Landscape ecology of coffee pests in smallholdings: influence of landscape fragmentation, farming systems and a warming climate in Murang'a County, Kenya

by

Gladys Jebiwot Mosomtai

Submitted in fulfilment of the academic requirements of

Doctor of Philosophy

In Environmental Science

School of Agricultural, Earth and Environmental Sciences

College of Agriculture, Engineering and Science

University of KwaZulu-Natal

Pietermaritzburg

South Africa

July, 2022

PREFACE

The research contained in this thesis was completed by the candidate while based in the Discipline of Geography, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal (UKZN), Pietermaritzburg, South Africa and International Centre of Insect Physiology and Ecology (*icipe*), Nairobi, Kenya from September 2017 – December 2021 under the supervision of Professors John Odindi, Onisimo Mutanga, Dr. Elfatih M. Abdel-Rahman and Dr. Guillaume David. The research was financially supported by the In-Region Postgraduate Scholarship from the German Academic Exchange Service (DAAD), Centre de Coopération Internationale en Recherche Agronomique pour le Développement (CIRAD), L'Oréal-UNESCO For Women in Science Fellowship and Combating Arthropod Pests for Better Health, Food and Resilience to Climate Change (CAP-Africa) Scholarship of *icipe*.

The content of this thesis has not been submitted in any form to another university and, except where the work of others is acknowledged in the text, the results reported herein are due to investigations by the candidate.

Gladys Jebiwot Mosomtai Signed [redacted] Date: 20/07/2022

As the candidate's supervisors, we certify the aforementioned statement and have approved this thesis for submission.

Supervisor

Prof. John Odindi Signed [redacted] Date: 20-7-2022

Co-supervisors

Dr. Guillaume David Signed [redacted] Date: 20/07/2022

Dr. Elfatih M. Abdel-Rahman Signed [redacted] Date: 20/07/2022

Prof. Onisimo Mutanga Signed [redacted] Date: 20-07-2022

DECLARATION 1: PLAGIARISM

I, **Gladys Jebiwot Mosomtai**, declare that:

i. The research reported in this dissertation, except where otherwise indicated or acknowledged, is my original work;
ii. This dissertation has not been submitted in full or in part for any degree or examination to any other university;
iii. This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;
iv. This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
    a. their words have been re-written but the general information attributed to them has been referenced;
    b. where their exact words have been used, their writing has been placed inside quotation marks, and referenced;
v. Where I have used material for which publications followed, I have indicated in detail my role in the work;
vi. This dissertation is primarily a collection of material, prepared by myself, published as journal articles or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;
vii. This dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source is being detailed in the dissertation and in the References section.

[redacted]

Gladys Jebiwot Mosomtai Date: 20/07/2022

DECLARATION 2: PUBLICATIONS

1. **Mosomtai, G**., Odindi, J., Abdel-Rahman, E.M., Babin, R., Fabrice, P., Mutanga, O., 2020. Landscape fragmentation in coffee agro-ecological sub-zones in central Kenya : a multiscale remote sensing approach. J. Appl. Remote Sens. 14. https://doi.org/10.1117/1.JRS.14.044513
2. **Mosomtai, G**., Azrag, A.G.A., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., 2021. Functional land cover scale for three insect pests with contrasting dispersal strategies in a fragmented coffee-based landscape in Central Kenya. Agric. Ecosyst. Environ. 319, 107558. https://doi.org/10.1016/j.agee.2021.107558
3. **Mosomtai, G**., Azrag, A.G.A., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., (*in preparation*). Linking shade and edge effect on microclimate and pest abundance in smallholder coffee landscape in central Kenya
4. **Mosomtai, G**., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., (*in preparation*). Multi-scale habitat suitability modelling of Arabica coffee (*Coffea arabica* L) in a steep agro-ecological gradient: the influence of under 2^{o}C global warming

In the above manuscripts, conceptualisation, data curation and analysis, and preparation and writing of original publications were done by the candidate, Gladys Jebiwot Mosomtai. This was done under the supervision of Professors John Odindi, Elfatih M. Abdel-Rahman and Onisimo Mutanga together with Dr. Guillaume David.

[redacted]

Gladys Jebiwot Mosomtai Date: 20/07/2022

ABSTRACT

Coffee production systems have resulted in simplified landscapes with fragments of natural and semi-natural vegetation characterised by loss of biodiversity, high pests and disease incidences and excessive pesticide input. Consequently, the resilience of coffee landscapes against climate change impacts such as high diurnal temperature range, erratic rains, and prolonged droughts is weakened. Equally, controlling pests and diseases using natural enemies is no longer effective due to the unselective use of harmful chemicals. The present study aimed to understand the role of landscape ecology in a typical smallholder coffee-based landscape in creating suitable ecological conditions for the proliferation of coffee pests, specifically, coffee berry borer (CBB), *Hypothenemus hampei*, and the Antestia bugs *Antestiopsis thunbergii* (ABT) and *A. facetoides* (ABF) in an important coffee growing zone in central Kenya. The study also examined the impact of limiting temperature rise to below 2^{o}C on habitat suitability for growing Arabica coffee to guide the implementation of the Paris agreement, which requires countries to stabilize the global mean surface temperature rise to below 1.5^{o}C and in the worst-case scenario, well below 2.0^{o}C above the pre-industrial levels. Firstly, the study explored Sentinel 2, Landsat 8 and PlanetScope datasets to characterise the smallholder coffee-based landscape and the level of fragmentation in each agro-ecological sub-zones of the upper midland (UM) agro-ecological zone. Sentinel 2 provides a robust dataset for land use and land cover (LULC) classification, with shortwave near-infrared and green bands being critical for classifying coffee bushes. Coffee was the dominant cover type in the higher agro-ecological sub-zones of Kenya, whereas annual crops dominated the lower sub-zones. Secondly, the study sought to identify the significant spatial scale and landscape structure that influenced the abundance of the three coffee pests, given that CBB had a low dispersal capacity and vice versa for the antestia bugs. The results showed that the pests foraged within a radius of 300m, with CBB having the shortest optimum foraging distance of 100m. The CBB abundance was strongly influenced by contiguous coffee patches, especially at higher elevations, whereas adjacent patches were more suitable for antestia bugs, especially cropland in the lower agro-ecological sub-zones. Thirdly, the shade and edge effect on microclimate and coffee pest abundance were examined. Generally, CBB preferred shaded coffee in the lower sub-zones and full-sun coffee in the higher sub-zones. For Antestia bugs, ABT preferred shaded coffee in all the agro-ecological sub-zones, whereas ABF preferred full-sun coffee, especially in the low sub-zones. Notable also was the influence of the edge effect of agroforest in lowering the mean temperature of full-sun coffee plots. Finally, the study looked at the impact of limiting temperature rise to below 2°C under the Representative Concentration Pathways (RCP) 2.6 scenario on habitat suitability for growing Arabica coffee. The results showed that the area under coffee will increase, especially in 2070, and the coffee suitable range will shift to lower sub-zones. Overall, the study revealed that the existing landscape structure in smallholder coffee agrosystems favours coffee pests proliferation. Pest pressure at the lower sub-zones is high, especially in coffee plots without shade. However, implementing climate-friendly policies will reverse the current trend, making the lower sub-zones more suitable for growing Arabica coffee. An increase in acreage for planting coffee will translate to more yields, which could alleviate poverty and grow Kenya's gross domestic product. The study underscores the urgency for smallholder farmers to shift their coffee production systems to climate-smart options such as increasing shade in their plots. This will increase their landscape resilience against climate change and pest control. Additionally, policy makers need to implement climate policies and promote clean energy development to limit temperature rise by the end of the century.

ACKNOWLEDGMENTS

First, I want to thank God for giving me the gift of life and good health to pursue my PhD study. ‘He has done exceedingly abundantly above all that I could ask or think, according to the power that works in me, to Him be glory in the church by Christ Jesus to all generations, forever and ever. Amen.’ Ephesians 3:20

Secondly, I am indebted to my supervisors, who have supported me throughout my study. Special gratitude goes to Prof. John Odindi and Prof. Onisimo Mutanga, who agreed to take me under their wing as one of their PhD students. I have greatly benefitted from their guidance and thought-provoking discussions that guided me in framing my objectives and bringing out the novelty of my research. I hope to pass on what I have learned from you to others. I am also grateful to Dr. Elfatih M. Abdel-Rahman, who remained to be my cornerstone. Your door was always open to me, and your thorough review of my manuscripts and follow-ups meeting to go through each comment has made me a better writer and reviewer. I also want to acknowledge Dr. Regis Babin and Dr. Guillaume David for introducing me to the field of entomology. Your constructive criticism has guided me in linking the macro scale of remote sensing to the micro scale of insects. Dr. Tobias Landmann deserves a special mention. Thank you for mentoring me from when I joined your team as an intern. You believed in me until I believed in myself, which laid the foundation for me to excel during my PhD. Finally, I want to thank Dr. Henri Tonnang, who particularly supported me when I applied for a CAP-Africa scholarship. That meant a lot to my family and I.

Thirdly, I want to thank my colleagues at the International Centre of Insect Physiology and Ecology (*icipe*) for supporting me throughout my study. To Emily Kimathi and Dr. Bester Mudereri whom we shared the same office for the longest part of my studies, thank you for always listening to my ideas even when they didn't make much sense. You always put things in perspective for me, and you were always the first people to listen to my dry runs. I also acknowledge the moral support received from my PhD scholarship cohort. I enjoyed our time together as we shared our frustrations and achievements, which made the PhD journey easier. Also, the *icipe* Scholars Association (IScA) fraternity for organizing team buildings and cultural day events, which reminded us that there was life outside books. Special gratitude to IScA members for nominating me to serve as the secretary of the student association. My leadership skills improved significantly, a soft skill that will help me in my career progression.

Fourthly, I want to thank my family and friends who walked this journey with me. To my sister Linda Mosomtai, who has been my cheerleader and support system, I am forever indepted to you. Thank you for stepping up to take care of my baby to allow me to finish my studies. May God richly bless your kind heart. To my husband Ben Kiprotich, I had no plans of getting married and having a baby at the start of my PhD until our paths crossed. Since then, I have never walked alone, and you have given me more reasons to push harder and finish my studies. To my parents, Reuben and Rebbecca Mosomtai and siblings, I have always strived to make you proud, and your belief in me has kept me going. My aunt Dr. Jane Binot, thank you for leaving the footprints for me to follow. Finally, to my friends who have become family, the Mountaineers, thank you for the prayers, moral support and bible study sessions that build my spiritual life. May God richly bless each one of you.

Finally, I would like to thank the institutions that allowed me to pursue the PhD program. First, I am grateful to *icipe* for giving me the opportunity to grow in my career. I have received mentorships and opportunities to attend training workshops and conferences and interacted with some of the most outstanding scientists in the world. I can stand out in my career because of the conducive environment I have received at *icipe*. Also, I am grateful for the In-Region Postgraduate Scholarship I received from the German Academic Exchange Service (DAAD), Centre de Coopération Internationale en Recherche Agronomique pour le Développement (CIRAD) and LOreal-UNESCO For Women in Science Fellowship, which provided funding for my stipend, conferences and fieldwork. I also acknowledge the financial support of *icipe*'s core donors; the Swedish International Development Cooperation Agency (Sida); the Swiss Agency for Development and Cooperation (SDC); the Federal Democratic Republic of Ethiopia; and the Government of the Republic of Kenya. Finally, I am grateful to the University of KwaZulu-Natal and the government of South Africa for giving me a fee remission period, which reduced the financial burden of pursuing a PhD.

DEDICATION

This thesis is dedicated to my son, Milan Kiprotich. You are my hope for tomorrow. To my husband, Ben Kiprotich, and my sister, Linda Mosomtai, I am forever indebted for your unwavering support during my studies. To my mum and dad, Reuben and Rebecca Mosomtai, your belief in me kept me going, and to my grandparents, Peter and Joyce Binot, I am the fulfilment of your dreams.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 A warming world

The sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) affirmed that anthropogenic activities primarily drive the current state of the climate. In the last two decades, the global mean surface temperature has risen by 0.99^{o}C compared to the pre-industrial period. Human-induced emissions of greenhouse gases (GHG) have contributed to global warming of 1 – 2^{o}C, with agriculture, forestry and other land use (AFOLU) accounting for 23% of the total anthropogenic emissions. Specifically, the emissions from AFOLU consist largely of 13% of carbon dioxide, 44% of methane and 81% of nitrous oxide (IPCC, 2021). As the world warms, extreme weather patterns such as flooding, prolonged droughts, heatwaves, dust storms and tropical cyclones are becoming more frequent, threatening human life and the environment. For instance, the Australian bush fire in 2019 – 2020 that burnt over 17 million hectares of land was propelled by prolonged drought with intense heatwaves and winds, resulting in the loss of human lives, wildlife, livelihoods and internal displacements of families (du Parc and Yasukawa, 2020). Climate change is also curtailing the efforts to achieve food security, particularly in developing countries, by negatively impacting crop yields and food systems value chain (Vermeulen et al., 2012).

Despite the expanding area under agricultural production, especially in the commercial crops, high yielding monocultures with intensive pesticides and fertiliser applications are becoming vulnerable to increased pest and disease pressures (Tscharntke et al., 2005). The resistant cultivars and chemical controls eventually become ineffective as the pathogens develop resistance (Robinson, 1977). Equally, many crops are grown in environments different from their native regions, where they are susceptible to new pathogens with limited self-defense mechanisms or natural enemies. Furthermore, the loss of biodiversity and fragmentation of natural and semi-natural vegetation in agricultural landscapes has led to the population decline of natural enemies (Plantegenest et al., 2007; Veres et al., 2013). Thus, Integrated Pest Management (IPM) strategies and climate-smart agriculture are being developed globally to reduce pest pressure and to adapt and mitigate against climate change impacts (Ribeyre and Avelino, 2012). For example, cocoa and coffee farmers are currently adopting agroforestry as a nature-based solution against climate change while improving the ecosystem services in their production system (Hajian-Forooshani et al., 2014; Suárez et al., 2021).

1.2 Coffee production

Coffee is one of the major crops with global socio-economic value. It is the largest traded beverage globally, with a global market share of 90 Billion USD (DaMatta et al., 2007). It belongs to the family *Rubiaceae* of the genus *Coffea* L. with over 100 species, but only three major species have economic importance; *Coffea arabica* (Arabica coffee), *Coffea canephora* (Robusta coffee) and *Coffea liberica* (Liberica coffee), which contribute to 70%, 29% and <1% of total global production, respectively (Anthony et al., 2002; Davis et al., 2006). Arabica coffee originated from Ethiopian highlands, the Boma plateau of Sudan and Mt. Marsabit in Kenya (Anthony et al., 2002), whereas, Robusta and Liberica coffee are native to Equatorial forests in the Congo Basin, Equatorial Guinea and the Lake Victoria region (Waller et al., 2007). Over 500 years ago, Arabica coffee was first domesticated away from its native region in the mountains of Yemen. Since then, it is grown in over 60 countries and islands on the five continents (Clarence-Smith and Topik, 2003).

Globally, the largest coffee producers are smallholder farmers with an average farm size of 1 hectare, creating employment for over 25 million farmers and over 75 million people across the production chain (DaMatta et al., 2007; Ovalle-Rivera et al., 2015; Talhinhas et al., 2017). Brazil, Colombia, Vietnam and Indonesia are the largest producers, contributing up to 65% of the total market share, while in several countries in the developing world, such as Kenya, Ethiopia, Burundi and Uganda, it is a key foreign exchange earner contributing significantly to their gross domestic production (Ovalle-Rivera et al., 2015). Despite increased acreage under cultivation, global coffee production has declined with fluctuating market prices (ICO, 2016). The cost of production has increased, forcing smallholder farmers to uproot their coffee bushes for other viable economic activities (Waller et al., 2007). Coffee pests and diseases contribute largely to this decline, which is further aggravated by the impacts of climate change (Chakraborty and Newton, 2011; Davis et al., 2012).

1.3 Coffee pests and climate change

The coffee tree hosts approximately 3,000 species of pests and pathogens worldwide (Ribeyre & Avelino, 2012; Waller et al., 2007). This wide range of hosts is due to the widespread cultivation of coffee from its native origin in Africa and predominantly in simplified landscapes. Furthermore, the perennial nature of coffee can support the lifecycles of pests and diseases for more than 30 years (Waller et al., 2007). Due to the high cost of chemical control, smallholder farmers primarily rely on cultural methods to control coffee pests and diseases. Moreover, the upsurge of coffee pests and diseases is now frequent due to global warming, even in previously unsuitable regions (Ovalle-Rivera et al., 2015). Notably, the habitat range for coffee berry borer is expanding to higher elevations (Atallah et al., 2018), and the humid areas are becoming more favourable for the coffee berry disease (Kebati et al., 2016; Ribeyre & Avelino, 2012). By the end of the 21st century, IPCC projects that temperature will have risen by 2 ^{o}C – 5.8 ^{o}C across all the emission scenarios if the current activities continues (Magrach and Ghazoul, 2015)

If current global emissions continue unmitigated, global warming will render 30 - 50% of current global coffee cropland unsuitable, leading to geographic shifts to higher altitudes (Bunn et al., 2015). Ideally, Arabica and Robusta coffee grow within an optimum temperature range of 18 to 23^{o} C and 23 to 26^{o} C, respectively, with a mean annual rainfall of 1000mm in well-drained volcanic soils (pH range of 4 – 6) at an altitude of 1400 to 2000 masl (Camargo, 2010). Beyond the optimum temperature range leads to accelerated ripening of coffee beans with low cup quality, depressed growth and yellowing of leaves (Davis et al., 2012; Lott et al., 2009). Additionally, a short dry spell that lasts for two to four months is required to stimulate flowering, otherwise, continuous rainfall year-round leads to scattered harvest, hence low production (DaMatta et al., 2007). The coffee tree physiology is currently under threat due to the rising temperature and extreme weather patterns, making it more susceptible to pest and disease infestation and low yields (DaMatta et al., 2007). Coffee berry borer and Antestia bug species are among the most devastating coffee pests contributing to 90% and 45% of crop loss, respectively (Mosomtai et al., 2021). Recent studies on their thermobiology indicate that increasing temperature will increase the number of eggs produced by females and shorter life cycles, increasing the number of generations per year (Azrag et al., 2017).

1.4 Coffee agroforest system

Coffee cultivation is increasingly adopting the agroforest system, also known as shade coffee, as a climate change adaptation strategy (Vaast et al., 2016). Shade coffee mimics the natural habitat, which grows as an understorey crop in its native land in East and Central Africa (Anthony et al., 2002). However, many smallholder farmers in East Africa still plant their coffee either as a mono-crop, also known as full-sun coffee, or intercropped with subsistence crops in plots less than two hectares (Clarence-Smith and Topik, 2003). Shade coffee has several advantages over full sun coffee; these include microclimate modification that buffers coffee trees from extreme weather (Ehrenbergerová et al. 2017), protection of soils from evapotranspiration during extended dry periods (Cannavo et al., 2011), increased biodiversity (Caudill et al., 2015) and reduction of pests and disease infestation (Bukomeko et al., 2018). Furthermore, shade coffee has a higher market value than full sun coffee, hence a better selling price (Albertin and Nair, 2004). However, these advantages are not universal in all coffee systems but site and cultivar specific. Shade, especially in higher elevation has been to shown to reduced bevarage quality such as body, fragrance, sweetness and acidity and the advantages being age specific (Bosselmann et al., 2009). For the case of Robusta coffee, older trees (>16 years) have been shown to benefit from shade while younger trees are negatively impacted (Piato et al., 2020).

Over the years, intensive coffee cultivation and expansion have modified the natural landscape in the tropics (Magrach and Ghazoul, 2015). Furthermore, cultivars, chemical controls, and landscape fragmentation have made coffee trees more susceptible to continually evolving pathogen strains (Meehan et al., 2011). Recent studies have shown concerted efforts to quantify the influence of landscape structure on coffee pests and diseases, especially at the plot level. The general approach by most studies, such as Samnegård et al. (2014), involves the general classification of coffee plots based on agronomic practices, topographic features, soil profiles, shade characteristics, climate data, and pest infestation and making inferences to the larger landscape scale. Despite these efforts, accurately describing landscape structure at plot scale in view of local to regional scale is an uphill task due to the cost and time needed to collect in-situ data (Cunniffe et al., 2015). Landscape ecology provides an opportunity to address this challenge by using remote sensing data to characterize and analyze landscapes, seamlessly covering large areas (Turner et al., 2001). This study adopted a multi-data approach linking coffee pest population dynamics to landscape characteristics from plot to regional scale.

1.5 Justification of the study

The impact of climate change on crop production is globally recognised (IPCC, 2019). Unpredicted weather patterns, the insurgence of pests and diseases, and the high cost of input disadvantage smallholder farmers who cannot meet the cost incurred. Expansion of croplands with single monocultures has resulted in simplified landscapes with pests and diseases becoming more aggressive due to resistance to cultivars and chemical controls. Furthermore, the croplands have limited biological control from their natural enemies due to the loss of biodiversity in the simplified landscapes. In Europe, frameworks such as Agri-environmental schemes have been implemented to restore biodiversity and ecosystem service provision in agricultural landscapes (Alison et al., 2017). Landscape management efforts still face critical challenges in Africa, especially in smallholding. For example, farming systems are complex in coffee landscapes, and plots are less than two hectares. Consequently, mapping efforts to provide baseline data that inform policy and planning are limited and not up to date.

For the coffee landscape in Kenya, significant progress has been made in developing cultivars resistant to diseases such as Ruiru 11 and Batian or with high yields such as SL28 and understanding the epidemiology of coffee pests and diseases (Hindorf and Omondi, 2011). On the other hand, few studies have been done to characterise smallholder farming systems and their contribution to defining local landscape ecology for supporting coffee and its pest populations, unlike in South America. The largest coffee-producing countries have studied the influence of landscape management on coffee pests broadly (Avelino et al., 2012; Bebber et al., 2016; Borkhataria et al., 2012; Messing, 2012; Ortega-Huerta et al., 2012). Unfortunately, the context of smallholder coffee farmers in the two continents varies, making it difficult to make a blanket conclusion on the best practices to be adopted. Therefore, to recommend spatially explicit best practices, there is a need to define the landscape context of African smallholder coffee farmers and their agronomic practices in relation to coffee pests and climate change.

1.6 Aim and objectives

This study aims to understand the landscape ecology of smallholder coffee landscapes and its influence on the proliferation of coffee pests. To achieve this aim, the study pursued the following objectives;

i. To explore the use 10-20-meter Sentinel 2, 30-meter Landsat 8 and 3-meter PlanetScope for characterising landscape structure in coffee agro-ecological sub-zones

ii. To determine the influence of multiscale spatial arrangement of land use and land cover (LULC) types on pests and their respective dispersal ability

iii. To evaluate the role of shade and edge effect on microclimate modification and pest abundance across the agro-ecological sub-zones

iv. To establish impacts of climate change on range shifts of coffee growing zones in Kenya under current and future climate scenarios

1.7 Scope of the study

This study focuses on coffee pests, specifically, coffee berry borer (*Hypothenemus hampei*) and antestia bugs (*Antestiopsis thunbergii* and *A. facetoides*). The species were chosen due to their varying dispersal ability, dominance in the study area, and economic importance. Coffee berry borer has a limited dispersal ability of less than 100m, whereas the antestia bugs have a higher dispersal capacity of up to 300m (Mosomtai et al., 2020). The species are representative of the general dispersal capacity of many coffee pests, allowing inferences to be made regarding the landscape contribution to population dynamics of coffee pests. A hierarchical multi-data approach was used to address the ecological scales of the coffee agrosystem where bioclimatic variables addressed the regional scale, remote sensing data for the landscape scale and microclimate data for the plot scale. Shade management is the only agronomic practice included in this study. Other practices such as the use of pesticides, fertilisers, pruning and weeding, which influence the pest population, are out of the scope of the study.

1.8 Outline of the dissertation

This thesis is structured into six chapters. Chapters 1 and 6 consists of the general introduction and the synthesis of the study. The remaining chapters adopt manuscript format, with chapters 2 and 3 already published, while Chapters 4 and 5 are currently under preparation for publication. Chapter 2 explores the utility of remotely sensed datasets from different satellite systems and random forest classifier in classifying LULC in the heterogeneous coffee landscape of smallholder farming in central Kenya. Using the generated LULC map, Chapter 3 looks at the influence of landscape structure on the population dynamics of two important coffee pests, coffee berry borer and two antestia bugs, which have varying flight capacity and feeding preferences. Chapter 4 identifies the spatial scale to which the surrounding landscape modifies the microclimate of coffee plots and its implication on coffee berry borer and antestia bug abundance. Finally, chapter 5 presents plausible scenarios of shifts in coffee-growing areas if global warming is kept under 2^{o}C and its implication on the studied coffee pests. It further identifies which environmental variables are vital in predicting habitat suitability for growing coffee.

CHAPTER 2: LANDSCAPE FRAGMENTATION IN COFFEE AGRO-ECOLOGICAL SUB-ZONES IN CENTRAL KENYA: A MULTI-SCALE REMOTE SENSING APPROACH

This chapter is based on: **Mosomtai, G**., Odindi, J., Abdel-Rahman, E.M., Babin, R., Fabrice, P., Mutanga, O., 2020. Landscape fragmentation in coffee agro-ecological sub-zones in central Kenya : a multiscale remote sensing approach. J. Appl. Remote Sens. 14. https://doi.org/10.1117/1.JRS.14.044513

2.1 Abstract

Smallholder agro-ecological sub-zones produce an array of crops, occupying large areas throughout Africa but remain largely unmapped. This study explored multisource satellite datasets to produce a seamless land use land cover (LULC) and fragmentation dataset for upper midland (UM1-4) agro-ecological sub-zones in central Kenya. Specifically, the utility of PlanetScope, Sentinel 2, and Landsat 8 images for mapping coffee-based landscape were tested using a random forest (RF) classifier. Vegetation indices (VI), texture variables, and wavelength bands from each satellite data were used as inputs in generating four RF models. A LULC baseline map was produced that was further analyzed using FRAGSTAT to generate landscape metrics for each agro-ecological sub-zones. The wavelength bands model from Sentinel 2 had the highest overall accuracy with shortwave near-infrared and green bands as the most important variables. In UM1 and UM2, coffee was the dominant cover type, while annual and other perennial crops dominated the landscape in UM3 and UM4. The patch density for coffee was five times higher in UM4 than in UM1. Since Sentinel 2 is freely available, the approach used in the present study can be adopted to support land use planning in smallholder agroecosystems.

Keywords: Agroecosystems, Remote sensing, Machine learning, *Coffea arabica*, Landscape fragmentation

2.2 Introduction

The fast-paced conversion of global terrestrial land into croplands, mainly attributed to the growing human population, continuously exerts pressure on flora and fauna and results in habitat loss and disturbance of species communities and their interactions (Tscharntke et al., 2012). In Africa, agricultural landscapes typically vary from extensive mono-crops with fragments of isolated natural vegetation to mixed crops interspersed with semi-natural vegetation remnants that form a matrix that can impede or facilitate species interactions (Martel et al., 2019). Unlike in Europe, where land-use policies have been developed and implemented, Africa's agricultural landscapes remain largely unplanned with limited baseline data that can guide sustainable development (Saah et al., 2019).

Smallholder farmers in Africa practice approximately 13 general farming systems types. According to Garrity et al. (2012), these systems are maize mixed farming systems, agro-pastoral farming systems, cereal-root crop mixed farming systems, root and tuber crop farming systems, highland perennial farming systems, highland mixed farming systems, humid lowland tree crop farming systems, pastoral farming systems, fish-based farming systems, forest-based farming systems, irrigated farming systems, sparse arid pastoralism and oases farming systems, urban and peri-urban farming systems. Typically these farms form complex and heterogeneous landscapes, with farms commonly small and intercropped, particularly in populated regions (Garrity et al., 2012). Capturing these landscapes' structures for ecological applications requires accurate land use and land cover (LULC) classifications generated from high-resolution satellite imagery with sufficient reference data. Ecological processes such as spillover edge effects of biodiversity across adjacent LULC types (Duflot et al., 2016), landscape connectivity effects on species flow (Diekötter and Crist, 2013), or the effects of fragmentation on patch size (Smith et al., 2011) in sustaining a viable species population can be estimated using LULC information (Avelino et al., 2012). Thus, accurate and up-to-date LULC maps are needed to capture the dynamics and better represent the heterogeneities that characterise specific agro-ecological setups.

Whereas global initiatives like the 300m GlobCover 2009 and 1km Global Land Cover 2000 have generated LULC baseline datasets, they remain insufficient in providing accurate maps at regional to sub-national scales (Vancutsem et al., 2013). LULC legends in these global datasets are generated to estimate global biogeochemical processes such as carbon sequestration, which have limited application to local scale dynamics (Reis et al., 2018). Data gaps, inconsistent acquisition periods, cloud cover, and insufficient validation data, especially in the context of Africa, increase the error margins in using the existing global maps (Hansen et al., 2016). According to Saah et al. (2019), policy makers in developing countries often use outdated maps or opt for global datasets that do not meet their specific needs. Furthermore, their unwillingness to share the existing data across government agencies, creating maps in silos that cannot be harmonized, low budget allocation, and inadequate human resources slow the creation of useful baseline datasets.

Remotely sensed data are the major source of LULC information, and the existing satellite datasets have different spatial, spectral, and temporal characteristics with differing cost implications that require users to make trade-offs in their utilization as per their objectives (Li and Roy, 2017). In the tropics, continuous cloud cover most of the year limits the use of optical satellite datasets; conversely, the cost of using below cloud options such as drones or flight campaigns are too expensive for extensive and wide-area mapping. A critical agro-ecological zone in the tropical regions is the coffee-based landscapes. Coffee is grown by 25 million smallholders in over 60 countries in the tropics and a significant source of gross domestic product in many developing countries. In Kenya, for instance, coffee is produced by 700,000 smallholder farmers and 3000 large estates, contributing approximately $230 Million of the GDP annually (ICO, 2019). Smallholder farmers grow coffee on less than 2-hectare farms, either as agroforestry systems (i.e., shade coffee), intercropped with mainly subsistence crops, or mono-cropping systems (i.e., full-sun coffee) (Anthony et al., 2002). Currently, there is no spatially explicit map for these coffee systems because it is often generalized either as croplands (intercropped coffee), shrublands (full-sun), or forest land (agroforest) in many tropical countries.

Existing coffee maps at the global scale are probability distributions generated from ecological niche models generated from climate variables, environmental layers, and presence-only data (Bunn et al., 2015). These maps limit further analysis of landscape composition and configuration. LULC maps from satellite imageries are mainly the primary baseline data for analysis in landscape ecology. Furthermore, LULC types and their spatial patterns vary according to different landscapes such as agro-ecological zones (AEZ) and landforms (e.g., rivers, mountains, cliffs, coasts, plateaus, etc.). They are often generalized in probability distribution maps, yet the subtle dynamics in LULC types influence ecological processes at varying scales (Ketema et al., 2020).

Herein, the hypothesis is that the landscape structure varies across the agro-ecological sub-zones in the coffee-based landscape. Using a random forest (RF) classifier and FRAGSTAT, this study aims to characterize the landscape setup in agro-ecological sub-zones of a coffee-based landscape in central Kenya using an optimal satellite dataset. Both tools provide a unique opportunity to determine landscape patterns in smallholder farming areas. RF classifier (Breiman, 2001) can handle non-linear effects in complex datasets with high accuracy and speed, while FRAGSTAT is an efficient tool that has become a reference in landscape ecological studies that involve highly complex agro-ecological systems (Ochungo et al., 2019).

2.2 Study location

The present study was conducted in Murang'a County, a major coffee and tea growing region in central Kenya. The County borders Nyeri and Kirinyaga Counties in the north, Machakos and Embu Counties in the east, and Kiambu County in the south (inset of Figure 2.1). The mean annual temperature and rainfall range from $18^{o}C$ – $21^{o}C$ and 1000 – 1500 mm within the coffee growing zone. The rainfall pattern is bimodal, where long rains occur from March to May, while short rains occur from October to December (Jaetzold et al., 2007). Consequently, this coincides with the coffee planting, management schedules (e.g., pruning, fertilizer and pesticide application) and harvesting season of the first and the main crop, respectively (ICO, 2019). Due to climate change, however, erratic rains and prolonged droughts have resulted in inconsistent planting seasons and interference with coffee tree phenology, making it more susceptible to pest and disease infestations and low yields (DaMatta et al., 2007).

A transect of 20240 ha at latitude -0.8295^{o} and -0.7538^{o} and longitude 36.9472^{o} and 37.1647^{o} was selected to represent the entire coffee belt (Figure 2.1). The study was conducted in the context of a bigger project that aimed to improve the coffee value chain for smallholder farmers. This informed the choice of the study transect, which covered all the coffee agro-ecological sub-zones (i.e., upper midland; UM1 - UM4). Specifically, coffee grows in four sub-zones that cut across an elevation gradient of 1300 – 2000 m a.s.l. (above sea level) (Jaetzold et al., 2007). UM1 is the transition zone for growing tea and coffee. UM2 and UM3 are the primary and marginal coffee-growing zones, respectively. Unlike UM1 – 3, where coffee is rainfed, at UM4, coffee is grown under irrigation (Jaetzold et al., 2007). Coffee is grown either as full-sun, intercrop, or under shade in the study area. Common shade trees include macadamia (*Macadamia integrifolia*), avocado (*Persea americana*), mango (*Mangifera indica*), and hedgerow trees like grevillea (*Grevillea robusta*), while intercrops include banana, maize, bean and sweet potato on an average farm size of 0.5 ha (GoK, 2018).

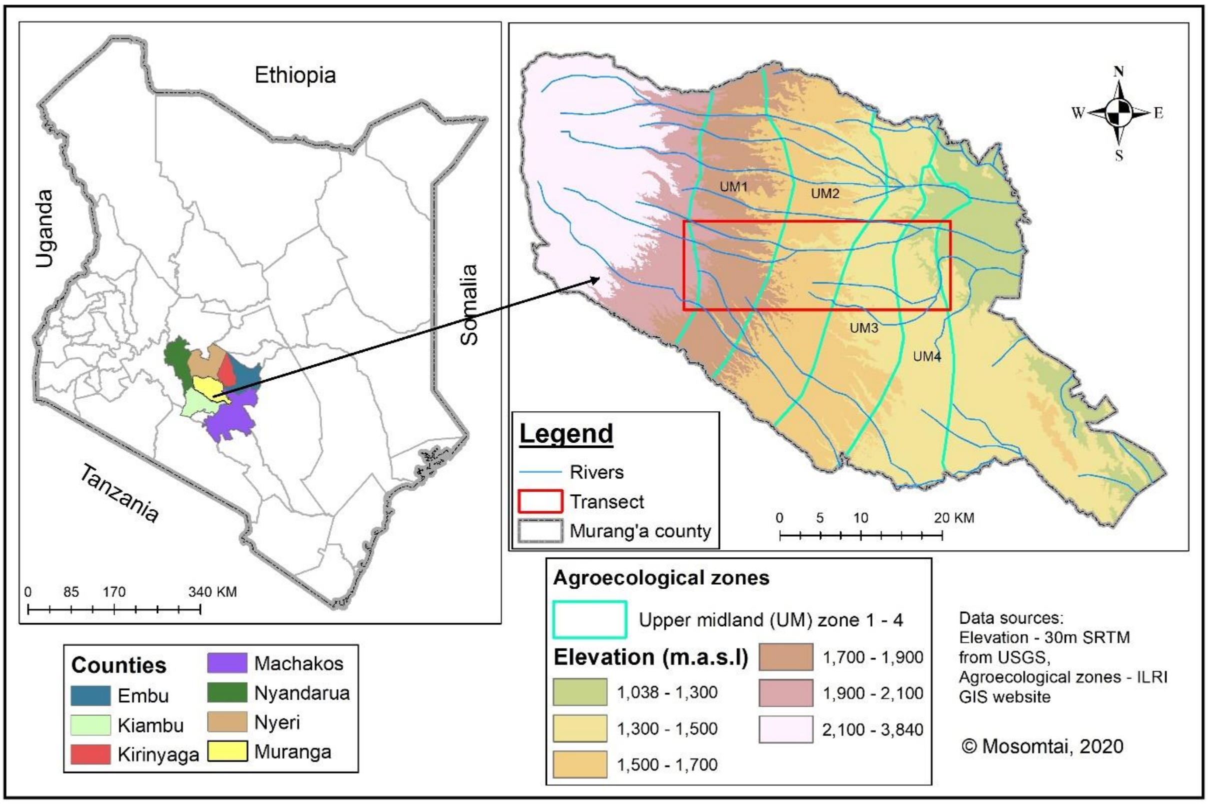

Figure 2.1: Map of agro-ecological zones of Murang'a County, Kenya, and position of the study transect

The topography of the region is undulating, with dissected hills sloping from northwest to southeast (GoK, 2018). Soils on the hills and minor escarpments are cambisols and rigosols formed on the homogenous basement system of gneiss rocks. In contrast, soils on the plateaus and foot-ridges such as nitisols developed on tertiary igneous rocks. Nitisols contain high nutrients from their primary minerals and montmorillonite clay, which make them suitable for coffee and tea plantation.

