of valuable benefits in the provision of ecosystem function and services (Edelman et al. 2014). These forests are distributed between the Tropics of Cancer and Capricorn: with types ranging from tropical rainforests to moist forests, dry forests, to montane cloud forests and mangroves. They are characterized by warm temperatures, year-round sunlight, high precipitation, and high biodiversity with specialized functions and services. In addition, tropical forests, being the most diverse system in the world, hold an essential role in preserving the genetic variation of species (Brandon 2014).

Unfortunately, in spite of the valuable ecosystem functions and services they provide tropical forests are under pressure in the Anthropocene. The recent report from Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) (Díaz et al. 2019) states that regardless of the decrease in the net rate of global forest loss, high-biodiversity tropical forests continue to decline, mainly as a result of land-use change. Tropical countries; many of which are developing and are of low to middle income, largely rely on their natural resource to meet economic development requirements. Thus, the resulting over-exploitation of tropical forests: through deforestation for agricultural expansion and human settlement, as well as through forest degradation for logging and grazing purposes, plays a large role in tropical forest habitat loss. Tropical forest biodiversity decline associated with such anthropogenic drivers of habitat loss has been widely reported for decades now. Many have indicated on the increasing loss of forest biodiversity, and showed alarming future trajectories with business as usual scenarios (Sala et al. 2000, Brooks et al. 2002, Feeley and Silman 2010, Gibson et al. 2011, Laurance et al. 2012, Dirzo et al. 2014, Barlow et al. 2016, Alroy 2017). The IPBES report (Díaz et al. 2019) while showcasing the threat for the extinction of one million animal and plant species in the coming decades, also confirmed that tropical forest habitats are experiencing the highest losses of intact ecosystems despite hosting the highest levels of biodiversity. This calls for the urgency of global actions to deter the possible loss.

Alongside the increasing loss in biodiversity, the last few decades have also shown progress in international efforts in assessing drivers of biodiversity change, monitoring species responses to disturbances, as well as conservation efforts. Such initiatives are mainly driven by international goals, such as the ambitious Aichi biodiversity targets of the United Nations Convention on Biological Diversity (CBD) (CBD 2010) that aim to reduce the direct pressures on biodiversity by 2020, and in compliance with the United Nations Sustainable Development Goals (SDG) (UN 2015); notably goal 15: Life on Land and goal 14: Life below water. Therefore, a growing demand for biodiversity data exists for the evaluation of National Biodiversity Strategies and Action Plans (NBSAPs) and progress in national SDGs.

The harmonization of global biodiversity observations is assisted by initiatives such as the Global Biodiversity Information Facility (GBIF), the group on geo-observation and biodiversity observation network (GEO-BON), and The Global Observation of Forest Cover and Land Dynamics (GOFC-GOLD). These initiatives provide free and open access to global biodiversity datasets and improve the acquisition, coordination, and delivery of biodiversity observations. These global efforts on monitoring of biodiversity have created a unique opportunity for tracking the dynamics of the vast biodiversity of tropical forests than ever before. The GOFC-GOLD - GEO-BON sourcebook (2017) is one of the leading documents that provided guidance on the harmonization of tropical forest biodiversity monitoring approaches with a combination of in-situ and remote sensing methods, on the bases of the Essential Biodiversity Variables (EBVs) (Pereira et al. 2013). In addition, climate change mitigation mechanisms for tropical forests, such as the Reduction of Emission from Deforestation and Forest Degradation (REDD+), creates an opportunity for the conservation of tropical forest habitats and ideally also for the unique biodiversity they host. Even though the impacts of such projects on biodiversity are regarded as safeguards, several opportunities exist for synergizing biodiversity and REDD+ monitoring (Goetz and Mora 2017).

1.2 Assessing biodiversity with indicators

Monitoring the impacts of disturbances and/or biodiversity conservation efforts are often challenged due to the lack of data on key elements of biodiversity and their response to changes in time (Turner 2014). The broad characteristics of biodiversity, having multiple taxonomic and spatio-temporal scales often make measurements complex and expensive. Noss (1990) proposed the use of measurable indicators to overcome the complexity of biodiversity measurements. The proposed indicators cover the three primary attributes of biodiversity: (i.e. composition, structure, and function), which could be analyzed over hierarchical organizations; (i.e. regional landscape, community-ecosystem, population-species, and genetic) with suitable inventory and monitoring tools. Such indicators are assumed to provide synthesized information on the status of biodiversity over time. Similarly, the recently proposed GEO-BON EBVs are said to capture the essential scales and dimensions of biodiversity, while staying sensitive to changes and being technically, economically, and sustainably feasible to monitor (Pereira et al. 2013). The EBV classes cover the essential aspects of biodiversity ranging from genetic composition to measurement of ecosystem structure. In both cases, the measurement of biodiversity variables would require diversified means of measurement techniques which can easily be accessed, integrated and up-scaled.

Ecosystem structure, which is stated as one of the EBVs, indicates the structural components of ecosystems that are essential for the existence and maintenance of biodiversity. Forest structure, which mainly represents the vertical stratification and the horizontal connectivity

of forests, is also found to relate to the species richness and productivity of forests (Poorter et al. 2015, Bohn and Huth 2017, Oliveira and Scheffers 2019). Tropical forests, being the most structurally complex ecosystem, provide diverse habitats at macro and micro levels for diverse species of flora, fauna, and microorganisms. The vertical stratification of tropical forest creates unique habitats with diverse availability of resources and microclimate (i.e. varying temperature and moisture conditions). The tropical forest floors are home for countless soil and litter arthropod communities (Decaëns et al. 2006, Hamilton et al. 2013) which have critical roles in the unique ecosystem process (Lavelle 1996). The understories provide a niche for flora species that grow under closed canopies, and for fauna species that live and hunt under such conditions, while the upper canopies are home for dominant tree species. Similarly, the horizontal connectivity of tropical forest habitats is essential for maintaining biotic interactions and seed dispersal (Hill et al. 2011).

The vertical and horizontal complexity of habitats is however reduced mainly due to deforestation and forest degradation. Deforestation disrupts connected tropical forests with large clearings that are often converted to agricultural lands or settlements. Such changes are often detectable as their operational scale is large. Forest degradation, on the other hand, is a subtle driver of tropical habitat loss as the changes in the forest structure are not clearly visible through the commonly used forest change monitoring approaches. Most activities that lead to forest degradation occur below the dense canopies of tropical forests which would make them difficult to detect and to identify their impacts. Forest degradation which mainly takes place due to activities such as selective logging and grazing is referred as the ‘silent killer’, as it slowly diminishes the habitat quality and quantity of tropical forests as well as their irreplaceable biodiversity; leading to ‘silent forests’ (Sasaki and Putz 2009, Barlow et al. 2016).

1.3 The use of remote sensing and other emerging technologies for forest biodiversity assessment

The measurements of forest biodiversity and habitats have for long relied on conventional techniques such as counts, transects, trapping and diameter at breast height (DBH) measurements, which often provide direct and generally accurate observations of species and habitat status. However, these techniques are costly, laborious, invasive and time-consuming. Therefore, the use of Earth observation data and advanced in-situ measurements are growingly being explored to support affordable, scalable and reliable biodiversity assessments and monitoring systems.

Remote sensing (RS), the acquisition of physical data of an object without touch or contact (Lintz and Simonent 1976), is key in mapping and understanding tropical forest ecosystems. The RS field is continuously advancing and is increasingly being used for several applications in ecological studies which for long relied on conventional field measurements.

Satellite remote sensing (SRS), which collects information about the earth surface using the reflected and/or emitted energy of the Earth in one or more regions of the electromagnetic spectrum is the most widely used RS approach (Campbell and Wynne 2011). The growing availability of SRS data with detail of information across spatial, spectral, and temporal scales has encouraged its ecological application. Biodiversity relevant forest structure parameters are increasingly being produced from SRS dataset following the increasing availability and the advancement in the field. Such efforts aim to use SRS as an alternative cost-effective means of collecting wide and rapid data in forest structure, instead of conventional forest measurements, which are often challenging to conduct in tropical forests. Optical SRS derived parameters are often used for estimation of canopy cover (Hansen et al. 2013, Tyukavina et al. 2016), canopy gaps (Basset et al. 2001, Souza Jr et al. 2005, Marthews et al. 2008), and canopy height (Hansen et al. 2016). Even though the three-dimensional forest structure elements such as vegetation density and number of canopy layers are not yet directly extracted from the commonly used SRS dataset, the canopy reflectance in specific spectral domains can be used to assess biophysical parameters of forests. The sensitivity of the red-edge, near-infrared (NIR), and middle infrared bands to the canopy chlorophyll content, leaf structure, and water content respectively, have made vegetation indices using the combination of these bands to represent the amount and/or condition of vegetation (Dash et al. 2015, Meng et al. 2016, Baloloy et al. 2018). Synthetic aperture radar (SAR), an active SRS field with frequencies in the microwave region of the electromagnetic spectrum, has been found to provide more detailed information on vegetation volume and density based on the backscatter intensities in the short and the long wavelengths i.e: (X-, C-, S-), (L-) bands respectively. The former bands are scattered back from the upper tree crown, thus represents canopy variables (Rüetschi et al. 2019), while the latter are capable of penetrating through tree canopies, and interacting with structural components of trees (trunks, branches, and leaves) that lead to typical volume scattering, relating with biomass (Nguyen et al. 2016, Ningthoujam et al. 2016, Rodríguez-Veiga et al. 2017).

Terrestrial Light Detection and Ranging (LiDAR), a field-based RS technique, is considered as the most reliable and accurate RS source for obtaining information on forest structure (Brede et al. 2017). This active remote sensing technique emits laser beam pulses to targets and calculates the distance and position of the objects in a three-dimensional space based on the reception of returned signals to the instrument. Such three-dimensional forest structure information has been used to calculate habitat parameters such as vegetation layers (Palace et al. 2016), vegetation density (Calders et al. 2015c), canopy height (Palace et al. 2015), and tree volume (Calders et al. 2015b). The parameters derived would provide insight not only on the quantity (i.e. abundance of vegetation) but also on the quality (i.e. the arrangement of vegetation) of forest habitats. Other platforms supporting LiDAR measurements are also important for upscaling and acquiring detailed structural data on larger areas. Airborne Laser Scanning (ALS), where the LiDAR equipment is mounted on (un)manned aircraft, provide a

lower density of point clouds in comparison to Terrestrial LiDAR. However, ALS provides a good representation of canopy tops, which Terrestrial LiDAR measurements cannot always detect (Brede et al. 2017). In addition, the upcoming SRS LiDAR acquisitions by the NASA's Global Ecosystem Dynamics Investigation (GEDI) mission is expected to provide systematic point cloud acquisition over the tropics to derive forest canopy height, canopy vertical structure, and surface elevation which are essential for forest habitat characterization (Stysley et al. 2015).

The technological advancement of in-situ measurements is also supporting the direct assessment of tropical forest biodiversity by facilitating the species sampling and analysis process. DNA metabarcoding, allows a rapid and relatively cheap sampling, analysis, and identification of biological samples (Ji et al. 2013). With parallel sequencing of DNA barcodes from the bulk trap samples, identification of taxonomic composition without the conventional approaches of specimen sorting is possible (Cristescu 2014, Beng et al. 2016, Barsoum et al. 2019). In addition, the identification of individual species using camera-trap (Buxton et al. 2018), acoustic monitoring (Wrege et al. 2017), and drone images (Koh and Wich 2012) are also introducing a new era in forest biodiversity monitoring.

Considering the availability of very high spatial resolution images, the increasing free access to SRS images, as well as the new satellite missions (e.g. GEDI, BIOMASS) that are designed to acquire detailed data on tropical forest conditions, new opportunities are surfacing for employing RS in biodiversity assessments than ever before. On top of that, the advancement and the growing incorporation of in-situ sensors into field measurements serves with detailed insight. The combined potential of such emerging technologies provides unprecedented opportunities for the assessment of the largely unknown biodiversity dynamics of tropical forests.

1.4 Research gaps

The application of remote sensing and in-situ based technologies need to be further explored in tropical forests, as most approaches have been developed and applied in forest ecosystems where the complexity of habitats and diversity of species are lower in comparison to tropical forests (Vaglio Laurin et al. 2014, Rocchini et al. 2016, Lopes et al. 2017).

Due to the complex structure of tropical forests, vegetation conditions under the canopy are often eluded from the commonly used SRS datasets. Thus, acquiring detailed information on structural variations, which makes up their unique forest habitats, would require measurements through efficient in-situ techniques. The applicability of TLS for deriving detailed structural parameters such as canopy height (Palace et al. 2015), number of layers (Palace et al. 2016), Plant Area Volume Density (PAVD) (Calders et al. 2015c) and tree

volume (Calders et al. 2015b, Ferraz et al. 2016) have been demonstrated. However, due to the complexity of tropical trees, TLS measurements are found to be limited in delivering certain parameters such as identification of tree species and tree volume (Gonzalez de Tanago et al. 2018), which are mainly acquired through conventional approaches. In addition, the applicability of TLS for estimation of forest structure on a larger area is limited considering its costliness. Thus, investigating the possibilities of linking plot-level TLS measurements to the growingly available SRS dataset would be feasible for up-scaling purposes. An integration of conventional field data, TLS measurements, and SRS estimations would then be required to acquire scalable structural information on tropical forest habitats.

Understanding of species response to the structural complexity of tropical habitats would require linking structural information to species data. However, considering the vast diversity in tropical ecosystems, performing detailed analysis on species-habitat relationship and dynamics would be extremely complicated, if not impossible. Thus, the use of proxies, indicator taxon that quickly responds to habitat change and that are also easy to sample would be necessary. Generally, connecting information on forest habitat conditions and the diversity they host using efficient, reliable, and repeatable approaches is a topic of interest for both the scientific and conservation communities. This is especially true for parts of the tropical forests that are experiencing severe disturbances despite being classified as biodiversity hotspots, such as the study area investigated in this thesis, the Kafa biosphere reserve, in Ethiopia. This study site is an internationally recognized protected area that is subject to different types and intensities of human disturbances. In addition, the understory of this moist evergreen montane rainforest is the origin of *Coffea arabica* with rich wild varieties (Schmitt 2006, Schmitt et al. 2010). Human-induced disturbances are posing threats on the original forest habitat and genetic diversity of *Coffea arabica* (Schmitt et al. 2010). Furthermore, the Kafa forest also poses important policy challenges, from the conservation of charismatic species, to designing an efficient Reduction of Emission for Deforestation and forest Degradation (REDD+) payment mechanism for carbon storage, and to the preservation of important genetic stocks (DeVries et al. 2012, NABU 2017).

1.5 Objectives

The main objective of this thesis is to investigate the application of emerging satellite remote sensing and in-situ measurements for the assessment of forest biodiversity in changing tropical forests. A particular focus is given to the use of terrestrial LiDAR and satellite remote sensing for deriving forest structure parameters that inform on the state of different tropical forest habitats. For this purpose, field plots were established in the UNESCO Kafa biosphere reserve, Ethiopia. The use of satellite remote sensing, terrestrial LiDAR, and DNA metabarcoding approaches were examined to track forest habitat differences and the

associated biodiversity dynamics. These objectives were addressed by asking the following research questions:

1. What is the potential of state-of-the-art and novel technologies to assess biodiversity in changing tropical forests?
2. How can Terrestrial LiDAR be used to derive biodiversity relevant forest structure parameters?
3. How does multi-modal satellite data relate to Terrestrial LiDAR-derived forest structure?
4. How can the integration of novel data sources (i.e. remote sensing and DNA metabarcoding) help to better understand and link forest structure and biodiversity?

1.6 Thesis structure

This thesis is composed of six chapters, including this chapter as an introductory to the main research that is presented from Chapter 2 to Chapter 5. The four research questions presented in section 1.5 are addressed through the contents of Chapters 2 to 5, while Chapter 6 provides a synthesis of the thesis. Figure 1.1 provides an overview of the chapters in this thesis.

Chapter 2 explores the application of the state-of-the-art technologies in the monitoring of tropical forest biodiversity dynamics, and how their potential integration can increase the detail and accuracy of biodiversity monitoring. Moreover, the relevance of these biodiversity monitoring techniques in support of the UNCBD Aichi targets was explored using the Essential Biodiversity Variables (EBVs) as a framework (Research question 1).

Chapter 3 investigates the applicability of the combination of TLS and conventional forest inventory measures to estimate forest structural parameters in four different forest types in a tropical montane cloud forest in Kafa, Ethiopia (Research question 2).

Chapter 4 relates TLS and conventionally measured forest structure parameters with SRS derived variables in order to explore the sensitivity of SRS to retrieve structural differences of tropical forests and the potential to be used to upscale biodiversity relevant field-based forest structure estimates (Research question 3).

Chapter 5 investigates the relationship and potential integration of remote sensing and DNA metabarcoding approaches to inform on biodiversity dynamics. Doing so, generating the hypothesis that structural variations would be able to explain species diversity in degrading tropical forests. This chapter relates DNA metabarcoding based identification of leaf litter arthropods with forest structure parameters that are derived through in-situ and SRS approaches (Research question 4).

Chapter 6 synthesizes the major findings of this thesis in relation to the research questions in section 1.5 and provides a reflection and outlook on key research topics related to forest biodiversity monitoring, based on the lessons learned from this thesis.

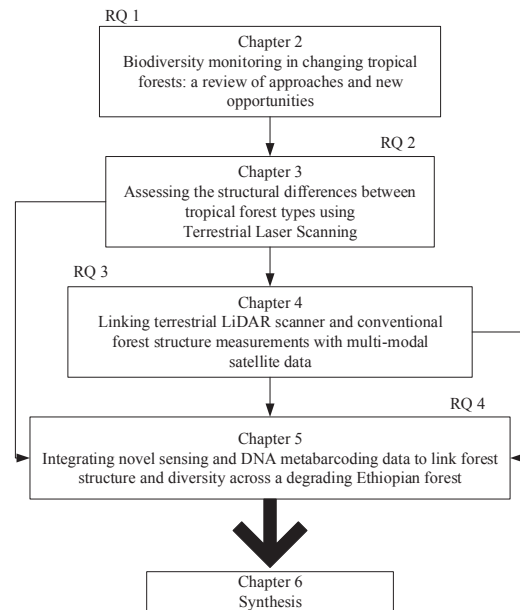


Figure 1.1: Overview of the core chapters of this thesis

Chapter 2

Biodiversity Monitoring in Changing Tropical Forests: A Review of Approaches and New Opportunities

This chapter is based on:

Mulatu, K. A., B. Mora, L. Kooistra and M. Herold (2017). "Biodiversity monitoring in changing tropical forests: a review of approaches and new opportunities." *Remote Sensing* **9**(10): 1059. DOI: [10.3390/rs9101059](https://doi.org/10.3390/rs9101059)

Supplementary material mentioned in the text can be found in the online publication

Abstract

Tropical forests host at least two-thirds of the world's flora and fauna diversity and store 25% of the terrestrial above and belowground carbon. However, biodiversity decline due to deforestation and forest degradation of tropical forest is increasing at an alarming rate. Biodiversity dynamics due to natural and anthropogenic disturbances are mainly monitored using established field survey approaches. However, such approaches appear to fall short at addressing complex disturbance factors and responses. We argue that the integration of state-of-the-art monitoring approaches can improve the detection of subtle biodiversity disturbances and responses in changing tropical forests, which are often data-poor. We assess the state-of-the-art technologies used to monitor biodiversity dynamics of changing tropical forests, and how their potential integration can increase the detail and accuracy of biodiversity monitoring. Moreover, the relevance of these biodiversity monitoring techniques in support of the UNCBD Aichi targets was explored using the Essential Biodiversity Variables (EBVs) as a framework. Our review indicates that although established field surveys were generally the dominant monitoring systems employed, the temporal trend of monitoring approaches indicates the increasing application of remote sensing and in-situ sensors in detecting disturbances related to agricultural activities, logging, hunting and infrastructure. The relevance of new technologies (i.e., remote sensing, in situ sensors, and DNA barcoding) in operationalising EBVs (especially towards the ecosystem structure, ecosystem function, and species population classes) and the Aichi targets has been assessed. Remote sensing application is limited for EBV classes such as genetic composition and species traits but was found most suitable for ecosystem structure class. The complementarity of remote sensing and emerging technologies were shown in relation to EBV candidates such as species distribution, net primary productivity, and habitat structure. We also developed a framework based on the primary biodiversity attributes, which indicated the potential of integration between monitoring approaches. In situ sensors are suitable to help measure biodiversity composition, while approaches based on remote sensing are powerful for addressing structural and functional biodiversity attributes. We conclude that, synergy between the recent biodiversity monitoring approaches is important and possible. However, testing the suitability of monitoring methods across scales, integrating heterogeneous monitoring technologies, setting up metadata standards, and making interpolation and/or extrapolation from observation at different scales is still required to design a robust biodiversity monitoring system that can contribute to effective conservation measures.

Keywords

Tropical forests; biodiversity monitoring; disturbances; remote sensing; in situ sensors; DNA barcoding

2.1 Introduction

Biodiversity decline due to habitat disturbance of tropical forests is increasing at an alarming rate (Barlow et al. 2016) and has led to growing interest in assessing the changing trend of their biological diversity by, for example, implementing and monitoring conservation efforts (Turnhout et al. 2016). The reason tropical forests are in the spotlight is that they host at least two-thirds of the world's flora and fauna diversity (Thomas and Baltzer 2001) and store 25% of the terrestrial above and belowground carbon (Bonan 2008). Moreover, their sustainable existence is threatened as a result of major anthropogenic and natural disturbances (Malhi et al. 2014). Yet the complexity of the biological diversity present and the variety of disturbance factors at work has made the monitoring process difficult. This situation is primarily attributable to the technological and resource limitations of tropical developing countries (Herold et al. 2011, Romijn et al. 2015).

Loss of tropical forests due to deforestation, forest degradation and forest fragmentation alters the habitat of many flora and fauna species. These threats mainly originate from anthropogenic pressure, which ranges from small-scale agricultural activities and selective logging practices that introduce subtle disturbances, to large-scale commercial agriculture, plantations, logging and mining activities that result in large-scale habitat disturbance and forest fragmentation (Scholes et al. 2012). When their habitat is modified, some species manage to adapt, some become threatened, others migrate and a few go extinct (Vié et al. 2009). Such resulting change in biological diversity is a complex process that is increasingly attracting research attention. This is due to the growing need to assess and report on the performance of policy regimes, such as those agreed in the Paris Climate Agreement and on efforts to reduce deforestation and forest degradation (Turnhout et al. 2016), and on the Aichi targets set by the Convention on Biological Diversity (CBD 2010). Accordingly, the United Nations (UN) Convention on Biological Diversity (CBD), the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), and the Group on Earth Observations and Biodiversity Observation Network (GEO BON) are among the international initiatives that are addressing the increasing threat to forest biodiversity. The UNCBD's Aichi Biodiversity Targets (ABT) have 20 measurable components and are aimed at reducing the pressure on global biodiversity and halting it by the year 2020 (CBD 2010). Countries that ratified the CBD Convention (Article 6) (Diversity 2001), have since developed National Biodiversity Strategies and Action Plans (NBSAPs), while countries that have embraced the UN Sustainable Development Goals (SDG) (goal 15: Life on Land and goal 14: Life below water, notably) (UN 2015) have developed national SDGs, with the result that when planning and executing national activities the impacts on biodiversity and on environmental sustainability are taken into account (Lucas et al. 2013). In support of the ABT, GEO BON has defined the concept of Essential Biodiversity Variables (EBVs) (Pereira et al. 2013) to globally standardise the monitoring of biodiversity change over time, across taxa and ecosystem types

(Pereira et al. 2013). EBVs are a transposition of what Essential Climate Variables (ECVs) are for climate change. Such ECVs are defined by Global Climatic Observation System (GCOS). EBVs aim to address the demand of biodiversity observation communities for establishing consistent and harmonised studying, reporting and management of biodiversity change at a global level (Pereira et al. 2013). It contributes towards policy initiatives at national and global levels through platforms such as IPBES and UNCBD, as well as towards actual biodiversity change monitoring practices. The EBVs have six classes (namely: genetic composition, species populations, species traits, community composition, ecosystem function, and ecosystem structure), with a total of 22 EBV candidates under them. These classes address relevant dimensions of biodiversity change with measurable parameters at different spatial, temporal, and taxonomic scales. EBV data products are to be used for deriving suitable indicators, thus EBVs lie between raw data and indicators (Kissling et al. 2017). Currently, several efforts are being made to assess the suitability of existing and emerging technologies to produce EBV products, and thus of progress towards the Aichi targets (CBD 2010).

Tropical countries have struggled to establish biodiversity monitoring systems and particularly for providing consistent time series for assessing trends and progress towards targets (Romijn et al. 2015). Hence the policy requirements for biodiversity data and monitoring systems are highlighting the need for consistent observations over time, both from on-the-ground observations and from satellite time series. This is to enable tracking and quantifying of ecosystem dynamics and the direct and indirect impacts of human activities (and related policy measures) that result change in biodiversity (i.e., from land use, climate change) (Pereira et al. 2013, Newbold et al. 2014). While this need is becoming more pressing, a key question is how previous research experiences and evolving technologies can help to better characterise tropical forest changes and the associated relationships and impacts on biodiversity.

Countries mainly rely on national forest and biodiversity inventories to acquire information on changes and trends. These inventories mostly use established field survey approaches, such as counts, transects, trapping and diameter at breast height (DBH) measurements, which yield direct and generally accurate observations of species status and trends. Such approaches, however, are costly, laborious, invasive and time-consuming (Lee et al. 2015, Thomsen and Willerslev 2015).

Remote sensing, in situ activity sensors and, more recently, Deoxyribonucleic Acid (DNA) barcoding techniques are seen as promising tools for designing a new generation of biodiversity monitoring systems (Pimm et al. 2015, Marvin et al. 2016, Bush et al. 2017). They are assumed to be able to address data gaps and to allow scalable studies which complement established field survey approaches (Lindenmayer et al. 2012, Lausch et al.

2016). From the genomics domain, DNA barcoding presents a new opportunity for establishing a robust biodiversity monitoring system.

From the remote sensing domain, free access to satellite images, the availability of very high spatial, spectral, and temporal resolution satellite images and of open source analytical software, and the development of algorithms for analysing and interpreting complex datasets are providing good opportunities for the ecological community to detect and monitor forest and biodiversity changes through time (Kuenzer et al. 2014, Rose et al. 2015). Remote sensing based biodiversity monitoring provides an opportunity of extended spatial and temporal resolution to the existing biodiversity monitoring systems. This approach not only has the potential to map indirect indicators such as human induced habitat disturbances (Mildrexler et al. 2007, Newbold et al. 2014) and forest cover changes (Butchart et al. 2010, Hansen et al. 2013) but it can also be used to measure direct physical parameters, such as individual trees (Schäfer et al. 2016) and large mammals (Koh and Wich 2012). Moreover, Light Detection And Ranging (LiDAR) and Synthetic Aperture Radar (SAR) data have demonstrated capabilities for mapping detailed forest structure and estimating biomass (Calders et al. 2015b). Thanks to the ongoing advancement of remote sensing technology, new satellite images with even higher spatial, spectral and temporal resolutions are often available for free (Lausch et al. 2016, Pettorelli et al. 2016b). In addition, the availability of remote-sensing -derived datasets such as the Global Forest Watch (Hansen et al. 2013) are used to derive indirect species occurrence indicators such as forest fragmentation (Riitters et al. 2000, Riitters et al. 2016).

The recent advances in in situ sensors such as bioacoustics, tags, and camera traps are providing non-destructive and semi-automated ground surveying opportunities (Butchart et al. 2010, Hansen et al. 2013). In situ activity sensors are non-invasive surveying techniques that often provide opportunities for measuring biodiversity directly, thereby revealing the presence or absence of species, and their behaviour (Kays et al. 2015). Recent technological advancements in this field have made possible real-time observation and rapid collection of biodiversity data (Pimm et al. 2015).

DNA barcoding techniques are emerging as monitoring systems that are rapidly evolving to further facilitate biodiversity data collection and species identification. This DNA barcoding technology ranges from using standardised barcodes to identify individual specimens, to identifying multiple specimens from bulk samples (the latter process is called metabarcoding). Such technology makes rapid biodiversity assessment possible through bulk sampling, and with automated species identification processes (Ji et al. 2013, Thomsen and Willerslev 2015). Furthermore, Environmental DNA (eDNA) technique is being used to extract cellular and extracellular DNA from environmental samples (water, soil, faeces, etc.),

enabling a rapid assessment of past and present biodiversity (Taberlet et al. 2012, Thomsen and Willerslev 2015).

Many scholars argue that the recent technologies (i.e., remote sensing and in situ sensors) and emerging opportunities (i.e., DNA barcoding) have not been well exploited for ecological studies, regardless of their immense potential to inform on subtle changes and to indicate future directions of study (Turner 2014, Pimm et al. 2015, Marvin et al. 2016, Pettorelli et al. 2016b). This is with regards to the limited application of the state-of-the-art technologies towards biodiversity studies, as well as the existing gap in exploration of the potential integration of such technologies for detailed studies and conservation efforts.

Taking into account the increasing need for reliable data to inform international policy processes, the current status of biodiversity monitoring activities and research, and the potential of new technologies, this paper aims to:

1. Give an overview of the state of the art and synthesise previous research on biodiversity monitoring in the context of changing tropical forests;
2. Assess the potential of using evolving technologies and tools to further increase the detail and accuracy of biodiversity monitoring;
3. Identify remaining gaps and opportunities on biodiversity monitoring approaches through evaluating their contribution to addressing the primary biodiversity attributes according to Noss (1990);
4. Assess how evolving technologies can help operationalise relevant EBVs for tropical forest environments.

We have deliberately focused on tropical forests and the issue of assessing changes and trends in biodiversity. Tropical areas are not only undergoing considerable forest changes of global relevance but are also particularly data-poor. In this context, we aim to help address these challenges by assessing new opportunities and to complement other review studies that have had a much broader scope (Kuenzer et al. 2014, Turner 2014, Pimm et al. 2015, Lausch et al. 2016).

2.2 Analytical Framework and Data Analysis

In this study, in order to categorise biodiversity groups and monitoring elements, we have adapted the CBD (2017) definition of forest biological diversity: “Forest biological diversity is a broad term that refers to all life forms found within forested areas and the ecological roles they perform. As such, forest biological diversity encompasses not just trees, but the multitude of plants, animals and micro-organisms that inhabit forest areas and their associated genetic diversity.”

We performed a systematic search of the scientific literature on the Web of Science platform, using the paired search terms: tropical forest biodiversity monitoring—forest change; and tropical forest biodiversity monitoring—forest disturbance. Further screening was made by reading the abstract of the articles, to identify those that are focusing on disturbed tropical forests and provide detailed description of their biodiversity monitoring approaches. Based on these search criteria, we identified 153 scientific papers (Supplementary) that are conducted across 38 tropical countries. Next, an analytical framework was developed to define systematic criteria for classifying and analysing monitoring details across essential biodiversity components. We considered six essential biodiversity monitoring components that align with our research objectives: (1) the spatial scale of the study (i.e., spatial extent of the study area); (2) the disturbance type reported (i.e., anthropogenic or natural sourced event that results alteration of natural tropical forest habitat); (3) the targeted groups studied (incl. taxa and their biotope); (4) the monitoring methods employed; (5) the relationship with EBV classes; and (6) the primary biodiversity attributes addressed (i.e., compositional biodiversity, functional biodiversity and structural biodiversity).

In regards to spatial scales of the study, we deemed studies of sites of <100 ha and transects 10 m to 20 m long as being local; those of 100 ha –500 ha and transects 200 m–500 m long as landscape; and those of >500 ha with transects >500 m long to be regional-scale studies (Whittaker et al. 2001). Studies were also categorised according to their source of disturbance, anthropogenic and natural. The types of monitoring approaches employed were studied in relation to targeted biodiversity groups, and disturbance types reported. In addition, we used subset of the series of EBVs that are relevant to tropical forests to frame our review findings, in relation to the use of new monitoring technologies and emerging opportunities (Figure 2.1). Finally, we synchronise our findings with two reference studies: the one by of Noss (1990), which identified the three primary attributes of biodiversity (i.e., compositional biodiversity, functional biodiversity and structural biodiversity). Noss (1990) defined compositional diversity as ‘the identity and variety of elements in a collection’, while structural diversity encompasses ‘physical organisation and pattern of a system’, finally functional diversity involves ‘ecological and evolutionary processes’. Another reference

study by Turner (2014), indicated on the role of upcoming technologies for biodiversity monitoring. These fundamental studies were used to explore and propose avenues of methodological complementarity and opportunities for integration.

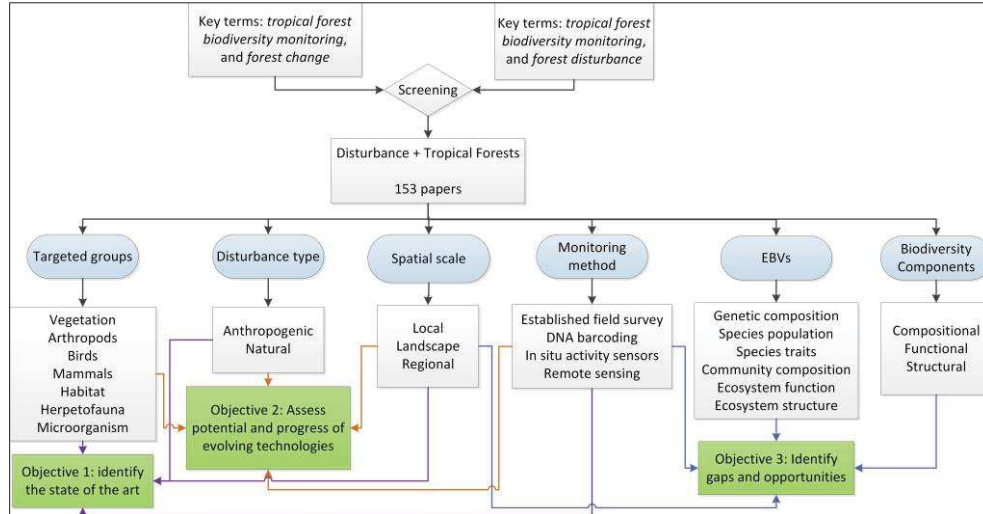


Figure 2.1: Criteria and categories defined to set up the review database.

