EVALUATION OF NORMALIZED DIFFERENCE VEGETATION INDEX OF COMMON VEGETATION HABITATS FOR MONITORING RODENT POPULATION AND OUTBREAKS IN ISIMANI, TANZANIA

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EXTENDED ABSTRACT

Rodent pest outbreaks are major concern for agriculture in Africa and Tanzania in particular, especially in drier areas such as arid and semi-arid agro ecosystems. This is due to the fact that, if the problem cannot be treated with seriousness it deserves, 80% of the potential harvest may be lost. Crop losses occur at all stages (i.e. field to market). However, higher losses occur at the field/harvest and storage where rodents play a major role. Severe rodent outbreaks have been reported in many areas in Tanzania e.g. the recent outbreak reported by farmers in Isimani division, Iringa, Tanzania. Based on literature, it is estimated that rodents cause 15% of the total crop pre and post-harvest losses. The problem is compounded by unpredictable rodent pest outbreaks, late control actions, and lack of adequate interventions guided by ecologically based rodent management strategies. Recently, efforts have been taken to develop an ecologically based rodent management strategy which requires knowledge about the pest species' ecology in order to reduce the damage experienced by farmers. However, this is constrained by the limited knowledge about rodent populations on individual farms to allow smarter approaches for control of rodent outbreaks.

Structural characterization and mapping of vegetation habitats could contribute knowledge about rodent populations on individual farms. Such studies may include describing and measuring vegetation and habitat structural component using geo spatial and statistical approaches (i.e. life form and cover types, terrain, soil and management practices) across various landscapes in different seasons and their influence to small mammal abundance. Recently, it has been reported that remote sensing derived vegetation indices could be used to explain rodent pest abundance at fine scale. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) have been reported to correlate well with vegetation productivity (i.e. biomass), forage quality and quantity

(i.e. food) at moderate resolutions over a range of spatial-temporal scales. Such indices have been reported to be vital tools for studying vegetation habitat characteristics (i.e. vegetation cover) and their association with rodents in space and time. Therefore, the current study was envisaged to evaluate the potential of NDVI of common vegetation habitats derived from satellite remote sensing data for monitoring rodent population dynamics and outbreaks in order to contribute knowledge for refining ecologically based rodent management strategies. More specifically, the study was carried out to i) characterise and spatially map the vegetation habitats associated with small mammal abundance in smallholder farming agro-ecosystem; ii) determine the Normalised Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall patterns in the study area; and iii) establish a relationship between NDVI of the common vegetation habitats and small mammals distribution and abundance in space and time.

The study was conducted between September 2015 and June 2016 in Isimani Division, Iringa Tanzania. A combination of field survey and Geospatial approach including the use of Multi temporal Landsat 8 (Operational Land Imager (OLI)) images were applied to identify and map the vegetation habitats and estimation of NDVI. The NDVI of common vegetation habitats and rainfall patterns were also explored. Small mammals were trapped in the mapped vegetation habitat units, and counted for abundances. In total, nine main types of vegetation habitats were investigated. A total of 597 small mammals, potentially related to major rodent pests were trapped. Different levels of scales and resolutions were considered. Linear regression analysis was employed to establish the important habitat characteristics (predictor variables) for relating rodent abundance with rainfall and NDVI. Linear regression analysis was also used to clarify the relationships between ground measured rodents and predicted rodent abundance from rainfall and NDVI across seasons, and calculation of the Pearson correlation coefficient (r) at $P \leq 0.05$.

Results show that, vegetation habitats identified based on land use/cover types were largely dominated by agriculture covering about 60% of the plateau landscape with intensive maize cultivation and frequent reported rodent outbreaks. The findings show further that, the plateau habitats support a large number of small mammals (80%) than the rest of the habitats in the other landscapes. A strong correlation (r=0.96) was obtained between ground measured point rainfall data and the real time Tropical Rainfall Measuring Mission (TRMM) Precipitation Analysis rainfall data across the identified vegetation habitats. Spatial variability of mean NDVI values with seasonal pattern across the studied vegetation habitat units were obtained whereby, higher values (0.2 to 0.6) were observed in wet season and lower values (0.0 to 0.2) in the dry season. The findings have demonstrated a good positive correlation between rainfall and NDVI along the elevation gradient of the studied landscape units with escarpment having higher correlation (r=0.688) than the plateau (r=0.653) and the valley floor (r =0.652). This relationship suggests that rainfall patterns could be easily predicted from a link between NDVI and elevation as predictor variables.

Results also show that, NDVI and rainfall derived from satellite data (Landsat 8 (OLI) images) have positive influence on the rodent abundance over the studied seasons. It was observed that 98% of the predicted rodent abundance was explained by NDVI while rainfall explained only 85%. NDVI predicted rodent abundance showed a strong positive correlation (r=0.99) with the field measured rodent abundance. The obtained NDVI values provide a robust measure of the presence and abundance of vegetation across the studied vegetation habitats which could be very useful in monitoring rainfall dynamics and as a proxy for predicting rodent pest abundance. The findings have revealed that rainfall, NDVI, and elevation were important predictor variables that could be considered for predicting small mammals or rodent pest abundance in the study area.

These results support the hypotheses that NDVI of common vegetation habitats has the potential for monitoring rodent population dynamics under smallholder farming agro-ecosystems. Hence, NDVI could be used to model rodent outbreaks within a reasonable short time compared to the sparse and not readily available rainfall data. Further research is required to explore the existing relationship between vegetation habitats with their associated microclimate and rodent pests in the hotspot areas. In addition, relationship between NDVI and rodent pest species composition and community structure in different habitats and seasonal rainfall patterns should be explored.

DECLARATION

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

____________________ ____________________

Davis J. Chidodo Date

(MSc. Candidate)

The above declaration is confirmed by;

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Prof. Didas Kimaro Date

(Main supervisor)

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Dr. Proches Hieronimo Date

(Co-supervisor)

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DEDICATION

This work is dedicated to the Almighty Father, Lord Jesus and my Parents: Joshua Chidodo and Dativa M. Lyimo for the love and support. Also to my brother Simon J. Chidodo, All my friends and Miss Salome Kudeli for the love and support.

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LIST OF ABBREVIATIONS AND SYMBOLS

AC	Acomys
AE	Aethomys
AEZ	Agro Ecological Zones
ALULCc	Any Land Use or Land Cover class
ANOVA	Analysis Of Variance
AV	Arvicanthis
AVHRR	Advanced Very High Resolution Radiometer
AW	Available Water
BRT	Boosted Regression Tree
2B42RT	TMPA-RT rainfall data product
CC	Cubic Convolution
CH	*Crocidural Shrew*
DEM	Digital Elevation Model
ECCS	Earth Cover Classification System
ENVI	Environment for Visualizing Images
EPSG	European Petroleum Survey Group
ES	*Elephant Shrew*
ETM+	Enhanced Thematic Mapper Plus sensor
EW	End of Wet Season
FAO	Food and Agriculture Organisation
FC	Field Capacity
GB	*Tatera-GB*
GDP	Gross Domestic Product
GHC	General Habitat Class

GIS	Geographical Information System
GR	Graphiurus
IDRIS	Integrated Development for Research Information System
IDW	Inverse Distant Weight
ITCZ	Intertropical Convergence Zone
LCCS	Land Cover Classification System
LSD	Least Significant Difference
LULC	Land use and land cover
LZ	*Lemniscomys Zebra*
MBD	Matric Bulk Density
MD	Mid of Dry Season
MN	Mastomys Natalensis
MODIS	Moderate Resolution Imaging Spectroradiometer
MVC	Maximum Value Composite
MW	Mid of Wet Season
NDVI	Normalized Difference Vegetation Index
OFI	Open Foris Initiative (OFI)
OLI	Operational Land Imager
PHL	Postharvest loses
QGIS	Quantum Geographical Information System
Sat	Saturation
SCP	Semi-Automatic Classification Plugin
SD	Start of Dry Season
SHC	Saturation Hydraulic Condition
SPOT	Satellite Pour l’Observation de la Terre

SRTM	Shuttle Radar Topographical Mission
SRTM DEM	Shutter Radar Topographic Mission Digital Elevation Model
SSA	Sub-Saharan Africa
SW	Start of Wet Season
SWIR	Short Wave Infra-Red
TMPA-RT	Real time TRMM Multi satellite Precipitation Analysis
TPI	Topographical Position Indices
TRMM	Tropical Rainfall Measuring Mission
UAV	Unmanned Aerial Vehicle
USGS	United States Geological Survey
VCI	Vegetation Condition Index
VI	Vegetation Index
WD	End of Dry Season
WP	Wilting Point

CHAPTER ONE

1.0 GENERAL INTRODUCTION

1.1 Agro Ecosystem Patterns and Small Mammal Dynamics

Rodent pest outbreaks are a major concern for agriculture in Africa and Tanzania in particular, especially in drier areas such as arid and semi-arid agro ecosystems (Table 1.1) (Mwanjabe and Leirs, 1997; FAO, 2006; Dabien *et al.*, 2010; Byrom *et al.*, 2014; Hieronimo *et al*., 2014a, b; Mulungu *et al*., 2015). The problem is compounded by unpredictable rodent pest outbreaks, late control actions and lack of adequate interventions guided by ecologically based rodent management strategies (Makundi and Massawe, 2011). Generally, integrated rodent pest management (IRPM) and biological control of rodent for most countries in Africa are almost unexplored phenomena (Leirs, 1999; Mulungu *et al*., 2015). Hence more interventions are required to evaluate the problem of rodent pests especially in the smallholder agro ecosystems.

Rodent outbreaks and their effects on agriculture can be traced back to 19th century for most countries in Africa (Fiedler, 1988; Neerinckx *et al*., 2010). It has been reported that about 5% of the 400 existing rodent species in the African continent cause damage to agricultural crops (Mwanjabe and Leirs, 1997; Makundi and Massawe, 2011). In sub-Saharan Africa (SSA) including Tanzania rodents are an integral part of biodiversity and agro-ecosystems (Leirs *et al*., 2010; Mulungu *et al*., 2008). Certain species of rodent have widely been reported as pests for crops and clearly exhibit habitat preference (Mulungu *et al*., 2015). For example, *Mastomys natalensis* (the *shamba* rat), Tatera-GB and Graphiurus commonly found in agricultural areas, grass/shrubs and forest/woodlands respectively are reported to be major crop pests (Massawe *et al*., 2011).

Table 1.1: Rodent outbreaks cases reported from various studies conducted in some selected agro ecosystems in Tanzania

Location	Description	Source
Isimani division in Iringa Tanzania	Pre and Post harvesting damages that resulted in food insecurity	Tewele, (2015); personal communication
Hembeti village in Mvomero district, Morogoro, Tanzania.	About 20-60% crop losses both in fields and stores yearly.	Mulungu *et al*. (2015)
Chunya district in Mbeya, Tanzania	Loss of about 40 – 80 % of planted maize seeds in the season of outbreaks	Mwanjabe and Leirs (1997)
Lindi region Tanzania	Rodent outbreaks about 1400 rats per hectare, causing yield loss of up to 48% in maize fields over the season	FAO (2006)
Serengeti National Park, Arusha region	Reported positive relationship between rainfall and rodent outbreaks	Byrom *et al.* (2014)
Lushoto district in Tanga Region	Rodents reported as vector for plague endemic disease	Dabien *et al.* (2010) Hieronimo *et al*. (2014,)

Rodent pest outbreaks threaten agriculture in Tanzania that currently contributes 24% of Gross Domestic Product (GDP) (Leirs *et al*., 2010). Rodents cause a wide range of damage and losses to crops such as cereals, legumes, vegetables, root crops, cotton and sugar cane (Fig. 1.1) (Abass *et al*., 2014; Suleiman and Rosentrater, 2015). Based on literature, it is estimated that rodent pests cause 15% of the total crop pre- and post-harvest losses (Mulungu *et al*., 2015). A major concern is, if the problem cannot be treated with the seriousness it deserves, 80% of the potential harvest may be lost (Neerinckx *et al*., 2010; Makundi and Massawe, 2011).

In Tanzania, the major constraints to maize production include pre- and post-harvest losses largely attributed to insect pests, diseases, weeds, rodents, fungi, pathogens, and viruses (Suleiman and Rosentrater, 2015). The post-harvest losses (PHL) of maize can be described by leaky food-pipeline (Fig. 1.1) (Abass *et al*., 2014; Suleiman and Rosentrater, 2015).

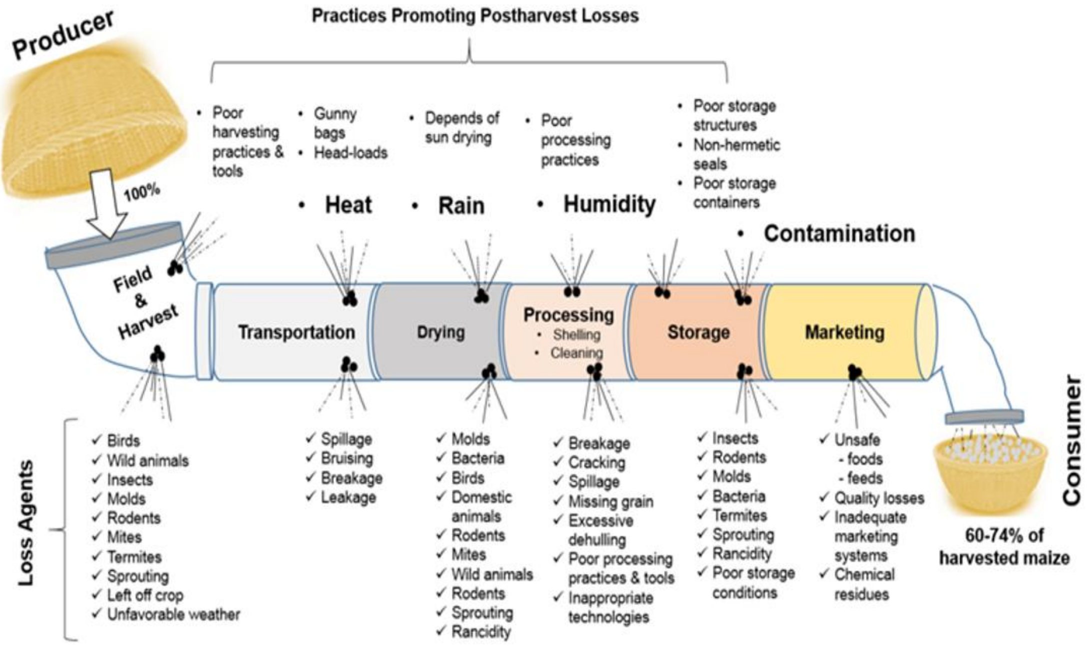

Figure 1.1: Postharvest losses pipeline for maize
(Source: Abass *et al*., 2014; Suleiman and Rosentrater, 2015).

As indicated in the pipeline, losses occur at all stages (field to market). However, higher losses occur at the field/harvest and storage where rodents play a major role. Severe rodent outbreaks have been reported in many areas in Tanzania e.g. the recent outbreak reported by farmers in Isimani division, Iringa, Tanzania (Myllymaki, 1989).

Rodent crop damage is generally compounded by unpredictable outbreaks, late control actions, and lack of inadequate interventions guided by ecologically based rodent management strategies (Makundi and Massawe, 2011).

Detailed modelling and understanding of complex specie-environmental relationship require continuous habitats tracking in ecological settings for successful outbreak predictions and control (Leirs, 1999; Taheri, 2010). Therefore fine-tuned ecologically based rodent management strategies including models that consider common vegetation habitat characteristics are vital.

1.2 Vegetation and Rodents Dynamics

Vegetation patterns and abundance of rodents have been related at coarse spatial scales i.e. macro and meso scale in ecological studies (Makundi and Massawe, 2011; Petorelli *et al.,* 2011; Sun *et al.*, 2015). For example, in the Usambara Mountains, Tanzania, Ralaizafisoloarivony *et al*. (2014) demonstrated that natural forest, cultivated lands and shrubs were the most favoured habitats by rodents.

Contrasts in vegetation and land use particularly in the agro-ecosystem of smallholder farmers and its influence on the abundance of rodents in a complex landscape are not well understood. Existing predictive models designed to provide early warning of potential rodent damage are mainly based on the amount and distribution of short rains hence are still insufficient to guide rodent pest management strategies (Marstona *et al.*, 2007; Makundi and Massawe, 2011). For example, the logistic regression models developed to demonstrate the relationship between rodent outbreaks and rainfall amount during short (*vuli*) rainy season in Tanzania (Leirs, 1999; Mulungu *et al.*, 2010), were site specific and scattered over a wide geographical and ecological areas hence insufficient for predicting rodent dynamics under smallholder farming agro-ecosystems.

Although most of these models form an integral part of rodent control strategies, they still require biological information particularly on vegetation dynamics that will make them effective in responding to rodent outbreaks. Recently, it has been reported that vegetation variables such as plant vigor, vegetation density and canopy cover including patterns could be used to explain rodent abundance at micro-ecological scale in a geographical gradient (Bannar-Martin, 2014; Hieronimo *et al*., 2014b). Other vegetation characteristics that have been used to explain the abundance of rodents include biomass, greenness and litter (Williams, 1998; Hieronimo *et al*., 2014a). Vegetation indices such as Normalized

Difference Vegetation Index (NDVI) have been used as tools for studying vegetation habitat characteristics and their association with rodents (Pettorelli *et al*., 2011; Hurley *et al*., 2014) hence, vital to be considered in this study.

1.3 Models for Predicting Rodents Dynamics and Outbreaks

Models for predicting rodent population and dynamics have involved complex interactions of factors ranging from direct environmental factors (i.e. vegetation, rainfall and terrain patterns) to indirect factors such as NDVI (Stenseth *et al*., 1975; Dabien *et al*., 2010; Pettorelli *et al*., 2011; Pirotti *et al*., 2014). For example, the population dynamic model by Stenseth *et al*. (1975) was developed in Alaska to evaluate rodents' abundance (including birth and death rate), habitats heterogeneity and dispersal by considering environmental and genetic patchiness (Fig. 1.2). The maximum activity budget of rodents in their natural habitats as evaluated by the model, influence utilization of energy through grazing as a function of vegetation, rodent size and its energy needs. The suitability of this model in prediction and dependency on the external environmental factors such as vegetation and rainfall pattern were not well evaluated. Hence, multi environment factors (i.e. vegetation, rainfall, geomorphology, soil, and terrain) considered in the current study along with NDVI to develop rodents' probabilistic predictive models for dominant vegetation habitats in small holder farming agro ecosystem to ensure food security by reducing rodent outbreaks.

Rainfall pattern has also been used as a key parameter for the prediction of abundance and distribution of rodents (Fig. 1.3) (Mulungu *et al*., 2010). Fiedler (1988) observed that many rodent outbreaks were preceded by abundant rainfall at the end of a dry spell. However, predictions based on rainfall pattern remained to be theoretical and in most cases have been proven to be site specific and even more difficult in areas where rainfall data are not available. Hence in this study the relationship between rainfall and NDVI were established as a proxy for predicting rodent abundance and outbreaks.

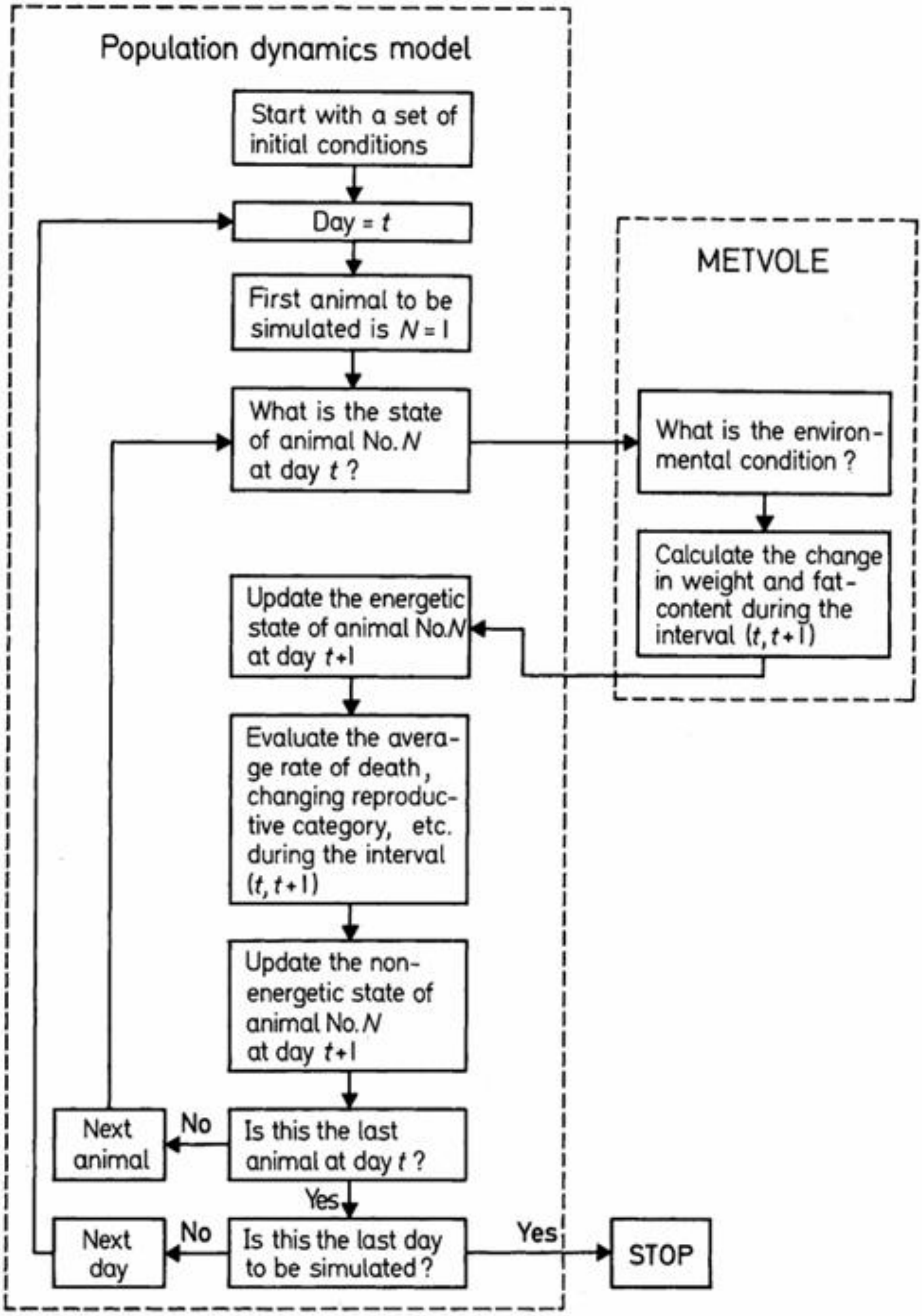

Figure 1.2: A typical basic structure Model for rodent population dynamics (Source: Stenseth *et al*., 1975)

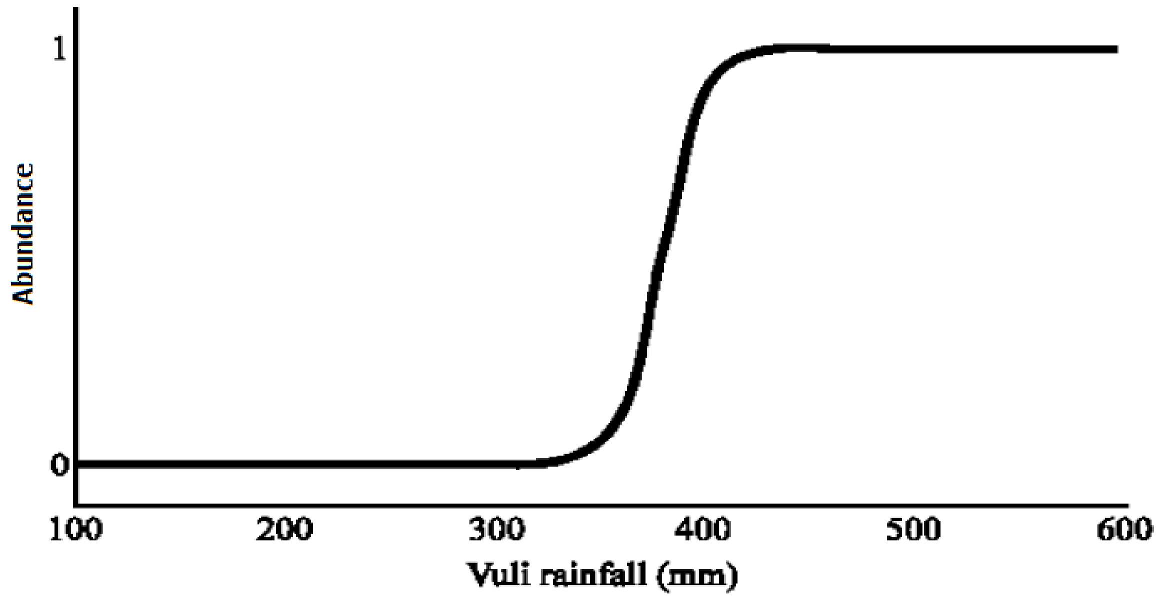

Figure 1.3: Probabilistic model for prediction of rodent outbreaks based on rainfall pattern (source: Mulungu *et al*., 2010).

Leirs *et al*. (1996) on the other hand, developed a conceptual rodent outbreaks prediction model to forecast occurrence of rodent outbreaks. The key factor was rainfall during the short rainy (*Vuli)* season. Since rainfall during the long rainy (*Masika)* season, was less important, the conceptual model was not sufficient to guide an ecologically based rodent management strategy (Fig. 1.4). Therefore, in this study, vegetation characteristics (i.e. life form and cover), seasonal rainfall pattern, management practices, soil and terrain characteristics (i.e. slope gradient, slope shape, slope aspect and Topographical Position Index (TPI)) are used to describe rodents' habitats in order to improve rodent pest prediction ability for the available models.

Leirs *et al*. (1996) developed a demographic model to predict M. *natalensis* outbreaks in Morogoro, Tanzania using trends of vegetation and rainfall pattern. In all these studies heterogeneity of habitats was reported to be a key challenge for understanding complex environmental trends towards prediction of rodent dynamics (Pettorelli *et al*., 2011; Ralaizafisoloarivony *et al*., 2014).