2.3 Methodology

Figure 2.2 presents the datasets and summarizes the methods used in the study. The initial stage involved pre-processing the satellite images and deriving vegetation indices and texture variables. The second stage involved running the RF model to generate LULC maps, and the final step was the analysis of the LULC map to generate landscape fragmentation metrics for each agro-ecological sub-zones.

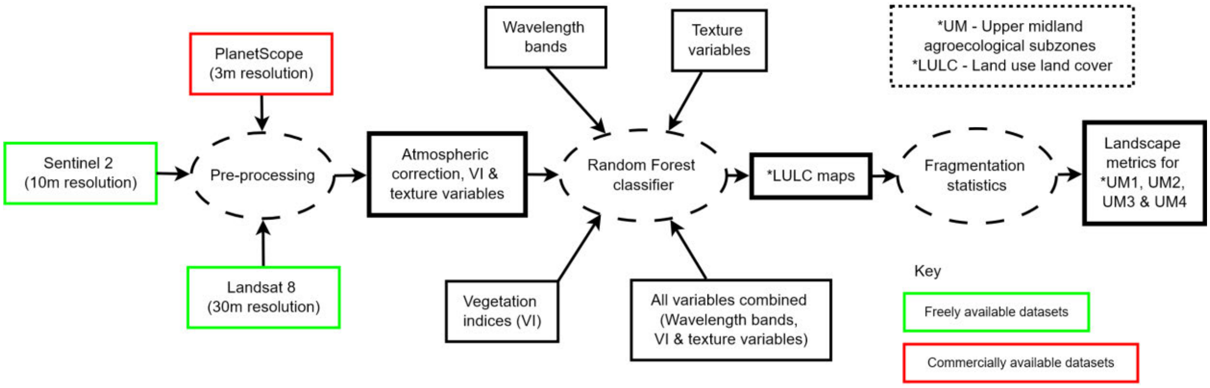

Figure 2.1: Flowchart of the datasets and methods used in the study

2.3.1 Datasets

2.3.1.1 Satellite imagery used

PlanetScope (PS) is a high-resolution satellite dataset from Planet labs that is available commercially (Table 2.1). In contrast, Sentinel 2 - S2 (high to medium resolution) and L8 (medium-resolution dataset) are freely available from the European Space Agency (ESA), and the United States Geological Survey (USGS), respectively. PS is a constellation of 130 CubeSat satellites with daily revisit time of the entire land surface, which measures the reflected energy within the blue (B), green (G), red (R), and near-infrared (NIR) wavelengths at 3 m spectral resolution (Planet Labs, 2016). S2 measures a broader range of the electromagnetic spectrum ranging from visible, near-infrared, and shortwave using the MultiSpectral Instrument (MSI) sensor at 10 m, 20 m, and 60 m spatial resolution, with a five day revisit time (Zhang et al., 2018). L8 measures similar wavelengths as S2 at 30 m spatial resolution (Table 2.1), however, S2 has additional red-edge bands, which have proven useful in various vegetation, agriculture, and LULC monitoring studies (Tawona et al., 2020). Due to the cost implications of high resolution images, PS was used in this study to test the utility of commercial satellites over freely available satellites and the expected trade-offs in the overall accuracy.

Table 2.1[1]: Summary of spatial and spectral characteristics of Sentinel-2, Landsat 8, and PlanetScope satellite imagery

Band	Description	Wavelength range (µm)	Spatial resolution (m)
		Sentinel 2	
B2	Blue	0.439 - 0.535	10
B3	Green	0.537 - 0.582	10
B4	Red	0.646 - 0.685	10
B5	Red edge1	0.694 - 0.714	20
B6	Red edge2	0.731 - 0.749	20
B7	Red edge3	0.768 - 0.796	20
B8	NIR	0.767 - 0.908	10
B8a	Narrow NIR	0.848 - 0.881	20
B11	SWIR1	1.539 - 1.681	20
B12	SWIR2	2.072 - 2.312	20
		Landsat 8	
B2	Blue	0.452 - 0.512	30
B3	Green	0.532 - 0.590	30
B4	Red	0.639 - 0.673	30
B5	NIR	0.851 - 0.879	30
B6	SWIR1	1.567 - 1.6511	30

[1] Refer to Supplementary Table 2.1 for details on the scene description for each satellite dataset

B7	SWIR2	2.107 - 2.294	30
		PlanetScope	
B1	Blue	0.455 - 0.515	3
B2	Green	0.500 - 0.590	3
B3	Red	0.590 - 0.670	3
B4	NIR	0.780 - 0.860	3

Good-quality images with less than 2% cloud cover were selected for this study. These images were found in August, October, and December 2017 for S2, PS, and L8, respectively. Supplementary Table 2.1 provides a detailed description of the image scenes used in this study. The images were already orthorectified to remove the topographic effects. Due to the bimodal rainfall patterns, the study area has two growing seasons annually that overlap (Ovuka and Lindqvist, 2000). Hence, the landscape has continuous cover crops all year round. In the pre-processing stage, the images were converted into surface reflectance values for further analysis. L8 bands were pan-sharpened to 15 m resolution using the Brovey transform method in QGIS (Vivone et al., 2015), while S2 bands of 20 m were resampled to 10 m spatial resolution (Figure 2.2). Out of 43 vegetation indices (VIs), variance inflation factor was used to select 11 uncorrelated VIs and five biophysical variables presented in Table 2.1. For texture analysis, ten indices were generated that represent contrast, statistic, and orderliness features from the NDVI band of each satellite dataset, as outlined in Table 2.2. VIs have been shown to be sensitive to chemical and morphological aspects of the leaf organs, which are used to estimate water content, plant types, nutrients content and pigmentation, among others.

Table 2.2: Summary of vegetation indices (VI), biophysical and texture variables used in the study

Variable	**Description**	**References**
	Vegetation index	

RI	Redness Index	(Mathieu et al., 1998)
NDPI	Normalized Difference Pond Index	(Lacaux et al., 2007)
MSAVI	Modified Soil Adjusted Vegetation Index	(Qi et al., 1994)
GEMI	Global Environmental Monitoring Index	(Xue and Su, 2017)
BI2	Second Brightness Index	(R. Escadafal, 1993)
BI	Brightness Index	(R. Escadafal, 1993)
MTCI	Modified Chlorophyll Absorption Ratio Index	(Delegido et al., 2013)
S2REP	Sentinel-2 Red-Edge Position Index	(Chemura et al., 2018)
GNDVI	Green Normalized Difference Vegetation Index	(Xue and Su, 2017)
REIP	Red-Edge Inflection Point Index	(Raper and Varco, 2014)
MCARI	Meris Terrestrial Chlorophyll Index	(Xue and Su, 2017)
	Biophysical variables	
LAI	Leaf Area Index	(Fang et al., 2019)
LAI_CW	Canopy Water Content	(Weiss and Baret, 2016)
LAI_CAB	Chlorophyll content in the leaf	(Weiss and Baret, 2016)
FCOVER	Fraction of vegetation cover	(Weiss and Baret, 2016)
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation	(Weiss and Baret, 2016)
	Texture analysis	
Contrast features	Contrast	(Haralick et al., 1973)
	Dissimilarity	(Haralick et al., 1973)
	Homogeneity	(Haralick et al., 1973)
Statistics features	Gray Level Co-occurrence Matrix (GLCM) variance	(Haralick et al., 1973)
	GLCM mean	(Haralick et al., 1973)
	GLCM correlation	(Haralick et al., 1973)
Orderliness features	Maximum Probability (MAX)	(Haralick et al., 1973)
	Entropy	(Haralick et al., 1973)
	Energy	(Haralick et al., 1973)
	Angular Second Moment (ASM)	(Haralick et al., 1973)

2.3.1.2 Classification reference data

Very high-resolution images from Google Earth Pro acquired in July 2017 was used to obtain reference data for training and testing the classification models. These are high spatial resolution images (< 1 m) obtained from different platforms with acquisition dates indicated, and studies have shown that they can be used to obtain reference data (Redzwan and Ramli, 2007). For the period of this study, only July had available images closer to the dates of the selected satellite images. Although there was no field reference data to distinguish crop types, especially annual crops, prior knowledge of the study area, interpretation of Google Earth Pro image texture, shape, canopy size, and literature on the crop types in the study area were used to generate the LULC classes. The following LULC classes were considered, coffee, tea, other perennial crops (herein referred to as perennials), banana, annual crops, grassland, agroforestry, bareland, settlements, and waterbody. The perennial crops comprised of avocado, mango, and macadamia, which are plantations in the lower sub-zones, but they also exist in the other sub-zones, often as shade trees, while coffee and tea were treated as independent perennial classes. The annual crops are mainly for subsistence and include maize, beans, arrowroots (majorly grown along the rivers), and sweet potatoes. On the other hand, bareland comprised of exposed soils from quarries and unfallowed land, whereas agroforest constituted mainly of shade coffee cropping system and clusters of woodlots. The coffee class consisted of full-sun coffee plots visible in the Google Earth Pro image with no shade.

2.3.2 Data analysis

2.3.2.1 Random forest classification algorithm

A random forest (RF) classifier by Breiman (2001) was used to assess the robustness of the satellite datasets for classifying the coffee-based landscape in the study transect (Figure 1). RF is a collection of decision trees, i.e., classification and regression trees (CART), that learn the characteristics of the training samples and predict similar characteristics in an unclassified dataset (Belgiu and Drăgu, 2016). Compared to other machine learning algorithms such as support vector machine (SVM), artificial neural network (ANN), and boosted regression trees (BRT), RF was found to produce robust results in fragmented smallholder farming areas in Zimbabwe than other methods (Tawona et al., 2020). RF can handle non-linear effects in complex datasets or few and imbalanced training samples with high accuracy and speed better than most other algorithms. Furthermore, the algorithm ranks the essential predictor variables negating users' selection errors and subjectivity (Belgiu and Drăgu, 2016; Boulesteix et al., 2012). The algorithm splits the training samples into two folds, approximately two-thirds for training the model, also known as in-bag samples, and one-third for testing the accuracy of the model, also known as out-of-bag samples (Breiman, 2001). The algorithm internally assesses the accuracy of the model based on the out-of-bag (OOB) error, which averages the error frequency of the decision trees built using in-bag samples. The OOB error is also used in ranking variable importance based on mean decrease accuracy (MDA) (Htitiou et al., 2019). Apart from MDA, RF also uses mean decrease gini (MDG) to assign variable importance based on decrease in node impurity of a variable at split node (Han et al., 2016).

This study used 70% of the classification reference data to train the RF model. Four sets of variables for each satellite dataset was used to build the models: (i) wavelength bands only, (ii) vegetation indices only, (iii) texture variables only, and (iv) combined wavelength bands with VI and texture variables (Figure 2). Both mean decrease accuracy and mean decrease gini were used to determine the important variables for LULC classification. The R software implemented the model using the '*randomForest*' package (Liaw and Wiener, 2002) (R Core Team, 2020). The default RF settings, which have been proven optimal for building accurate models, were used (Tawona et al., 2020). The remaining 30% of the reference data were used for model evaluation. The following accuracy assessment metrics from the confusion matrices were generated, overall accuracy (OA), user's (UA) and producer's (PA) accuracies, F1 score, and Kappa coefficient (K) (Tawona et al., 2020). F1 score is the mean metric of precision (PA) and recall (UA), where a value of 100% indicates that the model achieved perfect precision and recall of all the test data, and the inverse is true (Hurskainen et al., 2019). The equations for calculating the accuracy metrics are as follows;

$$\text{Overall accuracy } (OA) = \left({}^{1}/_{N}\right) \sum_{j=1}^{r} n_j$$

$$\text{Producer's accuracy } (PA) = \frac{n_j}{n_{icol}}$$

$$\text{User's accuracy } (UA) = \frac{n_j}{n_{irow}}$$

$$\text{F1 score} = 2 \times \frac{PA \times UA}{PA + UA}$$

Where N is the total number of pixels in the image, r is the number of rows, n_j are pixels correctly classified, and n_{icol} and n_{irow} are the total number of columns and rows, respectively (Verma et al., 2020).

2.3.2.2 Landscape metrics

LULC map with the highest accuracy was further analyzed using the FRAGSTAT tool (McGarigal et al., 2002) to quantify the composition of LULC types and landscape fragmentation across the four agro-ecological sub-zones (AEsZ) in the study transect (i.e., UM1, UM2, UM3, & UM4). FRAGSTAT computes several metrics measured at patch, class, and landscape levels that describe, among others, area, edge, shape, contagion, contrast, and aggregation from LULC maps. The present study assessed the mean patch, largest patch index, patch density, splitting index, contagion, and landscape percentage occupied by each LULC type across the four AEsZ at class and landscape levels. A patch defines a homogenous area that is different from its surroundings, herein referred to as the LULC type. Patches are computed based on the pixel size of the satellite image used to map the LULC; hence they are subjective to scale variability or specification of minimum patch size (McGarigal et al., 2002). Furthermore, patch size holds ecological significance compared to all metrics. It is shown that Patch sizes can influence species richness in semi forested coffee systems (Kumsa et al., 2016), bird species abundance in naturally heterogeneous landscapes (Crozier and Niemi, 2003), and insect pollinators in forest fragments in shaded coffee agrosystems (Krishnan et al., 2012). Table 3 summarizes the description of the FRAGSTAT metrics used in the present study.

Table 2.3: A description of class and landscape metrics used in the present study as defined by the FRAGSTAT user manual (McGarigal et al., 2002)

Level	**Metric**	**Description**	**Unit**
Class	Mean patch area (MPA)	The average-weighted mean of the number of patches in the class and total class area	ha
	Largest patch index (LPI)	The largest patch of the corresponding patch type divided by total landscape area	Percent
	Percentange of landscape (PLAND)	Proportional abundance of each patch type in the landscape	Percent
	Patch density (PD)	Number of patches in the landscape, divided by total landscape area	Number of patches /100 ha
Landscape	Splitting index (SPLIT)	Number of patches with a constant patch size when the landscape is subdivided into equal sizes	None
	Contagion (CONTAG)	A measure of both intermixing of patch types and spatial distribution of a patch type	Percent
	Euclidean nearest neighbor distance (ENN)	Shortest straight-line distance between the focal patch and its nearest neighbor of the same class	Meter

2.4 Results

2.4.1 RF model accuracy assessments

Table 2.4 shows the overall accuracies (OA) obtained using the RF classifier and the various satellite image datasets. Wavelength bands were better predictors of LULC in all the satellite datasets than VI or texture variables. For the bands only model, S2 had the highest OA (95%) compared to L8 (90%) and PS (83%). Combined with VI and texture variables, the OA for PS increased significantly compared to using only wavelength bands (by 3%) or texture variables (by 26%). For S2, there was no significant change when using combined variables in comparison to wavelength bands only (OA increased by 1%). For L8, the OA dropped by 4% when using combined variables compared to the wavelength bands only. VIs were the second ranked predictors in all the satellite datasets, while texture variables were the least. VIs from S2 had the highest OA (91%), while VIs from PS had the least (81%). Similar to the OA, the OOB error estimate showed that the texture variables from PS had the highest error rate (39%) in all the models, indicating its poor predictive ability of the internal out-of-bag samples.

Table 2.4: The overall accuracy (OA), out-of-bag error (OOB), and Kappa coefficient (K) for land use and land cover (LULC) maps of coffee-based landscape in Murang'a, Kenya using different satellite datasets and the random forest (RF) classification algorithm

Model	**Overall accuracy (%)**	**OOB error (%)**	**Kappa (K) (%)**
PS bands	83	19	80
PS vegetation indices	81	20	77
PS texture variables	60	39	51
PS bands, VI and texture	86	13	83
S2 bands	95	5	93
S2 vegetation indices	91	9	89
S2 texture variables	79	23	75
S2 bands, VI and texture	96	4	95
L8 bands	90	9	88
L8 vegetation indices	88	12	86
L8 texture variables	79	25	74
L8 bands, VI and texture	86	17	84

S2 variables showed better mapping results for all the classes with more than 90% PA, UA, and F1 scores than L8 and PS datasets (Table 2.5). The banana class was generally poorly mapped in all the satellite datasets (the least PA = 41% using PS, highest PA = 83% using S2) while the waterbody had the highest accuracies except in L8, which had the least PA of 38%. Coffee and agroforest classes had the highest accuracies (F1 score = 94% and 97% respectively) when mapped using S2 datasets. However, there was an increase in efficiency for PS (by 6% for coffee and 4% for agroforest) when the wavelength bands were combined with VI and texture variables.

2.4.2 Variable importance

In the wavelength bands model, SWIR1, SWIR2, and green bands from S2 and L8 were the most important variables contributing to a total of 36% and 53% MDA and 44% and 57% MDG, respectively (Figure 2.3). Additionally, the NIR bands from S2 and L8 contributed 10% and 18% MDA to the model accuracy, respectively. The red-edge band from S2 and the red band from L8 contributed 13% and 16% MDG in decreasing node impurity, respectively. For VI and texture variable models, BI, NDPI, RI, GNDVI, and additional LAI_CW and CAB from S2 were the most important variables. At the same time, contrast, GLCM mean, variance, and correlation were the most important texture variables in all the satellite datasets (Supplementary Table 2.2) for mapping the landscape classes. When all the variables were combined, the same important variables identified in the individual models contributed more to the model (Supplementary Table 2.3).

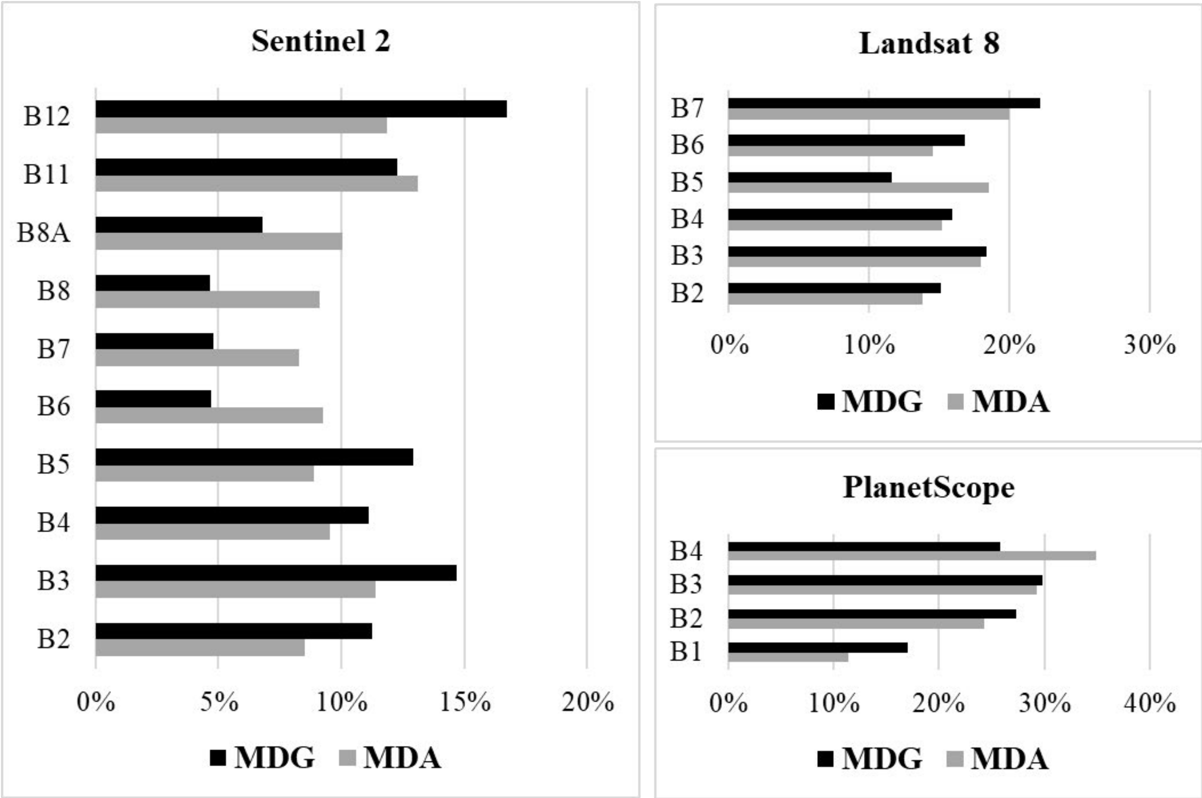

Figure 2.2: Variable importance of wavelength bands for Sentinel 2, Landsat 8 and PlanetScope datasets converted into percentage

Table 2.5: Producers' accuracy (PA), users' accuracy (UA), and F1 score for all the classification models used in the study to map the land use and land cover (LULC) classes of the study transect.

Model	(%)	Annuals	Banana	Bareland	Coffee	Agroforest	Grassland	Perennials	Settlement	Tea	Waterbody
PS bands	UA	76	69	91	80	85	97	74	90	95	100
	PA	89	41	91	81	85	96	53	92	91	100
	F1	82	52	91	80	85	97	62	91	93	100
PS bands, VI and texture	UA	79	76	90	84	88	97	75	95	95	100
	PA	89	46	90	87	91	97	47	90	91	100
	F1	84	57	90	86	89	97	57	93	93	100
S2 bands	UA	91	92	92	91	99	98	97	97	99	100
	PA	96	83	95	95	94	100	92	92	94	100
	F1	93	87	94	93	96	99	94	94	96	100
S2 bands, VI and texture	UA	95	94	95	93	97	99	97	97	100	100
	PA	99	74	95	96	96	99	95	96	92	100
	F1	97	83	95	94	97	99	96	96	96	100
L8 bands	UA	91	88	92	87	92	92	90	91	93	100
	PA	96	75	89	91	93	84	68	100	95	38
	F1	94	81	91	89	93	88	78	95	94	55
L8 bands, VI and texture	UA	88	89	73	86	90	91	93	71	95	90
	PA	98	56	81	94	78	87	98	74	92	94
	F1	93	69	77	90	83	89	95	72	94	92

PS = PlanetScope, S2 = Sentinel 2, and L8 = Landsat 8

2.4.3 Landscape fragmentation in each agro-ecological sub-zone

Figure 2.4 shows the LULC maps from the PS wavelength bands (map A), S2 (map C), and L8 (map B). Visually, PS and S2, unlike L8, mapped similar landscape structures, but with varying levels of accuracy. L8 overestimated annual crops and grassland at the expense of coffee, while agroforest appeared in larger patches than in PS and S2. Across the AEsZ, the primary coffee-growing zone is at UM2 and the lower region of UM1. At UM3, coffee is interspersed with annual crops, which form the landscape matrix, while grasslands and other perennials dominate UM4. Pockets of agroforests were evenly distributed in UM1 and UM2, but in UM3, patches took a more linear shape. In UM2, annual crops are grown along the riverine, while settlements appeared in linear patches with one major town situated at UM4. The settlement class was generally classified poorly in L8 compared to S2 and PS. A cloud shadow in L8 was misclassified as a waterbody. The S2 map was adopted for further analysis of the landscape structure. Its high accuracy captured the landscape physiognomy at 10m spatial resolution better than PS, which had the highest spatial resolution than all the datasets used at 3m.

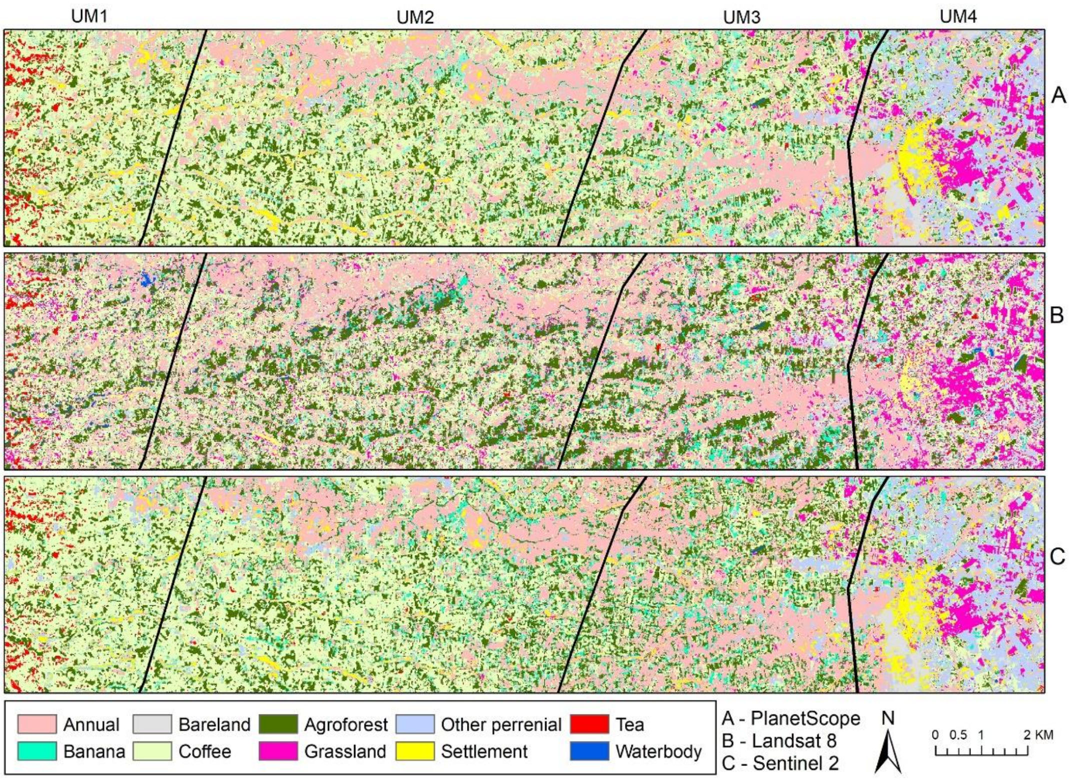

Figure 2.43: Land use and land cover (LULC) maps of coffee growing transect in Murang'a County produced using PlanetScope (A), Landsat 8 (B), and Sentinel 2 (C) datasets, and the random forest classifier. The black lines show the boundaries of the UM zones

2.4.3.1 Class level metrics

According to the S2 LULC map (Figure 2.4C), coffee covers 64% and 60% of the total landscape in UM1 and UM2, respectively, while the annual crops occupy 43% in UM3 (PLAND in Table 2.6). Other perennials and annual crops occupy 29% and 22% of UM4, respectively. All the dominant patch types that formed the matrix in each AEsZ, had the largest patch index (LPI), as shown in Table 2.6. Coffee patches in UM2 were more fragmented than in UM1. The most dominant patch (given by LPI) in UM1 is almost twice the size of the dominant patch in UM2 (UM1 = 63, UM2 = 33). Similarly, the mean patch area (MPA) for coffee in UM1 is more than three times the size in UM2 to UM4 (UM1 = 2.65ha, UM2 = 0.74ha, UM2 = 0.16ha, UM4 = 0.14ha). Agroforest patches occupy 14% of UM1 and 17% of UM2 and UM3, with the least cover in UM4, occupying approximately 5% of the landscape. Coffee intercropped with banana is more prevalent in UM2 and UM3, where banana patches have less than 0.06% of LPI. UM4 is the marginal coffee growing area characterized by more settlements, grassland, and bareland than all the other sub-zones. Coffee is highly fragmented in UM3 and UM4 as compared to UM1, with patch density (PD) of 157 and 120, respectively (Table 2.6). Additionally, forest cover and bananas have a high patch density in UM2 and UM3, while for annuals, shrubs, grassland, and settlements, the patch density is high in UM4.

2.4.3.2 Landscape level metrics

Distinct landscape structures exist in each AEsZ. Landscape connectedness, measured by CONTAG (contagion) index, is highest in UM1 and gradually declines along the altitudinal gradient, with the least connectedness in UM4 (Figure 2.5).

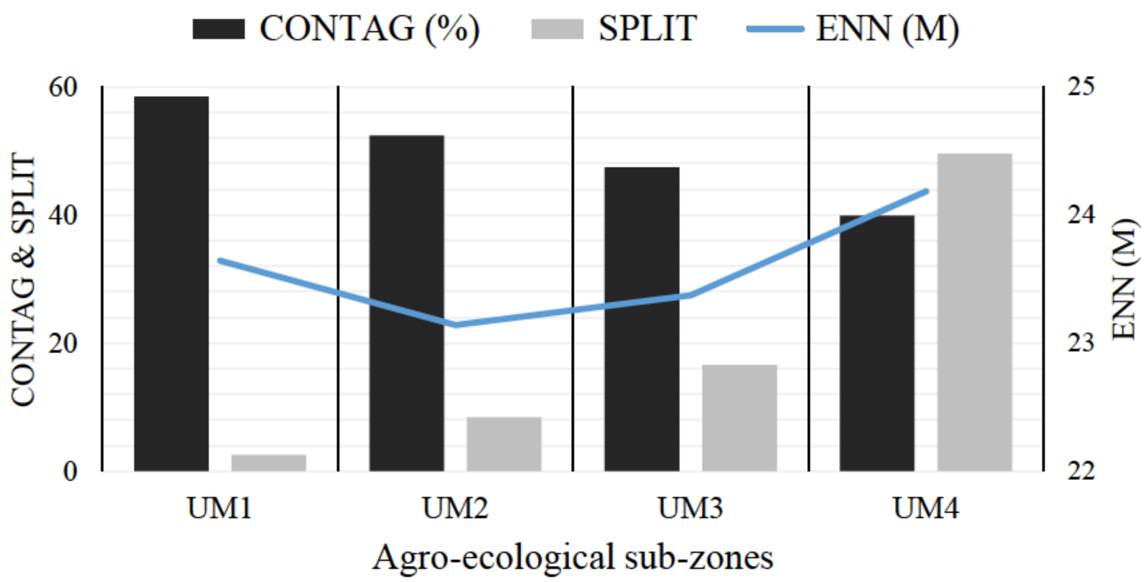

Figure 2.54: Landscape metrics that describe landscape connectivity (CONTAG index (%)), landscape fragmentation (SPLIT index), and patch isolation (ENN (m)) in UM1, UM2, UM3, and UM4

Furthermore, landscape fragmentation described by the SPLIT index showed that UM4 is fragmented five times more than UM1. The high CONTAG index in UM1 also describes a landscape with low diversity in cover types. Interestingly, the distance between patches was similar across all the AEsZ (ENN range 23 - 24 m), which meant that UM4 had more cover types that are well interspersed across the landscape, UM1 had similar interspersion but of the same or fewer patch types than UM4.

Figure 2.6: Percentage of landscape (PLAND (%)), largest patch index (LPI (%)), patch density (PD (number of patches/100 ha)) and mean patch area (MPA (ha)) for each land use and land cover (LULC) class across the four agro-ecological sub-zones of the study

	Metric	Annuals	Banana	Bareland	Coffee	Agroforest	Grassland	Perennials	Settlement	Tea	Waterbody
UM1	PLAND (%)	3.77	2.40	0.03	**64.25**	14.31	0.10	4.62	2.98	7.54	0.01
	LPI (%)	0.87	0.02	0.01	**62.97**	0.20	0.01	0.22	0.23	0.33	0.00
	PD	34.24	81.84	0.46	24.27	68.81	2.98	32.71	32.90	56.12	0.19
	MPA (ha)	0.11	0.03	0.07	2.65	0.21	0.03	0.14	0.09	0.13	0.03
UM2	PLAND (%)	18.83	5.65	0.05	50.99	17.35	0.17	3.64	2.95	0.35	0.01
	LPI (%)	5.36	0.04	0.02	33.20	0.17	0.01	0.08	0.11	0.01	0.00
	PD	53.41	145.22	0.36	69.05	114.08	5.51	27.09	36.81	10.10	0.24
	MPA (ha)	0.35	0.04	0.15	0.74	0.15	0.03	0.13	0.08	0.03	0.04
UM3	PLAND (%)	43.02	5.83	0.39	25.30	17.86	1.78	3.36	2.37	0.04	0.04
	LPI (%)	23.32	0.03	0.09	3.06	0.20	0.12	0.51	0.09	0.00	0.02
	PD	63.22	118.81	1.27	157.37	132.84	24.18	24.55	30.28	1.95	0.53
	MPA (ha)	0.68	0.05	0.31	0.16	0.13	0.07	0.14	0.08	0.02	0.08
UM4	PLAND (%)	22.84	1.37	5.17	17.26	5.35	10.75	29.30	7.76	0.18	0.02
	LPI (%)	5.07	0.05	0.89	1.42	0.17	1.56	10.10	2.00	0.02	0.01
	PD	93.06	26.45	13.86	120.62	67.11	44.71	73.42	58.83	6.89	0.10
	MPA (ha)	0.25	0.05	0.37	0.14	0.08	0.24	0.4	0.13	0.03	0.16

2.5 Discussion

This study explored three multisource satellite images from 3 m PlanetScope (PS), 10 m Sentinel 2 (S2), and 30 m Landsat 8 (L8) to identify the optimum dataset for mapping LULC of a coffee-based landscape in the highlands of East Africa, dominated by smallhold farms. Furthermore, landscape composition and the level of fragmentation on each agro-ecological sub-zones (AEsZ) was examined. The results showed that the spectral resolution of a sensor is a critical factor in delineating vegetation types in a heterogeneous agricultural landscape and that each AEsZ has a unique landscape physiognomy. This study fills a gap on the scarcity of detailed LULC maps, especially in Africa, since the available maps in public databases often generalize agricultural landscapes and are not up-to-date. LULC types that govern ecological processes in each AEsZ were delineated in detail and outlined its potential in improving production in agricultural landscapes (e.g., coffee production) while conserving biodiversity and providing ecosystem services.

2.5.1 Model accuracy assessment

The results showed that S2 datasets had the highest overall accuracy (OA) in all the models, followed by L8, while PS had the least OA, despite having the highest spatial resolution. Htitiou et al., (2019) and Shoko and Mutanga, (2017) reported similar findings when the S2 dataset outperformed other multispectral datasets in mapping crops and grasslands. The different accuracies in the mapping results could be associated with the differences in the spectral resolution (bandwidth and number of bands) among the sensor images (Levin, 1999). S2 measures a broader region of the electromagnetic spectrum ranging from the RGB to the SWIR region with additional red-edge bands, in contrast with PS, which covers only the visible and NIR regions with lower waveband data bits. Furthermore, the pixel depth (radiometric resolution) of S2 allows the bands to capture more details per pixel. This could explain the observed high accuracy of the wavelength bands with minor improvement when VI bands were added. Due to advancement of S2 sensor specifications, subtle differences in cover types can now be captured with the added advantage of shorter revisit time compared to L8. Additionally, the higher resolution in PS captures more features, which increases spectral confusion between classes with the narrow spectral bands.

