CARBON STOCKS VARIABILITY IN AGRO ECOSYSTEMS ALONG AN ALTITUDINAL GRADIENT: A CASE STUDY OF TAITA HILLS, KENYA

By

CRISPUS MUGAMBI NJERU

Reg. No: I80/90841/2013

B.Sc (Hons), Egerton University; M.Sc., Moi University

A thesis submitted to the University of Nairobi

in fulfillment of the requirements for the award of degree of doctor of Philosophy in

Plant Ecology

2016

DECLARATION

Declaration by the Candidate

This thesis is my original work and has not been presented for award of degree to any other University. No part of this thesis may be reproduced without prior permission of the Author and/or the University of Nairobi.

Njeru, Crispus Mugambi (Reg. No: I80/90841/2013)

Signature: ____________________________ Date: ______________________________

Approval by Supervisors

This thesis has been submitted for examination with our approval as University supervisors.

Prof. J.I. Kinyamario (University of Nairobi)

Signature: ____________________________ Date: ______________________________

Dr. Samuel Kiboi (University of Nairobi)

Signature: ____________________________ Date: ______________________________

Dr. Samira Mohamed (International Centre of Insect Physiology and Ecology)

Signature: ____________________________ Date: ______________________________

Dr. Sunday Ekesi (International Centre of Insect Physiology and Ecology)

Signature: ____________________________ Date: ______________________________

DEDICATION

To my beloved parents

ACKNOWLEDGEMENTS

This study was supported by the project Climate Change Impacts on Ecosystem Services and Food Security in Eastern Africa (CHIESA) project, funded by the Ministry for Foreign Affairs of Finland. I am extremely grateful my Ph.D. supervisors; Prof. Jenesio Kinyamario and Drs. Samuel Kiboi, Samira Mohamed and Sunday Ekesi for their support in development of the study proposal, implementation of field activities and thesis write-up. Special thanks to Dr. Eduardo Maeda from the University of Helsinki for co-authoring my manuscripts which appear as main chapters of this thesis. Dr James Mutegi is much appreciated for his ideas in formulating the original research proposal and review of publications derived from this study.

I thank the Director General, KARLO for according me study leave opportunity to pursue my dreams. The equipment, laboratory services and administrative support were highly appreciated.

The eighteen months of fieldwork could not have been possible without the kind assistance of CHIESA Coordinating office at ICIPE, Duduville Campus Nairobi. I am extremely grateful to the Project Coordinator, Dr Tino Johansson for welcoming me to doctoral studies at ICIPE, training opportunities offered and support he accorded me every step of the way. I remain indebted to M/s Karen Wambui for her tireless support in organizing field logistics and sorting administrative issues that touched on my wellbeing at the campus. God bless you.

My special thanks go to CHIESA P.I Prof. Petri Pellika from the University of Helsinki and his team at the department of Geosciences and Geography for the numerous GIS trainings and graciously hosting my stay in Finland as i struggled with laboratory analysis.

Fieldwork would also not have been possible without the many assistant who helped in field sampling, data entry and laboratory analysis. I remain extremely thankful to all of you. Thanks you Paul and Margaret at ICRAF for assistance in repair, service and calibration of the Gas Chromatograph used in chamber CO_2 gas measurements. Much thanks to staff at Irido springs Guesthouse in Wudanyi, for their hospitality and keeping my sampling equipment and samples safe while conducting fieldwork.

Finally, I express my sincere appreciation to my family, friends and colleagues at KALRO and ICIPE for their continued friendship, love and support during the four years spent engaged in this research.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ACRONYMS

BD	Bulk density
C	Carbon
CK	Co-Kriging
CO2	Carbon dioxide
CV	Coefficient of Variation
DEM	Digital Elevation Model
dNdC	Denitrification Decomposition
EABH	East Africa Biodiversity Hotspot
EVI	Enhanced Vegetation Index
EzANOVA	Analysis of Variance (ez = type “2”)
GHG	Greenhouse gas
GIS	Geographical Information Service
HSD	Honest significant differences
IDW	Inverse Distance Weighted
IPCC	Inter-parliamentary Panel on Climate Change
JF	January – February
JJAS	June - July – August - September
KALRO	Kenya Agricultural and Livestock Research Organization
KFS	Kenya Forestry Service
KNBS	Kenya National Bureau of statistics
LDSF	Land degradation Surveillance Framework

LST	Land Surface Temperature
MAM	March - April – May
MDD	Minimum Detectable Difference
MIR	Mid Infra-Red
MODIS	Moderate-resolution Imaging Spectro-radiometer
N	Nitrogen
NIR	Near Infra Red
OK	Ordinary Kriging
OND	October – November - December
PVC	Polyvinyl chloride
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SSA	sub Saharan Africa
TN	Total Nitrogen
VPD	Vapor pressure deficit
WFPS	Water Filled Pore Space
WWW	World Wide Web

ABSTRACT

This study quantifies the effect of land cover change and seasonality on soil organic carbon and carbon dioxide emissivity. It takes to account the coupled inter-relationships with other ecological factors such as temperature and moisture. Next, the study assesses how topographic and ecological factors drive spatial soil nutrient stock variations and quantifies the observations required to discriminate stock detection in the mountain ecosystem. Thereafter, the study derives and evaluates modeling frameworks that integrate remote sensing, geography information systems and field measured ecological data to maximally explain soil nutrient stocks variation from terrain and seasonal dimensions. In order to address the objectives and answer research questions, activities described in this thesis combined advanced tools with renowned (geo) statistical methods. The results present a simple yet effective approach to establish baseline soil gas emissions and nutrient stocks, taking into account limitations posed by terrain accessibility and resources availability.

The results of a one year chamber based soil CO_2 sampling investigation within the study transect show seasonal and spatial soil CO_2 emission patterns were most significantly explained by rainfall and land surface temperature patterns within the five land cover types assessed. Specifically, forest and agro-forestry land use situated from 1400 to 2200 m contributed to the highest mean monthly CO_2 fluxes compared to the shrub and cereal croplands mainly below 1400 m elevation. Similarly, the mean monthly soil CO_2 relationship with ambient temperature indices were highly variable below 1400 m elevation compared to transect areas beyond this range. Higher spatial and temporal soil CO_2 variability was derived in regression models combining altitude to either land surface temperature or rainfall compared to those solely using altitude. Soil organic carbon (soil OC) and total nitrogen (TN) stocks assessments show suppressed but positive linear relationship between altitude and either soil OC (R^2= 0.30; p-value < 0.05) or TN (R^2 = 0.35; p-value < 0.05) that varies within altitude categories. Moreover, nutrient stocks were comparable and lower in croplands and agro-forestry systems in contrast to nutrient rich natural land cover systems. Altitude, soil temperature and soil water were significant controls for soil OC and TN stocks explaining > 30 % and > 80 % variation in the low and high altitude ranges respectively. Detection of carbon and nitrogen stock varied with altitudinal ranges and depended on innate soil nutrient stocks. Derived landscape position and terrain ruggedness classification schemes were used to assess spatial soil OC and TN stocks and revealed subtle differences between land surface and intrinsic soil properties. Landscape position explained lower plot soil OC and TN stocks variation (CV < 0.5) compared to terrain ruggedness (CV > 0.5). Bulk density was a dominant soil OC predictor in the landscape position scheme, with valley ($r^2 = 0.74$) and plateau ($r^2 = 0.77$) models explaining higher variation by including slope and soil moisture. Finally, mixed soil OC and TN stocks patterns were revealed in the conventional wet (March-April-May, MAM and October-November-December, OND) and dry (January-February, JF and June-July-August-September, JJAS) seasonal evaluation. Significant inter-seasonal mean monthly soil OC and TN stocks variations were observed in maize and forest but were absent in avocado and shrub land cover plots. Seasonal mean monthly soil % C and % N concentrations revealed an increasing trend from low to high altitude categories, with large inter-seasonal coefficients of variation. The pattern is revealed for instance, in the more than 50 % change in soil % C concentration from MAM to JJAS seasons at 1300 - 1800 and 1800 - 2300 m elevation ranges. Soil OC stock revealed the highest statistical seasonal co-relationship with daytime and nighttime land surface temperature, soil water filled pore space and soil pH. Prediction models i.e soil C % predicted using Inverse Distance Weighting and using ordinary kriging, soil C % co-kriged with soil pH and with WFPS, compared favorably in their seasonal MAM (from 0.5 to 12 %) and JJAS (from 0.5 to 14 %) predictions. However, the models predicted varied inter-seasonal changes (from -5 to 1 % C) within different areas of the study transect. The study concludes that altitude driven land cover and topographic

micro-climates contributed differentially to seasonal - spatial soil CO_2 fluxes and nutrient heterogeneity in the Taita Hills. The baselines established in this study can be adopted for other environments bearing similar land cover and altitudinal characteristics within East Africa Afromontaine ecosystems. The framework(s) used for this study can similarly be adopted for comparative evaluation, and can be improved through use of rapidly advancing high resolution digital elevation models. The results from this study are an useful input to national carbon inventory exercises. They can also serve as a guide to design of rehabilitation, land health surveillance and soil fertility improvement options for use by smallholders, land resource managers and development partners in the Taita Taveta country.

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

1.1.1 Degraded state of mountain ecosystems

About 26 % of the global population is situated within and adjacent to mountain environments (Meybeck *et al.*, 2001). Mountain environments in Kenya and the rest of sub-Sahara Africa (SSA) region are mostly located in high potential areas suited to agriculture and human settlement. Their unique diversity in terms of agro-ecological conditions, territory characteristics, infrastructure availability, policy environments, economic and social-cultural conditions offer plenty of opportunities for livelihood sustenance and survival (Wymann von Dach *et al.*, 2013). In SSA region, mountain ecosystems are uniquely characterized by smallholder nature, diversified crop production and integration of forest, agro-forests and cropping activities. Furthermore, their rich floral and fauna diversity endears them as hotspots for tourism and biodiversity conservation.

Despite their rich ecosystems, mountain ecosystems are generally very fragile. Heterogeneity in elevation often results to extremities in moisture, temperature, humidity, winds and insolation, fostering conditions that contribute to slow soil formation, poor vegetation growth and soil erosion. In the recent past, studies (Huber *et al.*, 2013; Ward *et al.*, 2014; Zanini, 2015) assessing the vulnerability of mountain ecosystems have proved their declining agricultural potential, habitat destruction and poor management. These studies have shown that deforestation, land use and cover changes and the global climate change are affecting the mountain environments in an unprecedented manner. Low soil fertility has been recognized as a major contributor to reduced ecosystem productivity in East Africa mountain ecosystems. Soil nutrient stocks not only continue to decline as forest lands are converted to agricultural croplands (Bekunda *et al.*, 2004; Were *et al.*, 2015) but the rapid agricultural expansion in foothills and lowlands (Maeda *et al.*, 2010a) is a critical threat to soil and water conservation, nutrient mining and loss of biodiversity.

In Kenya, indigenous closed canopy forests between years 2005 - 2008 were estimated to constitute 2.4% of total area of the country (Businge *et al.*, 2011). Within the same duration, woodlands, bush lands and grasslands in Kenya constituted approximately 5.9%, which constitute less than 10% forest cover within the country when combined with canopy forests. A close scrutiny of the remaining forests in Kenya reveals a rapidly declining land cover trend. For instance, in the Eastern Arc Mountains (EAM) that traverse Kenya and Tanzania, indigenous forests have decreased by 50% (Pellikka *et al.*, 2009), with only 1% of native forest cover left within forest fragments of the Taita Hills in Kenya (Maeda *et al.*, 2010b). Similarly, massive deforestation in Kakamega destroyed about 14% of forest land cover between 1975 and 1986, incurring a net carbon loss between 0.4 - 0.6 Tg C (Glenday, 2006). This state of degradation is evident in similar ecosystems (Kairo *et al.*, 2001; Serneels and Lambin, 2001; Baldyga *et al.*, 2008; Swallow *et al.*, 2009) within East Africa Region.

Variations in soil nutrient stocks are driven by spatial magnitudes' in ecosystem land cover, thus forest destruction and land cover change reduces the potential for soil nutrient replenishments through biomass contribution. Moreover, model based assessments (Zöbisch *et al.*, 1995; Maeda *et al.*, 2010b) predict rapid soil erosion and accelerated run-off in forest converted agricultural croplands, whereas other studies (Shepherd and Soule, 1998; Tittonell *et al.*, 2007) show negative soil C, N and P budgets in converted croplands managed under varying farmer resource endowments

1.1.2 Soil surface emissions within land use and cover types

Agricultural and forestry land uses contribute to anthropogenic greenhouse (GHG) emissions in terrestrial atmosphere. However, the current GHG gas emissions from SSA are insignificant compared to emission from Asia, America and Europe (Conrad, 1996; Vågen *et al.,* 2005). Nevertheless, as intensification in crop production, agricultural mechanization and fertilizer use increases to cater for a rising population food requirement, the consequences to regional and continental emission budgets requires closer scrutiny. Surface soil carbon dioxide (CO_2) and other greenhouse gasses (GHG) emissions vary seasonally and spatially due to environmental and soil conditions in different ecosystems (Davidson *et al.*, 2000; Paustian *et al.*, 2000)

In tropical mountain ecosystems undergoing rapid land cover change, surface soil flux emission patterns are influenced by altitude driven environmental variables that control litterfall dynamics and nutrients depositions. These include temperature and moisture conditions (Epron *et al.,* 2006; Merbold *et al.*, 2009a; Otieno *et al.*, 2010).Moreover, distinct surface emissivity differences between land uses in tropical mountain ecosystems have been proved (Mosier *et al.*, 2004; Mutuo *et al.*, 2005), whereas the effect of management practices such tillage systems on soil fluxes has been shown by Guo *et al.* (2015). Variations in surface soil flux emissions result from methodological frameworks employed (Houghton *et al.*, 2001; Ogle *et al.*, 2013). Generally, globally generalized models take little consideration for the dynamic and diverse nature of tropical environments where climate, soil types, vegetation types, land use activities vary within short distances. In SSA mountain ecosystems, intensified inputs (e.g. fertilizer) use and continued land degradation is likely to increase the potential for biogenic GHG gas emissions (Batjes, 2004a; Burney *et al.,* 2010). On the other hand, the potential to sequester carbon and associated non-carbon GHG gasses through beneficial agricultural practices such as agro-forestry systems (Verchot *et al.*, 2007) and conservation agriculture (Abdalla *et al.*, 2013) in agricultural croplands remains high.

1.1.3 Perspectives for assessment of soil nutrient stocks

In the last few decades, methodological advances for measurement of soil nutrients turnover have enabled quantification of soil carbon and nitrogen stocks in space and time. In SSA region, baselines soil organic stocks and their change have been assessed at a national (Batjes, 2004a; Kamoni *et al.*, 2007) and supra-national (Hengl *et al.*, 2015; Kempen *et al.*, 2015) scales. At a smaller ecosystem and catchment scales, studies (Tamooh *et al.*, 2012; Vågen *et al.*, 2012; Were *et al.*, 2015) have mapped spatial distributions of soil nutrient stocks within different land use and cover types in Kenya.

Soil organic carbon and nutrient stocks are regulated by complex processes that are a combined effect of soils properties (e.g soil type and texture) and their interactions with management practices, farming systems and biophysical factors specific to an ecosystem. In the tropics, climate and topography play a critical role in influencing SOC stocks and their thresholds, with rainfall, temperature, humidity and solar radiation being long term drivers for nutrient translocation and decomposition (Knorr *et al.*, 2005). In elevated mountain ecosystems, topography also plays a central role at influencing soil physical chemical condition by controlling soil water balance and erosional processes (Takata *et al.*, 2007; Zhang *et al.*, 2011). Specific topographic attributes critical to soil nutrient stocks estimates and management in elevated ecosystems include; slope position, terrain ruggedness and elevation (Tan *et al.*, 2004). Land use management is another key driver for spatio-temporal SOC variations, influencing decomposition and mineralization processes in the tropics. Land conversion from forest to croplands influences the quantity and quality of organic material contribution thus having a direct influence of SOC levels (Shepherd *et al.*, 2005). Farming practices that incorporate agroforestry tree-crop systems increase the potential sources for SOM inputs, whereas, those that involve use of organic material for mulching, nutrient harvesting and burning deplete SOM pools.

Measurements of soil nutrient stocks has currently evolved to methodological frameworks that employ geospatial tools to define aerial environmental and topographic mapping units, which are then used to derive point data (Maeda *et al.*, 2010b; Hengl *et al.*, 2015). Derived empirical soil nutrient stocks models and predictions can then be tested and developed for any ecosystem under scrutiny using different scales aided by satellite imagery for interpolation.

1.2 Rationale for the study

In order to manage the fertility of degraded soils in mountain ecosystems and improve their crop productivity in Kenya, a proper understanding of soil nutrient stocks and balances within different land use and cover types is necessary. However, and with emphasis on mountain ecosystems, lack of empirical data hinders the crucial appraisal of the consequences of land cover loss to soil nutrient stocks along the elevation. Temperature, rainfall and other environmental drivers have a significant influence on spatial and temporal soil nutrient stock and gas flux patterns in Kenya mountain ecosystems, the magnitude of which remains largely unexplored. Similarly, topographic terrain attributes contribute significantly and differentially to soil nutrient stocks within land cover systems, of which less is known in tropical Kenya and the wider SSA mountain ecosystems. Although numerous studies have quantified the loss of soil quality when forests are converted to agricultural croplands, there exists few studies that have assessed such soil nutrient stocks changes in mountain ecosystems undergoing land use change.
The magnitude of soil C, N and P budgets in mountain (topographies with local elevation range > 600 masl), farming communities due to nutrient mining and soil losses and management counterbalance by households with varying resource endowment remain less explored. Additionally, the potential benefit of agro-forestry systems commonly practiced by majority of smallholder farmers, at improving soil quality through nutrient additions requires further and continued research in highland ecosystems.

This study explores the utility of a spatio-temporal framework that quantifies soil nutrient stocks and CO_2 emission levels at various scales; from plot (land cover), topographic (altitude gradient) and the temporal (seasonal) scales in the Taita Hills, a typical mountain ecosystem located in southeastern Kenya. The observed soil stock patterns are analyzed for patterns, trends and associations, which are then used to derive spatio-predictions over space and time using environmental and topographic variables. The study further explores soil nutrient stocks differences between different land cover types, topographic gradations and seasonal cycles in a bid to establish current baselines in the mountain ecosystem and how they are influenced by land cover change.

1.3 Study objectives

1.3.1 Broad Objective

The overall objective of the study was to assess the variability of soil carbon and nitrogen stocks and emissions, and their underlying ecological driver patterns within land uses and along an altitudinal gradient in the Taita Hills, southeastern Kenya.

1.3.2 Specific Objectives

The specific objectives of the study were;

(i) To determine the spatial and temporal variability in soil $CO_{2\text{-flux}}$ and their ecological drivers from land cover systems in an elevated ecosystem,

(ii) To determine the effect of topographic and environmental drivers on spatial soil organic carbon and nitrogen stocks and their detection thresholds and,

(iii) To quantify spatial and seasonal soil carbon and nitrogen changes and patterns in an elevated ecosystem using environmental and topographic proxies

1.4 Research Hypothesis

This study tested the following hypothesis;

(i) Surface soil emissions in tropical mountain (LER 400 - 2500 m) ecosystems have a spatial dependence whose magnitude is similar within land cover types,

(ii) The magnitude of soil organic carbon and nitrogen stocks is similar within land cover types along an elevation gradient

(iii) Soil organic carbon and nitrogen stocks have a temporal dependence whose magnitude is seasonally similar, and

(iv) In mountain ecosystems, topographic and environmental drivers influence soil organic and nitrogen stocks and their measurements precision in a similar manner

1.5 Outline of the thesis

Chapter 1 briefly introduces the mountain ecosystems, highlighting their current state of degradation and inherent limitations in assessing soil nutrient stocks. Study objectives and research hypothesis are also offered. Chapter 2 critically examines the vast literature on the carbon cycle and its partitioning to various sources and sinks. Current methodologies employed for the deeper understanding of carbon cycle are also discussed and critiqued. Chapter 3 depicts the general biophysical characteristics of the Taita Hills and delineation of different land use and cover types and altitude gradations within study transect. Chapter 4 explores the effects of topographic and environmental drivers on surface soil CO_2 emissions in both time and space. This assessment is explored within the land cover types assessed in the study. Chapter 5 evaluates soil organic carbon and nitrogen patterns in the study transect and how these patterns vary spatially with land cover types. The concept of soil nutrient stocks detection limits is applied within altitude gradations to assess the magnitude of samples required to detect nutrient stocks at a certain confidence. Chapter 6 investigates the influence of specific topographic and terrain attributes on spatial soil carbon and nitrogen stocks. It highlights the underlying environmental drivers within these radiometric classifications. Chapter 7 compliments chapter 5 by exploring the seasonal variations in soil organic carbon and nitrogen trends. Seasonal soil carbon and nitrogen nutrient stock maps are then derived using kriging prediction models within the study area. Chapter 8, which incorporates the general discussion and conclusions, synthesizes results from different chapters of this thesis. Lastly, the utility of topographic classification and gradation schemes is discussed. Potential refinements of the methodological framework utilized in the study are highlighted and finally, recommendations offered.

CHAPTER TWO

LITERATURE REVIEW

2.1 Soil organic Carbon (SOC).

Soil organic carbon (SOC) is defined as carbon (C) in the soil from an organic origin. Soil organic matter (SOM) is generally agreed to contain 58 % SOC (i.e elemental C) (Wander, 2004). Soil Organic Matter (SOM) is a continuum, generally constituted of plant, animal and microbial residues, their transformation products and by-products (Guggenberger *et al.*, 2006). The complexity of organic matter is defined by organic constituents of plant, microbial and animal tissues at various stages of decomposition. This property distinguishes soils from being not only a mass of fine mineral particles with molecular properties but rather a dynamic ecosystem property. Organic matter plays an important role in maintenance of soil physical, chemical and microbial characteristics and functions, such as colour, water holding capacity, nutrient source, soil complex formation and so on. The functional importance of organic matter is summarized in its contribution to soil productive capacity, its ability to transform and store matter and energy and its capacity to regulate water and air movements (Wander, 2004). Organic matter recently added to soil enhances its biological activity, whereas materials of recent and intermediate age contribute to soils physical status. In this sense, the loss of soil organic matter reduces soil productive capacity.

2.1.1 Environmental controls for SOM

Organic matter content of any soil is largely determined by the five major soil pedogenic factors; climate, organisms, relief, parent material and time, in addition to vegetation (White, 2013) and, ranges from less than 1% in predominantly sandy soils to 100% in wholly organic soils. Historically, the totality of soil organic matter in the top soil was ascribed to above ground plant carbon inputs and organic matter in the top 30 cm soil surface (Batjes, 1996). Stable organic matter was thought to comprise of preserved non decomposable plant inputs and humic substances whose chemical composition rendered them inert to microbial decomposition (Schmidt *et al.*, 2011). Emerging knowledge shows that plant roots and rhizosphere inputs make a large contribution to SOM pools through partial degradation and microbial products compared to the contribution of humic substances (Wander, 2004).

In the past, widely applied ecosystem models employed the chemical kinetic theory (Arrhenius, 1889), to show that decomposition rates increased with temperature when substrate availability and enzyme activity do not constrain reaction rates (Davidson and Janssens, 2006). However, reviews by later studies opposed the temperature dependency theory and instead proposed that either decomposition was controlled by OM chemical conformation and its physico-chemical protection (Conant *et al.*, 2011) or was a mechanistic process driven by soil microbial (abundance and composition) carbon use efficiency (Manzoni *et al.*, 2012). It is now generally considered that OM molecular structure (constituents of SOM fractions) does not determine its longevity in the soil, but rather, SOM cycling in terrestrial ecosystems is regulated by multiple biological and chemical processes shaped by environmental controls (Schmidt *et al.*, 2011). Moisture and temperature effect on microbial activity is thus a key driver determining litter decomposition rates, in addition to litter quality and composition of soil microbial community.

2.1.2 Soil organic matter factions

The separation of SOM for chemical characterization has vigorously been explored using many extraction methods (e.g HPLC, GC-MS, wet chemistry, and elemental analyses) that utilize the physical (size, density and aggregation) and the chemical (solubility, mineralogy) (Wander, 2004; Stockmann *et al.*, 2013). In tropical ecosystems, SOM is commonly classified according to physical fractionation (Parton *et al.*, 1994; Okalebo *et al.*, 2002) although most recently vis-NIR diffuse reflectance spectroscopy (Nawar *et al.*, 2016) and spectral libraries for predicting C fractions with MIR techniques (Shepherd and Walsh, 2002; Awiti *et al.*, 2008; Nocita *et al.*, 2015) have been developed.

According to Stockmann *et al.* (2013), SOM constitutes five pools divided according to biological stability (labile, stabile,, refractory and enert), decomposition rate (fast-active, slow-intermediate, and very slow/passive/inert) and turn-over time (short, long and very long). First is plant material that constitute leaf, litter and crop/pasture material on soil surface and comprise the fast (labile) pool which decomposes at timescales from days to years. Second is the buried plant residues which constitute plant material greater than 2mm in size residing in soil and comprise the fast (labile) pool that decomposes at timescales from days to years. Third is particulate organic matter (POC), which constitute semi-decomposed organic material smaller than 2 mm and greater than 50 µm in size and comprise the fast (labile) pool that decomposes at timescales from days to years. Fourth is the humus, which constitutes well decomposed organic material smaller than 50 µm associated with soil particles and comprise the slow (stable) pool that decomposes at timescales from years to decades. And finally, the resistant organic carbon (ROC), which constitutes charcoal or charred material from burning organic matter and comprise the passive (or recalcitrant) pool that decomposes at timescales from decades to thousands of years. During decomposition, plant and animal organic residues are broken down into smaller particles and eventually forming humus after repeated recycling through soil micro-organisms.

The carbon contents in each soil pool are determined by the net balance between SOC aggrading (addition of soil carbon through plant biomass production, humification, aggregation, and sediment deposition) and degrading (removal of soil carbon through soil erosion, leaching, and soil organic matter decomposition) processes (Lal, 2004).

2.1.3 Terrestrial soil organic carbon niches

The soil organic carbon pools of different ecosystems and biomes have been estimated at an ecosystem level, regionally and globally. Globally, the soil organic carbon pool is estimated at 1.5 x 10^{18} g according to Torn *et al.* (1997) and is about three times that contained in terrestrial biotic C pool (i.e atmosphere and terrestrial vegetation) which is estimated at ~ 560 Gt organic C. Soil carbon global estimates by biomes and regions have been extensively described by various studies (Batjes, 1996; Jobbágy and Jackson, 2000; Scharlemann *et al.*, 2014). Compared to temperate ecosystems, there is a lag in knowledge on the status of SOC within different national and geographical boundaries in the African continent. Comparatively, few reviews (Batjes, 2004b; Patrick *et al.*, 2013; Kamoni and Gicheru, 2014) exist comparing ecosystems where soil C and N assessments have been conducted and documented. Currently, studies (Hengl *et al.*, 2015) are underway to refine estimates of different soil chemical properties in an effort to derive a soil property map for the African continent.

Despite the handicap at the continental level, studies have been conducted to estimate SOC at country specific regional and catchment levels. In Kenya for instance, such studies (Batjes, 2004a; Kamoni *et al.*, 2007) showed an increase in spatial area where soil stocks were less than 18 t C ha^{-1}, and offer a predicted net national loss of 104 Tg C for a period of 40 years. These studies also compared areas with the highest SOC in humid highlands (15.4 – 15.7 kg C m^2) to those with lowest stocks in the sandy hot arid zones (4.4 – 4.5 kg C m^2). Studies of SOC budgets under different land uses in tropical savannas and dryland forest estimate that native savanna grasslands contain the highest C pools (7.5 – 18 t C ha^{-1}) compared to degraded savannas (7.5 - 9.9 t C ha^{-1}), while intensely cultivated agricultural lands have lowest amounts (4.5 to 13.5 t C ha^{-1}) that exceed moderately fertilized agricultural lands (6 – 14. 2 t C ha^{-1}) (Tiessen *et al.*, 1998). At smaller ecosystem scales, numerous studies have been conducted estimating top and sub soil SOC contents (Tamooh *et al.*, 2012; Vågen *et al.*, 2012; Omoro *et al.*, 2013;

Were *et al.*, 2015); to mention a few. Generally, and depending on ecological and biophysical condition, most agricultural soils in the tropics have been reported to contain between 1- 5 % OM in the upper 0. 3 - 1 m top soil layer (Houghton *et al.*, 2001)

2.2 Land use change effects on soil C and N stocks

The rate at which carbon is accumulated or lost from soils depends on many biotic and abiotic factors. Native forestlands maintain a tight nutrient and carbon re-cycling patterns that are disrupted when land is opened up for cultivation. Changes in land use results to perturbations of inherent soil organic carbon stocks, whose magnitude has been estimated (IPCC, 1997) from the equation;

$$C_m = C_n * B * T * I \qquad \text{(Equation 2.1)}$$

Where; C_m is the amount of soil carbon after duration (m) of land use change, C_n is the amount of soil carbon under original native vegetation, B is a base factor accounting for biotic factors that influence soil carbon changes (ranges from 0.5 to 1.1), T is the tillage factor (ranges from 1.1 in temperate regions to 0.9 in tropical regions) and I is the input factor accounting for soil management practices/systems within the land use (ranges from 8.0 in low input to 1.2 in high input systems). This equation is currently used in regional assessment of soil C stocks in circumstances where empirical data is lacking to conduct country specific stock inventories.

2.2.1 Quantifying soil nutrient stock changes

Generally, arable soils contain about 1 - 3% of SOC whereas grasslands and forestlands contain higher quantities (Jenkinson *et al.*, 1990). Pioneer studies on consequences of land use change in SSA (Woomer *et al.*, 1998) show that soil carbon losses are highest in the initial (0 - 3 years) period immediately after land conversion (initial C amount of 30.2 to 44.1 t C ha^{-1}) with the magnitude of loss (from to 50 - 67 % C in the top 0 - 20 cm soil depth) dependent on land use practice. A meta analysis (Guo and Gifford,

2002) showed SOC gain or loss following land use change in the following magnitudes; pasture to plantation (-10%), native forest to plantation (-13%) , native forest to crop (- 42%) and pasture to crop (- 59%). Conversely, total C stocks gain were incurred when land use change shifted from native forest to pasture (+8%), crop to pasture (+19%), crop to plantation (+18%) and crop to secondary forest (+53 %). These findings reveal that the greatest SOC gains from land use change were realized when croplands were converted to pasture or permanent forest. Other reviews (Houghton and Goodale, 2004; Vågen *et al.*, 2005) reported a SOC decline between by 0 - 60 % following deforestation and conversion to agricultural croplands depending on subsequent land use adopted.

Soil bulk density (BD) changes following a land use system change is a crucial factor hampering quantification of SOC. The comprehensive review of over 40 studies by (Murty *et al.*, 2002) showed that most analysis of soil C were confounded by changes in soil BD upon land use change. The study found that by factoring BD changes after land use, the average C and N loss were 24% and 15%, respectively, whereas losses above 30 % were observed for both nutrients when BD was omitted in deriving the estimates. These findings concur with other reviews (Guo and Gifford, 2002) that transition from forest to pastures resulted to non significant losses of either soil C or N, although soil C changes ranged from −50% to +160% depending on BD changes.

The scenario is similar when smaller ecosystems are considered. For instance, differences in SOC varied in Kakamega forest ecosystem varied from 7.27 kg C m^{-2} in forested area compared to 2.67 Kg C m^{-2} in cultivated land (Awiti *et al.*, 2008) whereas Lemma *et al.* (2006) showed losses up to 43% in southern highlands of Ethiopia croplands converted from forest lands. In summary, it is well established that changes in land use interferes with magnitude of soil C and N stocks, the magnitude of which depend on intrinsic soil factors and environmental conditions within an ecosystem.

2.2.2 Quantifying greenhouse gas (GHG) flux emissions

Agricultural activities release significant amounts of CO_2, CH_4 and N_2O gasses to the atmosphere (Houghton *et al.*, 2001). The mechanisms governing GHG exchange between soils and the atmosphere and their biogeochemical controls are well described (Smith *et al.*, 2003; Kim *et al.*, 2012). A comprehensive database for GHG estimates from various agricultural sources is described by the Food and Agricultural Organization (Tubiello *et al.*, 2013). These estimates show that from year 2000 - 2010, agricultural contribution to surface GHG emissions increased by 1.1 % (at 5.4 - 5.8 Gt CO_2 yr^{-1}), with enteric fermentation from livestock industry being the highest contributor, followed by manures on pasture, synthetic fertilizers biomass burning and so on. The database also reveals that emissions from mineral soils, resulting from tillage, fertilizer application and other cropping activities supersede net deforestation. This implies that land conversion has lower consequences compared to subsequent land management activities occurring in converted croplands. However, these estimates are based on IPCC "Tier 1" approach, which uses generalized estimates when empirical data is not available.

Few studies have been conducted in SSA ecosystems quantifying surface emission potentials from different land use systems to offer any solid review. However, pioneering studies (Mutuo *et al.*, 2005; Otieno *et al.*, 2010; Arias-Navarro *et al.*, 2013) promise plausible empirical data to facilitate comparison between land use and consequences of land use change to GHG emissions.

2.2.3 Potential for agro-forestry systems to mitigate soil C

Agroforestry systems offer an opportunity for replenishment of SOC in sub-Sahara Africa and other degraded landscapes. Trees sequester SOC in the soils *in situ* through root biomass and *ex-situ* through woody and harvested plant products. Globally, agroforestry systems comprise a wide range of tree-crop mixtures in both space and time, and thus differential contribution to SOM in different ecosystems and environments. Watson *et al.* (2000) estimated soil C sequestered in smallholder farms in the tropics ranging from 1.5 to 3.5 Mg C ha^{-1} yr^{-1} and a 3-fold increment over a 20-year period to 70 Mg C ha^{-1}. The review by Montagnini and Nair (2004) highlights the importance of proper design and management of agroforestry practices in order to make them effective sinks and quantifies the C sequestration rates by agroforestry systems in different ecosystems. Based on tree growth rates and wood production potential, Schroeder (1994) estimated that the average C storage in agroforestry systems as 9, 21, 50, and 63 Mg C ha^{-1} in semiarid, sub humid, humid, and temperate regions.

In tropical smallholder farms established with cereal crops, (Palm *et al.*, 2001) estimated a 3-fold increase in SOC stocks i.e 5 to 15 kg C ha^{-1}, when different agro-forestry species were introduced. Despite decades of research on the benefits of agro-forestry system to improve agricultural productivity and protect vulnerable soil properties, a recent review by Nair (2012) describes the bottleneck in procedures and assumptions used to measure the extent of C sequestration in various agroforestry systems. These include large scale global models based on allometric measurements that under-or over estimate the amount of C sequestered and the difficulty in estimating the area under practice due to the intergrated nature of AFS systems. However, Nyberg and Högberg (1995) showed that trees significantly alter soil and carbon stocks around their canopies up to 10 m length from trunk, thus allowing assessment of soil nutrient contribution by agro-forestry tree species in croplands. In conclusion differences in methodological approaches have consistently resulted to difficulties in interpreting site and system specific SOC stored from AFS thus undermining their accurate assessments.

2.3 Topographic controls for soil nutrient stocks

Soil nutrient stocks are varied across landscapes. This variability is dependent upon the nature and degree of landscape heterogeneity. Amongst landscape characteristics identified to influence soil nutrient stocks include slope steepness, aspect and land management (Zhang *et al.*, 2011), curvature and topographic indices (Gessler *et al.*, 1995) and the various geostatistical covariates used in development of soil property maps (Hengl *et al.*, 2015; Kempen *et al.*, 2015). Reviews (Hartemink *et al.*, 2013; Minasny and McBratney, 2016) describe the origin and progress in documenting spatial distribution of soil attributes that culminated to development of digital soil maps as early as 1978 (Tomlinson, 1978) and progress achieved to date.

Current efforts at development of the global soil map (Arrouays *et al.*, 2014; Láng *et al.*, 2016) is a confluence of several factors that extensively utilize topographic terrain attributes; availability of spatial data such as digital elevation model, satellite imagery; increased computing power for data processing, availability of data mining tools and the rapid advancement in geographical information systems (GIS) tools (Minasny and McBratney, 2016). The geospatial framework for assessment of soil C stocks (discussed in section 2.4) are based on topographic attribute data from Digital elevation models (DEM) and Moderate Resolution Imaging Spectroradiometer MODIS datasets, most of which are currently freely available from the Wide World Web (WWW).

2.4 Framework for measurement of SOC stocks

The transformation of SOC from above-ground to below ground and methods for measuring the magnitude of such transformations are fairly well understood (Stockmann *et al.*, 2013). However, approaches to measurement of soil C and N carbon, given their spatial heterogeneity, have often resulted to conflicting estimates for various reasons. First, sampling techniques and analytical procedures, such as measurements of soil BD though either core or clod methods, differ in their stocks output per unit of mass of soil tested (Murty *et al.*, 2002; Vågen *et al.*, 2005). Secondly, and depending on study objectives, SOC measurements are conducted to different soil depths, complicating comparisons of results even from a single study site. Thirdly, periodic measurements (matched by study objective) of soil C pools and their turn-over may overlook the influence of seasonal variations i.e seasonal cycles of Net Primary

Productivity (NPP), which has been shown (Holtgrieve *et al*., 2006) to influence soil nutrient stocks. Finally, reviews of spatial SOC sampling designs (VandenBygaart and Angers, 2006; Allen *et al.*, 2010) identify the flaws of using design and model based sampling approaches in random and purposive soil surveys. However, recent technological advances has ushered an era of new tools that have enabled development of sampling frameworks that overcome challenges in stock estimates and that permit reproducibility and replicability in spacio-temporal dimensions.

2.4.1 Geospatial frameworks for soil C stocks measurements

The key data sets for agricultural inventories are easily obtained from geospatial products for land use, land management, soils and climate; whose availability is well detailed in Smith *et al.* (2012). These datasets are widely available from various sources and resolutions on the Wide World Web (WWW). In their analysis of requirements for advancing national inventories in developing countries, (Ogle *et al.*, 2013), spatial data on land use change in developing countries remains a challenge. However, the rapid evolvement of satellite technology in data provision, such as the MODIS satellite data, has popularized mapping of ecosystems characteristics in Africa (Maeda *et al.*, 2010b; Sjöström *et al.*, 2011). Moreover, current spatial soil measurements frameworks in Africa, such as the Land Degradation Surveillance Framework (LDSF) (Vågen *et al.*, 2015) that contributed to mapping of Africa soil properties (Hengl *et al.*, 2015) have extensively utilized geospatial products. Both schemes are based on hierarchical soil sampling framework that integrates spatial variability in soil properties enabling comparison of data from wide range environmental conditions and at different scales.

2.4.2 Spectral measurement of soil nutrient stocks

In the recent past, determination of most soil properties were conducted "*conventionally*" by destructive soil analysis though wet chemistry techniques (Okalebo *et al.*, 2002). Although proved accurate, these methods are often laborious and are riddled with methodological errors, low analytical finesse, accuracy errors and so on. However, newer approaches under development and currently being tested have proved to be accurate, consistent and cost effective. These include; MIR calibrated using partial least squares, which has been used in predictions of soil C fractions (Zimmermann *et al.*, 2007). Using wavelength ranges in the visible (vis, 0.4 - 0.7 nm), the near infrared (NIR, 0.7 - 2.5 nm) and the mid infrared (MIR, 2.5- 25 nm), spectral libraries (Shepherd and Walsh, 2002; Nocita *et al.*, 2015) have been utilized to predict soil C and N in a variety of land uses (Awiti *et al.*, 2008; Waruru *et al.*, 2014; Kempen *et al.*, 2015) with reasonable accuracy ($R^2 > 0.9$). Due to their rapid and reliable measurements, the later methods have been extensively used in this study for determination of soil C and N stocks.

2.5 Models used to predict SOC stocks and fluxes

Models generated from empirical data enable nutrient stock comparison across land uses through either “point- location” scale mapping or spatial landscape extrapolation (up-scaling). By this definition, models present pathways for assessing nutrient stocks turn-over in spatial and temporal dimensions. Additionally, models facilitate simulation of soil properties responses to environmental drivers and their projection into the future biophysical scenario’s. Ultimately, soil nutrient models should provide a reliable prediction to soil C stock sizes for different soil types under different land use and management practices, such as crop rotation, SOM additions, tillage practices, climate regimes etc. A comprehensive review of current soil models frequently referred in scientific literature is well documented (Smith *et al.*, 1997; Stockmann *et al.*, 2013). For purposes of models employed in various chapters of this thesis, the review of the mechanistic organism oriented models that mostly perform analysis of environmental risks while providing above and below ground linkages in ecosystem food webs (Susilo *et al.*, 2004) is omitted. Their limitations in predicting soil C dynamic are well detailed in Brussaard (1998).

2.5.1 Empirical regression models

Small scale and ecosystem studies often utilize empirical regression models to estimate seasonal and spatial soil C stock changes in either short and long term field experiments or using empirical data (Tan *et al.*, 2004; Viaud *et al.*, 2010; Omoro *et al.*, 2013). With a defined dataset of environmental covariates obtained from a rigorous sampling framework, empirical regression methods are often cost effective in monitoring soil C changes at ecosystem and regional scales. The changes are empirically modeled to depict consequences to soil C stocks after a change in either management practice (Palm *et al.*, 2001; Patrick *et al.*, 2013), land use change (Were *et al.*, 2015) or seasonal changes (Merbold *et al.*, 2009a).

2.5.2 Process Oriented models

Process models are popularly used to simulate changes in SOM resulting from management practices as comprehensively detailed in recent reviews (Powlson *et al.*, 2013; Stockmann *et al.*, 2013). These models predict soil C based on conceptual C pools that are constantly changing through turnover processes and other stabilization mechanisms. The most common process oriented models are CENTURY, ROTHC (Batjes, 2004a; Kamoni *et al.*, 2007; Viaud *et al.*, 2010) and the dNdC models (Li *et al.*, 1992). With appropriate model calibrations, process oriented models have demonstrated good predictive ability for SOM dynamics over different soil types and climatic regions. However, predictive models are not without limitations. Most models do not take into account such details as soil depth, the influence of soil properties such as soil pH and management factors such as tillage to differentiate SOC contents (Angers and Eriksen-Hamel, 2008). Yet such details have a significant influence on crucial ecosystem soil properties (Smith *et al.*, 1998). Currently, most models only include the top 0-30 cm top layer in their simulations, where roots, inputs and microbial activity are at their maxima. Deep plough layers are often omitted from model simulations thus under-estimating ecosystem SOC stocks. Model calibration with long term spatial temporal datasets is crucial to improve the precision of process oriented models in simulating soil C stocks and their turnovers.

2.5.3 Other models used to predict soil C stocks

Despite the three models types mentioned in this review so far, other models, currently under development and/or refinement, exist and have been used to predict soil C changes in terrestrial environments. These include the 3-dimensional vertical, horizontal and depth landscape models that present functional interactions and soil C transfers such as erosion (Maeda *et al.*, 2010b), translocation of dissolved organic matter (Kaiser and Kalbitz, 2012), fluxes differentiation between landscapes (Viaud *et al.*, 2010) and 3-D hydrological models (Li *et al.*, 2008).

Current efforts in the realm of soil C dynamics are focused on theoretical development of "whole system models" that incorporate all the interactions of soil processes and biota (Stockmann *et al.*, 2013). As noted by Stockmann *et al.* (2013), development of whole system models has several challenges. These include current limited understanding of natural systems that hinder development of complex networks; the spatio-temporal knowledge needed to design local interactions within such networks; lack of knowledge of whole network behavior such as, direction of change, "metastable" states and non-linear behavior are other practical limitations. In summary, even if sufficient information is available to establish a whole network models, the computing capabilities for their design are currently unavailable, making them theoretical rather than functional.

2.6 Critical areas in soil nutrient stocks and flux research in SSA

To summarize this review, practical measures to enhance soil C are needed to enable design of mitigation measures for degraded and degrading landscapes; and especially that increase sequestered SOC due to its capacity to mitigate GHG emissions. Although soil C research has undergone tremendous advancement in other continents, more efforts are required within SSA ecosystems to accelerate the current pace. In reference to various studies mentioned in this review, a summary of four critical questions for soil nutrient stock research in SSA is as follows;

I. What is the impact of different management practices, enviomental and climatic conditions and their changes on soil C?

II. What are the patterns for redistribution of soil C to different parts of a landscape following land use change or due to to erosion and deposition processes?

