Sokoine University Of Agriculture

MSc. Dissertation

Large-Scale Estimation and Mapping of Forest Biodiversity Indicators and Ecological Threats in the West Usambara Montane Forests

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MAY 2024

LARGE-SCALE ESTIMATION AND MAPPING OF FOREST BIODIVERSITY INDICATORS AND ECOLOGICAL THREATS IN THE WEST USAMBARA MONTANE FORESTS

This dissertation is submitted in fulfilment of the requirements for the Master Degree of Science in Forestry to Sokoine University of Agriculture, Morogoro

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May 2024

EXTENDED ABSTRACT

Assessment of the indicators of forest biodiversity, such as tree species diversity, evenness, and richness, is crucial for monitoring and managing forest ecosystems. Quantifying the relationship between environmental factors, such as topography, soil, and climate, and tree species diversity and distribution is also critical for understanding the pattern of the indicators of forest biodiversity and informing conservation efforts.

Various studies have therefore, shown that environmental factors can significantly influence tree species diversity and distribution in forest ecosystems, with topography and soil moisture being important predictors of forest structure and species richness. Such factors have also been used to develop models for large scale predictions under different environmental conditions. However, in the recent decades, remote sensing based had been considered to be as one among the tools for facilitating the assessment of tree species diversity and distribution patterns across large areas of dense montane tropical forests. By modelling the relationship between remotely sensed data and tree species diversity, these techniques can help identify priority areas for conservation and guide management strategies. Furthermore, remotely sensed based techniques had useful in assessing ecological threats such as wildfire which essentially play a significant role in shaping the structure and composition of tropical forests.

This thesis consists of three manuscripts that assessed indicators of forest biodiversity in the West Usambara montane forests of Tanzania. The first manuscript aimed to determine the role of environmental factors on tree species composition and diversity in the West Usambara montane forests. The field data were collected through a two-phase systematic sampling approach, and environmental data were obtained from USGS, ISRIC, and NCCS for topographic, soil and climate respectively. The second manuscript aimed to assess the potential use of remotely sensed data to model and monitor forest biodiversity in the study area. The study computed field diversity, predicted diversity using GAM and XGBoost models for Sentinel 2 and PlanetScope imagery, and compared the efficiency of the sensors and models. The third manuscript aimed at studying the post fire recovery of forest composition and structure. It assessed the difference in structure and composition between burnt and unburnt areas and lastly burnt area mapping was conducted.

The results grouped the 183 identified tree species into three distinct forest communities using cluster analysis. Indicator species analysis identified species significantly associated with each community, like *Dombeya burgessiae* in the higher elevation community. Environmental data on climate, soil properties, and topography were compiled. Canonical correspondence analysis revealed variables like precipitation, soil nitrogen, and elevation were influential in driving community patterns. The communities differed significantly in diversity and richness, with greater values in lower elevation communities. Species turnover linked to environmental gradients was the primary contributor to beta diversity. Overall, the study highlighted the importance of multi-scale abiotic factors in shaping tropical montane forest communities. The findings have implications for ecological monitoring and conservation efforts in these biodiverse yet threatened ecosystems. An integrated assessment of climate, edaphic, and topographic variables is therefore key to understanding the environmental forces structuring tree communities and diversity in tropical montane systems.

Combining field-based approaches and remote sensing techniques provides valuable insights into the factors that influence tree species diversity and distribution in West Usambara Montane forests. The results highlight the strong influence of soil factors such as pH and nitrogen on tree diversity and distribution, while also demonstrating the potential of remote sensing data, particularly PlanetScope data, for assessing and estimating forest biodiversity indicators. The study recommends that conservation efforts should prioritize areas showing low tree species diversity and take into account the influence of environmental factors such as soil properties. The use of remote sensing techniques can facilitate the identification of these priority areas and guide management strategies. Additionally, further research is needed to explore the potential of other remote sensing data sources and models to improve the accuracy and reliability of biodiversity assessments.

Forest fires play a significant role in the diversity and composition patterns in the tropical montane forests. It is therefore important to understand the manner through which these ecosystems are affected by forest fires together with their recovery patterns. From this study, it was observed that while fire did not significantly alter overall tree species composition, it did reduce structural parameters like density, basal area, biomass, and diversity compared to unburned forest. However, these structural attributes exhibited recovery and increased with time since fire. Indicator species analysis identified unique taxa in burned areas. A 14-variable model integrating spectral, textural, and vegetation indices was used to map ~ 1430 ha of burned forest. The study demonstrated the resilience of tropical montane forest composition to fire disturbance, although more work is needed to fully understand post-fire dynamics and long-term recovery. Overall, the study highlights the utility of integrating field measurements and satellite data for assessing fire impacts in tropical ecosystems.

IKISIRI KUU

Tathmini ya viashiria vya bioanuai ya msitu, kama vile utofauti wa spishi za miti, usawa wao Pamoja na wingi wao ni muhimu katika ufuatiliaji na udhibiti wa mifumo ya kiikolojia ya misitu. Kukadiria uhusiano kati ya vipengele vya mazingira, kama vile topografia, udongo, na tabia ya nchi, na utofauti pamoja na ueneaji wa spishi za miti pia ni muhimu kwa ajili ya kuelewa muundo wa viashiria vya mifumo ya bioanuwai ya misitu na kufahamisha juhudi za uhifadhi.

Tafiti mbalimbali zimeonyesha kuwa vipengele vya mazingira vinaweza kuathiri kwa kiasi kikubwa aina na ueneaji wa spishi za miti katika mifumo ya misitu, ambapo topografia na unyevu wa udongo ni muhimu katika kuunda muundo wa msitu na wingi wa spishi. Vipengele kama hivyo pia vimekuwa vikitumika kutengeneza modeli (mifano) kwa ajili ya utabiri wa kipimo kikubwa chini ya hali tofauti za mazingira. Hata hivyo, katika miongo ya hivi karibuni, teknolojia za matumizi ya vihisi vya mbali zimekuwa zikizingatiwa kama moja ya zana za kusaidia katika tathmini ya aina na ueneaji wa spishi za miti katika maeneo makubwa ya misitu ya kitropiki ya milimani yenye misitu minene. Kwa kutengeneza modeli za uhusiano kati ya data zinazochunguzwa na vihisi mbali na aina za miti, njia hizi zinaweza kusaidia kutambua maeneo muhimu kwa uhifadhi na kuelekeza mikakati ya usimamizi. Zaidi ya hayo, njia zinazotumia vihisi mbali pia zimekuwa na manufaa katika kutathmini tishio la mazingira kama vile moto wa porini ambao kwa kiasi kikubwa umekua ukiathiri muundo wa misitu ya kitropiki.

Andiko hili lina jumla ya makala tatu zilizochunguza viashiria vya bioanuai ya msitu katika misitu ya milima ya Usambara Magharibi nchini Tanzania. Makala ya kwanza ililenga kujua jinsi vipengele vya mazingira vinavyoathiri muundo na utofauti wa spishi za miti katika misitu ya milima ya Usambara Magharibi. Data ya misitu kupitia njia za upimaji zifanyikazo ardhini ilikusanywa kwa njia ya sampuli ya mpangilio wa hatua mbili, na data ya mazingira ilipatikana kutoka USGS, ISRIC, na NCCS kwa data ya topografia, udongo, na hali ya hewa mtawalia. Makala ya pili ililenga kutathmini uwezo wa teknolojia ya vihisi mbali katika kumodeli, kukadiria na kufuatilia bioanuai ya misitu katika eneo la utafiti. Utafiti ulikokotoa utofauti wa spishi za miti kwa kutumia data ya misituni, ulitabiri utofauti kwa kutumia modeli ya GAM na XGBoost kwa kutumia picha za Satelaiti za Sentinel-2 na PlanetScope, na kulinganisha ufanisi wa kifaa cha kuhisi na modeli. Makala ya tatu ililenga kuchunguza urejesho baada ya moto kwenye utofauti wa spishi na muundo wa msitu. Ilichunguza tofauti kati ya maeneo

yaliyoungua na yale ambayo hayakuungua moto, na pia ilifanya upimaji na kutengenuza ramani kwa eneo lililoungua moto.

Matokeo yaligawanya aina 183 za miti zilizotambuliwa katika jamii tatu tofauti za msitu kwa kutumia uchambuzi wa vikundi. Uchambuzi wa viashiria ulitambua aina za miti zilizo na uhusiano mkubwa na kila jamii, kama vile *Dombeya burgessiae* katika jamii ya eneo lenye mwinuko wa juu. Data ya mazingira kuhusu hali ya hewa, sifa za udongo, na topografia ilikusanywa. Uchambuzi wa kutoa taarifa ya kanoni ulifunua kuwa vipengele kama mvua, nitrojeni ya udongo, na mwinuko wa ardhi vilikuwa na athari katika kuendesha muundo wa jamii za mimea. Jamii hizo zilitofautiana sana katika utofauti na wingi, na nyingi kati ya hizo zikipatikana zaidi katika jamii za eneo lenye mwinuko wa chini. Mabadiliko ya aina za mimea yaliyohusiana na matabaka ya mazingira yalikuwa mchango mkubwa kwa utofauti wa beta. Kwa ujumla, utafiti huu ulionyesha umuhimu wa vipengele vya mazingira katika kuunda jamii za misitu ya milimani ya kitropiki. Matokeo haya yana athari katika ufuatiliaji wa mazingira na jitihada za uhifadhi katika mifumo hii yenye bioanuai nyingi lakini iliyotishiwa. Uchunguzi wa kina wa hali ya hewa, udongo, na mambo ya topografia ni muhimu kwa kuelewa nguvu za mazingira zinazotengeneza jamii za miti na utofauti katika mifumo ya milima ya kitropiki.

Kuchanganya njia za upimaji zifanyikazo ardhini na mbinu za vihisi mbali hutoa ufahamu muhimu katika mambo yanayoathiri utofauti na ueneaji wa aina za miti katika misitu ya Milima ya Usambara Magharibi. Matokeo yanaonesha ushawishi mkubwa wa vipengele ya udongo kama vile pH na nitrojeni katika utofauti na ueneaji wa miti, wakati pia yakionyesha uwezo wa data za vihisi mbali, hasa data za PlanetScope, katika kutathmini na kupima viashiria vya bioanuai ya misitu. Utafiti unapendekeza kwamba jitihada za uhifadhi zizingatie maeneo yanayoonyesha utofauti mdogo wa spishi za miti na kuzingatia athari za vipengele vya mazingira kama vile sifa za udongo. Matumizi ya teknolojia ya vihisi mbali yanaweza kusaidia kutambua maeneo haya muhimu na kuelekeza mikakati ya usimamizi. Zaidi ya hayo, utafiti zaidi unahitajika kuchunguza uwezekano wa vyanzo vingine vya data za vihisi mbali na modeli ili kuboresha usahihi wa tathmini za bioanuai.

Moto uunguzao misitu una athari kubwa katika utofauti na muundo wa misitu ya milimani ya kitropiki. Hivyo basi, ni muhimu kuelewa jinsi mifumo hii inavyoathiriwa na moto wa misitu pamoja na mifumo yake ya urejesho. Kutoka kwenye utafiti huu, ilibainika kuwa ingawa moto haukubadilisha sana muundo wa jumla wa spishi za miti, ulipunguza vipimo vya kimuundo kama vile wingi, eneo, biomasi, na utofauti ikilinganishwa na msitu ambao haukuungua. Hata hivyo, sifa

hizi za kimuundo zilionyesha urejesho na kuongezeka kwa muda tangu moto ulipotokea. Uchambuzi wa spishi oneshi ulitambua taksa tofauti katika maeneo yaliyoungua na moto. Moleti yenye nyenzo 14 ikiunganisha vipimo vya spektrali, texture, na vipimo vya uoto, ilitumika kutengeneza ramani ya msitu uliochomwa wa takribani hekta 1430. Utafiti huu ulionyesha ustahimilivu wa muundo wa misitu ya milimani ya kitropiki kwa matukio ya moto, ingawa kuna haja ya kufanya kazi zaidi ili kuelewa kabisa mienendo ya baada ya moto na urejesho wa muda mrefu. Kwa ujumla, utafiti huu unasisitiza umuhimu wa kuunganisha njia za upimaji zifanyikazo ardhini na data za satelaiti katika kutathmini athari za moto katika mifumo ya kitropiki.

DECLARATION

I, **DIANA LAWRENCE TESHA**, do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

Diana L. Tesha Date
(MSc. Candidate)

The above is confirmed by;

Dr. Ernest W. Mauya Date
(Supervisor)

Prof. Salim M. S. Maliondo Date
(Supervisor)

LIST OF PAPERS

Paper 1: Role of Topography, Soil and Climate on Forest Species Composition and Diversity in the West Usambara Montane Forests of Tanzania

Paper 2: Modelling and Mapping Forest Biodiversity of Indicators Using Sentinel-2 and PlanetScope Remotely Sensed Data

Paper 3: Post-Fire Assessment of Recovery of Montane Forest Composition and Structure Using In-Situ Measurements and Remote Sensing Data

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ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to God Almighty, who made this research possible through His grace and mercy. I am grateful for His guidance and blessings, which kept me focused and motivated throughout the research process.

I sincerely appreciate the Eastern Arc Mountain Conservation Endowment Fund (EAMCEF), Tanzania Forest Fund (TaFF), and RMCRD/GMES and Africa grant for providing financial support. Their funding enabled field data collection, data analysis, manuscript publications, and thesis writing, which were crucial for completing this research. Their generous funding enabled me to collect the necessary forest inventory data, which formed the backbone of this research.

I would also like to acknowledge the immense contribution of my supervisor, Dr. Ernest W. Mauya, and co-supervisor, Prof. Salim M. S. Maliondo. Their guidance and supervision were invaluable in shaping the direction and scope of my research. Their knowledge and experience in the field of forest ecology and remote sensing were essential in ensuring the accuracy and reliability of the research findings. I am grateful for their unwavering support and encouragement, which kept me motivated and focused throughout the project. In addition, I would like to express my gratitude to Mr. Sami Madundo, who provided invaluable assistance in the statistical analysis of the data. His expertise and knowledge were crucial in analysing the large datasets and producing meaningful results. I am grateful for his support and the contribution he made to the research.

Finally, I would like to thank my parents Mr & Mrs Tesha, colleagues and friends who provided invaluable support and encouragement throughout the research process. Their feedback and insights were essential in shaping the direction and scope of the research. I am grateful for their support and the valuable contributions throughout the study.

DEDICATION

I dedicate this work to my dear parents Mr. & Mrs. Tesha together with my supervisor and mentor Dr. Ernest W. Mauya.

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LIST OF ABBREVIATIONS, ACRONYMS AND SYMBOLS

AGB	–	Above-ground biomass
ANOSIM	–	Analysis of Similarity
AP	–	Annual Precipitation
CCA	–	Canonical Correspondence Analysis
con	–	"contrast" texture metric
DBH	–	Diameter at Breast Height
EAM	–	Eastern Arc Mountains
ESA	–	European Space Agency
G	–	Basal area
GAM	–	Generalized Additive Model
GLCM	–	Grey Level Co-Occurrence Matrix
GLM	–	Generalized Linear Model
H'	–	Shannon-Weiner diversity index
IQR	–	Inter-Quartile Range
ISA	–	Indicator Species Analysis
J	–	Species evenness (Pielous evenness)
MAE	–	Mean Absolute Error
MDR	–	Mean Diurnal Range
mea	–	"mean" texture metric
N	–	Soil Nitrogen
NFR	–	Nature Forest Reserve
NMDS	–	Non-metric Multi-Dimensional Scaling
PH	–	Soil pH
ppm	–	parts per million
PS	–	PlanetScope
PWM	–	Precipitation in Wettest Month
R^2	–	Coefficient of Determination
RE	–	Relative efficiency
RFE	–	Recursive Feature Elimination
rRMSE	–	relative Root-Mean-Square Error
S	–	Species richness
S-2	–	Sentinel-2
TMF	–	Tropical Montane Forests
TWI	–	Topographical Wetness Index
var	–	"variance" texture metric
VSURF	–	Variable Selection Under Random Forests
XGB	–	eXtreme Gradient Boosting

CHAPTER 1

1.0 GENERAL INTRODUCTION

1.1 Background Information

Tropical forests are complex and dynamic ecosystems which provide a wide range of ecological, economic, and social benefits (Baskent et al., 2020). An example of such tropical forests include the Usambara montane forests located within the Eastern Arc Mountains of Tanzania which in turn are a globally significant biodiversity hotspot that host a large number of endemic plant and animal species (Bowie et al., 2023). The benefits offered by these ecosystems include water regulation, soil stabilization, nutrient cycling, carbon sequestration, and climate change mitigation (Rahman et al., 2021). Due to the vast amounts of benefits offered by these ecosystems, it is important to conserve their ecological values. However, despite the benefits obtained from forest ecosystems including those in the tropical mountains, they are under threat from deforestation, land-use change, wild fires and climate change, which can greatly influence their ecosystems functions (Abera et al., 2021).

In order to be able to properly conserve forest ecosystems, correct and timely forest biodiversity monitoring techniques need to be applied. Correct biodiversity assessment allows understanding of the ecosystem dynamics such as species distribution and diversity. Additionally, timely assessment of forest biodiversity provides room to study the temporal changes of forest ecosystems in response to environmental and anthropogenic factors. Mauya (2021) and Brin et al. (2009) have shown that it is impossible to directly measure forest biodiversity and therefore suggest the use of indicators of forest biodiversity such as species richness and species diversity indices as a comprehensive method for assessment of biodiversity as they can correctly describe biodiversity characteristics of forest communities. The indicators of forest biodiversity can be used for purposes such as reporting on the state of forest ecosystem (Winter et al., 2011), checking on the national achievements on multilateral environmental agreements such as the CBD (Danielsen et al., 2014), identifying priority areas and components of forest biodiversity for effective conservation (Lindenmayer et al., 2000), and evaluating the impacts of particular policies and decisions on ecosystems conservation (Rondeux & Sanchez, 2010).

To better understand and monitor forest biodiversity indicators (for this case species diversity and composition), it is essential to investigate the environmental factors that influence them and to develop effective methods for estimating and mapping them (Wang & Gamon, 2019). Environmental factors such as climate, topography, and soil play a key role in shaping forest communities (Ouyang et al., 2021), as they determine the biotic and abiotic conditions that support different plant and animal species. For example, climate influences the distribution and productivity of plant species, while topography affects the microclimate and soil properties that influence plant growth and nutrient availability (Lolila et al., 2023). Soil characteristics such as pH, texture, and nutrient content also play a key role in determining the species composition and diversity of forest ecosystems.

Traditional forests inventories have been the major method used in the assessment of forest biodiversity indicators (Winter et al., 2011) and have been known to produce reliable results although the method is considered to be resources consuming (time, money, and human resources) also it is a tiresome procedure. The advancement of satellite remote sensing technology has transformed approaches to monitoring natural and human resources on the Earth's surface, and this technology allows for the monitoring of large areas (Gyamfi-Ampadu et al., 2021). Observation of forest change requires fine resolution optical images which can now be acquired by multiple satellite platforms with a variety of temporal frequencies ranging from 26 to 5 days depending on the satellite(Cui et al., 2022).

Sentinel-2 is among the sensors used in studying the indicators of forest biodiversity whose high adoption can be attributed to its higher spatial resolution (10 m) than other medium spatial resolution satellite images, high temporal resolution of 5 days, and the availability of the red-edge bands with multiple applications specific for vegetation (Drusch et al., 2012). Another satellite is PlanetScope which is composed of Nanosatellites known as doves which are approximately 10 x 10 x 30 cm and are equipped with a relatively simple multi-spectral camera that acquires data in four bands in the visible and Near Infra-Red channels (between 455 and 860 nm). The satellite is equipped with an unprecedented combination of 3-m spatial resolution and 1-day temporal resolution representing a crucial technological advance for developing near-real-time remote sensing systems. With the improved spatial and temporal resolutions together with higher coverage area, Planet Scope data is showing promising potential for efficient mapping of indicators of forest biodiversity.

Despite the potential of remotely sensed data, particularly Sentinel-2 and Planet Scope data for forest biodiversity assessment and monitoring, their applicability in the tropical forests of Tanzania is limited. Therefore, this study intends to address this knowledge gap, and generate empirical evidence on the suitability of Sentinel2 and Planet Scope for large-scale estimation and mapping together with its usefulness in accurate species distribution modelling of indicators of biodiversity in the montane forests of West Usambara in Tanzania. The study also aims on studying the influence of environmental factors such as topography, climate and soil in shaping the tree species community's composition and distribution.

1.2 Problem Statement and Justification

The WUMFs are amongst the oldest and most bio-diverse forests on earth with the high richness of flora and fauna attributed to both biophysical and climatic conditions present in the area (J. C. Lovett, 1998). The forests offer a wide array of forest-based products and services including water for the surrounding villages, ecotourism, and hydropower to the distant cities. Irrespective of their biological and social-economic importance, WUMFs had experienced historically high rates of ecosystem disturbances caused by illegal logging, fire, land degradation, and loss of biodiversity (Conte, 1999). Because of such threats, several conservation efforts had been done since earlier 1990s to rescue the conservation status of the WUMFs. Among others include the designations of some of these forest reserves as nature reserves and heritage stages. All these efforts are accompanied by strict conservation management strategies which may support high rates of ecosystem recovery.

Despite such efforts, there is limited detailed quantitative information on the current status of indicators of forest biodiversity, their interactions with climatic, soil and topographical factors at different spatial and temporal scales together with the level of threats posed by ecological disturbance and the recovery trajectories. Furthermore, the existing information documented in different studies has mostly focused on the in-situ measurements of a few field plots, which cannot provide accurate temporal and spatial information on the indicators of forest biodiversity and fire occurrence patterns. Based on this premise, there is a need to swiftly identify affordable, timely, and readily-available data sets, together with robust data processing techniques, for the accurate retrieval of indicators of forest biodiversity in the WUMFs.

The advancement in remote sensing technologies provides one of the promising primary-data sources or methods urgently required for improving large-scale estimation and mapping of indicators of forest biodiversity and ecological threats. The introduction of Sentinel-2 together with Planet Scope satellites has once again transformed the potential of earth observation technology to contribute to spatially explicit forest biodiversity mapping and monitoring. Sentinel-2 provides multispectral information with a 5-day revisit cycle, along with a spatial resolution of up to 10 m, offering the potential to incorporate temporal–seasonal information in the biodiversity modelling process (Alleaume *et al.*, 2018). Planet Scope, on the other hand, has a shorter revisit time (1 day) together with a 4.77 m per pixel post-processing resolution which enables better studying of forest ecosystems (Mauya and Madundo, 2022). However, to date, there is no study in Tanzania, particularly in the UTMFS which has attempted to use Sentinel and Planet Scope data for quantification of indicators of forest biodiversity and ecological threats especially forest fires. This study, therefore, intends to address this knowledge gap.

This study has generated information on key indicators of biodiversity in UTMFs in detailed regional spatial scale, environmental influences, and their associated threats. Such information may support further conservation planning in the area. The information has additionally brought understanding on the impact of the imposed management strategies on ecosystem recovery as well as reporting to different subsidiary international bodies such as Conversion on Biological Diversity, the United Nations Sustainable Development Goals, as well as the programme on Reducing Emissions from Deforestation and Forest Degradation commonly (REDD+). The findings of this study have enabled the creation, application, and transferability of ecosystem models. This study has also provided information on the efficiency of remote sensing in mapping the forest's biodiversity indicators and assessing the threats facing forest ecosystems.

1.3 Objectives

1.3.1 Main objective

The overall objective of this study was to comprehensively understand the ecological dynamics of the West Usambara Montane Forests of Tanzania by investigating the influence of environmental factors (topography, soil, and climate), assessing the potential of remote sensing techniques for biodiversity assessment, and examining the post-fire recovery of forest composition and structure.

1.3.2 Specific objectives

The specific objectives of this study were as follows:

1. To investigate the influence of topography, soil characteristics, and climatic variables on the composition and diversity of forest species in the West Usambara Montane Forests of Tanzania.
2. To assess the effectiveness and accuracy of remote sensing techniques, specifically PlanetScope and Sentinel-2, in estimating and mapping indicators of biodiversity within the West Usambara Montane Forests.
3. To evaluate the post-fire recovery process of montane forest composition and structure in the West Usambara Montane Forests through the combined analysis of in-situ measurements and remote sensing data.

1.4 Limitations of the Study

In light of the overall findings, it is important to consider the potential limitations of this study including aspects such as data collection, sample size, and the chosen statistical analysis techniques. For instance, the limitations in data collection methods, such as potential constraints in the selection of environmental variables, could have influenced the accuracy and completeness of the dataset. Additionally, the relatively modest sample size in Magamba forest nature reserve, determined based on practical constraints and available resources, may have impacted the extent to which the identified variables explain the observed variation in species composition and diversity patterns. Furthermore, the chosen statistical analysis techniques, while appropriate for our study objectives, may have inherent assumptions or limitations that could affect the precision or generalizability of our findings.

1.5 Dissertation Structure

This dissertation is divided into five chapters and structured as a series of publishable manuscripts. The first chapter provides an introduction to the study, including background information, problem statement, study objectives, and limitations. Chapter Two is on the role of topography, soil, and climate on forest species composition and diversity. Chapter Three focuses on the potential of remote sensing techniques in estimating and mapping indicators of forest biodiversity. Chapter Four addressing post-fire recovery of montane forest composition and structure using in-situ measurements and remote sensing data. Chapter Five presents a general discussion of the study's findings, and Chapter Six provides a summary of the key contributions, conclusions, and recommendations for future research.

CHAPTER 2

PAPER ONE

2.0 Role of Topography, Soil and Climate on Forest Species Composition and Diversity in the West Usambara Montane Forests of Tanzania[1]

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Abstract

Understanding the variables that determine the variation in forest species composition and diversity in tropical montane systems remains a topic for discussion in plant ecology. This is especially true in areas where the topography is complex and forests are vulnerable to human activity. In this study, a set of topographic, soil, and climatic variables was used to determine their effects on the composition and diversity patterns of two forests in the West Usambara Mountains (Tanzania). Two-phase systematic sampling was used to collect vegetation data from 159 sample plots distributed across the forests. An agglomerative hierarchical clustering method was used for forest community classification, and indicator species analysis was used to determine the species significantly associated with forest communities. The influence of environmental variables on forest communities was analysed canonical correspondence analysis (CCA). Finally, we evaluated diversity patterns by comparing diversity indices (Shannon-Wiener diversity index, evenness, and richness) and beta diversity processes. In total, 7,767 individual trees belonged to 183 species, 132 genera, and 66 families. We found that (i) the forests of West Usambara can be divided into three different forest communities; (ii) each forest community has a

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[1] The material contained in this chapter has been published in **Folia Oecoligica**.

specific set of topographical, soil, and climate variables; (iii) there are significant differences in Shannon diversity and richness indices between communities; and (iv) community composition is mostly influenced by species turnover than by species nestedness. Our study revealed the importance of considering a set of environmental variables related to climate, soil, and topography to understand the variation in the composition and diversity of forest communities in tropical montane forests.

Keywords

Beta diversity; Canonical correspondence analysis (CCA); Indicator species; Species richness; Tropical mountains

2.1 Introduction

Tropical montane forests (TMFs) are important components of global biodiversity hotspots (Mata-Guel et al., 2023). They are characterized by their unique composition of flora and fauna, complex ecological interactions, and high levels of endemism (Brambach et al., 2017). TMFs occur at elevations between 1000 and 4000 m above sea level in tropical regions worldwide, where they represent a critical resource for local communities and significantly contribute to global carbon storage (Iwashita et al., 2013; Spracklen & Righelato, 2014). The ecological complexity of TMFs is attributed to a combination of factors including topographic heterogeneity (Jiang et al., 2023), climatic variability (Trew & Maclean, 2021), and high levels of endemism (Nery et al., 2023). These factors create a mosaic of microhabitats, each with distinct biotic and abiotic conditions, resulting in high levels of diversity and endemism at multiple scales (Noguerales et al., 2021; Tietje et al., 2022). The unique environmental conditions in TMFs have also led to the evolution of specialized species and communities, making them important sites for studying speciation and evolutionary processes (Trew & Maclean, 2021; Vasconcelos et al., 2022).

However, understanding the environmental variables that influence forest composition and diversity in TMFs remains a topic of discussion in plant ecology (Diogo et al., 2021; Hai et al., 2021; Hofhansl et al., 2020). Multiscale factors are thought to be important for determining forest composition and diversity patterns across these forests (Barczyk et al., 2023). Regional (e.g., climate) and local factors, such as topography and soil, are important drivers of forest composition and diversity in montane forests (Homeier & Leuschner, 2021; T. Li et al., 2020). For example, topography creates a wide range of microclimates that influence the distribution and abundance of various plant species (Macek et al., 2019; Oldfather & Ackerly, 2019). Soil type and chemistry also play critical roles in shaping the composition of TMFs, with different plant species adapted to specific soil types and their associated nutrient cycles (Dantas de Paula et al., 2021).

In addition to these factors, climate variability is a critical driver of forest composition and diversity in TMFs (Boyle et al., 2021), and is expected to become increasingly important in the face of ongoing climate change (Ntirugulirwa et al., 2022). Climate change is projected to result in warmer temperatures and altered precipitation patterns in tropical regions, leading to changes in moisture availability and nutrient cycling, which will have cascading effects on TMFs (Veintimilla et al., 2019). Therefore, it is important to understand how TMFs respond and adapt to changing climatic conditions, and how these changes may affect forest composition and diversity in the future (Salinas et al., 2021).