The commission and omission errors of LULC types described by UA and PA, respectively, were relatively lower when using S2 wavelengths bands. This reinforces the finding that S2 imagery is more suitable for discriminating LULC types in heterogeneous and complex landscapes. In the study area, where coffee and agroforest are important cover types and often difficult to differentiate, coffee and agroforest were mapped with a higher PA using S2 when compared to L8 and PS. Previous studies, however, attempted to map coffee from other LULC types using Landsat datasets; their results were comparable to what was obtained using L8. For example, Ortega-Huerta et al. (Ortega-Huerta et al., 2012) differentiated between the open canopy and closed canopy coffee in South-west El-Salvador with an OA of 85.7% using Landsat Thematic Mapper while Cordero-Sancho and Sader (Cordero-Sancho and Sader, 2007) attempted to classify shade coffee and sun coffee in Costa Rica with a PA of 91.8% and 86.2%, respectively, using Landsat Enhanced Thematic Mapper. Both S2 and L8 are freely available datasets, but the results showed a more accurate mapping from S2 than L8. This study, therefore, elucidates the potential of using S2 with limited resources to generate detailed LULC maps, especially for Africa, which often is missing in global LULC datasets. Furthermore, the temporal resolution of the S2 sensor of five days means that researchers and other stakeholders can have access to up-to-date maps to inform their policies.

2.5.2 Variable importance

Surprisingly, SWIR 1 and 2 bands were the most important variables in S2 and L8 as opposed to NIR, red edge, red or green bands, which are known to be the most important bands in LULC classification of vegetation types. In coffee-based landscapes, SWIR bands have been shown to be particularly important due to the soil background that is mixed with the spectral signal of coffee leaves (de Oliveira Pires et al., 2020). Often, coffee trees are planted with spacing in between the rows. Though these rows were not visible in the study due to smallholdings with low coffee density and possible defoliation of coffee leaves due to leaf rust disease, they still influenced the pixel purity. Notably also from the study was the significance of the red edge band in increasing class separation (MDG = 13%). Red edge bands measure the abrupt rise in the reflectance within the transition zone of the red and near-infrared region, this region of the EMS detects subtle variability in vegetation types, which would otherwise be generalized when using broadband widths such as the case of L8 (Delegido et al., 2013).

The VIs (including biophysical variables from S2) models had a lower OA compared to the only wavelength bands, while the texture variables had the least OA in all the satellite datasets. The most significant VIs included BI, RI, NDPI, and LAI_CW. On the other hand, contrast, correlation, mean, variance, and to a lesser extent, homogeneity were the most essential texture variables. When VIs and texture variables were combined with the wavelength bands, there was no considerable change in OA for S2, but for PS, there was an increase in OA; this was associated with the unique information that RI contributed to the model. RI and BI are soil-based indices that measure the colour properties of soil (Escadafal, 1993). These two indices further explain the particular soil background characteristics that were captured by the SWIR band in the wavelength bands model. Given the limited spectrum and data depth of PS, RI captured similar information in the SWIR band; hence, the utility of VIs, especially in sensors with limited spectral bands, is vital. Despite the significance of VIs, the low OA observed in the VIs models is associated with the oversimplification of VIs, especially in heterogeneous landscapes, where there is more than one vegetation type and species that could co-occur and occupy the same pixel (Xue and Su, 2017).

2.5.3 Landscape fragmentation in each AEsZ

The results further revealed that landscape composition varied according to agro-ecological sub-zones, which correspond to various elevation zones (Figure 4). Coffee is the dominant cover in UM1 and UM2 (elevation ranging 1900 m – 1600 m), while in UM3 and UM4 (elevation ranging 1500 m – 1300 m), the dominant cover types are annual crops and other perennials, respectively. The agroforest system in the study area is highly fragmented in UM3 (patch density = 157), with the least cover in UM4. Visual interpretation of the LULC map showed that the landscape physiognomy of agroforest cover in UM3 and UM4 is mostly hedgerows, however, in UM1 and UM2, it is an intersperse cluster in a matrix of full-sun coffee. Notably, bananas occupied a significant percentage of the landscape in UM2 and UM3 (5% of the landscape). Many smallholder farmers practice intercropping coffee with bananas to complement their food crop and income generation in many coffee-based landscapes in East Africa (Liebig et al., 2018).

The study showed that landscape connectivity is higher in UM1 than in UM4 (CONTAG index in Figure 2.5). LULC of UM1 can facilitate the flow of species from one patch to the other, which increases their survival capacity, unlike in UM4, which has more fragmented patches, as shown by the SPLIT index (Kindlmann and Burel, 2008). For instance, the contiguous patches of coffee farms that form the matrix of UM1 and UM2 can facilitate the flow of coffee pests that solely depend on coffee trees as their primary hosts (Delegido et al., 2013). For example, movements of the coffee berry borer, *Hypothenemus hampei* Ferrari, may be limited where coffee farms are pockets of fragmented patches, like in UM3 and UM4 (Avelino et al., 2012). Among other factors, such as higher temperatures in UM3 and UM4 (Jaramillo et al., 2009), fragmentation could potentially result in overutilization of the available patches by such coffee pests, leading to increased severity in infestation levels. With similar consequences, fragmentation may strengthen pest life-history traits involved in adaptation to changing environments, leading to a greater chance of survival (Ziv and Davidowitz, 2019). More pockets of agroforest cover, as observed in UM1 and UM2 when compared to UM3 and UM4 can benefit biodiversity conservation and ecosystem services, such as providing habitats to birds, other pest natural enemies, and pollinators. Ecosystem services benefit coffee production by improving yields through microclimate and soil quality improvement and pest and disease natural regulation (Lescourret et al., 2015).

2.5.4 Study implications and limitations

This study showed the robustness of RF and S2 in capturing subtle changes within such landscapes. This methodology can be adopted in other coffee growing regions in East Africa, Asia, and South America. The generated LULC maps can be used as baseline data to guide the restoration of degraded landscapes, development of land use policies such as the agri-environment scheme adopted in Europe, and model ecosystem services, especially from shade coffee generating integrated land management systems. Also, the LULC maps developed in this study could be integrated with crop phenological and climatic variables to understand the occurrence, abundance and spread of coffee pests and diseases.

A potential limitation to this study was the use of reference datasets obtained from very high-resolution Google Earth Pro (GE) images in lieu of field reference data. This limitation is also a growing opportunity for using GE alongside crowdsourced data from mobile apps (Landmann et al., 2015), Global Biodiversity Information Facility (GBIF, https://www.gbif.org/) and Open Street Map (OSM, https://www.openstreetmap.org/) to provide reference data for classification, especially in the era of big data (Hurskainen et al., 2019). Landmann et al. (2019) mapped rain-fed and irrigated lands in Zimbabwe using reference data obtained from GE, which shows the effectiveness of these new data sources for validation of LULC classification in data scares environments. Furthermore, this study area (i.e., the transect) was somewhat small, but as previously mentioned the transect was chosen as part of a bigger project to essentially cover the four coffee agro-ecological sub-zones. In future, the methods employed in this study could be applied in larger geographical areas to test its up-scalability. Also, since the study transect covers a gradient of 1300 – 2000 m a.s.l, this could have influenced the LULC mapping results. Further studies should include topographic variables such as elevation and slope to reduce their expected confounding effect in coffee mapping experiments in areas of varying topography (Hurskainen et al., 2019).

2.6 Conclusions

This study shows that S2 is reliable satellite data for mapping LULC types with a high level of accuracy in heterogeneous landscapes, such as coffee growing areas dominated by smallholder farms. This is due to a high number of spectral bands that delineate vegetation-based and other LULC types better than other satellites. The SWIR bands were the most important in the LULC classification. Since S2 is freely available, the approach used in this present study can be replicated in a resource-constrained context. The coffee growing area was studied to highlight the complex landscape dynamics in agrosystems that varied within an AEZ. Land-use policies on agricultural landscape management should recommend landscape-specific practices instead of blanket recommendations to improve landscape resilience and connectivity. For future studies, detailed studies should be conducted to quantify the ecological significance of unique landscape structures in each AEsZ.

CHAPTER 3: FUNCTIONAL LAND COVER SCALE FOR THREE INSECT PESTS WITH CONTRASTING DISPERSAL STRATEGIES IN A FRAGMENTED COFFEE-BASED LANDSCAPE IN CENTRAL KENYA

This chapter is based on: **Mosomtai, G**., Azrag, A.G.A., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., 2021. Functional land cover scale for three insect pests with contrasting dispersal strategies in a fragmented coffee-based landscape in Central Kenya. Agric. Ecosyst. Environ. 319, 107558.

3.1 Abstract

In the Eastern Africa highlands, the gradual transformation of natural ecosystems to smallholding coffee-based agrosystems has resulted in more fragmented landscapes. Major pests of coffee find appropriate living conditions leading to high infestation rates and the need for smallholder farmers to implement pest control measures. This study aims to understand the influence of landscapes on the ecology of three major coffee pests: the coffee berry borer CBB, (*Hypothenemus hampei)*, and the Antestia bugs ABT, (*Antestiopsis thunbergii)* and ABF *(A. facetoides).* The study was conducted on a typical smallholder coffee-based landscape in central Kenya. The pest abundance was assessed monthly for two years in a network of 30 coffee plots spread across the coffee agro-ecological sub-zones (AEsZ), namely upper midland UM1 and UM2, and the transition zones between UM1 and UM2 and between UM2 and UM3, herein referred to as TZ1 and TZ2, respectively. Landscape metrics, viz. patch density, Euclidean nearest neighbour distance, proximity index, contagion index, interspersion and juxtaposition index were derived from a spatially explicit land cover map, based on 10 m Sentinel 2 data for nine buffer zones of radius ranging from 50 m to 1000 m around each sampled plot. Redundancy analysis (RDA) was used to establish the relationships between the

observed pest abundances and landscape metrics, elevation, and AEsZ. Landscape indicators achieved the highest correlation with the pest abundances within a 300 m radius (Adjusted R^2 > 0.5). Whereas beyond 300 m landscape scale, the predictor variables resulted in weak relationships (Adjusted $R^2 < 0.5$) between the pests abundance and landscape metrics. A strong influence of elevation and adjacency to cropland on Antestia bug populations was observed. Specifically, ABF populations were negatively correlated with low elevation, whereas ABT's were positively correlated with high elevation zone. On the other hand, CBB was strongly influenced by contiguous coffee patches, especially in UM1 and UM2. Therefore, reducing connectivity between coffee patches is recommended for the management of CBB, whereas further studies should be conducted to identify secondary hosts of Antestia bugs that should not be adjacent or within coffee stands.

Keywords: Landscape ecology, Redundancy analysis, *Hypothenemus hampei*, *Antestiopsis thunbergii*, *Antestiopsis facetoides*, landscape scale

3.2 Introduction

Agriculture is one of the most significant drivers of landscape simplification and fragmentation (Donald, 2004). The destruction of natural ecosystems for agriculture has resulted in homogenized landscapes, with remains of natural vegetation juxtaposed in large tracks of croplands. As a consequence of unbalanced agrosystems, pest and disease pressure on crops has increased, exacerbated in developing countries by smallholder farmers' inability to mitigate their proliferation due to limited resources and information (Meehan et al., 2011). Thus, some pests multiply and spread in landscapes dominated by a single crop due to resource abundance and adequate connectivity between patches with little pressure from their natural enemies that often prefer more diversified habitats (Rusch et al., 2016). Generally, agrosystems with remnants of natural vegetation and semi-natural vegetation such as hedgerows, woodlots, grasslands, and field margins have shown a reduction in pest infestations to manageable thresholds (Rusch et al., 2016).

Arabica coffee (*Coffea arabica* L.) is one of the main cash crops in the tropics that has resulted in the subdivision of natural vegetation. It is grown by over 25 million smallholder farmers, with over 100 million people depending on the crop across the value chain (Anthony et al., 2002). In its native habitat in East Africa, Arabica coffee is an understorey crop; however, with increased demand and widespread cultivation across tropical regions, non-shade coffee system has been widely adopted due to its higher productivity (Cerda et al., 2017). Furthermore, the mechanization of coffee production has become more efficient in the non-shade system, especially in the Americas, which include the largest coffee producing countries in the world (Jha et al., 2014). As a consequence of coffee system simplification, increasing pest and disease pressures have been recorded globally (Kebati et al., 2016).

However, in East Africa, smallholder coffee landscapes are more complex, with various coffee production systems. In Uganda and Rwanda, the coffee-banana intercrop system is dominant (van Asten et al., 2011), while in Ethiopia, about 70% of coffee is produced under the garden coffee system, which consists of low input crops grown in home gardens, intercropped with fruit, roots, and cereal crops (Fekadu et al., 2016). In Tanzania, the *Chagga* system, characterized by multi-layered vegetation of shade trees, bananas, coffee, and vegetables, each grown under the other, is predominantly practised by smallholder farmers (Hemp, 2006). In Kenya, smallholder farmers produce 75% of the coffee in plots less than 2 ha, mostly grown without shade and intercropped with subsistence crops and fruit trees.

Pest and disease pressure amplified by susceptible coffee cultivars and low use of agricultural inputs contributes to low coffee yields in smallholding farming in eastern Africa (Monroy et al., 2013). Despite progress in breeding research and developing resistant cultivars, pest management still faces knowledge gaps, especially in the interaction between the pests and their surrounding environment (Hindorf and Omondi, 2011). Specifically, the interplay between landscape structure and pest ecology remains largely unknown, especially in Kenya. The functional traits of mosaic landscapes, such as its composition and spatial arrangement, as experienced by pests at different spatial scales, are generally understudied (Barbaro and van Halder, 2009). Therefore, this study seeks to fill these knowledge gaps by understanding the contribution of the existing landscape setup in supporting coffee pest abundance.

This study adopts a multi-pest and comparative approach in looking at coffee pest distribution within an environmental gradient over a coffee agro-ecological zone. The multi-pest approach provides a better inference on environmental factors that contribute to habitat integrity supporting several species (Schowalter, 2006). Thus, a holistic understanding of landscape ecology that accounts for multiple pests will benefit farmers through more efficient recommendations (Avelino et al., 2012). This study focused on three main destructive coffee pests in the smallholder farming systems of East Africa: the coffee berry borer CBB, (*Hypothenemus hampei* Ferrari) and two Antestia bug species ABT (*Antestiopsis thunbergii* Gmelin) and ABF (*A. facetoides* Greathead). The CBB is the most destructive coffee pest worldwide with a global spread that causes yield loss of up to 90% (Jaramillo et al., 2006). In comparison, Antestia bugs are major Arabica coffee pests in Africa that cause a yield loss of ~45% with an economic threshold of one to two bugs per tree (Azrag et al., 2017).

These pests have contrasted dispersion ability that may be influenced by landscape structure, especially patch fragmentation. Coffee berry borer is known to have a reduced dispersal capacity (Gil et al., 2015). Thus, a contiguous coffee landscape has been shown to facilitate its movement (Avelino et al., 2012). On the other hand, Antestia bugs have high dispersal abilities, especially during warmer hours of the day, which allows them to colonize new plantations, even isolated patches (Babin et al., 2018). Therefore, it was hypothesized that these pests may have different responses to landscape functional traits. Specifically, the spatial arrangement of land cover types at different buffer scale was highlighted to determine how it influences these pests regarding spatial scale. A multivariate redundancy analysis (RDA) approach was adopted to establish the relationship between landscape structure and coffee pest distribution.

3.3 Material and methods

3.3.1 Study area

The study was conducted in a transect located between longitude 36.9226^{o} and 37.1176^{o} and latitude -0.7262^{o} and -0.6948^{o} in Murang'a County, which is one of the primary coffee-growing areas in central Kenya, located on the slopes of the Aberdare mountain range (Figure 3.1). The agro-climatic zones in Murang'a extend from humid at the highest elevation to semi-arid at the lowest elevation (Figure 3.1). The area receives bimodal rainfall with a long rainy season from mid-March to the end of May and a short rain from mid-October to December. This rainfall regime offers two growing seasons from March to May and October to December, which coincides with the first and second coffee crop harvesting seasons. Coffee grows in the upper midland (UM) agro-ecological zone at an elevation gradient of 1300 to 2000 m above sea level, within four sub-zones (from UM1 to UM4), herein referred to as AEsZ (agro-ecological sub-zones). Due to high population density and limited land, many smallholder farmers grow Arabica coffee in plots less than 2 ha, mixed with food crops such as maize (*Zea mays* L.) and banana (*Musa* spp.), and trees such as *Grevillea robusta* (A. Cunn. ex R. Br.) and *Macadamia* spp., which provide coffee trees with shade (ICO, 2019).

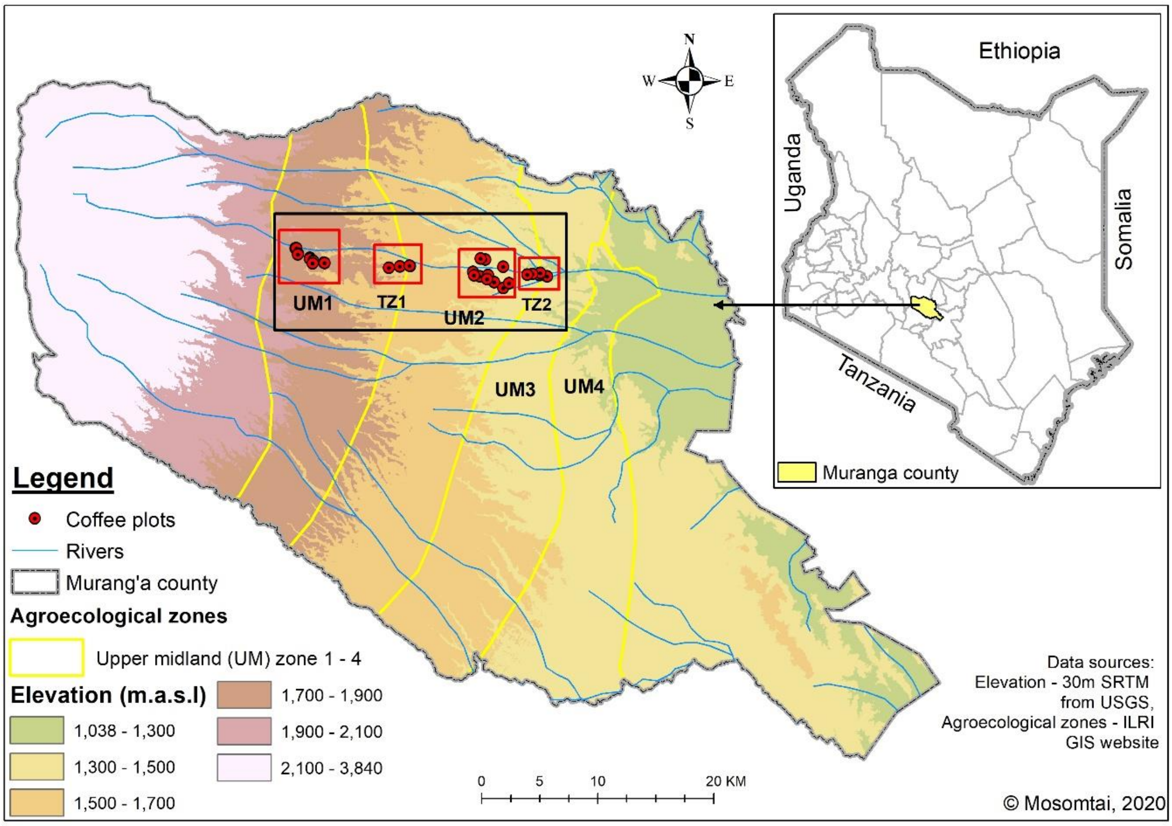

Figure 3.1: Location of the study area in Murang'a County in central Kenya. The sampling plots were located in the upper midland (UM) agro-ecological sub-zones UM1 and UM2 and in the transition zones between UM1 and UM2 (TZ1) and between UM2 and UM3 (TZ2)

3.3.2 Pest abundance

The abundance of the CBB, ABT and ABF were assessed monthly in a network of 30 plots of approximately 1 ha from June 2016 to May 2018. The plots were located in UM1, UM2, and the transition zones between UM1 and UM2 and between UM2 and UM3 herein referred to as TZ1 and TZ2, respectively (Figure 3.1). The selected plots contained approximately 100-500 coffee trees each, and the most common coffee variety in these plots was SL28. Figure 3.2 shows the sampling scheme adopted in this study. The abundance of CBB was sampled using the BROCAP® traps (Dufour & Frérot, 2008).

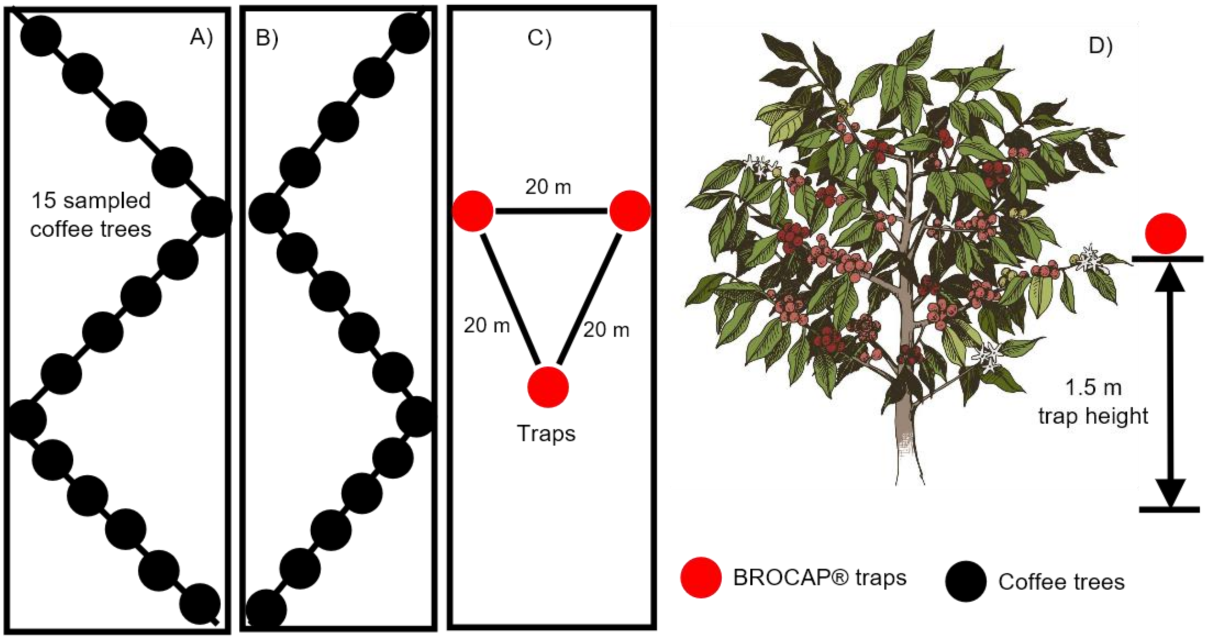

Figure 3.2: Field sampling scheme adopted in the present study. Fifteen coffee trees were sampled diagonally starting from a corner of the plot (either A or B) for Antestiopsis thunbergii and Antestiopsis facetoides, whereas BROCAP® traps were used to sample Hypothenemus hampei by hanging them on coffee trees at 1.5 m above ground and 20 m between traps forming either a triangle or rectangle shape depending on the size of the plot (C and D)

The abundances of ABT and ABF were assessed monthly using visual inspection of coffee trees (Azrag et al., 2018). A systematic random sampling of fifteen trees along a diagonal line in each experimental plot was adopted (starting from a corner of the plot - Figures 3.2A and B), and the number of bugs on these trees was recorded, irrespective of their life stages. For CBB, three to four traps were deployed in each experimental plot 20 m apart, forming a triangle or square depending on the plot size (Figure 3.2C). The traps were placed on tree branches at approximately 1.5 m above the ground (Figure 3.2D), containing a mixture of methanol and ethanol in a ratio of 1:1 to attract the CBB females (Dufour and Frerot, 2008). The number of CBB caught by each trap were counted and recorded monthly.

3.3.3 Land use/ cover characterization of the AEsZ

A contemporary 10-m land use/ land cover (LULC) map with an overall accuracy of 95%, produced using Sentinel-2 satellite imagery and random forest machine learning classifier, was utilized to estimate the spatial coverage of coffee and other LULC classes within each AEsZ. A detailed description of the scene ID, source of the training dataset, the method used for LULC classification and accuracy assessment is provided by Mosomtai et al. (2020). The following vegetation cover classes were considered for analysis: agroforestry, coffee, cropland, shrubland, banana and grassland. The coffee class represented monoculture of coffee grown in full sun, whereas the agroforestry class comprised of mosaics of woodlots, mostly *Grevillea robusta* and shade trees such as *Macadamia* spp. and avocado (*Persea americana*). Cropland consisted of annual crops (Jaetzold et al., 2007). In UM1 and UM2, coffee is the main crop covering >50% of the landscape, while in UM3 and UM4, coffee is a marginal crop in a landscape matrix dominated by crops like maize, bean, arrowroot and potato (Mosomtai et al., 2020).

3.3.4 Generation of landscape fragmentation metrics

Fragstat software (McGarigal et al., 2002) was used to generate the following landscape metrics from the LULC map: patch density (PD), Euclidean nearest neighbour distance (ENN), proximity index (PROX), contagion index (CONTAG), and interspersion and juxtaposition index (IJI), which describe the level of landscape connectivity. These landscape metrics were generated from nine different buffer radii, herein referred to as landscape scales of 50 m, 100 m, 150 m, 200 m, 250 m, 300 m, 500 m, 750 m, and 1000 m from each sampling site (Figure 3). It was hypothesized that landscape influences the pest ability to disperse and reach coffee plantations for establishment. Therefore, the question arising was how much the landscape influences the pest abundance in a given plantation? The landscape surrounding coffee plantations should be considered as much an obstacle as a living environment. The pest abundance should be different when moving away from the sampled coffee plantation. But much attention was given to the pest abundance in a given plantation as a consequence of their surrounding landscape and scale.

The landscape metrics were selected based on prior knowledge of the foraging behaviours and flight capacity of the pests. For instance, patch density informed the level of fragmentation across the sub-zones. At the same time, proximity and contagion indices alluded to the level of connectedness of patches giving a better idea of the overall patch composition and patterning, which was important, especially for the CBB due to low flight capacity. The Euclidean distance was essential for understanding the distance between patches, especially for Antestia bugs that display a higher flight capacity. Interspersion and juxtaposition index alluded to the neighbouring cover types that could potentially be alternative hosts for the pests or hinder/facilitate their movements across the landscape.

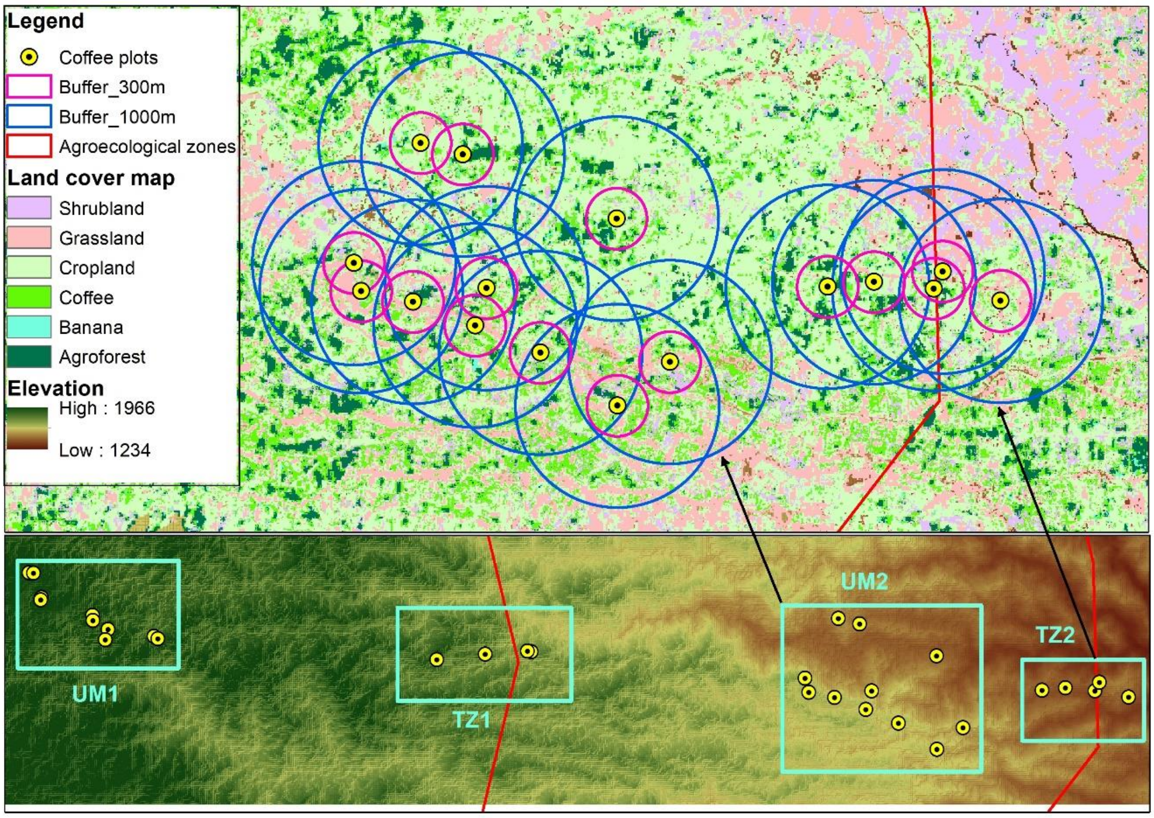

Figure 3.3: Land use/ land cover map of a portion of the study area (a zoom of the rectangle box with an arrow showing sites sampled in UM2) and illustration of landscape scales of 300 m and 1000 m buffer zones (in pink and blue) used to generate landscape metrics for each plot. The insert map shows the elevation gradient where the green and brown colours represent the high and low elevation zones, respectively.

Patch density measures the level of fragmentation based on the number of patches per 100 ha. Highly fragmented landscapes have a high patch density with smaller mean patch size and vice versa. The contagion index describes the 'clumpiness' of patches based on their cell adjacency (Li and Reynolds, 1993), which are calculated as the sum of two probabilities: (1) a probability of a pixel that belongs to patch type *i* in the map and (2) the conditional probability that the neighbouring cell belongs to a patch type *j* (Hargis et al., 1998). On the other hand, a high contagion index describes a landscape with contiguous patches, whereas a low index describes a fragmented landscape. Moreover, the interspersion and juxtaposition index measures the magnitude of intermixing of patches based on patch adjacency instead of cell adjacency. High

IJI describes a landscape where all the patches are well distributed and intermixed, but a low index represents a landscape with a disproportionate distribution of patches (McGarigal et al., 2002). Proximity index (PROX) and Euclidean nearest neighbour distance (ENN) measure the distance between similar patches in a landscape. ENN measures the Euclidean distance from the centroid of two similar patches, with the highest value representing isolated patches. The proximity index, however, combines the size and proximity of patches within a specified radius. Patch type within proximity with either large patches or well distributed in the landscape will have a higher proximity index than a patch type sparsely distributed and fragmented into small patches (Hargis et al., 1998).

3.3.5 Relationships between landscape predictor variables and pest abundance

Firstly, the seasonal variation of pest abundance for each of the studied species is presented. Secondly, a boxplot was used to show the abundance distribution of each pest across the AEsZ. Thirdly, the relationships between landscape characteristics and pest abundance through a redundancy analysis (RDA) was explored. RDA is a widely used multivariate analysis tool that elucidates how much of the explanatory variables (here the fragmentation variables) explain the observed response variables (here the species abundance) using multiple regression analysis (Legendre et al., 2011). The explained variance is represented by the constrained proportion, while the unconstrained proportion represents the unexplained variance (residuals). To test for compositional difference and variability along the environmental gradient, the monthly count of CBB, ABF and ABT were analyzed using Bray-Curtis dissimilarity index (Anderson et al., 2006; Ricotta and Podani, 2017). The results were further analyzed using Tukey’s post hoc test to identify where the difference in the pest composition existed before using it as the response variable.

A preliminary RDA analysis was conducted to test how much variability in the pest abundance was explained by the landscape variables alone and when combined with elevation and AEsZ. Based on the stronger predictors, another RDA analysis was conducted to test which landscape scale from the nine buffer radii achieved the highest correlation with the observed pests abundance. The adjusted R^2 metric from analysis of variance (ANOVA) was used to estimate the variability explained and to identify the significant landscape scale. Likewise, the same RDA steps were repeated to determine which LULC type had a significant role in explaining the pests abundance based on the identified landscape scale with the highest correlation. The RDA analysis was conducted using the *vegan* package (Oksanen et al., 2019) in R programming software (R Core Team, 2020).

3.4 Results

3.4.1 Spatial and temporal variation of pest abundance

Temporal variation of ABF, ABT and CBB abundance presented cyclic patterns with a minor and a major peak occurring in February and June for CBB (Figure 3.4C) and April and July for ABF and ABT (Figure 3.4A&B). Moreover, the monthly sum of the pest abundance for the 2-year period ranged between 263 and 36 for ABF, 82 and 24 for ABT and 5130 and 500 for CBB. Furthermore, the abundance of ABF was five times higher than ABT throughout the two-year observation period.

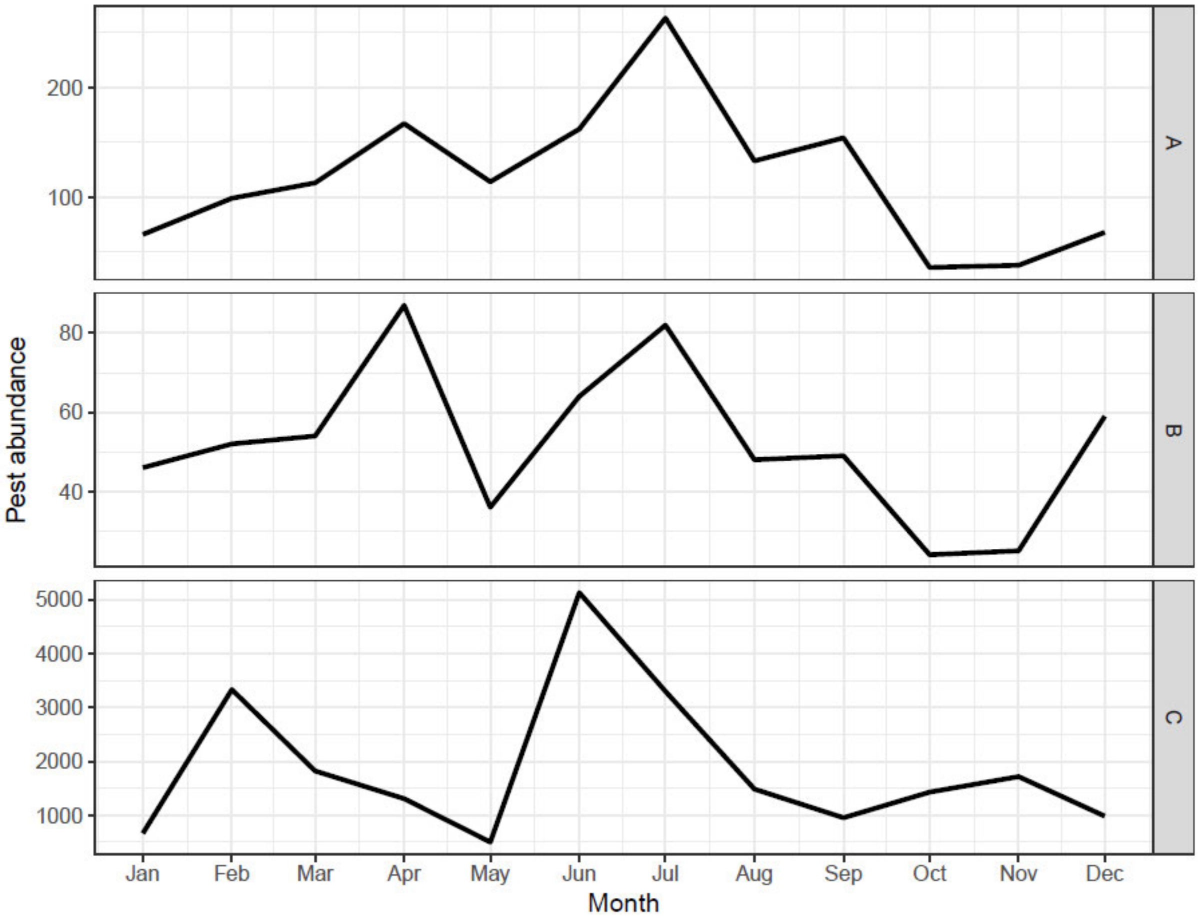

Figure 3.4: Monthly variation of A) A. facetoides (ABF), B) A. thunbergii (ABT), and C) H. hampei (CBB) abundance (monthly sums for a 2-year survey, from June 2016 to May 2018) in the sampled smallholder coffee plots.