III. What are the behaviors of SOM partictions and dynamics with soil depth in both cultivated and natural ecosystems?

IV. What are the impacts of human activities on stability of stored carbon stocks?

This study does not attempt to answer all these critical questions but rather seeks to bridge the gap by tackling two of them. The study examines the effect of land use change on soil nutrient stock changes (Qn I) while examining their distribution patterns with an elevated landscape (Qn II). The study does not critically investigate the the processes by which the nutrient stocks change, but rather offers plausible reaons for the change in land uses and micro-enviromental changes within the altitude gradient. It neither does not assess the effect of land management on soil nutrient stocks (Qn III) nor quantify the stability of stored soil C resulting from human activities (Qn IV). However, findings from this study constitute a significant resource critical in design of monitoring framework(s) that enable seek answers to the later questions.

CHAPTER THREE

STUDY AREA AND GENERAL MATERIALS AND METHODS

3.1 Study area location

The Taita Hills (03 25’ S and 38 20’ E) are situated in southeastern Kenya and constitute the northernmost part of the Eastern Arc Mountains Ecosystem. The Hills, that cover an area approximately 850 km^2 (Fig 3.1), are an important East Africa Biodiversity Hotspot (EABH), being host to endemic diverse insects, plants and animals species currently facing extinction (Myers *et al.*, 2000). The administrative jurisdictions of the Taita Hills cover Wudanyi and Mwatate sub-counties of Taita-Taveta County.

The study has undergone several decades’ of landscape research by several institutions; the University of Helsinki (UH), The Kenya Agricultural and Livestock Research Organization (KALRO), The Kenya Forestry Service (KFS) and several other research and development partners in the region. The work reported in this thesis constitutes part of wider studies under the “Climate Change Impacts on Ecosystem Services and Food Security in Eastern Africa (CHIESA)” project. The project focused to generate knowledge on impacts of climate change within EABH ecosystem in order to determine ecosystem vulnerability and promote adaptability of human, animal and plant communities

3.1.1 Demographics and biophysical conditions

Agriculture forms the basis of livelihoods for majority of smallholder communities living within and surrounding the Taita Hills. Increased population, which has more than doubled since 30 years ago (KNBS, 2010), has exerted pressure on land cover, soil and water resources leading to human -wildlife conflicts, and intensified land related disputes between native inhabitants and development and conservancy agencies in the area.

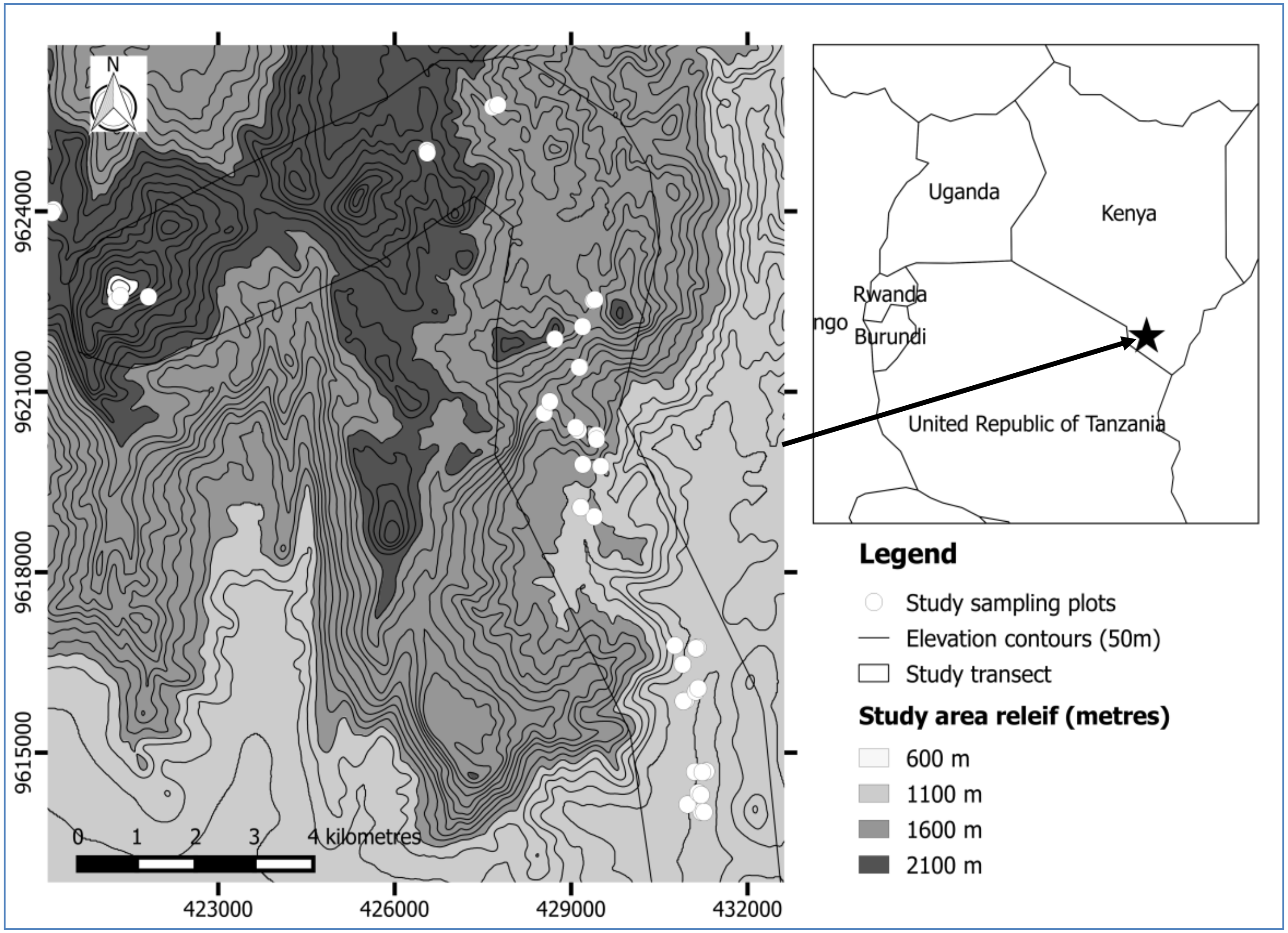


Figure 3.1: The Taita Hills study transect. Caption (top right) shows location relative to East African region

The main cause of environmental pressure in the Taita Hills, according to Clark (2010) is population growth. By year 2009, the population of the whole Taita taveta county had grown to approximately 284,657 persons, with a population density of 17 persons per Sq. Km (KNBS, 2010), with majority of people living in foot slopes and urban high potential areas.

3.1.2 Land use and cover type

The rapid population growth led to increase in area under cultivation for subsistence farming resulting to massive loss of indigenous cloud forests and shrub lands in the Taita Hills ecosystem. According to Pellikka *et al.* (2009), approximately half of the cloud forest were cleared for cultivation between years 1955 and 2004, and currently remaining about 1 % of original forest area. Intensive small scale agriculture is dominant within the Taita Hills. Low-lying uplands, plains and bottom areas are intensively cropped with cereals, tuber and horticultural crops. Shrub and grasslands also dominate low lying areas surrounding the hills. Mid slopes and highland areas are dominated with artificial and natural forests, and agro-forestry systems combining various agricultural crops with fruit trees (Table 3.1). Cash crops such as coffee and macadamia nuts are grown in few farms. Livestock rearing is common to farming households in the mid and upper slopes, nourished from established pastures in the sloping landscape. Average farm size varies with location, which for small scale farmers is about 0.4 ha in the highlands, 1.3 ha in the midlands and 4.8 ha in the lowlands. Plantation farms have an average size of 7,400 Sq. Km (KNBS, 2010). Description of agro-ecological zones and land cover classifications are offered in Boit *et al.* (2014) and Heikinheimo (2015).

3.1.3 Meteorological data

Rainfall in the Taita Hills follows a bimodal pattern, with long rains between March and May and short rains between November and December with alternated dry periods in-between. Average annual rainfall in the slopes and lower parts of the hills ranges between 600 and 900 mm, the lower midland zones between 500 and 700 mm and well beyond 1100 mm in upland forested highlands (Jaetzold and Schmidt, 1983).

3.1.4 Soil types and properties

The Taita Hills developed in the ancient Precambrian period, and ranges in altitude from 1200m to 2200 m above Tsavo Plains (Pellikka *et al.*, 2013). Soils originate from undifferentiated basement system whereas soil types are delineated along topographic characteristic. Cambisols with weatherable minerals dominate steep foot slopes, hills and high level uplands whereas Lixisols and Arenosols are found in lower level uplands and piedmont plains respectively. Bottom lands comprise of mainly Fluvisols while the non-dissected erosional plains are comprised mainly Luvisols and Acrisols (Jaetzold and Schmidt, 1983). Soil properties are characterized by landscape driven cropping and management activities that characterize small scale agriculture within the Taita Hills. Studies (Clark, 2010; Maeda *et al.*, 2010b; Pellikka *et al.,* 2013) describe massive land degradation due to agricultural land expansion resulting to erosion and soil fertility decline. Baseline soil chemical and landscape properties in December, 2012 start of field sampling is shown in Table 3.1.

3.2 Sites selection

In this study, data was collected over a 12 months period (January 2013 to December 2013) within a research transect 2 km wide and approximately 48 km long extending from Mwatate (~867 m) to Wudanyi (~1449 m) and to the highest peak at Vuria mountains (~2198 m) (Fig 3.1). For the purposes of sampling, the study research transect was first delineated five hierarchical altitudinal clusters (Fig 3.2:A) guided by topographic and edaphic variation in rainfall and temperature patterns, soil characteristics (such as color, surface soil texture) and vegetation transition patterns along the altitude gradient (Clark and Pellikka, 2009b). Thereafter, a nested sampling framework, where pockets of specific land uses comprising natural (forest and shrub), cereal (maize) and agroforestry (mango and avocado) land cover types (Fig 3.2: B) were identified from pre-existing land cover maps (Maeda, 2011) and overlaid against a 250 x 250 m sampling grid (Fig 3.2: C). The grid was derived perpendicular to contours within the study transect in order to capture terrain transitions between slope positions. Grid points within the land cover pockets where then derived to achieve a stratified cluster points (118 points) as shown in Fig 3.2: D.

3.2.1 Selection of sampling farms

Each cluster comprised between 8 and 18 sampling points (Fig 3.2: D), with each point representing a potential sampling farm, with a minimum separation of 200 meters. Thereafter, two clusters were randomly chosen within each elevation range after testing for spatial randomness and point clustering using R "spatstat" package, to see how well vegetation transition and altitude gradations are represented. Finally, from each of the two chosen clusters, a further randomization was conducted to select 8 sampling points (hereafter now referred to as *farms*) within each elevation range (except in 1800 - 2300 m range where one cluster was chosen due to terrain accessibility difficulties), making a total of 40 sampling farms (Table 3.1). Spatial autocorrelation was tested after farm identification (Moran's I index = 0.23, $P < 0.05$). In instances where identified farms were not conducive to support sampling (roads, rivers, swamps and other obstacles), purposive farm selection was conducted to replace such points. This was done by designating, for instance, farms with a continuous cereal and/or legume history as cereal plots. Agroforestry plots were chosen by selecting fields with at-least five agroforestry trees in 50 m x 50 m boundary and established with either a cereal or legume companion crop. Shrub and forest plots required replacement, although minor shifts was conducted to place them at least 50 m away from boundary paths and roads. The final sampling farms are illustrated in Fig 3: E

3.2.2 Identification of soil and CO_2 flux sampling points within farms

In each cereal, shrub and forest farms, five replicate sampling spots ~ 10 m apart and aligned in a straight line along a contour perpendicular to the main slope gradient were identified (Fig 3.3). In each avocado and mango agro-forestry plots, five soil sampling spots replicates placed ~ 5 m apart but in a semicircular pattern ~ 5 m from the tree trunk and within established dripline. The placement of sampling spots below tree canopy is in line with Nyberg and Högberg (1995). All fields sampling spots were chosen to be on a flat ground, with micro topographic differences between chambers (5 ± 8 cm) and between plots (12 ± 15cm) kept insignificantly minimal to maintain homogeneity. All sampling plots were georeferenced to enable acquisition of auxiliary information *via* geographical information systems platforms (Appendices 3.1 & 3.2 & 3.3).

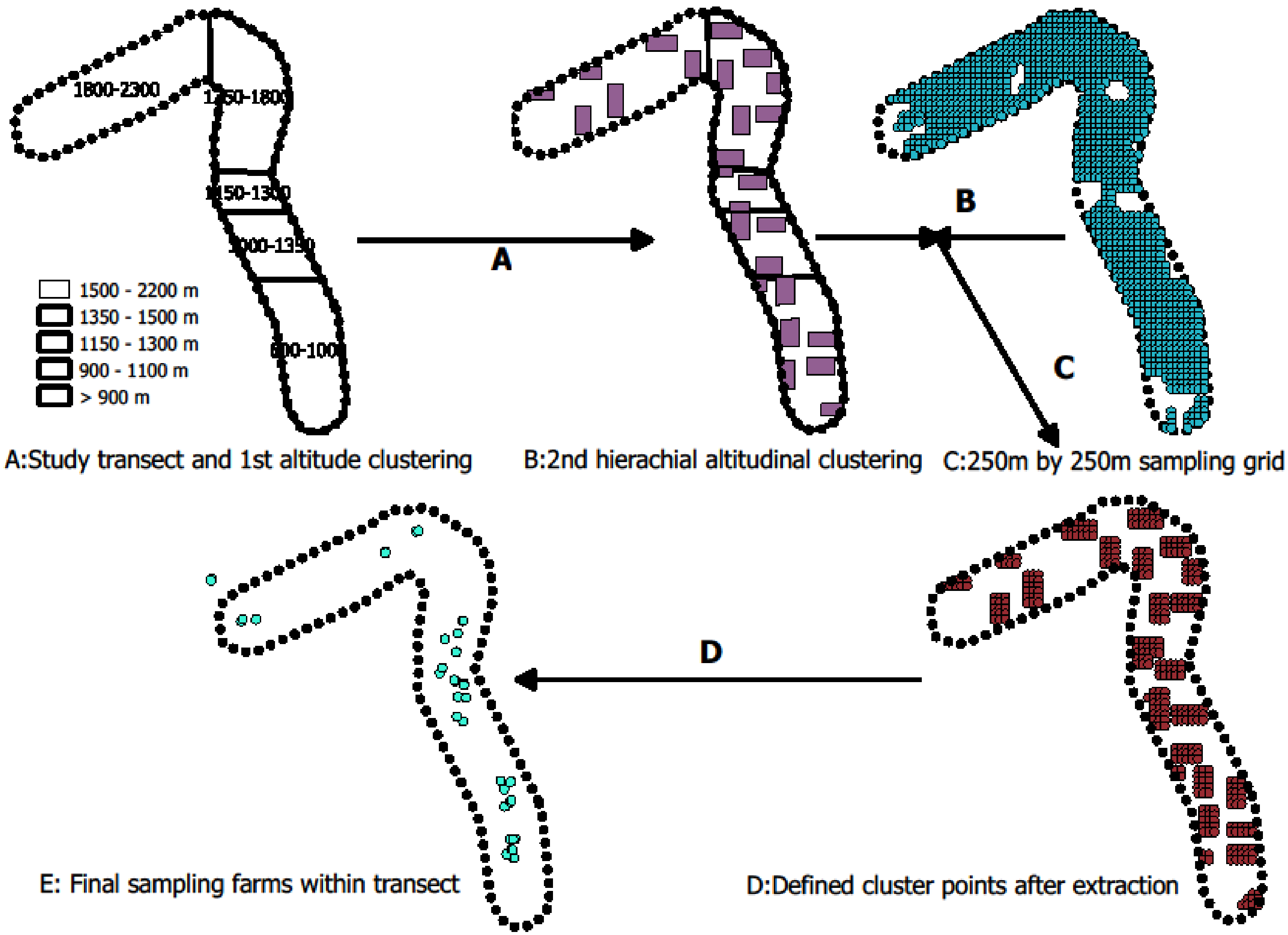
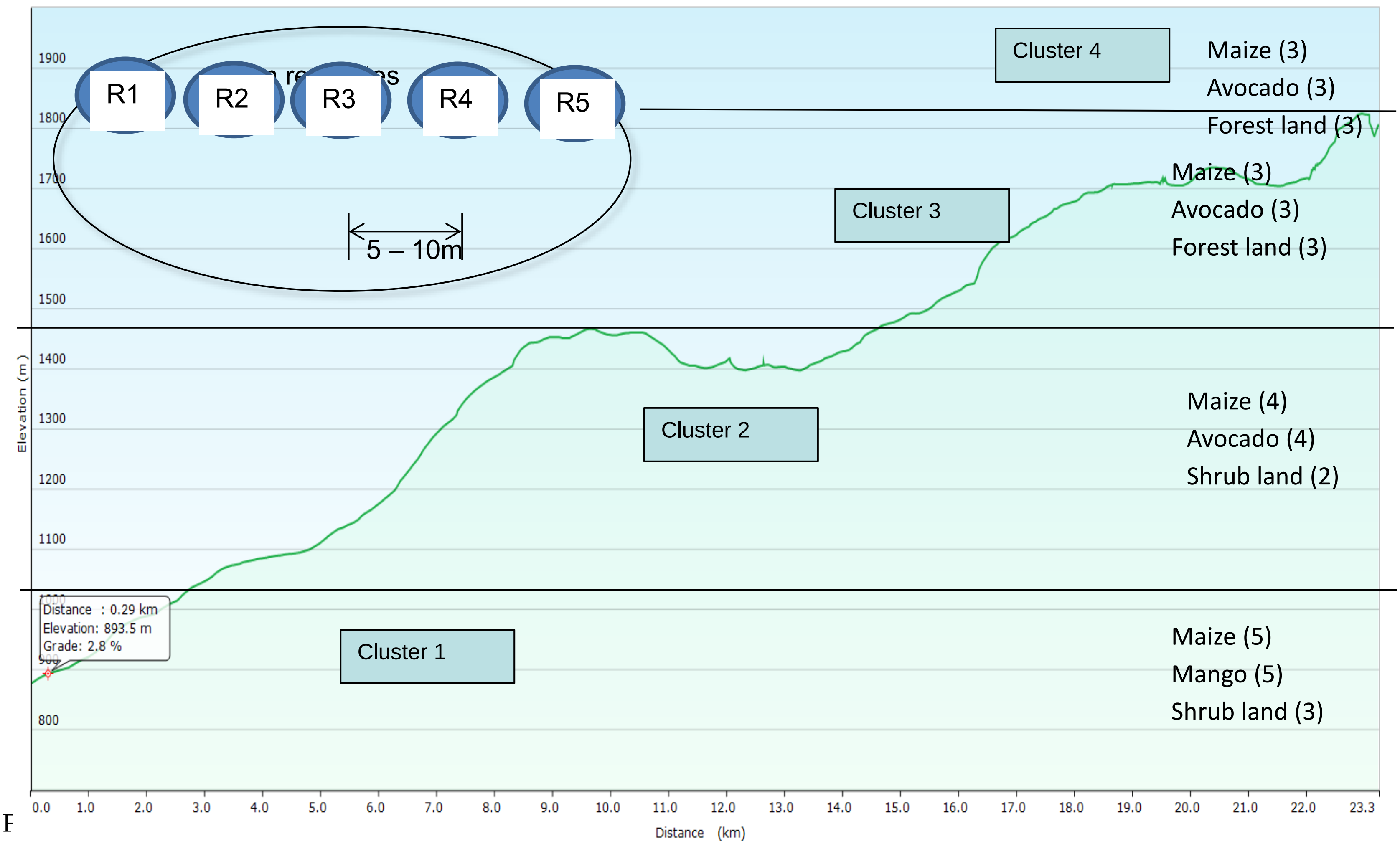


Figure 3.2: Hierarchical altitudinal clustering and randomized point selections used to identify sampling farms in study transect



R1
R2
R3
R4
R5
5 – 10m
Cluster 4
Maize (3)
Avocado (3)
Forest land (3)
Cluster 3
Maize (3)
Avocado (3)
Forest land (3)
Cluster 2
Maize (4)
Avocado (4)
Shrub land (2)
Cluster 1
Maize (5)
Mango (5)
Shrub land (3)
Distance : 0.29 km
Elevation: 893.5 m
Grade: 2.8 %
Elevation (m)
Distance (km)

F

Table 3.1 Soil chemical, slope and land cover characteristics in the Taita Hills

Altitude (masl*)	Land cover	No. of farms	C (g Kg^{-1})	N (g Kg^{-1})	pH	Slope (deg)	Land cover systems
600 to 1000	Maize	3	10.3 ± 0.9	1.4 ± 0.2	6.9 ± 0.5	0	Majorly shrub lands, cereal and agro-forestry systems
	Mango	3	11.8 ± 0.3	1.7 ± 0.2	6.68 ± 0.4	0.42 ± 0.11	
	Shrub	2	28.9 ± 0.9	2.4 ± 0.4	5.67 ± 0.1	0.25 ± 0.09	
1000 to 1350	Maize	3	18.9 ± 2.6	1.7 ± 0.2	6.34 ± 0.4	1.28 ± 0.21	Majorly shrub lands, cereal and agro-forestry systems
	Mango	3	19.6 ± 2.1	1.9 ± 0.2	6.23 ± 0.1	0.47 ± 0.08	
	Shrub	2	22.6 ± 1.4	1.6 ± 0.2	5.58 ± 0.5	1.19 ± 0.16	
1400 to 1800	Maize	6	23.7 ± 1.7	1.9 ± 0.1	5.61 ± 0.6	0.48 ± 0.06	Forest; mixed cereal, fruit, and horticultural crop system
	Avocado	6	20.3 ± 1.8	10 ± 7.5	5.19 ± 0.3	0.92 ± 0.11	
	Forest	3	74.3 ± 15.5	6.9 ± 1.4	5.03 ± 0.5	2.19 ± 0.21	
1800 to 2250	Maize	3	23.8 ± 2.3	2.3 ± 0.2	4.88 ± 0.1	1.11 ± 0.16	Forest; mixed cereal, fruit, horticultural crop systems
	Avocado	3	22.8 ± 4.1	10 ± 7.5	5.53 ± 0.5	1.03 ± 0.08	
	Forest	3	113.2 ± 9.9	10.6 ± 0.7	4.77 ± 0.9	0.91±0.09	

Values show mean ± standard error at 95% confidence interval: masl = metres above sea level

3.2.3 ***Pre*-sampling farm characterization**

Prior to start of field sampling, all identified farms were pre-characterized for initial soil OC, TN, slope degrees and a general description of land use types within farms (Table 3.1). Composite soil samples (0 - 20cm depth) were taken from five replicate spots and bulked. From each bulked sample (~ 1 kg), a subsample of ~500 g was taken for chemical soil OC, TN and pH analysis. The spots were also georeferenced and characterized for slope and a description of existing land cover classes within the cluster conducted. There were significantly large difference in soil OC and TN between the altitude ranges. Soil C and N concentrations increased with increasing altitude across elevation ranges whereas soil pH decreased with increasing elevation. Land use systems transited from shrubland and cereal-root crop mixed systems in the low transect end to forests and agroforestry mosaics in the higher transect end.

CHAPTER FOUR

SPATIAL AND SEASONAL SOIL CO_2 FLUX PATTERNS

4.1 Introduction

Current global soil carbon dioxide (CO_2) emission estimates show an increasing trend with increasing temperature (Davidson and Janssens, 2006; Trumbore, 2006). Most recently estimated at 103 Pg C a^{-1} (Yuan *et al.*, 2011b), soil CO_2 emissions resulting from root respiration and microbial organic matter decomposition are important pathways for the global biogeochemical cycles. Although quantification of soil borne CO_2 emissions has received considerable attention in other continents, little has been done in sub-Sahara Africa (SSA) landscapes e.g Hicks *et al.* (2015); O'Dell *et al.* (2015). It is well established that temperature and soil water are vital drivers for microbial decomposition of organic matter and root respiration, consequently regulating evolution of soil CO_2, CH_4, N_2O and other soil gasses (Singh *et al.*, 2009; Butterbach-Bahl *et al.*, 2011; Itoh *et al.*, 2012). Other studies (Brovkin *et al.*, 2004; Zhang *et al.*, 2007) show land cover characteristics play a critical role in determining surface soil CO_2 efflux patterns at ecosystem and continental scales.

In ecosystems undergoing rapid land cover conversion from forests to agricultural lands, soil borne CO_2 emissions are expected to increase from soil microbial activity, and deteriorated chemical and structural properties (Sahani and Behera, 2001; Change, 2006; Kaschuk *et al.*, 2011). Such changes have a direct implication on the global carbon cycle by modifying microbial environment. Temperature sensitivity ultimately changes with land cover change, and is an important parameter used to characterize soil carbon decomposition and respiration in various terrestrial biomes (Davidson and Janssens, 2006). Despite research efforts towards quantifying soil CO_2 contributions in terrestrial biosphere, difficulty in obtaining a reliable representation of spatial and temporal patterns remain a critical bottleneck (Subke and Bahn, 2010). This is particularly evident in sub-Saharan ecosystems where numerous biophysical and local scale ecological factors hamper consistent flux measurements in both time and space. In this respect, local scale and short term gas emission responses are prone to measurement errors (Savage *et al.*, 2008) and may be inadequate to capture spatial and temporal gas flux - weather variations.

Most studies quantifying greenhouse gases in East Africa ecosystems mainly rely on manual static chamber sampling techniques, where flux is determined from gas concentration at chamber head space over time (Butterbach-Bahl *et al.*, 2011; Arias-Navarro *et al.*, 2013). Often, gas flux emission measurements in mountain ecosystems pose numerous challenges such as; terrain accessibility, environmental variability and so on. Hence, there is need for short but intensive sampling campaigns that limit data acquisition at high spatial and temporal resolution. In the face of such challenges, interactions between biogeochemical processes and ecological factors such as temperature and moisture offer a plausible opportunity to map spatial temporal patterns in such ecosystems

Remote sensing data has been used to characterize soil borne CO_2 fluxes in various ecosystems. For instance, Moderate-resolution Imaging Spectro-radiometer (MODIS) on board Terra and Aqua satellites continually monitor land surface reflectance and emissivity. These data have been utilized to estimate soil respiration and moisture at an ecosystem (Wen *et al.*, 2006), continental scale (Yang *et al.*, 2007) and global scales (Yuan *et al.*, 2011a). The potential for MODIS Land Surface Temperature (LST) and Enhanced Vegetation Index (EVI) to directly estimate per pixel ecosystem respiration (Yamaji *et al.*, 2008) and vapor pressure deficit (VPD) (Hashimoto *et al.*, 2008) between biomes is well documented. The fact that MODIS derived LST show strong dependencies with land cover (Maeda and Hurskainen, 2014) and weather patterns presents an opportunity to address challenges in quantifying soil borne gas emissions in SSA.

Studies utilizing remote sensing indices to describe land characteristics are not new within East Africa region. For instance, models used to simulate soil carbon and nitrogen nutrient dynamics such as CENTURY (Kamoni *et al.*, 2007) and GEFSOC models (Milne *et al.*, 2007) have extensively linked climate, soils and land use data derived from geographical information systems (GIS). In these studies, robust indices are derived and used to estimate local scale soil carbon and nitrogen contents, and regional soil C stocks (Kamoni *et al.*, 2007). Despite significant reaps in the number of studies that have used MODIS satellite data to characterize ecosystems factors in Africa, such as gross primary productivity (Sjöström *et al.*, 2011), woodland productivity (Ryan *et al.*, 2012) and land cover changes (Townshend *et al.*, 1991), research in this area is still at its infancy within East Africa. Most recently, Maeda and Hurskainen (2014) and Maeda (2014) have utilized MODIS data at 250 m spatial resolution to characterize land cover and surface temperature characteristics in Mount Kilimanjaro. At this resolution, heterogeneity in ecological factors at local farm scale and field variations can be captured. Presently however, no literature was found that links either *in-situ* weather variables or remotely sensed temperature to explain spatial and temporal $CO_{2\text{-flux}}$ patterns in east African landscapes.

East Africa's Eastern Arc mountain ecosystem is currently undergoing rapid land use changes, with majority of native indigenous forests being cleared for agriculture and human settlement. Habitat destruction is also responsible for colossal loss of flora and fauna biodiversity (Clark and Pellikka, 2009b; Maitima *et al.*, 2009; Paron *et al.*, 2013), which is a key driver for carbon cycle within the ecosystem. These changes may ultimately result in increased soil borne greenhouse gas emissions, the magnitude of which remain unknown and undocumented. Therefore, a comprehensive assessment of the seasonal and spatial patterns of soil carbon flux in Kenya tropical mountain ecosystem is essential for a better understanding of how environmental changes will affect the carbon cycle in this biodiversity-rich region. In this study, we aim to address the following research questions: *How do soils $CO_{2\text{-}flux}$ vary* *temporally and spatially across an East African mountain ecosystem? How does moisture and temperature changes affect CO_2 flux patterns in heterogeneous mountain landscapes?*

4.2 Material and Methods

4.2.1 Field gas sampling design

Gas sampling farms were identified as explained in Chapter 3 (Section 3.2.2) whereas specific gas sampling replicates are detailed in Chapter 3 (Section 3.2.3)

4.2.2 Rainfall, soil moisture and temperature measurements

Rainfall was measured continually for one year using wireless rain gauges (Model No. RGP150 General®), with one installed at each of the four elevation ranges. Total daily rainfall was used to compute monthly rainfall amounts. Air temperature was measured using a digital min-max thermometer (*Model* ST 9263, range from – 50 ^oC to 150 ^oC) fitted with a 1-metre sensor cable. The sensor was always placed between 0.5 m and 1 m above the soil surface and ~ 5 cm to the chamber. Similarly, soil temperature was measured using a thermometer (*Model* Acurite - 00661) with a 15 cm probe inserted into the soil and placed adjacent to the third gas chamber. Air and soil temperature readings were taken immediately after stop-clock start of gas sampling and successive one-minute interval during gas sampling. Spatial replicated air and soil temperatures were first averaged to one value per plot during each sampling month.

At each monthly sampling period, core soil samples were acquired ~ 0.5 m length of each chamber at 5 cm soil depth and oven dried to obtain soil water content and enable calculate bulk density (BD) and water filled pore space (WFPS) (Brady, 1990).

4.2.3 Soil CO_2 flux measurements

Carbon dioxide gas fluxes were measured using the dynamic chamber technique (Hutchinson *et al.*, 2000). Chamber rings were made from polyvinyl chloride (PVC) ring (28 cm diameter x 15 cm height). One PVC chamber cover with a tight fitting groove was fitted with a rubber gasket to enable complete sealing of chamber rings by chamber tops. The cover has an inlet and outlet connected to a respective inlet and outlet ports of the carbon dioxide analyzer (*Model* LI-7000 CO_2/H_2O Analyzer) via teflon tube ~ 2 m long. Before the start of monthly sampling campaign, Licor-7000 analyzer was calibrated in the laboratory using gas standards with the following CO_2 concentrations; 0 *ppm* (total nitrogen), 200 *ppm*, 400 *ppm* and 1000 *ppm*. Monthly chamber $CO_{2\text{-flux}}$ results were corrected for CO_2/H_2O analyzer detection error using linear equations generated from gas standards data. Although other studies (Kutzbach *et al.*, 2007; Parkin *et al.*, 2012) found non-linear regression models more appropriate for estimating soil $CO_{2\text{-flux}}$, we observed consistent and highly significant linear changes of $CO_{2\text{-flux}}$ over the chamber closure time and therefore applied linear regression in calculating $CO_{2\text{-flux}}$ estimates.

4.2.4 MODIS Land Surface Temperature

Land surface temperature (LST) data was obtained from the MODIS MOD11A2 product, which offers daytime and nighttime LST data stored on a 1-km Sinusoidal grid as the average values of clear-sky LSTs during an 8-day period. In this study, only the daytime LST records (acquired at canopy height within ecosystems) were considered to compare and compliment *in-situ* soil temperature (acquired ~ 5 cm from sampling point) and ambient air temperature (acquired ~1 m from sampling point) measured during the gas sampling exercise. Monthly means were calculated as an average of the 8-day LST composites inside the month. This dataset was downscaled from 1km to 250m based on the assumption that, inside the area covered by a 1 km pixel, LST will be homogeneous unless significant changes in altitude and/or land cover occur. For a detailed description of the LST downscaling approach please refer to (Maeda, 2014). The 250m resolution was the finest resolution possible from acquired MODIS SPOT satellite during downscaling process.

4.2.5 Statistical analysis

Statistical analysis were performed using R-statistics (R Development Core Team, 2014). The relationships between soil $CO_{2\ flux}$ and altitude, moisture and temperature were assessed to identify dominant factors from which to assess flux trends, with variance inflation factors score used to eliminate inter-correlating variables. Mean annual spatial and temporal trends were obtained for soil $CO_{2\text{-flux}}$ and temperature and moisture parameters. Thereafter, time series analysis using ordinary least squares simple linear regression was used to evaluate the relationship between altitudinal $CO_{2\text{-flux}}$ and environment variables. The significance of the trends were assessed using t-test method at 0.05 and 0.01 confidence levels, depending on the strength of displayed relationships.

Finally, three factors were used to describe temporal and spatial $CO_{2\text{-flux}}$ patterns. We evaluated the effect of altitude on soil $CO_{2\text{-flux}}$ using simple linear regression, and thereafter coupled altitude to daytime LST and rainfall in separate multivariate linear regression analysis. Both the simple and multivariate analysis were conducted based on land cover types and monthly sampling durations.

4.3 Results

Results are presented in three parts. First, a general description of mean annual soil $CO_{2\text{-flux}}$ and environmental factors and its variations within individual land cover type is done. Second, the effect of altitude on soil flux relationship with soil moisture, temperature and physical variables is explored. Finally, temporal and spatial soil $CO_{2\text{-flux}}$ variation as influenced by soil moisture, temperature and physical variables are described.

4.3.1 General description of soil $CO_{2\text{-flux}}$ and environmental factor patterns

The mean annual $CO_{2\text{-flux}}$ and environmental factors pattern within the sampling period is presented in Fig. 4.1. During the sampling period, mean annual soil $CO_{2\text{-flux}}$ trend had two conspicuous peak i.e in April to May (734.9 - 984.2 mg m^{-2} hr^{-1}) and November to December (724.5 and 719 mg m^{-2} hr^{-1}) . Within the rest of sampling months, the flux ranged from 220 to 360 mg m^{-2} hr^{-1} except for January where flux recorded was 710.2 mg m^{-2} hr^{-1}. The $CO_{2\text{-flux}}$ peaks neatly coincide with the conventional rainfall occurrence between April and May and between November and December, and seem to occur one month after onset of the rains in both peak periods. After the peak duration in May, the flux decreases almost by half to 415 mg m^{-2} hr^{-1} in June and again to 220 mg m^{-2} hr^{-1} in July and to somewhat stabilize at about 360 mg m^{-2} hr^{-1} in the successive two months. The decrease is also observed in rainfall amount where sharp decreases are observed in June and July. However, peak increases in rainfall and soil $CO_{2\text{ flux}}$ in the wet season contrasted with decreased soil, air and land surface temperatures.

The three temperature indices showed slightly increasing trends in June - July and September - October durations, with the other months exhibiting mixed temperature patterns. Mean monthly $CO_{2\text{-flux}}$ in maize plots show identical peaks in May and December at 751.1 mg m^{-2} hr^{-1} and 762 mg m^{-2} hr^{-1} respectively, with lowest flux observed in July at 180.4 mg m^{-2} hr^{-1} (Fig 4.2). Mean monthly $CO_{2\text{-flux}}$ in mango plots was highest in November at 700.4 mg m^{-2} hr^{-1} although a slight peak was observed in April at 553.4 mg m^{-2} hr^{-1}. However, from June to October, soil $CO_{2\text{-flux}}$ maintained a more or less constant size in mango plots, with a varying margin of about ± 14 mg m^{-2} hr^{-1} across the five months. When defragmented along the altitude cluster, similar patterns observed in Fig 4.2 were replicated in Fig 4.3. Notably, the change is less conscious in 600 - 1000m altitude range or cereal, agroforestry and natural land covers types compared to altitude ranges beyond.

Table 4.1: Correlation between CO_2 flux and environmental covariates. All correlation coefficients are significant $P < 0.05$

Variable	Altitude	soil $CO_{2\text{-flux}}$	*VIF score
Altitude (m)	-	0.56	3.52
soil $CO_{2\text{-flux}}$ (mg m^{-2} hr^{-1})	0.55	-	1.84
Soil Temperature (°C)	-0.72	-0.36	2.74
Air Temperature (°C)	-0.67	-0.44	2.24
Daytime LST (°C)	-0.64	-0.55	2.00
Water Filled Pore space (%)	0.59	0.43	1.73
Rainfall (mm)	0.39	0.49	1.48

*VIF denotes variance inflation factor score

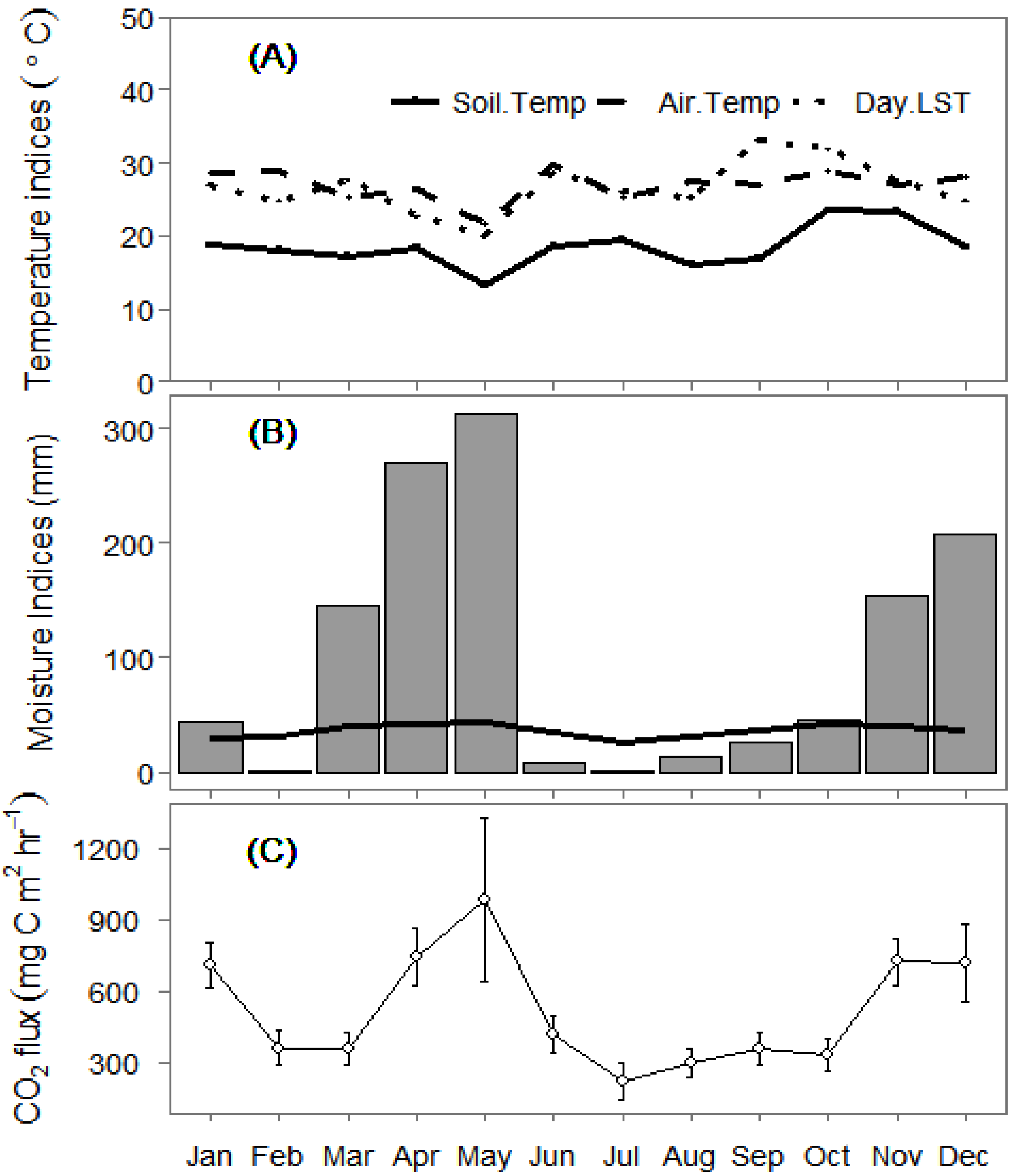


Figure 4.1: Patterns for (A) Mean monthly soil, air and land surface temperature trends, (B) Total monthly rainfall (bar plot) and mean monthly WFPS (line plot) (C) Mean monthly CO_2 flux with inter-quartile confidence range around the mean

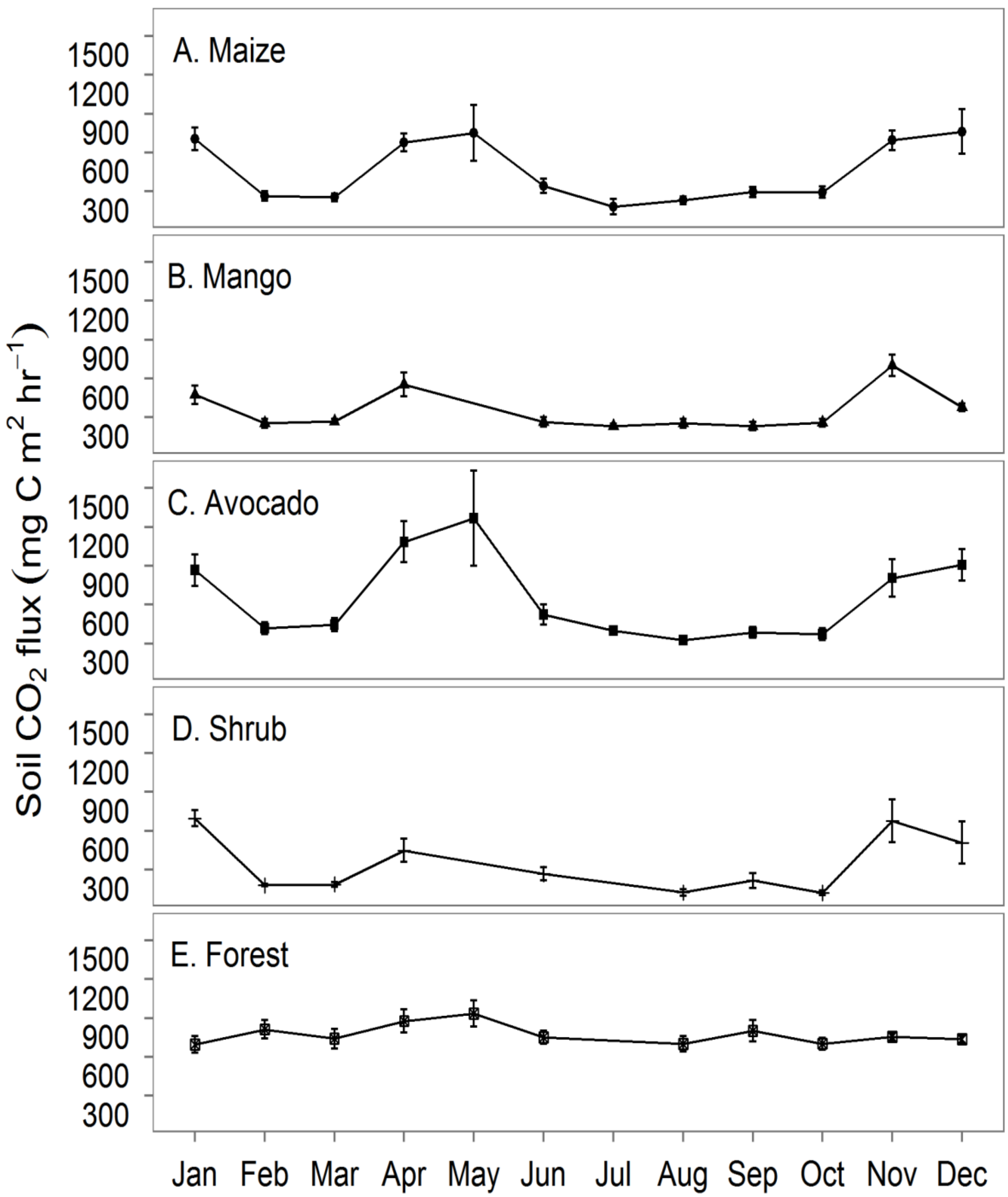


Figure 4.2: Mean monthly soil CO2 (mg m^{-2} hr^{-1}) in land cover types the Taita Hills. Vertical bars represent one standard error around sample mean

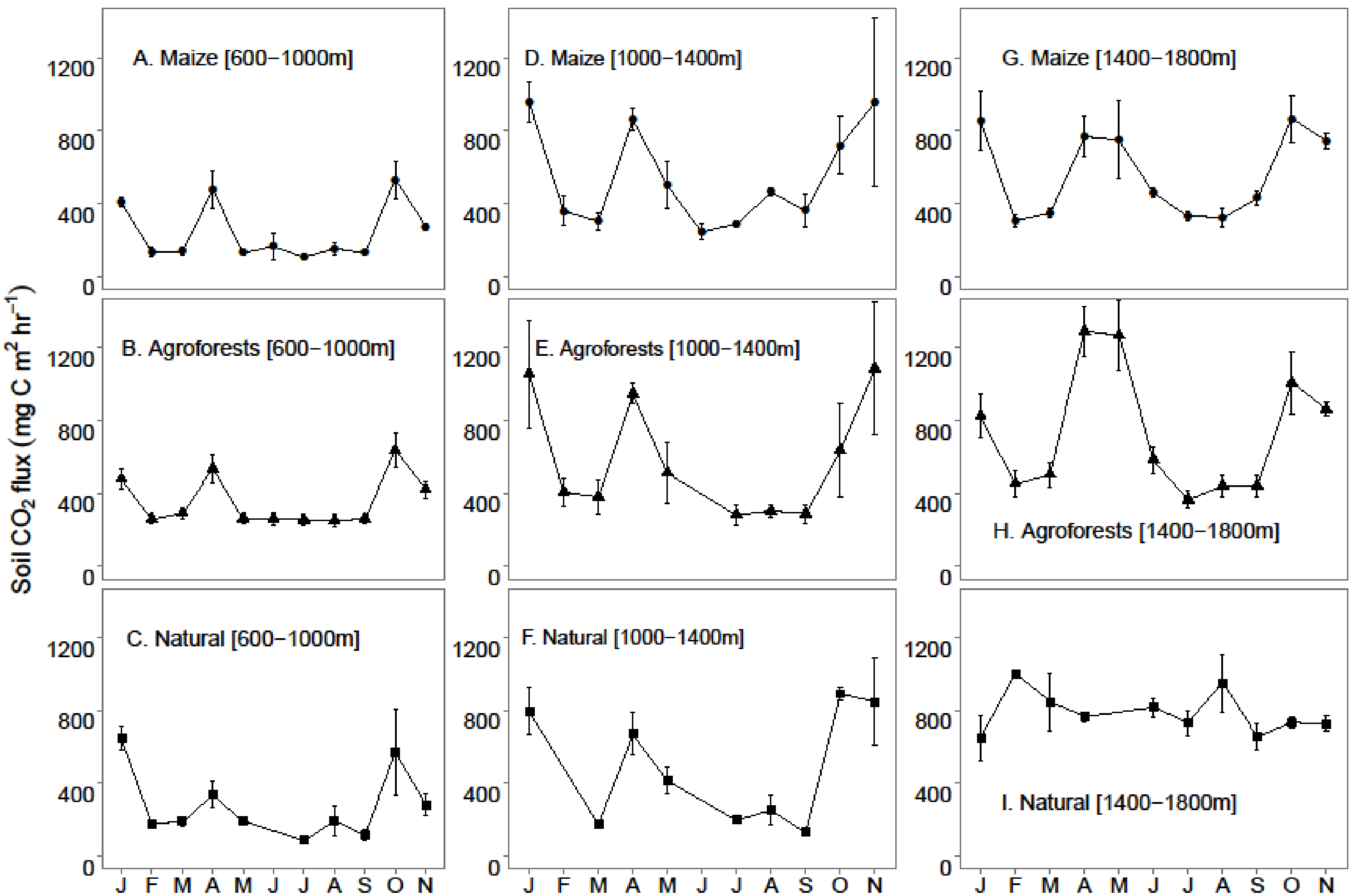


Figure 4.3: Mean monthly soil CO2 (mg m^{-2} hr^{-1}) within elevation ranges in individual land cover types the Taita Hills. Vertical bars represent one standard error around sample mean

The highest soil $CO_{2\text{-flux}}$ variation amongst the five land cover types was observed in avocado plots where mean monthly flux was 1268.2 mg m^{-2} hr^{-1} in May. Overall, six factors provided information that significantly explained spatial and temporal $CO_{2\text{-flux}}$ variability in our study sites (Table 4.1). Highly significant positive relationships were observed between soil $CO_{2\text{-flux}}$ and altitude (R^2 = 0.56), water filled pore space (R^2 = 0.43) and rainfall (R^2= 0.49). Conversely, soil $CO_{2\text{-flux}}$ correlated negatively with soil temperature (R^2 = 36), air temperatures (R^2 = 0.50) and daytime LST (R^2 = 0.56).