2.3 Results

2.3.1 Spatial Scale

The weight of the spatial scale of study sites in determining the choice of an appropriate biodiversity monitoring approach was revealed by the review. Most of the studies (58%) had been done at a local scale, followed by regional studies (32%), and with only a few studies (10%) performed at the landscape scale (Figure 2.2). Established field surveys had higher application on local and landscape scales, while remote sensing was used at all scales but found higher applicability in regional-scale studies. In situ activity sensors had higher association with studies at a local and regional scale, while its use was limited at landscape scale studies. The use of DNA barcoding methods was only at a local spatial scale.

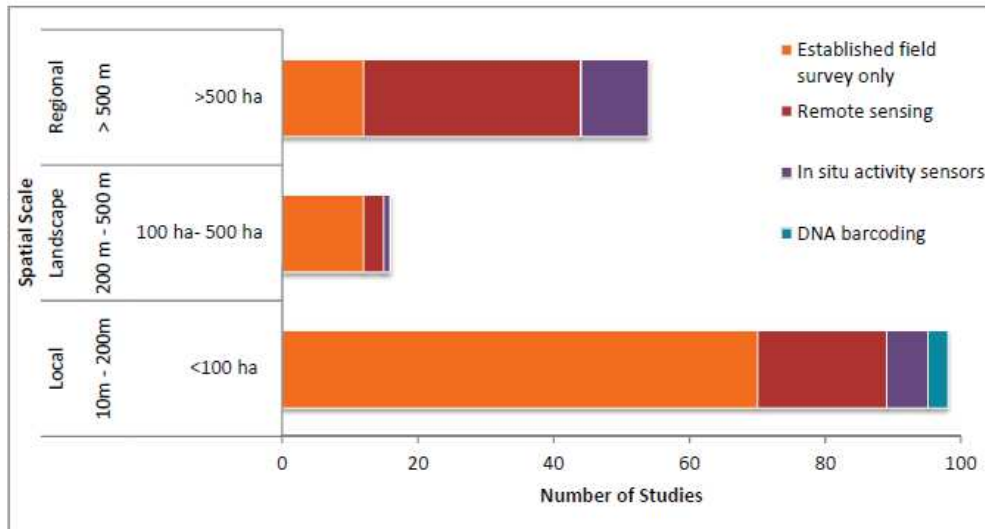


Figure 2.2: Spatial scale of studies and biodiversity monitoring techniques employed. Note: some studies address multiple spatial scales.

2.3.2 Disturbance Types

Anthropogenic factors accounted for 82% of disturbances related to biodiversity change, with the remaining 18% being accounted for natural events. Agricultural activities (32%) and logging (27%) were among the major anthropogenic drivers, followed by infrastructure (9%); hunting (7%) and mining (7%). Natural events included events like wildfire, disease outbreaks and extreme weather events. Established field surveys dominated the monitoring of all disturbance types, especially in the case of natural events, mining and infrastructure (Figure 2.3). In situ sensors were used in tandem with remote sensing, especially for detecting biodiversity changes in relation to infrastructure, agricultural activities, hunting and logging (Rovero et al. 2014, Beaudrot et al. 2016, Ellis et al. 2016). However, these approaches were also used independently, remote sensing contributed significantly to detect mining, while in situ sensors showed substantial capacity for tracking hunting activities. Finally, DNA barcoding was found to contribute to detecting changes related to agricultural activities and logging.

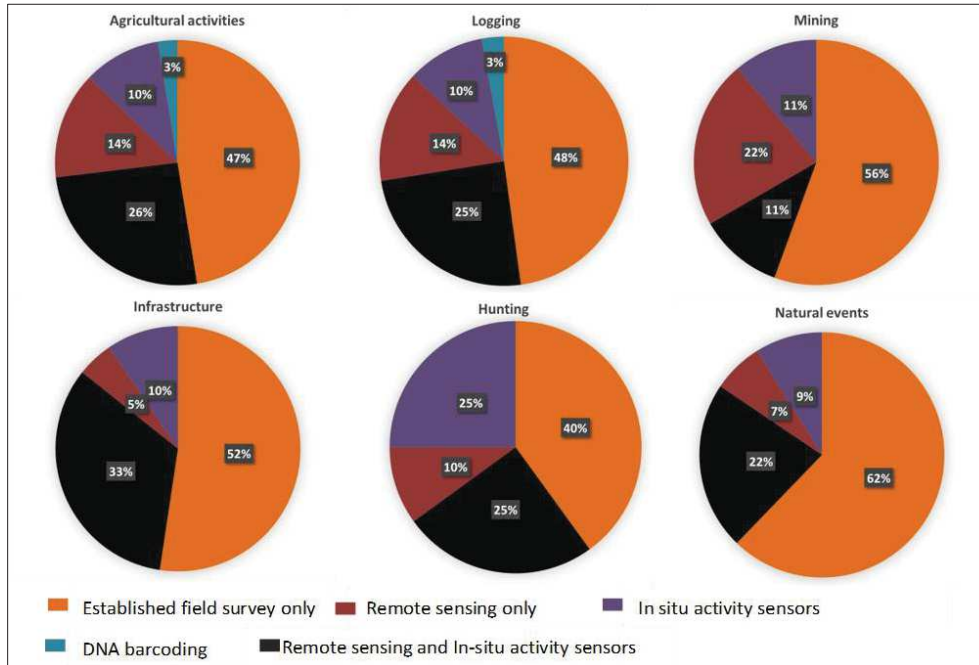


Figure 2.3: The use of monitoring methods for each disturbance type.

2.3.2.1 Disturbance Types per Country

The disturbance types were further analysed to identify drivers of biodiversity loss at country and regional scales. The reviewed studies were carried out in 38 tropical countries, distributed across five regions. The contrast of disturbance factors across the regions can be observed where human induced land use changes such as agriculture and logging were highly represented in South America, South East Asia, and East Africa (Figure 2.4). Infrastructure-related disturbances had their peak in South America and South Asia, but showed small impact in East African countries. Other disturbance factors such as hunting and mining had varying occurrence across regions, where the former had considerable appearance in Africa and the later in South American countries. Finally, the impact of natural events appeared dominant over the other disturbance factors in Oceania countries.

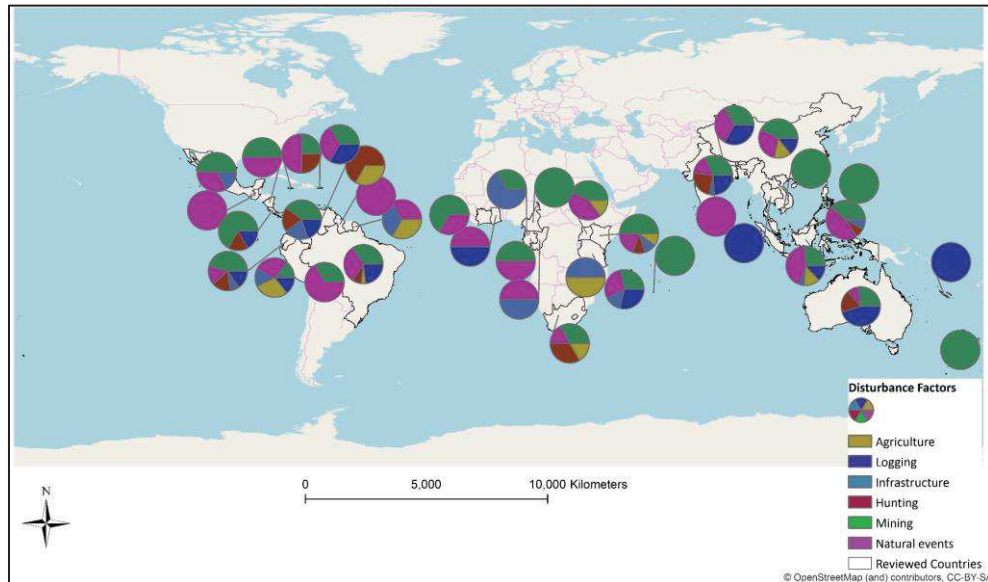


Figure 2.4: Global distribution of forest biodiversity disturbance factors.

2.3.3 Targeted Groups in Monitoring of Disturbed Tropical Forests

Vegetation and arthropods were the major targeted groups for monitoring in relation to changing tropical forests, and were also often used as surrogates for other biodiversity groups (Figure 2.5). Habitat condition, birds and mammals were studied much more often than herpetofauna and microorganisms.

Overall, established field surveys predominated over the other monitoring methods, except in the case of habitat monitoring, where remote sensing was applied the most (Figure 2.5). Similarly, remote sensing was employed appreciably to monitor vegetation, and to some extent for monitoring arthropods, birds, and mammals, but it was hardly used to monitor herpetofauna and microorganisms. Even though the overall application of in situ sensors to the different taxa was limited, they were employed in all groups except microorganisms. Finally, DNA barcoding was found to have been applied to only three taxa (i.e., vegetation, arthropods and microorganisms).

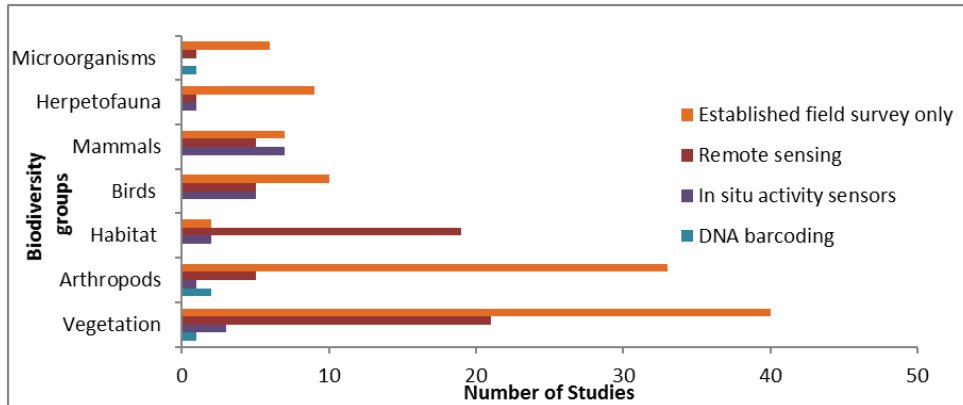


Figure 2.5: Biodiversity groups monitored and monitoring techniques applied. Note: some studies addresses multiple biodiversity groups.

2.3.4 Monitoring Approaches over Time

The temporal trend of integration of new technologies into the biodiversity monitoring of disturbed tropical forests has been indicated on the targeted article pool (Figure 2.6). In all years except 2015 and 2016, the dominant method was established field surveys. However, the trends show the growing incorporation of state-of-the-art technologies in to the monitoring system. Remote sensing approaches are the most consistently employed after established field surveys, and their application even dominated over the rest in the recent years. In situ sensors and DNA barcoding approaches are recent additions to the monitoring system.

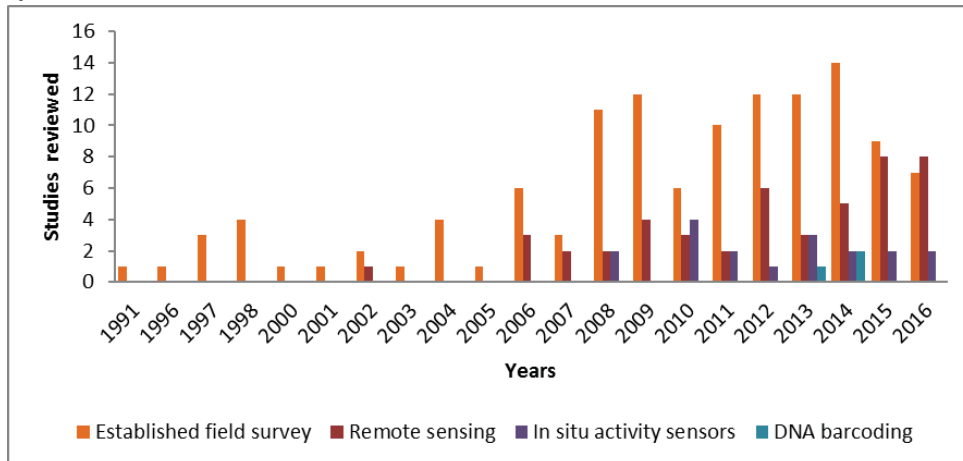


Figure 2.6: Temporal trends towards incorporation of new biodiversity monitoring techniques.

2.3.4.1 Monitoring Approaches vs. Biodiversity Estimation Significance Values

The accuracy results maintained from applying the different biodiversity monitoring approaches has been investigated looking into the statistical significance and accuracy values reported in the reviewed paper. These were used to compare the methods accuracy in terms of their estimation of biodiversity. Majority of the results from established field surveys (59%), and integrated approaches (i.e., established field surveys coupled with remote sensing) (71%) provide significant values (i.e., $p = 0.01$ – $p = 0.05$, $R^2 = 0.5$ – $R^2 = 0.7$, classification accuracy = 50%–70%), while 26% of established field surveys, and 21% of integrated approaches had highly significant results (i.e., $p < 0.01$, $R^2 > 0.7$, classification accuracy >70%). Yet, established field surveys also had its high share (16%) of non-significant results (i.e., $p > 0.05$, $R^2 < 0.5$, classification accuracy <50%). Remote sensing approaches also had majority (35%) of their results as highly significant and significant (47%), but also with considerable (18%) non-significant values. Even though there are few studies that used in situ sensors, 25% of the studies had both non-significant and highly significant results, and 50% had significant results. Finally, all DNA barcoding studies resulted significant values.

2.3.5 Recent Technologies and New Opportunities for EBVs

Satellite remote sensing techniques were found to be dominantly employed for three of the EBV classes, namely species population, ecosystem function and ecosystem structures but its application was limited in the classes of species traits and community composition (Figure 2.7). Hyperspectral and LiDAR remote sensing were found to be appropriate for species population and ecosystem function classes, while LiDAR also contributed substantially to assessing ecosystem structure and community composition. Similarly, in situ sensors were applied to all EBV classes except for genetic composition, and notably applied for monitoring of the species population. Finally, DNA barcoding was found appropriate for addressing genetic composition, species population, ecosystem function and ecosystem structure classes.

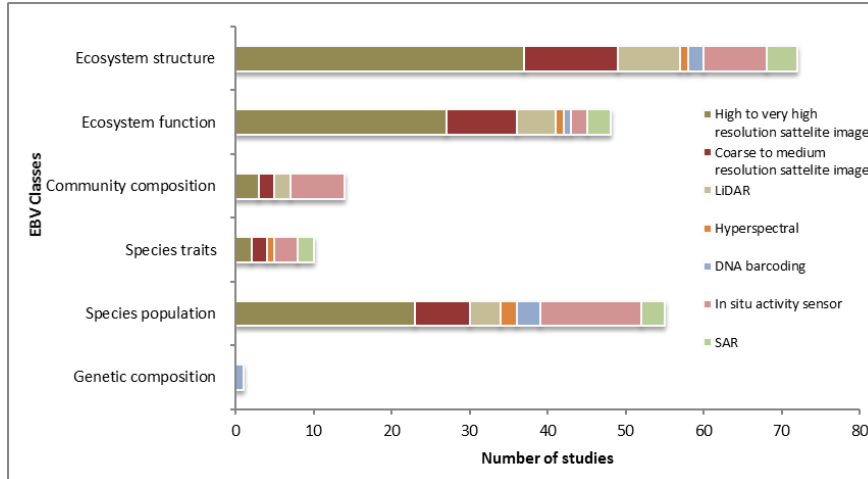


Figure 2.7: The use of new technologies and emerging opportunities in reviewed studies in relation to EBV classes. SAR: Synthetic aperture radar, LiDAR: Light Detection and Ranging. Note: some studies address multiple EBVs.

2.4 Discussion

2.4.1 State of the Art

The monitoring of biodiversity changes is scale-sensitive: the biodiversity elements to be monitored, indicators to be used and monitoring methods employed appeared to be determined by the spatial scale of the study areas (i.e., geographical coverage of the study area), the temporal scale (i.e., availability of longitudinal biodiversity data), and the thematic scale (i.e., targeted groups for monitoring and disturbance types). Different observation scales provide varying insight into changes, at times yielding contrasting outlooks (Henle et al. 2014). Even though established field surveys are assumed to be the most accurate sources of information on biodiversity data, ecological data acquired through this method are mostly collected at local spatial scale, which often makes it challenging to extrapolate results. In contrast, biodiversity indicators based on remote sensing have been demonstrated to be easily up-scalable by virtue of the nature of the data (Marvin et al. 2016), which is why species distribution models are now using remote-sensing-based environmental datasets to scale up ground observations. Rocchini (2013) and Pettorelli et al. (2014) indicated that the use of remote sensing data has opened up new opportunities for predicting the effect of anthropogenic activities and environmental conditions on the spatial distribution of species. Moreover, apart from the role of remote sensing in monitoring forest cover-change related habitat disturbances and its indication on biodiversity dynamics (Hansen et al. 2013, Haddad et al. 2015), very high spatial resolution satellite images (Fretwell et al. 2012) and airborne remote sensing (Anderson and Gaston 2013) are being used to estimate the occurrence and abundance of mammals, and large birds.

In situ activity sensors were found to have been used in multiple spatial scale studies (Figure 2.2) and across different taxa (Figure 2.5), allowing real-time observation. Such method allows insight into the spatial and temporal scales over which individuals and populations interact. It also allows a remote and non-invasive opportunity to survey on species, detect anthropogenic disturbances, assess social dynamics of species, and track responses to factors such as climate change and habitat disturbance (Blumstein et al. 2011). The drawbacks of this method (e.g., signal recognition across taxa) are being resolved with the development of automated visual and sound identification software (Yu et al. 2013).

Finally, DNA barcoding was found to be suitable for studies at a local level, and in general it appears to have been used only in few studies for monitoring changing tropical forests. However, it has been increasingly incorporated and tested in biodiversity studies of other ecosystem types, such as subtropical forest (Yu et al. 2012), temperate woodland (Hänfling et al. 2016) and the Arctic (Willerslev et al. 2014). Such a technology provides a unique opportunity for collecting and analysing mass biodiversity samples and rapid estimation of the total biodiversity. However, the use of this technology, especially in developing tropical countries, could be restricted due to high installation and processing costs as well as limited human resource. The drawbacks of this technology were reported to be high cost, contamination, errors during DNA amplification and a lack of high-quality taxonomic reference databases (Taberlet et al. 2012, Collins and Cruickshank 2013, Thomsen and Willerslev 2015). However, with the ongoing intensive research and technological advancements in the field, it seems likely to evolve into a valuable tool for measuring and monitoring of tropical biodiversity (Bush et al. 2017).

The temporal aspect of scale relates to the building and obtaining of longitudinal biodiversity monitoring datasets (Figure 2.6). This allows consistent estimation of changes in biodiversity and their drivers. Crucial for this is the availability of local, national, continental and global biodiversity data. In reality, such data are scarce due to inconsistency in monitoring approaches, data storage and sharing policies and shortcomings in the technical capacity of countries, as well as financial and human resource limitations (Proença et al. 2016). Established field surveys have great potential to provide historical data (Figure 2.6), while Landsat missions (dating back 40 years), the Copernicus Sentinel constellations (recently launched), as well other commercial satellite data providers provide long term, free, and open access data. The potential of emerging technologies is also important to populate biodiversity observation data. There is, however, a need for researchers, institutions and countries to systematically archive and share such datasets. There have been several independent initiatives to build long-term time series of biodiversity data. Ji et al. (2013) presented available databases for DNA sequence data, while GEO BON provides accessible datasets for EBVs through its portal (<https://boninabox.geobon.org/>). Similarly, in the case of the in situ activity sensors, open databases are becoming available through the Tropical Ecology

Assessment & Monitoring (TEAM) Network Education Portal (Sanderson 2004), TRY plant trait database (Kattge et al. 2011) and through the Bioacoustica online repository and analysis platform (Baker et al. 2015). Overall, the temporal trend also shows the growing inclusion of tropical biodiversity studies towards new monitoring techniques.

The thematic aspect of scale relates to the complexity of disturbance types and targeted biodiversity groups for monitoring. Overall, the major sources of tropical forest disturbance with associated impact on biodiversity are anthropogenic pressures (Morris 2010). The two main sources of anthropogenic forest disturbance (i.e., agricultural activities and logging) produce features that can be detected by all monitoring methods examined in our review. While large-scale agricultural activities and mining show a clear signal of change with canopy cover loss, other disturbance types that often take place below canopy (e.g., selective logging, and surface fire) introduce subtle changes. The role of remote sensing and in situ sensors in monitoring such drivers of change is especially noteworthy. Large-scale changes that result from deforestation and forest fragmentation have been well picked up by Landsat and other medium to coarse spatial resolution satellite images (De Sy et al. 2012, Hansen et al. 2013, Sexton et al. 2013). However, when it comes to understory disturbances and those that do not have spatially quantifiable features (such as hunting), there is a data gap. Peres et al. (2006) similarly described the nature of such disturbances in tropical forests and advised on the use of new technologies for identifying the ‘almost undetectable’ disturbance types such as hunting, selective logging, sub-canopy roads and invasive species. Newbold et al. (2014) discussed how such habitat alteration influences local richness and total abundance of species, and hence affects ecosystem functions and services. Our review indicated that vegetation and arthropods are the groups most studied in disturbed environments, while herpetofauna and microorganisms are poorly investigated. Most importantly, vegetation and arthropods embrace sensitive species that can quickly respond to habitat alteration and environmental changes, thus making them good to be used as surrogates. Our review revealed that arthropods were the major surrogates for other biodiversity groups. Yet, criticism occurs regarding the choice and use of surrogates and therefore systematic ways of selecting suitable indicators have been proposed to promote cost-effective and efficient biodiversity monitoring (Souza et al. 2016). In general, the identification of country specific biodiversity loss drivers and potential indicators can lead to the design of targeted mitigation and conservation programs (Wintle, Runge, and Bekessy 2010).

Over all, the role of biodiversity in ecosystem services needs to be properly assessed and understood in order to mainstream biodiversity across governments and society. Such a complex topic can only be clearly understood when the necessary data are acquired and analysed using proper tools. Unravelling of changes and trends in biodiversity can help us to understand not just about species composition and abundance but it can also inform on how forests adapt to pressures, indicates on the resilience of the forest ecosystem, and the impact

of mitigation and adaptation actions on the environment. Many argue that biodiversity conservation is placed in the background of climate change mitigation actions and carbon reduction efforts. However, Mant et al. (2014) pointed out that adaptation and mitigation actions that do not consider the role of, and potential impacts on, biodiversity can have adverse consequences. Therefore, such possible impacts on biodiversity must be measured and monitored alongside forest status and carbon stock assessments. Contrasting results appear when looking in to the relationship between carbon and biodiversity in tropical forest. Talbot (2010) found complex and limited correlation between the two, while Poorter et al. (2015) proved diversity's positive role in enhancing carbon storage of tropical forests. Even though there is a need for continuous research in the area, there are already promising steps towards promoting an all-inclusive measuring and monitoring of degrading tropical forest environments. Here, the role of remote sensing is especially recognised where same data that is collected to report on forest and carbon stock status can also be used to derive direct and indirect indicators of biodiversity status (Turner 2014, Bustamante et al. 2016).

2.4.2 Potential and Progress of Evolving Technologies

To detect and monitor changes at different spatial, temporal and thematic scale not only a variety of monitoring approaches is required but also their integrated deployment. The application of remote sensing has been limited to deriving indirect indicators of biodiversity; mostly through using coarse to high spatial resolution satellite images for habitat analysis. However, advances in the field are bringing opportunities to develop direct indicators, e.g., using very high spatial resolution satellite images to identify large trees and animals (Yang et al. 2015, Leblanc et al. 2016), using hyper spectral sensors to ascertain vegetation biochemistry (Thenkabail et al. 2016), and using LiDAR sensors to map the three-dimensional vegetation structure (Badreldin and Sanchez-Azofeifa 2015, Ioki et al. 2016). Moreover, such scale-related limitations can be overcome by coupling remote sensing with in situ sensors and DNA barcoding (Bush et al. 2017). The ability of in situ based sensors to provide real-time observation and automated data acquisition could overcome the limitations that emerge when established field survey methods are used independently (O'Brien et al. 2010). Moreover, the role of DNA barcoding is crucial for studying species that are elusive, and to acquire insight into ancient environments (Thomsen and Willerslev 2015). The accuracy of biodiversity estimation is expected to benefit from the integration of monitoring techniques as can be observed from the results of the review. However, one should be cautious of publication bias towards reporting only positive and significant results (Lortie et al. 2007, Peplow 2014).

2.4.3 Gaps and Opportunities

2.4.3.1 Monitoring of Primary Biodiversity Attributes

Based on our review, we map the actual and optimal application of biodiversity monitoring approaches (Table 2.1) specified by Turner (2014) in relation to primary biodiversity attributes specified by Noss (1990). classified between in situ and remote sensing based on their data acquisition technique.

Table 2.1: Complementarity of monitoring methods for assessing biodiversity change in tropical forests along primary biodiversity attributes. Brown: suitable, Orange: very suitable, Green: ideal; up arrow: well exploited potential, horizontal arrow: potential reasonably exploited, down arrow: used insufficiently. Note: Monitoring methods are classified between in situ and remote sensing based on their data acquisition technique.

		Compositional biodiversity	Functional biodiversity	Structural biodiversity
In situ	Established field survey	↑	↑	↑
	In situ activity sensors	→	↓	→
	DNA Barcoding	↓	↓	↓
	Citizen Science	↓	↓	↓
Remote sensing	Coarse to medium spatial resolution	↓	→	→
	High to very high spatial resolution	↑	↑	↑
	Hyperspectral	→	→	→
	SAR	→	→	→
	Airborne LiDAR	→	→	→
	Terrestrial Laser Scanner	↓	↓	↓

In the synthesis table (Table 2.1), we quantified how many of the reviewed articles used a certain method to monitor the biodiversity attributes that are defined by Noss (1990). This was further related to the potential application that the methods can provide according to key literatures in the field (Kuenzer et al. 2014, Turner 2014, Pimm et al. 2015, Lausch et al.

2016). It appears that none of the monitoring methods presented here are in themselves sufficient to properly address the three primary biodiversity attributes. However, this overview shows that there is complementarity between methods. As can be observed, in situ approaches perform well in biodiversity composition, while remote sensing based approaches are powerful for addressing structural and functional biodiversity. It can also be observed that despite their remarkable potential, these tools are underexploited. For instance, DNA barcoding, TLS and citizen science were among the methods least employed (not used in >80% of the reviewed studies). However, the role of citizen science on conservation efforts was demonstrated through various successful projects such as the breeding bird survey in the United States (Pardieck et al. 2017), global bird observation network—eBird (Sullivan et al. 2009), the Dutch phenological network (Dutch phenological network 2017), and ranger’s forest and biodiversity status observation in Ethiopia (Nature and Biodiversity Conservation Union 2017). Neither were in situ sensors, LiDAR, SAR, and hyperspectral sensors that are ranked from very suitable to ideal for monitoring some biodiversity attributes used to their full potential in tropical forest biodiversity monitoring studies. Such shortcomings can lead to the development of monitoring techniques that produce under-or overestimations of biodiversity metrics. Whereas remote sensing data can be used to detect changes, provide a stratified sampling scheme for efficient monitoring and to identify certain species characteristics, in situ methods can be used for calibration and validation. While it is advantageous to have various methods of detecting biodiversity changes, a difficulty arises when trying to combine the different types of data for modelling the characteristics of species, their association with their environment and their response to changes (Honrado et al. 2016). For instance, differences among datasets in terms of spatial/temporal/ taxonomic resolution, extrapolation, data standardisation, calibration and data format can be an obstacle. Thus, practicable spatial and ecological models need to be developed to map species distribution and ecosystem services, as well as to make projections. For these purposes, there is a pressing need to establish and strengthen networks such as GEO BON, which promote dialogue and collaboration between ecologists, biologists, remote sensing experts, modellers and statisticians. Such platforms can be used not only to overcome technological limitations and domain segregation, but also to address technical issues such as big-data processing capabilities and the skills needed to implement methods. Here, we can mention exemplary platforms, such as the Biodiversity Observation Network in a Box (BON in a Box), which provide information and access to biodiversity-relevant remote sensing datasets, protocols, and tools (<https://boninabox.geobon.org/>). Similarly, in situ data sources and analytical tools are provided by the Global biodiversity Information Facility (<https://www.gbif.org/>).

2.4.4 Operationalising EBVs with State-of-the-Art Technologies

EBVs are expected to promote standardised data workflows for harmonised monitoring and reporting of biodiversity change at a global scale, as a means to achieving the Aichi

biodiversity targets (CBD 2010). However, biodiversity monitoring methods operate at different spatial, temporal, and taxonomic scales (Kissling et al. 2017). The operationalisation of EBVs requires a statement of measurable EBV candidates that can be matched with multiple monitoring tools. Several studies assessed the possibilities of putting EBVs to practice and investigated how relevant indicators can be derived from them. Kissling (2017) investigated the necessary data and tools in order to operationalise species distribution and species abundance EBV candidates at a global level. Here, the requirement for multiple data sources was acknowledged, and limitations in the process of harmonizing and integrating observations from different data sources were indicated. Satellite remote sensing-based EBVs (SRS-EBVs) are being researched to provide scalable, rapid, and cost efficient global monitoring solutions towards operationalising EBVs (Pettorelli et al. 2016b). However, SRS-EBVs are proven to contribute towards direct derivable of only few EBVs, as most of them require higher resolution (in terms of spatial, temporal, and taxonomic details) datasets (Bush et al. 2017).

We developed a synthesis matrix that indicates the relevance of the state-of-the-art technologies in operationalising tropical forest-relevant EBV candidates (Tables 2.2 and 2.3). These syntheses are developed based on GEO BON strategy for EBVs (GEO BON 2017) (Table 2.3) and studies (Skidmore and Pettorelli 2015, Pettorelli et al. 2016b, Bush et al. 2017, GOFC-GOLD 2017, Kissling et al. 2017) that assessed avenues for multi sensor approaches in EBV product development (Table 2.2), especially focussing on remote sensing. In Table 2, the suitability of remote sensing in relation to multiple EBVs as well as Aichi biodiversity targets is presented. Most importantly, the application of the range of remote sensing techniques in relation to specific candidates is presented. Most remote sensing tools are applied towards vegetation and habitat-related EBV candidates. Here EBV products such as vegetation types and land use/cover maps can be produced using spectral characteristics of the remote sensing data. These maps are often produced with medium or high spatial resolution images such as those from Landsat or Sentinel 2 sensors, respectively. Remote sensing can also be used in relation to EBV candidates that require finer details such as taxonomic diversity and population structure by age/size class. In the latter case, data sources with higher spectral and spatial resolution are required from the remote sensing domain such as hyperspectral and LiDAR remote sensing; however, associated costs could hamper their applicability in several countries from the tropics.

Alternative approaches to deriving species diversity indices from satellite remote sensing datasets exist; however, acquiring a reliable estimation of beta-diversity and gamma-diversity is challenging (Rocchini et al. 2016). Remote sensing application is especially limited for EBV classes such as genetic composition and species traits that require monitoring at genetic (e.g., co-ancestry, population genetic differentiation) and species level (e.g., body mass, demographic traits). The spatial and spectral resolution of satellite remote sensing

products limits the ability to identify individual trees or animal species. Very high spatial resolution images that can help identify large mammals are costly (Kissling et al. 2017) and often have high cloud coverage over tropical forests, which makes them unsuitable for deriving tropical forest EBVs. The use of remote sensing is, however, suitable for ecosystem structure EBV class (i.e., habitat structure, ecosystem extent and fragmentation EBV candidates), where EBV data products can be directly derived from medium to high spatial resolution data sources (e.g., Landsat, Sentinel 2) that are often freely available, while habitats' three-dimensional structure can be accurately mapped using LiDAR. The role of SRS for ecosystem function classes is also recognised. Pettoirelli et al. (2017) and Mora et al. (2017) listed EBV products that can be derived from current and future SRS datasets.

Table 2.2: State-of-the-art monitoring tools for tropical forest-relevant EBV candidates and related Aichi targets. SR: spatial resolution.

EBV Classes	EBV Candidates	Aichi Target (CBD 2010)	Remote Sensing	Emerging Opportunities
Species Populations	Species distribution	4–12, 14, 15	High to very high SR (Fretwell et al. 2012), Hyperspectral (Carlson et al. 2007)	In situ activity sensors (Ahumada et al. 2011), DNA barcoding (Ji et al. 2013)
	Population abundance	4–12, 14, 15	High to very high SR (Fretwell et al. 2012), Hyperspectral (Carlson et al. 2007)	In situ activity sensors (Ahumada et al. 2011)
	Population structure by age/size class	4–12, 14, 15	LiDAR (Yao et al. 2012)	
Species Traits	Phenology	10, 15	High to very high SR (Fisher et al. 2006), coarse to medium SR (Atkinson et al. 2012), hyperspectral (Thenkabail et al. 2016)	
	Migratory behaviour	5, 6, 10, 11, 12		In situ activity sensors (Kays et al. 2015)

Community Composition	Taxonomic diversity	8, 10, 12, 14	Hyperspectral (Schäfer et al. 2016)	In situ activity sensors DNA barcoding (Ji et al. 2013)
Ecosystem Function	Net primary productivity	5, 8, 14	High to very high SR (Jay et al. 2016), coarse to medium SR (Cleveland et al. 2015), hyperspectral (Smith et al. 2002)	In situ activity sensors (Verma et al. 2015)
	Nutrient retention	5, 8, 14	Hyperspectral (Smith et al. 2002)	
	Disturbance regime	5, 7, 9, 10, 11, 14, 15	High to very high SR (Flores et al. 2014), coarse to medium SR (Jin and Sader 2005)	In situ activity sensors (Ngoprasert et al. 2007)
Ecosystem Structure	Habitat structure	5, 11, 14, 15	High to very high SR (Hansen et al. 2016), Coarse to medium SR (Tuanmu and Jetz 2015b), LiDAR (Simonson et al. 2014b), SAR (Betbeder et al. 2015)	In situ activity sensors (Leblanc and Fournier 2017)
	Ecosystem extent and fragmentation	5, 7, 10, 14, 15	coarse to medium SR (Lehner and Döll 2004)	

Even though several SRS and Earth observation datasets are being identified as suitable for monitoring of EBVs, there is still remaining work to be done towards a better definition of some EBV classes such as the ecosystem function class (Pettorelli et al. 2017). In addition, testing the suitability of methods across scales, integration of heterogeneous monitoring technologies, setting up metadata standards, and making interpolation and/or extrapolation from observation at different scales is required (Bush et al. 2017, Kissling et al. 2017). This is especially true for EBV classes such as genetic composition and species traits where little data are directly available.