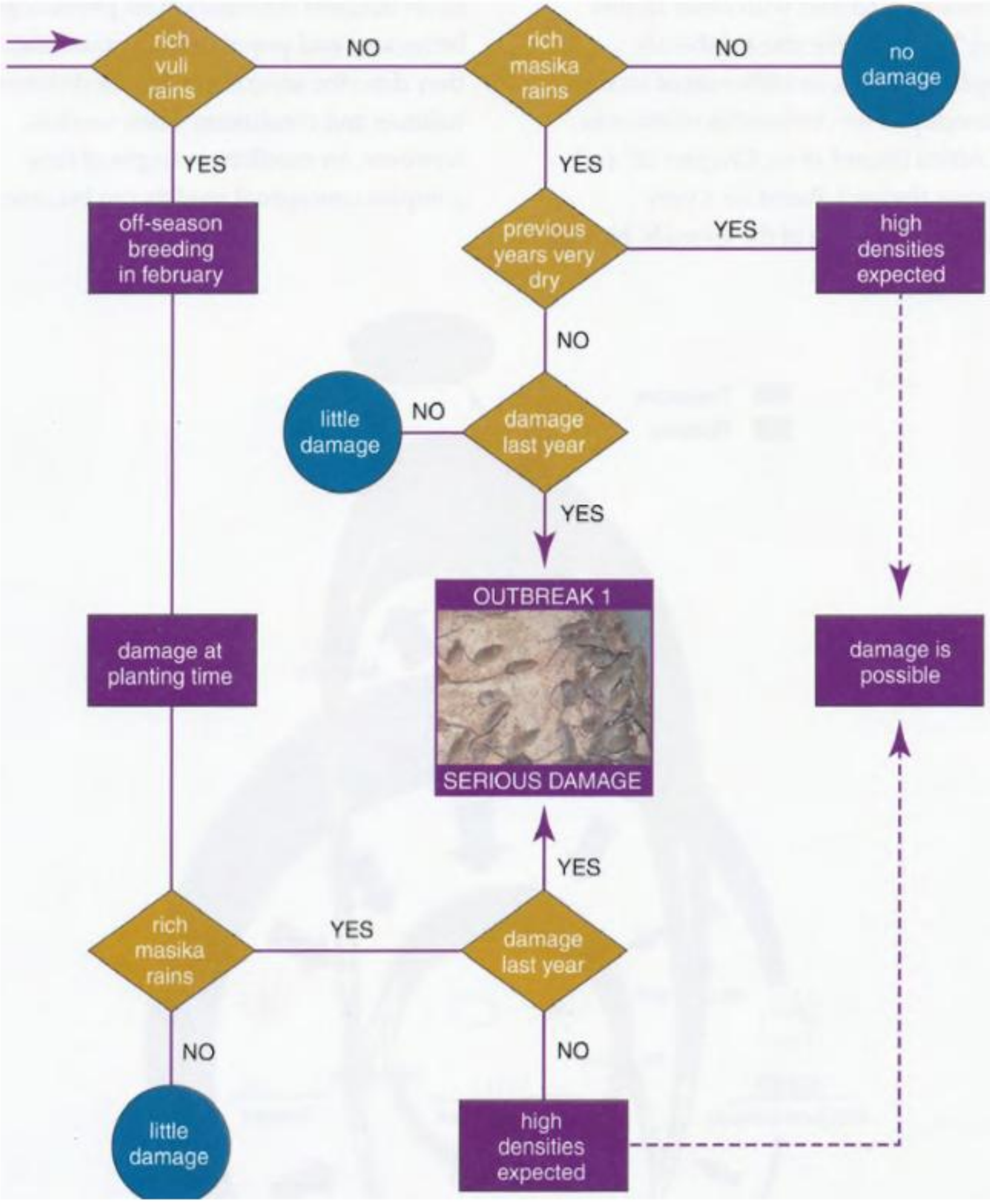

Figure 1.4: Schematic diagram for conceptual rodent outbreaks prediction model based on *vuli* rainfall season

Source: Leirs *et al*. (1996)

Recently, it has been reported that remote sensing derived vegetation indices could be used to explain rodents' abundance at fine scale (Dabien *et al*., 2010; Pettorelli *et al*., 2011; Bannar-Martin, 2014). Data from Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Satellite Pour l'Observation de la Terre (SPOT) have been used to derive metrics for analysing ecological processes including vegetation structural characteristics (i.e. plant height, life form, vegetation cover and type) for prediction of rodents' distribution and abundance (Pettorelli *et al*., 2011; Ralaizafisoloarivony *et al*., 2014).

Indices such as the Normalized Difference Vegetation Index (NDVI) have been reported to correlate well with vegetation productivity (i.e. biomass), forage quality and quantity (i.e. food), track crops growing season dynamics and different land cover types (i.e. forest, woodland and agriculture) at moderate resolutions over a range of spatial-temporal scales (Hurley *et al*., 2014; Pirotti *et al*., 2014; Kimaro, 2015). Such indices have been reported to be vital tools for studying vegetation habitat characteristics (i.e. vegetation cover) and their association with rodents in space and time (Pettorelli *et al*., 2011).

Studies conducted in Central Argentina to investigate the relationships between climate and NDVI in an agricultural ecosystem were able to demonstrate the dynamics exhibited by rodent population in the area (Andreo *et al*., 2009). Other studies have been conducted to relate NDVI and small mammal's abundance in Crete, Greece (Taheri, 2010), monitoring responses of biodiversity to environmental change at global scale worldwide (Marstona *et al.,* 2007), rodent population in agro-ecosystems of Kilombero valley Tanzania (STARS personal communication, 2015) and disease vectors in agro ecosystem of Lushoto district Tanzania (Dabien *et al*., 2010).

These studies have demonstrated that integration of NDVI in models to predict rodent outbreaks has not been done adequately (Pettorelli *et al*., 2011; Pirotti *et al*., 2014). The current readily and freely available remotely sensed data (i.e. satellite images, google earth images and SRTM) has made it possible to derive indices such as NDVI for incorporation in the models that could be used to explain rodent outbreaks. In this study NDVI was evaluated to establish vegetation indices of common vegetation habitats for predicting rodent dynamics in semi-arid areas of Tanzania. Evaluation of common vegetation habitats using NDVI is vital for elucidating ecological processes in rodent communities (Pettorelli *et al*., 2011). NDVI provides important biological information on vegetation dynamics that can be used to model rodent outbreaks within a reasonable short time when compared to the sparse weather and not readily available weather data.

1.4 Justification

In Tanzania, the average annual yield loss of maize and rice due to rodent damage is estimated to be around 5 to 15% (Makundi *et al*., 2010). Predictive models developed as an integral part of rodent control strategy for early warning of rodent damage in areas with frequent rodent outbreaks are still inadequate (Leirs *et al*., 1996; Mwanjabe and Leirs, 1997).

To some extent these models (i.e. logistic and demographic models) have not considered adequately the relationship between vegetation, land use and small mammals particularly rodents in smallholder farming agro-ecosystems. Biological information that considers the effect of vegetation patterns on rodent populations and outbreaks under smallholder farming conditions is of paramount importance for refining ecologically based rodent management strategies.

Therefore, the current study is envisaged to use NDVI of common vegetation habitats derived from satellite remote sensed data in smallholder farming landscapes to provide information on vegetation indices for refining probabilistic models for early prediction of rodent population and outbreaks. The knowledge gained from this study is aimed to be used by rodent ecologists and agricultural extension staff to develop field rodent management strategies for reducing crop damage. Therefore, the study contributes knowledge towards sustainable rodent management strategies to small scale farmers for improved livelihood and poverty reduction.

1.5 Objectives

1.5.1 Overall objective

The overall objective of the study was to establish the potential of NDVI of common vegetation habitats derived from satellite remote sensed data for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems.

1.5.2 Specific objectives

i. To map and characterize vegetation habitat patterns associated with rodents.

ii. To determine Normalised Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall pattern.

iii. To establish a relationship between NDVI of common vegetation habitats and rodent distribution and abundance in space and time.

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CHAPTER TWO

PAPER ONE

2.0 CHARACTERIZATION AND MAPPING OF VEGETATION HABITATS ASSOCIATED WITH SMALL MAMMALS ACROSS ISIMANI LANDSCAPE IN IRINGA, TANZANIA

ABSTRACT

Structural characterization and mapping of vegetation habitats is vital for early warning probabilistic prediction of rodent pest outbreaks. Such knowledge in sub-Saharan Africa is poorly understood. The current study was carried out to characterise and spatially map the vegetation habitats associated with small mammal abundance in smallholder farming agro-ecosystems. The Normalised Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall patterns were also explored. A combination of field survey and Multi temporal Landsat 8 (Operational Land Imager (OLI)) images were used to identify the vegetation habitats and estimation of NDVI. Small mammals were trapped in the mapped vegetation habitat units, and counted for abundances. In total, nine main types of vegetation habitats were investigated. A total of 597 small mammals, potentially related to major rodent pests were trapped. Geospatial and linear regression analysis were employed to establish the important habitat characteristics (predictor variables) for relating rodent abundance with rainfall and NDVI. Results show that vegetation habitats identified based on land use/cover types were largely dominated by agriculture covering about 60% of the plateau landscape with intensive maize cultivation and frequently reported rodent outbreaks. The findings show further that the plateau habitats support large number of small mammals (80%) than the rest of the habitats in the other landscapes. A strong correlation (r=0.96) was obtained between ground measured point rainfall data and the real time Tropical Rainfall Measuring Mission (TRMM) Precipitation Analysis (TMPA-RT) rainfall data across the identified vegetation habitats. Spatial variability of mean NDVI values with seasonal pattern across the studied vegetation habitat units were obtained whereby, higher values (0.2 to 0.6) were observed in wet season and lower values (0.0 to 0.2) in the dry season. The obtained NDVI values provide a robust measure of the presence and abundance of vegetation across the studied vegetation habitats which could be very useful in monitoring rainfall dynamics and as a proxy for predicting rodent pest abundance. The findings have revealed that rainfall, NDVI, and elevation were important predictor variables that could be considered for predicting small mammals or rodent pest abundance in the study area. Further research is required to explore the existing relationship between vegetation habitats with their associated microclimate and rodent pests in the hotspot areas.

Keywords: vegetation habitats, terrain characteristics, NDVI, small mammals

2.1 Introduction

Habitats characterization in space and time require a thorough understanding of the vegetation patterns, land use and physical environment including topography, and hydro-geomorphological parameters for which abundance of small mammals can be modelled (Debinski *et al.*, 1999; Orrock *et al.*, 2000; Komyakova, 2009). Such integrative evaluation describes additional habitat attributes of physical environment or human disturbance at fine scales than that evaluated by the field assessment alone (Kaufmann *et al*., 1999).

Habitat characteristics and mapping in most ecological models incorporate field data of limited spatial extent and/or remote sensing data (i.e. Landsat images) that do not characterize the vertical structure (i.e. vegetation composition) of the habitats pattern (Vierling *et al.,* 2008). Such barrier require integrative information framework presented for spatially explicit GIS based ecological modelling such as the land cover classification system (Di Gregorio, 2005; Morris and Kokhan, 2007). This integrative niche based techniques can provide potential physical habitat attributes (i.e. vegetation cover and structure) to describe and model species' geographic distribution in a remote sensing and Geographic Information Systems (GIS) framework (Ofulla *et al.,* 2013). For example Multi spectral (Landsat 8 (OLI), Radar (SRTM) and LIDAR derived habitat metrics combined with field data can characterize well three dimensional habitat structure and composition of terrestrial or aquatic environments at fine scale across broad landscapes (Robinson *et al.,* 2009; Pettorelli *et al.,* 2011). This can be achieved through measured and derived habitat variables associated with small mammal presence or absence (Robinson *et al.,* 2009; Pettorelli *et al.,* 2011; Pirotti *et al.,* 2014; Ralaizafisoloarivony *et al.,* 2014a).

Small mammal pest outbreaks is still a major problem in most smallholder farming agro-ecosystem in Tanzania (Mulunngu *et al.,* 2015). A major constraint is diversification in habitat preferences by various small mammal species (Hackley *et al.*, 2010; Taylor *et al.*, 2012). Although habitat selection by small mammals is known to be influenced by trends and patterns in vegetation, little has been done to evaluate the use of habitat metrics and characterisation of habitat conditions as predictive variables (Orrock *et al.,* 2000; Jorgensen, 2004; Hamrick, 2007). This requires fine-tuned studies on vegetation across various landscapes in space and time, to understand habitat characteristics and identify specific variables that may contribute in depiction of habitats features that influence small mammal pest abundance (Mulungu *et al.,* 2015). In this study, habitat characterisation and identification for specific variables were carried out as a step to overcome barriers for establishing the link between habitat uses, preference, selection and, ultimately fitness by various small mammal pest species in smallholder farming agro-ecosystem (Baltensperger and Huettmann, 2015).

Change in physical habitat attributes and ecological conditions can influence suitability of models for predicting small mammal pest outbreaks (Baltensperger and Huettmann, 2015). Such influence could be attributed to the new resulting drivers and interactions of the changes that can occur in the physical habitat attributes and ecological conditions (Vesey-Fitzgerald, 1966; Baltensperger and Huettmann, 2015).

Despite available studies on the effects of plant diversity on small mammals, predicting the direction and magnitude of these effects remains elusive (Guisan and Thuiller, 2005; Makundi *et al.,* 2010; Makundi and Massawe, 2011; Meredith *et al.*, 2013). The major challenge could be attributed to scale and limited predictors for modelling rodent distribution and abundance (Pettorelli *et al.*, 2011; Taheri, 2010). Quantitative species distribution and diversity pattern of rodents is influenced by habitats complexity and heterogeneity (Mulungu *et al.,* 2008). Therefore, integration of multi landscape variables and Spectral Signature Analysis (SSA) for vegetation habitats to predict small mammal outbreaks is vital.

In the west Usambara Mountains Tanzania, Ralaizafisoloarivony *et al.* (2014a) and Hieronimo *et al.* (2014b) explored vegetation and various landform characteristics respectively that influence small mammal dynamics. Although significant work was done, additional studies are required in other agro-ecological zones of Tanzania to clearly exhibit mapped vegetation habitats and landform metrics and conditions as predictive variables for small mammal dynamics particularly in agro-ecosystems of smallholder farmers (Hieronimo *et al.,* 2014a). Such studies may include; to describe and measure vegetation and habitat structural component using geo-spatial and statistical approaches (i.e. life form and cover types, terrain, soil and management practices) across various landscapes in different seasons and their influence to small mammal abundance (James and Shugart, 1970; Petorelli *et al.,* 2011; Hieronimo *et al.,* 2014b).

Therefore, the objectives of the study were to i) characterise and spatially map the vegetation habitats associated with small mammal abundance in smallholder farming agro-ecosystems and ii) determine the Normalised Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall patterns in the study area. This intervention was explored in order to provide key vegetation habitat variables that can be modelled to predict small mammal pest outbreaks in most smallholder farming agro-ecosystems of semi-arid Tanzania.

2.2 Materials and Methods

2.2.1 Description of the study area

This study was carried out in Isimani division located in the north-eastern part of Iringa district, Tanzania. The area is located between Universal Transverse Mercator (UTM) coordinates, 640 000 m E and 840 000 m E and 9 100 000 m N and 9 240 000 m N, Zone 36 M covering an area of about 12 66.7 km^2 (Fig. 2.1). Generally the study area is divided into three major zones based on landform characteristics (i.e. elevation and topography) as Plateau (1073 –1590m a.s.l), Escarpment (851 –999m a.s.l), and rift valley floor (704 -777 m a.s.l)). Landscape characteristics including vegetation, landforms and soils are described in Table 2.1.

Rainfall in the study area is influenced by topography (Mbilinyi, 2000). The rainy seasons are associated with the seasonal movement of the Intertropical Convergence Zone (ITCZ). The area has mean annual precipitation ranging from 200 to 750 mm/year. It is characterised by low erratic rainfall and periodic droughts giving it a characteristic of a semi-arid nature where precipitation is below potential evapotranspiration. Mean minimum and maximum temperature are between 12^0C in July and 29^0C in November respectively and has a unimodal rainfall pattern. Due to low and unevenly distributed rainfall, agricultural production is low (poor harvest) and irregular (Mbilinyi, 2000). The study area shows large differences in relief dissection and intensity, vegetation and land use patterns, and human activities.

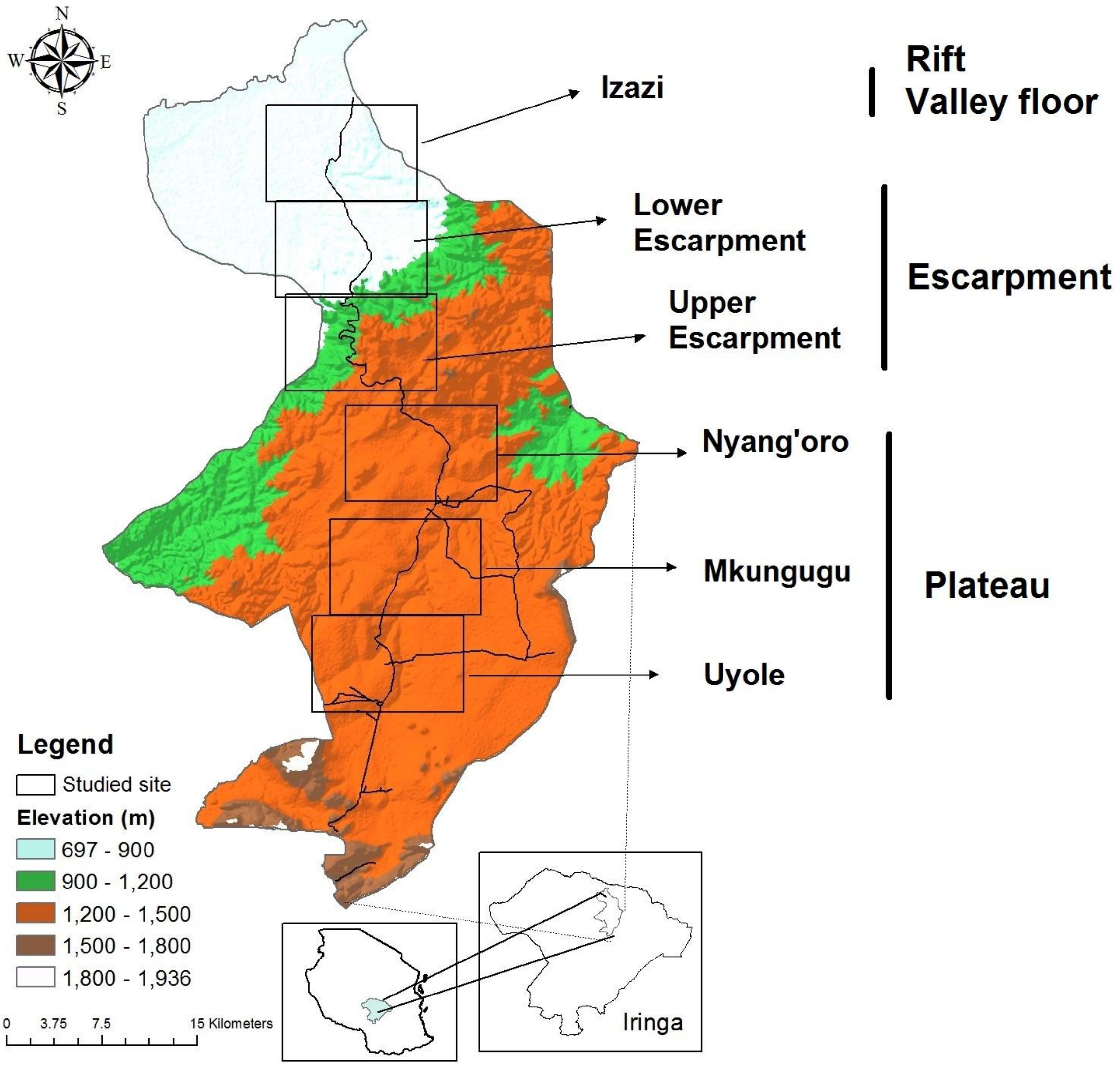


Figure 2.5: Location map of the study area

Table 2.1: Landscape characteristics of the studied sites

Landscape units	Landscape characteristics
Plateau Elevation: 1295 – 1590 m asl.	➢ Undulating hills (convex low ridge summits alternating with linear slopes grading to concave bottomlands) ➢ The convex low ridges summits - red soils with intensive maize cultivation, scattered acacia trees, grasses and shrubs ➢ The concave bottom lands - black soils with dense acacia trees and shrubs ➢ The linear ridge slopes; transition between convex and concave bottomlands - largely cultivated with maize
The escarpment Elevation: 926 - 1295 m asl.	➢ A long, steep slope at the edge of the plateau descending to the rift valley floor of the central rift valley in Tanzania ➢ Consist of rocky hills, boulder with pockets of red soils ➢ Large part is a conserved forest of miombo nature with grasses and shrubs underneath
The Low lying rift valley floor Elevation: 700 – 925 m asl.	➢ Rift valley floor - part of the central rift valley system bounded by central plateau (Dodoma-Singida system) and the southern highlands ➢ Dominantly grazing lands with scattered sorghum cultivation and settlement ➢ Crop cultivation and livestock keeping - practices (semi nomadic type) ➢ Cultivation - rainfed and irrigated agriculture along Ruaha Mkuu River which is feeding to Mtera dam ➢ Dominant vegetation - acacia wood land with baobab (*Adansonia digitata*)

Land use is dominated by agriculture and off-farm activities including livestock keeping (Mbilinyi, 2000). These land uses are surrounded by patches of natural vegetation and utility woodlots adjoining the plateau on the southern side and rift valley floor in the northern part. Isimani division was purposively selected for this study due to recently reported rodent outbreaks (Tewele, C. personal communication, 2016). Six sampling sites namely Uyole, Mkungugu, Nyang'oro (in the plateau), Upper escarpment, Lower escarpment (escarpment) and Izazi (rift valley floor) were selected for detailed study and characterisation on landform, vegetation pattern and management practices (Fig. 2.1).

2.2.2 Acquisition of remote sensing data

Multi temporal Landsat 8 (Operational Land Imager (OLI)) images were obtained to map vegetation habitat characteristics such as land use and land cover for various periods of dry and wet seasons (Tables 2.2 and 2.3). All the obtained images were already terrain corrected, orthorectified and geo-referenced. Shutter Radar Topographic Mission Digital Elevation Model (SRTM DEM) image of 1 arc-second for global coverage product (Table 2.4) and Google earth images of the area were also acquired. SRTM-DEM was used to rectify the Google earth images and to derive the landform attributes such as elevation ranges, slope gradient, slope aspect, slope shape, relief and Topographical Position Index (TPI). The Orthorectified Google earth satellite images were used for interpretation of land use and land cover (LULC) and to develop training datasets for supervised classification of vegetation habitat characteristics.

Table 2.2: Temporal characteristics of Landsat 8 (OLI) data acquisition

Seasonal		**Required period**	**L 8 (OLI 30 m) date**	**SRTM DEM (30 m)**
	SD	May, June and July	14th Jun-16	
Dry season	MD	August and September	1st Aug and 18th Sept-15	
	ED	October and November	20th Oct and 21st Nov-15	23rd Sept-14
Wet season	SW	December and January	7th Dec-15 and 8th Jan-16	
	MW	February	11th Feb-16	
	EW	March and April	10th March-16	

Key: SD = start dry, MD = mid dry, ED = end dry season, SW = start wet, MW = mid wet, EW = end wet season.

Table 2.3: Spectral characteristics of Landsat 8 (OLI) remote sensing data

Band	Name	Band width Spectral resolution (µm)	Spatial resolution	Sensor	Radiometric Resolution
1	Coastal/Aerosol	0.435 - 0.451	30m	OLI	8-bits
2	Blue	0.452 – 0.512	30m	OLI	8-bits
3	Green	0.533 - 0.590	30m	OLI	8-bits
4	Red	0.636- 0.673	30m	OLI	8-bits
5	Near Infrared	0.851 - 0.879	30m	OLI	8-bits
6	SWIR-l	1.566 - 1.651	30m	OLI	8-bits
7	SWIR-2	2.107 - 2.294	30m	OLI	8-bits
8	Pan	0.503 - 0.676	15m	OLI	8-bits
9	Cirrus	1.363 - 1.384	30m	OLI	8-bits

Key: OLI = operational land imager, SWIR-1 = Short wave infra-red one and SWIR-2 = Short wave infra-red two. (Source: USGS archives, www.usgs.com)

Table 2.4: SRTM Digital Elevation Model image of 1 arc-second for global coverage product

s/n	Criteria	Description
1	Spatial resolution	30m
2	Spectral resolution	C-band (l = 5.6 cm)
3	Data type	1 arc-second data (30 m, SRTM-1)

Key: SRTM = Shuttle Radar Topographic Mission (Source: USGS archives, www.usgs.com)

2.2.3 Characterisation and mapping of the vegetation habitats

Field survey, remote sensing and Geographic Information System (GIS) were used for characterisation and mapping of the vegetation habitats and their associated characteristics (Weih and Riggan, 2010; Ralaizafisoloarivony *et al*., 2014a). Vegetation habitats characteristics (i.e. cover, life form, management practices and land use and land cover (LULC)) were described and estimated using sample square quadrats (i.e. 100 m × 100 m) placed randomly along zones of each studied site. Spatial location of the vegetation habitats were recorded using Etrex 10 Garmin Global Position System (GPS) receiver with accuracy of less than 5 m. Land Cover Classification System (LCCS) and Earth Cover Classification System (ECCS) guidelines by FAO and Open Foris Initiative (OFI) respectively, were used to identify vegetation types to obtain General Habitat Classes (GHC) (Di-Gregorio, 2005, Adia *et al.*, 2015).