Altitude correlated highest with soil $CO_{2\text{-flux}}$ in comparison with other indices explored while water filled pore space correlated the least with soil CO_2 flux. The variance inflation score for the five environmental variables showed acceptable limit (> 4) to presume intercorrelation (Zuur *et al.*, 2010). We explored the scatter relationship between annual soil $CO_{2\text{-flux}}$ and four environmental variables (Fig 4.4). Generally, soil $CO_{2\text{-flux}}$ increased with rise in altitude (R^2 = 0.71) within the study transect. This was similarly observed for soil moisture WFPS index with an R^2 = 0.79. However, temperature inversion was observed for soil- air temperature relationship with $CO_{2\text{-flux}}$ and with all parameters that have a positive relationship with altitude.

4.3.2 Effect of altitude on soil $CO_{2\text{-flux}}$ relationship with environmental factors

A key focus of this study was to explore the spatial and temporal variability in soil $CO_{2\text{-flux}}$ and other environmental variables in the Taita Hills and how they vary within the various altitude ranges. Annual average $CO_{2\text{-flux}}$ and environmental variable summaries within study altitude ranges are presented in Table 4.2. Generally, high soil $CO_{2\text{-flux}}$ variability (CV > 50) was observed in altitude below 1800 m compared to 1800 to 2500 m range (CV > 20). Soil $CO_{2\text{-flux}}$ increased from 296.1 mg m^{-2} hr^{-1} in the lower altitude ranges to 760.5 mg m^{-2} hr^{-1} at the higher altitude ranges implying greater soil surface fluxes at higher altitude plots compared to mid and low altitude plots. On the contrally, temperature indices had an inverted pattern with increasing altitude; soil temperature decreasing from 22.4 to 11 ^{o}C, air temperature decreasing from 31 to 17.5 ^{o}C and Daytime LST decreasing from 30.4 to 21.7 ^{o}C. Rainfall and WFPS exhibited a gradually increasing trend with increasing altitude, with more or less similar variations in mid and upper altitude ranges.

4.3.2.1 Soil $CO_{2\text{-flux}}$ relationship with temperature indices

Generally, soil temperature revealed a significant and negative relationship with mean annual soil $CO_{2\text{-flux}}$. However, the relationship was varied when considered across altitude ranges. From elevation 0 to 1000 m, soil temperature revealed a constant trend up to November, when a spike corresponding to a $CO_{2\text{-flux}}$ spike was recorded (Fig 4.5). From elevation 1000 - 1400 m and 1400 - 1800 m, $CO_{2\text{-flux}}$ variation explained by soil temperature increases ($R^2 = 0.32$), then decreases ($R^2 = 0.21$).

In the high altitude range, flux variation explained by soil temperature patterns was lowest and insignificant. Mean monthly soil $CO_{2\text{-flux}}$ patterns across the elevation ranges were poorly explained by air temperature and thus not reported in this paper. From 800 - 1000 m, a poor and erratic relationship between the soil flux and air temperature is observed from January to July, which abruptly increases in June and again in November. Generally, air temperature explained soil $CO_{2\text{-flux}}$ in altitude range from 1000 to 1400m ($R^2= 0.16$). When compared to soil temperature and air temperature, daytime LST revealed somewhat clearer patterns explaining soil $CO_{2\text{-flux}}$ variation (Fig 4.6).

The effect of daytime on $CO_{2\text{-flux}}$ is difficult to observe from 1000 to 1400 m, with low R^2 vales < 0.1. However, at 1400 to 1800m ($R^2 = 0.32$) and 1800 – 2500 m ($R^2 = 0.51$) soil $CO_{2\text{-flux}}$ had a positive and significant match with daytime LST. Within the altitude ranges, low response of soil $CO_{2\text{-flux}}$ to daytime LST was observed in April - May and October - November periods, implying peak flux was observed when land surface was cooler at higher mountain ranges.

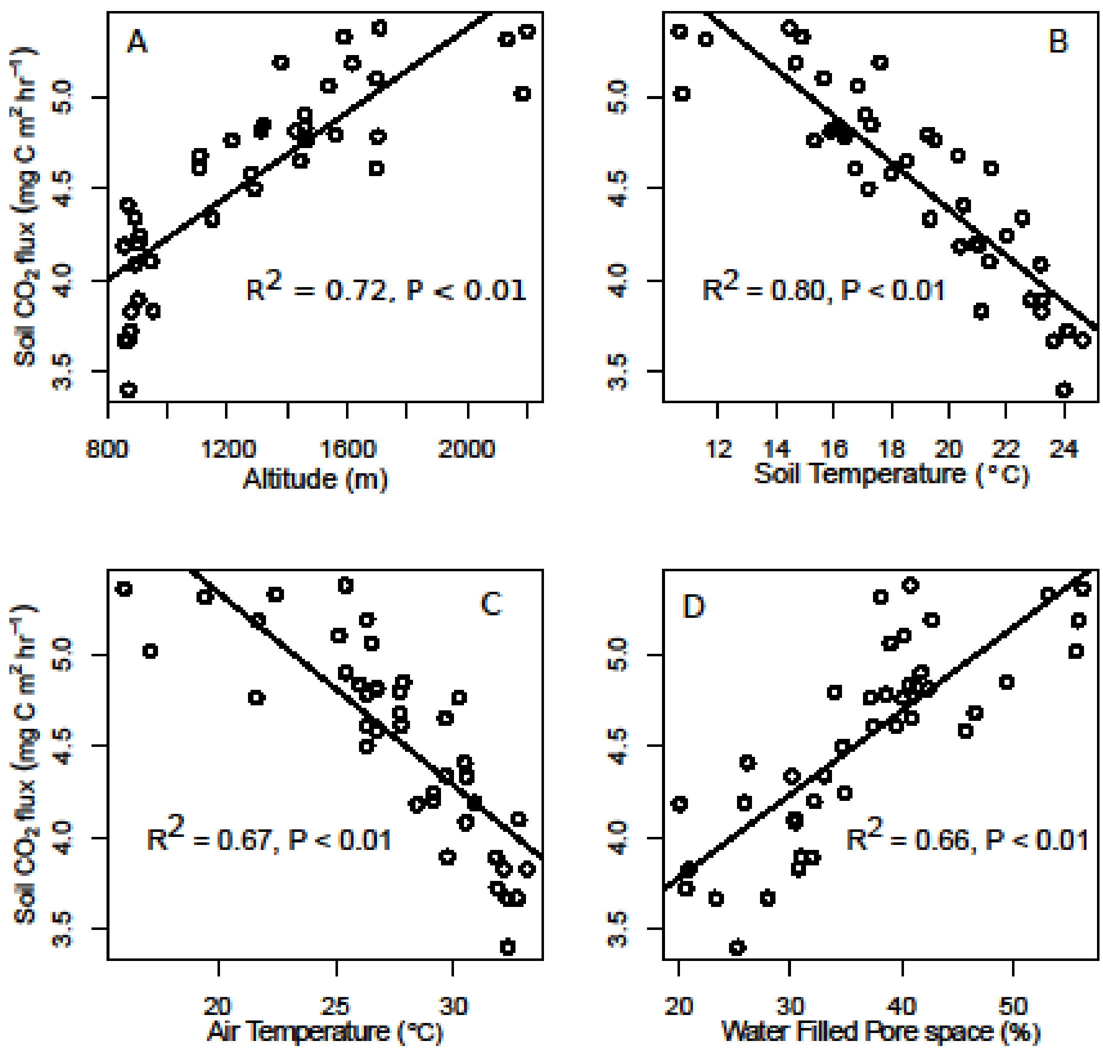


Figure 4.4: Scatter relationship between soil CO_2-flux and altitude (A), soil temperature (B), air temperature (C) and WFPS factors (D).

4.3.2.2 Soil $CO_{2\text{-flux}}$ relationship with moisture indices

Generally, soil $CO_{2\text{-flux}}$ had a positive and significant relationship with mean annual water filled pore space. Across all altitude ranges, $CO_{2\text{-flux}}$ relationship with WFPS is significantly matched in the months from May to December. Soil $CO_{2\text{-flux}}$ variation explained in elevation ranges from 0 - 1800m is poor and insignificant ($R^2 < 0.06$) compared to 1800 - 2500 m altitude range ($R^2 = 0.23$). In tropical ecosystems with distinct rainfall patterns such as the Taita Hills, WFPS patterns are likely precipitation driven, with soil properties as additional drivers that limit spatial and temporal patterns across land cover types. In this study a positive and significant correlation was observed between WFPS and rainfall ($R^2 = 0.49$). The relationship between annual $CO_{2\text{-flux}}$ $^{\text{and}}$ annual average rainfall was relatively low ($R^2 = 0.29$) compared to other environmental variables assessed (Fig 4.4), mainly because of the wide range (0 - 1336 mm) in rainfall data. The high coefficient of variation values demonstrates rainfall variability within the entire length of study transect. However, upon decomposition across altitude ranges (Fig 4.6), rainfall emerges as the best index to explain $CO_{2\text{-flux}}$ variations amongst all factors considered. From 0 to 1000 m and 1000 to 1400 m elevation ranges, soil $CO_{2\text{-flux}}$ neatly matched observed rainfall trends with $R^2 = 0.20$ and $R^2 = 0.40$ respectively. In the higher altitude ranges i.e from 1400 to 1800 m and 1800 to 2500 m, $CO_{2\text{-flux}}$ variation was best explained by rainfall ($R^2 > 0.50$) compared to the rest of environmental variables assessed.

4.3.3. Spatial-temporal relationship between soil $CO_{2\text{-flux}}$ and environmental factors

From our assessment of environmental variables, altitude, daytime LST and rainfall emerged as major factors determining spatial $CO_{2\text{-flux}}$ variation in our study site. The spatial variation in soil $CO_{2\text{-flux}}$ over the 12 month sampling period revealed a significant and negative correlation (r = - 0.85, P < 0.005) with spatially averaged daytime LST (Fig 4.8a). In contrast, the temporal variation averaged over 41 sampling plots showed an insignificant negative correlation (r = 0.56, P = 0.06) with temporary averaged daytime LST (Fig 4.7b). Similarly, spatial variation in soil CO_2 flux averaged over the 12 month sampling period indicated a highly significant (r = 0.0.73, P < 0.001) relationship with spatially averaged rainfall (Fig 4.7a). The temporal variation averaged over 41 sampling plots showed a significant correlation (r = 0.60, P = 0.005) with temporary averaged rainfall (Fig 4.8b) in the study site.

In the simple regression model, altitude explained about 14 % of soil CO_2 spatial variation in avocado plots, 16 % in shrub plots and 29 % in maize plots (Table 4.3). By combining altitude and rainfall slightly increased $CO_{2\text{-flux}}$ variation in maize and avocado plots, as compared to forest and mango plots. In mango plots, combining altitude to either daytime LST or rainfall improved explained observed variation by 2% and 26% respectively. We attribute this to the drier environment in the lower altitude (0 to 1400 masl) where soil moisture flushes during rainfall months resulted to corresponding CO_2 flushes from carbon rich surface under tree canopies. Altitude explained 37% and 4% $CO_{2\text{-flux}}$ variation in April and May peak durations respectively. By combining daytime to altitude in the multivariate analysis, variation explained in April - May durations was improved by a 3 - 10% margin. Similarly, and apart from the month of July when $CO_{2\text{-flux}}$ variability was insignificant, significant $CO_{2\text{-flux}}$ variation was observed in the rest of the months when altitude was combined with rainfall (R^2 > 0.26).

Table 4.2: Annual average values for $CO_{2\text{- flux}}$ and environmental indices within altitude ranges. Values show variable means while brackets denote coefficient of variation (CV)

Altitude (m)	$CO_{2\text{-flux}}$ (mg m^{-2} hr^{-1})	$Soil_T$ (°C)	Air_T (°C)	LST_{Day} (°C)	WFPS (%)	Rainfall (mm)
0 to 1000	296.1 (68.3)	22.4 (19.8)	31 (11.7)	30.4 (11.9)	27.7 (27.7)	49.2 (138.1)
1000 to 1400	585.3 (72.3)	18.4 (19.3)	27.6 (13.9)	26.8 (13.1)	41 (28.5)	80.4 (115.7)
1400 to 1800	655.7 (51.3)	16.4 (20.2)	25.8 (15.2)	24.9 (13)	41.6 (22.6)	91 (94)
1800 to 2300	760.5 (19.2)	11 (23.3)	17.5 (16.3)	21.7 (12.3)	49.9 (21.5)	365.6 (113.3)

$Soil_T$, soil temperature: Air_T, Air temperature: LST_{Day}, Daytime land surface temperature: WFPS, water filled pore space

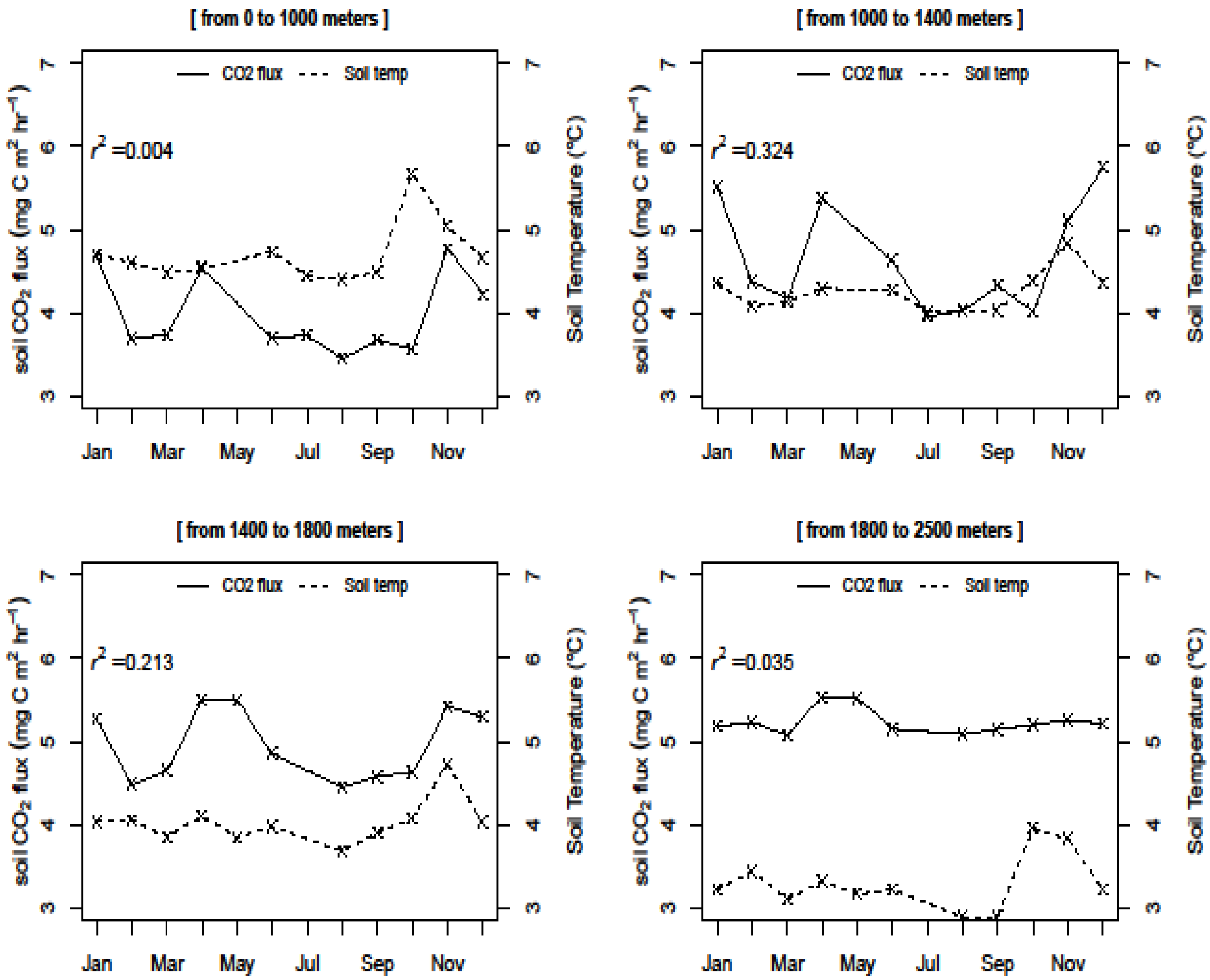


Figure 4.5: Mean annual CO_2-flux relationship with soil temperature. (Factor transformation as follows; CO_2-flux$^{1/4}$ and soilT ½)

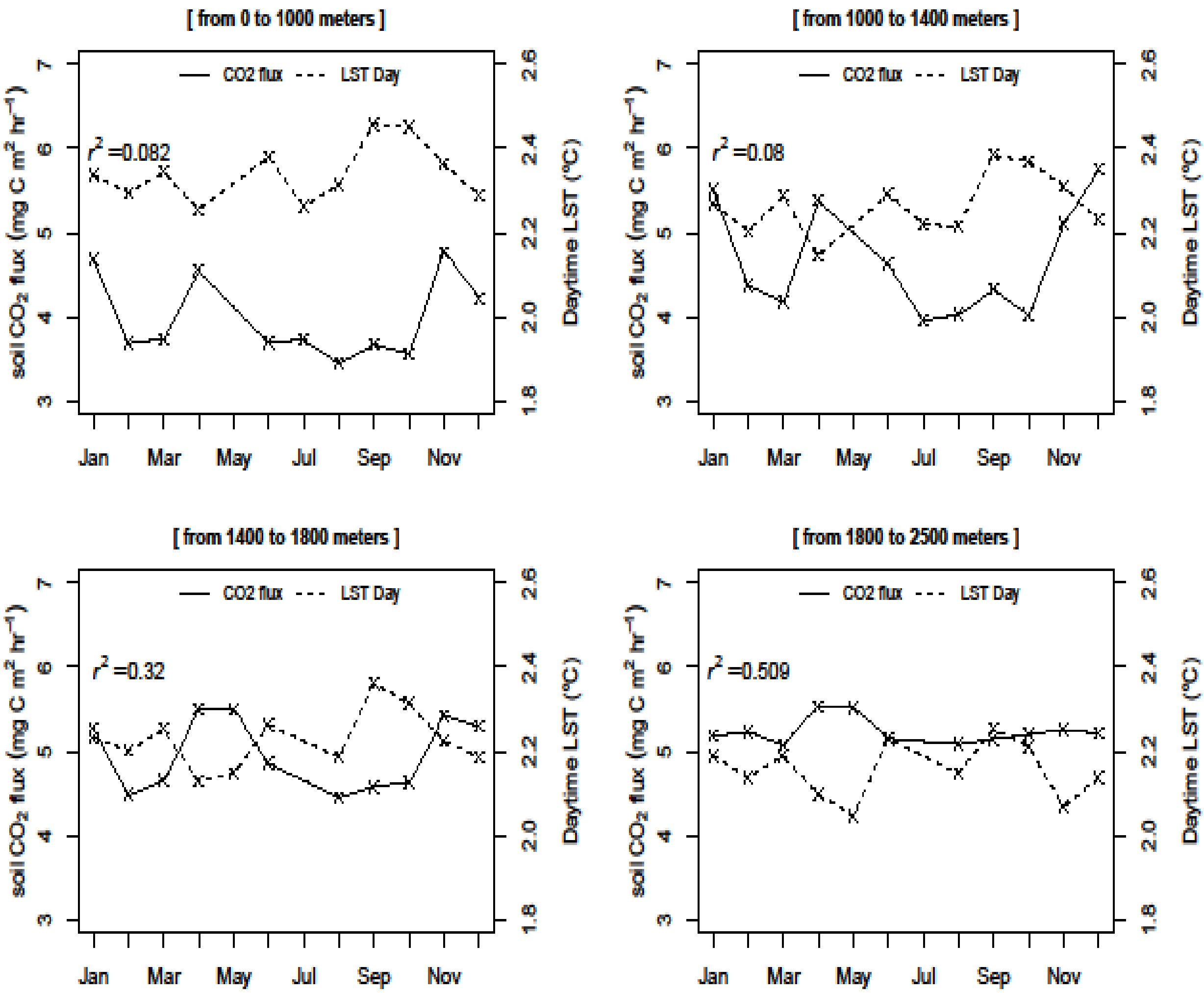


Figure 4.6: Mean annual CO2-flux relationship with daytime LST, with factors transformed as follows: CO_2-flux$^{1/4}$ and LSTDay$^{1/4}$.

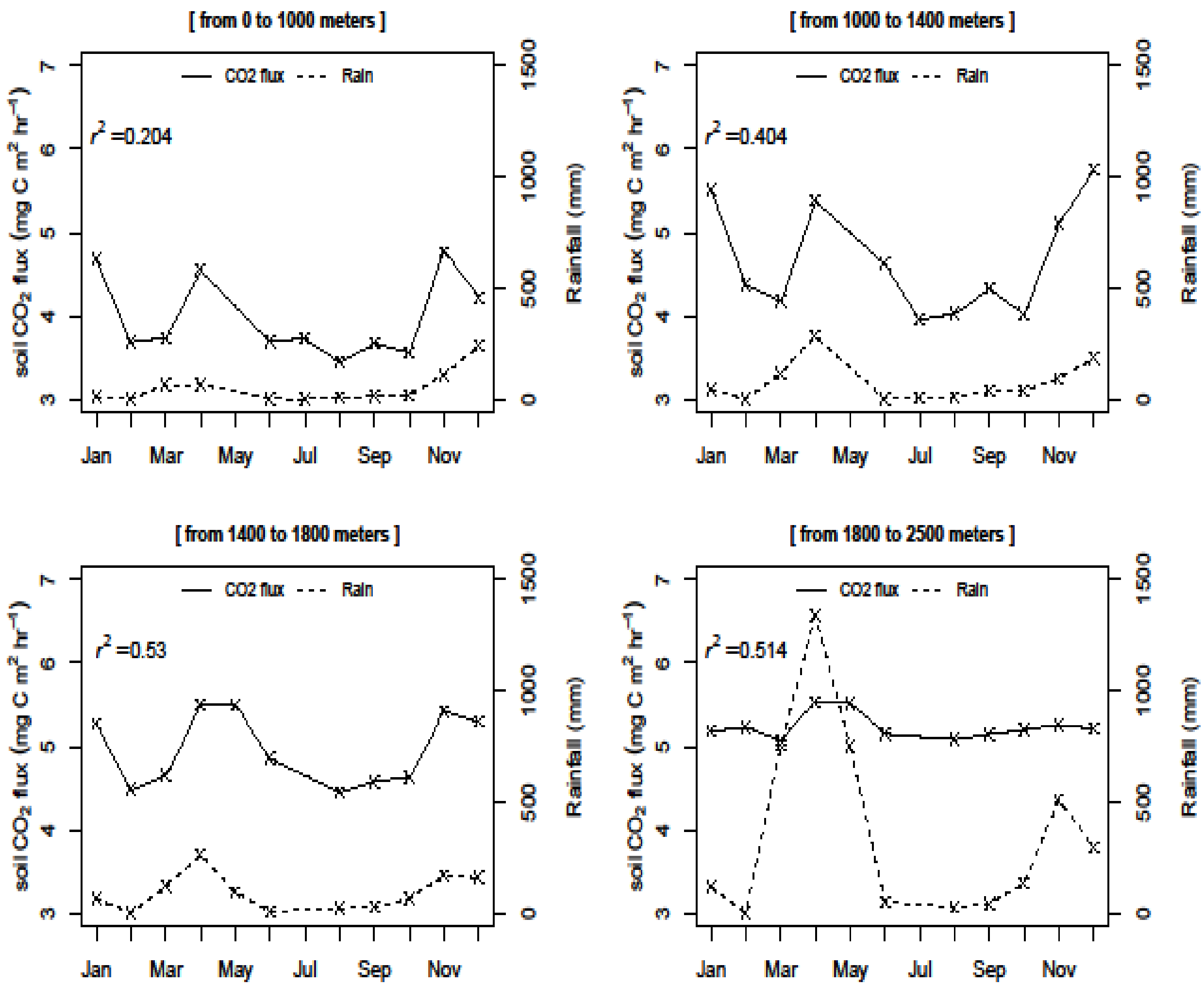


Figure 4.7: Mean annual soil CO_2 trend relationship with rainfall, with factor transformed as follows,

CO_2-flux$^{1/4}$

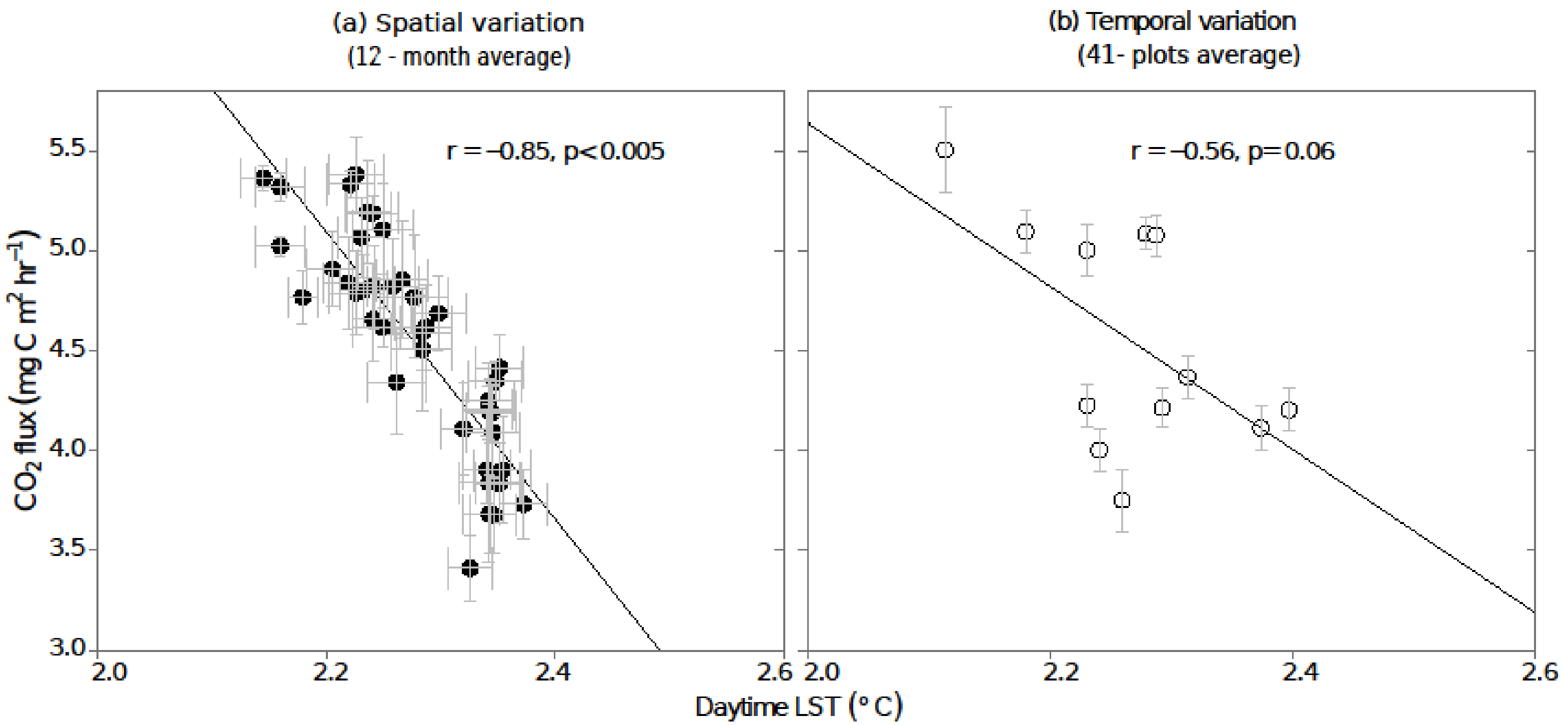


Figure 4.8: (a) Spatial variation relationship with temporary averaged soil flux and daytime LST for 41 plots. (b) Temporal variation relationship with spatially averaged flux and daytime LST for 12 months. Bars denote standard deviation in both plots. Transformations are as follows; (CO_2 flux) $^{1/4}$ and (Daytime LST) $^{1/4}$ in both Figures.

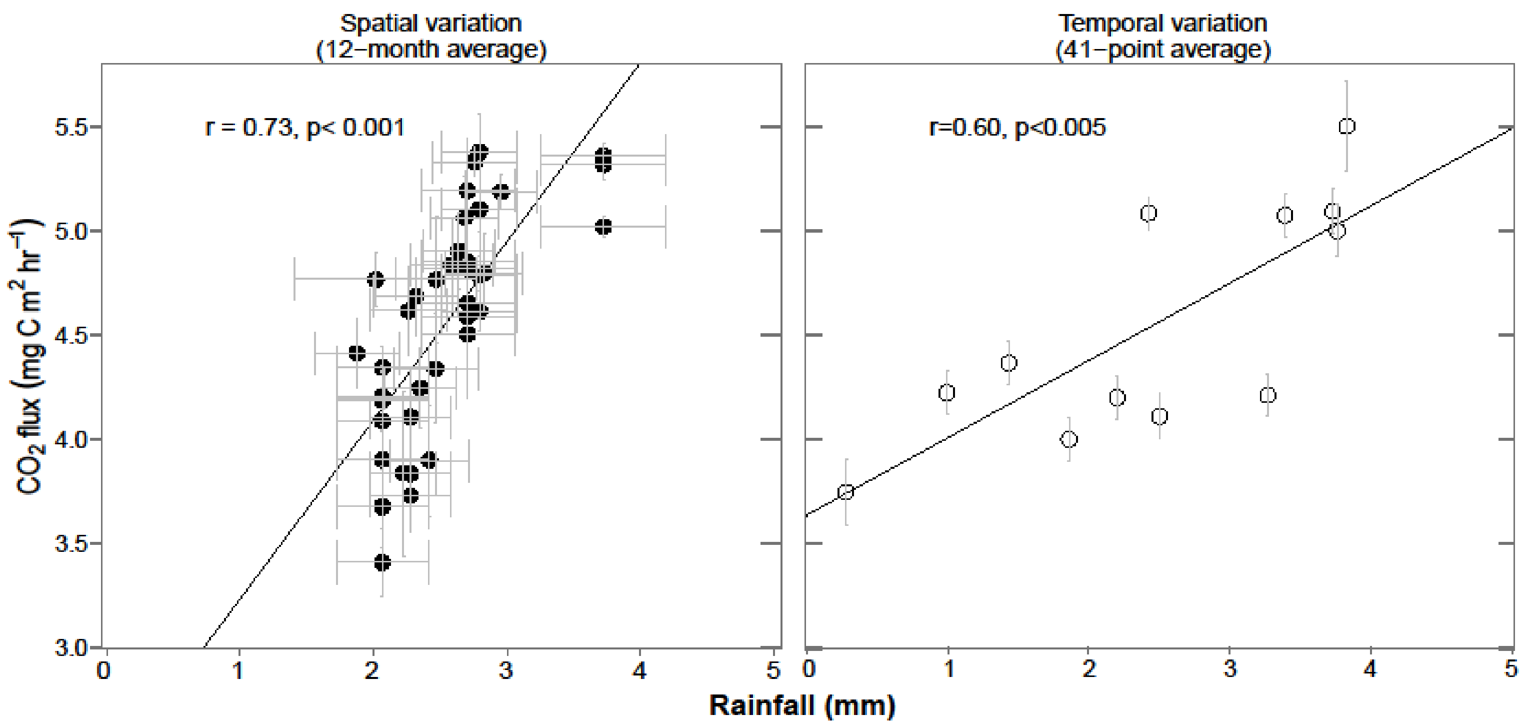


Figure 4.9: (a) Spatial variation relationship with temporary averaged soil flux and rainfall (mm) for 41 sampled plots. (b) Temporal variation relationship with spatially averaged and rainfall (mm) for 12 months. Bars denote standard deviation in both plots. Transformations are as follows; (CO_2 flux) $^{1/4}$ and (rainfall) $^{1/4}$.

Table 4.3: Regression coefficient from simple and multivariate analysis, where soil CO_2 flux is independent variable and altitude, daytime LST and rainfall are dependent variables

		Simple regression	Multivariate Regression	
		(Altitude)	(Altitude + Daytime)	(Altitude + Rainfall)
	n	R^2	R^2	R^2
Maize	158	0.29***	0.35**	0.45**
Mango	53	0.01^{NS}	0.13*	0.27*
Avocado	97	0.14**	0.3*	0.32**
Shrub	55	0.16**	0.24*	0.25*
Forest	52	0.01^{NS}	0.08^{NS}	0.04^{NS}
Jan	40	0.17***	0.3^{NS}	0.39*
Feb	35	0.61***	0.61**	0.61**
Mar	40	0.53***	0.57*	0.54**
Apr	40	0.37***	0.47^{NS}	0.37*
May	9	0.04^{NS}	0.07^{NS}	0.56*
Jun	41	0.63***	0.68***	0.67***
Jul	12	0.07^{NS}	0.15^{NS}	0.08^{NS}
Aug	40	0.61***	0.64*	0.61**
Sep	40	0.5***	0.5*	0.51**
Oct	40	0.66***	0.66**	0.73***
Nov	40	0.12**	0.15^{NS}	0.26*
Dec	38	0.28***	0.32^{NS}	0.3*

Prefix meaning; *** $P < 0.001$, ** = $P < 0.01$, *= $P < 0.05$; NS = Not Significant

4.4 Discussion

This study is a pioneering endeavor to describe the spatial and temporal soil $CO_{2\text{-flux}}$ patterns in elevated ecosystems of East Africa, where greenhouse gas emission data is insufficient. It is therefore crucial to mention some subtle methodological comparisons and differences with similar studies in Africa and other tropical ecosystems. The study research transect spans a 1530 m altitude gradient, from semi - arid lowlands to humid highlands (refer to Fig 3.1 and Table 3.1). In such diverse ecosystems, a high level of heterogeneity is implicit from topo-sequence variation of local ecological factors such as precipitation, temperature, soil types, etc. In western Kenya, similar studies (Arias-Navarro *et al.*, 2013) assessed forests, grassland and cropland fluxes in plots located at comparable altitude level and utilized the dynamic chamber method synonymous to this study. Merbold *et al.* (2011) and Quansah *et al.* (2015) assessed $CO_{2\text{-fluxes}}$ in a variety of Africa ecosystems heterogeneously comparable to our study transect, used closed chamber method and eddy covariance stations. Similar studies e.g Davidson *et al.* (2000); Sotta *et al.* (2007) used closed chamber methods to assess $CO_{2\text{-flux}}$ in the tropical Amazonian forests, with comparable ecological condition to our study site. Closed chamber systems have also been utilized in forest ecosystems of Asia to assess spatial and temporal soil $CO_{2\text{-fluxes}}$ (Kosugi *et al.*, 2007; Itoh *et al.*, 2012). Nevertheless, despite methodological similarities and differences in study site ecological conditions, design and equipments used to assess soil gas fluxes, important comparisons to describe the manner in which environmental factors influence spatial and temporal soil $CO_{2\text{-fluxes}}$ can be made.

4.4.1 Environmental factors effect on soil $CO_{2\text{-flux}}$

Several studies, such as Davidson *et al.* (2000); Kosugi *et al.* (2007); Merbold *et al.* (2011); Itoh *et al.* (2012) have identified rainfall-driven soil moisture patterns to be a major factor determining seasonal soil $CO_{2\text{-flux}}$ emissions in different ecosystems. The Taita Hills ecosystem experiences different rainfall regimes from lower to upper altitude zones thus altitude driven variations in soil moisture are expected (Fig 4.1). In this study, WFPS had a positive and significant relationship with soil $CO_{2\text{-flux}}$ which was poor at 0 - 1800 m elevation but improves at the higher altitude range (Table 4.2). Since WFPS is a function of rainfall, which is highly variable in the lower altitude ranges, it is likely that the low correlation arises from rainfall variability.

Soil textural characteristics may also be partly responsible for this observed altitude variability, considering that moisture has an influence on soil gas flux rates below or above critical extreme soil moisture condition (Sotta *et al*., 2004). Moreover in the Taita Hills, soils in low to mid altitude ranges have a highly porous sand structure hence a low moisture retention capacity. Therefore measurements conducted even immediately after a rainfall event are likely to show a weak WFPS - $CO_{2\text{-flux}}$ relationship in the lower ranges compared to moisture retaining silicate clay soils in the higher altitude end. On the contrally, rainfall patterns clearly mimicked soil $CO_{2\text{-flux}}$ patterns and especially in April- may and Oct - Dec peak periods (Fig 4.7) revealing precipitation to be a better indicator of soil $CO_{2\text{-flux}}$ compared to WFPS in the Taita Hills study transect. Thus a high correlation is observed when considering soil $CO_{2\text{-flux}}$ response to rainfall across altitude range. Similar positive and high associations were reported in primary forest in the Brazilian Amazon (Sota *et al*., 2004; Davidson et al., 2000; Chambers 2004) and tropical ecosystems in Asia (Merbold *et al.*, 2011; Itoh *et al.*, 2012) where $CO_{2\text{-flux}}$ peaks neatly coincided with durations of maximum rainfall intensity.

Temperature measurements at micro (soil temperature), macro (air temperature) and broader ecosystem (land surface temperature) levels were significantly correlated to soil $CO_{2\text{-flux}}$ (Table 4.3). The relationship between daytime LST and soil (R^2 = 0.32) and air (R^2 = 0. 24) is indicative of the wide temperature differences between chamber microclimate and that of surrounding environment (Figure not shown). Specifically, soil, air and daytime LST explained more than 60 % of $CO_{2\text{-flux}}$ variation, which is comparable to chamber-based studies conducted in the tropical forests of the Amazon by Meir *et al.* (2004) and Sota *et al*., (2004). However, when compared across altitude ranges, soil and air temperatures infinitesimally explained soil $CO_{2\text{-flux}}$ patterns between 0 to 1000 m and between 1800 to 2500 m. This poor altitudinal relationship between soil $CO_{2\text{-flux}}$ and soil/air temperature is partly explained by large coefficient of variation values observed within the four altitude ranges (Table 4.3).

Large differences in micro and macro climate temperature conditions within the Taita Hills, in addition to soil property differences at these spatial scales, are plausible reasons for observed high variation, as observed similarly by Kosugi et al., 2007. MODIS day-LST explained comparatively higher ($R^2 > 0.35$) soil $CO_{2\text{-flux}}$ variation in altitude ranges between 1400 to 2500 m in contrast to lower 0 to 1400 m elevation range (Fig 4.6). Its is plausible that the poor relationship for the 250 m downscaled MODIS LST was spatially inadequate to capture diminished $CO2_{\text{-flux}}$ variations at individual sampling plots, and especially at elevation ranges below 1400 m.

From Maeda and Hurskainen (2014), daytime LST is highly influenced by land cover characteristics and altitude, thus the higher observed flux - temperature relationship in forest plots that have a more uniform vegetation structure. Land cover change through deforestation and the pronounced seasonal phenological changes in vegetation obscure LST effect at the lower altitude ranges.

4.4.2 Spatial variation in soil $CO_{2\text{-flux}}$ patterns

Although the large area sampled complicates our explanations for spatial $CO_{2\text{-flux}}$ variation, the portable chamber system utilized in the study enabled consistent measurements in rugged terrains within the Taita Hills, with the disadvantage that permanent long term observations were not possible. From the results, the mean annual fluxes within sampling plots range from 351 to 766 mg C m^2 hr^{-1} (Fig 4.2), which compares with chamber based measurements conducted in western Kenya (Arias-Navarro *et al.*,

2013) where emissions ranged between 50 to 860 mg C m^2 hr^{-1}. Generally, land surface temperature shows a significant spatial dependence with soil $CO_{2\text{-flux}}$ (Fig 4.6) which implies that land cover has a significant influence on soil-based emissions. However, when altitude was considered, the flux values were highly varied. Phenological patterns in above ground land cover and below ground biological activities along the study altitude gradient are plausible reasons for the wide range of $CO_{2\text{-flux}}$ flux values in this study as observed elsewhere by Søe and Buchmann (2005).