Although previous studies have explored the influence of individual environmental variables on montane forest composition and diversity (Báez et al., 2022; Bunyan et al., 2015; Fahey et al., 2016; Homeier, 2010; Lakkana et al., 2002; Lippok et al., 2014; D. S. Rawat et al., 2020; Takyu et al., 2002; C. Zhang et al., 2016), there is a lack of comprehensive research that incorporates the interactive effects of climate, soil, and topography. The Eastern Arc Mountain forests are biodiversity hotspots, renowned for their species richness, endemism, and unique ecological characteristics (Dimitrov et al., 2012; Yessoufou et al., 2012). Within the Eastern Arc Mountain forests, the West Usambara Montane Forests offer an ideal setting for ecological research, with diverse forest communities and a wealth of endemic species (Huang et al., 2003; Rodgers & Homewood, 1982; Tallents et al., 2005). The West Usambara Montane Forests provide a condensed yet representative ecosystem within the Eastern Arc Mountain forests, making them an excellent study site for investigating the influences of climate, soil, and topography on forest composition and diversity. Therefore, this study aims to address this research gap by focusing on the West Usambara mountain forests and pursuing the following objectives: 1) to identify different forest communities in the study area, 2) to evaluate the influences of topography, soil, and climate on forest community composition, and 3) to determine the patterns of alpha diversity between forest communities and the underlying processes contributing to the beta diversity of these communities. It is important to note that this study intentionally excluded human disturbance as a factor in isolating the specific effects of abiotic factors. By focusing solely on climate, soil, and topography, we aimed to gain a clearer understanding of the natural drivers shaping forest composition and diversity in the absence of human-induced influences. This approach allowed us to assess the direct impacts of abiotic factors on the West Usambara mountain forests and provide valuable insights into their ecological dynamics and conservation needs.

2.2 Methodology

2.2.1 Study area

The West Usambara Montane Forests are located mainly in the Lushoto District, with a smaller area in the Korogwe District in Tanzania. These forests are confined to the Usambara Mountains, which consist of two highland blocks: East Usambara rising up to 1,484 m and West Usambara rising to nearly 2,294 m. These blocks are part of the Eastern Arc Mountains (EAMs), a group of isolated mountains stretching from Southeast Kenya to the Makambako Gap in south-central Tanzania (Fig 1). The study was carried out in two forests, the Magamba Nature Forest Reserve (MNFR) and the Shagayu Forest Reserve (SFR) (Fig. 2.1), both located in the West Usambara Mountain block. The MNFR, covering an area of 9,283 ha, is situated at 4°40 s and 38°15'E, with an altitude ranging from 1,650 to 2,300 m above sea level, a mean annual rainfall of 1,200 mm per year, and an annual temperature ranging from 15 °C to 30 °C. The SFR, with an area of 7,830 ha and is located at 4°31'0"S and 38°16'59"E, has an elevation of approximately 2,098 m asl and a mean annual rainfall of 1,000 mm per year (Lovett, 1996).

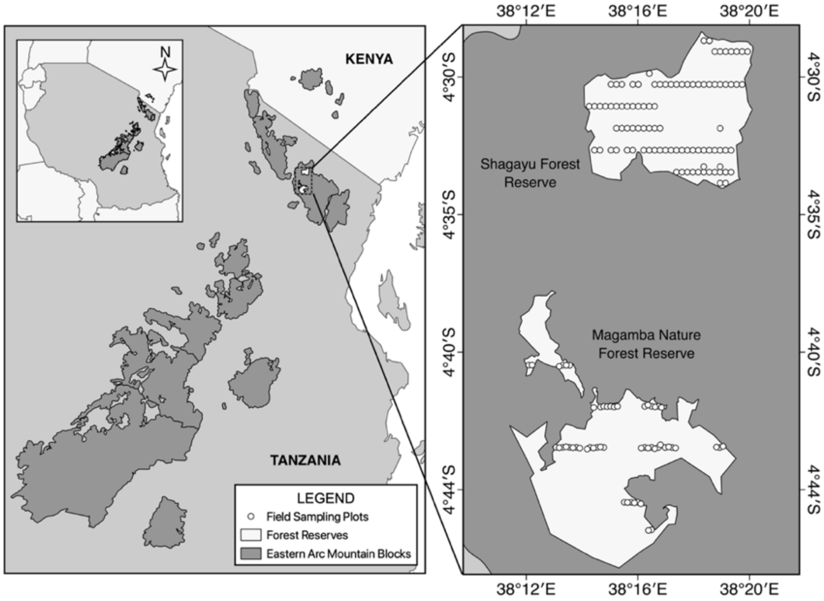

Figure 2.1: Shagayu forest (7,830 ha) and Magamba nature forest reserves (9,283 ha) and their localizations within the Eastern Arc Mountains of Tanzania.

2.2.2 Vegetation sampling and plant identification

A two-phase, systematic sampling design was used in this study. Grids (225 × 450 m in the MNFR and 350 × 700 m in the SFR) were established during the first phase, with each intersection being a sampling plot. During the field expedition, second-phase plots were selected for accessibility. A total of 159 circular field-sampling plots (radius = 15 m) were established across both forests (MNFR = 55; SFR = 105). In each plot, individual trees with a diameter at breast height (DBH) ≥ 5 cm were recorded and identified at the species level. The geographical location and elevation were also recorded using a handheld GPS (Garmin 73). For data collection, only trees were measured, whereas other plants, such as climbers, shrubs, and herbs, were excluded.

2.2.3 Environmental data

A total of 28 environmental variables, representing topographic (4), climate (19), and soil (5) variables, were used to determine the linkage between species composition and diversity as explanatory variables (Supplementary Table A1). Apart from elevation, the other topographical variables (slope, aspect, and topographic wetness index) were derived from a digital elevation model downloaded from https://glovis.usgs.com. The bioclimatic variables were extracted from global high resolution (~ 1 km^2) database https://www.worldclim.org. High resolution (~ 250 m) soil variables were downloaded from https://www.soilgrids.org. Pearson's correlation coefficient (r) and variance inflation factor (VIF) were used to assess collinearity between environmental variables. In cases of high collinearity ($r \geq 0.7$, VIF ≥10), the environmental variable that showed a greater relationship with the explanatory variable was retained (Lolila et al., 2023).

2.2.4 Statistical analyses

All statistical analyses were carried out using R v.4.2.1 (Team, 2022). Species area curves were generated using the R package 'biodiversityR' (Kindt & Kindt, 2023), following the method proposed by (Preston, 1962). In this study, species area curves were used to examine the relationship between sampling effort and number of species found in each forest. To classify the recorded tree species and sampling sites into different forest communities, we used agglomerative hierarchical clustering analysis with the Ward linkage method. The optimal number of forest communities was determined using a consensus-based algorithm carried out with the 'parameters' package (Lüdecke et al., 2023). Tree species that were significantly associated with the sampling plots for each forest community were identified using indicator species analysis via the 'indicspecies' package (De Caceres et al., 2014). The DCA analysis indicated that the data is heterogeneous in both study sites, as evidenced by an axis length exceeding 4.0. Consequently, Canonical Correspondence Analysis (CCA) was employed to assess the impact of environmental factors on the distribution of indicator tree species within each forest community (Quinn & Keough, 2002; Lolila et al., 2023). Canonical correspondence analysis ordination (CCA) was then conducted using matrices of species biomass and retained environmental variables to investigate the influence of environmental variables on indicator tree species distribution in each forest community. Stepwise forward selection was performed during the CCA ordination to identify significant environmental variables, which was carried out using the 'vegan' package (Oksanen et al., 2008). The Kruskal-Wallis test was used to assess differences in environmental variables across the three forest communities. This non-parametric test was appropriate for our data as it did not meet the assumptions of normality and equal variances. The test was followed by post-hoc analysis using Dunn's test, which allowed for the identification of significant differences within communities.

Alpha diversity indices, particularly the Shannon diversity index (H) (Shannon & Weaver, 1964), species richness (S), and evenness (J) (Pielou, 1966), were also calculated for each forest community using the 'vegan' package in R (Oksanen et al., 2008). These metrics were used to compare the alpha diversity among the three forest communities. The use of these indices is important, as they provide a comprehensive understanding of the diversity within each forest community and can be used to compare diversity between different communities. To compare the diversity indices evaluated among the three communities, generalized linear models (GLM) were conducted with a Gaussian error distribution, except for species richness, in which a Poisson distribution was used. Pairwise comparisons among forest communities were conducted with estimated marginal means using the package 'emmeans' (Lenth et al., 2018). Additionally, we partitioned the Bray-Curtis coefficient (beta diversity, β) into two measurements to test if any of the forest communities are distinct in terms of species turnover (β_{turn}) and nestedness (β_{nest}) (Baselga, 2013) using the 'betapart' package (Baselga & Orme, 2012). These results were used to infer whether the differences in species composition were due to the segregation of different species in different forest communities (turnover) or because one forest community had only a smaller amount of the same species as the other (nestedness). Therefore, if all forest communities have a large number of niche-specialist tree species, a higher β_{turn} is expected. In contrast, when most of the tree species in a forest community are generalists (e.g., found across other forest communities), a higher β_{nest} is expected.

2.3 Results

2.3.1 Sampling effort and forest communities

Data on 7,767 individual trees belonging to 183 species, 132 genera, and 66 families were recorded across both forests. In Shagayu FR, 130 species from 108 genera and 59 families were recorded, whereas in the Magamba NFR, there were a total of 113 species belonging to 89 genera and 53 families. The species area curve (Fig. 2.2) showed that the maximum tree species richness was under-sampled for the Magamba NFR and adequately sampled for the Shagayu FR. It also revealed that the species richness for Shagayu FR reached the asymptote, whereas for Magamba NFR, the species richness was close to the asymptote.

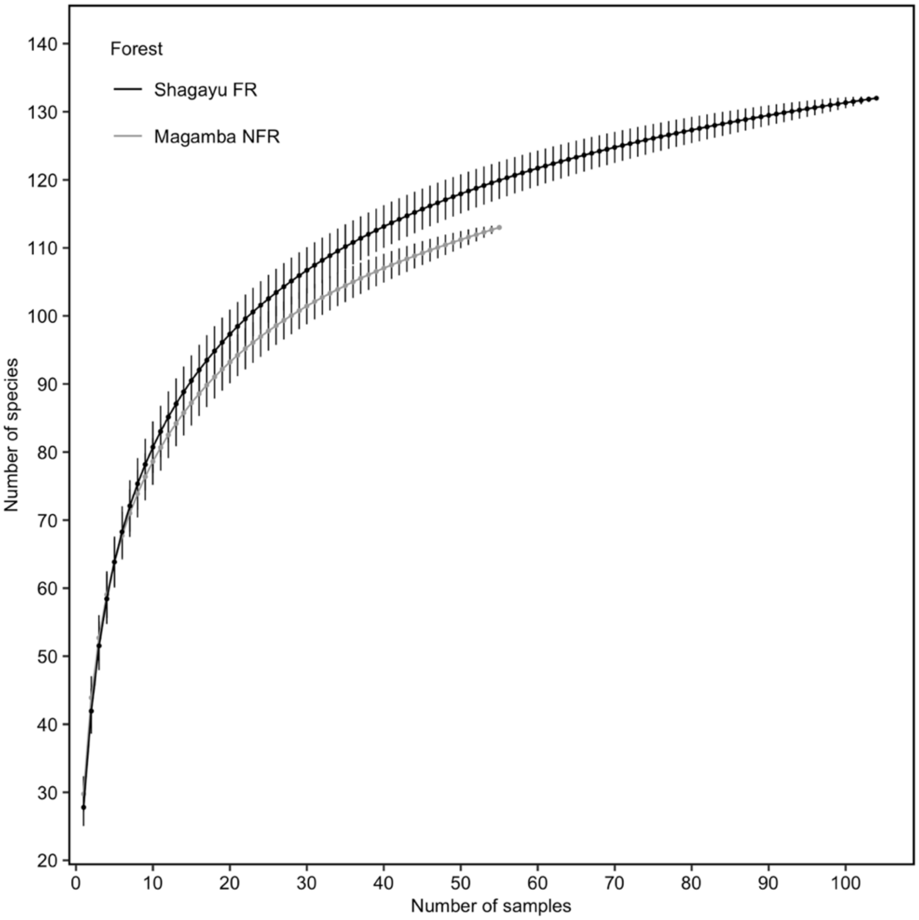

Figure 2.2: Species accumulation curves for Shagayu and Magamba forest reserves. The curves depict the expected number of species as a function of sampled area, with the upper and lower bounds representing the 95% confidence intervals.

Three forest communities were identified and described using agglomerative hierarchical clustering analysis (Fig. 2.3). A total of 62 indicator species were identified in the present study. Forest communities were named based on the two most important tree species that occurred in the forest community, using their indicator value (IV) (Table A2). The three forest communities identified were *Dombeya burgessiae-Cussonia spicata* (DC), *Aphloia theiformis-Syzygium cordatum* (AS), and *Newtonia buchananii-Parinari excelsa* (NP) (Fig. 2.3).

D. burgessiae-C. spicata (DC) community: This forest community is distributed between 1,734-2,103 m asl. It is represented by 42 plots and has the lowest number of significant indicator species associated with the community (14). *Dombeya burgessiae* Gerrard ex Harv., *Cussonia spicata* Thunb., *Bersama abyssinica* Fresen., *Maesa lanceolata* Forssk, and *Nuxia floribunda* Benth. were the five most dominant indicator species.

A. theiformis-S. cordatum (AS) community: This forest community is distributed over a wider elevation range of 1,683-2,105 m asl, showing a large overlap with that of DC. This community was the largest with 84 plots and was represented by the highest number of significant indicator species (29). Species indicative of this community include *Aphloia theiformis* (Vahl) Benn. And *Syzygium cordatum* Hochst. ex Krauss, *Macaranga kilimandscharica* Pax, *Lasianthus kilimandscharicus* K.Schum., and *Ocotea usambarensis* Engl.

N. buchananii-P. excelsa (NP) forest community: This forest community is distributed in the lowest elevation ranges of 1,425-1,883 m asl. It was the smallest of all communities and was represented by 33 plots and 19 indicator species. Species representative of this community are: *Newtonia buchananii* (Baker) G. C. C. Gilbert & Boutiqu, *Parinari excelsa* Sabine, *Sorindeia madagascariensis* Thouars ex DC., *Leptonychia usambarensis* K. Schum., and *Mimusops kummel* Bruce ex A. DC.

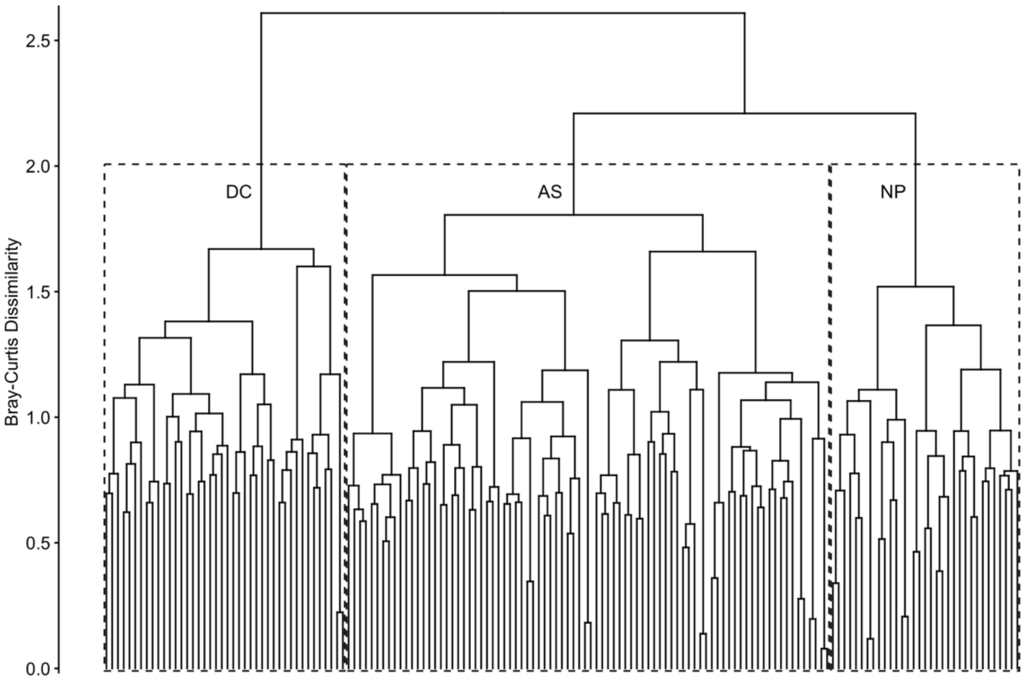

Figure 2.3: Hierarchical dendrogram expressing forest communities as a result of clustering analysis. Dashed rectangles indicate the forest communities. DC: *Dombeyaburgessiae-Cussoniaspicata*, AS: *Aphloiatheiformis-Syzygiumcordatum*, NP: *Newtoniabuchananii-Parinariexcelsa*.

2.3.2 Forest communities and associated environmental variables

Constrained ordination using canonical correspondence analysis (CCA) grouped all sites in a similar manner as in the cluster analysis (Fig. 2.4). The ordination diagram formed a set of linkages among different forest communities, along with environmental variables. The variables that were retained after performing the collinearity test with a VIF < 10 included topographical, soil, and climate variables, particularly elevation (E), soil nitrogen (N), precipitation in the wettest month (PWM), annual precipitation (AP), topographic wetness index (TWI), soil pH (PH), and (MDR). The CCA1 and CCA2 axes accounted for 2.74% and 2.10% of the variance, respectively, explained by these significant environmental variables. The results showed that the DC forest community was significantly ($P < 0.001$) associated with E, N, and MDR. The AS community was significantly associated with N and PWM, whereas the NP community was significantly associated with TWI and AP.

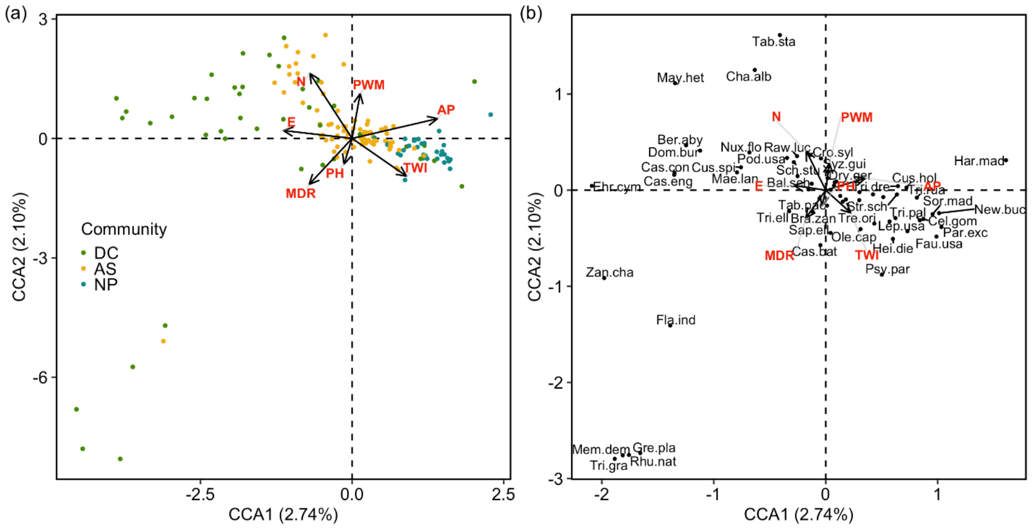

Figure 2.4: Canonical correspondence analysis (CCA) ordination diagram showing (a) relationship between environmental variables (elevation [E], soil nitrogen [N], precipitation in wettest month [PWM], annual precipitation [AP], topographic wetness index [TWI], soil pH [PH], and mean diurnal range [MDR]) and forest communities and (b) relationship between environmental variables on indicator tree species distribution in the three forest communities: *Dombeyaburgessiae-Cussoniaspicata* (DC), *Aphloiatheiformis-Syzygiumcordatum* (AS), *Newtoniabuchananii-Parinariexcelsa* (NP). Tree species abbreviations are listed in Table A2.

All environmental variables (E, N, PWM, AP, TWI, PH, and MDR) differed significantly among forest communities ($p < 0.05$).The DC community had the highest elevation, N, and MDR values, followed in rank order by the AS and NP communities. In contrast, AP and TWI were the highest in the NP community, lowest in DC, and intermediate in AS. Trends in PH were similar to those in N; however, the values were similar in the AS and NP communities. The AS community had the highest PWM, followed by the DC and NP communities, in rank order (Table 2.1).

Table 2.1. Environmental variable measures (median ± IQR) in each forest community their differences: Different lowercase letters in rows indicate significantly different medians (Kruskal-Wallis, $p < 0.05$) for elevation (E, metres above sea level m), soil nitrogen (N, ppm), precipitation in wettest month (PWM, mm), annual precipitation (AP, mm), topographic wetness index (TWI, unitless), soil pH (pH, unitless), and mean diurnal range (MDR, °C).

Environmental variable	Forest community			p-value
	DC	AS	NP	
E	1,918.0^{a}± 183.5	1,893.5^{a}± 211.0	1,654.0^{b}± 229.0	<0.001
N	2.49^{a}± 0.66	2.46^{a}± 0.55	1.97^{b}± 0.24	<0.001
PWM	171.0^{ab}± 16.00	175.0^{a}± 15.25	165.0^{b}± 9.00	0.006
AP	919.5^{a}± 75.75	952.0^{b}± 68.00	997.0^{c}± 43.00	<0.001
TWI	9.01^{a}± 0.90	9.45^{b}± 0.85	9.62^{c}± 0.46	0.007
PH	5.45^{a}± 0.20	5.30^{b}± 0.30	5.30^{b}± 0.10	<0.001
MDR	9.56^{a}± 0.32	9.43^{b}± 0.32	9.35^{b}± 0.22	0.006

Forest communities include: *Dombeya burgessiae-Cussonia spicata* (DC), *Aphloia theoformis-Syzygium cordatum* (AS), and *Newtonia buchananii-Parinari excelsa* (NP).

2.3.3 Species diversity and pattern

Among the three diversity indices, only Shannon diversity (GLM $\chi^2 = 6.72$, df = 2, $p < 0.05$) and species richness (GLM $\chi^2 = 134.39$, df = 2, $p < 0.001$) were found to be significantly different between forest communities. However, evenness showed no significant differences between forest communities (GLM $\chi^2 = 0.08$, df = 2, p-value > 0.05) (Fig. 2.5). Shannon diversity was highest in AS (1.79 ± 0.11), followed by NP (1.65 ± 0.165), and lowest in DC (1.34 ± 0.15) (Fig. 2.5a). *D. burgessiae-C. spicata* community showed a species evenness of (0.66 ± 0.044), followed by AS (0.66± 0.03), and finally (0.60 ± 0.05) (Fig. 2.5b). Finally, NP had the highest species richness (16.11 ± 1.37), followed by AS (15.95 ± 0.87) and DC (8.59± 0.89) respectively (Fig. 2.5c).

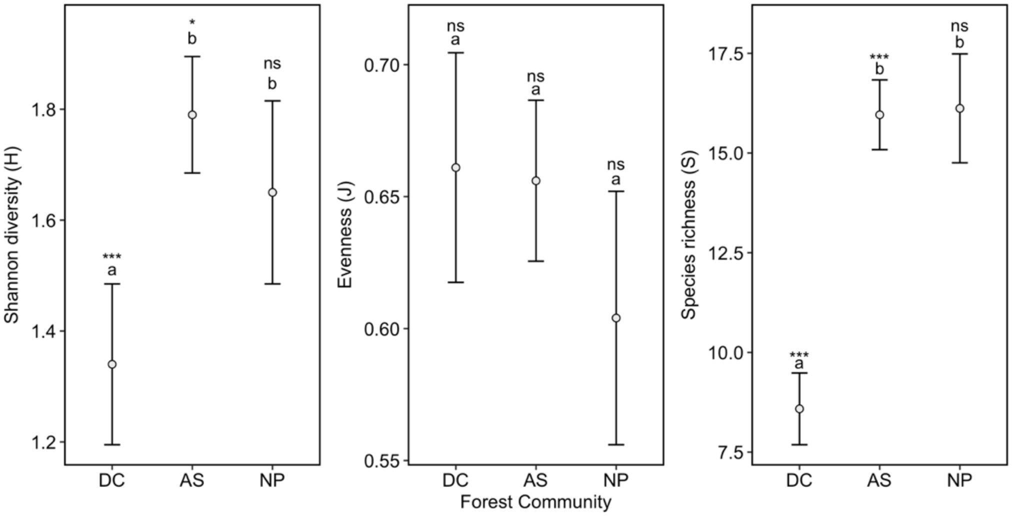

Figure 2.5: Variation of alpha diversity indices between the three forest communities of the West Usambara montane forests. Figures represent the diversity index mean (circle) and 95% confidence interval (error bars). Lowercase letters indicate group differences by an estimated marginal mean. DC: *Dombeya burgessiae-Cussonia spicata*, AS: *Aphloia theoformis-Syzygium cordatum*, NP: *Newtonia bucchananii-Parinari excelsa*.
Note: *p*- value: (GLM) with a Gaussian error distribution for Shannon's diversity index and species evenness, Poisson distribution for species richness: $^*p < 0.05$, $^{***}p < 0.001$.

The results of beta diversity partitioning showed that beta diversity was mainly contributed by species turnover in all three forest communities. Based on the Bray-Curtis dissimilarity index of each community, species turnover contributed 89% (DC), 78% (AS), and 75% (NP) of the beta diversity, respectively. Species nestedness, on the other hand, contributed only 6% (DC), 8% (AS), and 9% (NP) of the beta diversity, respectively (Table 2.2). This indicates that the differences between forest communities is mostly represented by specialist tree species instead of generalist tree species.

Table 2.2. Beta diversity partitioning results for three forest communities based on Bray-Curtis dissimilarity index.

Community	Beta diversity (β)	Turnover (β_{turn})	Nestedness (β_{nest})
DC	0.948	0.889	0.059
AS	0.858	0.783	0.075
NP	0.832	0.747	0.085

2.4 Discussion

2.4.1 Forest communities and associated environmental variables

This study classified Shagayu and Magamba forests into three communities corresponding to a combination of different environmental variables. This demonstrated the role of different environmental variables in the dispersion of these forest communities. Similar findings have been reported in other tropical forests (Latt & Park, 2022; Lolila et al., 2023; Rawat & Negi, 2021); these differences might be due to the unique environmental conditions in each community (Thakur et al., 2022).

The results from the canonical correspondence analysis showed that soil, topographic, and climate variables together played a significant role in determining species composition in montane forests. For example, CCA identified that the DC and AS forest communities had relatively higher levels of soil nitrogen than NP. Additionally, the AS and NP communities had relatively lower soil pH than DC, indicating that site conditions are important in determining the constitution and distribution of tropical forest communities (Sagar et al., 2003). These findings are further supported by those of (Lolila et al., 2023), in which soil pH significantly influenced the composition of forest communities in subtropical montane forests of north-eastern Tanzania.

Topographical variables, particularly elevation and topographic wetness index (TWI), were important variables influencing the species composition of the DC and NP communities at the study sites. The TWI measures the ability of the terrain to retain moisture, which can influence soil moisture and nutrient availability (Kopecký & Čížková, 2010). In general, areas with higher TWI values tended to have wetter soils, which can support a higher diversity of plant species. In tropical ecosystems, the importance of elevation and TWI, as observed in this study, is consistent with known morphological and hydrological landscape factors, which often create distinct forest types (Baldeck et al., 2016; Blanchard et al., 2019; Muscarella et al., 2020).

Additionally, the mean diurnal range (MDR), annual precipitation (AP), and precipitation during the wettest month (PWM) have been shown to significantly influence forest communities. Mean diurnal range is an important factor in determining temperature fluctuations within a given area (Braganza et al., 2004), whereas AP and PWM are important indicators of moisture availability (Li et al., 2016). Several studies have reported on the influence of climatic variables on forest communities. For example, the diurnal temperature range has been found to have a significant influence on the composition of tropical forest communities, despite the narrow annual and diurnal temperature range in the tropics (Punyasena et al., 2008). Similar to our findings, Bhatta et al. (2021) and Nettesheim et al. (2018) documented the influence of AP and PWM in shaping forest composition, with higher values of these variables favouring hygrophytic species growth.

2.4.2 Species diversity pattern

Diversity indices are essential tools for evaluating forest community dynamics and for understanding species diversity patterns (Rubio et al., 2011; Zhao et al., 2022). The results of this study showed that among the three diversity indices measured (Shannon diversity, species richness, and evenness), only Shannon diversity and species richness were significantly different between forest communities, with evenness showing no significant differences. These results indicate that patterns of tree species diversity are related to both large-scale (climate) and small-scale variables (topography and soil), which together determine assemblages of local communities and distribution of species in the forests. The variation in species diversity and richness might be due to the spatial heterogeneity of habitats within forests (Vleminckx et al., 2015; Wiegand et al., 2017). Shannon diversity and richness were the highest in the lower elevation forest communities (AS and NP), which is in line with previous studies that found higher diversity in lower elevation forests (Sharma et al., 2017; Thakur et al., 2022). The low species diversity and richness of the higher-elevation DC forest community could be attributed to harsh environmental conditions that cause physiological stress to the plants (i.e., lower temperature and precipitation), limiting plant growth and regeneration (Zhang et al., 2016).

The finding that species turnover was the main driver of beta diversity in all three forest communities suggests that environmental factors play a crucial role in shaping the forest community composition (Murphy et al., 2016). The strong species-environment relationships observed in this study highlight the importance of considering environmental variables, such as climate, soil nutrients, and topography, when studying forest diversity. These findings are consistent with previous studies that have shown species turnover to be the primary contributor to beta diversity in forest communities (Haq et al., 2021; Murphy et al., 2015; Rahman et al., 2022).

2.5 Conclusion

In conclusion, our study sheds light on the ecological characteristics and diversity patterns of tropical montane forests in the West Usambara Mountains. Our findings provide valuable insights into the conservation and management of these ecosystems by identifying distinct forest communities and the factors driving their composition. The observed differences in the diversity and richness indices between communities highlight the importance of considering local environmental factors when assessing and monitoring biodiversity. Furthermore, the dominance of species turnover over nestedness in shaping community composition underscores the need for conservation efforts that focus on preserving the entire range of species in these forests. Overall, our study contributes to a better understanding of the complex interactions between environmental factors and biodiversity patterns in tropical montane forests, and provides a foundation for future research and conservation efforts in this globally significant biodiversity hotspot.