Finally, using the GEO BON strategy for development of EBVs (GEO BON 2017), the integration of remote sensing with emerging tools appear as necessary to operationalise EBVs (Table 2.3). The complementary nature of the monitoring approaches highlights that synergy is required between the approaches to up/downscale observations between different spatiotemporal and taxonomic scales. EBV candidates such as species distribution, population abundance, net primary productivity, and habitat structure will benefit from such synergies. However, issues related with data standards, uncertainties, documentation of protocols and guidance, data sharing, as well as consensus on the usability of EBV derived products need to be dealt with to enable consistent global reporting of biodiversity changes using EBVs.

Table 2.3: The relevance of state-of-the-art monitoring approaches in the context of GEO BON strategy to operationalise EBVs. Colours represent readiness level for each subcategory. Brown = low level, Orange = medium level, Green = high level (adapted from GEO BON strategy for development of EBVs).

EBV Criteria Components	Remote Sensing	In situ	DNA Barcoding
Spatial extent	Global (Proença et al. 2016)	Global with gaps. Example: TEAM network (http://www.teamnetwork.org/), http://bio.acousti.ca Bioacoustics (Baker et al. 2015)	Local/regional (Bruford et al. 2017)
Spatial resolution	Optical satellite: coarse spatial resolution 250–1200 m (e.g., MODIS), Medium to high spatial resolution: 5–30 m (e.g., Landsat, sentinel 2, RapidEye), Very high spatial resolution (e.g., Ikonos, GeoEye): 0.5–4 m. Airborne Hyperspectral: 1–2 m (according to flight height). Active remote sensing (radar): 1–100 m (Vihervaara et al. 2017). Upcoming: GEDI (satellite LiDAR): 25 m footprint, EnMAP (satellite hyperspectral): 250 narrow bands (Mora et al. 2017)	Field based. Example: TEAM has 23 tropical forest sites (120–200 km ² resolution) (Kissling et al. 2017)	Requires physical sampling (Bruford et al. 2017)
Periodicity	Continuous long term time-series data, with high revisit-time period for high-resolution data (e.g., Landsat: every 16 days, Sentinel 2: every 10 days, RapidEye: Daily) (Vihervaara et al. 2017)	From real-time to different times of the day and seasons (Obrist et al. 2010)	No clear understanding (Bruford et al. 2017)
Taxonomic coverage	Multiple taxa can be covered (Pereira et al. 2017)	Multiple taxa can be covered (Pereira et al. 2017)	Multiple taxa can be covered (Pereira et al. 2017)

uncertainty	Imperfect detections, data uncertainties, model uncertainties (Rocchini et al. 2013)	Measurement error, detection algorithms (Wrege et al. 2017), spatial mismatches (Bustamante et al. 2016)	Reference datasets (Kissling et al. 2017), variation in primer use, amplification steps and sequencing platforms (Bucklin et al. 2016)
Operational definition	Several demonstrations are made to derive EBVs (Paganini et al. 2016, Geller et al. 2017, GOFC-GOLD 2017, Pettorelli et al. 2017)	The technology has been identified as candidate (Proença et al. 2016)	The technology has been identified as candidate (Creer et al. 2016, Bush et al. 2017)
Documentation	Documentations is available (Geller et al. 2017, GOFC-GOLD 2017, Pettorelli et al. 2017)	Lack of documentation and established protocols	Lack of documentation and established protocols
Abstraction	Few to several steps involved in derivation of products (GOFC-GOLD 2017, Pettorelli et al. 2017)	Few steps involved in derivation of products (Pereira et al. 2017)	Several steps in derivation of products (Creer et al. 2016)
Measurement and sampling schema	Sampling and measuring strategies are often well defined (Pettorelli et al. 2017)	Limited sampling and measuring strategies are available [14]. Camera traps: www.teamnetwork.org/protocols	Few sampling and measuring strategies are available (Creer et al. 2016) (www.barcodesoflife.org/ , www.genec.org/)
Automatisation	Automation of data acquisition and processing is possible (Geller et al. 2017)	Automation of data acquisition, processing, and management are possible. Example: automated and semi-automated sound recognition (Jeliazkov et al. 2016, Jahn et al. 2017), automated camera traps and image recognition (O'Brien 2008)	Automated DNA extraction is possible (Ivanova et al. 2006)
Interoperability	Global standards and protocols exist for harmonised data and metadata formats (e.g., http://docs.openeospatial.org/is/10-157r4/10-157r4.html)	Camera traps: individual initiatives exist (Forrester et al. 2016). Bioacoustics: metadata standards are proposed (Roch et al. 2016)	Data standards are defined (Ratnasingham and Hebert 2007)
Data availability	Data available for multiple EBVs (GOFC-GOLD 2017, Pettorelli et al. 2017). (e.g. https://scihub.copernicus.eu/dhus/#/home , https://gcmd.nasa.gov/ , https://boninabox.geobon.org/)	Data mobilisation opportunities exist www.TEAMNetwork.org , http://bio.acousti.ca/ , https://boninabox.geobon.org/ , https://www.movebank.org/	Data mobilisation opportunities exist http://www.barcodinglife.org , https://www.ncbi.nlm.nih.gov/ , https://boninabox.geobon.org/
Temporal sustainability	Data have been available from satellite agencies for 40 years now (e.g., Landsat) and is secured until the end of the	Data availability and methods are evolving (Aide et al. 2013)	Data availability and methods are evolving (Thomsen and Willerslev 2015)

	2020's (Paganini et al. 2016, Vihervaara et al. 2017)		
Baseline	Historical satellite datasets are available: e.g., Landsat program (since 1972) (Vihervaara et al. 2017)	Baselines can be made from past field inventories (Wrege et al. 2017)	Ancient DNA (e.g., from museum collections) (Bohmann et al. 2014), https://www.ncbi.nlm.nih.gov/
Relevancy	Relevance for multiple EBVs has been demonstrated (Pettorelli et al. 2017, Vihervaara et al. 2017)	Relevance for multiple EBVs has been demonstrated (Pereira et al. 2017, Wrege et al. 2017)	Relevance for multiple EBVs has been demonstrated (Bruford et al. 2017, Pereira et al. 2017)
Consensus	Large consensus exists (GOFC-GOLD 2017)	Consensus underway (Pereira et al. 2017)	Consensus underway (Bruford et al. 2017)
Scalability	Robust to scalability (e.g., diversity indices) (Rocchini et al. 2016)	Robust to scalability (e.g., Wildlife Picture Index) (O'Brien et al. 2010)	Robust to scalability using statistical models (e.g., species distribution models) (Bush et al. 2017)
Institutional support	Several institutions are contributing. Example: GEO BON (http://geobon.org/essential-biodiversity-variables/monitoring/), GOFC-GOLD: (http://www.gofcgold.wur.nl)	Several institutions are contributing. Example: GEO BON (Pereira et al. 2013), Map Of Life (https://mol.org/), Move bank (https://www.movebank.org/)	GEO BON (http://geobon.org/essential-biodiversity-variables/monitoring/), GOFC-GOLD: (http://www.gofcgold.wur.nl)

2.5 Future Directions and Recommendations

Our review has shown that the potential of some of the most recent technologies for monitoring biodiversity dynamics in tropical forests has been initially investigated but still needs to be explored further—notably their operational synergy across biophysical scales and extended taxonomic levels. This underlines the need to support further research and development activities to demonstrate the added value of such technologies; and learn from existing efforts such as the National Ecological Observatory Network (<http://www.neonscience.org>). Networks like GEO BON could, for instance, influence the formulation of research calls targeted specifically at closing such research and development gaps. To this end, the development of a Technology Readiness Level (TRL) framework could be initiated. Such TRLs could also be used to monitor scientific and technical progress and provide guidance to countries for the development of their monitoring systems. For instance, the GEO BON could build on the assessment framework for tropical forest monitoring developed by the Global Forest Observations Initiative (GFOI).

The lack of integration of the novel technologies also stresses the necessity to link up the different research communities that work on tropical forest environments. Different policy contexts with overlapping requirements co-exist, such as climate change mitigation and adaptation from the United Nations Framework Convention on Climate Change, but also the UN SDGs. More particularly, experts in the fields of genomics, Earth observation and information technology fields need to strengthen collaborations to tackle the challenges of the big-data era. In this context, successful efforts from the research community to incentivise free and open access to Earth observation data need to be maintained. Finally, guidance documents synthesising the operational monitoring methods and reviewing the state-of-the-art research should be developed. An appropriate platform for achieving this is the BON-in-a-Box concept tool (<https://boninabox.geobon.org/>) supported by the GEO initiative. One recent bon-in-a-box release is the sourcebook for biodiversity monitoring in tropical forests with SRS developed by GOFC-GOLD and the GEO BON presents techniques related to EBVs relevant to tropical forests (GOFC-GOLD 2017).

Acknowledgements

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Chapter 3

Assessing the structural differences between tropical forest types using Terrestrial Laser

This section is based on:

Decuyper, M., K. A. Mulatu, B. Brede, K. Calders, J. Armston, D. M. Rozendaal, B. Mora, J. G. Clevers, L. Kooistra, M. Herold and F. Bongers (2018). "Assessing the structural differences between tropical forest types using Terrestrial Laser Scanning." *Forest Ecology and Management* **429**: 327-335. DOI: [10.1016/j.foreco.2018.07.032](https://doi.org/10.1016/j.foreco.2018.07.032)

Supplementary material mentioned in the text can be found in the online publication

Abstract

Increasing anthropogenic pressure leads to loss of habitat through deforestation and degradation in tropical forests. While deforestation can be monitored relatively easily, forest management practices are often subtle processes, that are difficult to capture with for example satellite monitoring. Conventional measurements are well established and can be useful for management decisions, but it is believed that Terrestrial Laser Scanning (TLS) has a role in quantitative monitoring and continuous improvement of methods. In this study we used a combination of TLS and conventional forest inventory measures to estimate forest structural parameters in four different forest types in a tropical montane cloud forest in Kafa, Ethiopia. Here, the four forest types (intact forest, coffee forest, silvopasture, and plantations) are a result of specific management practices (e.g. clearance of understory in coffee forest), and not different forest communities or tree types. Both conventional and TLS derived parameters confirmed our assumptions that intact forest had the highest biomass, silvopasture had the largest canopy gaps, and plantations had the lowest canopy openness. Contrary to our expectations, coffee forest had higher canopy openness and similar biomass as silvopasture, indicating a significant loss of forest structure. The 3D vegetation structure (PAVD – Plant area vegetation density) was different between the forest types with the highest PAVD in intact forest and plantation canopy. Silvopasture was characterised by a low canopy but high understorey PAVD, indicating regeneration of the vegetation and infrequent fuelwood collection and/or non-intensive grazing. Coffee forest canopy had low PAVD, indicating that many trees had been removed, despite coffee needing canopy shade. These findings may advocate for more tangible criteria such as canopy openness thresholds in sustainable coffee certification schemes. TLS as tool for monitoring forest structure in plots with different forest types shows potential as it can capture the 3D position of the vegetation volume and open spaces at all heights in the forest. To quantify changes in different forest types, consistent monitoring of 3D structure is needed and here TLS is an add-on or an alternative to conventional forest structure monitoring. However, for the tropics, TLS-based automated segmentation of trees to derive DBH and biomass is not widely operational yet, nor is species richness determination in forest monitoring. Integration of data sources is needed to fully understand forest structural diversity and implications of forest management practices on different forest types.

Keywords

Plant Area Volume Density (PAVD), canopy openness, canopy gaps, coffee forests, Ethiopia, 3D structural heterogeneity.

3.1 Introduction

Tropical forests typically have high diversity, as they are characterized by a more complex canopy structure when compared to other forest types (Ghazoul and Sheil, 2010; Whitmore, 1982). Structurally complex habitats provide a large number of niches for different animal and plant species (habitat heterogeneity hypothesis; Tews et al., 2004). Increasing anthropogenic pressure leads to habitat loss, from deforestation that reduces the total forest area into smaller, isolated forest patches (Zipkin et al., 2009). In addition, degradation of remaining forests through selective logging, unsustainable use and extensive hunting leads to habitat loss (Harrison, 2011; Ticktin, 2004). In many seemingly intact forests the understorey has been heavily affected by human use, through cutting of poles for construction or fire wood, or planting of understorey species that are important commodities, such as coffee and cocoa (Harrison, 2011). Both processes lead to a steep decline in flora and fauna diversity with increasing degradation (Barlow et al., 2016; Pettorelli et al., 2014) and can for instance lead to ‘empty forests’ with no large animals remaining under an intact forest canopy (Redford, 1992). Accurate characterization and measurement of the intensity of forest management and use is required to understand the drivers of forest degradation, to prevent further degradation and to plan restoration actions (Ghazoul et al., 2015; Ghazoul and Chazdon, 2017). Anthropogenic pressure not only affects forest biodiversity, but also the provision of other ecosystem functions, such as carbon storage (Kissinger et al., 2012), soil stabilization, and water provision (Ellison et al., 2017). Besides the type, also the intensity and frequency of the disturbance events, and the time elapsed since the last event is important (Barlow et al., 2012). The combined effects of different management practices and the way they affect forest structure is not always clear, hampering the identification of management priorities for avoiding further forest loss and for restoring degraded forests (Berenguer et al., 2014).

To what extent, and in what way, forest structure is affected through forest degradation likely depends on the type of forest management. In this study, we assess the difference in forest structure between four forest types, characterized by different forest management practices, in the montane cloud forest of the UNESCO Kafa Biosphere Reserve, southwest Ethiopia. This area is a biodiversity hotspot and is considered the origin of the Arabica coffee (*Coffea arabica*). However, in the last decades large areas of these unique forests have been converted to other land-uses (Tadesse et al., 2014). Many of the previously untouched intact forests are currently managed, for example as semi-forest coffee systems, or as forests used for fuelwood collection and/or grazing by cattle (i.e. silvopasture). Other types of management in the area include the total clearance of natural forest for plantations for wood production and agriculture. In intact forest, the vegetation is dense in both understory vegetation (i.e. < 10m) and in the canopy, with little light reaching the understory vegetation. Management in the coffee forests often imply the removal of most understory vegetation,

while still leaving most of the canopy intact to provide shade for the coffee plants (Schmitt et al., 2009). *Coffea arabica* grows up to 10 m high, but is often pruned for easier harvesting and is planted with enough spacing, leaving a less dense vegetation structure. Management in the silvopasture system are diverse and can include fuelwood collection, grazing by cattle, and forests can be left to regrow after earlier use, which can result in a heterogeneous forest structure. Overall, silvopasture areas have a more open understory and canopy, and large canopy gaps. For plantations we assume a homogeneous canopy, with no canopy gaps and very little light reaching the ground floor, limiting the development of understory vegetation.

Generally, 3D (three dimensional) structural changes in forests are monitored in permanent sample plots in which trees are measured for their stem diameter and height, are mapped, and species are identified. Such conventional forest inventory methods capture some of the horizontal and vertical forest structural parameters, like aboveground biomass (Day et al., 2014), frequency distributions of canopy height (Brockelman, 1998), occupation of vegetation in space within canopy gaps (Bongers, 2001; van der Meer, 1997), and canopy openness (Chazdon and Percy, 1991; Oliver and Larson, 1996). However, to characterize the full spatial heterogeneity in forest structure, detailed 3D imagery is needed to measure an array of structural parameters, including the location of vegetation volumes (and in absence of this, empty-ness) in 3D space. These parameters are important for guiding management priorities or monitoring sustainable practices. Terrestrial Laser Scanning (TLS) provides high-accuracy data on both vertical and horizontal forest canopy structure (Liang et al., 2016; Palace et al., 2016; Wilkes et al., 2017) and therefore is promising for detailed monitoring of forest structure. It is well established that conventional measurements can be useful for management decisions, but it is believed that TLS has a role in quantitative monitoring and continuous improvement of methods. TLS provides a rapid, full coverage of the surrounding area and produces a high-detail 3D point cloud, which allows the estimation of a range of parameters such as canopy height (Palace et al., 2015), number of layers (Palace et al., 2016), Plant Area Volume Density (PAVD) (Calders et al., 2015a) and tree volume (Calders et al. 2015c, Ferraz et al. 2016). PAVD indicates the plant surface area to volume ratio, and provides a consistent, detailed quantification of vegetation elements (e.g. leaves, branches and stems) in a certain space. Consistent monitoring of changes in 3D structure is needed to monitor forest management implications, and here TLS could be an add-on or an alternative for monitoring conventional forest structure parameters. TLS-derived PAVD has been used to assess forest phenology (Calders et al., 2015a) and structural differences among forest types (Ashcroft et al., 2014), but effects of forest degradation have not been assessed. Small changes are difficult to detect by conventional satellite sensors due to their limited canopy penetration (Lefsky et al., 2002). Although synthetic aperture radar (SAR) and airborne laser scanning (ALS) have been successfully used to measure the 3D forest structure (Disney et al., 2006; Mura et al., 2015) and disturbances in the canopy (Joshi et al., 2015a), the data are

still limited to the birds-eye view of the canopy. TLS fills this gap by measuring both forest understorey vegetation and the canopy.

In this study we assess the forest structure in the Kafa region in Ethiopia of plots under four management types: (i) untouched natural forest (intact forest) with no signs of management, (ii) coffee forest, (iii) silvopasture and (iv) plantation. We compare 3D forest structure between these types based on conventional forest inventory methods and on TLS. We hypothesize that (1) aboveground biomass (AGB), tree density, basal area (BA), and diameter at breast height (DBH) are highest in intact forest and plantation, and slightly lower in coffee forest through creating space for coffee production. We expect that these parameters will be lowest in silvopasture, due to removal of trees e.g. for fuelwood; (2) the number and size of canopy gaps and canopy openings are expected to be lowest in intact forest and plantation; and (3) 3D forest structure, measured as PAVD, will be highest in intact forest, for both understory and canopy. Coffee forest is expected to have a lower PAVD in the understory, but values similar to intact forest in the canopy. Silvopasture is expected to have the lowest PAVD values in both understory and canopy, while plantation has canopy PAVD values similar to intact forest, but a very low understorey PAVD.

3.2 Methods

3.2.1 Study site

The research was conducted in the montane cloud forests of the Kafa Biosphere Reserve in Ethiopia (36°3'22.51" E, 7°22'13.67" N – Figure 3.1) which has an altitudinal range from 500 to 3500 m above sea level. The Kafa Biosphere Reserve is a hotspot for biodiversity with around 244 plant species, including 110 tree species, and over 300 mammal species (Mittermeier et al., 2004; NABU, 2014). The Kafa Biosphere Reserve is covered by more than 50% with forest, including 7% of protected intact forests and 48% of buffer zones or candidate core zones. About 45% of the Kafa Biosphere Reserve consists of agriculture and pasture. The candidate core zones include zones designated for coffee cultivation. Farmers producing coffee are doing so under a Participatory Forest Management (PFM) scheme. The idea behind the PFM scheme is to ensure a long-term source of income by sustainable management of forest resources.

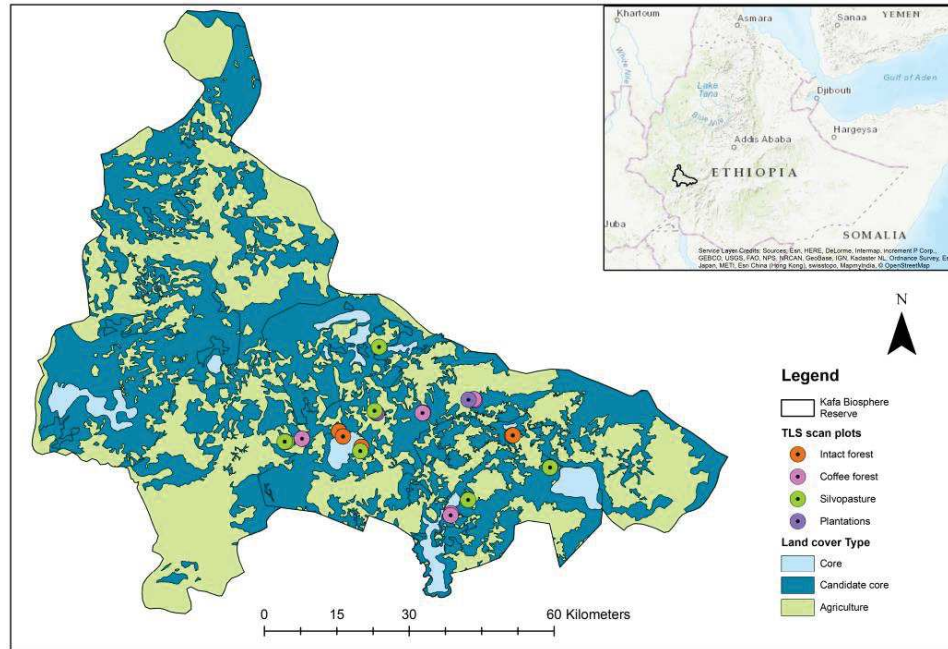


Figure 3.1: The location of the Kafa Biosphere Reserve in Ethiopia and location of the plots. Source: Dresen 2011.

3.2.2 Plot design and conventional measurements

Plots were selected according to a stratified sampling design. The stratification was based on an overlay between several GIS data layers: a fragmentation map (Mulatu, 2013), a land use/cover map (Dresen, 2011) and a topographic map. Within the four forest types, a total of 27 plots were established (Intact: 9 plots, coffee forest: 8 plots, silvopasture: 7 plots and plantation: 3 plots). From the 27 plots, 21 plots had a 20 m radius and six plots a 10 m radius due to difficult terrain (e.g. slope). We used a nested design, where all trees of ≥ 20 cm diameter at breast height (DBH) were measured for their diameter and identified to species in the 20 m (or 10 m) radius plot, while trees of 5-20 cm DBH were included within the centre 5m-radius subplot only (Figure 3.2b). Above-ground biomass (AGB) was derived from the DBH, species names and the wood density values for African tropical moist forests (Chave et al., 2009). Basal area (BA) and tree density were derived from the data. For an overview of all forest structural parameters derived from the TLS and conventional forest measures, including a detailed workflow on how the forest structural parameters were derived see Appendix A.

3.2.3 TLS measurements

A RIEGL VZ-400 terrestrial laser scanner (RIEGL Laser Measurement Systems GmbH, Austria) mounted on a tripod was used. The VZ-400 operates at a wavelength of 1550 nm and uses on-board waveform processing to record up to four returns per outgoing pulse with a range up to 350 m. For each plot, five scan positions were used: one in the centre and four in the cardinal directions (Figure 3.2b). Cylindrical, retroreflective targets (20 in total) were placed in the plot to allow co-registration of the individual point clouds (Wilkes et al., 2017). Pre-processing of the point cloud data was performed using RiSCAN PRO software (RIEGL Horn, Austria). Multiple scans per plot were co-registered based on their corresponding tie points using the 20 reflector targets from the field. Alignment errors were corrected using the multi-station adjustment (MSA) module, which improves the registration of the scan positions (Wilkes et al., 2017). Figure 5.2c shows an example of the 2D equiangular projection of the co-registered TLS point cloud.

3.2.4 TLS derived parameters

Vertical profiles of Plant Area Volume Density (PAVD) were derived for 0.5 m vertical bins from ground level to top of the canopy using individual TLS scans based on the method developed by Calders et al. (2014) (Figure 3.2a). The integral of PAVD over the whole canopy is the Plant Area Index (PAI) (Calders et al., 2015a). The retrieval method allows the estimation of PAI using multiple TLS returns and a height correction that accounts for sloped terrain. In short, the vertically resolved, directional gap fraction was estimated by relating the number of returned pulses to the total number of emitted pulses (Jupp et al., 2009). Next, PAVD was derived from the gap fraction at the hinge angle (57.5° zenith) to minimise the influence of leaf angle distribution (Jupp et al., 2009). The profiles can be aggregated into different height layers. In cases when one PAVD value per plot was needed, gap fractions of the single scans were averaged and then PAVD was derived. All plots are surrounded by forest of the same level of disturbance, to ensure PAVD (not limited to the 20 m radius) was representative for the plot.

To extract the canopy and canopy height parameters, the registered point clouds were loaded into CompuTree point cloud analysis open source software (Hackenberg et al., 2015). The detailed processing steps can be found in Appendix A. The derived 2D canopy height models (DHM) were exported as 0.5 m resolution raster files and further analysed in ArcMap (ESRI Redlands USA) (Figure 3.2d). The following parameters were derived from the DHM: (i) Canopy height: the top of the canopy at 0.5 m resolution for the 20 (or 10) m radius plot; (ii) Canopy gaps: defined here as neighbouring pixels with canopy height of <10 m and with an area of ≥ 1 m² (Hunter et al., 2015). From the canopy gaps the maximum and mean gap area, and the number of gaps per plot were derived; (iii) Canopy openness, defined here as all

empty spaces of $\geq 1 \text{ m}^2$ at 5 m height intervals, calculated until the maximum canopy height (Figure 3.2b, green layers). With the canopy openness we do not capture the empty space underneath the upper canopy (this would be the inverse of the PAVD).

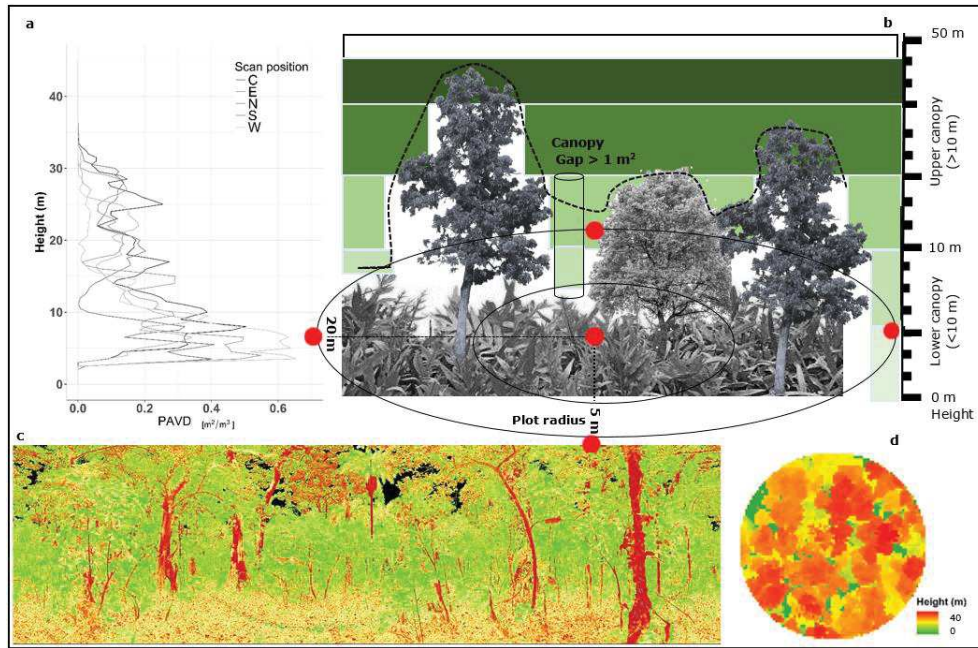


Figure 3.2: Overview of the TLS derived parameters capturing forest structure. (a) Example of the Plant Area Volume Density (PAVD) of one plot with the different scan positions. (b) Canopy related parameters derived from the TLS Digital Height Model (DHM): Canopy height as the height of the vegetation (see dotted line); Canopy gap: number of canopy gaps with a size of $> 1 \text{ m}^2$ and $< 10 \text{ m}$ height; Canopy openness: area of open space (seen from the top) relative to the highest tree in the plot at 5 m height intervals (indicated by the shades of green). Scan positions are indicated by red dots. (c) 2D equiangular projection of the TLS point cloud (projections for each forest type can be found in Appendix B). (d) DHM for a 20 m radius plot at 0.5 m resolution.

3.2.5 Statistical analysis

Linear mixed-effects models were used to compare the forest types for the conventional forest structure measurements (i.e. AGB, BA, tree density and the DBH distribution). The model selection was based on Akaike's Information Criterion, adjusted for small sample sizes (AICc). Models within 2 AICc-units from the model are equally supported (Burnham and Anderson, 2002). Similarly, we used linear mixed-effects models to compare TLS derived PAVD at 5 m height intervals among forest types. Mixed-effect models were used because

multiple values (i.e. PAVD for each 5 m height interval) per plot are included, thus accounting for the fact that data points within a plot cannot be regarded as independent data points. We compared five models with varying fixed effects structures: (1) height interval, forest type and their interaction and including a random slope in height interval; (2) height interval, forest type and their interaction; (3) forest type; (4) height interval; and (5) only an intercept. In addition, we added a random slope for height interval to account for plot-to-plot variation in the relation between height interval and PAVD, which significantly improved model fit based on a likelihood-ratio test (see Appendix C). The same model comparison was used for the TLS derived canopy openness. Similarly, we compared the forest types for the TLS derived canopy height distribution, using mixed-effect models with a random intercept per plot, and compared the model with a model with a fixed intercept. Where needed, data were transformed (Appendix C) to enhance normality and homoscedasticity. All analyses were performed in R, version 3.3.3 (R core team); mixed-effects models were performed using the lme4 R package (Bates et al., 2014).

3.3 Results

3.3.1 Conventional forest structure parameters

Mean DBH, AGB and BA differed between forest types, but this was not the case for tree density (Appendix C). Predicted mean DBH values ranged from 62 ± 12 cm for intact forest (median = 40 ± 54.5 cm) to 34 ± 18 cm for plantation (median = 34.3 ± 15.5 cm). Coffee forest and silvopasture were similar with mean DBH values of about 46 ± 12 cm (median = 37.0 ± 31.8 cm and 33.5 ± 29.3 cm, respectively). Large trees (> 100 cm DBH) were most abundant in intact forest, and also present in coffee forest, although to a lesser extent (Appendix D). The DBH distributions show that trees with a DBH > 100 cm were almost absent in silvopasture and plantation, with plantation having many trees of 25-50 cm DBH (Appendix D). Mean BA and AGB were largest in intact forest (respectively 97 ± 28 m²/ha and 753 ± 259 t/ha), followed by plantation (respectively 47 ± 49 m²/ha and 422 ± 449 t/ha), coffee forest (respectively 40 ± 30 m²/ha and 295 ± 275 t/ha) and silvopasture (respectively 33 ± 32 m²/ha and 282 ± 294 t/ha). Although no significant effect of forest type was found, mean tree density followed the same order (intact forest $>$ plantation $>$ coffee forest $>$ silvopasture) (Appendix D).

3.3.2 TLS derived canopy forest structure parameters

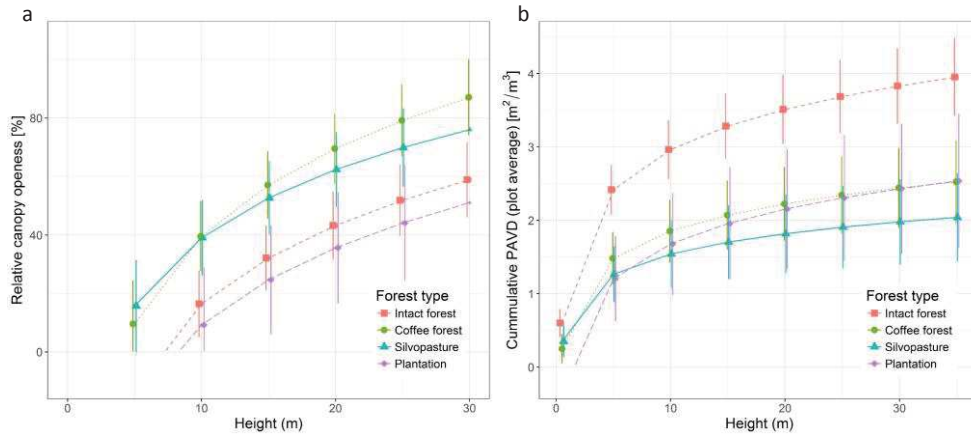


Figure 3.3: (a) Canopy openness per forest type at 5 m height intervals. (b) Cumulative Plant Area Volume Density (PAVD) as a function of height across four forest types. Predicted values are indicated (\pm SE; $n = 27$ plots).

Canopy openness differed between forest types and was also influenced by height classes. Coffee forest had a lower canopy openness between 0 – 10 m compared to silvopasture, but had higher canopy openness in the higher height classes (predicted values range from 10% to 94% and 15% to 86%, respectively) (Figure 3.3a; Appendix C). Intact forest and plantation had similar canopy openness (predicted values range from -9% to 63% and -17% to 57%, respectively).

Average canopy height, mean and maximum gap size, and the number of gaps also differed among forest types (Figure 3.4; Appendix C). Canopy height was highest in plantation (26.4 ± 9.7 m), followed by intact forest (19.0 ± 4.7 m), while silvopasture and coffee forest had the lowest canopy heights (17 ± 5.3 m and 15.5 ± 5.6 m respectively) (Figure 5.4a). Maximum gap size was higher in coffee forest and silvopasture (18.3 ± 4.6 m² and 19.8 ± 4.9 m², respectively) than in intact forest (7.5 ± 4.3 m²) and plantation (2.7 ± 7.5 m²) (Figure 3.4c - square root transformed values). Similar differences were found for the mean gap size with the lowest values in plantation (0.8 ± 0.5 m²), followed by intact forest (0.9 ± 0.3 m²), silvopasture (1.8 ± 0.3 m²) and coffee forest (2.0 ± 0.3 m²) (Figure 3.4b - log transformed values). Plantation also had the lowest number of gaps per plot (0.5 ± 0.8), followed by coffee forest (1.2 ± 0.5). The number of gaps was the highest in intact forest (1.5 ± 0.5) and silvopasture (1.3 ± 0.5) (Figure 3.4d - log transformed values). However, gaps in intact forest were mainly small, with an average size of approximately 1.5 m² (equals 0.2 m² when log transformed).