2.2.3.1 Generation of general vegetation classes from land use and land cover

Landsat 8 (OLI) satellite images captured in mid dry season, free from clouds with 30 m spatial resolution were used for mapping land use and land cover as described by a set of classifier (i.e. life form, cover, soil texture, crop type, and land use and management practices) for each studied site (Table 2.5). Landsat 8 (OLI) satellite images from other seasons as described in Table 2.2 were used to verify and improve the classification obtained from the satellite image of the mid dry season. Spatial referenced field data allowed to define characteristic tone, texture and pattern of the land cover classes on the display of the Landsat 8 (OLI) colour composite image (Hieronimo *et al.*, 2014b). These attributes were described at macro and micro spatial scales to obtain sample data sets for classification of the image into land use/land cover attributes (Table 2.5) for predicting small mammals’ distribution and abundance in space and time

Table 2.5: Macro and Micro vegetation habitats characteristics based on land use/land cover classes

Macro Class	Micro Class	Description
Bare	1. Bare Areas	≥ 60%/ALULCc without crop
Forest	2. Forest	≥ 60%/ ALULCc without crop
	3. Woodland	≥ 60%/ ALULCc without crop
Herbaceous	4. Grassland 5. Brush land	≥ 60%/bare and tree < 40%, without crop
Shrub	6. Shrubs land 7. Thicket	≥ 80% without crop and tree.
Agriculture	8. Cultivated 9. Fallow 10. Agroforestry	≥ 5%/ ALULCc it can be fallow (uncultivated) or cultivated.
Built up	11. Settlement 12. Structures	Manmade structures e.g. buildings and roads
Water bodies	13. Dam 14. River 15. Wetland	≥ 20%/ ALULCc includes seasonal and permanent rivers, stream, lakes dam and wetlands

Key**:** ALULCc = Any Land Use or Land Cover class

2.2.3.2 Classification

Supervised classification was performed to cluster pixels in the Landsat 8 (OLI) satellite images into twelve classes namely: bare, woodland with patches of shrubs, woodland, forest patches, shrubland, built up areas, agricultural areas, wetlands with riverine vegetation, mixed land uses, wetlands/grassland, grassland and grassland with patches of shrubs. This was done by defining region of interest (ROI) that represented each of the twelve land cover classes in the output image. The maximum likelihood classification was performed to assign each pixel in the image to the class that has the highest probability to obtain vegetation habitat map for each studied landscape site at a spatial resolution of 30 m by 30 m (i.e. Uyole, Mkungugu, Nyangoro (for the plateau), upper and lower escarpment (for the escarpment) and Izazi (for the rift valley floor). Sample data sets created for each vegetation habitat class was used for categorisation of the spectral classes into general vegetation habitat classes (land use/land cover classes) in IDRIS selva version 17.01 and Semi-Automatic Classification Plugin (SCP) in QGIS software.

2.2.4 Terrain characteristics

Digital Elevation Model (DEM) was used to obtain various landform characteristics for various vegetation habitats. Terrain analysis module in QGIS and IDRIS selva were used to obtain landform attributes namely slope gradient, slope aspect, slope shape and relief across the studied landscapes. Topographical Position Index (TPI) was also determined to obtain various landforms characteristics as described by De Reu *et al*., 2013 and refined to match the terminology of the FAO Guidelines for soil profile Description (Jahn *et al*., 2006).

Landform characteristics which includes; elevation, slope gradient (percentage), slope aspect (radians), slope length (m), slope shapes (straight, convexity and concavity) and Topographical Position Indices (TPI) obtained from SRTM-DEM using landform analysis tools in IDRIS selva software version 17.01. These attributes were used to extract point values at each data collection site for modelling rodent outbreaks.

Field observed soil physical properties i.e. texture, organic matter, gravel, salinity, and compaction were analysed to estimates soil water tension, conductivity and water holding capability using the Soil and Water characteristics model by USDA (Saxton and Willey, 2005). The technique is a set of generalized equations which describe soil tension and conductivity relationships versus moisture content as a function of sand and clay textures and organic matter (Saxton and Rawls, 2004). The soil water characteristic equations are valid within a range of soil textures approximately 0-60% clay content and 0-95% sand content. Also bulk density, gravel and salinity are estimated in the model. This information are vital for detailed evaluation of small mammal distributions with respect to the habitats characteristics.

2.2.5 Field survey

Based on landscape characteristics, 24 quadrats (1ha or 100 X 100 m) in each sampling site (i.e. making a total of 144 quadrants) were geographically located for ground truthing and further detailed spatial landscape characterization on land use and land cover types (i.e. farming and management practices), landform characteristics (i.e. concavities and convexities, slope gradient, slope aspects, elevation), vegetation characteristics and soil characteristics. Additional parameters that were measured in the field include species of vegetation, their number, height, growth stages and crop calendar of the agricultural crops and related management practices.

2.2.6 Compilation of climatic data

Only one rainfall station namely Nduli Meteorological Station is available near Iringa Airport in the plateau landscape of the study area. This station has long-term daily rainfall records covering the period from 1960 to 2016. Mean daily rainfall data from this weather station were compiled to get an idea of rainfall distribution pattern for the study area. The analysis of rainfall characteristics (i.e. rainfall profile and seasonal patterns) was done using INSTAT software version 3.33 and the corresponding graphs were plotted using EXCEL computer software.

Generally available rainfall data are localized to source point data and do not cover the whole study area neither consider spatial landscape variation hence inadequate to represent the dominant habitats characteristics of the study area. Therefore, to complement and improve this situation, monthly rainfall data derived from 3B42RT version 7 product data real time of the Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis (TMPA-RT) available from USGS archives (www.usgs.com) at 0.25^0 by 0.25^0 grid accessed on March, 2016 were used (Huffman and Bolvin, 2015). TMPA-RT monthly rainfall data were used as proxy for ground measured rainfall data from March 2015 to March 2016 for determination of spatial rainfall across the landscape in the study area (Table 2.6).

Table 2.6: Description of the TMPA-RT rainfall data

Character	Description
Algorithm	TRMM Multi-satellite Precipitation Analysis
data sets	3B42RT V7
spatial grid coverage	0.25°x0.25° lat/lon; 50°N-S
time interval span	monthly; Jan 1998-to date

Key: TRMM = Tropical Rainfall Measuring Mission, RT = Real Time,
Lat/Lon = Latitude/Longitudes

2.2.7 Determination of NDVI across vegetation habitats of the studied landscapes

NDVI was determined from Landsat 8 (Operational Land Imager (OLI) sensor) satellite images covering the periods corresponding to start, mid and end of each dry and wet season (Table 2.2). It was calculated as the normalized difference in reflectance band between Red channel (0.636- 0.673 μm) and Near Infrared (NIR) channel (0.851 - 0.879 μm) of electromagnetic spectrum using Equation 2.1 (Knight and Kvaran, 2014; Pirotti *et al*., 2014).

$$NDVI=\frac{NIR-R}{NIR+R} \quad \text{...} \quad 2.1$$

Where by: NDVI = Normalized Difference Vegetation Index
R = Surface reflectance in the red portion of the electromagnetic spectrum
NIR = Reflectance in the Near Infra-Red band of the Electromagnetic spectrum

The images were geo-referenced to EPSG: 21036 for uniform coordinate system. To eliminate the effect of clouds, the Maximum Value Composite (MVC) algorithm in QGIS was used during NDVI data processing (Mingjun, 2007). In MVC procedure, the multi-temporal geo-referenced NDVI data were evaluated on a pixel basis, to retain the highest NDVI value for each pixel location. Trends of NDVI variation for each season were evaluated for each vegetation habitat class across the landscape. An overall map showing annual mean NDVI categories was created and correlated with vegetation habitats classes in ArcGIS version 10.2.2.

2.2.8 Data Collection on small mammals

Trapping sites for small mammals were randomly allocated based on the reconstructed vegetation habitats map. A total of 144 trap sites (quadrats) were located for the six established sample study sites (i.e. Uyole, Mkungugu, Nyang'oro (for the plateau), upper and lower positions of the escarpment (for the escarpment) and Izazi village area for the Rift valley floor). For each sample site, 24 quadrats each measuring 100 m x 100 m were randomly located for detailed characterisation of vegetation habitats and small mammal trapping. In each quadrant 49 Sherman live traps were set, making a total of 1,176 traps in all 24 spatial located quadrants (Hieronimo *et al*., 2014a).

Sherman LFA live traps (7.5 x 9.0 x 23 cm; HB Sherman Traps, Tallahassee, USA) baited with peanut butter and maize flour were used (Hieronimo *et al*., 2014b). Number of animals captured for each quadrat were counted and the trap success was calculated based on the number of small mammals trapped divided by the product of the number of traps used and number of trapping nights (Ralaizafisoloarivony *et al*., 2014a), without considering their species within one or different vegetation habitats over a certain period of time (Equation 2.2).

$$\text{Trap success} = \frac{N}{Nt \times Nn} \times 100 \qquad \text{.......... 2.2}$$

Where by:	N	=	Number of small mammals trapped
	Nt	=	Number of traps used
	Nn	=	Duration in terms of nights during which the trap was set

2.2.9 Data analysis

Quantitative and qualitative assessments were employed in the exploratory analysis of vegetation habitats characteristics associated with small mammal abundance. This includes estimation of the average and percentage cover of vegetation types, elevation, slope, slope shape, slope length, slope shape, soil and landform profiles. Wherever it was applicable the degree of association between variables was measured by linear regression, scatter plot analysis and the Pearson correlation coefficient (R) at $P \leq 0.05$.

Analysis of variance (ANOVA) and Boosted Regression Trees (BRT) modelling technique in STATISTICA software version 13.0 and R software version 2.11 respectively were used to establish the important habitat characteristics (predictor variables) for predicting small mammal abundance and distribution. Significant variations ($P \leq 0.05$) of the vegetation habitat and terrain characteristics among vegetation habitat types were identified. Geo-statistical analysis technique (i.e. maximum likelihood and surface tools) in ArcGIS version 10.3 were used to characterize spatially vegetation habitats along the Isimani landscape.

2.3 Results and Discussion

2.3.1 Vegetation habitat characteristics identified based on land use/cover types

Land use and land cover (LULC) maps at a scale of 1: 10,000 of the studied sites (plateau, escarpment, and rift valley floor) are presented in Figures 2.2, 2.3 and 2.4 respectively. The total area of the studied sites was 534 km^2. The plateau occupies about 267 km^2

(50%), escarpment 178 km^2 (33%), and rift valley floor 89 km^2 (17%). Agriculture is the most important land use/cover in the plateau area where rodent pests have been reported. In terms of coverage, agricultural areas cover 59.2% of the plateau area, 3.3% of the escarpment area and 0.8% for the rift valley floor area (Fig. 2.5). As for the other land use/cover, forest and woodland vegetation dominated the escarpment area by 71.1% while sparse vegetation of acacia and baobab tree with grassland and shrubs, occupies about 51% of the rift valley floor area (Fig. 2.5).

Land use and land cover patterns can influence the biotic and abiotic characteristics with significant implications to small mammals (Hieronimo *et al*., 2014a). For example, in the west Usambara Mountains Tanzania, Hieronimo *et al*. (2014a,b) and Ralaizafisoloarivony *et al*. (2014a) observed that there was a significant variation ($P<0.05$) in small mammal abundance among Land Use and Land Cover (LULC) types. The study in the west Usambara Mountains, Tanzania by Ralaizafisoloarivony *et al*. (2014a) showed that annual cultivated crops habitat accounted for 80% of *Mastomys natalensis* while natural forest accounted for 60% of *Praomys delectorum*. Vegetation habitats and their associated characteristics are important indicators of the composition and abundance of small mammals (Mulungu *et al*., 2008). Any change in vegetation through human activities such as cultivation and cropping patterns could induce changes in the small mammal communities in an area.

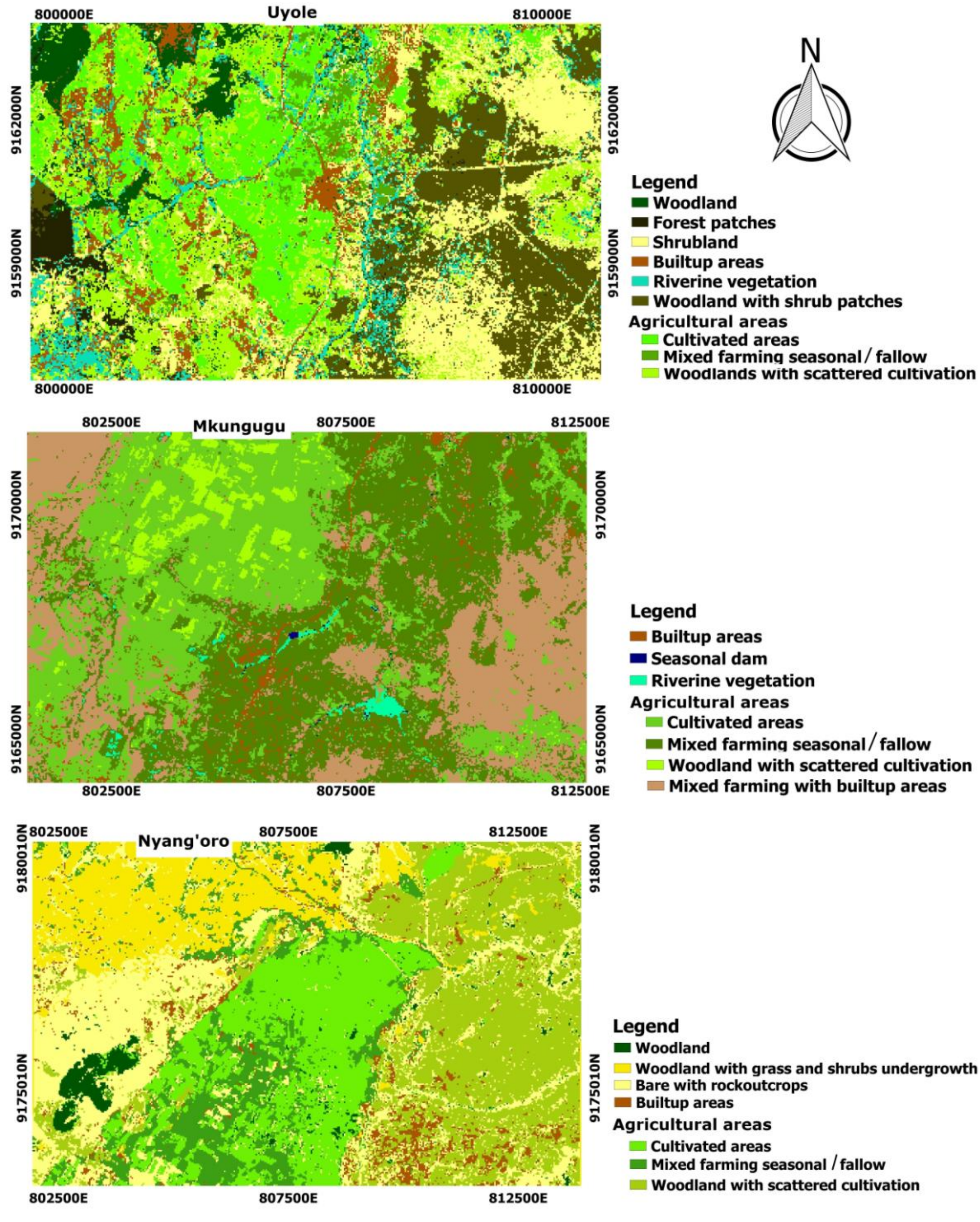


Figure 2.6: Land use/land cover (LULC) maps of the Plateau studied sites (Uyole, Mkungugu and Nyang’oro)

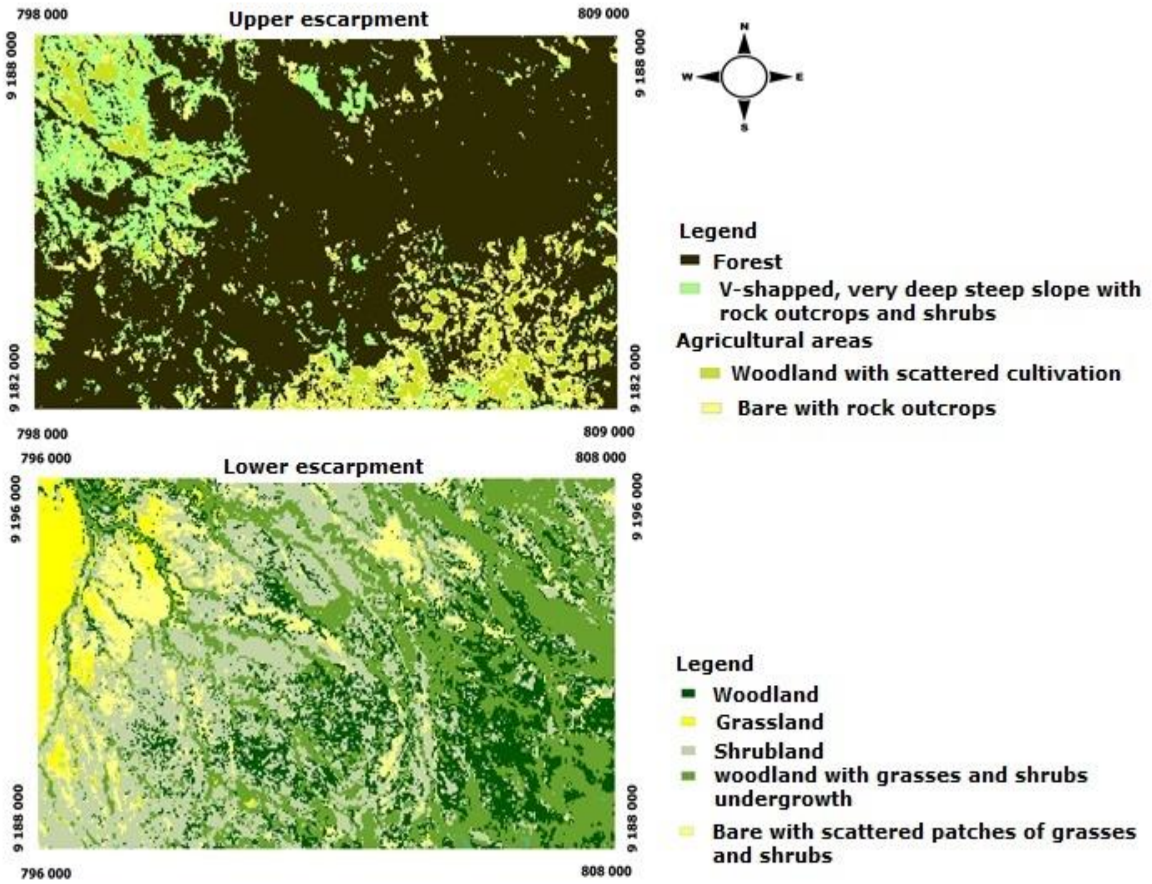


Figure 2.7: Land use/land cover (LULC) maps of the escarpment studied sites (Upper and Lower escarpment)

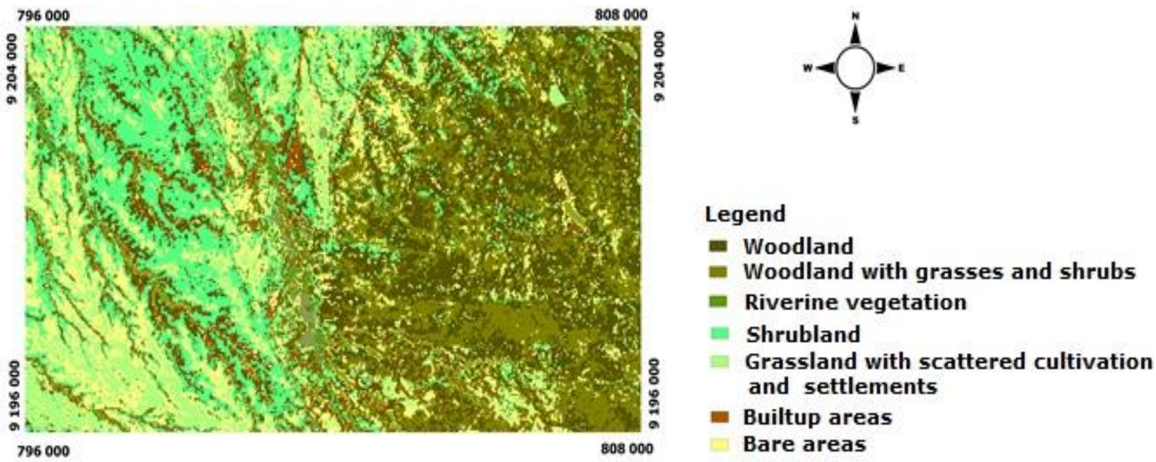


Figure 2.8: Land use/land cover (LULC) map representative of the rift valley floor (Izazi area)

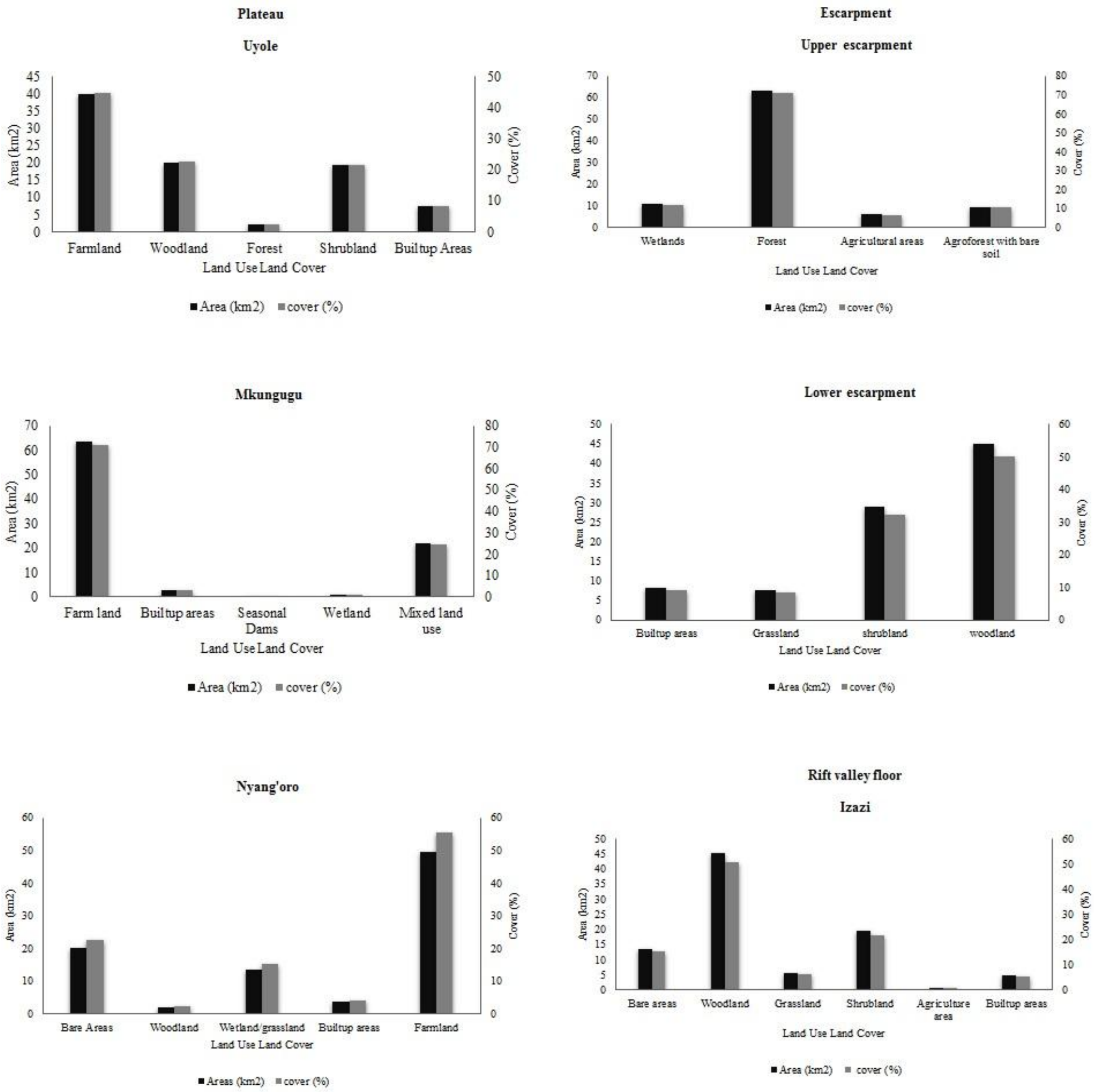


Figure 2.9: Proportions of vegetation habitat types based on land use/cover identified on different studied sites across Isimani landscape in Iringa, Tanzania.

2.3.2 Terrain characteristics across Isimani landscape

Terrain characteristics across Isimani landscape are presented in Figure 2.6 and Table 2.7. In the plateau area (1295 – 1590 m a.s.l.) a series of undulating hills were observed, that give rise to convex low ridge summits and concave valley bottoms (Fig. 2.6) mainly characterised by red and black soils respectively (Table 2.7).

The undulating hills are also characterised by the linear ridge slopes with very deep sand clay loam soils commonly occurring on the transition between convex and concave landscapes. This land unit is largely cultivated with maize where severe and frequent rodent outbreaks have been reported.

The escarpment area (926 - 1295 m a.s.l.) forms a long stretch of about 3 km of very steep slopes at the edge of the plateau descending sharply to the rift valley floor (Fig. 2.6). The escarpment is characterised by rocky hills and boulders with pockets of red shallow clay loam soils (Table 2.7). A large part of the escarpment is a conserved forest dominated by miombo woodlands in nature with grasses and shrubs underneath. This land unit is not inhabited and hence no rodent outbreaks have been reported, neither have rodent ecological studies been carried out in the escarpment. It comprises of high small mammal's diversity including Mystomys Natalensis (At the edges near the plateau), Graphurus, shrews and Avicansis (at the edges near valley floor). This observation resembles that of a study conducted in the west Usambara Mountains, Tanzania which indicated that, the escarpment habitat had higher rodent species diversity than other habitats with A. chrysophlilus and P. delectorum comprising 60% of the trapped small mammals (Ralaizafisoloarivony *et al.,* 2014b).