When compared across land cover types, indigenous forest in the Taita Hills ecosystem attained the highest $CO_{2\text{-flux}}$ emissions with a relative low coefficient of variation. High forest $CO_{2\text{-flux}}$ emissions are directly related to high decomposition rates taking place under microbe-rich soils with exogenous and native organic matter (Singh *et al.*, 2009). In contrast, maize system obtained an average annual flux of 448 mg C m^2 hr^{-1}. Maize is a common staple food grown by smallholder fields within the entire length of the Taita Hills study transect under different soil and environmental conditions (refer to table 4.1). Similar high variation was observed in shrubs, avocado and mango fields located from low to mid altitude ranges. This high variability was similarly observed by Han *et al.* (2007) in farmlands with CV's varying from 43 to 53 %. Merbold *et al.* (2011) also reported high heterogeneity in soil respiration rates from miombo woodlands of western Zambia attributed to soil carbon hotspots from cattle grazing and differences in ground vegetation densities. Similar flux patterns were observed in west Africa savanna ecosystems (Sjöström *et al.*, 2011; Quansah *et al.*, 2015). As a first step towards understanding spatial $CO_{2\text{-flux}}$ variations in East Africa mountain systems, our study focused on quantifying flux magnitudes in space time continuum. Thus more detailed measurements are needed to identify and quantify main factors driving spatial $CO_{2\text{-flux}}$ heterogeneity in the Taita Hills ecosystem.

4.4.3 Temporal variation in soil $CO_{2\text{-flux}}$ patterns

Changes in soil properties resulting from soil water condition play a crucial role in driving soil borne $CO_{2\text{-flux}}$ patterns within an ecosystem (Lee *et al.*, 2007; Itoh *et al.*, 2012). In SSA ecosystems, altitude - driven precipitation patterns regulate seasonal biomass and substrate availability for microbial decomposition thus limiting season $CO_{2\text{-flux}}$ emissions (Merbold *et al.*, 2009b; Quansah *et al.*, 2015). Similarly in our study, mean annual soil $CO_{2\text{-flux}}$ trend within various land cover plots (Fig 4.2) closely correlate to monthly precipitation patterns (Fig 4.1). In May, a month after 'long rain" rains onset in the Taita Hills ecosystem, $CO_{2\text{-flux}}$ flux attains a peak then decreases to July onset of dry spell. This pattern is again repeated in November - December duration, a month after "short rain" onset where $CO_{2\text{-flux}}$ peak is observed. The occurrence of two $CO_{2\text{-flux}}$ peaks that neatly coincide with peak rainfall seasons is consistent with other studies elsewhere (Hollinger *et al.*, 2004; Søe and Buchmann, 2005). Peak soil $CO_{2\text{-flux}}$ emissions in the rainy season are due to increased microbial decompositions under optimal temperature conditions. Other reasons for increased soil emissions at peak moisture periods include rapid displacement of soil pore space air as rain water percolates down to the soil profile and microbial cell rapture (Hollinger *et al.*, 2004).

4.5 Conclusions

This study provides a spatial and temporal description of soil $CO_{2\text{-flux}}$ along an altitude gradient in the Taita Hills conducted in year 2013. The results contribute to understanding the interactions between local ecological factors and land cover in driving soil borne CO_2 emissions in mountain systems in east Africa. The average annual soil $CO_{2\text{-flux}}$ is differentially correlated to various environmental variables and at different elevation ranges. Although soil water seemed to have little influence on soil $CO_{2\text{-flux}}$ emissions in the lower 0 to 1800 m elevation, rainfall played an important role at controlling $CO_{2\text{-flux}}$ at all altitude ranges. On the other hand, air and soil temperatures have a positive but inconsistent control of soil emissions in the lower 0 to 1800 m altitude range, which is totally absent in the higher 1800 - 2500 m elevation. MODIS daytime LST presented an excellent alternative to in situ temperature indices assessed in the study and explained reasonable soil $CO_{2\text{-flux}}$ variation from 1400 to 2500 m elevation range. This study is the first step at mapping soil surface fluxes in poorly inventoried east Africa mountain systems and underlies the importance of topographic variability in determining soil $CO_{2\text{-flux}}$ emission patterns and trends.

CHAPTER FIVE

ASSESSING SOIL C AND N STOCKS AND DETECTION THRESHOLDS ALONG AN ALTITUDE GRADIENT

5.1 Introduction

Agricultural expansion poses the greatest threat to conservation and rehabilitation of degraded natural ecosystems in Sub Sahara Africa (SSA). According to Brink and Eva (2009), the accelerated rate of deforestation at 5 million hectares per year in sub-Sahara Africa (SSA) resulted to a loss of 16 % of natural forests between years 1975 to 2000, and concomitantly expanded agricultural land by 57 % within the same duration. Smaller biodiversity hotspots within the region are similarly under threat. Natural forests, grasslands and other natural landscapes in East Africa's eastern Arc Mountain systems are currently over-exploited resulting to species loss and over-exploitation of soil nutrient resources. For instance, deforestation has cleared large areas of natural forest in the Taita Hills, an important biodiversity hotspot situated in Southeast Kenya, leaving barely 1% of the original tropical forest. Land for agricultural expansion has steadily increased with forest destruction and is projected to increase to 60 % by year 2030 (Maeda *et al.*, 2010a; Maeda *et al.*, 2010b).

A major concern in this fragile ecosystem is intensified land use activities that deplete soils of essential soil minerals, disrupt soil structure and contribute to low smallholder productivity and household food security. The gradual loss of soil organic carbon when forest lands are converted to croplands, accompanied by increased atmospheric emissions are well documented (Trumbore, 1997). Globally, deforestation is responsible for 10 to 30 % of total C emissions estimated for global tropical regions (Houghton, 2003), which represents 25 to 70% loss from originally present soil organic matter stock (Don *et al.*, 2011). Vågen *et al.* (2005) review of SOC changes in SSA shows huge discrepancies, from

-24 to 6 Mg C ha^{-1}, when natural land is turned to cultivated croplands and other land use type. Studies by Hartemink (1997) and Veldkamp *et al.* (2003) show that soil nutrient stocks at the upper 0 to 20 cm soil layer are more prone to perturbations following land use change thus exemplifying their vulnerability.

Despite drawbacks in land conversion, the potential for agricultural lands to sequester atmospheric carbon are well documented (Albrecht and Kandji, 2003; Verchot *et al.*, 2005). In SSA, agro-forestry systems have been widely established to supplement food resources from traditional cereal crops, mitigate low soil inputs use through litter fall and provide livestock fodder. The benefits of agro-forestry to soil carbon sequestration within the region are well documented (Vågen *et al.*, 2005; Thangata and Hildebrand, 2012). However, productivity of agro-forestry systems in terms of C sequestered through plant biomass is highly variable and dependent on several factors such as climate, soil types and fertility status, tree species and system management (Verchot *et al.*, 2007). Albrecht and Kandji (2003) showed that management practices such as pruning and fertilizer application improved agro-forestry tree biomass production and soil carbon stock by up to 2.5 times.

Although soil degradation is a natural and inevitable process after land is opened for cultivation, the accelerated loss of SOC and other nutrients poses numerous ecological challenges in cereal and agro-forestry systems. For instance, low levels of soil macro and micro nutrients are directly associated with low stand establishment and maturation (Nandwa, 2001), poor performance of associated crop species and susceptibility of the agro-forestry system species to hosts of plant diseases and pathogens (Sileshi *et al.*, 2000). In mountain areas, fields located in steep slopes are highly susceptible to sheet and gully erosion resulting to low tree-crop establishment and rendering these areas unsuitable for agriculture. In order to account for soil nutrient loss and variability in spatial and temporal soil stocks, a number of process and geo-statistical models have been used for ecosystems in Kenya (Batjes, 2004a; Kamoni *et* *al.*, 2007). Most recently, a supra national study of African ecosystems has developed soil nutrient profile maps using a combination of digital and analogues databases for the region (Leenaars, 2013; Leenaars *et al.*, 2014). However, given the inherently high topographic and ecological heterogeneity in SSA, models representing large spatial areas are unsuitable to guide land management and rehabilitation activities at a smaller ecosystem scale.

This study aims to identify spatial patterns and ecological drivers for soil nutrient conditions from an altitudinal transect in the Taita Hills, which is part of the heterogeneous Eastern Arc Mountains systems. In this ecosystem, there is scarcity of baseline data describing soil nutrient stock changes when forest land is converted to agricultural production and the ecological drivers that discriminate stock patterns within land covers types. This scarcity hampers design of judicious long term agricultural land management and forest rehabilitation activities aimed to curb decline in soil nutrient stocks. Moreover, the influence of topographic attributes and significant temperature and moisture weather events on spatial distribution of soil nutrient stocks requires attention. Our specific objective were : - (i) to determine effect of altitude, land use and cover types on spatial soil carbon and nitrogen stocks (ii) to identify the major drivers for soil carbon and nitrogen stocks across the altitude gradient (iii) assess the detection limits for soil carbon and nitrogen stocks along altitudinal categories.

5.2 Material and Methods

5.2.1 Field sampling strategy

Sampling was conducted as explained in Chapter 3 (Section 3.2)

5.2.2 Soil sampling

Soils samples for carbon and nitrogen nutrient analysis were collected using a soil auger marked to a 20 cm soil depth. This depth constitutes the fast cycling soil organic carbon and nitrogen pools and is also most affected by land use and cover change (Woomer *et al.*, 2001). In each plot, five composite samples were acquired, with each sample comprising a sub-composite (~ 500 g) of one sub-sample (~ 500 g) taken at exact GPS sampling spot mixed with three additional sub-samples (each ~500g) acquired around 1 m radius of the sampling spot. For the purpose of this study, only three sampling spots were analyzed for soil carbon and nitrogen contents. Additionally, three core soil samples were acquired to a 10 cm depth (at 1st, 3rd and 5th sampling spots). Sampling period coincided with tapering of short rains in December, thus rainfall was measured at sampling using wireless rain gauges (*Model* No. RGP150 General ®) installed at various sites within the altitude ranges. Total daily rainfall (mm) was recorded and used to compute inter-annual rainfall totals per plot within each elevation range. Air temperature was measured using a digital min-max thermometer (*Model* ST 9263, range from - 50^{o}C to 150 ^{o}C) fitted with a 1-metre sensor cable. The sensor was always placed between 0.5 m and 1 m above the soil surface and ~10 m to the sampled plot. Similarly, soil temperature was measured using a thermometer (*Model* Acurite - 00661) with a 15 cm probe inserted into the soil and placed adjacent to the sampling spots during field sampling.

5.2.3 Soil analyses

Acquired soil samples were air dried, weighed then sieved (< 2 mm) to remove roots and rock debris. The samples were transported to the University of Helsinki, department of Geosciences and Geography for laboratory analysis. During analysis, samples were weighed in triplicates then ground to < 100 µm using a ball mill and a sample less than 100 mg weighed into a tin boat without any pretreatment. They were then analyzed for total organic carbon and total organic nitrogen by dry combustion using a CN analyzer “Vario MICRO cube” (Elementar Analysensysteme GmbH, Hanau, Germany). Organic C and N stocks (kg m^{-2}) were calculated as a function of C and N concentration (%), plot soil bulk density (g cm^{-3}) and sampling depth (20 cm). Soil pH was analyzed using pH/^{o}C meter (pH Tutor, EUTECH instruments, Singapore) and reading corrected for temperature fluctuations during analysis. Field obtained core samples were pre-weighed then oven dried at 105 ºC for 48 hours and again re-weighed to determine soil water content and to enable calculate water filled pore space (WFPS). Soil textural analysis was performed using the hygrometer method on a sub-set of the samples representing the three altitude categories to describe the textural classes (Table 5.1) although data is not presented.

5.2.4 Statistical analyses

All statistical analysis were performed using R-statistics (R Development Core Team, 2014). Prior to analysis data were examined for normality by Shapiro-wilk test and homogeneity of variance by Levene test. Data not normally distributed were either transformed by square-root (N % and N stock), cube root (bulk density) or log transformed (C % and C stock) as appropriate. Statistical tests were thereafter performed using transformed values, although the non-transformed values were used to report the averages. Significant differences between means in C stock, C/N ratio, C percent and bulk density within altitude range, land use and cover types were tested using a repeated one way analysis of variance (ezANOVA, type = 3, for unbalanced data due to size differences in factor categories). *Post hoc* Tukey HSD test was used to test carbon and nitrogen stocks differences within different factor categories.

Prior to the back-forward stepwise regression procedure to derive predictive models for soil OC and TN stocks along altitude range, intercorrelation was assessed. The variables were then entered as following order (Altitude, pH, C: N, soil temperature and Water filled pore space (WFPS), guided by explained variance from simple linear regression model. Minimum detectable differences (MDD) in soil carbon and nitrogen stocks were calculated to distinguish detectable stock changes within altitude ranges. MDD indicates the smallest difference detectable between means with a given number samples under different altitude ranges with 90 % confidence ($1 - \beta = 0.90$) and $\alpha = 0.05$ (Conant *et al.*, 2003). As field sampling plots were a minimum of ~ 200 m from each other, samples were considered independent and therefore the following formulae applied;

$$MDD(unpaired\ sampe) = \sqrt{[(4\sigma^2(Z_{(1-(\alpha/2),v)} + Z_{(1-\beta,v)})\ \ ^2) \div N]} \qquad (1)$$

Where; σ is the standard deviation, Z is the test statistic at a given significant level (α), β is the probability of type II error and v is the degree of freedom. For comparisons of MDD values across different altitude range under different levels of carbon and nitrogen stocks, the relative MDD was computed using altitude range means ($\bar{\chi}$) as follows;

$$MDD_{\mathbf{rel.}} = \frac{MDD}{\bar{\chi}}.100\% \qquad (2)$$

Table 5.1: Pre-study soil textural characteristics within three altitude gradations in Taita research transect. Note that altitude gradation below 1400 m have been merged to 600 to 1400 m altitude range

Altitude range (masl*)	Soil textural properties	MAT (°C)	MAP (mm)
600 to 1400	sand: 50 - 78 % clay: 12 - 30 % silt: 8 - 28 %	29.3	438
1400 to 1800	sand: 38 - 58 % clay: 24 - 44 % silt: 14 - 20 %	25.8	970
1800 to 2250	sand: 40 - 68 % clay: 30 - 46 % silt: 16 - 24 %	17.5	1685

MAT, Mean annual Temperature; MAP, mean annual precipitation: both indices obtained from data by field data loggers installed within the study transect; masl, metres above sea level,

5.3 Results

5.3.1 Variation of soil properties along elevation gradient, land use and cover types

Due to the nature of smallholder agricultural and land management practices, soil organic and nitrogen pools most prone to frequent perturbations lie from the surface to about 20 cm soil depth. In the Taita Hills land use systems, this depth variation is regulated by land cover patterns as determined by altitude and slope characteristics. The omnibus analysis of variance table is shown in Table 5.2, whereas the separated means are shown in Table 5.3. An altitude increase to an 82 % increase in percent slope from low (800 - 1300 m) to mid (1300 - 1800 m) and 134 % increase from low to high (1800 - 2300 m) altitude ranges. Bulk density (BD) significantly ($F_{2, 37} = 43.64$, $P < 0.001$) decreased by 13% from low to mid and about 3.5 times from low to high altitude ranges. Similarly, soil pH (CV from 7 to 12%) and soil temperature (CV from 5 to 14%) revealed a significantly decreasing trend with increasing altitude. WFPS and soil C and N stocks significantly ($P < 0.05$) increased with increase in altitude and with varying percent coefficient variation values within plots located in similar altitude range. Compared across land uses, bulk density (BD), soil pH and soil temperature (ST) maintained a decreasing and a non-significant trend in the order; cereal > agro-forestry > natural (Fig 5.1). The converse is true for slope, WFPS, C and N stocks. Generally, variability in soil OC and TN stocks was comparable in factor categories assessed; altitude ranges (CV from 48 to 52 %), land uses (CV from 43 to 55 %) and cover (CV from 27 to 50%). The converse was true for soil properties such as pH, soil temperature, and WFPS where land use categories percent CV values were higher compared altitude categories.

Table 5.2. One way analysis of variance (ezANOVA) in study plots within ecological factors in the Taita Hills, computed at Tukey 5% significant level

	Altitude range			**Land cover type**			**Plot land use**		
	Df	F	P	Df	F	P	Df	F	P
Soil bulk density	2	43.646	0.000	2	6.314	0.004	4	19.531	0.000
Soil pH (H_2O)	2	13.78	0.000	2	1.441	**0.250**	4	6.756	0.000
Soil total C (0 - 20cm)	2	6.380	0.004	2	5.959	0.005	4	19.531	0.000
Soil total N (0 - 20cm)	2	8.148	0.001	2	5.387	0.000	4	7.803	0.000
Soil C:N (0 - 20cm)	2	0.110	**0.900**	2	0.624	**0.541**	4	10.764	**0.437**
Soil temperature (^oC)	2	36.855	0.000	2	4.251	0.028	4	0.968	0.000
WFPS (%)	2	3.264	0.049	2	0.187	**0.839**	4	10.636	0.011

Df, degree of freedom; Values in bold show non significance at Tukey 5% significant level

Table 5.3: Arithmetic mean (coefficient of variation) for topsoil (0-20 cm) physico -chemical properties in study site

	N	Altitude	Slope	BD	pH	SOC	STN	C: N	Soil.temp	WFPS
		(m)	(%)	(g cm^2)	(H_2O)	(kg m^2)	(kg m^2)		(oC)	(%)
Altitude range										
600 - 1400 m	62	964 (15)	2.3 (58)	1.4a (13)	6.6a (11)	4.2a (52)	0.4a (41)	10.8a (20)	21.5a (12)	27.1a (47)
1400 - 1800 m	43	1534 (9)	4.2 (26)	1.2b (16)	5.8b (12)	6ab (48)	0.6a (52)	11a (10)	16.7a (14)	30.1a (16)
1800 - 2300 m	9	2170 (1)	5.4 (11.7)	0.4c (40)	4.9c (7)	9.4b (48)	0.9b (41)	10.5a (11)	10.3b (5)	43.9a (35)
Land use type										
Cereal	43	1211 (26)	2.9 (50)	1.3a (13)	6.2a (12)	4.5a (43)	0.4a (37)	10.5a (15)	20.7a (17)	28.4a (29)
Agro-forestry	40	1201 (27)	2.9 (55)	1.4a (16)	6.3a (14)	4.3a (35)	0.4a (34)	10.8a (12)	18.9a (16)	28.6a (37)
Natural	31	1456 (36)	4.1 (38)	1.1 a (46)	5.8a (15)	7.8b (55)	0.7b (56)	11.3a (22)	16.1a (28)	32.4a (49)
Plot land cover										
Maize	43	1211 (26)	2.9 (50)	1.3a (13)	6.2ab (12)	4.5ab (43)	0.4ab (37)	10.5a (15)	20.7a (17)	28.4b (29)
Mango	12	869 (2)	1 (42)	1.5a (7)	7.2c (7)	2.9a (25)	0.3a (18)	10.2a (10)	21.8a (13)	23.8a (62)
Shrub	16	1000 (13)	3 (44)	1.3a (14)	6.5ab (10)	5.6ab (50)	0.5ab (40)	12.1a (26)	20.1a (5)	25.4a (61)
Avocado	28	1344 (22)	3.8 (32)	1.3a (16)	6ab (13)	5ab (27)	0.5ab (28)	11a (12)	17.6b (13)	30.6b (25)
Forest	15	1942 (15)	5.3 (14)	0.6b (43)	5.1a (8)	10.1c (45)	0.9c (43)	10.6a (10)	11.8c (16)	39.9c (32)

Values are means and percent CV's of three replicates per plot. Means within a column followed by the same letter are not statistically significant (pairwise t-test, P = 0.05). BD, Bulk density; SOC, Soil organic Carbon; STN, soil total Nitrogen; soil .temp, soil temperature; WFPS, water filled pore space

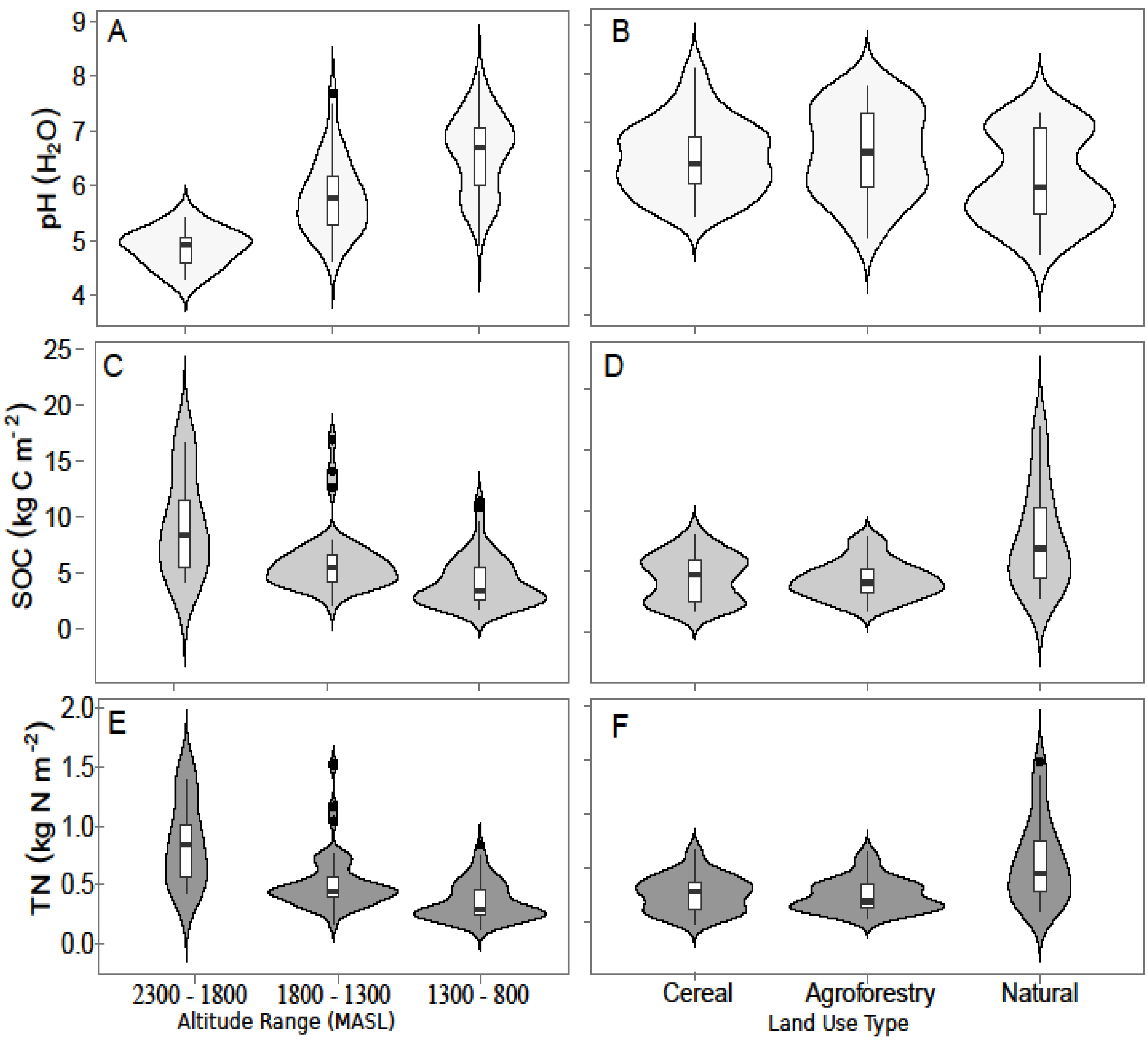


Figure 5.1: Soil pH, SOC and STN stocks (kg m^2) across altitude range (plots a, c and e) and major land use types (plots b, d and f) in study site

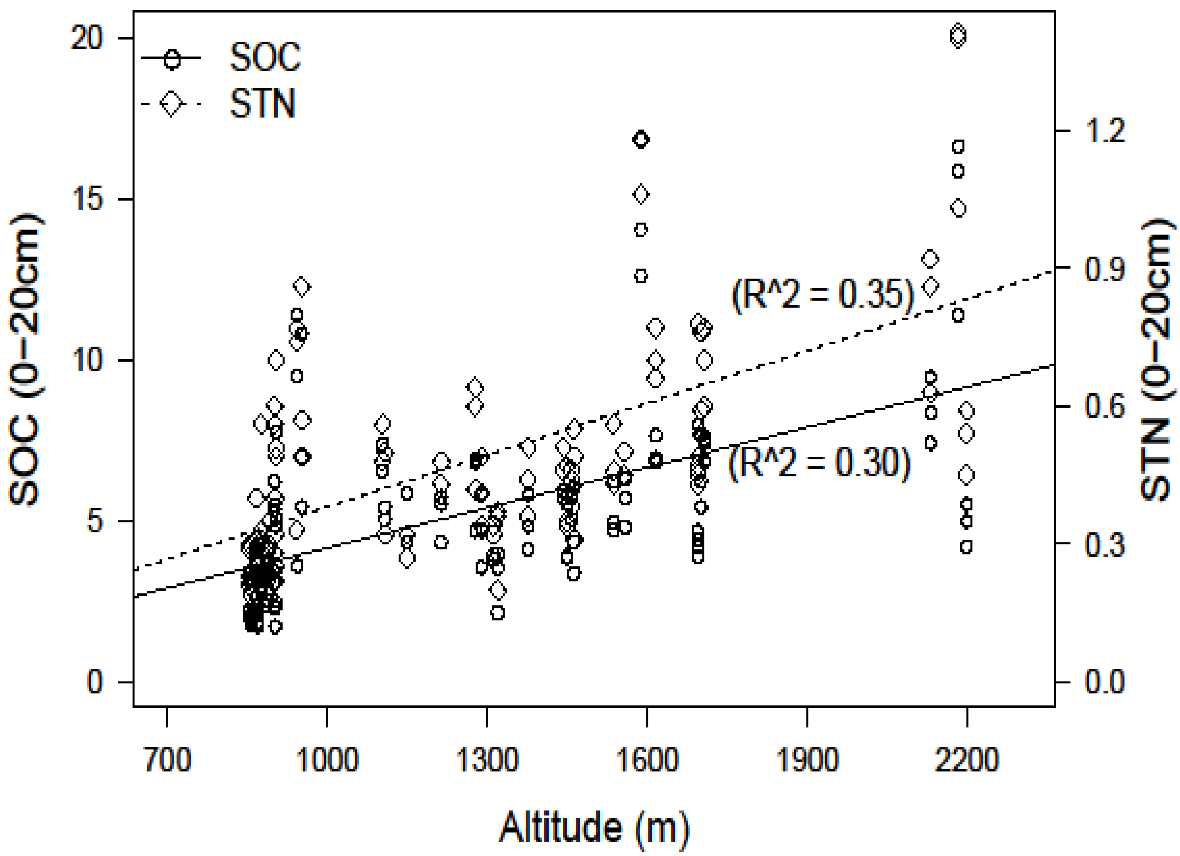


Figure 5.2: Scatter relationship between altitude (m) and soil organic carbon (SOC) and total nitrogen (TN) in 0 - 20 cm soil depth in study site

Land use categories showed more explicit trends compared to altitude range and land uses. Forest revealed significantly lower pH ($F_{4, 35}$= 6.756; P < 0.001) and bulk density ($F_{4,35}$ = 19.53; P < 0.001) values but had the highest SOC and TN stocks amongst all land cover categories assessed.

On the contrally, mango plots has the highest mean soil pH value and lowest mean SOC, TN and percent WFPS amongst all the land cover assessed. The coefficient of variation in mango plot for soil pH, OC and TN was between 7 and 13 % indicating a modestly low plot level variation. A high degree of similarity was observed in mean soil parameter (such as OC, TN, C: N and BD) values in avocado, mango, and shrub cover types. However, relatively high percent CV's values were observed in shrub (SOC = 50%, TN = 40%) compared to avocado (SOC = 27%, TN = 28%) and maize (OC = 43%, TN = 37%) cover types. At plot level, altitude, land use and land cover were characterized by non-significant C: N ratio (CV ranges between 10 - 26 %).

5.3.2 Altitude gradient influence on soil organic carbon and nitrogen stocks

The relationship between altitude and soil organic carbon (R^2 = 0.35) and TN (R^2 = 0.30) was linear and relatively weak. However, a different pattern emerged when this relationship was defragmented along individual altitude categories (Fig 5.3: d).

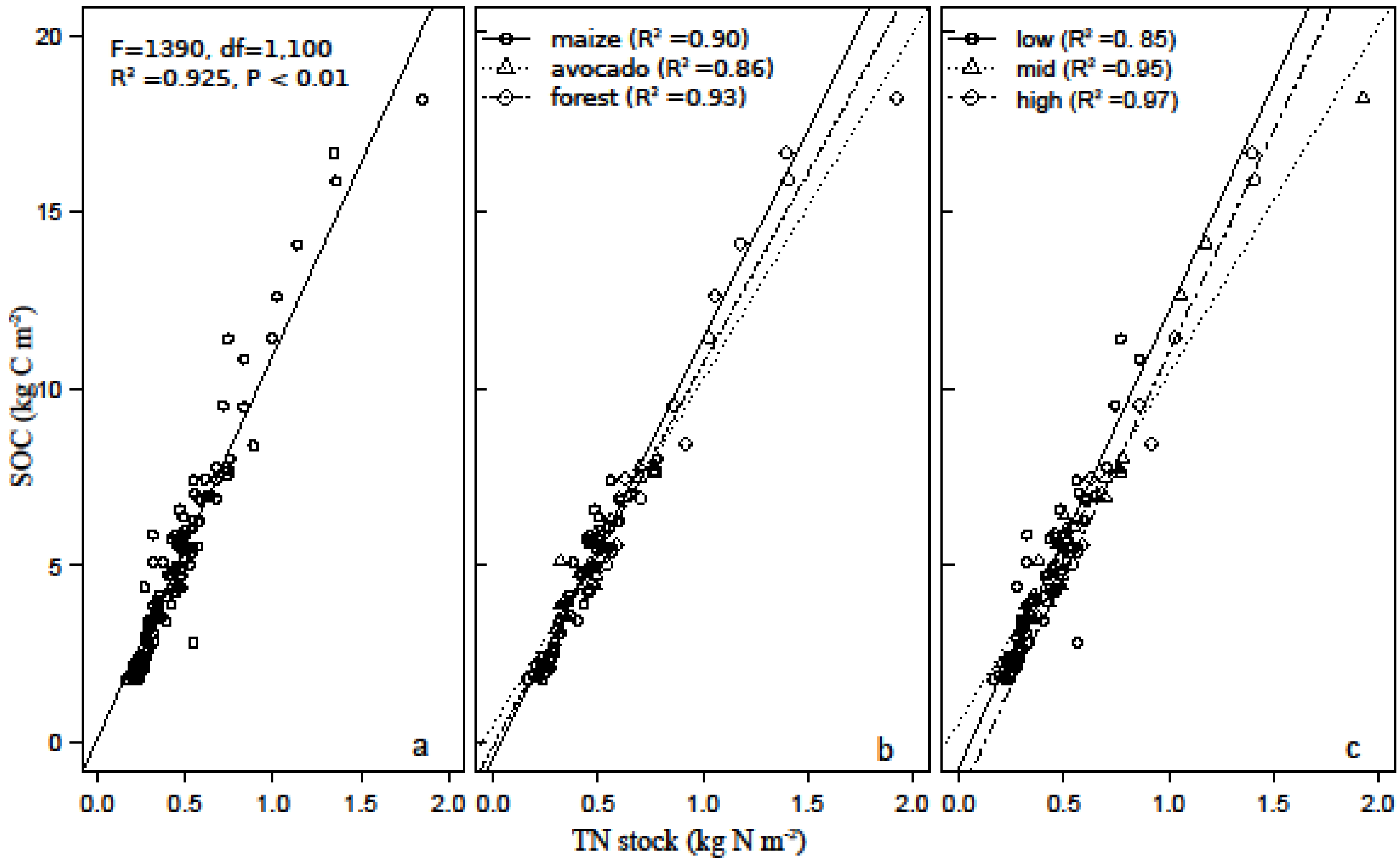


Figure 5.3: Scatter relationship between SOC stocks (kg C m^2) and TN stocks (kg C m^2) compared (a) across study site (b) within land cover types and (c)within altitude range (**low**: 600 - 1400 m), (**mid**: 1400 - 1800 m) and (**high**: 1800 - 2300 m)

When considered across altitude ranges, SOC values in low elevation significantly ($F_{4, 35}$= 6.38; P < 0.05) had a positive and significant correlation with soil TN stocks (R^2 = 0.85) with mid and high altitude range showing correlations of R^2 > 0.90. Mean SOC stocks in the low elevation category were 33 % and 123 % lower when compared to mid and high altitude ranges respectively ($F_{4, 35}$= 6.380; P < 0.001) (Table 5.1). Mean soil TN showed an increasing trend across altitude categories, with stocks in the mid and high altitude categories having 50 % and 125 % higher stocks compared to low altitude category respectively. The coefficient variation within altitude categories varied from 41 to 52 %. Soil C: N ratio was non-significant and comparable across all altitude categories and maintained almost a small margin around 10.7 (Table 5.2)

5.3.3 Influence of land use and cover on SOC and N stocks

There were significant differences in SOC ($F_{4, 35}$ = 7.80; P < 0.001) and TN ($F_{4, 35}$ = 8.54; P < 0.001) between land use categories, although no such differences were observed in mean altitude, slope, BD, C: N, pH, soil temp and WFPS (Table 5.2). Generally, SOC stock in cereal systems had a pronounced bimodal pattern which was less apparent in the agroforestry land use category (refer to Fig 5.1). Further, soil OC stock difference between cereal and natural land use categories was 3.3 kg m^{-2} whereas the difference between agroforestry and natural categories was 3.5 kg m^{-2}. Soil TN in natural land use category was more than 75 % higher compared to cereal and agroforestry land use categories. Land cover differences were more pronounced in soil OC stocks ($F_{4, 35}$=7.80; P < 0.001) compared to TN stocks ($F_{4, 35}$ = 8.54; P < 0.001). Maize plots had about 55 % higher SOC stock compared to mango plots, while avocado plots had 72 % and 11 % higher SOC stock compared to mango and maize plots respectively. A strong linear relationship explained SOC and TN trend within land cover categories (Fig 5.3), with avocado plots (R^2 = 0.86) having lower correlation compared maize (R^2 = 0.90) and forest

(R^2 = 0.93) land cover categories. Mango plots had the lowest SOC and TN stocks compared to maize, avocado, shrub and forest plots (Fig 5.4: b and c). Soil C: N values within land cover categories were comparable and non-significant.

5.3.4 Multiple regression modeling

Results from stepwise regression models report only significant ($P < 0.05$) predictors for soil nutrient stocks within each altitude category (Table 5.4). Altitude played a key role in determining SOC and TN stocks variability in our study plots. The significant ($P < 0.05$) predictors of SOC stocks in the low (800 - 1300 m) altitude categories were altitude, C: N and water filled pore space (WFPS), which explained about 55 % of total variance. The mid (1300 - 1800 m) category had similar SOC predictors to low altitude category, with the model explaining 35 % of total observed variance. In contrast, the high (1800 - 2300 m) altitude range had 92 % total OC variation explained by altitude and soil temperature only. Considering soil total nitrogen stocks (STN), altitude and soil temperature (ST) explained about 86 % of observed stock variance in the high altitude category, whereas altitude and WFPS accounted for 33 % observed variance in the low altitude category. An 8 % increment in explained variance was observed in the mid altitude category when soil pH was added as predictor from low altitude category. The Akaike Information Criterion (AIC) values shows a decreasing pattern from low to high altitude categories in SOC and STN assessments, which underscore model fit within altitude models.

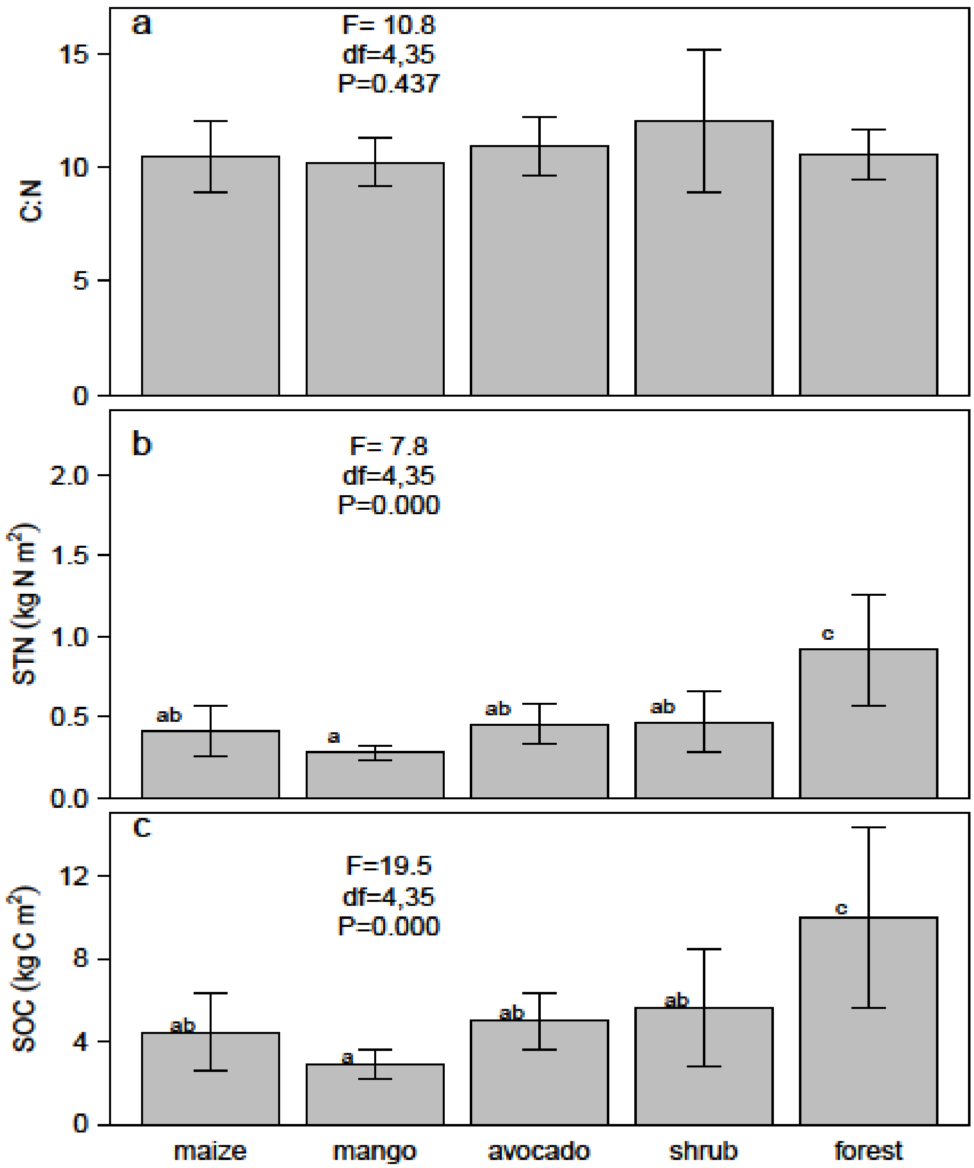


Figure 5.4: Spatial patterns for (a) soil C: N and (b) STN and (c) SOC stocks within land cover categories in the Taita Hills. Bar and associated error bar represent mean of plots values and standard error respectively. Bar means with same letter are not significantly different (Pairwise t test, *P* = 0.05). Plot (a) means not significant hence error bars not shown

Table 5.4: Regression models for SOC and TN stocks within low, mid and high altitude categories in the Taita Hills. Values show coefficients (standard error)

Predictors	**Soil Organic Carbon (Kg C m^{-2})**		
	Low (800 - 1400 m)	Mid (1400 - 1800 m)	High (1800 - 2300 m)
Altitude (m)	0.003* (0.0001)	0.001*** (0.0002)	-0.033*** (0.010)
Soil Temperature	-0.018** (0.009)	-0.018 (0.011)	-1.740** (0.356)
Water Filled pore space	0.007*** (0.001)	0.009* (0.005)	
Constant	0.137 (0.300)	-0.928 (0.556)	81.745** (16.985)
Adjusted R^2	0.58	0.35	0.87
Residual Std. Error	0.134 (df = 56)	0.133 (df = 38)	0.075 (df = 5)
F Statistic	22.038*** (df = 4; 57)	6.724*** (df = 4; 38)	19.330*** (df = 3; 5)
	Soil Total Nitrogen (Kg N m^{-2})		
Altitude (m)	0.002* (0.0001)	0.001*** (0.0002)	- 0.025*** (0.004)
Soil Temperature	-0.012* (0.006)	-0.019 * (0.009)	-1.5483** * (0.659)
Water Filled pore space	0.005*** (0.001)	0.009** (0.004)	
Constant	0.569*** (0.195)	-0.046 (0.544)	71.691*** (11.594)
Adjusted R^2	0.34	0.34	0.81
Residual Std. Error	0.098 (df = 58)	0.130 (df = 39)	0.081 (df = 6)
F Statistic	11.314*** (df = 3; 58)	8.226*** (df = 3; 39)	18.669*** (df = 2; 6)

*p<0.1; **p<0.05; ***p<0.01

5.3.5 Minimum detectable SOC and STN stock differences

The relative minimum detectable differences (MDD) of SOC and TN stocks were estimated under assumption of spatial independence of sampling plots within the three altitude categories (Fig 5.5: a - c). MDD differences between SOC and TN stocks were minimal in all the three altitude ranges. However, in the low (800 -1300 m) altitude range, detection of stock differences < 10 % require more than 350 SOC samples compared with 250 samples for TN. Similarly, in the high (1800 -2300 m) altitude range, detection of stock differences < 10 % require 350 TN samples compared to 500 OC samples. These differences are not evident in the mid (1300 - 1800 m) altitude range.

Calculations of absolute MMD's at small sample sizes revealed pronounced differences when OC and TN stocks are considered across altitude ranges (Table 5.5). For equivalent sample sizes, the low altitude range showed the lowest absolute MDD values while the high altitude range showed the largest. For instance, a sample size = 20, SOC stock changes of 2 kg C m^{-2} were detected in the low altitude range whereas higher values were shown in mid (2.8 kg C m^{-2}) and high (5 kg C m^{-2}) altitude ranges. For soil TN stocks, detection of absolute MDD values < 0.10 kg N m^{-2} require more than 20 samples in the low altitude, more than 100 samples in the mid altitude and 300 samples in the high altitude range.

