Hyperspectral remote sensing for cropland assessment and modeling for agro-ecological zones: A case study of Taita Hills, Kenya.

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A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy in Remote Sensing in Jomo Kenyatta University of Agriculture and Technology

2016

DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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

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University of Helsinki, Finland.

DEDICATION

This work is a dedication to my wife Jane Kenda and to my son Andrew Kiprono Kurwa for their unwavering support and prayers.

ACKNOWLEDGEMENT

I would like to thank the ministry of foreign affairs, Finland for the support they provided to sponsor me in the CHIESA project. I thank the CHIESA coordinator, Dr. Tino Johannson for his coordination of the project together with the project assistants, Wambui Karen and Sarah Marubula.

I am grateful to my supervisors; Prof. Petri K. E. Pellikka and Prof. Charles Ndegwa Mundia for their support. I thank Prof. Mundia for the proposal and comments from the start of this thesis to the end. Your contribution and supervision in this research was of importance. Special Thanks to my colleague, Dr. Patroba Odera for the review of the thesis.

I am thankful to the team of scientists at the University of Helsinki. These include: Dr. Mika Siljander, Dr. Janne Heiskainen, Dr. Eduardo Maeda, Pekka Hurskainen, Rami Piirroinen, Arto Viinikka, Johanna Hohental, Binyam Hailu and Samuel Nthuni. The team was of much help while living and processing the hyperspectral data in Helsinki, Finland.

My sincere appreciation goes to Prof. Thomas Blaschke, Zahra Dabiri and the other members of ZGIS at the University of Salzburg for your warm welcome and guidance on object based image classification when I visited your institution. To my family, I appreciate the support you gave me and allowing me time to do this research including travelling out of the country for some couple of months.

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LIST OF ABBREVIATIONS AND ACRONYMS

IPCC	Intergovernmental Panel on Climate Change
FAO	Food and Agricultural Organization
CHIESA	Climate Change Impacts on Ecosystems Services in East Africa
EABH	Eastern Afromontane Biodiversity Hotspot
AISA	Airborne Imaging Spectrometer for Applications

SAM	Spectral Angle Mapper
SID	Spectral Information Divergence
VNIR	Very Near-Infra-Red
GCM	General Circulation Model
LUCC	Land Use and Land Cover Change
DEM	Digital Elevation Model
SWIR	Short-Wave Infra-Red
RUSLE	Revised Universal Soil Loss Equation

ABSTRACT

This dissertation seeks mainly to provide an assessment of cropland characteristics in the Taita Hills. The objectives of this research are: Identification of crops using hyperspectral imagery, delineation of agro-ecological zones, modeling the impacts of climate change on agro-ecological zones and mapping suitable agricultural land in Taita Hills. The study area is composed of low to high variation in altitude within about 22km stretch. The main economic activity is mixed farming. Research in land use and land cover in the area have been done using remote sensed datasets. The data used in this research included a high resolution hyperspectral image which covered a transect area of 22 km long and 2 km wide, running from the low to high zones of the study area. It

constituted 64 bands with spatial resolution of 0.6 meters. In addition, climate data of 1960-2010 (current climate), predicted climate of 2050 (future climate), soils of Taita Hills, slope, digital elevation model (DEM) and land use / land cover maps. In order to achieve the set objectives, several methodologies were applied. Initially, the hyperspectral imagery in the low, mid and high zones were classified. Training areas of crops were generated from 25 selected plots digitized from an aerial image (Nikon D3X) taken simultaneously with the hyperspectral image. Spectral angle mapper (SAM) and spectral information divergence (SID) were used as the pixel-based algorithms for classification. A combination of the Principal Component Analysis (PCA) that generated the Eigen vectors (best data) and a multivariate geostatistical clustering techniques were used to delineate the agro-ecological zones (AEZ) for Taita Hills. A difference between the future and the current zones delineated was also done. Finally, the assessment of suitable cropland areas incorporated the development of elevation models, watersheds and soil erosion mapping that applied the revised universal soil loss empirical model (RUSLE) and multi-criteria evaluation analysis. The analysis was done using the sum weighted overlay of soil erodibility, slopes, rainfall availability and land cover in the modeling. The results achieved for the research were: Classified hyperspectral imagery showing crops with an overall mean accuracy of **81%** and a kappa index of **0.8**. The main crops mapped were: Maize, mangoes, bananas, avocadoes and sugarcane. Agro-ecological zones (AEZ) for 1960-2010 (current) and AEZ for 2050 (future) were modeled. The difference of the two models gave an indication of the potential impacts of climate on AEZ. In the assessment of suitable cropland areas, four categories were mapped out: most suitable, more suitable, less suitable and least suitable. In conclusion, various crops can be identified using hyperspectral imagery. It is evident that agricultural activities are more intensive in the mid zones than in both low zones (warm) and high zones (cold) of Taita Hills. Furthermore, if current climate trends persist, some agro-ecological zones will increase and others will decrease to about 1 kilometer wide from the original size of a single AEZ, hampering the agricultural activities in the future (2050). In assessing suitable cropland areas, soil erosion is seen as a potential impact

especially on the steep slopes rendering the land not suitable for agriculture. Moreover, agricultural activities are projected to do well in the lower zones if farmers will irrigate crops. Farmers need to be aware of the best farming practices to adapt to changing climate variations. The county government through the Kenya Forest Service (KFS), Kenya Wildlife Service (KWS) and other stakeholders need to embrace the laws governing forest areas, protected areas and the catchment areas in order to reduce soil degradation and loss of the ecosystems and biodiversity in the region.

Keywords: Hyperspectral data, spectral angle mapper; climate variation; agro-ecological zones; principal component analysis; soil erosion and revised universal soil loss empirical model.

CHAPTER ONE
INTRODUCTION

The chapter introduces agricultural activities in Kenya. It highlights the technological advancement for studying agriculture using satellite remote sensing and airborne high resolution imaging which has improved the accuracies and the reliability of the data obtained. Suitable cropland areas can be assessed by studying the agro-ecological zones of a region that in turn give the possible crops to grow in that area. It incorporates the soil and climate variation in every zone which could be linked to the type of crops to be grown in each zone. However, climate variability hampers the zones hence farmers need to be aware of this at all times. The chapter also defines the root problem of the research and justifies it. The main and specific objectives are also given in the chapter. The research gaps and the limitation of the research are presented.

1.1 Agriculture in Kenya

i) Agricultural systems in Kenya

Agriculture is the main economic activity in Kenya. By 2009, agriculture was responsible for approximately 21% of the country's Gross Domestic Product (GDP), followed by industry, with approximately 16% (KMA, 2009a). The main agricultural products currently produced are corn, wheat, tea, coffee, sugarcane, fruits, vegetables, beef, pork, and poultry. Kenya has a great variety of climatic and topographic conditions, ranging from low arid plains to fertile environments in the Kenyan highlands. This diversity is reflected in the cropland characteristics. Throughout the country it is possible to observe a large range of agricultural activities, from small-scale and low-productive subsistence practices to market-oriented, large-scale mechanized farms. The poor performance of the agricultural sector in the last years severely affected Kenya‘s economic growth. In particular for the year 2008, post-election violence associated with reduced and inconsistent rainfall significantly affected the national GDP growth. Namely, the GDP growth rate dropped from 7.1% in 2007 to 1.7% in 2008

(KMA, 2009a). This situation was aggravated by an international financial crisis, which affected global economy during this same period. These recent events clearly expose the fragility of Kenya's agricultural sector in relation to economic and environmental factors. Agriculture in Kenya continues to face many endemic and emerging constrains at global, regional and national levels. From a global perspective, international financial crisis and climate variations are considered the main threats to the country's economy in recent years (KMA, 2009b). From the regional point of view, armed conflicts in neighbouring countries, crop pests and diseases are issues that have continuously threatened the growth of agricultural sector. Finally, the Kenyan Ministry of Agriculture points out several factors that currently constrain agriculture from a national level. For instance, poor infrastructure, low access to affordable credit, multiplicity of taxes, corruption and outdated technology are some of the issues that limit the growth of agricultural activities (KMA, 2009b). Besides the risk that global climate change may impose to the agricultural industry, regional climate instabilities have constantly damage the country's food production. A recent example occurred in the year 2009, when rainfall during the short rains season, did not provide the moisture crops required during its maturing period in eastern Kenya. This event resulted in a poor harvest by the end of the year, obligating the government to declare a state of emergency to free up funds for food aid. Despite all constrains, agriculture is expected to play a central role in the future of Kenya's economy. According to the country's national planning strategy for 2030, agriculture was identified as one of the six key economic sectors expected to drive the economy to the projected 10% annual economic growth over the next two decades (KMA 2009a).

ii) Climate variability in relevance to agriculture in Kenya

The term 'climate' refers to general weather patterns over long periods of time (i.e. decades or longer). The climate of a particular region is usually defined based on conditions that last over 30 years or more. Many factors have influence on the climate characteristics of a specific site. For instance, latitude and topography are important

features in the definition of the climate conditions. Figure 1 shows projected changes in climate for the years 2030 to 2090 in Kenya.

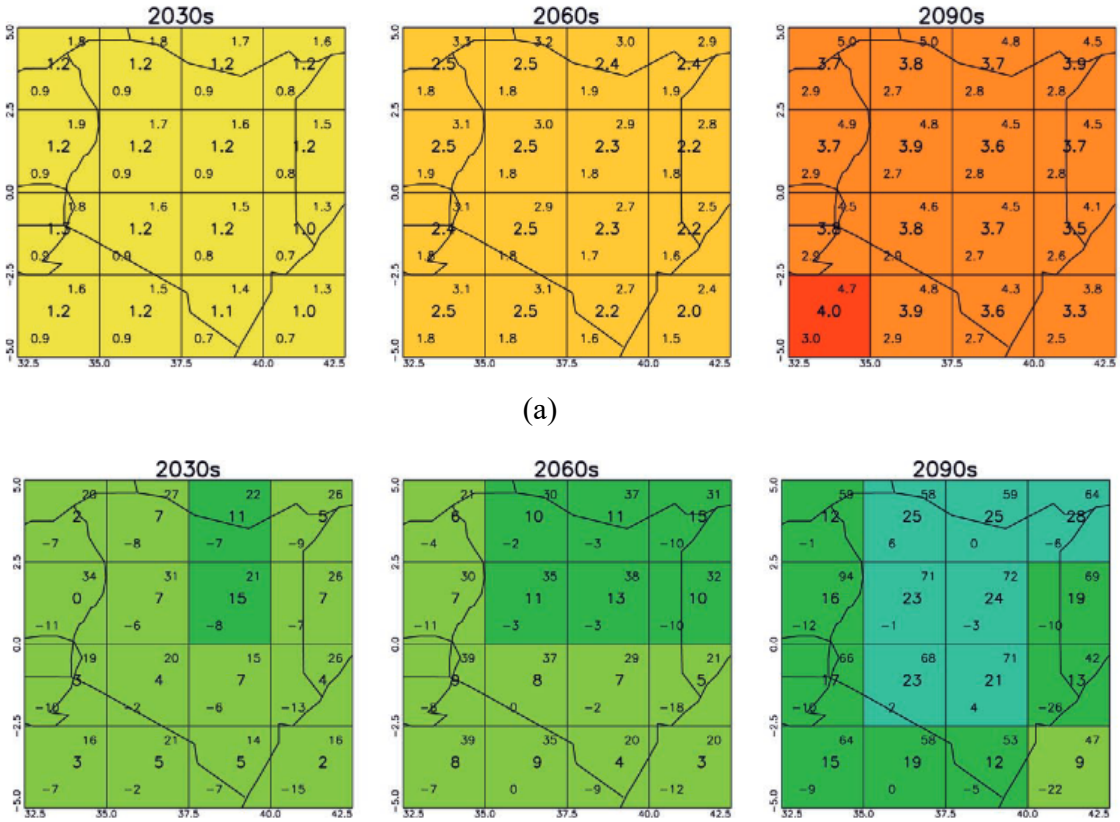


Figure 1 Projected changes in mean temperature (ºC) in (a) above and the projected (%) mean annual rainfall in (b) above for Kenya (McSweeney et al., 2010)

From figure 1 (a) above, in each grid box for temperature variations, the central value and colour give the multimodal ensemble median, and the values in the upper and lower corners give the ensemble maximum and minimum. Figure 1 (b) above shows each grid box for rainfall variations, the central value gives the multimodal ensemble median, and the values in the upper and lower corners give the ensemble maximum and minimum.

The earth's climate has continuously changed throughout history. Climate variability can be caused by natural internal processes, natural external forces or anthropogenic factors.

Although annual rainfall is likely to decrease in most of Mediterranean Africa and northern Sahara, an increase in annual mean rainfall is likely to occur in East Africa, Kenya being part of it (Maslin & Christensen, 2007). These climatic variations have a lot of impacts to agriculture and in most cases negatively: First, it results in low crop production which translates to low yield hence food insecurity. Second, each country is naturally concerned with potential damages and benefits that may arise over the coming decades from climate change impacts on its territory as well as globally, since these will affect domestic and international policies, trading patterns, resource use, regional planning and ultimately the welfare of its people.

Current research confirms that, while crops would respond positively to elevated CO_2 in the absence of climate change, the associated impacts of high temperatures, altered patterns of precipitation and possibly increased frequency of extreme events such as drought and floods, will probably combine to depress yields and increase production risks in many world regions, widening the gap between rich and poor countries (Fisher et al., 2005 & IPCC, 2007). A consensus has emerged that developing countries are more vulnerable to climate variations than developed countries, because of the predominance of agriculture in their economies, the scarcity of capital for adaptation measures, their warmer baseline climates and their heightened exposure to extreme events. Thus, climate variations may have particularly serious consequences in the developing world, where some 800 million people are undernourished. Of great concern is a group of more than 40 'least-developed' countries, mostly in sub-Saharan Africa, where domestic per capita food production declined by 10% in the last 20 years. Kenya and particularly, Taita Hills constitutes this vulnerable group.

iii) GIS and remote sensing technologies for agricultural studies

Reliable and timely information on agricultural activities are essential to guarantee the construction of adequate infrastructure, provide proper crop management and efficient economic planning. Nevertheless, changes in agricultural activities through time and space are in general very dynamic, making the achievement of such goals a challenging

task. Hence, the importance of earth-observation satellite systems for monitoring agricultural activities has been well recognized since the first sensors for civilian usage were launched in the early 1970's. The capability of acquiring frequent information from large areas makes satellite remote sensing a unique and indispensable tool for monitoring and managing agriculture. Moreover, the development of new sensors and techniques continues to expand the range of applications available. The improvement of the spectral and spatial resolutions of satellite and airborne sensors has allowed important progress in agricultural remote sensing analysis. Among the remote sensing applications for agriculture, it is worth mentioning precision agriculture, crop yield forecast and crop area estimation. In precision agriculture, remote sensing is often used to retrieve information on the spatial variability of crops biophysical characteristics or to detect priority management areas.

The low temporal resolution of these sensors is a limitation for its use in global assessments due to the high dynamism of agricultural activities together with the high incidence of clouds in tropical regions. To overcome this problem, sensors with coarser spatial resolution of about 1km (e.g. MODIS, AVHRR) are usually applied, as such sensors are able to re-visit a target with higher periodicity. In Africa, remote sensing has been largely applied during the last decades in order to monitor agricultural activities. Remote sensing has also been recently applied in Africa to assess drought probability in agricultural areas, achieving promising results for future drought monitoring. GIS on the other hand has been a powerful tool that is used to map out geographical features. It is a very important tool for analysis, assessment and also for selection and creating a database. Coupled with remote sensing, this tool is very essential in studying agricultural phenomena.

iv) Importance of crop identification for climate variations studies

Crops exhibit known observed responses to weather and climate that can have a large impact on crop yield. Since atmospheric concentrations of greenhouse gases continue to rise at rates that are both unprecedented and alarming, efforts have been made to

understand the implications for crop production. These efforts are primarily based on climate models, which use spatial grids with resolutions typically of the order of a hundred kilometers. Such simplification of the spatial heterogeneity of processes has direct implications for the assessment of the impacts of climate change. Some of these assessments are performed at the regional scale (referring here to from tens to a couple of hundred kilometers—commensurate with climate model grids). In contrast, location-specific methods have also been developed, to account for the variety of climatic and non-climatic stresses on crop productivity often not observable at aggregated spatial scales (Challinor et al., 2009). An accurate methodology to locate existing crops in an agricultural landscape is always essential. High resolution satellite imagery or airborne imagery coupled with accurate classification algorithms provide information on the location of crops in such agricultural regions. The extent of a given crop in an agricultural area can be mapped well. The environmental conditions that supports its growth can also be mapped out using various techniques. The most common one is to map the agro-ecological zones which identifies regions of same environmental and ecological conditions. Crops can be linked to these conditions.

v) The need for agro-ecological studies with varying climate

Crops do well in regions of same environmental and ecological conditions. Climate plays a key role too in the development of a crop in a given region. Availability of rainfall (moisture) and temperatures that are good for a specific crop in a good agro-ecological zone can give a great yield. However, changes in the climatic conditions can reduce the yield of the said crop tremendously. Climate variations have great impacts on crop yield of a given agricultural region. The regions affected by climate variation can be of great concern to the farmers who always cultivate crops. Awareness of such variations need to be addressed to enable them prepare adequately and to reduce cost as they maximize profits especially with their crops and even livestock hence achieving the economic value of their land. Modelling the impacts of climate change on agro-ecological zones clearly explains the extent that will be affected by the variations and those that will not be affected by the climatic changes.

vi) Assessment of suitable croplands in relation to climate

Since natural resources are finite and environmental concerns increase, land use planners are beginning to take a "bottom-up" approach to planning. That is to say that physical land capability, environmental considerations, ecological issues, and landscape amenities are scrutinized more closely. An evaluation of these issues serves as an important source of information that can be used by officials to help make better decisions concerning the pattern of future land use. A land use suitability assessment is considered such a piece of information. Results of suitability analysis can serve as constraints in the preparation of alternative land use plans. Such analysis can tell us the amount of land available for specific activities and the relative degree of environmental impact that would occur if the land were developed.

Evaluation of land suitability has been regarded as a difficult task due in part to the large number of criteria and the large amount of data that play a role in determining the suitability. These criteria, or factors, may include certain physical, environmental, or socially-related phenomena. In order to arrive at a highly consistent and viable suitability result, it is necessary to synthesize this data into a composite form, from which results on maps can be generated. Historically, practical assessments of suitability have been limited, due in part to the inefficiency of manually integrating a set of factors into a composite effect. Technological advances in computerized mapping and geographic information systems (GIS) have recently given land use planners a more efficient and effective way of handling large amounts of spatial data.

The impact of climate change on production of various crops varies markedly depending mainly on the region, growing season, the crops and their temperature thresholds (Olesen et al., 2011). Cereals, oilseed and protein crops depend on temperature and, in many cases, day length, to reach maturity. Temperature increase may shorten the length of the growing period for these crops and, in the absence of compensatory management responses, reduce yields (Tubiello et al., 2000) and change the area of cultivation by rendering unsuitable some currently cultivated areas and suitable for those not currently

cultivated. Areas suitable for cultivation of a wide range of the world's most important crops will shift as a result of climate change. Overall, suitable cropland areas will increase, but most affected by loss of area will generally be regions that are already struggling from the impacts of irregular and extreme climate events (Lane & Jarvis, 2007).

vii) The choice of Taita Hills as a case study

The Taita Hills are the northern most part of the Eastern Arc Mountain range in East Africa. The Hills cover an area of around 1000 square kilometers in the Taita Taveta County. In prehistorical times, the Taita Hills may have been covered with hundreds of square kilometers of indigenous rainforest that have since been cleared for agriculture. Now there are only few indigenous forest patches left in the highest peaks and most of the area is converted to the use of agriculture, agroforestry and human habitation (Pellikka et al., 2009). The hills sustain some of the endemic animal and plant species of the world. And it is considered one of the 25 world's biodiversity hotspots (Myers et al., 2000). The area is mainly inhabited by farmers who cultivate crops intensively in small-scale farms. Although it is not the food basket of Kenya, it is the main source of food crops for the whole of the coastal region of Kenya. The area is good to support growth of a wide variety of crops from maize, beans, vegetables, bananas, avocadoes, mangoes, sugarcane among many other crops. The altitude range is high within short ranges. The forest patches on top of hills act as water towers (catchment) for the extensive agricultural activities in the highly populated areas. Several studies have been done in this region that can be linked with this study.

1.2 Problem Statement

In the Taita Hills, previous studies on the land use/land cover change have been done (Pellikka et al., 2009 & Maeda, 2011). These studies have shown that during the past decades, cropland areas have mainly expanded at the expense of shrub lands and thickets especially in the lower foothill areas of the Taita Hills. Some forest areas are also converted for agricultural use in the higher altitudes, but this has amounted to only 20 ha

of the total increase of 10,478 ha of cropland areas during the period of 1987 to 2003 (Clark et al., 2009). These studies show the transformation of forests, woodlands or bush lands for agricultural use, but they do not have information of the actual food crops that are being farmed. There is a need to identify these crops in the area in order to understand the reason for agricultural expansion in the area.

Moreover, there is a drastic change in the health of the crops grown by the local farmers. In Taita Hills, pest and disease invasion on maize, avocadoes and mangoes has been a major problem experienced by the local farmers especially the midland areas where crops do well. Earlier, this problem was common only in the lower areas but now it has become common in the upper areas. It is widely accepted that climate variation is responsible for these effects. There is a need to provide a scientific solution to the problem through understanding the current and future climate variations in the region.

Furthermore, other research studies have shown that cropland areas will occupy roughly 60% of Taita Hills by 2030 (Maeda et al., 2010; Clark et al., 2009 & Pellikka et al., 2009). Although the simulated land use changes will certainly increase soil erosion, new croplands are likely to come up predominantly in the lowlands, which comprises areas with lower soil erosion potential. Population increase according to Kenya national bureau of statistics (90,000 in 1962 to about 300,000 in 2009) and agricultural expansion in the mid and high zones have depleted the water towers of Taita Hills hence low crop productivity is experienced in those areas that were suitable for agriculture but a gradual reverse in the areas where agriculture was not possible. The removal of fertile soil through erosion from the productive land deposited to the unproductive areas coupled with favorable climate and environmental conditions, is one of the root causes of the above changes (Erdogan et al., 2011). There is a need to assess the suitable cropland areas in the Taita Hills.

Knowledge and information is scarce on the best farming practices by the local farmers. Lack of knowledge on the types of crops to grow in a particular land, the needs

assessment of the crops, the market value among other issues have not been addressed to the farmer who plays the major role in implementation. There is a need to understand the local land use practices in relation to climate change and their impacts on the ecosystem and food production. In best case scenarios, it is possible to achieve environmental, social and economic benefits by optimizing the land use practices. This is only possible if the full ecosystem functionality is well understood. An assessment of the underlying root cause of the above problem can be understood through a research that incorporates; crop mapping, climate variation and its potential impacts on agriculture and suitability mapping for cropland areas.

1.3 Justification

In Taita Hills, Kenya, the locals have increasingly defined their livelihood through the utilization of agriculture which in turn has improved their economy and wellbeing. The advancement in knowledge and technology that has allowed farmers to irrigate their crops, use manure, spray their crops, create drought resistant cultivars among other advancements has changed their perspectives. Despite technological advancement, many modern developing countries have difficulty in food security and sustainability and majority still remain poor.

Previous research in Taita Hills have dealt a lot in the expansion of agriculture, deforestation and losing the biodiversity (flora and fauna). All these have been accurately and precisely defined by new approaches such as remote sensing technology and GIS, (Maeda et al., 2010, Clark et al., 2009 & Pellikka et al., 2009). The idea of what agricultural activity is expanding and why there is deforestation in the area raises questions like: What kind of crops are actually being cultivated? Why would the local farmers clear forests instead of preserving them? Does it imply that population increase creates demand for more land? The point is that population is increasing, climate variation is hampering agriculture and at the same time there is need to acquire more

land – a vital resource, but there is lack of knowledge and information with regard to such undertakings to their livelihoods.

Furthermore, farmers in the area have been relying very much on rain-fed agriculture. This creates some human perception on the areas to grow their crops. Highlands are majorly regarded to be on higher altitudes and lowlands are those on the lower altitude. This understanding created the migration of population from lowland areas to occupy highland areas 'fertile land'. Since Kenya at large depended on agriculture during independence, everyone was motivated to do farming for their subsistence and also as a cash crop which tremendously improved their livelihood. In fact, farmers were provided with loans through agricultural finance cooperation of Kenya (AFCK) and were even trained by motivated agricultural officers on best farming practices. Over time, the country's economy went down and farmers have been forced to do their farming with no proper guidance leading to poor yield and resource depletion.

The classification of the suitable cropland areas 'fertile lands' and the unsuitable cropland areas in the region created an imbalance. Highland areas have faced a lot of population pressure while lowland areas have had no development and less value tied to it. The underlying fact is that, such decisions in occupying 'fertile lands' did not consider very important aspects like the type of soils for agriculture, the increasing soil erosion and its impacts, the effects of agricultural activities on catchment areas and lack of awareness that lowlands could be suitable areas for such agricultural activities and do not need to depend on rain but irrigation. This imbalance creates an avenue to address the importance of understanding the value of a given land so as to define suitable areas for agriculture.

Therefore, there is a need to research on the possible crops that are grown in Taita Hills. The location and the identification of such crops becomes an indicator of the reason behind agricultural land expansion in the area. Also, understanding the climate change impacts on agriculture and the cropland characteristics of Taita Hills creates awareness

to the farmers and stakeholders on the main food crops to grow in a specific place, the breeds of livestock to rear, best farming practices and improvement of their economy at large. The research is aimed at addressing the root causes of the above issues for sustainable food security. Taita Hills thus becomes a pilot project for such agricultural studies and the same methods could be applied in any other part of the world.

1.4 Objectives

This study seeks to provide an assessment of the suitable cropland areas for growing crops in Taita Hills by: identifying the existing crops using hyperspectral data, delineating and modeling the impacts of climate variation on agro-ecological zones and mapping of suitable cropland areas. The specific objectives include:

1. Identification of crop types within a transect area of the Taita Hills using hyperspectral remote sensed data utilizing spectral algorithms in three zones: Lower zone, mid zone and high zone.
2. Delineating the current (1960 to 2010) and the future (2050) agro-ecological zones of Taita Hills using climate data and bio-geophysical data and assessing the impacts of climate variations on the delineated zones with respect to future prediction of the year 2050 for Taita Hills.
3. Determination of suitable agricultural land in Taita Hills using revised universal soil loss equation (RUSLE) for soil erosion and multi-criteria decision techniques for land suitability assessment.