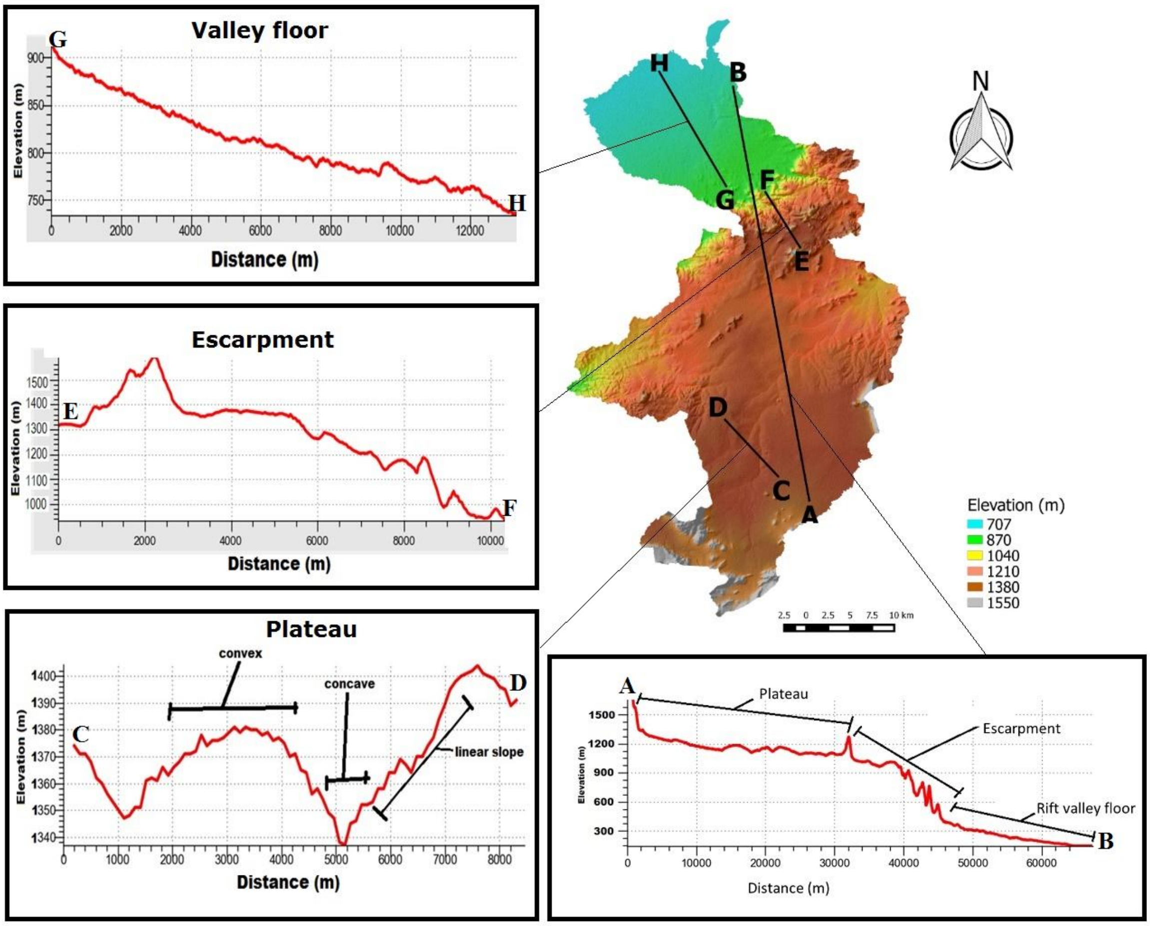


Figure 2.10: Cross section of terrain characteristics depicting variation in elevation and slopes of the studied landscapes as captured from Digital Elevation Model (DEM)

Table 2.7: Selected soil physical properties in the study area determined using the USDA Soil Water characteristic (SPAW model)

Landscapes units	Means of soil properties								Textural class	Soil colour
	Sand (%)	Silt (%)	Clay (%)	WP (%Vol)	FC (%Vol)	AW (mm/m)	SHC (cm/hr)	BD (kg/m^3)		
Plateau	60	12	28	18.3	28.3	93.3	0.79	1.5	Sandy clay loam	Reddish, Black and brownish
Escarpment	33	33	34	21.3	35	137.5	0.47	1.4	Clay loam	Brownish and black
Rift valley floor	52	6	42	26	37.1	110	0.76	1.5	Sandy clay	Whitish and black

Key: WP = wilting point, FC = field capacity, AW = available water, SHC = saturation hydraulic conductivity, BD = bulk density

The rift valley floor is a low lying terrain with altitude ranging from 700 to 925 m a.s.l. The soils are dominantly very deep sandy clay with clayey soils in some places along the *Ruaha Mkuu* floodplain where flooded rice is grown especially during wet season (Fig. 2.6 and Table 2.7). This land unit is predominantly grazing land (semi nomadic type) with scattered sorghum cultivation and settlements. Rainfed and irrigated agriculture is practiced along *Ruaha Mkuu* River which is feeding into Mtera dam. The dominant vegetation is acacia woodland with scattered *baobab* (*Adansonia digitata*) in some places. Rodent outbreaks observed not to be common in this land unit.

Distinctive landscape characteristics can influence the abundance and distribution of small mammals (Ralaizafisoloarivony *et al*., 2014a). In this study it was observed that landform including Plateau, Escarpment and valley floor differing in altitude, slope gradient and slope aspect demonstrated distinctive abundance and distribution of small mammals as discussed in section 2.3.5. In the west Usambara Mountains, Landform and soil characteristics are the key factors that were reported to be associated with rodent abundance and rodent burrowing (Meliyo *et al*., 2014). Field observations show that, there were many rodent burrows including wide and deep surface cracks in areas with heavy clay soils in the plateau landscape (predominantly maize growing area), while the escarpment had many surface stones and rock outcrops and boulders. These features could provide safe shelter for rodents from predators. Also in the plateau landscape positions there were food crops intercropped with trees and scattered settlements which are terrain features that may provide good places on which rodents could live.

2.3.3 Climate, rainfall regime and seasonal cropping patterns

Figures 2.7 and 2.8 present the cumulative mean daily rainfall and water balance for the study area respectively. Using rainfall data from Nduli Meteorological Station located in the plateau landscape, it was observed that, Isimani area has a unimodal rainfall pattern with two seasons namely dry and wet season (Fig. 2.7). Dry season starts in May and ends in November and wet season starts at the end of November (or early December) and ends in April. The site has short growing period (i.e. 60 to 64 number of rainy days) attributed to relatively long dry season (Fig. 2.7). Based on the rainfall and evapotranspiration characteristics, the studied site was further divided into six seasonal periods namely Start Dry (June and July), Mid Dry (August and September), End Dry (October and November), Start Wet (December and January), Mid Wet (February/March) and End Wet (March, April and partly May) (Fig. 2.8).

Temporal patterns of rainfall have been a key factor for determining spatial patterns of vegetation habitats and for predicting small mammal population dynamics in most agro ecosystems (Mulungu *et al*., 2010; Dabien *et al*., 2010). Vegetation production in dry lands is often assumed to be closely related to inter-annual rainfall variability (Herrmann *et al*., 2005). Moderate to strong linear relationships between rainfall and vegetation production have been noted in the drier parts (<800 mm) of South Africa and the Sahel (Nicholson *et al*., 1990; Wessels *et al*., 2007). However, lack of a network of accurately recorded rainfall time series data in the tropics and Tanzania in particular, is a problem faced in many studies (Grist *et al*., 1997).

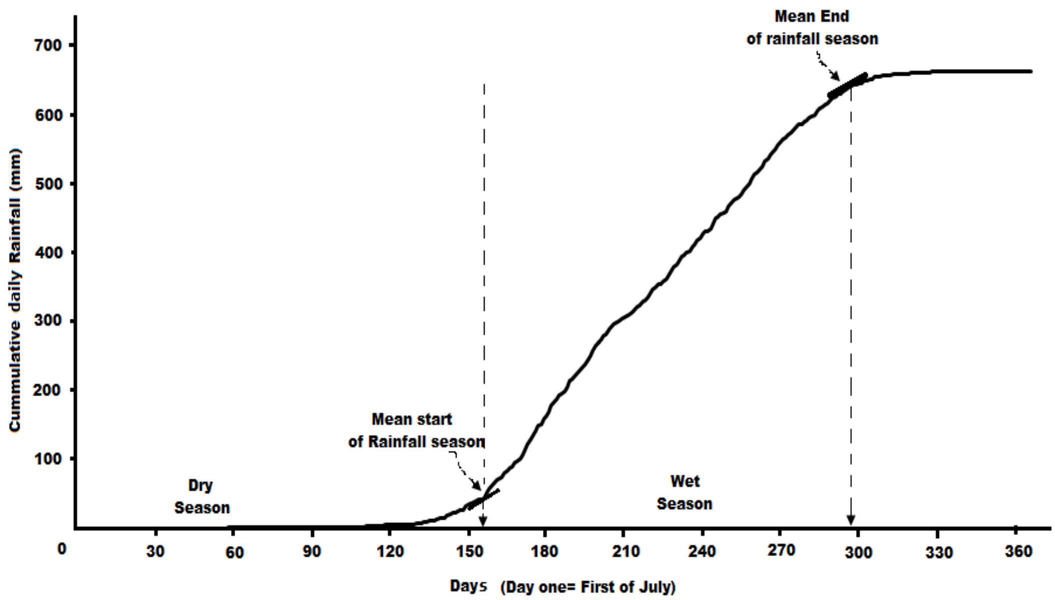
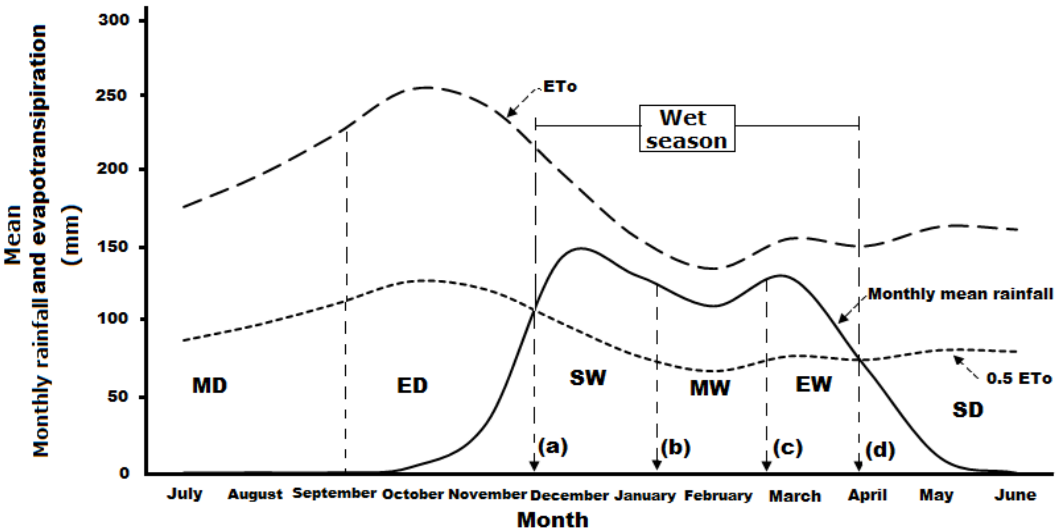


Figure 2.11: Cumulative mean daily annual rainfall for Isimani area, Tanzania with points of maximum curvature representing mean onset and cessation of rainy season (day one is equal to 1st of July)



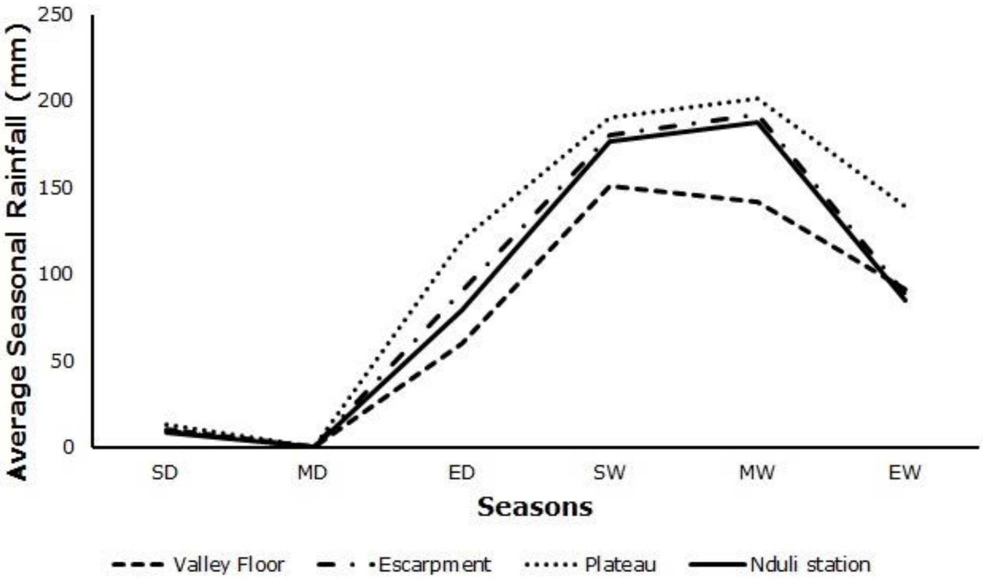
Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season

Figure 2.12: Water balance typical for Isimani area in Iringa, Tanzania (day one is equal to 1st of July)

To minimize the problem of rainfall data availability, satellite data at a resolution of 1 km (MODIS NDVI), and TRMM data have been used widely instead of point measurements of rainfall (Dabien *et al*., 2010; Rishmawi *et al*., 2016). Also, land cover and elevation have been integrated in the analysis to obtain NDVI-rainfall relationships in homogeneous areas (Grist *et al*., 1997; Dabien *et al*., 2010). In the study area only one point measurement of rainfall is available which is not adequate for predicting spatial distribution of small mammals, hence the real time Tropical Measuring Rainfall Mission Precipitation Analysis (TMPA-RT) was used in this study to describe rainfall pattern across various landscapes (http://trmm.gsfc.nasa.gov).

Despite the fact that TMPA-RT provides accurate spatial and temporal measurements of rainfall over the tropics, it only gives information at coarse resolutions (0.25° × 0.25° resolution) (http://trmm.gsfc.nasa.gov), often not suited for studies at finer resolutions. To describe its usefulness in the current study, a relationship was obtained between TMPA-RT rainfall and point rainfall measurement available in the study area as illustrated in Figure 2.9. Temporal pattern of field measured rainfall resembled well with TMPA-RT rainfall. Since Infra-Red (IR) band depict well vegetation dynamics and used to obtain TMPA-RT rainfall data, hence at the escarpment presence of forest resulted to field measured rainfall pattern to resemble well with TMPA-RT rainfall patter.

A strong positive correlation (r = 0.96) was depicted between ground measured rainfall data (Nduli Meteorological Station) available in the study area and real time Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis (TMPA-RT) rainfall data (TRMM version 7) (Fig 2.10). In this study the influence of rainfall pattern on NDVI was considered as a proxy for spatial prediction of small mammals. Previous research showed that the reconstruction of (historical) rainfall patterns based on established relationships between rainfall and NDVI can give satisfactory results (Grist *et al*., 1997; Immerzeel *et al*., 2009).



Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season.

Figure 2.13: Seasonal comparison for Nduli meteorological station measured rainfall and satellite measured TMPA-RT rainfall data for valley floor, escarpment and plateau respectively

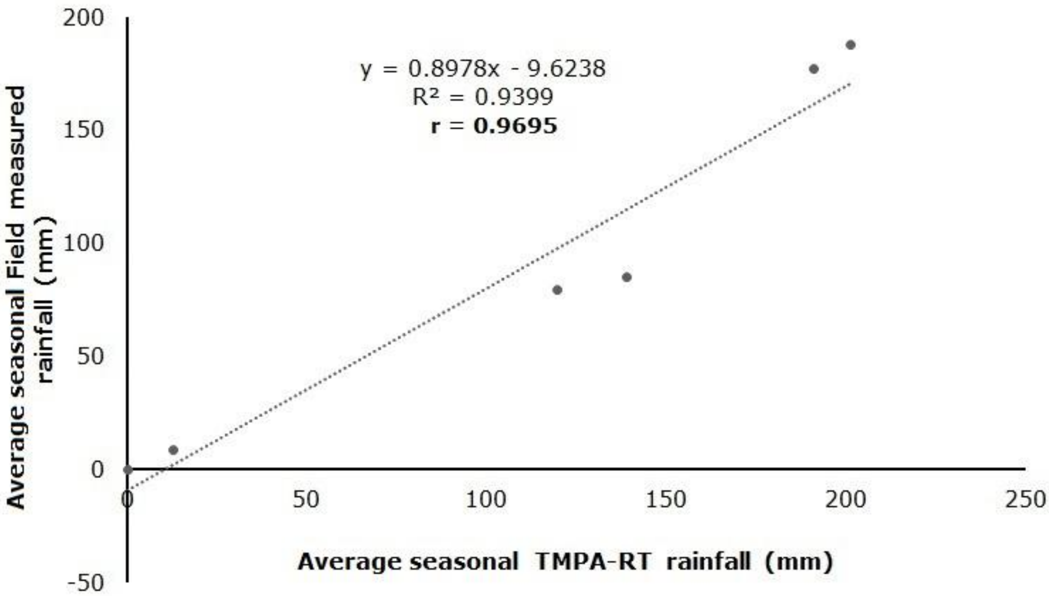


Figure 2.14: Relationship between field measured and TMPA-RT average seasonal rainfall

2.3.4 Seasonal NDVI of different vegetation habitats across the Isimani landscape

The mean annual Normalised Difference Vegetation Index (NDVI) across the studied landscape is presented in Figure 2.11. Derived mean annual NDVI values range between -1 and +1 NDVI units, with values less than zero indicating absence of vegetation and values greater than 0 showing increasing amounts of green vegetation. Low values of mean annual NDVI were observed in the plateau landscape dominated by farmlands and largely in the low lying rift valley floor where the dominant land use is grazing of semi nomadic type with scattered sorghum cultivation and settlement (-0.06 – 0.197) (Fig. 2.11). The escarpment had relatively higher values of mean annual NDVI ranging from 0.246 to 0.346. This landscape unit is dominantly a conserved forest characterised by *miombo* woodlands with grasses and shrubs underneath.

On the other hand, Figure 2.12 describes the spatial variability of mean seasonal NDVI across the landscapes in different seasons. The mean seasonal pattern of NDVI for the landscape units (plateau, escarpment and rift valley floor) had both similarities and differences. The major similarity was the general spatial variability of mean NDVI value with seasonal pattern across the landscape units, whereby, higher values (0.2 to 0.6) were observed in the start, mid and end of wet season and lower values (0.0 to 0.2) at the start, mid and end of dry season. In the northern flooding Pampa grasslands in Argentina, Di Bella *et al*. (2009), demonstrated the utility of coarse resolution NDVI in identifying patterns in seasonal and inter-annual canopy characteristics of different landscape types. Multiple regressions from that study showed that, NDVI values of the studied landscapes were positively associated with precipitation. Relationships of this nature could be used to predict forage production rates for animals.

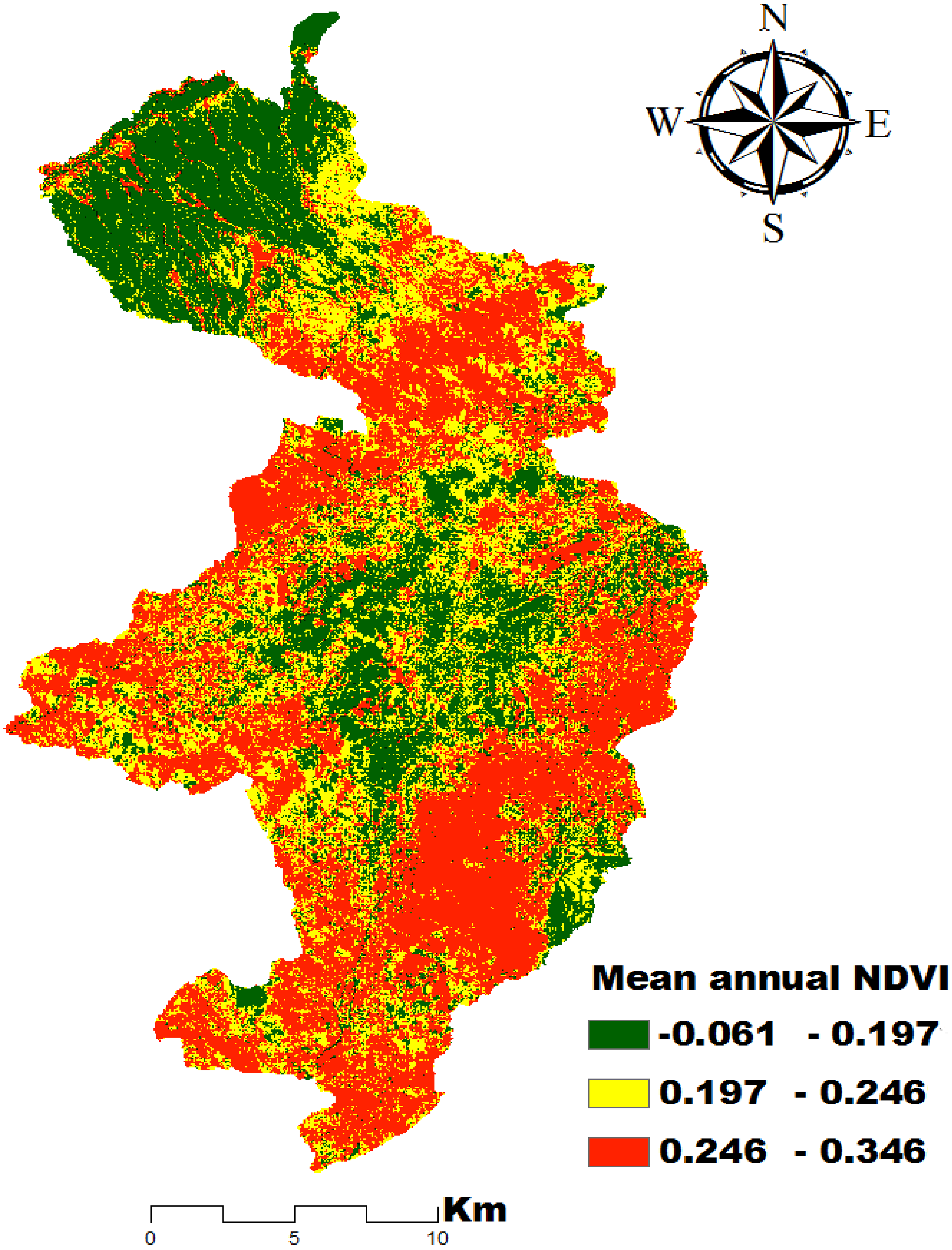


Figure 2.15: Annual Mean NDVI of vegetation habitats across the Isimani landscape in Iringa, Tanzania

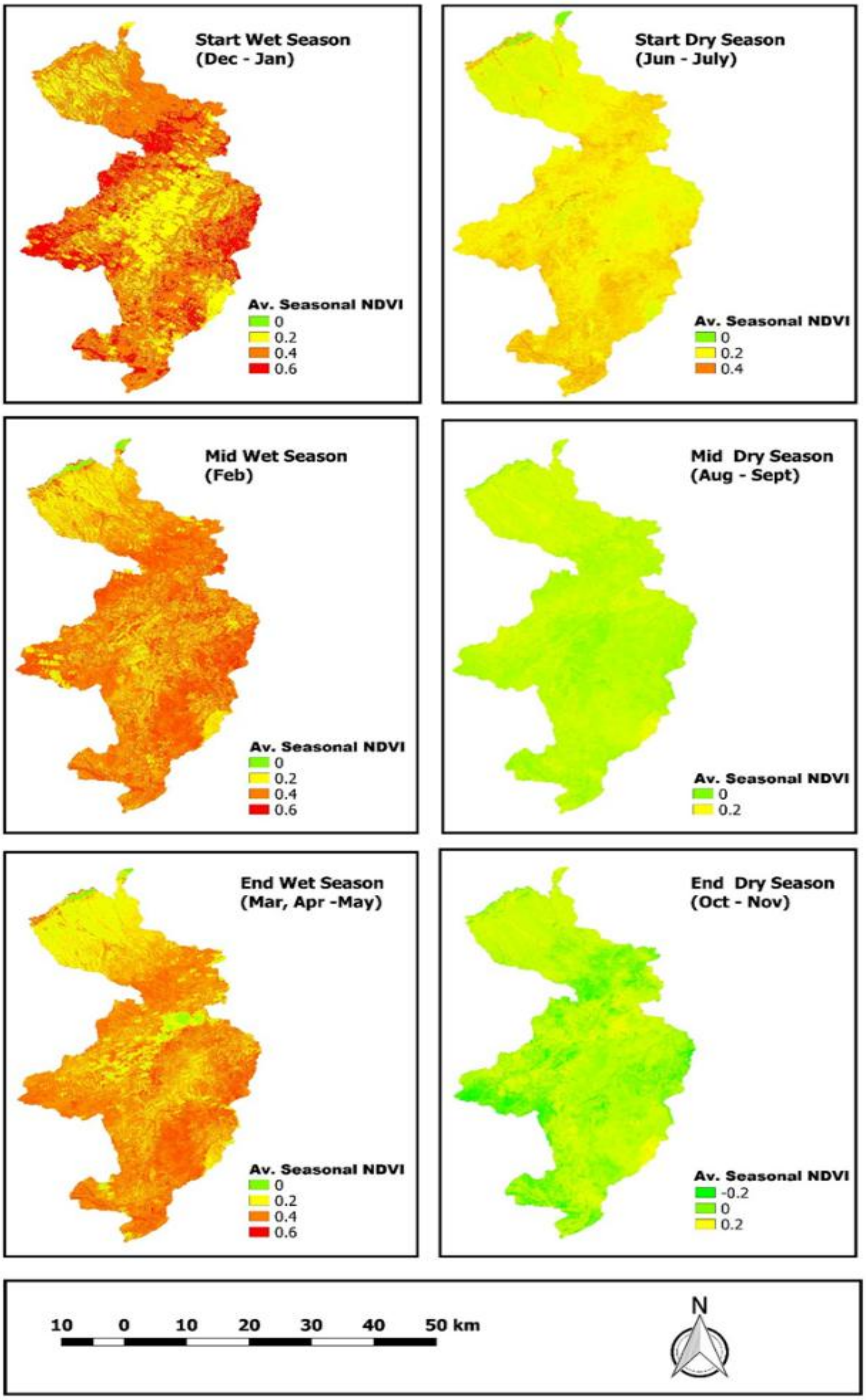


Figure 2.16: Spatial average seasonal NDVI derived from Landsat 8 (OLI)

Several studies have reported the strength of the vegetation-precipitation relationship yielding converging results to this study that NDVI is positively correlated with precipitation. For example, In South Asia, seasonality of *rotavirus* was assessed by considering the association between rate of *rotavirus* and vegetation index, a remote sensing measure of the combined effects of temperature and precipitation (Jagai *et al*., 2012). In a study conducted in the north-east part of Italy, NDVI from Landsat 8 vegetation indices was used to study movement dynamics of Capra ibex (*mountain goat*) in mountain areas (Pirroti *et al*., 2014). In that study a correlation was obtained between the spatial positions of Capra ibex with respect to its movements in different periods of the year following in some way the phenological stage of vegetation (Pirroti *et al*., 2014).

NDVI provides a robust measure of the presence and abundance of vegetation in a wide range of environmental conditions (Prince, 1991). The NDVI has been found to be very useful in monitoring rainfall dynamics in semi-arid and arid areas where grasslands and savannah bushlands are the dominant vegetation types (Hiernaux and Justice, 1986; Prince and Tucker, 1986), primarily because semi-arid vegetation is very sensitive to variations in precipitation. For example, comparative data show an approximate linear relationship between NDVI and precipitation in a range of semi-arid lands of Africa (Nicholson *et al*., 1990). Precipitation and green vegetation dynamics are major determinants of life cycle of animals and insects in semi-arid lands in many parts of the world (Nicholson *et al*., 1990; Rishmawi *et al*., 2016).