The distribution of the pest abundance in the sampled plots varied across the altitudinal gradient, as shown in the boxplots in Figure 3.5. Bray-Curtis dissimilarity index revealed distinct pest abundance in plots located in TZ2, which are located in the lower elevation, whereas the rest of the AEsZ share common pest abundance (Tukey honest test $P < 0.05$). TZ2 predominantly consisted of the ABF population, while UM1 and TZ1 consisted of ABT. In comparison, CBB was dominant in UM1 and UM2 and low in both transition zones. Notably, there was a high data dispersion between maximum and minimum pest abundance within the same AEsZ, especially in UM1 (CBB) and TZ1 (ABT), indicating high variability in pest abundance even within the same locality.

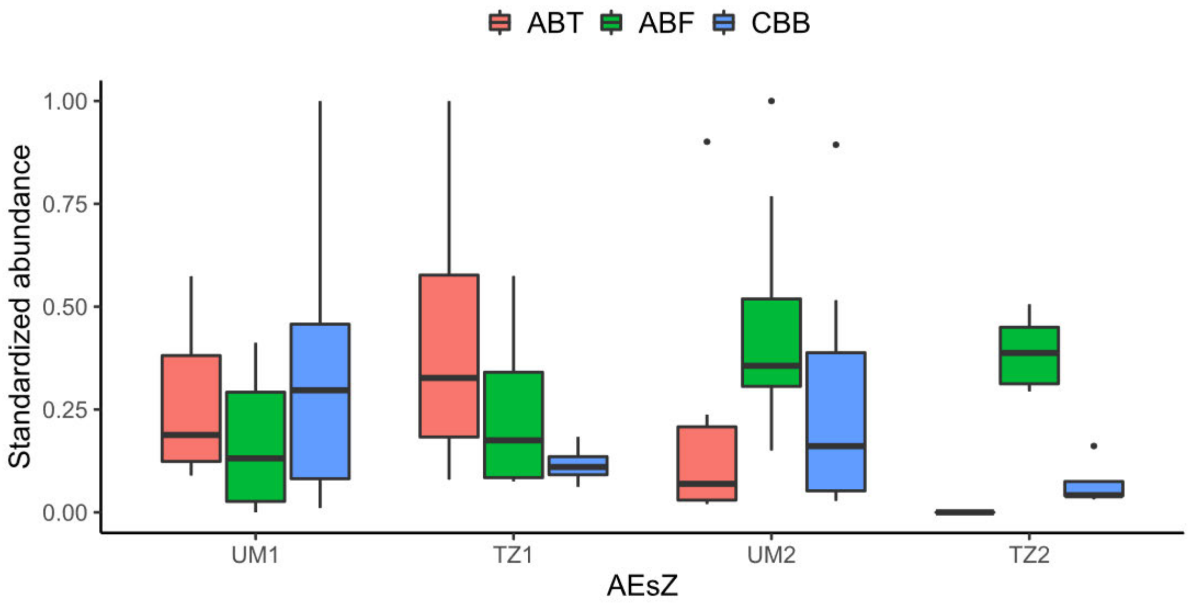

Figure 3.5: Boxplots showing the distribution of standardized pest abundance across the agro-ecological sub-zones (AEsZ). Sampled plots located in TZ2 (transition zone of UM2 to UM3) predominantly consisted of A. facetoides (ABF), whereas UM1 and TZ1 consisted of high H. hampei (CBB) and A. thunbergii (ABT) variability, respectively.

3.4.2 The influence of the landscape fragmentation and land use/ cover variables on the pest abundance

Figure 3.6 shows the variability in pests abundance explained (adjusted R^2) by the landscape fragmentation metrics, elevation and AEsZ predictors tested at different landscape scales. There were no common trends in the adjusted R^2 values of the different pests across the landscape scale; however, CBB achieved the highest adjusted R^2 values, especially at 100m as opposed to the other pests. The ABF and ABT ANOVA models showed reasonably moderate adjusted R^2 values (> 0.05) with landscape scales of 200 m and 300 m, respectively. When the pests abundance was combined in a multi-pests approach (multivariate response), there was a strong correlation at 300 m, when landscape metrics were used only and when combined with elevation and AEsZ (Figure 3.6; Table 3.1). However, the proportion of the explained variance in the multi-pest model improved considerably (i.e., the constrained variance increased from

0.36 to 0.70) when elevation and AEsZ variables were added to the RDA model compared to when the landscape metrics were used alone (Table 3.1). Thus, the multi-pest model, with landscape fragmentation metrics, elevation and AEsZ as predictor variables, was adopted for further analysis in this study.

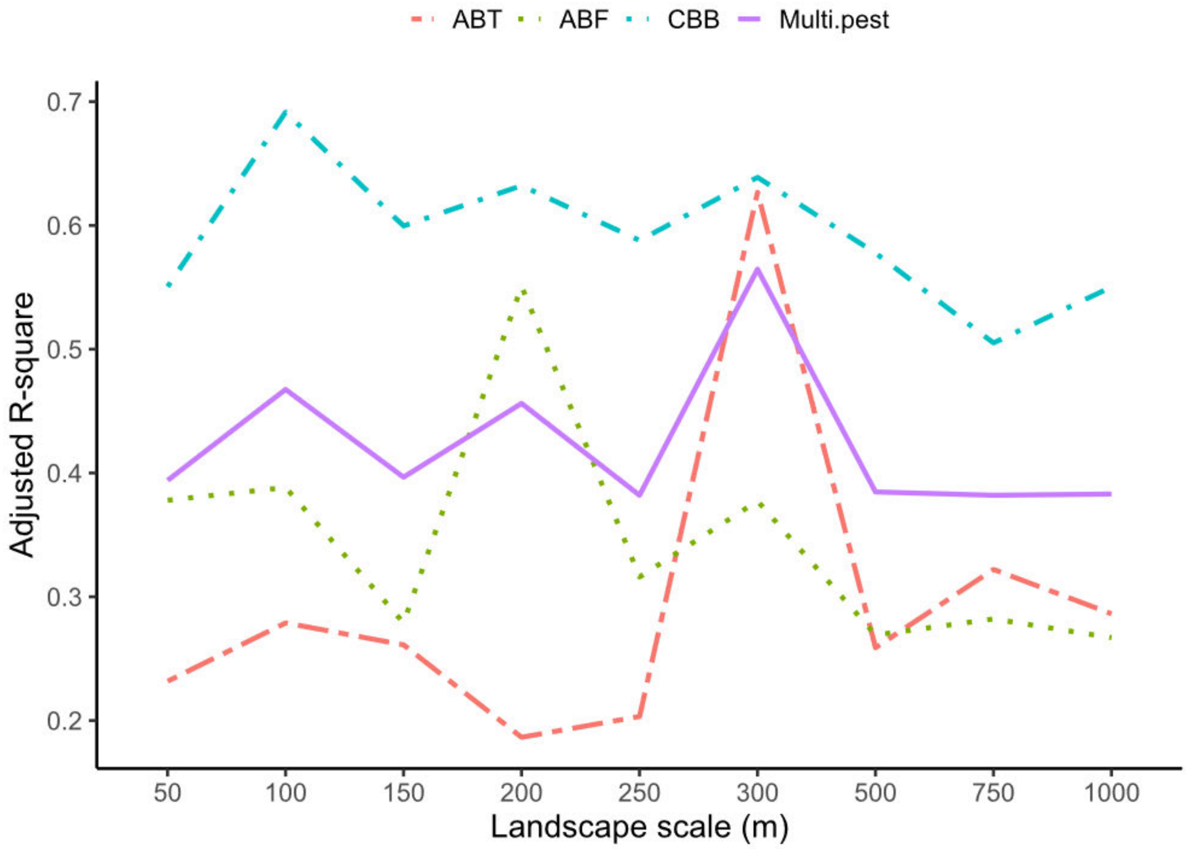

Figure 3.6: Correlation (Adjusted R^2) of pests abundance with landscape fragmentation metrics, elevation, and agro-ecological sub-zones (AEsZ) within increasing landscape scales for CBB (H. hampei), ABF (A. facetoides), ABT (A. thunbergii) and Multi.pest (combined pests data) ANOVA models.

Table 3.1 shows the influence of each of the predictor variables on the RDA model when landscape fragmentation metrics are used alone and when combined with elevation and AEsZ for the combined pests' abundance at 300 m landscape scale. Specifically, PD and CONTAG predictor variables did not show any significant ($p \geq 0.1$) influence on the variability of the combined pest abundance, while other variables significantly ($p \leq 0.1$) associated with the combined pest abundance (Table 3.1).

Table 3.1: Significant predictor variables (p value < 0.1) from redundancy analysis at 300 m landscape scale for the three-pests combined abundance, when landscape fragmentation metrics are used alone and when combined with elevation and agro-ecological sub-zones.

Landscape metrics	**Landscape fragmentation metrics, elevation, and AesZ**	**Landscape fragmentation metrics only**
Patch density (PD)	0.989	0.992
Proximity (PROX)	0.107	**0.098**
Euclidean neighbour (ENN)	**0.002**	**0.002**
Contagion (CONTAG)	0.885	0.910
Intespersion juxtaposition index (IJI)	**0.042**	**0.034**
Elevation (elev)	**0.007**	*NA
Agro-ecological sub-zones (AEsZ)	**0.046**	*NA
Constrained variance	**0.7098**	**0.3657**
Unconstrained variance	0.2903	0.6343

*NA = not available

The RDA biplot in Figure 3.7 shows the distribution of sampling sites grouped by elevation and the relationships between the observed pest abundance and landscape fragmentation variables, including elevation and AEsZs. ABF abundance correlated with low elevation points (in green) clustered in TZ2, while ABT positively correlated with high elevation sites (red points) spread out in UM1. The correlation between CBB abundance and elevation was not clear. CBB abundance was strongly influenced by the proximity of similar patch types (PROX), while ABT abundance by elevation and patch isolation (ENN). On the other hand, ABF abundance was correlated with inter-patch adjacency (IJI), especially in UM2 (Figure 3.7).

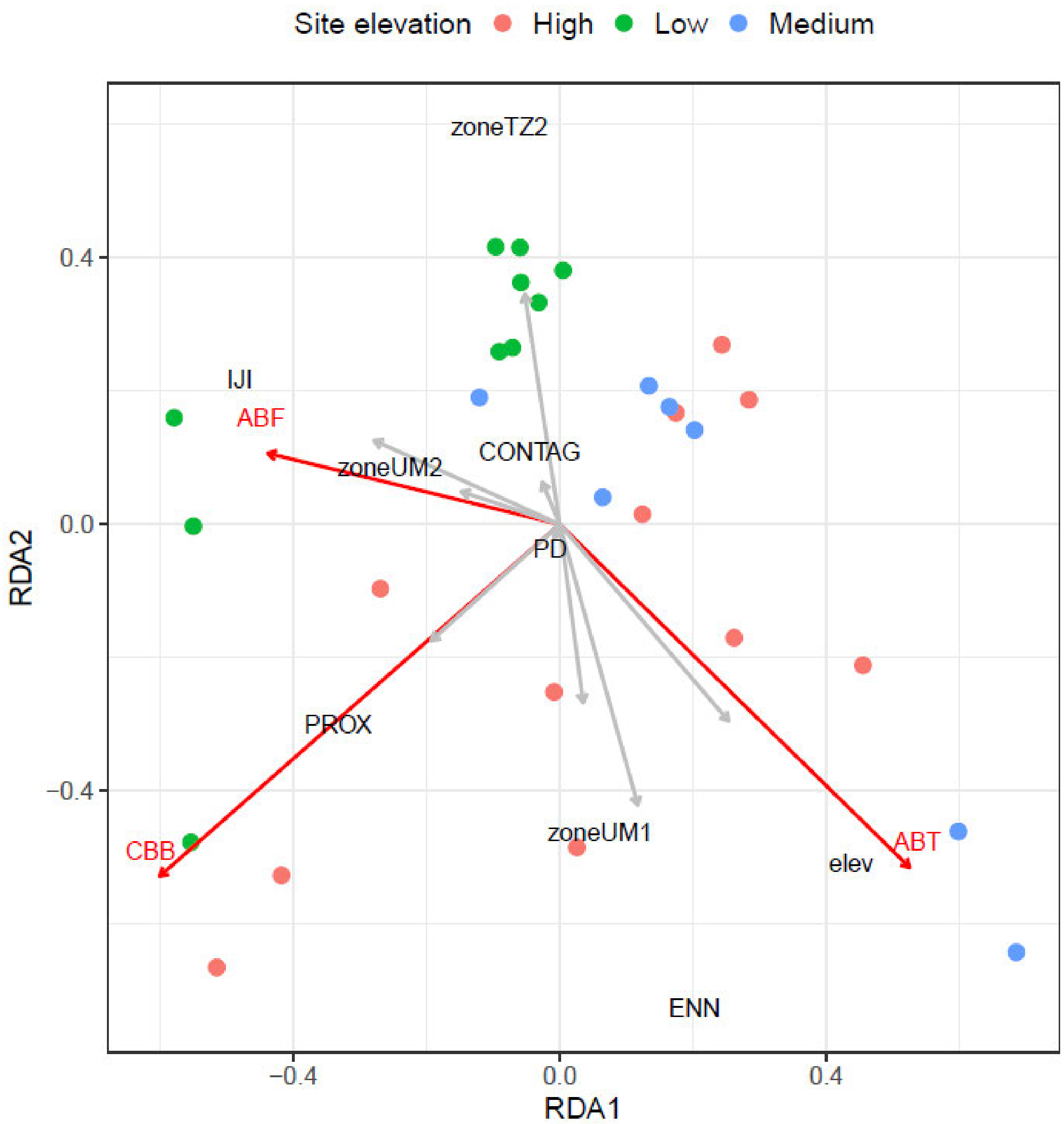

Figure 3.7: Redundancy analysis biplot showing the correlation between pest abundance (in red arrows) and landscape fragmentation variables (in grey arrows), i.e., IJI, ENN, PROX, CONT, and PD, elevation (elev) and AEsZ (zoneUM1, zoneUM2, and zoneTZ2) within 300 m landscape scale. Variables with arrows facing the same direction are positively correlated, while the arrows of negatively correlated variables face the opposite directions. The length of the arrows represents the proportion of influence while the red, green, and blue coloured points represent sampled plots based on high, low, and medium elevation respectively.

Further analysis of the significant landscape fragmentation metrics (i.e., ENN, IJI, and PROX indices) within the 300 m radius revealed which LULC types influence the observed pest abundance (Table 3.2). Contiguous cover of coffee and cropland patches in the landscape influenced the PROX metric, while the distance between grassland patches and adjacency to cropland patches influenced the ENN and IJI metrics, respectively. RDA plots in Figure 3.8 shows the relationships between the observed pest abundance and LULC types based on IJI and ENN metrics. CBB abundance correlated positively with adjacency (IJI) of coffee patches while correlated negatively with grasslands and shrublands. For Antestia bugs, intermixing of coffee with cropland patches positively correlated with ABF abundance, but negatively correlated with the ABT abundance (Figure 3.8A). For ENN, the distance between coffee and agroforest patches influenced the ABF abundance at the lower elevation, specifically at TZ2, whereas CBB and ABT abundances were equally influenced with patch distance between coffee and grassland and, to a lesser extent, shrubland, especially at a higher elevation in UM1 (Figure 3.8B). Additionally, ABT abundance was also influenced by the patch distance within the cropland at TZ1.

Table 3.2: Significance of the land use/ cover types in proximity (PROX), isolation (ENN), and interspersion and juxtaposition (IJI) metrics in Redundancy analysis of the multi-pest abundance at 300 m landscape scale. The significant (p-value ≤ 0.1) variables are highlighted in bold.

Cover types	**PROX**	**ENN**	**IJI**
Agroforest	0.233	0.199	0.624
Banana	0.221	0.317	0.236
Coffee	**0.077**	0.105	0.486
Cropland	**0.068**	0.111	**0.049**
Grassland	0.202	**0.002**	0.759

Shrubland	0.544	0.694	0.687
Elevation	**0.002**	**0.003**	**0.001**
Agro-ecological sub-zones	**0.008**	**0.007**	**0.008**

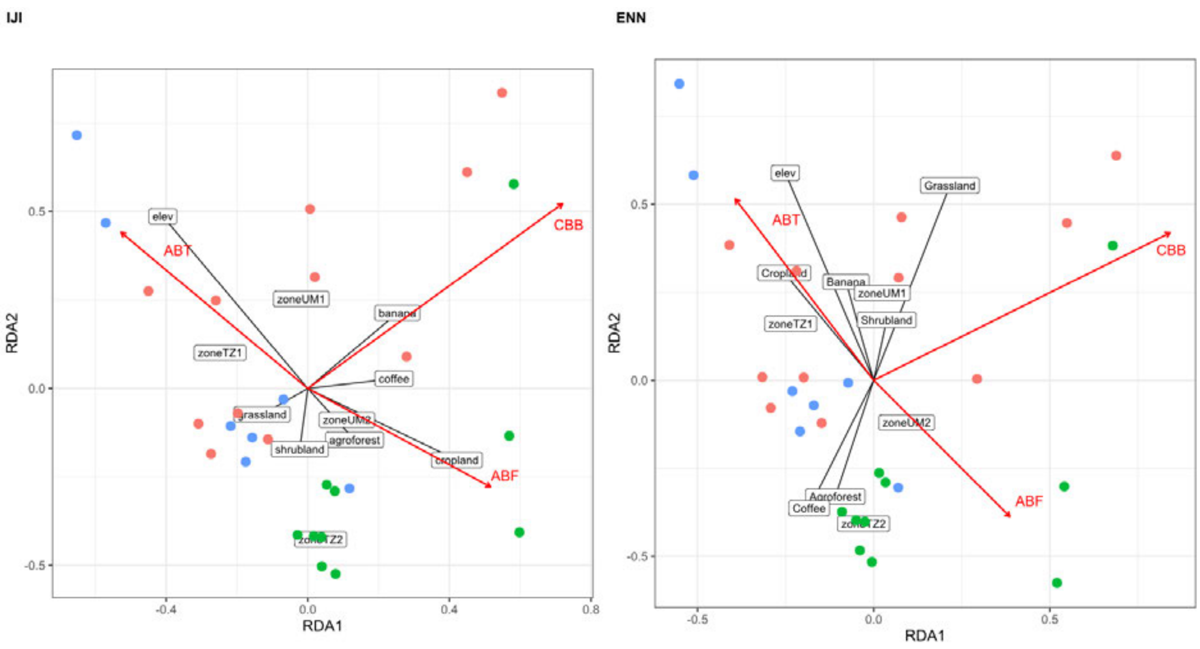

Figure 3.8: RDA biplots showing the relationship between pest abundance and land use/ cover types based on interspersion juxtaposition index (IJI) and Euclidean nearest neighbour distance (ENN) at 300 m radius. Variables facing the same direction are positively correlated, and the length of the arrow represents the proportion of the explained variance. The red, green, and blue coloured points represent sampled plots based on high, low, and medium elevation. The red arrows represent the studied pest, while the LULC types in grey arrows.

3.5 Discussion and conclusions

The composition and abundance of species are influenced by ecological processes within a specific landscape scale, patch composition and configuration pattern (Schweiger et al., 2005). In this study, the abundance of CBB and Antestia bugs showed a regular pattern, with low and high abundance occurring during the fly (secondary) and the main coffee crop seasons (Damon, 2000). The cyclic pest pattern was associated with the coffee fruiting cycle, which varies depending on the pest's preference for food and reproduction. For instance, the Antestia bugs are known to prefer fully developed green berries because it contains optimal substrate for feeding and reproduction of the bugs (Gesmalla Ahmed et al., 2016). Furthermore, green berries are more attractive to Antestia bugs than ripe berries, which emit volatiles that repel the bugs (Njihia et al., 2018). In contrast, CBB is attracted to the red berries, which are dominant during harvest seasons (November – December (main crop) and March – April (fly crop)) (Jaramillo et al., 2006). In this study however, low count of CBB was observed during the harvesting periods because the Brocap traps became less attractive in the presence of red berries available on trees but when the berries were green (from May - August), the Brocap traps become more attractive to flying female CBB, resulting in higher catches. Thus, the observed monthly CBB count in the study is not the true seasonal variation of the pest

Pest abundance varied across the AEsZ, with notable differences in plots sampled in TZ2 from those sampled in UM1 and UM2. TZ2 plots predominantly consisted of ABF populations, unlike UM1, TZ1, and UM2, which had high ABT and CBB populations. ABF's preference for higher temperatures limits its distribution to coffee of lower elevations (Babin et al., 2018). In contrast, ABT's preference for cooler environment is due to its limited thermal requirements for population growth, ranging from 19 – 26°C (Azrag et al., 2018, 2017). The results, therefore, confirm those of previous studies that showed ABT prefers the highest elevations (1500-2100 m asl), where temperatures are appropriate for its development, survival, and reproduction (Azrag et al., 2017, 2018; Babin et al., 2018). On the other hand, CBB seems to support a larger range of temperatures that leads to a wider distribution over the study area (Jaramillo et al., 2009).

Furthermore, the high variation in pest abundance within the same AEsZ (especially CBB in UM1 and ABT in TZ1) indicates that other factors apart from elevation, such as agronomic practices, shade management, or natural enemies, influence the variability of the pest. For example, ABT populations are abundant in bushy coffee trees and shaded coffee plantations (Kirkpatrick, 1937; Mugo et la., 2013). As one of the agronomic practices, farmers use pruning to improve coffee yield and manage the pest. Good pruning of coffee trees exposes Antestia bugs to extreme temperatures that can be lethal, especially for the immature stages (Azrag et al., 2018). These could be one of the reasons that explain the variations in ABT population for plots located in the same zone. Equally, Jaramillo et al., (2006) recorded a higher CBB population in full-sun coffee than those under the shade, yet sampling was done in the same coffee estate. Often, the microclimate in shaded coffee varies from that in non-shade coffee. For instance, Siles et al. (2010) noted that *Inga densiflora,* a commonly used shade tree in Costa Rica, reduced the maximum coffee leaf temperature by 5ºC and increased the minimum temperature at night by 0.5ºC when compared to the non-shade system. Consequently, pest infestation levels, even in plots located within the same elevation, can vary due to variation in microclimatic conditions.

The study also sought to understand which spatial patterning of LULC types and landscape scale significantly influenced the observed pest populations. Similar studies have been conducted on bee pollinators (Saturni et al., 2016), bird species (Tscharntke et al., 2008), and parasitoids (Liu et al., 2016) due to the recognition of the importance of landscape ecology in supporting or limiting viable species communities. The results showed that the functional landscape scale for the observed pests was up to 300 m and this spatial limit was related to their dispersal capacity, which is influenced by their body size and their foraging preferences (Barbaro and van Halder, 2009). Individually, CBB was significant at 100 m, while Antestia bugs were significant at 200 m (ABF) and 300 m (ABT). CBB are small-bodied insects with limited dispersal capacity unlike Antestia bugs, which are about four times bigger in body size than CBB with long flight ranges (Waller et al., 2007). Consequently, a connected landscape with coffee as the main cover is vital for survival of CBB (Gil et al., 2015). The significance of the PROX index from the results reinforces the importance of landscape connectivity for CBB, especially in UM1 and UM2, which are the central coffee growing sub-zones in the study area.

Interestingly, the results also noted that ABT correlated to a larger landscape scale than ABF. It is thought that the body size between the two species differ with ABF having a smaller body size than ABT, which limits its dispersal capacity (R. Babin, Personal Communication). The ease of mobility allows the ABF population in the study area to thrive in TZ2 where coffee is more interspersed in a matrix of cropland, allowing the pest to move from one patch to the other for forage (Babin et al., 2018). Additionally, Antestia bugs have been shown to feed on secondary wild host plants (Babin et al., 2018). This underscores the significance of IJI metric to Antestia bugs populations, which could suggest that grasslands and croplands could be providing alternative host plants.

This study concludes that the landscape ecology of the study area influences the population dynamics of the two species of Antestia bugs and CBB. Thus, land use planning at landscape scale should be considered when establishing coffee plots with the awareness of the neighbouring patch types, especially within a radius of 300 m (Karungi et al., 2015). For CBB, homogenized landscapes should be disrupted by introducing new patches of natural vegetation such as edge trees, which will also limit the dispersal of Antestia bugs (Avelino et al., 2012). In the lower AEsZ, where croplands form the matrix, further studies should be conducted to evaluate which cover types host the preferred secondary host plant of Antestia bugs, to be discouraged from neighbouring coffee patches. Finally, policy frameworks such as the agri-environment schemes in Europe should be formulated to guide farmers on landscape management that preserve biodiversity, while reducing the negative impacts of excessive use of pesticides to control pests (Kleijn and Sutherland, 2003). This can be achieved by compensating farmers for conservation by promoting speciality markets that have better coffee prices.

CHAPTER 4: LINKING SHADE AND EDGE EFFECT ON MICROCLIMATE AND PEST ABUNDANCE IN SMALLHOLDER COFFEE LANDSCAPES IN CENTRAL KENYA

This chapter is based on: **Mosomtai, G**., Azrag, A.G.A., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., (*in preparation*). Linking shade and edge effect on microclimate and pest abundance in smallholder coffee landscape in central Kenya

4.1 Abstract

Landscape structure in an agricultural system plays a crucial role in modifying local microclimate that influences biological processes such as population dynamics of pests. This study examined the contribution of shade and edge effects in smallholder coffee landscape in modifying the microclimate of coffee plots and, consequently, its implication on coffee pest abundance. We conducted a monthly assessment of coffee berry borer, *Hypothenemus hampei* (CBB) using BROCAP® traps, and two antestia bugs, *Antestiopsis thunbergii* (ABT) and *A. facetoides* (ABF) systematically sampled from fifteen coffee trees using visual inspection in central Kenya from June 2016 to May 2018. Simultaneously, hourly temperature data was collected from 10 data loggers installed randomly across the elevation gradient of sampled plots. Finally, a land cover predicted from 10-20-meter Sentinel 2 satellite data was used to generate landscape metrics within buffer zones of radii 50 - 300 m. The proportion of full-sun coffee and agroforest, edge density (ED) and total edge contrast index (TECI) for each sampling site with a data logger was calculated using FRAGSTAT software. The results showed that CBB preferred shaded coffee in the lower elevation and full-sun coffee in the higher elevation. For Antestia bugs, ABT preferred shaded coffee in all the elevations, whereas ABF preferred full-sun coffee, especially in the low elevation. Within agro-forested stands, there was a notable

influence of the edge effect in lowering the mean temperature. It was concluded that the proportion of shade and edge surrounding coffee plots in smallholder landscapes play a crucial role in modifying the microclimate, especially in the full-sun system.

Keywords: Edge effects, Agroforest, coffee landscapes, Coffee berry borer, Antestia bugs

4.2 Introduction

In agricultural agro-ecological landscapes, the role of edges has widely been studied to understand insect-herbivore interactions such as pests and their natural enemies (Plećaš et al., 2014; Rand et al., 2006; Bianchi et al., 2006), pollinators (Zou et al., 2017; Saturni et al., 2016) and life cycle development (Duflot et al., 2016). The studies show that in contrasting edges between cropland and semi-natural vegetation, natural enemies are in high abundance, providing effective biological control of the pests in the cropland. Equally, the diversity of pollinators increases in the non-crop habitat more than in the simplified landscape, benefiting the adjacent crops. The degree of contrast between adjacent patches alters population dynamics, community structure, and abiotic conditions at the boundary; an ecological phenomenon known as the edge effect (Baez and Balslev, 2007). Edges are proxies to the level of fragmentation in the landscape, such that highly fragmented patches have more edges and less of the core/interior area. This threatens the existence of some species, especially low dispersal species due to the reduced amount of habitable area (Zurita et al., 2012). Thus, management of edge effects has become an integral part of land use planning and policy development, such as the Europe’s Common Agriculture Policy that established the Agri-environment scheme that aims to protect biodiversity in the agricultural landscape (European Commission, 2017)

In the coffee landscape, intercropping coffee with shade trees has become a widespread practice to mitigate against the climate change impacts (Albertin and Nair, 2004). These trees provide an appropriate microclimate for coffee, thus increasing the quality of beans even in extreme climatic conditions (Nesper et al., 2017). Studies have shown that coffee fields grown under uniform shade trees reduce mean air temperature by 0.4^{o}C and increase humidity by 3.9% (Ehrenbergerová et al. 2017). It protects the soil moisture from evapotranspiration, especially during prolonged dry spells, while the leaf fall provide manure on decomposition (Cannavo et al., 2011). However, the density of shade on coffee farms differ depending on the type, and density of shade trees on the farm (Teodoro et al., 2009). These disparities lead to variations in microclimate, especially temperature and relative humidity, which affect the population densities and dynamics of coffee insect pests (Azrag et al., 2018). The heterogeneity in smallholder coffee landscapes, unlike large homogenous coffee estates, increases the complexity of the shade effect.

In Kenya, many smallholder farmers grow their coffee interspersed in mosaics of natural vegetation or intermixed with semi-natural vegetation or subsistent crops in plots less than 2 ha (Mosomtai et al., 2020). The highly fragmented landscape plays a vital role in impeding or facilitating the movement of coffee pests and pathogens or modifying the microclimate, underscoring the significance of the shade and the neighbouring patches (Alignier et al., 2014; Báldi, 1999). The results in chapter three showed that coffee berry borer, *Hypothenemus hampei* (CBB) preferred contiguous coffee patches to facilitate their movements due to their limited dispersal ability. In contrast, the Antestia bug, *Antestiopsis facetoides* (ABF) thrived in interspersed coffee patches in a matrix of cropland. Their high dispersal ability facilitates their movement while the cropland act as secondary hosts (Mosomtai et al., 2021). These findings alluded to the importance of patch adjacency for the survival of the two pests. However, studies on shade and edge effects are limited in Kenya, and the existing literature mainly focused on large coffee plantations (>20 ha) (e.g. Smith et al., 2015), unlike smallholder coffee farms (<2 ha), which this study seeks to explore.

Antestia bugs and CBB were chosen due to their economic significance in the coffee industry. CBB is the most important coffee pest globally. It feeds on beans inside the berries, and its proliferation leads to significant crop loss estimated at 90% of the yield, with an annual revenue loss of US$500 million globally (Pardey, 2015). Antestia bugs feed on coffee leaves, shoots and berries, leading to a yield loss of up to 45%, with an economic threshold of two pests per tree (Mosomtai et al., 2021). Additionally, they are responsible for other indirect yield losses. Their feeding punctures allow the stigmatomycosis fungi *Nematospor*a sp. to colonize the berries, resulting in endosperm rotting and damage known as zebra beans (Le Pelley, 1942). ABT also transmit a bacteria that causes the potato taste defect (PTD), an undesirable raw potato like-smell found in green and roasted coffee beans and in brewed cups of coffee (Jackels et al., 2014; Gueule et al., 2015). These pests also have different dispersal capacities and therefore utilize the landscape differently (Mosomtai et al., 2021). Thus, they represent other pests by providing meaningful insights that inform landscape management strategies that can be adopted to reduce pest pressure in smallholder coffee landscapes.

Decisions at the farm level (whether to plant coffee under shade or full sun) contribute to local and regional landscape management that is crucial in coffee pest management and creating resilient landscapes against climate change impacts (Jha et al., 2014). Farmers' decisions are often influenced by various factors such as advice from cooperative societies, government incentives, mechanization, yields, and access to the speciality market. Given that the landscape structure of smallholder coffee farmers differs from the homogeneous large coffee plantations, it was hypothesized that the contrast between adjacent patches will alter the microclimate conditions of coffee plots and population dynamics/habitat suitability of these coffee pests (Baez and Balslev, 2007). This hypothesis was tested using observational data of CBB and the two species of antestia bugs sampled for two years in central Kenya.

4.3 Materials and methods

4.3.1 Study location

The study was conducted in a transect (approximately 25km x 7km) that cuts across the primary coffee-growing zone in Murang'a county in Central Kenya (Figure 4.1). The transect is located at latitude S 0.7432° and S 0.6775° and longitude E 36.9089° and E 37.1335° with an elevation gradient of 1400 to 2000 m (above sea level). Coffee grows in the upper midland (UM) agro-ecological zone with four sub-zones, UM1 to UM4. UM1 is the transition zone from tea to coffee in the higher elevation, UM2 and UM3 are the primary growing zones, whereas UM4 is the marginal zone where perennial crops are the dominant cover types (Mosomtai et al., 2020).

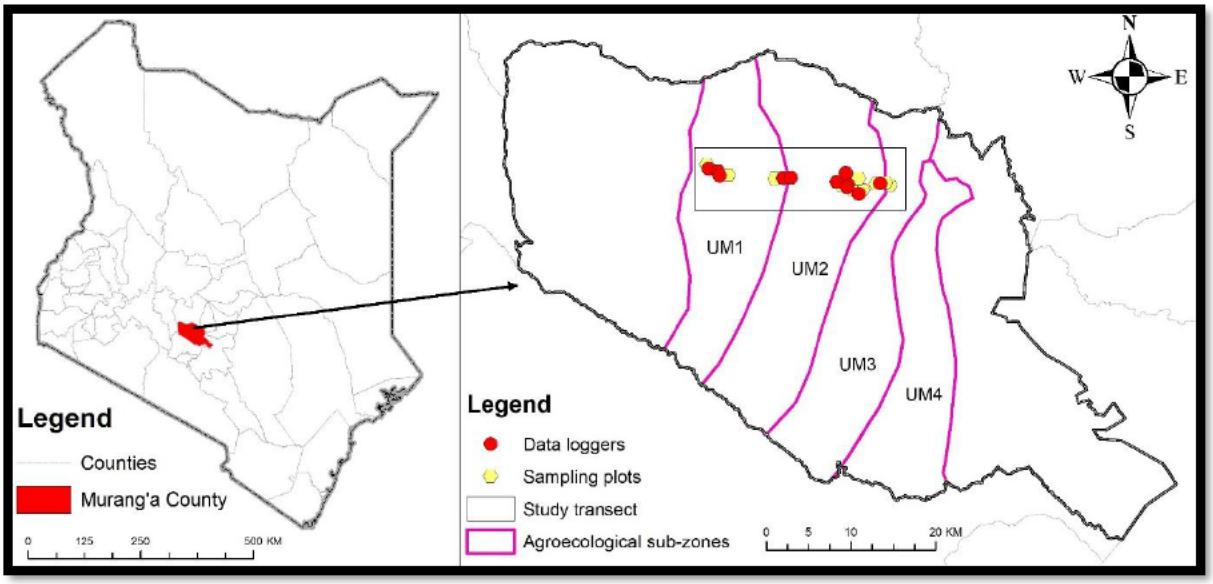

Figure 4.1: Study location in Murang'a county, Kenya, with sampling plots (yellow) and data loggers (red) located in a transect that cuts across upper midland (UM) agro-ecological sub-zones UM1 to UM3.