Conflict of Interest

The authors declare no conflicts of interest.

Acknowledgements

The authors would like to express their gratitude to the Eastern Arc Mountain Conservation Endowment Fund (EAMCEF) for providing financial support for the collection of forest inventory data through their project entitled "Meta-Analysis of Forest Carbon Information Using Existing Data and Remote Sensing Techniques". Also, the authors would like to express their gratitude to Tanzania Forest Fund together with RMCRD/GMES and Africa grant for their financial assistance which aided data acquisition both for field and remote sensing data, data cleaning and analysis together with the manuscript writing and publication.

Author Contributions

DLT conceptualized the study, developed the methodology, curated the data, conducted formal analysis, and wrote the original draft. EWM supervised the study, contributed to the conceptualization and methodology, and reviewed and edited the manuscript. SDM conducted the formal analysis, created the visualizations, and wrote the original draft. CJE supervised, reviewed, and edited the manuscript.

Data Availability Statement

The data used were primarily reflected in this study. Other relevant data and codes are available upon request.

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References

Báez, S., Fadrique, B., Feeley, K., & Homeier, J. (2022). Changes in tree functional composition across topographic gradients and through time in a tropical montane forest. *PLoS ONE*, *17*(4 April), 1–20. https://doi.org/10.1371/journal.pone.0263508

Baldeck, C. A., Tupayachi, R., Sinca, F., Jaramillo, N., & Asner, G. P. (2016). Environmental drivers of tree community turnover in western Amazonian forests. *Ecography*, *39*(11), 1089–1099. https://doi.org/10.1111/ecog.01575

Barczyk, M. K., Acosta-Rojas, D. C., Espinosa, C. I., Schleuning, M., & Neuschulz, E. L. (2023). Biotic pressures and environmental heterogeneity shape beta-diversity of seedling communities in tropical montane forests. *Ecography*, 1–11. https://doi.org/10.1111/ecog.06538

Baselga, A. (2013). Separating the two components of abundance-based dissimilarity: Balanced changes in abundance vs. Abundance gradients. *Methods in Ecology and Evolution*, *4*(6), 552–557. https://doi.org/10.1111/2041-210X.12029

Baselga, A., & Orme, C. D. L. (2012). betapart: An R package for the study of beta diversity. *Methods in Ecology and Evolution*, *3*(5), 808–812. https://doi.org/10.1111/j.2041-210X.2012.00224.x

Bhatta, K. P., Aryal, A., Baral, H., Khanal, S., Acharya, A. K., Phomphakdy, C., & Dorji, R. (2021). Forest structure and composition under contrasting precipitation regimes in the high mountains, western nepal. *Sustainability (Switzerland)*, *13*(13). https://doi.org/10.3390/su13137510

Blanchard, G., Munoz, F., Ibanez, T., Hequet, V., Vandrot, H., Girardi, J., & Birnbaum, P. (2019). Regional rainfall and local topography jointly drive tree community assembly in lowland tropical forests of New Caledonia. *Journal of Vegetation Science*, *30*(5), 845–856. https://doi.org/10.1111/jvs.12781

Boyle, M. J. W., Bishop, T. R., Luke, S. H., van Breugel, M., Evans, T. A., Pfeifer, M., Fayle, T. M., Hardwick, S. R., Lane-Shaw, R. I., Yusah, K. M., Ashford, I. C. R., Ashford, O. S., Garnett, E., Turner, E. C., Wilkinson, C. L., Chung, A. Y. C., & Ewers, R. M. (2021). Localised climate change defines ant communities in human-modified tropical landscapes. *Functional Ecology*, *35*(5), 1094–1108. https://doi.org/10.1111/1365-2435.13737

Braganza, K., Karoly, D. J., & Arblaster, J. M. (2004). Diurnal temperature range as an index of global climate change during the twentieth century. *Geophysical Research Letters*, *31*(13), 2–5. https://doi.org/10.1029/2004GL019998

Brambach, F., Leuschner, C., Tjoa, A., & Culmsee, H. (2017). Diversity, endemism, and composition of tropical mountain forest communities in Sulawesi, Indonesia, in relation to elevation and soil properties. *Perspectives in Plant Ecology, Evolution and Systematics*, *27*, 68–79. https://doi.org/10.1016/j.ppees.2017.06.003

Bunyan, M., Bardhan, S., Singh, A., & Jose, S. (2015). Effect of topography on the distribution of tropical montane forest fragments: A predictive modelling approach. *Journal of Tropical Forest Science*, *27*(1), 30–38.

Dantas de Paula, M., Forrest, M., Langan, L., Bendix, J., Homeier, J., Velescu, A., Wilcke, W., & Hickler, T. (2021). Nutrient cycling drives plant community trait assembly and ecosystem functioning in a tropical mountain biodiversity hotspot. *New Phytologist*, *232*(2), 551–566. https://doi.org/10.1111/nph.17600

De Caceres, M., Jansen, F., & De Caceres, M. M. (2014). Package ‘indicspecies’. *Indicators*, *8*(1), 1–31.

Dimitrov, D., Nogués-Bravo, D., & Scharff, N. (2012). Why Do Tropical Mountains Support Exceptionally High Biodiversity? The Eastern Arc Mountains and the Drivers of Saintpaulia Diversity. *PLoS ONE*, *7*(11). https://doi.org/10.1371/journal.pone.0048908

Diogo, I. J. S., dos Santos, K., da Costa, I. R., & dos Santos, F. A. M. (2021). Effects of topography and climate on Neotropical mountain forests structure in the semiarid region. *Applied Vegetation Science*, *24*(1). https://doi.org/10.1111/avsc.12527

Fahey, T. J., Sherman, R. E., & Tanner, E. V. J. (2016). Tropical montane cloud forest: Environmental drivers of vegetation structure and ecosystem function. *Journal of Tropical Ecology*, *32*(5), 355–367. https://doi.org/10.1017/S0266467415000176

Hai, N. H., Erfanifard, Y., Bui, V. B., Mai, T. H., Petritan, A. M., & Petritan, I. C. (2021). Topographic effects on the spatial species associations in diverse heterogeneous tropical evergreen forests. *Sustainability (Switzerland)*, *13*(5), 1–14. https://doi.org/10.3390/su13052468

Haq, S. M., Calixto, E. S., & Kumar, M. (2021). Assessing Biodiversity and Productivity over a Small-scale Gradient in the Protected Forests of Indian Western Himalayas. *Journal of Sustainable Forestry*, *40*(7), 675–694. https://doi.org/10.1080/10549811.2020.1803918

Hofhansl, F., Chacón-Madrigal, E., Fuchslueger, L., Jenking, D., Morera-Beita, A., Plutzar, C., Silla, F., Andersen, K. M., Buchs, D. M., Dullinger, S., Fiedler, K., Franklin, O., Hietz, P., Huber, W., Quesada, C. A., Rammig, A., Schrodt, F., Vincent, A. G., Weissenhofer, A., & Wanek, W. (2020). Climatic and edaphic controls over tropical forest diversity and vegetation carbon storage. *Scientific Reports*, *10*(1), 1–11. https://doi.org/10.1038/s41598-020-61868-5

Homeier, J. (2010). The influence of topography on forest structure and regeneration dynamics in an Ecuadorian montane forest. *Tropical Mountain Forest: Patterns and Processes in a Biodiversity Hotspot*, *2*(2008), 97–107.

Homeier, J., & Leuschner, C. (2021). Factors controlling the productivity of tropical Andean forests: Climate and soil are more important than tree diversity. *Biogeosciences*, *18*(4), 1525–1541. https://doi.org/10.5194/bg-18-1525-2021

Huang, W., Pohjonen, V., Johansson, S., Nashanda, M., Katigula, M. I. L., & Luukkanen, O. (2003). Species diversity, forest structure and species composition in Tanzanian tropical forests. *Forest Ecology and Management*, *173*(1–3), 11–24. https://doi.org/10.1016/S0378-1127(01)00820-9

Iwashita, D. K., Litton, C. M., & Giardina, C. P. (2013). Coarse woody debris carbon storage across a mean annual temperature gradient in tropical montane wet forest. *Forest Ecology and Management*, *291*, 336–343. https://doi.org/10.1016/j.foreco.2012.11.043

Jiang, M., Kong, J., Zhang, Z., Hu, J., Qin, Y., Shang, K., Zhao, M., & Zhang, J. (2023). Seeing Trees from Drones: The Role of Leaf Phenology Transition in Mapping Species Distribution in Species-Rich Montane Forests. *Forests*, *14*(5), 908. https://doi.org/10.3390/f14050908

Kindt, R., & Kindt, M. R. (2023). Package ‘BiodiversityR’. Package for community ecology and suitability analysis. *The R Journal*, *2*, 1–12. http://www.worldagroforestry.org/output/tree-diversity-analysis

Kopecký, M., & Čížková, Š. (2010). Using topographic wetness index in vegetation ecology: Does the algorithm matter? *Applied Vegetation Science*, *13*(4), 450–459. https://doi.org/10.1111/j.1654-109X.2010.01083.x

Lakkana, T., Ashton, M. S., Hooper, E. R., Perera, A., & Ediriweera, S. (2002). Tropical montane forest in South Asia: Composition, structure, and dieback in relation to soils and topography. *Ecosphere*, *13*(5), 35–49. https://doi.org/10.1002/ecs2.4049

Latt, M. M., & Park, B. B. (2022). Tree Species Composition and Forest Community Types along Environmental Gradients in Htamanthi Wildlife Sanctuary, Myanmar: Implications for Action Prioritization in Conservation. *Plants*, *11*(16). https://doi.org/10.3390/plants11162180

Lenth, Russel., Love, Jonathon., & Herve, Maxime. (2018). Package ‘emmeans’. *The R Journal*, 1–57. https://doi.org/10.1080/00031305.1980.10483031>.License

Li, G., Du, S., & Wen, Z. (2016). Mapping the climatic suitable habitat of oriental arborvitae (Platycladus orientalis) for introduction and cultivation at a global scale. *Scientific Reports*, *6*(July), 1–9. https://doi.org/10.1038/srep30009

Li, T., Xiong, Q., Luo, P., Zhang, Y., Gu, X., & Lin, B. (2020). Direct and indirect effects of environmental factors, spatial constraints, and functional traits on shaping the plant diversity of montane forests. *Ecology and Evolution*, *10*(1), 557–568. https://doi.org/10.1002/ece3.5931

Lippok, D., Beck, S. G., Renison, D., Hensen, I., Apaza, A. E., & Schleuning, M. (2014). Topography and edge effects are more important than elevation as drivers of vegetation patterns in a neotropical montane forest. *Journal of Vegetation Science*, *25*(3), 724–733. https://doi.org/10.1111/jvs.12132

Lolila, N. J., Shirima, D. D., & Mauya, E. W. (2023a). Tree species composition along environmental and disturbance gradients in tropical sub-montane forests, Tanzania. *PLoS ONE*, *18*(3 March). https://doi.org/10.1371/journal.pone.0282528

Lolila, N. J., Shirima, D. D., & Mauya, E. W. (2023b). Tree species composition along environmental and disturbance gradients in tropical sub-montane forests, Tanzania. *Plos One*, *18*(3), e0282528.

Lovett, J. C. (1996). Elevational and latitudinal changes in tree associations and diversity in the Eastern Arc mountains of Tanzania. *Journal of Tropical Ecology*, *12*(5), 629–650. https://doi.org/10.1017/S0266467400009846

Lüdecke, D., Makowski, D., Ben-Shachar, M. S., Højsgaard, S., & Wiernik, B. M. (2023). Package ‘parameters’. *The R Journal*, 1–194. https://easystats.github.io/parameters/

Macek, M., Kopecký, M., & Wild, J. (2019). Maximum air temperature controlled by landscape topography affects plant species composition in temperate forests. *Landscape Ecology*, *34*(11), 2541–2556. https://doi.org/10.1007/s10980-019-00903-x

Mata-Guel, E. O., Soh, M. C. K., Butler, C. W., Morris, R. J., Razgour, O., & Peh, K. S. H. (2023). Impacts of anthropogenic climate change on tropical montane forests: An appraisal of the evidence. *Biological Reviews*, *6*. https://doi.org/10.1111/brv.12950

Murphy, S. J., Li´, L., Audino, L. D., Whitacre, J., Eck, J. L., Wenzel, J. W., Queenborough, S. A., & Comita, L. S. (2015). Species associations structured by environment and land-use history promote beta-diversity in a temperate forest. *Ecology*, *96*(3), 705–715.

Murphy, S. J., Salpeter, K., & Comita, L. S. (2016). Higher β-diversity observed for herbs over woody plants is driven by stronger habitat filtering in a tropical understory. *Ecology*, *97*(8), 2074–2084. https://doi.org/10.1890/15-1801.1

Muscarella, R., Kolyaie, S., Morton, D. C., Zimmerman, J. K., & Uriarte, M. (2020). Effects of topography on tropical forest structure depend on climate context. *Journal of Ecology*, *108*(1), 145–159. https://doi.org/10.1111/1365-2745.13261

Nery, E. K., Caddah, M. K., Santos, M. F., & Nogueira, A. (2023). The evolution of ecological specialization underlies plant endemism in the Atlantic Forest. *Annals of Botany*, 1–20. https://doi.org/10.1093/aob/mcad029

Nettesheim, F. C., Garbin, M. L., Rajão, P. H. M., Araujo, D. S. D., & Grelle, C. E. V. (2018). Environment is more relevant than spatial structure as a driver of regional variation in tropical tree community richness and composition. *Plant Ecology and Diversity*, *11*(1), 27–40. https://doi.org/10.1080/17550874.2018.1473520

Noguerales, V., Meramveliotakis, E., Castro-Insua, A., Andújar, C., Arribas, P., Creedy, T. J., Overcast, I., Morlon, H., Emerson, B. C., Vogler, A. P., & Papadopoulou, A. (2021). Community metabarcoding reveals the relative role of environmental filtering and spatial processes in metacommunity dynamics of soil microarthropods across a mosaic of montane forests. *Molecular Ecology*, *2*, 1–19. https://doi.org/10.1111/mec.16275

Ntirugulirwa, B., Manishimwe, A., Uddling, J., & Wallin, G. (2022). Contrasting growth and mortality responses of different species lead to shifts in tropical montane tree community composition in a warmer climate. *Biogeosciences*, *March*, 1–39. https://doi.org/10.5194/bg-2023-42

Oksanen, J., Kindt, R., Legendre, P., O'Hara, B., Simpson, G. L., Solymos, P., Henry, M., Stevens, H., & Wagner, H. (2008). The vegan package. *Community Ecology Package*, *2*(9), 1–295.

Oldfather, M. F., & Ackerly, D. D. (2019). Microclimate and demography interact to shape stable population dynamics across the range of an alpine plant. *New Phytologist*, *222*(1), 193–205. https://doi.org/10.1111/nph.15565

Pielou, E. C. (1966). The measurement of diversity in different types of biological collections. *Journal of Theoretical Biology*, *13*(C), 131–144. https://doi.org/10.1016/0022-5193(66)90013-0

Preston, F. W. (1962). The Canonical Distribution of Commonness and Rarity: Part I. *Ecology*, *43*(2), 185–215.

Punyasena, S. W., Eshel, G., & McElwain, J. C. (2008). The influence of climate on the spatial patterning of Neotropical plant families. *Journal of Biogeography*, *35*(1), 117–130. https://doi.org/10.1111/j.1365-2699.2007.01773.x

Quinn, G. P., & Keough, M. J. (2002). *Experimental design and data analysis for biologists*. Cambridge university press.

Rahman, I. U., Hart, R. E., Ijaz, F., Afzal, A., Iqbal, Z., Calixto, E. S., Abd-Allah, E. F., Alqarawi, A. A., Hashem, A., Al-Arjani, A. B. F., Kausar, R., & Haq, S. M. (2022). Environmental variables drive plant species composition and distribution in the moist temperate forests of Northwestern Himalaya, Pakistan. *PLoS ONE*, *17*(2 February), 1–27. https://doi.org/10.1371/journal.pone.0260687

Rawat, B., & Negi, A. S. (2021). Plant diversity patterns along environmental gradients in Nanda Devi Biosphere Reserve, West Himalaya. *Tropical Ecology*, *62*(1), 61–70. https://doi.org/10.1007/s42965-020-00122-5

Rawat, D. S., Tiwari, P., Das, S. K., & Tiwari, J. K. (2020). Tree species composition and diversity in montane forests of Garhwal Himalaya in relation to environmental and soil properties. *Journal of Mountain Science*, *17*(12), 3097–3111. https://doi.org/10.1007/s11629-019-5761-8

Rodgers, W. A., & Homewood, K. M. (1982). Species richness and endemism in the Usambara mountain forests, Tanzania. *Biological Journal of the*

Linnean Society, *18*(3), 197–242. https://doi.org/10.1111/j.1095-8312.1982.tb02037.x

Rubio, A., Gavilán, R. G., Montes, F., Gutiérrez-Girón, A., Díaz-Pines, E., & Mezquida, E. T. (2011). Biodiversity measures applied to stand-level management: Can they really be useful? *Ecological Indicators*, *11*(2), 545–556. https://doi.org/10.1016/j.ecolind.2010.07.011

Sagar, R., Raghubanshi, A. S., & Singh, J. S. (2003). Tree species composition, dispersion and diversity along a disturbance gradient in a dry tropical forest region of India. *Forest Ecology and Management*, *186*(1–3), 61–71. https://doi.org/10.1016/S0378-1127(03)00235-4

Salinas, N., Cosio, E. G., Silman, M., Meir, P., Nottingham, A. T., Roman-Cuesta, R. M., & Malhi, Y. (2021). Editorial: Tropical Montane Forests in a Changing Environment. *Frontiers in Plant Science*, *12*(August), 1–5. https://doi.org/10.3389/fpls.2021.712748

Shannon, C. E., & Weaver, W. (1964). The Theory of Mathematical Communication. *International Business*, 131.

Sharma, C. M., Mishra, A. K., Tiwari, O. P., Krishan, R., & Rana, Y. S. (2017). Effect of altitudinal gradients on forest structure and composition on ridge tops in Garhwal Himalaya. *Energy, Ecology and Environment*, *2*(6), 404–417. https://doi.org/10.1007/s40974-017-0067-6

Spracklen, D. V., & Righelato, R. (2014). Tropical montane forests are a larger than expected global carbon store. *Biogeosciences*, *11*(10), 2741–2754. https://doi.org/10.5194/bg-11-2741-2014

Takyu, M., Aiba, S.-I., & Kitayama, K. (2002). Effects of topography on tropical lower montane on Mount Kinabulu, Borneo. *Plant Ecology*, *159*(1), 35–49.

Tallents, L. A., Lovett, J. C., Hall, J. B., & Hamilton, A. C. (2005). Phylogenetic diversity of forest trees in the Usambara mountains of Tanzania: Correlations with altitude. *Botanical Journal of the Linnean Society*, *149*(2), 217–228. https://doi.org/10.1111/j.1095-8339.2005.00431.x

Team, R. C. (2022). R: A Language and Environment for Statistical Computing. *R Foundation for Statistical Computing, Vienna, Austria*. http://www.R-project.org/.

Thakur, S., Negi, V. S., Dhyani, R., Bhatt, I. D., & Yadava, A. K. (2022). Influence of environmental factors on tree species diversity and composition in the Indian western Himalaya. *Forest Ecology and Management*, *503*(October 2021), 119746. https://doi.org/10.1016/j.foreco.2021.119746

Tietje, M., Antonelli, A., Baker, W. J., Govaerts, R., Smith, S. A., & Eiserhardt, W. L. (2022). Global variation in diversification rate and species richness are unlinked in plants. *Proceedings of the National Academy of Sciences*, *119*(27), 1–9. https://doi.org/10.1073/pnas.2120662119

Trew, B. T., & Maclean, I. M. D. (2021). Vulnerability of global biodiversity hotspots to climate change. *Global Ecology and Biogeography*, *30*(4), 768–783. https://doi.org/10.1111/geb.13272

Vasconcelos, T., O'Meara, B. C., & Beaulieu, J. M. (2022). Retiring "Cradles" and "Museums" of Biodiversity. *The American Naturalist*, *199*(2), 194–205. https://doi.org/10.1086/717412

Veintimilla, D., Ngo Bieng, M. A., Delgado, D., Vilchez-Mendoza, S., Zamora, N., & Finegan, B. (2019). Drivers of tropical rainforest composition and alpha diversity patterns over a 2,520 m altitudinal gradient. *Ecology and Evolution*, *9*(10), 5720–5730. https://doi.org/10.1002/ece3.5155

Vleminckx, J., Drouet, T., Amani, C., Lisingo, J., Lejoly, J., & Hardy, O. J. (2015). Impact of fine-scale edaphic heterogeneity on tree species assembly in a central African rainforest. *Journal of Vegetation Science*, *26*(1), 134–144. https://doi.org/10.1111/jvs.12209

Wiegand, T., May, F., Kazmierczak, M., & Huth, A. (2017). What drives the spatial distribution and dynamics of local species richness in tropical forest? *Proceedings of the Royal Society B: Biological Sciences*, *284*(1863). https://doi.org/10.1098/rspb.2017.1503

Yessoufou, K., Daru, B. H., & Davies, T. J. (2012). Phylogenetic Patterns of Extinction Risk in the Eastern Arc Ecosystems, an African Biodiversity Hotspot. *PLoS ONE*, *7*(10). https://doi.org/10.1371/journal.pone.0047082

Zhang, C., Li, X., Chen, L., Xie, G., Liu, C., & Pei, S. (2016). Effects of topographical and edaphic factors on tree community structure and diversity of subtropical mountain forests in the Lower Lancang River Basin. *Forests*, *7*(10). https://doi.org/10.3390/f7100222

Zhang, W., Huang, D., Wang, R., Liu, J., & Du, N. (2016). Altitudinal patterns of species diversity and phylogenetic diversity across temperate mountain forests of northern China. *PLoS ONE*, *11*(7), 1–13. https://doi.org/10.1371/journal.pone.0159995

Zhao, Z., Hui, G., Yang, A., Zhang, G., & Hu, Y. (2022). Assessing tree species diversity in forest ecosystems: A new approach. *Frontiers in Ecology and Evolution*, *10*(October), 1–12. https://doi.org/10.3389/fevo.2022.971585

CHAPTER 3

PAPER TWO

3.0 Modelling and Mapping Indicators of Forest Biodiversity Using Senntinel-2 and PlanetScope Remotely Sensed Data[2]

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Abstract

Tropical montane forests harbour exceptionally high biodiversity yet face severe threats from human activities. Assessing forest biodiversity over large areas is crucial yet extremely challenging. Remote sensing provides an efficient monitoring solution, but few studies have focused on Tanzania's diverse, montane forests. We collected field data on tree species composition within 159 plots across montane forests in Tanzania's West Usambara region. We calculated species richness, evenness, and Shannon diversity index as indicators of tree diversity. Using Sentinel-2 and PlanetScope satellite imagery, we derived spectral, textural, and vegetation index predictors to model these indices via generalized additive models and extreme gradient boosting. PlanetScope-based XGBoost models performed best, explaining 19.7% of variation in Shannon diversity. Incorporating textural predictors further improved model accuracy. Despite inherent challenges in modelling complex tropical forests, our findings demonstrate promising potential of Sentinel-2 and PlanetScope for regional biodiversity monitoring where field surveys are limited. Further research could

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[2] The material contained in this section has published in **Tanzania Journal of Science**.

enhance these initial results by leveraging higher resolution data and increasing field sampling for effective monitoring of tropical biodiversity.

Keywords

Tree species richness, montane forests, textures, GAM, XGBoost

3.1 Introduction

Tropical montane forests including the West Usambara Mountains of Tanzania offer various ecosystem services while harbouring exceptionally high biodiversity. They face severe threats from human activities like agricultural expansion and illegal logging (Arroyo-Rodríguez et al., 2020). In many jurisdictions, public forest authorities are requested to monitor biodiversity and report their management efforts to maintain or improve biodiversity to various bodies (Storch et al. 2023). Such bodies include the Division for Sustainable Development Goals (DSDG), the IUCN's Post-2020 Global Biodiversity Framework (Strategic Plan for Biodiversity 2011–2020), and the United Nations Convention on Biological Diversity (Storch et al. 2023).

Reaching the conservation and protection targets require accurate information on the state of the indicators of forest biodiversity such as species richness, evenness, and diversity at different geographical scales. This is challenging in most tropical montane forest environments, given the large coverage associated with many tree species and dense forests located in less accessible and difficult terrain areas (Beyene et al. 2020). Due to the difficulties, field based assessments are rather difficult, cover limited areas (Mauya et al. 2015) and expensive (Corte et al. 2020, Goodbody et al. 2019) which calls the need for integrating them with remote sensing approaches.

Freely available Sentinel-2 and recently released high-resolution PlanetScope satellite data provide valuable opportunities for forest biodiversity monitoring. Sentinel-2 offers open-access optical imagery with enhanced spectral, spatial, and temporal resolution compared to past sensors (Drusch et al., 2012). PlanetScope likewise captures key spectral bands at very high 4.77 m resolution and monthly revisit rate (Poortinga et al., 2021). Combined capabilities enable modelling ecosystem processes and mapping indicators like tree diversity for conservation support (Potapov et al. 2008, Wang and Gamon 2019).

Extreme gradient boosting (XGBoost) and generalized additive models (GAMs) are two common modelling techniques for leveraging satellite remote sensing data to assess biodiversity. XGBoost is an ensemble method combining multiple decision trees with gradient boosting for high performance prediction. It can handle sparse, complex ecological data and scale efficiently to massive datasets (Schratz et al. 2021). GAMs provide flexible nonlinear regression using data-driven smoothing splines, easily incorporating nonlinear relationships common in ecological systems (Wang and Gamon 2019). When derived vegetation indices, spatial textures, and spectral data serve as predictor variables, these methods show utility for modelling patterns in tree diversity, species composition, habitat heterogeneity and other indicators relevant to conservation planning.

While remote sensing has demonstrated potential for assessing biodiversity in tropical forests globally (Abbas et al. 2020), few studies have focused specifically on the diverse, montane forests of Tanzania. In this study, we demonstrate the applicability of Sentinel-2's spectral resolution and PlanetScope's high revisit frequency for mapping key biodiversity indicators like tree species diversity and habitat heterogeneity across extensive, challenging terrain in the West Usambara Mountains. Therefore, this study specifically aimed to (i) quantify the indicators of forest biodiversity (i.e., species richness, evenness, and Shannon diversity) of the study site, (ii) model and predict the biodiversity indicators using semi-parametric and non-parametric models for Sentinel-2 and PlanetScope data, (iii) create a spatial map for each forest biodiversity indicator, and (iv) assess the gain in precision of each remote sensing data (relative efficiency) compared to that of the field-based inventory alone.

3.2 Materials and Methods

3.2.1 Study sites

Two forests, the Shagayu Forest Reserve (SFR) and Magamba Nature Forest Reserve (MNFR), were selected from the West Usambara Montane forest block. This block is part of a collection of isolated mountains known as the Eastern Arc Mountains (EAMs), which span from southeast Kenya to south-central Tanzania (Fig. 3.1). There are many protected forests within these blocks, including nature and forest reserves, which are recognized as having extreme global biological importance (Burgess et al., 2007). The SFR is positioned at 4° 31' 0" S and 38° 16' 59" E and has an estimated elevation between 1340 and 2150 m above sea level. In comparison, the MNFR is positioned at 4°40' S and 38°15' E, and its altitude varies between 1650 and 2300 m above sea level. West Usambara mountain forests are acknowledged for their copious amounts of precipitation that foster a diverse range of flora and fauna. This area exhibits a bimodal rainfall distribution pattern consisting of two annual rainy seasons. The long rainy season typically starts in March and lasts until May, whereas the short rainy season occurs between October and December (Lovett, 1996).

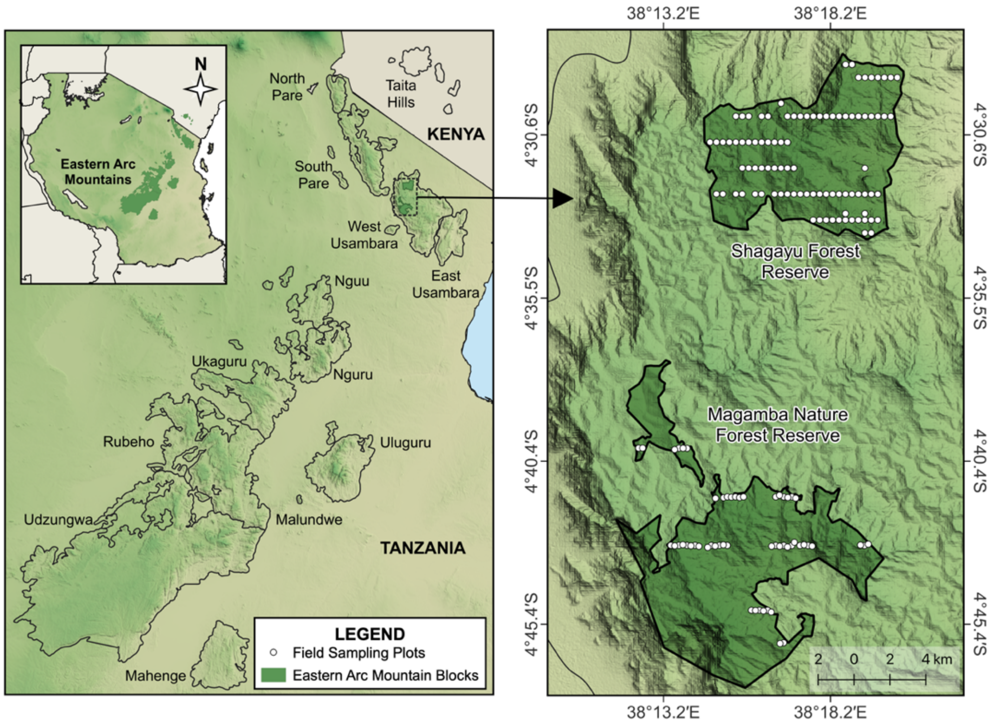

Figure 3.1: Location of the study forests, in the Eastern Arc Mountains of Tanzania.