2.3.5 Habitat types and their associated characteristics and small mammal abundance

Important habitat characteristics for prediction of small mammals are presented in Figure 2.13. The predictor values range between 0 and 1 with values approaching 0 indicating less importance while values approaching 1 showing an increasing strength or importance of a predictor variable. It was observed that rainfall, NDVI, soil texture, elevation, slope aspect, slope gradient, slope shape and landform were important predictor variables (in order of importance) that could be considered for predicting small mammals or rodent pest outbreaks in the smallholder farming agro-ecosystems in the study area.

These results are similar with previous studies which postulated that rainfall (Mulungu *et al.,* 2010) and NDVI (Taheri, 2010) are relevant variables for predicting small mammal abundance as illustrated in Figure 2.14. In a study conducted in the west Usambara Mountains, Tanzania, Meliyo *et al*. (2014) reported that available phosphorus, slope aspect and elevation were statistically significant ($P<0.05$) predictors for explaining richness and abundance of small mammals. In this study small mammal’s abundance and species richness also increased with increase in elevation.

A study conducted by Hieronimo *et al*. (2014b) in the Usambara Mountains Tanzania, depicted that elevation was the most important predictor which contributed more than two thirds (80.1%) of the total predictor level of importance and showed a strong positive effect. In that study, elevation of 1,700 m appeared to be the threshold for a sharp increase in trap success. The second important predictor was the slope aspect which contributed 11.4% of the total predictor level of importance and showed a moderate positive effect. In terms of elevation and slope aspect, results in that study resembles well with findings this study.

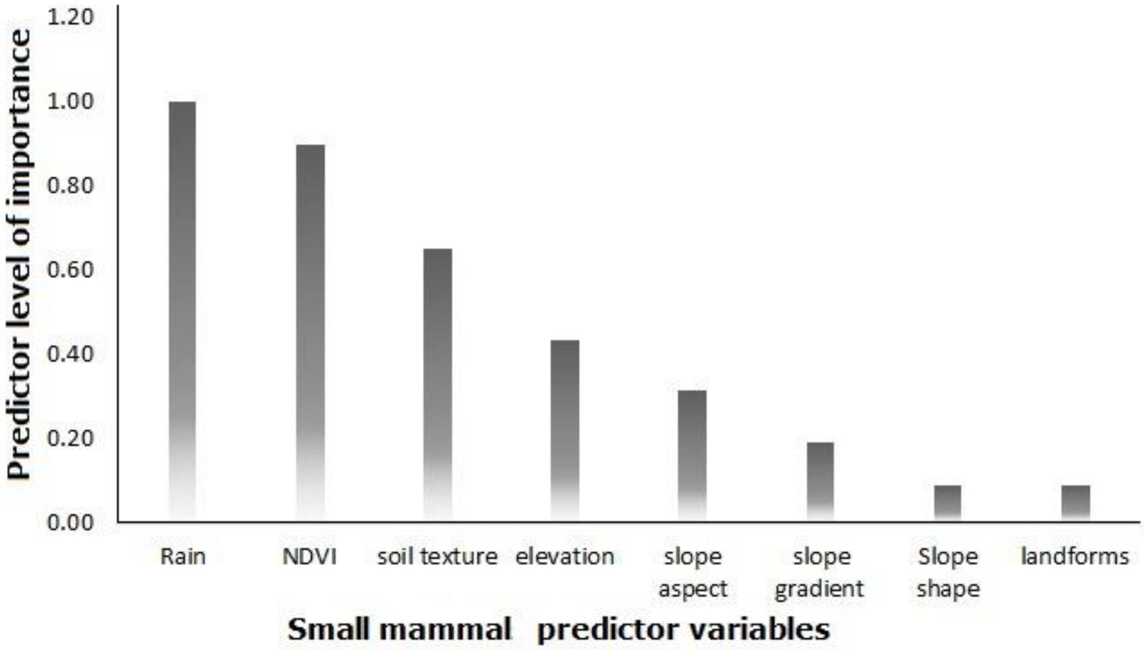


Figure 2.17: Relative ranking of small mammal predictor variables identified by Boosted Regression Trees (BRT) model at P < 0.05

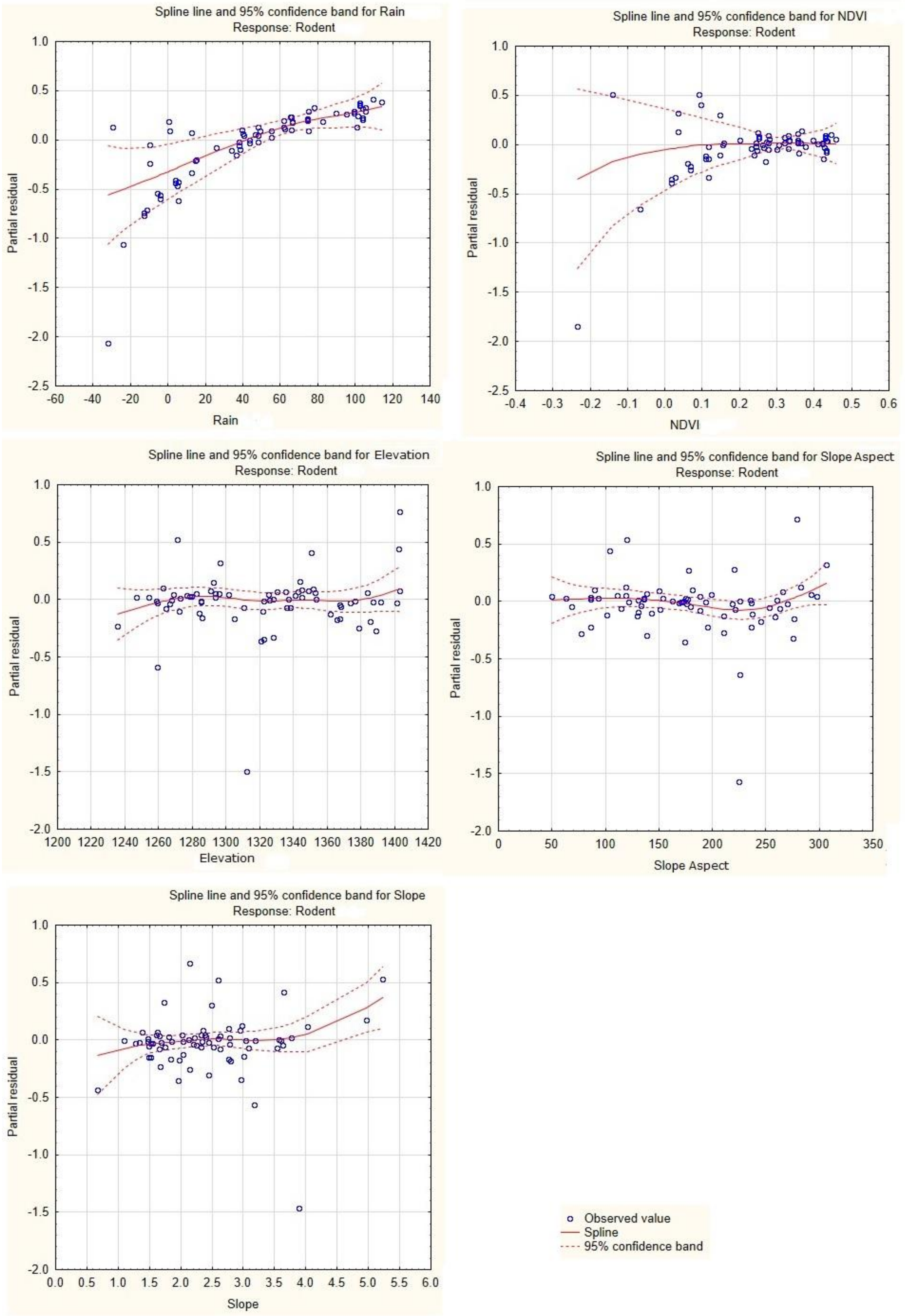


Figure 2.18: Partial dependence plots showing the effect of landscape and remote sensing attributes on small mammal abundance in space and time. The predictor becomes more significant when scatter points are fitted well within upper and lower limit of the confidence band at 95% confidence interval

The overall vegetation habitat characteristics associated with small mammal abundance are well presented in Table 2.8. In the plateau, agricultural areas that include cultivated land, mixed farming and seasonal fallow and woodland with scattered cultivation depicted high rodent population abundance (Mean habitat trap success (MhTs) = 25.8). Both the escarpment and valley floor had lower rodent abundance (MhTs $\leq$ 4). Primarily fragmentation of the vegetation habitats as influenced by terrain features appears to be key determinants for assessing the abundance and distribution of small mammals. For example the number of rodents trapped (Trn) were higher in the plateau landscape (Trn = 579) with higher elevation ranges (1073m – 1590m a.s.l) than in the rest of the landscapes. This agrees with findings of Meliyo *et al*. (2014) in the west Usambara Mountains who observed that, the abundance of small mammals increased with increase in elevation.

Table 2.8: Distribution of small mammals in various vegetation habitats across the landscape

Landscape units	Small Mammals Vegetation habitats	Characteristics										
		Av. SAR (mm)	Av. S.NDVI	St	ER (m asl)	Sa	Slope G (%)	S.shp	Lf	Trn	Rp (%)	MhTs
Plateau	Agricultural areas	110.7	0.19 – 0.28	Sand clay loam	1296 – 1590	EN	< 20	Straight	GUP	466	78	25.8
	Shrubland	110.7	0.26	Sand clay loam	1297 – 1590	EN	10 - 30	Straight	GUP	17	3	6.25
	Riverine vegetation	110.7	0.346	Sand clay loam	1298 – 1590	EN	< 40	Concave	GUP	5	1	5
	Mixed farming with built-up areas	110.7	0 – 0.2	Sand clay loam	1299 – 1590	EN	< 10	Straight	GUP	61	10	6.9
	Woodland with grasses and shrubs undergrowth	110.7	0.25	Sand clay loam	1300 – 1590	EN	< 30	Concave	GUP	30	5	15
Escarpment	Forest and woodland	89.76	0.34	Clay loam	1200 – 900	NW	< 100	Convex	SRR	3	1	1
	Woodland with grasses and shrubs undergrowth	89.76	0.3	Clay loam	1201 – 900	NW	< 90	Convex	SRR	3	1	3
Rift valley floor	Woodland with grasses and shrubs undergrowth	75.94	0.3	Sand clay	700 – 925	NW	< 10	Straight	FF	3	1	1
	Grassland with scattered cultivation and settlement	75.94	0.2	Sand clay	701 – 925	NW	< 10	Straight	FF	9	2	3.5
		Total								597	100	

Key: Av. SAR = Average seasonal annual rainfall, Av. SNDVI = Average Seasonal NDVI, St = Soil texture, ER = Elevation range, Sa = Slope aspect (NE = North east, NW = North west), slope G = Slope gradient, S.shp = Slope shape, Lf = Landform, GUP = Gently Undulating Plain, SRR = Steep Rock outcrops and rock cliffs, FF = Flat to almost flat valley flats, Trn = Number of rodents trapped, Rp = Proportion of rodent per habitat and MhTs = Mean habitat trap success.

2.4 Conclusions and Recommendations

2.4.1 Conclusions

Small mammal pest outbreaks is still a major problem in most smallholder farming agro-ecosystems in Tanzania. The major constraint is diversification in habitat preferences by various small mammal species. Habitat characterization in space and time require a thorough understanding of the vegetation patterns, climate and terrain parameters for which abundance of small mammals can be predicted. Such knowledge in sub-Saharan Africa is poorly understood. The current study was carried out to characterize and spatially map the vegetation habitats associated with small mammal abundance in smallholder farming agro-ecosystems. The Normalized Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall patterns were also explored. The study was carried out as an intervention to provide key vegetation habitat variables that can be modelled to predict rodent pest abundance in smallholder farming agro-ecosystems in Isimani division, Iringa, Tanzania. The following conclusions are made in the light of the findings revealed in this study:

Generally, land use land cover types were observed to influence small mammal’s habitats fragmentation and heterogeneity in space and time. In the studied site, it was revealed that vegetation habitat characteristics identified based on land use land cover types are largely dominated by agriculture that account for about 60% of the plateau landscape with intensive annual and cereal crop cultivation. Forest and woodland vegetation dominated the escarpment while the majority of sparse vegetation of acacia type and baobab tree with grassland and shrubs were dominant in the rift valley floor.

In the plateau area (1295 – 1590 m a.s.l.) a series of undulating hills were observed, that give rise to convex low ridge summits and concave valley bottoms characterised by the linear ridge slopes with very deep sandy clay loam soils commonly occurring on the transition between convex and concave landscapes. Maize cultivation is the dominant land use with severe and frequently reported rodent outbreaks.

A strong correlation (r=0.96) was obtained between ground measured point rainfall data and the real time Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA-RT) rainfall data across vegetation habitats. From this relationship it is suggested that rainfall pattern and NDVI could be related and used as a proxy for spatial prediction of small mammals.

In this study, a general spatial variability of mean NDVI values with seasonal pattern across the studied landscape units was observed, whereby, higher values (0.2 to 0.6) were observed in the start, mid and end of wet season and lower values (0.0 to 0.2) at the start, mid and end of dry season. The results suggest that NDVI could be used as an index of vegetation and also as an index of food resources in the semi-arid areas of Tanzania for monitoring rodent pests. Also, the obtained NDVI values provide a robust measure of the presence and abundance of vegetation across the studied landscapes which could be very useful in monitoring rainfall dynamics and as a proxy for predicting rodent pest outbreaks in the study area.

It has been demonstrated in the current study that the plateau habitats support more small mammals (80%) than the habitats in the other landscapes. The plateau landscape is largely dominated by agriculture with intensive maize cultivation, scattered acacia trees, grasses and shrubs, settlements in the upper and middle linear-convex slopes and dense acacia trees and shrubs in the concave bottom lands. This suggests that the land use/cover observed in this unit provides relatively "better" habitats for rodent pests in the study area.

Results show further that the escarpment landscape acts like an interface between the rift valley floor and the plateau, a place where small mammal species from both landforms intermix (Appendix I). For example Mystomys and Arvicanthis trapped in the escarpment, also were captured in the plateau and rift valley floor respectively.

The study revealed that rainfall, NDVI, soil texture, elevation, slope aspect, slope gradient, slope shape and landform were important predictor variables that could be considered for predicting small mammals or rodent pest outbreaks in the smallholder farming agro-ecosystems in the study area

2.4.2 Recommendations

Temporal patterns of rainfall could be used to describe vegetation habitats and small mammal population dynamics in most agro ecosystems. However, lack of a network of accurately recorded rainfall time series data in the study area has posed a significant challenge. To minimize the problem of rainfall data availability, further research is recommended to explore the use of satellite data such as MODIS-NDVI, and TMPA-RT at fine resolution to generate rainfall data for use instead of relying on commonly not available point rainfall measurements.

Further research to explore the existing relationship between vegetation habitats with their associated microclimate and small mammal particularly rodent pest’s hotspot areas is recommended.

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CHAPTER THREE

PAPER TWO

3.0 APPLICATION OF NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI) TO FORECAST RODENT POPULATION IN SMALLHOLDER AGRO-ECOSYSTEMS OF ISIMANI LANDSCAPE, IRINGA, TANZANIA

ABSTRACT

Normalized Difference Vegetation Index (NDVI) of common vegetation habitats derived from satellite remote sensing can provide greater possibility for monitoring rodent population dynamics and outbreaks. Such information could be used to fine tune ecologically based rodent management strategies. However, these technologies have not widely been used in tropical sub-Saharan Africa. The objective of this study was to evaluate the potential of NDVI of common vegetation habitats derived from satellite remote sensing data for monitoring rodent pests in Isimani Division, Iringa, Tanzania. The study estimated NDVI across vegetation habitats and landscapes as the normalized difference in reflectance between Red channel (0.636- 0.673 mm) and near Infrared (NIR) channel (0.851 - 0.879 mm) of the electromagnetic spectrum from Landsat 8 (Operational Land Imager (OLI)) sensor. Geospatial approach was used to examine NDVI of vegetation habitats in a semi-arid area with unimodal rainfall pattern and established a relationship between NDVI and small mammals (rodents) distribution and abundance for each period covering the corresponding start, mid and end of dry and wet seasons. Different levels of scale and resolution were considered. Linear regression analysis was used to clarify the relationships between NDVI and predicted rodent abundance from rainfall and NDVI across seasons, and calculation of the Pearson correlation coefficient (r) at $P \leq 0.05$. Results have demonstrated a good positive correlation between rainfall and NDVI along the elevation gradient of landscape units with escarpment having higher correlation (r=0.688) than the plateau (r=0.653) and the valley floor (r =0.652). This relationship suggests that rainfall patterns could be easily predicted from a link between NDVI and elevation as predictor variables. Results show that NDVI and rainfall derived from NDVI have positive influence on the rodent abundance over the studied seasons. It was observed that 98% of the predicted rodent abundance was explained by NDVI while rainfall explained only 85%. NDVI predicted rodent abundance showed a strong positive correlation (r=0.99) with the field measured rodent abundance. These results support the hypotheses that NDVI of common vegetation habitats has the potential for monitoring rodent population dynamics under smallholder farming agro-ecosystems. Hence, NDVI could be used to model rodent outbreaks within a reasonable short time when compared to the sparse and not readily available rainfall data. Further research is required to establish the relationship between NDVI and rodent pest species composition and community structure in different habitats and seasonal rainfall patterns.

Keywords: NDVI, vegetation habitats, rainfall, rodent abundance, Isimani Tanzania

3.1 Introduction

The amount of energy reflected from a plant in the visible and near infrared (NIR) portion of the spectrum has commonly been applied for generation of vegetation indices (VIs), such as the Normalized Difference Vegetation Index (NDVI). NDVI is the sensor value displayed on optical sensors (Govaerts *et al*., 2007). It is calculated from reflectance measurement in the red (R) and Near Infrared (NIR) portion of the electromagnetic spectrum as shown in Figure 3.1 and Equation 3.1. NDVI has been correlated to plant growth characteristics including chlorophyll content, light use efficiency and canopy density (Verhulst *et al*., 2009). Also NDVI has been correlated to many variables such as crop nutrient efficiency, yield and long term water stress (verhulst *et al*., 2009). The Normalised Difference Vegetation Index, is the most commonly used index of greenness derived from multispectral remote sensing data, and is used in several other studies on vegetation, where it has been proven to be positively correlated with density of green matter (Moran *et al*., 1994; Huete *et al*., 2002).

The latest developments associated with the use of Normalized Difference Vegetation Index include the works that have demonstrated successes in animal ecology related studies (Pettorelli *et al*., 2011). Over the last decade, numerous studies have highlighted the potential role of satellite data in ecological studies (Kerr and Ostrovsky, 2003; Turner *et al*., 2003), in particular the use of Normalized Difference Vegetation Index (Pettorelli *et al*., 2005). In 2005, Pettorelli *et al*. (2005) highlighted examples of issues studied based on the use of NDVI, emphasizing on how NDVI-based indices could be linked to animal distribution and abundance (Table 3.1).

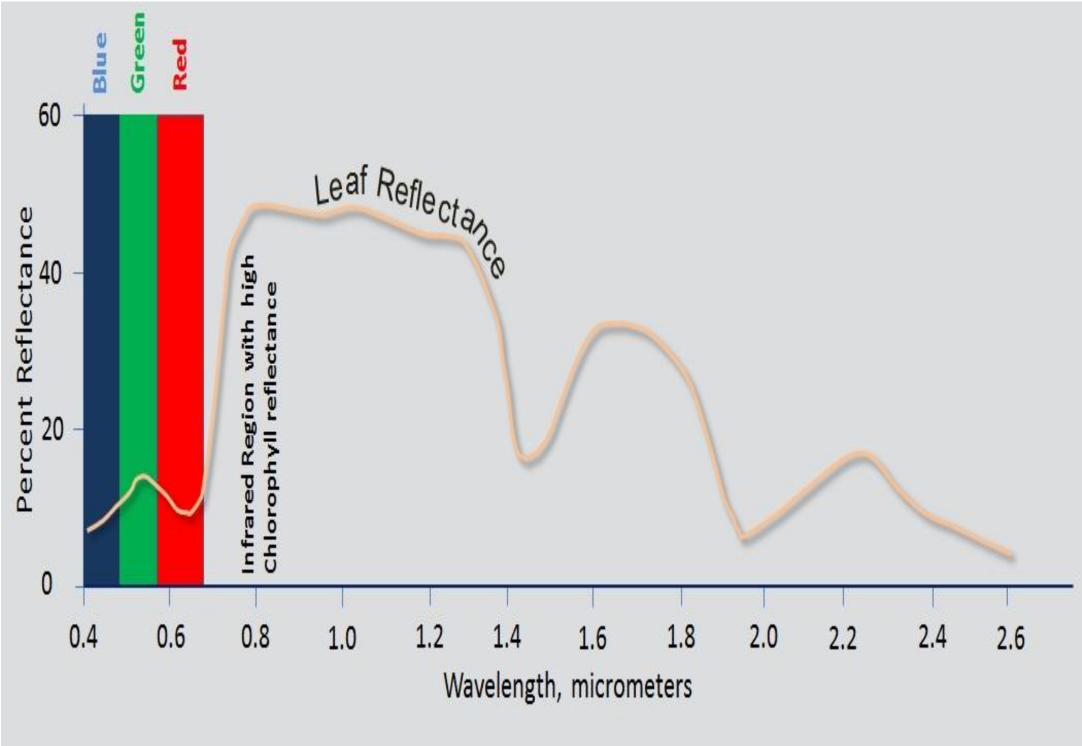


Figure 3.19: Idealized spectral reflectance of healthy vegetation (Source: Janssen and Huuenemen, 2001)

$$NDVI = \frac{NIR - R}{NIR + R} \qquad \text{......} 3.1$$

Where by: NDVI = Normalized Difference Vegetation Index

R = Surface reflectance in the red portion of the electromagnetic spectrum

NIR = Near Infra-Red band respectively

Table 3.1: Examples of issues studied based on NDVI which could be linked to animal distribution and abundance

Issue	Group/species	Sub-discipline	Source
Energy–abundance relationship	African ungulates	Macroecology	Pettorelli *et al.* (2009)
Energy–species richness relationship	Birds	Macroecology	Ding *et al*. (2006)
Energy–community composition relationship	Beetles	Macroecology	Lassau and Hochuli (2008)
Resource distribution, resource dynamics and space use	Brown bears	Habitat selection	Wiegand *et al*. (2008)
Resource dynamics and population dynamics	Rodents	Population dynamics	Andreo *et al*. (2009)
Climate, vegetation dynamics and past ecological processes	Plague outbreaks	Paleoecology	Kausrud *et al*. (2007)

(Source: modified from Pettorelli *et al*., 2011)

NDVI has provided significant opportunities in behavioural ecology, habitat selection studies, movement ecology, environmental conservation and paleo-ecology across sub-disciplines, ranging from macro-ecology and species niche modelling to evolution (Table 3.1). It can also provide critical information about vegetation dynamics that allow the investigation of relationships between animal populations and environmental variability (Pirotti *et al*., 2014). For example, De la Maza *et al*. (2009) demonstrated that NDVI could be related to ground-truthed measurement of vegetation productivity, allowing exploration of the relationship between rainfall patterns and vegetation cover and productivity in semi-arid Chile. In that study, the authors were able to demonstrate that rainfall not only influences plant productivity, but also has a strong effect on plant phenology, determining the length of the growing season, which in turn contributes to increased plant biomass.

The NDVI was found to be very useful in monitoring rainfall dynamics in semi-arid and arid areas where grasslands and savannah bushlands are the dominant vegetation types primarily because semi-arid vegetation is very sensitive to variations in precipitation (Prince and Tucker, 1986). For example, a linear relationship between NDVI and precipitation was demonstrated in a range of semi-arid lands of Africa (Nicholson *et al*., 1990). Precipitation and green vegetation dynamics are a major determinant of life cycles of animals and insects in semi-arid lands in many parts of the world (Wu, 2014; Masemola, 2015).

In many other studies abundant precipitation has been well demonstrated to increase the population growth of rodents as reported in southern and eastern Australia (Singleton 1989; Pech *et al*., 1999), western South America (Lima *et al*., 1999), and Inner Mongolia, China (Li and Zhang, 1993). The causal mechanism behind the impact of precipitation on rodent abundance appears to be an increased primary production, both as herbage production and seed-bank storage. The rodent distribution was modelled in relation to landscape characteristics in a study conducted in Shiqu County, China using (i) a Landsat ETM+ derived hard classification, (ii) single-image Landsat ETM+ derived NDVI, (iii) single-image MODIS 16-day composite NDVI and (iv) time-series MODIS 16-day composite NDVI imagery (Marston *et al*., 2007). The results of that study confirmed that time-series NDVI data can be used to model rodent distributions with success. In the Wyoming Basin Eco-regional Assessment area, Western United States of America, deer mice were associated with areas having moderately productive habitat as measured by NDVI, increased grassland land cover, and proximity to intermittent water (Hanser *et al*., 2011).

In the tropics, rainfall data are seldom accurately recorded, and are often discontinuous in time. In the scope of plague-research in northeast Tanzania, rainfall patterns were reconstructed, based on time series of NDVI (Debien *et al*., 2010). In that study satellite imagery in the form of MODIS NDVI, and rainfall data collected from the TRMM sensors were successfully used to reconstruct historic precipitation patterns over a mountainous area in north-eastern Tanzania. Rainfall promotes abundant primary productivity of particularly nutritious seeds and vegetation cover, which enable natural habitats to maintain large numbers of rodent species (Leirs, 1999). In Tanzania, it is widely accepted that rainfall plays an indirect role in the ecology of rodent species such as *Mastomys natalensis* by determining when, where and how much food will be available (Massawe *et al*., 2011). However, studies that relate rodent abundance, rainfall patterns and NDVI in smallholder agro-ecosystems in the tropics and Tanzania in particular are relatively few. The use of Vegetation Indices (VIs) such as NDVI to correlate with rainfall patterns and other landscape characteristics is likely to enhance the understanding on the diversity, breeding patterns and density fluctuations of rodents in rural farming communities, hence contributing important knowledge towards ecologically based management of rodent pests in East Africa.

This study intended to provide insights into the use of NDVI in complementing efforts towards sustainable ecologically based management of rodent pests, which is as an important step to reduce rodent crop damage and losses experienced by farmers. Therefore, the main objective of the current study was to evaluate the potential of NDVI of common vegetation habitats derived from satellite remote sensed data for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems. More specifically the study i) examined NDVI of vegetation habitats in a semi-arid area with unimodal rainfall pattern and ii) established a relationship between NDVI of the common vegetation habitats and small mammals distribution and abundance in space and time. The study hypothesized that rainfall pattern, greenness of vegetation and terrain characteristics synchronize with rodent pest abundances in the semi-arid areas of Isimani in Iringa Tanzania.