1.5 Limitations of the Study

The limitations of this research were:

i) Hyperspectral remote sensed data was not covering the whole of Taita Hills but instead a chosen transect, hence the data achieved for crop identification do not represent whole of Taita Hills especially when it comes to assessment of the cropland suitability analysis.

ii) There was no in situ calibration for the signatures for crops of Taita hills although we used ASD spectrometer to measure some of the crops in the sampled plots but these needed some in situ measurement to be able to calibrate the signatures before using them as classifiers or training areas.

iii) The DEM used in the analysis was of a coarser resolution (20 meter).

iv) The weather station data that were observed for a period of 2-3 years in study area were used for checking and validating the historical climate data sets.

1.6 Research Gaps

Remote sensing technologies have been used extensively in Taita Hills for land use and land cover changes, agricultural expansions, impacts of this expansion on soil erosion and many more. Little has been provided on the types of crops that farmers cultivate. The agro-ecological zones were general definition based on crop specific parameters and were of the entire country (FAO, 1983), none was defined for a specific area and none projected the impacts of climate variations on them.

Although the models for 2030 agricultural expansion have been predicted by Maeda et al., (2011), cropland suitability assessments have not been done for Taita Hills. Furthermore, the studies on the expansion of agricultural activities do not address the specific areas in which agriculture will take place. These form the research gaps that this thesis seeks to address in Taita Hills.

CHAPTER TWO
LITERATURE REVIEW

The chapter gives an overall overview of the research that have been done in regard to the study area. It entails the overview of the remote sensing studies for agricultural studies which include the airborne and space-borne remote sensing, the recent application of hyperspectral imagery to identify crops in agricultural landscapes and entirely provides a background information of the agricultural studies that have been previously done in Taita Hills using the technologies.

Moreover, it gives an understanding of the need to delineate agro-ecological zones for agricultural studies. The importance of the zones in planning and monitoring of land resource is outlined. In addition it provides an overview of the existing agro-ecological zones in Taita Hills according to previous studies. Finally, the chapter gives relevant agricultural studies that have been recently done in the areas which include: agricultural expansion and its impacts on the soil erosion. Prediction of land use land cover changes to the year 2030 are outlined in the chapter.

2.1 Remote Sensing for Agricultural Studies

i) Remote Sensing for agriculture

Hyperspectral remote sensing data can provide a significant spectral measurement capability over the conventional remote sensor systems and hence becomes very useful in identification and modelling of terrestrial ecosystem characteristics (Kamal & Phinn, 2011; Clark et al., 2005). Not long ago, mapping was mainly using satellite (space-borne) data for large area mapping but for small regions, it used aerial images and in most cases, the result was just a land cover map combining several classes of pixels having some broad similarity. The need to discriminate crop species to know their health, location and distribution has paved way in this decade due to available sensors

which can detect at high spatial and spectral resolutions, the natural and man-made features on the surface of the earth.

The New Partnership for African Developments (NEPAD) focuses on agriculture and food security programme which deals on helping African countries improve economic growth through agriculture-led development. Specifically, the NEPAD agency aims to ensure that smallholder farmers – the majority of Africans – get better access to markets, finance and technical support, in order to improve their income and get out of poverty (ICIPE 2012). Quite a lot of research has been done regarding agricultural techniques that improve food security in Africa.

Precision agriculture dates back to the middle of the 1980's. Remote sensing applications in precision agriculture began with sensors for soil organic matter, and have quickly diversified to include satellite, aerial, and hand held or tractor mounted sensors .Spectral bandwidth has decreased dramatically with the advent of hyperspectral remote sensing, allowing improved analysis of specific compounds, molecular interactions, crop stress, and crop biophysical or biochemical characteristics (Mulla, 2013). A variety of spectral indices now exist for various precision agriculture applications, rather than a focus on only normalized difference vegetation indices. Satellite-or aerial-based remote sensing technologies will become important tools in improving the present system(s) of acquiring and generating agricultural and natural resource data (Liaghat & Balasundram, 2010). Hyperspectral remote sensing for soil nutrients and crops aims at precision agriculture in the future (Boggs et al., 2003; Thenkabail et al., 2000).

The advancement not only on the sensor availability but also the technology used to discriminate the various spectra of different species has become a boost to mapping. Many technologies have been used for extracting terrestrial features from hyperspectral imagery. Tarabalka et al (2009), have studied the spectral-spatial classification of hyper spectral imagery based on partitioned clustering techniques (Pixel-wise). Tiwari, et al (2000), investigated land use changes in Himalaya and their impact on the ecosystem,

their conclusion is that there is need for sustainable land use. Principal component analysis (PCA) among other algorithms for crop classification has yielded good results. Step-wise discriminant analysis (SDA) and derivative greenish vegetation indices (DGVI) to classify and characterize both vegetation and agricultural crops have been used (Hargrove & Hoffman, 1999). Dissimilarity based approaches have also given good representation of hyperspectral data (Carter et al., 1997; Galvão et al.,2005). Support Vector Machines (SVM) have also been used in a small area of Taita Hills and gave very good accuracies (Piiroinen et al., 2015). Tree species identification has been one area of interests for scientist dealing with forests and vegetation mapping. Flowering tree mapping has been done recently in Kitui County in Kenya using the AISA Eagle spectrometer (Landmann et al., 2015). Statistical methods to identify tree species in forest have shown good and accurate results. Nevertheless, Artificial Neural Networks (ANN) and Linear Discriminant Analysis (LDA) have given reliable results in tree species identification. Some other approaches in coastal environments have been made to identify mangrove species using both object-based and pixel-based classification methods. A comparison has been given and in this regard, results indicates that object based mapping approach is better than pixel-based approach with a difference of just about 7% overall accuracy and 0.1 kappa index (Thenkabail et al., 2004). All these shows that crop species can be discriminated in a similar if not a different but close approach.

Studies on land use and land cover changes utilizing remote sensing data, Landsat and SPOT HRVIR, have shown that there is a lot of agricultural land expansion in Taita Hills (Clark & Pellikka, 2009). Figure 2 shows the land use changes in the Taita Hills.

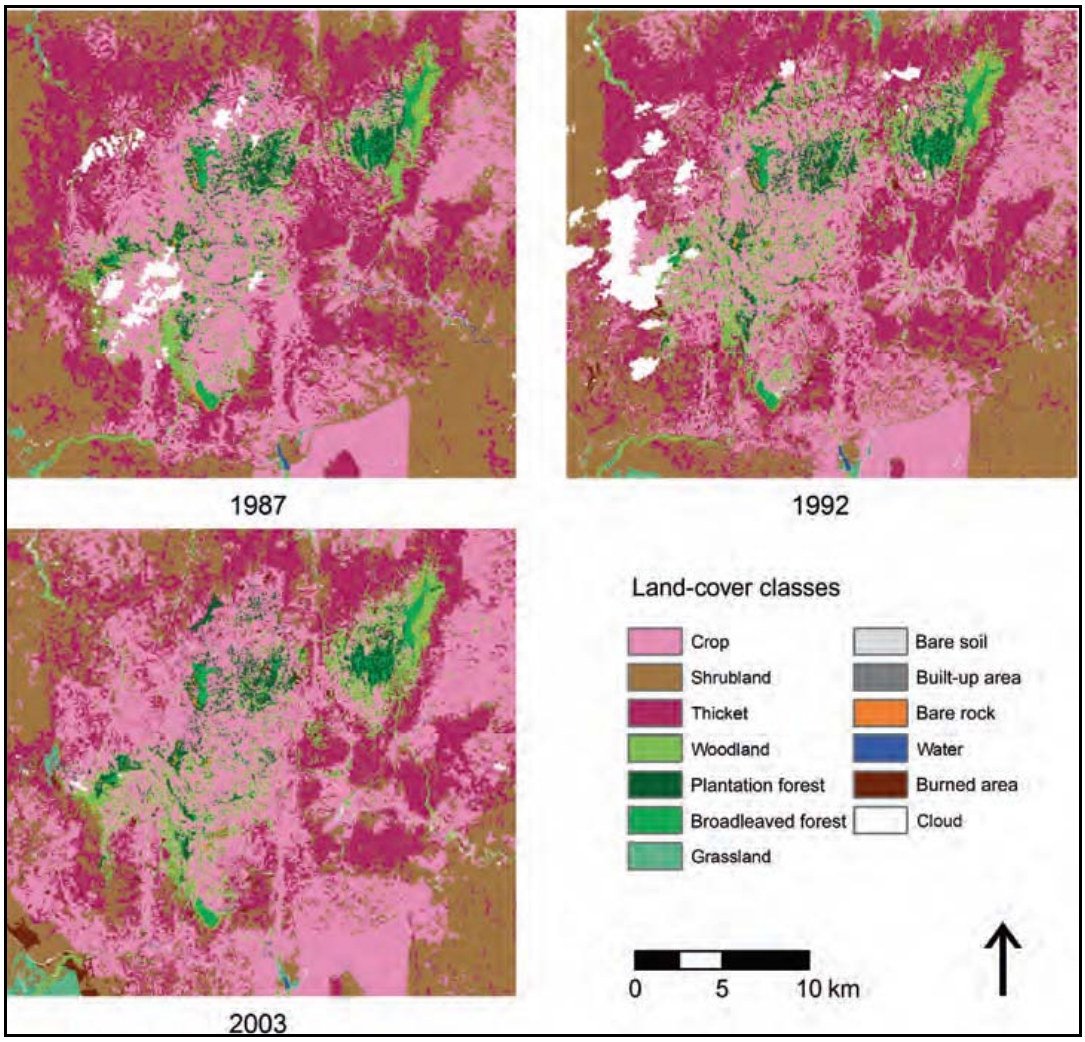


Figure 2 Land use / land cover map for Taita Hills for 1987, 1992 and 2003. Remote sensing was used to achieve the result (Clark & Pellikka, 2009)

The studies have utilised multi-scale segmentation (object oriented modelling) to generate land use land cover (LUCC) maps for Taita Hills between 1987 and 2003. Land-cover change in the Taita Hills was significant between 1987 and 2003; the amount of croplands increased by 39% (9.3 km^2) from 30% to 41% of the study area (Clark & Pellikka, 2009). The new fields were mostly cleared from the foothills and lowlands around the hills and, to a lesser extent, within the higher areas in the hills.

These land-cover changes have been shown to have a very strong impact on the soil-loss potential.

ii) Definition of an agro-ecological zone

Agro-ecological zoning is the delineation of landscapes into relatively homogeneous regions of expected similar crop performance. Past classification was crop-specific but a quantitative approach is more essential in order to locate and characterize agro-ecological zones (AEZ) in relation to different environmental conditions. This zoning is very necessary for improvement of agricultural production and natural resource conservation. An AEZ is defined as that geographical unit with similar land resource potential and limitations related to agriculture (Bailey, 1983; Williams et al., 2008). Although there is the uncertainty in delineating the boundary between two consecutive zones, using several approaches such as: fuzzy theory, wavelet analysis and geographical clustering, there is no single method that has been deemed to be the best (Hargrove & Hoffman 1999). GIS on the other hand has tremendously improved the processing and visualization of AEZ (Castrignano et al., 2010). Multivariate clustering has given good results in other fields such as geology, constant fertility, uniform regions for crops and many more (Carter et al., 1997). Most of the recent development utilizing agro-ecological zones have focused in the United States of America.

iii) Importance of agro-ecological zones

It is a very useful tool for assessment of land resources for better planning, management and monitoring of these resources Food and Agricultural Organization (FAO, 1983). AEZ can be used in various assessment applications including: Land resource inventory; inventory of land utilization types and production systems, including indigenous systems and their requirements; potential yield calculation; land suitability and land productivity evaluation; forestry and livestock productivity; estimation of arable areas; mapping agro-climatic zones; mapping soil erosion areas; land suitability; quantitative estimates on potential crop areas; yields and production; land degradation assessment; population supporting capacity assessment and land use optimization modelling; assessing and

mapping flood and drought damages to crops; assessment of impact of climate change; monitoring land resources development and many more applications.

iv) Existing agro-ecological zones of Taita Hills

Taita Hills is mainly composed of mixed intensive agriculture that range from small zero-grazing farming to large sisal farming in the lower areas and also borders the Tsavo national parks both in the East and West of the hills. Figure 3 shows the five existing agro-ecological zones.

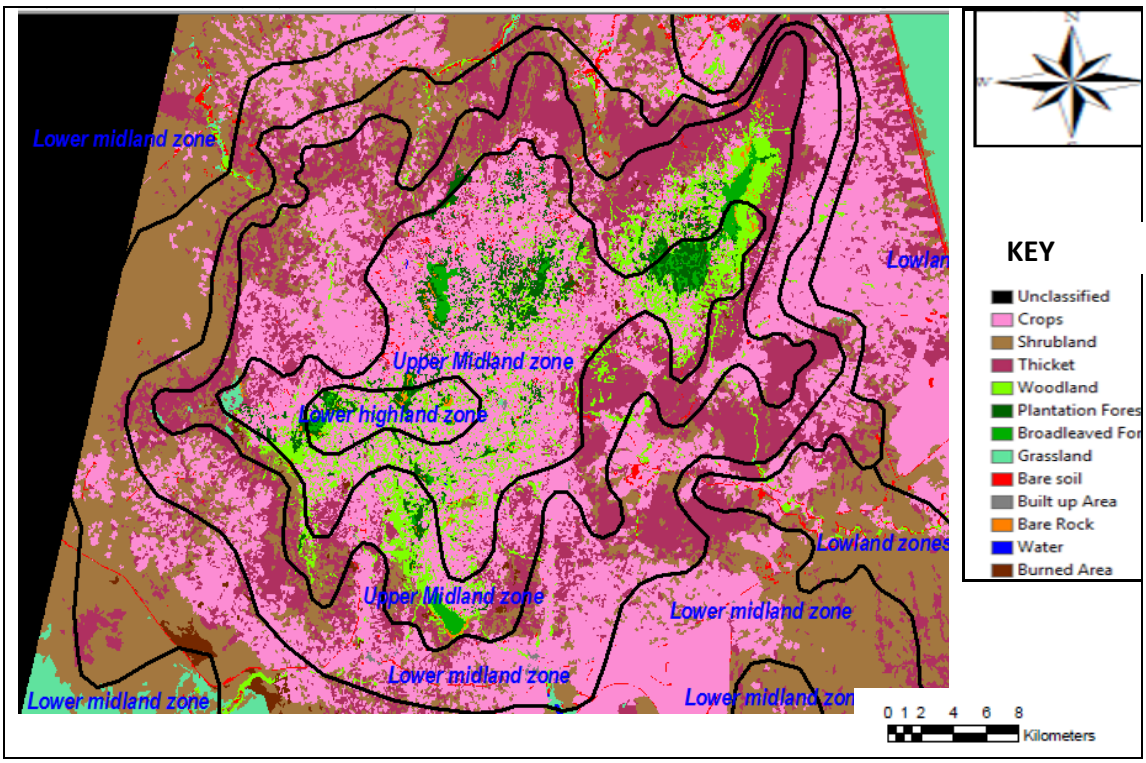


Figure 3 Existing agro-ecological zones of Taita Hills overlaid onto a classified SPOT 5 image of 2003. (Data source: Geonetwork of the University of Helsinki, Finland)

AEZ that exists were those created by (FAO, 1983) and utilized more of soil samples, crop growing periods and thermal regimes. The result for Taita hills had only five zones: *Highland, lower highland, upper mid-land, lower midlands and lowland zones*. These

five zones do not give a true characteristic of the whole region hence prompting a more precise method with many zone-characterization that utilizes land use, elevation structures, soil types, climate and land inventory datasets in a GIS platform.

2.2 Agricultural Expansion in Taita Hills

In order to increase food production and provide food security, there is need to understand the interaction of climate, crops, soil and water with a view to having regional land use planning for improved productivity and commercialization of crops and livestock systems. A regional plan for land use requires collection and analysis of information on soils, climate, present and potential land uses, markets, prices and population. Application of modern analytical tools such as Geographic Information Systems (GIS) makes it easy to manipulate and analyze data in a cost-effective and efficient way.

a) Agricultural expansion modeling in the Taita Hills

A simulation of future scenario modeling of the agricultural expansion has been done for Taita Hills for 2030. Figure 4 shows land use maps and the projected scenarios up to 2030. The LUCC model receives as inputs land use transition rates, landscape variables and landscape parameters (Maeda, 2011). The landscape parameters are intrinsic spatially distributed features, such as soil type and slope, which are kept constant during the simulation process.

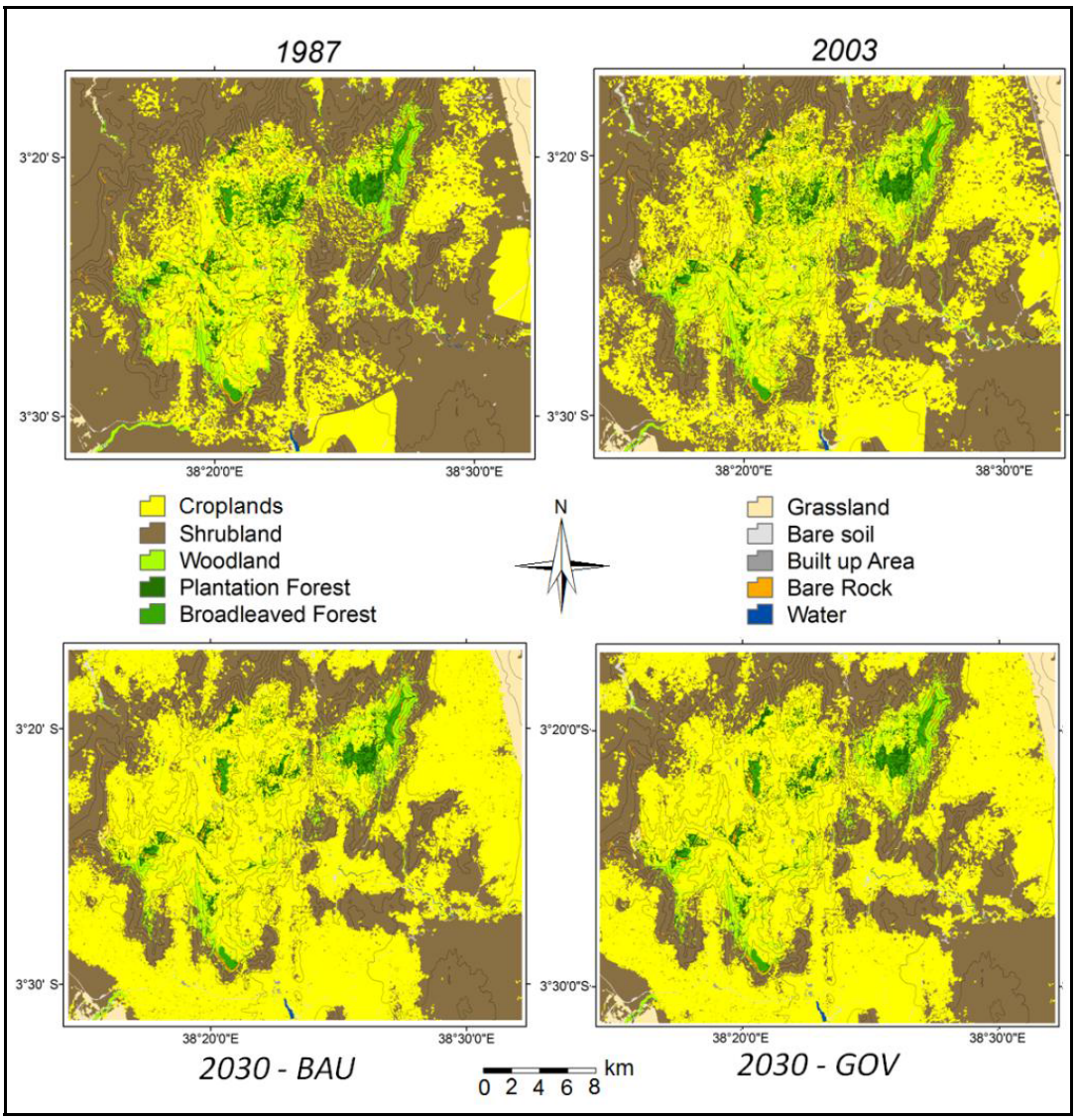


Figure 4 Land use maps for 1987 and 2003 at the top and simulated land use scenarios for the year 2030 on the bottom (Maeda, 2011)

b) Impacts of agricultural expansion on soil erosion in the Taita Hills

Maeda et al (2011) also focused on the impacts of the agricultural expansion on soil loss in the Taita Hills. He concluded that the replacement of shrub lands and woodlands in

favour of croplands expected for the next decades is very likely to reduce the vegetation cover protecting the soil against the direct impact of rainfall, resulting in accelerated soil erosion. By the year 2030, rainfall erosivity is likely to increase during April and November. All scenarios converge to a slight erosivity decrease during March and May. Accounting for land changes and climate changes in an integrated manner, it is plausible to conclude that the highlands of the Taita Hills must be prioritized for soil conservation policies during the next 20 years. Although new croplands are likely to be settled in lowlands over the next decades, increase in precipitation volumes are expected to be higher in highlands. Figure 5 shows the annual irrigation water requirement for Taita Hills.

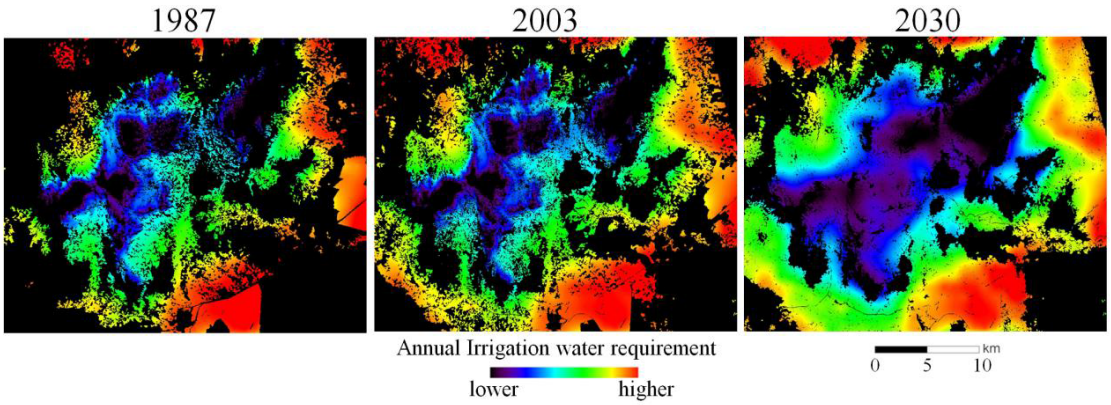


Figure 5 Annual irrigation water requirement (IWR) maps for 1987, 2003 and simulated model for 2030 (Maeda et al., 2010). The black spots are areas where there is no agricultural activity

CHAPTER THREE
MATERIALS AND METHODS

This chapter gives a brief description of the study area, the transect area chosen for hyperspectral data acquisition for crop mapping, the climate, terrain, population, and the economic activities of Taita Hills. Included also in this chapter are the data used and the procedures undertaken to acquire them. The software used is also given with their specific tasks in the study.

The chapter also gives the methodology in assessment of suitable cropland areas in Taita Hills, Kenya. Based on the scope and the methods that were relevant in achieving the objectives of the research, the process is in three fold; one which shows methods that were used to identify crops, second is that which was used to delineate and model the impacts of climate change on agro-ecological zones and finally that which was used in a suitability analysis of cropland areas of Taita Hills. All these three processes were used to assess suitable cropland areas of Taita Hills.

3.1 Study Area

The area of research, Taita Hills (03°20'S, 38°15'E), is located in South Eastern Kenya, about 150 Km inland from the Indian Ocean. It lies in the Taita-Taveta County, close to the Tanzanian border. The hills cover around 250 Km (Fleuret & Fleuret, 1991). Figure 6 shows a map of the study area.

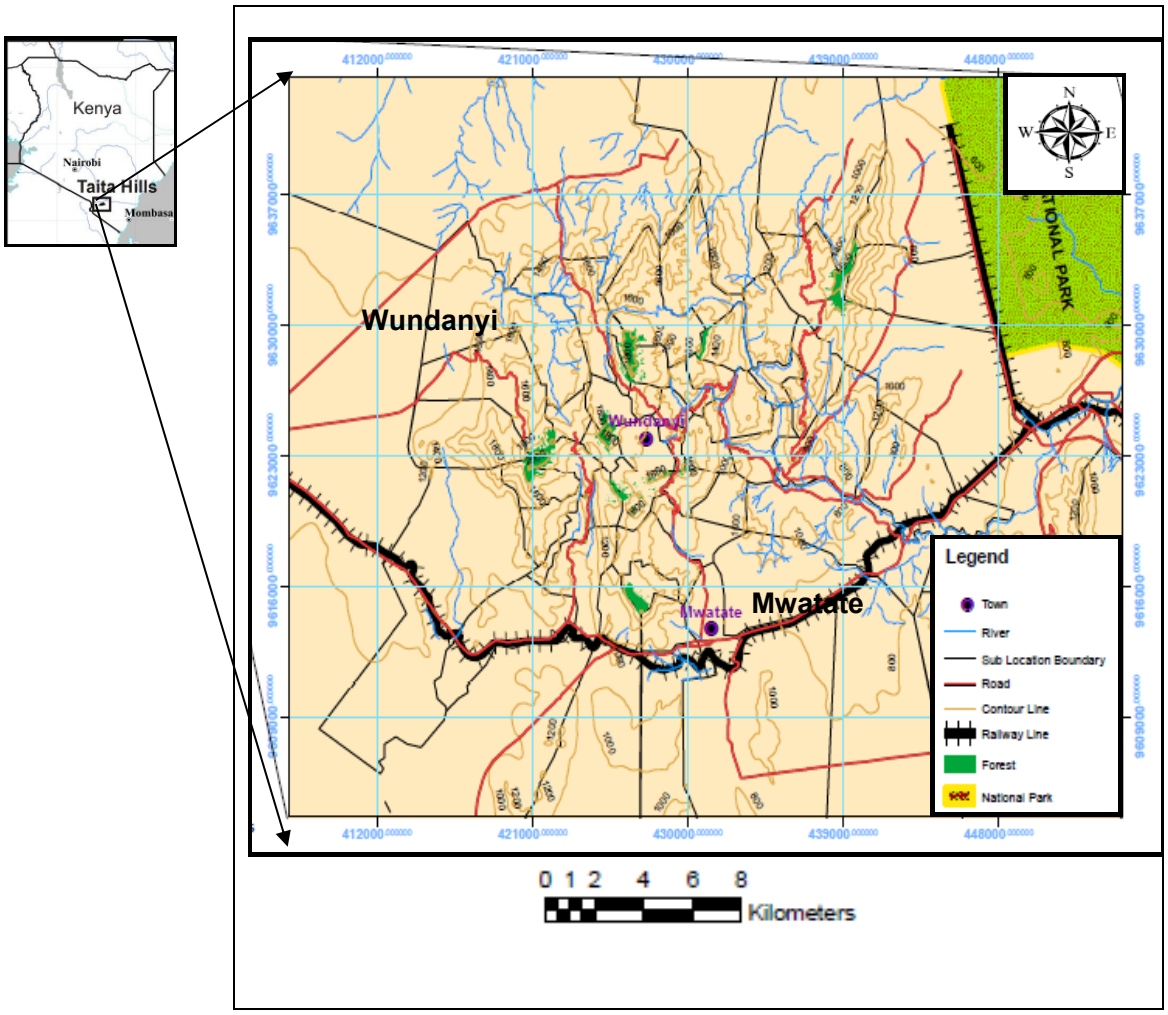


Figure 6 Taita Hills showing rail/road networks, indigenous forest patches and the terrain bounded by sub-location boundaries

Taita Hills is chosen as a model development area since it is relatively small, and has high elevation range, rich in biodiversity, good logistical location with facilities and several previous research activities, which have already produced a good set of geographical, ecological and agricultural data. Figure 7 shows a photograph showing part of agricultural landscape in Taita Hills.