The study area receives bimodal rainfall with long rains from March to May (MAM) and short rains from October to December (OND). On the other hand, the dry seasons are experienced in January and February (JF) and from June to September (JJUS); however, the coldest season occurs in July, before the temperature increases in August and September (Jaetzold et al., 2007). This bimodal rainfall pattern results in two coffee harvests of the first crop (secondary harvest) and the second crop (primary harvest), which occur during the long and short rains, respectively (ICO, 2019). Overall, the coffee-growing zone receives an annual rainfall of 1000mm to 1500mm, with a mean annual temperature range of 18°C to 21°C (Jaetzold et al., 2007). Many smallholder farmers grow Arabica coffee (*Coffea arabica*) either as Ruiru 11, SL 28, SL 34, or Batian varieties on less than 2 ha plots.

4.3.2 Data collection

A network of 30 plots located in the study transect (Figure 4.1) was assessed monthly for the abundance of coffee berry borer, *Hypothenemus hampei* (CBB), and Antestia bugs, *Antestiopsis thunbergii* (ABT) and *A. facetoides* (ABF), from June 2016 to May 2018. The plots consisted of 10 high shade, 10 low shade and 10 open sun well spread across the sub-zones to minimize variation in data collection. Field sampling was done from 10:00 to 15:00 and in each visit, the population abundances of ABT and ABF were visually inspected in each coffee plot by randomly sampling 15 coffee trees (Azrag et al., 2018). The number of ABT and ABF on these trees were counted and recorded, irrespective of their life stages. On the other hand, the CBB population was assessed by deploying three to four traps in each coffee plot with a 20 m distance between the traps. The traps contained a lure (mixture of methanol and ethanol in a ratio of 1:1) in a dispenser to attract CBB females (Dufour and Frerot, 2008), and placed on tree branches at approximately 1.5 m above the ground. The dispensers were re-filled on monthly bases and the number of CBB females caught by each trap in each month were counted and recorded. In addition, 10 data loggers (iButtons Hygrochron, Maxim Integrated, San Jose, USA) were installed randomly in 10 of the sampled plots spread out from UM1 to UM3 (high to low elevation). The hourly temperature and humidity data collected by the loggers were used to determine the microclimatic conditions in the sampled plots. For this study, only the temperature data collected for the same period was used as the sampling period; however, some data loggers failed and created data gaps, which was interpolated to create seamless data for further analysis. Given that the pests were sampled monthly, the temperature data was aggregated to monthly mean (Tmean), minimum (Tmin) and maximum (Tmax).

4.3.3 Landscape configuration and composition in nested scales

Figure 4.2 shows the land cover map of coffee and agroforest of the study transect generated by Mosomtai et al. (2020) from 10-20-meter Sentinel 2 data with other classes masked out. Full-sun coffee was classified as coffee, whereas both woodlots and coffee planted under shade as agroforest. Many smallholder farmers in the study area grow coffee under the full-sun system within fragments of woodlots, often made up of *Grevillea robusta*, while others have adopted planting coffee under the shade system due to its ecosystem benefits and as an adaptation to climate change impacts (ICO, 2019). Common shade trees include macadamia (*Macadamia integrifolia*), avocado (*Persea americana*), mango (*Mangifera indica*), and *Grevillea robusta* which is also predominantly used as hedgerow trees like. This study focused on these two land cover types due to their dominance in the primary coffee growing sub-zones, and their effect on microclimate has been shown to vary (Gosme et al., 2020). Buffer zones of radii 50 m to 300 m (with an interval of 50 m) were used to calculate the percentage of landscape composition

(PLAND) for each of the two cover types and two configuration variables, namely edge density (ED) and total edge contrast index (TECI) for each sampling site with a data logger using Fragstat software (Figure 4.2). To estimate shade heterogeneity within the smallholder landscape, an inhouse shade index (SI) was generated for each buffer zone by calculating the ratio of the percentage of agroforest ($PLAND_{AF}$) over the percentage of coffee ($PLAND_{FS}$) in each nested scale, such that high SI values indicated more agroforest cover within the buffer zone, while low values indicated more full-sun coffee in the buffer.

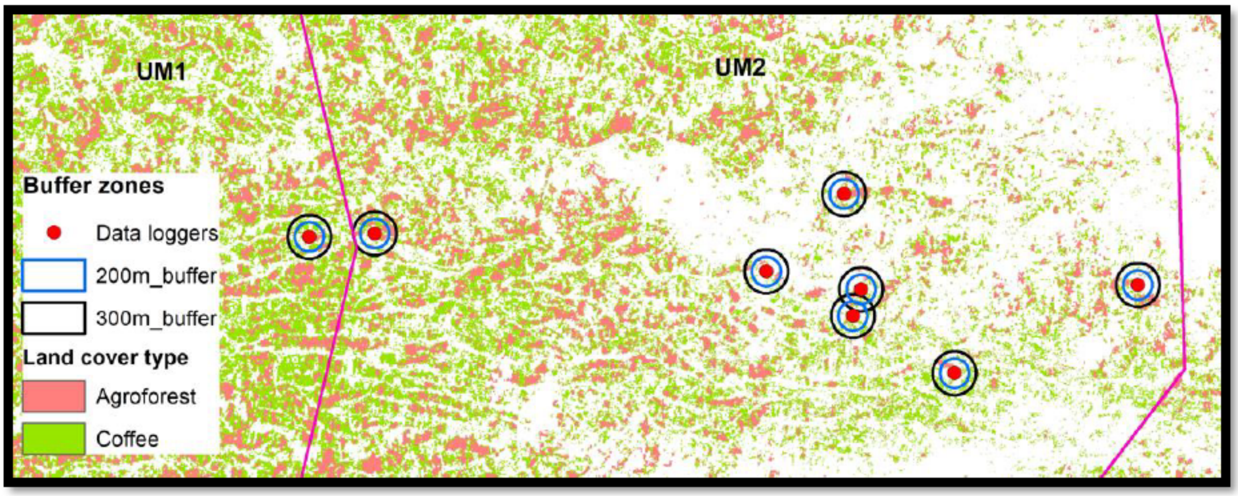

Figure 4.2: Land cover map of full-sun and agroforest coffee with buffer zones created around each data logger at radii 200 m and 300 m.

Table 4.1 shows the description of the landscape metrics used in this study. According to McGarigal et al. (2002), the percentage of landscape composition (PLAND) refers to the proportion of a cover type within a landscape and, in this case, the amount of full-sun coffee and agroforest within the buffer zones. Edge refers to the length (perimeter) of a particular patch, whereas edge contrast index refers to the degree of difference within adjacent patches in view of an ecological process. Fragstat computes landscape metrics for patch, class and landscape level. In this study, class level metrics were generated. Edge density (ED) measured the edge length of coffee class per unit area, where edge density = 0 means that the same patch dominates the landscape, but a high value translates to fragmented patches. For the total edge contrast index (TECI), weight was applied to measure the degree of contrast in each edge segment where a value of zero translates to no difference between the patch and its neighbouring patches in influencing ecological phenomena such as microclimate modification, whereas a value of one translates to a maximum difference. Fragstat then converts the degree of contrast to a percentage of the total perimeter. Given the ecological significance of the edge effect of agroforest in modifying the surrounding microclimate, a maximum contrast between full-sun coffee and agroforest edges was applied.

Table 4.1: Class metrics adopted in this study to quantify the shade and edge effect on pest abundance in nested scales (McGarigal et al., 2002)

Metric	**Description**	**Unit**
Percentage of landscape composition (PLAND)	The sum of the total area occupied by coffee/ agroforest, divided by the total area of the buffer divided by 100	Percent
Edge density (ED)	The sum of the total length of edges of coffee patches in each buffer, divided by the total area of the buffer and multiplied by 10,000 to convert it to hectares	metres/hectare
Total edge contrast index (TECI)	The sum of the total length of coffee patches in each buffer multiplied by the weighted contrast, divided by the sum of the total length of coffee edges in the buffer and multiplied by 100	Percent

Shade index (SI)*	The percentage of agroforest divided by the percentage of coffee in each buffer zone	None

*In house generated index: $\text{Shade index (SI)} = \%\ \text{of} \frac{\text{PLAND(AF)}}{\text{PLAND(FS)}}$

4.3.4 Data analysis

First the effect of landscape structure and scale on microclimate modification was tested. Using a linear model for each buffer zone, the influence of shade and edge effect on the temperature measured by the data loggers was evaluated. Mean (Tmean), minimum (Tmin) and maximum (Tmax) temperature of the observation period was used as the dependant variables, while TECI, ED and percentage of agroforest ($PLAND_{AF}$) and full-sun coffee ($PLAND_{FS}$) for each buffer zone as explanatory variables. The linear models were further evaluated using the analysis of variance (ANOVA) to compare how well the explanatory variables explain the observed microclimate in each buffer zone.

Secondly, a generalized additive mixed model from the *gamm4* package in R (Pedersen et al., 2019) was used to test the influence of micro-climate, shade and edge effect on the observed pest abundance. Given that the pest data were sampled monthly in the same plots, this presented the challenge of pseudo-replication effects, which violate the assumption of independent errors (Crawley, 2007). Therefore, a mixed-effect model was used, which accounts for the fixed and random effects that influenced the observed pest's mean and variance (Zuur et al., 2009). The fixed effects were the temperature variables (Tmean, Tmax, Tmin), seasonality (i.e. dry seasons (JF & JJUS), long rains (MAM), short rains (OND)), shade (full-sun coffee or shaded) and edge variables (ED and TECI), while the random effects were the date of observation and the sampled plots.

4.4 Results

4.4.1 Distribution of pest abundance and microclimate across elevation and shade

The temporal distribution of the pest abundance and temperature varied across the elevation gradient and shade (Figures 4.3 and 4.4). Without shade, CBB abundance was high in the first quarter of the year in high elevation plots, whereas the population peaked during the last quarter in coffee plots at low elevation (Figure 4.3a). Similarly, CBB abundance varied at mid and low elevation based on shade level. In mid-elevation, full-sun coffee plots recorded a high abundance from January to August (Figure 4.3b), while shaded coffee plots in low elevation recorded a high abundance from September to December (Figure 4.3c). For Antestia bugs, ABF predominantly occupied the low elevation with a preference for full sun coffee plots (Figure 4.3g-i), contrary to its counterpart ABT, which preferred shaded plots across the elevations (Figure 4.3d-f).

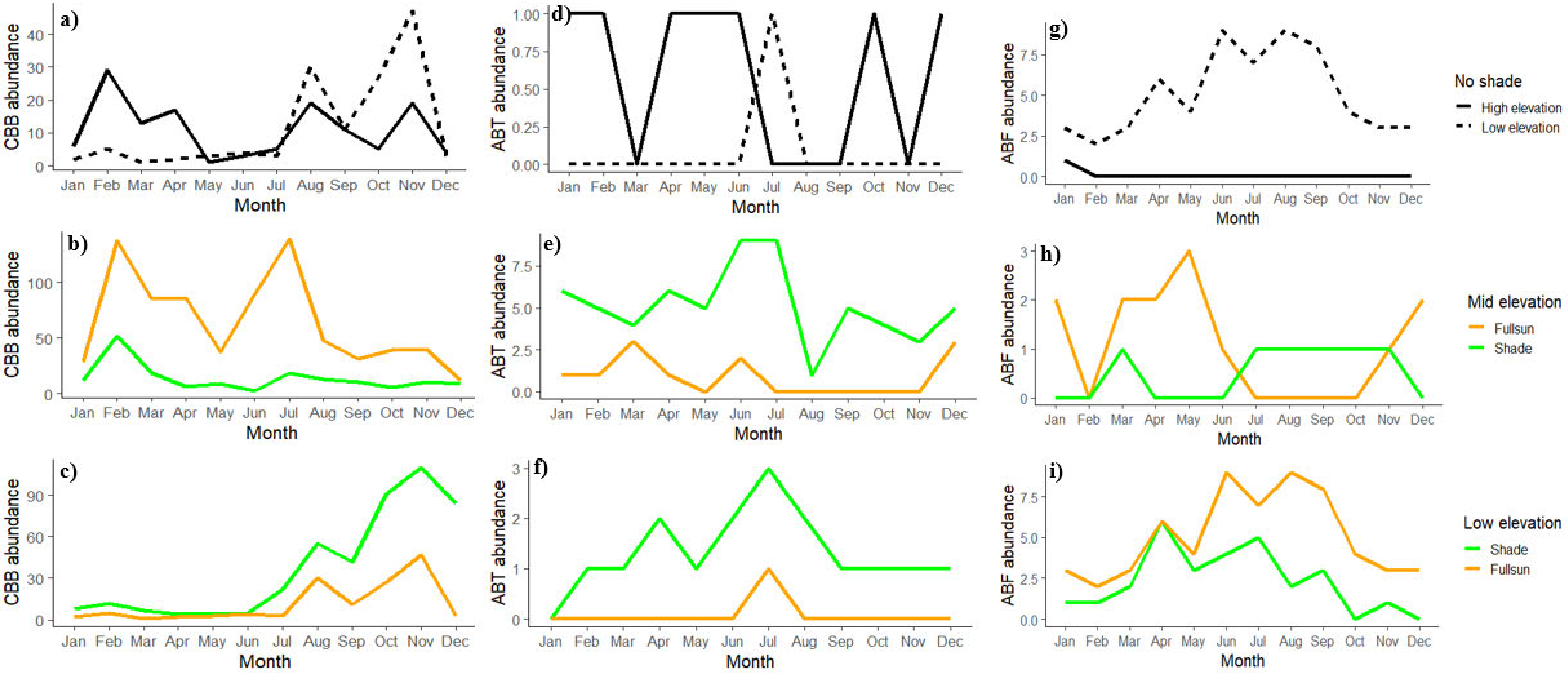

Figure 4.3: Sum of monthly abundance of three coffee insect pests, H. hampei (CBB), A. thunbergii (ABT) and A. facetoides (ABF) collected in 2 years at high (2000 meters above sea level) and low (1400 masl) elevation zones, shade and full-sun coffee plantations.

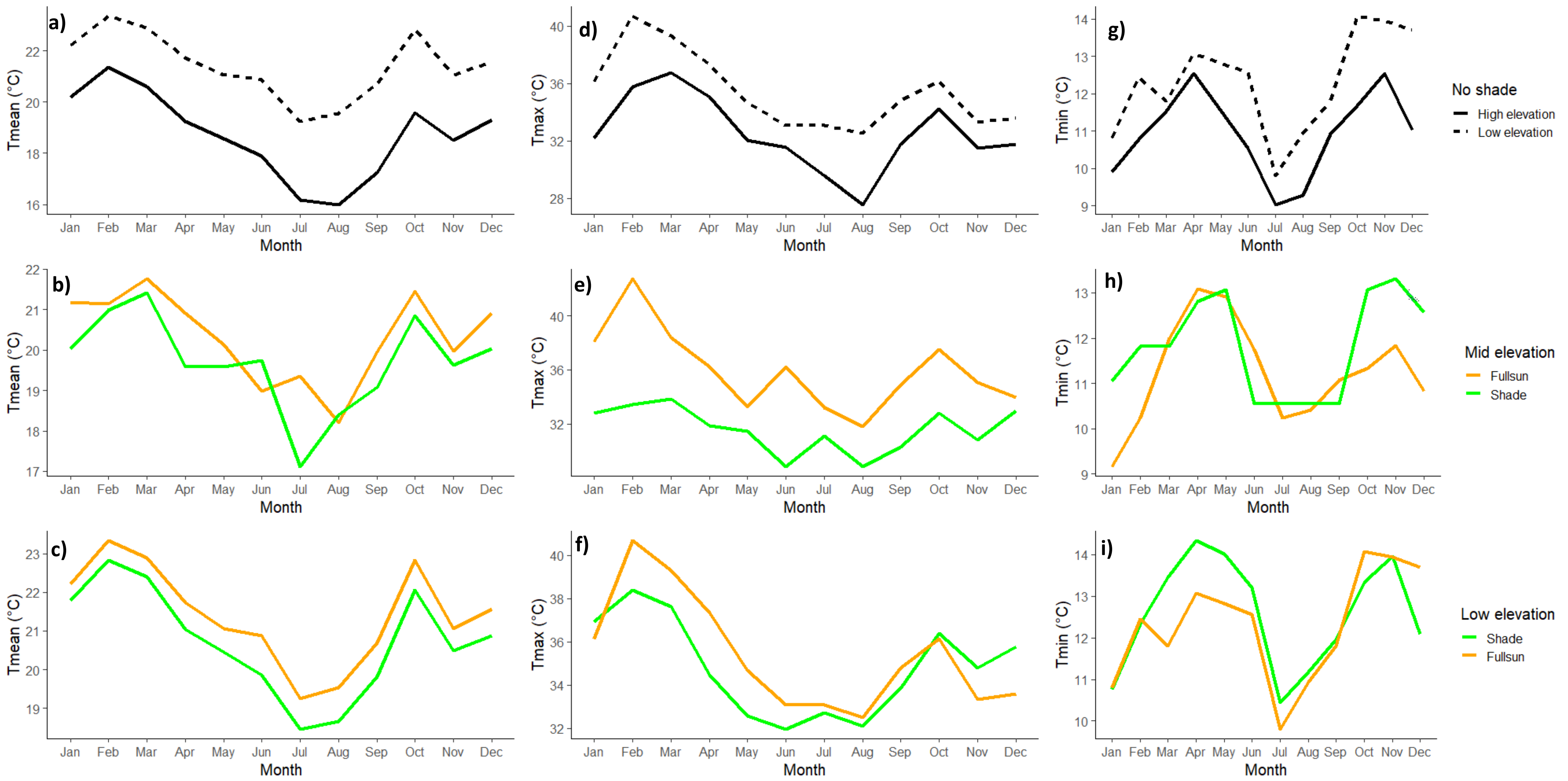

Figure 4.4: Monthly mean (Tmean), minimum (Tmax) and maximum (Tmin) temperature variations within shaded and full-sun coffee plot located at different elevation zone across the year.

Temperature variation was also notable across the elevation gradient and shade. Overall, the mean temperature (Tmean) ranged from 16 - 23°C, while the minimum (Tmin) and maximum (Tmax) temperatures ranged from 9 – 14°C and 28 – 40°C, with high elevation plots recording low Tmean temperature and vice versa in low elevation plots. January and February were the hottest months, whereas July and August were the coldest. However, shade influence was particularly noteworthy at mid and low elevation. Shaded coffee plots recorded lower mean and maximum temperatures throughout the year than the full sun coffee plots (Figure 4.4b,c,e,f). Similarly, at mid-elevation, shade increased the minimum temperature by 2°C during the hottest months in January and February compared to full sun coffee plots (Figure 4.4h). The amount of shade surrounding the sampled plots was of interest to this study. Based on the nested scales measured, the 100m buffer zone had the highest variability of shade index, but as the distance increased, the amount of shade stabilized, but generally, the mean shade index was constant across the scales, as shown in Figure 4.5.

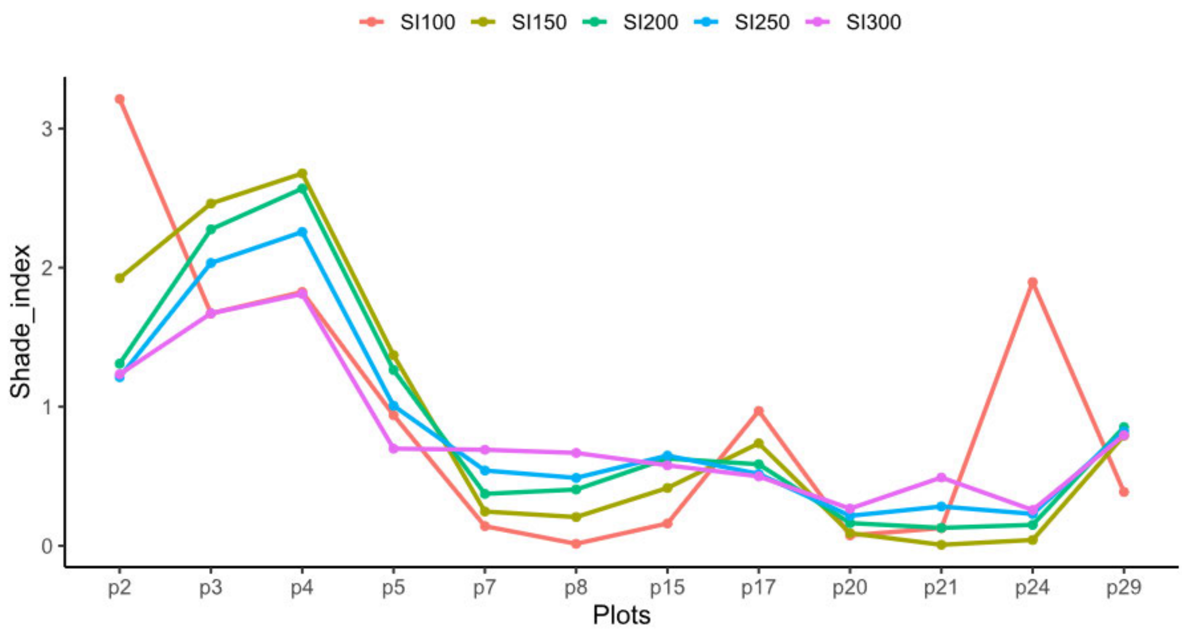

Figure 4.5: Shade index (SI) across the nested landscape scales of plots (p2 – p29) with data loggers. High elevation plots (p2 – p5) had the highest shade index than low elevation plots (p20 – p29) with 100 m buffer (SI100) recording the most variability in the shade index

4.4.2 Influence of edge contrast and shade on microclimate across landscape scales

Table 2 and Figure 6 show the influence of the shade and edge effect in every landscape scale. The influence of edge effect and shade level was only significant on the mean temperature of the selected coffee plots as the landscape scale increased. The amount of full-sun coffee (FS) was only significant at 50 m buffer, with mean temperature decreasing significantly with the increasing proportion of full-sun coffee (Figure 6b). However, as the landscape scale increased, the amount of agroforest (AF) became more significant (from 150 – 300 m). The mean temperature increased with the increasing proportion of agroforest in the landscape (Figure 6a). The edge effect was also important in modifying the microclimate of the selected plots. Specifically, the total edge contrast index (TECI) was more significant than the edge density (ED). The mean temperature decreased with increasing edge contrast between adjacent full-sun coffee and agroforest (Figure 6d).

Table 4.2: Influence of edge effect and amount of shade on mean monthly temperature across landscape scales. Values highlighted in bold represent *p values* < 0.05

Landscape-scale (Metres)	Agroforest (AF)	Full sun coffee (FS)	Edge density (ED)	Total edge contrast index (TECI)
50	0.70	**0.00**	0.71	0.27
100	0.30	0.51	0.23	**0.04**
150	**0.03**	0.79	0.67	**0.04**
200	**0.01**	0.91	0.79	**0.05**
250	**0.01**	0.59	0.74	**0.03**
300	**0.02**	0.52	0.85	**0.05**

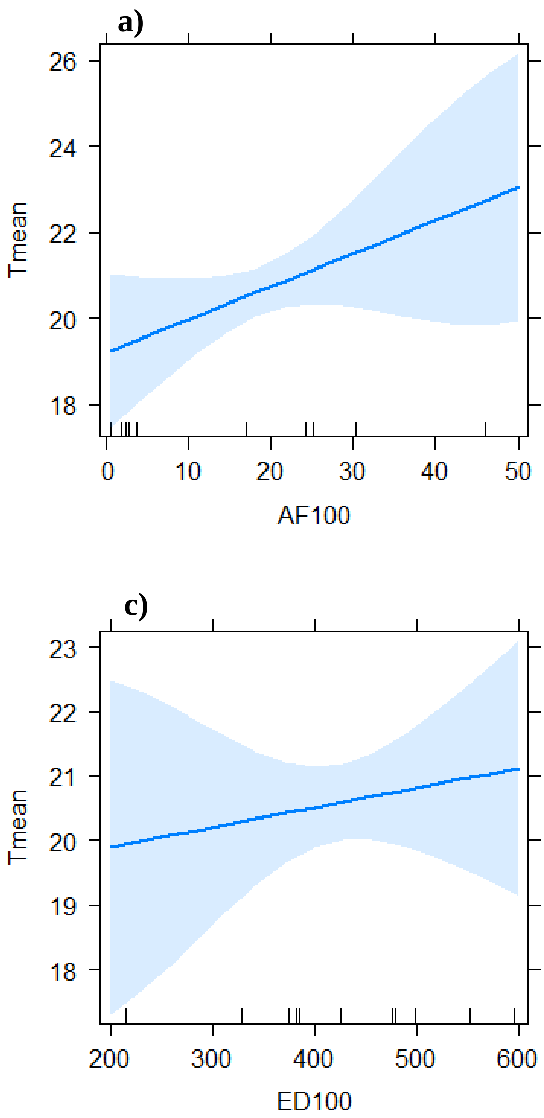

Figure 4.6: Relationship of mean temperature (Tmean) with total edge contrast index (TECI100), edge density (ED100) and the percentage of agroforest (AF100) and full-sun coffee (FS100) at 100 m buffer.

4.4.3 Influence of microclimate, edge effect and amount of shade on pest abundance

Temperature variables were only significant to CBB abundance, whereas ABT and ABF were influenced by seasonality, edge effect and shade (Table 4.3). On seasonality, JJAS (dry) and MAM (long rains) seasons influenced the abundance of ABF and CBB but not ABT. Instead, shade and edge density were vital for ABT abundance (Table 4.3). It is important to note that the edge effect was only significant at using the100 m landscape buffer, and as shown in Figure 4.5, it was the only landscape scale with the highest variability.

Table 4.3: Significance of edge effect, shade, temperature and seasonality on coffee berry borer (CBB), antestia bugs (*A. facetoides* (ABF) and *A. thunbergii* (ABT)) abundance. Values highlighted in bold represent *p values* < 0.05

Variables	CBB	ABF	ABT
(Intercept)	0.00	0.21	0.19
Season JJAS*	**0.01**	**0.04**	0.77
Season MAM**	**0.05**	**0.02**	0.34
Season OND***	0.92	-	0.11
Shaded coffee	-	0.13	**0.00**
Tmean	**0.00**	0.45	0.37
Tmin	**0.00**	0.28	0.07
Tmax	**0.00**	0.74	0.69
ED100	0.75	**0.02**	**0.01**
TECI100	**0.00**	**0.03**	0.10

*June, July, August, September, **March, April, May, ***October, November, December

4.5 Discussion

Landscape management in the agricultural system plays a crucial role in modifying microclimate at the local level, influencing biological processes such as population dynamics of pests (Ismangil et al., 2016). This study explored the interplay of landscape management of smallholder coffee farms and its role in modifying microclimate in coffee plots and, consequently, its implication on coffee pest abundance. The results showed that the proportion of shade trees and the contrast of edges surrounding coffee plots play a crucial role in modifying the microclimate and influencing pest abundance.

Pest distribution varied with shade across the elevation gradient. For CBB, the abundance was higher at mid elevations between January and May, and in low elevations between June and December. This might be linked to the harvesting periods of the fly crop (February - April) and the main crop (October - December), which suggests that the mid elevation had a better harvest of the second crop than the lower elevation. Another explanation could be higher temperatures recorded between January and May at lower elevation might have influenced alcohol evaporation from the disperser, hence affecting trap catches. Similarly, high abundance of CBB was noted in full-sun coffee at mid-elevation and shaded coffee at low elevation. Shade play a vital role in modifying microclimate in low elevation by lowering the mean and maximum temperatures and increasing the minimum temperature. This could explain why the CBB preferred shaded coffee at low elevations.

Thermal tolerance of immature stages of CBB requires a temperature range of 20 – 28^{o}C, with an optimum of 23^{o}C to develop, therefore, high temperature at low elevation was less suitable for the pest, possibly contributing to the low abundance observed in the full-sun coffee (Azrag et al., 2020). There is no unanimous agreement on the influence of shade on CBB. The results of this study suggest that the conflicting influence of shade can be resolved by considering shade alongside the elevation gradient of the plot. At an altitude of 1722 m.a.s.l, Jaramillo et al., (2013) recorded high CBB infestation in full-sun coffee in Kiambu county, Kenya, whereas Mariño et al. (2016) observed high CBB infestation in shaded coffee plots located at an altitude of ~550 m.a.s.l in Puerto Rico, corroborating the findings.

On the other hand, the antestia bugs had contrasting preferences to the shade. ABT preferred shaded plantations at low and mid-elevations, whereas ABF preferred full-sun coffee predominantly at low elevations. This suggests that the two pests have different thermal tolerance, though they share the same habitat and host plant. Generally, the population abundance of ABT is usually higher at high-elevation coffee farms where the temperature is cooler (Azrag et al., 2018). The preference for high elevations is due to the ABT narrow thermal tolerance for population growth (between 19 and 25°C) and to avoid high temperatures (above 25°C), which leads to a high mortality rate of immature stages (Azrag et al., 2017). Therefore, the high ABT population on shaded coffee plantations at low and mid-elevations could be explained by the fact that shade reduces the extreme temperatures at these elevations, hence it offers a habitable environment for the pest to develop (Azrag et al., 2017). These findings agree with those reported by Mugo et al. (2013), who recorded a high ABT population on shaded coffee plantations in Kenya, compared to full-sun plantations. In fact, during the hottest hours of the day, ABT adults and nymphs avoid direct sunlight by hiding in coffee bushes, which could also explain the preference of this pest to shaded plantations given that the field sampling was done between 10 am to 3 pm, which is generally hot in the study region

Unlike ABT and CBB, whose bioecology is well studied, there is limited information on ABF, other than its preference for low elevations (Babin et al., 2018). Perhaps, the exclusive distribution of ABF to Kenya and Tanzania might have undermined its importance, thus it was neglected compared to other coffee pests. Nevertheless, ABF was dominant in the study area, compared to ABT and the number of the bugs observed in the plots exceeded the economic threshold, especially in sunny plantations (Azrag et al., 2018). The preference of ABF to full-sun coffee suggests that this pest has a wide thermal tolerance for development. In this regard, ABF needs considerable attention as it can spread to new areas, especially in light of global warming. Hence, further studies should be conducted to understand the bioecology of ABF and develop appropriate management strategies to minimize its risk in coffee plantations.

Also notable was the influence of seasonality on pest abundance. At low elevation, CBB abundance peaked in November, unlike the mid-elevation, which recorded two peak populations in February and July, making the March-May and June-August seasons significant. CBB completes its life cycle development inside the berry, and this cryptic nature means that coffee tree phenology underpins the observed population (Damon, 2000). The study area has two harvesting seasons, the first crop in March-May and the main harvest in October-December. Colonizing CBB females are more attracted to red berries ripe for harvesting (Aristizábal et al., 2015). Therefore, flight activities are highest in March-May and October-December when mature berries are available on coffee trees. Only CBB at low elevation recorded this expected trend. However, at the mid-elevation, the peak periods lagged to when coffee berries are green, making the ethanol bait on the trap more attractive to the pest, which explains the high number recorded (Mosomtai et al., 2021).

For the antestia bugs, the June-September period recorded the highest abundance, especially at the low elevation. During this period, mature green berries, which are the preferred food source for the bugs, are available on the trees, and this could explain the high abundance of the pest during this period. The results also support the findings of Njihia et al. (2018), which showed that the second nymph instar of ABF was more attractive to the volatiles of mature green berries compared to the red ones. Interestingly, ABF recorded a high abundance from March-June at mid-elevation, followed by no observation during the cold month until October. Apart from green berries, antestia bugs also feed on green shoots and flower buds, which could explain the high abundance during the coffee tree flowering period (Waller et al., 2007) in the mid-elevation. Additionally, they have a high flight capacity, and when temperatures became unfavourable in the cold month, they could have migrated to the lower elevation with warmer temperatures (Mosomtai et al., 2021).

Unlike large coffee plantations with homogenous coffee systems, the microclimate in smallholder coffee plots is regulated by the configuration of the surrounding cover types. In particular, the edge effect of the adjacent patches is vital in modifying the microclimate and influencing the population dynamics of pests (McGarigal et al., 2002). In this study, edge contrast (i.e. full-sun coffee surrounded by agroforest) significantly lowered the mean temperature across landscape scales. Contrary to the expected temperature increase in full-sun coffee, a significant decrease in mean temperature was noted in full-sun coffee at the plot scale (50 m buffer). The edge effect (from contrasting edges) of agroforest on the full-sun coffee plots could be a plausible explanation. Hence, this finding suggests that the microclimate dynamics of a full-sun coffee system in large coffee plantations differ from smallholder coffee plots. Notably, the influence of the surrounding landscape on microclimate was significant within a 100 m buffer zone. Consequently, it underscores the importance of landscape management in smallholdings. Edge contrast was also significant to the observed pests. Given their dispersal abilities, edge contrast can impede or facilitate the movement of the pests across the landscape. CBB has a low dispersal capacity and requires a contiguous coffee landscape, therefore, contrasting edges inhibit their movement. In contrast, Antestia bugs are not limited due to their high dispersal capacity (Mosomtai et al., 2021).

4.6 Conclusions

Climate change continues to significantly impact sources of livelihood like coffee production. Planting coffee under shade is one of the adaptation strategies for building resilient livelihoods that mitigate the negative impacts of a warming world. The study evaluated the influence of shade and edge contrast in regulating microclimate and pest abundance in smallholding landscapes and concluded that pest distribution varied with shade across the elevation gradient. Therefore, control strategies should be pests specific, i.e. factor in the thermal tolerance of the pest, exposing it to the extreme conditions that inhibit its proliferation. Also, the edge effect of the adjacent patches is vital. The edge effect of agroforest regulates the microclimate of full-sun coffee

CHAPTER 5: MULTI-SCALE HABITAT SUITABILITY MODELLING OF ARABICA COFFEE (*Coffea arabica* L) IN A STEEP AGRO-ECOLOGICAL GRADIENT: THE INFLUENCE OF UNDER 2ºC GLOBAL WARMING

This chapter is based on: **Mosomtai, G**., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., (*in preparation*). Multi-scale habitat suitability modelling of Arabica coffee (*Coffea arabica* L) in a steep agro-ecological gradient: the influence of under 2ºC global warming

5.1 Abstract

Limiting temperature rise to below 2ºC has become a priority to mitigate the adverse consequences of global warming on food and nutrition systems. For instance, if the current anthropogenic activities continue, the livelihoods of smallholder coffee farmers are at stake due to the anticipated loss of suitable coffee growing areas and proliferation of the crop pests and diseases. The Representative Concentration Pathways (RCP) 2.6 presents an alternative future climate scenario that suggests limiting temperature rise to below 2ºC by adopting climate policies and clean energy technologies. This study explores the impact of the RCP 2.6 scenario on the range shift of Arabica coffee (*Coffea arabica* L) and its implication on coffee pests to guide policies and designing of possible adaptation strategies. Present and future bioclimatic variables (at moderate to coarse resolutions) for 2050 and 2070 from WorldClim and vegetation indices from 30-meter Landsat 8 and 30-meter digital elevation model (DEM) data were used as predictor variables. A network of 50 Arabica coffee plots in Murang'a county, Kenya, were surveyed and utilised as occurrence data for predicting habitat suitability using the maximum entropy (MaxEnt) algorithm. Furthermore, the influence of different pixel resolutions (30 m and 1000 m) and landscape scales (100 m, 200 m, 300 m, 500 m, and 1000 m) was explored in predicting the distribution of Arabica coffee. Seven models were generated from landscape scales and pixel resolution and a final model that combined the most significant variable from each landscape scale. The results showed an increase in area under Arabic coffee, especially in 2070. A shift in the coffee range was towards the lower zone, with rainfall in the wettest quarter (> 500 mm) and mean elevation (1700 m) significantly influencing the model predictions. Additionally, the landscape scale of 100 m and resampled variables at 30 m had the highest modelling accuracy, whereas a larger landscape scale of 1000 m and resampled pixel resolution at 1000 m were the least suitable predictors. The study demonstrated the importance of pixel size and landscape scale in improving model prediction accuracies suggesting that localized predictions tailored to species-specific scales should be used to inform policy. Furthermore, the increase in the extent of growing coffee areas under the RCP 2.6 scenario can improve the livelihoods of smallholder farmers, especially in the lower elevation areas. This should accelerate the implementation of climate policies and the development of clean technologies to achieve the scenario envisioned by RCP2.6 to limit temperature rise to below 2^{o}C.