Table 5.5: Absolute minimum detectable differences of soil organic carbon and soil total nitrogen stocks (kg m^2) in different altitude ranges of study site

	800 - 1400 m		1400 - 1800 m		1800 - 2300 m	
N	SOC	STN	SOC	STN	SOC	STN
450	0.42	0.03	0.59	0.06	1.06	0.08
300	0.52	0.04	0.72	0.07	1.3	0.1
200	0.63	0.05	0.88	0.08	1.59	0.12
100	0.89	0.06	1.25	0.12	2.25	0.17
50	1.26	0.09	1.77	0.17	3.19	0.25
20	2	0.14	2.8	0.27	5.04	0.39

n, sample size; SOC, soil organic carbon; STN, soil total nitrogen

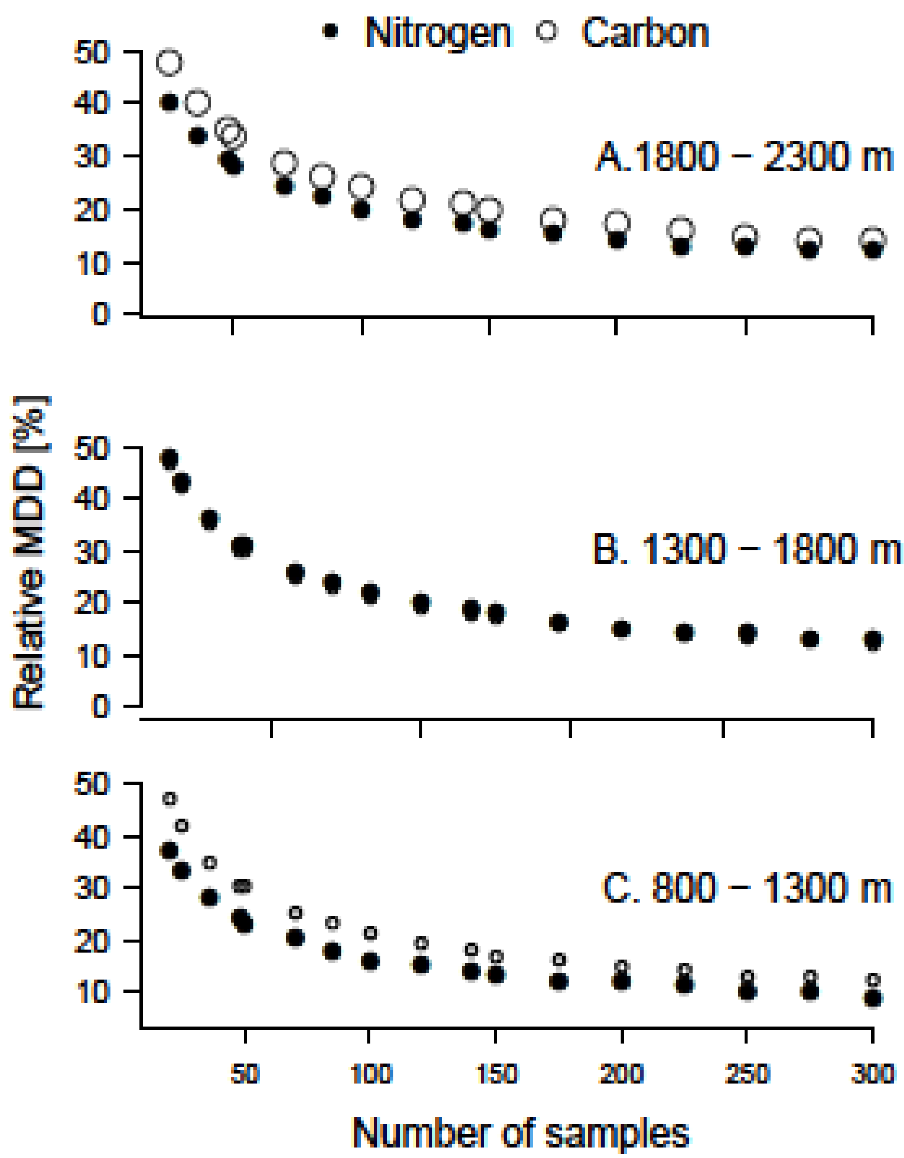


Figure 5.5: Relative soil C and N minimum detectable differences (MDD) in relation to samples within altitude classes: A: 1800 - 2300 m, B: 1400 - 1800 m, C: 800 - 1400 m

5.4 Discussion

5.4.1 Variation of soil OC and TN stocks along altitude range

Favorable moisture and temperature conditions in tropical ecosystems encourage microbial decomposition resulting in increased soil C and N sequestration. However, with altitude increase in mountain ecosystems, cold and wet soils hinder the decomposition process resulting to plant residue accumulation on the soil surface. Similarly, low amounts of labile soil carbon are often observed in low lying areas experiencing high temperature and sparse soil moisture conditions. These facts are well documented in studies (Lal, 2004; Lemenih and Itanna, 2004; Leifeld *et al.*, 2005; Garten and Hanson, 2006) investigating SOC distribution in various ecosystems. Soil organic stocks in the low altitude range were lowest compared to those in the mid and high altitude categories (Table 5.2, Fig 5.1). Although the values obtained in this study are within range of previous SOC assessments within the region (Batjes, 2004a; Kamoni *et al.*, 2007; Omoro *et al.*, 2013), studies on altitude-graded carbon and nitrogen stocks assessment are scarce within the region. Generally, linear relationship exists between altitude and soil carbon and nitrogen stock when all plots are combined (Fig 5.2), with the low correlation resulting from concealment of inherent heterogeneity in individual plots within individual altitude categories.

Variation in SOC and TN stocks in the Taita Hills can be explained by altitude driven transition in agro-ecological factors such as temperature, moisture and slope (Table 5.2). Localized micro climates are demonstrated by significant variations in soil temperature (5 - 11 ^{o}C drop from low to high altitude) and WFPS (3 - 17 % increase from low to high altitude) within altitude categories. Variations in relief are demonstrated by slope differences (82 - 134 % increase from low to mid and high altitude range. Soil textural variations from calcic sandy loam soils in the low altitude range to 2:1 clay dominated soils in the high altitude suggest differences in parent material on which inherent soils are developed (Table

5.1). Clay dominated soils are capable of higher SOC storage compared to course textured sandy soils due to stabilizing effects by soil macro aggregates and associated iron oxides on soil organic matter (Six *et al.*, 2000). A strong relationship exists between soil carbon and nitrogen stocks (R^2 = 0.92), with the low altitude range (R^2 = 0.85) being significantly lower compared to the mid (R^2 = 0.95) and high (R^2 = 0.97) altitude range (Fig 5.3). Studies by Bell and Worrall (2009) reported SOC differences within farms located at similar altitude levels, highlighting the impact of latitude driven land cover characteristics on SOC levels. Topsoil C: N ratio (Fig 5.4: a) did not vary significantly across the three altitude ranges, implying either similarities in composition of soil organic matter within this ecosystem or stabilization of decomposition and mineralization processes to comparable rates within the altitude categories. Similar ranges of C: N ratio's have been observed in tropical ecosystems elsewhere, such as Groppo *et al.* (2015).

5.4.2 Changes in SOC and TN stocks with land use and cover

It is well documented that the Taita Hills ecosystem has under gone massive land use and cover changes (Clark and Pellikka, 2009a; Pellikka *et al.*, 2013), with a negative impact on soil physical characteristics (Maeda *et al.*, 2010b). The large coefficient of variation (CV) values in slope, WFPS, SOC and TN, in comparison to soil pH for instance, suggests extensive variation within the three major land use types assessed and a pointer to topographic heterogeneity as a driver for soil nutrient stocks. No significant differences were observed between cereal and agroforestry land uses, which is expected since both exists within similar altitude and slope typologies in study site. However, a wide disparity was observed in natural compared to agricultural land use systems (Fig 5.1). The observed differences in SOC and TN stock magnitude between lands uses located at different altitude range justifies our transect stratification along altitude categories in this study. That natural land use category showed the large inter-quartile variation highlights the intricacy expected by combining shrubs and forest land categories in assessment of soil nutrient stocks. Similar SOC stock ranges were observed in Batjes (2004a) and Kamoni *et al.* (2007) from 4.3 to 5.0 kg C m^{-2} at 0 - 30cm soil depth, although the studies combined cereal and agroforestry croplands in larger agro ecological zones in Kenya.

When land use is stratified to individual land cover categories, distinct soil nutrient patterns were revealed which describe the degree of soil heterogeneity within farms in the Taita Hills. Our sampling grid captured mango (*Mangifera indica*) plots at the low end of the study transect where it is naturalized from 800 to 950 m (average altitude of 869 m) and at a relatively flat soil surface (mean slope of 1 %). Mango plots showed the lowest mean soil OC and TN stocks amongst all land cover categories assessed. Maize (*Zea mays*) and mango farms situated in the low altitude category were once part of the semi arid vegetation regime that dominate Mwatate and other low lying parts of Taita Taveta County.

Although this research does not include assessments of farm management practices by smallholders to soil stock quantities, it is possible that crop management and fallow practices on cereal plots were partly responsible for the slightly improved SOC stock status in maize (1.82 kg m^{-2}) compared to mango (1.72 kg m^{-2}) plots in the low altitude category. Additionally, highly lignified mango leaves tend to resist decomposition and promote soil acidity (Mubarak *et al.*, 2008) hence low mean soil pH and reduced soil organic matter turnover shown through low soil nutrient stocks. Soil OC and TN stocks in avocado (*Persea Americana*) and shrub plots were comparable (Fig 5.4), in contrast to forest plots which had significantly about twice the amount of SOC and TN stocks. Considering that land cover types situated from 1300 to 1800 m (i. e avocado and cereal farms) were once occupied by natural forests, the decrease in SOC by about 50 % after forest conversions attests to deleterious effects of land cultivation on soil C inventory (Murty *et al.*, 2002; Garten and Hanson, 2006; Don *et al.*, 2011). This result exemplifies the utility of establishing agroforestry tree species such as avocado to maintain soil nutrients of agricultural land in the Taita Hills, with additional benefits in food and feed provision (Albrecht and Kandji, 2003). Omoro *et al.* (2013) studies in forest fragments within the Taita Hills reported mean percent soil C values ranging between 8.2 and 11.8 % (0 - 20 cm soil depth) which fairly correlate with our observed value of 9.4 % in forest plots. Similar studies (Assad *et al.*, 2013; Groppo *et al.*, 2015) have highlighted differences in soil C and N land use distribution patterns in Brazil tropical ecosystems amongst native, pasture and crop - livestock systems.

Despite observed differences in soil nutrients stocks and efforts towards developing a robust *in-situ* spatial sampling strategy to capture altitudinal variation, these findings represent a rough estimate differentiating observed spatial SOC and TN variation from plot to altitude, land use and cover categories in the Taita Hills. Additionally, carbon and nitrogen stocks highlighted in this study are baseline estimates obtained by aggregating mean values across land cover types whose accuracy is subject to methodological and spatial sampling limitations.

5.4.3 Predicting soil C and N stocks from biophysical variables

Altitude had confounding effects on physical soil properties and spatial distribution of SOC and STN stocks along the elevation gradient. Bulk density and soil temperature decreased with increasing altitude, contrasting with a decrease in soil organic carbon and nitrogen (Table 5.2). On the contrally, increase in altitude favored an increase in WFPS, a trend similarly observed in soil carbon and nitrogen stocks. These observations are in line with Trumbore (1997) synopsis on sensitivity controls for fast cycling soil C inventories, where favorable soil moisture conditions in tropical mountain environments is associated with high SOC levels due to higher microbial activity and vice versa. Distinct topographic and ecological factors were identified to reasonably predict SOC and STN patterns within altitude categories (Table 5.4). Differences in explanatory factors observed within each altitude category are based on dominant micro-climate drivers inherent within each altitude range.

Altitude, C:N and WFPS were significant SOC predictors at the low and mid altitude categories. The presence of C:N and WFPS predictors in the low and mid altitude regression models highlight the importance of nitrogen in predicting soil carbon stocks under limiting soil moisture conditions. Similarly, soil TN stocks were significantly predicted by altitude and WFPS in the low and mid altitude categories, probably pointing to the potential role of WFPS at regulating soil biochemical processes (Bateman and Baggs, 2005). Beyond 1800 m altitude range, which constitutes an ecosystem exclusively colonized by forests, and where soil moisture is not limiting, diurnal temperature trends were the dominant predictors for SON and TN stocks. Generally, inter-annual precipitation and temperature cycles are major drivers for net primary productivity, responsible for spatial distribution and heterogeneity in carbon and nitrogen stocks in most tropical ecosystems (Trumbore, 1997).

5.4.4 Implications for nutrient detection in elevated ecosystems

Topographic and ecological variability influence land use, cover and management activities in mountain ecosystems, and ultimately the magnitude of soil carbon and nitrogen stocks at a particular field or sampling plot i.e site specificity. Our results (Fig 5.5) show that plot variability can undermine the detection of carbon and nitrogen stock changes within altitude categories. At the low altitude, detection of soil TN stock differences of < 10 % relative MDD required about half the number of samples needed in the mid and high altitude categories.

There were no significant differences in either SOC or TN samples required to detect a specific MDD range in the mid altitude category (Fig 5.5: B), implying field sampling may be conducted simultaneously for both elements. On the contrally, the low and the high altitude categories had slight differences in relative MDD detection (Fig 5.5: A & C), thus different samples sizes for SOC and TN are needed to achieve a certain measurement precision. These differences are well exemplified in studies assessing effect of soil type and incremental depth on detection of SOC changes by VandenBygaart *et al.* (2007) where detection of carbon stock equivalent to 0.3 kg m^{-2} in topsoil 30 cm depth required less than 3 samples whereas Grüneberg *et al.* (2010) required about 300 samples from A horizon in a Dark brown Chernozem soil.

Absolute MDD values showed that sample size was highly depended on SOC and TN stocks within the three altitude ranges required to detect a certain magnitude of carbon and nitrogen stock (Table 5.5). For instance, to detect absolute differences equivalent to 0.9 kg C m^{-2} and 0.06 N m^{-2} required 100 samples for either carbon or nitrogen in the low altitude, 200 samples for carbon and 450 samples for N samples in the mid altitude and about 650 samples for carbon and 500 samples for N samples in the high altitude category. This observation that soils containing higher carbon and nitrogen quantities require higher number of samples to detect a certain level of absolute differences and vice versa is well corroborated by VandenBygaart *et al.* (2007). The absolute MDD differences showed in this study highlights altitude driven soil property variation in the Taita Hills and potential challenges in design of efficient sampling methods to achieve fair microsites representation.

5.5 Conclusions

Land use and cover changes in elevated ecosystems play a crucial role in regulating soil organic carbon and nitrogen stocks. Additionally, the spatial patterns for these changes are driven by topographic and ecological differences resulting from altitudinal macro and micro climates, a phenomenon well demonstrated in this study. While WFPS, SOC and TN stocks increased with altitude increase, soil BD, pH and temperature decreased correspondingly. Categorizing our study research transect along altitude range resulted to new information explaining spatial distribution SOC and TN stocks along land use and cover categories. High SOC and TN variation observed in the altitudinal analysis is ascribed to differences in ecological properties such as parent material and textural difference with our altitude categories.

The low and mid altitude ranges had significantly lower SOC and TN stocks compared to high altitude range, indicating low availability of N in croplands compared to natural land cover types such as forest and shrub lands. Non significant C:N ratio observed within the three altitude range demonstrates that the composition of input material is either similar or has a common origin. There were minimal differences in soil nutrient properties between cereal and agroforestry land use, which is expected given the two land uses share similar topographic characteristics in terms of altitude and slope. However, contrally to our expectations, soil nutrient stocks contribution by agro-forestry systems were minimal compared to natural systems, which was probably due to aggregating land cover categories into the broader land use category. The order of land cover soil C and N stocks magnitude; mango < maize = Avocado = Shrub < Forests, emphasizes the role of natural land cover in soil nutrient recycling. The impact of multipurpose agroforestry systems such as avocado in rehabilitating forest and shrub lands converted to croplands through nutrient sequestration is observed. Finally, future sampling endeavors should recognize that inherent carbon and nitrogen stocks play a role in guiding the accuracy of their field detection within altitude categories in mountain ecosystems.

CHAPTER SIX

SOIL C AND N STOCKS VARIATION FROM TERRAIN CLASSIFICATION

6.1 Introduction

Soil organic carbon (OC) and nitrogen are among soil attributes that play an essential role in the soil macro and micro nutrient availability. However, their spatial distribution in terrestrial ecosystems is dependent on a number of intrinsic environmental factors such as temperature, moisture and land cover patterns (Takata *et al.*, 2007; Rhanor, 2013). In heterogonous mountain ecosystems of East Africa where rapid agricultural expansion and land use change are currently taking place (Clark and Pellikka, 2009a; Maeda *et al.*, 2010a), accurate information on spatial soil carbon and nitrogen distribution and change is vital to sustainable soil fertility management and replenishment.

However, mountainous ecosystems that are topologically and ecologically diverse reveal large spatial variations that complicate quantification of soil nutrient stocks (Rhanor, 2013). For instance, in the Taita Hills, an ecosystem that is part of the eastern Arc mountains of East Africa, forest conversion to agricultural croplands has interfered with native floral soil C input potential (Omoro *et al.*, 2011) and increased agricultural land vulnerability to surface erosion and soil loss (Maeda *et al.*, 2010b; Erdogan *et al.*, 2011). Given the importance of the Taita Hills ecosystem as a biodiversity hotspot, and the requisite to maintain a balance between positive impacts of agricultural expansion and negative impacts on biodiversity, there is need for easily applied tools to rapidly assess soil OC inventories.

It is well established that geomorphological terrain attributes such as elevation, slope and curvature properties influence intrinsic spatial soil carbon stock patterns (Qin *et al.*, 2012; Zhang *et al.*, 2012). This relationship, together with other terrain information such as land use type and soil texture has been exploited by Hengl *et al.* (2015) to derive 250 m soil property maps for Africa. Moreover, as soil C is highly dependent on above ground plant biomass input, mostly expressed as Net Primary Productivity (NPP), a strong positive correlation exists between vegetation cover and soil OC (Kunkel *et al.*, 2011). At a smaller ecosystem scale, for instance in the Taita Hills, models integrating landscape attributes, precipitation data and soil erosion potential have been derived to assess the impacts of agricultural expansion and climate change on soil erosion (Maeda *et al.*, 2010b; Erdogan *et al.*, 2011).

However, the lack of soil attribute data at high temporal and spatial scales poses a bottleneck to advancing our knowledge on spatial soil OC and nitrogen trends in the Eastern Arc mountain ecosystems. Furthermore, currently there is a poor understanding on how altitude driven environmental factors influence spatial soil nutrient trends. The loss of biodiversity in this ecosystem, as it undergoes conversion to agricultural croplands, has mobilized efforts towards ecosystem restoration and examination of how biological processes are affected by such change. Moreover, from a pedology perspective, ecological productivity resulting from plant diversity correlates highly to soil microbial activity and soil nutrient content (Lange *et al.*, 2015). Such change has direct consequence to soil quality indicators e.g soil fertility and water holding capacity and thus impacting on soil nutrient inventories and regional climate cycles. Additional environmental variables that influence soil nutrients stock patterns in tropical ecosystems include climate, topography and land management practice (Don *et al.*, 2011; Winowiecki *et al.*, 2015).

Topographic transitions in elevated ecosystems influence biogeochemical processes in space and time (Moore *et al.*, 1993; Gessler *et al.*, 1995; Zhang *et al.*, 2012) thereby determining spatial soil OC and total nitrogen distribution. Using digital elevation models (DEM) derived from shuttle Radar Topography Mission (STRM) radar, this study derived and tested two terrain classification schemes (Riley, 1999; De Reu *et al.*, 2013) to explain spatial variation in soil nutrient stocks in the Taita Hills. Terrain analysis has been used elsewhere in forest management planning (Zawawi, 2015) and landform analysis (De Reu *et al.*, 2013). Although previous studies within (Omoro *et al.*, 2013) and adjacent (Winowiecki *et al.*, 2015) to the Taita Hills ecosystem have assessed the relationship between tree species diversity and soil properties, there is limited knowledge correlating terrain attribute properties with spatial soil nutrient sticks in this ecosystem.

Such information is necessary in development of geo-statistical models for mapping of spatial soil nutrient stocks and their properties. They also assist to understand the influence of land cover and management on soil nutrient stocks within an ecosystem. This study tests whether the variation explained from topographic gradation is reasonable to support development of purposive sampling framework for the Taita Hills ecosystem. Specifically, the study addressed the following questions; 1) To what extent does slope, elevation and ruggedness terrain attributes explain spatial soil OC and nitrogen variation in Taita Hills?, 2). By classifying topography using terrain attributes, to what extent do extraneous environmental variables correlate to soil nutrient stocks?, and 3). Which intrinsic soil factors best explain spatial soil OC variation within the Taita Hills when terrain classification is considered?

6.2 Materials and Method

6.2.1 Field sampling strategy

Sampling was conducted as explained in Chapter 3 (Section 3.2)

6.2.2 Landscape and terrain classification

In this approach, landscape position in each plot was derived by formulating a set of rules based on specific terrain attributes, which was then validated using domain knowledge. The landscape position classification algorithm (Weiss, 2001; Jenness, 2006) employs two criteria namely; topographic position index (TPI) which computes the difference between a cell elevation value and cells within its neighborhood, and its slope value (Table 6.1).

To further confirm our topographic assessment, we derived a topographic ruggedness index (TRI) classification which computes elevation differences between cells and but does not incorporate other factors such as slope (Beasom *et al.*, 1983; Riley, 1999) (Table 6.2). To derive these plot terrain indices, plot coordinates were overlaid against a 20 m DEM for the Taita Hills (supplied by geosciences department of University of Helsinki). Using Raster terrain analysis tool from Quantum GIS (Development Team, 2013), topographic maps for slope and TRI were produced (Fig's. 6.1 & 6.2), from where index values were derived using sampling plots coordinates.

6.2.3 Moisture and temperature measurements

Details in chapter 4 (sections 4.2.2 and 4.2.4)

6.2.4 Soil sampling

Sampling was conducted as explained in Chapter 5 (section 5.2.2)

6.2.5 Soil analyses

Analysis was conducted as explained in Chapter 5 (section 5.2.3)

Table 6.1: Values used to delineate landscape position (LP) classification

Category	Slope (%)	TPI value
Valley	< 5	< 0
Gentle	1 – 15	< 1
High	10 - 19	> 1
Plateau	> 20	> 1

Table 6.2: Values used to delineate Terrain ruggedness Index (TRI)

Position	TRI range %
Slightly	< 0.9 %
Intermediate	1 - 1.9 %
Highly	< 2 %

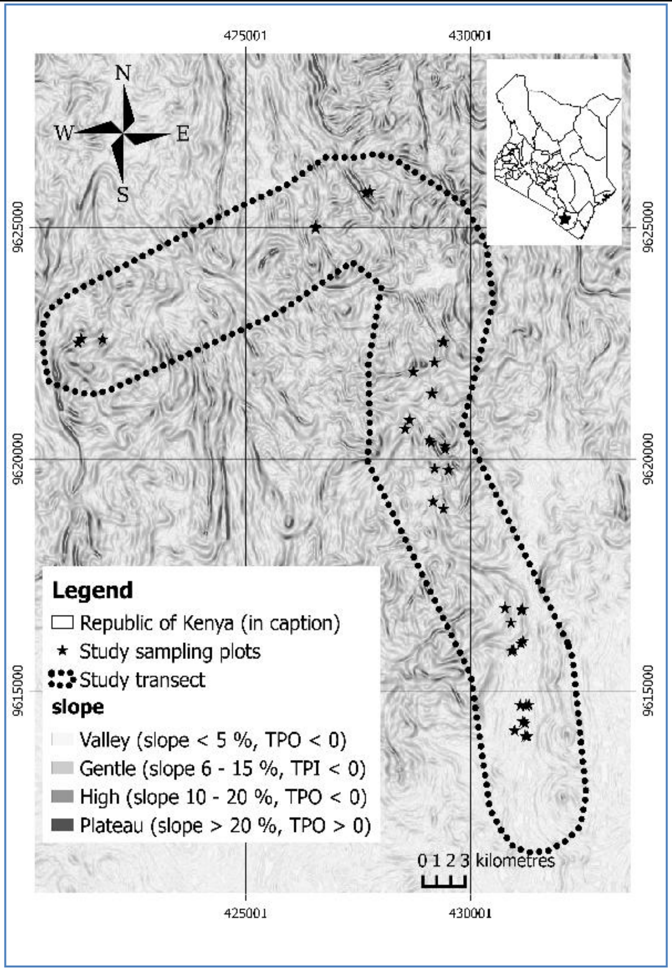


Figure 6.1: Topographic position map

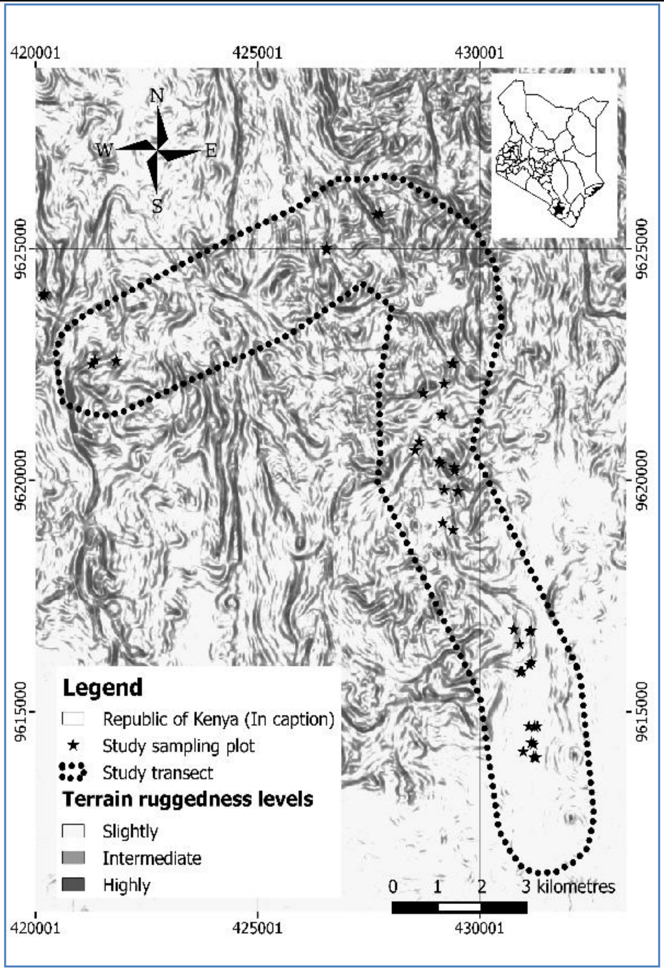


Figure 6.2: Terrain ruggedness map

6.2.6 Statistical analyses

Statistical analysis were performed using R-software, version 3.2.1 (R Development Core Team, 2014). Prior to analysis, data was examined for normality using Shapiro - Wilk test and homogeneity of variance using Levene test. Data not normally distributed were transformed either by square-root (TN), cube root (bulk density, BD) or log transformed (soil OC) as appropriate. Statistical tests were performed using transformed values, although the non-transformed values were used to report the averages. Parameters assessed comprised radiometric indices (LST, slope, Aspect and TRI) and *in-situ* acquired parameters (soil OC, TN, C: N, pH, BD, WFPS and soil temperature). Significant differences within slope position and heterogeneity categories were tested using post hoc Tukey honest significant differences (HSD) test after conducting omnibus repeated measures analysis of variance (ezANOVA, type = 3). Intercorrelation between variables was assessed before stepwise regression was used to derive predictive models for soil OC stocks. The final predictor table was based on Hlavac (2014)

6.3 Results

6.3.1 Spatial soil properties within classifications schemes

Omnibus tests are shown in Table 6. 3 and means for soil properties in Tables 6.4 and 6.5. Daytime land surface temperature (LST_{Day}) was significantly ($F_{3, 37} = 11.097$, $P < 0.001$) different within slope position categories in contrast to Nighttime land surface temperatures (LST_{Night}) which was non-significant (Table 6.4). Slope percent and TRI had an increasing trend from valley to plateau levels, thus affirm their utility in terrain classification schemes utilized in the study. An inspection of aspect values reveals majority of slopes in the study area either face south-East or south-West direction, which is the windward “wet” side of the mountain ecosystem. Apart from soil C:N ($F_{3, 37}$ = 2.185, P = 0.107), the rest of soil physical and chemical properties revealed significant trends within the four slope levels Soil temperatures ($soil_T$) in the valley were twice as high compared to the plateau, whereas mean values in gentle and high slopes were more or less similar (Table 6.5).

Similarly, a decreasing trend is evident in mean BD and pH values in both classification schemes. However, the converse was true for WFPS, where plots situated in the plateau, gentle and high slopes had 129 % and 88 % higher soil moisture compared to valley plots. Mean soil OC from the valley was 60 % higher compared to gentle to high slopes and about three times higher compared to the plateau. Additionally, soil TN in the plateau was three-times higher compared to the valley, but similar in the gentle and high slopes. The influence of terrain heterogeneity on soil properties was less pronounced compared to the landscape position, although the patterns were more or less similar.

For instance, no differences were found amongst terrain ruggedness categories for daytime LST and night time LST indices in contrast to landscape position categories that significantly influenced daytime LST. Although $soil_T$ and BD were non-significant, the other soil physic-chemical properties revealed significant mean differences within terrain ruggedness classification levels (Table 6.5). Plots in the intermediate terrain ruggedness had 54 % higher soil WFPS compared those in slightly rugged terrain, and did not significantly differ with those situated in highly rugged terrains.

The relatively high CV values in WFPS, soil OC and total nitrogen at the slightly rugged terrain categories (Table 6.5) suggest higher plot differences compared to intermediate and highly rugged terrain categories. The small variation in mean soil OC and TN values within terrain ruggedness classification imply plot level means were more homogeneous compared to landscape position classification. Furthermore, mean soil OC and TN values in valley category compare to slightly rugged terrain class thus implying similar plots may have been captured the analysis (Fig 6. 3)

Table 6.3: One way repeated measures analysis of variance (ezANOVA) for environmental and soil properties within classifications schemes

Soil parameters	Landscape Position			Terrain Ruggedness		
	df	F-value	*p*-value	Df	F-value	p-value
Chemical properties						
pH (H_2O)	3	9.006	< 0.001	2	5.394	0.008
†BD	3	16.374	< 0.001	2	9.949	0.103
C: N	3	2.185	0.107	2	6.708	0.003
Soil OC (kg C m^{-3})	3	8.497	< 0.001	2	13.248	< 0.001
Soil TN (kg N m^{-3})	3	10.898	< 0.001	2	10.429	< 0.001
Physical properties						
‡$Soil_T$ (^{o} C)	3	11.322	< 0.001	2	7.313	0.121
§WFPS	3	7.313	< 0.001	2	4.427	0.019
Radiometric Indices						
†LST_{Day} (^oC)	3	11.907	< 0.001	2	23.886	0.218
LST_{Night} (^oC)	3	11.740	0.163	2	25.787	0.970
Slope	3	69.967	< 0.001	2	12.709	< 0.001
Aspect	3	1.138	0.346	2	1.890	0.165

† denoted bulk density

‡ denotes soil temperatures

§ denotes water filled pore space

† denotes Land surface temperature

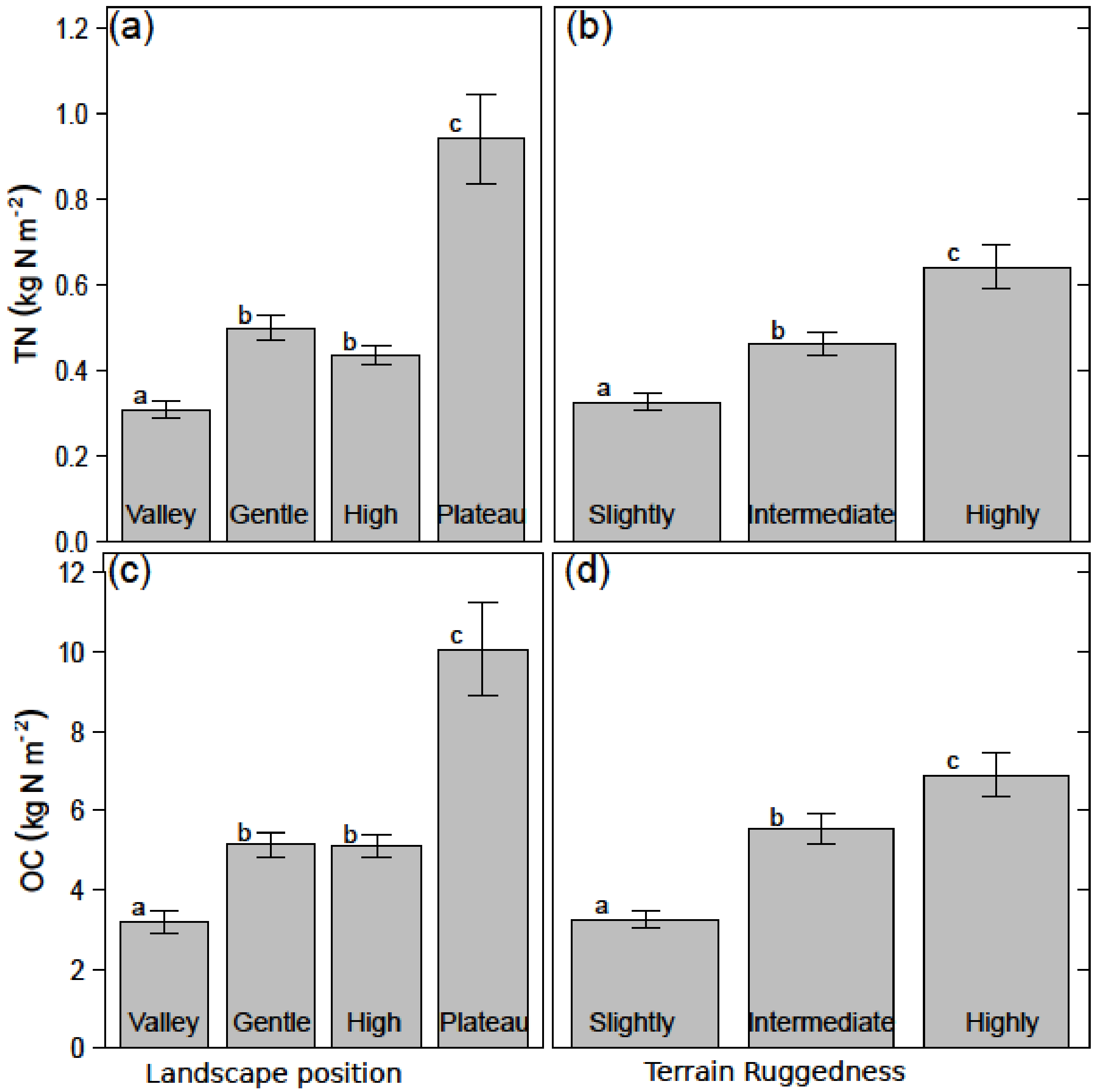


Figure 6.3: soil TN and organic carbon stocks along landscape position (a & c) and terrain ruggedness (b & d). Bar denote mean stock with standard error bars. Letters (a-c) denote significant differences between categories within same classification scheme**.**

Table 6.4 : Description of radiometric indices spatial patterns within classification schemes in the Taita Hills research transect Values denote mean (coefficient of variation)

Category	n	† LST $_{(day)}$ **	‡ LST $_{(Night)}$	Slope *	Aspect	§ TRI***
		(^{o}C)	(^{o}C)	(%)		(%)
Landscape position						
Valley	27	27.27^{a} (3.7)	19.41 (3.3)	1.93^{a} (91)	153.88 (52.8)	0.52^{a} (80.3)
Gentle	27	24.91^{b} (9.7)	17.56 (10.1)	11.08^{b} (35.1)	173.51 (47.6)	2.05^{b} (45)
High	45	24.51^{b} (6.1)	17.62 (6.6)	17.58^{c} (8.5)	150.98 (73.4)	1.88^{b} (56.3)
Plateau	15	21.8^{b} (5.7)	15.08 (9.4)	27.98^{d} (26.3)	242.09 (44.5)	3.09^{c} (30.4)
Terrain ruggedness						
Slightly	37	26.9 (5.3)	19.2 (5.3)	6.3^{a} (110)	158.1 (56.4)	0.5^{a} (52.3)
intermediate	33	25.5 (6.7)	18.2 (6.3)	13.7^{b} (40.6)	215.7 (44.3)	1.5^{b} (22.4)
highly	44	22.8 (6.1)	16.1 (7.7)	19.9^{c} (38.7)	143.1 (73)	3.2^{c} (25.1)

*, **, *** denotes level of Significant at 0.05, 0.01 and 0.001 probability levels.

† denotes daytime LST

‡ denotes night time LST

Different letters (a-d) against values indicate classification categories with significant differences within each factor ($P < 0.05$)

Table 6.5: Spatial soil physical and chemical characteristics with classification scheme in the Taita Hills study transect. Values denote mean (coefficient of variation)

Category	n	†$Soil_T$ **	‡WFPS***	pH**	§ BD**	OC***	TN***
		(^{o} C)	(%)	(H_2O)	(g/m^{-3})	(kg/ m^3)	(kg/m^3)
A. Landscape position							
valley	27	21.22^b (10.5)	17.19^a (42.6)	6.82^a (8.4)	1.49^a (9.8)	3.2^a (45.3)	0.31^a (33.9)
gentle	27	18.67^b (19.6)	32.05^b (19.2)	6.28^a (11)	1.38^a (14.8)	5.13^b (33.5)	0.52^b (31.4)
high	45	19.73^b (16.1)	32.0^b (30.8)	6.04^a (14)	1.24^a (11.3)	5.11^b (39.4)	0.44^b (32.1)
plateau	15	11.81^a (16.1)	39.88^c (32.1)	5.07^b (7.6)	0.57^b (42.6)	10.07^c (44.7)	0.94^b (42.9)
B. Terrain heterogeneity							
slightly	37	21.7 (16.1)	22.19^a (52.6)	6.65^a (14.1)	1.43 (1.4)	3.24^a (40.1)	0.33^a (35)
intermediate	33	19.67 (9.3)	34.53^b (24.2)	6.18^a (9.8)	1.35 (1.4)	5.53^b (39.7)	0.46^a (34.2)
highly	44	15.68 (23.5)	31.98^b (33.3)	5.71^b (13)	1 (1)	6.89^c (52.8)	0.64^b (52.4)

*, **, *** denotes level of Significant at 0.05, 0.01 and 0.001 probability levels

† denotes soil temperature

‡ denotes Water Filled Pore Space

Different letters (a-d) against values indicate classification categories with significant differences within each factor ($P < 0.05$)

6.3.2 Soil C and N relationship with ecological variables

Our results reveal mean BD decreased with increasing altitude whereas $soil_T$ and WFPS increased with the increasing magnitude of landscape classifications. Therefore, significant and high correlations between BD, $soil_T$, WFPS and soil OC and TN stocks were expected. However, results (Table 6.6) show our hypothesis applies only for BD and $soil_T$ which is significantly correlated to OC stocks in the valley, gentle and high slope categories. Altitude was highly correlated to OC stocks in the valley ($R^2 = 0.79$) and to a lesser extent the gentle ($R^2 = 0.47$) positions, but no such significance was observed in high ($R^2 = 0.18$) and plateau ($R^2 = - 0.25$) landscape categories, probably arising from locational placement of both landscape positions in the high latitude end of the transect.

In contrast, soil TN stocks had a low correlation with BD and $soil_T$ in all landscape categories when compared to OC stocks. Generally, most environmental factors that decreased with increasing order of landscape position classes revealed significant correlations. This is demonstrated in Fig. 6.4 where BD revealed significant and negative correlation with SOC ($R^2 = - 0.34$, $p < 0.001$) and TN ($R^2 = - 0.36$, $p < 0.001$). Replicate trends were observed for $soil_T$, WFPS and soil pH parameters, and thus omitted from this paper. Soil pH was least correlated to soil OC and TN stocks across all landscape classification categories with no significant correlations observed (Table 6.6). Collinearity was detected between LST_{Day}, LST_{Night} and altitude parameters and thus all were excluded from regression analysis and subsequent predictive models. When compared to soil OC, the strength of correlation between soil TN and soil pH, $soil_T$, WFPS and altitude was less pronounced but exhibited a similar trend to soil OC stocks within the landscape categories.

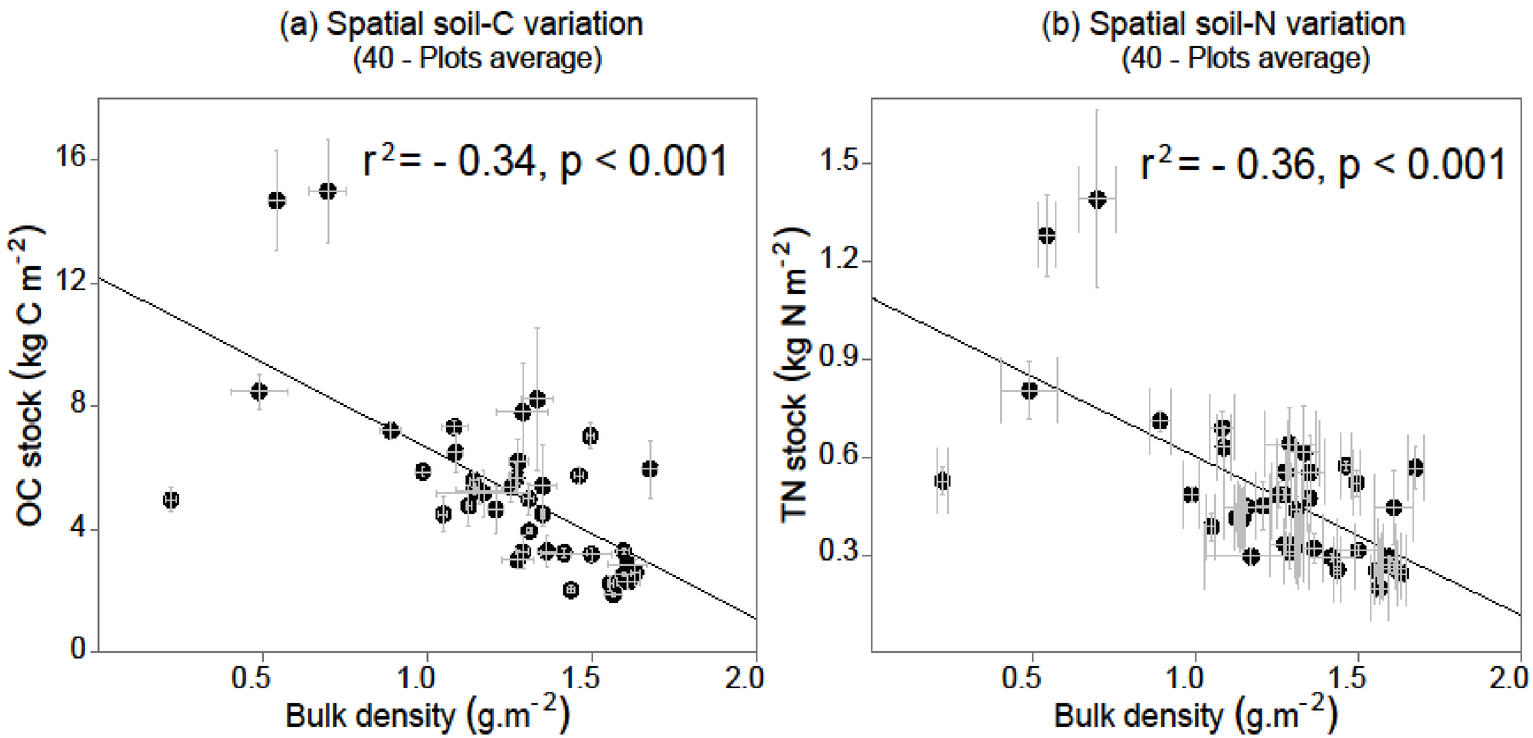


Figure 6.4: Scatter plot of soil OC and TN against soil bulk density (g/m^2) for all plots in study transect (a - b).

Table 6.6: Correlations (Spearman's) between plot mean soil OC (kg C m^{-3}) and TN (kg N m^{-3}) and soil chemical, physical and radiometric properties by slope position classes. Values in bold show significant correlations (*P < 0.05*).

	Slope position	† BD	pH	‡ $Soil_T$	§ WFPS	Slope	Altitude
		(g/m^2)	(H_2O)	(°C)	(°C)	**(%)**	**(m)**
SOC	Valley	**-0.39**	-0.17	**-0.56**	**0.75**	**0.77**	**0.79**
	Gentle	**-0.50**	-0.13	**-0.43**	-0.02	0.09	**0.47**
	High	**-0.36**	-0.21	**-0.34**	-0.14	0.16	0.18
	Plateau	0.12	0.34	0.22	-0.24	**0.71**	-0.25
TN	Valley	-0.30	-0.15	**-0.38**	**0.57**	**0.61**	**0.65**
	Gentle	**-0.48**	-0.11	**-0.43**	-0.08	0.03	**0.49**
	High	-0.20	-0.04	-0.17	0.06	0.21	0.07
	Plateau	0.15	0.44	0.21	-0.16	**0.66**	-0.25

† denoted bulk density

‡ denotes soil temperatures

§ denotes water filled pore space

Table 6.7: OLS regression models for SOC (kg C m^{-3}) stock within topographic position categories with estimated coefficients and standard errors (brackets). Only factors with coefficients statistically significantly different from zero (*P < 0.01*) shown.

	Topographic Position categories			
	Valley	Gentle	High	Plateau
Slope (%)	0.032*			0.034***
	(0.017)			(0.005)
$Soil_T$ (^oC)	-0.024**			-0.037*
	(0.009)			(0.027)
WFPS (%)	0.012***			0.008**
	(0.004)			(0.003)
BD (g/m^2)		-0.067***	-0.090**	0.768***
		(0.023)	(0.035)	(0.207)
Constant	0.399	0.872***	0.853***	-0.102
	(0.357)	(0.070)	(0.073)	(0.352)
Observations	27	27	45	15
Adjusted R^2	0.744	0.222	0.111	0.771
† AIC	128.34	105.31	163.24	66.87
Residual Std. Error	0.085	0.137	0.160	0.094
F-Statistic	19.907***	8.426***	6.511**	12.784***
	(df = 4; 22)	(df = 1; 25)	(df = 1; 43)	(df = 4; 10)

† AIC, Akaike Information Criteria.