Figure 7 Part of Taita Hills (Date: 20.01.2012, image by Boitt K. M)

Taita Hills are characterized as an island of fertile mountain area surrounded by the dry bush lands of Tsavo East and West national parks (Soini, 2005). The hills make up the administrative divisions of Wundanyi and Mwatate in Taita-Taveta County. These ancient precambrian hills sit on an altitude ranging from 1200 – 2200 meters above sea level rising from the Tsavo plains (Pellikka et al., 2009).

3.2 Taita Hills Transect Area

Figure 8 shows the 22km transect area chosen running from Mwatate to Vuria. This is the area that covered studies for hyperspectral and digital aerial images. The transect area covered low, mid and high zones that followed the topography of the area. Small holder farming is evident along this transect and good road networks for transportation of food crops to the markets. Sample plots chosen on the transect were used for training areas (Appendix I).

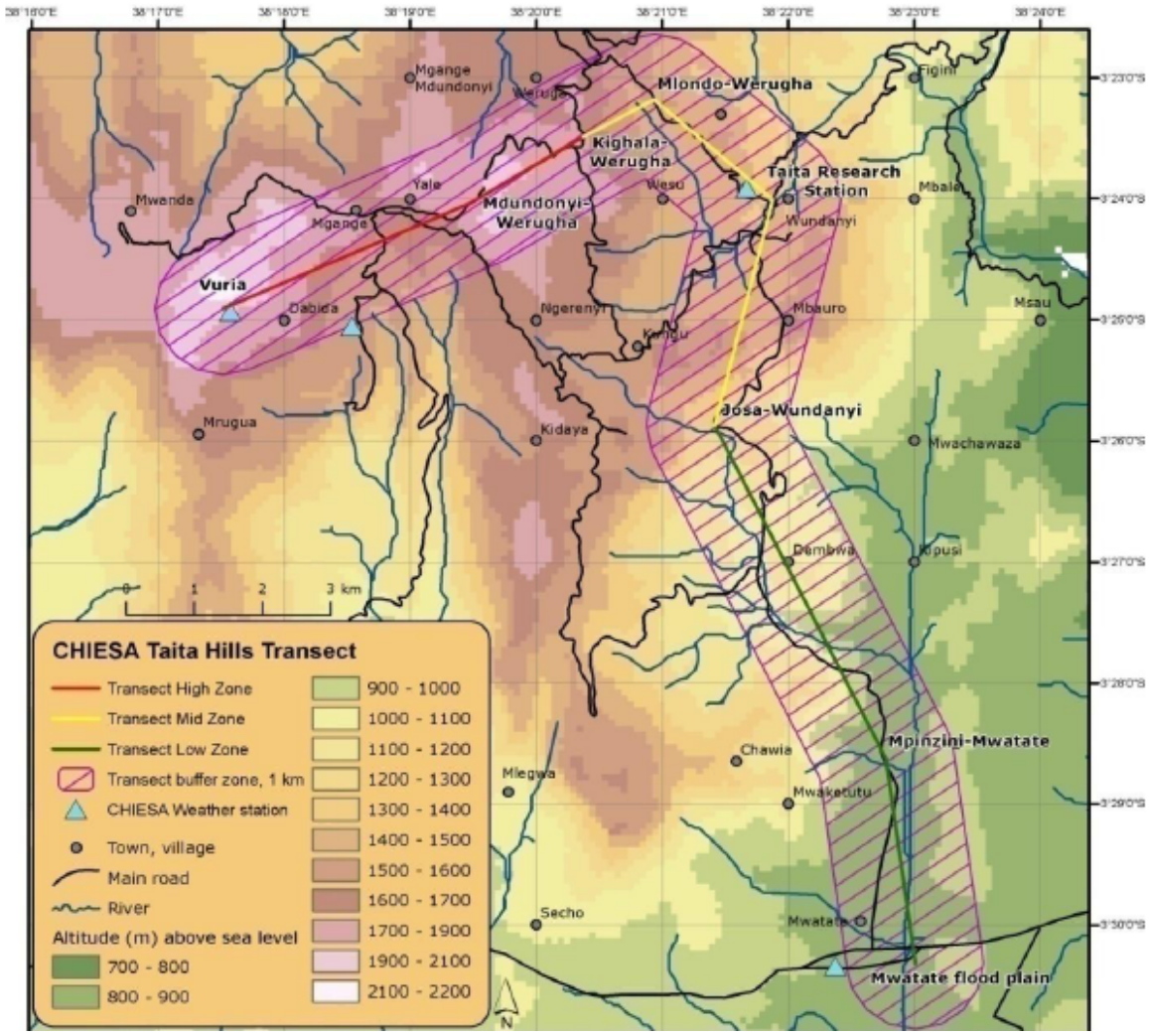


Figure 8 22 Kilometer transect area chosen from Mwatate through Wundanyi to Vuria (Piiroinen, 2014)

3.3 Climate of Taita Hills

The Taita Hills are strongly influenced by the Indian Ocean, forming a barrier to moisture-laden winds (Salminen, 2004). As a result, the area has two rainy seasons, one occurring during March-May and a shorter one during November-December. The mean annual rainfall ranges from 1332 mm to 1910 mm, with the southern and eastern slopes

receiving more rainfall than western and northern slopes (Omoro et al., 2013). In addition, some parts of the Taita Hills receive cloud precipitation (Jaetzold & Schmidt, 1983). The amount of additional rainfall due to cloud precipitation (sometimes referred to as occult or horizontal precipitation) is unknown and difficult to quantify. Stadmüller et al., (1987) reported relative values for cloud forest in the humid tropics ranging from 7 to 159% of annual rainfall while Bruijnzeel et al. (2010) reports that through fall exceeds annual rainfall in upper montane cloud forests by about 20% on average.

Recent research by the National Environment Management Authority (NEMA) in their Taita-Taveta County environment action plan for the period of 2009 – 2013 (Funder & Marani, 2013), reveals that Taita Hills receive the highest amount of rainfall compared to other parts of the county. The high potential areas in the Taita Hills receive more than 1000 mm of rainfall per annum (e.g. Wundanyi 1300 mm and Wesu 1400 mm) with temperatures average of 15 – 20^{0}C (Figure 9). The medium potential areas receive 700 mm to 900 mm, with higher temperatures, and evaporation for instance at Voi (Clark et al., 2009; Maeda et al., 2010).

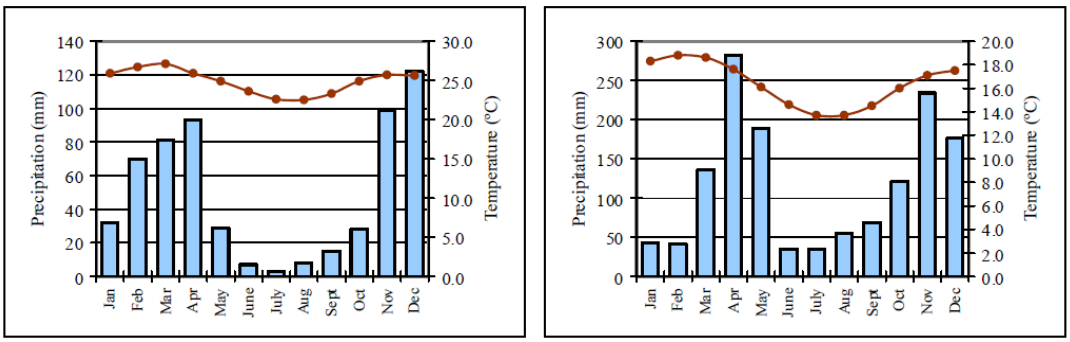


Figure 9 Mean annual precipitation at Voi meteorological station (560 m.a.s.l) on the left and on the right is at Wesu hospital (1675m.a.s.l). (Clark et al., 2009)

3.4 Terrain and Population of Taita Hills

The Taita hills complex rises above the erosional plains of the lowlands with small inselbergs (Figure 10). Its terrain pattern is largely contributed with geological processes

whereby it is constituted by three major blocks namely Sagalla, Taita and Kasigau (NEMA, 2009). The surrounding plains lay at 500 m - 600 m above sea level, while the highest peak of Taita Hills, Vuria, reaches up to 2208 m (Pellikka et al., 2009).

The population of the whole Taita-Taveta county has grown from 90,146 persons in 1962 to approximately 280,000 in the year 2009 (KNBS, 2010). According to Clark & Pellikka (2009), population growth has been a central driving factor behind rising environmental pressure. The population distribution is varied with most people living in the high potential areas of the foot slopes of the hills and in urban centers (NEMA, 2009). The upward trend of population growth in the Taita hills started in the mid 1920's (Soini, 2005; Pellikka et al., 2009).

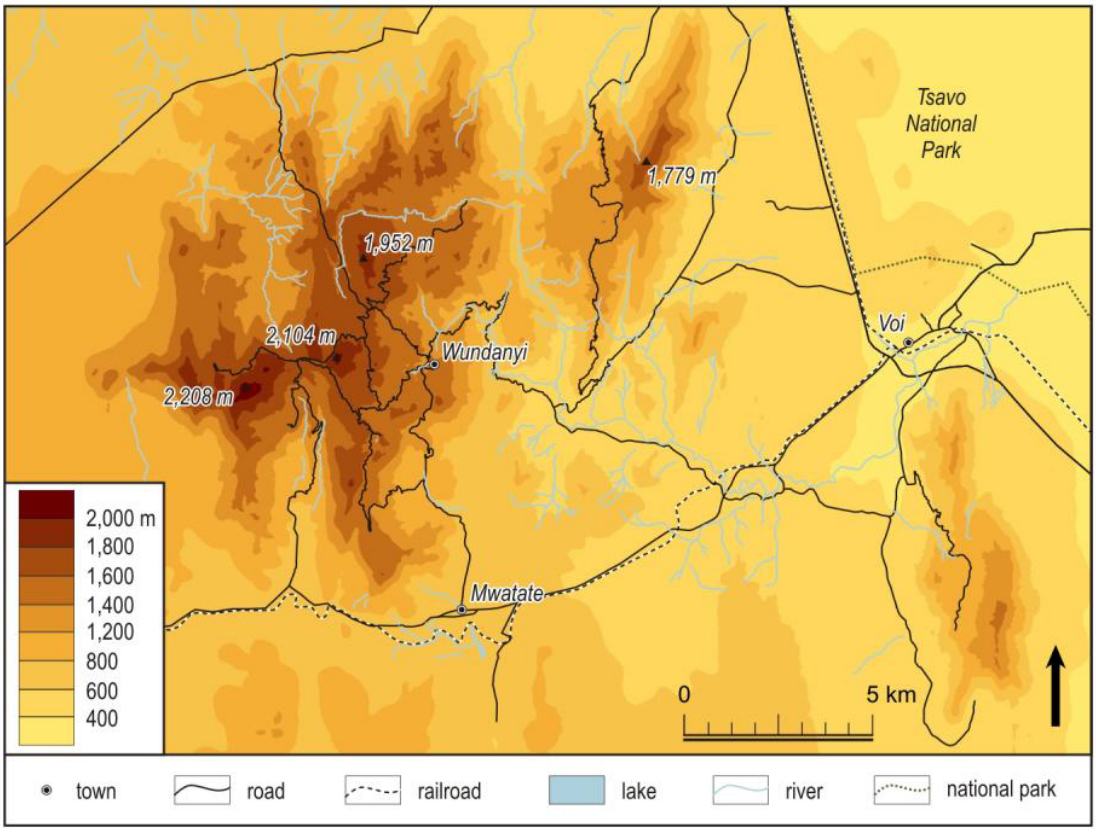


Figure 10 Terrain of Taita Hills

3.5 Economic Activities in Taita Hills

The main basis of living in the highlands is intensive agriculture, which is the main source of livelihood for 78% of people in the district (Pellikka et al., 2009). The indigenous cloud forests have suffered substantial loss and degradation for several centuries as abundant rainfall and rich soils have created good conditions for agriculture. Between 1955 and 2004, approximately half of the cloud forests in the hills have been cleared for agricultural lands (Pellikka et al., 2009). Population growth and increasing areas under cultivation for subsistence farming have caused a serious scarcity of available land in the hills and contributed to the clearance of new agricultural land in the lowlands (Clark & Pellikka., 2009). Currently, it is estimated that only 1% of the original forested area remains preserved (Pellikka et al., 2009).

The agriculture in the hills is characterized by intensive small-scale subsistence farming. Located in the inter-tropical convergence zone, the area has a bimodal rainfall pattern, the long rains occurring in March–May and short rains in November-December. The region has two crop growing seasons, which coincide with the long and the short rains (Jaetzold & Schmidt, 1983). Together, both crop growing seasons account for 150 – 170 days. The land is prepared during the dry season, and the crops are seeded prior to the short rains and long rains. Harvesting takes place after the end of the rainy seasons.

a) Agriculture

Taita Hills is experiencing a rapid population growth and intensification of agriculture, which is the major economic activity for the Taita community (Boitt et al., 2014) with horticulture dominating the agriculture based economic activity in the area (Funder & Marani, 2013). The crops grown in Taita Hills follow the altitudinal pattern of the area which in turn influences the agro-ecological zones present. In the lower highland zone and in upper midland zone, the typical crops are maize, beans, peas, potatoes, cabbages, tomatoes, cassava and banana (Jaetzold & Schmidt, 1983). In the slopes and lower parts of the hills with average annual rainfall between 600 mm and 900 mm, early maturing maize, sorghum and millet species are cultivated. In the lower midland zones with

average rainfall between 500 mm and 700 mm, dryland maize varieties and onions are cultivated, among others (Maeda, 2011). Maize and beans are the most important food crops and are mainly grown for subsistence (Figure 11).

Figure 11 Crops that are grown in Taita Hills: Maize, bananas, vegetables, beans and various fruits. (Taken on 18.1.2012, Boitt M. K)

Other pulses are also grown and are mainly intercropped with maize. Planting of sorghum and millet in the hills is however rare, because their acceptance as food crops is low due to their unpopularity as food (NEMA, 2009). Arrow root and cassava are very important food crops and an alternative when the maize crop fails. Sweet and Irish potatoes are also grown and consumed locally. Understanding the driving forces, tendencies and patterns of land changes is an essential step for elaborating policies that can conciliate land use allocation and natural resources conservation. The expansion of agricultural areas in the Taita Hills and changes in precipitation patterns associated with climate change are imminent threats for soil conservation (Maeda, 2011).

b) Livestock production

The main livestock products are meat, milk, and hides (NEMA, 2009). Dairy production is more common in the upper zone of the Taita hills where the climatic condition and small land holdings are favorable for *zero-grazing.* The types of dairy cattle found in those areas are Friesian, Ayrshire, Guernsey and Jersey as well as cross-breeds. However, Taita Hills lack beef production because of small farm sizes (NEMA, 2009).

c) Fish farming and other economic activities

Farmers are also considering fish farming as an economic activity. Considerate fish ponds are being constructed for fish farming. Other economic activities include businesses such as retail shops, sand harvesting, mining, and transportation among many others.

3.6 Data

Table 1 gives the datasets and their description. The hyperspectral imagery, the aerial camera specification and other existing datasets that were used in the study are described in the table which constituted the primary data. The secondary data sources included the University of Helsinki, Geonetwork (Finland), International Livestock Research Institute (ILRI) in Kenya and Food and Agricultural Organization (FAO).

Hyperspectral images and aerial images were acquired simultaneously when the cloud cover was low. The digital Terrain Model (DEM) that was available was of a coarser resolution (20 meter but was resampled to 0.6 meters to enable it to be used for topographical correction during the processing of the hyperspectral remote sensed imagery.

Table 1 Datasets used for the research.

Data sets	Description
Hyper spectral images (AISA Eagle Imagery)	Acquired in January 2012, the whole transect area, (*Figure 8)* covering the low, mid and the high zones. It has 64 bands ranging from 400 nm to 1000 nm.
Aerial Images (NIKON D3X)	Acquired at the same time as that of hyperspectral images and processed using Ensomoasic software to produce a mosaic imagery of the transect area.
Satellite image (SPOT 5)	Basis for land use and land cover mapping. Available at the University of Helsinki geonetwork. Classified image for the land use was used in the study.
Existing GIS data	Available at the University of Helsinki geonetwork.
DEM (20 meter –resolution)	Available at the University of Helsinki geonetwork. Resampled from the 50 meter 1: 50,000 national topographical maps.
Climate data sets	WorldClim data of FAO for 1960-2010 and projection of 2050. Weather station data for 2009-2012.
Soils of Kenya	ILRI databases, Kenya. Soil properties described on each soil type.
GPS (SPAD measurement)	Crops mapped and put in databases for each plot. Chlorophyll information reading from 0 to 99.

3.7 Imaging Spectroscopy

Hyperspectral systems are complete, push broom imaging systems, consisting of a hyperspectral sensor, a high-performance GPS/INS sensor and a data acquisition unit housed in a rugged PC (Figure 12). The sensors employ high quality transmissive imaging spectrographs which feature sub-pixel smile and keystone distortions, and very low polarization dependency. The system includes also the control and operating software packages.

Figure 12 AISA eagle sensor system components

Table 2 Sensor specifications

Numerical aperture	F/2.4
Spectral range	circa 400 nm -1000 nm
Spectral resolution	3.3 nm (maximum)
FOV	37.7 degrees
Detector	Progressive scan CCD detector
Spectral binning	8x
Number of bands	64
Spectral sampling	8.64 - 9.55 nm
Frame rate	120 Hz
Spatial pixels	969
Output	12 bits digital
Weight	6.5kg

The sensor specification are given in Table 2 above. AISA Eagle is an imaging spectrometer that is used in the fields of research, commercial use and public services. The applications include forestry management, vegetation studies, environmental investigations, precision farming, target identification, water assessment etc. Imaging spectrometers are sensitive systems and each sensor is individually calibrated.

3.8 Flight Campaign

The flight campaign for hyperspectral data acquisition and field work kicked off in January 2012. January and February in Taita Hills and most parts of Kenya experience dryness and very little if no rain weather conditions. It was in this time that flight planning and data collection exercise for this research work was done. Figure 13 shows the flight planning information for hyperspectral and aerial image acquisition in the three transect areas (running from Mwatate through Wundanyi to Vuria) including some other areas which were not for this study although the data was captured at that time for other studies. The choice of transect was such that it reduces the expenses of flying the hyperspectral sensor.

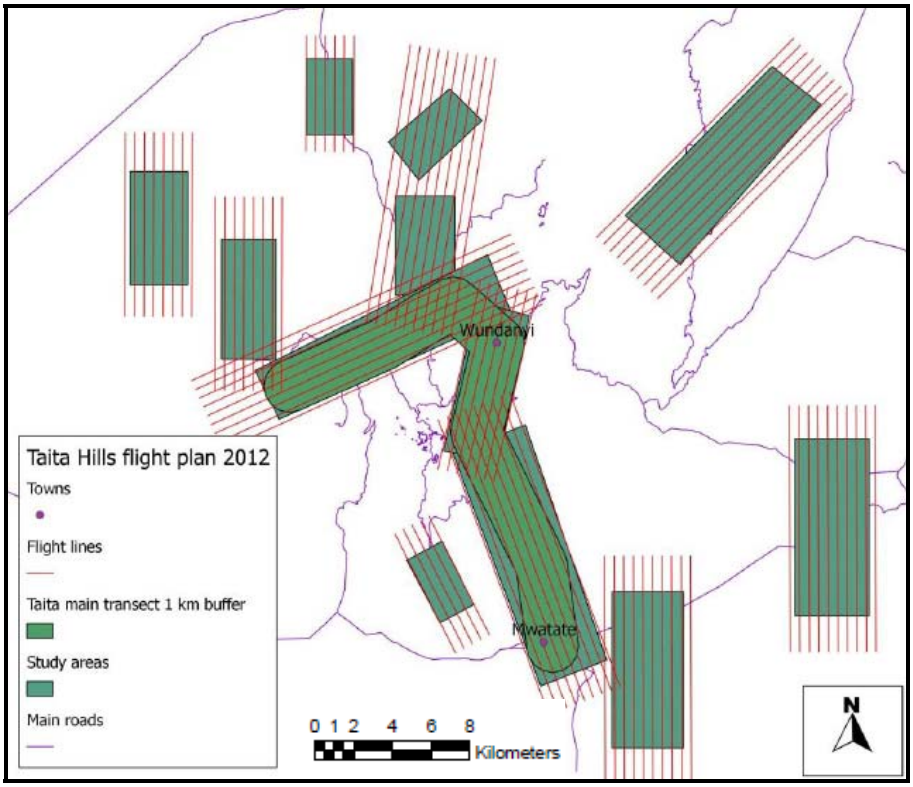


Figure 13 Flight planning for Taita Hills showing the main transect area running from Mwatate town through Wundanyi and other study areas for other studies (Piiroinen, 2014)

The sensor mounting was done at Wilson Airport and a test ran over Voi town in Kenya where the plane was to operate from (Figure 14). Data acquisition was done when the sky was clear (cloudless) and from the time period: 11 am to 3 pm to avoid shadows, running for three days in order to cover the whole transect. The fieldwork measurements were conducted simultaneously with hyperspectral data acquisition. The flying height was about 2,400 m.a.s.l. accurate photographs taken by the Nikon D3X camera (Figure 15), which was attached together with the AISA sensor on board during the time of flight, were used to map every species in the selected plots. These data sets were used as both ground truth and training data.

Figure 14 Cessna caravan aircraft at Voi, Kenya (image by Pekka Hurskainnen)

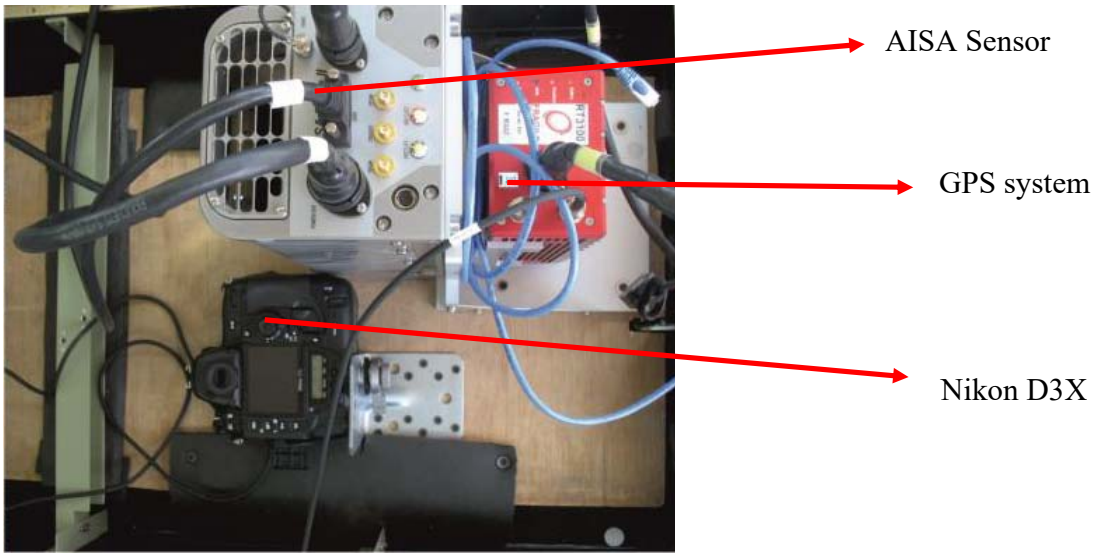


Figure 15 Sensor assembly on board (image by Pekka Hurskainnen)

3.9 Crop Mapping

In the chosen transect, 25 plots were randomly picked ensuring that it covered both the lower, the middle and the upper zones. The digital aerial photographs that were printed on site were used for field work measurements for each plot (Figure 16). This ensured that the data signatures that would be obtained from the hyperspectral data would conform well to the field data that was collected since the time difference was almost null. After the field work exercise, the mapped photographs were georeferenced onto the hyperspectral imagery and they were digitized as training areas for a classification. Some training areas from some plots were reserved for accuracy assessment.