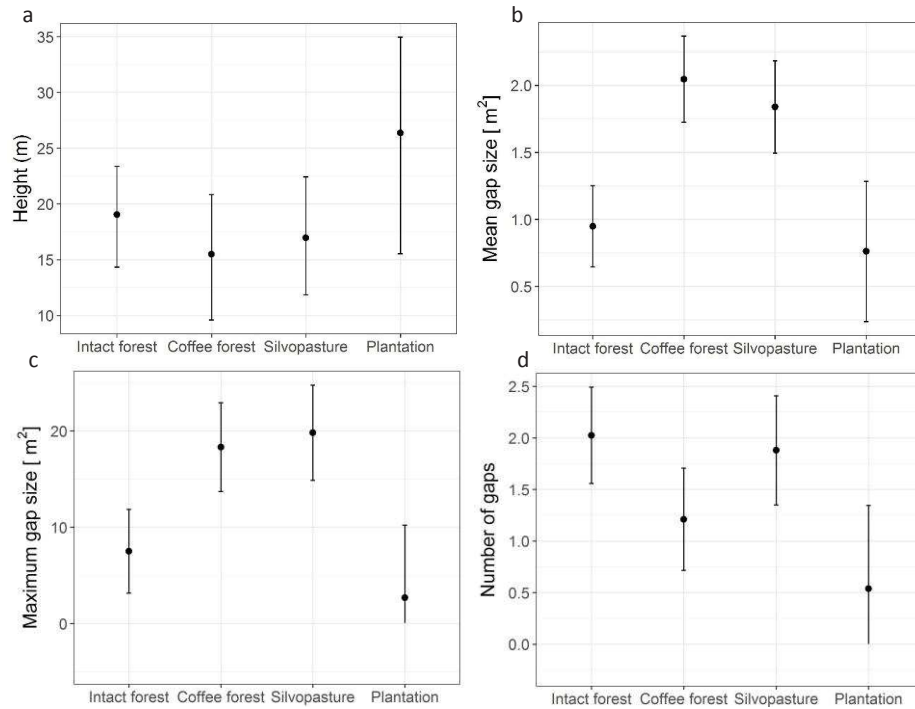


Figure 3.4: Structural parameters derived from the Digital Height Model (DHM) at 0.5 m grid resolution for four forest types. (a) Canopy height. (b) Mean gap size (log transformed). (c) Maximum gap size (square root transformed). (d) Number of gaps (log transformed). Predicted values are indicated (\pm SE; $n = 27$ plots).

3.3.3. TLS derived 3D Plant Area Volume Density (PAVD)

Plant Area Volume Density (PAVD) was generally highest in intact forest, for both understory and canopy compared to the other forest types (Figure 3.5). In both coffee forest and silvopasture the variation in PAVD was high in the 0-10 m height range (Figure 3.5a,b). In contrast to coffee forest and silvopasture, plantation consistently had very low PAVD values in the understory (Figure 3.5a,b).

PAVD varied among forest types and height classes (Figure 3.3b; Appendix C). The difference in PAVD is most apparent in the understory (< 10 m), with intact forest having most vegetation (estimated $\text{PAVD} = 3.0 \pm 0.4$) and plantation the lowest amount of vegetation (estimated $\text{PAVD} = 1.7 \pm 0.7$) (Figure 5.3b). At a height of 35 m, intact forest reached an estimated PAVD of 4.0 ± 0.5 , while plantation had an estimated PAVD of 2.5 ± 0.9 . Coffee forest and silvopasture were very similar to each other in the understory (< 10 m) with the

same estimated PAVD of respectively 1.9 ± 0.4 and 1.5 ± 0.4 , but differed in the canopy (respectively 2.5 ± 0.6 and 2.0 ± 0.6) (Figure 3.3b).

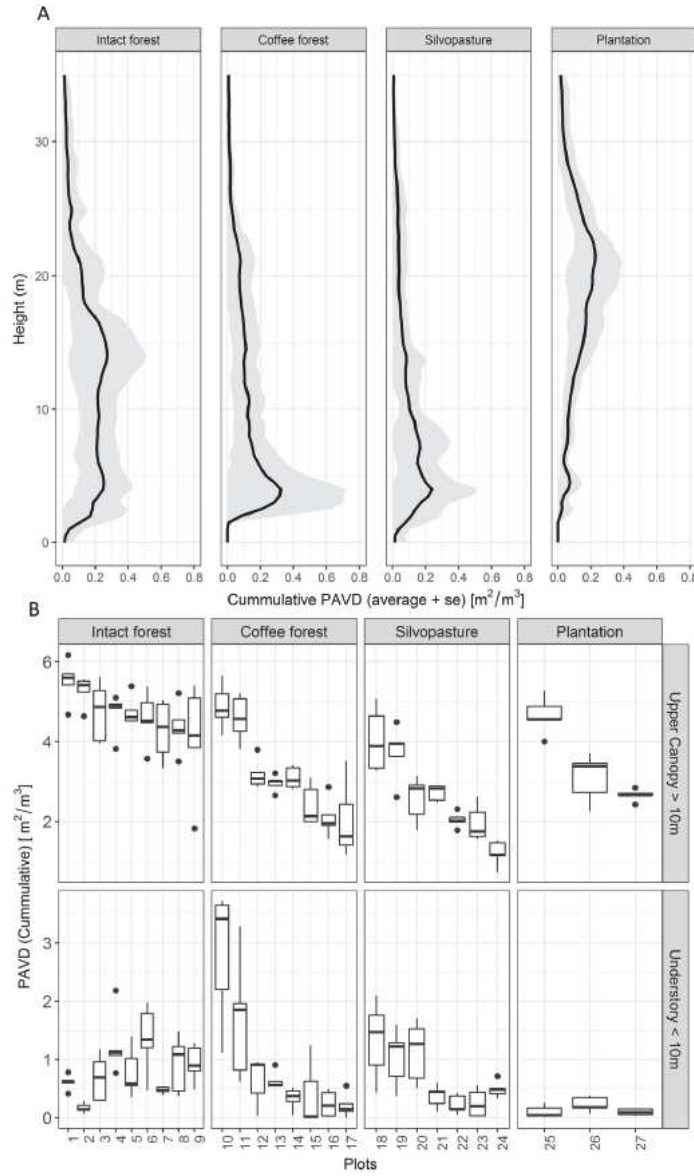


Figure 3.5: (a) Mean Plant Area Volume Density (PAVD) and standard error (SE – shaded area) for all plots per forest type. (b) Boxplots, with the median (horizontal line) lower and upper quartiles (hinges), presenting the maximum PAVD at plot level and its variation (different scan positions within the plots), for the canopy (>10 m) and understory (<10 m) (vertical panelling) along the different forest types (horizontal panelling).

3.4 Discussion

3.4.1 Management impacts on forest structure and management implications

The conventional measures of AGB, BA and DBH differed among forest types (Berenguer et al., 2014; Clark and Clark, 2000), with highest values for intact forest (Appendix D). Unexpectedly, both AGB, BA and DBH were very similar for coffee forest and silvopasture. This means that in coffee forest not only the understory was cleared, but also many trees were removed, indicating a larger management impact than expected and also indicated by other authors (Aerts et al., 2011; Hundera et al., 2013; Schmitt et al., 2009). The large variation in BA and DBH in plantation is probably due to the different tree ages between the three forest plantation plots.

TLS estimated canopy openness was the lowest in plantation because the plantation plots consisted of even-aged monocultures, followed by intact forest. The higher canopy openness, and large canopy gaps, in coffee forest in comparison to silvopasture (especially ≥ 10 m, i.e. height above the coffee), contradicted the idea of coffee being produced underneath a relatively intact forest canopy. The high canopy openness in the investigated coffee forests suggested that canopy loss is much higher than the 30% canopy loss reported for nearby semi-coffee forests (Schmitt et al., 2009). Also canopy gap size (mean and maximum) was in line with these results of canopy openness. The large number of small gaps in intact forest could indicate canopy heterogeneity (i.e. multiple tree height levels). Such heterogeneity in canopy structure increases light levels in the understory, which is beneficial for the understory vegetation (Chazdon and Pearcy, 1991; Montgomery and Chazdon, 2001). Average canopy height was highest in plantation, but in contrast to our hypothesis, the differences between the intact forest, coffee forest and silvopasture were small, probably due to the large variation between plots. Overall canopy height in coffee forest and silvopasture was the lowest, which could be detrimental for habitat heterogeneity and associated biodiversity (Ghazoul and Sheil, 2010; Martins et al., 2017).

The differences in 3D vegetation structure (PAVD) between forest types were significantly different for the different vegetation heights. Intact forest had, in general, the highest vegetation density over the complete height range. In addition to the conventional parameters and canopy gap parameters, the vegetation density in coffee forest at the canopy level (> 10 m) was lower than expected. Our assumption that coffee forest plots have a relatively intact canopy (intended to shade the coffee) was confirmed only for two out of the eight coffee forest plots (i.e. plot 10 and 11; Figure 3.5b). As expected coffee forest had high vegetation density between 2 and 10 m due to the coffee plants. The PAVD in silvopasture partially confirmed our assumption of low vegetation density in the canopy, supported by large canopy

gaps and low conventional parameters (DBH, AGB, BA and tree density). However, the understory vegetation in silvopasture was dense, most likely due to infrequent fuelwood collection and non-intensive grazing in most of the plots. Partial removal of the canopy enables light to reach the forest floor and creates a dense layer of heliophile species (M. Decuyper, personal observation). Cuni-Sanchez et al. (2016) found similar results for PAVD along a successional gradient in colonizing forest and young successional forest in Gabon. In all plantation plots there was little understory (indicated by the very low PAVD values), probably due to clearance of the vegetation and/or lack of sunlight. Tripathi and Singh (2009) identified similar patterns comparing vegetation structure from natural forests to plantations. Plantations could therefore be seen as structurally poor and offering only few habitat niches for flora and fauna (Tews et al., 2004).

Most parameters, both conventional and TLS derived, followed our prior expectations, but the forest structure of coffee forest did not. The high canopy openness together with the low BA estimations, and our field experiences (M. Decuyper, personal observation) in coffee forest warrant more tangible measures for sustainable forest management of coffee forest under the PFM certification, such as thresholds on canopy cover (Aerts et al., 2011; Hundera et al., 2013). Currently, large differences exist between PFM rules and regulations and objectives of policy makers on the one hand, and the interpretation and implementation of sustainable forest management in PFM sites by local communities on the other (Ayana et al., 2017). More tangible measures could relieve concerns regarding sustainability of the PFM scheme and the produced coffee, currently leading to heavy degradation and severely jeopardizing the sustainability of the coffee production, the diversity of wild coffee varieties, and ecosystem resilience (Aerts et al., 2011; Ayana et al., 2017).

3.4.2 TLS monitoring helps determining management impacts on 3D forest structure

While habitat loss through forest area loss and forest fragmentation is relatively easy to monitor and demonstrate, small scale changes in forest structure due to forest management (a more internal qualitative habitat loss) is much more difficult to monitor (Mitchell et al., 2017). The impact of small scale forest management (as is the case in this study area) mainly affects the understory while the canopy is left relatively intact, making such forest alterations undetectable by current satellites (Mitchell et al., 2017).

TLS measurements captured the variation in vegetation structure in the understory and canopy for different forest types. These TLS measurements enabled 3D quantification of forest structural measurements such as PAVD, but also the 2D canopy gaps and canopy openness at different heights to evaluate the effect of management implications. These parameters could potentially be used for habitat heterogeneity proxies and linked to

biodiversity analysis (Tews et al., 2004; Zipkin et al., 2009). Several of these parameters cannot be measured by conventional forest inventories, such as 3D position of plant volume (quantified by PAVD) and open spaces (i.e. inverse of PAVD). The 3D leaf positioning is important as it influences light extinction, tree architecture and photosynthetic leaf traits (e.g. Montgomery and Chazdon, 2001). Open space in different forest layers, including the forest understorey, is of great importance for many flora and fauna (Chazdon and Pearcy, 1991; Zahawi et al., 2015). With TLS, open spaces can be measured by assessing canopy openness and gaps at different heights. For example, open spaces and light between 0 and 1 m is highly important for seedling germination (Chazdon and Pearcy, 1991), at 0 and 5 m for coffee plants and their pollinators (i.e. bees) (Aerts et al., 2011), while between 5 and 30 m this can be important for bird species and epiphytes (Zahawi et al., 2015). For quantifying management effects on forest structure, consistent monitoring of changes in 3D structure is needed and here TLS is clearly an add-on or an alternative for monitoring conventional forest structure parameters. TLS is also an add-on for small scale canopy gap research, as it fills a gap between conventional geometric gap measurements (Van der Meer et al., 1994), grid-based top of canopy measures (Hubbell and Foster, 1986), hemispherical cameras (Jonckheere et al., 2004) and airborne or satellite data (Joshi et al., 2015b).

Besides the capability of TLS of measuring stem based structural parameters (i.e. AGB, BA, DBH and tree density) (Gonzalez de Tanago et al., 2018), there is still a need for the development of operational TLS data processing tools since there is not yet a fully automated way to measure DBH, AGB and BA in tropical forests. For example, deriving structural parameters such as biomass for tropical forests is quite challenging due to the dense understorey (Gonzalez de Tanago et al., 2018). Additionally, from a forest conservation perspective, TLS cannot capture information on tree species richness in tropical forests, thus there is a need for integrating different data sources in order to fully understand the forest structural diversity. Complementing conventional parameters with TLS derived parameters shows potential in describing the sometimes subtle differences in forest management.

TLS derived structural parameters can benefit from further integration with other datasets to better characterize forest structural differences across spatial scales (van Leeuwen and Nieuwenhuis, 2010). Not only data from conventional forest inventory methods, but also space borne and airborne LiDAR (Brede et al., 2017), multispectral TLS, as well as satellite remote sensing derived structural parameters are important to consider. Several studies have investigated the potential integration and upscaling opportunities of LiDAR and satellite remote sensing data, for example for stand height estimation (Mora et al., 2013). Further research is needed to link other TLS derived parameters with conventional forest inventory data, satellite or airborne data (Pettorelli et al., 2014) for better monitoring of management impacts on forest structure and biodiversity.

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Chapter 4

Linking Terrestrial LiDAR Scanner and Conventional Forest Structure Measurements with Multi-Modal Satellite Data

This thesis is based on:

Mulatu, K. A., M. Decuyper, B. Brede, L. Kooistra, J. Reiche, B. Mora and M. Herold (2019).
"Linking Terrestrial LiDAR Scanner and Conventional Forest Structure Measurements with
Multi-Modal Satellite Data." Forests **10**(3): 291

Abstract

Obtaining information on vertical forest structure requires detailed data acquisition and analysis which is often performed at a plot level. With the growing availability of multi-modal satellite remote sensing (SRS) datasets, their usability towards forest structure estimation is increasing. We assessed the relationship of PlanetScope-, Sentinel-2-, and Landsat-7-derived vegetation indices (VIs), as well as ALOS-2 PALSAR-2- and Sentinel-1-derived backscatter intensities with a terrestrial laser scanner (TLS) and conventionally measured forest structure parameters acquired from 25 field plots in a tropical montane cloud forest in Kafa, Ethiopia. Results showed that canopy gap-related forest structure parameters had their highest correlation ($|r|$ 0.4 – 0.48) with optical sensor-derived VIs, while vegetation volume-related parameters were mainly correlated with red-edge- and short-wave infrared band-derived VIs (i.e., inverted red-edge chlorophyll index (IRECI), normalized difference moisture index), and synthetic aperture radar (SAR) backscatters ($|r|$ = –0.57 – 0.49). Using stepwise multi-linear regression with the Akaike information criterion as evaluation parameter, we found that the fusion of different SRS-derived variables can improve the estimation of field-measured structural parameters. The combination of Sentinel-2 VIs and SAR backscatters was dominant in most of the predictive models, while IRECI was found to be the most common predictor for field-measured variables. The statistically significant regression models were able to estimate cumulative plant area volume density with an R^2 of 0.58 and with the lowest relative root mean square error (RRMSE) value (0.23). Mean gap and number of gaps were also significantly estimated, but with higher RRMSE (R^2 = 0.52, RRMSE = 1.4, R^2 = 0.68, and RRMSE = 0.58, respectively). The models showed poor performance in predicting tree density and number of tree species (R^2 = 0.28, RRMSE = 0.41, and R^2 = 0.21, RRMSE = 0.39, respectively). This exploratory study demonstrated that SRS variables are sensitive to retrieve structural differences of tropical forests and have the potential to be used to upscale biodiversity relevant field-based forest structure estimates.

Keywords

Forest structure; terrestrial LiDAR; synthetic aperture radar; satellite remote sensing; data fusion; Ethiopia

4.1 Introduction

The horizontal and vertical structure of vegetation is important as it provides niches for forest dependent plant and animal species (Lindenmayer et al. 2000). The structural complication of habitats has direct effect on the availability of resources and microclimate conditions which can affect for example the abundance and diversity of species. Even though tropical forests host the most endemic and valuable biodiversity, they are threatened with increasing deforestation and forest degradation that alters the complexity of the habitat (Giam 2017). Understanding the structural configuration and diversity of tropical forest habitats will help explain the state of forest degradation and the resulting biodiversity dynamics. Thus, forest habitat heterogeneity has become one of the most commonly used indicators in forest biodiversity conservation and management studies (Simonson et al. 2014b, Tuanmu and Jetz 2015b). Ecosystem structure (encompassing the vertical structural complexity and the horizontal fragmentation status of habitats) is listed by the Group on Earth Observations Biodiversity Observation Network (GEOBON) as one of the essential biodiversity variables (EBVs) to monitor and to understand global biodiversity change (Skidmore and Pettorelli 2015); contributing towards the realization of the United Nations (UN) Convention on Biological Diversity (CBD) Aichi targets (Pereira et al. 2013). However, the accurate characterization and monitoring of forest structure is challenging. This is often due to the complex three-dimensional configuration of tropical forests (Leblanc and Fournier 2017).

Ground-based traditional measurements are among the most accurate methods for forest structure estimations and are a typical source for conservation studies (Day et al. 2014, Gao et al. 2014). However, their time consuming, spatial limitedness, and laborious nature opened up a growing exploration towards using remotely sensed datasets to overcome such limitations (Zellweger et al. 2014, Mitchell et al. 2017). In this context, Light detection and ranging (LiDAR) is a rather recent remote sensing technique that is increasingly being used in forestry. It has active sensors that transmit laser pulses to targets and uses the time-of-flight principle to measure the distance to an object. The three-dimensional position of an object can be defined using the known position of the sensor and the range measurement between the sensor and the targeted object (Kaasalainen et al. 2015). Information on the three-dimensionality of forests helps with the understanding of essential habitat parameters such as gap formation and dynamics, light penetration, and understory vegetation (Alexander et al. 2013). TLS measurements are used for rapid and detailed quantification of forest structure variables such as tree height (Van Leeuwen and Nieuwenhuis 2010, Srinivasan et al. 2015), vertical plant profiles (Calders et al. 2015c), canopy gap fraction (Hancock et al. 2014), and DBH measurements (Calders et al. 2015b, Hackenberg et al. 2015b). These measurements are made at a plot scale and can be used to characterize forest

structural complexity across different forest types (Decuyper et al. 2018). Even though TLS data provide good estimates of forest structure, the small coverage, operational costs, and complex analytical process limit its usability (Van Leeuwen and Nieuwenhuis 2010).

Concomitantly, satellite remote sensing (SRS) is being explored as an alternative resource to facilitate synoptic and scalable forest structure estimation (Pettorelli et al. 2014, Meng et al. 2016). The use of SRS for structural assessment of forest environments is based on the distinct characteristics expected from forest canopies when in contact with solar radiation and/or with signals from active satellites. Even though three-dimensional forest structure elements such as tree height, and number of layers are not yet directly extractable from the commonly used optical satellite images, the spectral signals recorded from leaf reflectance across different spectral regions could be used to assess biophysical parameters of forests (Baloloy et al. 2018). Especially, the leaf reflectance in the red-edge, near-infrared (NIR), and middle infrared regions are affected by chlorophyll content, leaf structure, and water content respectively. Therefore, short wave infrared (SWIR), NIR, red edge bands are often used to calculate vegetation indices that could represent the amount and/or condition of vegetation within a pixel (Dash et al. 2015). Several studies have demonstrated the usability and relation of spectral vegetation indices (VIs) with field measured vertical forest structure attributes such as tree species diversity (Meng et al. 2016), biomass (Baloloy et al. 2018, Matasci et al. 2018), and tree height (Hansen et al. 2016). Here, the spatial, spectral, radiometric, and temporal resolution of images affects the usability of SRS for extracting structural information of forests. Medium spatial resolution imagery such as Landsat images are the most commonly used data for studying time series dynamics of biophysical forest attributes (Freitas et al. 2005, Frazier et al. 2014, Hansen et al. 2016). The inclusion of red-edge spectrum specific bands, and the availability of higher spatial resolution images in Sentinel-2 have improved the use of SRS data to assess forest structure related parameters (Majasalmi and Rautiainen 2016, Castillo et al. 2017).

Continuous acquisition of cloud and haze free optical images, especially over the tropics is difficult. Synthetic Aperture Radar (SAR) acquires continuous imagery that is largely independent of cloud cover and solar illumination condition. SAR sensors transmit polarized microwaves (on horizontal (H) or vertical (V) plane) that interact with surface objects, and record the backscattered signal (in a either horizontal (H) or vertical (V) plane). In the case of forests, complex structural components (trunks, branches, and leaves) lead to typical volume scattering which can be identified well in the HV (horizontal transmit and vertical received) polarization (Ningthoujam et al. 2016). The wavelength, incidence angles, and polarizations of SAR signals; as well

as the canopy complexity of forests determines backscatter intensities. Long wavelengths (i.e. L- and P- band) have a greater ability to penetrate the canopy and acquire backscatter signals from stems and large branches (Rodríguez-Veiga et al. 2017). For example, with ALOS-2 PALSAR-2 L-band, high HV backscatters are expected from dense vegetation of tropical forests, which correlates with biomass (Nguyen et al. 2016). The short wavelengths (i.e. X-, C-, S-band) are mainly scattered back from the upper tree crown and less from beneath; thus mainly indicating on canopy structural variables (Rüetschi et al. 2019). In addition to structural components, other environmental factors such as topography, and moisture causes variations in backscatter signals (Lucas et al. 2007, Joshi et al. 2015c).

The ecological application of SRS is supported by the growing availability of very high spatial resolution satellite data (e.g. RapidEye, IKONOS, and PlanetScope), and with the freely available high to medium spatial resolution data from Sentinel and Landsat satellites. The unique characteristics of each SRS data type can provide valuable input in acquiring timely and continuous information on forest structure and to the understanding of its implication on habitat requirements of forest-dependent species (Mulatu et al. 2017). Coupled with powerful analytical approaches, SRS datasets could provide wall-to-wall and repeatable information on forest structure which would otherwise be very expensive to collect with field-based analysis.

The overall objective of this study was to explore, at plot level, the applicability of optical SRS (i.e. PlanetScope, Sentinel-2, Landsat-7); and SAR images (ALOS-2 PALSAR-2 and Sentinel-1), for estimating field measured (i.e. using TLS and conventional forestry measurements) forest structure parameters in the tropical cloud forests of Kafa, Ethiopia. In doing so, we aim (i) to identify the relationship between SRS derived variables and field measured forest structure parameters; and (ii) to develop models estimating field-measured forest structure parameters through the fusion of SRS derived predictors. We hypothesize that SRS derived indices and backscatters will show a significant correlation with some TLS measurements; and that SRS variable based models will be able, to some extent estimate the forest structure of montane cloud forest.

4.2 Material and methods

4.2.1 Study site

The study area is located in Kafa biosphere reserve (KBR), Ethiopia (36°3'22.51" E, 7°22'13.67" N) (Fig. 4.1). It covers a total area of 744,919 ha, of which 47% is comprised of different forest types (i.e. intact to highly degraded) and diverse habitats

(i.e. Sub-Afroalpine to wetland). The Afromontane mountain cloud forests of KBR are the origin of wild varieties of *Coffea arabica* L., and home to many endemic and threatened species (NABU 2017). However, the ongoing deforestation, forest fragmentation, and forest degradation due to anthropogenic pressure raise threats on the biological diversity of KBR (Tadesse et al. 2014a). Thus, placing it as part of the Eastern Afromontane Biodiversity Hotspot and under the national forest priority area protection schemes (NABU 2017).

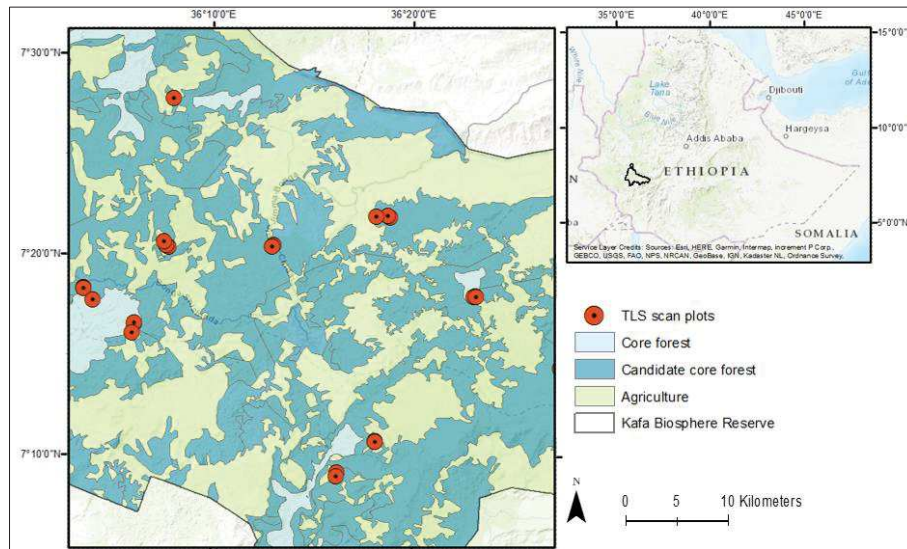


Figure 4.1: Location of the study area Kafa biosphere reserve in Ethiopia, indicating the field plots (n=25) used for this study. Note: some plots are invisible due to the spatial proximity from mapping scale used

4.2.2 Field data collection

The field data on forest structure were collected in November 2015 in Kafa biosphere reserve, Ethiopia, consisting of 25 plots across four forest management types (Intact: 7 plots, coffee forest: 8 plots, silvopasture: 7 plots, and plantation: 3 plots). The details on the collection and analysis of the TLS and conventional forest measurements can be found in Decuyper et al. (2018). In short, a stratified sampling design was made based on various GIS data layers (i.e. fragmentation map, land use/cover map, and biodiversity assessment plots) of the study area to select field plots for measurements. The chosen plot locations were representative of their surrounding forest type. TLS measurements were made with a RIEGL VZ-400 terrestrial laser scanner (RIEGL Laser Measurement Systems GmbH, Horn, Austria). From the 25 plots, 21 plots had a radius of 20 m, while 4 plots had a 10 m radius due to difficult terrain. Five scanning

positions (i.e. one in the center and four in the cardinal directions) were used per each plot to acquire three-dimensional measurements.

The point cloud data was preprocessed and co-registered using RiSCAN PRO software (RIEGL Horn, Austria). The vertical profiles of Plant Area Volume Density (PAVD) were derived based on a method developed by Calders et al. (2014), while the canopy gap and canopy height parameters, were derived by analyzing the point clouds in CompuTree point cloud analysis open source software (Hackenberg et al. 2015a). The PAVD from 0 m to 10 m were considered as understory vegetation, while PAVD from 0 m to top of canopy level were considered as cumulative PAVD (Calders et al. 2014). Additional canopy parameters (i.e. canopy heights, canopy gaps, and canopy openness) were derived from digital height models produced at a 0.5m resolution. The canopy gaps derived from TLS were defined by canopy height of <10 m and with an area of $\geq 1 \text{ m}^2$ (Decuyper et al. 2018).

Conventional forestry measurements were also taken on all 25 plots. Measurements included diameter at breast height (DBH), total basal area (BA), tree density and tree species identification. Above-ground biomass (AGB) was derived by using the wood density values for African tropical moist forests (Chave et al. 2009). The field measured structural variables (Table 4.1) showed distinct characteristics across different forest management types.

Table 4.1. Descriptive statistics of field-measured forest structural parameters from field plots (n = 25). PAVD = plant area volume density, AGB = above ground biomass, BA = basal area.

	TLS							Conventional			
	Mean gap (m ²)	Maximum gap (m ²)	Canopy Openness (%)	Number of gaps	PAVD 10m (m ² /m ³)	Cumulative PAVD (m ² /m ³)	Average Height (m)	AGB (t/ha)	Tree Density	Total BA (m ² /ha)	Number of tree Species
Mean	105.7	276.9	24.3	6.9	1.5	3.1	17.8	479.2	730.8	58.3	7.9
Min	2.85	5.5	0.6	1	0.4	1.1	6	102.4	95.5	14.9	2
Max	826.1	893.5	70.9	24	3.5	5.3	37.1	1825.8	1655.2	220.3	16

4.2.3 Satellite Remote Sensing Data

An overview of the datasets used in this study is presented in table 4.2. We acquired the least clouded scenes from PlanetScope, Sentinel-2, Landsat-7, Sentinel-1, and ALOS-2 PALSAR-2 satellites that are closest to the field campaign date (i.e. November 2015). Since the change in forest vertical structure is often a slow process, we do not assume the time-lag between field data collection and SRS data acquisition will affect the relations between field parameters and SRS derived variables. The very high spatial resolution PlanetScope images were accessed through the PlanetScope ambassadorship quota (<https://www.planet.com/markets/education-and-research/>).

The four-band analytic PlanetScope (Red, Green, Blue, and near infra-red) images were downloaded as orthorectified Top of Atmosphere (TOA) Radiance products (Level 3B). The images were converted to TOA reflectance using the PlanetScope guide (PlanetLabs). The Sentinel-2 Multispectral Imager Instrument (MSI) Level 1-C images were acquired from the Sentinel Scientific Data Hub (ESA). The products were atmospherically corrected using Sen2Cor (Mueller-Wilm et al. 2017). The geometrically and atmospherically corrected Landsat-7/ETM+ images were obtained from The United State of America's Geological Survey (USGS) Landsat surface Reflectance (SR) archive (http://landsat.usgs.gov/CDR_LSR.php). The CFmask cloud-shadow mask product (Zhu and Woodcock 2012) was used to generate cloud and cloud shadow free images.

The SAR images from Sentinel-1 and ALOS-2 PALSAR-2 were obtained for three time steps, covering the wet and dry season. The Sentinel-1 VV-polarised C-band SAR images were acquired in Interferometric Wide Swath mode (IWS, 250 km swath width) and downloaded from the Sentinel science hub (<https://scihub.copernicus.eu/>). The ALOS-2 PALSAR-2 HV-polarised L-band SAR images were acquired in Fine Beam Dual mode (FBD, 70km swath width) and obtained from the ALOS-2 data archive (<https://aui2.jaxa.jp/ips/home>). The pre-processing and speckle removal of the SAR images was conducted following the procedure by Reiche et al. (2018a). Both Sentinel-1 and ALOS-2 PALSAR-2 backscatter images were geocoded to 30 m resolution and were co-registered to Landsat images (Reiche et al. 2018a).

Table 4.2: Data sources and acquisition dates for estimating forest structure using satellite remote sensing

Data type	Acquisition Date	Parameters derived	Spatial resolution
PlanetScope images	2016-11	Vegetation indices	3m
Sentinel-2	2016-11-15	Vegetation indices	10m
Landsat-7/ETM+	2015-01-01	Vegetation indices	30m
Sentinel 1 (C-band)	2015-09-22, 2015-11-09, 2015-12-03	VV backscatter	30m
ALOS-2 PALSAR-2 (L-band)	2015-01-25, 2015-09-06, 2016-01-24	HH, HV backscatter, Forest backscatter	30m

4.2.3.1 Satellite Remote Sensing-Derived Vegetation Indices and Backscatter Intensities

The Red (R), Green (G), and Near Infrared (NIR) bands of optical SRS images, with their original spatial resolution (table 4.2), were used to calculate forest biophysical sensitive VIs (Wallner et al. 2015, Meng et al. 2016, Baloloy et al. 2018, LaRue et al. 2018, Navarro et al. 2019) for each field plot and their surrounding forests in the KBR (Table 4.3). The indices produced were Green Normalized Difference Vegetation

Index (GNDVI), Enhanced Vegetation Index (EVI), and Green chlorophyll index (CI green). In addition, the shortwave infrared (SWIR) bands of Sentinel-2 and Landsat-7 were used to produce the Normalized difference moisture index (NDMI), while the Sentinel-2 specific red-edge bands were used to produce Inverted Red-Edge Chlorophyll Index (IRECI).

Table 4.3: Equations used for the calculation of vegetation indices from satellite remote sensing dataset

Vegetation index	Description	Satellite	Source
GNDVI	$(nir - green)/(nir + green)$	PlanetScope, Sentinel-2, Landsat-7	(Gitelson et al. 1996)
EVI	$G*((nir-red)/(nir+CI*red-C2*blue+Levi))$	PlanetScope, Sentinel-2, Landsat-7	(Heute et al. 1997)
CI green	$(NIR/green) - 1$	PlanetScope, Sentinel-2, Landsat-7	(Gitelson et al. 2003)
NDMI	$(NIR - SWIR) / (NIR + SWIR)$	Sentinel-2, Landsat-7	(Gao 1996)
IRECI	$(NIR-Red)/(RE2/RE1)$	Sentinel-2	(Frampton et al. 2013)
HV backscatter	<i>HV backscatter of ALOS-2 PALSAR-2 sensor presented in sigma-nought values</i>	ALOS-2 PALSAR-2	(Joshi et al. 2015c, Viet Nguyen et al. 2016)
Forest Backscatter index	$\sigma^{\circ}HV + \sigma^{\circ}HH * \frac{\sigma^{\circ}HH}{\sigma^{\circ}HV}$	ALOS-2 PALSAR-2	(Lucas et al. 2007)
VV polarization	<i>VV backscatter of sentinel1 sensor presented in sigma-nought values</i>	Sentinel-1	(Reiche et al. 2018b)

The C-band VV-polarization from Sentinel-1, as well as the L-band HH and HV polarizations from ALOS-2 PALSAR-2, were used to acquire backscatter intensities (Joshi et al. 2015c, Viet Nguyen et al. 2016) and to calculate forest-specific backscatter (FB) values (Viet Nguyen et al. 2016). Vegetation indices were calculated for a 3m*3m raster of pixels of PlanetScope, for 10m*10m raster pixels of Sentinel-2 10m bands, as well as for 20m*20m raster pixels of Sentinel-2 red-edge bands. Similarly, 30m*30m raster pixels were used to calculate vegetation indices for Landsat-7 images, and for calculating backscatter values of Sentinel-1 and ALOS PALSAR-2 images. For the high spatial resolution derived SRS variables the area-weighted mean values of the variables were calculated by overlaying the circular ground plots of 20 m radius (area = 0.1ha). Whereas for the medium spatial resolution images, we extracted the area-weighted mean values with an overlay of 50 m radius plots. We chose to use the 50 m radius of plots for the medium resolution images as our field plots are representative of the surrounding forest area, and especially for the SAR images, looking into multiple pixels will help eliminate errors and noises while using small raster pixels (Saatchi et al. 2011, Joshi et al. 2015c). In addition, to account for the limited sensitivity of SAR backscatters to forest structure during wet seasons due to vegetation and soil moisture (Nguyen et al. 2016, Urbazaev et al. 2016), we

calculated the temporal standard deviation (TSD) of backscattered values between the three SAR images (Table 4.2).