Asterisk (s) denote * p < 0.1; ** p < 0.05; *** p < 0.01

6.3.3 Predictive SOC models within slope categories

Regression analysis of the best environmental predictors for soil OC and total N revealed similar patterns, and thus only the former is reported in this paper. Best soil OC stock predictors within landscape position categories revealed significant and divergent trends (Table 6.7). Soil OC stocks variation in the valley were significantly explained by slope, $soil_T$, WFPS and soil pH ($R^2 = 0.74$, $F = 19.907$, $P < 0.01$). Similarly, soil OC variation in plateau were significantly explained by slope, $soil_T$, WFPS and BD ($R^2 = 0.77$). The low standard error (SE = 0.09) value in the valley and plateau models imply the robust nature of these predictors at explaining observed spatial variation. On the contrally, soil OC stock variation in the gentle ($R^2 = 0.22$) and high ($R^2 = 0.11$) slope was dictated only by BD, which explained about three-folds less the variation when compared to valley and plateau landscape categories. From the Akaike Information criteria values, high slope position (AIC = 163.24) had the highest variability when compared with the rest of landscape position categories

6.4 Discussion

6.4.1 Spatial soil C and N variation within radiometric schemes

The landscape position and terrain ruggedness classification schemes offered a simple yet robust opportunity to assess soil OC and N stocks in complex tropical mountain environments. The classification schemes, which have been used elsewhere, for instance to study cougar movements (Dickson and Beier, 2007), estimates plot topographic landscape position and terrain ruggedness thresholds to discriminate plots located in areas with similar neighborhood variability. This fact not only allows the classification scheme to be localized on a study area of interest, but offers flexibility for adoption in similar ecosystems elsewhere. Study plots situated in the plateau had about twice higher soil

OC and total N stock compared to plots located in gentle and high slope areas and about three-folds compared to valley plots (Table 6.5). Similarly, plots in the highly rugged terrain had 25 % higher soil OC stocks compared to those in the intermediate rugged terrain and about two-folds compared to slightly rugged terrain. Similar trends have been reported elsewhere (Luizão *et al.*, 2004; de Castilho *et al.*, 2006) from topo - sequence studies in tropical Amazonia forest, where highly rugged terrains in higher elevation landscapes possessed higher quantities of soil OC compared to low elevation terrains.

An appraisal of ecological soil OC and N drivers revealed significant trends within landscape and terrain heterogeneity categories (Table 6.4). Temperature (LST and $soil_T$) had an inverse relationship with soil OC whereas soil moisture (WFPS) had direct linear relationship with soil OC and TN when both classification schemes are considered. Wet soil condition under low temperatures imply slow decomposition (Garcia-Pausas *et al.*, 2007) in the plateau compared to high, low and valley slope classes where higher temperatures may speed up soil OC losses. This observation is confirmed by low C:N values that depict an ecosystem comprised of highly mineralizable C input material (Manzoni *et al.*, 2010). The mixed trends and comparatively lower margins in mean temperature and moisture values are equally matched by a lower range of soil OC and TN stocks in ruggedness compared to landscape position categories.

It is well established that land use and vegetation density patterns are closely correlated to soil carbon stocks in tropical ecosystems (Don *et al.*, 2011). Plots situated in the plateau were dominated by forest and agroforestry species with greater litter production (Omoro *et al.*, 2013) compared to shrubs and cereal vegetation in slopes and valley plots whose litter supply capacity is lower. Moreover, soil OC losses and turnover are higher in areas undergoing rapid land use changes in the tropics (Batjes, 2004a; Don *et al.*, 2011) as is evident from slopes and highly rugged terrains of the Taita Hills. Most slopes in this ecosystem point from south east to south west direction, thus the effect of insolation is more or less similar either from low to high slopes or from slightly to highly rugged terrains. The shading effect by clouds in the high altitude shields solar exposure in plots located in the plateau and thus a likely contributor to low temperatures (Nadkarni and Solano, 2002) and contributes to high rainfall, being on the windward side. Land cover in plots situated in the low slope and valleys comprised mostly of cereal and shrub vegetation. Although the study did not assess litter C: N contents, plant tissue in valley vegetation is of lower quality compared to plateau vegetation in the Taita Hills. Furthermore, favorable soil temperatures , and moisture conditions encourages rapid litter decomposition thus significantly lowering soil OC status in the valley plots (Luizão *et al.*, 2004).

6.4.2 Radiometric schemes comparison in mapping soil C stocks

Comparisons between landscape position and terrain ruggedness classifications in assessments of soil OC stocks in mountain ecosystems have not been previously attempted in research endeavors within the African continent. That both classifications schemes attempt to scale and classify landscape heterogeneity using various topographic indices validate their utility in assessing spatial soil nutrient stocks in mountain ecosystems. In this study, both classification schemes show a strong consistency in soil OC and TN stocks, soil temperatures, pH and BD increase or decrease in a similar manner. Omnibus tests for soil chemical, physical and radiometric differences within the two classification systems showed more or less similar trends (Table 6.3). This similarity is expected due to methodological protocols used to derive the slope and ruggedness indices (Riley, 1999; Weiss, 2001). However, examination of coefficient of variation differences (CV) (Tables 6.4 & 6.5) revealed subtle differences in describing spatial soil and environmental parameters in the Taita Hills. For instance, the range of soil temperature values between plateau and valley in heterogeneity scheme was 10^{o}C with CV's between

10 and 16, whereas slope position scheme had a range of 6 ^{o}C with CV ranging from 16 to 23 in slightly to highly rugged terrains.

Considering soil physical and chemical characteristics, most parameters (excluding BD and C:N) showed a wide range of mean values and a narrower range of CV in landscape position classification as compared that to ruggedness scheme, implying greater accuracy in capturing variability in the former. Radiometric indices CV values in ruggedness scheme were consistently lower compared landscape position scheme implying the former was able to better capture inherent spatial variability compared to the latter. Despite reasonable mean OC and N stock estimates that do not appreciably effect data interpretation in both classification schemes, the large CV values suggests further refinements are needed in order to capture finer landscape variability details in the Taita Hills.

6.4.3. Efficacy of landscape position in predicting soil C stocks

Part of the study focus was to compare the two classification methods in assessing factors that contribute to spatial soil C variation and use these variables to assess the strength of soil C prediction using the best performing classification scheme. Slope position classification was able to capture more variability in soil C and N stocks compared to the ruggedness classification. Soil OC and TN revealed identical spatial trends (Fig 6.5) in both classification schemes, thus slope position classification was solely used to assess influence of ecosystem moisture, temperature and topographic properties on soil C (Table 6.6). Bulk density and soil temperature were highly correlated to spatial soil C variation in the valley, gentle and high slopes. In tropical ecosystem, bulk density has an inverse relationship with soil OC especially in soils with substantial sand content (Lugo *et al.*, 1986; Woomer *et al.*, 2001). In the slopes and valleys of the Taita Hills where soils originate from metamorphic gneiss type rock (Pohl *et al.*, 1980) bulk density is largely regulated by textural characteristics and organic matter contents. Under optimum moisture conditions, hot and aerated soil conditions support rapid decomposition of soil C inputs, thus explaining the significant soil OC correlations in valley, low and high slope landscape positions. The low bulk density in plateau dominated forest land cover systems arises from continuous organic matter accumulations from above ground forest C resources.

Multiple linear regression models derived in this study show bulk density as an excellent predictor for spatial variation soil C (Table 6.7). However, depending on landscape position, various environmental factors accounted for differential spatial variation. For instance, WFPS was a significant determinant for soil OC stocks in the valley and plateau landscape positions, whereas BD was a key driver for spatial soil OC patterns in the gentle and high slopes. These patterns possibly result from intrinsic soil properties from land cover change and management in plots at different landscape positions, as observed elsewhere by Feller and Beare (1997) and Don *et al.* (2011). Future studies should further explore the influence of stratifying landscape position along land use and cover patterns as well as soil properties such as soil type.

6.4.4. Implications for landscape classification in soil C stocks assessment

The Taita Hills slope and elevation gradients are highly diverse in terms of climate, soil types, vegetation, land use and cover types, whose interaction requires a meta-analysis to effectively describe their collective effect. However, the terrain attributes classification derived in this study managed to reasonably explain a significant spatial soil OC and TN variation in the valley and plateau positions compared the low and high slope lands. That the coefficient of variation (CV) in soil OC and TN stocks was reasonably below 50% in landscape position classification demonstrates its suitability to describe spatial soil OC and TN patterns in the mountain ecosystem. However, results from this study describe spatial soil nutrient status in plots situated at clustered intervals and do not exhaustively represent the various slope characteristics within the altitude gradient. The latter is especially evident in the low and high landscape categories where bulk density was the sore predictor of soil OC stocks describing less than 25 % spatial variation. In order to address such uncertainty in future stocks estimates, more sampling plots are required to comprehensively represent landscape transitions within this ecosystem. It is also difficult to establish a consistent relationship between topography and spatial soil property trends because topography encompasses soil types and vegetation (Garcia-Pausas *et al.*, 2007) , moisture regimes (Burt and Butcher, 1985) and other environmental variables. Thus, the effect of slope on soil OC and TN stocks described in this study are certainly not due to topography *per se* but a combined interactive effect defined by slope properties within the study area.

6.5 Conclusion

The high cost of *in-situ* soil sampling coupled to limitations posed by landscape accessibility has created a need to derive inference methodologies for determining spatial soil OC and TN patterns. In heterogeneously complex landscapes such as mountainous ecosystems, terrain analysis models show high potential for spatial description and prediction of soil properties. The spatial soil OC and TN stocks variation in the Taita Hills mountain ecosystem has not previously assessed along changing topographic gradation. This study demonstrated that terrain attributes can be used as proxy for assessing soil nutrient stock and explained reasonable margins of spatial variation in valley and plateau topographic positions. The 20 m DEM from SRTM employed in this study is widely accessible and enabled description of topographic attributes and their spatial relationships with soil properties over a large area. The distribution of soil stocks in topographic positions were influenced by soil bulk density and to a lesser extent soil temperature and moisture. However, plot measurements employed in this study constitutes a baseline analysis, and certainly do not offer sufficient functional relationships to make reliable estimates and generalizations for mountain ecosystem elsewhere. Integration of topographic position classification with other auxiliary information such as land use and management, vegetation and land cover variables should be considered to further refine the observed spatial patterns observed in this study.

CHAPTER SEVEN

TEMPORAL SOIL C AND N STOCK VARIATION IN AN ALTITUDE GRADED ECOSYSTEM

7.1 Introduction

Soil organic carbon (soil OC), a crucial physical and chemical parameter defining land productivity, is particularly vulnerable to nutrient management in tropical ecosystems. In mountain ecosystems undergoing rapid deforestation, soil OC loss is accompanied by loss of other plant essential soil nutrients, the magnitude which is well understood and quantified (Don *et al.*, 2011; Stockmann *et al.*, 2013). Tropical subsistence agriculture is particularly vulnerable to nutrient perturbations due to lack of adequate land management inputs required to offset such losses.

The role of land use and cover systems and their potential to act as soil carbon (C) sinks has attracted significant scientific attention on a global (Lal, 2004; Ward *et al.*, 2014), regional (Batjes, 2004a; Vågen *et al.*, 2005) and ecosystem (Thangata and Hildebrand, 2012) levels. Despite the knowledge generated from these and other numerous studies, the less explored options in tropical soils are the critical minimum and maximum thresholds at which soils can favorably support crop production and the influence of seasonal weather cycles on these thresholds. Such information is crucial to determine the response of external soil fertility and amelioration inputs in forest converted croplands (Palm *et al.*, 2001; Patrick *et al.*, 2013). Furthermore, restoration of degraded ecosystems require prudent design strategies that rely on robust soil nutrient information baselines.

In mountainous ecosystems, localized differences in soil types and physic-chemical attributes often arise due to differences in topography (i.e altitude, slope and aspect) and weather conditions and regulate soil nutrient thresholds (Lemenih and Itanna, 2004; Takata *et al.*, 2007). The influence of weather parameters is mostly through seasonal and diurnal moisture and temperature cycles. Additionally, the role of land use management in maintaining soil nutrient budgets such as losses through leaching and erosion (Maeda *et al.*, 2010b) and inputs through quantity and quality of decomposable organic material (Palm *et al.*, 2001) is well recognized. However, land use management control on observed spatial soil attributes variation is an ecosystem specific trait that is un-documented in most sub-Sahara Africa ecosystems.

This study seeks to assess seasonally driven soil biophysical changes in a topologically heterogeneous mountain ecosystem and how they influence soil C patterns. Using one of the factors as an example, the change is then explicitly mapped to the region to enable spatial comparison on areas undergoing either positive, negative or no change. In Africa, such mapping endeavors have been in the recent past (Vågen *et al.*, 2012; Hengl *et al.*, 2015) used to predict and map soil functional properties and land degradation status at regional and continental scales. In the approach used in this paper, geostatistical models often used for soil mapping (Kempen *et al.*, 2015; Minasny and McBratney, 2016) are used to derive spatial soil C concentration maps, which are then analyzed for wet to dry inter-seasonal change. These models differ in their predictive assumptions of non-data areas using point observation that are either closer or further from each other. In the focus area for this study, such models have been used to map soil erosivity potential (Maeda *et al.*, 2010b) after land conversion to croplands. Such existing maps can be used concurrently with predictive maps derived in this study to develop indicators for monitoring soil and ecosystem health. Furthermore, information on seasonally driven soil nutrient changes is crucial to management of on-farm nutrient flows by smallholder farmers.

Broadly, this study sought to understand the patterns and relationship of seasonally driven soil properties in an elevated mountain ecosystem, and thereafter demonstrate the spatio-temporal change using one soil factor. Along an altitude gradient in the Taita Hills Kenya, this study addressed the following research questions? 1. *What are the seasonal patterns for SOC and TN stocks within land cover types along an altitude gradient*? 2. *What is the nature of relationship between innate soil physical properties and spatio-temporal SOC stock patterns along the elevation gradient?* 3. *How much change in soil C concentration occurs in seasonal transition from a wet -to- dry periods?*

7.2 Materials and Method

7.2.1 Field sampling strategy

Sampling was conducted as explained in Chapter 3 (Section 3.2)

7.2.2 Soil sampling

Soil sampling was conducted from January to December 2013, for 12 months. The seasonal cycles were then adopted from conventional meteorological calendar seasons as follows; January - February (Dry), March - April - May (Wet), June - July - August - September (Dry) and October - November - December (Wet).

Further details are offered in chapter 5 (section 5.2.2)

7.2.3 Moisture and temperature measurements

Measurements were conducted as explained in Chapter 4 (Sections 4.2.2 and 4.2.4)

7.2.4 Soil analyses

Soil analysis was conducted as explained in Chapter 5 (section 5.2.3)

7.2.5 Statistical analyses

7.2.5.1 Descriptive and regression analysis

All statistical analysis were performed using R-statistics (R Development Core Team, 2014). Krystal Wallis one way analysis of variance (krustal.test) was employed to detect significant differences within seasons for individual land cover plots, then pairwise comparison performed using Tukey - Krammer - Nemenyi *post hoc* test (Pohlert, 2014). An assessment of data clustering tendency was conducted and validated as appropriate (Appendix 7.4). Spearman correlation coefficients were derived to describe the dependencies of plot soil functional and radiometric properties along seasonal and altitude - graded dimensions. Variables with correlations either > 0.7 or VIF > 3 or both were eliminated from subsequent linear regressions. Finally, seasonally significant soil C predictors within maize and forest land uses were compared to those representing the overall study area following Hlavac (2014).

7.2.5.2 Geostatistical analysis

The georeferenced dataset was converted to a spatial data frame to enable mapping of soil carbon concentration from the wet MAM to dry JJAS seasonal transition. This was done by comparing four prediction techniques as follows; 1) soil C % as single covariate predicted using Inverse Distance Weighting (IDW), soil C (%) as single covariate predicted using ordinary kriging, 3) co-kriging soil C % with soil pH and 4) co-kriging soil C % with WFPS. Prediction model parameters are shown in Table 7.1. The choice for co-kringing variables was determined by the best linear relationship between soil % C and other assessed soil properties. The accuracy of prediction and errors associated with each prediction method were determined and quantified. The overall soil C % change in transiting from the wet to the dry weather seasons was then assessed and quantified.

Table 7.1. Model parameters for soil kriging prediction in the Taita Hills research transect

Prediction model	Model parameters
IDW soil C	Nmax (3), idp (2:5), block (200,200)
OK soil C	Model = Ste, Nugget (0.009), psil (0.118), range (931), Kappa (10), block (200,200)
CK soil C and soil pH	Model = Exp, Nugget (0), psil (0.09), range (644), Kappa (-), block (200,200)
CK C and soil WFPS	Model = Ste, Nugget (0), psil (0.115), range (701), Kappa (0.5), block (200,200)

Refer to Pebesma and Graeler (2015) for parameter details

7.3 Results

7.3.1 Seasonal variation in spatial soil patterns with land cover

There were significant seasonal SOC and TN stocks variations in maize and forest land cover plots which were absent in avocado and shrub land cover plot (Table 7.2). Specifically, mean SOC stocks in maize land cover plots were significantly (χ (3) = 28.26, p = 0.001) higher in the wet MAM (4.99 kg C m^{-2}) and OND (4.99 kg C m^{-2}) seasons compared to the drier JF (4.3 kg C m^{-2}) and JJAS (4.08kg C m^{-2}) seasons, depicting rainfall as key drivers for nutrient stocks within land cover types assessed. This however contrasted sharply with forest plots where mean SOC stocks in the dry JF (6.48 kg C m^{-2}) and JJAS (7.23 kg C m^{-2}) where higher compared to the wet MAM (5.09 kg C m^{-2}) and OND (4.83 kg C m^{-2}) seasons.

Similarly, mean SOC stocks in shrub plots were higher in the dry compared to wet months, although these differences were not significant ((χ (3) = 4.66, p = 0.198). Mean avocado SOC stock followed a declining trend from the dry JF duration to wet OND end of sampling period, although no major inter-seasonal differences were observed. Seasonal soil TN stock patterns were closely related to stock SOC patterns. For instance, significant (χ (3) = 28.28, p = 0.033) mean seasonal TN stocks were observed within maize plots, where the dry JJAS season had about 12 % stock higher compared to MAM and OND wet seasons. Similarly, mean forest TN stocks were 30 % higher in JF compared to MAM season, whereas OND season had 55 % lower mean stock compared to preceding JJAS season. Mean seasonal shrub STN values remained more or less similar. The declining SOC trend in avocado plots was similarly maintained by TN, although significant (χ (3) = 10.85, p = 0.013) inter-seasonal differences were observed.

Table 7.2: Seasonal mean rank sums (R̄) and coefficients of variation (in brackets) for soil OC (kg C m^{-2}) and TN (kg C m^{-2}) stocks compared for land cover categories. Letters after mean value indicate significant differences ($p < 0.05$) between seasons (JF, MAM, JJAS, OND) according to Tukey - Kramer - Nemenyi *post hoc* test. Krustal -Wallis (KW) statistic (χ) and p-values for land cover plots are shown below column means

	Plot land cover categories							
Season	*N*	R̄ (Maize)	*n*	R̄ (Avocado)	*n*	R̄ (Shrub)	*n*	R̄ (Forest)
A: Soil Organic Carbon								
JF	86	4.3^{a} (50)	56	5.3 (63)	32	4.93 (59)	30	6.48^{ab} (71)
MAM	129	4.99^{b} (43)	84	5.27 (42)	48	4.5 (25)	45	5.09^{a} (49)
JJAS	172	4.08^{a} (43)	112	4.51 (30)	64	4.8 (28)	60	7.23^{b} (39)
OND	129	4.88^{b} (52)	84	4.64 (31)	48	5.29 (39)	45	4.83^{a} (74)
KW χ (3)		28.26		5.83		4.66		27.49
p		0.001		0.121		0.198		0.001
B: Soil total Nitrogen								
JF	86	0.46^{ab} (40)	56	0.54^{b} (52)	32	0.54 (42)	30	0.59^{ab} (64)
MAM	129	0.47^{b} (42)	84	0.49^{a} (39)	48	0.42 (26)	45	0.47^{a} (51)
JJAS	172	0.42^{a} (42)	112	0.46^{a} (27)	64	0.46 (25)	60	0.67^{b} (38)
OND	129	0.46^{ab} (53)	84	0.42^{a} (28)	48	0.48 (42)	45	0.43^{a} (71)
KW χ (3)		8.74		10.85		6.21		30.56
p		0.033		0.013		0.102		0.001

7.3.2 Seasonal variation in spatial soil patterns with land cover

Soil bulk density (BD), pH and soil C:N showed an almost constant mean seasonal trend within the three altitude categories (Table 7.3). Mean soil C:N ratio, an indicator of biomass decomposition potential, showed a stable inter-seasonal range from 9 to 11 units within the three altitude categories. In the contrast, mean seasonal BD showed a declining trend within altitude categories. Seasonal mean soil C and N concentrations revealed an increasing trend from low to high altitude categories, with large coefficients of variation differences between different seasons. For instance, soil % C was 1.54 times lower in 1300 - 1800 m compared to 1800 - 2300 m altitude categories in MAM season, whereas in JJAS season the change was more than 2-folds. Mean soil % C in 800 - 1300 m altitude category in the dry and wet seasons were more or less similar. However, in the 1800 - 2300 m altitude category, mean soil % C in the dry (JJAS= 9.26 %, JJAS = 10.71%) seasons far exceeded the wet (MAM = 7.17 %, OND = 8.14 %) levels. Mean seasonal soil % patterns closely mimicked those of soil % C.

The sequential mean SOC and TN stocks increase from low to mid altitude categories, followed by a decrease in the high altitude category occurred with varying inter-seasonal magnitudes. For instance, mean soil C stock in 800 - 1300 m elevation for the wet MAM (4.26 kg C m^{-2}) and OND (4.58 kg C m^{-2}) seasons were about 12 % higher compared to the dry JF (3.79 kg C m^{-2}) and JJAS (3.78 kg C m^{-2}) seasons. On the contrally, mean soil C stocks in 1800 - 2300 m elevation for the dry JF (4.91 kg C m^{-2}) and JJAS (6.44 kg C m^{-2}) season were 16 to 52 % higher compared to the wet MAM (4.22 kg C m^{-2}) and OND (4.59 kg C m^{-2}) seasons.

7.3.3 Spatio-temporal SOC relationship with ecological parameters

Significant and higher seasonal correlations were observed between SOC stock and temperature, moisture and physic-chemical conditions compared to altitudinal correlation (Table 7.4). Amongst the variables assessed, SOC stock showed the highest seasonal co-relationship with daytime and nighttime LST, WFPS, soil pH and C: N. In the contrally, rainfall, a key driver for soil moisture in the tropics, showed the least correlation in the dry JF and wet OND seasons. Whereas stable and consistent trends were observed in seasonal SOC co-relationships with assessed soil biophysical factors, the spatial altitudinal relationships were poor and inconsistent. Seasonally defragmented land cover trends revealed significant correlations between SOC and mean WFPS in maize (r = 0.24, P < 0.001) and shrub (r = 0.34, P < 0.001) plots, in contrast to avocado (r = 0.08, P = 0.143) and forest plots (r = 00.06, P = 0.726) (Fig 7.1)

Amongst croplands, maize plots showed an expected inter-seasonal SOC increase in the wet MAM and OND seasons and a decline in the dry JF and JJAS seasons. Avocado plots showed declining pattern from JF - MAM to JJAS - OND seasons. In natural lands, forests plots showed highest SOC stocks in the dry seasons and vice versa in the wet season whereas shrub plots showed mixed inter-seasonal patterns. There were mixed SOC stock response to soil temperature and WFPS within the three altitude ranges (Fig 7.2). In 800 - 1300 m elevation, an increase in mean SOC stock corresponded to a slight increase in WFPS and soil temperature in MAM season, which substantially increased in OND season. Notably, the expected decrease in WFPS in the dry JJAS season was not observed. In 1300 - 1800 m elevation, WFPS and soil temperature fluctuations had an insignificant influence on spatial mean SOC, which revealed an almost constant trend. In the 1800 - 2300 m elevation majorly colonized by forests, distinct SOC peaks and troughs in the wet and dry seasons were matched by inconsistent moisture trend and contrasting temperature trends. A substantial increase in soil WFPS was observed in the wet MAM season which declined in the preceding JJAS and OND seasons. Soil temperature peaks were observed in the wet compared to dry season troughs.

Table 7.3: Seasonal mean values for descriptive soil properties within altitude categories. Table values show mean (coefficient of variation)

	Altitude level	*n*	BD (g m $^{-2}$)	C (%)	N (%)	pH (H_2O)	C: N	C (kg m^{-2})	N (kg m^{-2})
JF	800 - 1300 m	124	1.45 (14.3)	1.35 (58.6)	0.15 (46.7)	6.63 (8.9)	9.16 (28.6)	3.79 (52.9)	0.42 (42.2)
	1300 - 1800 m	86	1.15 (22.2)	3.08 (79.3)	0.31 (70.2)	5.6 (5.8)	9.98 (26)	6.29 (59.4)	0.63 (47.1)
	1800 - 2300 m	18	0.28 (36.3)	9.36 (34.5)	0.8 (36.7)	5.11 (5)	11.9 (22.2)	4.91 (38.3)	0.42 (38.7)
MAM	800 - 1300 m	186	1.47 (13.6)	1.48 (29.6)	0.14 (36.2)	6.58 (6.7)	10.58 (9.3)	4.26 (25.2)	0.4 (24.6)
	1300 - 1800 m	129	1.16 (22.3)	2.82 (57.9)	0.28 (74.7)	5.68 (6)	10.91 (10.7)	5.98 (42.3)	0.55 (42.2)
	1800 - 2300 m	27	0.32 (38.7)	7.17 (48.5)	1.01 (27.4)	4.93 (5.5)	11.27 (7.9)	4.22 (50.8)	0.38 (53.5)
JJAS	800 - 1300 m	248	1.43 (14.2)	1.37 (40.7)	0.14 (28.9)	6.92 (7.2)	9.8 (13.5)	3.78 (33.4)	0.38 (28.5)
	1300 - 1800 m	172	1.11 (22.9)	2.91 (87.1)	0.26 (57)	5.95 (7.6)	10.2 (17.6)	5.45 (42.6)	0.54 (38.9)
	1800 - 2300 m	36	0.32 (39.8)	10.71 (27.1)	0.63 (46.8)	5.66 (10.3)	10.8 (16.8)	6.44 (32.7)	0.61 (35.8)
OND	800 - 1300 m	186	1.43 (13.5)	1.63 (46.2)	0.15 (45.7)	6.82 (8.1)	10.68 (9.2)	4.58 (45.4)	0.43 (45.6)
	1300 - 1800 m	129	1.11 (21)	2.36 (62.6)	0.22 (59.6)	6.13 (7.7)	10.89 (12.9)	5.09 (52.5)	0.47 (52.1)
	1800 - 2300 m	27	0.3 (39.1)	8.14 (38.8)	0.72 (30)	5.51 (6.4)	11.06 (10.9)	4.59 (37.8)	0.41 (35.4)

JF, January - February; MAM, March - Apri l - May; JJAS, June - July - August-September; OND, October - November – December;

Table 7.4: Seasonal (JF, MAM, JJAS, OND) and spatial (800 - 1300 m, 1300 – 1800 m, 1800 – 2300 m) SOC (kg C m^{-2}) relationship with mean soil temperature, moisture and physico - chemical factors. Bold values denote significant Kendall's tau rank correlation coefficients (p = 0.05)

		Temperature				Moisture		Physico-chemico		
Season	*N*	LST_{Day}	LST_{Night}	Air_T	$Soil_T$	WFPS	$Rain_T$	BD	pH	C: N
JF	328	**-0.30**	**-0.23**	**-0.23**	**-0.36**	**0.24**	0.07	**-0.27**	**-0.40**	**0.38**
MAM	342	**-0.23**	**-0.16**	**-0.13**	**-0.16**	**0.20**	**0.21**	**-0.13**	**-0.30**	**0.19**
JJAS	342	**-0.25**	**-0.32**	**-0.27**	**-0.38**	**0.33**	**0.20**	**-0.38**	**-0.47**	**0.32**
OND	342	**-0.12**	**-0.11**	*	-0.09	**0.18**	0.01	-0.03	**-0.20**	**0.21**
Low	744	**-0.11**	0.02	-0.04	-0.05	**0.23**	**0.14**	-0.08	**-0.15**	**0.35**
Mid	516	-0.09	-0.07	**-0.11**	**-0.12**	-0.01	-0.01	**-0.11**	**-0.26**	**0.24**
High	108	0.02	**-0.22**	-0.09	**-0.23**	0.09	**-0.26**	**0.37**	**-0.33**	0.04

LST_{Day} = Daytime land surface temperature; LST_{Night} = Nighttime land surface temperature, Air_T =Air temperature; $soil_T$ = soil temperature, WFPS = water filled pore space; $Rain_T$ = Monthly total Rainfall, BD = bulk density, * denotes missing data

7.3.4 Seasonal plot land cover predictors for soil organic carbon stock

We tested the hypothesis that seasonal soil C stock predictors would vary across land use types, with wet seasons having significant temperature and moisture predictors compared to the dry season. This was done for maize and forest plots and a mean average across all land cover types assessed in the study. Generally, a higher number of biophysical predictors significantly explained SOC stocks in the wet MAM compared to dry JJAS seasons when individual land cover categories and all plot averaged means were considered (Table 7.5).

Soil pH and WFPS had a highly significant seasonal influence on SOC stocks across maize, forest and across land covers. Soil temperature was a significant driver for maize plots C stock in the wet and dry seasons, and together pH, WFPS and rainfall explained about 31 % soil C stock variation in MAM season, and about 42 % variation in JJAS in absence of rainfall. As expected, rainfall had a significant influence on spatial SOC stocks in maize and forest plots in the wet MAM season, whereas soil BD had a pronounced effect in forest plots across wet and dry seasons. This observation also hold true when across plots mean average is considered.

In forest plots, WFPS, soil pH and BD together explained 36 % SOC variation in the dry JJAS season, which was comparable to the wet MAM season variation, explained by adding daytime LST and rainfall. The Akaike Information Criterioa (AIC) from the regression models showed higher values in maize (MAM = 813 ; JJAS = 799) and forest (MAM = 730 ; JJAS = 776) land plots as compared to an across plot average (MAM = 331 ; JJAS = 368).

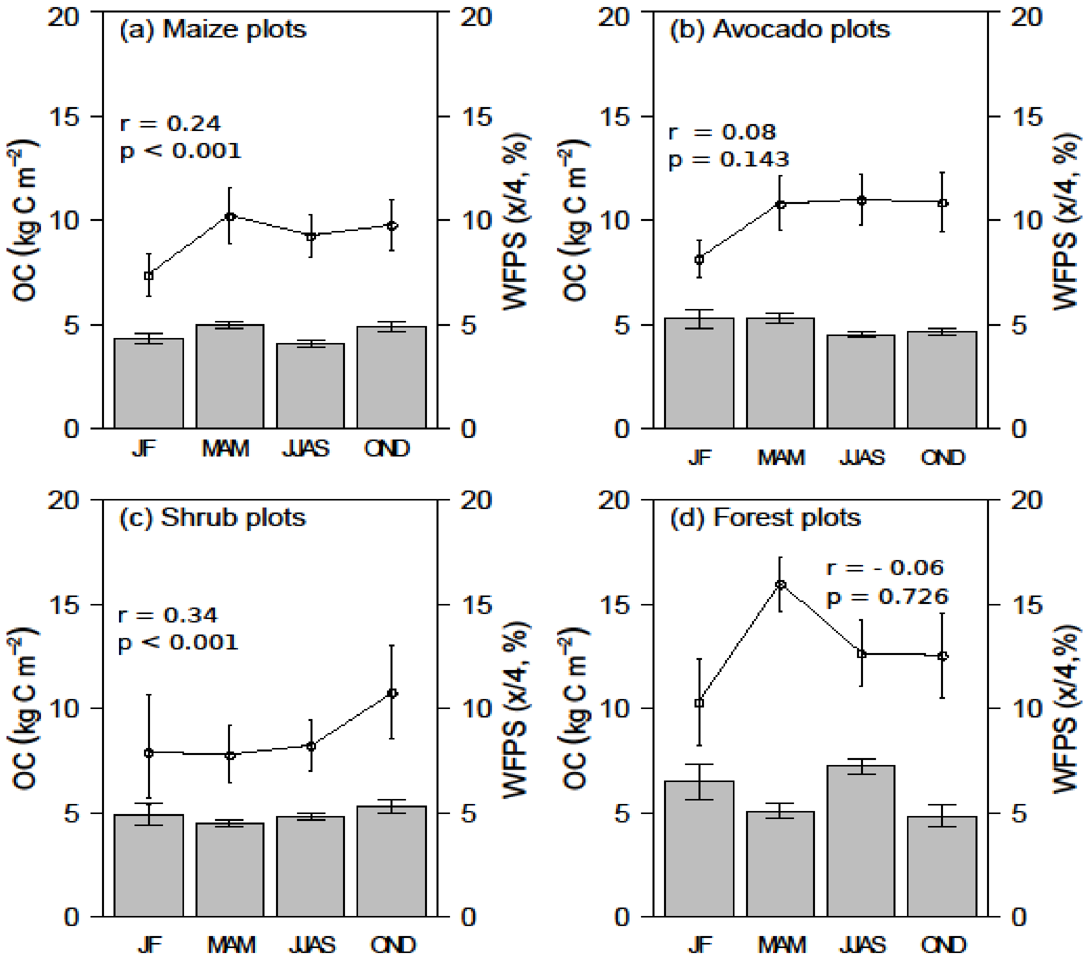


Figure 7.1: Mean seasonal SOC (kg m^{-2}) stocks within land uses (bar plot) and corresponding mean seasonal WFPS (line plot) trends within the study sites. Values show person correlation coefficient (r) and p-value. Line plot values are compressed (division by 4) to facilitate visual inspection.

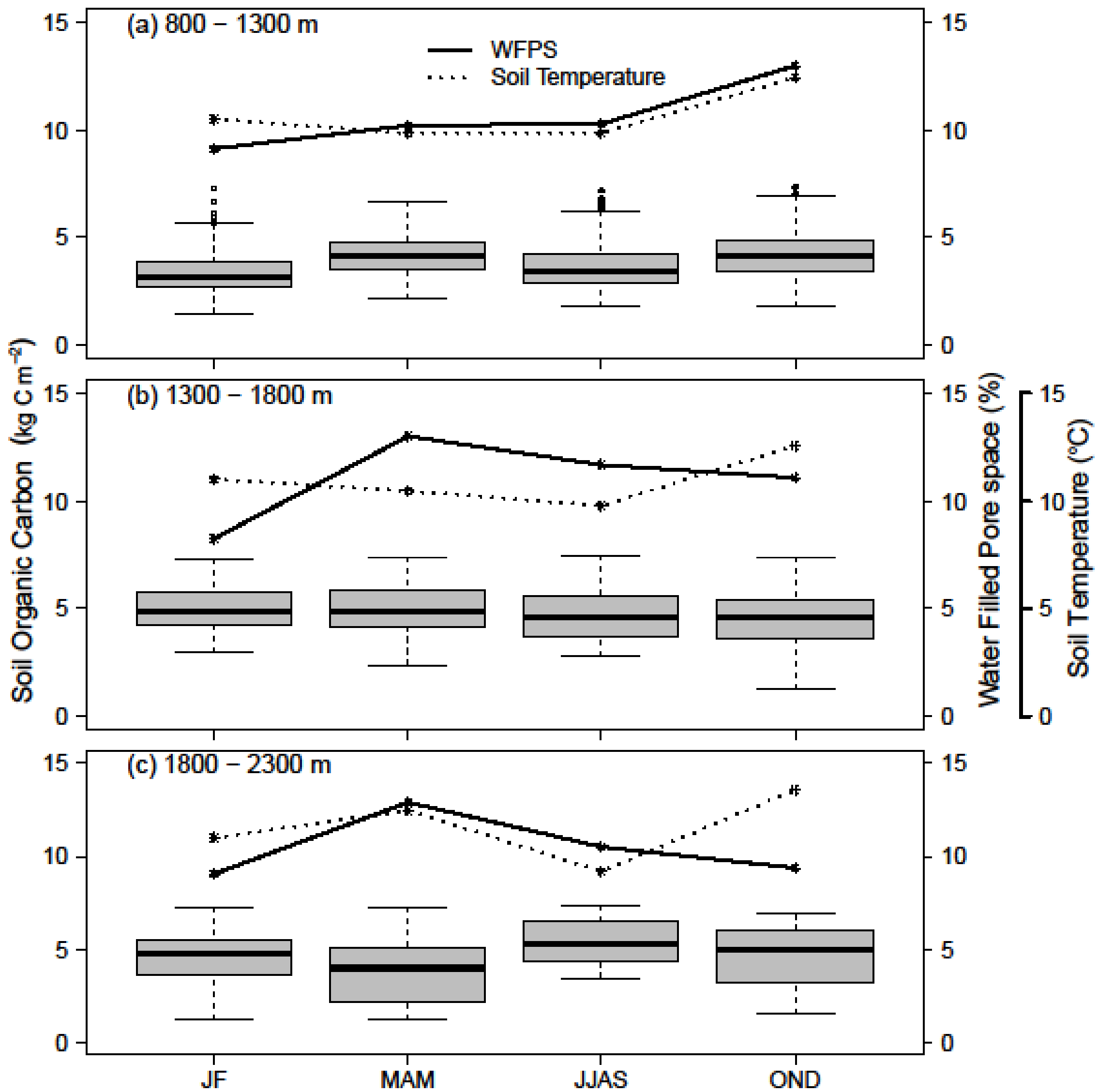


Figure 7.2: Seasonal SOC (box plot) stocks variation with elevation ranges (plots a, b,c) with corresponding mean WFPS (filled line) and mean soil temperature (dotted line) trends. Mean WFPS and temperature values were transformed by division to facilitate visual comparison

Table 7.5: Seasonal (MAM and JJAS) ordinary least squares regression models for SOC (kg C m^{-2}) stock in maize ,forest and across all land covers assessed within study transect

	Maize		Forest		Across land cover	
	MAM	JJAS	MAM	JJAS	MAM	JJAS
$Soil_T$ (^{o} C)	0.061***	0.065***				
	(0.016)	(0.016)				
LST_{Day} (^{o} C)			-0.123***		-0.116***	
			(0.038)		(0.035)	
$Rain_{Total}$ (mm)	0.002***		-0.002***		-0.021***	
	(0.001)		(0.001)		(0.006)	
BD (%)		0.636**	2.240***	1.083***	1.798***	
		(0.290)	(0.333)	(0.302)	(0.412)	
pH (H_2O)	-1.650***	-2.147***	-2.989***	-2.209***	-1.959***	-1.838***
	(0.110)	(0.134)	(0.235)	(0.180)	(0.158)	(0.122)
WFPS (%)	0.476***	0.461***	0.323***	0.435***	0.359***	0.418***
	(0.044)	(0.038)	(0.079)	(0.054)	(0.094)	(0.045)
Constant	9.073***	11.248***	16.393***	12.536***	14.549***	11.935***
	(0.758)	(0.687)	(1.608)	(1.064)	(1.724)	(0.958)
R^2	0.321	0.425	0.362	0.364	0.374	0.467
Adjusted R^2	0.318	0.421	0.354	0.360	0.364	0.463
AIC	813.3	799.67	730.99	776.8	331.37	368.61
Residual SE	1.74	1.642	2.136	1.954	1.609	1.492
F-Statistics	114.074***	117.364***	44.397***	81.742***	40.104***	131.817***
Df	(df = 3; 725)	(df = 5; 794)	(df = 6; 470)	(df = 4; 571)	(df = 5; 336)	(df = 3; 452)

*p<0.1; **p<0.05; ***p<0.01

7.3.5 Seasonal changes in soil C concentration

Methodological differences resulted in subtle differences in soil % C predicted along the altitude gradient. Generally however, predicted soil % C showed an increasing trend with increasing altitude. Mean soil % C varied between 0.05 - 12 % and 0.05 - 14 % in the wet and dry JJAS seasons respectively (Appendix 7.4). Relatively larger spatial soil % C in the higher 1800 - 2100 m elevation range was observed in all the four methods, which decreased as follows; Inverse distance Weightings > Ordinary Kriging > Co-kriging soil % C and pH > Co-kriging soil % C and WFPS. The four methods captured somewhat similar spatial patterns when MAM and JJAS seasons are separately considered. For instance, the area under 0.5 - 2 % C concentration in MAM season remained more or less constant amongst the four prediction methods.This was similarly observed for the JJAS season.

The validity of change, assessed through the standard error graphs (Appendices 7.3 & 7.5), show large standard deviations in areas further from sampling points. A visual assessment of accuracy of predictions depicts the following order in magnitude of standard deviations; co-kriging soil C and pH < Ordinary kriging soil C < Co-kriging soil C and WFPS. IDW method was not validated for change as the model does not have any residuals. The five-fold cross validation of predictions in the MAM season show ordinary kriging and co-kriging soil C and WFPS had lower relative ME and RMSE compared to co-kriging soil C and pH (Table 7.6). Similarly, the two models explained a higher amount of soil % C variation compared to the latter. Differences in soil % C between the four methods are shown Figure 3. The predicted change in soil % C concentration varied from -5 to 1 % within all the four prediction methods. Similarly, the highest wet - dry season change was ± 1 % soil C and occurred in the highest proportion of the study transect, whereas smaller changes occurred in lesser proportions. However, different methods captured the inter-seasonal change to various extents.

Table 7.6: Five-fold cross validation comparison of prediction models. Further parameter detail explained in Pebesma and Graeler (2015)

Parameter	Model used for soil C % predictions			
	IDW soil C	OK soil C	CK soil C and pH	CK soil C and WFPS
ME	-	0.06	0.13	0.07
URMSE	-	0.38	0.45	0.38
RMSE/sd	-	0.55	0.66	0.55
R^2	-	0.98	0.97	0.98

ME = Mean Error ; URMSE = Unbiased Root Mean Squared Error; RMSE/sd = RMSE divided by the standard deviation of the observed values ; R^2 = Amount of variation explained by the model. Parameters for IDW model not reported due absence of variance

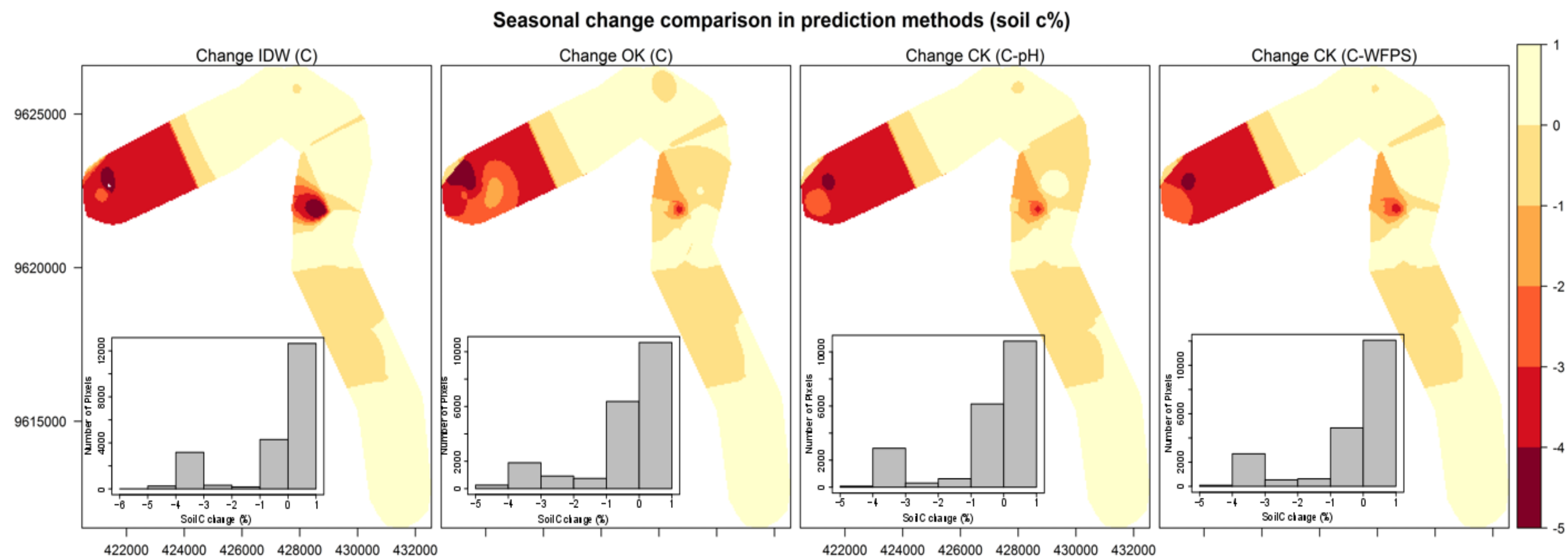


Figure 7.3: Seasonal changes in soil % C concentration from four interpolation methods, (a) Inverse Distance Weighting of % C (b) Ordinary Kringing of % C,using soil pH as a covariate and (d) co-kriging % C using soil WFPS as a covariate. Bar charts inside each graph quantify the relative change in corresponding rasterized image.