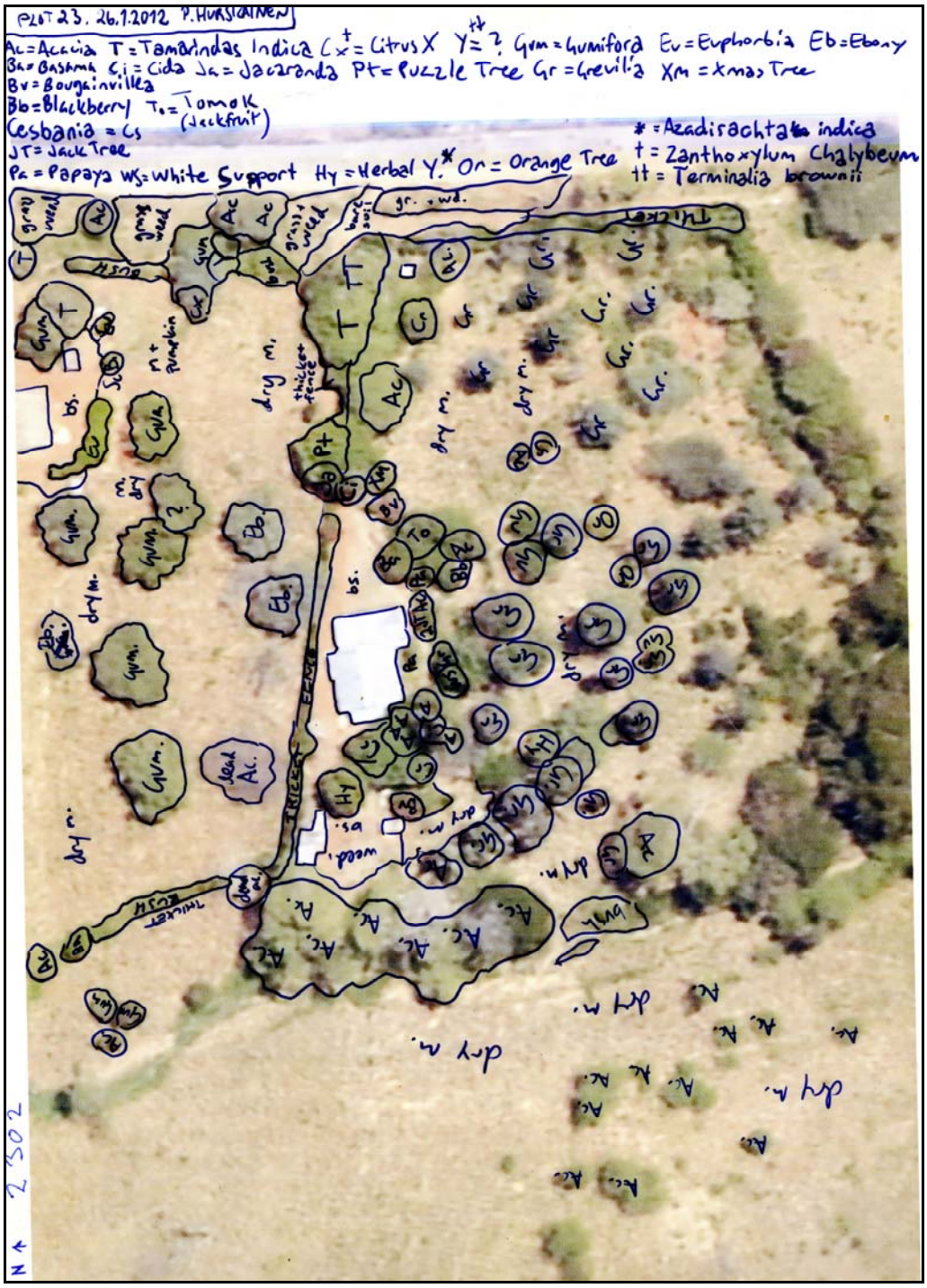


Figure 16 Fieldwork mapping on aerial photograph for crops and marked using a blue felt pen

3.10 Climate Data

The climate data sets generated from 'WorldClim' data have been used in this study for the agro-ecological and land suitability assessments. WorldClim is a set of global climate layers (climate grids) with a spatial resolution of about 1 square kilometer. The data can be used for mapping and spatial modeling in a GIS or with other computer programs (Hijmans et al., 2005). To validate this data for a local area, rainfall and temperature recordings were used from the weather stations in Taita Hills (Table 3). 'Worldclim' data and the field data collected gave little variations in both temperature and rainfall and therefore were used for climate studies for this research.

Table 3 Observed weather station data for Taita Hills (annual means).

Easting (m)	Northing (m)	Elevation (m)	Mean Temp. (^oC)	Mean Rainfall (mm)	ID	Location
429325	9624413	1407	20.83	1390	88531	Wundanyi
426825	9623401	1657	18.69	1460	88534	Wesu
430248	9612549	887	24.42	980	88535	Mwatate
429293	9619152	1114	22.42	790	88536	Dembwa
425591	9626700	1644	19.04	1220	88537	Werugha
427245	9614524	1625	20.44	910	88538	Chawia
428129	9625476	1489	20.09	1380	88539	Kitukunyi
423583	9619062	1122	22.38	1040	88540	Buraura
420496	9624927	1693	18.66	540	88535	Mwanda

3.11 Software

The software that has been used for all the processing and analysis work included the ***CaliGeo Pro*** was used explicitly to pre-process AISA Eagle raw data to formats that could be opened and analyzed in other remote sensing application software. ***ATCOR-4*** was used to correct for geometric, radiometric and atmospheric effects of the AISA data. ***Envi*** was entirely used for image processing and classification. Accuracy assessments for the classified hyperspectral data were generated using the same software.

ArcGIS was used basically as a main tool for GIS analysis in terms of multivariate clustering, modelling the impacts of agro-ecological zones, assessing the land cover and land use changes. Land resource database systems was developed using this software where all land resources such as soil, DEM, land cover, administrative and political boundaries were grouped. Land suitability assessments have as well been generated using the software package.

Global Mapper was used in visualizing the terrain models of Taita. Global Mapper was used to link one datasets to another software application for instance, it could read ASCII files and export them to shape files or DXFs which could be used in other applications such as ArcGIS.

3.12 Work Flow

A main workflow (Figure 17) is shown that summarizes the processes for achieving the objective of the study. Two other sub-workflows that explains the processes in detail for agro-ecological zones modeling and suitability assessments is provided.

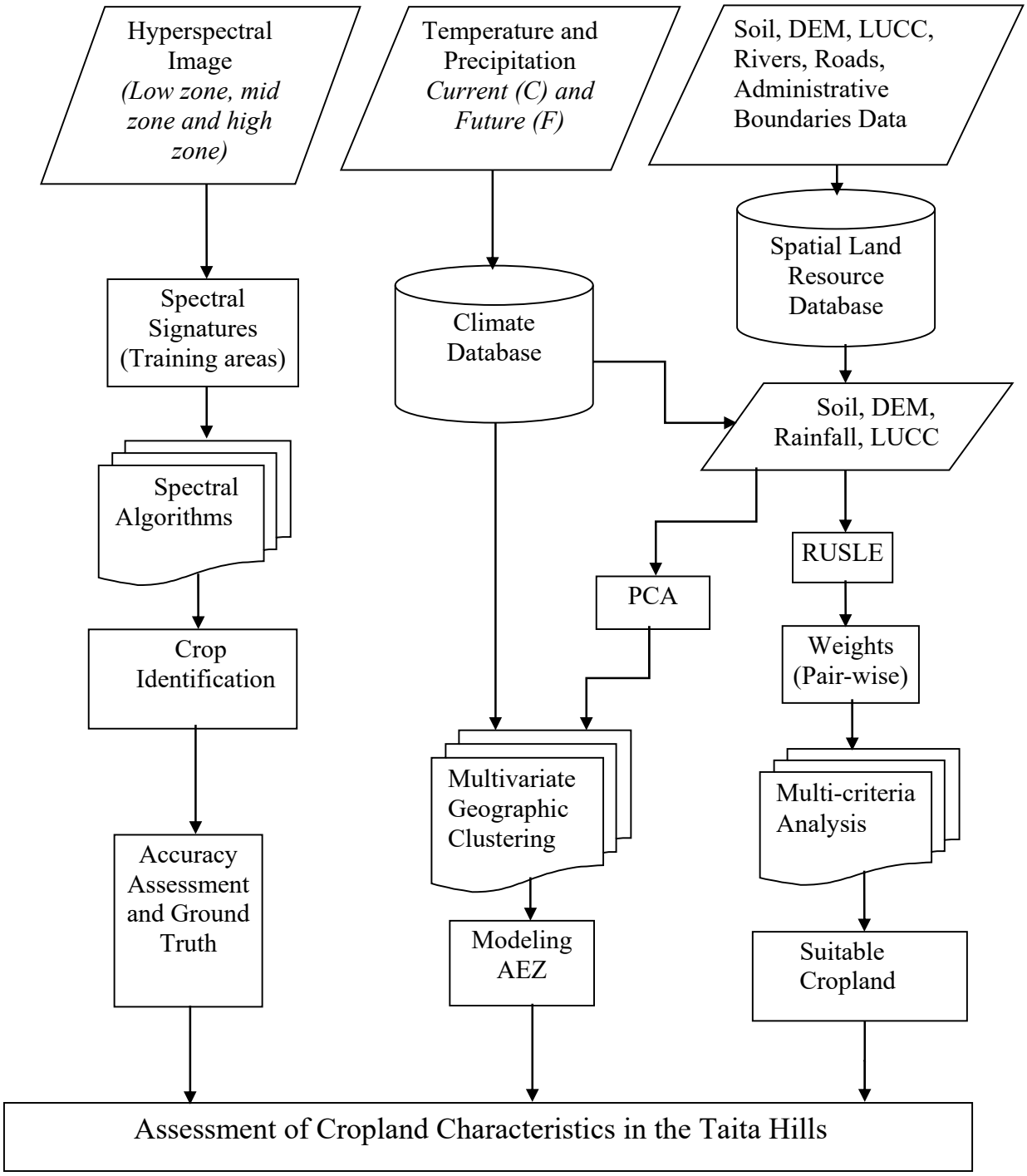


Figure 17 Main work flow

3.13 Pre-processing of the Raw Hyperspectral Data

The raw hyperspectral image was pre-processed. Three distortions: Radiometric, geometric and atmospheric effects were corrected for. Radiometric corrections for sensor sensitivity, solar angle and topography. Geometric correction was basically applied to have a geometrically correct image. Digital elevation model at 20-meter resolution was resampled to 0.6 meter spatial resolution which conformed to the hyper spectral image spatial resolution. Atmospheric correction was finally done to remove the atmospheric effects. The image was checked using the z-profile tools and spectral reflectance on every cursor location of the image and was analyzed. There was no distortion. This procedure was conducted using the ATCOR-4 software which is specifically designed for correcting for atmospheric distortions.

3.14 Hyperspectral Image Classification

i) Spectral Angle Mapper

Spectral Angle Mapper (SAM) is a physically-based spectral classification that uses an n-D angle to match pixels to reference spectra. It assumes that data have been reduced to apparent reflectance (true reflectance multiplied by some unknown gain factor controlled by topography and shadows). The algorithm determines the spectral similarity between two spectra by calculating the angle between them as vectors in a space with dimensionality equal to the number of bands (n). This technique, when used on calibrated reflectance data, is relatively insensitive to illumination and albedo effects. Endmember spectra used by SAM can come from ASCII files or spectral libraries, or one can extract them directly from an image (as ROI average spectra). SAM compares the angle between the endmember spectrum vector and each pixel vector in n-D space.

Smaller angles represent closer matches to the reference spectrum. The result is a classification image showing the best match. Pixels further away than the specified maximum angle threshold in radians are not classified. SAM was used to classify the

selected crop species in Taita hills. The spectral angle of dissimilarity was kept at 0.1 radians (see Figure 18 below).

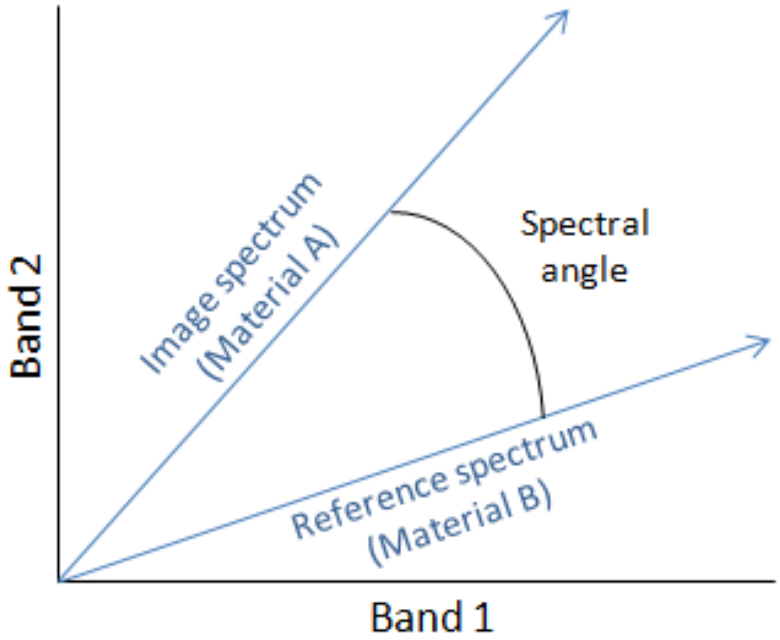


Figure 18 2D Scatter plot of an image spectrum in two bands

SAM determines the similarity between an image spectrum (representing an unknown material) and a reference spectrum (representing a known material) by computing the spectral angle between them, treating them as vectors in *n*-dimensional spectral space, where *n* is the number of bands. To illustrate this method is to create a 2D scatter plot of an image spectrum and library spectrum in a two-band image (Figure 18).

$$\alpha = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\left(\sum_{i=1}^{nb} t_i^2\right)^{1/2}\left(\sum_{i=1}^{nb} r_i^2\right)^{1/2}}\right)$$

Where:

nb = the number of bands
t_i = test spectrum
r_i = reference spectrum

The equation above shows the functionality of the algorithm in comparing two bands of an image. This method was used to classify crops in the mid zone areas. Spectra from several regions outside the classification region can be used to classify data in another region so long as the features in the data are similar to those of the spectral training data in the other region. This is very essential when training samples from a given area cannot be easily acquired. This method was also used in the high zone imagery to classify crops.

ii) Spectral Information Divergence

Spectral Information Divergence (SID) is a spectral classification method that uses a divergence measure to match pixels to reference spectra. The smaller the divergence, the more likely the pixels are similar. Pixels with a measurement greater than the specified maximum divergence threshold are not classified. Endmember spectra used by SID can come from ASCII files or spectral libraries, or you can extract them directly from an image (as ROI average spectra). This method was used in the low zone imagery to classify crops. Low zone constituted small leaved crops and shrubs that were a bit similar to crops. Sugarcane needed to be discriminated from maize although during the time of field data collection, maize were drier in this zone than in mid zone.

3.15 Crop Identification

Spectral signatures of crops are known to vary due to leaf optical properties, leaf angles and spatial distribution. Signatures also vary from leaf to canopy scales. The spatial resolution for this datasets was kept at 0.6 meters, which is more accurate in discriminating the various crops especially for areas such as maize plantations, banana farms, and large fruits trees such as mangoes and avocadoes. Eight sampled plots in the mid zone areas were geo-referenced in order to get exact location of the crops in the plots. A detailed aerial mosaic was used to overlay the geo-referenced maps onto it and training polygons with respect to the crops were on-screen digitized with ArcGIS 10 out of the maps. Small regions depicting the spectral patterns for the specified crops were then generated and saved as regions of interests (ROIs) and later used as endmembers.

For spectral extraction, 148 digitized polygons were used to derive endmembers for crop classification. They were extracted from the sampled plots. These comprised of maize (*Zea mays*), bananas (*Musa paradisiaca*), mangoes (*Mangifera indica*), avocados (*Persea americana*), sugarcane (*Socharum spp.)* and farm trees such as Cypress (*Cupressus lucitanica*), Grevillea (*Grievillea robusta*) among many others. They were further divided into two datasets so that about 30% of every class was reserved for accuracy assessment and 70% was used for classification. Theoretically, existing pure features in mixed pixels are referred to as endmembers and their collection describes all spectral variability for all pixels in a given image. Endmembers for this study were selected to enable mapping of the selected crops using spectral angle mapper (SAM) algorithm of Envi software. Figure 19 below shows the spectral reflectance profile of the six-collected endmembers in different colors for the mid zone. Blue corresponds to maize plantations, cyan on the other hand corresponds to sugarcane whereas yellow is for mango trees. Magenta is representing agro-forestry, green for bananas and finally the avocados are represented by red color.

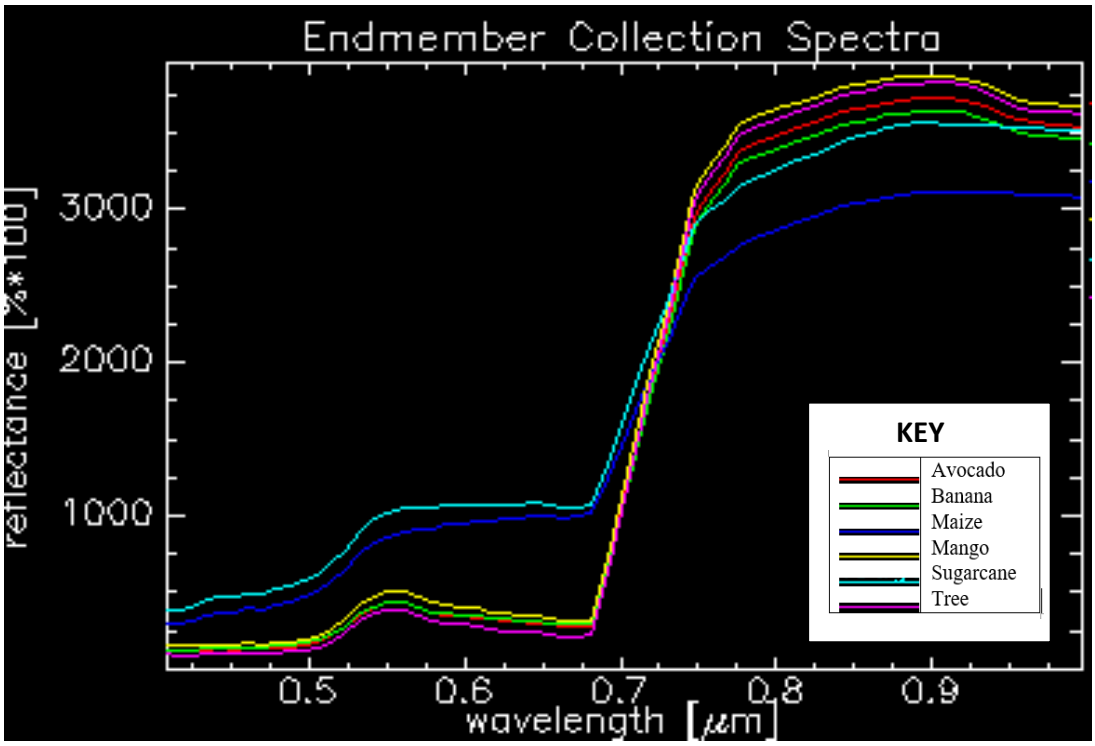


Figure 19 Spectral profiles of six classes extracted from input image of the mid zone

3.16 Accuracy Assessment and Ground Truthing

Digitized polygons from the aerial imagery for crops were divided into two datasets so that about 30% of every class was reserved for accuracy assessment and 70% was used as training areas classification. Table 4 shows the number of polygons corresponding to each crop that were used for classification in the mid zone area. The total number of plots in the transect areas were 25. The same procedure was used for low zone and high zone datasets with different training areas for each case.

Ground truthing was done in the field using hand held GPS and locating crops in the selected plots. A dialogue with farmers was conducted especially to know if the farmer had planted the same crops such as maize in the same plot during the time of study. In the low zone areas, maize had been harvested already but other crops were measured.

Table 4 Training samples for mid zone

Classes	Classification	Accuracy Assessment	Total
Bananas	12	3	15
Trees	5	2	7
Mangoes	39	9	48
Sugarcane	5	2	7
Avocado	39	8	47
Maize	18	6	24

3.17 Modeling Agro-ecological Zones

Multivariate geographical clustering analysis represents a relatively recent development, characterizing discontinuities into subsets according to multiple parameters, such as orientation, spacing, and roughness. Instead of considering one variable at a time, a number of parameters can be treated simultaneously, so that the interactions between parameters are taken into account. Several investigators have recognized the potential of multivariate geographic clustering for delineating homogeneous regions objectively within small maps. Multiple geographic areas can be classified into a single common set of quantitative eco-regions to provide a basis for comparison, or maps of a single area through time, can be classified to portray climatic or environmental changes geographically in terms of current conditions. This tool has also been widely used in delineating ecosystems regions, environmental management, water resource planning and decisions. Figure 20 shows the clustering technique.

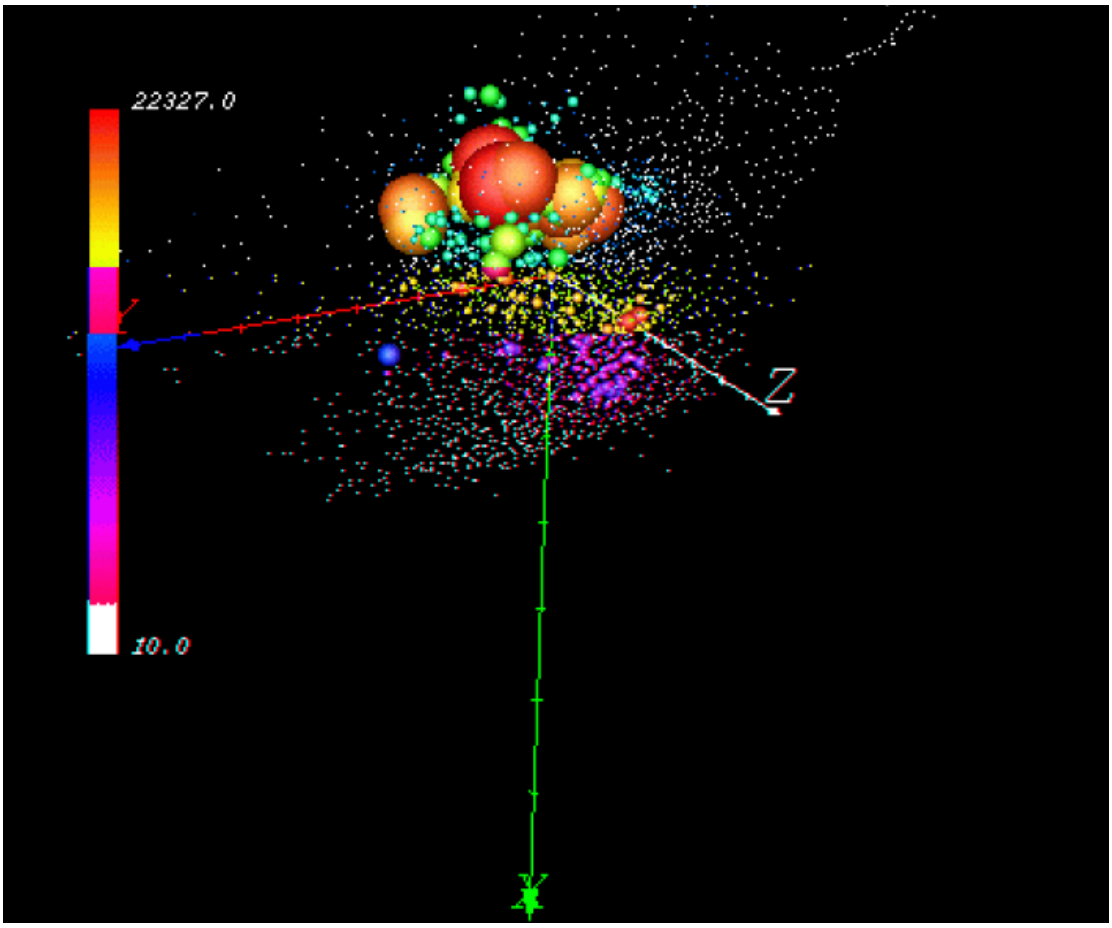


Figure 20 Clusters in 3-dimensional space. Sphere, color and size are indicative of the number of map cells in each cluster

Multivariate geographic clustering employs non-hierarchical clustering on the individual pixels in a digital map from a Geographic Information System (GIS) to classify the cells into types or categories. The non-hierarchical algorithm, which is nearly perfectly parallelizable, consists of two parts: initial centroid determination (called seed finding) and iterative clustering until convergence is reached. The algorithm begins with a series of 'seed' centroid locations in data space—one for each cluster desired by the user. In the iterative part of the algorithm, each map cell is assigned to the cluster whose centroid is closest, by simple Euclidean distance, to the cell. After all map cells are assigned to a centroid, new centroid positions are calculated for each cluster using the mean values for

each coordinate of all map cells in that cluster (Figure 20). The iterative classification procedure is repeated, each time using the newly recalculated mean centroids, until the number of map cells which change cluster assignments within a single iteration is smaller than a convergence threshold. Once the threshold is met, the final cluster assignments are saved. Figure 21 shows the description of geographic space variables in database for clustering (Mahinthakumar et al., 1999).

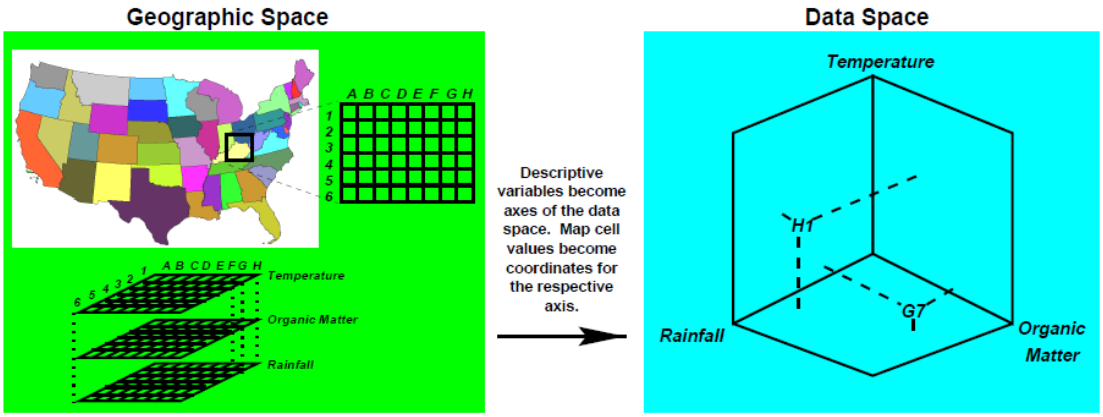


Figure 21 Description of variables in geographic space to data space (Mahinthakumar et al., 1999)

PCA is a standard statistical technique that can be used to reduce the dimensionality of a data set. It is known as Karhunen-Loeve transform (Dony et al., 2001). It has proven to be an exceedingly useful tool for dimensionality reduction of multivariate data with many application areas in image analysis, pattern recognition and appearance-based visual recognition, data compression, time series prediction, and analysis of biological data among many other applications. The strength of PCA for data analysis comes from its efficient computational mechanism, the fact that it is well understood, and from its general applicability. PCA is a method of transforming the initial data set represented by vector samples into a new set of vector samples with derived dimensions. The basic idea can be described as follows: A set of m-dimensional vector samples X = {x1, x2, x3,..., xm} should be transformed into another set Y = {y1, y2, ..., ym} of the same dimensionality, but y-s have the properties that most of their information content is

stored in the first few dimensions. So, we can reduce the data set to a smaller number of dimensions with low information loss.