3.2.2 Sampling design and data collection

A two-phase, systematic sampling design was used in this study. Grids (225 × 450 m in the MNFR and 350 × 700 m in the SFR) were established during the first phase, with each intersection being a sampling plot. During field expedition, second-phase plots were selected for accessibility.

3.2.3 Forest biodiversity indicators

A total of 159 circular field sampling plots (radius = 15 m) were established across both forests (MNFR = 55; SFR = 104). In each plot, individual trees with a diameter at breast height (DBH) ≥ 5 cm were recorded and identified to the species level. The geographical location and elevation were also recorded using a handheld GPS (Garmin 78). Finally, three diversity indices that considered the total number of species and their abundances were computed from the tree species information using the following equations:

(i) Species richness (S), was determined as the total number of unique tree species recorded per sampling plot;

(ii) Pileou's evenness (J), also known as the equitability index, measures the evenness of individual tree species distribution among taxa and was calculated as the ratio between the Shannon diversity index and the logarithm of the species richness (eqn. 1).

$$J = {}^{H}\!/_{\log{(S)}} \tag{1}$$

(iii) The Shannon index (H), which considers the number of individuals and the number of taxa (eqn. 2). Where p_i is the proportion of abundance of each species relative to the total abundance per sampling plot.

$$H = -\sum_{i=1}^{n} p_i \cdot \ln{(p_i)} \tag{2}$$

3.2.4 Remote sensing data, pre-processing, and predictor variables

Two Level 1C Sentinel-2 image tiles (acquired on March 12, 2019, and April 16, 2019) were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home). Level 1C top of the atmosphere (TOA) reflectance data were subsequently processed to Level-2A via the European Space Agency's (ESA) Sen2Cor algorithm (Louis et al., 2016) to acquire bottom of the atmosphere (BOA) reflectance images using the "sen2r" package (Ranghetti et al., 2020). Only the 10 m and 20 m spatial resolution bands were used in this study, and the 20 m bands were resampled to a 10 m resolution using bilinear interpolation (Li et al., 2020) to ensure spatial coherence. Image mosaicking was also performed, because two tiles were required to cover the study sites. PlanetScope imagery were downloaded from https://www.planet.com/basemaps. The imagery did not require pre-processing as it was provided in an analysis-ready form. Therefore, the data were only required to be re-projected to Arc 1960 UTM 37/S along with the pre-processed Sentinel-2 data.

The atmospherically corrected images from each sensor were used to compute the selected vegetation indices (Table B1) using the "RStoolbox" package (Hamzehpour et al., 2019) implemented in the R statistical software. We included five broadband optical vegetation indices and three narrowband indices specific to Sentinel-2 data. Sentinel-2 narrowband indices were utilized to assess the tree diversity modelling capability. Furthermore, the grey level co-occurrence matrix (GLCM) textural metrics 'mean', 'variance' and 'dissimilarity' (Haralick, 1979), were also computed for all the spectral bands and indices, using the "glcm" package (Zvoleff, 2020) in R (Table B2). Texture metrics were computed using a 3 × 3 window for each sensor band and vegetation index.

3.2.5 Statistical analysis

3.2.5.1 Variable selection

To identify key predictors for modelling forest biodiversity indicators, we utilized the variable selection package VSURF (Genuer et al. 2015) in R. This approach leverages the machine learning algorithm random forests to rank predictor importance through an iterative process of creating multiple random models and assessing mean decrease in accuracy when a given variable is excluded. We grouped the top 30 predictors selected by VSURF into four categories: 1) original Sentinel-2 and PlanetScope spectral bands, providing surface reflectance information; 2) derived vegetation indices like NDVI, sensitive to canopy properties; 3) image textures capturing spatial patterns; and 4) all variables (bands, textures and vegetation indices) combined. This allowed comparison of different predictor sets for modelling tree species diversity and other indicators relevant to tropical montane forest conservation. The VSURF selection process identified key spectral bands, indices, and textures related to vegetation characteristics in these complex forest environments.

3.2.5.2 Model development

Semi-parametric and non-parametric statistical modelling approaches were used to estimate tree diversity. Details of each approach are provided below.

Extreme gradient boosting (XGBoost) is a boosting algorithm based on gradient-boosting decision trees and random forest methods. In very large-scale data training, it is a versatile and highly scalable tree-structure enhancement model that can handle sparse data, significantly increase algorithm performance, and reduce computational memory. The R package “xgboost” (Chen & Guestrin, 2016) was used to implement the XGBoost.

The GAMs were fitted for each satellite sensor using a Gaussian error distribution and logarithmic link function to relate plot-level diversity with remote sensing data. This model form is preferred because it offers acceptable estimates when true zeros are present in the tree diversity estimate, which has continuous positive values. The R package “mgcv” (Wood & Wood, 2015) was used to perform the GAM regression. Each predictor variable that entered the model received a smoothing spline with a smoothing parameter, k, of 3.

$$ln(y_i) = b_0 - \sum_{i=1}^{n} f_i(x_i) \tag{3}$$

where y_i is the ground reference diversity index value, b_0 is a constant term (intercept), and $f_i(x_i)(i$ = 1, 2,…, $n)$ is the smoothing function for each independent variable.

Modelling was carried out on the pre-identified predictor variables from both sensors to determine the best model to explain the prediction accuracy of H, S, and J in the study area.

3.2.5.3 Accuracy assessment

To assess the accuracy and generalizability of the models, k-fold cross-validation (k=10) was implemented to facilitate a comprehensive evaluation of model performance and enhance the reliability of the estimated tree diversity indices. Three criteria for model validation and selection were chosen and computed to identify the best models: adjusted coefficient of determination (R^2), mean absolute error (MAE), and relative root-mean-square error (rRMSE). A model was considered to be the best if it had a relatively high R^2 and lower MAE and rRMSE values computed from the predictions of the 10-fold cross-validation, as presented below:

$$R^2 = \frac{(n-1)\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{(n-2)\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

$$rRMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}{n-2}} \tag{6}$$

where $\hat{y}_i$ and y_i are the predicted and observed values for each biodiversity indicator for the i^{th} plot respectively, n is the number of observations, and $\bar{y}$ is observed mean of the respective biodiversity indicator.

3.2.5.4 Relative efficiency

To quantify potential improvements in precision from incorporating remote sensing data, we calculated relative efficiency (RE) as the ratio of variances between estimates with and without satellite data (Eqn 7). Specifically, RE compares the variance of biodiversity indicators estimated using remote sensing data (VAR_{RS}) to the variance using field plot data alone (VAR_{FD}). An RE value greater than 1 indicates the variance is lower (precision is higher) when integrating remote sensing versus using field plots alone. For example, an RE of

2 suggests the satellite-enhanced estimate could achieve the same level of precision as doubling the number of field plots sampled. This metric demonstrates the potential of remote sensing predictors from Sentinel-2 and PlanetScope to reduce uncertainty in biodiversity indicator estimates across landscapes compared to field surveys alone. Higher RE values highlight situations where integrating satellite data can strengthen precision for informing conservation and management decisions in tropical montane forests.

$$RE = VAR_{RS}/VAR_{FD} \tag{7}$$

3.2.6 Diversity mapping

To map biodiversity indicators across the study area, we used the raster package (Hijmans et al. 2013) in R to apply the optimal models to predict each indicator's values for all pixels from the remote sensing data. Specifically, we performed spatial prediction using the highest performing model for each indicator - either linear regression or random forest regression based on accuracy assessment. This generated continuous raster maps representing predicted tree species richness, diversity, and evenness across the landscape. We optimized spatial prediction by leveraging the full coverage and resolution of the Sentinel-2 and PlanetScope datasets through the fitted models. The resulting maps provide visualizations of spatial variability, patterns, and estimated values for key forest biodiversity indicators across inaccessible montane terrain. These high-resolution biodiversity distributions can support conservation planning and monitoring in the region.

3.3 Results

3.3.1 Tree Species diversity

Descriptive statistics of the diversity indices are presented in Table 1. Species richness exhibited an average value of 14 per plot, indicating a relatively diverse species composition within the study area. Evenness, with an average value of 0.84, suggested a balanced distribution of tree species abundance, highlighting a more equitable representation of different taxa. The calculated Shannon diversity index averaged 2.14 per plot, signifying a moderate to high level of overall tree diversity. Overall, Shagayu FR is faring better across all three assessed diversity indices as it has higher species richness, slightly higher evenness, and notably higher Shannon diversity compared to the Magamba NFR. This indicates the tree communities in the Shagayu FR are more diverse and evenly distributed. The lower indices for the Magamba NFR may suggest higher disturbance or threats to biodiversity in that reserve.

Table 3.1: Descriptive statistics of forest biodiversity indicators across the study forests.

Indicator	Forest	n	Minimum	Maximum	Mean ± CI
Shannon	Magamba NFR	55	0.86	2.94	1.94 ± 0.10^{a}
	Shagayu FR	104	0.00	3.11	2.24 ± 0.09^{b}
	Overall	159	0.00	3.11	$2.14 \pm 0.04b^{c}$
Evenness	Magamba NFR	55	0.41	0.97	0.83 ± 0.02^{a}
	Shagayu FR	104	0.10	0.97	0.84 ± 0.02^{a}
	Overall	159	0.10	0.97	0.84 ± 0.01^{a}
Richness	Magamba NFR	55	3	22	11 ± 0.91^{a}
	Shagayu FR	104	1	33	15 ± 0.98^{b}
	Overall	159	1	33	14 ± 0.67^{bc}

Different lowercase letters in rows indicate significantly different means (independent sample t-test, $p < 0.05$). n = number of plots, CI = Confidence interval (95%).

3.3.2 Model performances

Twenty-four (24) models were developed to predict tree species diversity indices using Sentinel-2 and PlanetScope predictor variables. The best model fit for predicting Shannon's diversity index was obtained using the XGBoost statistical approach with PlanetScope texture variables. The model had an R^2 of 0.2, MAE of 18%, and rRMSE of 23.52%. The best model for predicting tree species richness was obtained using the GAM statistical approach with PlanetScope texture variables (R^2 = 0.193, MAE = 30.72%, rRMSE = 38.91%). Tree species evenness was best predicted using the XGBoost model with combined PlanetScope variables (R^2 = 0.115, MAE = 9.2%, rRMSE = 13.8%). Generally, combining all predictor variables (bands, textures, and vegetation indices) for each sensor (i.e., Sentinel-2 and PlanetScope) improved the predictive power of all the models (Fig. 3.2). The selected predictor variables and performance criteria for each model are listed in Table B3.

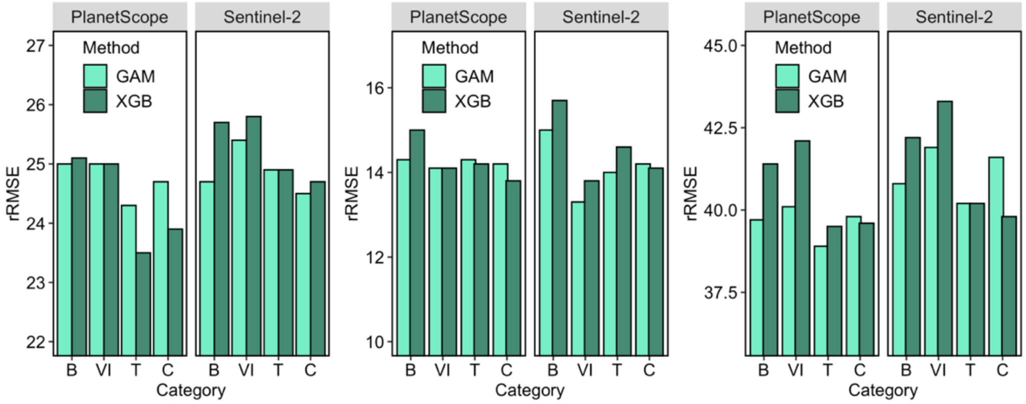

Figure 3.2: Performance of GAM and XGBoost models fitted with predictors from two satellite sensors.

Scatterplots were constructed to further demonstrate the relationship between the observed and predicted indices (Fig. 3.3).

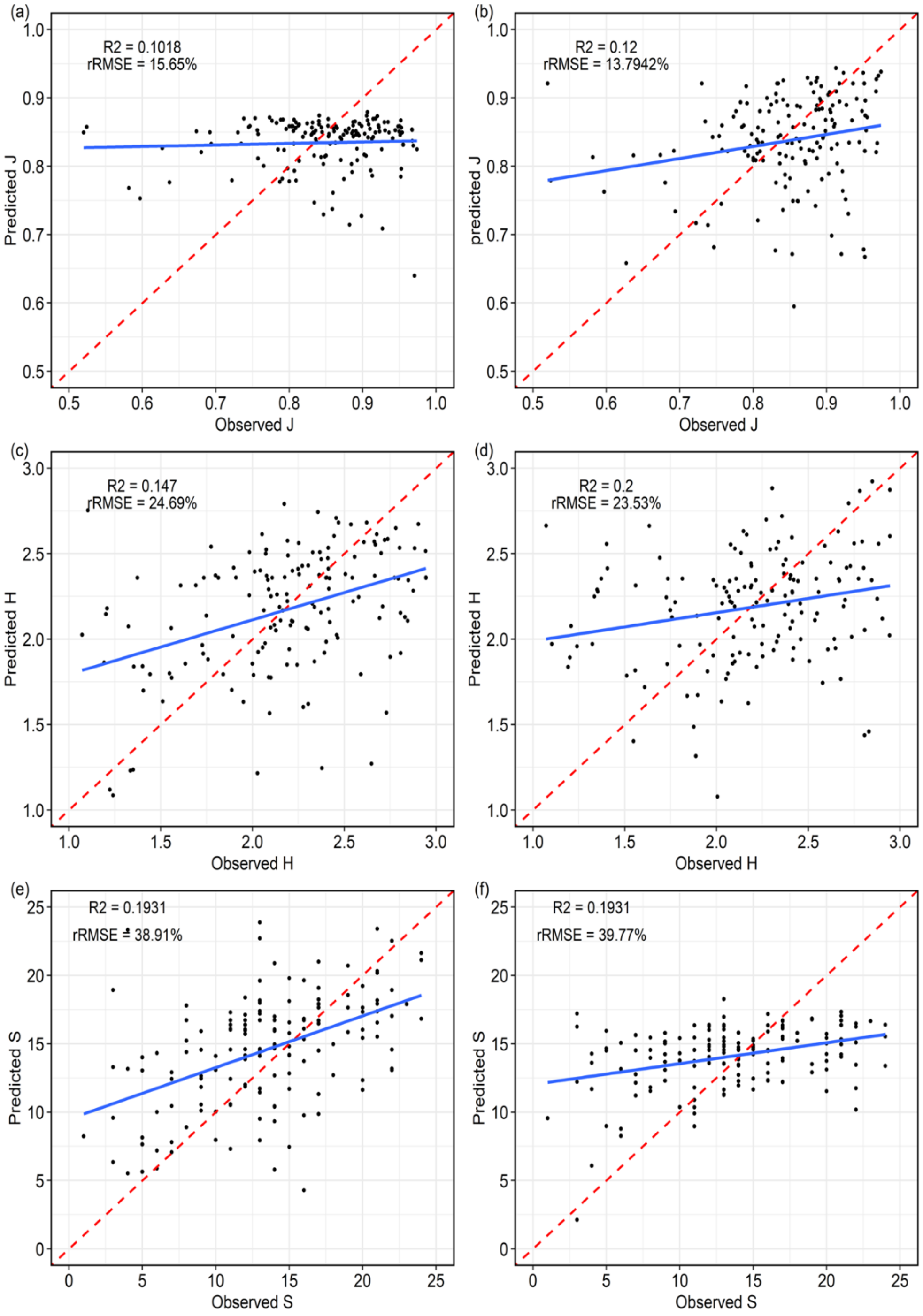

Figure 3.3: Scatter plots showing the relationship between the predicted and observed species evenness (a-b), Shannon diversity (c-d), and richness (e-f) for Sentinel-2 and PlanetScope, respectively.

3.3.3 Diversity mapping

The best models were used to generate spatial prediction maps for the Shannon's diversity index, tree species evenness, and species richness across the entire forest area (Fig. 3.4-3.6).

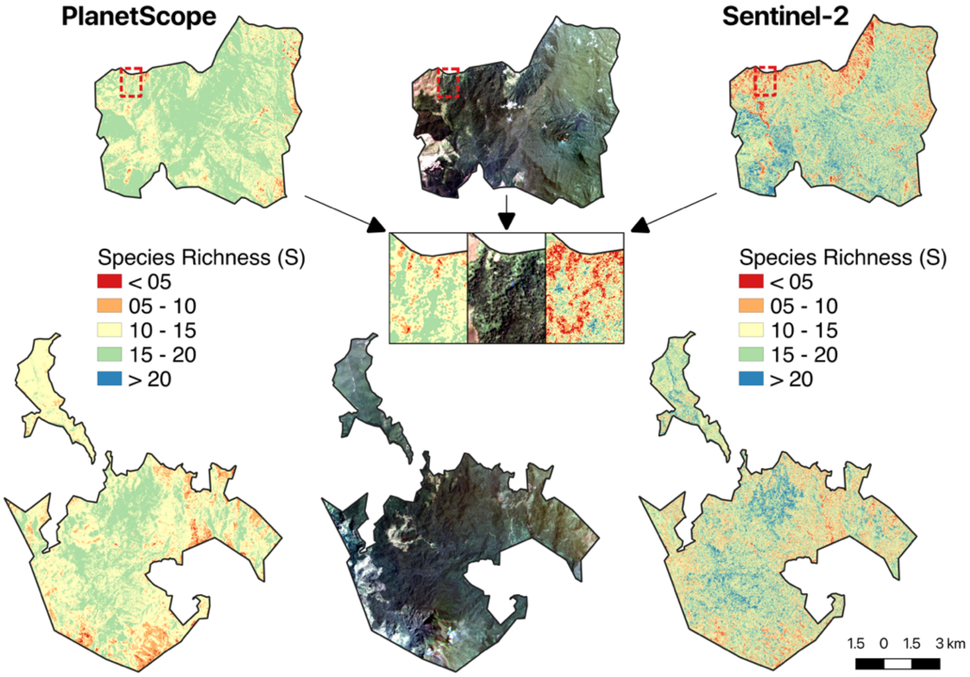

Figure 3.4: Prediction maps for tree species richness PlanetScope and Sentinel-2.

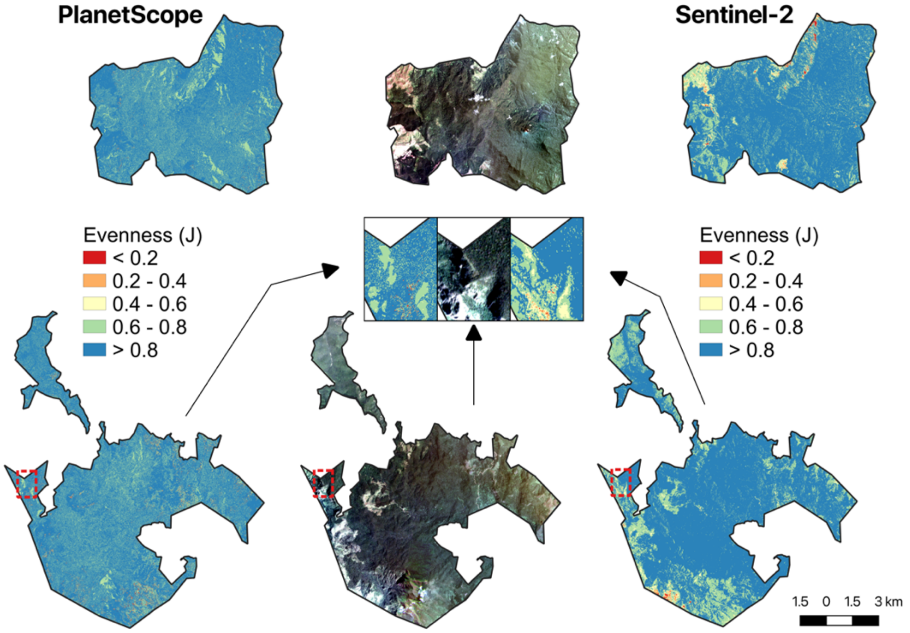

Figure 3.5: Prediction maps for tree species evenness from PlanetScope and Sentinel-2.

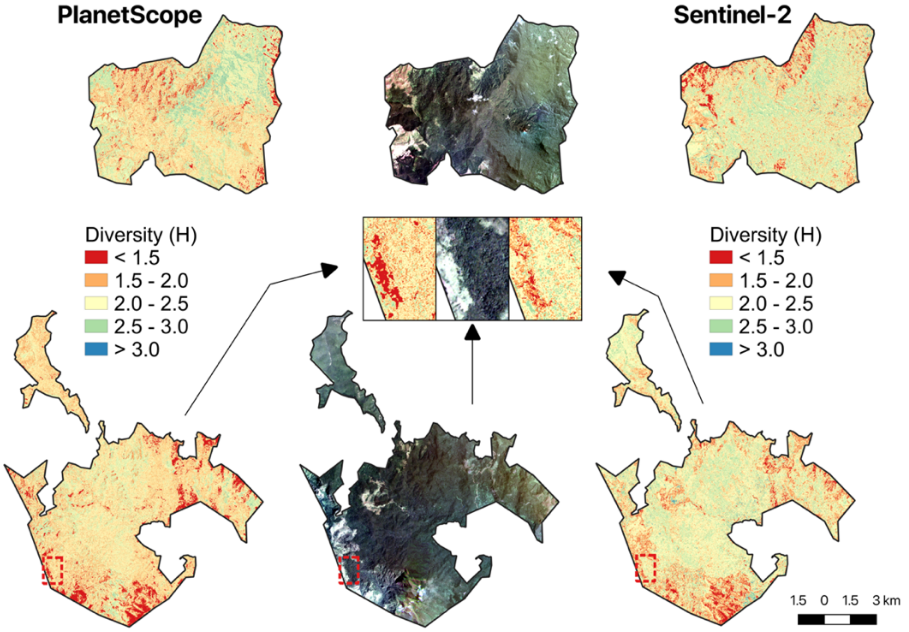

Figure 3.6: Prediction maps for Shannon’s diversity index from PlanetScope and Sentinel-2.

3.3.4 Relative efficiency of the remote sensing data

An analysis of the relative efficiency of predicting tree species diversity revealed notable differences between the PlanetScope and Sentinel-2 datasets in the West Usambara. The results indicated that the PlanetScope dataset exhibited a higher efficiency in predicting tree species diversity than Sentinel-2, as evidenced by the relative efficiency (RE) values for tree species richness and Shannon's diversity index, which were 1.47 and 2.01, respectively. These findings suggest that the PlanetScope dataset provides accurate and reliable predictions of these diversity measures. Conversely, the Sentinel-2 dataset demonstrated efficiency in predicting tree species evenness, as indicated by the RE value of 1.21, as shown in Figure 3.7. Generally, irrespective of the marginal differences between the sensors, the RE values indicate that remotely sensed data enhanced the precision of tree species diversity estimates as compared to conventional field-based methods.

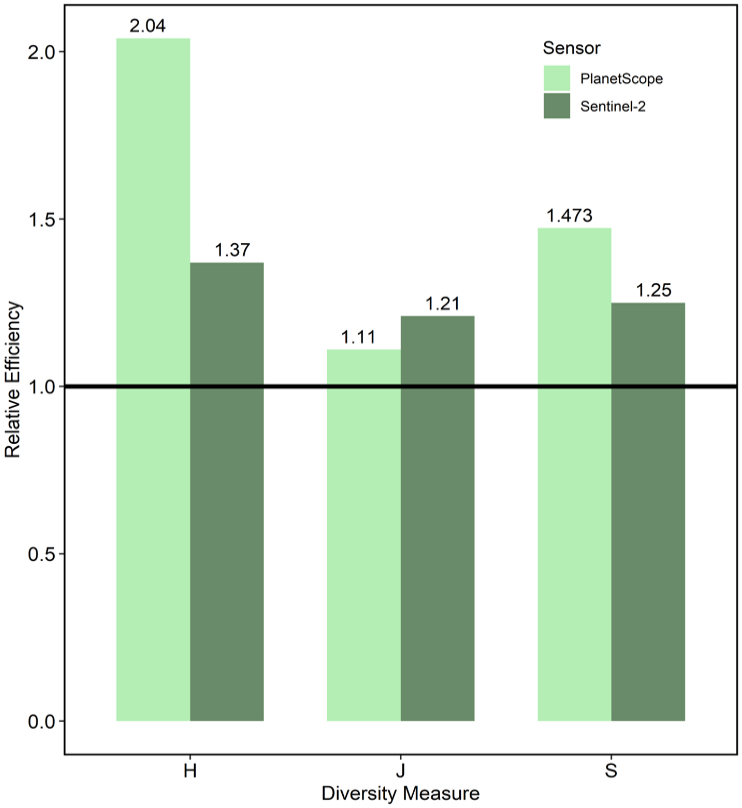

Figure 3.7: Graph showing relative efficiency of PlanetScope and Sentinel-2 in prediction of tree species diversity (H), Evenness (J) and Richness (S).

3.4 Discussion

The aim of this study was to assess the utility of Sentinel-2 and PlanetScope remotely sensed data for large-scale estimation of tropical forest tree diversity in the West Usambara mountain forests. The predictors used in the estimations were spatial bands, vegetation indices, textures, and a combination of the three. The combination of all the three predictors improved the predictive power of the models. Various studies (Metcalfe et al., 2015; Rovero et al., 2014) have shown different contributions of predictors to improving the efficiency of model prediction power. A high spatial resolution has also been shown to affect the efficiency of model predictions as elaborated by Wulder et al. (2004), Potapov et al. (2008) and Getzin et al. (2012). The results of this study showed that the models from PlanetScope, a high-resolution sensor, had higher prediction power and overall prediction accuracy.

The higher spatial resolution of PlanetScope may have enabled a better separation of tree species with varying canopy greenness, which may have played a significant role in predicting tree species diversity (Wu et al., 2021). Additionally, high-resolution textures derived from PlanetScope imagery provide a more detailed representation of vegetation structural components, leading to greater model precision (Mauya & Madundo, 2022). These findings align with those of previous studies (Gyamfi-Ampadu et al., 2021; Baloloy et al., 2018), which reported a similar performance of PlanetScope imagery for estimating tree species diversity and other vegetation properties.

Compared with similar studies (Wang and Gamon, 2019; Guisan and Zimmermann, 2000), the results of this study showed relatively lower R^2 values. However, this does not indicate that the proposed models have poor performance considering the rRMSE and MAE, which shows that the models have relatively lower prediction errors, and hence, good performance. Among the three diversity measures, the predictive power of the models using PlanetScope was the best for estimating tree species diversity. This can mainly be attributed to the high spatial resolution of the PlanetScope sensors compared to the Sentinel-2 sensors, which enhances the identification of plant features. Sentinel-2 only explained a small percentage of the variance in diversity across the study sites, whereas similar results were reported by Ma et al. (2019). PlanetScope data were shown to be able to accurately estimate tree species richness and Shannon’s diversity index as compared to Sentinel-2 data, which have been shown to underestimate species richness and Shannon’s diversity index. However, Sentinel-2 variables were able to better estimate species evenness than PlanetScope variables.

On the other hand, the XGBoost model has proven to have a higher utility in estimating tree species diversity than the GAM. Schratz et al. (2021) has shown that, in terms of performance, XGBoost has been shown to outperform GAM in many benchmarks, particularly when dealing with high-dimensional datasets (e.g., Ecological data). In this study, the datasets can be regarded as highly dimensional given the number and types of variables used for the development of predictive models. Lopatin et al., (2016), using LiDAR technology reported R^2 =0.33 for predicting tree species richness using Random Forest model. Irrespective of the model choice and sensor type, the results align with the results from this study, considering the potential of LiDAR in capturing the three-dimensional structure of the forest, which is important for ecological assessment and monitoring the higher spatial resolution offered by LiDAR technology.

A comparison between the produced diversity prediction maps and near real-time imagery showed that the prediction accuracy using data from the two sensors matched the tree species diversity in the study area (Fig. 3.4 to 3.6). This means that the developed models can be used to predict tree species diversity in tropical mountain forests. However, data from PlanetScope have been shown to enhance the performance of the models and produce more accurate prediction maps than Sentinel-2 data. This can mainly be attributed to the high spatial resolution offered by PlanetScope sensors (4.77 m) in contrast to Sentinel-2 sensors (10 m) (Vizzari, 2022; Mauya & Madundo, 2021). Therefore, these results indicate that spatial resolution plays a vital role in the accurate estimation and mapping of forest biodiversity attributes using Remote Sensing techniques.

Prediction maps for tree species richness, species evenness, and Shannon diversity index showed a general trend of lower values in areas located near the forest border, indicating high proximity to community settlement areas. This matches the actual situation at the study sites, which is mainly caused by the human over-exploitation of forest resources. Thus, it may be considered an indicator of forest encroachment activities that involve clearing forests for various human uses such as agriculture, settlements, and human-induced forest fires. This shows that the models used in the creation of the prediction map were efficient because they could effectively reflect the conditions present in the study sites. Generally, the use of remote sensing techniques has been shown to improve the estimation of forest biodiversity indicators, as the calculated relative efficiency values were all greater than one. This suggests that using remote sensing in forest inventories is more efficient than relying solely on field-based estimates (Puliti et al., 2017; Ene et al., 2017). To achieve a similar level of precision as a pure field-based estimate that employs simple random sampling, the sample size for the field-based inventory must be increased by a factor equivalent to the value of RE (Næsset et al., 2016). This increase in sample size would significantly impact the costs associated with field inventory.