3.2 Materials and Methods

3.2.1 Description of the study area

The study was conducted between September 2015 and June 2016 in Isimani Division, Tanzania. The area is located between Universal Transverse Mercator (UTM) coordinates, 640 000 m and 840 000 m E and 9 100 000 m and 9 240 000 m N, Zone 36 M (Fig. 3.2). It covers an area of about 1266.7 km^2. The area is characterized by three geomorphic units, namely Plateau, Escarpment and rift valley floor.

The plateau is situated on a gentle NE sloping terrain with minor depressions along river courses which are tributaries of Great Ruaha River. It is marked by a network of low ridges characterized by low relief with gentle to undulating slopes (2 to 10 %) and drainage patterns that follow fault-controlled troughs. The valleys which were originally V-shaped are now filled in with sediments, resulting in U-shaped, and/or flat valley bottoms. The escarpment rises abruptly from the surrounding rift valley floor (850 m a.s.l.) to about 1000 m a.s.l. It is characterised by steep slopes of over 100% and in some areas the escarpment forms a series of vertical rocky cliffs. A large part of the escarpment is conserved forest of *miombo* woodland type with grasses and shrubs underneath. The rift valley floor is located within the altitude range of 700 - 850 m a .s. l. It is part of the central rift valley system bounded by the central plateau (Dodoma-Singida system) and the southern highlands with a gently undulating topography.

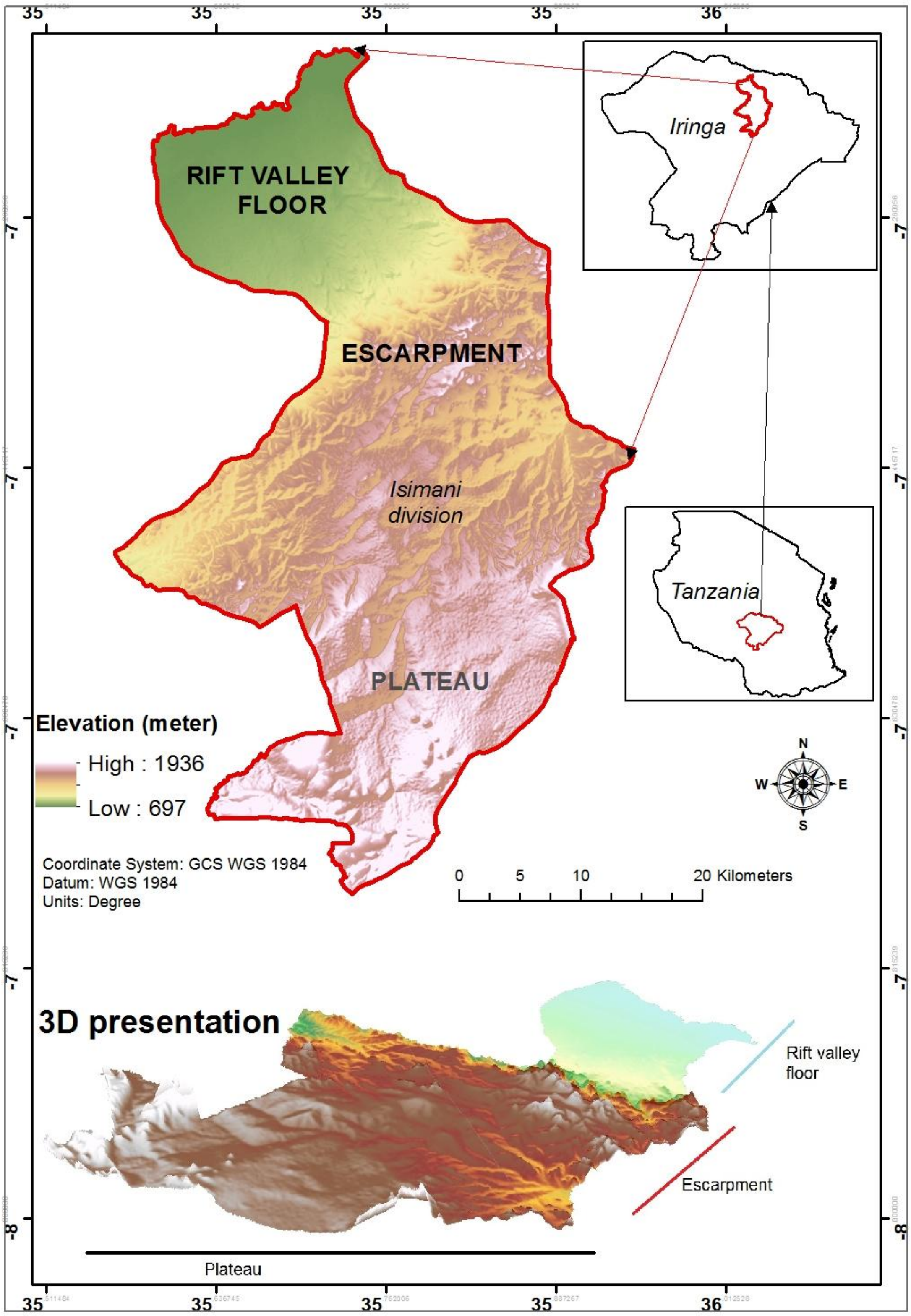


Figure 3.20: Location map of the study area

The landscape of Isimani division is part of the southern highlands of Tanzania, which were tectonically uplifted with the formation of the East and Central African Rift valley system during the Tertiary Epoch. The main rock types consist of Precambrian metamorphic rocks including gneisses, amphibolites and lenses of granulites of the Isimani Suite. The area is in the dry part of the Iringa Region in the transition between Agro-ecological Zone (AEZ) 8 and 16 which is described as having harsh agricultural conditions (De Pauw, 1984). The soils of the study area are sandy clay loam in the plateau, sandy clay in the escarpment and clayey in the rift valley floor. The study area shows large differences in relief dissection and intensity, vegetation and land use patterns, and human activities. Due to low and unevenly distributed rainfall, agricultural production is low (characterised by poor harvest) and irregular (Mbilinyi, 2000).

The study area receives a unimodal annual rainfall that ranges from 200 to 700 mm/year. The rainy season is associated with the seasonal movement of the Intertropical Convergence Zone (ITCZ) and is characterized by low erratic rainfall and periodic droughts giving it the characteristic of a semi-arid nature where precipitation consistently below potential evapotranspiration. The mean annual temperature and relative humidity are variable depending on the relief. The maximum temperature ranges from $27^{o}C$ to over $30^{o}C$, whereas the minimum temperature ranges from $15^{o}C$ to 19^{o} C.

Vegetation characteristics vary with topography, soil type and elevation. The plateau is intensively cultivated with maize and sunflower in association with patches of scattered acacia trees, grasses and shrubs while a large part of the escarpment is conserved forest of *miombo* woodland with grasses and shrubs underneath. The rift valley floor is covered by acacia trees, scattered baobab trees and grasses with patches of woodland. Land use in the rift valley is predominantly scattered cultivation (sorghum cropping system) and extensive grazing (Mbilinyi, 2000).

Isimani division was purposively selected for this study due to recently reported rodent outbreaks (Tewele, C. personal communication, 2015). Six sampling sites including Uyole, Mkungugu and Nyang'oro for the plateau landscape; upper and lower positions of escarpment for the escarpment landscape and Izazi village area for the rift valley floor were selected where detailed studies including terrain characterization, identification and mapping of vegetation for NDVI determination and rodent trapping were carried out.

3.2.2 Estimation of NDVI across vegetation habitats and landscapes

NDVI was calculated from Landsat 8 (Operational Land Imager (OLI)) sensor with satellite images for each period covering the corresponding start, mid and end of dry and wet seasons (Table 3.2). It was calculated as the normalized difference in reflectance between Red channel (0.636- 0.673 μm) and near Infrared (NIR) channel (0.851 - 0.879 μm) of electromagnetic spectrum using Equation 3.2 (Knight and Kvaran, 2014; Pirotti *et al*., 2014). The Landsat 8 OLI sensor provides 16-bit images at 30 m spatial resolution for multispectral bands (10m for panchromatic and 100m for thermal) (Knight and Kvaran, 2014). The images were obtained from level 1 product of the USGS Landsat archives considering cloud free and day time as criteria for obtaining good satellite images. The images were geo-referenced to EPSG: 21036 for uniform coordinate system and to eliminate the effect of clouds, the Maximum Value Composite (MVC) was used in NDVI data processing (Mingjun, 2007). In MVC procedure, the multi-temporal geo-referenced NDVI data were evaluated on a pixel basis, to retain the highest NDVI value for each pixel location.

Table 3.2: Remote sensing data acquisition

Seasonal		Required period	L 8 (OLI 30 m) date	SRTM DEM (30 m)
	SD	May, June and July	14^{th} Jun-16	
Dry season	MD	August and September	1^{st} Aug and 18^{th} Sept-15	
	ED	October and November	20^{th} Oct and 21^{st} Nov-15	23^{rd} Sept-14
Wet season	SW	December and January	7^{th} Dec-15 and 8^{th} Jan-16	
	MW	February	11^{th} Feb-16	
	EW	March and April	10^{th} March-16	

Key: SD = start dry, MD = mid dry, ED = end dry season,
SW = start wet, MW = mid wet and EW = end wet season.

$$\text{NDVI} = \frac{\text{NIR- R}}{\text{NIR+R}} \qquad \text{.......... 3.2}$$

Where by:
NDVI = Normalized Difference Vegetation Index
R = Surface reflectance in the red portion of the electromagnetic spectrum
NIR = Near Infra-Red band respectively

3.2.3 Rainfall data collection

Rainfall datasets were obtained from both the real time, Tropical Rainfall Measuring Mission (TRMM) Multi satellite precipitation analysis (TMPA-RT, 3B42RT-V7) and Nduli Meteorological Station. The mean Monthly rainfall data from TMPA-RT grids with a spatial resolution of 0.25^0 by 0.25^0 were acquired from March, 2015 to March, 2016 for start, mid and end periods of each wet and dry season. Point rainfall data available from Nduli Meteorological Station recorded from 1986 to 2016 was used for evaluating site climatic patterns and for validating both NDVI predicted rainfall and the TMPA-RT derived data. Rainfall patterns from point rainfall measurement available for Nduli Meteorological Station located in the plateau area was related with TMPA-RT rainfall measurement in order to obtain a temporal relationship that could be used to relate with NDVI for predicting rainfall in space and time and for predicting small mammals at a fine scale.

3.2.4 Data collection procedures

The highway from Iringa to Dodoma was used as a transect to guide sampling and data collection where a buffer of 1 km on each side of the road/highway was created to mark crosswise boundary for the extent of the study area across six sample sites located along the road from Nduli to Izazi. Ground survey was carried out in both dry and wet seasons for three different periods covering Start, Mid and End of each season (Table 3.2). Considering spatial variability of the landscape characteristics throughout the study site, stratified random sampling procedure based on broad land cover types and topography was used to locate the quadrats in each sample area (Hieronimo *et al*., 2014).

A total of 144 quadrats were established for the six sample sites (i.e. Uyole, Mkungugu, Nyang'oro (for the plateau), upper and lower positions of the escarpment (for the escarpment) and Izazi village area for the Rift valley floor). For each sample site, 24 quadrats each measuring 100 m x 100 m were randomly located for detailed characterisation of vegetation habitats and small mammal trapping. Decision on the number of observations/quadrats per site was determined following the experience gained from a similar study in the west Usambara Mountains, Tanzania (Hieronimo *et al*., 2014), the size and representativeness of the sample site, time and resources availability. At each observation site, information on vegetation habitat characteristics was documented for interpretation of NDVI and small mammal trapping was carried out.

3.2.5 Small mammal trapping

A total of 49 traps (in a grid of 7 x 7 traps at 10m intervals) were set for each spatially located quadrat (Hieronimo *et al*., 2014). Sherman LFA live traps (7.5 x 9.0 x 23 cm; HB Sherman Traps, Tallahassee, USA) baited with peanut butter and maize flour were used (Hieronimo *et al*., 2014). Animals captured for each quadrat were counted and rodent trap success was then calculated based on the number of small mammals trapped divided by the product of the number of traps used and number of trapping nights as shown in equation 3.3 (Ralaizafisoloarivony *et al.*, 2014).

$$\text{Trap success} = \frac{N}{Nt \times Nn} \times 100 \qquad \text{..........3.3}$$

Whereby;

N = number of small mammal trapped,
Nt = number of traps used,
Nn = Duration in terms of nights during which the trap was set.

3.2.6 Data Analysis

Statistical analysis was conducted using STATISTICA and R software and spatial analysis modules available in the QGIS version 2.12.2 and ArcGIS version 10.3 software. In STATISTICA version 12 and R version 3.3.2 software, both linear and multiple regression were used for deriving relationships and model for predicting rodent abundance from rainfall and NDVI.

The degree of association between variables (rainfall and NDVI across seasons, NDVI derived rainfall, predicted rodent abundance from rainfall and predicted rodent abundance from NDVI) was measured by linear regression and calculation of the Pearson correlation coefficient (r) at $P \leq 0.05$. The model predicted values were validated by linear regression analysis between model predicted and the actual recorded abundance of small mammals across habitats and seasons and the degree of association was calculated using Pearson correlation coefficient (r) at $P \leq 0.05$. Predicted small mammal abundance maps across habitats and seasons were created using geospatial analysis tools in QGIS version 2.12.2 and ArcGIS version 10.3 across the studied landscapes and seasons.

3.3 Results and Discussion

3.3.1 Relationship between TMPA-RT measured rainfall and NDVI across Isimani landscapes

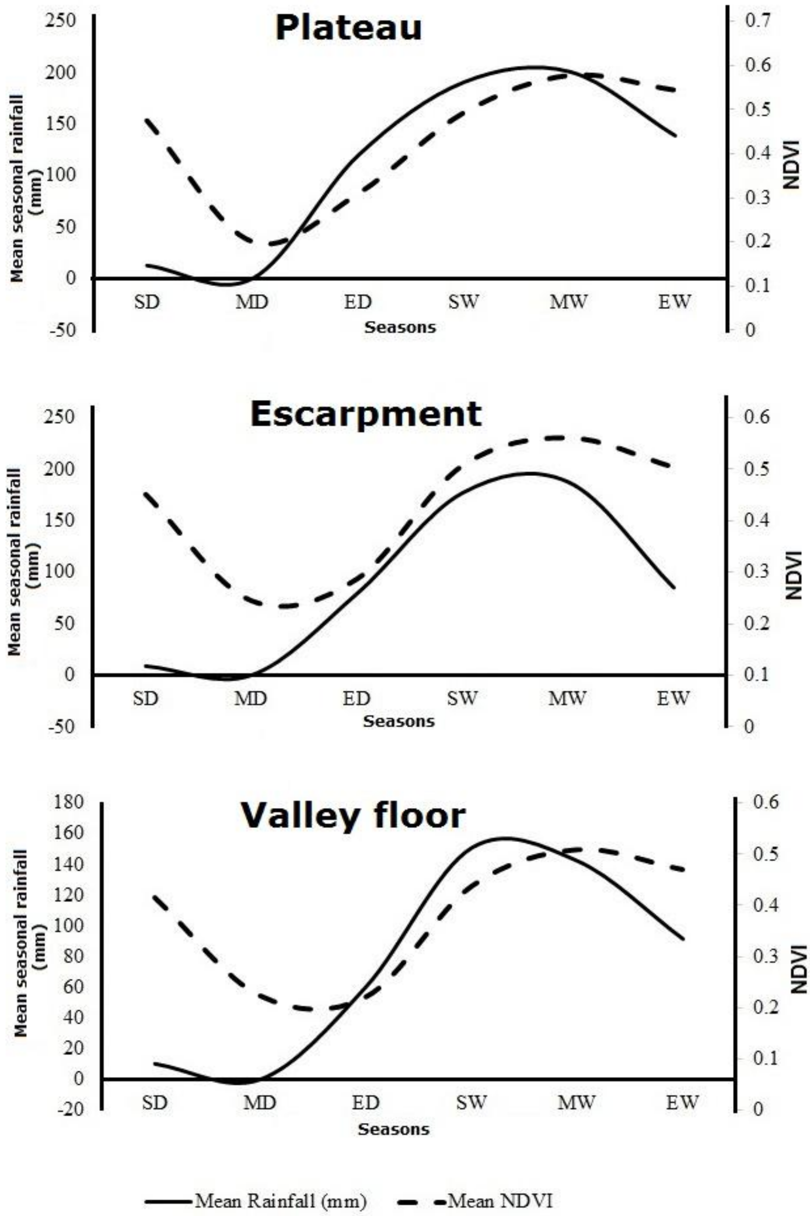
The relationship between rainfall and NDVI across Isimani landscapes is presented in Table 3.3. Results show that there is a good correlation (r>0.6) between rainfall and NDVI across the studied landscapes (plateau, escarpment and valley floor). A slight variation was observed in different landscape units with escarpment having higher correlation (r = 0.688) than the plateau (r=0.653) and the valley floor (r =0.652). The Normalised Difference Vegetation Index, is the most commonly used index of greenness derived from multispectral remote sensing data, and is used in several studies on vegetation, since it has been proven to be positively correlated with density of green matter (Huete *et al*., 2002; Dabien *et al*., 2010). Several studies that have explored the strength of the vegetation-rainfall relationship have yielded converging results similar to the findings of this study that NDVI is positively correlated with TMPA-RT measured rainfall (Ji and Peters, 2004; Dabien *et al*., 2010).

The spatial patterns between seasonal rainfall (i.e. obtained from TMPA-RT, 3B42RT-V7) and NDVI across the Isimani landscape are presented in (Fig. 3.3). The results show that seasonal peaks of rainfall are followed by seasonal peaks of NDVI. Higher rainfall amounts are observed in December or January (start wet season) resulting in higher NDVI peaks in February or March, generally after a time lag of one month, which could be explained by the delay in the vegetation water uptake.

Table 3.3: Correlation between rainfall and NDVI in different landscape units

Landscape units	r	R^2
Plateau	0.653	0.5124
Escarpment	0.688	0.617
Valley floor	0.652	0.4289

Key: r = Pearson correlation coefficient, R^2 = coefficient of determination



Key: SD = start dry, MD = mid dry, ED = end dry season, SW = start wet, MW = mid wet and EW = end wet season.

Figure 3.21: Seasonal comparison of TMPA-RT rainfall and NDVI across different landscapes zones in Isimani Division, Iringa Tanzania.

Similar results were obtained by Dabien *et al.* (2010) in the west Usambara Mountains, Tanzania where higher rainfall was observed for the month of March 2000 and September 2002, resulting in higher NDVI peaks with a time lag of one or two months. The rainfall spatial distribution pattern across the Isimani landscape and NDVI were similar for all the studied seasons. Therefore, by considering the time lag, time series relationship between rainfall and NDVI could be used with success to improve the prediction of rainfall distribution at local level (Liu *et al*., 2016).

Results obtained in this study are in agreement with other studies conducted in semiarid and arid Africa and around the world (Ding *et al*., 2007). For example, a study conducted in the African Sahel of Mali and Niger by Nicholson *et al*. (1990) reported good relationship between monthly NDVI and monthly rainfall. Mahmoud *et al*. (2001) demonstrated varying degree of correlation between vegetation cover and rainfall across different land units in south-western part of Iran. In the study of Mahmoud *et al*. (2001), a strong correlation between the two variables was noted in the alluvial and flood plains. In the Isimani division and in the tropics in general rainfall data are not readily available and if available are not accurately recorded, and are often discontinuous in time. The results obtained in this study suggest that NDVI could be applied fruitfully to estimate rainfall variability and seasonality across the landscape. Therefore representative locations can be chosen for sampling of NDVI values to explain rainfall scenarios instead of being dependent on the locations of the meteorological stations.

3.3.2 Predicting rainfall from NDVI across Isimani landscapes

The graphical comparison of NDVI and rainfall as an exploratory test of the relationship between NDVI and rainfall show a weak relationship (R^2 = 0.45) (Fig. 3.4). Only 45 % of the predicted rainfall was explained by NDVI. Rainfall data used in this relationship is derived from TMPA-RT (Huffman and Bolvin, 2015). TMPA-RT provides accurate spatial and temporal measurements of rainfall information over the tropics, but only at coarse resolutions (0.25° × 0.25° resolution) often not suited for studies at finer resolutions (Huffman and Bolvin, 2015; Dabien *et al*., 2010).

In the study area vegetation communities vary spatially on different landscapes and follow elevation gradient. Ralaizafisoloarivony *et al.* (2014) noted in the west Usambara Mountains, Tanzania that most of the vegetation habitats including natural forest, plantation forest, cultivation, horticulture, settlements and bare dominantly occupied the elevations ranging from 1000 m a.s.l. to 1900 m a.s.l while the shrubs occupied lower altitudes (<1000 m a.s.l.) comprising the plain landscape. These landscape features portray a similar pattern observed in the study area of Isimani landscape where elevation seems to control the behaviour of vegetation patterns and rainfall distribution.

Therefore, to overcome the resolution problem of TMPA-RT rainfall measurements, a link was made between rainfall, elevation and NDVI of the common vegetation habitats in the study area. Previous research showed that the reconstruction of (historical) rainfall patterns based on the established relationship between rainfall and NDVI could give satisfactory results (Grist *et al*., 1997; Immerzeel *et al*., 2009). Hence, the relationship between elevation and rainfall in the study area was explored in this study.

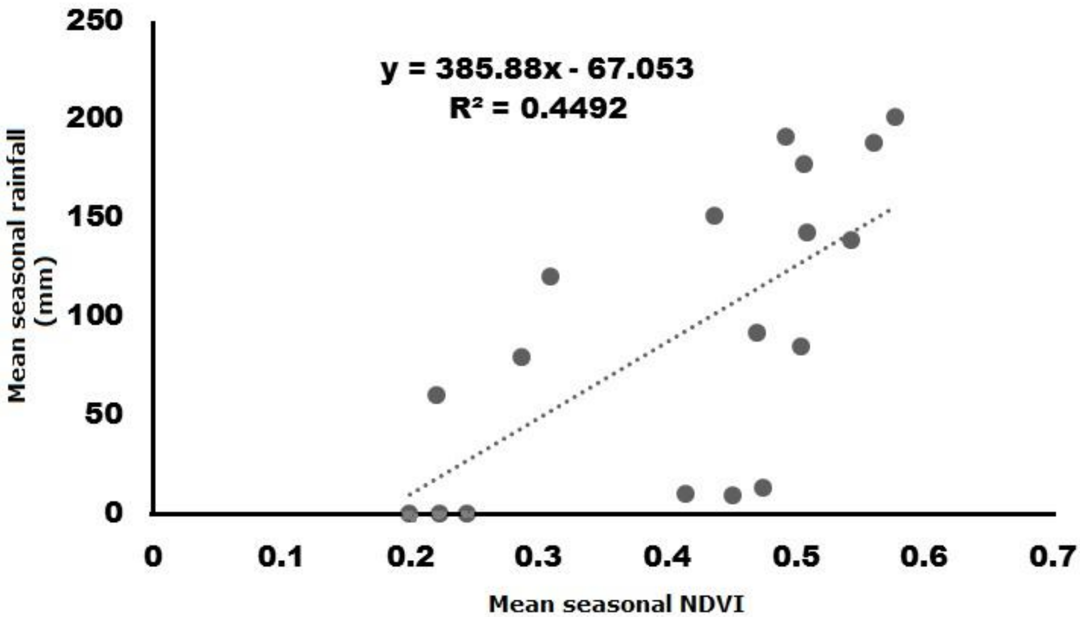
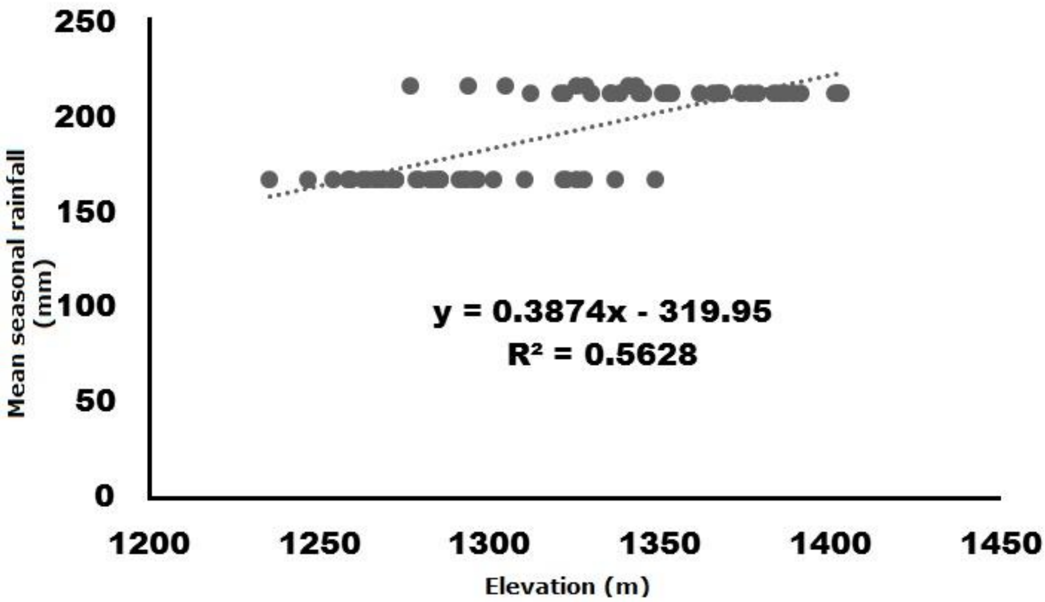


Figure 3.22: Relationship between rainfall and NDVI of different vegetation habitats in the study area

The rainfall regime in the Isimani landscape is closely related to elevation with the direction of slope having a secondary effect (Fig. 3.5). TMPA-RT derived mean seasonal rainfall in the study area shows a significant correlation with elevation (R^2 = 0.56) (Fig. 3.5). TMPA-RT mean seasonal rainfall on the lower elevations (< 900 m asl) was less than 80 mm while that at a higher elevations was more than 110 mm. From this relationship NDVI and elevation were used as predictor variables for predicting rainfall based on TMPA-RT rainfall measurements. NDVI-elevation model for quantification of rainfall across vegetation habitats in Isimani landscape is presented in Table 3.4.

According to the model, the rainfall pattern in Isimani division was significantly (r = 0.76) correlated with NDVI and elevation and hence rainfall patterns in Isimani division could be predicted as shown in Equation 3.4. The linear regression model obtained during the calibration was used as the model equation for calculating rainfall. The general pattern of the predicted rainfall is presented in Figure 3.6. The results showed that the spatial distribution of the predicted rainfall across vegetation habitats and seasons is generally good. Leilei *et al*. (2014) reported good relationship between seasonal changes of NDVI and rainfall based on remote sensing in Tibet, China.