The transformation is based on the assumption that high information corresponds to high variance. If we want to reduce a set of input dimensions X to a single dimension Y, we should transform X into Y as a matrix computation: [Y] = [A·X] choosing A such that Y has the largest variance possible for a given data set. The single dimension Y obtained in this transformation is called the first principal component. This component is an axis in the direction of maximum variance. The first principal component minimizes the distance of the sum of squares between data points and their projections on the component axis. Figure 22 shows the schematic diagram for generating variables for agro-ecological zones from the data sets.

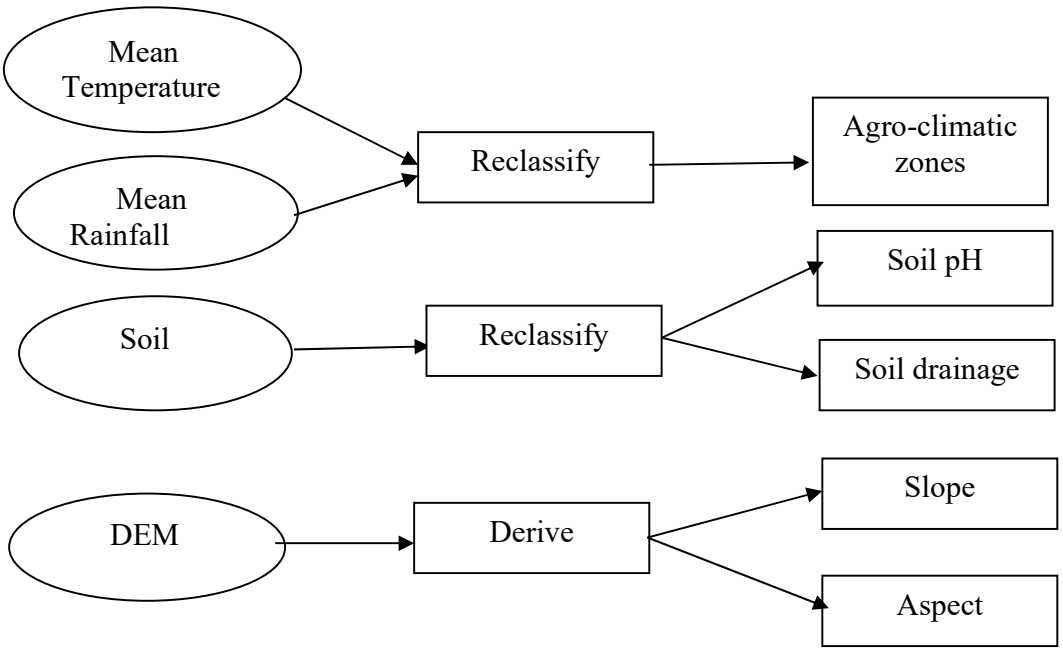


Figure 22 Schematic diagram for the dataset conversion to achieve the agro-ecological zones of Taita Hills

Principal components analysis (PCA) was run for soil, aspect and slope (GIS datasets) and combined with agro-climatic zones using the multivariate geographic clustering techniques (Figure 23). The result indicated that the major variance were mainly contributed by soils hence the main parameter for understanding agricultural phenomena in Taita Hills. With the initial iteration of 5 zones (which already FAO provided in 1983 for whole of Kenya), the result was coarse for analysis although it had a huge similarity to it. A new iteration was ran for 10 AEZ, the result was good to analyze and assess. More than 10 AEZ did not give a significant result that could be necessary for analysis.

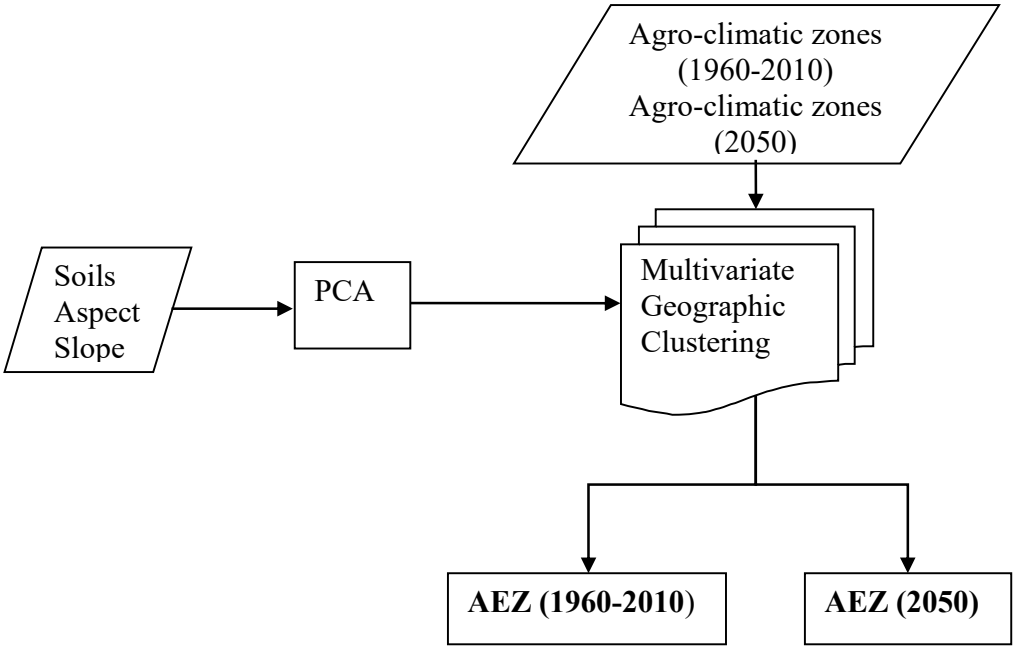


Figure 23 PCA and multivariate geographic clustering for modeling agro-ecological zones

The results of PCA were subjected to multivariate geographic clustering (Williams et al., 2008) in conjunction with the climate data sets (historic and future) to delineate agro-ecological zones respectively (Figure 23).

3.18 Assessment of Suitable Croplands

The assessment of suitable croplands utilizes soil data, climate data, LUCC and digital terrain model (DEM). The crop suitability mapping was accomplished by having all data weighted sum overlaid. Weighted sum overlay tool in ArcGIS overlays several raster multiplying each by their given weight and summing them up. Each of the determinants for crop suitability used in this project was given weight based on the multi-criteria decision approach in which it uses a matrix pairwise comparison by characterizing the properties of the soils of the area, climate and the DEM. Analytical Hierarchical Process (AHP) was used in the pairwise comparisons. It uses weighted linear combination technique and expert wise comparison approach (Malczweski et al., 2000). The formula to calculate index value is based on the equation below:

$$I_i = \sum_{i=1}^{n} w_i x_i$$

Where:

$\mathbf{I_i}$ = is the index value

$\mathbf{W_i}$ = is the weight

$\mathbf{X_i}$ = is the standard value.

Several ranking criteria (Table 5) were used to come up with weights. Each factor in consideration is ranked according to decision's makers preference. 5 indicates high sensitivity and 1 indicates low sensitivity to suitability study (Table 6). Assigning weights is a very complex decision problem and it takes care of several aspects in the function. AHP is a very widely accepted statistical and popular means to calculate weights for variables.

Table 5 Ranking parameters

Erosion Parameters	Sub-class Parameters	Rank
1.Rainfall	More than – 1400 mm	3
	1201 mm – 1400 mm	2
	1000 mm – 1200 mm	1
2. Temperature	Less than 15° C	5
	15° C to 17° C	4
	17° C to 19° C	3
	19° C to 22° C	2
	More than 22° C	1
3. Soil type / pH levels	Low PH (shallow & loamy)	3
	Moderate pH (loamy sand to sandy loam)	2
	High pH (sandy loam to clayey loam)	1
4. Slope	Very Steep (>40%)	5
	Steep (30.1-40%)	4
	Moderate (20.1-30%)	3
	Gentle (10.1-20%)	2
	Very Gentle (<10%)	1
5. Drainage density	>6 km/sq.km	5
	5.1-6.0 km/sq.km	4
	4.1-5.0 km/sq.km	3
	2.1-4.0 km/sq.km	2
	<2 km/sq.km	1
6.Land use and land cover	Agriculture	5
	Sparse vegetation	4
	Forest	3
	Water bodies	2
	Built-up	1

Table 6 Description of weights based on intensity of importance

Intensity of Importance	Description
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance
Reciprocals	Values for Inverse Comparison

Since soil erosion generally occurs when the soil is displaced by rain and transported from the specific area, therefore rainfall is considered as the major driving factor of soil erosion. High rainfall amount is indicative of significant soil loss hence where the rainfall is more than annual average, chance of erosion will be more. The factor that significantly affects the soil displacement by rain is vegetation cover. The reduction of vegetation cover can increase soil erosion.

Soil map is ranked according to the infiltration/retaining characteristics of the soil type. The zone in the study area having soil with low retaining property produced high runoff causing high soil erosion. Thus higher rank is tagged to the zone with low retaining capacity and vice-versa. Generally, wherever steeper the slope, chance of soil erosion will be high. Higher drainage density areas are assigned higher rank and vice versa. Different land use types in terms of area size and pattern influenced the crop suitability and soil erosion risk. Figure 24 gives a detailed work flow for cropland suitability mapping.

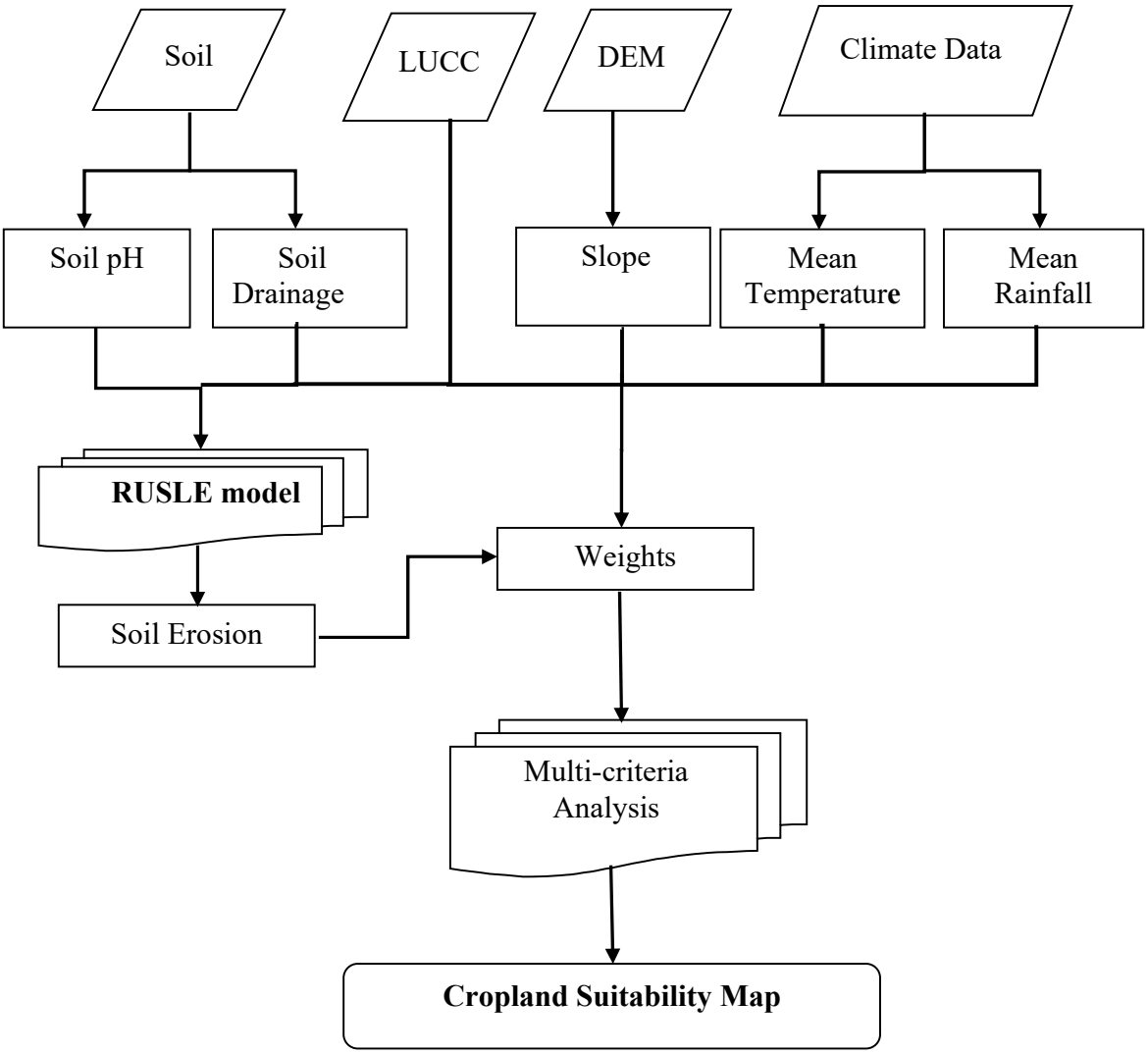


Figure 24 Workflow for cropland suitability mapping

With cropland suitability mapping being the main focus of the research, all local factors positively and negatively affecting crop farming in Taita Hills were explored. A conclusion was therefore drawn that crop farming in this area is not only affected by amount and distribution of rainfall, temperatures, altitude, and soils properties but also soil erosion. The analysis was consequently procedurally broken down into seven phases as follows:

i) Slope analysis

Land suitable for crop farming in Taita Hills is to a large extent affected by the topography the area is characterized with. The study therefore considered running 3-D analysis that have direct impact on the crop farming suitability situation. Soil erosion has been significantly affecting crop farming in Taita Hills with terrain slope being considered as the main factor. The slopes in Taita Hills were then generated and mapped using the DEM with the aid of Arc GIS. Contours were then generated using the DEM so as to bring out the topographical pattern of the study area. Water and eroded materials flowing from higher elevations follow certain pattern depending on the nature of the land and therefore all watersheds were analytically delineated using the DEM.

ii) Mean annual rainfall categorization

The mean annual rainfall spatial distribution from the original data was mapped. Areas that receive the highest (high elevations at windward side) and lowest rainfall (low elevations at lee-ward side) were consequently identified.

iii) Soil drainage categorization

The study used the soils data to map the drainage properties of soils in Taita Hills revealing the spatial distribution of this soil property. The following parameters: W (well drained), S (slowly drained), R (rapidly drained) and E (extremely drained) soils were mapped out from the soil drainage properties.

iv) Mean annual temperature categorization

The mean annual temperature data was used in generating a map showing the spatial variations in temperatures within the area of study. This was used to infer the levels of evapo-transpirations.

v) Soil erosion mapping

Soil erosion was treated as one of the major determinants of crop farming in Taita Hills with areas associated with high soil erosion realizing low crop yields as opposed to areas with low or no soil erosion. GIS was used to model soil erosion by use of USLE/RUSLE

(Renard et al, 1997) soil loss empirical model. Figure 25 shows the flow chart for the RUSLE model for soil erosion mapping in Taita Hills. The formula to apply is given by the following equation:

$$(A) = R*K*LS*C*P$$

Where:

A = Soil loss per unit area measured in (ton/hectare),

R = Rainfall - runoff erosivity computed using energy and maximum 30 minutes intensity,

K = Soil erodibility factor which is a function of inherent soil properties,

LS = Slope-Length steepness and it accounts for slope length rate of erosion,

C = Cover management factor and it depends on management practices such as tillage, crop rotation and crop types,

P= Conservation practice factor which depends on support factors such as crop rotation, terracing, contouring among others.

The spatial differences in the levels of soil erosion in Taita Hills by using mean annual rainfall to compute the rainfall intensities with intensity (Knijft et al., 1999) and a thresholds of 40mm and above was deemed erosive in the computation (Hariss et al., 2012). Soil erodibility was a combine of soil texture, available water content and gravel.

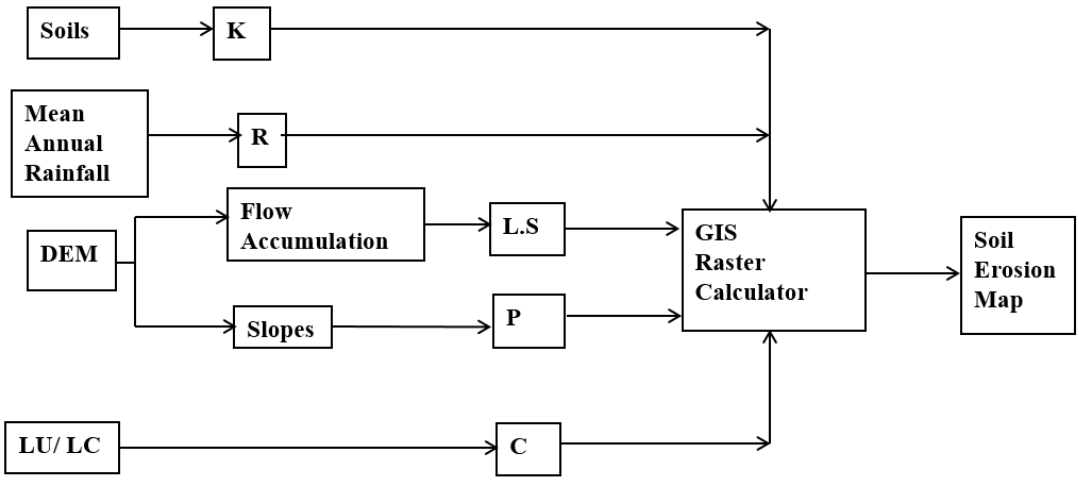


Figure 25 RUSLE model for soil erosion mapping

Equation below shows the formula for computing runoff erosivity factor.

$R = 0.0483P^{1.610}$ *When* $P \leq 50$ *mm*

Otherwise;

$R = 0.004105P^2 - 1.249P + 587$, *when* $P > 850$ *mm*

Where:

R = Runoff erosivity index factor.

P = Annual rainfall in mm.

The slope generated from DEM as detailed in (Morgan, 1978; Mitasova et al., 1996) as the determinants used in the modeling. The slope factor was a combine of slope length and steepness (LS factor) and the vegetation index derived from the NDVI and the land use for the study area.

$$LS = \sqrt{\frac{l}{22}(0.065 + 0.045s + 0.0065s^2)}$$

Where: L = slope length in m and S = percentage slope

This task was accomplished by running weighted overlay of the determinants in a GIS raster calculator.

vi) Soil pH level categorization

The relationship of soils pH and the levels of yields associated with them was studied and the same was linked to the situation in Taita Hills. Consequently, all soils with soil pH zero (0) were categorized as lowest crop yields soils, those with soil pH of ranges 5.1-5.3 & 8.3 were categorized as low crop yields soils, and soils with pH ranges of 5.7-6.4 & 7.9-8.0 were taken as soils which give high crop yields. This analysis was then mapped to bring out the spatial aspect.

vii) Cropland suitability assessment

Crop farming in Taita Hills was thought to be affected by soil erosion, soil pH, rainfall and temperature. All these aspects were analyzed and mapped in the prior phases, they were therefore used to run a sum weighted overlay with the aid of Arc GIS using a pair-wise weighting method. The mapping categorized Taita Hills in four crop suitability conditional zones terming them as *most suitable, more suitable, less suitable and least suitable*. All regions with lowest temperatures but high rainfall and least soil erosion as well as soil pH ranges that realize high crop yields to be the most suitable for crop farming. Whereas, regions which record low temperatures, above average rainfall, low soil erosion, and soil pH ranges which realize high crop yields to be more suitable for crop farming. Less suitable regions for crop farming are thought to be areas with high temperatures and average rainfall but with high soil erosion and soil pH range which realizes low crop yields. Least suitable regions in Taita Hills for crop farming are taken to be those which record highest temperatures and low rainfall but with highest soil erosion and soil pH which realizes lowest crop yields (Table 7).

Table 7 Multi-criteria analysis for suitability assessment

Mean Annual Temperature Level	Mean Annual Rainfall Level	Soil Erosion Levels	Soil pH (Crop yields)	
Lowest	Low	Least	Least	
Low	Average	Low	Lowest	
High	Above Average	High	High	Low
Highest	High	Highest	Highest	

Fuzzy logic was used where the input variables were subjected to the modelling. Fuzzy logics are the process of formulating the mapping from inputs to an output using fuzzy logic methods. The fuzzy logic mapping provides a basis for decision making, and logical arrangements of variables. The process of fuzzy logic inference involves Membership functions, Logical Operations, and If-Then Rules (Riad et al., 2011).

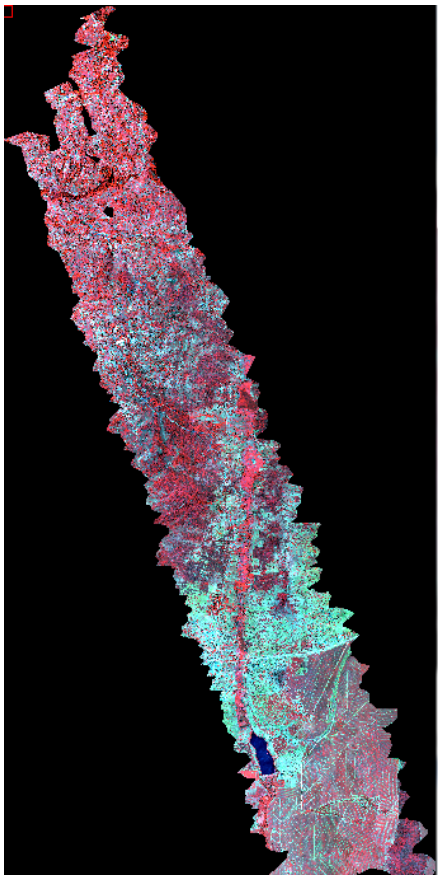
CHAPTER FOUR
RESULTS AND DISCUSSION

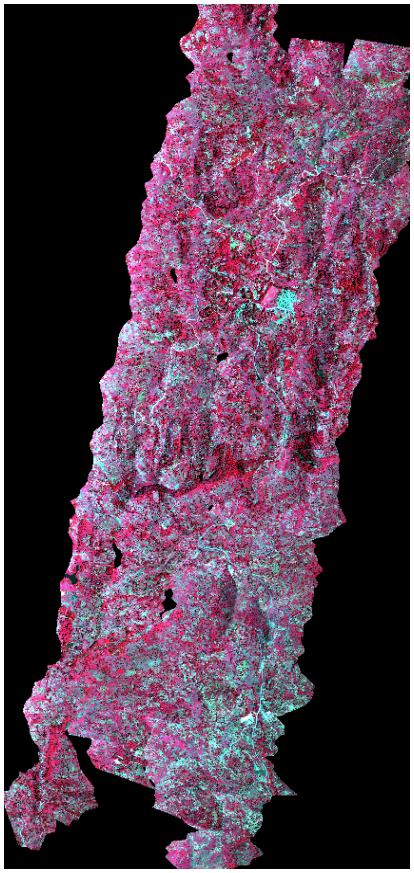
The chapter shows the results achieved in the study: The first being the pre-processed hyperspectral images for the low, mid and high zones. Secondly it shows the specific algorithms that were used to identify crops in Taita Hills. These constitute mainly the pixel based methods. It also gives the results for the delineated agro-ecological zones in the current situation (1960-2010) and the future scenarios of 2050. Further, it discusses the shifts implication of the AEZ in the future with varying climate. The description of each delineated zone with specific crops is given. Finally the chapter gives the steps used to arrive at a suitable map showing suitable areas for agricultural activities in Taita Hills.

4.1 Pre-processed Hyperspectral Data

Figure 26 (a, b, c) shows the results of radiometric, geometric and atmospheric correct color composites hyperspectral imagery. The corrections catered for sensor sensitivity, solar angle, topography and atmospheric effects. The spectral reflectance on every cursor location of the image was analyzed and the images were ready for crop identification.

The various three zones of the study areas were processed separately but using the same pre-processing specifications. The dark spot in Figure 26(c) indicates the undulating terrain in the high zone. The high zone is forested and with less farming activities. Some areas in this zone are protected since it constitutes the endemic species of Taita Hills. Reddish color entirely depicts vegetation which includes agriculture and forested areas. Brighter pixels in Figure 26(a), shows the expansion of urban centers and built up areas in the lower zone of Taita Hills. The lower part of it with blue color is a dam area with sisal farms dominating the lower part with a regular line pattern.


(a),


(b),

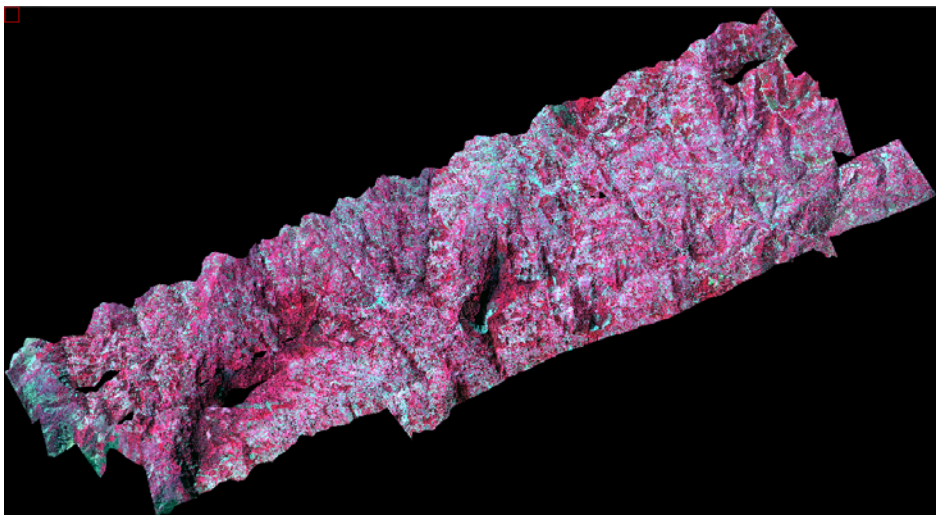

(c).

Figure 26 Color infra-red hyperspectral data (a, b and c) for three zones of Taita Hills: Low, mid and high respectively

4.2 Crop Classification Using Pixel-Based Methods

i) Classification in the mid zone

Figures 27 and 28 show the color infra-red (left) and the corresponding classified hyperspectral image (right) in the mid zone (full view and partial view respectively). Figure 28 shows partial color composites within the mid zone of the study area showing classification on the agricultural landscapes. From Figures 19, the spectra colors gives the key for the classifications. Figures 27 and 28 show crops such as maize, bananas, sugarcane and some trees have.