3.5 Conclusion

The results of this study show that the integration of field-based approaches and remote sensing techniques can facilitate accurate large-scale estimation of forest biodiversity indicators for dense tropical mountain forests. In addition, the results demonstrated the contribution of high spatial resolution to the accurate estimation and mapping of various attributes of forest ecosystem biodiversity. It has also been observed from the tree diversity prediction maps that areas located in the forest peripherals have low tree species richness and diversity, implying a high level of destruction of forest ecosystems in the study area through various human activities. Therefore, to ensure that ecological systems within the forest and nature reserves remain intact, it is necessary to put in place and implement conservation measures that are more rigorous and efficient.

Acknowledgements

Forest inventory data collection was supported by the Eastern Arc Mountain Conservation Endowment Fund through the project "Meta-Analysis of Forest Carbon Information Using Existing Data and Remote Sensing Techniques". We also thank the Tanzania Forest Fund and the Regional Centre for Mapping of Resources for Development/Global Monitoring for Environment and Security Africa (RCMRD/GMES Africa) for their financial support.

Conflict of Interest

The authors declare no conflicts of interest.

References

Abbas S, Wong MS, Wu J, Shahzad N and Muhammad IS 2020 Approaches of satellite remote sensing for the assessment of above-ground biomass across tropical forests: Pan-tropical to national scales. *Remote Sens* 1220: 20.

Arroyo-Rodríguez V, Fahrig L, Tabarelli M, Watling JI, Tischendorf L, Benchimol M, Cazetta E, Faria D, Leal IR, and Melo FP 2020 Designing optimal human-modified landscapes for forest biodiversity conservation. *Ecology Letters*, *23*(9), 1404–1420.

Baloloy AB, Blanco AC, Candido CG, Argamosa RJL, Dumalag JBLC, Dimapilis LLLC and Paringit EC 2018 Estimation of mangrove forest aboveground biomass using multispectral bands, vegetation indices and biophysical variables derived from optical satellite imageries: Rapideye, planetscope and sentinel-2. ISPRS Ann Photogramm *Remote Sens Spatial Inf Sci* 4: 29–36.

Barnes EM, Clarke TR, Richards SE, Colaizzi PD, Haberland J, Kostrzewski M, Waller P, Choi CRE, Thompson T, Lascano RJ, Li Hand Moran MS 2000 Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data. *Proc 5th Int Conf Precis Agric*

Beyene SM, Hussin YA, Kloosterman HE and Ismail MH 2020 Forest inventory and aboveground biomass estimation with terrestrial LiDAR in the tropical forest of Malaysia. *Can J Remote Sens* 46(2): 130–145.

Burgess Nd, Butynski TM, Cordeiro NJ, Doggart NH, Fjeldså J, Howell KM, Kilahama FB, Loader SP, Lovett JC and Mbilinyi B 2007 The biological importance of the Eastern Arc Mountains of Tanzania and Kenya. *Biol.Conserv.* 134(2): 209–231.

Chen T and Guestrin C 2016 Xgboost: A scalable tree boosting system. Proc 22nd *Acm Sigkdd Int Conf Knowledge Discovery Data Mining*: 785–794.

Corte APD, Souza DV, Rex FE, Sanquetta CR, Mohan M, Silva CA, Zambrano AMA, Prata G, Alves de Almeida DR, Trautenmüller JW, Klauberg C, de Moraes A, Sanquetta MN, Wilkinson Band Broadbent EN 2020 Forest inventory with high-density UAV-Lidar: Machine learning approaches for predicting individual tree attributes. *Comput. Electron Agric.* 179: 105815.

Dainelli R, Toscano P, Di Gennaro SF and Matese A 2021 Recent advances in unmanned aerial vehicle forest remote sensing-A systematic review. Part I: A general framework. *Forests* 12(3): 3.

Drusch M, Del Bello U, Carlier S, Colin O, Fernandez V, Gascon F, Hoersch B, Isola C, Laberinti P, and Martimort P 2012. Sentinel-2: ESA’s optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, *120*, 25–36.

Ene LT, Næsset E, Gobakken T, Bollandsås OM, Mauya, EW and Zahabu E 2017 Large-scale estimation of change in aboveground biomass in miombo woodlands using airborne laser scanning and national forest inventory data. *Remote Sens. Environ.* 188: 106–117.

Genuer R, Poggi JMandTuleau-Malot C 2015 VSURF: An R package for variable selection using random forests. *R J.* 7(2): 19–33.

Getzin S, Wiegand K and Schöning I 2012 Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. *Methods Ecol. Evol.* 3(2): 397–404.

Gitelson AA, Gritz YandMerzlyak MN 2003 Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *J. Plant Physiol.*(1603): 271–282.

Gitelson AA, Kaufman YJ and Merzlyak MN 1996 Use of a green channel in remote sensing of global vegetation from EOS- MODIS. *Remote Sens. Environ.* 58: 289–298.

Gitelson A and Merzlyak MN 1994 Spectral reflectance changes associated with autumn senescence of Aesculus hippocastanum L and Acer platanoides L leaves. Spectral features and relation to chlorophyll estimation. *J. Plant Physiol.* 143(3): 286–292.

Goodbody TRH, Coops NC and White JC 2019 Digital aerial photogrammetry for updating area-based forest inventories: A review of opportunities, challenges, and future directions. *Curr. Forestry Rep.* 5(2): 55–75.

Guisan A and Zimmermann NE 2000 Predictive habitat distribution models in ecology. *Ecol. Modell.* 135(2–3): 147–186.

Gyamfi-Ampadu E, Gebreslasie M and Mendoza-Ponce A 2021 Evaluating multi-sensors spectral and spatial resolutions for tree species diversity prediction. *Remote Sens.* 13(5): 1033.

Hamzehpour N, Shafizadeh-Moghadam H and Valavi R 2019 Exploring the driving forces and digital mapping of soil organic carbon using remote sensing and soil texture. *Catena* 182: 104141.

Haralick RM 1979 Statistical and structural approaches to texture. *Proc IEEE* 67(5): 786–804.

Hijmans RJ, Van Etten J, Mattiuzzi M, Sumner M, Greenberg JA, Lamigueiro OP, Bevan A, Racine EB and Shortridge A 2013 Raster package in R. Version. https://mirrors.sjtug.sjtu.edu.cn/cran/web/packages/raster/raster.pdf

Hui QL and Huete A 1995 A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. *IEEE Trans Geosci. Remote Sens.* 33(2): 457–465.

Li Z, Zhang HK, Roy DP, Yan Land Huang H 2020 Sharpening the Sentinel-2 10 and 20 m Bands to Planetscope-0 3 m Resolution. *Remote Sens.* 12(15): 2406.

Lopatin J, Dolos K, Hernández HJ, Galleguillos Mand Fassnacht FE 2016 Comparing generalized linear models and random forest to model vascular plant species richness using LiDAR data in a natural forest in central Chile. *Remote Sens. Environ.* 173: 200–210.

Louis J, Debaecker V, Pflug B, Main-Knorn M, Bieniarz J, Mueller-Wilm U, Cadau E and Gascon F 2016 Sentinel-2 Sen2Cor: L2A processor for users. *Proc Living Planet Symp* 2016: 1–8.

Lovett JC 1996 Elevational and latitudinal changes in tree associations and diversity in the Eastern Arc mountains of Tanzania. *J. Trop. Ecol.* 12(5): 629–650.

Ma X, Mahecha MD, Migliavacca M, van der Plas F, Benavides R, Ratcliffe S, Kattge J, Richter R, Musavi T and Baeten L 2019 Inferring plant functional diversity from space: The potential of Sentinel-2. *Remote Sens. Environ.* 233: 111368.

Mauya EW and Hansen EH, Gobakken T, Bollandsås OM, Malimbwi RE, Næsset E 2015 Effects of field plot size on prediction accuracy of aboveground biomass in airborne laser scanning-assisted inventories in tropical rain forests of Tanzania. *Carbon Balance Manage.* 10: 1–14.

Mauya EW and Madundo S 2022 Modelling Above Ground Biomass Using Sentinel 2 and Planet Scope Data in Dense Tropical Montane Forests of Tanzania. *Tanz. J. Forestry Nature Conserv.* 91(1): 132–153.

Metcalfe P, Beven Kand Freer J 2015 Dynamic TOPMODEL: A new implementation in R and its sensitivity to time and space steps. *Environ Model Softw.* 72: 155–172.

Næsset E, Ørka HO, Solberg S, Bollandsås OM, Hansen EH, Mauya E, Zahabu E, Malimbwi R, Chamuya N, Olsson HandGobakken T 2016 Mapping and estimating forest area and aboveground biomass in miombo woodlands in Tanzania using data from airborne laser scanning, TanDEM-X, RapidEye, and global forest maps: A comparison of estimated precision. *Remote Sens. Environ.* 175: 282–300.

Pearson RL and Milton LD 1972 Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie, Pawnee National Grasslands, Colorado. *Proc Eighth Int. Symp. Remote Sens. Environ.* October 2–6, 1972.

Poortinga A, Thwal NS, Khanal N, Mayer T, Bhandari B, Markert K, Nicolau AP, Dilger J, Tenneson K and Clinton N 2021 Mapping sugarcane in Thailand using transfer learning, a lightweight convolutional neural network, NICFI high resolution satellite imagery and Google Earth Engine. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, *1*, 100003.

Potapov P, Yaroshenko A, Turubanova S, Dubinin M, Laestadius L, Thies C, Aksenov D, Egorov A, Yesipova Y, Glushkov I, Karpachevskiy M, Kostikova A, Manisha A, Tsybikova E and Zhuravleva I 2008 Mapping the World's Intact Forest Landscapes by Remote Sensing. *Ecology and Society*, *13*(2).

Puliti S, Ene LT, Gobakken T and Næsset E 2017 Use of partial-coverage UAV data in sampling for large scale forest inventories. *Remote Sens. Environ.* 194: 115–126.

Ranghetti L, Boschetti M, Nutini F and Busetto L 2020 "sen2r": An R toolbox for automatically downloading and pre-processing Sentinel-2 satellite data. *Comput. Geosci.* 139: 104473.

Richardson AJ and Wiegand CL 1977 Distinguishing vegetation from soil background information. *Photogramm Eng. Remote Sens.* 43(12): 1541–1552.

Rouse JW Jr, Haas RH, Schell JA and Deering DW 1974 Monitoring Vegetation Systems in the Great Plains with Erts, NASA Special Publication. Proc Third Earth Resources Technology Satellite- 1 Symp, 309–317.

Rovero F, Menegon M, FjeldsAa J, Collett L, Doggart N, Leonard C, Norton G, Owen N, Perkin A and Spitale D 2014 Targeted vertebrate surveys enhance the faunal importance and improve explanatory models within the Eastern Arc Mountains of Kenya and Tanzania. *Divers Distrib.* 20(12): 1438–1449.

Schratz P, Muenchow J, Iturritxa E, Cortés J, Bischl B and Brenning A 2021 Monitoring forest health using hyperspectral imagery: Does feature selection improve the performance of machine-learning techniques? *Remote Sens.* 13(23): 4832.

Storch F, Boch S, Gossner MM, Feldhaar H, Ammer C, Schall P, Polle A, Kroiher F, Müller J and Bauhus J 2023 Linking structure and species richness to support forest biodiversity monitoring at large scales. *Ann. Forest Sci.* 80(1): 1–17.

Vizzari M 2022 PlanetScope, Sentinel-2, and Sentinel-1 Data Integration for Object-Based Land Cover Classification in Google Earth Engine. *Remote Sens.* 14(11): 2628.

Wang R and Gamon JA 2019 Remote sensing of terrestrial plant biodiversity. *Remote Sens. Environ.* 231: 111218.

Wood S and Wood MS 2015 Package 'mgcv'. R Package Version 1(29): 729.

Wu S, Wang J, Yan Z, Song G, Chen Y, Ma Q, Deng M, Wu Y, Zhao Y and Guo Z 2021 Monitoring tree-crown scale autumn leaf phenology in a temperate forest with an integration of PlanetScope and drone remote sensing observations. *ISPRS J. Photogramm Remote Sens.* 171: 36–48.

Wulder MA, Hall RJ, Coops NCand Franklin SE 2004 High Spatial Resolution Remotely Sensed Data for Ecosystem Characterization. *BioScience* 54(6): 511–521.

Zvoleff A 2020 Glcm: Calculate textures from grey-level Co-occurrence matrices (GLCMs) version 1.6.5 from CRAN. CRAN Package ‘glcm’.

CHAPTER 4

PAPER THREE

4.0 Post-Fire Assessment of Recovery of Montane Forest Composition and Structure Using In Situ Measurements and Remote Sensing Data[3]

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Abstract

Tree diversity in the tropical forests face escalating threats from wildfires. This study assessed post-fire impacts and recovery patterns in Tanzanian Eastern Arc Mountains forests from 2017 to 2022 using field measurements and remote sensing techniques. Tree species diversity, composition, and forest stand parameters were compared between burned and unburned forest plots across two reserves. A predictive model utilizing 14 key variables derived from multispectral satellite data was developed to accurately map burned areas and spatial fire patterns. Results revealed significantly lower tree density, aboveground biomass, species richness, and Shannon diversity in burned areas compared to unburned forests. However, compositional analysis showed extensive species overlap between burned and unburned sites, with burned areas containing more indicative pioneer and disturbance-adapted species such as *Apodytes dimidiata*. Over time since fire events, tree density, basal area, aboveground biomass, species richness, evenness, and diversity increased markedly, evidencing active tree recovery. The remote sensing model effectively delineated approximately 1430 hectares of burned areas concentrated near

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[3] The materials contained in this chapter have been published in **Trees, Forests and People.**

villages, suggesting prevalent anthropogenic fire ignitions. Although wildfires substantially impacted forest structure and biodiversity, the limited compositional shifts point to resilience of these tropical montane forests. Integration of diverse spectral bands and textural metrics from multispectral satellite data can support precise mapping of fire effects and forest recovery dynamics in these ecologically vital yet threatened ecosystems, aiding conservation and management. Overall, this study provides novel insights into post-fire responses in Eastern Arc Mountain forests using a synergistic field and remote sensing approaches.

Keywords

Analysis of similarity; Generalized linear modelling; Textures; Tropical montane forests; Wildfire recovery

4.1 Introduction

Tropical montane forest ecosystems, characterized by their unique ecological attributes and intricate biodiversity, occupy a pivotal position in the global natural (Rurangwa et al., 2021). These ecosystems, often situated at higher altitudes, harbour a diverse array of flora and fauna species that are endemic to the specific conditions of these regions (Pinedo-Escatel et al., 2021). As repositories of diverse life forms, these forests not only contribute to the overall biodiversity of our planet but also offer vital ecosystem services, including carbon sequestration, soil stability, and provision of habitats for numerous species (Imbert et al., 2021). The imperative of conserving forests, particularly in tropical and montane regions, is deeply underlined by the complex functions they fulfil. Beyond their ecological significance, these forests play a crucial role in supporting local communities, providing essential resources, and even influencing regional climatic patterns (Imbert et al., 2021). However, in the face of escalating anthropogenic pressures, such as deforestation, land-use changes, and notably, fires, the integrity of these vital ecosystems is increasingly compromised (Santos Rodrigues, 2020)

The global landscape of forest ecosystems is deliberately affected by and linked to fire dynamics, with human-induced fires emerging as a potent and pervasive threat especially in the tropical montane ecosystems (Shuman et al., 2022;Tyukavina et al., 2022). The impact of fires on the achievement of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) goals and carbon storage are profound, exerting a significant influence on global climate change mitigation efforts (Fawzy et al., 2020). REDD+ initiatives aim to curtail carbon emissions by conserving and sustainably managing forests, recognizing their pivotal role in carbon sequestration (Shin et al., 2022). However, the occurrence of fires, particularly in tropical and montane forest ecosystems, can disrupt this delicate equilibrium.

Fires release substantial carbon stored within trees and vegetation, contributing to atmospheric greenhouse gas concentrations (Singh, 2022). This not only negates the progress made in carbon storage through forest conservation but also worsens climate change impacts (Bowman et al., 2020). Furthermore, a study by Prichard et al., (2021) suggested that, fires alter forest structure, impeding regeneration and potentially transforming forests into carbon sources instead of sinks. Therefore, effective fire management and mitigation strategies are essential to safeguard the accomplishments of REDD+ initiatives and to ensure the preservation of vital carbon reservoirs in forests, thereby contributing significantly to global climate change mitigation objectives (Tyukavina et al., 2022). The aftermath of a fire event in a forested landscape can greatly influence a wide range of ecological changes that reverberate may have implications on the entire ecosystem (Riley & Loehman, 2016). Understanding the patterns of recovery in the wake of such disturbances is of paramount importance for effective conservation and management (González, 2005).

The influence of fire on biodiversity, forest structure, and ecosystem composition can be profound, potentially leading to shifts in species dominance, alterations in vegetation dynamics, and modifications in habitat availability (Han et al., 2018). Within this context, the case of Tanzania is of particular significance, given its richness in forest types, including tropical and montane forests, and the associated challenges posed by fires that disrupt these ecosystems' natural equilibrium.

The crucial role of remote sensing technologies in advancing fire ecology studies is exemplified by the potent attributes of PlanetScope and Sentinel-2 satellites (Han et al., 2021; Fernández-Guisuraga et al., 2019). These satellites, equipped with a versatile array of capabilities, offer a unique toolkit for comprehensively investigating fire occurrences, their ecological impacts, and subsequent recovery processes (Han et al., 2021). PlanetScope satellites, renowned for their high-resolution multispectral imagery, empower researchers to investigate the details of fire-affected landscapes (Dempewolf et al., 2007). The availability of various spectral bands, including near-infrared, red, and green, facilitates the computation of indices such as the Normalized Burn Ratio (NBR) and Enhanced Vegetation Index (EVI), pivotal for assessing burn severity and revealing post-fire vegetation health (Holden et al., 2010). The ability to acquire frequent revisits enables near-real-time monitoring, capturing the dynamic evolution of fires and their aftermath. Sentinel-2 satellite imagery, on the other hand, provides a wealth of multispectral data, including red-edge and shortwave infrared bands, which, when coupled with texture analysis techniques, uncover fine-scale heterogeneity in burned landscapes (Hill, 2013). Texture measures, like the variance, contrast, and mean, enhance the detection of nuanced fire impacts and vegetation regeneration patterns (Lu et al., 2008).

These remote sensing platforms also offer indices that unveil post-fire ecological recovery through the use of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Green Normalized Burn Ratio (GNBR) shed light on vegetation regrowth, aiding in the identification of areas showing signs of positive recovery (João et al., 2018). Moreover, the satellites' capacity to capture changes in land cover and land use contributes to the understanding of long-term ecosystem responses to fires (Burton et al., 2019). The high spatial resolution of both PlanetScope and Sentinel-2 satellites empowers localized analyses, enabling the characterization of fine-scale fire effects on diverse vegetation types and landscape features. Furthermore, the temporal resolution provided by these satellites facilitates dynamic monitoring, allowing researchers to track seasonal and annual changes in burned landscapes. This temporal dimension enables the assessment of recovery rates, the identification of lagged responses in different vegetation types, and the observation of secondary ecological effects beyond the immediate post-fire period.

Therefore, this study intends to unravel the complex aspects of post-fire recovery in tropical and montane forests by adopting a multifaceted approach that combines field-based measurements with cutting-edge remote sensing techniques. The specific objectives of this study are to study the following; (i) effect of fire on forest composition, (ii) effects of fire on forest structural parameters (iii) post-fire recovery of forest structure (iv) estimate and map the burnt areas. By investigating the trajectories of forest composition and structural reconfiguration in the aftermath of fires, this study contributes valuable insights into the ecological resilience of the Eastern Arc Mountains especially the West Usambara montane forests ecosystems. Moreover, the role of remote sensing, particularly through platforms like PlanetScope and Sentinel-2, in monitoring fire occurrences, assessing their impact, and guiding conservation strategies, is central to this exploration.

4.2 Methodology

4.2.1 Study sites

The West Usambara Montane Forests, located in Tanzania's Lushoto and Korogwe Districts, are part of the Eastern Arc Mountains (EAMs) and consist of two highland blocks: East Usambara (up to 1,484 meters) and West Usambara (almost 2,294 meters). Our study focuses on the Magamba Nature Forest Reserve (MNFR) and the Shagayu Forest Reserve (SFR) in the West Usambara block (Fig. 4.1). MNFR covers 9,283 hectares at 1,650-2,300 meters above sea level, with a mean annual rainfall of 1,200 mm and temperatures between 15°C and 30°C. SFR spans 7,830 hectares at approximately 2,098 meters above sea level, with an annual rainfall of 1,000 mm. These reserves feature a unique montane climate that supports dominant tree species like *Ocotea usambarensis, Podocarpus latifolius, Albizia gummifera, Hagenia abyssinica, Syzygium guineense*, and *Ilex mitis* (Lovett, 1996). Both reserves experience a notable fire regime, primarily from September to January, significantly influencing their dynamic montane forest ecosystems (Kilawe et al., 2021).

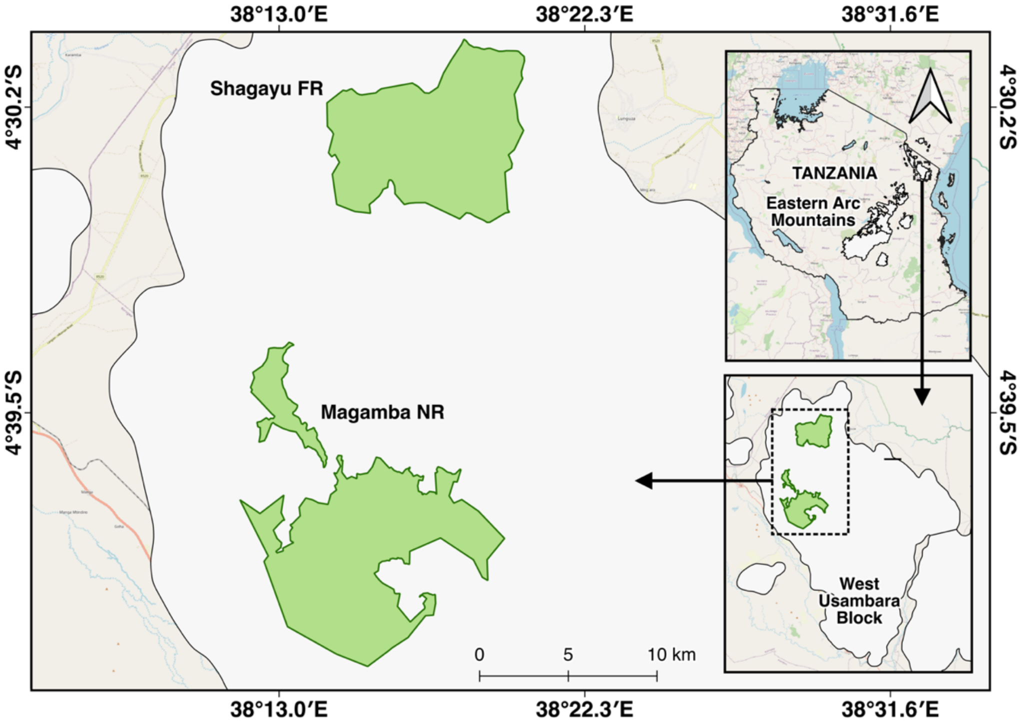


Figure 4.1: Location of the study forests, in the Eastern Arc Mountains of Tanzania.

4.2.2 Study design

In this study, vegetation attributes were recorded in the Magamba Nature Forest Reserve (MNFR) and the Shagayu Forest Reserve (SFR) using a two-phase systematic sampling approach. In the first phase, a grid of sampling plots was established, with 225 × 450 m spacing in the MNFR and 350 × 700 m spacing in the SFR. During the field expedition (second phase), accessible plots from the grid intersections were selected as field sampling sites.

4.2.3 Data collection

4.2.3.1 Field data collection

In total, we established 195 circular field-sampling plots, with 90 in MNFR and 105 in SFR. Within each plot, all trees with a diameter at breast height (DBH) ≥ 5 cm were identified to species level and recorded. To provide a comprehensive assessment of the forest, we measured the height of three representative trees within each plot, specifically the smallest, medium-sized, and largest tree based on DBH using a vertex hypsometer. Plot locations were documented at the centre of the plot using a handheld Garmin 73 GPS device with 5 m accuracy. Additionally, we determined the status of each plot (burned or unburned) and the year of the fire event (ranging from 2022 to 2017) based on documented records on the fire occurrences in the study sites. Signs of fire disturbance, such as charred tree trunks, scorched vegetation, and fire-damaged ground cover, were also considered in this determination. Notably, data on climbers, shrubs, or herbs were not collected.

4.2.3.2 Sentinel-2 data acquisition and pre-processing

We acquired two Level 1C Sentinel-2 image tiles from the Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus) both dated on October 12, 2022. These images were initially in Level-1C top of the atmosphere (TOA) reflectance format. Using the ESA Sen2Cor algorithm, we transformed them into Level-2A bottom of the atmosphere (BOA) surface reflectance images, employing the “sen2r” package (Ranghetti et al., 2020). We selected bands with 10 m and 20 m spatial resolutions, with the 20 m bands resampled to 10 m for spatial consistency. To cover our study area, we mosaicked the two tiles. Additionally, we sourced PlanetScope imagery for the month of October 2022, which is accessed in a pre-processed and ready for analysis form. To match our projection requirements, we re-projected the Sentinel-2 and PlanetScope data to Arc 1960 UTM 37/S (EPSG 21,037).

After data preparation, atmospherically corrected images from both sensors were used to compute vegetation indices (Table A1). We employed the “RStoolbox” package (Leutner et al., 2017), integrated into R, for this analysis. This included five fire-based vegetation indices (Alcaras et al., 2022), five broadband optical vegetation indices, and three narrowband indices specific to Sentinel-2 data. Furthermore, we calculated grey level co-occurrence matrix (GLCM) textural metrics - ’mean,’ ’variance,’ and ’dissimilarity’ - across all spectral bands and indices. This texture analysis, performed with the “glcm” package in R (Zvoleff, 2020), used a 3 × 3 window size to capture spatial patterns within the imagery.

4.2.4 Statistical analyses

Tree species composition: To determine significant differences in tree species composition between burned and unburned sites, a non-metric multidimensional scaling analysis (NMDS) using a Bray-Curtis dissimilarity coefficient and analysis of similarity of the abundance matrix (ANOSIM) with P value of 0.05 were used (Huang et al., 2016). By ordinating sites based on their species compositions, the NMDS enabled the visual assessment of whether burned and unburned forest sites differ systematically based on their species abundances. NMDS provided an unconstrained visualization of the patterns in this complex dataset, complementing the ANOSIM results to understand differences between burned and unburned conditions. Only tree species with an abundance of more than 5 individuals were used for the analyses. The ANOSIM calculates the differences of the ranked dissimilarities between and within a-priori specified groups. This method calculates an R value that can be interpreted as the amount of overlap of the groups in multivariate space. *R* values range from 0 to 1, with values less than 0.5 indicating strong overlap and values of more than 0.75 indicating clearly different clusters in multivariate space (Anderson and Walsh, 2013). Indicator species analysis was then performed to identify significant associations of tree species to burned and unburned sites based on indicator value. The NMDS and ANOSIM analysis were implemented using the ‘vegan’ R package v2.6-4 (Oksanen et al., 2007), while indicator species analysis was conducted using the ‘indicspecies’ R package (De Caceres et al., 2016).

Tree diversity, stand parameters and recovery: To determine the relationship between wildfire and forest diversity, stand parameters and their recovery over time, we calculated for all plots; density (N, total number of trees ha□ 1), basal area (G, m2ha□ 1), above-ground biomass (AGB, Mgha□ 1), species richness (S, total number of species per plot), Pileous evenness (J), and species diversity expressed as Shannon’s index (H’). Prior to analysis, these parameters were tested for normality, revealing that they were not normally distributed. Generalized linear models (GLMs) were used to analyse whether fire (burned vs unburned) had a significant impact on the forest diversity and stand parameters (Butler et al., 2017). For the six different models based on each specific parameter, the following families and link functions were employed: a Gaussian family with log link for both density and above-ground biomass, a gamma family with a log link for basal area, and a Poisson family and log link for species richness, evenness, and diversity. All forest diversity and stand parameters that were significantly influenced by fire were then compared between burned and unburned forest sites to quantify effects using Mann-Whitney *U* tests. Spearman correlations were calculated between all forest diversity and stand parameters and time since fire occurrence to determine if the parameters recover over time (Armenteras et al., 2021).

Fire mapping: A predictive model was developed for mapping the most recent burned forest areas using the Sentinel-2 and PlanetScope spectral bands, vegetation and burn indices, and textures. We employed XGBoost, a powerful machine learning algorithm, using a training dataset containing both burned and unburned plot locations under k-fold cross-validation (k = 10). To enhance model accuracy and efficiency, we conducted an in-depth analysis of variable importance using Recursive Feature Elimination (RFE) (Zhang et al., 2022). RFE allowed us to iteratively identify the most influential predictors which were then used to create a final optimised model to generate a detailed burned area map of the study forests.

4.3 Results

4.3.1 Post-fire effects on forest composition

The results of the ANOSIM analysis showed that there are no clear groups formed by the effects of wildfires (ANOSIM-R = 0.11). These results were significant at the 95% significance level after 999 permutations (Fig. 4.2). This demonstrates a strong overlap of forest species composition. On the other hand, indicator species analysis revealed that 21 of the 195 species significantly occurred across the sites respectively (Table 4.1). We found a total of 13 species, including *Apodytes dimidiata* E.Mey. ex Arn. and *Canthium captum* Bullock, occurred in burnt sites. In unburnt sites, *Cyathea manniana* Hook. was the most indicative species. Generally, more species were indicative of burnt areas compared to unburned areas (Table 4.1).