Keywords: RCP2.6 scenario, landscape scale, habitat modelling, Arabica coffee, coffee pests

5.2 Introduction

The sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) conveyed that greenhouse gas emissions are currently at unprecedented levels, mainly due to eco-unfriendly anthropogenic activities (IPCC, 2021). In the last decade (2011 – 2020), the global mean surface temperature (GMST) has risen by 1.09 ^{o}C compared to the 1850 – 1900 period. The IPCC special report on global warming of 1.5 ^{o}C estimates that temperature will increase by 1.4 – 5.8 ^{o}C by 2100 if the current anthropogenic activities continue (IPCC, 2018). At 1.5 ^{o}C, mid-latitudes will experience warmer days by 3.0 ^{o}C and even exacerbate to 4.0^{o}C if the globe warms by 2.0^{o}C. This will translate to continued shifts in climatic zones of crops like coffee and pests distribution, their abundance and seasonal activities. Extreme events such as flooding, droughts and crop pest and disease outbreaks will be frequent with increased invasion and severity; threatening the food and nutrition security, and human health (IPCC, 2019).

Crops in the tropics such as coffee will be adversely affected by the changing climate, impacting the livelihoods of over 25 million smallholder farmers in over 60 countries (Waller et al., 2007). Arabica coffee (*Coffea arabica* L.), which accounts for 70% of the global coffee production, will be negatively impacted by the rising temperature due to the limited optimum temperature range of 18 - 23°C for the crop growth and development. It is reported that beyond 23°C, substantial coffee losses will occur due to reduced crop growth, yellowing of leaves and accelerated ripening of beans that causes low cup quality (Damatta et al., 2006). Equally, coffee pests are already thriving due to favourable temperatures that shorten their life cycle, as a result of temperature rising by 1.09^{o}C compared to the pre-industrial era (Azrag et al., 2018). For instance, the habitat range of coffee berry borer (*Hypothenemus hampei*) is expanding to higher elevations (Atallah et al., 2018), while coffee leaf rust (*Hemileia vastatrix*) occurrences are increasing due to frequent extreme weather patterns that favour establishment and build-up (Talhinhas et al., 2017). Hence, the legally binding global treaty under the UNFCC from the 21st conference of parties (COP21), commonly known as the Paris agreement, set out the ambitious goals for countries to stabilize the GMST to below 1.5^{o}C and in the worst-case scenario, well below 2.0^{o}C above the pre-industrial levels (IPCC, 2018).

Species distribution models (SDM) have become a powerful tool for making informed decisions regarding the impact of climate change on species distribution and their habitat suitability, guiding conservation planning, biodiversity assessment, habitat restoration and management of invasive species (Franklin, 2010). Essentially, SDMs combine the occurrence of species, often presence-only, with environmental layers that define the species' niche and extrapolate it to unsampled regions based on conventional statistical or machine learning approaches (Múrria et al., 2019). For instance, SDMs have been used to identify the potential breeding sites for desert locusts (Kimathi et al., 2020), map the impact of climate change on coffee pests (Kutywayo et al., 2013), identify barriers for gene flows (Razgour et al., 2014), guide conservation planning (Khosravi et al., 2019; Tôrres et al., 2012) and map potential impact of climate change on the distribution of key forest plant species (Hsu et al., 2012). These studies used bioclimatic variables from the WorldClim database as one of the key explanatory variables elucidating the most important climatic variables that influence habitat suitability of the studied species under different current or future climatic scenarios. Other explanatory variables used in SDMs include edaphic, topographic, land cover, vegetation indices and other variables such as roads and rivers (Makori et al., 2017; Sun et al., 2021; Kimathi et al., 2020; Rather et al., 2020).

In recent decades, bioclimatic variables have become the basis for substantiating the impacts of climate change based on four future climatic scenarios generated from several greenhouse gases (GHG), air pollutants and land-use emission pathways adopted during the IPCC fifth assessment report (AR5) (i.e., representative concentration pathways: RCP 2.6, 4.5, 6.0 and 8.5) (van Vuuren et al., 2011a). RCP2.6, which is the focus of this study, envisions a world with the least GHG emissions, where climate policies are implemented, limiting the rise of GMST to under 2^{o}C by the end of the 21st century inline with the 2015 Paris agreement on limiting temperature to well below 2 ^{o}C. RCP4.5 and 6.0 represent intermediate implementations of climate policies, while RCP8.5 represent the extreme scenario with possibly no climate policy implementation (Lyon et al., 2021). In these scenarios, the temperature will rise beyond 2°C by the end of the current century, which is detrimental to human, plant, animal and the environmental health.

Therefore, to guide the implementation of the Paris agreement, this study aims to quantify the implication of RCP2.6 on the geographic distribution of suitable areas for growing Arabica coffee, the primary host of important coffee pests in Kenya, including coffee berry borer (*Hypothenemus hampei*) and two Antestia bug species (*Antestiopsis thunbergii* and *A. facetoides*). Furthermore, this study explores the role of the pixel resolution (i.e. pixel resolutions of 30 and 1000 m) and landscape scales (i.e. 100 m, 200 m, 300 m, 500 m, and 1000 m) of the environmental variables in predicting the habitat suitability and range shift of Arabica coffee under current and future climatic scenarios and its implication on the coffee pests. Coffee pests interact with their environment within a limited landscape scale as shown by Mosomtai et al. (2021). Also, studies like Sun et al. (2021) and Rather et al. (2020) have shown that multi-scale variables are better predictors of species than single scale variables.

5.3 Material and methods

The study was conducted in Murang'a county, Kenya, which lies on the slopes of Aberdare ranges with an elevation gradient of 1000 to 3900 m asl (above sea level). The core coffee growing zone in Murang'a is in the upper midland (UM) agro-ecological zone with four sub-zones; UM1, UM2, UM3 and UM4 (Figure 5.1). UM1 is the highest point for growing coffee, with an elevation ranging from 1800 - 2000 m asl. UM2 and UM3 are the primary and marginal coffee sub-zones, while UM4 lies at the lowest elevation ranging from 1300 to 1400 m asl. The study area receives 1000 - 1500 mm of bimodal rainfall with long and short rains occurring from March to May and October to December, respectively, and a temperature range of 18 –

21^{o}C. The dominant Arabica coffee varieties in the study area are SL28 and Ruiru 11, which are grown under agroforestry, full-sun system or intercropped with subsistent crops such as maize, beans and bananas (ICO, 2019).

5.3.1 Study area

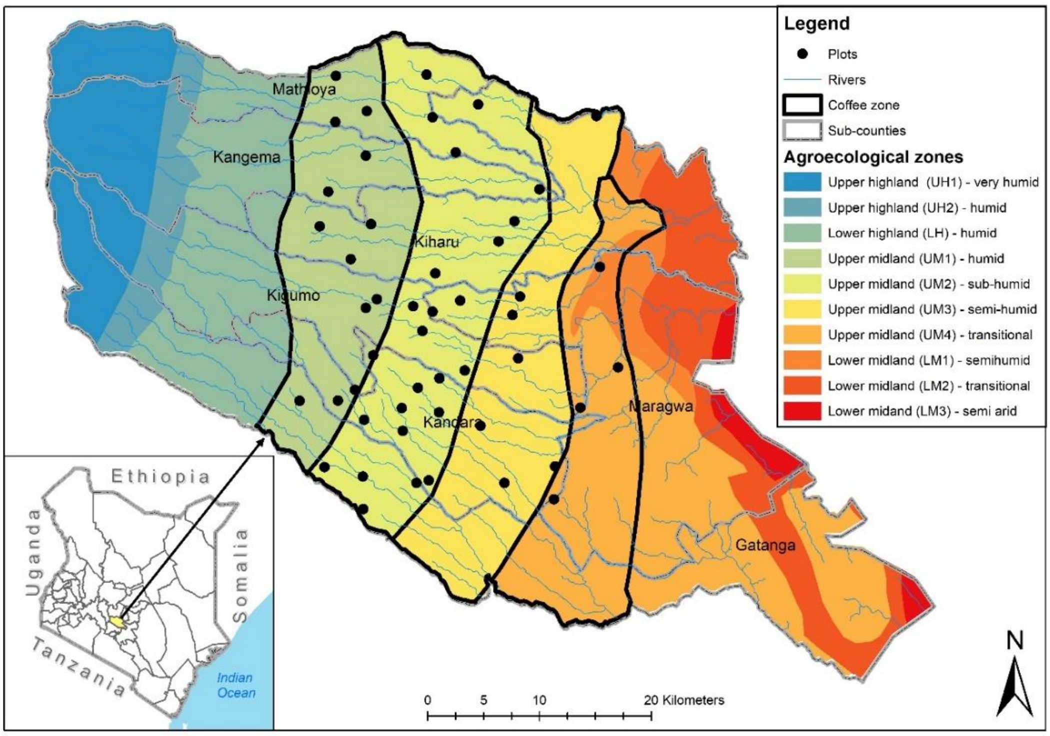

Figure 5.1: Map of Murang'a county, Kenya showing the agro-ecological zones with the upper midland (UM) sub-zones, where coffee is grown, highlighted in black. The black spots represent the sampled Arabica coffee plots

5.3.2 Datasets

5.3.2.1 Occurrence data

Locations of 50 Arabica coffee plots were sampled from 18th to 31st of January 2018 using a Garmin GPS (Global Positioning System) with an accuracy of ±3 m. The sampled plots were well distributed across the four coffee agro-ecological sub-zones of the study area and were used as the occurrence data for the species distribution modelling framework (Figure 5.1). Specifically, a stratified random sampling approach was followed based on the four agro-ecological sub-zones. On average, each plot had 200 - 400 coffee bushes, with SL28 being the dominant variety of more than 20 years old. Other prominent variety included Ruiru 11 and Batian, which are known to be resistant to coffee berry diseases and coffee leaf rust. The occurrence data were specifically used to predict the distribution of Arabica coffee

5.3.2.2 Environmental layers

Topographic, bioclimatic and remotely sensed vegetation indices were used as explanatory variables (Table 5.1). In addition, bioclimatic variables (1 km spatial resolution) obtained from the Worldclim database (https://www.worldclim.org/data/bioclim.html) were used to simulate the present and future climatic scenario under the RCP2.6 concentration pathway for 2050 (2041-2060 average) and 2070 (2061-2080 average). The RCP2.6 is a mitigation scenario with a substantial reduction in emissions to about 70% expected by the end of the 21st century if all countries implement their climate policies (van Vuuren et al., 2011b). Specifically, RCP2.6 trajectory predicts a peak in radiative forcing of 3W/m^2 by mid-century, then a decline to 2.6W/m^2 at the end of the century (van Vuuren et al., 2011a). The nineteen bioclimatic variables of Worldclim database were used to select uncorrelated variables based on variance inflation factor (VIF) as recommended by Naimi and Araújo, (2016). The few selected variables included Isothermality (bio3), temperature seasonality (bio4), annual temperature range (bio7) and precipitation of the warmest quarter (bio18). Additionally, three remotely sensed vegetation indices from the 30 m Landsat 8 surface reflectance (Level-2 Science Products) collected in the same month of the field sampling. The indices were extracted to capture information on soil (Modified Soil-Adjusted Vegetation Index - MSAVI), water (Normalized Difference Water Index - NDWI) and vegetation cover (Green Normalized Difference Vegetation Index - GNDVI) of the study area. Moreover, a tasselled cap transformation of the seven bands of Landsat 8 (except thermal and aerosol bands) was done to mimic the greenness, wetness and brightness for further landscape characterization. Finally, a 30 m digital elevation model (DEM) was used to estimate the elevation of the study area.

5.3.2.3 Generating multi-scale environmental layers

The variables were initially resampled to 30 m (res30) and later to 1km (res1000) pixel resolution to evaluate the effectiveness of cell size in predicting coffee habitats. Additionally, five landscape scales (i.e. 100 m, 200 m, 300 m, 500 m, and 1000 m) generated from the mean focal statistic of 30 m spatial resolution using the Multiscale Maxent Toolbox v2 in ArcMap 10.3.1 were evaluated (Bellamy et al., 2013).

Table 5.1: List of the environmental variables used in modelling species distribution

Variable	**Name**	**Resolution**	**Source**
Climatic	Bio3 - Isothermality	1km	WorldClim database
	Bio4 - Temperature Seasonality	1km	WorldClim database
	Bio7 - Temperature Annual Range	1km	WorldClim database
	Bio18 - Precipitation of Warmest Quarter	1km	WorldClim database
Remotely sensed	GNDVI - Green Normalized Difference Vegetation Index	30m	Earth Explorer
(*from Landsat 8 mosaic*)	MSAVI - Modified Soil-Adjusted Vegetation Index	30m	Earth Explorer

	NDWI - Normalized Difference Water Index	30m	Earth Explorer
	Greeness_tasseled_cap	30m	Earth Explorer
Topographic	DEM - Digital Elevation Model	30m	Earth Explorer

5.3.3 Maximum entropy (MaxEnt) model

Figure 5.2 summarises the general methodological framework of the MaxEnt experiment adopted in this study. MaxEnt machine learning algorithm was preferred due to its robustness in handling presence-only occurrence data, especially when the sampled data are few (Phillips et al., 2006). The principle behind MaxEnt is that the best probability of unknown distribution is one where the most spread out are towards known constraints (Franklin, 2010). In the case of SDM, MaxEnt generates background data to mimic the absence of observations in the study area, known as pseudo points, while the occurrence data define the known constraints of where the species is most likely to be present (Hijmans and Elith, 2016). MaxEnt model has several features and parameters that can be set at default, but the default settings might not always be suitable for every modelling scenario. Therefore, optimizing the MaxEnt settings and parameter is vital to achieving accurate predictions (Merow et al., 2013). In this study, the MaxEnt regularization parameter was optimized to avoid overfitting. Preliminary analysis of regularization multiplier of 3 resulted in overprediction compared to the default value of 1. Also, the feature selection was optimized, which is the basic function that uses explanatory variables to constrain the probability distribution of the species of interest. This study opted for the auto features that use the general empirical derived rules to select the appropriate features as suggested by Phillips et al., (2006)

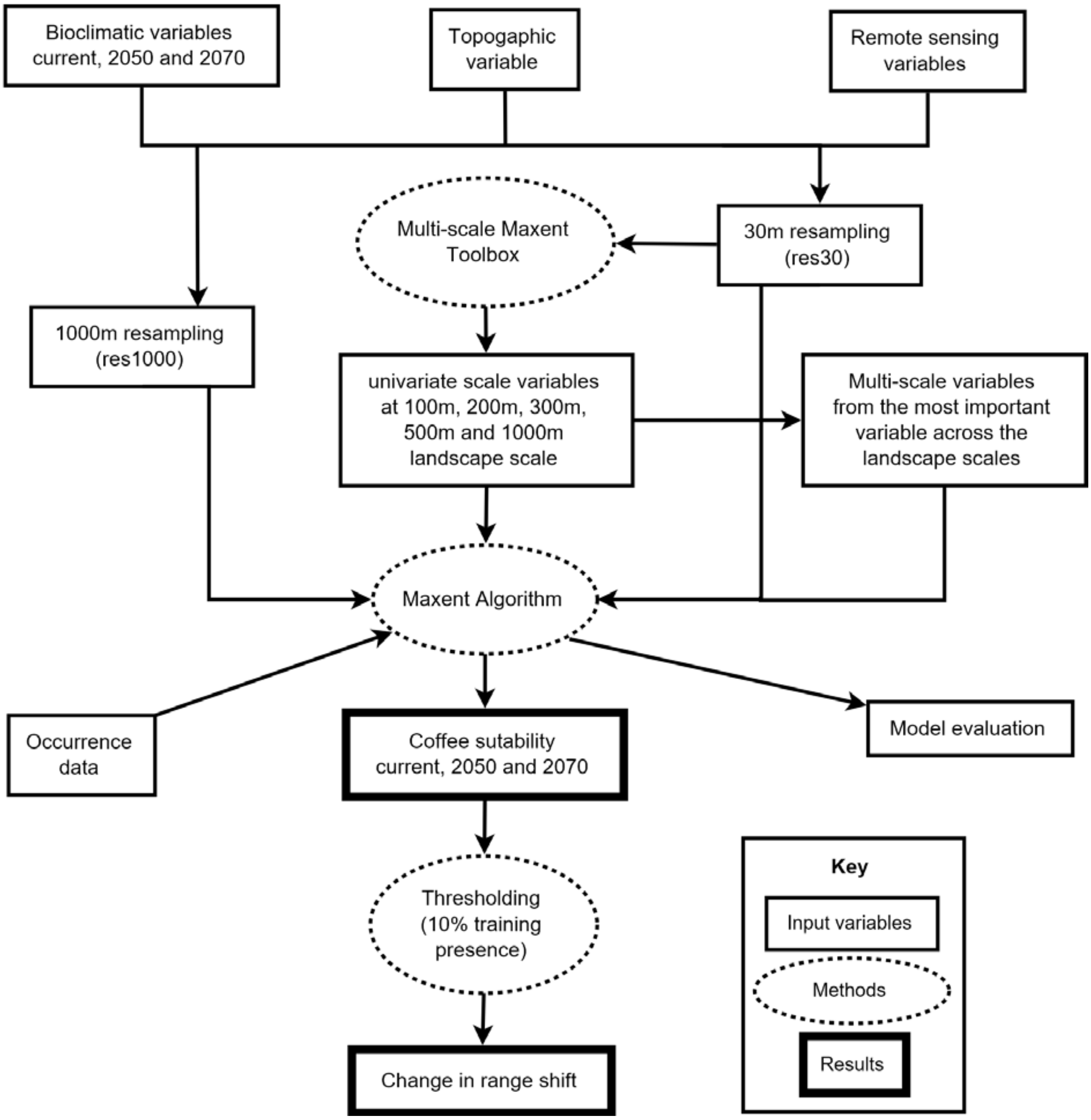

Figure 5.2: The flowchart of the methodological frame for the Maximum Entropy (MaxEnt) model adopted in this study

In total, eight MaxEnt models derived were generated from eight sets of the explanotory variables, two from resampled environmental layers at 30 and 1000 spatial resolutions, five from single landscape scales of 100 m - 1000 m and a final model from the most important variables in the single landscape scale, herein referred as a multi-scale model. A crossvalidation method with K - folds = 5 was employed to assess the models performance in predicting Arabica coffee. In specific, k-1 folds (k is number of species occurrence observations) were used to train the model, whereas the left-out fold was retained to evaluate the model accuracy (Fletcher and Fortin, 2018). The area under curve (AUC) of the receiver operating characteristics (ROC) was used to assess the accuracy of the models. It is suggested that an AUC of 0.5 or less represents a model that is as good as random with poor discrimination of presence from the absence, whereas the inverse is true for models with an AUC greater than 0.75 (Jiménez-Valverde, 2012). Since AUC is a threshold independent, binary maps were generated by applying a threshold of 10 percentile of the training presence observations, which allowed for the detection of species range shifts in the future

5.4 Results

5.4.1 Single landscape scale verse multi-scale

The average AUCs of the eight MaxEnt models are presented in Figure 5.3. Overall, the multi-scale and 100 m landscape scale models had the highest AUCs of 0.83. Equally, variables resampled to 30 m spatial resolution had the same predictive ability as the multi-scale and the 100 m landscape scale variables (AUC = 0.82). On the other hand, variables resampled to 1000 m and landscape scale of 1000 m had the least AUCs of 0.80. As the landscape scale increased, a notable predictive ability decreased.

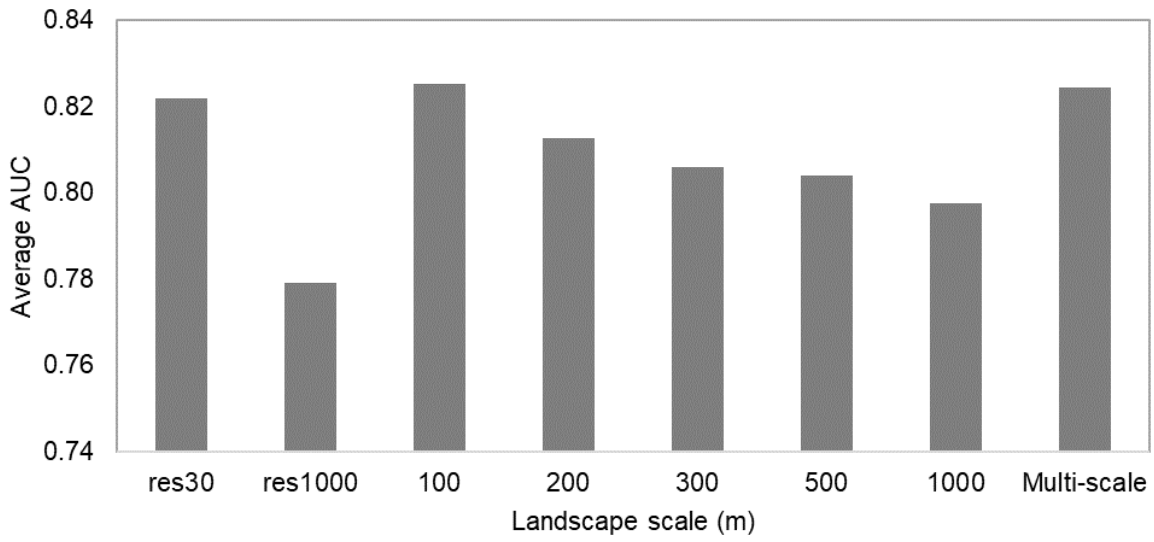

Figure 5.3: Average test area under curve (AUC) of single and multi-scale environmental variables. res30 and res1000 represent resampling f environmental variables to 30 m and 1000 m pixel resolution.

Visual interpretation of the final graphical model outputs showed that all the models were able to predict similar suitable habitats for Arabica coffee in the study area. Pixelation was dominant in maps generated from resampled variables at 1000 m spatial resolution, whereas predictive maps generated from landscape scales of 300 - 1000 m were smoother but generalized than those from 30 m spatial resolution, multi-scale and 100 m landscape scale, which predicted almost the same suitable areas. All the models predicted the UM1 and UM2 as the most suitable habitats for growing coffee, whereas the UM3 and UM4 were predicted as the marginal suitable sub-zones. Also, the models predicted areas of relatively higher elevations to be unfavourable for Arabica coffee, which are currently a tea growing areas and the protected Aberdare forest.

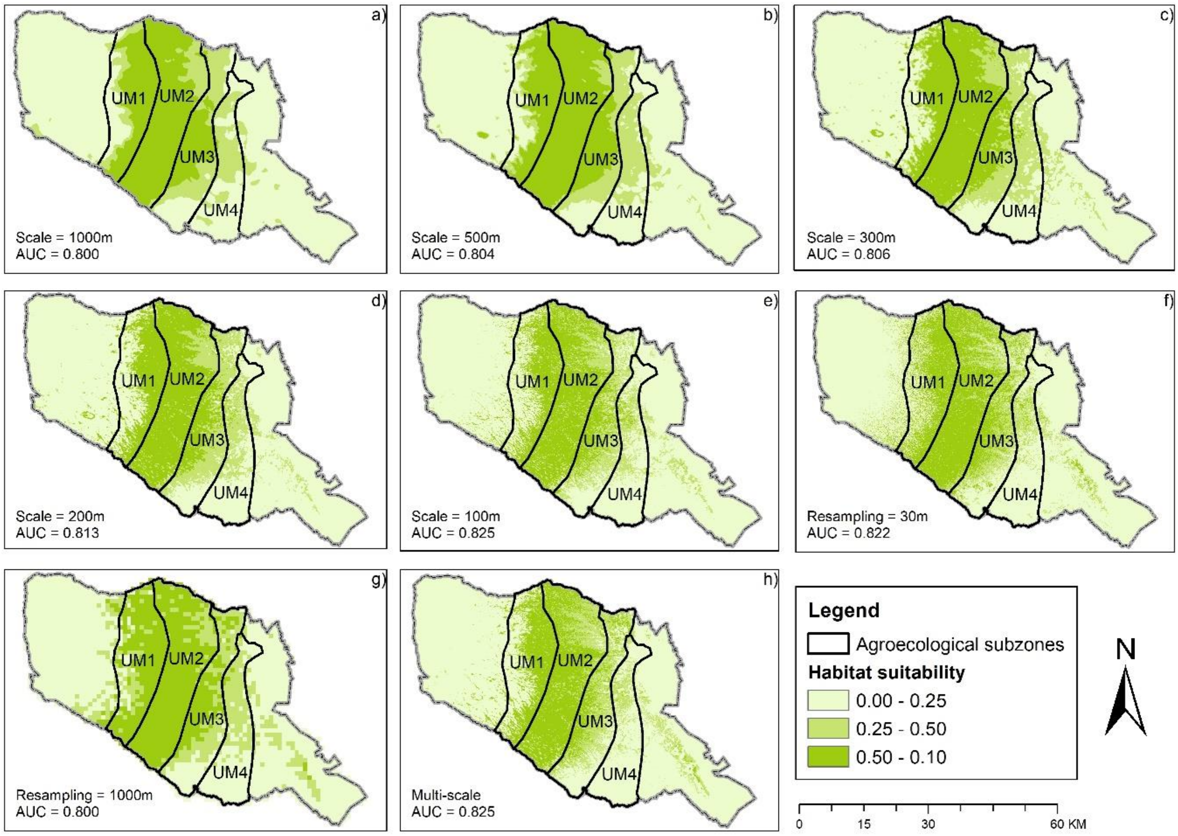

Figure 5.4: Habitat suitability maps for Arabica coffee in Murang'a, Kenya generated using explanatory variables from landscape scales of 100 m to 1000 m (a - e), resampling at 30 m (f) and 1000 m (g) pixel resolution, and multi-scale (h)

5.4.2 Variable importance

The results illustrated that the most important variable for predicting the habitat suitability of Arabica coffee in all the developed models was Bio18 (precipitation of the warmest quarter), while the elevation was the second most important variable (Table 5.2). Notably, there was a clear difference in the contribution of GNDVI when different landscape scales were considered. The GNDVI became more important for predicting the habitat suitability of Arabica coffee as the landscape scale increased, with the highest contribution noted at the 1000 m landscape scale. Interestingly, in the multi-scale model, which used the 1000 m scale GNDVI as the input variable, GNDV was the second most important variable after the Bio18 with a difference of only 1% contribution (Table 5.2). Likewise, the importance of NDWI increase with an increasing landscape scale. For instance, NDWI contributed less than 3.5% in the model performance when used at 30 m spatial resolution, however its contribution substantially increased to 16% (Table 5.2) when used at landscape scale of 100 m in the multi-scale model. On the other hand, the results showed that temperature derivatives (Bio3, Bio4 and Bio7) were the least contributing predictor in all the models, with less than 4% contribution.

Table 5.2: Contribution of each explanatory variable in the maximum entropy (MaxEnt) model for predicting habitat suitability of Arabica coffee across different pixel resolution and landscape scales. Values highlighted in bold represent the most important variables. res30 and res1000 are resampled variables at 30 m and 1000 m, respectively

	Variable contribution (%)								
Scale	Bio18	Bio3	Bio4	Bio7	GNDVI	Greeness	MSAVI	NDWI	DEM
res30	**50.2**	**3.8**	**1.4**	0.5	4.3	**11.7**	3.9	3.3	**20.8**
res1000	**58.3**	1.8	1.5	1.3	0.6	2.1	8.6	1.8	**24**
100m	**40**	2.3	0	3.2	**20.6**	6.5	1.8	7.9	**17.8**
200m	**36.3**	1.3	0.2	2.5	**21**	13.1	5	3.4	**17.1**
300m	**36.4**	2.7	0.2	3.7	**28.9**	4.6	3.3	3.5	**16.7**
500m	**42.1**	1.3	0.1	2.9	**30.3**	0	5	1	**17.3**
1000m	**34.4**	0.3	0	2.1	**35.9**	0.2	4.8	5.5	**16.7**
Multiscale	**28.2**	2.7	0	1.9	**27.3**	0.7	5.5	**15.9**	**17.7**

5.4.3 Range shifts in 2050 and 2070

Given that the multiscale and resampling to 30 m resolution produced similarly accurate Arabica coffee and pest distribution predictions, 30 m model output was used to evaluate the changes in range shifts in Arabica coffee habitat under the changing climate scenario of

RCP2.6. Table 5.3 presents the current total area (km^2) suitable for growing Arabica coffee as compared to the suitable area in 2050 and 2070 in each agro-ecological sub-zones. Overall, there is an increment in suitable areas for Arabica coffee cultivation when the temperature rise is kept under 2^{o}C. However, the suitable areas in the sub-zones are different. In specific, in UM1 and UM2, there was an increase and decrease in Arabic coffee suitable areas in 2050 and 2070, respectively. Whereas in UM3 and UM4 the suitable Arabica coffee growing area will increase in both epochs. Figure 5.5 shows the shifts in Arabica coffee suitable habitats from current to 2050 and 2070, and changes expected between 2050 and 2070. The figure shows a downward shift in area of Arabica coffee in 2070, with an increased suitable area in the UM3 and UM4 sub-zones. Notably, this shift will occur between 2050 and 2070

Table 5.3: Area in km^2 of suitable habitat for Arabica coffee under the emission pathways of RCP2.6 in 2050 and 2070 across the agro-ecological sub-zones

AEsZ	**Current (km^2)**	**In 2050 (km^2)**	**In 2070 (km^2)**
UM1	183.17	206.15	185.05
UM2	358.76	393.90	377.89
UM3	133.06	151.53	206.51
UM4	11.60	13.15	62.61
Total	686.59	764.74	832.07

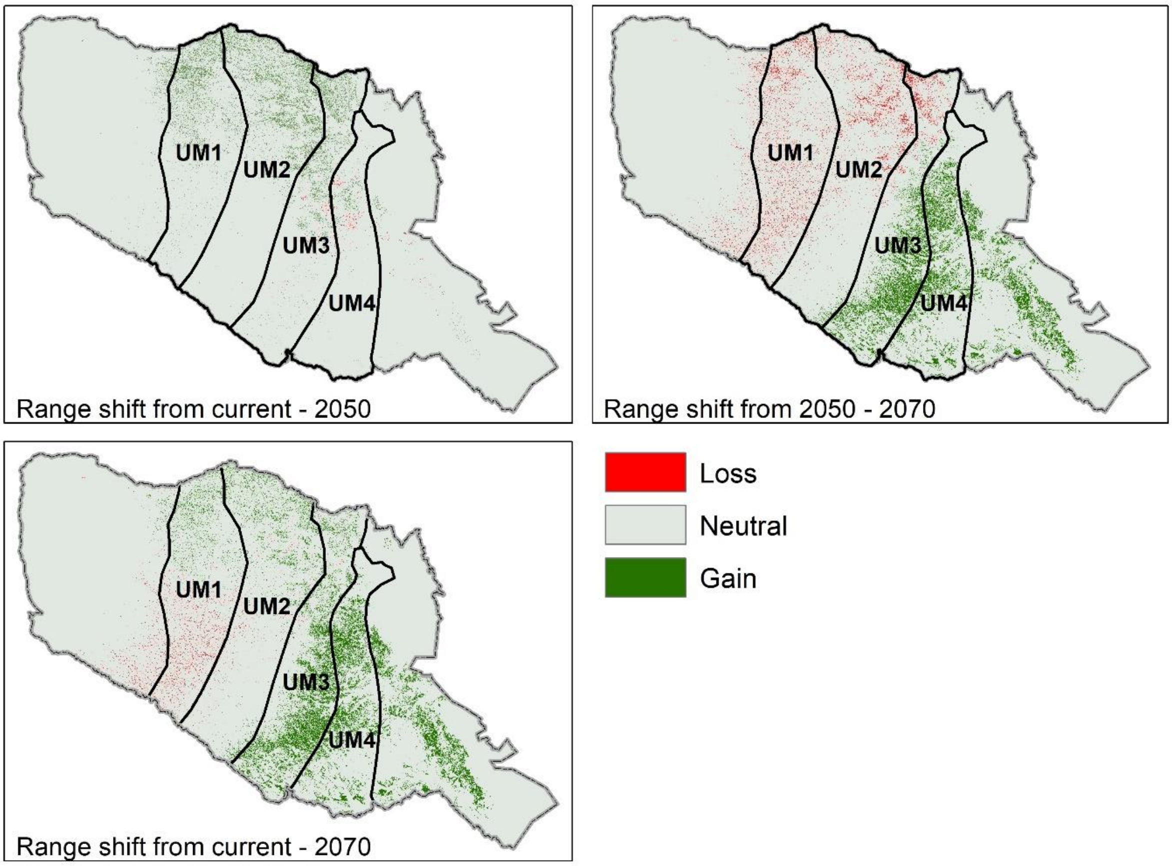

Figure 5.5: Range shifts expected in habitat distribution for Arabica coffee, H. hampei and Antestiopsis spp., in 2050 and 2070 under the RCP2.6 emission pathway

5.5 Discussion

Understanding the future impact of climate change is vital for planning and implementing climate policies that regulate anthropogenic activities. This study predicts the implication of implementing adaptation and mitigation measures against climate change as envisioned in the RCP2.6 trajectory that limits temperature rise to below 2^{o}C on Arabica coffee distribution. The study focused on the smallholder coffee agrosystem, a valuable cash crop in many developing economies that will be negatively impacted by climate change if the current anthropogenic activities that induce temperature rise continue (Bunn et al., 2015). The evidence provided in this study will help the policymakers accelerate the implementation of climate policies to avert the consequences of adopting the business-as-usual model by the end of the current century.

The study also explored the importance of landscape scale and and varying pixel sizes in predicting the habitat suitability of the Arabica coffee.

The study underscored the need for using appropriate spatial resolutions based on the geographic scale under consideration. Resampling variables to a coarse spatial resolution predicted poorly accurate Arabica coffee habitat suitability than a finer resolution. Gottschalk et al. (2011) noted similar findings on the influence of pixel size on predicting the distribution of birds using SDM. Variables with finer pixel size were better predictors than the coarse pixel ones. The study also noted the significance of the landscape scale on the environmental variables. Given that species perceive their landscape based on the scale that meets their biological needs, tailoring the environmental variables according to the landscape scale of their habitat has shown significant improvement in predicting their habitats (Bellamy et al., 2013; Grand et al., 2004). The habitat predictive models achieved the highest accuracy at 100 m landscape and the accuracy gradually declined as the landscape scale increased.