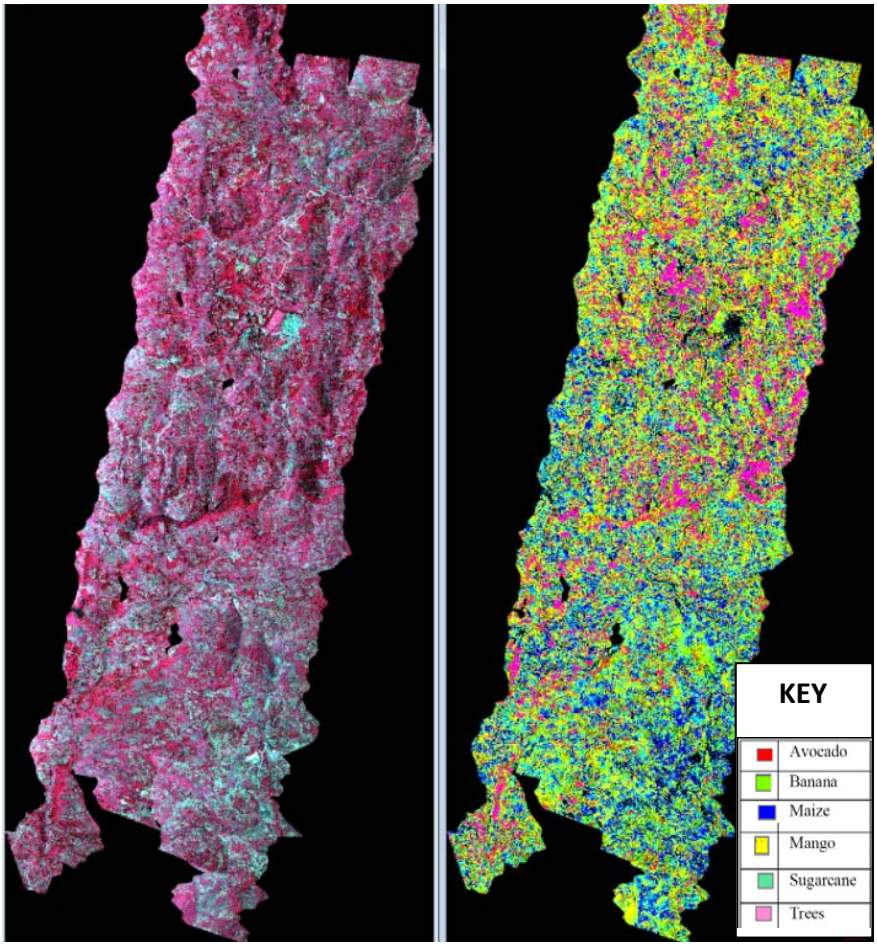


Figure 27 False color composite and classified image for mid zone area showing various crops in Taita Hills

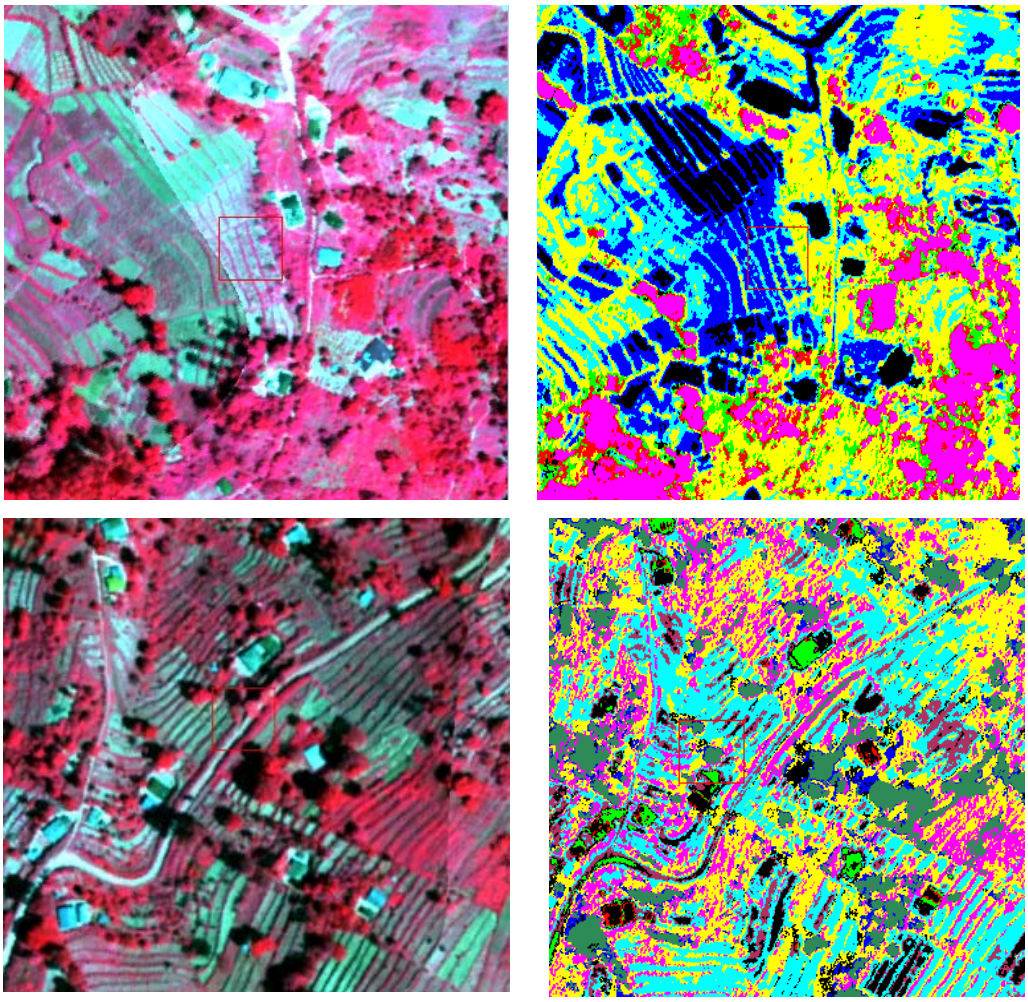


Figure 28 Partial views for false color composite imagery and the corresponding classified images using spectral angle mapper algorithm.

Accuracy assessment was also done to ascertain the validity of the results using independent polygons of the crops. Table 8 shows the confusion matrix and results of the accuracies respectively. Producer's and user's accuracies were also tabulated.

Table 8 Confusion matrix in the mid zone

Reference (Polygons)	Others	Trees	Avocado	Banana	Maize	Mango	Sugar	Total	**Producer's %**
Others	**78**	0	0	0	0	0	0	78	99.9
Trees	0	**0**	6	2	0	0	0	8	0.5
Avocado	0	1	**0**	3	0	3	0	7	6.8
Banana	0	1	**0**	4	0	3	0	8	49.1
Maize	0	0	0	4	**5**	0	5	14	50.1
Mango	0	3	1	0	0	**0**	0	4	78.7
Sugar	0	0	0	0	4	23	**7**	34	52.4
Total	78	5	7	9	9	28	12	**148**	
User's %	99.4	0.3	8.4	43.2	42.8	87.3	49.6		

Trees had some similar spectra to those of some crops, hence a misclassification of avocado species for trees. The selection of tree samples was achieved from forest patches from aerial mosaic in which there exists various species of trees however the training samples categorized these as one species. The overall accuracy was achieved at **77%** with a kappa index of **0.67**. It is this similarity in spectra of some crops and the misclassification of these crops affected the overall accuracy.

ii) Classification in the low zone

Figure 29 and 30 shows results of the low zone classification. It is worth noting that during the time of data acquisition, maize had dried up in the area but sugarcane (purple) was well mapped. The grasslands were well defined and the mango trees (cyan) are mapped on the image. Tarmac roads and water bodies were also captured in the mapping. The classifications were specifically for every zone since the zones contained various crops that were not similar in nature. For instance, one could only find mangoes on lower zones and not avocadoes, similarly in the upper zone, one could find avocadoes and not mangoes. The choice of the algorithms were based on the availability of the crops but the same parameters were maintained in all the zones.

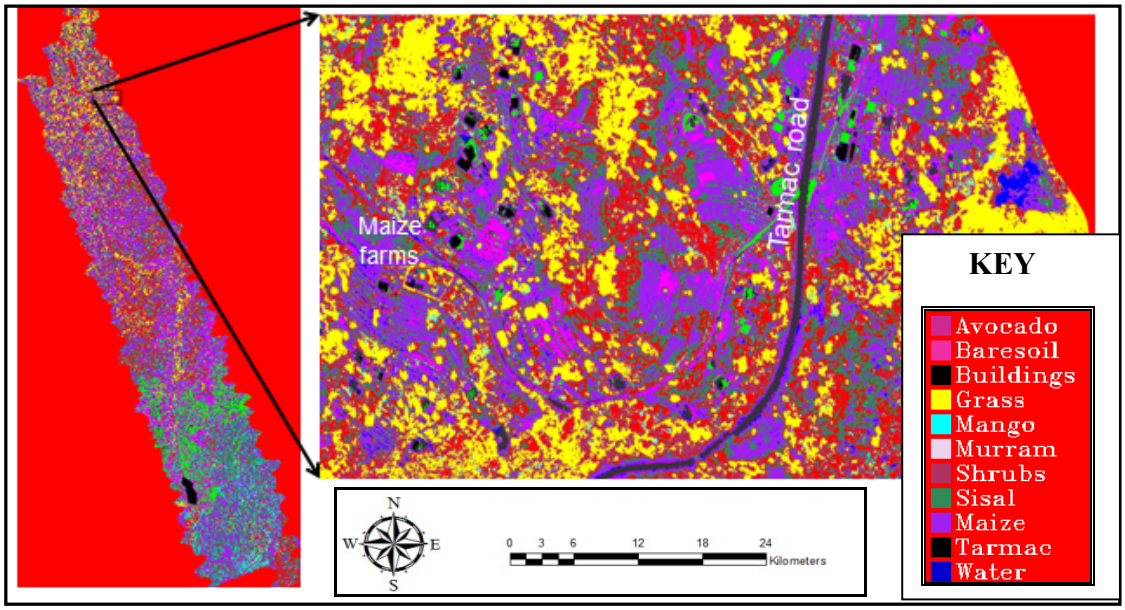


Figure 29 Classified imagery in the lower zone

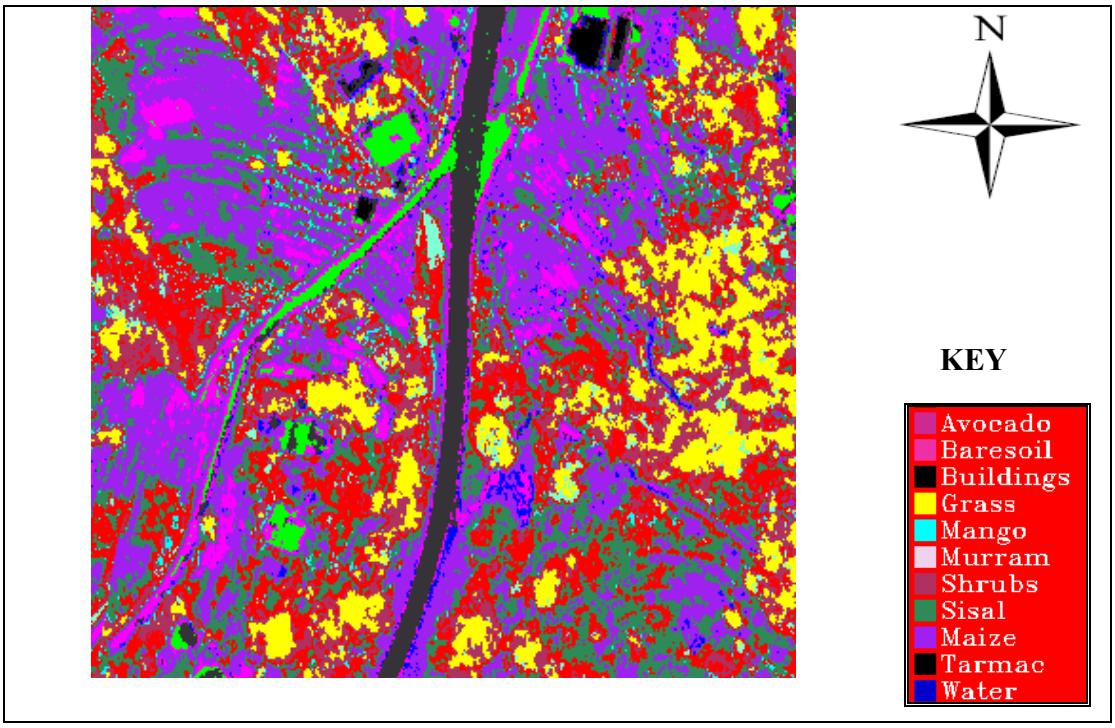


Figure 30 Classification of lower zone showing various crops and man-made features

Producer's and user's accuracies were also tabulated, (Table 9). The selection of more training areas such as bare soil, buildings and tarmac helped in improving the accuracy. In this zone, the maize plantation had been harvested already because the area is quite dry and the farmers grow short term maize unlike in the other zones. Sugarcane (along the river banks) and mangoes were the major crops in the zone and were classified. Avocadoes were not available however sisal is grown in the lower parts of Mwatate as a cash crop. The overall accuracy was achieved at **87.6%** with kappa index of **0.8**. Table 9 shows that most crop types were classified as it can be seen in the diagonal matrix of the table. Bare soil, shrubs and tarmac road were also included in order to reduce the pixels being misclassified to other crops in the zone.

Table 9 Confusion matrix in the lower zone

Reference (Polygons)	Bare soil	Buildings	Grass	Mango	Shrubs	Sisal	Sugar	Tarmac	Total	**Producer's %**
Bare soil	**34**	0	0	0	0	0	0	0	34	99.7
Buildings	0	**17**	1	1	0	0	0	0	19	89.0
Grass	0	1	**8**	0	0	2	0	0	11	72.7
Mango	0	0	**0**	7	0	1	0	0	8	87.1
Shrubs	0	0	0	1	**10**	0	3	0	14	71.4
sisal	0	1	1	0	0	**16**	0	0	18	88.7
Sugar	0	0	0	0	1	1	**7**	0	9	77.4
Tarmac	0	0	0	0	0	0	0	**11**	11	99.6
Total	34	19	10	9	11	20	10	11	**124**	
User's %	99.4	89.4	80	77.4	90.8	80.2	69.6	99.6		

iii) Classification in the high zone

This involved the spectra from training samples outside the image to be classified (multi-endmember). It was essential to use this method in the high zone image (Figure 31) since there were very few sample plots for training areas. The spectra from mid-zone were used to map crops and other features in the high zone. High zone is mountainous, rocky and a little bit inaccessible by road. Furthermore, in this zone, there is more forested land than agricultural lands. Figures 32 and 33 show the classified image (full view and partial view respectively) of the high zone area.

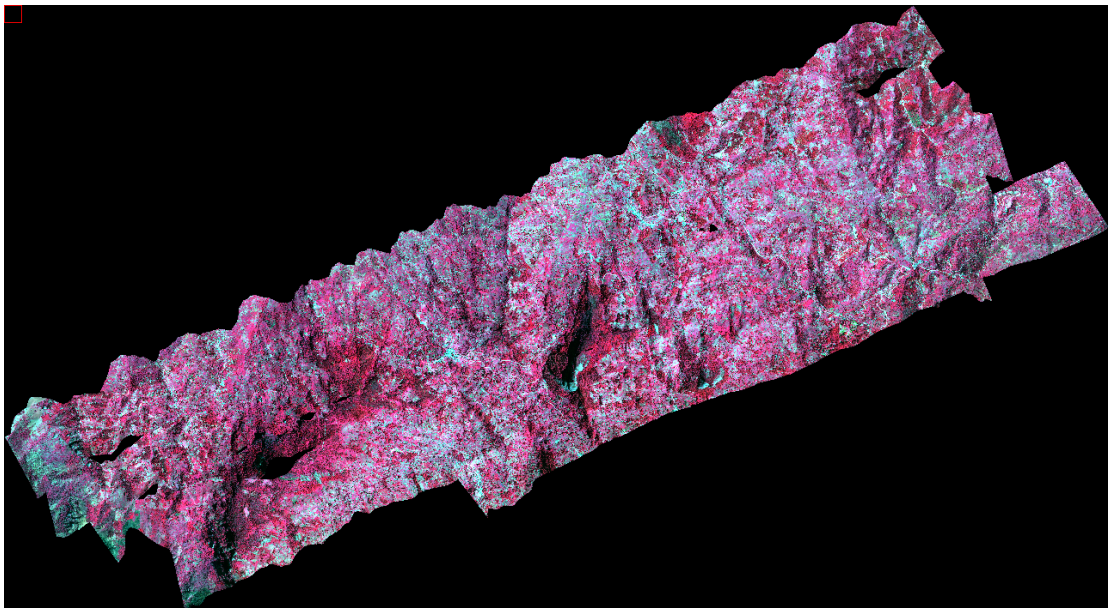


Figure 31 False color composite image of the high zone

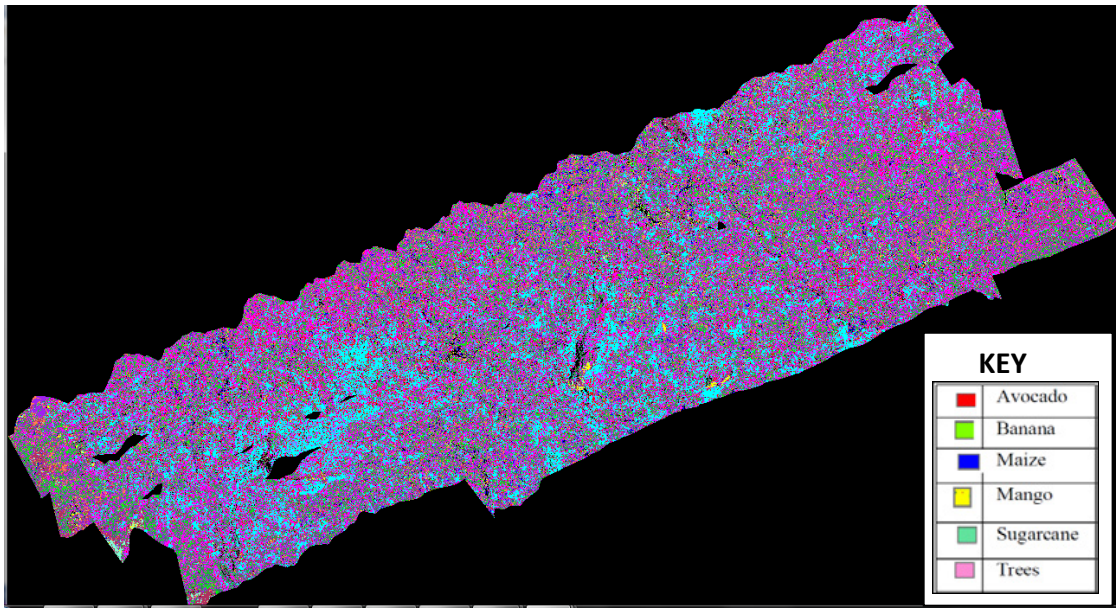


Figure 32 Upper zone classified hyperspectral image

In this zone (Figure 32 and Figure 33), crops were not much, in fact most of it was forest land. Spectra from the mid zone was used to classify the crops and forest areas in this zone. The magenta color is dominating and it is showing it is mainly forested area. Red spots, as can be seen in Figure 33 (partial view), were some few avocado trees near homesteads, however black spots were unclassified areas which constituted roads and built up areas.

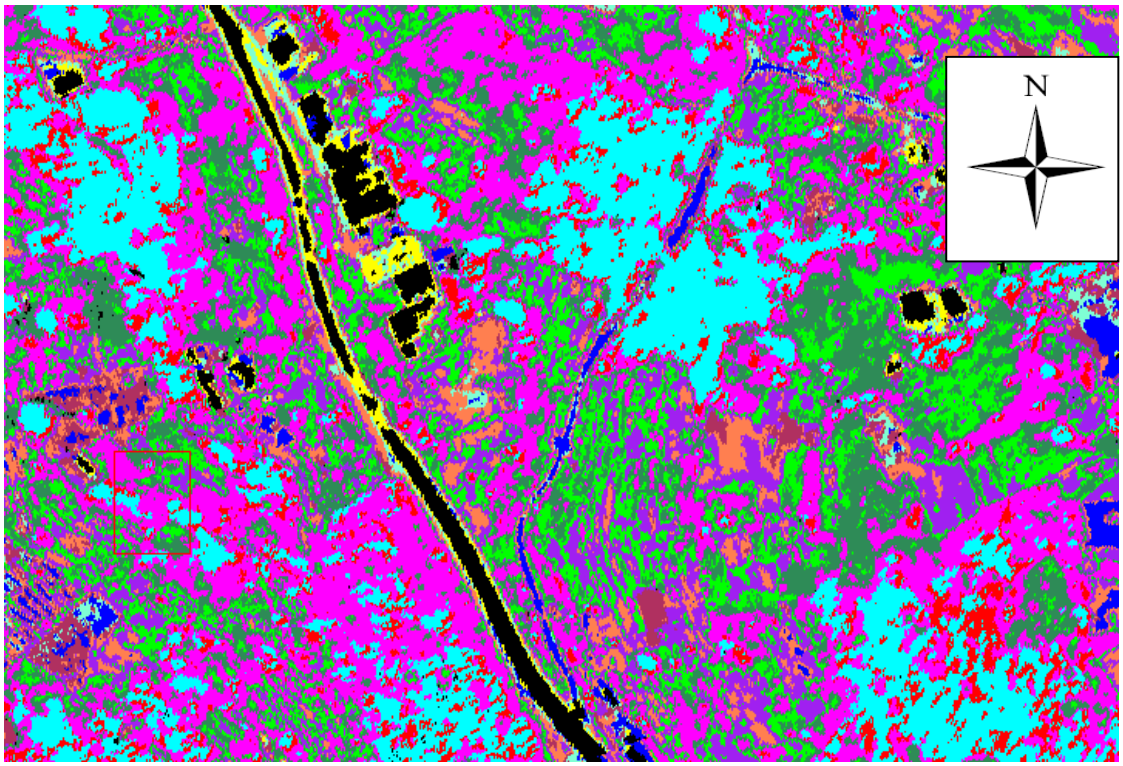


Figure 33 Partial view of the classification in the upper zone showing crops

Table 10 shows the confusion matrix of the classification in the high zone area. Although several pixels were classified as other in the study, it can be seen from Figure 33 that they were not classified as crops (this includes the built up areas and roads). The dark pixels were categorized as others. The accuracy achieved was not better than that of the low zone areas even though the spectra originated from mid-zone. The underlying reason for this is that the high zone area had very few plots and very

minimal farming activity takes place. In fact, it is the catchment area and also constitutes protected areas. Overall accuracy of **84.9 %** and Kappa index of **0.8** was achieved.

Table 10 Confusion matrix in the high zone

Reference (Polygons)	Others	Trees	Avocado	Banana	Maize	Mango	Sugar	Total	**Producer's %**
Others	**40**	0	0	0	0	0	0	40	99.8
Trees	0	**23**	4	1	0	0	0	28	82.1
Avocado	0	1	**8**	1	0	1	0	11	72.7
Banana	0	1	0	**7**	0	1	0	9	77.7
Maize	0	0	0	2	**6**	0	1	9	65.1
Mango	0	1	1	0	0	**2**	0	4	48.7
Sugar	0	0	0	0	1	0	**5**	6	83.4
Total	40	26	13	11	7	4	6	**107**	
User's %	99.7	88.4	61.5	63.2	85.8	49.9	83.3		

4.3 Modeling Agro-ecological Zones

Principal component analysis (PCA) was run for soil, land use, aspect and slope (GIS datasets) but not for temperature and precipitation (climate datasets) which were the main parameters of change over time. Multivariate geographical clustering for AEZ was done for both GIS and climate datasets, first for 1960-2010 group of data. 5 AEZ were first generated to see if there was any similarity with those that were developed by FAO provided in 1983 for the whole of Kenya (Figure 3). The result was coarser to even analyze. A new iteration was ran for 10 AEZ (Figure 34 and Figure 35). Increasing the number of zones to 15 created more thin layer-like elevation contours that could be difficult to analyze and assess and the characterization would be impossible. The iteration was best achieved at 10 zones. This procedure was done also for the future datasets (2050) in order to assess the future scenario of the delineated agro-ecological zones.

Figure 34 and Figure 35 shows the results for zones (Z1, Z2 ...Z10). Although they look similar by visual judgement, there was need to analyze them to see if they were varying especially in their width sizes. These zones were compared again using the differencing tools of GIS in order to see the variations of climate change on the zones in the future 2050.

Figure 34 and Figure 35 was labeled with zones (Z1 ……to …..Z10). It was necessary to name those zones which had similar color resemblance based on visual check. Z4 and Z6 were almost similar and labelling was necessary. Similarly, Z2 and Z10 were labelled. Z10 is in the highland zones whereas Z2 is in the low zone. Z4 and Z6 are in the mid zone areas of the Taita Hills.