4.2.4 Statistical methods

The study initially assessed the relationship between field-measured forest structure parameters and SRS derived variables based on the Pearson correlation coefficient using ‘Hmisc’ package (Harrell 2006) with the *R Studio* software (Team 2013). We used $p < 0.05$ as the threshold to identify significant correlations. Then, the field measured forest parameters were modelled as a function of their correlated SRS variables (Figure 4.2). Multiple linear regression models with both forward and backward stepwise selection procedure were developed to combine and assess the contribution of SRS variables in predicting field measured structural parameters. The SRS variables used in the multiple linear regression models were derived using the original pixel size of the high to medium spatial resolution images (Table 4.2), so as to capture the possible detailed information on the corresponding field measured structural variables from the high-resolution SRS images. Multicollinearity between predictors was checked to avoid overfitting. Predictors with correlations of >0.6 were excluded and a variance inflation factor of < 2 was set as a threshold. The multiple linear regression model is described as:

$$\text{FMP} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + \varepsilon \quad (1)$$

where FMP is the response field measured parameter, x_1, x_2, \dots, x_p , are SRS variables, β represent model coefficients, and ε is the additive normal distributed error term with zero mean.

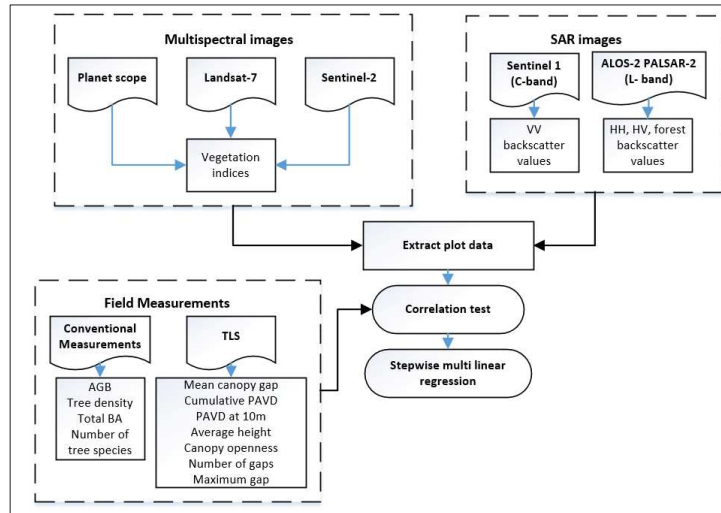


Figure 4.2: Data and methodological steps followed in estimating field measured forest structure parameters using satellite remote sensing data. PAVD= Plant area volume density, AGB= Above ground biomass, BA= Basal Area

The stepwise model selection procedure identified the best-fitted model based on Akaike's Information Criterion (AIC). The accuracy of the fitted models was evaluated by exploring the coefficient of determination (R^2), and the root mean square error (RMSE) between observed and predicted forest structural parameters. Relative root mean square error (RRMSE) is used to make the RMSE's of the estimation models comparable. We tested the distribution of our dataset and used a logarithmic transformation on field-measured parameters that did not have a normal distribution (i.e. mean gap, PAVD at 10 m, maximum gap, AGB, and total basal area). The predicted results were then back-transformed and compared with the observed structural parameters.

4.3 Results

4.3.1 Correlation analysis

The relationship between field-measured structural parameters and satellite remote sensing derived variables based on the visualization of scatter plots showed most relationships are linear, especially with the optical VIs. Figure 4.3 represents a scatter plot of the relationship between the field measured structural parameters and the most correlated SRS variables from optical and SAR domain. The Pearson correlation coefficient showed the strength and significance of these relationships. We found statistically significant correlations between the field measured structural parameters and the SRS derived variables (Table 4.4).

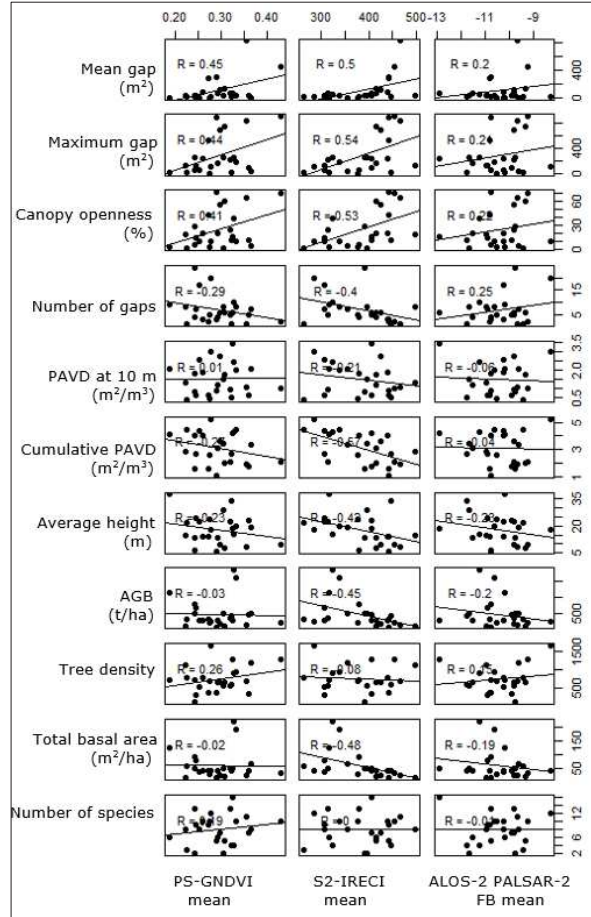


Figure 4.3: Correlation between field-measured forest structure parameters and most correlated satellite remote sensing variables from optical and Synthetic Aperture Radar domain. PAVD= Plant area volume density, AGB= Above ground biomass, PS-GNDVI= PlanetScope derived Green Normalized Difference Vegetation Index, S2-IRECI= Sentinel-2 derived Inverted Red-Edge Chlorophyll Index, FB= Forest backscatter

In summary, the gap related parameters (i.e. mean gap, maximum gap, and canopy openness) especially showed highly significant correlations ($|r| = 0.4 - 0.48$, $p < 0.01$) with PlanetScope derived GNDVI, and CIGreen, as well as with Sentinel 2 derived EVI and IRECI VIs ($|r| = 0.5-0.75$, $p < 0.05$), as well as with Sentinel-1 VV TSD ($|r| = 0.4-0.43$, $p < 0.01$). The PAVD parameters, on the other hand, showed significant correlations ($|r| = -0.57-0.49$, $p < 0.01$) with the Sentinel-2 (IRECI), Landsat-7 (CIGreen, NDMI), as well as with Sentinel-1, and ALOS-2 PALSAR-2 (HV TSD) SAR backscatter variables. In addition, the conventionally measured structural parameters (except number of tree species) were found highly correlated ($|r| = -0.45-$

0.43, $p < 0.01$) with Sentinel-2 derived NDMI and IRECI indices as well as with Landsat-7 derived GNDVI and CIGreen indices ($|r| = 0.41\text{--}0.44$, $p < 0.01$). No significant correlations were found between the number of species and SRS variables.

Table 4.4: Summary of the Pearson linear correlation r values between satellite remote sensing variables and field-measured structural parameters. . ** = $p < 0.01$, * = $p < 0.05$, grey = $p > 0.05$.

RS group	SRS variables	Mean gap	Max gap	Canopy openness	Nr of gaps	PAVD 10m	PAVD	Average height	AGB	Tree density	Total BA
PlanetScope	GNDVI Mean	0.45*	0.44*	0.41*							
	EVI Mean	0.56**	0.53*								
	CIGreen Mean	0.4*	0.45*	0.48*							
Sentinel-2	GNDVI Mean	0.7**	0.55*	0.5*				-0.4*			
	EVI Mean	0.75**	0.67*	0.63**	-0.49*			-0.48*			
	CIGreen Mean										
	NDMI Mean								0.42*		0.43*
	IRECI Mean	0.5*	0.54*	0.53**	-0.4*		-0.57**	-0.42*	-0.45*		-0.48*
Landsat-7	GNDVI Mean									0.44*	
	EVI Mean									0.4*	
	CIGreen Mean						0.44*		0.41*		0.42*
	NDMI Mean						0.46*				
Sentinel-1	VV Mean				0.44*	0.49*					
	VV TSD		0.4*	0.43*							
	HV Mean										
ALOS-2 PALSAR-2	HV TSD					0.49*	0.41*				
	HH Mean									0.49*	
	HH TSD										
	FB Mean										
	FB TSD										

4.3.2 Prediction of Field-Measured Forest Structure Parameters

Stepwise multi-linear regression was used for identifying best-fitted models to predict field-observed forest structure parameters. The model with the lowest AIC was chosen as the best one and was used to make predictions. All field-measured structural parameters were estimated by the fusion of several SRS-derived variables, showing the complementarity of SRS products (Table 4.5). Field-measured variables that were log-transformed (i.e., mean gap, PAVD at 10 m, maximum gap, AGB, and total basal area) were able to be estimated using SAR data. Sentinel-2-based variables were dominant in most of the predictive models. IRECI was the common predictor for most field-measured variables, and especially in estimating mean gap, AGB, and cumulative PAVD. Backscatter values from ALOS-2 PALSAR-2 and Sentinel-1 were

also valid predictors in most models, especially for predicting PAVD at 10 m and the number of gaps. Indices from PlanetScope and Landsat-7 were found to be the least relevant on the predictive models. The combination of red-edge band-derived IRECI of Sentinel-2, and ALOS-2 PALSAR-2 backscatters were found very important for AGB, total BA, and canopy openness estimation.

Table 4.5: Stepwise multilinear regression with Akaike information criterion (AIC) for estimating field-measured forest structure parameters using satellite remote sensing variables. Significance code: 0.0001***, 0.001 **, 0.01*, 0.05#.

	Field Measured	Model Variables	R ²	RMSE /RRMSE	Predicted vs. Observed Correlation
TLS	Mean Gap	S2_IRECI_Mean**, PS_GNDVI_Mean#, S1_VV_TSD	0.52	148.6 (1.4)	0.77
	Maximum gap	S2_EVI_Mean*, S1_VV_Mean, S2_IRECI_Mean#	0.51	181.74 (0.66)	0.81
	Canopy openness	S2_EVI_Mean*, S2_IRECI_Mean*, S1_VV_TSD*, ALOS_FB_Mean#	0.66	13.23 (0.54)	0.81
	Number of gaps	S1_VV_Mean***, S1_VV_TSD**, S2_EVI_Mean**	0.68	3.96 (0.58)	0.72
	PAVD at 10 m	S1_VV_Mean**, ALOS_HV_TSD**	0.47	0.62 (0.41)	0.71
	Cumulative PAVD	S2_IRECI_Mean**, ALOS_HV_TSD*, LS_NDMI_Mean#	0.58	0.73 (0.23)	0.76
	Average Height	S2_IRECI_Mean, S2_EVI_Mean, ALOS_FB_Mean#	0.37	6.28 (0.35)	0.61
Conventional	AGB	S2_IRECI_Mean***, S2_NDMI_Mean*, ALOS_FB_TSD*, S1_VV_Mean	0.62	292.4 (0.61)	0.78
	Tree density	LS_GNDVI_Mean*, ALOS_HV_TSD	0.28	296.95 (0.41)	0.53
	Total basal area	S2_IRECI_Mean***, S2_NDMI_Mean*, ALOS_FB_Mean#	0.61	32.12 (0.55)	0.81
	Number of species	S2_EVI_Mean, S1_VV_TSD#	0.21	3.14 (0.39)	0.46

S1: Sentinel-1, S2: Sentinel-2, PS: PlanetScope, LS: Landsat-7, ALOS: ALOS-2 PALSAR-2, FB: Forest backscatter, TSD: Temporal standard deviation.

All regression models (except for average height) were statistically significant ($p < 0.01$), with cumulative PAVD having the highest R^2 (0.58) and lowest RRMSE value (0.23) (Table 4.5). For TLS-measured structural parameters, number of gaps and mean gap were well predicted ($R^2 = 0.68$, RRMSE = 0.58, and $R^2 = 0.66$, RRMSE = 0.54, respectively), while PAVD at 10 m and average height had poor predictions ($R^2 =$

0.47, RRMSE = 0.41, and $R^2 = 0.37$, RRMSE = 0.35, respectively). As for the conventional measurements, S2-IRECI and S2-NDMI explained much of the variation in AGB and total basal area ($R^2 = 0.62$, RRMSE = 0.61, and $R^2 = 0.61$, RRMSE = 0.55, respectively), while tree density and number of species had the lowest R^2 values ($R^2 = 0.28$, RRMSE = 0.41, and $R^2 = 0.21$, RRMSE = 0.39, respectively). The relationship between field-measured (observed) (e.g., cumulative PAVD, canopy openness, mean gap, and AGB) and satellite remote sensing-predicted forest structure variables are visualized in Figure 4.4.

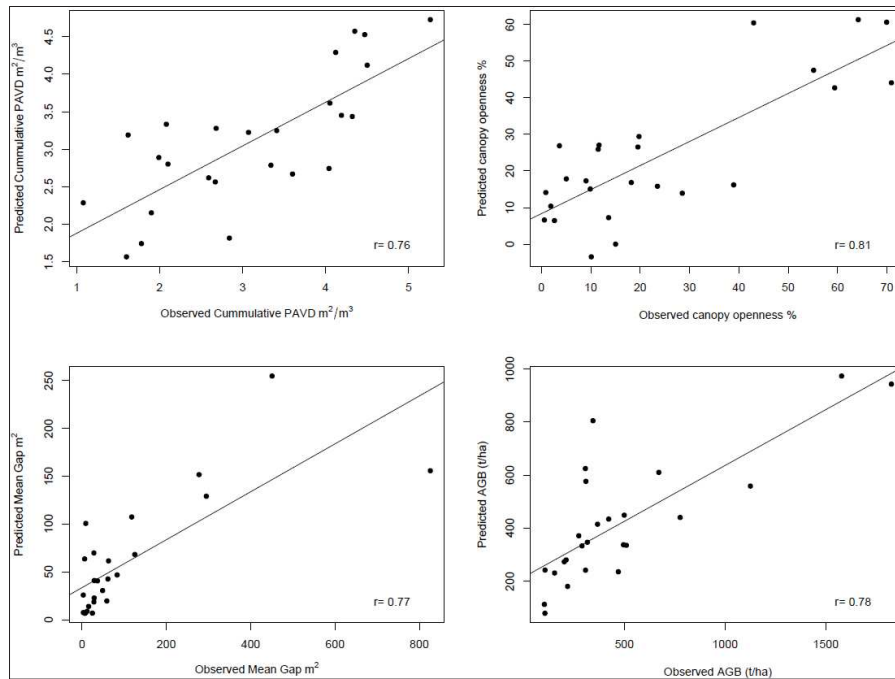


Figure 4.4: Relationship between field-measured (observed) and satellite remote sensing-predicted forest structure variables.

4.4 Discussion

The study shows that optical SRS-derived VIs, despite being underestimated for saturating in forest environments, can inform on forest structural differences. Indices calculated with higher weighing coefficients of the SWIR, NIR, and red-edge bands were sensitive to most field-measured forest structure parameters (Table 4.4). The sensitivity of SWIR to plant leaf water content, which is correlated with canopy biomass, enabled NDMI to respond to vegetation volume-related parameters, thus supporting the estimation of the TLS-measured cumulative PAVD, and the

conventionally measured AGB and basal area (Table 4.5), as did the sensitivity of NIR to multiple scattering of canopy leaves, canopy gaps, and shadowing; thus, sensitivity to forest canopy structure was associated with EVI's response towards the estimation of TLS-measured, canopy gap-related parameters (Table 4.5). Similarly, the sensitivity of NIR to multiple scattering of canopy leaves, and canopy gaps and shadowing, thus sensitivity to forest canopy structure associates with EVI's response towards the estimation of TLS measured canopy gap related parameters (Table 4.5). The canopy chlorophyll content and leaf area index (LAI) sensitive red-edge bands of Sentinel-2 (Frampton et al. 2013), were associated with both vegetation volume (Dube et al. 2018) and canopy gaps (Malahlela et al. 2014), which made S2-IRECI the most important index in estimating both TLS and conventionally measured structural parameters (Table 4.6). Our findings are in line with, the study of Huete et al. (1997), Healey et al. (2006), Brede et al. (2015), and Martin et al. (2008) that also found the SWIR, NIR, and red-edge bands important in exploring forests biophysical parameters. The PlanetScope derived vegetation indices, despite being correlated with many canopy gap related parameters, did not have a significant contribution to the prediction of field measured structural estimates. This stands in contrast to other studies that found highly significant relationships between vegetation indices derived from very high-resolution images and forest structure parameters. Meng et al. (2016) and Wallner et al. (2015) for example successfully estimated basal area, DBH and other diversity indices using spectral and textural information from SPOT-5 and RapidEye images, respectively. Similar to the findings of this study, Baloloy et al. (2018) found Sentinel-2 and RapidEye based predictors to perform better towards estimating AGB compared to PlanetScope derived predictors. A study by Houborg et al. (2018) suggests that the potential applicability of PlanetScope derived variables for monitoring might be limited due to its low radiometric quality and cross-sensor inconsistencies. The topographical and structural complexity of tropical forests can also affect estimation qualities. Castillo-Santiago et al. (2010) stated that the nature of tropical forests and the quantity of shadows present on satellite images affects the prediction of forest structure variables using vegetation indices. Such topographic factors could also affect our study plots as they are located in cloud forest characterized by rough terrain and a mixture of different forest types (i.e. intact forest to silvopasture). Due to the terrain conditions, our plot sizes are small, which could complicate the exact link between SRS and field measured parameters. In addition, the conservative threshold we used to identify canopy gaps (canopy height of <10m and with an area of $\geq 1\text{m}^2$) from the TLS measurements, and the reflectance of the dense understory in such forests despite having gaps, could have also affected the sensitivity of vegetation indices to the mean and maximum canopy gap parameters.

As for the SAR data, the standard deviation of multi-temporal ALOS-2 PALSAR-2 backscatters (HV-TSD), and forest backscatter (FB-TSD) were significant predictors of field measured structural parameters, rather than single-date observations. Since SAR backscatters, obtained in wet season are highly sensitive to the canopy moisture, using observations from dry seasons or multi-temporal observations is advised (Nguyen et al. 2016). Similar to our findings, Nguyen et al. (2016) also found ALOS-FB to be a significant predictor for AGB compared to HV polarization and other indices. Castillo et al. (2017) identified the sensitivity of Sentinel-1 C-band VV and VH polarization to AGB, but the sensitivity of the later was higher in comparison. However, due to the unavailability of the Sentinel-1 VH polarization in 2015, we could not use it in our study. However, we could still learn from our results that an analysis of multi-seasonal, dense time series and multiple polarization of SAR data could provide improved estimations. In addition, as elaborated by a study of Joshi et al. (2015c), the accuracy of AGB estimation improved when the pixel sizes were increased from 50 m to 250 m. This is also the reason we chose 50 m radius plots for the SAR backscatters rather than the 20m plots we used for optical images. In doing so, errors originating from speckle, thermal noise, geolocation, canopy layover and variations due to moisture or topography while using small SAR pixels could be addressed (Saatchi et al. 2011). Even though SAR backscatters are heavily used in AGB estimations, our results also show they can contribute largely towards estimation of understory vegetation estimation (i.e. PAVD at 10 m). The strong penetration of SAR pulses even in densely vegetated tropical forest environments makes them uniquely valuable in estimating the lower canopy vegetation density, which otherwise had not been picked up by indices derived from the optical sensors (Table 4.5).

Overall, the canopy gap related forest structure parameters (e.g., mean gap, maximum gap, canopy openness) were better correlated to SRS variables than the vegetation volume-related parameters (e.g., AGB, PAVD at 10m). Other studies support this finding (Woodhouse 2005, Gibbs et al. 2007, Rodríguez-Veiga et al. 2017) as SRS signals are weakened by canopy closure in tropical forests, thus providing limited information on volume-related parameters such as AGB and PAVD. In addition, studies have also shown that the relationship between forest structure and SRS derivatives might not always be linear (Næsset et al. 2011, Chen et al. 2012, Rodríguez-Veiga et al. 2017). These algorithms have different assumptions on the distribution of the data, which have an effect on the models chosen for modelling the relationships, thus an implication on the upscaling or extrapolation of structural estimations (Lu et al. 2016, Rodríguez-Veiga et al. 2017). The use of parametric methods, such as the linear regression model used in this study, are arguably suitable for a small dataset, whereas non-parametric methods, such as random forest, would

be an appropriate choice for larger datasets where non-linear relationships could be reliably picked up (Lu et al. 2016).

Several studies have investigated the estimation of forest structure using SRS data in other forest ecosystems, with different analytical and statistical approaches. Studies in temperate (Joshi et al. 2015c, Wallner et al. 2015, Noorian et al. 2016) and boreal forests (Suzuki et al. 2013, Matasci et al. 2018), compared to tropical forests (Goh et al. 2014, Viet Nguyen et al. 2016) shows higher correlations and model estimation power. This can arguably be due to the relatively higher saturation of SRS derivable (i.e. vegetation indices and SAR backscatters) in forests with high vegetation density and complex structure, such as in case of tropical forests, compared to, for instance, temperate and boreal forests. The use of texture measures (Barbier et al. 2012), object-based image analysis (Silveira et al. 2019), and radiative transfer models (Ligot et al. 2014) showed improved estimations and provide detailed insight into the structural assessment of tropical forests. A common recommendation from most studies is that SRS based forest structure assessments will benefit from data acquired in dry seasons. As for optical data, cloud cover, especially in tropical forests, are an important concerns. As for SAR data, humid and wet canopies reduces the signals sensitivity to biomass and structure of forests. A comparative study by Nguyen et al. (2016) showed increased sensitivity of backscattering during the dry season ($R^2 = 0.05-0.47$) compared to the wet season ($R^2 = 0.02-0.27$). The most common limitation that our study shares with other similar studies that applies SRS for forest structure estimation is, the issue with an insufficient number of field observations, which is due to the large effort required to acquire field data on structural parameters. The low number of field data in turn limits the identification of subtle relationships, validation of models, and upscaling of point estimations to landscape level.

The availability of different SRS datasets creates an opportunity to assess the possibilities of data fusion to achieve an improved estimation of field-measured forest structure parameters. Our findings point out that a combination of different SRS predictors provided better estimates than using single predictors in our study area (Table 4.6). Instead of taking the single best correlated SRS variable to estimate field observations, we tested all combinations using stepwise multilinear regression with AIC as an evaluation parameter. As a result, we learned that except the cases where we had insignificant models and/or predictors (i.e. average height, tree density, and number of species) the combination between Sentinel-2 and SAR variables provided significant estimates of field measurements. Sentinel-2 and Sentinel-1 derived predictors mainly estimated canopy gap related parameters; the fusion of Sentinel-2, ALOS-2 PALSAR-2, and Sentinel-1 variables best estimated cumulative PAVD; while the combination of Sentinel-1 and ALOS-2 PALSAR-2 backscatters best

predicted PAVD at 10 m. Similarly, the fusion of Sentinel-2 and ALOS-2 PALSAR-2 provided the best estimation for AGB. Goh et al. (2014) also found the integration of NIR band from Spot-5 and the HV backscatter from ALOS-2 PALSAR-2 to be the best predictive model of AGB in humid tropical forests. Nguyen et al. (2016) also performed a similar study in dense tropical forest, where the best predictive models of AGB were attained through fusing maximum NDVI from Landsat-8, SAR textures from HV polarization and FB from ALOS-2. The complementary nature of optical and SAR data in terms of data availability, sensitivity to vegetation features, and the difference in saturation levels would make the use of multimodal data for forest structure estimation appealing. However, Mura et al. (2015) advise that fusion of SRS dataset should be efficient and reliable as unique technical and methodological challenges could be introduced with each modality.

Table 4: Field-measured forest structure parameters estimation through single and fusion of satellite remote sensing for this study. Synthesized based on the correlation results of Table 4 and modeling results of Table 5. Green = best estimators, orange = good estimator

Field Measurements	Structural Parameters	Univariate Predictors	Multivariate Predictors
TLS	Canopy gap parameters	PlanetScope	Sentinel-2 + Sentinel-1
	PAVD	ALOS-2 PALSAR-2, Sentinel-1	Sentinel-2 + ALOS-2 PALSAR-2 + Sentinel-1
	Average height	Sentinel-2	-
Conventional	AGB/basal area	Sentinel-2	Sentinel-2 + ALOS-2 PALSAR-2
	Tree density	Landsat-7, ALOS-2 PALSAR-2	-
	Number of tree species	-	-

Estimation of field-measured structural parameters through the fusion of SRS data precedes the upscaling of plot measurements to the landscape. As for our study, the upscaling of field measurements to landscape observations using the link between field-measured and SRS was challenging, because of the small number of field observations we had on forest structure parameters, and the small plot size used. The small number of samples would make the modeling and prediction accuracy unreliable. Such spatial upscaling demands large number of field observations and suitable modelling approaches to effectively train, validate, and map structural parameters.

4.5 Conclusions

This study identified the relationship between satellite remote sensing derived variables and field measured forest structure parameters. TLS derived three-dimensional structural parameters showed significant correlation with satellite remote

sensing (SRS) derived vegetation indices and backscatter intensities. Another important contribution of this study is the identification of useful combinations of optical and SAR remote sensing variables for structure parameter estimation via data fusion. In summary, we found the strongest relationship between TLS measured canopy gap related parameters and optical data-based vegetation indices, while some significant correlations were also observed between vegetation volume related field measured variables and SAR backscatter.

As can be concluded from our study, the growing availability and potential integration of SRS datasets could bring new opportunities to derive biodiversity relevant forest structure estimates. In our case, we were able to derive suitable estimates of forest vertical structure (i.e. canopy gap and canopy volume-related parameters) which are also identified by the GEOBON as SRS-Essential Biodiversity Variables (EBVs) which can support monitoring of biodiversity change (Pettorelli et al. 2016b). In doing so, the information gathered from multi-modal satellite data and the modeling approach used to combine them shows the possibilities of upscaling field measured structural data to landscape level. However, further assessment of the use and efficient combination of SRS dataset through employing physical studies (e.g. through radiative transfer models), and in different forest ecosystems might provide more insight into the relationship between forest structure and SRS.

The need to go from expensive, but highly accurate plot measurements, to reliable landscape level estimations that can be used to inform conservation and management efforts, drive the use of multi-sensor and multi-scale approaches. With the need for continuous, repetitive and affordable data on forest structure, great expectations are laid on National Aeronautics and Space Administration's Global Ecosystem Dynamics Investigation (GEDI) mission which provides the first high resolution LiDAR observation of the 3D structure of the Earth making precise measurements of forest canopy height, canopy vertical structure, and surface elevation (Stysley et al. 2015); and European Space Agency's BIOMASS mission which is a SAR based system that aims to take measurements of forest biomass to assess terrestrial carbon stocks and fluxes for a better understanding of the carbon cycle (Le Toan et al. 2011). The data from such missions are expected to address the data gap on tropical forests and support climate change mitigation programs such as the monitoring reporting and verification (MRV) for Reducing Emissions from Deforestation and forest Degradation (REDD+), as well as for the development and use of EBVs.

Even though sensible explanations could be given using the implication of forest structure parameters on biodiversity, a next step should be linking the structural estimates with actual biodiversity dataset from the field to determine the effect of the vertical structure of forests on biological diversity.

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Chapter 5

Integrating novel sensing and DNA metabarcoding data to link forest structure and diversity across a degrading Ethiopian forest

This chapter is based on:

K. A. Mulatu, X. Wang, D.W. Yu, L. Kooistra, M. Decuyper, B. Mora and M. Herold and M. Herold (in preparation). " Integrating novel sensing and DNA metabarcoding data to link forest structure and diversity across a degrading Ethiopian forest"

Abstract

The growing evidence on global biodiversity decline has called for the establishment of rapid and reliable biodiversity monitoring approaches that can assist conservation efforts. The assessment of biodiversity dynamics in tropical forests, a hotspot of biodiversity loss, requires advanced monitoring techniques considering the complexity of tropical forest habitats and their biodiversity. We performed an exploratory study to establish the hypothesis that the integration of leaf-litter-arthropod DNA metabarcoding and remote sensing derived information on forest structure can provide an elaborated insight to the biodiversity dynamics in the changing montane tropical forest of Kafa, Ethiopia. The leaf-litter-arthropod data was collected across forest types with different disturbance levels. We used DNA metabarcoding analysis and bioinformatics techniques to identify operational taxonomic units that were later used to develop diversity measures. Comparing the alpha and beta diversity across forest types, high species richness estimates were found in the disturbed forests, while the intact forests were found to host a different community composition to the degraded forest types. We then assessed the influence of habitat conditions on leaf-litter-arthropod community composition using multivariate models of remote sensing and conventional forest measurement derived vertical forest structure parameters. The model with the combination of information on vegetation density, canopy gaps, total basal area, tree diversity and level of disturbance could explain about 43% of the variation in leaf-litter-arthropod composition. We also identified that the increasing number of gaps, high basal area, and the abundance of understory vegetation showed a significant relationship with the composition of leaf-litter-arthropods in intact forest, while canopy openness and tree species diversity were related to the community composition of disturbed forests. Even though our study had limited number of plots due to logistic reasons, we found promising results which indicate that both forest structure and biodiversity dataset acquired using evolving technologies in ecology could provide novel insights to habitat-biodiversity relationships, and with possible implications on resulting ecosystem functions and services. Such integration of technologies that could lead to an understanding of complex forest ecosystem processes is key for tracking progress towards global biodiversity goals and for operationalization of the essential biodiversity variables.

Keywords

Biodiversity, Tropical forests, Remote sensing, DNA Metabarcoding, Leaf-litter-arthropods.

5.1 Introduction

Global biodiversity loss is increasingly being reported in the Anthropocene (Butchart et al. 2010, Maxwell et al. 2016, Ceballos et al. 2017, Sánchez-Bayo and Wyckhuys 2019). The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) report confirmed the acceleration in species loss and presented a concerning figure: an estimated 1 Million species at risk of extinction (Díaz et al. 2019). Such losses mainly originate from land-cover changes, pollution, climate change, over-harvesting, as well as through the introduction of invasive species (McGill et al. 2015, Díaz et al. 2019). Tropical forest ecosystems are one of the most affected of these alarming global biodiversity losses. Habitat loss due to anthropogenic pressure is one of the major drivers of biodiversity decline in tropical forests where forest habitats are either modified by complete removal of vegetation (i.e. referred to as deforestation) or through selective removal of vegetation parts and understories (i.e. referred to as forest degradation). A recent review (Mulatu et al. 2017) showed that anthropogenic pressure accounted for 82% of forest disturbance related to biodiversity dynamics in changing tropical forests. As the niche theory states (Chase and Leibold 2003), each species requires specific environmental conditions to survive, but with the modification of habitats such niches are altered which lead to species migration, over-exploitation (Wright 2005) and the introduction and dominance of invasive species (Didham et al. 2005) which could lead to an overall homogeneous species composition and low recovery rate of indigenous species communities (McKinney and Lockwood 1999).

Tropical forests are known to be more structurally complex compared to any other forest types, and thus it is assumed that high habitat complexity also exists in such forests. The vertical arrangement of vegetation in a tropical forest can affect the understory and forest floor species diversity through their influence on the availability of resources such as light, nutrients, and water (Ningthoujam et al. 2016). Vertical stratification allows different species to use the forest floor, the understory, and canopies as their habitat (Grelle 2003). On the contrary, the simplification of vertical forest structure reduces the deliverance of ecosystem services and forest biodiversity (Ishii et al. 2004). The modification of forest structure (both on the vertical and horizontal dimension) has an effect on the abundance of resources for feed, shelter, movement, as well as pollination and nesting grounds. Studies have shown that the same species richness and composition of primary forests may not be reached with the recovery of forests after disturbances (Acevedo-Charry and Aide, Chazdon 2008, Rozendaal et al. 2019). Protecting biodiversity from habitat loss would then require to understand how biodiversity is distributed and identify which habitat conditions affect species richness and composition (Gavish et al. 2019).