For instance, the proportion of change occurred between from 0 and - 1 % C was lowest in IDW method, whereas ordinary kriging and co-kriging soil C - pH showed the highest change at this range. Similarly, the change between -3 and - 4 % was lowest in ordinary kriging whereas the other three methods changed with more or less similar magnitudes. Spatially, all the four methods predicted the highest change (- 4 to -5 % c) in the highly elevated areas occurring at mid and upper end of the transect, mostly under natural forest and agroforestry croplands. Finally, the "artifact" strip "high SD error" region at the upper transect end, was captured by all four prediction models, although IDW had a lower proportion compared to the rest.

7.4 Discussion

In this study, we assessed seasonal patterns for the various biophysical parameters and how they influence SOC and TN stocks in an altitude graded ecosystem, with the ultimate aim of deriving a predictive soil % C map with the best possible predictors. However, biophysical factors exhibited seasonally distinct and somewhat mixed patterns and relationships within land cover and altitude categories assessed.

7.4.1 Influence of altitude and land cover on seasonal soil nutrient stock

Our results show mixed inter-seasonal SOC and TN stock patterns within the study transect. For instance, in croplands bearing maize and avocado agro-forestry species, the wet MAM and OND months resulted to slightly higher SOC increments compared to the dry JJAS and JF seasons (Table 2). The perennial planting and harvesting cycles in agricultural croplands drive SOC pools and their fluctuations through organic matter input and decomposition pathways. In the tropics, the amount of added organic carbon input (from root, crop reside and vegetation) and its loss through microbial decomposition determine the amount present at a given time (Patrick *et al.*, 2013). In intensely cropped mountain ecosystems such as the Taita Hills, topography and land use and management activities play a crucial role in confounding the seasonal effect, resulting to high spatial variations as observed in Table 7.2 and 7.3. Explaining such variation has been the subject of much research by studies in the past (Jenkinson *et al.*, 1990) and present (Stockmann *et al.*, 2013; Groppo *et al.*, 2015). In our study, the relatively higher SOC stocks in avocado plots indicates higher SOC sequestration age in agro-forestry systems through surface and root soil C input as compared to maize croplands (Albrecht and Kandji, 2003; Thangata and Hildebrand, 2012)

On the contrally, shrub and forest lands showed higher SOC and TN values in the dry JF and JJAS seasons compared to the wet seasons. Unlike agricultural cereal and agroforestry croplands where decomposition and mineralization processes occur more rapidly (Mubarak *et al.*, 2008) undisturbed shrub and forest lands maintain close soil nutrient cycling systems tightly regulated by seasonal moisture patterns (Murty *et al.*, 2002). Depending on tree species potential for biomass contribution (Omoro *et al.*, 2011), the net SOC stock at a given time is the balance between stored soil C and surface contribution from vegetation and leaf biomass. The higher SOC stock can be explained by higher organic C additions in moisture-deficient compared to a moisture available season (Zhang *et al.*, 2007). Furthermore, the consistently higher inter-seasonal SOC stock values in forest lands compared to maize and agro-forestry croplands indicate the negative effects of land conversion on soil condition and quality (Davidson and Ackerman, 1993; Murty *et al.*, 2002)

Smallholder farmers in the Taita Hills hardly apply either organic or inorganic amendments to improve croplands soil fertility. Therefore, the total nitrogen stock reported for this ecosystem in this study results exclusively from mineralization of decomposable organic materials, hence the similarities in seasonal and spatial trends with SOC stocks. The range of soil SOC and TN stocks in forest ecosystem reported in this study are within the range of values reported in forest fragments in the Taita Hills (Omoro *et al.*, 2013) and southern Ethiopian highlands (Lemenih and Itanna, 2004). The seasonally inconsistent SOC and TN spatial stock patterns (Table 2) probably arise from the salient land cover effects not factored in the altitude based analysis. Such confounding patterns have been reported elsewhere (Leifeld *et al.*, 2005; Groppo *et al.*, 2015) and constitute critical bottlenecks hindering soil nutrient stock assessments and inventories in the tropics (Smith *et al.*, 2012; Ogle *et al.*, 2013).

7.4.2 Seasonal trends in soil factors and their influence nutrient stocks

Soil BD revealed a decreasing trend with increase in elevation, which maintained relatively constant inter-seasonal trend in the year long sampling duration (Table 7.3). The decreasing mean BD values with increase in elevation gradient exemplify the heterogeneous nature of soil types within the study transect, with sandy soils (BD > 1.1 g/cm^3) dominating the lower altitude and transiting to organic matter rich soils (BD < 0.5 g/cm^3) in the high altitude (VandenBygaart and Angers, 2006; Mubarak *et al.*, 2008; Omoro *et al.*, 2013). Land use and cover influence on soil textural and bulk density changes in the tropics are well described (Batjes, 2004a; Grüneberg *et al.*, 2010) .

Similarly, soil pH and C: N index revealed an almost constant inter-seasonal trend, which sharply contrasts to mixed patterns exhibited by soil N and C stocks within the study ecosystem. Soil pH was the only factor that revealed a stable and significant trend within the three altitude categories, highlighting both its temporal and spatial dependence on SOC stock. The low soil pH values (4.93) observed in MAM season at 1800 - 2300 m range shows the acidic environment in forest ecosystems when optimum temperature encounter optimum moisture conditions to drive decomposition and mineralization during the rainy season. Furthermore, that soil C and N stocks are lowest at this altitude range suggest slow decomposition of organic C inputs and accumulation of soil acids (Bateman and Baggs, 2005; Manzoni *et al.*, 2010)

Our results also reveal two unique co-relationship patterns amongst the biophysical parameters assessed (Table 4). First is the relatively significant relationship between biophysical indices in the dry (JF, JJAS) compared to wet (MAM, OND) seasons and the weak relationship in OND compared to MAM seasons.

For instance, the co-relationship between SOC and soil temperature in the dry seasons (JF, R^2 = -0.36: JJAS, R^2 = -0.38) far exceeds that observed in the wet (MAM, R^2 = -0.16 : OND, R^2 = -0.09) seasons. This pattern is similarly observed in inter-seasonal mean averages for daytime and nighttime LST, WFPS, BD and soil pH. The differences in wet - dry inter seasonal patterns arise from localized moisture and temperature micro-climates resulting to distinct micro-ecosystem differences more pronounced in the dry compared to rainfall periods (Wen *et al.*, 2006; Han *et al.*, 2007). These micro-ecosystem differences were more easily detected for dry compared to wet rainfall periods.

Soil biophysical factor differences between MAM and OND rainy seasons likely arose from differences in moisture intensity, where higher rainfall (MAM) resulted to pronounced spatial biophysical patterns compared to lower (OND) rainfall amounts. An inter-seasonal analysis (Fig 1) show the relationship between SOC and WFPS was varied between different land cover types. Whereas SOC and WFPS showed a significant increasing trend in the wet MAM and JJAS seasons for croplands (Fig 1, a) as conventionally understood (Patrick *et al.*, 2013) forest plots (Fig 1, d) revealed an opposing pattern. Avocado (Fig 1, b) and shrub (Fig 1,c) revealed mixed inter-seasonal patterns, with a poor relationship in the former and a somewhat strong relationship in the later. The low co-relationships may result from ignoring land cover effects in the seasonal analysis. Similar studies in the Amazon (Davidson *et al.*, 2000; Itoh *et al.*, 2012) have showed the influence of soil moisture on soil respiration within different land covers, and attributed SOC changes to land cover driven inter-seasonal change.

With the exception of soil pH, the results (Table 7.4) reveal poor and mostly insignificant soil biophysical factor patterns within the altitude categories assessed. Again, this analysis ignores the effect of seasonality and land cover types present within the derived altitude transitions. First, an assessment of the seasonality effect (Fig 1) revealed mixed SOC, WFPS and soil Temperature parameters patterns between the three altitude transitions. Generally, and in tropical mountain environments, moisture (WFPS) and temperature (soil) have opposite inter-seasonal patterns (Feller and Beare, 1997). However, the mixed and often matching seasonal patterns observed (Fig 7.1: a, c) does not heed to this norm, and thus a likely contributor to low co-relationships observed. Such confounding effects of seasonality are well documented (Zhang *et al.*, 2007; Merbold *et al.*, 2009b). Other confounding effects are likely to arise from soil types (Kamoni *et al.*, 2007), relief and topography (Takata *et al.*, 2007) and land management (Bell and Worrall, 2009).

Finally, rainfall ($Rain_T$) had the lowest co-relationship amongst all the biophysical factors assessed. Since rainfall is the major driver for soil moisture in mountain ecosystems, these low correlations may be attributed to challenges in capturing localized rainfall trends due stationary nature of rain measurement points employed in our study. This limitation significantly challenged the choice of seasonal SOC prediction models.

7.4.3 Mapping seasonal soil % C concentration change in mountain ecosystems

The regression analysis (Table 7.5) employed to assess the best seasonal predictors for SOC stocks within maize croplands and natural forests highlights the issue of scale involved in determining the accuracy levels for soil nutrient stocks prediction in the tropics. The results show that the rainy MAM season has a large number of possible SOC controls compared to the dry JJAS season. Secondly, the derived models show higher variation explained in JJAS season in maize (R^2 = 0.42) and forest (R^2= 0.36) plots compared to MAM season (R^2 =0.32 (maize) and 0.35 (forest)). This observation is confirmed when an across plot summary is considered. The Akaike Information Criterion (AIC) used to compare goodness of fit between different models further suggests higher seasonal variation in maize and forest plots when compared to the across plot average. In the Taita Hills research transect, soil pH and WFPS were the most accurate predictors for seasonal soil C, when individual land cover types and an across plot average are considered. The two variables were used as covariates to derive variogram models (Table 7.1).

This study compared four methods for spatial prediction of soil % C in the Taita Hills research transect, with different models differing in their predictive analysis and change (Fig 3). The Inverse Distance Weighted (IDW) interpolation model, preferred mainly due to its efficacy in interpolating prediction locations within the range of data observations (Bivand *et al.*, 2008), showed least inter-seasonal change in the range from -5 to -1 % C compared to the other three prediction techniques. IDW method has been widely used to predict various biophysical phenomena such as evaporation (Hiemstra and Sluiter, 2011) and various soil functional properties (Li and Heap, 2011).

Ordinary regression kriging compared favorably with both co-kriging techniques (soil C with soil pH/ soil C with WFPS) used in the study, with change from -5 to -1 % C being more or less comparable. Indeed, the quantified performance for each model observed in the cross validation results (Table 6) confirms the similarity of the latter three methods (R^2 difference of ± 1 %). The highest negative seasonal change (-3 to -4 % C) in all the four techniques was observed in the high altitude end (1800 - 2300 m) bearing the natural forest ecosystem. This observation confirms the massive soil C transitions occurring in natural forested ecosystems as a result of changing inter-seasonal moisture cycles (Luizão *et al.*, 2004; Maeda, 2011). The highest positive change (0 to +1 % C) was observed in the highest portion of the study transect at an elevation from 800 to 1500 m. This area is comprised of mostly croplands and small patches of agro-forestry fields. From a management perspective, identifying these areas undergoing such minute change is important in order to target interventions that increase soil C and soil deprived - plant essential nutrients.

Within the four prediction methods, conducted using the same observation dataset, derived spatial predicted maps (Appendices 7.2 and 7.4) are within range values obtained by similar mapping endeavors for the Africa continent (Vågen *et al.*, 2016) and (Hengl *et al.*, 2015).

This study highlights the opportunities available in mapping seasonal soil % C change, and is by no means exhaustive in either the techniques used for spatial prediction or the choice of covariates used jointly for prediction. The covariates used in this study i.e soil pH and WFPS had the highest relationship with soil % C and have been used elsewhere (Bell and Worrall, 2009) as spatial predictors for SOC. Additionally, the four methods utilized in this study derived reasonable seasonal soil C prediction for the Taita hills transect, although numerous interpolation methods exist, each with strong and weak points (Li and Heap, 2011). A more rigorous assessment may require more than the four methods utilized in this study to derive the best optimal method for interpolating soil % C data.

The derived predictions in this study are not without limitations. Although the overall accuracy of prediction was well above 90 %, the 40 observation points utilized in the spatial analysis had a somewhat skewed spatial structure. Moreover, in such a heterogeneous ecosystem as the Taita Hills, the total observation used in the study may be inadequate to cater for expected high variations in biophysical factors. Such challenges arose from terrain inaccessibility that hindered plot selections in the hilly and steeply curved slopes of the Taita Hills. Moreover, difficulties in data normalizing using log transformation to correct for the positive soil %C skew and the back transformation used to produce spatially coherent % C predictions further compound the prediction errors. Such errors are exhaustively summarized in (Hengl *et al.*, 2004)

7.5 Conclusions

In this study, seasonal and spatial patterns in soil temperature, moisture and physical-chemical soil parameters were assessed and described. The seasonal change in one soil factor (soil %C) was mapped with reasonable accuracy for the Taita Hills transect. The results indicate an almost constant inter-seasonal trend in soil bulk density and soil pH that decreased with increasing altitude gradient. The mixed changes in seasonal soil % C, % N, SOC and TN stocks that decreased with increasing altitude resulted from land cover and localized altitudinal micro-climates that characterize the heterogeneous mountain ecosystems. The poor co-relationships observed in biophysical variables amongst altitudinal categories contrast sharply to the excellent co-relationships observed in seasonal categories.

Although the available several methodologies for spatial prediction could not be exhaustively assessed in this study, the four methodologies employed gave reasonable soil % C estimates. The prediction results for mapping soil % C were satisfactory, with the quantified change within the margins established by other studies in similar ecosystems within SSA. The procedure utilized in this study can be used to establish equivalent seasonal changes in other degraded soil nutrients and condition such as % N and soil pH. Such mapping products that can be used to design soil fertility management packages and ecosystems restoration strategies for use by smallholders and development players. A key challenge remains development of sampling approaches that address spatial variability highly inherent in tropical mountain ecosystems. While this study present a crucial understanding of seasonal soil C changes, future endeavors should consider more robust prediction approaches that caters for complex biophysical relationship prevalent in tropical land use systems.

CHAPTER EIGHT

GENERAL CONCLUSIONS AND RECOMMENDATION

8.1 Conclusions

This study sought to establish the spatial and temporal patterns and changes in soil C, N and other functional properties in a mountain ecosystem located in the Taita Hills, and where possible, quantify the observed change. To achieve this, the study area was subjected to altitudinal, radiometric, land use and seasonal categorizations to describe the highest possible soil property variations.

In chapter 4, the study concludes that differences in localized ecological conditions of temperature, moisture and land cover play a critical role in driving soil CO_2 flux emissions. Soil and air temperature were a key drivers for flux emissions from 0 to 1800 m elevation whereas soil moisture was dominant in areas above this elevation range. The influence of land cover on surface flux emissions was pronounced in natural forest and shrub land contributions and disparate from less emitting agricultural croplands.

In chapter 5, the influence of localized ecological and topographic differences is observed through differential soil organic carbon and nitrogen stocks in elevation categories that delineate the study transect. Yet again, the dominant role of land cover as a spatial driver for nutrient stock patterns is established, where croplands in the lower altitude contribute less compared to agro-forestry and forest ecosystems at the higher altitude end. The widely acclaimed benefits of agro-forestry species in maintaining soil nutrient stocks are proved in an ecosystem undergoing rapid degradation through deforestation and poor land management. The study further shows soil C and N detection limits along the graded transect by providing quantified sample estimates for different detection thresholds.

In chapter 6, the study demonstrates the utility of radiometric terrain attributes derived from a 20m digital elevation model to assess spatial nutrient stocks. The study shows upper slopes colonized by forests and agro-forests contain significant inherent soil C stocks compared to low slopes and valleys of the Taita Hills. With high erosivity potential reported by other studies, the information established in this study provides a preliminary basis for design of rehabilitation packages for areas undergoing rapid change in slopes and upper highlands areas.

Finally, in chapter 7, the study describes the seasonal SOC patterns within the various altitude gradations. Temporal heterogeneity in mountain ecosystems is showed through mixed inter-seasonal patterns and changes in moisture, temperature and soil C, N properties. The study showed distinct seasonal co-relationships with soil properties, which contrast to obscure altitudinal co-relationships. Using four prediction methodologies, the study derived three maps; two maps showing the predicted spatial soil % C concentration in MAM and JJAS seasons and, a third map showing the change arising from the seasonal transition. These ready to use products can be used by agricultural extension agents to advice smallholder farmers on farm soil C management as well as a basis for planning ecosystem restoration initiatives.

In summary, the assessments conducted in the Taita Hills ecosystem can be adopted for similar ecosystems within SSA where baseline soil property data is often missing. Furthermore, the soil CO_2 gas emissions thresholds established for this ecosystem in this study form an excellent baseline for design of guestimates often used in national GHG inventories for the east Africa region.

8.2 Recommendations

Based on the results of this study, the following recommendations are offered for future action;

i. The rapid agricultural expansion in the Taita Hills has resulted to rapid loss of soil carbon and nitrogen stocks, especially at low altitude zones where moisture availability is contrained. Rehabilitation of such degraded croplands with agro-forestry practices is a cost effective and affordable option available to communities living under these soil conditions.

ii. Mountain ecosystems often comprise of steep slopes, sharp mountains and in case of the Taita Hills, deep gulleys that hinder access during land survillence monitoring and soil sampling. Design of robust sampling schemes with good spatial structures is necessary to capture spatial and temporal variability in such ecosystems. Results from this study offer a baseline guide for design of such a scheme

iii. With modern advances in satellite technolgy such as high resolution digital elevation models, it is now possible to derive excellent land cover change estimates for the Taita Hills ecosystem. By combining such output with soil attribute maps derived in this study, an ecosystem monitoring framework can be readily designed and implemented.

iv. Low soil fertility is a key challenge to smallholder farmers in the Taita Hills. Design and implementation of judicious soil fertility improving strategies comprising organic and inorganic input use, change in cropping systems and land management practices is a crucial first step to maximise the productive capacity of existing croplands.

v. It is necessary to inform and sensitize policy makers on outputs from this and other silimar studies for two reasons; First to urge farmers to pay more attention to problems posed by poor land management and defforestation. Secondly, to support rehabilitation and training programmes in communities living around these fragile ecosystems.

8.3 Suggested further research

This study was conducted in a small transect portion of an elevation gradient in Taita Hills. Being part of a larger Afromontaine mountain ecosystem, it is worthwhile to compare the soil functional results obtained from this study to a duplicate study in a similar mountain ecosystem such as Usambara, Manyara and Kilimanjaro mountains in Tanzania. With recently developed Taita Hills land use and cover maps by study partnering institutions, a more comprehensive land cover effect on soil nutrient stocks scenario could be achieved by incorporating more land cover types in future assessments. Future research should also evaluate available geostatistical prediction models and methods not used in this study for finer and accurate soil nutrient maps.

REFERENCES

Abdalla, M., Osborne, B., Lanigan, G., Forristal, D., Williams, M., Smith, P., Jones, M., 2013. Conservation tillage systems: a review of its consequences for greenhouse gas emissions. Soil Use and Management 29: 199-209.

Albrecht, A., Kandji, S.T., 2003. Carbon sequestration in tropical agroforestry systems. Agriculture, ecosystems & environment 99: 15-27.

Allen, D., Pringle, M., Page, K., Dalal, R., 2010. A review of sampling designs for the measurement of soil organic carbon in Australian grazing lands. The Rangeland Journal 32: 227-246.

Angers, D., Eriksen-Hamel, N., 2008. Full-inversion tillage and organic carbon distribution in soil profiles: a meta-analysis. Soil Science Society of America Journal 72: 1370-1374.

Arias-Navarro, C., Díaz-Pinés, E., Kiese, R., Rosenstock, T.S., Rufino, M.C., Stern, D., Neufeldt, H., Verchot, L.V., Butterbach-Bahl, K., 2013. Gas pooling: A sampling technique to overcome spatial heterogeneity of soil carbon dioxide and nitrous oxide fluxes. Soil Biology and Biochemistry 67: 20-23.

Arrhenius, S., 1889. Über die Reaktionsgeschwindigkeit bei der Inversion von Rohrzucker durch Säuren. Zeitschrift für physikalische Chemie 4: 226-248.

Arrouays, D., McKenzie, N., Hempel, J., de Forges, A.R., McBratney, A.B., 2014. GlobalSoilMap: basis of the global spatial soil information system. CRC Press.

Assad, E., Pinto, H., Martins, S., Groppo, J., Salgado, P., Evangelista, B., Vasconcellos, E., Sano, E., Pavão, E., Luna, R., 2013. Changes in soil carbon stocks in Brazil due to land use: paired site comparisons and a regional pasture soil survey. Biogeosciences 10: 6141-6160.

Awiti, A.O., Walsh, M.G., Shepherd, K.D., Kinyamario, J., 2008. Soil condition classification using infrared spectroscopy: A proposition for assessment of soil condition along a tropical forest-cropland chronosequence. Geoderma 143: 73-84.

Baldyga, T.J., Miller, S.N., Driese, K.L., Gichaba, C.M., 2008. Assessing land cover change in Kenya's Mau Forest region using remotely sensed data. African Journal of Ecology 46: 46-54.

Bateman, E., Baggs, E., 2005. Contributions of nitrification and denitrification to N2O emissions from soils at different water-filled pore space. Biology and Fertility of Soils 41: 379-388.

Batjes, N., 2004a. Soil carbon stocks and projected changes according to land use and management: a case study for Kenya. Soil Use and Management 20: 350-356.

Batjes, N.H., 1996. Total carbon and nitrogen in the soils of the world. European Journal of Soil Science 47: 151-163.

Batjes, N.H., 2004b. Estimation of soil carbon gains upon improved management within croplands and grasslands of Africa. Environment, Development and Sustainability 6: 133-143.

Beasom, S.L., Wiggers, E.P., Giardino, J.R., 1983. A technique for assessing land surface ruggedness. The Journal of Wildlife Management: 1163-1166.

Bekunda, M., Nkonya, E., Mugendi, D., Msaky, J., 2004. Soil fertility status, management, and research in East Africa. East African Journal of Rural Development 20: 94-112.

Bell, M., Worrall, F., 2009. Estimating a region's soil organic carbon baseline: the undervalued role of land-management. Geoderma 152: 74-84.

Bivand, R.S., Pebesma, E.J., Gómez-Rubio, V., 2008. Interpolation and geostatistics. Applied Spatial Data Analysis With R: 191-235.

Boit, M.K., Mundia, C., Pellikka, P., 2014. Modelling the Impacts of Climate Change on Agro-Ecological Zones–a Case Study of Taita Hills, Kenya. Universal Journal of Geoscience 2: 172-179.

Brady, N., 1990. Physical properties of mineral soils. the Nature and Properties of Soils: 91-175.

Brink, A.B., Eva, H.D., 2009. Monitoring 25 years of land cover change dynamics in Africa: A sample based remote sensing approach. Applied Geography 29: 501-512.

Brovkin, V., Sitch, S., Von Bloh, W., Claussen, M., Bauer, E., Cramer, W., 2004. Role of land cover changes for atmospheric CO2 increase and climate change during the last 150 years. Global Change Biology 10: 1253-1266.

Brussaard, L., 1998. Soil fauna, guilds, functional groups and ecosystem processes. Applied Soil Ecology 9: 123-135.

Burney, J.A., Davis, S.J., Lobell, D.B., 2010. Greenhouse gas mitigation by agricultural intensification. Proceedings of the National Academy of Sciences 107: 12052-12057.

Burt, T., Butcher, D., 1985. Topographic controls of soil moisture distributions. Journal of Soil Science 36: 469-486.

Businge, M., Ondimu, K., Maina, I., Mutai, C., Ochola, S., Ali, A., Nyangena, W., 2011. Kenya State of the Environment and Outlook 2010. Nairobi: National Environment Management Authority.

Butterbach-Bahl, K., Kiese, R., Liu, C., 2011. Measurements of biosphere-atmosphere exchange of CH4 in terrestrial ecosystems. Methods Enzymol 495: 271-287.

Change, I.P.P.C., 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

Clark, B., 2010. Enhanced processing of SPOT multispectral satellite imagery for environmental monitoring and modelling. PhD Dissertation, University of Helsinki, Finland.

Clark, B., Pellikka, P., 2009a. Landscape analysis using multi-scale segmentation and objectoriented classification. Recent advances in remote sensing and geoinformation processing for land degradation assessment: 323-341.

Clark, B., Pellikka, P., 2009b. Landscape analysis using multi-scale segmentation and objectoriented classification. Recent Advances in Remote Sensing and Geoinformation Processing for Land Degradation Assessment 8: 323.

Conant, R.T., Ryan, M.G., Ågren, G.I., Birge, H.E., Davidson, E.A., Eliasson, P.E., Evans, S.E., Frey, S.D., Giardina, C.P., Hopkins, F.M., 2011. Temperature and soil organic matter decomposition rates–synthesis of current knowledge and a way forward. Global Change Biology 17: 3392-3404.

Conant, R.T., Smith, G.R., Paustian, K., 2003. Spatial variability of soil carbon in forested and cultivated sites. Journal of Environmental Quality 32: 278-286.

Conrad, R., 1996. Soil microorganisms as controllers of atmospheric trace gases (H2, CO, CH4, OCS, N2O, and NO). Microbiological Reviews 60: 609-640.

Davidson, E.A., Ackerman, I.L., 1993. Changes in soil carbon inventories following cultivation of previously untilled soils. Biogeochemistry 20: 161-193.

Davidson, E.A., Janssens, I.A., 2006. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. Nature 440: 165-173.

Davidson, E.A., Verchot, L.V., Cattânio, J.H., Ackerman, I.L., Carvalho, J., 2000. Effects of soil water content on soil respiration in forests and cattle pastures of eastern Amazonia. Biogeochemistry 48: 53-69.

de Castilho, C.V., Magnusson, W.E., de Araújo, R.N.O., Luizao, R.C., Luizao, F.J., Lima, A.P., Higuchi, N., 2006. Variation in aboveground tree live biomass in a central Amazonian Forest: Effects of soil and topography. Forest Ecology and Management 234: 85-96.

De Reu, J., Bourgeois, J., Bats, M., Zwertvaegher, A., Gelorini, V., De Smedt, P., Chu, W., Antrop, M., De Maeyer, P., Finke, P., 2013. Application of the topographic position index to heterogeneous landscapes. Geomorphology 186: 39-49.

Development Team, 2013. Quantum GIS Geographic Information System. Open Source Geospatial Foundation Project. Free Software Foundation, India.

Dickson, B., Beier, P., 2007. Quantifying the influence of topographic position on cougar (Puma concolor) movement in southern California, USA. Journal of Zoology 271: 270-277.

Don, A., Schumacher, J., Freibauer, A., 2011. Impact of tropical land-use change on soil organic carbon stocks–a meta-analysis. Global Change Biology 17: 1658-1670.

Epron, D., Bosc, A., Bonal, D., Freycon, V., 2006. Spatial variation of soil respiration across a topographic gradient in a tropical rain forest in French Guiana. Journal of Tropical Ecology 22: 565-574.

Erdogan, H.E., Pellikka, P.K., Clark, B., 2011. Modelling the impact of land-cover change on potential soil loss in the Taita Hills, Kenya, between 1987 and 2003 using remote-sensing and geospatial data. International Journal of Remote Sensing 32: 5919-5945.

Feller, C., Beare, M., 1997. Physical control of soil organic matter dynamics in the tropics. Geoderma 79: 69-116.

Garcia-Pausas, J., Casals, P., Camarero, L., Huguet, C., Sebastia, M.-T., Thompson, R., Romanya, J., 2007. Soil organic carbon storage in mountain grasslands of the Pyrenees: effects of climate and topography. Biogeochemistry 82: 279-289.

Garten, C.T., Hanson, P.J., 2006. Measured forest soil C stocks and estimated turnover times along an elevation gradient. Geoderma 136: 342-352.

Gessler, P.E., Moore, I., McKenzie, N., Ryan, P., 1995. Soil-landscape modelling and spatial prediction of soil attributes. International Journal of Geographical Information Systems 9: 421-432.

Glenday, J., 2006. Carbon storage and emissions offset potential in an East African tropical rainforest. Forest Ecology and Management 235: 72-83.

Groppo, J., Lins, S., Camargo, P., Assad, E., Pinto, H., Martins, S., Salgado, P., Evangelista, B., Vasconcellos, E., Sano, E., 2015. Changes in soil carbon, nitrogen and phosphorus due to land-use changes in Brazil. Biogeosciences Discussions 12: 2533-2571.

Grüneberg, E., Schöning, I., Kalko, E.K., Weisser, W.W., 2010. Regional organic carbon stock variability: a comparison between depth increments and soil horizons. Geoderma 155: 426-433.

Guggenberger, G., Marschner, B., Flessa, H., 2006. Stabilization of organic matter in temperate soils: mechanisms and their relevance under different soil conditionsa review. Eur J Soil Sci 57: 426445.

Guo, L.-l., Nishimura, T., Miyazaki, T., Imoto, H., 2015. Behavior of carbon dioxide in soils affected by tillage systems. Paddy and Water Environment 13: 291-301.

Guo, L.B., Gifford, R., 2002. Soil carbon stocks and land use change: a meta analysis. Global change biology 8: 345-360.

Han, G., Zhou, G., Xu, Z., Yang, Y., Liu, J., Shi, K., 2007. Biotic and abiotic factors controlling the spatial and temporal variation of soil respiration in an agricultural ecosystem. Soil Biology and Biochemistry 39: 418-425.

Hartemink, A.E., 1997. Soil fertility decline in some major soil groupings under permanent cropping in Tanga region, Tanzania. Geoderma 75: 215-229.

Hartemink, A.E., Krasilnikov, P., Bockheim, J., 2013. Soil maps of the world. Geoderma 207: 256-267.

Hashimoto, H., Dungan, J.L., White, M.A., Yang, F., Michaelis, A.R., Running, S.W., Nemani, R.R., 2008. Satellite-based estimation of surface vapor pressure deficits using MODIS land surface temperature data. Remote Sensing of Environment 112: 142-155.

Heikinheimo, V., 2015. Impact of land cover change on aboveground carbon stocks in the Taita Hills, Kenya.

Hengl, T., Heuvelink, G.B., Kempen, B., Leenaars, J.G., Walsh, M.G., Shepherd, K.D., Sila, A., MacMillan, R.A., de Jesus, J.M., Tamene, L., 2015. Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. PloS one 10: e0125814.

Hengl, T., Heuvelink, G.B., Stein, A., 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma 120: 75-93.

Hicks, B., O'Dell, D., Eash, N., Sauer, T., 2015. Nocturnal intermittency in surface CO 2 concentrations in sub-Saharan Africa. Agricultural and Forest Meteorology 200: 129-134.

Hiemstra, P., Sluiter, R., 2011. Interpolation of Makkink evaporation in the Netherlands. KNMI.

Hlavac, M., 2014. stargazer: LaTeX/HTML code and ASCII text for well-formatted regression and summary statistics tables. Harvard University, Cambridge, USA. R package version 5.

Hollinger, D., Aber, J., Dail, B., Davidson, E., Goltz, S., Hughes, H., Leclerc, M., Lee, J., Richardson, A., Rodrigues, C., 2004. Spatial and temporal variability in forest–atmosphere CO2 exchange. Global Change Biology 10: 1689-1706.

Houghton, J., Ding, Y., Griggs, D., Noguer, M., van der Linden, P., Dai, X., Maskell, K., Johnson, C., 2001. IPCC 2001: Climate Change 2001. The Climate change Contribution of Working Group I to the Third Assessment Report of the Intergovemmental Panel on Climate Change 159.

Houghton, R., Goodale, C., 2004. Effects of Land-Use Change on the Carbon Balance of Terrestrial Ecosystems. Ecosystems and Land Use Change: 85-98.

Houghton, R.A., 2003. Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850–2000. Tellus B 55: 378-390.

Huber, R., Rigling, A., Bebi, P., Brand, F.S., Briner, S., Buttler, A., Elkin, C., Gillet, F., Grêt-Regamey, A., Hirschi, C., 2013. Sustainable land use in mountain regions under global change: synthesis across scales and disciplines. Ecology and Society 18: 20 p.

Hutchinson, G., Livingston, G., Healy, R., Striegl, R., 2000. Chamber measurement of surface-atmosphere trace gas exchange: Numerical evaluation of dependence on soil, interfacial layer, and source/sink properties. Journal of Geophysical Research: Atmospheres (1984–2012) 105: 8865-8875.

Itoh, M., Kosugi, Y., Takanashi, S., Kanemitsu, S., Osaka, K.i., Hayashi, Y., Tani, M., Rahim Nik, A., 2012. Effects of soil water status on the spatial variation of carbon dioxide, methane and nitrous oxide fluxes in tropical rain-forest soils in Peninsular Malaysia. Journal of Tropical Ecology 28: 557-570.

Jaetzold, R., Schmidt, H., 1983. Farm management handbook of Kenya: Natural conditions and farm management information. Part C, Eastern Kenya (Eastern and Coast provinces). Farm Management Handbook of Kenya 2.

Jenkinson, D., Andrew, S., Lynch, J., Goss, M., Tinker, P., 1990. The turnover of organic carbon and nitrogen in soil [and discussion]. Philosophical Transactions of the Royal Society of London B: Biological Sciences 329: 361-368.

Jenness, J., 2006. Topographic Position Index (TPI) v. 1.3 a. Jenness Enterprises.

Jobbágy, E.G., Jackson, R.B., 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecological Applications 10: 423-436.

Kairo, J.G., Dahdouh-Guebas, F., Bosire, J., Koedam, N., 2001. Restoration and management of mangrove systems—a lesson for and from the East African region. South African Journal of Botany 67: 383-389.

Kaiser, K., Kalbitz, K., 2012. Cycling downwards–dissolved organic matter in soils. Soil Biology and Biochemistry 52: 29-32.

Kamoni, P., Gicheru, P., Wokabi, S., Easter, M., Milne, E., Coleman, K., Falloon, P., Paustian, K., 2007. Predicted soil organic carbon stocks and changes in Kenya between 1990 and 2030. Agriculture, Ecosystems & Environment 122: 105-113.

Kamoni, P.T., Gicheru, P.T., 2014. 26 Managing Soil Organic Carbon for Multiple Benefits: The Case of Africa. Soil Carbon: Science, Management and Policy for Multiple Benefits 71: 307.

Kaschuk, G., Alberton, O., Hungria, M., 2011. Quantifying effects of different agricultural land uses on soil microbial biomass and activity in Brazilian biomes: inferences to improve soil quality. Plant and Soil 338: 467-481.

Kempen, B., Hengl, T., Heuvelink, G., Leenaars, J.G., Walsh, M.G., MacMillan, R.A., Mendes de Jesus, J.S., Shepherd, K., Sila, A., Desta, L.T., 2015. Soil property maps of Africa at 250 m resolution. EGU General Assembly Conference Abstracts, p. 5649.

Kim, D.-G., Vargas, R., Bond-Lamberty, B., Turetsky, M., 2012. Effects of soil rewetting and thawing on soil gas fluxes: a review of current literature and suggestions for future research. Biogeosciences 9: 2459-2483.

KNBS, 2010. Kenya Demographic and Health Survey 2008-09. Kenya National Bureau of Statistics.

Knorr, W., Prentice, I., House, J., Holland, E., 2005. Long-term sensitivity of soil carbon turnover to warming. Nature 433: 298-301.

Kosugi, Y., Mitani, T., Itoh, M., Noguchi, S., Tani, M., Matsuo, N., Takanashi, S., Ohkubo, S., Nik, A.R., 2007. Spatial and temporal variation in soil respiration in a Southeast Asian tropical rainforest. Agricultural and Forest Meteorology 147: 35-47.

Kunkel, M.L., Flores, A.N., Smith, T.J., McNamara, J.P., Benner, S.G., 2011. A simplified approach for estimating soil carbon and nitrogen stocks in semi-arid complex terrain. Geoderma 165: 1-11.

Kutzbach, L., Schneider, J., Sachs, T., Giebels, M., Nykänen, H., Shurpali, N., Martikainen, P., Alm, J., Wilmking, M., 2007. CO 2 flux determination by closed-chamber methods can be seriously biased by inappropriate application of linear regression. Biogeosciences 4: 1005-1025.

Lal, R., 2004. Soil carbon sequestration impacts on global climate change and food security. Science 304: 1623-1627.

Láng, V., Fuchs, M., Szegi, T., Csorba, Á., Michéli, E., 2016. Deriving World Reference Base Reference Soil Groups from the prospective Global Soil Map product—A case study on major soil types of Africa. Geoderma 263: 226-233.

Lange, M., Eisenhauer, N., Sierra, C.A., Bessler, H., Engels, C., Griffiths, R.I., Mellado-Vázquez, P.G., Malik, A.A., Roy, J., Scheu, S., 2015. Plant diversity increases soil microbial activity and soil carbon storage. Nature communications 6.

Lee, D., Doolittle, J., Owens, V., 2007. Soil carbon dioxide fluxes in established switchgrass land managed for biomass production. Soil Biology and Biochemistry 39: 178-186.

Leenaars, J., 2013. Africa Soil Profiles Database, Version 1.1. A compilation of georeferenced and standardised legacy soil profile data for Sub-Saharan Africa (with dataset). ISRIC Report 3.

Leenaars, J., Kempen, B., van Oostrum, A., Batjes, N., 2014. Africa Soil Profiles database: A compilation of georeferenced and standardised legacy soil profile data for Sub-Saharan Africa. GlobalSoilMap: Basis of the global spatial soil information system: 51.

Leifeld, J., Bassin, S., Fuhrer, J., 2005. Carbon stocks in Swiss agricultural soils predicted by land-use, soil characteristics, and altitude. Agriculture, Ecosystems & Environment 105: 255-266.

Lemenih, M., Itanna, F., 2004. Soil carbon stocks and turnovers in various vegetation types and arable lands along an elevation gradient in southern Ethiopia. Geoderma 123: 177-188.

Lemma, B., Kleja, D.B., Nilsson, I., Olsson, M., 2006. Soil carbon sequestration under different exotic tree species in the southwestern highlands of Ethiopia. Geoderma 136: 886-898.

Li, C., Frolking, S., Frolking, T.A., 1992. A model of nitrous oxide evolution from soil driven by rainfall events: 2. Model applications. J. Geophys. Res 97: 9777-9783.

Li, J., Heap, A.D., 2011. A review of comparative studies of spatial interpolation methods in environmental sciences: performance and impact factors. Ecological Informatics 6: 228-241.

Li, Q., Unger, A., Sudicky, E., Kassenaar, D., Wexler, E., Shikaze, S., 2008. Simulating the multi-seasonal response of a large-scale watershed with a 3D physically-based hydrologic model. Journal of Hydrology 357: 317-336.

Lugo, A.E., Sanchez, M.J., Brown, S., 1986. Land use and organic carbon content of some subtropical soils. Plant and Soil 96: 185-196.

Luizão, R.C., Luizão, F.J., Paiva, R.Q., Monteiro, T.F., Sousa, L.S., Kruijt, B., 2004. Variation of carbon and nitrogen cycling processes along a topographic gradient in a central Amazonian forest. Global Change Biology 10: 592-600.

Maeda, E., 2011. Agricultural expansion and climate change in the Taita Hills, Kenya: an assessment of potential environmental impacts.

Maeda, E.E., 2014. Downscaling MODIS LST in the East African mountains using elevation gradient and land-cover information. International Journal of Remote Sensing 35: 3094-3108.

Maeda, E.E., Clark, B.J., Pellikka, P., Siljander, M., 2010a. Modelling agricultural expansion in Kenya's Eastern Arc Mountains biodiversity hotspot. Agricultural Systems 103: 609-620.

Maeda, E.E., Hurskainen, P., 2014. Spatiotemporal characterization of land surface temperature in Mount Kilimanjaro using satellite data. Theoretical and Applied Climatology 118: 497-509.

Maeda, E.E., Pellikka, P.K., Siljander, M., Clark, B.J., 2010b. Potential impacts of agricultural expansion and climate change on soil erosion in the Eastern Arc Mountains of Kenya. Geomorphology 123: 279-289.

Maitima, J.M., Mugatha, S.M., Reid, R.S., Gachimbi, L.N., Majule, A., Lyaruu, H., Pomery, D., Mathai, S., Mugisha, S., 2009. The linkages between land use change, land degradation and biodiversity across East Africa. African Journal of Environmental Science and Technology 3.

Manzoni, S., Taylor, P., Richter, A., Porporato, A., Ågren, G.I., 2012. Environmental and stoichiometric controls on microbial carbon-use efficiency in soils. New Phytologist 196: 79-91.

Manzoni, S., Trofymow, J.A., Jackson, R.B., Porporato, A., 2010. Stoichiometric controls on carbon, nitrogen, and phosphorus dynamics in decomposing litter. Ecological Monographs 80: 89-106.

Meir, P., Malhi, Y., Hodnett, M., Grace, J., 2004. Soil CO2 efflux in a tropical forest in the central Amazon. Global Change Biology 10: 601-617.

Merbold, L., Ardö, J., Arneth, A., Scholes, R., Nouvellon, Y., De Grandcourt, A., Archibald, S., Bonnefond, J., Boulain, N., Brueggemann, N., 2009a. Precipitation as driver of carbon fluxes in 11 African ecosystems. Biogeosciences 6: 1027-1041.

Merbold, L., Ardö, J., Arneth, A., Scholes, R., Nouvellon, Y., De Grandcourt, A., Archibald, S., Bonnefond, J., Boulain, N., Brueggemann, N., 2009b. Precipitation as driver of carbon fluxes in 11 African ecosystems. Biogeosciences 6: 1027-1041.

Merbold, L., Ziegler, W., Mukelabai, M., Kutsch, W., 2011. Spatial and temporal variation of CO 2 efflux along a disturbance gradient in a miombo woodland in Western Zambia. Biogeosciences 8: 147-164.

Meybeck, M., Green, P., Vörösmarty, C., 2001. A new typology for mountains and other relief classes: an application to global continental water resources and population distribution. Mountain Research and Development 21: 34-45.

Milne, E., Al Adamat, R., Batjes, N., Bernoux, M., Bhattacharyya, T., Cerri, C., Cerri, C., Coleman, K., Easter, M., Falloon, P., 2007. National and sub-national assessments of soil organic carbon stocks and changes: The GEFSOC modelling system. Agriculture, Ecosystems & Environment 122: 3-12.

Minasny, B., McBratney, A.B., 2016. Digital soil mapping: A brief history and some lessons. Geoderma 264: 301-311.

Montagnini, F., Nair, P., 2004. Carbon sequestration: an underexploited environmental benefit of agroforestry systems. Agroforestry Systems 61: 281-295.

Moore, I.D., Gessler, P., Nielsen, G., Peterson, G., 1993. Soil attribute prediction using terrain analysis. Soil Science Society of America Journal 57: 443-452.

Mosier, A., Wassmann, R., Verchot, L., King, J., Palm, C., 2004. Methane and nitrogen oxide fluxes in tropical agricultural soils: sources, sinks and mechanisms. Tropical Agriculture in Transition—Opportunities for Mitigating Greenhouse Gas Emissions? Springer, pp. 11-49.

Mubarak, A., Elbashir, A., Elamin, L., Daldoum, D., Steffens, D., Benckiser, G., 2008. Decomposition and Nutrient Release from Litter Fall in the Semi-arid Tropics of Sudan. Communications in Soil Science and Plant Analysis 39: 2359-2377.

Murty, D., Kirschbaum, M.U., Mcmurtrie, R.E., Mcgilvray, H., 2002. Does conversion of forest to agricultural land change soil carbon and nitrogen? A review of the literature. Global Change Biology 8: 105-123.

Mutuo, P.K., Cadisch, G., Albrecht, A., Palm, C., Verchot, L., 2005. Potential of agroforestry for carbon sequestration and mitigation of greenhouse gas emissions from soils in the tropics. Nutrient Cycling in Agroecosystems 71: 43-54.

Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A., Kent, J., 2000. Biodiversity hotspots for conservation priorities. Nature 403: 853-858.

Nadkarni, N.M., Solano, R., 2002. Potential effects of climate change on canopy communities in a tropical cloud forest: an experimental approach. Oecologia 131: 580-586.

Nair, P., 2012. Carbon sequestration studies in agroforestry systems: a reality-check. Agroforestry Systems 86: 243-253.