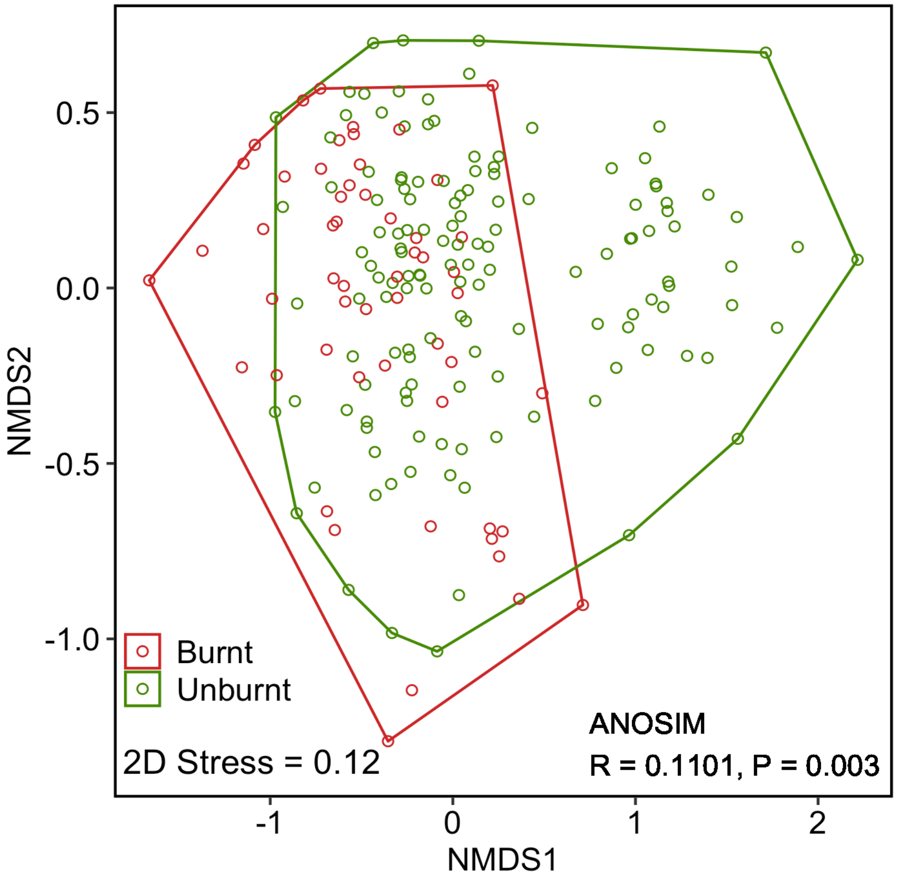


Figure 4.2: Non-metric multidimensional scaling ordination (NMDS) for forest plots showing convex hulls.

Table 4.1: Indicator species analysis for the burnt and unburnt sites of the forests.

Site status	Scientific name	Code	IV	p-value
Burnt	*Apodytes dimidiata* E.Mey. ex Arn.	Apo.dim	0.438	0.010
	Canthium captum Bullock	Can.cap	0.339	0.003
	Cussonia holstii Harms ex Engl.	Cus.hol	0.326	0.045
	Diospyros natalensis (Harv.) Brenan	Dio.nat	0.268	0.039
	Euclea divinorum Hiern	Euc.div	0.472	0.001
	Maytenus senegalensis (Lam.) Exell	May.sen	0.416	0.002
	Mystroxylon aethiopicum (Thunb.) Loes.	Mys.aet	0.453	0.001
	Ochna holstii Engl.	Och.hol	0.443	0.011
	Olea europaea subsp. africana (Mill.) P.S.Green	Ole.eur	0.339	0.005
	Olinia rochetiana A.Juss.	Oli.roc	0.386	0.004
	Rhus natalensis Bernh. ex C.Krauss	Rhu.nat	0.379	0.004
	Trichocladus ellipticus Eckl. & Zeyh.	Tri.ell	0.464	0.018
	Warburgia ugandensis Sprague	War.uga	0.281	0.026
Unburnt	*Cyathea manniana* Hook.	Cya.man	0.835	0.001
	Dasylepis integra Warb.	Das.int	0.417	0.049
	Ehretia cymosa Thonn.	Ehr.cym	0.231	0.024
	Entandrophragma excelsum (Dawe & Sprague) Sprague	Ent.exc	0.244	0.018
	Leptonychia usambarensis K. Schum.	Lep.usa	0.332	0.007
	Margaritaria discoidea (Baill.) G.L.Webster	Mar.dis	0.239	0.030
	Mussaenda microdonta Wernham	Mus.mic	0.388	0.001
	Turraea holstii Gürke	Tur.hol	0.333	0.004

4.3.2 Post-fire effects on tree diversity and stand parameters

Fire was found to have an effect on all stand and diversity parameters with the exception of species evenness (Table 4.2). Focusing on tree parameters with significant effects by fire, we compared them between burned and unburned areas of the forests. As shown in Table 4.3, all included parameters were found to differ significantly between burned and unburned forest areas. The tree density was 38.4 % lower after fire disturbance, as was the basal area (41.7 %). In addition, we found about 52.2 % fewer species in burned forests as compared to unburned forests. The comparison of species diversity between burned and unburned forests showed that there was 31.3 % less species diversity (H’) in burned forests.

Table 4.2: Influence of fire on tree density, basal area, above-ground biomass, species richness, evenness, and diversity, mean (SE) of all plots (burned and unburned), and P-values.

Structural parameter	*N*	Mean (SE)	Fire influence
Tree density (N, trees ha^{-1})	195	651.87 ± 29.19	<0.001
Basal area (G, m^{2}ha^{-1})	195	25.78 ± 1.66	0.002
Above-ground biomass (AGB, Mgha^{-1})	195	255.54 ± 15.85	<0.001
Species richness (S)	195	12.77 ± 0.44	<0.001
Species evenness (J)	192*	0.82 ± 0.01	0.689
Shannon diversity (H’)	195	2.03 ± 0.04	0.001

**N* is smaller, as the computation of species evenness is only possible for plots with at least two tree species.

Table 4.3: Differences between burnt and unburnt forest sites (N = 56 burnt, N = 139 unburnt).

Structural parameter	Unburnt	Burnt	P-value
Tree density (N, trees ha^{-1})	949 ± 66.30	585 ± 30.10	<0.001
Basal area (G, m^{2}ha^{-1})	39.1 ± 3.46	22.8 ± 1.80	0.002
Above-ground biomass (AGB, Mgha^{-1})	393 ± 32.00	224 ± 17.10	<0.001
Species richness (S)	22.2 ± 0.56	10.6 ± 0.34	<0.001
Shannon diversity (H’)	2.72 ± 0.03	1.87 ± 0.04	0.001

4.3.3 Post-fire recovery of tree diversity and stand parameters

In our study, we found strong and statistically significant positive correlations between years since fire disturbance and all forest structural parameters (Fig. 4.3). Tree density increased significantly with time since fire (P = <0.001, r = 0.491), as did basal area (P = <0.001, r = 0.577), and above-ground biomass (AGB) (P = <0.001, r = 0.604). The Shannon diversity index exhibited a highly significant positive correlation (P = <0.001, r = 0.871), indicating an increase in species diversity over time. Similarly, species richness showed a remarkable increase (P = <0.001, r = 0.945), accompanied by a significant positive correlation with years since fire. Evenness also displayed a positive correlation (P = 0.003, r = 0.385) with time since fire, albeit with a lower coefficient.

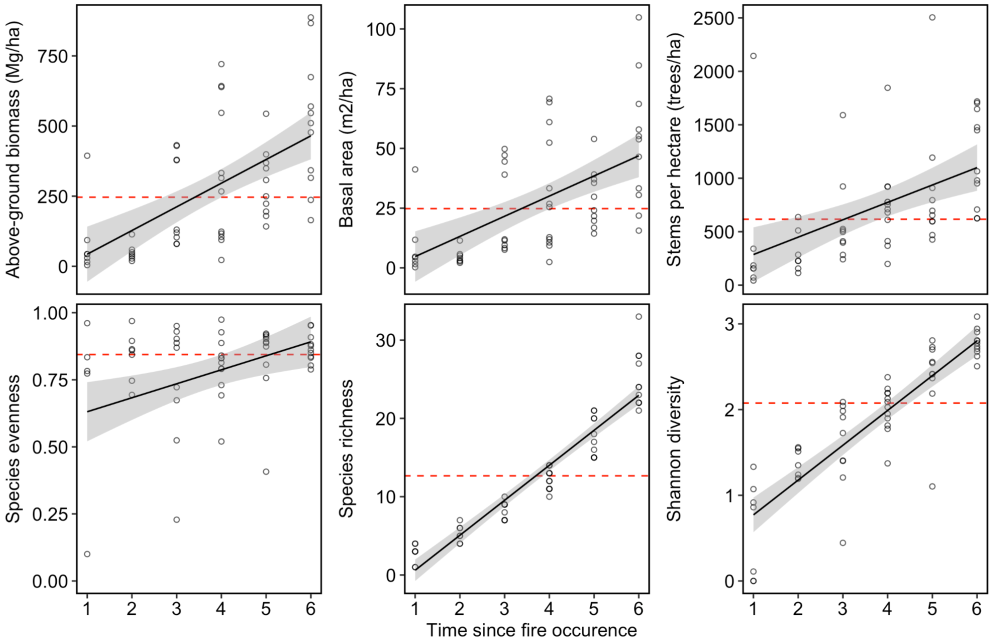


Figure 4.3: Post-fire recovery of (a) above-ground biomass, (b) basal area, (c) density, (d) species evenness, (e) richness, and (f) diversity, in the forests. Dots represent plots burned in 2022 (n = 7), 2021 (n = 7), 2020 (n = 9), 2019 (n = 12), 2018 (n = 10), and 2017 (n = 11). The solid black line indicates the linear trend line of the burnt forest parameter values, with 95% confidence interval. Mean unburnt forest structural parameter is indicated by the red horizontal dashed line.

4.3.4 Burnt Area Mapping

Through Recursive Feature Elimination (RFE), we identified an optimal model comprising 14 key predictor variables that effectively captured post-fire landscape dynamics for the study sites. Notable variables in this selection included the contrast of NBRplus, the mean texture of Sentinel-2 red band (B04), PlanetScopes DVI and others (Fig. C1).

The optimised model demonstrated robust performance, with an accuracy of 0.688 (SD: 0.083) and a kappa value of 0.0998 (SD: 0.261), showing its ability to distinguish burnt and unburnt areas accurately (Table C1). Using the model, a burned area prediction map was created to visually depict the spatial distribution of burnt areas (Fig. 4.4). From the map a total burned area of approximately 1430 hectares was found.

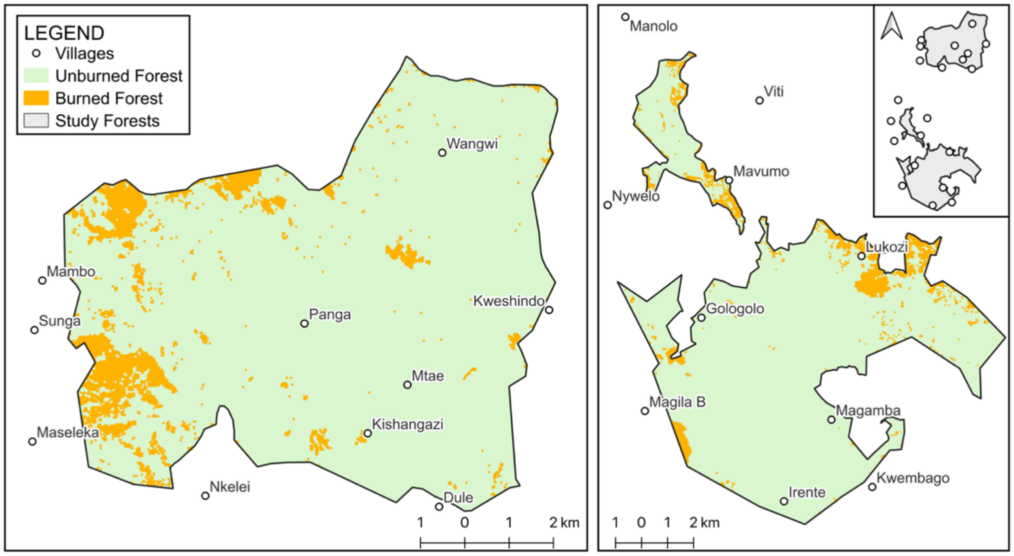


Figure 4.4: Burned area prediction map derived from the optimised XGBoost model.

4.4 Discussion

The findings of this study point to a degree of ecological resilience of Tanzanian Eastern Arc montane forests to wildfire disturbances. Despite the significant impacts of tree species stand parameters like above-ground biomass and tree density, we found minimal shifts in overall tree species composition between burned and unburned forest areas. The extensive overlap shown by the ANOSIM analysis suggests that many dominant tropical montane tree species are able to persist through or rapidly recolonize following fires (Ford and Hardesty, 2012; Mondal and Sukumar, 2015). This aligns with other studies in tropical forests that found limited changes to fundamental tree species composition after even high-severity burns compared to more pronounced compositional shifts in temperate and boreal systems (Barlow and Peres, 2004; Oliveras et al., 2014, 2018).

Certain inherent traits like resprouting allow many tropical tree species to regenerate after fire (Teixeira et al., 2020). Our identification of disturbance-associated pioneer species as indicators in burned plots points to prevalence of fire-adapted species, although most species were shared across sites. This underscores the vital capacity of these forests to naturally restore ecological structure and functions despite disruptions (Mori et al., 2017). However, potential lags and thresholds exist – increased frequencies of fire could overcome resilience mechanisms if insufficient recovery time is allowed between burns (Wilcox et al., 2020).

Active ecological recovery processes within these tropical montane forests were shown in this study through post-fire regeneration patterns across a 5-year period. We found strong positive correlations between stand and diversity parameters like density, biomass, and Shannon's index and time since fire. This accumulation of biomass over time highlights the forests capacity to gradually restore carbon storage and sequestration functions that are central to climate change mitigation (Chazdon et al., 2016). The recovery of species diversity and richness also demonstrates the steady re-establishment of complex ecological niches and habitats (Derroire et al., 2016). However, some parameters may recover faster than others – tree density and basal area rebounded more rapidly compared to diversity (Majumdar et al., 2016; McGregory et al., 2016). Varied regeneration rates across diversity and stand parameters point to potential time lags (Subashree et al., 2020). While forests may regain simpler structural complexity shortly after fire, elements like species richness and heterogeneity may require longer undisturbed periods to fully recover (Cavallero et al., 2015).

The value of integrating multispectral remote sensing data from PlanetScope and Sentinel-2 platforms to map and analyse fire patterns in these tropical montane forests was demonstrated in this study. The optimized predictive model accurately delineated burn areas totalling approximately 1430 hectares, with hotspots clustered near villages. This suggests prevalent anthropogenic ignitions, aligning with other tropical forest studies (Balch et al., 2008; Morris, 2010; Kelley et al., 2019). The model optimization using Recursive Feature Elimination highlighted the importance of textural metrics like contrast of NBR+ for quantifying landscape heterogeneity (Chen et al., 2018; Mishra et al., 2018). The approach also revealed the utility of diverse spectral bands and indices for capturing fire impacts on vegetation health (Bar et al., 2020; Miller and Thode, 2007). While some key predictors differed from previous tropical forest models, the overall effectiveness underscores the adaptability of this mapping methodology. The capacity to integrate datasets from multiple sensors provides a flexible toolkit to generate time-series analyses that reveal both immediate and lagged ecological responses over the post-fire recovery trajectory (Chuvieco et al., 2020).

While this study gives important insights into post-fire assessment on tree species composition, diversity, and stand parameters, there are some limitations to consider. The relatively short interval of 5 years since fire events may not capture longer-term successional dynamics. Legacy effects and cumulative impacts of previous fires, as well as other disturbances like land use changes, were not accounted for but may influence vegetation patterns. The restricted spatial scale focused on only two forest reserves, which could limit generalization. Monitoring across broader temporal and spatial scales would build understanding of recovery patterns. Despite these limitations, this work makes a significant contribution by assessing post-fire tree responses in an important region and ecosystem type while providing a foundation for further investigations into tropical montane forest dynamics.

4.5 Conclusion

Our study highlights post-fire effects in Eastern Arc Mountain forests using an integrative approach combining field measurements and optical remote sensing. Despite fire disturbances, the forests display extensive tree species overlap, and only slight compositional shifts were observed. Strong correlations between diversity and stand parameters with time since fire demonstrate regeneration, showing the forests capacity to reaccumulate biomass and regenerate tree diversity. The remote sensing model effectively mapped burn areas and revealed fire hotspots near villages, the utility of spectral indices and textures for monitoring wildfires. These findings have important implications for the conservation of threatened yet critical tropical montane forests. Further investigations should build on these findings, focusing on long-term monitoring, fire frequency thresholds, strategies to mitigate wildfire ignitions, and the effects on overall biodiversity of the area.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Diana L. Tesha: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Sami D. Madundo:** Formal analysis, Visualization, Writing – review & editing. **Ernest W. Mauya:** Supervision, Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ernest William Mauya reports financial support was provided by Eastern Arc Mountains Conservation Endowment Fund. Diana Lawrence Tesha reports financial support was provided by Regional Centre for Mapping of Resources for Development. Diana Lawrence Tesha reports financial support was provided by Tanzania Forest Fund.

Acknowledgements

The authors would like to thank the Eastern Arc Mountains Conservation Endowment Fund (EAMCEF), the Tanzania Forest Fund (TaFF), and the Regional Centre for Mapping of Resources for Development/ Global Monitoring for Environment and Security Africa (RCMRD/GMES Africa) for their invaluable support in funding this research study.

References

Alcaras, E., Costantino, D., Guastaferro, F., Parente, C., & Pepe, M. (2022). Normalized Burn Ratio Plus (NBR+): a new index for sentinel-2 imagery. *Remote Sensing*, 14(7), 1727. https://doi.org/10.3390/rs14071727.

Anderson, M. J., & Walsh, D. C. (2013). PERMANOVA, ANOSIM, and the Mantel test in the face of heterogeneous dispersions: What null hypothesis are you testing? *Ecological Monographs*, *83*(4), 557–574.

Armenteras, D., Dávalos, L. M., Barreto, J. S., Miranda, A., Hernández-Moreno, A., Zamorano-Elgueta, C., González-Delgado, T. M., Meza-Elizalde, M. C., & Retana, J. (2021). Fire-induced loss of the world's most biodiverse forests in Latin America. *Science Advances*, *7*(33), eabd3357.

Bar, S., Parida, B., & Pandey, A. (2020). Landsat-8 and Sentinel-2 based Forest fire burn area mapping using machine learning algorithms on GEE cloud platform over Uttarakhand, Western Himalaya. *Remote Sensing Applications: Society and Environment*, 18, 100324. https://doi.org/10.1016/j.rsase.2020.100324.

Bartels, S. F., Chen, H. Y. H., Wulder, M. A., & White, J. C. (2016). Trends in post-disturbance recovery rates of Canada's forests following wildfire and harvest. *Forest Ecology and Management*, *361*, 194–207. https://doi.org/10.1016/j.foreco.2015.11.015

Barzani, A. R., Pahlavani, P., Ghorbanzadeh, O., & Ghamisi, P. (2023). How the recursive feature elimination affects the SVM and RF for wildfire modeling? A mountainous case study area. *EGUsphere*, 1–25. https://doi.org/10.5194/egusphere-2022-1294

Bowman, D. M., Kolden, C. A., Abatzoglou, J. T., Johnston, F. H., van der Werf, G. R., & Flannigan, M. (2020). Vegetation fires in the Anthropocene. *Nature Reviews Earth & Environment*, *1*(10), 500–515.

Burton, C., Betts, R., Cardoso, M., Feldpausch, T. R., Harper, A., Jones, C. D., Kelley, D. I., Robertson, E., & Wiltshire, A. (2019). Representation of fire, land-use change and vegetation dynamics in the Joint UK Land Environment Simulator vn4.9 (JULES). *Geoscientific Model Development*, *12*(1), 179–193. https://doi.org/10.5194/gmd-12-179-2019

Butler, O. M., Lewis, T., & Chen, C. (2017). Prescribed fire alters foliar stoichiometry and nutrient resorption in the understorey of a subtropical eucalypt forest. *Plant and Soil*, *410*(1), 181–191. https://doi.org/10.1007/s11104-016-2995-x

Cavallero, L., López, D., Raffaele, E., & Aizen, M. (2015). Structural-functional approach to identify post-disturbance recovery indicators in forests from northwestern Patagonia: a tool to prevent state transitions. *Ecological Indicators*, 52, 85-95. https://doi.org/10.1016/J.ECOLIND.2014.11.019.

Chazdon, R., Broadbent, E., Rozendaal, D., Bongers, F., Zambrano, A., Aide, T., Balvanera, P., Becknell, J., Boukili, V., Brancalion, P., Craven, D., Almeida-Cortez, J., Cabral, G., Jong, B., Denslow, J., Dent, D., DeWalt, S., Dupuy, J., Durán, S., Espírito-Santo, M., Fandino, M., César, R., Hall, J., Hernández-Stefanoni, J., Jakovac, C., Junqueira, A., Kennard, D., Letcher, S., Lohbeck, M., Martínez-Ramos, M., Massoca, P., Meave, J., Mesquita, R., Mora, F., Muñoz, R., Muscarella, R., Nunes, Y., Ochoa-Gaona, S., Orihuela-Belmonte, E., Peña-Claros, M., Pérez-García, E., Piotto, D., Powers, J., Rodríguez-Velázquez, J., Romero-Pérez, I., Ruíz, J., Saldarriaga, J., Sánchez-Azofeifa, A., Schwartz, N., Steininger, M., Swenson, N., Uriarte, M., Breugel, M., Wal, H., Veloso, M., Vester, H., Vieira, I., Bentos, T., Williamson, G., & Poorter, L. (2016). Carbon sequestration potential of second-growth forest regeneration in the Latin American tropics. *Science Advances*, 2. https://doi.org/10.1126/sciadv.1501639.

Chen, Q., Meng, Z., Liu, X., Jin, Q., & Su, R. (2018). Decision Variants for the Automatic Determination of Optimal Feature Subset in RF-RFE. *Genes*, 9. https://doi.org/10.3390/genes9060301.

Chuvieco, E., Aguado, I., Salas, J., García, M., Yebra, M., & Oliva, P. (2020). Satellite Remote Sensing Contributions to Wildland Fire Science and Management. *Current Forestry Reports*, 6, 81-96. https://doi.org/10.1007/s40725-020-00116-5.

De Caceres, M., Jansen, F., & De Caceres, M. M. (2016). Package 'indicspecies'. *Indicators*, *8*(1).

de Oliveira-Júnior, J. F., Shah, M., Abbas, A., Correia Filho, W. L. F., da Silva Junior, C. A., de Barros Santiago, D., Teodoro, P. E., Mendes, D., de Souza, A., & Aviv-Sharon, E. (2022). Spatiotemporal analysis of fire foci and environmental degradation in the biomes of Northeastern Brazil. *Sustainability*, *14*(11), 6935.

Dempewolf, J., Trigg, S., DeFries, R. S., & Eby, S. (2007). Burned-Area Mapping of the Serengeti–Mara Region Using MODIS Reflectance Data. *IEEE Geoscience and Remote Sensing Letters*, *4*(2), 312–316. https://doi.org/10.1109/LGRS.2007.894140

Derroire, G., Balvanera, P., Castellanos-Castro, C., Decocq, G., Kennard, D., Lebrija-Trejos, E., Leiva, J., Odén, P., Powers, J., Rico-Gray, V., Tigabu, M., & Healey, J. (2016). Resilience of tropical dry forests – a meta-analysis of changes in species diversity and composition during secondary succession. *Oikos*, 125, 1386-1397. https://doi.org/10.1111/OIK.03229.

Fawzy, S., Osman, A. I., Doran, J., & Rooney, D. W. (2020). Strategies for mitigation of climate change: A review. *Environmental Chemistry Letters*, *18*, 2069–2094.

Fernández-Guisuraga, J. M., Suárez-Seoane, S., & Calvo, L. (2019). Modeling Pinus pinaster forest structure after a large wildfire using remote sensing data at high spatial resolution. *Forest Ecology and Management*, *446*, 257–271. https://doi.org/10.1016/j.foreco.2019.05.028

Filipponi, F. (2018, March). BAIS2: Burned area index for Sentinel-2. *In Proceedings* (Vol. 2, No. 7, p. 364). MDPI. https://doi.org/10.3390/ecrs-2-05177.

Ford, A., & Hardesty, B. (2012). Species adaptation to both fire and climate change in tropical montane heath: Can Melaleuca uxorum (Myrtaceae) survive?. *Pacific Conservation Biology*, 18, 319-324. https://doi.org/10.1071/PC120319.

García, M. L., & Caselles, V. (1991). Mapping burns and natural reforestation using Thematic Mapper data. *Geocarto International*, 6(1), 31-37. https://doi.org/10.1080/10106049109354290.

Gerard, F., Plummer, S., Wadsworth, R., Sanfeliu, A. F., Iliffe, L., Balzter, H., & Wyatt, B. (2003). Forest fire scar detection in the boreal forest with multitemporal SPOT-VEGETATION data. *IEEE Transactions on Geoscience and Remote Sensing*, 41(11), 2575-2585. http://dx.doi.org/10.1109/TGRS.2003.819190.

Gibson, R. K., Mitchell, A., & Chang, H.-C. (2023). Image Texture Analysis Enhances Classification of Fire Extent and Severity Using Sentinel 1 and 2 Satellite Imagery. *Remote Sensing*, *15*(14), Article 14. https://doi.org/10.3390/rs15143512

Goldammer, J. G. (2007). History of equatorial vegetation fires and fire research in Southeast Asia before the 1997–98 episode: A reconstruction of creeping environmental changes. *Mitigation and Adaptation Strategies for Global Change*, *12*(1), 13–32. https://doi.org/10.1007/s11027-006-9044-7

González, M. E. (2005). Fire history data as reference information in ecological restoration. *Dendrochronologia*, *22*(3), 149–154.

Hall, J. B., & Swaine, M. D. (1981). Descriptions of forest types. In J. B. Hall & M. D. Swaine (Eds.), *Distribution and ecology of vascular plants in a tropical rain forest: Forest vegetation in Ghana* (pp. 71–100). Springer Netherlands. https://doi.org/10.1007/978-94-009-8650-3_8

Han, A., Qing, S., Bao, Y., Na, L., Bao, Y., Liu, X., Zhang, J., & Wang, C. (2021). Short-term effects of fire severity on vegetation based on sentinel-2 satellite data. *Sustainability*, *13*(1), 432.

Han, J., Shen, Z., Li, Y., Luo, C., Xu, Q., Yang, K., & Zhang, Z. (2018). Beta diversity patterns of post-fire forests in central Yunnan Plateau, southwest China: Disturbances intensify the priority effect in the community assembly. *Frontiers in Plant Science*, *9*, 1000.

Han, J., Shen, Z., Ying, L., Li, G., & Chen, A. (2015). Early post-fire regeneration of a fire-prone subtropical mixed Yunnan pine forest in Southwest China: Effects of pre-fire vegetation, fire severity and topographic factors. *Forest Ecology and Management*, *356*, 31–40. https://doi.org/10.1016/j.foreco.2015.06.016

Hill, M. J. (2013). Vegetation index suites as indicators of vegetation state in grassland and savanna: An analysis with simulated SENTINEL 2 data for a North American transect. *Remote Sensing of Environment*, *137*, 94–111. https://doi.org/10.1016/j.rse.2013.06.004

Hillman, S., Hally, B., Wallace, L., Turner, D., Lucieer, A., Reinke, K., & Jones, S. (2021). High-resolution estimates of fire severity—An evaluation of UAS image and LiDAR mapping approaches on a sedgeland forest boundary in Tasmania, Australia. *Fire*, *4*(1), 14.

Hislop, S., Haywood, A., Jones, S., Soto-Berelov, M., Skidmore, A., & Nguyen, T. H. (2020). A satellite data driven approach to monitoring and reporting fire disturbance and recovery across boreal and temperate forests. *International Journal of Applied Earth Observation and Geoinformation*, *87*, 102034. https://doi.org/10.1016/j.jag.2019.102034

Holden, Z. A., Morgan, P., & Hudak, A. T. (2010). Burn Severity of Areas Reburned by Wildfires in the Gila National Forest, New Mexico, USA. *Fire Ecology*, *6*(3), 77–85. https://doi.org/10.4996/fireecology.0603085

Huang, Y.-L., Devan, M. N., U'Ren, J. M., Furr, S. H., & Arnold, A. E. (2016). Pervasive effects of wildfire on foliar endophyte communities in montane forest trees. *Microbial Ecology*, *71*, 452–468.

Imbert, J. B., Blanco, J. A., Candel-Pérez, D., Lo, Y.-H., González de Andrés, E., Yeste, A., Herrera-Álvarez, X., Rivadeneira Barba, G., Liu, Y., & Chang, S.-C. (2021). Synergies between climate change, biodiversity, ecosystem function and services, indirect drivers of change and human well-being in forests. *Exploring Synergies and Trade-Offs between Climate Change and the Sustainable Development Goals*, 263–320.

Jain, P., Castellanos-Acuna, D., Coogan, S. C., Abatzoglou, J. T., & Flannigan, M. D. (2022). Observed increases in extreme fire weather driven by atmospheric humidity and temperature. *Nature Climate Change*, *12*(1), 63–70.

João, T., João, G., Bruno, M., & João, H. (2018). Indicator-based assessment of post-fire recovery dynamics using satellite NDVI time-series. *Ecological Indicators*, *89*, 199–212. https://doi.org/10.1016/j.ecolind.2018.02.008

Kelley, D., Bistinas, I., Whitley, R., Burton, C., Marthews, T., & Dong, N. (2019). How contemporary bioclimatic and human controls change global fire regimes. *Nature Climate Change*, 1-7. https://doi.org/10.1038/s41558-019-0540-7.