Understanding the distribution and status of forest biodiversity require measurements that are comprehensive, repeatable, and scalable (Walpole et al. 2009, Pereira et al. 2013). These

requirements are however difficult to achieve with the use of traditional biodiversity measurement techniques which are known to be time-consuming and expensive; especially in ecosystems like tropical forests where high biodiversity is present. Therefore, proxies, the use of a subset of taxa as indicators, and advancement in the biodiversity data collection, analysis and identification are required (Yu et al. 2012). Among the vast arrays of biodiversity, arthropods are considered as the sentinels of the ecosystem's well-being as they appear to respond quickly to microclimate modifications induced by for example forest structure changes (Nakamura et al. 2007, Maleque et al. 2009, Uehara-Prado et al. 2009). Their roles as pollinators, predators, decomposers, and their essential contribution in the detrital food web make them critical ecological bio-indicators; thus potentially reflecting on the overall forest biodiversity dynamics (Yang et al. 2014). Effective measurement and monitoring of Arthropods is said to be feasible through techniques like DNA barcoding which uses short gene sequences to identify species (Ji et al. 2013, Yang et al. 2014, Morinière et al. 2016, Barsoum et al. 2019). DNA barcoding provides a reliable alternative to assess biodiversity in space and time through its quick and cheap sequencing approaches. Metabarcoding (MBC), a high-throughput DNA barcoding approach is most suitable to identify species with the sequencing of mass-samples (Cristescu 2014, Yang et al. 2014). It follows a procedure of extraction of DNA, mass-PCR-amplification of the interest taxonomic group, and sequencing to identify individual DNA molecules, which is followed by bioinformatic analysis that produce high-quality reads that could be further used for ecological analysis (Yu et al. 2012). In comparison to conventional approaches, MBC allows a rather complete discovery of taxonomic diversity, as well as reliable quantification of patterns and assemblage composition along habitat gradients (Beng et al. 2016). Recent studies have shown that accurate and reliable alpha and beta diversity information of arthropods can be derived from DNA metabarcoding analysis (Ji et al. 2013, Morinière et al. 2016, Barsoum et al. 2019).

Forest structure parameters are also used to represent the habitat complexity of tropical forests that has an impact on biodiversity abundance and distribution (Gardner et al. 1995, Grelle 2003, Müller et al. 2018, Carrasco et al. 2019). Conventional forest measurement techniques are often used to collect data on structural parameters such as tree-size, tree height, basal area, and canopy gap distribution, which only captures a brief dimension of the complex three-dimensional structure of tropical forest ecosystems (Ishii et al. 2004). With the evolvement of remote sensing, several tools and techniques that enable a rapid, continuous and scalable assessment of forest ecosystems are being introduced. Several studies have investigated the use of satellite remote sensing (SRS) data with a range of spatial, spectral, and temporal resolutions to acquire information on the structural complexity of forest habitats. Vegetation indices and texture measures that are derived from short wave infrared (SWIR), near-infrared (NIR), and red-edge bands, which are sensitive to canopy chlorophyll content, leaf structure, and water content, have been found to relate to field-measured vertical forest

structure attributes such as tree species diversity (Meng et al. 2016), biomass (Baloloy et al. 2018, Matasci et al. 2018), tree height (Hansen et al. 2016), and habitat heterogeneity (Tuanmu and Jetz 2015a). The long wave bands (i.e., L- and P-band) of Synthetic aperture radar (SAR), an active SRS field, are also useful as they can penetrate the forest canopy and acquire the backscatter from forest structural elements (trunks, branches, and leaves), providing information on vegetation volume and density (Ningthoujam et al. 2016). Terrestrial Light Detection and Ranging (LiDAR), also known as Terrestrial Laser Scanning (TLS), is a ground-based active remote sensing technique, which uses laser beam pulses to calculate the distance and position of the objects in a three-dimensional space based on the reception of returned signals to the instrument, is by far the most favourable approach to acquire detailed and high-accuracy data on the three-dimensional representation of forest structure. A number of structural parameters such as plant area volume density PAVD, canopy gaps, canopy height, number of layers, and basal area can be derived from TLS observations by applying allometric equations and algorithms (Calders et al. 2014, Decuyper et al. 2018).

Considering the impact of habitat disturbance in forest biodiversity, and the subtlety of both processes, integrating technological advancements on both fields would provide new insights into biodiversity dynamics. Linking biodiversity and forest structure measures from novel data sources of DNA metabarcoding and remote sensing would enable a rapid assessment on biodiversity dynamics that could inform timely conservation measures.

Here, we perform an exploratory study with the aim of forming a hypothesis that the integration of leaf-litter-arthropod DNA metabarcoding and remote sensing derived information on forest structure can provide an elaborated insight to biodiversity dynamics in changing montane tropical forest of Kafa, Ethiopia. In doing so we aim to answer the following research questions: i) how does leaf-litter-arthropod diversity vary across plots of different forest types? and ii) which forest structure parameters are important to explain leaf litter insect community composition? To our knowledge, this is the first study that combined two of the most recent and technologically advanced monitoring techniques, terrestrial laser scanning (TLS) and DNA metabarcoding, to assess the relationship between forest structure and biodiversity.

5.2 Materials and methods

5.2.1 Study site

The research was conducted in the Kafa Biosphere Reserve (KBR), located in the southwestern highlands of Ethiopia (Figure 5.1). The KBR is characterized by Afromontane cloud forests with an altitudinal range from 500 to 3500 m asl. It has high conservation values as it

is home to the East Afromontane biodiversity hotspot, hosting half of the remaining montane forests in Ethiopia, and is a centre of origin and genetic diversity for wild *Coffea arabica*. Covering an area of 744,919 ha, of which 47% is covered with forests, the KBR hosts approximately 300 species of mammals including 14 carnivores and 8 primates, 300 bird species, 244 plant species and more than 110 tree species (NABU 2014) .

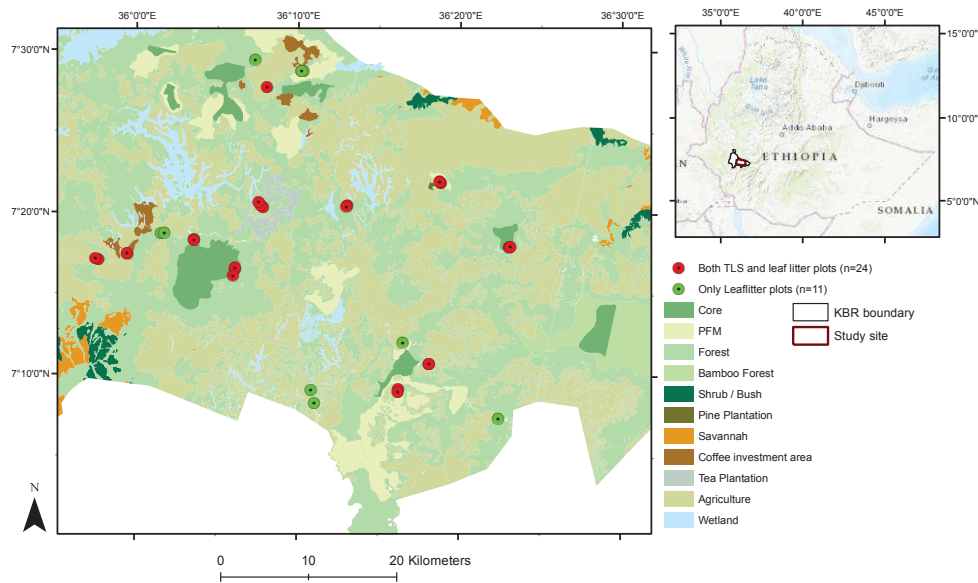


Figure 5.1: Location of the study area Kafa biosphere reserve in Ethiopia, indicating the field plots used for this study. Note: Some plots are not visible due to the spatial proximity from the mapping scale used

The field plots were selected with a stratified random sampling design representing forest types differing in level of disturbance. The plots were identified using an overlay of different GIS data layers representing the fragmentation (Mulatu 2013), land-use and land-cover and topography of the biosphere reserve (Dresen 2011a). Our sampling plots were distributed across forest types described as *intact*: untouched natural forest with no signs of human disturbance; *Participatory forest management* (PFM): where wild coffee is harvested from the forest understory; *old degraded*: forests that has been disturbed before 2012 and are now left to recover; *recently degraded*: forests have been disturbed between 2012-2015 and mainly used for grazing and logging; and *highly degraded*: forests that have been disturbed since 2005 for grazing and logging purposes.

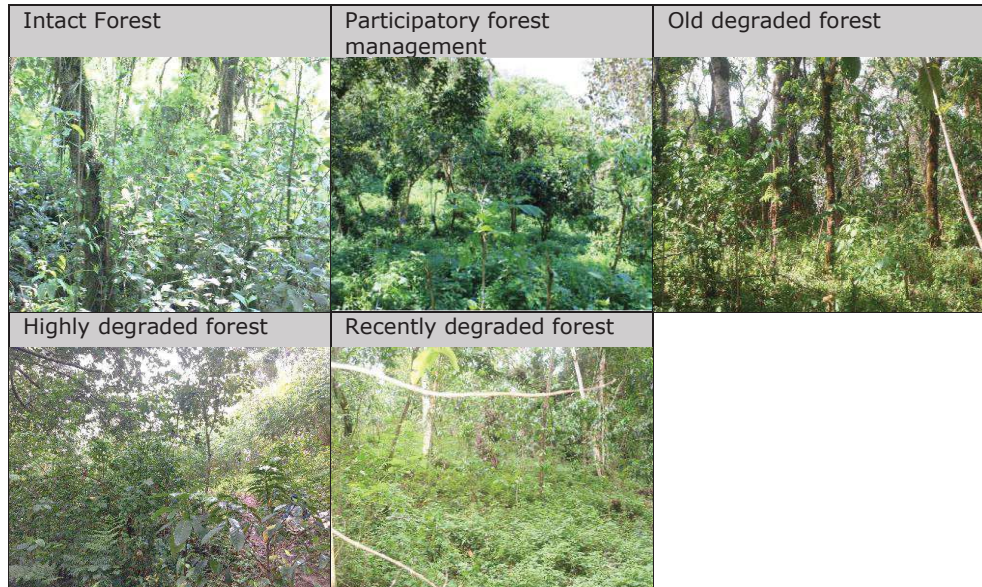


Figure 5.2: Pictorial description of the forest types (as a function of disturbance) used for the study.

The data on leaf-litter-arthropods were collected in 35 plots (i.e. intact: 8, PFM: 8, old degraded: 7, highly degraded: 6, recently degraded: 6; Figure 5.2). We acquired TLS and conventional forest structure measurements on 24 of these plots (i.e. intact: 7, PFM: 8, old degraded: 4, highly degraded: 5). The field data on forest structure was acquired in November 2015, while the leaf litter data were collected on March 2016. Both data collection periods were during the dry season.

5.2.2 Leaf-litter arthropod collection and processing

5.2.2.1 Field procedure

Leaf litter samples were collected in 35 plots with samples taken at the centre of each plot and 3 other subplots (about 50 m apart) located in the direction of 0° , 120° , and 240° from the centre plot (i.e. 4 samples per plot, a total of 140 samples). The leaf litter was collected from an average area of a 3×3 m quadrant per plot and was sifted through a 10 mm litter-sifter for approximately 1 minute to remove whole leaves. Then the concentrated leaf litter was placed into a cloth bag and was labelled with the sub-plot ID. To avoid cross-contamination, the sifters were thoroughly cleaned between sampling plots. The samples were left to dry for 72 hours inside a Winkler litter extractor. As the concentrated leaf litter dries through the days, the arthropods move from the top part of the extractor that is covered with a mesh bag, to the bottom part that has a cup filled with 70% ethanol. The arthropods are then transferred from

the extractor cup to centrifuge-tubes that were filled with 99.9% ethanol and are kept in a freezer at -4 °C until transported to the Laboratory of Genetic Resources and Evolution, Kunming Institute of Zoology, where the samples were kept in a -20 °C freezer until the metabarcoding procedure.

5.2.2.2 Metabarcoding of leaf-litter-arthropod

For each sample, we first removed storage ethanol and air-dried all individuals on single-use filter papers. We equalized input DNA across species by using one leg of every individual larger than an ant (~5 mm long) and the whole body if smaller. This was to reduce the effect of large-biomass individuals outcompeting small-biomass individuals during PCR, which improves taxon detection (Elbrecht et al. 2017). DNA extraction followed the protocols of Qiagen DNeasy Blood&Tissue Kit (Hilden, Germany), followed by DNA quantification via Nanodrop 2000 (Thermo Fisher Scientific, Wilmington, DE). One sample was failed in DNA extraction.

We chose a 313-bp fragment of COI as our barcode sequence with forward primer mICOIntF and reverse primer jgHCO2198 (Leray et al. 2013). We followed the DAME protocol (Zepeda-Mendoza et al. 2016) by subjecting each sample to three, independently tagged PCRs and to bioinformatically filtering out sequences that failed to appear in more than one PCR above a minimum number of reads; such sequences are more likely to be PCR or sequencing errors. We tailed the forward and reverse primers were tailed with ‘Twin tags’ (the same sample-identifying, 8-9 bp oligonucleotide sequence) for sample identification after PCR (Zepeda-Mendoza et al. 2016). This strategy allows the elimination of ‘tag-jumping’ events during library preparation that results in sample-misassignment (Schnell et al. 2015).

A quantitative PCR (qPCR) was performed to estimate the minimum cycle number. All PCRs were performed on a Mastercycler Pro (Eppendorf, Germany) in 25- μ l reaction volumes, each containing 2.5 μ l 10x buffer (Mg^{2+} plus), 0.2 mM dNTPs, 0.5 μ M of each primer, 1.25 μ l DMSO, 0.5 μ l BSA (bovine serum albumin) (TaKaRa Biotechnology Co. Ltd, Dalian, China), 0.75 U exTaq DNA polymerase (TaKaRa Biotechnology), and approximately 60 ng genomic DNA. Each round of PCR started with an initial denaturation at 95 °C for 5 mins, followed by 25 cycles of 95 °C for 10 s, 52 °C for 30 s, 72 °C for 60s, and finishing at 4 °C.

All amplicon products were run on 2% agarose gels and pooled in equivalent ratios based on band intensity to form roughly equimolar sequencing libraries, then purified with the Agencourt AMPure XP kit (Beckman Coulter, Inc., USA), and then sequencing libraries were created with the NEXTflex Rapid DNA-Seq Kit for Illumina (Bioo Scientific Corp., Austin,

USA), following manufacturer instructions. The libraries were sequenced with Illumina's Reagent Kit v3 300 PE on an Illumina MiSeq at the Southwest Biodiversity Institute, Regional Instrument Center in Kunming.

We processed the raw reads by removing remnant Illumina adapter sequences with *AdapterRemoval* 2.2.0 software (Schubert et al. 2016) and then followed Schirmer et al. (2015) recommended pipeline by trimming low-quality ends using *sickle* 1.33 (Joshi and Fass 2011), correcting sequence errors using *BayesHammer* in *SPAdes* 3.10.1 (Nikolenko et al. 2013), and merging pair-end reads using *PandaSeq* 2.11 (Masella et al. 2012), all with default parameters. The merged reads were demultiplexed to sample and error-filtered by with a new version of DAME (Zepeda-Mendoza et al., 2016) (repository <https://github.com/shyamsg/DAME>) using the positive-control sample as a guide, we kept only sequences that were present in ≥ 2 PCR replicates with a minimum of >3 reads per PCR. Those filtered-in reads were clustered by *sumacust* 1.0.31 (Mercier et al. 2013) at 96% and got 1,872 OTUs, and we assigned taxonomies of the OTUs using a Naïve Bayesian Classifier model (Wang et al. 2007) trained on the Midori 1.1 UNIQUE COI dataset (Machida et al. 2017). OTUs assigned to non-Arthropoda taxa were removed, and we also used the 'lulu' R package 0.1.0 (Frøslev et al. 2017) to combine OTUs that were likely from the same species but which had failed to cluster, and we got 1,350 OTUs after finishing this step. 'lulu' infers (and combines) such 'parent-child' sets by first calculating pairwise similarities of all OTU representative sequences to identify sets of high-similarity OTUs and then combining OTUs within such sets that show nested distributions across samples.

5.2.3 Community diversity and composition analysis

Total species richness, Shannon diversity, and Simpson diversity for each forest type were estimated using the final OTU dataset in 'iNEXT' 2.0.12 (Hsieh et al. 2016). The community composition differences across forest types were visualized and compared using non-metric multidimensional scaling (NMDS) ordination of Jaccard dissimilarity matrices with metaMDS function in 'vegan' package 2.5-5 (Oksanen et al. 2007). Beta diversity was partitioned into turnover and nestedness components using 'betapart' 1.4-1 (Baselga and Orme 2012). An intersection diagram was also made using 'UpSetR' 1.3.3 (Conway et al. 2017) to show the presence of unique and shared species across forest types (Conway et al. 2017). All community analyses was performed using R 3.5.0.

5.2.4 Forest structure measurements

The TLS scans were taken in 20 plots with a radius of 20 m, and 4 plots with a radius of 10 m, due to difficult terrain. The three-dimensional setup of each plot was acquired with five

scanning positions (i.e., one in the centre and four in the cardinal directions). The TLS point clouds were acquired using a RIEGL VZ-400 terrestrial laser scanner (RIEGL Laser Measurement Systems GmbH, Austria), and were pre-processed and co-registered using RiSCAN PRO software (RIEGL Horn, Austria). Forest vertical structure parameters were extracted from both the individual TLS scans and the co-registered point clouds (Table 5.1). Vertical profiles of Plant Area Volume Density (PAVD) were derived using the method developed by Calders et al. (Calders et al. 2014), while canopy related parameters (i.e., canopy heights, canopy gaps, and canopy openness) were extracted using the CompuTree point cloud analysis open source software (Hackenberg et al. 2015a). The details on the collection and analysis of the TLS and conventional forest measurements can be found in Decuyper et al. (2018). In addition, conventional forest measurements were made using a nested design. Total basal area (TBA) was calculated by measuring all trees of ≥ 20 cm diameter at breast height (DBH) in the 20 m (or 10 m) radius plot, while trees of 5–20 cm DBH were included within the centre 5 m-radius subplot only, and tree species were identified and tree density was also calculated accordingly. Above-ground biomass (AGB) was further calculated by using the wood density values for African tropical moist forests (Chave et al. 2009).

5.2.5 Satellite remote sensing data

Vegetation indices (VIs) derived from optical satellite images (Planetscope, Landsat-7, and Sentinel-2), and backscatter values from radar satellite images (ALOS-2 PALSAR-2, and Sentinel-1) were calculated for each plot. The VIs produced were green normalized difference vegetation index (GNDVI), enhanced vegetation index (EVI), and green forests chlorophyll index (CI green). In addition, the shortwave infrared (SWIR) bands of Sentinel-2 and Landsat-7 were used to produce the normalized difference moisture index (NDMI), while the Sentinel-2 specific red-edge bands were used to produce inverted red-edge chlorophyll Index (IRECI). The C-band VV-polarization from Sentinel-1, as well as the L-band HH and HV polarizations from ALOS-2 PALSAR-2, were used to acquire backscatter intensities (Joshi et al. 2015c, Viet Nguyen et al. 2016). The HH and HV polarizations from ALOS-2 PALSAR-2 were also used to calculate forest-specific backscatter (FB) values (Lucas et al. 2007). In addition, to account for the limited sensitivity of SAR backscatters to forest structure during wet seasons due to vegetation and soil moisture (Nguyen et al. 2016, Urbazaev et al. 2016), we calculated the temporal standard deviation (TSD) of backscattered values between the three SAR images. Details on the collection and processing of the SRS datasets can be found in Mulatu et al (2019).

Table 5.1: Description of forest structure parameters used.

Measurement type	Variable	Descriptions
Forest type	A Factor description of forest disturbance level	Plot selection criteria/field visit
Conventional	Total basal area (TBA)	Average amount of an area occupied by tree stems
	Above ground biomass (AGB)	derived from the DBH, species names and the wood density values for African tropical moist forests
	Tree density	Measure of the stocking of a stand of trees based on the number of trees per unit area
	Tree species diversity	Shannon index values characterizing tree species diversity in a plot
TLS	Cumulative Plant area volume density (PAVD)	Plant surface area to volume ratio
	Plant area volume density (PAVD at 10m)	Aggregated PAVD at 10 m (understory vegetation)
	Canopy height	Top of the forest canopy height at 0.5 m resolution
	Mean canopy gap size	Mean of neighbouring pixels with canopy height of <10 m and with an area of $\geq 1 \text{ m}^2$
	Maximum canopy gap size	Maximum value of neighbouring pixels with canopy height of <10 m and with an area of $\geq 1 \text{ m}^2$
	Canopy openness	All empty spaces of $\geq 1 \text{ m}^2$ at 5 m height intervals, calculated until the maximum canopy height
Satellite remote sensing	Green normalized difference vegetation index (GNDVI)	Index of vegetation photosynthetic activity
	Enhanced vegetation index (EVI)	Index designed to enhance vegetation signal with improved sensitivity in high biomass regions
	Chlorophyll index (CI green)	Index of canopy chlorophyll content
	Normalized difference moisture index (NDMI)	Index of vegetation moisture content
	Inverted red-edge Chlorophyll Index (IRECI)	Index on canopy chlorophyll content and red-edge position
	HH, HV backscatter, Forest backscatter	Vegetation backscatter on HH and HV polarizations
	VV backscatter	Vegetation backscatter on VV polarization

5.2.6 Linking forest structure and Community composition

Redundancy Analysis (RDA), a constrained ordination technique, was used to develop multivariate models for performing an exploratory analysis that identifies the linear combination of limited number of structural parameters which can explain the variation in leaf-litter-arthropod community composition. *Canoco 5.10* (Ter Braak and Šmilauer 2012) was used to perform the RDA constrained multivariate analysis. We used the data from 24 plots that have both structural and biodiversity observations. The semi-automated forward selection approach with Canoco allows a stepwise selection of important structural variables that can significantly explain the residual variation in community composition (Palmer 2004, Ter Braak and Šmilauer 2015).

We tested the distribution of our dataset and used a logarithmic transformation on field-measured parameters that did not have a normal distribution (i.e., mean gap, PAVD at 10 m, maximum gap, AGB, and total basal area). A square root transformation of OTU counts was made to eliminate the influence of outliers. Such transformation allows an even spread of plots and species (Palmer 2004). Ten multivariate models, with a separate and combination of forest structure variables measurement approaches (field measured, satellite remote sensing, TLS, etc.) were prepared to estimate community composition. The statistical significance (P-value) of the models was evaluated using the Monte Carlo permutation tests, while the models were compared using their adjusted-R² values.

5.3 Results

5.3.1 Comparing species richness between forest types

The ‘iNext’ results (Figure 5.3) show that the estimated alpha diversity measures (i.e. species richness, Shannon and Simpson indices) are the highest in PFM and old degraded forest, followed by highly degraded forest and intact forest, and are the lowest in recently degraded forest. Considering the 95% confidence-interval overlap as a conservative test for significance at the $p=0.05$ level (MacGregor-Fors and Payton 2013), it can be observed that the recently degraded forest species richness and diversity are significantly lower than the other forest types.

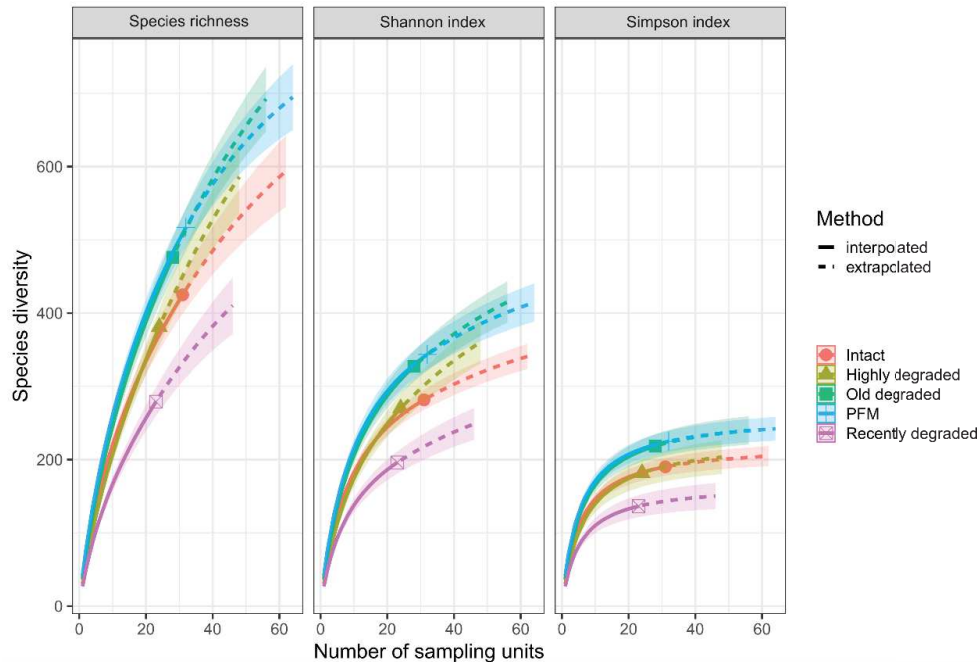


Figure 5.3: Estimates of leaf-litter-arthropod species richness, Shannon diversity, and Simpson diversity by forest type, using sample-based rarefaction and extrapolation. Solid lines represent ‘iNEXT’ interpolations, and dashed lines represent ‘iNEXT’ extrapolations, with 95% confidence intervals. Statistically significant pairwise differences are detected visually by non-overlapping confidence intervals.

5.3.2 Community composition between forest types

The dissimilarity in leaf litter species composition across forest types is presented in the NMDS plot (Figure 5.4). The overall beta diversity plot shows that the species composition in intact forest is different from the other forest types, having a spread to the left end of the NMDS second axis. The turnover versus nestedness analysis results show that the species compositions in the four non-intact-forest plots are made up of species that are distinct from the intact forest type, and not just subsets of the intact forest type.

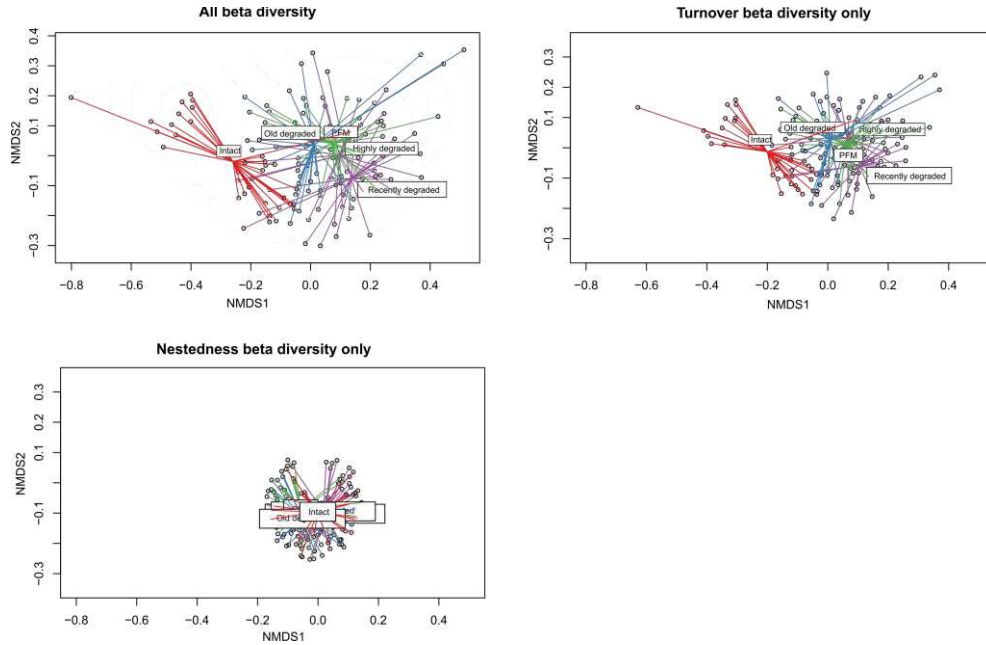


Figure 5.4: Non-metric multidimensional scaling (NMDS) ordination of leaf-litter-arthropod beta diversity by forest type.

The NMDS plots were found to be in agreement with the results of the intersection diagram (Figure 5.5). Intact and PFM forests are found to host the largest number of ‘unique’ species, 184 and 182 OTUs respectively, while the lowest number of unique species (76 OTUs) recorded belongs to recently degraded forests. The largest number of uniquely shared species were found between intact forest and old degraded forest (49 OTUs), while the lowest number of uniquely shared species were between intact and recently degraded forest (5 OTUs). Both highly and recently degraded forests have their highest share with PFM, having 33 and 29 shared species respectively.

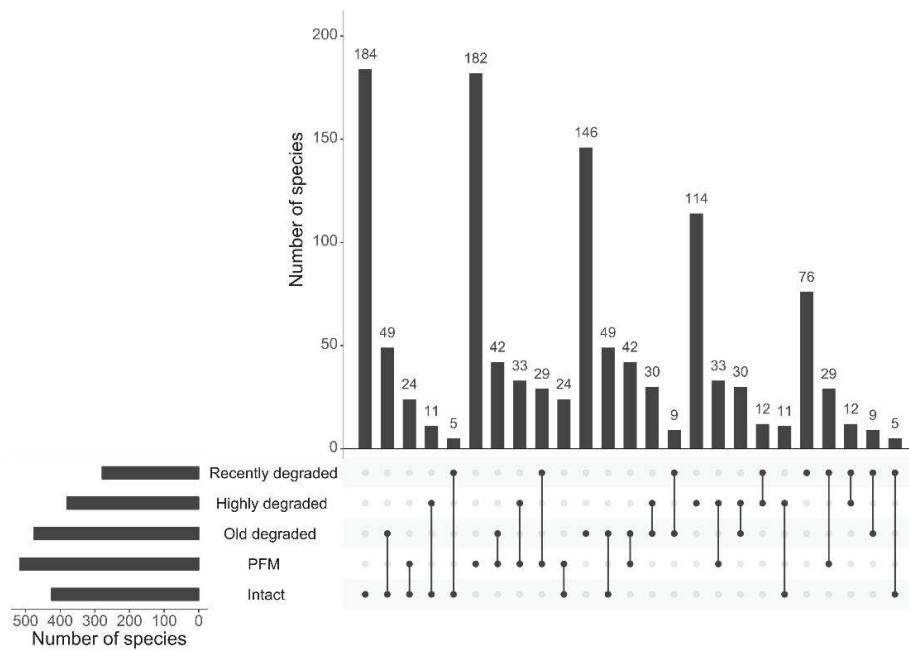


Figure 5.5: Intersection map of leaf-litter-arthropod species that are unique to and shared among forest types. The horizontal bars represent the total number of species per forest type while the vertical bars represent the number of unique species in each forest.

5.3.3 Relationship between forest structure and community composition

5.3.3.1 Multivariate model results

The multivariate analysis of forest structure and leaf litter composition showed that there are several forest structure parameters that have an effect on the composition of leaf-litter-arthropods. The forward selection models were able to eliminate multicollinearity of predictors and allows the selection of important structural variables that could explain patterns in community composition (Supplementary materials, Table S5.1). The explanatory power of the models increased with the integration of multi-sourced forest structure data rather than using single forest structure measurement approaches (Figure 5.6). The lowest explanatory power was found using conventional field observations (adjusted $R^2 = 4.84\%$, $P = 0.0044$), which had TBA as the only significant explanatory variable. The explanatory power improved (adjusted R^2 of 14.17% , and $p = 0.0004$) when the conventional measurements were joined with TLS measurement and forest type information, which when used independently had a lower explanatory power (adjusted $R^2 = 7.15\%$, $P = 0.0817$, and adjusted $R^2 = 7.25\%$, $P = 0.0001$ respectively). The remote sensing derived forest structure variables also showed a promising potential, both with the SRS only model (adjusted $R^2 = 9.8\%$, $P = 0.0199$) and with the model that joined SRS and TLS parameters giving improved estimations (adjusted $R^2 = 13.05\%$, $P = 0.0352$). Most of the TLS-derived parameters were excluded from the model due to multicollinearity. The highest explanation potential of the

model (adjusted $R^2 = 18.02\%$, $P = 0.0001$) was reached when the forest structure parameters from all measurement types and were combined with the information on forest habitat type.

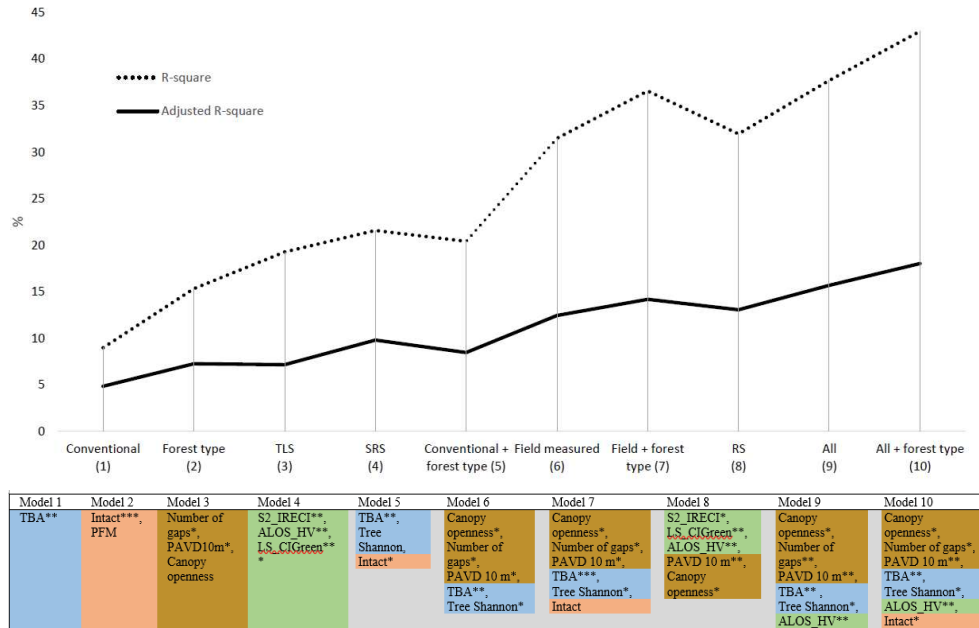


Figure 5.6: Multivariate models for estimating leaf-litter-arthropod community composition using a combination of different forest structure parameters. Colour codes represent the approaches used to acquire forest structure information (blue: conventional, rose: forest type, brown: terrestrial laser scanner, green: satellite remote sensing). P-values: $P \leq 0.05$ *, $P \leq 0.01$ **, $P \leq 0.001$ ***

5.3.3.2 Selected forest structure variables and their effect on community composition

The forest structure variables that contributed to the best model which explained 43% of the variation in leaf litter species composition were estimated through TLS, conventional, and SRS methods. The biplot diagram (Figure 5.7) represents the estimated dissimilarity of plots in terms of their species composition, and the structural variables that are related to these variations. The distance between plots approximates their dissimilarity, thus presenting the distinguishability of leaf litter species in intact forests in comparison to the other forest types. The arrows, representing the explanatory structural variables, increases in the direction of the highest relationship with the plots as a function of their community composition dissimilarity. Thus, TBA, number of gaps, PAVD at 10M, and ALOS HV show the highest relation to the leaf litter community composition in intact forests. These structural parameters were found to be negatively correlated to tree Shannon index and canopy openness which are mainly related to the leaf litter species composition of PFM and the degraded forest types. The bi-plots of selected models can be found on Supplementary materials, Figure S5.1.