Nandwa, S.M., 2001. Soil organic carbon (SOC) management for sustainable productivity of cropping and agro-forestry systems in Eastern and Southern Africa. Managing Organic matter in tropical soils: Scope and limitations. Springer, pp. 143-158.

Nawar, S., Buddenbaum, H., Hill, J., Kozak, J., Mouazen, A.M., 2016. Estimating the soil clay content and organic matter by means of different calibration methods of vis-NIR diffuse reflectance spectroscopy. Soil and Tillage Research 155: 510-522.

Nocita, M., Stevens, A., Wesemael, B., Brown, D.J., Shepherd, K.D., Towett, E., Vargas, R., Montanarella, L., 2015. Soil spectroscopy: an opportunity to be seized. Global Change Biology 21: 10-11.

Nyberg, G., Högberg, P., 1995. Effects of young agroforestry trees on soils in on-farm situations in western Kenya. Agroforestry Systems 32: 45-52.

O'Dell, D., Sauer, T.J., Hicks, B.B., Thierfelder, C., Lambert, D.M., Logan, J., Eash, N.S., 2015. A short-term assessment of carbon dioxide fluxes under contrasting agricultural and soil management practices in Zimbabwe. Journal of Agricultural Science 7: p32.

Ogle, S.M., Buendia, L., Butterbach-Bahl, K., Breidt, F.J., Hartman, M., Yagi, K., Nayamuth, R., Spencer, S., Wirth, T., Smith, P., 2013. Advancing national greenhouse gas inventories for agriculture in developing countries: improving activity data, emission factors and software technology. Environmental Research Letters 8: 015030.

Okalebo, J., Gathua, K., Woomer, P., 2002. Laboratory methods of plant and soil analysis: a working manual. TSBF-UNESCO, Nairobi, Kenya.

Omoro, L., Starr, M., Pellikka, P.K., 2013. Tree biomass and soil carbon stocks in indigenous forests in comparison to plantations of exotic species in the Taita Hills of Kenya. Silva Fennica.

Omoro, L.M.A., Laiho, R., Starr, M., Pellikka, P.K., 2011. Relationships between native tree species and soil properties in the indigenous forest fragments of the Eastern Arc Mountains of the Taita Hills, Kenya. Forestry Studies in China 13: 198-210.

Otieno, D., K'Otuto, G., Maina, J., Kuzyakov, Y., Onyango, J., 2010. Responses of ecosystem carbon dioxide fluxes to soil moisture fluctuations in a moist Kenyan savanna. Journal of Tropical Ecology 26: 605-618.

Palm, C.A., Gachengo, C.N., Delve, R.J., Cadisch, G., Giller, K.E., 2001. Organic inputs for soil fertility management in tropical agroecosystems: application of an organic resource database. Agriculture, Ecosystems & Environment 83: 27-42.

Parkin, T., Venterea, R., Hargreaves, S., 2012. Calculating the detection limits of chamber-based soil greenhouse gas flux measurements. Journal of Environmental Quality 41: 705-715.

Paron, P., Olago, D.O., Omuto, C.T., 2013. Kenya: A Natural Outlook: Geo-Environmental Resources and Hazards. Newnes.

Parton, W.J., Schimel, D., Ojima, D., Cole, C.V., Bryant, R., Arnold, R., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. Quantitative modeling of soil forming processes: proceedings of a symposium sponsored by Divisions S-5 and S-9 of the Soil Science Society of America in Minneapolis, Minnesota, USA, 2 Nov. 1992. Soil Science Society of America Inc., pp. 147-167.

Patrick, M., Tenywa, J.S., Ebanyat, P., Tenywa, M.M., Mubiru, D.N., Basamba, T.A., Leip, A., 2013. Soil organic carbon thresholds and nitrogen management in tropical agroecosystems: concepts and prospects. Journal of Sustainable Development 6: 31.

Paustian, K., Six, J., Elliott, E., Hunt, H., 2000. Management options for reducing CO2 emissions from agricultural soils. Biogeochemistry 48: 147-163.

Pebesma, E., Graeler, B., 2015. Spatial and Spatio-Temporal Geostatistical Modelling, Prediction and Simulation. Package "gstat'. R Foundation for Statistical Computing, Vienna, Austria.

Pellikka, P., Clark, B., Gonsamo Gosa, A., Himberg, N., Hurskainen, P., Maeda, E.E., Omoro, L., Siljander, M., 2013. Agricultural expansion and its consequences in the Taita Hills, Kenya. Kenya: a Natural Outlook Geo-Environmental Resources and Hazards.

Pellikka, P.K., Lötjönen, M., Siljander, M., Lens, L., 2009. Airborne remote sensing of spatiotemporal change (1955–2004) in indigenous and exotic forest cover in the Taita Hills, Kenya. International Journal of Applied Earth Observation and Geoinformation 11: 221-232.

Pohl, W., Horkel, A., Neubauer, W., Niedermayr, G., Okelo, R., Wachira, J., Werneck, W., 1980. Notes on the geology and mineral resources of the Mtito Andei-Taita area (southern Kenya). ÖGG.

Pohlert, T., 2014. The pairwise multiple comparison of mean ranks package (PMCMR). R package.

Powlson, D.S., Smith, P., Smith, J.U., 2013. Evaluation of soil organic matter models: using existing long-term datasets. Springer Science & Business Media.

Qin, C.-Z., Zhu, A.-X., Qiu, W.-L., Lu, Y.-J., Li, B.-L., Pei, T., 2012. Mapping soil organic matter in small low-relief catchments using fuzzy slope position information. Geoderma 171: 64-74.

Quansah, E., Mauder, M., Balogun, A.A., Amekudzi, L.K., Hingerl, L., Bliefernicht, J., Kunstmann, H., 2015. Carbon dioxide fluxes from contrasting ecosystems in the Sudanian Savanna in West Africa. Carbon Balance and Management: 1.

R Development Core Team, 2014. R: A Laguage and Enviroment for Statistical Computing (Ver R-3.2.2). R Foundation for Statistical Computing. , Vienna, Austria, p. Software.

Rhanor, T., 2013. Topographic position and land cover effects on soil organic carbon distribution of loess-veneered hillslopes in the central United States. MSc Dissertation. Southern Illinois University Carbondale.

Riley, S.J., 1999. Index That Quantifies Topographic Heterogeneity. Intermountain Jounal of Sciences, pp. 23-27,.

Ryan, C.M., Hill, T., Woollen, E., Ghee, C., Mitchard, E., Cassells, G., Grace, J., Woodhouse, I.H., Williams, M., 2012. Quantifying small-scale deforestation and forest degradation in African woodlands using radar imagery. Global Change Biology 18: 243-257.

Sahani, U., Behera, N., 2001. Impact of deforestation on soil physicochemical characteristics, microbial biomass and microbial activity of tropical soil. Land Degradation & Development 12: 93-105.

Savage, K., Davidson, E., Richardson, A., 2008. A conceptual and practical approach to data quality and analysis procedures for high-frequency soil respiration measurements. Functional Ecology 22: 1000-1007.

Scharlemann, J.P., Tanner, E.V., Hiederer, R., Kapos, V., 2014. Global soil carbon: understanding and managing the largest terrestrial carbon pool. Carbon Management 5: 81-91.

Schmidt, M.W., Torn, M.S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I.A., Kleber, M., Kögel-Knabner, I., Lehmann, J., Manning, D.A., 2011. Persistence of soil organic matter as an ecosystem property. Nature 478: 49-56.

Schroeder, P., 1994. Carbon storage benefits of agroforestry systems. Agroforestry Systems 27: 89-97.

Serneels, S., Lambin, E.F., 2001. Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. Agriculture, Ecosystems & Environment 85: 65-81.

Shepherd, K., Soule, M., 1998. Soil fertility management in west Kenya: dynamic simulation of productivity, profitability and sustainability at different resource endowment levels. Agriculture, Ecosystems & Environment 71: 131-145.

Shepherd, K.D., Vanlauwe, B., Gachengo, C.N., Palm, C.A., 2005. Decomposition and mineralization of organic residues predicted using near infrared spectroscopy. Plant and Soil 277: 315-333.

Shepherd, K.D., Walsh, M.G., 2002. Development of reflectance spectral libraries for characterization of soil properties. Soil Science Society of America Journal 66: 988-998.

Sileshi, G., Maghembe, J., Rao, M., Ogol, C., Sithanantham, S., 2000. Insects feeding on Sesbania species in natural stands and agroforestry systems in southern Malawi. Agroforestry Systems 49: 41-52.

Singh, K., Ghoshal, N., Singh, S., 2009. Soil carbon dioxide flux, carbon sequestration and crop productivity in a tropical dryland agroecosystem: Influence of organic inputs of varying resource quality. Applied Soil Ecology 42: 243-253.

Six, J., Paustian, K., Elliott, E., Combrink, C., 2000. Soil structure and organic matter I. Distribution of aggregate-size classes and aggregate-associated carbon. Soil Science Society of America Journal 64: 681-689.

Sjöström, M., Ardö, J., Arneth, A., Boulain, N., Cappelaere, B., Eklundh, L., De Grandcourt, A., Kutsch, W., Merbold, L., Nouvellon, Y., 2011. Exploring the potential of MODIS EVI for modeling gross primary production across African ecosystems. Remote Sensing of Environment 115: 1081-1089.

Smith, K., Ball, T., Conen, F., Dobbie, K., Massheder, J., Rey, A., 2003. Exchange of greenhouse gases between soil and atmosphere: interactions of soil physical factors and biological processes. European Journal of Soil Science 54: 779-791.

Smith, P., Andren, O., Brussaard, L., Dangerfield, M., Ekschmitt, K., Lavelle, P., Tate, K., 1998. Soil biota and global change at the ecosystem level: describing soil biota in mathematical models. Global Change Biology 4: 773-784.

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., Boddey, R.M., McNamara, N.P., Powlson, D., Cowie, A., 2012. Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. Global Change Biology 18: 2089-2101.

Smith, P., Smith, J., Powlson, D., McGill, W., Arah, J., Chertov, O., Coleman, K., Franko, U., Frolking, S., Jenkinson, D., 1997. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. Geoderma 81: 153-225.

Søe, A.R., Buchmann, N., 2005. Spatial and temporal variations in soil respiration in relation to stand structure and soil parameters in an unmanaged beech forest. Tree physiology 25: 1427-1436.

Sotta, E.D., Veldkamp, E., Schwendenmann, L., Guimaraes, B.R., Paixao, R.K., Ruivo, M.D.L.P., da COSTA, L., CARLOS, A., MEIR, P., 2007. Effects of an induced drought on soil carbon dioxide (CO2) efflux and soil CO2 production in an Eastern Amazonian rainforest, Brazil. Global Change Biology 13: 2218-2229.

Stockmann, U., Adams, M.A., Crawford, J.W., Field, D.J., Henakaarchchi, N., Jenkins, M., Minasny, B., McBratney, A.B., de Courcelles, V.d.R., Singh, K., 2013. The knowns, known unknowns and unknowns of sequestration of soil organic carbon. Agriculture, Ecosystems & Environment 164: 80-99.

Subke, J.-A., Bahn, M., 2010. On the 'temperature sensitivity'of soil respiration: Can we use the immeasurable to predict the unknown? Soil Biology and Biochemistry 42: 1653-1656.

Susilo, F., Neutel, A., Noordwijk, M.v., Hairiah, K., Brown, G., Swift, M.J., Cadisch, G., Ong, C., 2004. Soil biodiversity and food webs. Below-ground interactions in tropical agroecosystems: concepts and models with multiple plant components: 285-307.

Swallow, B.M., Sang, J.K., Nyabenge, M., Bundotich, D.K., Duraiappah, A.K., Yatich, T.B., 2009. Tradeoffs, synergies and traps among ecosystem services in the Lake Victoria basin of East Africa. Environmental Science & Policy 12: 504-519.

Takata, Y., Funakawa, S., Akshalov, K., Ishida, N., Kosaki, T., 2007. Spatial prediction of soil organic matter in northern Kazakhstan based on topographic and vegetation information. Soil Science and Plant Nutrition 53: 289-299.

Tamooh, F., Meersche, K., Meysman, F., Marwick, T.R., Borges, A., Merckx, R., Dehairs, F., Schmidt, S., Nyunja, J., Bouillon, S., 2012. Distribution and origin of suspended matter and organic carbon pools in the Tana River Basin, Kenya. Biogeosciences 9: 2905-2920.

Tan, Z., Lal, R., Smeck, N., Calhoun, F., 2004. Relationships between surface soil organic carbon pool and site variables. Geoderma 121: 187-195.

Thangata, P., Hildebrand, P., 2012. Carbon stock and sequestration potential of agroforestry systems in smallholder agroecosystems of sub-Saharan Africa: Mechanisms for 'reducing emissions from deforestation and forest degradation'(REDD+). Agriculture, Ecosystems & Environment 158: 172-183.

Tiessen, H., Feller, C., Sampaio, E., Garin, P., 1998. Carbon sequestration and turnover in semiarid savannas and dry forest. Climatic Change 40: 105-117.

Tittonell, P., Vanlauwe, B., De Ridder, N., Giller, K.E., 2007. Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: Soil fertility gradients or management intensity gradients? Agricultural Systems 94: 376-390.

Tomlinson, R., 1978. Design considerations for digital soil map systems. 11th Congress of Soil Science. ISSS, Edmonton, Canada.

Torn, M.S., Trumbore, S.E., Chadwick, O.A., Vitousek, P.M., Hendricks, D.M., 1997. Mineral control of soil organic carbon storage and turnover. Nature 389: 170-173.

Townshend, J., Justice, C., Li, W., Gurney, C., McManus, J., 1991. Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sensing of Environment 35: 243-255.

Trumbore, S., 2006. Carbon respired by terrestrial ecosystems–recent progress and challenges. Global Change Biology 12: 141-153.

Trumbore, S.E., 1997. Potential responses of soil organic carbon to global environmental change. Proceedings of the National Academy of Sciences 94: 8284-8291.

Tubiello, F.N., Salvatore, M., Rossi, S., Ferrara, A., Fitton, N., Smith, P., 2013. The FAOSTAT database of greenhouse gas emissions from agriculture. Environmental Research Letters 8: 015009.

Vågen, T.-G., Davey, F.A., Shepherd, K.D., 2012. Land health surveillance: mapping soil carbon in Kenyan rangelands. Agroforestry-The Future of Global Land Use. Springer, pp. 455-462.

Vågen, T.-G., Winowiecki, L.A., Tondoh, J.E., Desta, L.T., Gumbricht, T., 2016. Mapping of soil properties and land degradation risk in Africa using MODIS reflectance. Geoderma 263: 216-225.

Vågen, T., Winowiecki, L., Tamene Desta, L., Tondoh, J., 2015. The Land Degradation Surveillance Framework (LDSF)—Field Guide v4_1. World Agroforestry Centre, Nairobi, Kenya.

Vågen, T.G., Lal, R., Singh, B., 2005. Soil carbon sequestration in sub-Saharan Africa: a review. Land Degradation & Development 16: 53-71.

VandenBygaart, A., Angers, D., 2006. Towards accurate measurements of soil organic carbon stock change in agroecosystems. Canadian Journal of Soil Science 86: 465-471.

VandenBygaart, A., Gregorich, E., Angers, D., McConkey, B., 2007. Assessment of the lateral and vertical variability of soil organic carbon. Canadian Journal of Soil Science 87: 433-444.

Veldkamp, E., Becker, A., Schwendenmann, L., Clark, D.A., Schulte-Bisping, H., 2003. Substantial labile carbon stocks and microbial activity in deeply weathered soils below a tropical wet forest. Global Change Biology 9: 1171-1184.

Verchot, L.V., Mackensen, J., Kandji, S., van Noordwijk, M., Tomich, T., Ong, C., Albrecht, A., Bantilan, C., Anupama, K., Palm, C., 2005. Opportunities for linking adaptation and mitigation in agroforestry systems. Tropical forests and adaptation to climate change: In search of synergies: 103-121.

Verchot, L.V., Van Noordwijk, M., Kandji, S., Tomich, T., Ong, C., Albrecht, A., Mackensen, J., Bantilan, C., Anupama, K., Palm, C., 2007. Climate change: linking adaptation and mitigation through agroforestry. Mitigation and Adaptation Strategies for Global Change 12: 901-918.

Viaud, V., Angers, D.A., Walter, C., 2010. Toward landscape-scale modeling of soil organic matter dynamics in agroecosystems. Soil Science Society of America Journal 74: 1847-1860.

Wander, M., 2004. Soil organic matter fractions and their relevance to soil function. Soil Organic Matter in Sustainable Agriculture. : 67-102.

Ward, A., Dargusch, P., Thomas, S., Liu, Y., Fulton, E.A., 2014. A global estimate of carbon stored in the world's mountain grasslands and shrublands, and the implications for climate policy. Global Environmental Change 28: 14-24.

Waruru, B.K., Shepherd, K.D., Ndegwa, G.M., Kamoni, P.T., Sila, A.M., 2014. Rapid estimation of soil engineering properties using diffuse reflectance near infrared spectroscopy. Biosystems Engineering 121: 177-185.

Watson, R., Noble, I., Bolin, B., Ravindranath, N., Verardo, D., Dokken, D., 2000. Land use, land-use change, and forestry, 2000. Special report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge 75: 67-75.

Weiss, A., 2001. Topographic position and landforms analysis. Poster presentation, ESRI User Conference, San Diego, CA, pp. 200-200.

Wen, X.-F., Yu, G.-R., Sun, X.-M., Li, Q.-K., Liu, Y.-F., Zhang, L.-M., Ren, C.-Y., Fu, Y.-L., Li, Z.-Q., 2006. Soil moisture effect on the temperature dependence of ecosystem respiration in a subtropical Pinus plantation of southeastern China. Agricultural and Forest Meteorology 137: 166-175.

Were, K.O., Singh, B.R., Dick, Ø.B., 2015. Effects of Land Cover Changes on Soil Organic Carbon and Total Nitrogen Stocks in the Eastern Mau Forest Reserve, Kenya. Sustainable Intensification to Advance Food Security and Enhance Climate Resilience in Africa. Springer, pp. 113-133.

White, R.E., 2013. Principles and practice of soil science: the soil as a natural resource. Blackwell Publishing, John Wiley & Sons, 350 Street, Malden, MA 02148-5020 USA.

Winowiecki, L., Vågen, T.-G., Massawe, B., Jelinski, N.A., Lyamchai, C., Sayula, G., Msoka, E., 2015. Landscape-scale variability of soil health indicators: effects of cultivation on soil organic carbon in the Usambara Mountains of Tanzania. Nutrient Cycling in Agroecosystems: 1-12.

Woomer, P., Karanja, N., Murage, E., 2001. Estimating total system C in smallhold farming systems of the East Africa Highlands. Assessment Methods for Soil Carbon (R. Lal, JM Kimble, RF Follett and BA Stewart, eds.). Advances in Soil Science (series). Lewis Publishers, Boca Raton, USA: 147-166.

Woomer, P.L., Palm, C.A., Qureshi, J.N., Kotto-Same, J., Lal, R., Kimble, J., Follett, R., Stewart, B., 1998. Carbon sequestration and organic resource management in African smallholder agriculture. Management of Carbon Sequestration in Soil: 153-171.

Wymann von Dach, S., Romeo, R., Vita, A., Wurzinger, M., Kohler, T., 2013. Mountain Farming Is Family Farm-ing: A contribution from mountain areas to the International Year of Family Farming 2014. FAO, CDE, BOKU; Rome, Italy: 100.

Yamaji, T., Sakai, T., Endo, T., Baruah, P.J., Akiyama, T., Saigusa, N., Nakai, Y., Kitamura, K., Ishizuka, M., Yasuoka, Y., 2008. Scaling-up technique for net ecosystem productivity of deciduous broadleaved forests in Japan using MODIS data. Ecological Research 23: 765-775.

Yang, F., Ichii, K., White, M.A., Hashimoto, H., Michaelis, A.R., Votava, P., Zhu, A.-X., Huete, A., Running, S.W., Nemani, R.R., 2007. Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. Remote Sensing of Environment 110: 109-122.

Yuan, H., Dai, Y., Xiao, Z., Ji, D., Shangguan, W., 2011a. Reprocessing the MODIS Leaf Area Index products for land surface and climate modelling. Remote Sensing of Environment 115: 1171-1187.

Yuan, W., Luo, Y., Li, X., Liu, S., Yu, G., Zhou, T., Bahn, M., Black, A., Desai, A.R., Cescatti, A., 2011b. Redefinition and global estimation of basal ecosystem respiration rate. Global Biogeochemical Cycles 25.

Zanini, E., 2015. Understanding Mountain Soils. FAO, Rome, Italy.

Zawawi, A.B.A., 2015. Terrain Analysis and Site Evaluation: Integrating a Geospatial Approach for Subtropical Forest Management Planning. PhD Dissertation,United Graduate School of Agricultural Sciences,Kagoshima University, Japan.

Zhang, L., Chen, Y., Li, W., Zhao, R., 2007. Seasonal variation of soil respiration under different land use/land cover in arid region. Science in China Series D: Earth Sciences 50: 76-85.

Zhang, S., Huang, Y., Shen, C., Ye, H., Du, Y., 2012. Spatial prediction of soil organic matter using terrain indices and categorical variables as auxiliary information. Geoderma 171: 35-43.

Zhang, S., Zhang, X., Huffman, T., Liu, X., Yang, J., 2011. Influence of topography and land management on soil nutrients variability in Northeast China. Nutrient Cycling in Agroecosystems 89: 427-438.

Zimmermann, M., Leifeld, J., Fuhrer, J., 2007. Quantifying soil organic carbon fractions by infrared-spectroscopy. Soil Biology and Biochemistry 39: 224-231.

Zöbisch, M., Richter, C., Heiligtag, B., Schlott, R., 1995. Nutrient losses from cropland in the Central Highlands of Kenya due to surface runoff and soil erosion. Soil and Tillage Research 33: 109-116.

Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution 1: 3-14.

APPENDICES

Appendix 3.1: Data sheet used in carbon dioxide gas measurements

CARBON DIOXIDE FLUX MEASUREMENT DATA SHEET

Point Field Code: ________________________ Date: ______________________

Team members: ____

Chamber No.	*4 point Chamber heights (in cm)*				*Sampling Start time*	*Sampling End time*
1						
2						
3						
4						
5						

Chamber No.	*Chamber Flux (Per min)*									
	0 Min	**1 Min**	**2 Min**	**3 Min**	**4 Min**	**5 Min**	**6 Min**	**7 Min**	**8 Min**	**9 Min**
1										
2										
3										
4										
5										

Air temp			*Soil temp*			*Atmospheric Pressure readings*
Start	*Mid*	*End*	*Start*	*Mid*	*End*	

Weather Condition: Wet Dry

Cloud Cover: Less Cloudy Relatively Cloudy Heavily Cloudy

General weather at sampling: Sunny Hot Misty Cold Rainy/Drizzling

State of Soil at sampling time (Wet or Dry): _________________________

State of erosion (Present/Absent): ________**Litter at Soil surface (Present/Absent)**: _______

Appendix 3.2: Data sheet used in soil properties measurements

SOIL SAMPLING DATA SHEET

Date: ______________________________ Season (Rainy/Dry season): ___________________

Point Field Code: ________________ Name of sampling Person: ___________________

Chamber No.	**Soil/Core sample (Comment from soils acquired from each chamber site (if necessary)**	**Sampling time (start time)**
1		
2		
3		
4		
5		

Above ground Biomass and Tree Canopy Characteristics						
Chamber No.	***Biomass from each chamber (grams)***	***Tree/Bush Number (if place is disturbed)***	***Tree/Bush Height***	***Tree/Bush Length***	***Tree/Bush Width***	***Tree/Bush Girdle***
1						
2						
3						
4						
5						

<u>Observations/Notes (Tick appropriate)</u>

State of vegetation: No Change/Forest_Disturbed/Shrub_Disturbed/AFS Prunned Below Canopy_MaizeInSeason/Below Canopy_ MaizeOffSeason/ MaizeField_Inseason/MaizeField_Offseason

Changes on site: NoneGrazed/Tree_Felled/ Shrub_Destroyed/Field Tilled/Field_Fallow/Field Cropped

Appendix 3.3: Data sheet used in subsidiary plot information

CHIESA SOIL CARBON DATA ENTRY FORM

Point Number		Collectors Name	
Elevation Cluster		Latitude	
Date(dd/mm/yr)		Longitude	
Time		Elevation	
Photo Number		Pos Error	

WEATHER INFORMATION

Air temperature (^{o}C)			Wind description		
Soil Temperature (^{o}C)					Silent
Time since Last Rains (days)					Steady
					Gushy
					Variable speed
					Shifting directions
Cloud/Sky		Clear Skies			
		Partly Cloudy			
		Partly Sunny			
		Overcast Skies			
		Mixed & Rain			
		Fog			
		Unknown			
Rainfall Patterns		Fog rain	Visibility at sampling		Clear
		Misty Rain			Light fog
		Sprinkles			Moderate Fog
		Light Dizzle			Heavy Fog
		Showers steady			
		Showers on & off			
		Heavy dizzle			

PLOT INFRASTRUCTURE

Human Path		Trail head	Erosion Control		Divergence Gully
		Secondary Footpath			Tree stumbs to Slow Water
		Primary Footpath			Drain
		Permanent Footpath			Gabions
		Livestock Trail			Trees planted
		Other Path-type			Dike
		None			None

Erosion Control Status	☐ Very Recent ☐ Moths Old ☐ Years Old ☐ Small-scale ☐ Medium-Scale ☐ Large-Scale ☐ Very Effective ☐ Not very effective ☐ Failing ☐ NONE	Livestock within plot	☐ Goat ☐ Sheep ☐ Chicken ☐ Ducks ☐ Cows ☐ Donkeys ☐ Other ☐ NONE
Human Structures Within Plot	☐ Brick/charcoal Burn Hillrock ☐ House ☐ Garden ☐ Campsite ☐ Tree plantation ☐ Field Crop ☐ Urban area ☐ Other structure ☐ NONE	**Note**	

ECOLOGICAL ANALYSIS

Landform	☐ Level ☐ Sloping ☐ Steep ☐ Composite ☐	Position in Topo sequence	☐ Upland ☐ Ridge/Crest ☐ Mid-slope ☐ Foot slope ☐ Bottomland
Slope and Landform	☐ Plain ☐ Plateau ☐ Major Depression ☐ Low gradient foot slope ☐ Valley Floor ☐ Medium gradient Mountain ☐ Medium gradient hill ☐ Medium gradient Escarpment ☐ High Gradient Hill	Slope	☐ Steep ☐ Moderate ☐ Flat ☐ East Facing ☐ West facing ☐ South facing ☐ North Facing

	☐ High Gradient Escarpment		
Flood and Bare	☐ YES flood Area ☐ NO Flood Area	Bare	☐ YES Plot Bare ☐ NO Plot Bare
Vegetation Structure	☐ Forest ☐ Bushland ☐ Scrubland ☐ Wooded grassland ☐ Cropland ☐ Marsh land ☐ Bare land ☐ Agro-forest ☐ Other Vegetation structure	Vegetation Abundance Index	☐ None ☐ Light ☐ Medium ☐ Heavy ☐ Really Heavy ☐
Leaf Type	☐ Broad leaf ☐ Needle Lead ☐ NONE	**NOTE**	

PLOT LAND-OWNERSHIP

Land ownership	☐ Private ☐ Communal ☐ Government Agency ☐ Government trustland ☐ Other	Year Converted To Agriculture	☐ 1800 - 1900 ☐ 1900 - 1950 ☐ 1950 - 1990 ☐ 1990 - 2010 ☐ 2100 - Now ☐ NONE
Primary Current Use	☐ Food and beverage ☐ Forage Place ☐ Timber (Firewood) ☐ Other Uses ☐ NONE	Visible Erosion	☐ Sheet ☐ Rill ☐ Gully ☐ None
Note			

PLOT CHARACTERISTICS

<table>
<tr><td>Soil Texture</td><td><table><tr><td></td><td>< 5 % rock, stone, gravel</td></tr><tr><td></td><td>5-40 % rock, stone, gravel</td></tr><tr><td></td><td>> 40 % rock, stone, gravel</td></tr></table></td><td>Soil Color</td><td><table><tr><td>Hue</td><td></td></tr><tr><td>Value</td><td></td></tr><tr><td>Chroma</td><td></td></tr></table></td></tr>
<tr><td>Auger Depth restriction (cm)</td><td></td><td>Crop season</td><td><table><tr><td></td><td>In-season</td></tr><tr><td></td><td>Offseason</td></tr><tr><td></td><td>NOT applicable</td></tr></table></td></tr>
<tr><td>Plot Field Status</td><td><table><tr><td></td><td>Planted</td></tr><tr><td></td><td>Tilled NOT planted</td></tr><tr><td></td><td>Harrowed</td></tr><tr><td></td><td>Fallow (with weed/crops)</td></tr><tr><td></td><td>Natural Field</td></tr><tr><td></td><td>NONE</td></tr></table></td><td>Plot crop species</td><td><table><tr><td></td><td>Cereal</td></tr><tr><td></td><td>Legume</td></tr><tr><td></td><td>Root</td></tr><tr><td></td><td>Vegetable</td></tr><tr><td></td><td>Plantation</td></tr><tr><td></td><td>Fruit Fops</td></tr><tr><td></td><td>NONE</td></tr></table></td></tr>
<tr><td>DISTANCE TO land

co. types</td><td><table><tr><th>Type</th><th>< 200m</th><th>> 200m</th></tr><tr><td>Agroforestry Spp</td><td></td><td></td></tr><tr><td>Cereal</td><td></td><td></td></tr><tr><td>Homestead</td><td></td><td></td></tr><tr><td></td><td></td><td></td></tr></table>
Agroforestry species:..................

Cereal Crop Spp:.......................</td><td>IMPACTS

on LAND

USE</td><td>NB: Rank scale on visual Assessment<table><tr><td></td><td>1</td><td>2</td><td>3</td><td>4</td></tr><tr><td>Tree cutting</td><td></td><td></td><td></td><td></td></tr><tr><td>Grazing</td><td></td><td></td><td></td><td></td></tr><tr><td>Agriculture</td><td></td><td></td><td></td><td></td></tr></table><u>Scale:</u> 1= Less Damage:

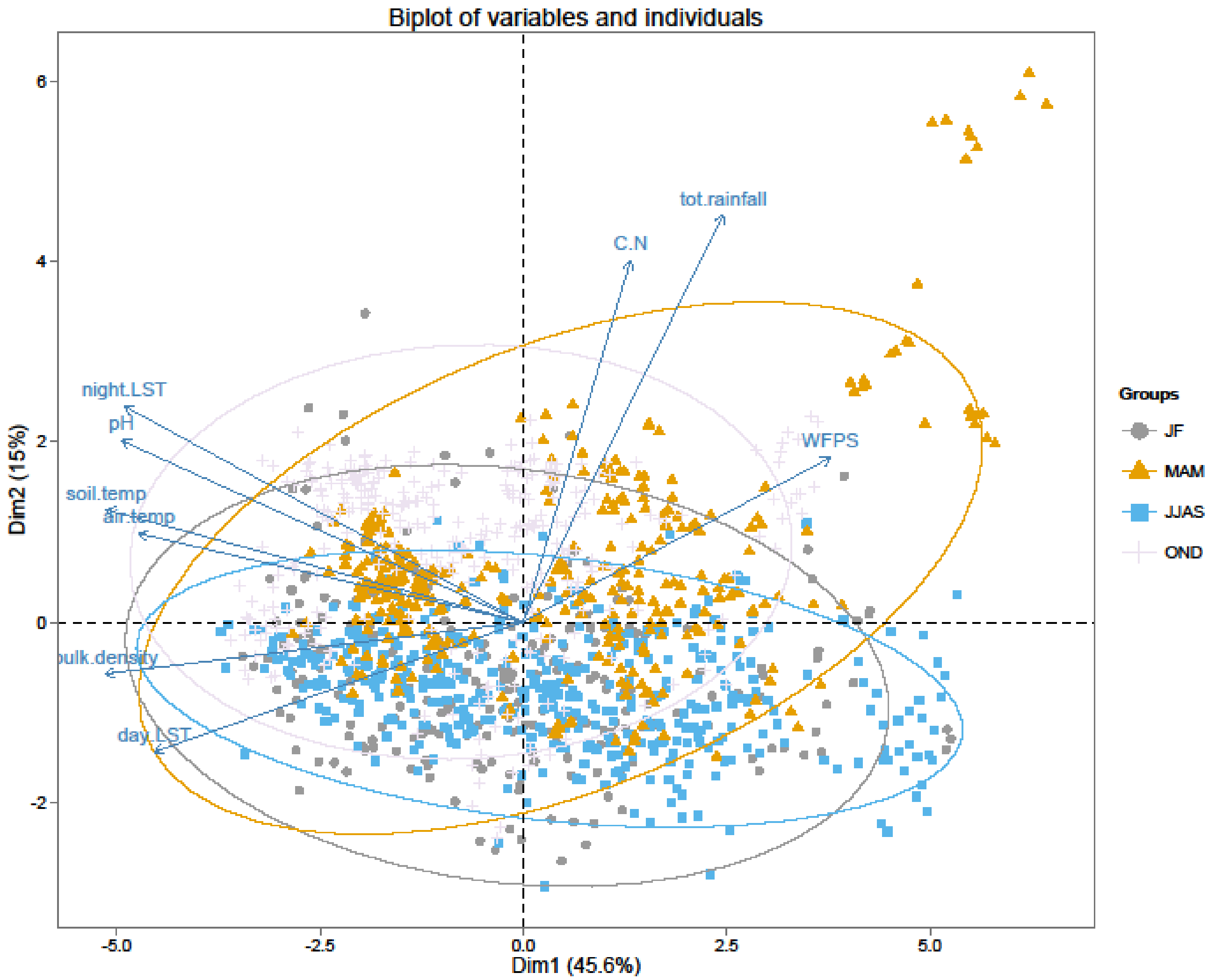
4= Worst Damage<table><tr><td>Tree

cutting</td><td>Grazing</td><td>Agric</td></tr></table></td></tr>
</table>

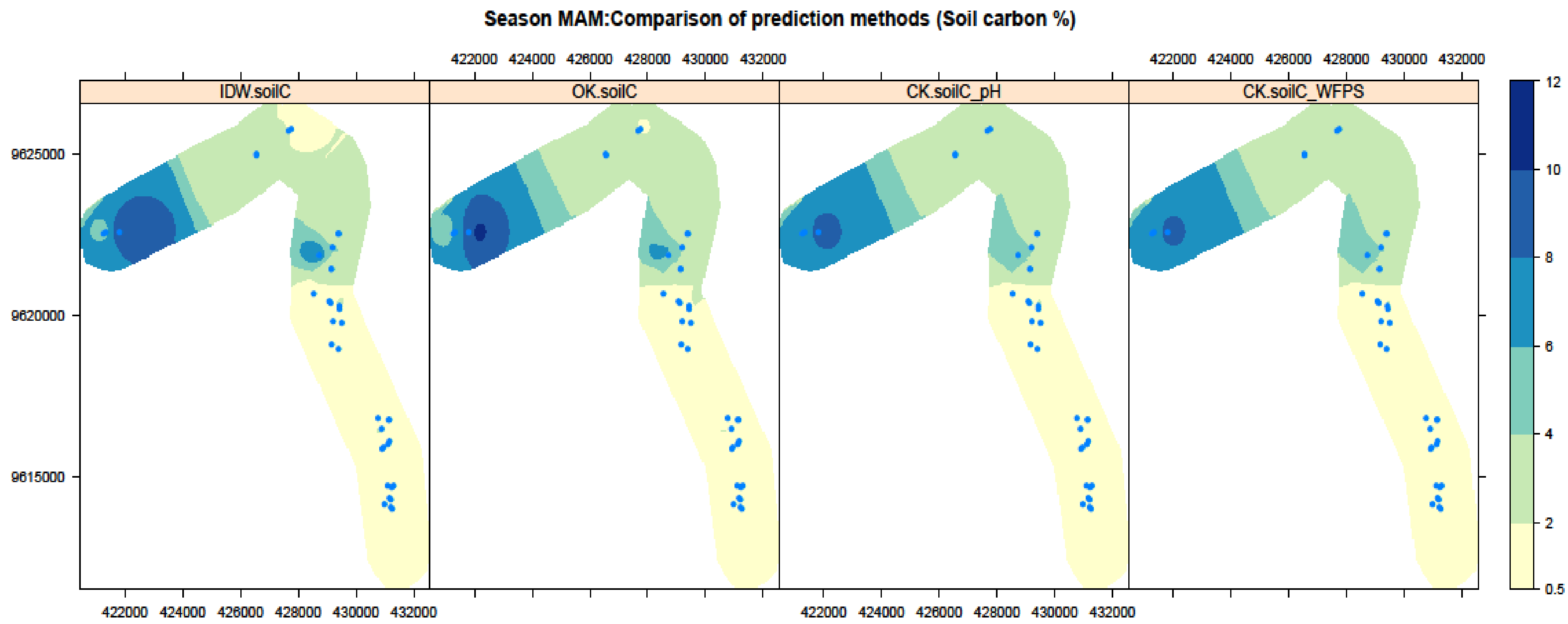
PLOT MEASUREMENTS

SPECIES	Density (No.)	Height (m) (> 3)	Tree Circumference (cm)	Canopy Length (> 3)	Canopy Width (> 3)	Point to plant Dist. (m)	Plant to plant Dist. (m)
Trees Present | Absent Species Name:							
Shrubs Present | Absent Species Name:							
Agro forestry species Present | Absent Species name:							
Crop Species Present | Absent Species Name:							

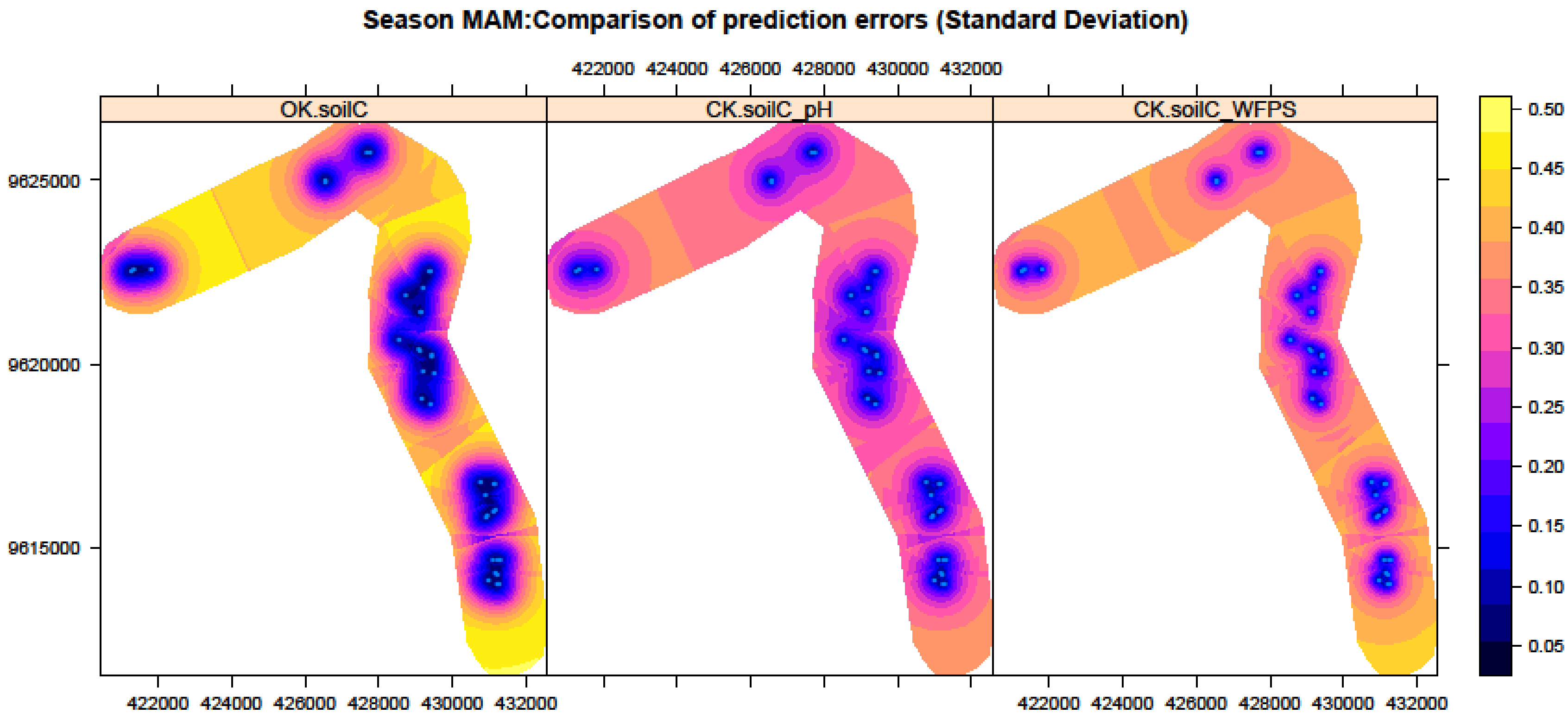
Appendix 7.1: Assessing clustering tendency in soil attributes using PCA



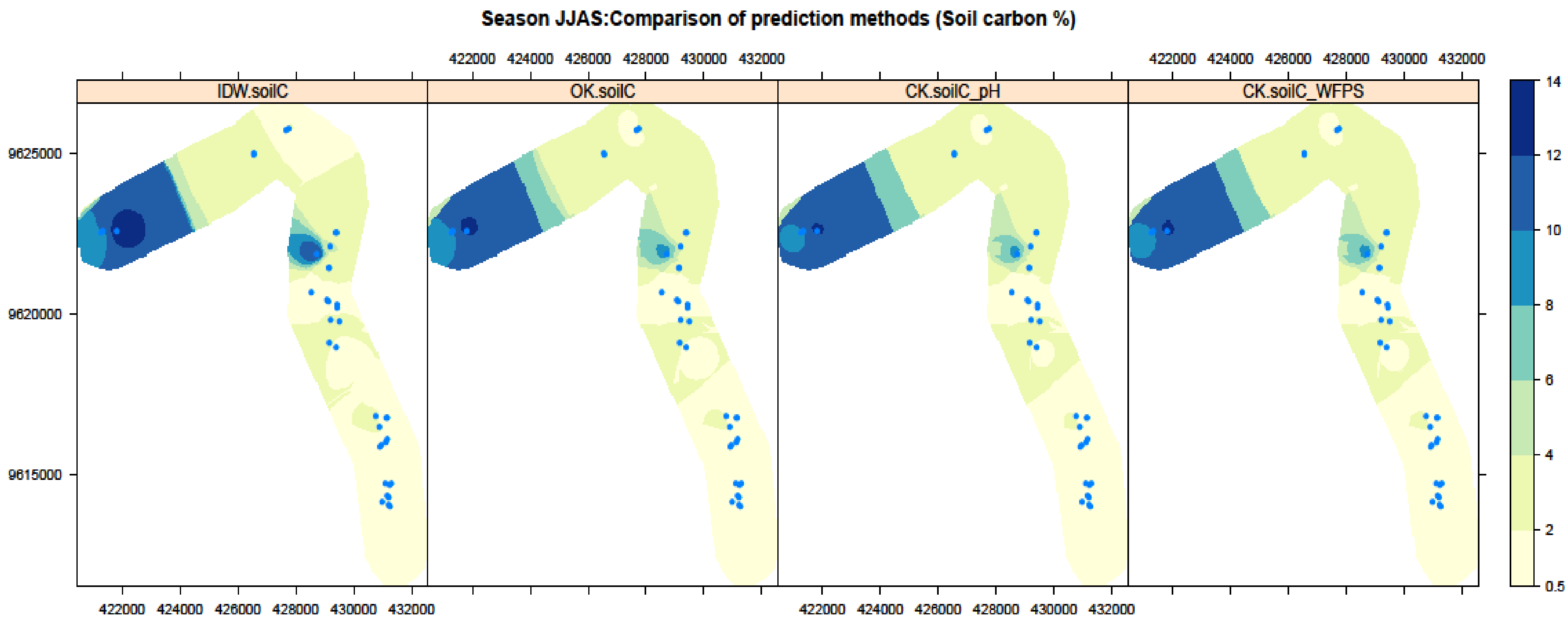
Appendix 7.1: Season MAM soil %C prediction compared amongst the four kriging models



Appendix 7.2: Season MAM soil %C prediction errors compared amongst the four kriging models



Appendix 7.3: Season JJAS soil %C prediction compared amongst the four kriging models



Appendix 7.4: Season JJAS soil %C prediction errors compared amongst the four kriging models

Season JJAS:Comparison of prediction errors (Standard Deviation)