Kilawe, C. J., Kaaya, O. E., Kolonel, C. P., Macrice, S. A., Mshama, C. P., Lyimo, P. J., & Emily, C. J. (2021). Wildfires in the Eastern Arc Mountains of Tanzania: Burned areas, underlying causes and management challenges. *African Journal of Ecology*, *59*(1), 204–215.

Kuosmanen, N., Seppä, H., Alenius, T., Bradshaw, R. H. W., Clear, J. I., Filimonova, L., Heikkilä, M., Renssen, H., Tallavaara, M., & Reitalu, T. (2016). Importance of climate, forest fires and human population size in the Holocene boreal forest composition change in northern Europe. *Boreas*, *45*(4), 688–702. https://doi.org/10.1111/bor.12183

Liu, S., Zheng, Y., Dalponte, M., & Tong, X. (2020). A novel fire index-based burned area change detection approach using Landsat-8 OLI data. *European journal of remote sensing*, 53(1), 104-112. https://doi.org/10.1080/22797254.2020.1738900.

Lovett, J. C. (1996). Elevational and latitudinal changes in tree associations and diversity in the Eastern Arc mountains of Tanzania. *Journal of Tropical Ecology*, *12*(5), 629–650.

Lu, D., Batistella, M., Moran, E., & de Miranda, E. E. (2008). A Comparative Study of Landsat TM and SPOT HRG Images for Vegetation Classification in the Brazilian Amazon. *Photogrammetric Engineering & Remote Sensing*, *74*(3), 311–321. https://doi.org/10.14358/PERS.74.3.311

Majumdar, K., Choudhary, B., & Datta, B. (2016). Changes of woody species diversity, horizontal and vertical distribution of stems across interior to outside within a primate rich habitat of Northeast India. *Journal of Forestry Research*, 27, 787 - 798. https://doi.org/10.1007/s11676-016-0231-4.

McGregor, H., Colloff, M., & Lunt, I. (2016). Did early logging or changes in disturbance regimes promote high tree densities in river red gum forests. *Australian Journal of Botany*, 64, 530-538. https://doi.org/10.1071/BT16025.

Menezes, L. S., de Oliveira, A. M., Santos, F. L., Russo, A., de Souza, R. A., Roque, F. O., & Libonati, R. (2022). Lightning patterns in the Pantanal: Untangling natural and anthropogenic-induced wildfires. *Science of the Total Environment*, *820*, 153021.

Meng, R., Wu, J., Zhao, F., Cook, B. D., Hanavan, R. P., & Serbin, S. P. (2018). Measuring short-term post-fire forest recovery across a burn severity gradient in a mixed pine-oak forest using multi-sensor remote sensing techniques. *Remote Sensing of Environment*, *210*, 282–296. https://doi.org/10.1016/j.rse.2018.03.019

Miller, J., & Thode, A. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, 109, 66-80. https://doi.org/10.1016/J.RSE.2006.12.006.

Mishra, V., Prasad, R., Rai, P., Vishwakarma, A., & Arora, A. (2018). Performance evaluation of textural features in improving land use/land cover classification accuracy of heterogeneous landscape using multi-sensor remote sensing data. *Earth Science Informatics*, 12, 71-86. https://doi.org/10.1007/s12145-018-0369-z.

Mondal, N., & Sukumar, R. (2015). Regeneration of Juvenile Woody Plants after Fire in a Seasonally Dry Tropical Forest of Southern India. *Biotropica*, 47. https://doi.org/10.1111/btp.12219.

Mori, A., Lertzman, K., & Gustafsson, L. (2017). Biodiversity and ecosystem services in forest ecosystems: a research agenda for applied forest ecology. *Journal of Applied Ecology*, 54, 12-27. https://doi.org/10.1111/1365-2664.12669.

Morris, R. (2010). Anthropogenic impacts on tropical forest biodiversity: a network structure and ecosystem functioning perspective. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365, 3709 - 3718. https://doi.org/10.1098/rstb.2010.0273.

Oliveras, I., Malhi, Y., Salinas, N., Huamán, V., Urquiaga-Flores, E., Kala-Mamani, J., Quintano-Loaiza, J., Cuba-Torres, I., Lizarraga-Morales, N., & Roman-Cuesta, R. (2014). Changes in forest structure and composition after fire in tropical montane cloud forests near the Andean treeline. *Plant Ecology & Diversity*, 7, 329 - 340. https://doi.org/10.1080/17550874.2013.816800.

Oliveras, I., Roman-Cuesta, R., Urquiaga-Flores, E., Loayza, J., Kala, J., Huamán, V., Lizárraga, N., Sans, G., Quispe, K., López, E., Lopez, D., Torres, I., Enquist, B., & Malhi, Y. (2018). Fire effects and ecological recovery pathways of tropical montane cloud forests along a time chronosequence. *Global Change Biology*, 24, 758 - 772. https://doi.org/10.1111/gcb.13951.

Oksanen, J., Kindt, R., Legendre, P., O'Hara, B., Stevens, M. H. H., Oksanen, M. J., & Suggests, M. (2007). The vegan package. *Community Ecology Package*, *10*(631–637), 719.

Pilon, N. A. L., Cava, M. G. B., Hoffmann, W. A., Abreu, R. C. R., Fidelis, A., & Durigan, G. (2021). The diversity of post-fire regeneration strategies in the cerrado ground layer. *Journal of Ecology*, *109*(1), 154–166. https://doi.org/10.1111/1365-2745.13456

Pinedo-Escatel, J. A., Aragón-Parada, J., Dietrich, C. H., Moya-Raygoza, G., Zahniser, J. N., & Portillo, L. (2021). Biogeographical evaluation and conservation assessment of arboreal leafhoppers in the Mexican Transition Zone biodiversity hotspot. *Diversity and Distributions*, *27*(6), 1051–1065.

Prichard, S. J., Hessburg, P. F., Hagmann, R. K., Povak, N. A., Dobrowski, S. Z., Hurteau, M. D., Kane, V. R., Keane, R. E., Kobziar, L. N., & Kolden, C. A. (2021). Adapting western North American forests to climate change and wildfires: 10 common questions. *Ecological Applications*, *31*(8), e02433.

Qin, Y., Xiao, X., Wigneron, J.-P., Ciais, P., Canadell, J. G., Brandt, M., Li, X., Fan, L., Wu, X., Tang, H., Dubayah, R., Doughty, R., Crowell, S., Zheng, B., & Moore, B. (2022). Large loss and rapid recovery of vegetation cover and aboveground biomass over forest areas in Australia during 2019–

2020. *Remote Sensing of Environment*, *278*, 113087. https://doi.org/10.1016/j.rse.2022.113087

Reilly, M. J., Dunn, C. J., Meigs, G. W., Spies, T. A., Kennedy, R. E., Bailey, J. D., & Briggs, K. (2017). Contemporary patterns of fire extent and severity in forests of the Pacific Northwest, USA (1985–2010). *Ecosphere*, *8*(3), e01695. https://doi.org/10.1002/ecs2.1695

Richter, C., Rejmánek, M., Miller, J. E. D., Welch, K. R., Weeks, J., & Safford, H. (2019). The species diversity × fire severity relationship is hump-shaped in semiarid yellow pine and mixed conifer forests. *Ecosphere*, *10*(10), e02882. https://doi.org/10.1002/ecs2.2882

Riley, K. L., & Loehman, R. A. (2016). Mid-21st-century climate changes increase predicted fire occurrence and fire season length, Northern Rocky Mountains, United States. *Ecosphere*, *7*(11), e01543.

Rurangwa, M. L., Aguirre-Gutiérrez, J., Matthews, T. J., Niyigaba, P., Wayman, J. P., Tobias, J. A., & Whittaker, R. J. (2021). Effects of land-use change on avian taxonomic, functional and phylogenetic diversity in a tropical montane rainforest. *Diversity and Distributions*, *27*(9), 1732–1746.

Santos Rodrigues, P. A. (2020). *Prospects for tropical forest biodiversity in the landscapes of Southwestern Ethiopia: Conservation in a context of land use change and human population growth*. Dissertation, Lüneburg, Leuphana Universität Lüneburg.

Shea, K., Roxburgh, S. H., & Rauschert, E. S. J. (2004). Moving from pattern to process: Coexistence mechanisms under intermediate disturbance regimes. *Ecology Letters*, *7*(6), 491–508. https://doi.org/10.1111/j.1461-0248.2004.00600.x

Shin, Y.-J., Midgley, G. F., Archer, E. R., Arneth, A., Barnes, D. K., Chan, L., Hashimoto, S., Hoegh-Guldberg, O., Insarov, G., & Leadley, P. (2022). Actions to halt biodiversity loss generally benefit the climate. *Global Change Biology*, *28*(9), 2846–2874.

Shuman, J. K., Balch, J. K., Barnes, R. T., Higuera, P. E., Roos, C. I., Schwilk, D. W., Stavros, E. N., Banerjee, T., Bela, M. M., & Bendix, J. (2022). Reimagine fire science for the anthropocene. *PNAS Nexus*, *1*(3), pgac115.

Silva-Junior, C. H., Buna, A. T., Bezerra, D. S., Costa Jr, O. S., Santos, A. L., Basson, L. O., Santos, A. L., Alvarado, S. T., Almeida, C. T., & Freire, A. T. (2022). Forest fragmentation and fires in the eastern Brazilian Amazon–Maranhão State, Brazil. *Fire*, *5*(3), 77.

Singh, S. (2022). Forest fire emissions: A contribution to global climate change. *Frontiers in Forests and Global Change*, *5*, 925480.

Sofan, P., Bruce, D., Schroeder, W., Jones, E., & Marsden, J. (2020). Assessment of VIIRS 375 m active fire using tropical peatland combustion algorithm applied to Landsat-8 over Indonesia's peatlands. *International Journal of Digital Earth*, *13*(12), 1695–1716.

Subashree, K., Dar, J., Karuppusamy, S., & Sundarapandian, S. (2020). Plant diversity, structure and regeneration potential in tropical forests of Western Ghats, India. *Acta Ecologica Sinica*. https://doi.org/10.1016/j.chnaes.2020.02.004.

Taylor, A. H. (2010). Fire disturbance and forest structure in an old-growth Pinus ponderosa forest, southern Cascades, USA. *Journal of Vegetation Science*, *21*(3), 561–572. https://doi.org/10.1111/j.1654-1103.2009.01164.x

Teixeira, A., Curran, T., Jameson, P., Meurk, C., & Norton, D. (2020). Post-Fire Resprouting in New Zealand Woody Vegetation: Implications for Restoration. *Forests*. https://doi.org/10.3390/f11030269.

Trigg, S., & Flasse, S. (2001). An evaluation of different bi-spectral spaces for discriminating burned shrub-savannah. *International Journal of Remote Sensing*, 22(13), 2641-2647. https://doi.org/10.1080/01431160110053185.

Trouvé, R., Oborne, L., & Baker, P. J. (2021). The effect of species, size, and fire intensity on tree mortality within a catastrophic bushfire complex. *Ecological Applications*, *31*(6), e02383. https://doi.org/10.1002/eap.2383

Tyukavina, A., Potapov, P., Hansen, M. C., Pickens, A. H., Stehman, S. V., Turubanova, S., Parker, D., Zalles, V., Lima, A., & Kommareddy, I. (2022). Global trends of forest loss due to fire from 2001 to 2019. *Frontiers in Remote Sensing*, *3*, 825190.

Valor, T., González-Olabarria, J. R., & Piqué, M. (2015). Assessing the impact of prescribed burning on the growth of European pines. *Forest Ecology and Management*, *343*, 101–109. https://doi.org/10.1016/j.foreco.2015.02.002

Whitman, E., Parisien, M.-A., Thompson, D. K., & Flannigan, M. D. (2018). Topoedaphic and Forest Controls on Post-Fire Vegetation Assemblies Are Modified by Fire History and Burn Severity in the Northwestern Canadian Boreal Forest. *Forests*, *9*(3), Article 3. https://doi.org/10.3390/f9030151

Wilcox, K., Koerner, S., Hoover, D., Borkenhagen, A., Burkepile, D., Collins, S., Hoffman, A., Kirkman, K., Knapp, A., Strydom, T., Thompson, D., & Smith, M. (2020). Rapid recovery of ecosystem function following extreme drought in a South African savanna-grassland. *Ecology*. https://doi.org/10.1002/ecy.2983.

Zhang, N., Chen, M., Yang, F., Yang, C., Yang, P., Gao, Y., Shang, Y., & Peng, D. (2022). Forest height mapping using feature selection and machine learning by integrating multi-source satellite data in Baoding City, North China. *Remote Sensing*, *14*(18), 4434.

CHAPTER 5

5.0 GENERAL DIDSCUSSION

5.1 Tree Species Diversity and Composition in the West Usambara Mountain Forests

The aim of this study was to estimate and map forest biodiversity and associated ecological threats in the West Usambara Mountains at a larger spatial scale through integration of remote sensing technologies and ground-based methods. The Eastern Arc Mountains are known for their high biodiversity and endemism, making them an important area for conservation (Kilawe et al., 2021). Firstly, we studied the tree species diversity and composition patterns in the study sites and analyse their relationship with soil, topographic and climatic factors in attempt to study the respective biodiversity indicators. The influence of climate, soil, and topography on shaping distinct forest communities observed in this study is consistent with other research in tropical montane forests (Homeier et al., 2010; Sharma et al., 2015). Comparable patterns have been found in the Eastern Arc Mountains, where vegetation composition was significantly correlated to elevation, temperature, rainfall seasonality, and soil fertility (Lovett et al., 2006). However, unlike our study, these previous Eastern Arc studies did not evaluate multiple environmental variables simultaneously. By incorporating several key climatic, edaphic, and topographic factors, this study provides a more comprehensive understanding of how these elements work in concert to determine species distributions and diversity. Their multi-factor approach aligns with evidence from Neotropical montane forests showing interactive effects of precipitation, soil nutrients, temperature, and topography on local forest composition (Hietz et al., 2022). Nevertheless, additional research examining a wider range of predictors across broader spatial scales would further improve our knowledge of environmental controls over community assemblages in the Eastern Arc Mountains.

The significant differences in diversity and composition between the three forest communities in this study mirror patterns documented across tropical montane forests globally. For instance, the decline in diversity and richness at higher elevations found in the DC community follows trends observed along extensive elevational gradients in the Andes and Himalayas (Bhattarai and Vetaas, 2003; Kessler et al., 2011). This likely reflects the harsher environmental conditions that limit plant growth and regeneration at higher elevations (Zhang et al., 2016). However, other work in the Eastern Arc Mountains found highest tree diversity at mid elevations instead of a monotonic decline (Hemp, 2006). This contrast highlights the potential for complex diversity patterns based on localized factors like human disturbance history and land use. Regarding floristic composition, the importance of species turnover in driving community differences here aligns with findings from the Bolivian Andes, where turnover was the dominant process structuring elevational bands of distinct forest types (Tovar et al., 2013). Yet, patterns can be variable, as emphasized by research in Costa Rica showing nestedness making a greater contribution to beta diversity (Hietz et al., 2022). More extensive sampling across the Eastern Arc Mountains would provide valuable insights into the relative influence of environmental sorting versus spatial processes in shaping elevational gradients in these forests.

5.2 Influence of Forest Fires on Tree Species Composition and Diversity

This study revealed limited fire impacts on tree species composition, contrasting with substantial alterations to structural parameters like density and biomass. The minor compositional shifts mirror findings from African tropical montane forests showing similarity between burnt and unburnt sites (Enright et al., 2012). However, Neotropical forests exhibit more pronounced compositional changes post-fire (Barlow et al., 2003). Regarding structural alterations, the fire-induced declines in density, basal area, and biomass align with impacts reported for Mexican tropical montane cloud forests (Alvarado-Celestino et al., 2022), underscoring the disruptive ecological influence of fire. Comparable fire-driven decreases in biomass and density occurred in Tanzania’s Udzungwa Mountains (Rurangwa et al., 2021), highlighting consistency across the Eastern Arc Mountains. The positive correlations between structural recovery and time since fire match patterns in Cameroonian mountain forests (Mitchard et al., 2009), emphasizing montane forest resilience given sufficient recovery periods. However, regeneration trajectories vary across sites as seen by contrasting diversity and richness rebounds in the Udzungwa and West Usambara forests. Ultimately, while burning severely impacts structure, montane forests retain a capacity for regeneration when spared recurring frequent fires. Additional monitoring focused on the Eastern Arc Mountains would provide vital context-specific insights into post-fire dynamics to inform management.

This study revealed distinctive indicator species for both the burnt and unburnt forest areas. The prevalence of Apodytes 77elation77 in burnt sites mirrors its indicator status for recently burned areas in the Mau Forest of Kenya (Kanga et al., 2011). Its resilience likely derives from vigorous resprouting post-fire. Meanwhile, the dominance of Cyathea manniana in unburnt sites aligns with its identification as an indicator of undisturbed forest in the Taita Hills of Kenya (Aerts et al., 2011). As a fire-sensitive fern, its absence serves as an indicator of past burns. More broadly, research in the Australian Wet Tropics highlights the utility of indicator species like these in monitoring ecosystem responses to fire regimes (Buffer et al., 2022). Species-specific traits like fire-tolerance and competitive ability enable indicators to act as barometers of disturbance history. Our findings demonstrate how targeted indicator species can provide valuable ecological insights into the complex dynamics of fire-prone tropical montane forests. Further research should explore traits underlying indicator species' post-fire preferences to deepen understanding of tropical forest resilience.

5.3 Utility of Satellite Imagery in Assessment of Indicators of Forest Biodiversity

The analysis of the utility of Sentinel-2 and PlanetScope satellite imagery in assessment of indicators of forest biodiversity has yielded interesting results. In particular, the study focused on the relative efficiency of prediction of tree species diversity using the two satellite datasets. The results showed that PlanetScope data have more efficiently predicted tree species diversity in the study area compared to Sentinel-2 whereas similar observations were made by Kpienbaareh *et al*. (2021). The study considered three measures of tree species diversity, namely tree species richness and Shannon's diversity index and tree species evenness. The Relative Efficiency (R.E) values of tree species richness and Shannon's diversity were higher when using PlanetScope dataset. This suggests that PlanetScope data was able to more accurately predict the number of tree species in the study area, as well as Shannon's diversity index. The results from this study are however in contrast with results from Kluczek et al. (2023) who reported PlanetScope dataset had produced slightly less accurate results . On the other hand, Sentinel-2 data was found to be efficient in predicting tree species evenness in the study area, with an R.E value of 1.21. This means that while the dataset may not be as effective in predicting the number of tree species in the area, it is better at predicting the evenness of species distribution.

These findings have important implications for forest biodiversity assessment and management. Accurate prediction of tree species diversity is crucial for understanding the ecological health of a forest ecosystem (Weinstein *et al*., 2021). Inaccurate predictions can lead to incorrect management decisions and potentially harm the ecosystem. Therefore, the use of remote sensing data such as Sentinel-2 and PlanetScope can be valuable in providing accurate and efficient predictions of tree species diversity (Nagendra *et al*., 2013; Rocchini *et al*., 2010). It is worth noting that the differences in the R.E values between the two datasets may be attributed to several factors such as the spatial resolution, spectral bands, and temporal frequency of the datasets which may have influenced their predictive power. PlanetScope data has a higher spatial resolution compared to Sentinel-2, which may have contributed to its higher efficiency in predicting tree species richness and Shannon's diversity index. Additionally, the spectral bands captured by the two datasets may have differed, which may have affected their ability to predict tree species diversity. Overall, the findings of this study demonstrate the potential of remote sensing data in forest biodiversity assessment. However, further research is needed to explore the factors that influence the predictive power of these datasets and to determine the most effective strategies for using remote sensing data in forest management.

5.4 Efficiency of Modelling Techniques in Predicting Tree Species Diversity

The study evaluated the performance of XGBoost and GAM modelling techniques in predicting Shannon's diversity index and species richness on PlanetScope textures, vegetation indices, and bands. The results revealed that the best model for predicting Shannon's diversity index was XGBoost with an R^2 value of 0.2, rRMSE of 23.52%, and rMAE of 18%. On the other hand, the best model for predicting species richness was GAM with an R^2 value of 0.193, rRMSE of 38.91%, and rMAE of 30.72%.

The performance of the models could be attributed to the predictor variables used. In this study, the combination of all predictors, including bands, textures, and vegetation indices, showed an improvement in the predictive power of the models. This finding is consistent with previous studies (St-Louis et al., 2009; Huechacona-Ruiz et al., 2020; Zhang et al., 2022) that have shown that combining different types of predictors can improve the accuracy of predictive models. The use of multiple predictors can help capture the complexity of the relationship between the response variable and the predictors, leading to a better understanding of the underlying processes (Smith et al., 2019).

The XGBoost model outperformed the GAM model in predicting Shannon's diversity index. This could be due to the fact that XGBoost is a more powerful machine learning algorithm that is capable of handling large datasets and capturing non-linear relationships between variables (Ma et al., 2020). The XGBoost model is also less sensitive to outliers, which could explain its superior performance in predicting Shannon's diversity index (Wu et al., 2019). On the other hand, the GAM model performed better in predicting species richness, which could be due to its ability to capture the relationship between the response variable and the predictors through non-parametric smoothing functions (Lehmann et al., 2002; McCune, 2006). Cai et al. (2023) has shown that the GAM model is also less prone to overfitting, which is a common problem in machine learning models.

The R^2 values obtained in this study were relatively low, indicating that the models did not explain all the variability in the data. However, it is important to note that predicting tree species diversity is a complex task that is influenced by many factors, including environmental variables, land use history, and ecological processes. Therefore, it is not surprising that the models did not perform exceptionally well in predicting the response variables. This study demonstrates the potential of machine learning algorithms in predicting tree species diversity. The results indicate that combining different types of predictors can improve the predictive power of the models. However, further research is needed to improve the accuracy of the models, including the incorporation of additional predictors and the use of more advanced modelling techniques.

CHAPTER 6

6.0 KEY CONTRIBUTIONS, CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

The major contributions of this study to the field of knowledge are highlighted in this chapter. This chapter also outlines important recommendations and summarizes the findings of this study.

6.2 Key Contributions of the Study

In this dissertation, it was shown that the effective estimation and mapping of forest AGB and cover depend on the choice of remote sensing data, input features/variables, and modelling method.

The major contributions of this dissertation are as follows:

a) Identification of Distinct Forest Communities: The study identified and characterized distinct forest communities in the West Usambara Montane forests, demonstrating their intricate relationship with topography, soil, and climate.
b) Multi-Scale Abiotic Variables: This study emphasizes the importance of considering multi-scale abiotic variables in tropical montane ecosystems, with a specific focus on the significant influence of precipitation and soil nutrients as key drivers of community patterns.
c) Efficient Remote Sensing Data: This study showcases the efficiency of using remotely sensed data, particularly PlanetScope for predicting tree species diversity and richness, and Sentinel-2 for assessing tree species diversity, enhancing the accuracy of biodiversity assessments.
d) Impact of Forest Fires: Insights into the impact of forest fires on tree species structure and composition highlight the resilience of the West Usambara mountains to such disturbances.

6.3 Conclusions

The results from this study have demonstrated that forest communities are greatly shaped by the environmental factors such as topography, soil and climate. Three distinct forest communities linked to specific environmental variables, with diversity and richness differing between communities have been identified. Environmental factors like precipitation and soil nutrients were key drivers of community patterns, underscoring the importance of considering multi-scale abiotic variables in tropical montane ecosystems. The study has demonstrated that the use of remotely sensed data, particularly PlanetScope was efficient in predicting tree species diversity (H) and tree species richness (S) while Sentinel 2, was useful in predicting tree species evenness (J) in the study area. The results from this study provides a useful insight for management and conservation activities through highlighting areas with high and low tree species diversity which can guide management efforts. The combination of field-based approaches and remote sensing techniques has proven to provide valuable insights into the assessment of factors that influence tree species diversity and distribution in West Usambara Montane forests. Also, this study has highlighted the impact of forests fire on the tree species structure and composition showing the high recovery together with resilience of the West Usambara mountains to forest fires through the overlapping of species between the burnt and unburnt areas. Lastly, the study has shown the role of human activities in the starting and spreading of wildfires. Overall, these findings can inform conservation efforts and guide management strategies for the West Usambara montane forests of Tanzania. Furthermore, further research is needed to explore the potential of other remote sensing data sources and modelling techniques to improve the accuracy and reliability of biodiversity assessments.

6.4 Recommendations

The results highlight the strong influence of soil factors such as pH and nitrogen on tree diversity and distribution, while also demonstrating the potential of remote sensing data, particularly PlanetScope data, for assessing and estimating forest biodiversity indicators such as tree species evenness. The study recommends that conservation efforts should prioritize areas showing low tree species diversity and take into account the influence of environmental factors such as soil properties. Due to the utility of Remote sensing techniques that has been demonstrated from this study, it can be recommended that countrywide biodiversity assessment and estimation by using Remote sensing techniques should be carried out to compliment the field-based inventories. Additionally, further research is needed to explore the potential of other remote sensing data sources and modelling techniques to improve the accuracy and reliability of biodiversity assessments. Overall, the findings of this study are of great significance for forest management and conservation efforts in the West Usambara montane forests and other montane tropical forests around the world that face similar challenges.

REFERENCES

Abera, W., Tamene, L., Kassawmar, T., Mulatu, K., Kassa, H., Verchot, L., & Quintero, M. (2021). Impacts of land use and land cover dynamics on ecosystem services in the Yayo coffee forest biosphere reserve, southwestern Ethiopia. *Ecosystem Services*, *50*, 101338.

Baskent, E. Z., Borges, J. G., Kašpar, J., & Tahri, M. (2020). A design for addressing multiple ecosystem services in forest management planning. *Forests*, *11*(10), 1108.

Bowie, R. C., Monahan, W. B., & Fjeldså, J. (2023). Climate Cycles, Habitat Stability, and Lineage Diversification in an African Biodiversity Hotspot. *Diversity*, *15*(3), 394.

Cai, L., Kreft, H., Taylor, A., Denelle, P., Schrader, J., Essl, F., van Kleunen, M., Pergl, J., Pyšek, P., & Stein, A. (2023). Global models and predictions of plant diversity based on advanced machine learning techniques. *New Phytologist*, *237*(4), 1432–1445.

Conte, C. A. (1999). The forest becomes desert: Forest use and environmental change in Tanzania's West Usambara mountains. *Land Degradation & Development*, *10*(4), 291–309.

Cui, R., Han, J., & Hu, Z. (2022). Assessment of Spatial Temporal Changes of Ecological Environment Quality: A Case Study in Huaibei City, China. *Land*, *11*(6), Article 6. https://doi.org/10.3390/land11060944

Danielsen, F., Pirhofer-Walzl, K., Adrian, T. P., Kapijimpanga, D. R., Burgess, N. D., Jensen, P. M., Bonney, R., Funder, M., Landa, A., & Levermann, N. (2014). Linking public participation in scientific research to the indicators and needs of international environmental agreements. *Conservation Letters*, *7*(1), 12–24.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., & Martimort, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, *120*, 25–36.

Gyamfi-Ampadu, E., Gebreslasie, M., & Mendoza-Ponce, A. (2021). Evaluating multi-sensors spectral and spatial resolutions for tree species diversity prediction. *Remote Sensing*, *13*(5), 1033.

Homeier, J., & Leuschner, C. (2021). Factors controlling the productivity of tropical Andean forests: Climate and soil are more important than tree diversity. *Biogeosciences*, *18*(4), 1525–1541.

Huechacona-Ruiz, A. H., Dupuy, J. M., Schwartz, N. B., Powers, J. S., Reyes-García, C., Tun-Dzul, F., & Hernández-Stefanoni, J. L. (2020). Mapping

Tree Species Deciduousness of Tropical Dry Forests Combining Reflectance, Spectral Unmixing, and Texture Data from High-Resolution Imagery. *Forests*, *11*(11), Article 11. https://doi.org/10.3390/f11111234

Kilawe, C. J., Kaaya, O. E., Kolonel, C. P., Macrice, S. A., Mshama, C. P., Lyimo, P. J., & Emily, C. J. (2021). Wildfires in the Eastern Arc Mountains of Tanzania: Burned areas, underlying causes and management challenges. *African Journal of Ecology*, *59*(1), 204–215.

Kluczek, M., Zagajewski, B., & Zwijacz-Kozica, T. (2023). Mountain Tree Species Mapping Using Sentinel-2, PlanetScope, and Airborne HySpex Hyperspectral Imagery. *Remote Sensing*, *15*(3), Article 3. https://doi.org/10.3390/rs15030844

Kpienbaareh, D., Sun, X., Wang, J., Luginaah, I., Bezner Kerr, R., Lupafya, E., & Dakishoni, L. (2021). Crop type and land cover mapping in northern Malawi using the integration of sentinel-1, sentinel-2, and planetscope satellite data. *Remote Sensing*, *13*(4), 700.

Lehmann, A., Overton, J. M., & Leathwick, J. R. (2002). GRASP: generalized regression analysis and spatial prediction. *Ecological Modelling*, *157*(2–3), 189–207.

Lindenmayer, D. B., Margules, C. R., & Botkin, D. B. (2000). Indicators of biodiversity for ecologically sustainable forest management. *Conservation Biology*, *14*(4), 941–950.

Lolila, N. J., Shirima, D. D., & Mauya, E. W. (2023). Tree species composition along environmental and disturbance gradients in tropical sub-montane forests, Tanzania. *Plos One*, *18*(3), e0282528.

Lovett, G. M., Canham, C. D., Arthur, M. A., Weathers, K. C., & Fitzhugh, R. D. (2006). Forest ecosystem responses to exotic pests and pathogens in eastern North America. *BioScience*, *56*(5), 395–405.