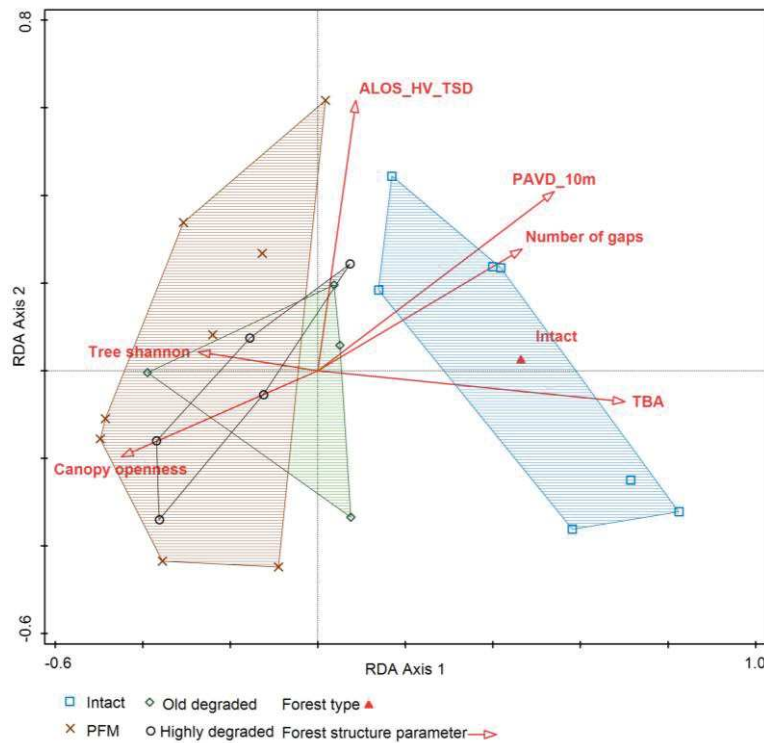


Figure 5.7: Biplot diagram of the redundancy analysis results. Forest structure arrows: each arrow shows the marginal effect of the particular structure variable upon the plot scores in the ordination diagram. Plot symbols: the distance between the symbols approximates the dissimilarity of their operational taxonomic unit composition as measured by the Euclidean distance.

5.4 Discussion

5.4.1 Community analysis

We found the metabarcoding analysed leaf-litter-arthropods diversity to vary across different forest habitat types, as a function of forest disturbance levels. In terms of species richness, PFM and old degraded forests were found to host the highest estimated leaf-litter-arthropods richness in comparison to the other forest types. This finding could relate to the intermediate disturbance hypothesis (Grime 1973, Connell 1978) which states that local species diversity is maximized with a disturbance that is ‘neither too rare nor too frequent’. Such intermediate disturbances would create an opportunity for other species to compete in an environment which has been monopolized by species that were dominant in a low level of disturbance, thus resulting in high diversity as species at both early and late successional stages coexist. The PFM and old degraded forests are indeed characterized by such intermediate disturbances, as in case of PFM forests, their understory is cut, thinned, and annually cleared

to harvest wild coffee (NABU 2017), while the old degraded forests are recovering for several years from a similar or more drastic form of disturbances. Other studies in the KBR have also found forests with intermediate disturbances to host higher species richness of flower-visiting insect (Flügel 2017) and avifauna (Teshahunegn et al. 2016), whereas in terms of vascular plants, PFM sites were found to have low species diversity compared to intact forests (Leßmeister et al. 2017). The beetle assessment (Schöller and Wiersborski 2017) in the KBR, also with the use of leaf litter samples, similarly found species richness and abundance to be low in intact forests.

The beta diversity analysis, which represents the dissimilarity in species composition across different forest types, on the other hand, shows that intact forests despite having an estimate of lower species richness hosts unique species in comparison to the others forest types (fig. 4). This finding is in line with studies (Lindenmayer and Franklin 2002, Irwin et al. 2014, Brockerhoff et al. 2017) that also found intact forests to host the rarest and often specialist species. The turnover led beta diversity (Figure 5.4) indicates that the unique species in intact forests are lost and replaced by new species in the disturbed forests. However, the high number of species that are only shared between intact and old degraded forest (Figure 5.5) could indicate on the potential of a successful recovery of old degraded forests in terms of regaining the original species diversity and composition. Studies have shown that the natural recovery rate of degraded tropical forests is quicker (Lamb et al. 2005, Letcher and Chazdon 2009) in comparison to recoveries from disturbances that are related to forest conversions (Chazdon 2003, Álvarez-Yépiz et al. 2018). On the other hand, the small number of shared species between intact and recently degraded forests could reflect on the resilience of leaf-litter-arthropod communities to disturbances. The study of Moretti et al. (Moretti et al. 2006) showed that the level of resilience and recovery of arthropod species depends on the type and frequency of disturbance, and the responses could vary across different functional groups of arthropods. Our findings are also in support of the cautious interpretation of species richness information when used as a measure of biodiversity status (Lindenmayer et al. 2015, Magurran 2016). As it is shown here, disturbed habitats could host as equal or higher species richness in comparison to intact forests, but with a possible loss of unique species with specialist roles.

5.4.2 Linking forest structure and diversity

Our explorative study was able to identify sets of forest habitat parameters that could explain variations in leaf-litter-arthropod composition. The results from the models showed that the structural information derived from the different data sources were important as an independent model and also were complementary when used in combination. For example, TBA, which is considered as a surrogate of biomass and net production, was an important predictor in both the conventional and combined models (Figure 5.6). This finding is

consistent to previous studies (Solar et al. 2016) that has found systematic variation in arthropod composition across gradients of AGB (i.e. from primary forest to agriculture), and with studies that explored the relation of productivity and biodiversity (Isbell et al. 2015, Nieto et al. 2015). The TLS-derived structural parameters were found to be significantly important when used in the combined models than as an independent model. We were able to identify that an increasing number of gaps, and the abundance of understory vegetation were key structural conditions that associate to the leaf-litter-arthropod composition of intact forests, while canopy openness related to the degraded forests. We found a few number of studies that looked in to species diversity and LiDAR derived forest structure. Müller et al. (Müller et al. 2014, Müller et al. 2018) found relations between airborne LIDAR-derived tree height and vertical distribution of vegetation and canopy arthropod diversity where an increase in the number of individuals with increasing vertical distribution of vegetation was found, also indicating that structural complication and high biomass plots would provide suitable conditions for feed, shelter, and reduced competition. Structural estimates derived from airborne LIDAR were also used to assess mammals response to foliage density and forest gaps in temperate forests (Froidevaux et al. 2016), and to identify the relationship between bird species diversity and the vertical and horizontal forest habitat heterogeneity (Carrasco et al. 2019). The SRS derived structural parameters, even though overshadowed by the TLS and conventional measured variables on the combined models, they were found promising in explaining compositional variations as an independent model. These results could be due to the sensitivity of the parameters to different biophysical states of the forest types. This finding is in line with studies that also found the influence of forest biomass and moisture conditions on species composition and richness (both flora and fauna) with radar SRS (Bergen et al. 2007, Wolter and Townsend 2011, Attarchi and Gloaguen 2018), while the influence of forest health and stress conditions on species diversity were identified with the optical indices (Nieto et al. 2015, Wallis et al. 2016, George-Chacon et al. 2019). Finally, the categorical forest habitat type information, even though considered as an arbitrary predictor, was useful in providing additional information on the status of plots. Our findings indicate that the integration of different data sources are key in identifying patterns and explaining biodiversity using forest structure parameters. Several guidelines have advised on the integration of data sources for the same reason.

In this study, we have been able to explore an important impact that habitat-related forest structure parameters have on leaf litter species composition. The unexplained variations in community composition could still be addressed by investigating other physical variables such as habitat heterogeneity (horizontal distribution of forests) which allows the co-existence of different species through habitat separation (Didham et al. 2005) and through providing multiple habitats for some species with specific requirements such as nesting and foraging (Ishii et al. 2004), as well as through exploring other environmental factors such as

rainfall, elevation, moisture, soil condition that has been proven to have an impact on tropical forest species diversity.

5.4.3 Technological advances for tropical forest biodiversity assessment

We have been able to trace the subtle biodiversity dynamics within tropical forests that are different based on their disturbance levels, with the use of advanced technologies. Even though other studies were also able to trace differences in species diversity using metabarcoding analysis, these studies were mainly performed across different land use types, such as a comparison of species diversity between forests and agriculture lands (Yang et al. 2014, Beng et al. 2016, Barsoum et al. 2019). The same applies regarding the use of remote sensing for obtaining details on structural variation across forest types, where if it was not for the detailed information that we get out of TLS measurements on certain structural components such as PAVD and canopy openness at different height levels, they could remain elusive. The identification of a relationship between forest habitat condition and biodiversity dynamics at a plot level could lay bases for upscaling to landscape level representations and production of continuous biodiversity data.

In complex ecosystems such as the tropics, the effect of forest structure and other environmental determinants on biodiversity have been proven to vary depending on the geographic scale of the observation used (Gavish et al. 2019). Thus, monitoring such interactions would require a system that can operate at different spatial, temporal, and taxonomic scales. Both DNA metabarcoding and remote sensing have the potential for conducting such assessments at multiple scales. Remote sensing approaches can provide an opportunity to explore and upscale habitat complexity (vertical stratification) and habitat heterogeneity (fragmentation) information at different spatial scales. Similarly, environmental DNA (eDNA), a developing field in DNA metabarcoding, is a valuable survey method for landscape-level studies as it obtains DNA samples directly from the environment and allows the identification of broad taxonomic scales (Adams et al. 2019).

5.5 Conclusion

We have been able to form our hypothesis, that with the integration of evolving technologies in the field of ecology, it will be possible to detect subtle forest habitat changes and biodiversity dynamics in changing tropical forests. Further investigation would be needed to build upon this knowledge with large observations in order to test the hypothesis with independent datasets. In addition, relating habitat conditions and species diversity from functional perspective will provide an important understanding on the roles these arthropods have in the ecosystem and how habitat disturbance led compositional change can affect important ecosystem functions and services. Such integration of technologies that could lead to an understanding of complex forest ecosystem processes is key for tracking progress

towards global biodiversity goals and for operationalization of the essential biodiversity variables.

Acknowledgments

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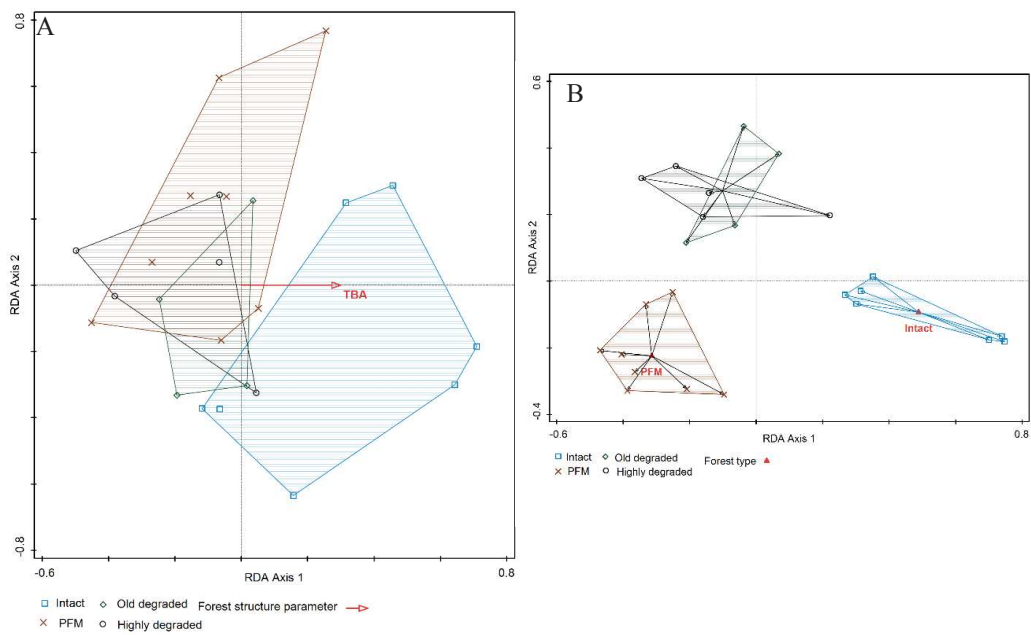
Supplementary materials

Table S5.1: Multivariate model outputs for estimating leaf litter community composition

Variables	Explain/ contribute (%)	pseudo-F	P	P(adj)
Model 1: Conventional	R ² =8.98%,	Adj. R ² =4.84%,	pseudo-F=1.3, P=0.0044	
Log_TBA	9% (33.4%)	2.2	0.0011	0.0035
Model 2: Forest type	R ² =15.32%,	Adj. R ² =7.25%,	pseudo-F=1.9,	
P=0.0001				
FT2.Intact	10.2 (66.5)	2.5	0.0001	0.0002
FT2.PFM	5.1 (33.5)	1.3	0.0888	0.0888
Model 3: TLS	R ² =19.26%,	Adj. R ² =7.15%,	pseudo-F=1.1,	P=0.0817
Number of gaps	7.4 (22.1)	1.7	0.0114	0.0266
Log_PAVD10m	6.5 (19.4)	1.6	0.0185	0.04317
Canopy openness	5.5 (16.4)	1.4	0.0655	0.09987
Model 4: SRS	R ² =21.57%,	Adj. R ² =9.80%,	pseudo-F=1.2,	P=0.0199
S2_IRECI_Mean	6.8 (9.8)	1.6	0.0135	0.0675
ALOS_HV_TSD	7.2 (10.4)	1.8	0.003	0.0225
LS_CIGreen_Mean	7.6 (10.9)	1.9	0.001	0.015
Model 5: Conventional + forest type	R ² =20.41%,	Adj. R ² =8.47%,	pseudo-F=1.6,	
P=0.0002				
log_TBA	9.0 (36.2)	2.2	0.0011	0.0022
Tree_shannon	5.2 (21.0)	1.3	0.0962	0.0962
FT2.Intac	6.2 (25.0)	1.6	0.0113	0.0226
Model 6: Field measured	R ² =31.48%,	Adj. R ² =12.45%,	pseudo-F=1.2,	P=0.0084
CanopyOpenness	6.3 (11.0)	1.5	0.0298	0.05109
NumberOfGaps	6.4 (11.2)	1.5	0.0262	0.0596
log_PAVD10m	6.5 (11.3)	1.6	0.0144	0.0576
log_TBA	6.7 (11.7)	1.7	0.0094	0.0576
Tree_shannon	5.5 (9.6)	1.4	0.037	0.0888
Model 7: Field measured + forest type	R ² =36.56%,	Adj. R ² =14.17%,	pseudo-F=1.4,	
P=0.0004				
CanopyOpenness	6.3 (12.3)	1.5	0.0319	0.04557
NumberOfGaps	6.4 (12.5)	1.5	0.0291	0.05317
log_TBA	7.6 (14.8)	1.9	0.0042	0.021
log_PAVD10m	5.6 (10.9)	1.4	0.0351	0.0702
Tree_shannon	5.5 (10.7)	1.4	0.0378	0.063
FT2.Intact	5.1 (9.9)	1.4	0.0669	0.09557
Model 8: RS	R ² =31.95%,	Adj. R ² =13.05%,	pseudo-F=1.2,	P=0.0352
S2_IRECI_Mean	6.8 (8.8)	1.6	0.0133	0.03768
log_PAVD10	6.7 (8.7)	1.6	0.0095	0.04038
LS_CIGreen_Mean	6.9 (8.9)	1.7	0.0046	0.07537
CanopyOpenness	5.4 (7.0)	1.4	0.0388	0.09423

Chapter 5

ALOS_HV_TSD	6.2 (8.0)	1.6	0.0081	0.05383
Model 9: All	R²=37.68%,	Adj. R²=15.68%,	pseudo-F=1.5,	P=0.00018
CanopyOpenness	6.3 (9.6)	1.5	0.0318	0.05906
NumberOfGaps	6.4 (9.8)	1.5	0.0243	0.06318
log_PAVD10m	6.5 (9.9)	1.6	0.0146	0.04745
log_TBA	6.7 (10.2)	1.7	0.0079	0.0468
Tree_shannon	5.5 (8.4)	1.4	0.0418	0.07763
ALOS_HV_TSD	6.2 (9.4)	1.7	0.0066	0.05135
Model 10: All +forest type	R²=42.97%,	Adj. R²=18.02%,	pseudo-F=1.6,	P=0.0001
CanopyOpenness	6.3 (8.5)	1.5	0.0298	0.0447
NumberOfGaps	6.4 (8.6)	1.5	0.027	0.05588
log_PAVD10m	6.5 (8.7)	1.6	0.0145	0.0435
log_TBA	6.7 (9.0)	1.7	0.009	0.0435
Tree_shannon	5.5 (7.4)	1.4	0.0365	0.06844
ALOS_HV_TSD	6.2 (8.3)	1.7	0.0072	0.0675
FT2.Intact	5.3 (7.1)	1.5	0.0261	0.06844



Integrating novel sensing and DNA metabarcoding to link forest structure and diversity

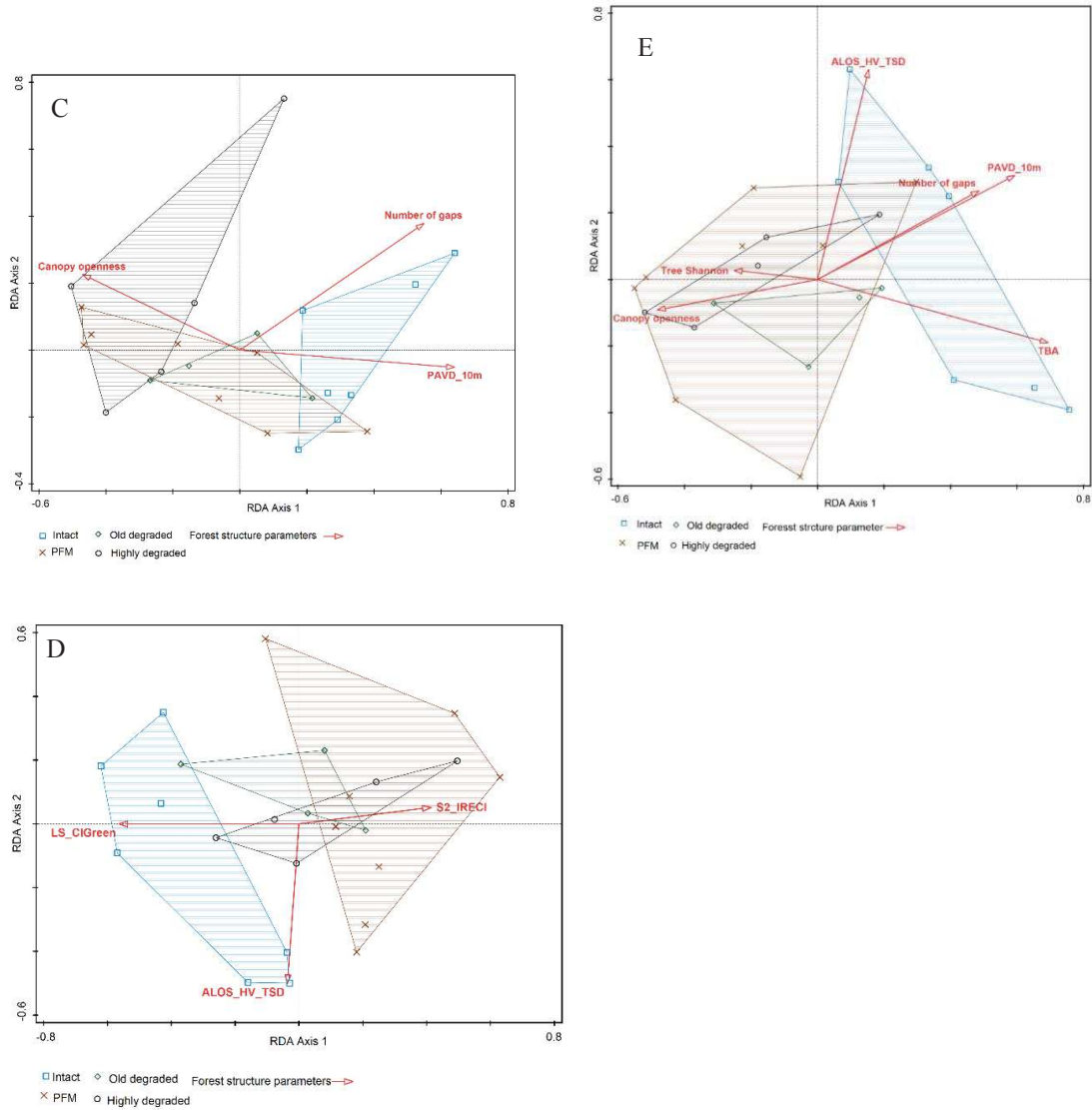


Figure S5.1: Biplot diagram of the redundancy analysis model results. Forest structure arrows: each arrow shows the marginal effect of the particular structure variable upon the plot scores in the ordination diagram. Plot symbols: the distance between the symbols approximates the dissimilarity of their operational taxonomic unit composition as measured by the Euclidean distance. A: Conventional, B: forest type, C: Terrestrial Lidar D: Satellite remote sensing E: All combined except forest type

Chapter 6

Synthesis

6.1 Main findings

To address the objective of this thesis, the chapters explored the application of emerging technologies (with an emphasis on remote sensing) for biodiversity assessment of changing tropical forests. Biodiversity attributes that were identified, as quantifiable and scalable using satellite remote sensing and in-situ measurements (chapter 2), were further explored (chapter 3, 4, and 5): to demonstrate their applicability for increasing the access to and detail of tropical biodiversity assessments. The four research questions in section 1.5 were addressed in detail in the previous chapters (2 to 5) of this thesis. Remote sensing was used for the profiling of forest structure parameters across different disturbance levels (chapter 3 & 4). This information was later integrated with actual biodiversity dataset acquired through DNA metabarcoding analysis (chapter 5). In this chapter, a summary of key findings for each of the research questions will be provided.

6.1.1 What is the potential of state-of-the-art and novel approaches to assess biodiversity in changing tropical forests?

The main finding of chapter 2 shows that **synergies between in-situ and satellite remote sensing approaches can provide unique and quantitative details on tropical forest disturbance, habitats, and biodiversity.**

The results of the systematic review in chapter 2 identified that:

i) Anthropogenic factors account for 82% of disturbances related to tropical forest biodiversity change, with the remaining 18% being accounted for disturbances originating from natural events. Agricultural activities (32%) and logging (27%) were the major anthropogenic drivers of tropical forest biodiversity dynamics in South America, South East Asia, and East Africa countries (Figure 2.4). The recent Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) report (Díaz et al. 2019) have similarly identified agricultural expansion such as cattle ranching in Latin America and plantations in South-East Asia to be the main drivers of habitat loss in intact tropical forests. The identification of such country-specific biodiversity change drivers and the use of biodiversity indicators can lead to the design of targeted biodiversity change monitoring and conservation programs (Wintle et al. 2010).

ii) biodiversity assessment techniques are determined by the spatial scale (i.e., geographical coverage of the study area), temporal scale (i.e., availability of longitudinal biodiversity data), and thematic scale (i.e., targeted groups for monitoring and disturbance types) of studies (Figure 2.2, 2.3, & 2.5). Accounting for these scale factors is important, as biodiversity

patterns and processes have varying responses to disturbances across different scales (Henle et al. 2014).

iii) remote sensing (RS) and in-situ measurements have complementary application for biodiversity assessment, on the bases of the primary biodiversity attributes (Noss 1990) and the essential biodiversity variables (Pereira et al. 2013). The RS sources are important to provide not only indirect measures (e.g. forest cover-change related habitat disturbances) of changes in biodiversity but also in providing direct information (e.g. occurrence and abundance of mammals, and large birds) on biodiversity status, across spatial and temporal scales. In-situ sensors are essential for remote, non-invasive, and real-time monitoring of tropical forest-dependent species, as well as forest disturbances. DNA barcoding, albeit being one of the most recently introduced biodiversity assessment tools, is an essential technique for the mass sampling and identification of the vast tropical forest species.

Even though the integration of RS and in-situ sensors is expected to increase the accuracy and details of tropical forest biodiversity assessments, further studies are needed on how to tackle difficulties that could arise while combining different datasets (in terms of their spatial, temporal, and taxonomic scale) for modelling species-habitat relationships, and their response to changes (Honrado et al. 2016).

6.1.2 How can Terrestrial LiDAR be used to derive biodiversity relevant forest structure parameters?

The main finding of chapter 3 shows that **TLS measurements are valuable to identify tropical forest habitat complexity by capturing the small variation of vegetation structure in the understory and canopy of different forest types.**

Following the knowledge acquired in chapter 2 regarding the need of novel remote sensing techniques for assessing forest disturbance related biodiversity dynamics; the use of terrestrial LiDAR was demonstrated in chapter 3 to measure forest habitat complexity parameters across four forest types (intact forest, coffee forest, silvopasture, and plantations). The TLS measurements together with conventional approaches provided quantitative details on vegetation volume, canopy gaps, and open spaces at all heights across the forest habitat types. The main conclusions drawn from the results were:

(i) impacts of disturbance on forest structure can be captured with TLS measurements. For instance, in coffee forests, the high canopy openness from TLS measurements as well as the low basal area (BA) and diameter at breast height (DBH) values from conventional forest measurements appeared contrary to the idea of coffee being produced underneath a relatively intact forest canopy. In coffee forest, not only the understory was cleared, but also many trees

were removed, indicating a larger management impact than expected (Schmitt et al. 2010, Aerts et al. 2011, Hundera et al. 2013). However, as expected, the coffee forest had high vegetation density between 2 and 10m due to the coffee plants (Figure 3.5).

(ii) TLS measurements can be used for deriving habitat heterogeneity proxies that are relevant to biodiversity monitoring. The TLS measurements enabled the 3D quantification of forest structural measurements such as plant area volume density (PAVD), and also deriving 2D canopy gaps and canopy openness at different heights. Several of these parameters cannot be measured by conventional forest inventories. The 3D position of plant volume (quantified by PAVD) and open spaces (i.e. the inverse of PAVD) were measured. The 3D leaf positioning is important for forest-dependent species as it influences light conditions, tree architecture and photosynthetic leaf traits (Montgomery and Chazdon 2001). Open space in different forest layers, including the forest understory, is of great importance for many flora and fauna diversity (Chazdon and Pearcy 1991, Zahawi et al. 2015). With TLS, open spaces can be measured by assessing canopy openness and gaps at different heights. For example, open spaces and light between 0 and 1m is highly important for seedling germination (Chazdon and Pearcy 1991), at 0 and 5m for coffee plants and their pollinators (i.e. bees) (Aerts et al. 2011), while between 5 and 30m this can be important for bird species and epiphytes (Zahawi et al. 2015).

Further advancement in automated approaches is required for optimal use of TLS observations in tropical forests, such as for deriving biomass estimates from TLS data (Gonzalez de Tanago et al. 2018). In-situ measured structural parameters can benefit from further integration with spaceborne and airborne LiDAR, satellite remote sensing data for upscaling plot-based structural measurements. In addition, linking structural data with biodiversity dataset would be necessary for better monitoring the impacts of habitat conditions on forest biodiversity.

6.1.3 How does multi-modal Satellite data relate to Terrestrial LiDAR-derived forest structure?

The main finding of chapter 4 shows that **satellite remote sensing (SRS) variables are sensitive to structural conditions of tropical forests and have the potential to be used to upscale biodiversity relevant in-situ forest structure estimates.**

The empirical study in chapter 4 explored the relationship between in-situ measured forest structure parameters and SRS derived biophysical sensitive vegetation indices (VIs) and backscatter information. SRS is valuable for producing wall-to-wall and repeatable information on forest structure which would otherwise be very expensive to collect with field-based analysis. The main findings from this chapter show that:

(i) optical sensor-derived VIs are most sensitive to canopy gap-related forest structure parameters, while synthetic aperture radar (SAR) backscatters and the red-edge- and short-wave infrared band-derived VIs: (i.e., inverted red-edge chlorophyll index, normalized difference moisture index) are most sensitive towards the in-situ measured vegetation volume-related parameters (Figure 4.3). The optical SRS-derived VIs, despite being underestimated for saturating in forest environments were sensitive to forest structure (Morley et al. 2019). The sensitivity of SWIR to plant leaf water content, which is correlated with canopy biomass (Wang et al. 2011), enabled NDMI to respond to vegetation volume-related parameters (i.e., AGB, PAVD). The sensitivity of NIR to multiple scattering of canopy leaves, canopy gaps, and shadowing; thus, sensitivity to forest canopy structure (Malahlela et al. 2014) was associated with EVI's response towards the estimation of TLS-measured canopy gap-related parameters. The Sentinel-2 red-edge bands derived IRECI which is sensitive to canopy chlorophyll content and leaf area index (Frampton et al. 2013), was the most important index in estimating both conventionally and TLS-measured structural parameters as it was associated with both vegetation volume and canopy gap (Majasalmi and Rautiainen 2016, Castillo et al. 2017). On the other hand, the SAR data, due to the strong penetration of its pulses, even in densely vegetated tropical forest environments, were found uniquely valuable in estimating the lower canopy vegetation density, which was not picked up by vegetation indices derived from the optical sensors.

(ii) the availability of different SRS datasets creates an opportunity to assess the possibilities of data fusion to achieve an improved estimation of field-measured forest structure parameters (table 4.5). Sentinel-2- and Sentinel-1-derived predictors mainly estimated canopy gap-related parameters; the fusion of Sentinel-2, ALOS-2 PALSAR-2, and Sentinel-1 variables best estimated cumulative PAVD, while the combination of Sentinel-1 and ALOS-2 PALSAR-2 backscatters best predicted PAVD at 10 m. Similarly, the fusion of Sentinel-2 and ALOS-2 PALSAR-2 provided the best estimation for above ground biomass (AGB). The complementary nature of optical and SAR data in terms of data availability, sensitivity to vegetation features, and the difference in saturation levels would make the use of multimodal data for forest structure estimation feasible.

The main limitation of this study was the small number of field samples which would restrict the identification of subtle relationships, validation of models, and upscaling of plot estimations to landscape level. The use of parametric methods, such as the linear regression model used in this study, was then considered suitable, whereas non-parametric methods such as; random forest model, would be an appropriate choice for larger datasets where non-linear relationships could be reliably picked up (Lu et al. 2016). Further research should follow this exploratory study with larger field observations, and through employing physical studies (e.g., radiative transfer models) to provide detailed insight into the relationship between in-situ measurements and SRS estimates in order to upscale forest structure parameters that are

relevant to forest biodiversity assessment (Pfeifer et al. 2016, Ochoa-Franco et al. 2019). The upcoming satellite-based LiDAR and SAR missions (GEDI and BIOMASS) will be essential to experiment how to derive wall-to-wall forest structure estimates and in general, to address the data gap on tropical forests.

6.1.4 How can the combination of novel data sources (i.e. remote sensing and DNA metabarcoding) help to better understand and link forest structure and biodiversity?

The main finding of chapter 4 shows that the **integration of remote sensing and DNA metabarcoding techniques are capable of providing a detailed insight into the biodiversity dynamics of changing tropical forest.**

Based on the knowledge acquired from chapter 3 and 4 on the applicability of remote sensing for the assessment of forest habitat conditions, and from chapter 2 on the applicability of DNA metabarcoding for rapid and reliable biodiversity assessment; Chapter 5 explored the hypothesis formation: that the integration of remote sensing and DNA metabarcoding will give an insight into habitat-biodiversity dynamics. The results of this chapter show that:

(i) high species richness estimates of leaf litter arthropods exist in the disturbed forests (PFM and old degraded) of the Kafa biosphere reserve (KBR) in comparison to intact forests (Figure 5.3). This result was found in line with the species diversity assessment in KBR on flower-visiting insect (Flügel 2017), avifauna (Tesfahunegn et al. 2016), and beetle assessment (Schöller and Wiersborski 2017); whereas in terms of vascular plants, the disturbed plots were found to have low species diversity compared to intact forests (Leßmeister et al. 2017). The finding also relates with the intermediate disturbance hypothesis (Grime 1973, Connell 1978).

(ii) intact forests host unique species of leaf litter arthropods in comparison to the degraded forest types (Figure 5.4). This finding is in line with studies (Lindenmayer and Franklin 2002, Irwin et al. 2014, Brockerhoff et al. 2017) that found intact forests to host the rarest and often specialist species.

(iii) the influence of forest habitat conditions on leaf-litter-arthropod composition can be identified by linking forest structure parameters that are derived from remote sensing and conventional measurement with DNA metabarcoding diversity dataset. A multivariate model that combines structural information on vegetation density, canopy gaps, total basal area, tree diversity and level of forest disturbance was found to be the most important to explain the variation in leaf-litter-arthropod composition. The increasing number of gaps, high basal area, and the abundance of understory vegetation was found related with the composition of leaf-

litter-arthropods in intact forest, while higher canopy openness and tree species diversity were found related with the community composition of disturbed forests. Similar effects of forest structure parameters (e.g. AGB, vertical distribution of vegetation, and gaps) on the diversity of arthropods (Müller et al. 2014, Solar et al. 2016, Müller et al. 2018), mammals (Froidevaux et al. 2016), and birds (Carrasco et al. 2019) have been reported.

Even though the study had a limited number of plots due to logistical reasons, the findings were promising in indicating that both forest structure and biodiversity datasets acquired using novel technologies could provide detailed insights to habitat-biodiversity relationships (Bush et al. 2017, Yamasaki et al. 2017), with possible implications on resulting ecosystem functions and services. Further investigation is needed for building upon this knowledge with large field observations in order to test the hypothesis. In addition, relating habitat conditions and species diversity from functional perspective will provide an understanding on the roles of species in the ecosystem and how habitat disturbance can affect important ecosystem functions and services.