Furthermore, the greenness of vegetation extracted from satellite-based data played a major role in predicting Arabica coffee habitats when landscape scale was considered. Studies have shown that coffee was distinguishable from other vegetation using satellite-based vegetation variables (Chemura et al., 2018). This could partly interpret the high importance of GNDV and NDWI in predicting the distribution of Arabica coffee. Also, the scale of landscape could have been influenced by the fact that smallholder farmers usually grow their coffee in plots less than 2 hectares. This corroborated Mosomtai et al. (2021) findings that showed the importance of landscape scale to coffee pests such as coffee berry borer and antestia bugs. Pest with limited dispersal capacity such as coffee berry borer responds to their landscape within 100m and prefers contiguous coffee patches to facilitate their movement, unlike the antestia bugs, which have a higher dispersal capacity and can forage within 300m landscape scale.

In general, the MaxEnt models showed that there will be an increase in acreage under Arabica coffee by the end of the century. The results agree with Bunn et al. (2015), who mapped habitat suitability for Arabica and Robusta coffee globally. The notable shift in the coffee range will occur between 2050 – 2070. This is attributed to the decline in temperature rise after peaking in 2050 due to technological advancement and environmental awareness envisioned in RCP2.6. Fossil fuels will be abated by adopting bioenergy, renewable and nuclear energy, achieving net-zero emissions at the end of 2100 (van Vuuren et al., 2011b). Even beyond 2100, the advantages of keeping temperature rise below 2^{o}C will be significant. Lyon et al. (2021) modelled the impact of climate change in 2500 on agriculture and noted that under RCP2.6 there would still be an increase in suitable land for tropical crops. Range shifts of Arabica coffee will also affect primary insect pests such as coffee berry borer and the antestia bugs. Geographic shifts of Arabica coffee imply that their habitats will also shift following their host. Differences will only exist on which sub-zones would be more preferred. Previous studies show that coffee berry borer prefer a wider distribution, unlike antestia bugs, which are confined to low (*A. facetoides)* and high (*A. thunbergii)* elevations (Mosomtai et al., 2020).

Precipitation of the wettest quarter was the most significant variable in predicting the habitat suitability for Arabica coffee. The wettest quarter coincides with the long rains of March to May in Kenya, which is also the flowering period of coffee in the study area, eventually influencing the yield harvested in December. Furthermore, Arabica coffee requires a short dry spell to stimulate flowering for a guaranteed good harvest, which occurs in January and

February in Kenya (DaMatta et al., 2007). However, with erratic rainfall patterns due to climate change, continuous rainfall will lead to low yields (Damatta et al., 2006). Assessment of rainfall patterns under RCP scenarios by USAID (2017) in the East Africa region noted that there would be an increase in rainfall patterns during the short rains than the long rains (October - December), especially under RCP8.5 than RCP2.6. Possible threat to harvest loss will exist due to too much rainfall in December and the possible confounding effect of pests and diseases such as leaf rust and coffee berry borer infestation. Consequently, smallholder farmers will have to incur more costs in managing these pests and diseases.

Elevation was also a key variable in mapping habitat suitability for Arabica coffee. Studies such as Ovalle-Rivera et al. (2015) and Magrach and Ghazoul (2015) noted a shift in Arabica coffee range to higher elevations at a global scale, with little or no change when considering the East African region. In contrast, this study noted a downward shift to lower elevation, specifically in UM3 and UM4. The differences could be attributed to the scale of study, resolution and type of variables used (i.e., RCP scenario and other explanatory variables) and the source of occurrence data for making the prediction. Global studies often use variables with coarser spatial resolution and occurrence data obtained from repositories such as Global Biodiversity Information Facility (GBIF) that require data cleaning to remove duplicates, missing coordinates or oversampling before making predictions (Soberón and Peterson, 2004). This study was at a landscape scale with occurrence data collected at coffee plot level. Furthermore, additional variables from vegetation indices and topography apart from bioclimatic variables substantially contributed on the characterization of the habitat suitability of Arabica coffee. Initial preliminary results that used only bioclimatic variables noted a shift in Arabica coffee suitable habitats to a higher elevation in 2050 and a downward shift in 2070. However, when remotely sensed biophysical variables were added, the shift in Arabica coffee habitat happened in specific regions. This shows the potential bias that commonly exists when only bioclimatic variables are used to make predictions in SDM experiments (Makori et al., 2017).

5.6 Conclusion

The study underscore the need for countries to act now, formulating and implementing climate policies that will limit temperature rise to well below 2^{o}C. RCP2.6 scenario presents a hopeful future if climate policies are implemented and technological advancements in managing GHG emissions are adopted globally. Despite an increase in area under coffee, pests and diseases pressure will continue to be a challenge for smallholder farmers, but the severity under RCP2.6, especially in 2070, will be less compared to all the other scenarios.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

6.1 Introduction

Mapping farming systems in an agricultural landscape is essential for informing land use policies, quantifying ecosystem services such as pests and pathogens management, conserving beneficial arthropods, and improving crop pollination and yields (Kuemmerle et al., 2013). Agricultural landscapes are characterized by spatial arrangement (configuration) of land cover types (composition), which influence ecological processes and biodiversity at varying scales. Agricultural activities have modified the natural environment, resulting in habitat loss and disturbance of species communities and their biotic interaction. This thesis focused on the landscape ecology of smallholder coffee farms that largely drive the landscape structure and habitat integrity for supporting coffee and pest populations. In view of the changing climate, developing integrated pest management strategies relevant to each farming system and agro-ecological zone requires understanding pests, farming systems, and landscape structure to equip farmers and policymakers with the necessary mitigation, adaptation, and resilience knowledge.

This study provides essential insights into the role of landscape management of smallholdings in creating conducive ecological environments allowing for improved management of coffee pest populations. The following research questions were answered in the present study;

1. Which remote sensing dataset accurately delineates the cover types in a heterogenous coffee landscape?
2. Which critical landscape configuration and compositions influence the population dynamics of coffee berry borer and antestia bugs?

3. Does the shade and edge effects of shade and full sun coffee influence microclimate and pest abundance in coffee plots?
4. What is the impact of global warming of 1.5 ºC and 2.0 ºC on Arabica coffee growing zones and the species distribution range of the Antestia bug?

The novelty of this thesis is the longitudinal approach used to understand the factors that influence coffee pests across ecological scales. At mesoscale, the study explored the impact of a warming world under 2 ºC on habitat suitability of Arabica coffee and possible geographic shifts. This builds upon the recent findings of the IPCC special report on the impact of half a degree temperature increase on man and the environment. At the landscape scale, the study used satellite images to characterize smallholder coffee landscapes and further examine the role of landscape setup in sustaining coffee pests across an altitudinal gradient. Finally, the study links the shade and edge effects to microclimate modification and pest abundance at the farm scale.

6.2 Summary of the findings

6.2.1 Leveraging satellite-based data to map smallholder coffee farms

Data from earth observation and the use of the machine learning algorithms provide an unprecedented opportunity for mapping agricultural landscapes. Chapter two evaluated multi-source satellite images with the least cost for mapping smallholder coffee farms in central Kenya. Commercially available 3 m PlanetScope and freely available Sentinel 2 (10 – 20 m pixel resolution), and Landsat 8 (30 m pixel resolution) spectral reflectance data combined with vegetation indices (VI) were tested using a random forest classifier to characterize landscape fragmention of coffee smallhloings in central Kenya. The dataset with the highest accuracy for land cover classification was further analyzed using FRAGSTAT software to predict fragmentation indices in coffee agro-ecological sub-zones (Upper Midland UM1 – UM4) in the study area.

Thirteen-band Sentinel 2 had the highest accuracy for mapping coffee (kappa - 0.98) compared to 4-band PlanetScope (kappa – 0.85) and 11-band Landsat 8 (kappa – 0.88). Despite having the highest spatial resolution, PlanetScope had the lowest accuracy, which only improved when combined with vegetation indices. Sentinel 2 was the most robust satellite data due to the high number of spectral bands that delineated vegetation type more accurately than other satellite datasets. Similar findings were noted by Htitiou et al., (2019), Shoko and Mutanga, (2017) and Tawona et al., (2020) when using Sentinel 2 for mapping crops and grassland. The final land cover map from Sentinel 2 mapped the following classes: annual crops, banana, bareland, coffee, agroforest, grassland, perennials/shrubs, settlements, tea and waterbodies. Coffee covered over 50% of the total landscape in UM1 and UM2, while annual crops occupied 43% of the total landscape in UM3. Coffee was highly fragmented in UM3 and UM4, with the largest patches occupying 3% and 1.4% of the total landscape compared to UM1.

6.2.2 Spatial scale and landscape metrics that influence coffee pests

A network of 30 plots was assessed monthly for coffee berry borer (*Hypothenemus hampei*) and two species of antestia bugs (*Antestiopsis thunbergii* and *Antestiopsis facetoides*). The results showed a cyclic pattern with high variability of pest populations in plots across the elevation gradient and within the same agro-ecological sub-zones. The cyclic pattern was due to the coffee fruiting cycle and varied based on food and reproduction preferences. The antestia bugs prefer fully developed green berries for feeding and reproduction (Gesmalla Ahmed et al., 2016), whereas the coffee berry borer prefers the red berries dominant during the harvest seasons (Damon, 2000). However, the coffee berry observation made during this study may not accurately represent the cyclic pattern of pest population dynamic due to the competition of Brocap traps with ripe berries during the harvest season or the availability of berries on the ground or on the tree due to the absence of total picking. In the absence of red berries, the Brocap traps become more attractive to flying female borers.

Antestia bugs were mainly influenced by elevation, with *A. facetoides* preferring lower elevations and *A. thunbergii* at high elevations. This was in line with previous studies by Azrag et al. (2017, 2018) and Babin et al. (2018) that showed *A. thunbergii* preference for the high elevations where temperatures are cold enough for its development, survival, and reproduction, unlike its counterpart *A. facetoides* that prefer higher temperature. For the coffee berry borer, a wider distribution range was noted. However, localized factors such as agronomic practices, shade management, localized flowering or natural enemies could have influenced the observed abundance. Notable also was the influence of landscape structure on coffee berry borer abundance. Contiguous coffee patches in the higher agro-ecological sub-zones favoured coffee berry borer, whereas adjacency of coffee patches to either cropland or grassland favoured the abundance of antestia bugs. The limited flight capacity of the borer influenced the preference of the connected coffee patches to facilitate its movements, unlike the antestia bugs that have a high flight capacity and can thrive where coffee patches are interspersed. Patch diversity, composition, and configuration of land cover types varied in each agro-ecological sub-zones. In UM1 and UM2, coffee patches dominated the landscape, while UM3 and UM4 were the marginal coffee areas within a matrix of annual crops.

6.2.3 Shade and edge effect on microclimate and pest abundance

Coffee farming systems play a significant role in regulating coffee pest populations and modifying microclimate. This study used data loggers to measure the microclimate of shaded and full sun coffee plots, whereas the edge effect was measured using the edge density and total edge contrast index from FRAGSTAT. The role of shade was significant in modifying the microclimate of plots in the lower sub-zones. Shaded plots recorded lower mean and maximum temperature than the full sun coffee plots throughout the year. Furthermore, the mean temperature decreased with increasing edge contrast between adjacent full-sun coffee and agroforest, alluding to the importance of the adjacent cover types. For the pests, *A. thunbergii* preferred shaded plots contrary to *A. facetoides,* which preferred full sun coffee. On the other hand, coffee berry borer preference varied with elevation. The borer preferred the full sun coffee at high and mid-elevation and shaded coffee at the lower elevation.

6.2.4 Impacts of climate change on range shift of Arabica coffee habitat

IPCC's special report on the 1.5 ^{o}C global warming showed that the tropical regions, where coffee and other crops with economic importance are grown, would adversely be affected and even worsen if the temperature rises by 2 ^{o}C. Given the new findings on the importance of shade in modifying the microclimate in coffee plots, the study examined the importance of countries implementing climate-friendly policies and its impact on habitat suitability for growing Arabica coffee, the primary host of the studied pests. RCP 2.6 predicts a scenario where temperature rise is limited to below 2^{o}C by countries implementing climate-friendly policies. For the study area, the results showed an increase in the suitable coffee growing area with a shift towards the lower agro-ecological sub-zones, especially from 2050 to 2070. The models used in this study evaluated the robustness of resampling environmental variables to high and low resolution and accounting for spatial scale in the prediction accuracy, given that species perceive their landscape based on the scale that meets their biological needs. The results showed that resampling to a coarser resolution is ineffective in making accurate predictions. Furthermore, tailoring environmental variables to the optimum spatial scale for resource utilization and foraging of the species improved the prediction accuracy.

6.3 Implication of the study

Countries with limited resources can exploit the robustness of freely available 10-20 m Sentinel 2 time line datasets to generate updated land cover data. This will significantly meet the data gap in global datasets and assist in planning and policy formulations that guide the restoration of degraded landscapes and model ecosystem services, especially from shade coffee, generating integrated land management systems. The maps can also be integrated with crop phenology and climatic variables to understand the occurrence of coffee pests and diseases and predict yields for food security. Recently, land cover maps have become a critical baseline data in crop insurance against loss from extreme weather and pests and diseases and the development of AgriTech companies. The only cost that countries would have to incur is the collection of field data for verification. However, alternative methods that involve citizen science are now widely adopted, especially for large scale collection of reference data. The potential challenges with these new methodologies however, is on data integrity, but several data quality control levels are currently being adopted to minimize the errors.

Landscape structure, which is a result of landscape management by smallholder coffee farmers, limits or contributes to the thriving of coffee pests. Therefore, land use planning should be considered when establishing coffee plots with the awareness of the neighbouring patches, especially within a 300m radius. Participatory methods such as participatory geographyical information system (PGIS) can be adopted to involve the community in the decision-making process (Ujamaa Community Resource Team, 2010). Furthermore, there is a need to introduce new patches of natural vegetation in simplified coffee landscapes to disrupt the dispersal of antestia bugs and coffee berry borer. To achieve this, farmers can plant shade trees as one of the climate-smart adaptation strategies that will mitigate against the impact of climate change whilst increasing biodiversity in their farms, which will offer biological control of pests through natural enemies. Additionally, farmers can benefit from the speciality market, which often has high prices for shade coffee.

The RCP 2.6 scenario underscores the importance of implementing climate policies and investing in green technology to limit temperature rise to below 2^{o}C. The future scenario under RCP 4.5 and 8.5 predicts a loss of 50% of the current coffee-growing areas if the current anthropogenic activities continue or minimal mitigation is implemented. Achieving net-zero carbon footprints by the end of the century requires concerted efforts by all the countries, and this will reverse the negative trend of lower agro-ecological sub-zones becoming unsuitable for coffee production. Infact, these regions will create a new source of revenue for smallholder farmers and increase the country's gross domestic product.

6.4 Conclusions

The overall aim of this study was to understand the landscape ecology in smallholder coffee systems and its role in supporting coffee pests. The study adopted a hierarchical approach at ecological scales by examining the influence of shade on pest abundance at the plot scale to the impact of climate change at the regional/global level. The study concludes that,

1. Sentinel 2 provides a robust dataset for mapping land cover types due to the number of spectral bands. The SWIR bands were particularly critical for mapping the smallholder coffee landscape,
2. The landscape structure in each Kenyan agro-ecological sub-zones was unique. Therefore, landscape management recommendations should be specific to each sub-zones instead of blanket recommendations to improve the resilience of the coffee landscapes,
3. The optimum landscape scale that influences coffee berry borer is 100m and 300m for antestia bugs,
4. Due to the limited dispersal capacity, the coffee berry borer preferred connected coffee patches for ease of movement. Management strategies should introduce barriers to limit the dispersal of the borer,
5. Shade and the elevation gradient strongly influence pest distribution and should be used as control strategies for exposing pests to extreme conditions that inhibit their proliferation,
6. The edge effects of the adjacent patches are vital. Agroforest regulated the microclimate in full sun coffee plots, whereas cropland acted as alternative hosts for the antestia bugs,
7. There is an urgent need for countries to formulate and implement climate policies that will limit temperature rise to below 2^{o}C for optimum coffee production,
8. Under the RCP 2.6 scenario, there will be an increase in suitable habitats for growing Arabica coffee, especially in the lower agro-ecological sub-zones of Kenya,
9. Despite an increase in area under coffee, pests' pressure will continue to be a challenge for smallholder farmers, but the severity under RCP 2.6, especially in 2070, will be less than all the other scenarios, and

10. Policy frameworks that encourage smallholder farmers to plant shade trees to improve landscape resilience and preserve biodiversity while reducing the negative impacts of excessive use of pesticides to control pests should be formulated.

6.5 Future outlook

Earth observation data are one of the primary inputs for understanding landscape ecology. Despite the advantages of seamless data acquisition and coverage on consistent temporal periods over the strenuous and often resource constraint *in situ* data collection, satellite-based datasets face pixel resolution challenges. This study adopted the 10-20 m Sentinel 2 images, however, satellite datasets with higher resolutions, such as the WorldView series with less than a centimetre resolution, can be explored to reveal further details on the existing landscape structure in smallholding or fusing Sentinel 1 (which is synthetic aperture radar data) with the Sentinel 2 to increase the delineation of features (Ochungo et al., 2019). This study used field observations and a land cover map to classify coffee plots into full sun and shaded systems. Future studies can adopt hemispherical photography with Fisheye lenses or a Spherical crown densitometer to measure the shade level of coffee plots and biophysical variables such as leaf area index (LAI) and fraction of absorbed photosynthetically active radiation (fPAR). These biophysical variables can be upscaled to the biophysical bands in Sentinel 2, which would improve the classification of coffee bushes. Equally, agronomic practices such as pruning, fertilizer and pesticide application should be accounted for while assessing pest population dynamics. Finally, educating the community and the local stakeholders on the state of their landscape and the adaptation options available to them is key to developing resilient landscapes. Future studies can build a recommender system to facilitate this awareness process by providing location-specific landscape management options, consequently initiating behavioural change on how they manage their landscapes.

APPENDIX

Supplementary Table 2.1: Scene description for each satellite dataset

Satellite imagery	**Scene identity (ID)**	**Date of Acquisition**	**Cloud cover**	**Source**
PlanetScope (PS)	Analytic Ortho Tile no.807181	03/10/2017	0%	https://www.planet.com/
Sentinel 2 (S2)	S2A_MSIL1C_20170827T075211_N0205_R092_T37MBV	27/08/2017	2%	scihub.esa.int/dhus/
Landsat 8 (L8)	LC08_L1TP_168061_20171228_20180103_01_T1	28/12/2017	0%	https://earthexplorer.usgs.gov/

Supplementary Table 2.2: Variable importance (%) for vegetation indices and texture variables (described in Table 2) from Sentinel 2, Landsat 8, and PlanetScope datasets.

Vegetation indices						
	Sentinel 2		**Landsat 8**		**PlanetScope**	
Variables	MDA	MDG	MDA	MDG	MDA	MDG
BI	25	42	16	22	26	27
BI2	18	14	11	8	15	14
GEMI	12	10	9	8	10	12
GNDVI	10	15	14	18	11	11
MSAVI	10	9	8	12	11	14
NDPI	29	30	28	20	-	-
RI	19	20	16	12	28	22
MCARI	13	10	-	-	-	-
MTCI	14	6	-	-	-	-
REIP	11	4	-	-	-	-
S2REP	11	4	-	-	-	-
LAI	11	19	-	-	-	-
LAI_CW	15	19	-	-	-	-
LAI_CAB	10	16	-	-	-	-
FCOVER	7	10	-	-	-	-
FAPAR	7	11	-	-	-	-

Texture variables						
	Sentinel 2		**Landsat 8**		**PlanetScope**	
Variables	MDA	MDG	MDA	MDG	MDA	MDG
MAX	9	8	9	7	9	7
Homogeneity	11	7	11	8	8	8
GLCM variance	11	16	12	18	13	16
GLCM mean	8	13	10	15	11	16
GLCM correlation	11	12	11	12	11	13
Entropy	8	8	9	7	8	7
Energy	8	8	7	7	8	8
Dissimilarity	10	8	10	9	10	7
Contrast	15	11	14	11	14	9
ASM	9	8	7	7	7	8

Supplementary Table 2.3: Variable importance (%) for wavelength bands (described in Table 1) combined with vegetation indices and texture variables (described in Table 2) for PlanetScope, Landsat 8 and Sentinel 2 datasets

Sentinel 2			**PlanetScope**			**Landsat 8**		
Variables	MDA	MDG	Variables	MDA	MDG	Variables	MDA	MDG
B12	4	9	RI	12	12	B7	5	8
B3	4	7	B2	6	10	B4	4	6
B5	4	7	BI	5	9	NDPI	7	6
B11	4	5	B3	5	8	GLCM Mean	4	6
NDPI	5	5	B1	5	8	GLCM Variance	4	5
BI	3	5	GLCM Mean	5	6	B2	3	5
B2	3	5	BI2	6	6	GLCM Correlation	4	5
GLCM Variance	3	4	GLCM Variance	5	6	GNDVI	3	5
RI	4	4	B4	6	5	B3	4	5
GLCM Mean	2	3	MSAVI	4	5	Contrast	6	4
GLCM Correlation	3	3	GEMI	4	4	Dissimilarity	5	4
B4	2	3	GLCM Correlation	6	4	BI	3	4
LAI_CW	3	3	GNDVI	5	3	B6	4	4
Contrast	4	3	Contrast	5	2	RI	5	4
Energy	2	2	Energy	4	2	B5	5	4
ASM	2	2	ASM	4	2	Entropy	4	3
LAI	2	2	Dissimilarity	4	2	MSAVI	3	3
MAX	3	2	Entropy	4	2	GEMI	4	3
GNDVI	2	2	Homogeneity	4	2	BI2	4	3
LAI_CAI	2	2	MAX	4	2	Homogeneity	5	3

REFERENCES

Albertin, A., Nair, P.K.R., 2004. Farmers' Perspectives on the Role of Shade Trees in Coffee Production Systems: An Assessment from the Nicoya Peninsula, Costa Rica. Hum. Ecol. 32, 443–463. https://doi.org/10.1023/B:HUEC.0000043515.84334.76

Alignier, A., Raymond, L., Deconchat, M., Menozzi, P., Monteil, C., Sarthou, J.P., Vialatte, A., Ouin, A., 2014. The effect of semi-natural habitats on aphids and their natural enemies across spatial and temporal scales. Biol. Control 77, 76–82. https://doi.org/10.1016/j.biocontrol.2014.06.006

Alison, J., Duffield, S.J., Morecroft, M.D., Marrs, R.H., Hodgson, J.A., 2017. Successful restoration of moth abundance and species-richness in grassland created under agri-environment schemes. Biol. Conserv. 213, 51–58. https://doi.org/10.1016/j.biocon.2017.07.003

Anthony, F., Combes, M.C., Astorga, C., Bertrand, B., Graziosi, G., Lashermes, P., 2002. The origin of cultivated Coffea arabica L. varieties revealed by AFLP and SSR markers. Theor. Appl. Genet. 104, 894–900. https://doi.org/10.1007/s00122-001-0798-8

Aristizábal, L.F., Jiménez, M., Bustillo, A.E., Trujillo, H.I., P., S., 2015. (Coleoptera : Curculionidae), populations with alcohol- baited funnel traps in coffee farms in Colombia. Florida Entomol. 98, 381–383.

Avelino, J., Romero-Gurdián, A., Cruz-Cuellar, H.F., Declerck, F.A.J., 2012. Landscape context and scale differentially impact coffee leaf rust, coffee berry borer, and coffee root-knot nematodes. Ecol. Appl. 22, 584–596. https://doi.org/10.1890/11-0869.1

Azrag, A.G.A., Murungi, L.K., Tonnang, H.E.Z., Mwenda, D., Babin, R., 2017. Temperature-dependent models of development and survival of an insect pest of African tropical highlands, the coffee antestia bug Antestiopsis thunbergii (Hemiptera: Pentatomidae). J. Therm. Biol. 70, 27–36. https://doi.org/10.1016/j.jtherbio.2017.10.009

Azrag, A.G.A., Pirk, C.W.W., Yusuf, A.A., Pinard, F., Niassy, S., Mosomtai, G., Babin, R., 2018. Prediction of insect pest distribution as influenced by elevation: Combining field observations and temperature-dependent development models for the coffee stink bug, antestiopsis thunbergii (gmelin). PLoS One 13, e0199569. https://doi.org/10.1371/journal.pone.0199569

Azrag, A.G.A., Yusuf, A.A., Pirk, C.W.W., Niassy, S., Mbugua, K.K., Babin, R., 2020. Temperature-dependent development and survival of immature stages of the coffee berry borer Hypothenemus hampei (Coleoptera: Curculionidae). Bull. Entomol. Res. 110, 207–218. https://doi.org/10.1017/S0007485319000476

Babin, R., Mbondji Mbonji, P., Mendesil, E., Mugo, H.M., Lee, J.-H., Serracin, M., Rukazambuga, N.D.T.M., Miller, T.A., 2018. The Antestia Bug Complex in Africa and Asia, in: McPherson, J.E. (Ed.), Invasive Stink Bugs and Related Species (Pentatomoidea). CRC Press, Boca Raton : Taylor & Francis, 2017. https://doi.org/10.1201/9781315371221

Baez, S., Balslev, H., 2007. Edge effects on palm diversity in rain forest fragments in western Ecuador. Biodivers. Conserv. 16, 2201–2211. https://doi.org/10.1007/s10531-007-9159-5

Báldi, A., 1999. Microclimate and vegetation edge effects in a reedbed in Hungary. Biodivers. Conserv. 8, 1697–1706. https://doi.org/10.1023/A:1008901514944

Barbaro, L., van Halder, I., 2009. Linking bird, carabid beetle and butterfly life-history traits to habitat fragmentation in mosaic landscapes. Ecography (Cop.). 32, 321–333. https://doi.org/10.1111/j.1600-0587.2008.05546.x

Bebber, D.P., Castillo, Á.D., Gurr, S.J., 2016. Modelling coffee leaf rust risk in Colombia with climate reanalysis data. Philos. Trans. R. Soc. B Biol. Sci. 371. https://doi.org/10.1098/rstb.2015.0458

Belgiu, M., Drăgu, L., 2016. Random forest in remote sensing: A review of applications and future directions. ISPRS J. Photogramm. Remote Sens. 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Bellamy, C., Scott, C., Altringham, J., 2013. Multiscale, presence-only habitat suitability models: Fine-resolution maps for eight bat species. J. Appl. Ecol. 50, 892–901. https://doi.org/10.1111/1365-2664.12117

Bianchi, F.J.J.., Booij, C.J.., Tscharntke, T., 2006. Sustainable pest regulation in agricultural landscapes: a review on landscape composition, biodiversity and natural pest control. Proc. R. Soc. B Biol. Sci. 273, 1715–1727. https://doi.org/10.1098/rspb.2006.3530

Borkhataria, R., Collazo, J.A., Groom, M.J., Jordan-Garcia, A., 2012. Shade-grown coffee in Puerto Rico: Opportunities to preserve biodiversity while reinvigorating a struggling agricultural commodity. Agric. Ecosyst. Environ. 149, 164–170. https://doi.org/10.1016/j.agee.2010.12.023

Bosselmann, A.S., Dons, K., Oberthur, T., Olsen, C.S., Ræbild, A., Usma, H., 2009. The influence of shade trees on coffee quality in small holder coffee agroforestry systems in Southern Colombia. Agric. Ecosyst. Environ. 129, 253–260. https://doi.org/10.1016/j.agee.2008.09.004

Boulesteix, A.-L., Janitza, S., Kruppa, J., König, I.R., 2012. Overview of random forest methodology and practical guidance with emphasis on computational biology and bioinformatics. Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 2, 493–507. https://doi.org/10.1002/widm.1072

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324

Bukomeko, H., Jassogne, L., Kagezi, G.H., Mukasa, D., Vaast, P., 2018. Influence of shaded systems on Xylosandrus compactus infestation in Robusta coffee along a rainfall gradient in Uganda. Agric. For. Entomol. 20, 327–333. https://doi.org/10.1111/afe.12265

Bunn, C., Läderach, P., Ovalle Rivera, O., Kirschke, D., 2015. A bitter cup: climate change profile of global production of Arabica and Robusta coffee. Clim. Change 129, 89–101. https://doi.org/10.1007/s10584-014-1306-x

Camargo, M.B.P. de, 2010. The impact of climatic variability and climate change on arabic coffee crop in Brazil. Bragantia 69, 239–247. https://doi.org/10.1590/S0006-87052010000100030

Cannavo, P., Sansoulet, J., Harmand, J.M., Siles, P., Dreyer, E., Vaast, P., 2011. Agroforestry associating coffee and Inga densiflora results in complementarity for water uptake and decreases deep drainage in Costa Rica. Agric. Ecosyst. Environ. 140, 1–13. https://doi.org/10.1016/j.agee.2010.11.005

Caudill, S.A., DeClerck, F.J.A., Husband, T.P., 2015. Connecting sustainable agriculture and wildlife conservation: Does shade coffee provide habitat for mammals? Agric. Ecosyst. Environ. 199, 85–93. https://doi.org/10.1016/j.agee.2014.08.023

Cerda, R., Allinne, C., Gary, C., Tixier, P., Harvey, C.A., Krolczyk, L., Mathiot, C., Clément, E., Aubertot, J.N., Avelino, J., 2017. Effects of shade, altitude and management on multiple ecosystem services in coffee agroecosystems. Eur. J. Agron. 82, 308–319. https://doi.org/10.1016/j.eja.2016.09.019

Chakraborty, S., Newton, A.C., 2011. Climate change, plant diseases and food security: An overview. Plant Pathol. 60, 2–14. https://doi.org/10.1111/j.1365-3059.2010.02411.x

Chemura, A., Mutanga, O., Odindi, J., Kutywayo, D., 2018. Mapping spatial variability of foliar nitrogen in coffee (Coffea arabica L.) plantations with multispectral Sentinel-2 MSI data. ISPRS J. Photogramm. Remote Sens. 138, 1–11. https://doi.org/10.1016/j.isprsjprs.2018.02.004

Clarence-Smith, W.G., Topik, S., 2003. The global coffee economy in Africa, Asia, and Latin America, 1500 - 1989, The Global Coffee Economy in Africa, Asia, and Latin America, 1500-1989. https://doi.org/10.1017/CBO9780511512193

Cordero-Sancho, S., Sader, S.A., 2007. Spectral analysis and classification accuracy of coffee crops using Landsat and a topographic-environmental model. Int. J. Remote Sens. 28, 1577–1593. https://doi.org/10.1080/01431160600887680

Crawley, M.J., 2007. The R Book, Second Edi. ed. John Wiley & Sons, Ltd, Chichester, UK. https://doi.org/10.1002/9780470515075

Crozier, G.E., Niemi, G.J., 2003. Using patch and landscape variables to model bird abundance in a naturally heterogeneous landscape. Can. J. Zool. 81, 441–452. https://doi.org/10.1139/z03-022

Cunniffe, N.J., Koskella, B., E. Metcalf, C.J., Parnell, S., Gottwald, T.R., Gilligan, C.A., 2015. Thirteen challenges in modelling plant diseases. Epidemics 10, 6–10. https://doi.org/10.1016/j.epidem.2014.06.002

DaMatta, F.M., Ronchi, C.P., Maestri, M., Barros, R.S., 2007. Ecophysiology of coffee growth and production. Brazilian J. Plant Physiol. 19, 485–510. https://doi.org/10.1590/S1677-04202007000400014

Damatta, Fábio M, Cochicho Ramalho, J.D., Damatta, F M, Ramalho, J.D.C., 2006. Impacts of drought and temperature stress on coffee physiology and production: a review, Braz. J. Plant Physiol.

Damon, A., 2000. A review of the biology and control of the coffee berry borer, Hypothenemus hampei (Coleoptera: Scolytidae). Bull. Entomol. Res. 90, 453–465. https://doi.org/10.1017/s0007485300000584

Davis, A.P., Gole, T.W., Baena, S., Moat, J., 2012. The Impact of Climate Change on Indigenous Arabica Coffee (Coffea arabica): Predicting Future Trends and Identifying Priorities. PLoS One 7, 10–14. https://doi.org/10.1371/journal.pone.0047981

Davis, A.P., Govaerts, R., Bridson, D.M., Stoffelen, P., 2006. An annotatated taxonomic of the genus coffea (Rubiaceae). Bot. J. Linn. Soc. 152, 465–512. https://doi.org/10.1111/j.1095-8339.2006.00584.x

de Oliveira Pires, M.S., de Carvalho Alves, M., Pozza, E.A., 2020. Multispectral radiometric characterization of coffee rust epidemic in different irrigation management systems. Int. J. Appl. Earth Obs. Geoinf. 86, 102016. https://doi.org/10.1016/j.jag.2019.102016

Delegido, J., Verrelst, J., Meza, C.M., Rivera, J.P., Alonso, L., Moreno, J., 2013. A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems. Eur. J. Agron. 46, 42–52. https://doi.org/10.1016/j.eja.2012.12.001

Diekötter, T., Crist, T.O., 2013. Quantifying habitat-specific contributions to insect diversity in agricultural mosaic landscapes. Insect Conserv. Divers. 6, 607–618. https://doi.org/10.1111/icad.12015

Donald, P.F., 2004. Biodiversity Impacts of Some Agricultural Commodity Production Systems. Conserv. Biol. 18, 17–38. https://doi.org/10.1111/j.1523-1739.2004.01803.x du Parc, E., Yasukawa, L., 2020. The 2019-2020 Australian bushfires: from temporary evacuation to longer-term displacement, Idmc.

Duflot, R., Ernoult, A., Burel, F., Aviron, S., 2016. Landscape level processes driving carabid crop assemblage in dynamic farmlands. Popul. Ecol. 58, 265–275. https://doi.org/10.1007/s10144-015-0534-x

Dufour, B.P., Frerot, B., 2008. Optimization of coffee berry borer, Hypothenemus hampei Ferrari (Col., Scolytidae), mass trapping with an attractant mixture. J. Appl. Entomol. 132, 591–600. https://doi.org/10.1111/j.1439-0418.2008.01291.x

Ehrenbergerová, L., Šenfeldr, M., Habrová, H., 2017. Impact of tree shading on the microclimate of a coffee plantation: A case study from the Peruvian Amazon. Bois Forets des Trop. 4, 13–22.

Escadafal, 1993. SOIL OPTICAL PROPERTIES AND ENVIRONMENTAL APPLICATIONS. Int. Arch. Photogramm. Remote Sens. 29, 709–715.

Escadafal, R., 1993. Remote sensing of soil color: principles and applications. Remote Sens. Rev. 7, 261–279. https://doi.org/10.1080/02757259309532181

European Commission, 2017. Agri-environmental schemes: impacts on the agricultural environment, Science for Environment Policy. https://doi.org/10.2779/633983

Fang, H., Baret, F., Plummer, S., Schaepman-Strub, G., 2019. An Overview of Global Leaf Area Index (LAI): Methods, Products, Validation, and Applications. Rev. Geophys. 57, 739–799. https://doi.org/10.1029/2018RG000608

Fekadu, G., Melesse, M., Girmaye, B., 2016. The prevalence and impact of coffee arthropod pests in the gedeo indigenous agro forestry systems, Southern Ethiopia. Int. J. Biodivers. Conserv. 8, 233–243. https://doi.org/10.5897/IJBC2016.0954

Fletcher, R., Fortin, M.-J., 2018. Spatial Ecology and Conservation Modeling. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-01989-1

Franklin, J., 2010. Mapping species distributions, Mapping Species Distributions: Spatial Inference and Prediction. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511810602

Garrity, D., Dixon, J., Boffa Jean-Marc, 2012. Understanding African Farming Systems, Science and Policy Implications, Food Security in Africa: Bridging Research and Practice.