Key: The grouping of the data points was mainly due to course spatial resolution of the TMPA-RT rainfall data when applied at smallholder farming scale. Apart from its course resolution effect, it showed a great relationship with elevation across the plateau area of the Isimani division (R^2 = 0.56)

Figure 3.23: Relationship between mean seasonal rainfall and elevation in the study area

Table 3.4: Multiple regression statistics for predicting rainfall from NDVI and elevation

Variables	Coefficients	P-value	R^2	Multiple R	F	F_{signif}
Intercept	- 31.041	**	0.57	0.76	46.17	1.88×10^{-13}
NDVI	374.606	**				
elevation	0.0118	**				

Key: ** = P < 0.01, F_{signif} = significance F

$$Y = 374.606 (X_{ndvi}) + 0.0118 (X_{elev}) - 31.041 \quad \text{.......... } 3.4$$

Where; Y = Average seasonal Rainfall (mm)

X_{ndvi} = NDVI

X_{elev} = Elevation

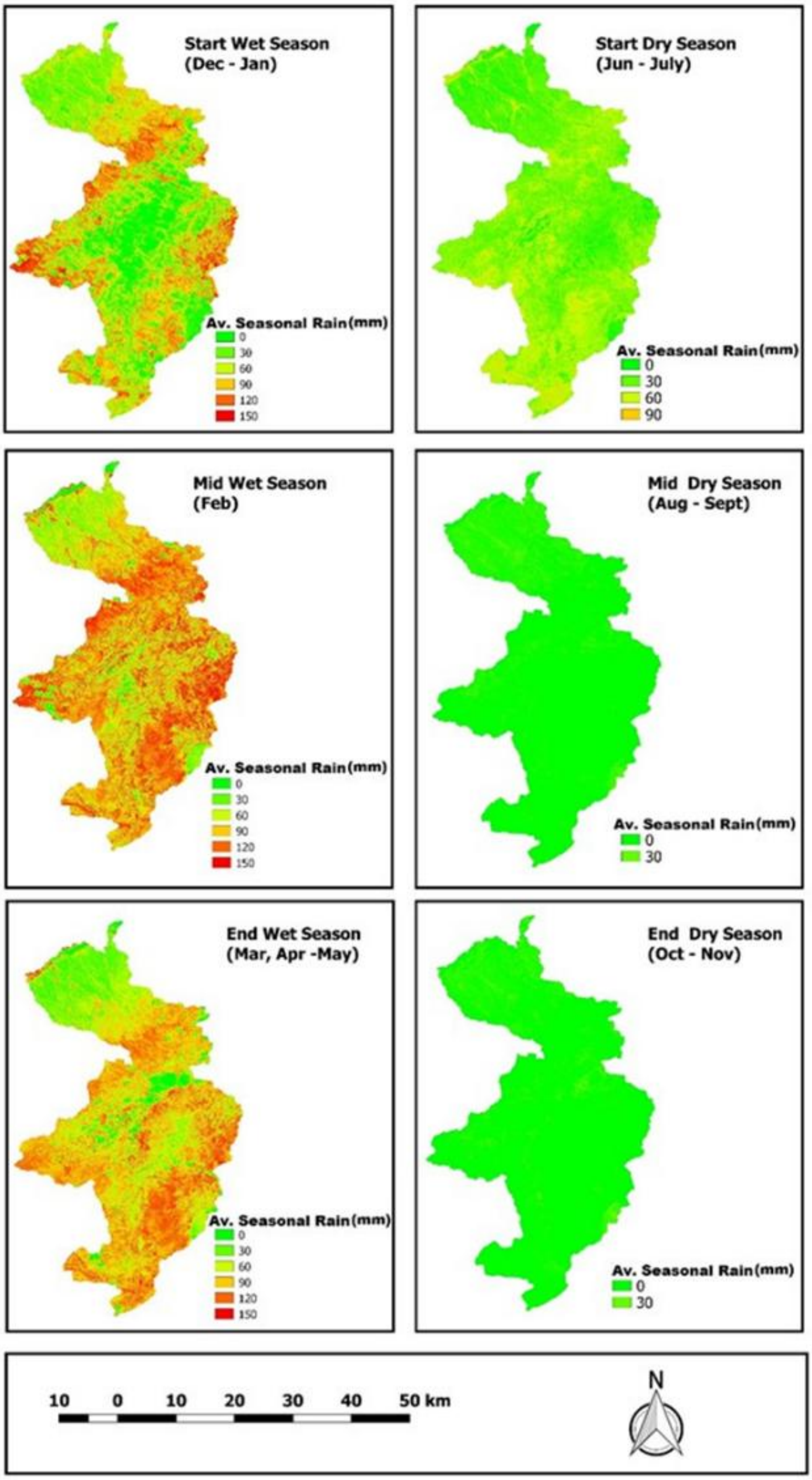
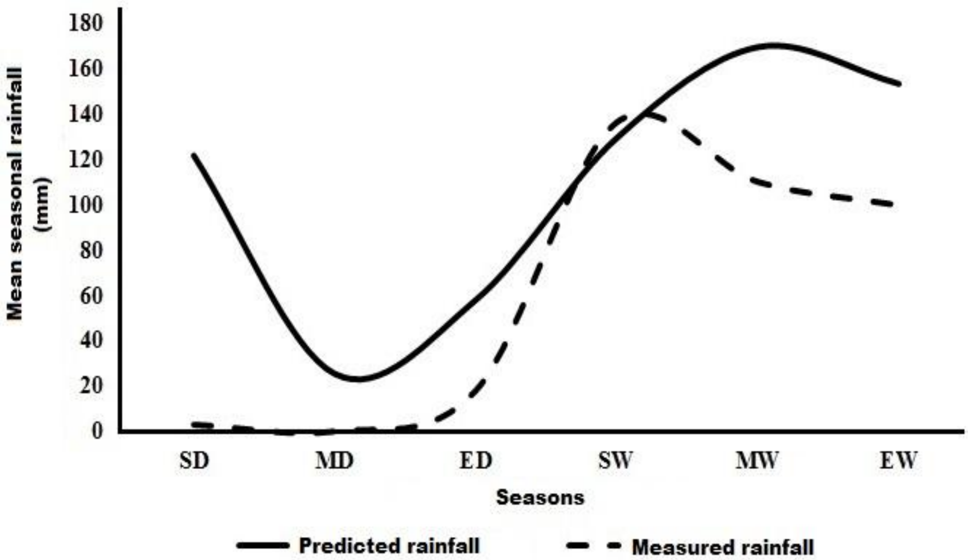


Figure 3.24: Spatial average seasonal rainfall predicted from NDVI and elevation

Despite the fact that TMPA-RT provides accurate measurements of rainfall in space and time, it only gives information at coarse resolutions (0.25° × 0.25° resolution), which is not suitable for studies like this i.e. at finer resolutions (Dabien *et al.*, 2010). Hence, in this study, a relationship between NDVI and TMPA-RT rainfall established to derive rainfall at a scale of smallholder farming agro-ecosystems. Similar approach conducted by Dabien *et al.*, 2010 in the Usambara mountains, where the link between TRMM coarse resolution rainfall measurement and NDVI established to reconstruct rainfall patterns at finer resolution.

To validate the model, predicted seasonal rainfall values calculated from NDVI images were compared with measured rainfall rates of Nduli Meteorological Station located in the plateau for the same seasonal periods. For every seasonal period, the rainfall rates at the location of the meteorological station were extracted for each seasonal raster image of estimated rainfall. These seasonal estimated rainfall rates were then compared with the seasonal in situ measurements of rainfall (Fig. 3.7).

As observed in Figure 3.7, the predicted seasonal rainfall values were high as compared to field measured seasonal rainfall values. Although the inter-seasonal patterns resembled well, the coinciding rainfall peaks of predicted seasonal rainfall versus measured seasonal rainfall observed to differ by a time lag of one month. To some extent, results in this study resembles that by Dabien *et al.*, 2010 in west Usambara Mountains. In that study the inter-annual and inter-seasonal trends, fall and rise at the same time in the estimated and measured rainfall time series.



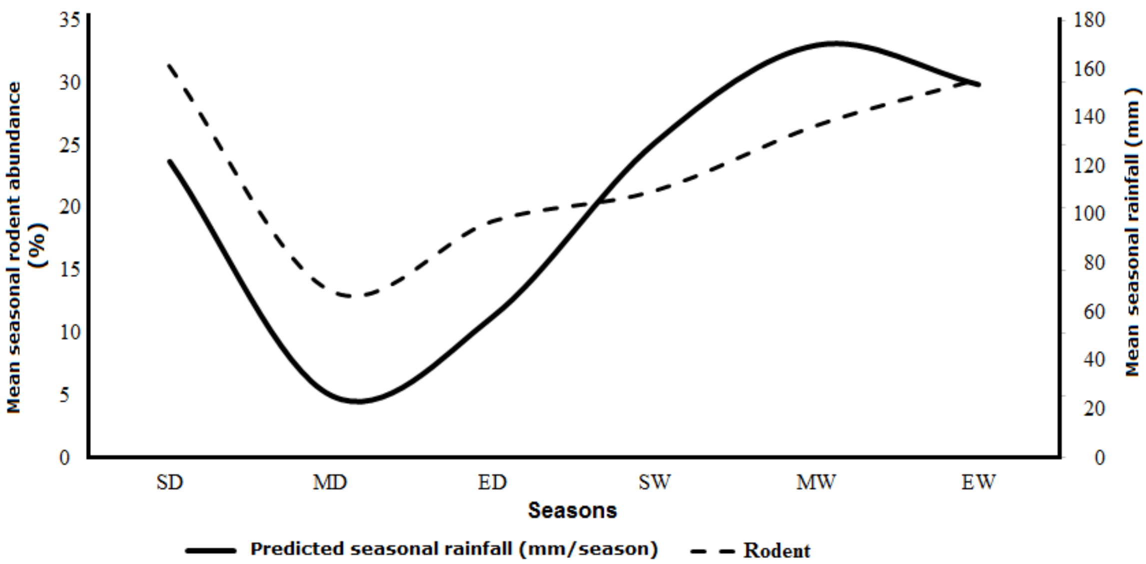
Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season.

Figure 3.25: Comparison of predicted seasonal rainfall values calculated from NDVI images with measured rainfall rates of Nduli Meteorological Station located in the plateau area

3.3.3 Seasonal comparison of rodent abundance and rainfall derived from NDVI and elevation

Results show that rainfall has a positive influence on the rodent abundance over the studied seasons. Increasing rodent population is observed at the start of the rainy season or end of the dry season i.e. in the months of November and December (Fig. 3.8). During the wet season (i.e. from December to March) lower rodent abundancies are observed followed by higher abundancies at the end of wet season (Fig. 3.8). Visually, higher rainfall amounts between December and March are followed by lower rodent abundancies (Fig. 3.9). Low rodent abundancies correspond with high rainfall amounts and peaks of dry periods.

In semi-arid grasslands of Inner Mongolia, China, Jiang *et al*. (2011) reported significant positive correlations between precipitation and abundances of rodent species. In agro-ecosystems of central Argentina, herbivorous rodents were more affected by rainfall and temperature, probably because of their effects on primary productivity (Andreo *et al.*, 2009). In the west Usambara Mountains in Tanzania, an increase in elevation was linked with concurrent increase in small mammal's abundance in space and time, both in number and diversity due to increased water and food availability (Ralaizafisoloarivony *et al.*, 2014). Bayessa (2010) indicated that, modified habitats including plantation forest and cultivation influenced rodent distribution due to availability and quality of food, shelter and rainfall. A study conducted in Simpson Desert, Queensland by Letnic (2003) reported that, heavy rainfalls in 2000 increased seed production which prompted increases in the populations of rodent species. Therefore, rainfall influences rodent abundance through its linkage to increase in primary production and water availability, which in turn increases food resources for small mammals (Witecha, 2011).



Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season.

Figure 3.26: Seasonal comparison of rodent abundance and rainfall derived from NDVI in the study area

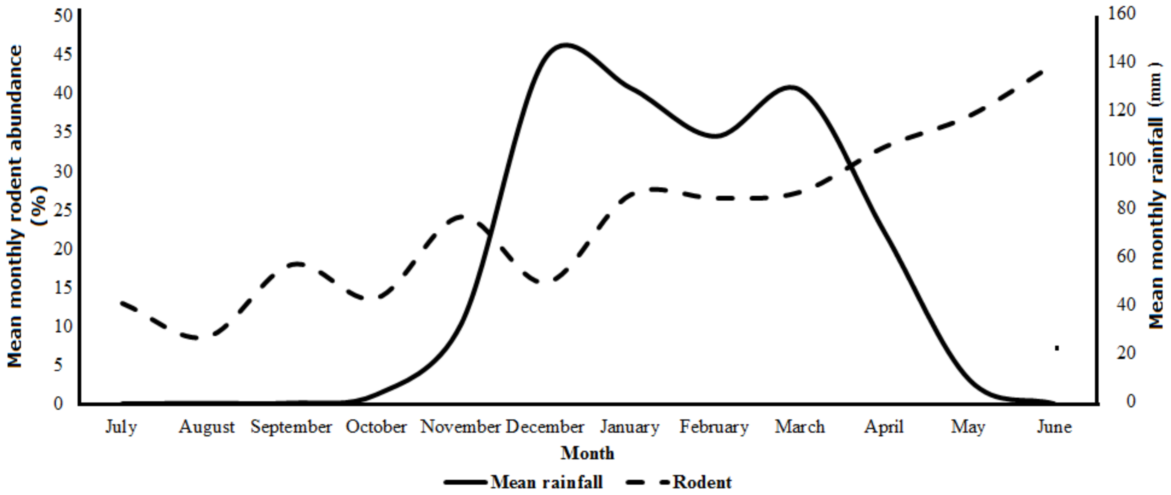
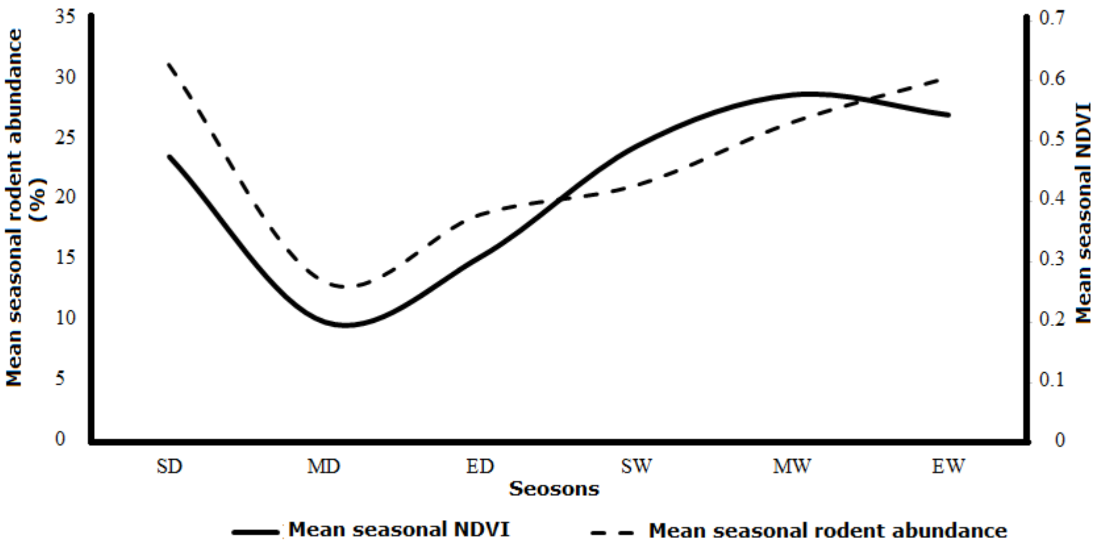


Figure 3.27: Monthly comparison of rodent abundance and field measured rainfall in the study area.

3.3.4 Seasonal comparison of rodent abundance and NDVI of common vegetation habitats

Rodent abundance was lowest in mid dry season (MD = August - September) and highest towards the end of wet season (EW = April and May) (Fig. 3.10). Temporal distribution of rodent abundance followed the NDVI pattern which is a proxy of primary productivity (Fig. 3.10). Peak NDVI has frequently been shown to correlate strongly with peak aboveground biomass in grasslands (Pettorelli, 2013).

In desert grasslands of California, USA a clear, positive correlation between primary productivity (measured as peak NDVI) and the presence of giant kangaroo rat (*Dipodomys ingens*) was reported (Bean *et al.*, 2014). In north-eastern Tanzania a stronger relationship between NDVI (MODIS) and rainfall (TRMM) was reported by Dabien *et al.* (2010) and that this relationship could be used to reconstruct rainfall patterns which has been shown to correlate with ground biomass or primary productivity; a proxy for rodent abundance (Butterfield and Malmström, 2009). In East Africa, where rainfall data is not readily available, studies that demonstrate the relationship between primary productivity measured as NDVI and rodent abundance are lacking. This study has demonstrated the power of NDVI for use in ecological research and in particular for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystem.



Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season.

Figure 3.28: Seasonal comparison of rodent abundance and NDVI of common vegetation habitats in the study area

3.3.5 Predicting rodent abundance using rainfall derived from NDVI of common vegetation habitats in different seasons

A strong linear relationship (R^2 = 0.7) was observed between rodent abundance and rainfall derived from NDVI across the Isimani landscape (Fig. 3.11). Mean seasonal rodent abundance increases with an increase in mean seasonal rainfall. Results also show that rodent population was higher in the wet season compared to the dry season in the study area (Fig. 3.12).

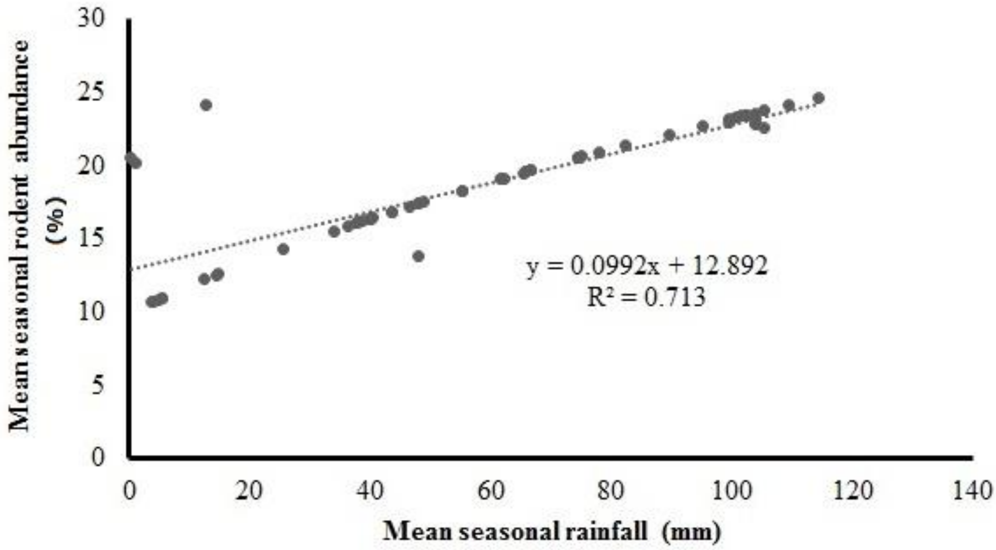


Figure 3.29: Relationship between rodent abundance and rainfall derived from NDVI across the Isimani landscape

Literature suggests that population dynamics of *Mastomys natalensis* rats in Tanzania are significantly affected by the distribution of rainfall during the rainy season (Leirs *et al*., 1996). For example, a logistic regression model explained 69% of the variation in occurrence of rodent outbreaks when rainfall data of the two peak months of the short (*vuli*) rainy season (December - January) in Tabora, Tanzania was used as the independent variable (Leirs *et al*., 1996). It is hypothesised that prolongation of the rainy season could generate excess food and cover, allowing for better survival and/or reproduction of rodents (Leirs *et al*., 2010), hence rainfall derived from NDVI could be a good predictor of rodent pest abundance. Patterns of growth and reproduction of multimammate rats, *Mastomys natalensis* (Smith, 1834) in Morogoro, Tanzania were also related to onset and abundance of rains (Leirs *et al*., 1990).

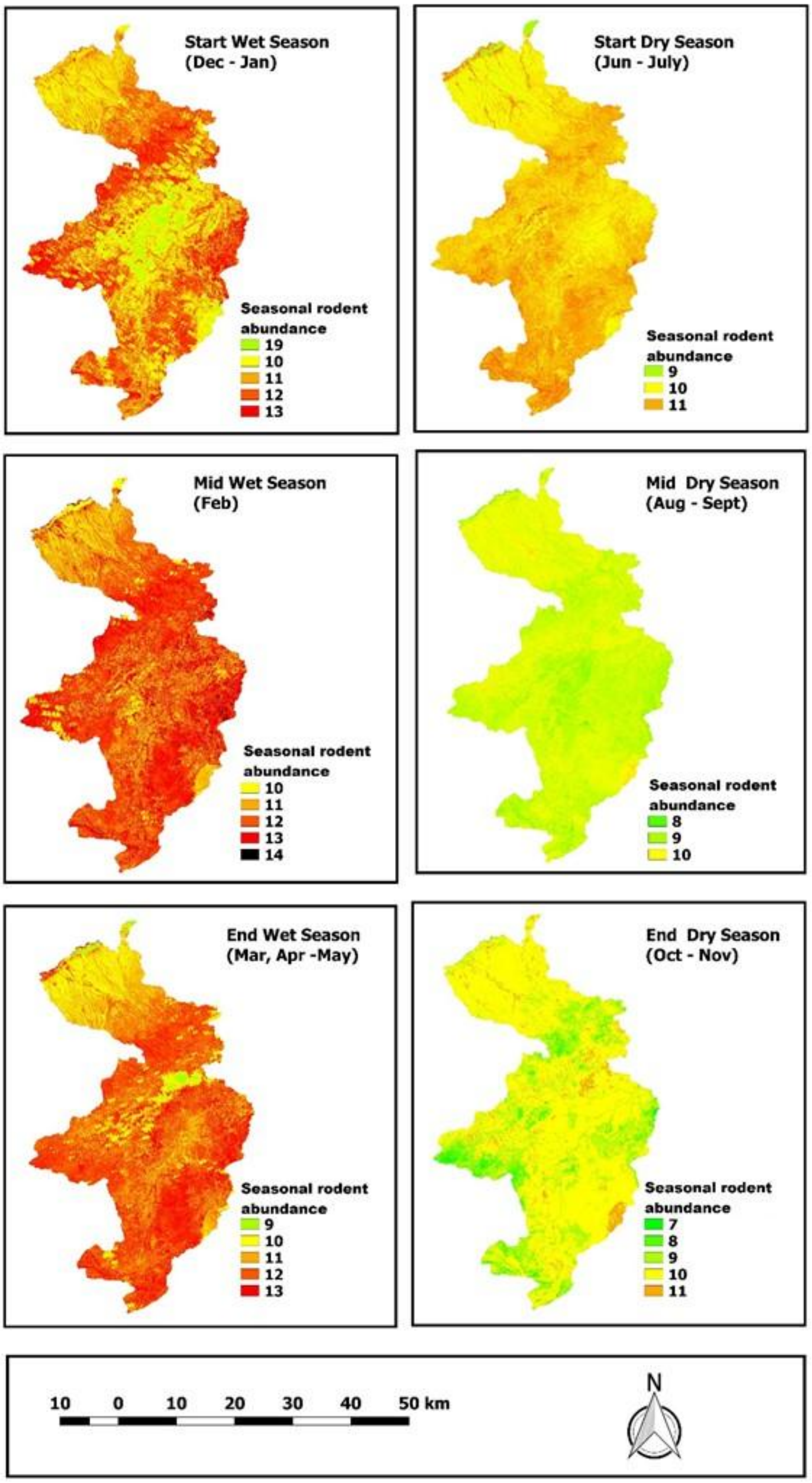


Figure 3.30: Spatial rodent abundance predicted using rainfall derived from NDVI of common vegetation habitats for different seasons

Rainfall data in many localities under smallholder farming are not readily available. The relationship obtained between rodent pest abundance and rainfall derived from NDVI provides a quick insight that could help in ameliorating pest control planning in some areas in Tanzania. It should be noted that NDVI derived rainfall is retrospective due to the time lag that has been mentioned earlier.

3.3.6 Predicting rodent abundance using NDVI of common vegetation habitats for different seasons

The relationship between rodent abundance and NDVI is presented in Figure 3.13. The results show positive linear relationship (R^2 = 0.706) between rodent abundance and NDVI (a measure of primary productivity). The linear regression model demonstrated in this study explained about 71% of the rodent abundance predictions by NDVI. Spatial-temporal rodent abundance predicted using NDVI of common vegetation habitats is given in Figure 3.14. Results show that the model predicted higher rodent abundances in the wet season (December to May) when compared to dry season (June to November) (Fig. 3.14). The lowest predicted abundances occur at the end of dry season during the months of October and November.

In the tropics and in semi-arid areas of East Africa in particular studies that relate rodent abundance and NDVI are rare. In central Argentina, population dynamics of grass mouse (*Akodon azarae*) was reported to be strongly influenced by human land use, indexed by NDVI (Andreo *et al*., 2009). NDVI has been used as an index of food or vegetation resources (Young *et al.*, 2009). In this study, mean NDVI values varied across the landscape and in different seasons. Higher values (0.2 to 0.6) were observed in the wet season and lower values (0.0 to 0.2) in the dry season corresponding to the spatial patterns of the predicted rodent abundances (Fig. 3.14). The results of this study suggest that

NDVI could be used as an index of vegetation and also as an index of food resources in the semi-arid areas of Tanzania for monitoring rodent pest.