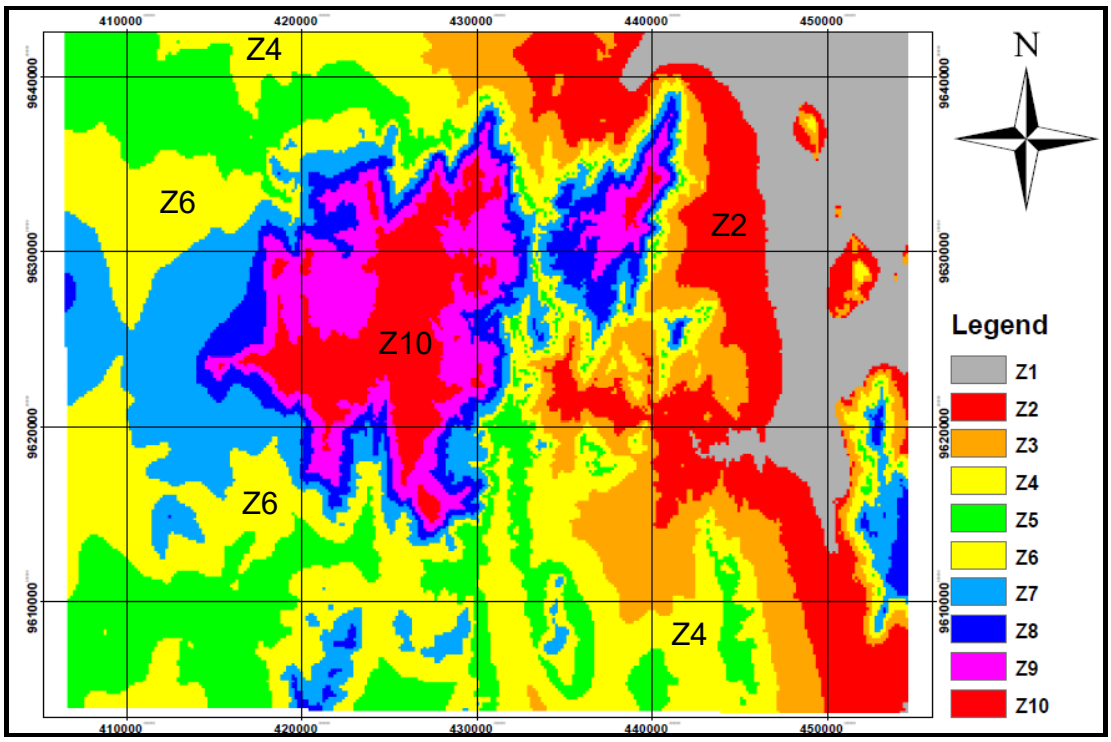


Figure 34 AEZ Map of 1960-2010

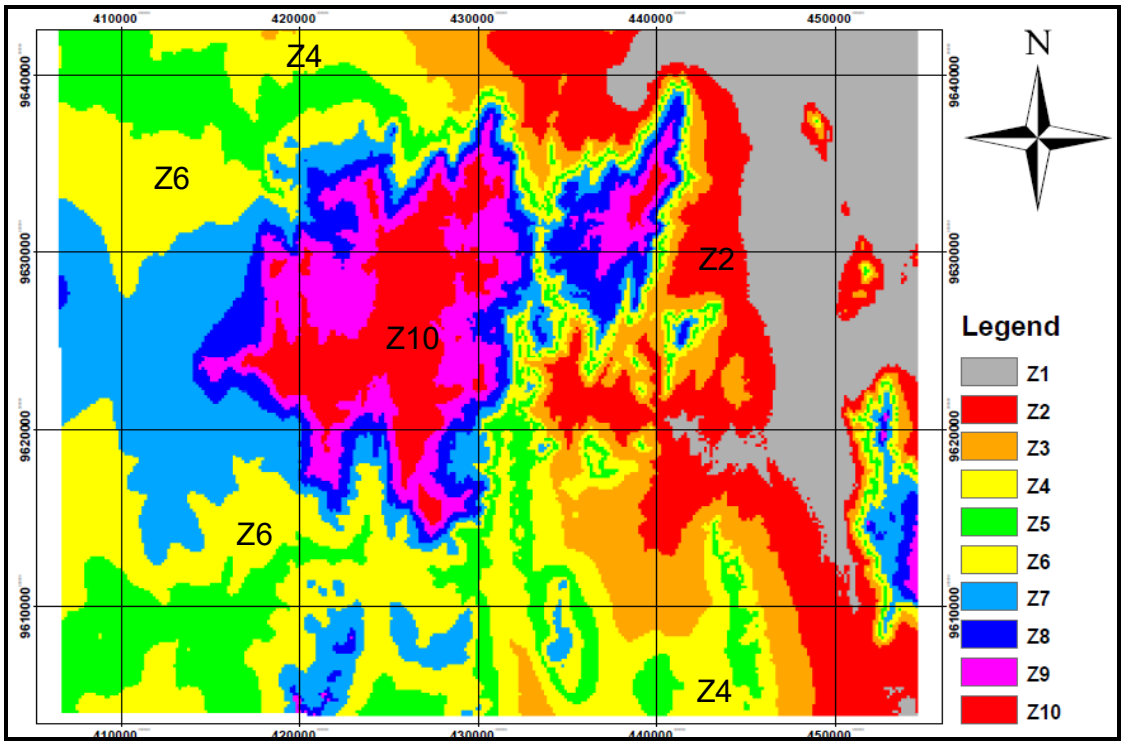


Figure 35 AEZ for 2050 as projected

4.4 Zone Differencing

The zones represented for the current and the future AEZ did not show a huge difference in their spatial location and pattern. To analyze for a discrepancy (shift in zones), it prompted the need to subtract the zones by what is defined here as *'zone differencing'*. With the classified zones from Z1, Z2…...Z10 for each of the two groups of data, a differencing of the zones was done. The recent AEZ subtracted from the future AEZ gave a result for the difference in zones. Zones that increased are shown on the legend with positive values, whereas those that decreased are shown with the negative values (Figure 36). A map of the changes is shown and can likely to be used as a model for *'zone shift'* analysis in the future. Care need to be taken into this result since the analysis is based on climate data projections which has some uncertainty in its use.

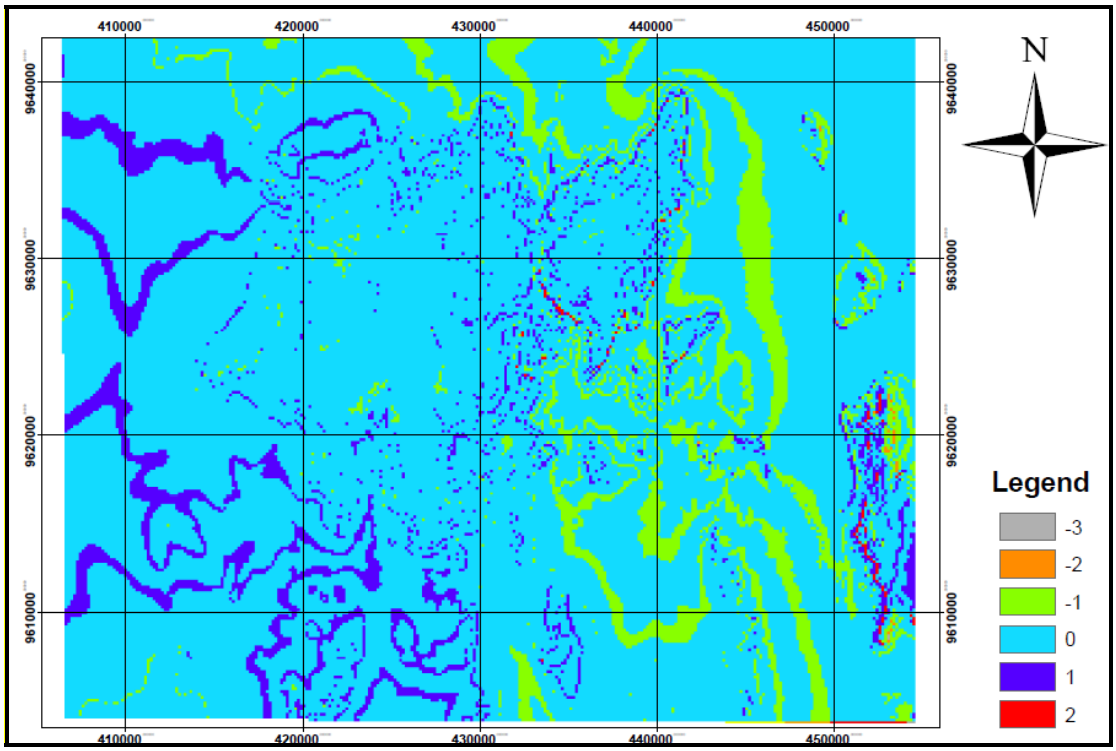


Figure 36 Zone differencing map

The legend on Figure 36 shows the values from (-3, -2, -1, 0 +1 and +2). The generated map of the changes can be used as a model for 'zone shift' analysis in the year 2050. Some zones will in the future likely reduce while others will likely increase. For instance, in the lower zone areas (extreme right hand side), where on the Figure 36, we have green-colored strips, this are the (-1) values meaning there will be a reduction in zone 1, zone 2 and zone 3. On the other hand where we have blue strips on the left hand side of the same figure, the values are (+1) meaning in 2050, some of the upper zones will likely increase in size. Zero value meant no change in the future with respect to varying climate.

4.5 Zone Description and Quantification

Describing the ten zones was based on the standard categorization of FAO. Name of each zone with characteristics in climate and possible crop type suitable for that zone

was done (Table 11). Taita Hills comprises of regions with lowlands, midlands to highlands at top of Vuria. Quantification of the zones was analyzed using graphs. The values in terms of counts (number of pixels) were tabulated. Graphs in Figure 37(a) and Figure 37(b) elaborate the comparisons between the zones. Quantification of the value of each zone in the current state and in 2050 (future scenario) was also done.

Table 11 Agro-ecological zone description

Zone	Name of Zone	Descriptor	Characteristics
Z1 - Z2	**L1** **L2**	Lowlands	- Higher temperatures, low rainfall. - Crops: Typically sisal and sugarcane on the river banks.
Z3 - Z4	**UL1** **UL2**	Upper Lowlands	- High temperatures and low rainfall. - Crops: Sorghum, millet, mangoes, early maturing maize and beans.
Z5 - Z6	**LM1** **LM2**	Lower Mid-lands	- Mid temperatures, average rainfall. - Crops: Mangoes, maize, cassava, sweet potatoes.
Z7 - Z8	**UM1** **UM2**	Upper Mid-lands	- Low temperatures, above average rainfall. - Crops: Bananas, avocadoes, maize, sugarcane, potatoes, tomatoes and agro-forestry.
Z9 - Z10	**H1** **H2**	Highlands	- Lower temperatures, higher rainfall. - Crops/vegetation: Agro-forestry, Indigenous trees.

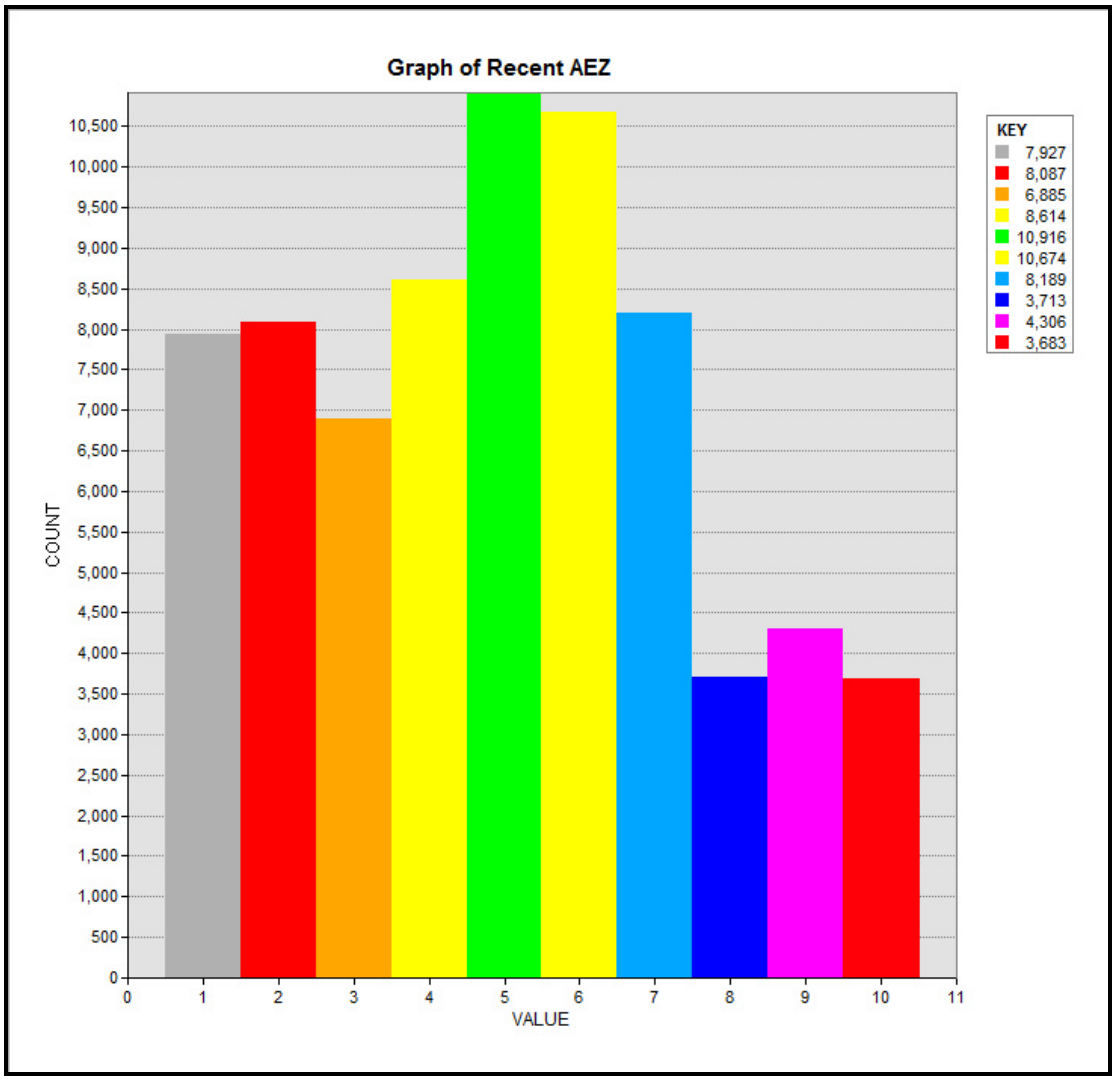


Figure 37 (a) Graph showing the current agro-ecological zones variations

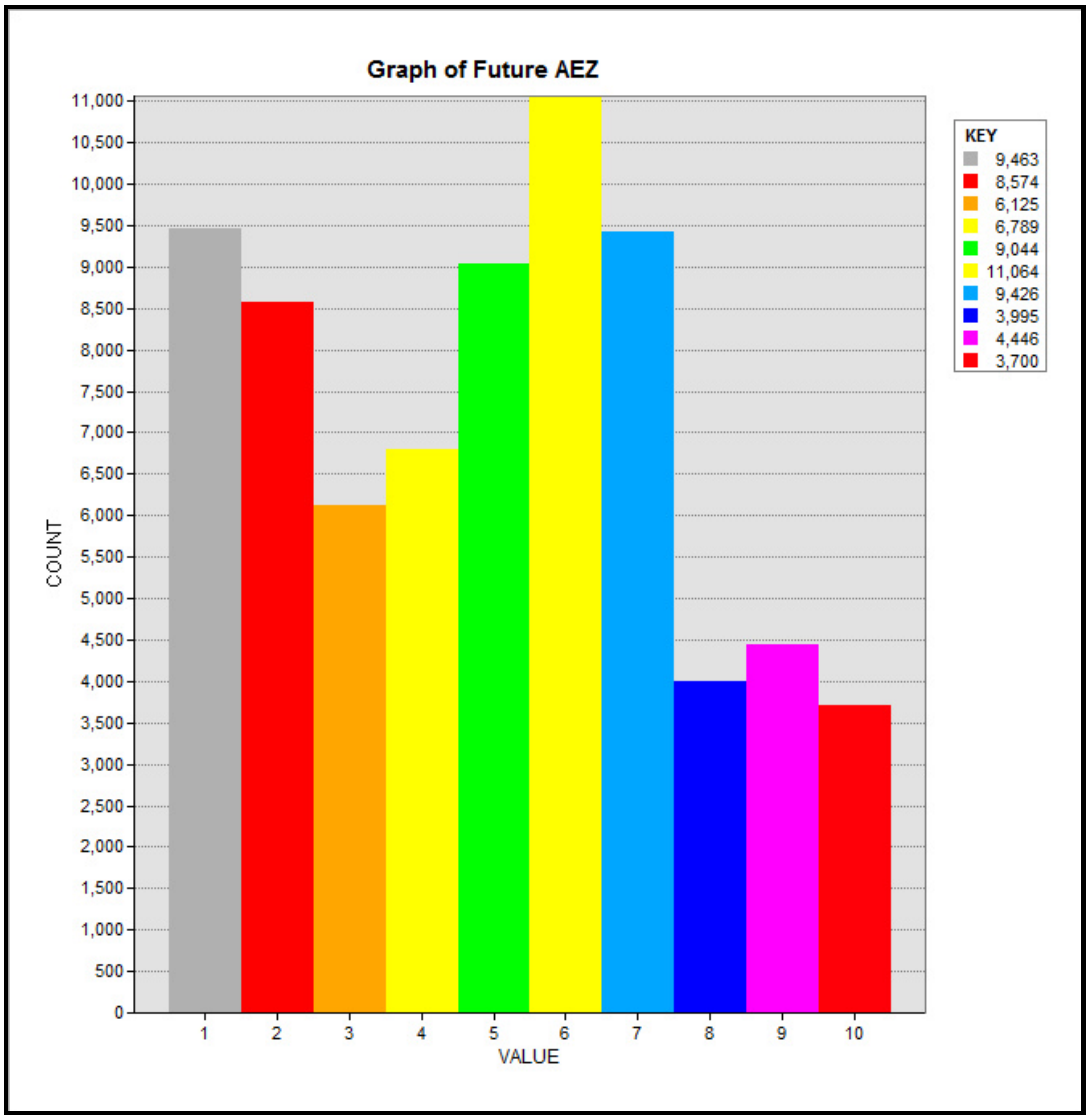


Figure 37 (b) Graph showing the future agro-ecological zones variations

4.6 Suitability Assessment

i) Watersheds of Taita Hills

An application of flow process modelling uses the concept of spatially distributed land surface parameters to calculate run-off over a watershed area. This research applied the concept of spatially distributed unit hydrographs over an area of cells. These unit responses, which are each independent of the surrounding responses, are convoluted

along a watershed flow path to produce a total run-off response at the watershed outlet. Figure 38, shows the delineated watersheds of Taita Hills. The water sheds indicates stream channels and flow direction of water to support the soil erosion assessments in this study.

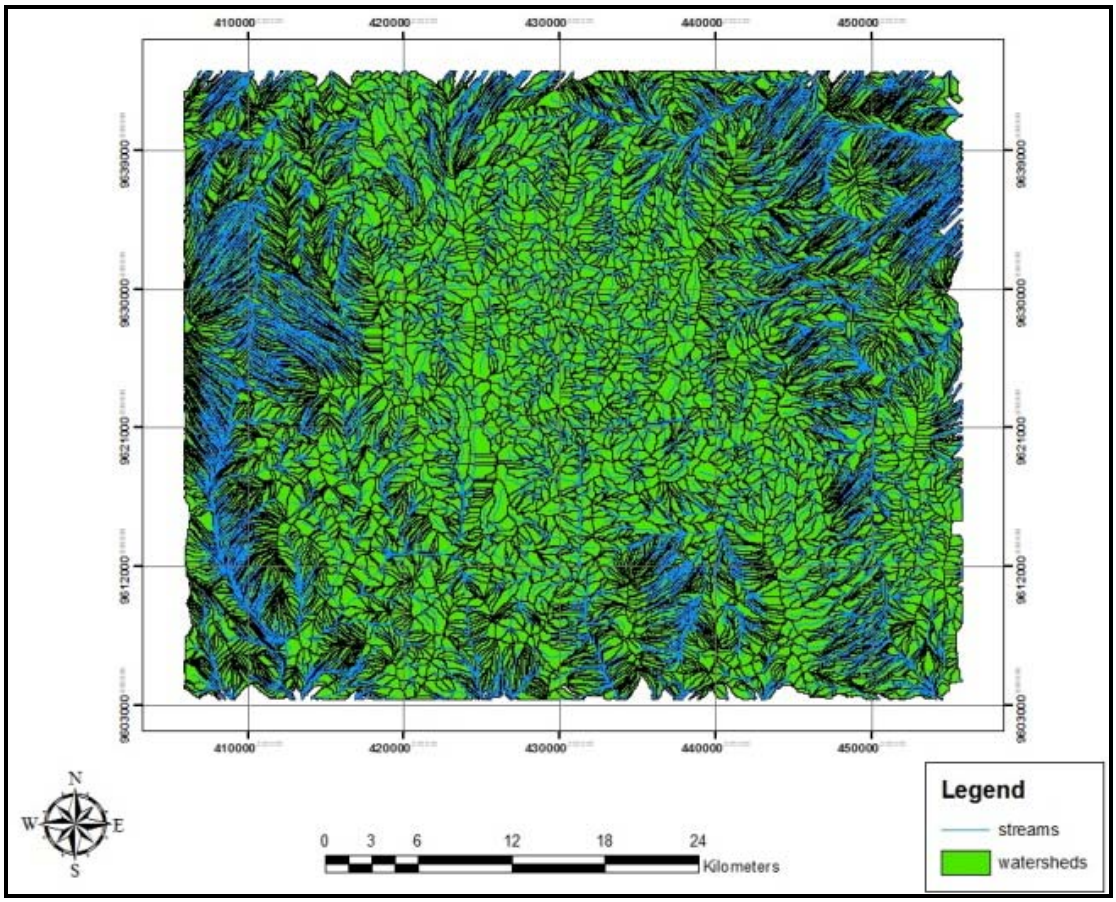


Figure 38 Watersheds of Taita Hills

ii) Mean annual rainfall Categorization

From 'WorldClim' datasets for the current climate (1960-2010) that was used to map and delineate agro-ecological zones, the mean rainfall map was generated. Figure 39, shows the mean annual rainfall pattern of Taita Hills. Below 600mm was categorized low and above 850mm was categorized high.

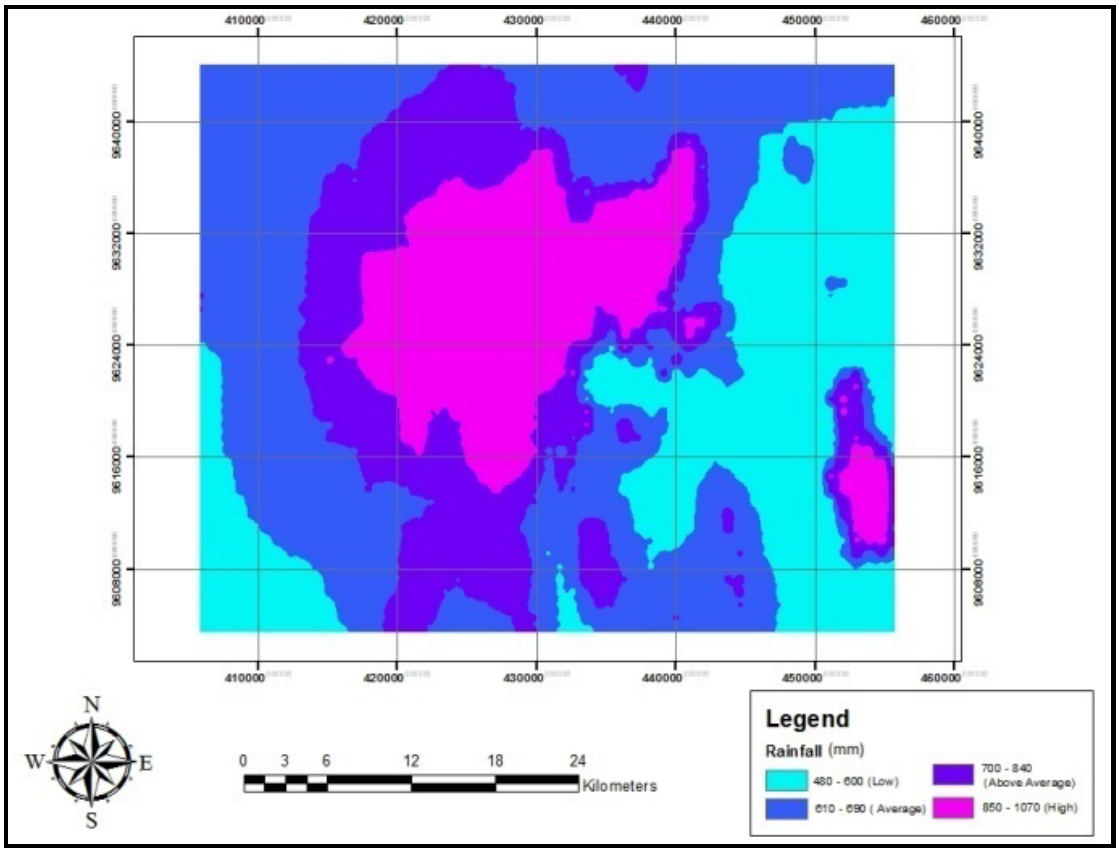


Figure 39 Mean annual rainfall of Taita Hills from WorldClim

iii) Soil drainage pattern of Taita Hills

Figure 40 shows the soil drainage with parameters: **W** (well drained), **S** (slowly drained), **R** (rapidly drained) and **E** (extremely drained). At the hills the drainage pattern is slow and at steep slopes the drainage is extreme and rapid. This data helped in the understanding and development of the soil erosion mapping of the area.

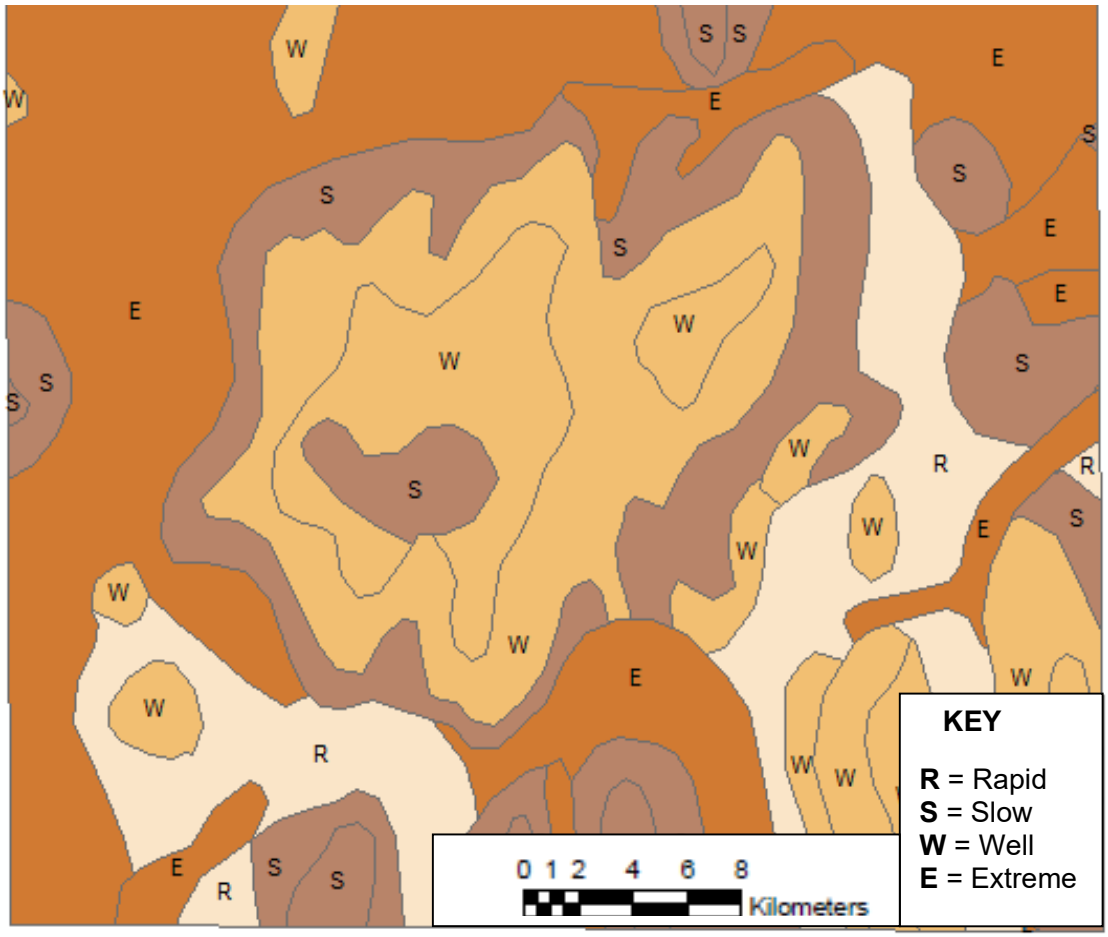


Figure 40 Soil drainage pattern for Taita Hills

iv) Mean annual temperature categorization

The mean annual temperature map is as shown in Figure 41. Hot regions are in the lowlands (above 24ºC) and cooler regions at the high altitudes (below 22ºC). The temperature value in the legend of the map is to be divided by 10 units. Decimal points are not considered in the 'WorldClim' data sets that were used for categorizing the annual mean temperature, therefore it prompts the division of the values obtained by 10 units (a factor of 0.1) to achieve the temperature of a given location.