Gesmalla Ahmed, A., Kananu Murungi, L., Babin, R., 2016. Developmental biology and demographic parameters of antestia bug Antestiopsis thunbergii (Hemiptera: Pentatomidae), on Coffea arabica (Rubiaceae) at different constant temperatures. Int. J. Trop. Insect Sci. 36, 119–127. https://doi.org/10.1017/S1742758416000072

Gil, Z.N., Benavides, P., De Souza, O., Acevedo, F.E., Lima, E., Zhang, Y., 2015. Molecular markers as a method to evaluate the movement of Hypothenemus hampei (Ferrari). J. Insect Sci. 15, 1–8. https://doi.org/10.1093/jisesa/iev058

GoK, 2018. Murang ' a County Integrated Development Plan 2018 - 2022.

Gosme, M., Dufour, L., Daniel, H., Aguirre, I., Gosme, M., Dufour, L., Daniel, H., Aguirre, I., Dupraz, C., 2020. Microclimatic effect of agroforestry on diurnal temperature cycle To cite this version : HAL Id : hal-02744212 MICROCLIMATIC EFFECT OF AGROFORESTRY ON.

Gottschalk, T.K., Aue, B., Hotes, S., Ekschmitt, K., 2011. Influence of grain size on species-habitat models. Ecol. Modell. 222, 3403–3412. https://doi.org/10.1016/j.ecolmodel.2011.07.008

Grand, J., Buonaccorsi, J., Cushman, S.A., Griffin, C.R., Neel, M.C., 2004. A multiscale landscape approach to predicting bird and moth rarity hotspots in a threatened pitch pine-scrub oak community. Conserv. Biol. https://doi.org/10.1111/j.1523-1739.2004.00555.x

Hajian-Forooshani, Z., Gonthier, D.J., Marín, L., Iverson, A.L., Perfecto, I., 2014. Changes in species diversity of arboreal spiders in Mexican coffee agroecosystems: Untangling the web of local and landscape influences driving diversity. PeerJ 2014. https://doi.org/10.7717/peerj.623

Han, H., Guo, X., Yu, H., 2016. Variable selection using Mean Decrease Accuracy and Mean Decrease Gini based on Random Forest. Proc. IEEE Int. Conf. Softw. Eng. Serv. Sci. ICSESS 0, 219–224. https://doi.org/10.1109/ICSESS.2016.7883053

Hansen, M.C., Potapov, P. V., Goetz, S.J., Turubanova, S., Tyukavina, A., Krylov, A., Kommareddy, A., Egorov, A., 2016. Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data. Remote Sens. Environ. 185, 221–232. https://doi.org/10.1016/j.rse.2016.02.023

Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Haralick, Shanmugam, Dinstein_1973_Textural features for image classification.pdf. IEEE Trans. Syst. Man. Cybern.

Hargis, C.D., Bissonette, J.A., David, J.L., 1998. The behavior of landscape metrics commonly used in the study of habitat fragmentation. Landsc. Ecol. 13, 167–186. https://doi.org/10.1023/A:1007965018633

Hemp, A., 2006. The Banana Forests of Kilimanjaro: Biodiversity and Conservation of the Chagga Homegardens. Biodivers. Conserv. 15, 1193–1217. https://doi.org/10.1007/s10531-004-8230-8

Hijmans, R.J., Elith, J., 2016. Species distribution modeling with R Introduction.

Hindorf, H., Omondi, C.O., 2011. A review of three major fungal diseases of Coffea arabica L. in the rainforests of Ethiopia and progress in breeding for resistance in Kenya. J. Adv. Res. 2, 109–120. https://doi.org/10.1016/j.jare.2010.08.006

Hsu, R.C.-C., Tamis, W.L.M., Raes, N., de Snoo, G.R., Wolf, J.H.D., Oostermeijer, G., Lin, S.-H., 2012. Simulating climate change impacts on forests and associated vascular epiphytes in a subtropical island of East Asia. Divers. Distrib. 18, 334–347. https://doi.org/10.1111/j.1472-4642.2011.00819.x

Htitiou, A., Boudhar, A., Lebrini, Y., Hadria, R., Lionboui, H., Elmansouri, L., Tychon, B., Benabdelouahab, T., 2019. The Performance of Random Forest Classification Based on Phenological Metrics Derived from Sentinel-2 and Landsat 8 to Map Crop Cover in an Irrigated Semi-arid Region. Remote Sens. Earth Syst. Sci. 2, 208–224. https://doi.org/10.1007/s41976-019-00023-9

Hurskainen, P., Adhikari, H., Siljander, M., Pellikka, P.K.E., Hemp, A., 2019. Auxiliary datasets improve accuracy of object-based land use/land cover classification in heterogeneous savanna landscapes. Remote Sens. Environ. 233, 111354. https://doi.org/10.1016/j.rse.2019.111354

ICO, 2019. Country Coffee Profile.

ICO, 2016. Coffee production to remain stable despite Arabica / Robusta divergence.

IPCC, 2021. Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

IPCC, 2019. Summary for Policymakers. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

IPCC, 2018. Summary for Poliymakers, in: Global Warming of 1.5°C: An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change. p. 32.

Ismangil, D., Wiegant, D., Hagos, E., van Steenbergen, F., Kool, M., Sambalino, F., Castelli, G., Bresci, E., Hagos, F., 2016. Managing the Microclimate, Practical Note 27.

Jaetzold, R., Schmidt, H., Hornetz, B., Shisanya, C., 2007. FARM MANAGEMENT HANDBOOK OF KENYA Subpart B2, Farm Management Handbook.

Jaramillo, J., Borgemeister, C., Baker, P., 2006. Coffee berry borer Hypothenemus hampei (Coleoptera: Curculionidae): searching for sustainable control strategies. Bull. Entomol. Res. 96, 223–233. https://doi.org/10.1079/BER2006434

Jaramillo, J., Chabi-Olaye, A., Kamonjo, C., Jaramillo, A., Vega, F.E., Poehling, H.M., Borgemeister, C., 2009. Thermal tolerance of the coffee berry borer Hypothenemus hampei: Predictions of climate change impact on a tropical insect pest. PLoS One 4, 1–11. https://doi.org/10.1371/journal.pone.0006487

Jaramillo, J., Setamou, M., Muchugu, E., Chabi-Olaye, A., Jaramillo, A., Mukabana, J., Maina, J., Gathara, S., Borgemeister, C., 2013. Climate Change or Urbanization? Impacts on a Traditional Coffee Production System in East Africa over the Last 80 Years. PLoS One 8. https://doi.org/10.1371/journal.pone.0051815

Jha, S., Bacon, C.M., Philpott, S.M., Ernesto Méndez, V., Läderach, P., Rice, R.A., 2014. Shade Coffee: Update on a Disappearing Refuge for Biodiversity. Bioscience 64, 416–

428. https://doi.org/10.1093/biosci/biu038

Jiménez-Valverde, A., 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling. Glob. Ecol. Biogeogr. 21, 498–507. https://doi.org/10.1111/j.1466-8238.2011.00683.x

Karungi, J., Nambi, N., Ijala, A.R., Jonsson, M., Kyamanywa, S., Ekbom, B., 2015. Relating shading levels and distance from natural vegetation with hemipteran pests and predators occurrence on coffee. J. Appl. Entomol. 139, 669–678. https://doi.org/10.1111/jen.12203

Kebati, R., Nyangeri, J., Omondi, C., Kubochi, J., 2016. Effect of Artificial Shading on Severity of Coffee Berry Disease in Kiambu County, Kenya. Annu. Res. Rev. Biol. 9, 1–11. https://doi.org/10.9734/ARRB/2016/23326

Ketema, H., Wei, W., Legesse, A., Wolde, Z., Temesgen, H., Yimer, F., Mamo, A., 2020. Quantifying smallholder farmers' managed land use/land cover dynamics and its drivers in contrasting agro-ecological zones of the East African Rift. Glob. Ecol. Conserv. 21. https://doi.org/10.1016/j.gecco.2019.e00898

Khosravi, R., Hemami, M.R., Cushman, S.A., 2019. Multi-scale niche modeling of three sympatric felids of conservation importance in central Iran. Landsc. Ecol. 34, 2451–2467. https://doi.org/10.1007/s10980-019-00900-0

Kimathi, E., Tonnang, H.E.Z., Subramanian, S., Cressman, K., Abdel-Rahman, E.M., Tesfayohannes, M., Niassy, S., Torto, B., Dubois, T., Tanga, C.M., Kassie, M., Ekesi, S., Mwangi, D., Kelemu, S., 2020. Prediction of breeding regions for the desert locust Schistocerca gregaria in East Africa. Sci. Rep. 10, 1–10. https://doi.org/10.1038/s41598-020-68895-2

Kindlmann, P., Burel, F., 2008. Connectivity measures: A review. Landsc. Ecol. 23, 879–890. https://doi.org/10.1007/s10980-008-9245-4

Kirkpatrick, T.W., 1937. STUDIES ON THE ECOLOGY OF COFFEE PLANTATIONS IN EAST AFRICA. II. THE AUTECOLOGY OF ANTESTIA SPP. (PENTATOMIDAE) WITH A PARTICULAR ACCOUNT OF A STREPSIPTEROUS PARASITE. Trans. R. Entomol. Soc. London 86, 247–343. https://doi.org/10.1111/j.1365-2311.1937.tb00245.x

Kleijn, D., Sutherland, W.J., 2003. How effective are European agri-environment schemes in conserving and promoting biodiversity? J. Appl. Ecol. https://doi.org/10.1111/j.1365-2664.2003.00868.x

Krishnan, S., Kushalappa, C.G., Shaanker, R.U., Ghazoul, J., 2012. Status of pollinators and their efficiency in coffee fruit set in a fragmented landscape mosaic in South India. Basic Appl. Ecol. 13, 277–285. https://doi.org/10.1016/j.baae.2012.03.007

Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., Levers, C., Lindner, M., Plutzar, C., Verkerk, P.J., van der Zanden, E.H., Reenberg, A., 2013. Challenges and opportunities in mapping land use intensity globally. Curr. Opin. Environ. Sustain. https://doi.org/10.1016/j.cosust.2013.06.002

Kumsa, L., Hylander, K., Gurmessa, D., Nemomissa, S., 2016. Patch area and current coffee management determine woody plant diversity in patches of semi-forest coffee embedded in an agricultural matrix. Glob. Ecol. Conserv. 8, 230–240. https://doi.org/10.1016/j.gecco.2016.09.012

Kutywayo, D., Chemura, A., Kusena, W., Chidoko, P., Mahoya, C., 2013. The Impact of Climate Change on the Potential Distribution of Agricultural Pests: The Case of the

Coffee White Stem Borer (Monochamus leuconotus P.) in Zimbabwe. PLoS One 8, 1–11. https://doi.org/10.1371/journal.pone.0073432

Lacaux, J.P., Tourre, Y.M., Vignolles, C., Ndione, J.A., Lafaye, M., 2007. Classification of ponds from high-spatial resolution remote sensing: Application to Rift Valley Fever epidemics in Senegal. Remote Sens. Environ. 106, 66–74. https://doi.org/10.1016/j.rse.2006.07.012

Landmann, T., Eidmann, D., Cornish, N., Franke, J., Siebert, S., 2019. Optimizing harmonics from Landsat time series data: the case of mapping rainfed and irrigated agriculture in Zimbabwe. Remote Sens. Lett. 10, 1038–1046. https://doi.org/10.1080/2150704X.2019.1648901

Landmann, T., Piiroinen, R., Makori, D.M., Abdel-Rahman, E.M., Makau, S., Pellikka, P., Raina, S.K., 2015. Application of hyperspectral remote sensing for flower mapping in African savannas. Remote Sens. Environ. 166, 50–60. https://doi.org/10.1016/j.rse.2015.06.006

Legendre, P., Oksanen, J., ter Braak, C.J.F., 2011. Testing the significance of canonical axes in redundancy analysis. Methods Ecol. Evol. 2, 269–277. https://doi.org/10.1111/j.2041-210X.2010.00078.x

Lescourret, F., Magda, D., Richard, G., Adam-Blondon, A.-F., Bardy, M., Baudry, J., Doussan, I., Dumont, B., Lefèvre, F., Litrico, I., Martin-Clouaire, R., Montuelle, B., Pellerin, S., Plantegenest, M., Tancoigne, E., Thomas, A., Guyomard, H., Soussana, J.-F., 2015. A social–ecological approach to managing multiple agro-ecosystem services. Curr. Opin. Environ. Sustain. 14, 68–75. https://doi.org/10.1016/J.COSUST.2015.04.001

Levin, N., 1999. Fundamentals of remote sensing. Tel Aviv University, Tel Aviv, Israel.

https://doi.org/http://www.geoservis.ftn.uns.ac.rs/downloads/ISP/1999-fundamentals-of-remote-sensing.pdf

Li, H., Reynolds, J.F., 1993. A new contagion index to quantify spatial patterns of landscapes. Landsc. Ecol. 8, 155–162. https://doi.org/10.1007/BF00125347

Li, J., Roy, D.P., 2017. A global analysis of Sentinel-2a, Sentinel-2b and Landsat-8 data revisit intervals and implications for terrestrial monitoring. Remote Sens. 9. https://doi.org/10.3390/rs9090902

Liebig, T., Babin, R., Ribeyre, F., Läderach, P., van Asten, P., Poehling, H.M., Jassogne, L., Cilas, C., Avelino, J., 2018. Local and regional drivers of the African coffee white stem borer (Monochamus leuconotus) in Uganda. Agric. For. Entomol. 20, 514–522. https://doi.org/10.1111/afe.12284

Liu, B., Yang, L., Yang, Y., Lu, Y., 2016. Influence of landscape diversity and composition on the parasitism of cotton bollworm eggs in maize. PLoS One 11, 1–12. https://doi.org/10.1371/journal.pone.0149476

Lott, J.E., Ong, C.K., Black, C.R., 2009. Understorey microclimate and crop performance in a Grevillea robusta-based agroforestry system in semi-arid Kenya. Agric. For. Meteorol. 149, 1140–1151. https://doi.org/10.1016/j.agrformet.2009.02.002

Lyon, C., Saupe, E.E., Smith, C.J., Hill, D.J., Beckerman, A.P., Stringer, L.C., Marchant, R., McKay, J., Burke, A., O'Higgins, P., Dunhill, A.M., Allen, B.J., Riel-Salvatore, J., Aze, T., 2021. Climate change research and action must look beyond 2100. Glob. Chang. Biol. 1–13. https://doi.org/10.1111/gcb.15871

Magrach, A., Ghazoul, J., 2015. Climate and pest-driven geographic shifts in global coffee production: Implications for forest cover, biodiversity and carbon storage. PLoS One 10, 1–15. https://doi.org/10.1371/journal.pone.0133071

Makori, D., Fombong, A., Abdel-Rahman, E., Nkoba, K., Ongus, J., Irungu, J., Mosomtai, G., Makau, S., Mutanga, O., Odindi, J., Raina, S., Landmann, T., 2017. Predicting Spatial Distribution of Key Honeybee Pests in Kenya Using Remotely Sensed and Bioclimatic Variables: Key Honeybee Pests Distribution Models. ISPRS Int. J. Geo-Information 6, 66. https://doi.org/10.3390/ijgi6030066

Mariño, Y.A., Pérez, M., Gallardo, F., Trifilio, M., Cruz, M., Bayman, P., 2016. Sun vs. shade affects infestation, total population and sex ratio of the coffee berry borer (Hypothenemus hampei) in Puerto Rico. Agric. Ecosyst. Environ. 222, 258–266. https://doi.org/10.1016/j.agee.2015.12.031

Martel, G., Aviron, S., Joannon, A., Lalechère, E., Roche, B., Boussard, H., 2019. Impact of farming systems on agricultural landscapes and biodiversity: From plot to farm and landscape scales. Eur. J. Agron. 107, 53–62. https://doi.org/10.1016/J.EJA.2017.07.014

Mathieu, R., Pouget, M., Cervelle, B., Escadafal, R., 1998. Relationships between satellite-based radiometric indices simulated using laboratory reflectance data and typic soil color of an arid environment. Remote Sens. Environ. 66, 17–28. https://doi.org/10.1016/S0034-4257(98)00030-3

McGarigal, K., Cushman, S.A., Neel, M.C., Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program. https://doi.org/10.1016/S0022-3913(12)00047-9

Meehan, T.D., Werling, B.P., Landis, D.A., Gratton, C., 2011. Agricultural landscape simplification and insecticide use in the Midwestern United States. Proc. Natl. Acad. Sci. U. S. A. 108, 11500–11505. https://doi.org/10.1073/pnas.1100751108

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. Ecography (Cop.). 36, 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x

Messing, R.H., 2012. The coffee berry borer (hypothenemus hampei) invades hawaii: Preliminary investigations on trap response and alternate hosts. Insects 3, 640–652. https://doi.org/10.3390/insects3030640

Monroy, L., Mulinge, W., Witwer, M., 2013. Analysis of incentives and disincentives for coffee in Kenya. Technical notes series. Rome.

Mosomtai, G., Azrag, A.G.A., Babin, R., Abdel-Rahman, E.M., Odindi, J., Mutanga, O., Tonnang, H.E.Z., Landmann, T., David, G., 2021. Functional land cover scale for three insect pests with contrasting dispersal strategies in a fragmented coffee-based landscape in Central Kenya. Agric. Ecosyst. Environ. 319, 107558. https://doi.org/10.1016/j.agee.2021.107558

Mosomtai, G., Odindi, J., Abdel-rahman, E.M., Babin, R., Fabrice, P., Mutanga, O., 2020. Landscape fragmentation in coffee agroecological subzones in central Kenya : a multiscale remote sensing approach. J. Appl. Remote Sens. 14. https://doi.org/10.1117/1.JRS.14.044513

Múrria, C., Sáinz-Bariáin, M., Vogler, A.P., Viza, A., González, M., Zamora-Muñoz, C., 2019. Vulnerability to climate change for two endemic high-elevation, low-dispersive *Annitella* species (Trichoptera) in Sierra Nevada, the southernmost high mountain in Europe. Insect Conserv. Divers. icad.12387. https://doi.org/10.1111/icad.12387

Naimi, B., Araújo, M.B., 2016. Sdm: A reproducible and extensible R platform for species distribution modelling. Ecography (Cop.). 39, 368–375. https://doi.org/10.1111/ecog.01881

Nesper, M., Kueffer, C., Krishnan, S., Kushalappa, C.G., Ghazoul, J., 2017. Shade tree diversity enhances coffee production and quality in agroforestry systems in the Western Ghats. Agric. Ecosyst. Environ. 247, 172–181. https://doi.org/10.1016/j.agee.2017.06.024

Njihia, T.N., Torto, B., Murungi, L.K., Irungu, J., Mwenda, D.M., Babin, R., 2018. Ripe coffee berry volatiles repel second instar nymphs of Antestia bugs (Heteroptera: Pentatomidae: Antestiopsis thunbergii). Chemoecology 28, 91–100. https://doi.org/10.1007/s00049-018-0259-3

Ochungo, P., Veldtman, R., Abdel-Rahman, E.M., Raina, S., Muli, E., Landmann, T., 2019. Multi-sensor mapping of honey bee habitats and fragmentation in agro-ecological landscapes in Eastern Kenya. Geocarto Int. 0, 1–22. https://doi.org/10.1080/10106049.2019.1629645

Oksanen, J., Blanchet, F.G., Friendly, M., Kindt, R., Legendre, P., Mcglinn, D., Minchin, P.R., O'hara, R.B., Simpson, G.L., Solymos, P., Henry, M., Stevens, H., Szoecs, E., Maintainer, H.W., 2019. Package "vegan" Title Community Ecology Package. Community Ecol. Packag. 2, 1–297.

Ortega-Huerta, M.A., Komar, O., Price, K.P., Ventura, H.J., 2012. Mapping coffee plantations with land sat imagery: An example from El Salvador. Int. J. Remote Sens. 33, 220–242. https://doi.org/10.1080/01431161.2011.591442

Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., Schroth, G., 2015. Projected shifts in Coffea arabica suitability among major global producing regions due to climate change. PLoS One 10, 1–13. https://doi.org/10.1371/journal.pone.0124155

Ovuka, M., Lindqvist, S., 2000. Rainfall variability in Murang'a district, Kenya: Meteorological data and farmers' perception. Geogr. Ann. Ser. A Phys. Geogr. 82, 107–

119. https://doi.org/10.1111/j.0435-3676.2000.00116.x

Pedersen, E.J., Miller, D.L., Simpson, G.L., Ross, N., 2019. Hierarchical generalized additive models in ecology: An introduction with mgcv. PeerJ 2019. https://doi.org/10.7717/peerj.6876

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Modell. 190, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Piato, K., Lefort, F., Subía, C., Caicedo, C., Calderón, D., Pico, J., Norgrove, L., 2020. Effects of shade trees on robusta coffee growth, yield and quality. A meta-analysis. Agron. Sustain. Dev. 40. https://doi.org/10.1007/s13593-020-00642-3

Planet Labs, 2016. Planet Imagery Product Specification.

Plantegenest, M., Le May, C., Fabre, F., 2007. Landscape epidemiology of plant diseases. J. R. Soc. Interface 4, 963–972. https://doi.org/10.1098/rsif.2007.1114

Plećaš, M., Gagić, V., Janković, M., Petrović-Obradović, O., Kavallieratos, N.G., Tomanović, Ž., Thies, C., Tscharntke, T., Ćetković, A., 2014. Landscape composition and configuration influence cereal aphid-parasitoid-hyperparasitoid interactions and biological control differentially across years. Agric. Ecosyst. Environ. 183, 1–10. https://doi.org/10.1016/j.agee.2013.10.016

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H., Sorooshian, S., 1994. A modified soil adjusted vegetation index. Remote Sens. Environ. 48, 119–126. https://doi.org/10.1016/0034-4257(94)90134-1

R Core Team, 2020. R: The R Project for Statistical Computing [WWW Document]. https://doi.org/r-project.org/

Rand, T.A., Tylianakis, J.M., Tscharntke, T., 2006. Spillover edge effects: The dispersal of agriculturally subsidized insect natural enemies into adjacent natural habitats. Ecol. Lett. https://doi.org/10.1111/j.1461-0248.2006.00911.x

Raper, T.B., Varco, J.J., 2014. Canopy-scale wavelength and vegetative index sensitivities to cotton growth parameters and nitrogen status. Precis. Agric. 16, 62–76. https://doi.org/10.1007/s11119-014-9383-4

Rather, T.A., Kumar, S., Khan, J.A., 2020. Multi-scale habitat selection and impacts of climate change on the distribution of four sympatric meso-carnivores using random forest algorithm. Ecol. Process. 9. https://doi.org/10.1186/s13717-020-00265-2

Razgour, O., Rebelo, H., Puechmaille, S.J., Juste, J., Ibáñez, C., Kiefer, A., Burke, T., Dawson, D.A., Jones, G., 2014. Scale-dependent effects of landscape variables on gene flow and population structure in bats. Divers. Distrib. 20. https://doi.org/10.1111/ddi.12200

Redzwan, G., Ramli, M.F., 2007. Geo-referencing the satellite image from Google Earth by relative and absolute positioning. Malaysian J. Sci. 26, 135–141.

Reis, M.S., Escada, M.I.S., Dutra, L. V., Sant'Anna, S.J.S., Vogt, N.D., 2018. Towards a reproducible LULC hierarchical class legend for use in the Southwest of Pará State, Brazil: A comparison with remote sensing data-driven hierarchies. Land 7. https://doi.org/10.3390/land7020065

Ribeyre, F., Avelino, J., 2012. Impact of field pests and diseases on coffee quality. pp. 151–176.

Robinson, R.A., 1977. Plant Pathosystems. Ann. N. Y. Acad. Sci. 287, 238–242. https://doi.org/10.1111/j.1749-6632.1977.tb34243.x

Rusch, A., Chaplin-Kramer, R., Gardiner, M.M., Hawro, V., Holland, J., Landis, D., Thies, C., Tscharntke, T., Weisser, W.W., Winqvist, C., Woltz, M., Bommarco, R., 2016. Agricultural landscape simplification reduces natural pest control: A quantitative synthesis. Agric. Ecosyst. Environ. 221, 198–204. https://doi.org/10.1016/j.agee.2016.01.039

Saah, D., Tenneson, K., Matin, M., Uddin, K., Cutter, P., Poortinga, A., Ngyuen, Q.H., Patterson, M., Johnson, G., Markert, K., Flores, A., Anderson, E., Weigel, A., Ellenburg, W.L., Bhagarva, R., Aekakkararungroj, A., Bhandari, B., Khanal, N., Housman, I., Potapov, P., Tyukavina, A., Maus, P., Ganz, D., Clinton, N., Chishtie, F., 2019. Land cover mapping in data scarce environments: challenges and opportunities. Front. Environ. Sci. 7, 150. https://doi.org/10.3389/FENVS.2019.00150

Samnegård, U., Hambäck, P.A., Nemomissa, S., Hylander, K., 2014. Local and Regional Variation in Local Frequency of Multiple Coffee Pests Across a Mosaic Landscape in Coffea arabica's Native Range. Biotropica 46, 276–284. https://doi.org/10.1111/btp.12106

Saturni, F.T., Jaffé, R., Metzger, J.P., 2016. Landscape structure influences bee community and coffee pollination at different spatial scales. Agric. Ecosyst. Environ. 235, 1–12. https://doi.org/10.1016/j.agee.2016.10.008

Schowalter, T.D., 2006. Insect Ecology. Elsevier. https://doi.org/10.1016/B978-0-12-088772-9.X5022-5

Schweiger, O., Maelfait, J.P., Van Wingerden, W., Hendrickx, F., Billeter, R., Speelmans, M., Augenstein, I., Aukema, B., Aviron, S., Bailey, D., Bukacek, R., Burel, F., Diekötter, T., Dirksen, J., Frenzel, M., Herzog, F., Liira, J., Roubalova, M., Bugter, R., 2005. Quantifying the impact of environmental factors on arthropod communities in agricultural landscapes across organizational levels and spatial scales. J. Appl. Ecol. 42, 1129–1139. https://doi.org/10.1111/j.1365-2664.2005.01085.x

Shoko, C., Mutanga, O., 2017. Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species. ISPRS J. Photogramm. Remote Sens. 129, 32–40. https://doi.org/10.1016/j.isprsjprs.2017.04.016

Siles, P., Harmand, J.M., Vaast, P., 2010. Effects of Inga densiflora on the microclimate of coffee (Coffea arabica L.) and overall biomass under optimal growing conditions in Costa Rica. Agrofor. Syst. 78, 269–286. https://doi.org/10.1007/s10457-009-9241-y

Smith, A.C., Fahrig, L., Francis, C.M., 2011. Landscape size affects the relative importance of habitat amount, habitat fragmentation, and matrix quality on forest birds. Ecography (Cop.). 34, 103–113. https://doi.org/10.1111/j.1600-0587.2010.06201.x

Smith, C., Barton, D., Johnson, M.D., Wendt, C., Milligan, M.C., Njoroge, P., Gichuki, P., 2015. Bird communities in sun and shade coffee farms in Kenya. Glob. Ecol. Conserv. 4, 479–490. https://doi.org/10.1016/j.gecco.2015.09.004

Soberón, J., Peterson, a T., 2004. Biodiversity informatics: managing and applying primary biodiversity data. Philos. Trans. R. Soc. Lond. B. Biol. Sci. 359, 689–698. https://doi.org/10.1098/rstb.2003.1439

Suárez, L.R., Suárez Salazar, J.C., Casanoves, F., Ngo Bieng, M.A., 2021. Cacao agroforestry systems improve soil fertility: Comparison of soil properties between forest, cacao agroforestry systems, and pasture in the Colombian Amazon. Agric. Ecosyst. Environ. 314. https://doi.org/10.1016/j.agee.2021.107349

Sun, X., Long, Z., Jia, J., 2021. A multi-scale Maxent approach to model habitat suitability for the giant pandas in the Qionglai mountain, China. Glob. Ecol. Conserv. 30, e01766. https://doi.org/10.1016/j.gecco.2021.e01766

Talhinhas, P., Batista, D., Diniz, I., Vieira, A., Silva, D.N., Loureiro, A., Tavares, S., Pereira, A.P., Azinheira, H.G., Guerra-Guimarães, L., Várzea, V., Silva, M. do C., 2017. The coffee leaf rust pathogen Hemileia vastatrix: one and a half centuries around the tropics. Mol. Plant Pathol. 18, 1039–1051. https://doi.org/10.1111/mpp.12512

Tawona, B., Dube, T., Niassy, S., Kimathi, E., Landmann, T., Khan, Z., Abdel-rahman, E.M., 2020. Int J Appl Earth Obs Geoinformation Is it possible to discern Striga weed (Striga hermonthica) infestation levels in maize agro-ecological systems using in-situ spectroscopy ? Int J Appl Earth Obs Geoinf. 85, 102008. https://doi.org/10.1016/j.jag.2019.102008

Tôrres, N.M., De Marco, P., Santos, T., Silveira, L., de Almeida Jácomo, A.T., Diniz-Filho, J. a. F., 2012. Can species distribution modelling provide estimates of population densities? A case study with jaguars in the Neotropics. Divers. Distrib. 18, 615–627. https://doi.org/10.1111/j.1472-4642.2012.00892.x

Tscharntke, T., Klein, A.M., Kruess, A., Steffan-Dewenter, I., Thies, C., 2005. Landscape perspectives on agricultural intensification and biodiversity - Ecosystem service management. Ecol. Lett. https://doi.org/10.1111/j.1461-0248.2005.00782.x

Tscharntke, T., Sekercioglu, C.H., Dietsch, T. V., Sodhi, N.S., Hoehn, P., Tylianakis, J.M., 2008. Landscape constraints on functional diversity of birds and insects in tropical agroecosystems. Ecology. https://doi.org/10.1890/07-0455.1

Tscharntke, T., Tylianakis, J.M., Rand, T.A., Didham, R.K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T.O., Dormann, C.F., Ewers, R.M., Fründ, J., Holt, R.D., Holzschuh, A., Klein, A.M., Kleijn, D., Kremen, C., Landis, D.A., Laurance, W., Lindenmayer, D., Scherber, C., Sodhi, N., Steffan-Dewenter, I., Thies, C., van der Putten, W.H., Westphal, C., 2012. Landscape moderation of biodiversity patterns and processes - eight hypotheses. Biol. Rev. https://doi.org/10.1111/j.1469-185X.2011.00216.x

Turner, M.G., Gardner, R.H., O'Neill, R. V., 2001. Landscape Ecology in Theory and Practice. Pattern and Process, National Geographic. https://doi.org/10.1007/b97434

Ujamaa Community Resource Team, 2010. Participatory Land Use Planning as a Tool for Community Empowerment in Northern Tanzania.

USAID, 2017. Vulnerability , Impacts and Adaptation Assessment in the East Africa Region, Vulnerability, Impacts and Adaptation Assessment in the East Africa Region.

Vaast, P., Harmand, J., Rapidel, B., Jagoret, P., Deheuvels, O., 2016. Climate Change and Agriculture Worldwide. Clim. Chang. Agric. Worldw. 209–224. https://doi.org/10.1007/978-94-017-7462-8

van Asten, P.J.A., Wairegi, L.W.I., Mukasa, D., Uringi, N.O., 2011. Agronomic and economic benefits of coffee-banana intercropping in Uganda's smallholder farming systems. Agric. Syst. 104, 326–334. https://doi.org/10.1016/j.agsy.2010.12.004

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011a. The representative concentration pathways: An overview. Clim. Change 109, 5–31. https://doi.org/10.1007/s10584-011-0148-z

van Vuuren, D.P., Stehfest, E., den Elzen, M.G.J., Kram, T., van Vliet, J., Deetman, S., Isaac, M., Goldewijk, K.K., Hof, A., Beltran, A.M., Oostenrijk, R., van Ruijven, B., 2011b. RCP2.6: Exploring the possibility to keep global mean temperature increase below 2°C.

Clim. Change 109, 95–116. https://doi.org/10.1007/s10584-011-0152-3

Vancutsem, C., Marinho, E., Kayitakire, F., See, L., Fritz, S., 2013. Remote Sensing Harmonizing and Combining Existing Land Cover/Land Use Datasets for Cropland Area Monitoring at the African Continental Scale. Remote Sens 5, 19–41. https://doi.org/10.3390/rs5010019

Veres, A., Petit, S., Conord, C., Lavigne, C., 2013. Does landscape composition affect pest abundance and their control by natural enemies? A review. Agric. Ecosyst. Environ. 166, 110–117. https://doi.org/10.1016/j.agee.2011.05.027

Verma, P., Raghubanshi, A., Srivastava, P.K., Raghubanshi, A.S., 2020. Appraisal of kappa-based metrics and disagreement indices of accuracy assessment for parametric and nonparametric techniques used in LULC classification and change detection. Model. Earth Syst. Environ. https://doi.org/10.1007/s40808-020-00740-x

Vermeulen, S.J., Campbell, B.M., Ingram, J.S.I., 2012. Climate change and food systems. Annu. Rev. Environ. Resour. 37, 195–222. https://doi.org/10.1146/annurev-environ-020411-130608

Vivone, Gemine, Alparone, L., Chanussot, J., Dalla Mura, Mauro, Garzelli, Andrea, Member, S., Licciardi, G.A., Restaino, R., Wald, L., Vivone, G, Dalla Mura, M, Garzelli, A, 2015. A Critical Comparison Among Pansharpening Algorithms. IEEE Trans. Geosci. Remote Sens. 53. https://doi.org/10.1109/TGRS.2014.2361734

Waller, J.., Bigger, M., Hillocks, R.., 2007. Coffee pests, diseases and their management. CABI, Wallingford. https://doi.org/10.1079/9781845931292.0000

Weiss, M., Baret, F., 2016. S2ToolBox Level 2 products: LAI, FAPAR, FCOVER - Version 1.1. Sentin. ToolBox Level2 Prod. 53.

Xue, J., Su, B., 2017. Significant remote sensing vegetation indices: A review of developments and applications. J. Sensors 2017. https://doi.org/10.1155/2017/1353691

Zhang, H.K., Roy, D.P., Yan, L., Li, Z., Huang, H., Vermote, E., Skakun, S., Roger, J.C., 2018. Characterization of Sentinel-2A and Landsat-8 top of atmosphere, surface, and nadir BRDF adjusted reflectance and NDVI differences. Remote Sens. Environ. 215, 482–494. https://doi.org/10.1016/j.rse.2018.04.031

Ziv, Y., Davidowitz, G., 2019. When landscape ecology meets physiology: Effects of habitat fragmentation on resource allocation trade-offs. Front. Ecol. Evol. 7, 1–8. https://doi.org/10.3389/fevo.2019.00137

Zou, Y., Bianchi, F.J.J.A., Jauker, F., Xiao, H., Chen, J., Cresswell, J., Luo, S., Huang, J., Deng, X., Hou, L., van der Werf, W., 2017. Landscape effects on pollinator communities and pollination services in small-holder agroecosystems. Agric. Ecosyst. Environ. 246, 109–116. https://doi.org/10.1016/j.agee.2017.05.035

Zurita, G., Pe'er, G., Bellocq, M.I., Hansbauer, M.M., 2012. Edge effects and their influence on habitat suitability calculations: A continuous approach applied to birds of the Atlantic forest. J. Appl. Ecol. https://doi.org/10.1111/j.1365-2664.2011.02104.x

Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A., Smith, G.M., 2009. Mixed effects models and extensions in ecology with R, Mixed Effects Models and Extensions in Ecology with R, Statistics for Biology and Health. Springer New York, New York, NY. https://doi.org/10.1007/978-0-387-87458-6