Lovett, J. C. (1998). Importance of the Eastern Arc Mountains for Vascular Plants. *Journal of East African Natural History*, *87*(1), 59–74. https://doi.org/10.2982/0012-8317(1998)87[59:IOTEAM]2.0.CO;2

Ma, J., Ding, Y., Cheng, J. C. P., Jiang, F., Tan, Y., Gan, V. J. L., & Wan, Z. (2020). Identification of high impact factors of air quality on a national scale using big data and machine learning techniques. *Journal of Cleaner Production*, *244*, 118955. https://doi.org/10.1016/j.jclepro.2019.118955

Mauya, E. W. (2021). MODELLING AND PREDICTING MEASURES OF TREE SPECIES DIVERSITY USING AIRBORNE LASER SCANNING DATA IN MIOMBO WOODLANDS OF TANZANIA. *Tanzania Journal of Forestry and Nature Conservation*, *90*(1), 1–17.

Mauya, E. W., & Madundo, S. (2022). Modelling Above Ground Biomass Using Sentinel 2 and Planet Scope Data in Dense Tropical Montane Forests of Tanzania. *Tanzania Journal of Forestry and Nature Conservation*, *91*(1), 132–153.

McCune, B. (2006). Non-parametric habitat models with automatic interactions. *Journal of Vegetation Science*, *17*(6), 819–830.

Nagendra, H., Lucas, R., Honrado, J. P., Jongman, R. H. G., Tarantino, C., Adamo, M., & Mairota, P. (2013). Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators*, *33*, 45–59. https://doi.org/10.1016/j.ecolind.2012.09.014

Ouyang, S., Xiang, W., Gou, M., Chen, L., Lei, P., Xiao, W., Deng, X., Zeng, L., Li, J., & Zhang, T. (2021). Stability in subtropical forests: The role of tree species diversity, stand structure, environmental and socio-economic conditions. *Global Ecology and Biogeography*, *30*(2), 500–513.

Rahman, M. M., Zimmer, M., Ahmed, I., Donato, D., Kanzaki, M., & Xu, M. (2021). Co-benefits of protecting mangroves for biodiversity conservation and carbon storage. *Nature Communications*, *12*(1), 3875.

Rocchini, D., Balkenhol, N., Carter, G. A., Foody, G. M., Gillespie, T. W., He, K. S., Kark, S., Levin, N., Lucas, K., Luoto, M., Nagendra, H., Oldeland, J., Ricotta, C., Southworth, J., & Neteler, M. (2010). Remotely sensed spectral heterogeneity as a proxy of species diversity: Recent advances and open challenges. *Ecological Informatics*, *5*(5), 318–329. https://doi.org/10.1016/j.ecoinf.2010.06.001

Rondeux, J., & Sanchez, C. (2010). Review of indicators and field methods for monitoring biodiversity within national forest inventories. Core variable: Deadwood. *Environmental Monitoring and Assessment*, *164*(1), 617–630. https://doi.org/10.1007/s10661-009-0917-6

Smith, P., Adams, J., Beerling, D. J., Beringer, T., Calvin, K. V., Fuss, S., Griscom, B., Hagemann, N., Kammann, C., & Kraxner, F. (2019). Impacts of land-based greenhouse gas removal options on ecosystem services and the United Nations sustainable development goals. *Annu. Rev. Environ. Resour*, *44*, 255–286.

St-Louis, V., Pidgeon, A. M., Clayton, M. K., Locke, B. A., Bash, D., & Radeloff, V. C. (2009). Satellite image texture and a vegetation index predict avian biodiversity in the Chihuahuan Desert of New Mexico. *Ecography*, *32*(3), 468–480. https://doi.org/10.1111/j.1600-0587.2008.05512.x

Wang, R., & Gamon, J. A. (2019). Remote sensing of terrestrial plant biodiversity. *Remote Sensing of Environment*, *231*, 111218. https://doi.org/10.1016/j.rse.2019.111218

Weinstein, B. G., Marconi, S., Bohlman, S. A., Zare, A., Singh, A., Graves, S. J., & White, E. P. (2021). A remote sensing derived data set of 100 million individual tree crowns for the National Ecological Observatory Network. *eLife*, *10*, e62922. https://doi.org/10.7554/eLife.62922

Winter, S., McRoberts, R. E., Chirici, G., Bastrup-Birk, A., Rondeux, J., Brändli, U.-B., Nilsen, J.-E. Ø., & Marchetti, M. (2011). The need for harmonized estimates of forest biodiversity indicators. *National Forest Inventories: Contributions to Forest Biodiversity Assessments*, 1–23.

Wu, T., Luo, J., Dong, W., Sun, Y., Xia, L., & Zhang, X. (2019). Geo-object-based soil organic matter mapping using machine learning algorithms with multi-source geo-spatial data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(4), 1091–1106.

Zhang, C., Zeng, F., Zeng, Z., Du, H., Zhang, L., Su, L., Lu, M., & Zhang, H. (2022). Carbon, Nitrogen and Phosphorus Stoichiometry and Its Influencing Factors in Karst Primary Forest. *Forests*, *13*(12), Article 12. https://doi.org/10.3390/f13121990

APPENDICES

Table A1: Environmental variables included in the analysis and their attributes.

Category	Environmental variable	Mean	SD	Min	Max
Topo	Aspect (A, degrees)	173.6	110.2	1.2	353.7
	Elevation (E, m)	1862.9	166.0	1433.0	2180.0
	Slope (S, %)	33.5	15.5	3.9	84.1
	Topographic wetness index (TWI)	9.3	0.8	7.1	11.3
Soil	Soil pH (PH)	5.4	0.2	4.9	5.7
	Soil bulk density (BD, g cm^{-3})	1157.5	56.0	997.0	1300.0
	Soil cation exchange capacity(CEC,cmol kg^{-1})	16.9	3.3	10.0	26.0
	Soil organic carbon (OC, g kg^{-1})	35.4	6.0	22.0	56.0
	Soil nitrogen (N, ppm)	2.4	0.5	1.3	3.9
Climatic	Annual mean temperature (AMT, °C)	15.3	1.2	13.6	18.7
	Mean diurnal range (MDR, °C)	9.5	0.3	8.9	10.4
	Isothermality (ISO, %)	63.1	1.1	59.8	64.9
	Temperature seasonality (TS, %)	181.3	6.9	166.0	194.8
	Max. temp. of warmest month (MaTWM, °C)	23.1	1.1	21.5	26.1
	Min. temp. of coldest month (MiTCM, °C)	8.1	1.3	6.5	11.6
	Temperature annual range (TAR, °C)	15.0	0.4	14.2	16.2
	Mean temp. of wettest quarter (MTWeQ, °C)	16.6	1.1	14.7	19.5
	Mean temp. of driest quarter (MTDQ, °C)	13.0	1.3	11.3	16.6
	Mean temp of warmest quarter (MTWaQ, °C)	17.3	1.2	15.6	20.6
	Mean temp. of coldest quarter (MTCQ, °C)	13.0	1.3	11.3	16.6
	Annual precipitation (AP, mm)	949.2	50.5	846.0	1053.0
	Precipitation in wettest month (PWM, mm)	173.0	8.9	157.0	197.0
	Precipitation in driest month (PDM, mm)	12.3	3.7	7.0	21.0
	Precipitation seasonality (PS)	72.5	4.4	63.1	79.8
	Precipitation in wettest quarter (PWeQ, mm)	397.1	18.3	359.0	434.0
	Precipitation in driest quarter (PDQ, mm)	45.5	11.4	26.0	68.0
	Precipitation in warmest quarter (PWaQ, mm)	303.8	19.3	268.0	339.0
	Precipitation in coldest quarter (PCQ, mm)	47.8	13.5	26.0	78.0

Table A2: Indicator species analysis results for the West Usamabara forests. The species listed in bold had the highest indicator values (IV) and were used to name the forest community that were strongly associated with them.

Scientific name	Code	Cluster	IV	p-val
***Dombeyaburgessiae*Gerrard ex Harv.**	**Dom.bur**	**1**	**0.60**	**0.001**
***Cussoniaspicata*Thunb.**	**Cus.spi**	**1**	**0.54**	**0.001**
*Bersamaabyssinica*Fresen.	Ber.aby	1	0.53	0.001
*Maesalanceolata*Forssk	Mae.lan	1	0.47	0.001
*Nuxia floribunda*Benth.	Nux.flo	1	0.43	0.006
Cassipoureacongensis R.Br. ex DC.	Cas.con	1	0.41	0.002
*Rhusnatalensis*Bernh. ex C.Krauss	Rhu.nat	1	0.35	0.003
Maytenusheterophylla (Eckl. &Zeyh.) N.Robson	May.het	1	0.31	0.012
Memecylondeminutum Brenan	Mem.dem	1	0.31	0.005
Trimeriagrandifolia (Hochst.) Warb.	Tri.gra	1	0.31	0.008
Flacourtiaindica (Burm.f.) Merr.	Fla.ind	1	0.30	0.012
*Ehretiacymosa*Thonn.	Ehr.cym	1	0.27	0.019
*Grewiaplatyclada*K.Schum.	Gre.pla	1	0.27	0.026
Zanthoxylumchalybeum Engl.	Zan.cha	1	0.27	0.024
***Aphloiatheiformis* (Vahl) Benn.**	**Aph.the**	**2**	**0.76**	**0.001**
***Syzygiumcordatum*Hochst. ex Krauss**	**Syz.cor**	**2**	**0.72**	**0.001**
*Macarangakilimandscharica*Pax	Mac.kil	2	0.69	0.002
*Lasianthuskilimandscharicus*K.Schum.	Las.kil	2	0.68	0.003
Ocoteausambarensis Engl.	Oco.usa	2	0.67	0.002
Psychotriagoetzei (K.Schum.) E.M.A.Petit	Psy.goe	2	0.66	0.001
*Podocarpususambarensis*Pilg.	Pod.usa	2	0.60	0.001
Drypetesgerrardii Hutch.	Dry.ger	2	0.59	0.001
Rapaneamelanophloeos (L.) Mez	Rap.mel	2	0.58	0.001
*Rawsonialucida*Harv.	Raw.luc	2	0.56	0.003
Veprisnobilis (Delile) Mziray	Vep.nob	2	0.55	0.037
Maytenusacuminata (L.f.) Loes.	May.acu	2	0.54	0.009
*Tabernaemontanapachysiphon*Stapf	Tab.pac	2	0.54	0.001
*Trichocladusellipticus*Eckl. &Zeyh.	Tri.ell	2	0.53	0.001
Pauridianthapaucinervis (Hiern) Bremek.	Pau.pau	2	0.52	0.014
Syzygiumguineense (Willd.) DC.	Syz.gui	2	0.51	0.009
*Apodytesdimidiata*E.Mey. exArn.	Apo.dim	2	0.50	0.002
Schefflerastuhlmannii Harms	Sch.stu	2	0.49	0.001

Balthasariaschliebenii (Melch.) Verdc.	Bal.sch	2	0.49	0.003
*Brackenridgeazanguebarica*Oliv.	Bra.zan	2	0.46	0.007
*Croton sylvaticus*Hochst.	Cro.syl	2	0.45	0.019
Garciniabuchananii Baker	Gar.buc	2	0.45	0.005
*Chassaliaalbiflora*K.Krause	Cha.alb	2	0.39	0.004
Oleacapensis L.	Ole.cap	2	0.36	0.022
Tabernaemontanastapfiana Britten	Tab.sta	2	0.35	0.009
Cassipoureamalosana (Baker) Alston	Cas.mal	2	0.32	0.047
Caseariabattiscombei R.E.Fr.	Cas.bat	2	0.31	0.023
Macarangaconglomerata Brenan	Mac.con	2	0.29	0.036
Rauvolfiavolkensii (K.Schum.) Stapf	Rau.vol	2	0.29	0.025
***Newtoniabuchananii* (Baker) G.C.C.Gilbert&Boutiqu**	**New.buc**	**3**	**0.87**	**0.001**
***Parinariexcelsa* Sabine**	**Par.exc**	**3**	**0.69**	**0.001**
*Sorindeiamadagascariensis*Thouars ex DC.	Sor.mad	3	0.67	0.001
Leptonychiausambarensis K. Schum.	Lep.usa	3	0.53	0.001
Mimusops kummel Bruce ex A.DC.	Mim.kum	3	0.52	0.002
Strombosiascheffleri Engl.	Str.sch	3	0.52	0.001
*Mammeausambarensis*Verdc.	Mam.usa	3	0.50	0.001
Xymalosmonospora (Harv.) Baill.	Xym.mon	3	0.49	0.001
Faureausambarensis Engl.	Fau.usa	3	0.46	0.001
Harunganamadagascariensis Lam. ex Poir.	Har.mad	3	0.42	0.001
Zenkerellacapparidacea (Taub.) J.Leonard	Zen.cap	3	0.39	0.004
*Trichiliadregeana*Sond.	Tri.dre	3	0.39	0.001
Tremaorientalis (L.) Blume	Tre.ori	3	0.37	0.008
*Tricalysiapallens*Hiern	Tri.pal	3	0.34	0.008
Sapiumellipticum (Hochst.) Pax	Sap.ell	3	0.30	0.009
*Tricalysiaruandensis*Bremek.	Tri.rua	3	0.29	0.006
*Heinseniadiervilleoides*K.Schum.	Hei.die	3	0.27	0.022
Celtisgomphophylla Baker	Cel.gom	3	0.25	0.032
Psydraxparviflora (Afzel.) Bridson	Psy.par	3	0.25	0.043

Table B1: Description of vegetation indices used as predictor variables for tree species diversity index modelling.

Index	**Name**	**Expression**	**Sensor**	**Reference**
DVI	Difference Vegetation Index	NIR-Red	S-2, PS	Richardson & Wiegand (1977)
EVI	Enhanced Vegetation Index	2.5[(NIR-Red)/(NIR+2.4Red + 1)]	S-2, PS	Liu & Huete (1995)
GNDVI	Green Normalized Difference Vegetation Index	(NIR - Green)/(NIR + Green)	S-2, PS	Gitelson et al. (1996)
NDVI	Normalized Difference Vegetation Index	(NIR - Red)/(NIR + Red)	S-2, PS	Rouse et al. (1974)
RVI	Ratio Vegetation Index	NIR/Red	S-2, PS	Pearson & Milton (1972)
CLRE	Chlorophyll Red-Edge	(RE3/RE1) - 1	S-2	Gitelson et al. (2003)
ND-RE1	Normalized Difference Red Edge	(RE2 – RE1)/(RE2 + RE1)	S-2	Gitelson & Merzlyak (1994)
ND-RE2	Normalized Difference Red Edge	(RE3 – RE1)/(RE3 + RE1)	S-2	Barnes et al. (2000)

Table B2: General description of grey-level co-occurrence matrix (GLCM) texture metrics used in this study.

Texture	Expression	Expression
Mean (**mea**)	$\mu_i = \sum_{i,j=0}^{N-1} iP_{i,j}$	Mean of grey level (GL) distribution of the image.
Variance **(var**)	$\sum_{i,j=0}^{N-1} iP_{i,j}\,(i - \mu_i)^2$	GLCM variance is a measure of the dispersion of GL distribution
Contrast (**con**)	$\sum_{i,j=0}^{N-1} iP_{ij}\,(i - j)^2$	Contrast indicates the amount of local GL variation in an image. Large values indicate the presence of edges, noise or wrinkled features.

Source: Haralick et al., (1973)

Table B3: Performance of the GAM and XGBoost diversity models fitted with predictors from two satellite sensors. Bold values indicate the best diversity index model.

				GAM			**XGB**		
Satellite	**Index**	**Category**	**Predictors**	**rRMSE**	**R2**	**MAE**	**rRMSE**	**R2**	**MAE**
PlanetScope	Evenness	Bands	B, G, NIR, R	0.14	0.05	0.10	0.15	0.06	0.10
		VegIndices	DVI, GNDVI, NDVI, RVI, EVI	0.14	0.04	0.09	0.14	0.10	0.09
		Textures	EVI.mea, NIR.mea, NIR.mea	0.14	0.07	0.10	0.14	0.11	0.08
		Combined	EVI, DVI.var, NDVI, EVI.mea, RVI	0.14	0.05	0.09	**0.14**	**0.11**	**0.09**
	Richness	Bands	B, G, NIR, R	0.40	0.18	0.32	0.41	0.11	0.32
		VegIndices	DVI, GNDVI, NDVI, RVI, EVI	0.40	0.17	0.31	0.42	0.09	0.34
		Textures	DVI.vaR, EVI.con	**0.39**	**0.19**	**0.01**	0.39	0.17	0.31
		Combined	DVI, NIR, DVI.var, EVI.con, G.con	0.40	0.18	0.31	0.40	0.18	0.31
	Shannon	Bands	B, G, NIR, R	0.25	0.09	0.19	0.25	0.14	0.19
		VegIndices	DVI, GNDVI, NDVI, RVI, EVI	0.25	0.11	0.19	0.25	0.12	0.19
		Textures	EVI.con, NIR.mea, NIR.var, RVI.var	0.24	0.15	0.18	**0.24**	**0.20**	**0.18**
		Combined	EVI.con, NIR.var, NDVI.con, NIR.mea, NIR, RVI.var, RVI.mea, G.con	0.25	0.14	0.19	0.24	0.17	0.18
Sentinel-2	Evenness	Bands	B04, B03, B12, B11	**0.15**	**0.10**	**0.10**	0.16	0.07	0.10
		VegIndices	NDRE.1, GNDVI	0.13	0.06	0.09	0.14	0.07	0.10
		Textures	NDVI.var, B04.con, GNDVI.mea, B06.con, RVI.var	0.14	0.04	0.09	0.15	0.05	0.10
		Combined	GNDVI, B04.con, GNDVI.mea, NDVI.var	0.14	0.04	0.09	0.14	0.08	0.10
	Richness	Bands	B07, B06, B05, B11, B08, B04	0.41	0.12	0.32	0.42	0.08	0.33
		VegIndices	NDRE.1, GNDVI, NDRE.2, CLRE, EVI	0.42	0.07	0.33	0.43	0.05	0.34
		Textures	B06.var, B07.var, B11.mea, RVI.con, B8A.var, B08.mea, B03.con, B08.var	0.40	0.15	0.32	0.40	0.13	0.32
		Combined	B06, B07, B11, B07.var, RVI.con, B08.mea, GNDVI, B11.con, B03.con	0.42	0.14	0.33	**0.40**	**0.16**	**0.31**
	Shannon	Bands	B06, B07, B8A, B11	0.25	0.13	0.19	0.26	0.08	0.20
		VegIndices	NDRE.1, GNDVI	0.25	0.08	0.19	0.26	0.08	0.20
		Textures	B04.var, B04.con, B06.con, B12.var, GNDVI.mea, CLRE.con, DVI.con	0.25	0.09	0.19	0.25	0.15	0.19
		Combined	B11.var, B06, B04.var, GNDVI, CLRE.con	0.25	0.14	0.19	**0.25**	**0.15**	**0.19**

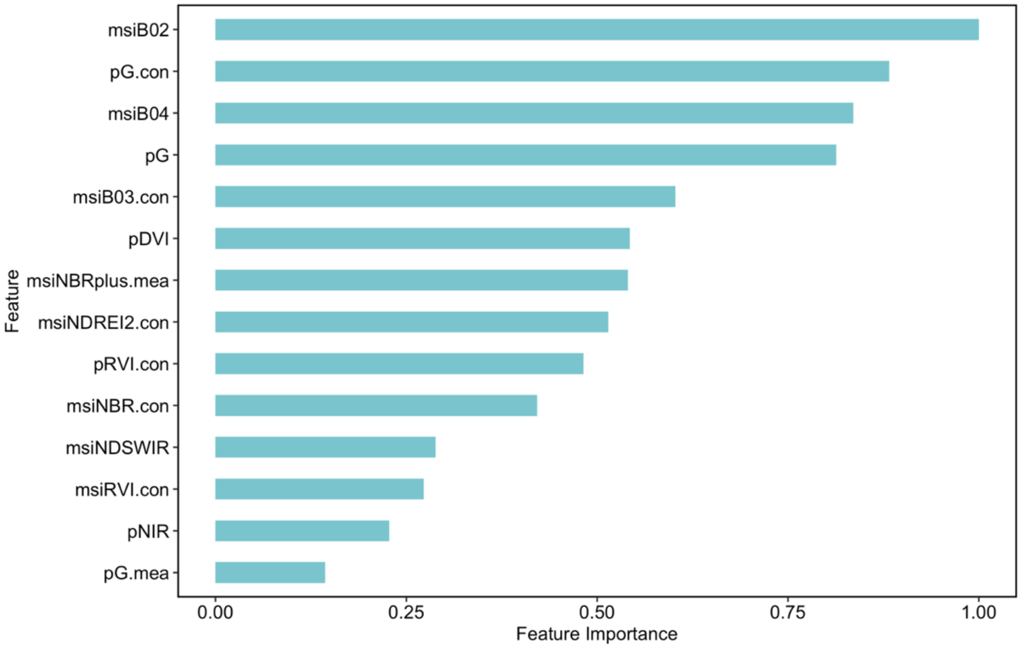
Sentinel-2 bands; B03 – green band, B04 – red band, B05 – red-edge band 1, B06 – red-edge band 2, B07 – red-edge band 3, B08 – near infrared band, B8A – narrow near infrared band, B11 – shortwave infrared band 1, B12 – shortwave infrared band 2.

PlanetScope bands: B – blue band, G – green band, R – red band, NIR – near infrared band.

Vegetation indices: DVI – difference vegetation index, GNDVI – green normalized difference vegetation index, NDVI – normalized difference vegetation index, RVI – ratio vegetation index, EVI – enhanced vegetation index, NDRE.1 – normalized difference red-edge 2, NDRE.2 – normalized difference red-edge 2, CLRE – chlorophyll red edge vegetation index.

Textures: mea – mean texture, con – contrast texture, var – variance texture.

Figure C1: Relative importance plot of optimal Sentinel-2 and PlanetScope remote sensing features in mapping burnt forest areas using XGBoost.



Features include: *msiB02* = Sentinel-2 Band 2 (Blue), *pG.con* = contrast of PlanetScope green band, *msiB04* = Sentinel-2 Band 4 (Red), *pG* = PlanetScope green band, *msiB03.con* = contrast of Sentinel-2 Band 3 (Green), *pDVI* = PlanetScope Difference Vegetation Index, *msiNBRplus.mea* = mean of Sentinel-2 NBRplus, *pRVI.con* = contrast of PlanetScope Ratio Vegetation Index, *msiNBR.con* = contrast of Sentinel-2 Normalized Burn Ratio, *msiNDSWIR* = Sentinel-2 Normalized Difference Short-ware Infrared Burn Index, *msiRVI.con* = contrast of Sentinel-2 Ratio Vegetation Index, *pNIR* = PlanetScope near-infrared band, and *pG.mea* = mean of PlanetScope green band.

Table C1: Recursive feature elimination (RFE) results under 10-fold cross-validation showing performance of feature resampling over total feature subset size (132). The row in bold indicates the optimal feature subset.

Number of features	Accuracy	Kappa	AccuracySD	KappaSD
1	0.533	-0.118	0.058	0.190
2	0.626	0.013	0.073	0.181
3	0.632	0.036	0.102	0.263
4	0.617	0.008	0.090	0.179
5	0.658	0.093	0.089	0.187
6	0.662	0.056	0.087	0.244
7	0.677	0.080	0.084	0.218
8	0.688	0.097	0.094	0.262
9	0.688	0.123	0.099	0.250
10	0.668	0.081	0.107	0.256
11	0.657	0.040	0.078	0.163
12	0.662	0.038	0.073	0.185
13	0.673	0.058	0.071	0.181
14	**0.693**	**0.140**	**0.067**	**0.155**
15	0.662	0.032	0.075	0.183
16	0.683	0.104	0.072	0.171
17	0.678	0.098	0.074	0.162
18	0.683	0.107	0.083	0.191
19	0.678	0.109	0.081	0.151
20	0.688	0.114	0.076	0.192
21	0.678	0.072	0.059	0.169
22	0.673	0.063	0.059	0.169
23	0.688	0.089	0.052	0.164
24	0.662	0.033	0.053	0.163
25	0.677	0.070	0.076	0.211
26	0.683	0.095	0.067	0.213
27	0.672	0.060	0.068	0.191
28	0.662	0.042	0.062	0.189
29	0.673	0.073	0.075	0.196
30	0.683	0.084	0.078	0.228
31	0.672	0.073	0.073	0.202
32	0.673	0.054	0.078	0.208
33	0.668	0.044	0.071	0.180
34	0.683	0.093	0.074	0.184
35	0.673	0.073	0.080	0.167
36	0.678	0.062	0.067	0.148
37	0.688	0.093	0.073	0.173
38	0.678	0.064	0.075	0.165
39	0.688	0.087	0.057	0.151
40	0.693	0.108	0.079	0.203
41	0.678	0.075	0.088	0.194
42	0.682	0.079	0.060	0.154
43	0.678	0.092	0.075	0.169
44	0.667	0.034	0.079	0.195

Number of features	Accuracy	Kappa	AccuracySD	KappaSD
45	0.662	0.026	0.080	0.195
46	0.667	0.035	0.080	0.188
47	0.667	0.046	0.076	0.186
48	0.657	0.017	0.079	0.200
49	0.672	0.046	0.067	0.144
50	0.672	0.042	0.072	0.184
51	0.662	0.024	0.069	0.180
52	0.657	0.017	0.079	0.200
53	0.672	0.059	0.077	0.183
54	0.667	0.033	0.070	0.174
55	0.677	0.050	0.069	0.175
56	0.683	0.060	0.071	0.169
57	0.672	0.044	0.077	0.200
58	0.672	0.042	0.072	0.184
59	0.662	0.026	0.080	0.203
60	0.672	0.046	0.087	0.206
61	0.667	0.021	0.072	0.187
62	0.678	0.067	0.075	0.181
63	0.678	0.077	0.093	0.229
64	0.673	0.054	0.088	0.228
65	0.667	0.034	0.079	0.195
66	0.662	0.026	0.080	0.203
67	0.678	0.056	0.076	0.208
68	0.677	0.063	0.073	0.199
69	0.683	0.083	0.085	0.231
70	0.667	0.034	0.079	0.195
71	0.678	0.047	0.088	0.221
72	0.667	0.046	0.073	0.181
73	0.667	0.040	0.083	0.201
74	0.652	-0.003	0.079	0.202
75	0.668	0.028	0.086	0.229
76	0.657	0.005	0.079	0.196
77	0.662	0.026	0.080	0.203
78	0.668	0.028	0.086	0.229
79	0.662	0.013	0.079	0.197
80	0.667	0.034	0.079	0.195
81	0.657	0.011	0.082	0.224
82	0.662	0.020	0.086	0.236
83	0.667	0.033	0.070	0.182
84	0.678	0.032	0.078	0.212
85	0.662	0.020	0.086	0.236
86	0.677	0.052	0.076	0.192
87	0.667	0.021	0.070	0.179
88	0.657	0.006	0.080	0.200
89	0.673	0.061	0.083	0.194
90	0.672	0.037	0.080	0.224
91	0.667	0.022	0.071	0.183

Number of features	Accuracy	Kappa	AccuracySD	KappaSD
92	0.662	0.013	0.070	0.186
93	0.667	0.030	0.091	0.253
94	0.672	0.062	0.084	0.202
95	0.657	0.012	0.086	0.235
96	0.672	0.029	0.068	0.179
97	0.673	0.037	0.083	0.217
98	0.662	0.012	0.073	0.186
99	0.662	0.014	0.077	0.190
100	0.662	0.014	0.077	0.190
101	0.667	0.028	0.078	0.221
102	0.667	0.021	0.072	0.187
103	0.652	-0.003	0.079	0.202
104	0.662	0.013	0.070	0.186
105	0.682	0.078	0.077	0.203
106	0.683	0.066	0.078	0.202
107	0.662	0.020	0.086	0.229
108	0.683	0.072	0.085	0.220
109	0.667	0.026	0.070	0.225
110	0.662	0.009	0.073	0.201
111	0.667	0.026	0.070	0.225
112	0.673	0.025	0.083	0.215
113	0.683	0.072	0.080	0.227
114	0.657	0.010	0.070	0.162
115	0.662	0.013	0.096	0.239
116	0.667	0.037	0.072	0.195
117	0.667	0.021	0.072	0.187
118	0.683	0.073	0.089	0.223
119	0.667	0.041	0.084	0.206
120	0.683	0.084	0.080	0.226
121	0.652	-0.016	0.077	0.201
122	0.673	0.031	0.079	0.209
123	0.678	0.040	0.075	0.178
124	0.677	0.038	0.069	0.174
125	0.672	0.060	0.081	0.214
126	0.667	0.022	0.073	0.191
127	0.682	0.060	0.069	0.183
128	0.672	0.030	0.070	0.183
129	0.672	0.047	0.090	0.229
130	0.678	0.057	0.080	0.197
131	0.672	0.018	0.056	0.156
132	0.678	0.055	0.072	0.212

Kuhusu Tasfnifu Hii

Milima ya tao la mashariki nchini Tanzania inatambulika kimataifa kuwa sehemu muhimu ya utofauti wa viumbe hai na inatajwa kuwa na umuhimu mkubwa wa kimazingira. Utafiti huu ulilenga hifadhi za msitu wa Shagayu na Magamba katika Milima ya Usambara magharibi, ili kuchunguza jinsi vipengele vya kimazingira kama vile udongo, tabia ya nchi na topografia pamoja na matishio ya kiikolojia kama vile moto wa msitu vinavyoathiri muundo na utofauti wa spishi. Kwa kuunganisha upimaji wa ardhini pamoja na mbinu za kisasa za viona umbali, utafiti huu unatoa mtazamo juu ya namna bora ya upimaji wa viashiria vya baioanuawai ya misitu. Utafiti huu umeonesha ya kuwa, vipengele vya kimazingira vinaathiri muundo wa mifumo ya kiikolojia katika misitu hii. Vilevile, kutumia njia za viona mbali zenye rezolusheni ya juu husaidia upimaji wa viashiria vya baioanuawai ya misitu kwa usahihi. Pia, misitu ya Usambara magharibi ina ustahimilivu wa juu kufuatia matukio ya moto.