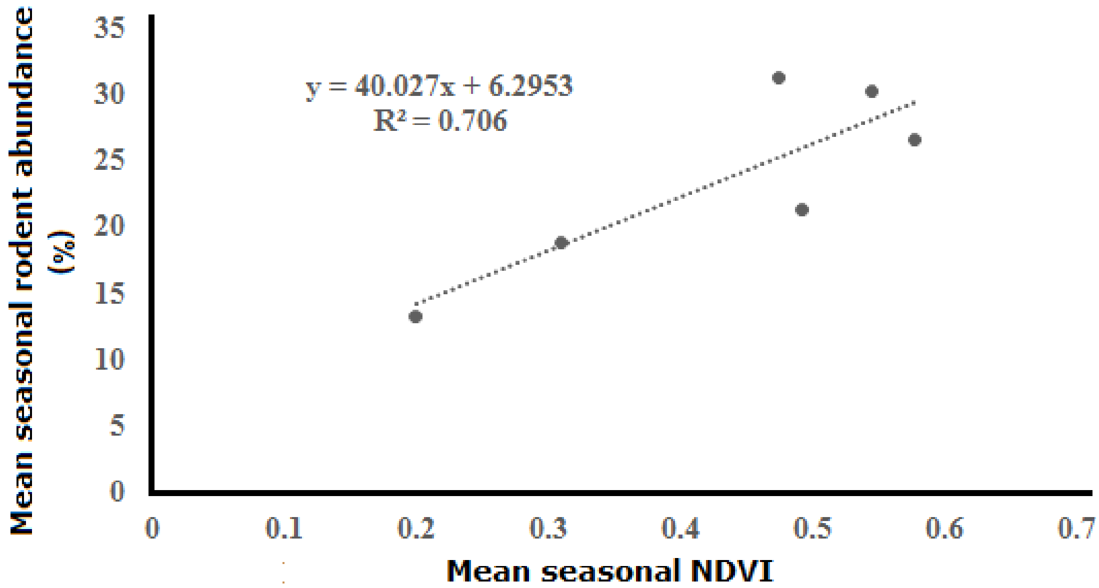


Figure 3.31: Relationship between seasonal rodent abundance and NDVI of common vegetation habitats

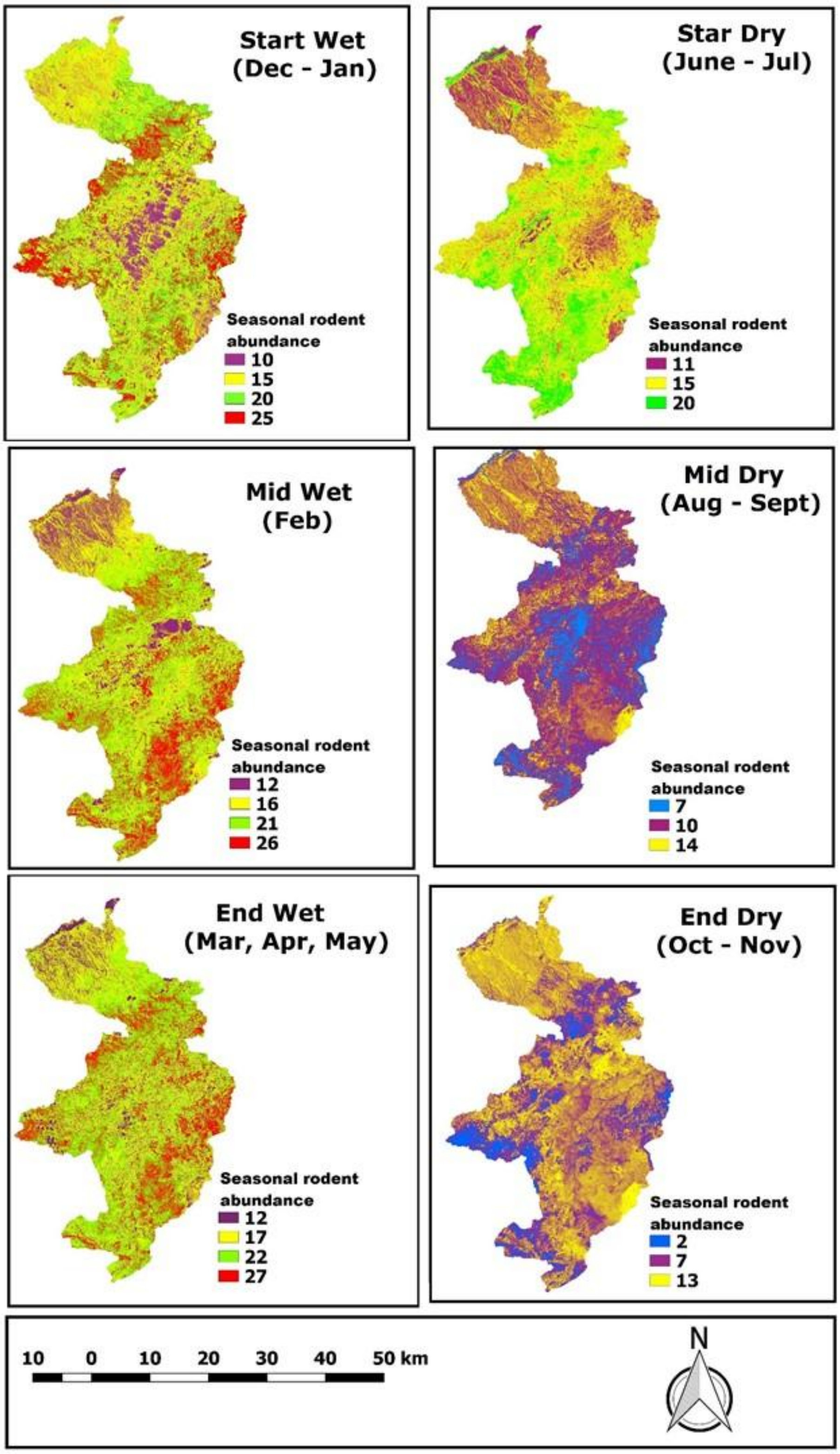
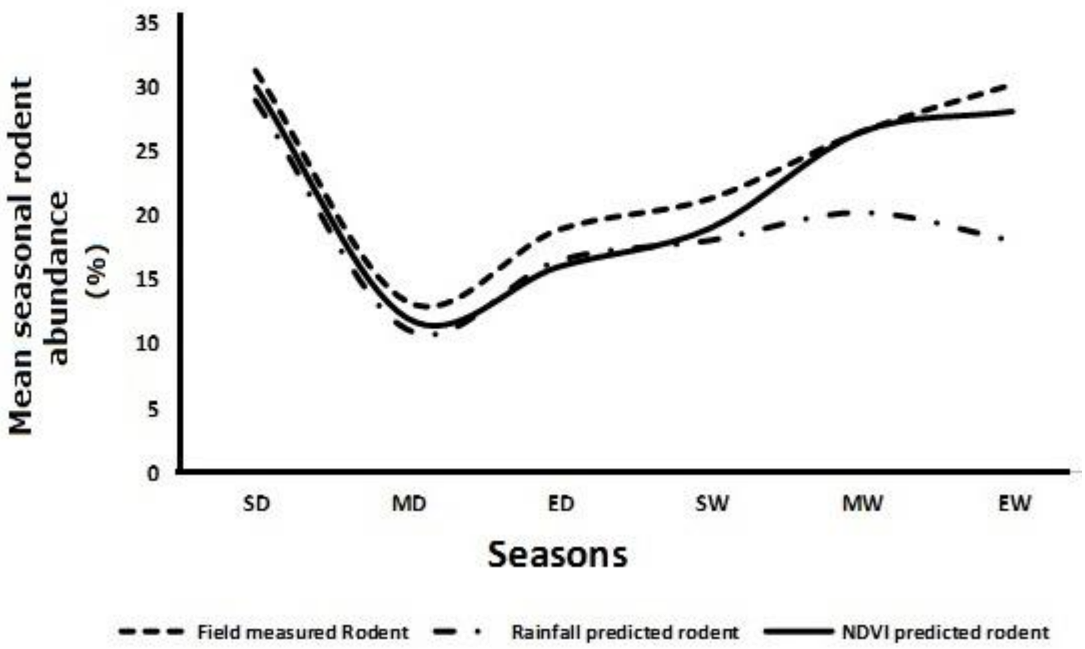


Figure 3.32: Spatial rodent abundance predicted using NDVI of common vegetation habitats in different seasons

3.3.7 Seasonal pattern of field measured rodents and predicted rodent abundance from rainfall and NDVI in the study area

Comparison of seasonal patterns for the field measured rodent and the predicted rodent abundances from rainfall and NDVI is presented in Figure 3.15. The NDVI predicted rodent abundance compares better with field measured rodent abundance than the rainfall predicted abundance (Fig. 3.15). Results from this study suggest that in a situation where rainfall data is hardly available, NDVI values of the studied landscapes could easily be used to predict rodent population particularly in smallholder farming ecosystems. These results confirm the hypothesis of this study that NDVI, vegetation derived index could be used to explain rodent abundance at fine scale.



Key: SD = Start of dry season, MD = mid of dry season, ED = End of dry season, SW = Start of wet season, MW = mid of wet season and EW = End of wet season.

Figure 3.33: Seasonal comparison of field measured rodents and rodent abundance predicted from rainfall and NDVI

3.3.8 Relationship between field measured rodents and predicted rodent abundance from rainfall and NDVI

The relationships between fields measured rodent abundance and predicted rodent abundance from rainfall and NDVI are presented in Figures 3.16 and 3.17. A strong relationship (R^2 = 0.98) was observed between the average seasonal field measured rodent abundance and NDVI predicted rodent abundance (Fig. 3.16). The exploratory test of the relationship between the average seasonal field measured rodent abundance and rainfall predicted rodent abundance also show a strong relationship (R^2 = 0.85) (Fig. 3.17). The results show that 98% of the predicted rodent abundance was explained by NDVI while rainfall explained only 85%. Both NDVI and rainfall predicted rodent abundance showed a strong correlation with the field measured rodent abundance (Table 3.5).

These results have therefore, supported the hypothesis that NDVI of common vegetation habitats derived from satellite remote sensing data has the potential for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems in the study area. Further, due to course resolution of TMPA-RT rainfall data and the sparse and not readily available ground measured rainfall data, the results also support the hypothesis that NDVI could be used to model rodent outbreaks within a reasonable short time compared to the sparse and not readily available rainfall data. Many studies have demonstrated good correlation between NDVI and crop parameters such as Biomass (Wiegand and Richardson, 1990; Verma *et al.*, 1998) and grain yield (Ali *et al.*, 2014).

Studies that have demonstrated correlation between NDVI and abundance of small mammals (rodent pests) are lacking in tropical sub-Saharan Africa (SSA). It is apparent from the results of this study that there is more work that remains to be done on the application of remote sensing derived NDVI in monitoring rodent pest population dynamics for fine-tuning ecologically based rodent management strategies.

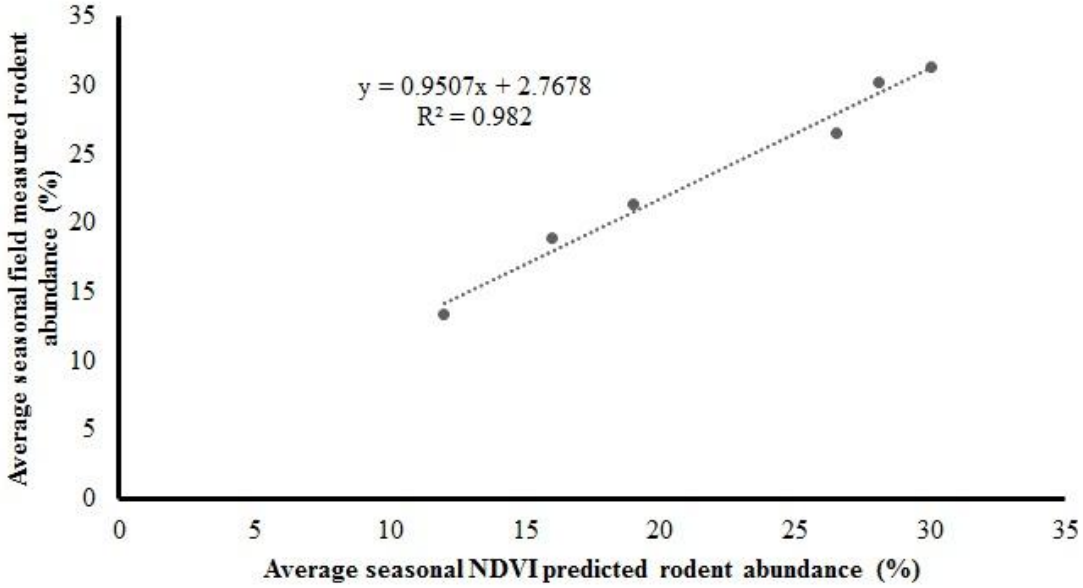


Figure 3.34: Relationship between the average seasonal field measured rodent abundance and NDVI predicted rodent abundance.

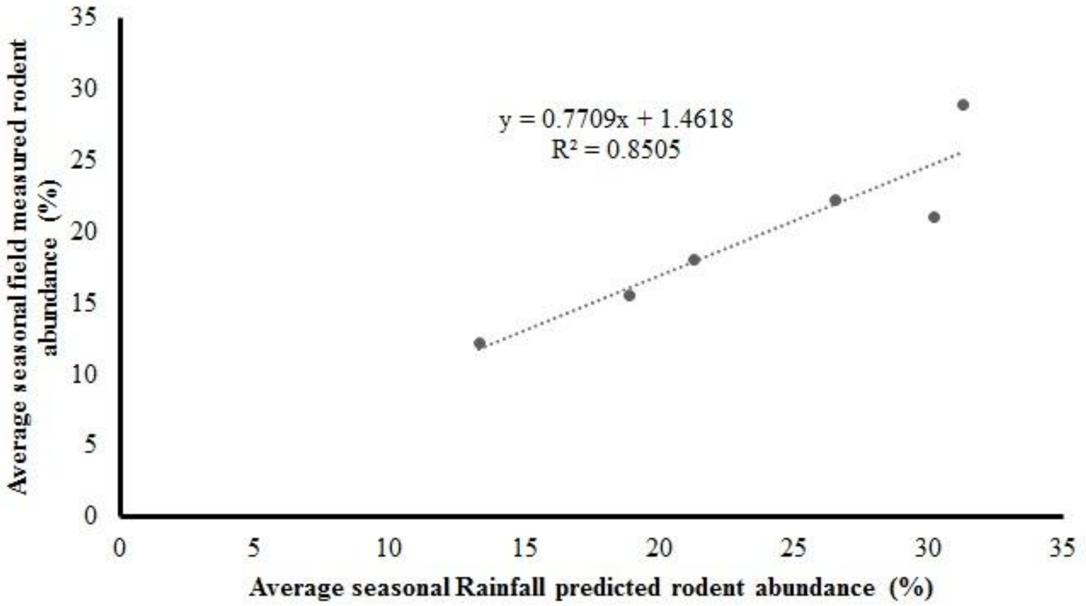


Figure 3.35: Relationship between the average seasonal field measured rodent abundance and rainfall predicted rodent abundance.

Table 3.5: Correlation matrix between fields measured rodent abundance and rodent abundance derived from rainfall and NDVI

	Field measured Rodent	Rainfall predicted rodent	NDVI predicted rodent
Field measured Rodent	1		
Rainfall predicted rodent	0.92*	1	
NDVI predicted rodent	0.99**	0.93*	1

Key: * = p < 0.05 and ** = p < 0.01.

3.4 Conclusions and Recommendations

3.4.1 Conclusions

The Normalised Difference Vegetation Index (NDVI), is the most commonly used index of greenness derived from multispectral remote sensing data, and has been used in many studies on vegetation, where it has been proven to be positively correlated with density of green matter. Over the last decade, numerous studies have highlighted the potential role of satellite data in ecological studies, in particular the use of Normalized Difference Vegetation Index. Recently, the use of NDVI-based indices linked to animal distribution and abundance has been emphasised. However, these technologies have not widely been adopted in the tropical sub-Saharan Africa (SSA) and Tanzania in particular. In this study, the potential of NDVI of common vegetation habitats derived from satellite remote sensing data was evaluated for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems. The following conclusions are made in the light of the results obtained in this study;

The study demonstrated a good correlation between TMPA-RT rainfall and NDVI across the studied landscapes with the escarpment having relatively higher correlation (r = 0.688), than the plateau (r = 0.653) and the rift valley floor (r = 0.652). These results suggest that NDVI could be applied fruitfully to estimate rainfall variability and seasonality across the studied landscapes. This implies that representative locations can be chosen for sampling of NDVI values to explain rainfall scenarios instead of being dependent on the locations of the meteorological stations.

In the study area, vegetation communities vary spatially on different landscapes and follow elevation gradient. The study has also observed that the rainfall regime in the Isimani landscape is closely related to elevation (R^2 = 0.56) with the direction of slope having a secondary effect. From this relationship, the study has demonstrated that rainfall pattern in Isimani division was significantly positively correlated (r=0.76) with NDVI of common vegetation habitats and elevation. This relationship suggests that rainfall pattern in the study area could be easily predicted from a link between NDVI and elevation as predictor variables.

Generally, temporal distribution of rodent abundance in the study area followed the NDVI pattern which is a proxy of primary productivity. This study has therefore demonstrated the power of NDVI for use in ecological research and in particular for monitoring rodent population dynamics and outbreaks in smallholder farming agro-ecosystems in the study area and other areas with similar conditions in Tanzania.

In this study, a strong linear relationship (R^2 = 0.7) was observed between rodent abundance and rainfall derived from NDVI across the Isimani landscape. Mean seasonal rodent abundance increases with an increase in mean seasonal rainfall. The relationship obtained between rodent abundance and rainfall derived from NDVI provide a quick insight that could help in ameliorating pest control planning in semi-arid areas of Tanzania.

Generally, there was positive linear relationship (R^2 = 0.706) between rodent abundance and NDVI (a measure of primary productivity). The linear regression model demonstrated in this study explained about 71 % of the rodent abundance predictions by NDVI.

The NDVI predicted rodent abundance compares better with field measured rodent abundance than the rainfall predicted abundance. This suggests that in a situation where rainfall data is hardly available, NDVI values of the studied landscapes could easily be used to predict rodent population particularly in smallholder farming ecosystems. The study show further that 98% of the predicted rodent abundance was explained by NDVI while rainfall explained only 85%.

This study has therefore supported the hypothesis that NDVI of common vegetation habitats derived from satellite remote sensing data has the potential for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems in the study area.

3.4.2 Recommendation

Findings from this study have provided some insights into the potential use of NDVI of common vegetation habitats derived from satellite remote sensing data for monitoring rodent pests under smallholder farming agro-ecosystems. However, results obtained revealed some gaps which require further research so as to provide future guidelines for monitoring rodent pest population dynamics and ecological based rodent management decisions, hence the following recommendations:

Studies that have demonstrated correlation between NDVI and abundance of small mammals (rodent pests) elsewhere are lacking in tropical sub-Saharan Africa. It is apparent from the results of this study that there is more work that remains to be done on the application of remote sensing derived NDVI in monitoring rodent pest population dynamics taking into consideration the major rodent pest species such as *Mastomys natalensis*, Arvicanthis spp, and Gerbillicus spp which are common in smallholder agro ecosystems.

Further research is also required to establish relationships between NDVI and rodent pest species composition and community structure in different habitats and seasonal rainfall patterns.

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CHAPTER FOUR

4.0 GENERAL CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

Small mammal pest outbreaks is still a major problem in most smallholder farming agro-ecosystems in Tanzania. The major constraint is diversification in habitat preferences by various small mammal species. Habitat characterization in space and time require a thorough understanding of the vegetation patterns, climate and terrain parameters for which abundance of small mammals can be predicted. Such knowledge in sub-Saharan Africa is poorly understood. The current study was carried out to characterize and spatially map the vegetation habitats associated with small mammal abundance in smallholder farming agro-ecosystems.

The Normalized Difference Vegetation Index (NDVI) of common vegetation habitats and rainfall patterns were also explored. NDVI, is the most commonly used index of greenness derived from multispectral remote sensing data, and has been used in many studies on vegetation, where it has been proven to be positively correlated with density of green matter. Over the last decade, numerous studies have highlighted the potential role of satellite data in ecological studies, in particular the use of Normalized Difference Vegetation Index. Recently, the use of NDVI-based indices linked to animal distribution and abundance has been emphasised. However, these technologies have not widely been adopted in the tropical sub-Saharan Africa (SSA) and Tanzania in particular.

The current study was therefore carried out as an intervention to provide key vegetation habitat variables that can be modelled to predict rodent pest abundance in smallholder farming agro-ecosystems in Isimani division, Iringa, Tanzania. In this study, the potential of NDVI of common vegetation habitats derived from satellite remote sensing data was evaluated for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems. In the light of the results obtained, the following conclusions can be drawn.

Generally, land use land cover types were observed to influence small mammal's habitats fragmentation and heterogeneity in space and time. In the studied site, it was revealed that vegetation habitat characteristics identified based on land use land cover types are largely dominated by agriculture that account for about 60% of the plateau landscape with intensive annual and cereal crop cultivation. Forest and woodland vegetation dominated the escarpment while the majority of sparse vegetation of acacia type and baobab tree with grassland and shrubs were dominant in the rift valley floor.

In the plateau area (1295 – 1590 m a.s.l.) a series of undulating hills were observed, that give rise to convex low ridge summits and concave valley bottoms characterised by the linear ridge slopes with very deep sandy clay loam soils commonly occurring on the transition between convex and concave landscapes. Maize cultivation is the dominant land use with severe and frequently reported rodent outbreaks. It has been demonstrated in the current study that the plateau habitats support more small mammals (80%) than the habitats in the other landscapes. This suggests that the land use/cover observed in this unit provides relatively "better" habitats for rodent pests in the study area.

A strong correlation (r=0.96) was obtained between ground measured point rainfall data and the real time Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA-RT) rainfall data across vegetation habitats. From this relationship it is suggested that rainfall pattern and NDVI could be related and used as a proxy for spatial prediction of small mammals.

In this study, a general spatial variability of mean NDVI values with seasonal pattern across the studied landscape units was observed, whereby, higher values (0.2 to 0.6) were observed in the wet season and lower values (0.0 to 0.2) in the dry season. The results suggest that NDVI could be used as an index of vegetation and also as an index of food resources in the semi-arid areas of Tanzania for monitoring rodent pests. Also, the obtained NDVI values provide a robust measure of the presence and abundance of vegetation across the studied landscapes which could be very useful in monitoring rainfall dynamics and as a proxy for predicting rodent pest outbreaks in the study area.

The study has further demonstrated a good correlation between TMPA-RT rainfall and NDVI across the studied landscapes with the escarpment having relatively higher correlation ($r = 0.688$), than the plateau ($r = 0.653$) and the rift valley floor ($r = 0.652$). These results suggest that NDVI could be applied fruitfully to estimate rainfall variability and seasonality across the studied landscapes. This implies that representative locations can be chosen for sampling of NDVI values to explain rainfall scenarios instead of being dependent on the locations of the meteorological stations.

Generally, temporal distribution of rodent abundance in the study area followed the NDVI pattern which is a proxy of primary productivity. This study has therefore demonstrated the power of NDVI for use in ecological research and in particular for monitoring rodent population dynamics and outbreaks in smallholder farming agro-ecosystems in the study area and other areas with similar conditions in Tanzania.

In this study, a strong linear relationship ($R^2 = 0.7$) was observed between rodent abundance and rainfall derived from NDVI across the Isimani landscape. Mean seasonal rodent abundance increases with an increase in mean seasonal rainfall. The relationship obtained between rodent abundance and rainfall derived from NDVI provide a quick insight that could help in ameliorating pest control planning in semi-arid areas of Tanzania.

The study has demonstrated that 98% of the predicted rodent abundance was explained by NDVI while rainfall explained only 85%. This study has therefore supported the hypothesis that NDVI of common vegetation habitats derived from satellite remote sensing data has the potential for monitoring rodent population dynamics and outbreaks under smallholder farming agro-ecosystems in the study area.

4.2 Recommendations

Findings from this study have provided some insights into the structural characterization and mapping of vegetation habitats that could contribute knowledge about rodent populations on individual farms. Thorough understanding of the vegetation patterns, climate and terrain parameters for habitat characterization and for which abundance of small mammals can be predicted were established. Results also demonstrated the potential use of NDVI of common vegetation habitats derived from satellite remote sensing data for monitoring rodent pests under smallholder farming agro-ecosystems. However, results obtained revealed some gaps which require further research so as to provide future guidelines for monitoring rodent pest population dynamics and ecological based rodent management decisions, hence the following recommendations:

Temporal patterns of rainfall could be used to describe vegetation habitats and small mammal population dynamics in most agro ecosystems. However, lack of a network of accurately recorded rainfall time series data in the study area has posed a significant challenge. To minimize the problem of rainfall data availability, further research is recommended to explore the use of satellite data such as MODIS-NDVI, and TMPA-RT at fine resolution to generate rainfall data for use instead of relying on commonly not readily available point rainfall measurements.

Further research to explore the existing relationship between vegetation habitats with their associated microclimate and small mammal particularly rodent pest's hotspot areas is recommended.

Studies that have demonstrated correlation between NDVI and abundance of small mammals (rodent pests) elsewhere are lacking in tropical sub-Saharan Africa. It is apparent from the results of this study that there is more work that remains to be done on the application of remote sensing derived NDVI in monitoring rodent pest population dynamics taking into consideration the major rodent pest species such as *Mastomys natalensis*, *Arvicanthis* spp, and *Gerbillicus* spp which are common in smallholder agro ecosystems.

Further research is also required to establish relationships between NDVI and rodent pest species composition and community structure in different habitats and seasonal rainfall patterns.

In the light of findings of this study and similar studies in other areas, there are several research questions that require further consideration in the future research. This include for example, to conduct a research to establish threshold for rodent outbreaks in smallholder farming conditions, minimum NDVI value that will be needed by smallholder farmers with regard to risk of rodent outbreaks in the study area and at what point in time is prediction of such nature important to enable corrective measures.

APPENDIX

Appendix 1: Population of small mammals' species across the Isimani landscapes

Landscape unit	Vegetation habitats	Number of small mammal (trapped)									Total
		MN	GB	LZ	AE	AC	GR	ES	AV	CH	
Plateau	Grassland/shrub land/tree	271	14	1	2	2				7	297
	Agriculture	150	8	1		5			1	4	169
	Shrub land	9		1	6					1	17
	River line vegetation/litters/valley bottoms	1			4						5
	Bare/grasses/sparse tree	57								4	61
	Valley bottom/grass land	25	5								30
	Sub total	**513**	**27**	**3**	**12**	**7**			**1**	**16**	**579**
Escarpment	Forest/ dried acacia trees				2	1					3
	Grasses and tree				1		1	1			3
	Sub total				**3**	**1**	**1**	**1**			**6**
Rift valley flow	Woodland/shrubs/grasses		2			1					3
	Grassland/ sunflower					4			5		9
	Sub total		**2**			**5**			**5**		**12**
Grand total		**513**	**29**	**3**	**15**	**13**	**1**	**1**	**6**	**16**	**597**

Key: MN = *Mystomys Natalensis*, GB = *Tatera*, LZ = *Lemniscomys Zebra*, AE = Aethomys, AC = Acomys, GR = Graphiurus, ES = Elephant shrew, AV = Avicansis, CH = Crocidura shrew