6.2 Reflection and outlook

This thesis was conducted with the aim of identifying and demonstrating how emerging technologies, mainly from the remote sensing field, could be used for the assessment and monitoring of forest biodiversity in changing tropical forests. This thesis was able to address the aim of the study by making a systematic review on the topic (chapter 2) and with a demonstration of empirical studies (chapter 3, 4 & 5). The findings of each chapter also indicate to further opportunities that could be taken as a way forward for more efficient use of emerging technologies and their potential integration. Such integration can be used to improve the monitoring of tropical forest changes and their associated impact on forest-dependent species. In this section, a reflection is made on cross-cutting topics that have been identified across this thesis. In addition, limitations encountered as well as suggestions for future avenues are discussed.

6.2.1 Evolving technologies for tropical forest biodiversity assessments

The complexity of tropical forests, as well as the different disturbance factors that drive their dynamics, requires an equally advanced monitoring approach to identify relationships and patterns at different scales. The contents of this thesis are founded on the applicability of technological advancements for biodiversity data acquisitions to obtain timely and reliable estimates on tropical forests biodiversity status and dynamics. In Chapter 2, the technological progress in remote sensing and in-situ measurements and their potential integration was presented as essential for this purpose. Chapter 3 demonstrated how TLS measurements can be used to profile different forest habitat types. In chapter 4 an empirical study was made to

identify the use of SRS derived vegetation indices and backscatter intensities in order to acquire similar information on in-situ measured tropical forest structure parameters. Even though promising results were obtained with the SRS parameters, acquiring highly accurate measures of tropical forest structural parameters from SRS is still desirable. Currently, the freely available SRS datasets such as Landsat and Sentinel can only be used to derive proxies on forest vertical structure while the commercially available, very high-spatial resolution images, which could be used to derive canopy gap parameters are expensive to be practical. Here, very recent developments and near future missions in the field of SRS that has promising opportunities for consistent and scalable forest biodiversity assessment and monitoring are presented.

The Global Ecosystem Dynamics Investigation (GEDI) mission of NASA and the BIOMASS mission of the European Space Agency are among the top RS data sources that are expected to bring ground-breaking changes on tropical forest studies. The GEDI mission that has been launched on the international space station in December 2018 and which started to collect data since March 2019, will be providing the first high-spatial-resolution LiDAR observation on the 3D structure to derive forest canopy height, canopy vertical structure, and surface elevation (Stysley et al. 2015). The GEDI observation can be used to quantify and upscale similar TLS derived biodiversity relevant structural variables, such as canopy vertical structure, canopy height, and ground elevation at a comparable vertical resolution (0.5 m) (<https://directory.eoportal.org/web/eoportal/satellite-missions/content/-/article/iss-gedi>). Similarly, the BIOMASS mission, to be launched in the year 2020, will be equipped with the first P-band synthetic aperture radar (SAR) measurements from space. The P-band is capable of penetrating the dense canopy of tropical forests to strongly interact with the large woody vegetation elements, and is more sensitive to biomass than the L- and C-band SAR dataset explored in this thesis (Quegan et al. 2019). Beyond its mission of determining the amount of biomass and forest height, it will also provide a unique opportunity to map forest habitat quality and to assess the relationship between forest biomass and forest biodiversity (Le Toan et al. 2011). These upcoming SRS data sources, when coupled with sufficient in-situ reference data (for calibration of modes and validation of estimates), will have a substantial contribution for the upscaling and wall-to-wall mapping of forest habitat parameters in tropical and sub-tropical ecosystems where most of the data gap exist (Proença et al. 2016).

Moreover, as demonstrated in chapter 5 of this study, the integration of forest structure measurements and leaf litter arthropod dataset were useful for detecting changes in forest habitat and the resulting arthropod community composition. Even though arthropods are often selected as good biodiversity indicators, the impact that forest habitat conditions have on other taxa could be comprehensively assessed with the use of other advanced in-situ approaches. Camera traps and acoustic recorders (Buxton et al. 2018), drones equipped with cameras (Kellenberger et al. 2018, Hernandez-Santin et al. 2019), as well as environmental

DNA (eDNA) technology (Díaz-Ferguson and Moyer 2014), coupled with automatic species identification and image recognition techniques are some of the recent powerful tools that could be explored. In addition, citizen-based forest biodiversity assessment, coupled with sampling protocols, could densify field-based observation of biodiversity data (van Strien et al. 2013, Isaac et al. 2014).

The RS and DNA metabarcoding techniques explored in this study can also be adopted for biodiversity assessment of other terrestrial and aquatic ecosystems. RS data can be used for estimating forest structure with better accuracies in temperate forests (Müller et al. 2018), boreal forests (Matasci et al. 2018), as well as savanna and woodlands (Vaglio Laurin et al. 2017) which have lower ecological and physical complexity in comparison to tropical forests. Both RS (Geller et al. 2017) and eDNA techniques (Díaz-Ferguson and Moyer 2014) are growingly being explored in marine and freshwater ecosystems for measurement of parameters such as habitat extent and conditions, and for identification of ancient and present species respectively. The possible integration of these two approaches could provide new insights in research and conservation efforts of these unique ecosystems, which as tropical forests, are under heavy pressure in the Anthropocene (Kopf et al. 2015).

Even though the application of these emerging technologies beyond research would demand additional resources (financial and technical) from tropical countries, a quick and efficient adaptation of remote sensing techniques for the monitoring and reporting of forest cover changes (mainly in relation to REDD+ and national forest inventories) has already been observed (Romijn et al. 2015). This could be taken as a positive indicator that tropical countries could have similar capacities for adopting advanced biodiversity monitoring techniques for supporting their national biodiversity assessments and reporting for international targets.

6.2.2 Biodiversity relevant data sources and integration approaches

The research in this thesis has focused on the identification of forest biodiversity relevant datasets obtained from remote sensing and in-situ sources. Chapter 2 outlined some of the available lists of RS and in-situ datasets that are relevant for addressing the Aichi biodiversity targets and for operationalizing Essential Biodiversity Variables (EBVs). Accordingly, the datasets used throughout the thesis were either acquired from remote sensing sources or collected from in-situ measurements. In chapter 3, we combined TLS and conventional measurements to characterize the structural differences across forest types. These datasets (from chapter 3) were used in chapter 4 to explore their potential link with optical and SAR satellite images. Moreover, the structural parameters estimated from both RS and conventional methods were linked with leaf-litter-arthropod DNA metabarcoding dataset to identify the relationship between forest structure and biodiversity. Working with large

number of datasets that are different in their data acquisition system, as well as the content and detail of information that they carry, could provide with an opportunity of large sets of information. However, it could also pose a challenge of identifying efficient methods in order to extract the best possible information that can help achieve the aim of the study. In this thesis, the structural data was harmonized by calculating the mean value of parameters per plot size of 20 m radius for the in-situ measured and high resolution (i.e. PlanetScope, Sentinel-2) images, while mean value per plot size of 50 m radius were used for the medium spatial resolution dataset (i.e. Landsat-7, Sentinel-1, ALOS-2 PALSAR-2). The relation and integration between the different datasets were investigated using correlation analysis and simple linear regression models that fitted the small number of observation used for the empirical analysis. With the availability of time-series genomics and remote sensing observations, identification of appropriate indicators and employment of novel algorithms can be used to detect non-linear relationships (Sugihara et al. 2012). Predictive models that are based on time-series data can be used to estimate biodiversity responses to forest change (Yamasaki et al. 2017).

The identification and integration of relevant data sources at different spatio-temporal scales are also important (Maron et al. 2015) (Figure 6.1). In this study, the freely available SRS datasets of Landsat and Sentinel, as well as the commercially available PlanetScope (note: accessed at no cost through research ambassador quota) and ALOS-2 PALSAR-2 images were used. The Landsat archives have been mainly valuable to make a temporal analysis of forest cover changes and to assess their possible implication on forest biodiversity (Margono et al. 2012, Matthew et al. 2016). The Sentinel-2 high-resolution images have also created new opportunities to make use of high-resolution data with red-edge specific bands that are sensitive to biophysical conditions of forests (Majasalmi and Rautiainen 2016, Castillo et al. 2017). Very high spatial resolution datasets (e.g. PlanetScope) are also favored for their frequent revisit and the spatial details they provide in tropical forests where the number of cloudless images available is limited (Dalagnol et al. 2019). The optical SRS images, can also be used to acquire structural estimates of tropical forests using radiative transfer modelling (Ligot et al. 2014), texture analysis (Wallis et al. 2016), object-based analysis (Silveira et al. 2019), and fragmentation analysis (Peter et al. 2015).

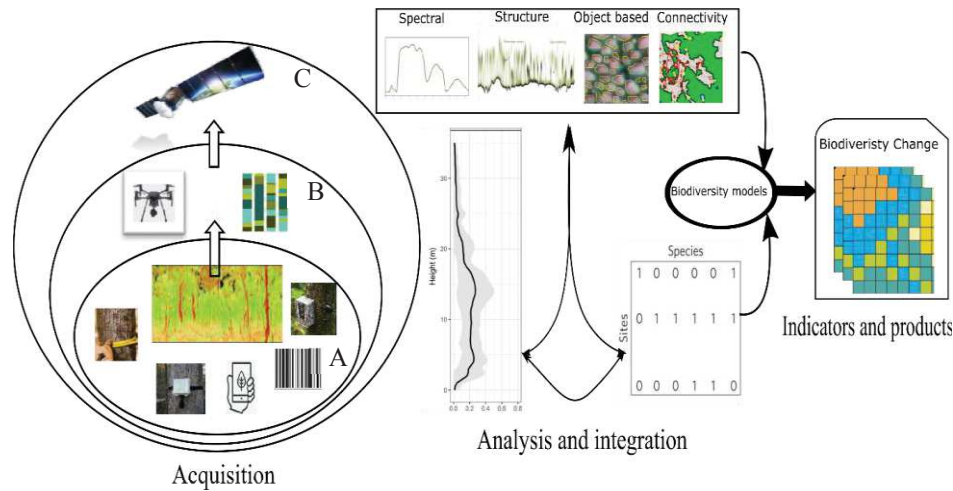


Figure 6.1: Simultaneous acquisition of forest structure and biodiversity data and their integration for producing continuous biodiversity monitoring products. A: in-situ measurements (TLS, conventional, DNA barcoding, audio-video recordings, citizen science), B: landscape level data acquisition (Drone, eDNA), C: Satellite remote sensing: global observation with optical, LiDAR, SAR, hyperspectral sensors

In-situ measurements with Terrestrial LiDAR, and DNA metabarcoding, are found to provide highly accurate estimates for plot-level studies while compared in reference to conventional measurements (Yang et al. 2014, Liang et al. 2016, Barsoum et al. 2019). They however require consistent sampling designs and a rather advanced data analysis approach. The spatial coverage and representation of in-situ measurements are often limited which restricts them from being used in advanced statistical approaches, e.g. for making ecological predictions. This was a challenge faced in chapter 4 of this thesis while exploring the relationship between in-situ measured forest structure parameters and SRS variables for upscaling plot-level measurements to landscape structural estimations. The number of field observations (i.e., 24 plots) were too small to be divided between training and test dataset, for cross-validating the model before upscaling the plot based structural observations. Similarly, in chapter 5, the prediction and upscaling of leaf-litter arthropod diversity using structural parameters was avoided for the same reason. Thus, empirical studies were made in both chapter 4 and 5 where correlations and simple linear regression approaches were used to identify and explain the relationships without overfitting the models. A possible solution to the limited number of field observations would be investing resources on the establishment of a network of permanent field plots that could be continuously monitored to acquire data on both forest structure and forest biodiversity. The observations could be analysed with machine learning algorithms to train series of SRS datasets in order to make reliable upscaling of plot observations, as well as, to forecast future trends with possible scenarios. Furthermore, a collaboration between researchers, practitioners, and the general public is necessary to

increase access to in-situ measurements through publishing observations as open datasets. Promising initiatives such as Tropical Ecology Assessment & Monitoring (TEAM) Network Education Portal (Sanderson 2004), TRY plant trait database (Kattge et al. 2011) and the Bioacoustica online repository and analysis platform (Baker et al. 2015) can be mentioned.

6.2.3 From data to EBVs

The concept of EBVs is another cross-cutting topic that connects the different chapters in this thesis. Chapter 2 investigated the relevance of SRS and in-situ data sources to operationalize EBVs. In chapter 3 & 4 forest structure variables derived from in-situ measurements and SRS datasets, as well as in Chapter 5, the DNA metabarcoding derived leaf litter arthropod diversity estimates were discussed in relation to EBVs.

GEO BON considers in-situ measurements and remote sensing as primary observation datasets to derive EBV products (BON 2015). In-situ measurements are essential to provide datasets for genetic composition, species populations, species traits, and community composition EBV classes. SRS is considered most suited for providing information on ecosystem function and ecosystem structure EBVs such as: net primary productivity, ecosystem extent and fragmentation, habitat structure and disturbance regime, but also with a potential of monitoring broader EBVs (Pettorelli et al. 2016a, Pettorelli et al. 2016b, GOFC-GOLD 2017). The data sources used in this thesis enabled the derivation of parameters that relate to several EBV classes (Table 6.1). The in-situ sources had the highest contribution to EBV classes in comparison to SRS. According to the study of Proença et al. (2016), the in-situ datasets used in this thesis could be classified as an intensive monitoring scheme where details on biodiversity responses to changes in the ecosystem are captured often with low spatial coverage, while the SRS datasets could be related with an extensive monitoring scheme where long-term data series can be used to monitor trends in biodiversity with extensive spatial coverage.

Table 6.1: Summary forest biodiversity relevant parameters produced and their relation to the GEO-BON essential biodiversity classes

Sources	Parameter derived	Essential Biodiversity classes
In-situ (conventional)	Total basal area (TBA)	Ecosystem structure Ecosystem function Species traits Species populations
	Tree density	Ecosystem structure Ecosystem function Species populations
	Tree species diversity	Ecosystem structure Ecosystem function Species populations Species traits Community composition
In-situ (Terrestrial LiDAR)	Plant area volume density (PAVD)	Ecosystem structure Ecosystem function Species trait
	Canopy height	Ecosystem structure Ecosystem function Species trait
	Canopy gap	Ecosystem structure Ecosystem function Species trait
In-situ (DNA metabarcoding)	Arthropod species diversity	Genetic composition Species populations Species traits Community composition
Satellite remote sensing	Vegetation indices	Ecosystem function Ecosystem structure
	Backscatter intensity	Ecosystem function Ecosystem structure

The use of remote sensing for EBV developments is one of the main foci in the effort of operationalizing global biodiversity change assessment, for filling in data gaps, maintaining standardized approaches, and providing global continuous coverages. Furthermore, a full operationalization of EBVs could be achieved through identification of existing and upcoming dataset (in-situ and SRS), enhancement of global collaboration between experts

and data providers, development of robust biodiversity models, as well as mainstreaming of EBVs.

6.2.4 Relevance to managers and ecologists

The findings of this thesis provide added knowledge not only to the research community but also for managers and ecologists. As demonstrated and discussed throughout the thesis, the technological advancements in remote sensing and in-situ measurements have immeasurable benefits for quantifying biodiversity elements that have for long stayed elusive through space and time. Ecologists and managers can use open source databases and tools to design biodiversity monitoring approaches for projects operating at different spatial scales. Platforms such as Biodiversity Observation Network in a Box (BON in a Box, <https://boninabox.geobon.org/>) provide access to biodiversity-relevant remote sensing datasets, protocols, and tools. Similarly, in situ data sources and analytical tools are provided by the Global Biodiversity Information Facility (<https://www.gbif.org/>).

In chapter 3 of this thesis, with the use of TLS derived canopy gap size information; it was possible to observe that the Participatory Forest Management (PFM) forest types, despite their expected characteristics of maintaining relatively intact canopy cover and dense understory vegetation condition (due to wild coffee), some plots had high canopy gaps and less understory density, almost resembling the structural characteristics of highly degraded forests (Figure 3.4). A similar observation was also made with the species composition analysis of chapter 5, where PFM forests had the least shared leaf-litter-arthropod species with intact forests and the highest with the degraded forests (Figure 5.6). Such information will be of use to managers in order to assess the impact of PFM activities on forest structure and habitat conditions, for ultimately taking measures, such as setting thresholds on expected canopy covers of PFM forests (Hundera et al. 2013). Considering the recent alarming reports on the decline of wild coffee species diversity due to deforestation and climate change (Davis et al. 2019, Moat et al. 2019), adopting the techniques used in this study would be relevant to further investigate the status of wild coffee varieties and pollinators (e.g. bees) in the UNESCO Kafa Biosphere Reserve (KBR). Here, an efficient channel between researchers, ecologists, and managers should be established to communicate research findings that can support effective management decisions. For example, in KBR, this communication channel is maintained between the combined effort of the researchers, environmental NGOs, rangers, and the zonal forestry office. An interactive web-based system with SRS based near real-time forest monitoring that is supported with a field-based validation of forest disturbance and monitoring of key biodiversity indicators by rangers have been put in place to support the biosphere management (Pratihast et al. 2016). Furthermore, ecologists can link the forest habitat-leaf litter arthropod diversity relationship to identify the ecosystem functions of rare species, how they are challenged, and how their functions could stay sustained.

The novel techniques in forest biodiversity monitoring can also be used by ecologists to test and support ecological theories. For instance, the sunflecks theory (Chazdon and Pearcy 1991) which relates the presence of small gaps on forest canopies with the density and diversity of understory vegetation was depicted with the findings in chapter 3. The TLS derived canopy gap and understory estimates showed distinct results across intact and degraded forests (Figure 6.2). In addition, in Chapter 5, the intermediate-disturbance theory (Connell 1978) was discussed based on the TLS and DNA- metabarcoding derived results which showed the presence of higher species richness in disturbed forest types compared to intact forests. Interdisciplinary collaboration should be encouraged to further advance the exploration and understanding of the links between physical observations and ecological concepts (Yamasaki et al. 2017).

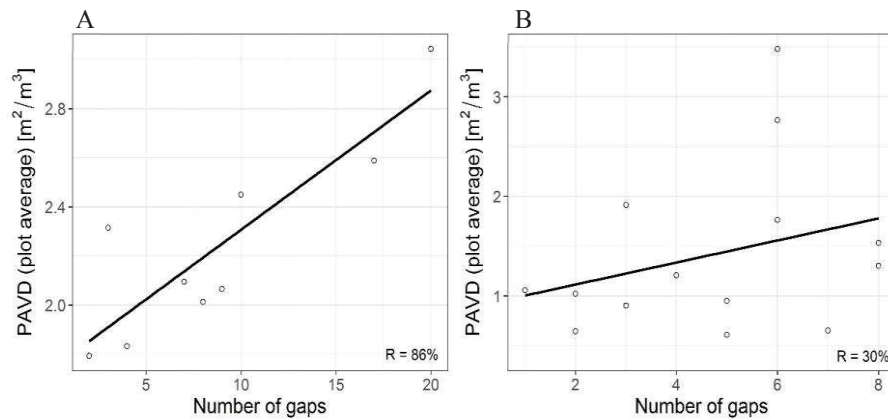


Figure 6.2: Relation between the number of gaps in the upper canopy and plant area volume density (PAVD) in the lower canopy in intact forest. A: Intact forest (n=9). B: Managed and degraded forest (n=14).

6.2.5 Linking carbon-biodiversity gradients for REDD+

The impact of tropical forest loss on forest biodiversity is poorly-understood, in comparison to carbon sequestration (Krause and Nielsen 2019). This could be due to the case that forest biodiversity stayed elusive for as long as quantitative approaches for tracking changes have been lacking. However, with the implementation of reduction of emission from deforestation and forest degradation (REDD+) and its monitoring, reporting, and verification (MRV) system in tropical forest countries, several studies have been proposing to use this platform to monitor in parallel the response of biodiversity to forest changes (Gardner et al. 2012, Goetz and Mora 2017). The results of this thesis show that the same dataset that can be used to monitor carbon relevant forest measurements can as well be used to derive forest habitat conditions that are important for tropical forest-dependent species. Thus, linking biodiversity

and carbon monitoring through REDD+ mechanism is practically feasible and efficient, even if it is not yet presented as mandatory in REDD+ MRV. For example, based on our results of chapter 3 and chapter 5, it is possible to identify that levels of disturbance have a relation with both carbon stock and biodiversity conditions (Figure 6.3). A decline in above ground biomass accumulation was observed while comparing intact forest to degraded forests, and a similar decline in a number of unique species of leaf-litter-arthropod was observed using the same comparison (chapter 5). Creating such links between carbon, biodiversity, and forests is needed considering tropical forest exceptional relevance for both carbon sequestration and sheltering of unique species. It is also important to monitor the impacts of REDD+ implementation on biodiversity. This is especially true for the KBR and Ethiopia in general, which is identified by the IUCN as a biodiversity hotspot. Mechanisms such as REDD+ can be taken as an opportunity to strengthen the technical and institutional capacities of tropical countries to study and conserve the unique flora and fauna diversity while achieving climate change mitigation goals through the conservation of tropical forests.

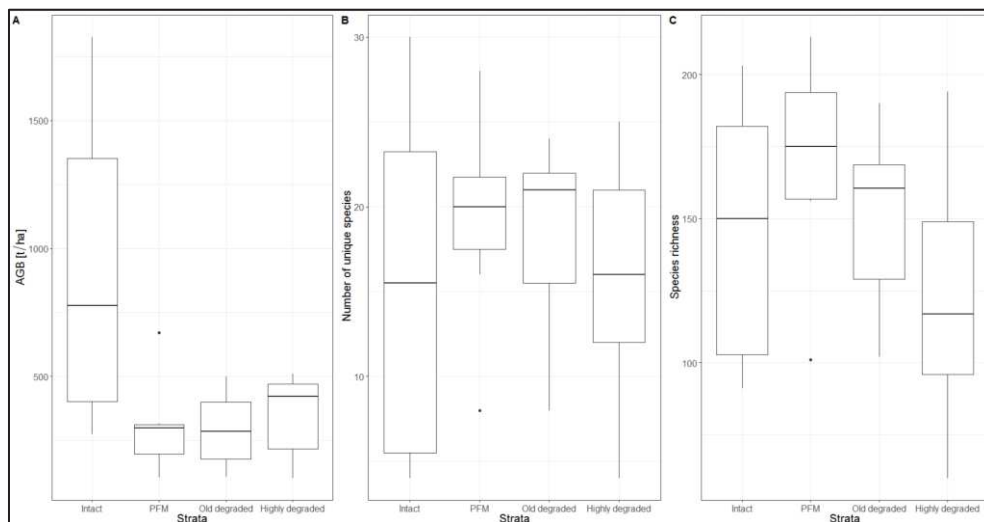


Figure 6.3: Linking forest carbon (A) and biodiversity (B and C) trends across forest disturbance gradients

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Summary

Increasing anthropogenic pressure leads to habitat loss of tropical forests through deforestation and forest degradation. The most endemic and valuable tropical forest-dependent species are threatened with such disturbances that alter the complexity of their habitat. The structural complexity of habitats has a direct effect on the availability of resources and microclimate conditions which can affect, for example, the abundance and diversity of species. Measuring the structural configuration and diversity of tropical forest habitats will help explain the state of forest degradation and the resulting biodiversity dynamics. Thus, forest habitat heterogeneity has become one of the most commonly used indicators in forest biodiversity conservation and management efforts. Biodiversity dynamics due to natural and anthropogenic disturbances are mainly monitored using conventional field survey approaches. However, these approaches often fall short at addressing complex disturbance factors and responses at different spatiotemporal scales. The integration of novel monitoring approaches such as satellite remote sensing, terrestrial LiDAR, and high-throughput DNA metabarcoding have the potential to improve the detection of subtle tropical forest disturbances and responses of species to changing tropical forests, which are largely unknown.

This thesis' aim is to investigate the application of emerging satellite remote sensing and in-situ measurements to assess the complex forest biodiversity dynamics in changing tropical forests. Thus, the main objective of this thesis is to explore the potential of using emerging remote sensing technologies to assess differences in forest structure of habitats and to integrate such information with actual biodiversity data to further increase the detail and accuracy of biodiversity assessments. A particular focus is given to the use of terrestrial LiDAR and satellite remote sensing for deriving forest structure parameters that inform on the state of different tropical forest habitats. For this purpose, field plots were established in the UNESCO Kafa biosphere reserve (KBR), Ethiopia. The use of satellite remote sensing, terrestrial LiDAR, and DNA metabarcoding methods were explored to track forest habitat differences and the associated biodiversity dynamics.

In Chapter 2 a systematic review was made on assessing the potential of emerging remote sensing and in situ monitoring technologies for informing on biodiversity dynamics in changing tropical forests. Their relevance in support of the UNCBD Aichi targets was also explored using the Essential Biodiversity Variables (EBVs) as a framework. Established field

Summary

surveys were generally found to be the dominant monitoring systems employed, whereas the temporal trend of monitoring approaches demonstrates the increasing application of remote sensing and in-situ sensors in detecting biodiversity change related to tropical forest disturbances. The complementarity of remote sensing and emerging technologies were shown in relation to EBV candidates such as species distribution, net primary productivity, and habitat structure. Even though synergy between the recent biodiversity monitoring approaches is important and possible, further testing of the suitability of monitoring methods across scales, integration of heterogeneous monitoring technologies, and setting up metadata standards is still required to design a robust biodiversity monitoring system that can contribute to effective conservation measures in tropical forests.

In Chapter 3, the use of Terrestrial LiDAR (TLS) derivatives (such as plant area volume density and canopy gaps), in combination with conventional forest inventory measures (such as above ground biomass, tree density, and tree species) was investigated to estimate forest structural parameters in four different forest types (as a function of forest disturbance) of the tropical montane cloud forest in KBR. The different forest types (intact forest, coffee forest, silvopasture, and plantation) showed distinguishable structural differences both with the TLS and conventional measurements. TLS showed its unique relevance, as it was able to capture with the 3D position of the vegetation volume, canopy gaps, and open spaces at all heights in the forest. Further integration of data sources is needed to fully understand the implications of forest disturbance and/or management practices on forest structure and forest-dependent species.

In Chapter 4, the link between multi-modal satellite remote sensing (SRS) datasets and plot level TLS measurements was explored in order to assess the potential use of SRS datasets for deriving wall-to-wall and repeatable information on forest structure parameters which would otherwise be very expensive to collect through conventional field measurements. The relationship of optical remote satellite sensing (PlanetScope-, Sentinel-2-, and Landsat-7-) derived vegetation indices (VIs) and SAR (ALOS-2 PALSAR-2- and Sentinel-1-) backscatter intensities, with a terrestrial LiDAR and conventionally measured forest structure parameters were investigated. The canopy gap-related forest structure parameters had their highest correlation with optical sensor-derived VIs, while vegetation volume-related parameters were mainly correlated with red-edge- and short-wave infrared band-derived VI. The fusion of different SRS-derived variables was also found to improve the estimation of field-measured structural parameters. The exploratory study demonstrated that SRS variables are sensitive to retrieve structural differences of tropical forests and have the potential to be used to upscale biodiversity relevant field-based forest structure estimates. The upcoming satellite-based LIDAR and SAR missions (GEDI and BIOMASS) will be essential to enable derivation of wall-to-wall forest structure estimates and in general, to address the data gap on tropical forests.

In Chapter 5, the remote sensing data on forest structure was integrated with DNA metabarcoding data on leaf litter insects to assess the relationship and influence of forest structure on leaf litter arthropods across different forest types in KBR. High species richness estimates of leaf litter arthropods were found in disturbed forests of KBR in comparison to intact forests, while intact forests were found to host unique species of leaf litter arthropods in comparison to the degraded forest types. The influence of forest habitat conditions on leaf-litter-arthropod composition was also identified using multivariate models that showed the increasing number of gaps, high basal area, and the abundance of understory vegetation were related with the composition of leaf-litter-arthropods in intact forest, while higher canopy openness and tree species diversity were found to relate with the community composition of disturbed forests. Relating habitat conditions and species diversity from functional perspective will provide an important understanding on the roles of the leaf litter arthropod species in the ecosystem and how habitat disturbance led compositional change can affect important ecosystem functions and services.

This thesis provides a scientific contribution to the exploration of integrating technological advancements in remote sensing and in-situ measurements to derive information that is essential for assessing forest biodiversity change.

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Publications

Peer reviewed journal publications

K. A. Mulatu, X. Wang, D.W. Yu, L. Kooistra, M. Decuyper, B. Mora and M. Herold and M. Herold (in preparation). Integrating novel sensing and DNA metabarcoding data to link forest structure and diversity across a degrading Ethiopian forest.

K.A. Mulatu, M. Decuyper, B. Brede, B. Mora, Johannes Reiche, L. Kooistra, M. Herold (2019). Linking terrestrial LiDAR and conventional forest structure measurements with multi-modal satellite data, *Forests*.

M. Decuyper, K.A Mulatu, B. Brede, Kim. Calders, J. Armston, D.M.A. Rozendaal, B. Mora, J.G.P.W. Clevers, L. Kooistra, M. Herold, F. Bongers (2018). Assessing the structural differences between tropical forest types using Terrestrial Laser Scanning, *Forest Ecology and Management*.

K.A. Mulatu, B. Mora, L. Kooistra, M. Herold (2017), Biodiversity monitoring in changing tropical forests: a review of approaches and new opportunities, *Remote Sensing*.

K.A. Mulatu, M. Herold, H. Koster, N. Aguilar-Amuchastegui, D. Thompson, B. Mora, A. Wijaya, M. Skutsch and M. Calmel (2013). Science solutions to policy challenges for evolving REDD+ measuring, reporting and verification requirements: report from a multistakeholder workshop, *Carbon Management*.

Other Scientific publications

K.A. Mulatu, M. Decuyper, B. Brede, B. Mora, Johannes Reiche, L. Kooistra, M. Herold. (2018). Estimation of biodiversity relevant forest structure parameters using a multi-sensor and multiscale remote sensing approach. In NCG symposium 2018. 29 November 2018, Wageningen, The Netherlands.

K.A. Mulatu, M. Decuyper, B. Brede, B. Mora, Johannes Reiche, L. Kooistra, M. Herold (2018). Estimation of biodiversity relevant forest structure parameters using a multi-sensor and multiscale remote sensing approach. In Forestsat 2018. 1-5 October 2018, Maryland, USA.

M. Decuyper, K.A. Mulatu, B. Brede, Kim. Calders, J. Armston, F. Bongers, J.G.P.W. Clevers, M. Herold (2017). Measuring forest structural diversity across a degradation gradient in an Ethiopian cloud forest. In 54th Annual Meeting of the Association for Tropical Biology and Conservation (ATBC). 9-14 July 2017, Merida, Mexico.

K.A. Mulatu, B. Mora, L. Kooistra, M. Herold (2016). Biodiversity monitoring in a changing world: an integration of established approaches with emerging technologies. In GEO BON Open Science Conference & All Hands Meeting. 4th -8th July 2016, Leipzig, Germany.

Short biography

Kalkidan Ayele was born in Addis Ababa, Ethiopia on 04 May 1988. She attended her primary and secondary education at the Meskaye Hizunan Medhanialemon Monastery school in Addis Ababa. She joined the school of social sciences, Addis Ababa University in 2006 for her bachelor degree program, majoring in geography and environmental studies, and minoring in demography, which she completed in 2008.

In 2009, Kalkidan joined the photogrammetry department of the Ethiopian mapping agency as a mapping expert. She worked on several projects until 2011 when she moved to The Netherlands for pursuing her MSc in Geo-information and Remote Sensing in Wageningen University. During her thesis and internship phase, her interest in the application of remote sensing for forest-based climate change mitigation actions excelled. This led her to work with the World Wildlife Fund Netherlands (WWF-NL) for her internship, and with Center for International Forestry Research (CIFOR) as a consultant, and later to join the Ethiopian national REDD+ task force after completing her MSc study in 2013.

Kalkidan worked as a researcher and trainer in Ethiopian mapping agency before returning back to Wageningen in 2015 for starting her PhD in the investigation of “emerging technologies for biodiversity assessment of changing tropical forests” with the Laboratory of Geo-information and Remote Sensing. During the period of her PhD research, she conducted field works in Kafa Ethiopia, collaborated with national and international multidisciplinary experts, wrote scientific papers, and presented her work on international conferences.

Kalkidan’s professional and research interest lays in the conservation and sustainable utilization of natural resources. In addition, she is motivated in mobilizing scholars and experts for contributing to the design and implementation of developmental projects that have societal impacts.

PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)



Review of literature (6 ECTS)

- Biodiversity monitoring in changing tropical forests: a review of approaches and new opportunities (2017)

Writing of project proposal (4.5 ECTS)

- Integrating satellite time-series, terrestrial laser scanning and genomics technologies for the monitoring of biodiversity changes in degrading tropical forest environments, Kafa, Ethiopia

Post-graduate courses (7.5 ECTS)

- Spatial sampling for mapping; PE&RC (2015)
- Introduction to R for statistical analysis; PE&RC (2015)
- Multivariate analysis course; PE&RC and SENSE (2016)
- Spring metabarcoding school; Kunming University (2016)
- Thematic school in “Remote sensing for tropical biodiversity mapping and management across scales”; CEBA (2017)
- Geostatistics; PE&RC and SENSE (2018)

Laboratory training and working visits (1.5 ECTS)

PE&RC Training and Education Statement

- DNA metabarcoding; University of Kunming, China (2016)

Invited review of (unpublished) journal manuscript (1 ECTS)

- Forests: mount Taishan forest ecosystem health assessment based on forest inventory data and remote sensing images (2019)

Competence strengthening / skills courses (4 ECTS)

- Techniques of writing and presenting a scientific paper; WGS (2016)
- Reviewing scientific papers; WGS (2016)
- Career orientation; WGS (2019)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.8 ECTS)

- PE&RC Mid years weekend (2015)
- PE&RC Day (2016)
- PE&RC Last years weekend (2018)

Discussion groups / local seminars / other scientific meetings (4.6 ECTS)

- Ecological theory and application (2015-2017)
- GIS/rs Group meeting (2015-2019)
- Agriculture–climate-forests-food (2015-2019)
- R-users (2017-2019)
- Landscape dynamics (2018)

International symposia, workshops and conferences (6.3 ECTS)

- GEO BON Open science conference (2016)
- ForestSAT Conference: entering a new era in forest observation and analysis (2018)
- NCG Symposium (2018).

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