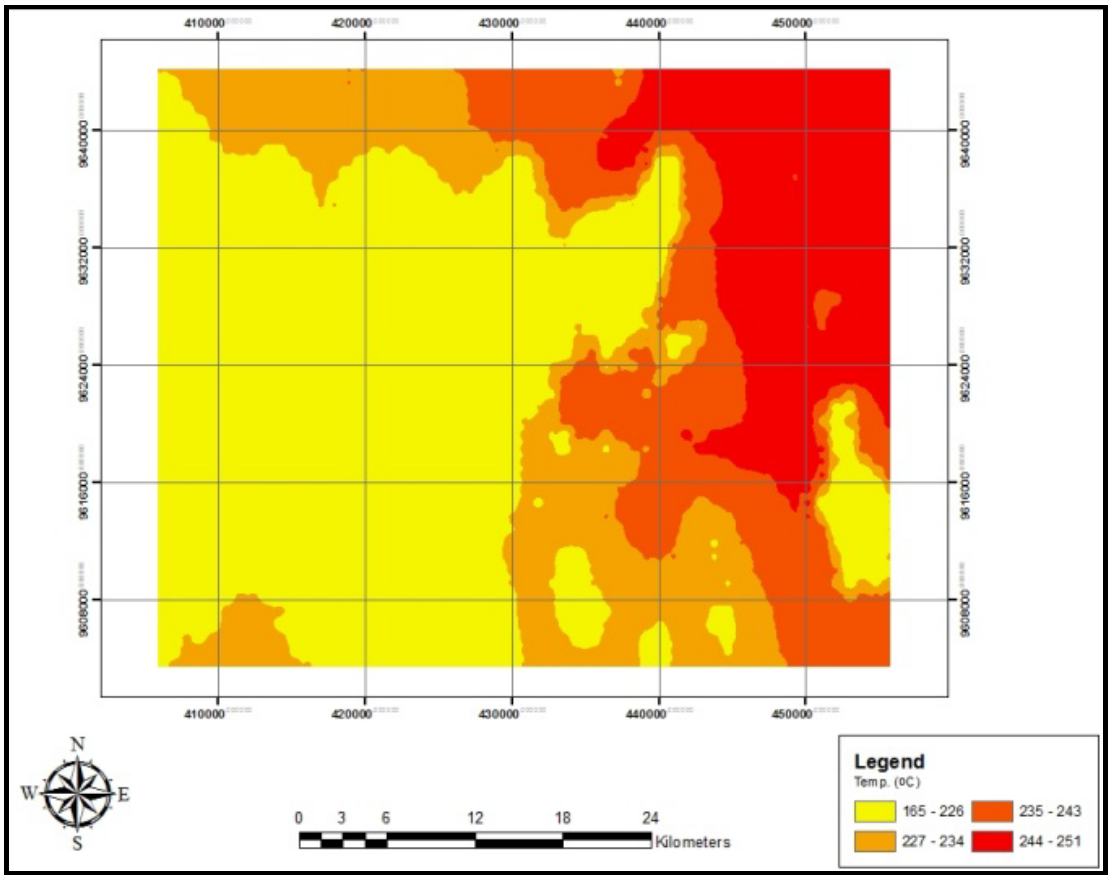


Figure 41 Mean annual temperature map (ºC * 0.1) from WorldClim

v) Soil pH categorization

The relationship of soils pH and the levels of yields associated with them was studied and the same was linked to the situation in Taita Hills. Consequently, all soils with soil pH zero (0) were categorized as lowest crop yields soils, those with soil pH of ranges 5.1- 5.3 & 8.3 were categorized as low crop yields soils, and soils with pH ranges of 5.7-6.4 & 7.9-8.0 were taken as soils which give high crop yields (Figure 42). This is based on the acidity of soils and some being base. Crops do well in the region where it is neither acidic nor base.

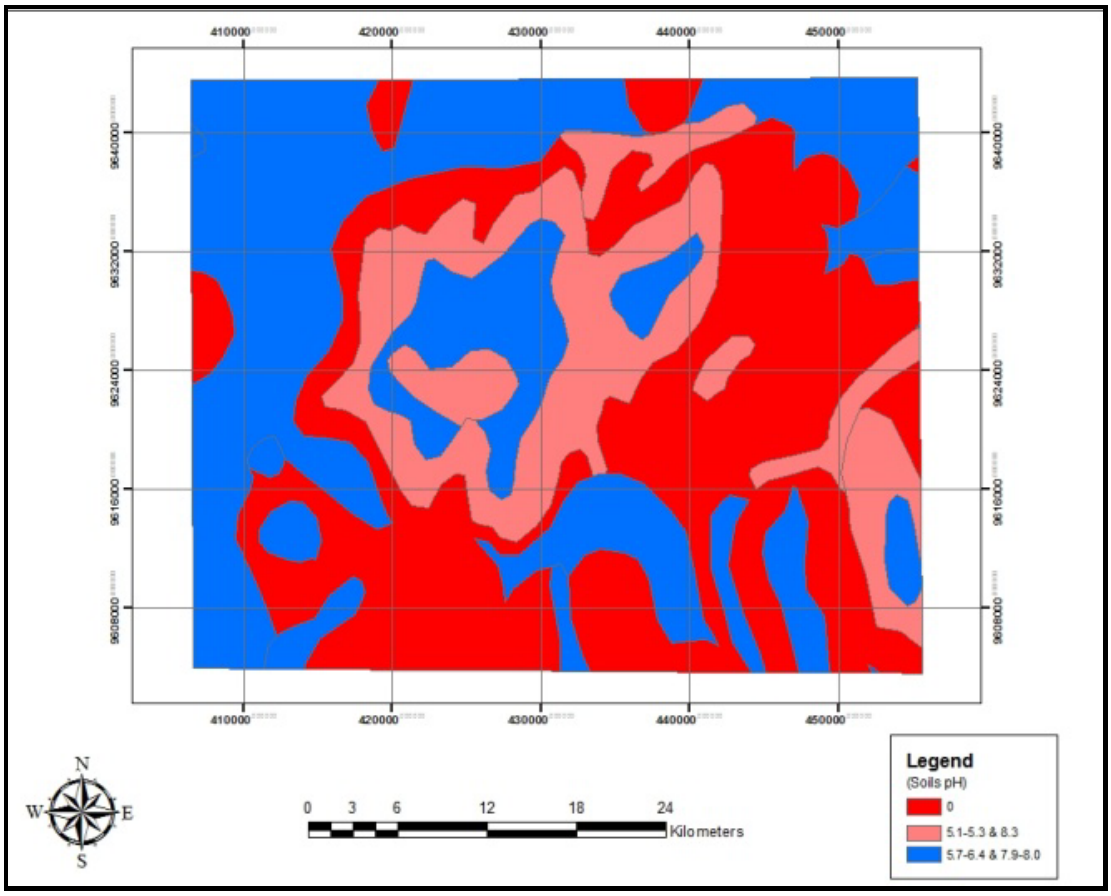


Figure 42 Taita Hills soil pH

vi) Soil erosion map

Soil erosion was obtained from the use of parameters generated from the RUSSLE model given in Figure 25. With the use of raster calculator, it was possible to map the soil erosion of Taita Hills. The analysis was ran with data composition of soil erodibility, slopes, vegetation index, rainfall erosivity and population index carrying weights in the modeling based on the analytical hierarchical process (AHP) and utilized weights as shown in Table 6. The mean annual rainfall was used to calculate the rainfall erosivity factor by applying the equation pioneered by Renard (1997). The variables was validated with site visits to the specific locations of erosion levels and was found to be corresponding with the results obtained. Figure 43, was generated using the variables and procedures above showed the least to the highest prone areas to soil erosion.

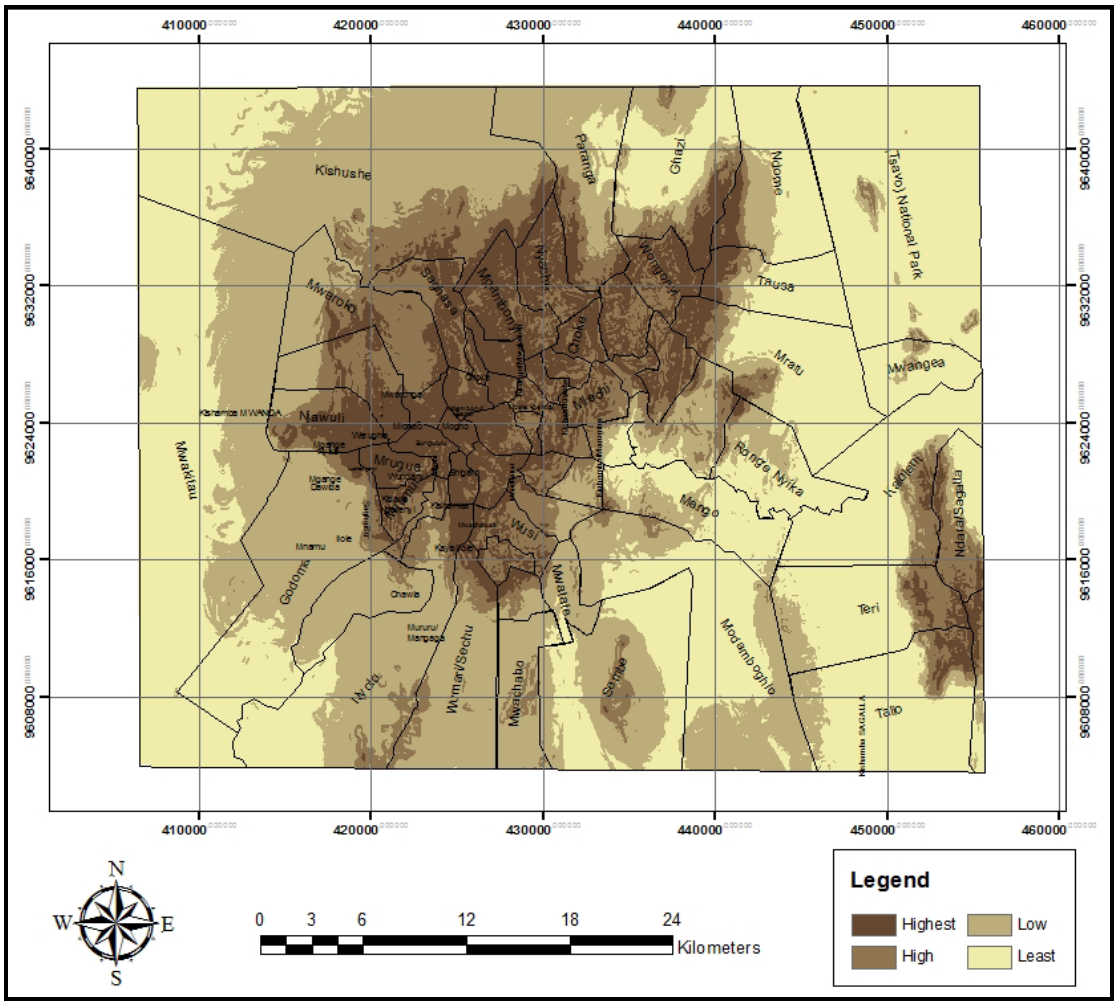


Figure 43 Soil erosion overlaid on to political boundaries in Taita Hills

vii) Cropland suitability mapping

The analyses utilized the procedure outlined and the multi-criteria analysis variables as shown in Table 7. The following hierarchical terminologies were used to describe crop suitability differences in Taita Hills: ***most suitable, more suitable, less suitable and least suitable.*** The combination of the spatial location of crops in Taita Hills, the delineated and projected agro-ecological zones and the suitability maps constituted the basis to assess suitable agricultural areas in the study area.

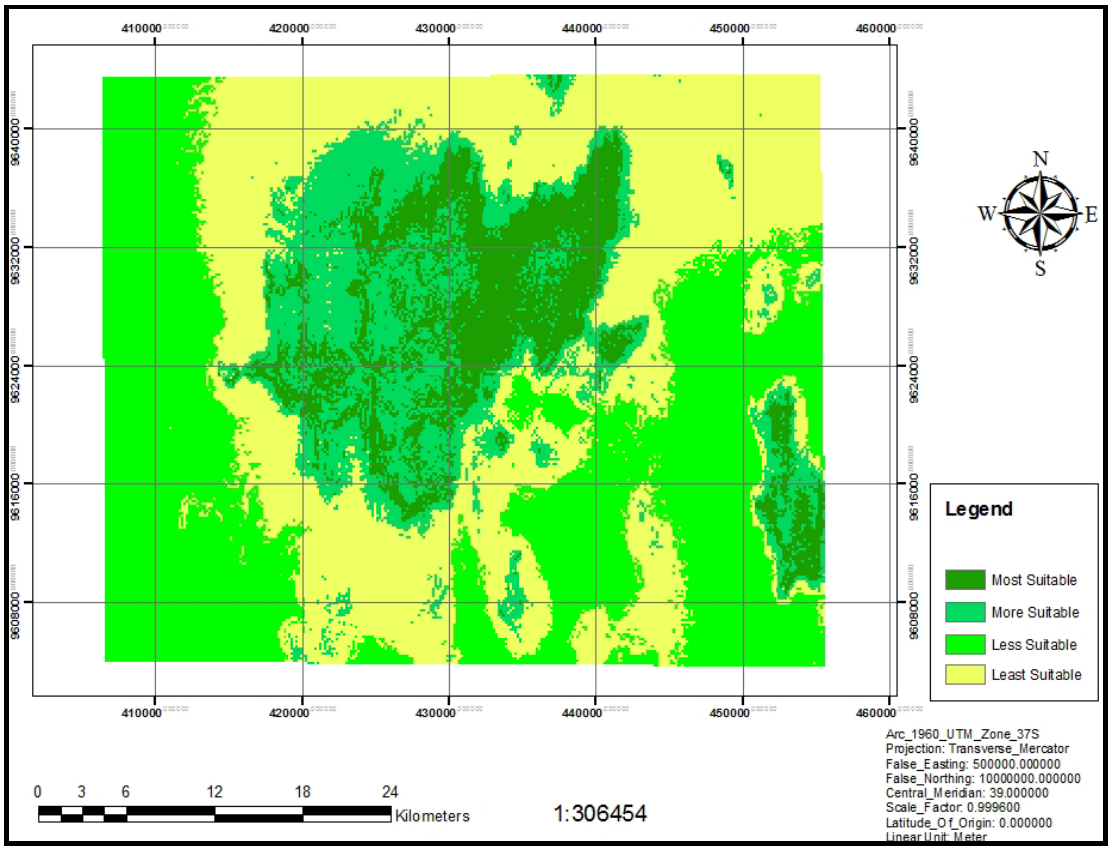


Figure 44 Cropland suitability map for Taita Hills

Figure 44 above, shows the result of crop suitability map generated based on the process. It can be shown that, the most suitable areas are those in the midlands whereas, the least suitable areas are majorly those in the north-eastern part of the region. It can be seen also that the less suitable and the more suitable areas occupies the biggest land area of the Taita Hills. This means almost all the region can be utilized for various agricultural crop production.

4.7 Cropland Assessment in Taita Hills

a) Crop identification

Crop type classification indicates that it is possible to discriminate various crops using AISA Eagle VNIR data using pixel based classification algorithms in a cultivated landscape. The confusion matrix in mid zone areas shows that most classes were classified to be trees due to the spectral angle between them being small. Bananas, avocadoes, mangoes and trees (*cluster 1*) had very similar profile. A distinction between maize and sugarcane (*cluster 2*) is much better than that of *cluster 1*. Spectral range between 500nm to 700nm can be seen to separate not only the two clusters but also the different crop types. Using very high spatial resolution data is an advantage when small targets are mapped in heterogeneous landscape (Piiroinen et al., 2015).

The unclassified pixels (others) constituted mainly reflective natural and man-made features such as buildings, roads and water bodies. These were not considered for endmember selection but the pixels are part of the input image for classification. Table 8, 9 and 10 shows the producer's and user's accuracies. Mangoes, sugarcane, maize and bananas had good producer's and user's accuracies. Avocadoes were poorly classified and likely linked to the fact that they had close reflectance with other trees.

One disadvantage endured in this study is the limitation to distinguish the trees in croplands. Piiroinen (2014) proposed to combine the object based methods and pixel based methods in classification of hyperspectral data. Tree crowns could be mapped using the object based methods while crops could use the pixels. It can be argued that, just as crops differ in their reflectance from crop to crop, it is also true that there's a reflectance difference between tree to tree and that crop types such as mangoes and avocadoes are also trees in their nature. In identifying crop types in a cultivated landscape area, it is wise to identify various tree species within the agro-forestry environment too.

In addition, the camera mounted digital imagery (Nikon D3X) does not have physical reflectance values covering the full electromagnetic spectrum needed for spectral mixture modeling (i.e. linear unmixing) and spectral change detection. However, future tests should be done to explore the utility of low cost digital imagery from unmanned aerial vehicles (UAS) to map crops within smaller study site, using visual interpretation (Landmann et al., 2015). Crops identified on the lower zone were mostly the sugarcane and grassland. This area, due to high temperatures and low rainfall has low productivity of crops unlike in the mid zone. A lot of crop farming is done in the mid zone which is more than those in the high and low zones. This showed that crops are majorly grown in the mid zone areas of Taita Hills.

b) Impacts of climate change on agro-ecological zones of Taita Hills

The zones in each descriptor has two zones. In the lower and upper mid lands (mid zone), there is intensive cultivation while in the lowland zones and upper lowlands, there is generally not much agricultural activities. Zone definition is possible with the use of multivariate geographical clustering analysis (Hargrove & Hoffman, 1999) in conjunction with the principal component analysis (PCA). It was evident that there will likely be a shift in some zones in 2050 (Figure 35). Some zones will in the future reduce while others will increase. During quantification, refer to the graphs in Figure 37(a) and Figure 37(b), zones: Z1, Z2, Z3, Z6 and Z7 will increase in their sizes. Zones Z4 and Z5 will decrease but Zones: Z8, Z9 and Z10 will remain unchanged. Based on widths of the zone difference result, it can be stated that about a tenth (1/10) of the total grid size is significantly a 'zone-shift'. Given that the grid size for the map is 10,000 meters then the shift in a zone is equivalent to 1000 meters which is a kilometer on the ground. This will be a large area of land probably affecting several farmers who will experience a change in their cultivation patterns of some unresisting crops to climate variations.

A proper farm management practice is very essential to the farmer. With this AEZ delineation and its projection in the year 2050, the farmer and the stakeholders can be advised in advance so that they start preparing for the changes that will have impact on

their agricultural production and the economy at large. Furthermore, the method of multivariate geographical clustering in conjunction with PCA is a tool that can give precise agro-ecological zone definition (Hargrove & Hoffman, 1999). Iteration is necessary to have a good delineation of a zone hence a powerful tool to analyze regions of the same climate variation in any given region and even quantify them so that the general public are informed. The government and the stakeholders on the other hand can find ways of helping farmers maintain their farm produce and still earn a living from it. It is meaningful to state that climate projections are based on physical models which are better at forecasting mean values of rainfall and temperature than their extremes. It follows that the impacts forecasted for the future represent averages of values which can sometimes strongly fluctuate from one year to another, hence creating uncertainty of the data.

c) Impacts of soil erosion on agricultural activities in Taita Hills

Soil erosion in Taita Hills is caused mainly by intensive agriculture, cutting down of trees and even overgrazing (Erdogan et al., 2011). Huge amount of indigenous forest has been lost to agriculture between 1955 and 2004 although a balance was created by large-scale planting of exotic pines, eucalyptus, grevillea, black wattle and cypress on barren land during the same period which has not contributed much to the productivity of water catchment or more agricultural yield. Indigenous forest loss may adversely affect ecosystem services in Taita Hills (Pellikka et al., 2009). From site visits and field measurements, the impacts of climate variations and / or change to agricultural land in the region will be severe in the future if nothing is done to reduce such effects.

d) Cropland assessment in Taita Hills

The results obtained from this research study were presented in form of maps. The product outcome was reclassified into four main classes; less suitable, least suitable, more suitable and most suitable (Figure 44). The results that were obtained from this research study were presented in form of maps that showed the scenarios in Taita Hills. The mapping concept for this suitability analysis using GIS is very important to farmers

in the current situation of global climate variations. Coupled with the Agro-ecological zones and having shown that there shall be zone shifting in the coming years, precisely 2050, then farmers need to be aware of this situation so that they get prepared in time (Boitt et al., 2014).

This study employed climate analysis and geophysical parameters in which the geophysical parameters weren't contributing much in the change however, with the issue to do with soil erosion, due to huge amount of rains, the soil types and drainage pattern of Taita Hills can be of importance or consideration (Erdogan et al., 2011). The annual water requirement for irrigation (Maeda et al., 2010) is seen to coincide with this research in that, lowland areas are seen to be least suitable for agriculture but with some irrigation, it is possible to make them productive. It is shown that there can be suitable areas and unsuitable areas for growing crops in Taita Hills. This study helps farmers to be aware of the environmental conditions and its impacts that may arise with the varying climate in the future. It is a tool that can be used to plan and manage agricultural activities for a better yield.

CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The objectives of this study were: Identifying crops using hyperspectral imagery, delineating agro-ecological zones, modeling the impacts of climate change on delineated agro-ecological zones in the current and in the future scenarios and finally mapping suitable agricultural areas for Taita Hills through suitability analysis method.

Three general contributions can be highlighted from the results obtained in this study. First, it is shown that airborne hyperspectral imagery is used to identify various crops in a given cultivated landscape which is a very new technology in Kenya and Eastern Africa. Secondly, an alternative approaches (combination of PCA and multivariate geographical clustering techniques) to delineate agro-ecological zones in Taita Hills is developed. Thirdly, but not least, demonstrates a modeling approach of the agro-ecological zones to assess cropland characteristics in relation to climate variations and / or chage.

Considering the above contributions, this study is important to the stakeholders (local farmers), researchers and policy makers. The spectral and spatial resolution of hyperspectral imagery is greater and able to identify various crops in a cultivated landscape. It cannot be compared with other available satellite images. In this study, it was shown that the crops could be classified to over **80%**, accuracies using pixel based algorithms; spectral angle mapper (SAM) and spectral information divergence (SID) when the angle of divergence is kept at 0.1 radians. The mid zone areas constituted a lot of farming activities whereas the high zone had less crops but more forest lands. The agricultural activities in the mid zone is attributed to the high population, availability of moisture and good environmental conditions for farming.

Furthermore, the climate projections are very useful in modeling scenarios especially with regard to climate change impacts on agriculture. This study used climate analysis

and geophysical parameters. The assumption was that the geophysical parameters can neither affect nor contribute so much to change in the agro-ecological zones. However, with soil erosion, the soil types and drainage pattern of Taita Hills can be of important consideration. With good scientific approaches that helps in understanding these impacts, it is possible to address the impacts and educate the locals and policy makers about the underlying effects of the future climate variations. Results obtained for the projected agro-ecological zones (2050) in this dissertation need to be compared with upcoming reports from the Kenya Ministry of Agriculture (KMA) and other Kenyan research organizations to ascertain possible uncertainties investigated. Currently, there is no climate projections that is valid and accurate for Eastern Africa.

In relation to the suitable cropland areas in the Taita Hills, it is expected that agricultural areas will expand in the lowlands of the study area. Previous studies concluded that agricultural expansion is likely to take place predominantly in lowlands and foothills throughout the next 20 years and this corresponds with the results obtained in this study. This study has shown that there can be suitable and unsuitable cropland areas in Taita Hills. Major crops to be grown in the lowland areas would be early maturing maize, beans, millet, cassava and sugarcane on the lower streams and swampy areas. Mangoes will still dominate in the lower areas but not in the mid and high zones of Taita. Maize, Avocadoes, potatoes, various vegetables, and bananas will do very well in the mid zone. High zone areas need to be protected since it serves as the catchment area for Taita Hills.

Moreover, soil erosion is a main driving factor when analyzing the agricultural areas of Taita Hills. Soil erosion in Taita Hills is caused mainly by intensive agriculture, cutting down of trees and even overgrazing. From site visits and field measurements, it can be concluded that the highlands of the Taita Hills must be prioritized for soil conservation policies during the next 20 - 50 years. In spite of increased agricultural activities and population in the study area, this study generally shows that climate change is a future threat to the economy and the entire livelihood of the people of Taita Hills.

There is need for climate adaptation and mitigation strategies to reduce climate effects on agriculture and the population at large. Farmers need also to have knowledge and information regarding climate variability and / or change. In the event that climate variations becomes severe to agriculture and the whole of the ecosystems, there is need to educate them and inform on the adaptation strategies through practices, culture and livelihoods suited to the local conditions. This will help them to maintain a favorable environmental condition that lowers the risks posed by the consequences of climate change.

5.2 Recommendations

The study for hyperspectral image classification can be extended to cover the whole of Taita Hills to give a real picture of the crops that the farmers grow. This study only covered a chosen transect area. The use of combined pixel based and object based classification approaches could be used in further research. A combination of the two methods is recommended.

It is also recommended that further work be done in understanding the relationship between the suitable areas mapped and the crops to be grown even in the future due to climate variations and / or change. The scientific correlation between the identified crops using hyperspectral remote sensing techniques and the suitable areas shown needs to be analyzed. There could be an underlying relationship between the two that this thesis did not show.

Furthermore, impacts of climate change for this study is only limited up to the year, 2050. More predictions and analysis can be projected even up to the year, 2100. Cropland assessments done for this project gave four suitability areas. It is recommended that more analysis and assessments can be build based on these information.

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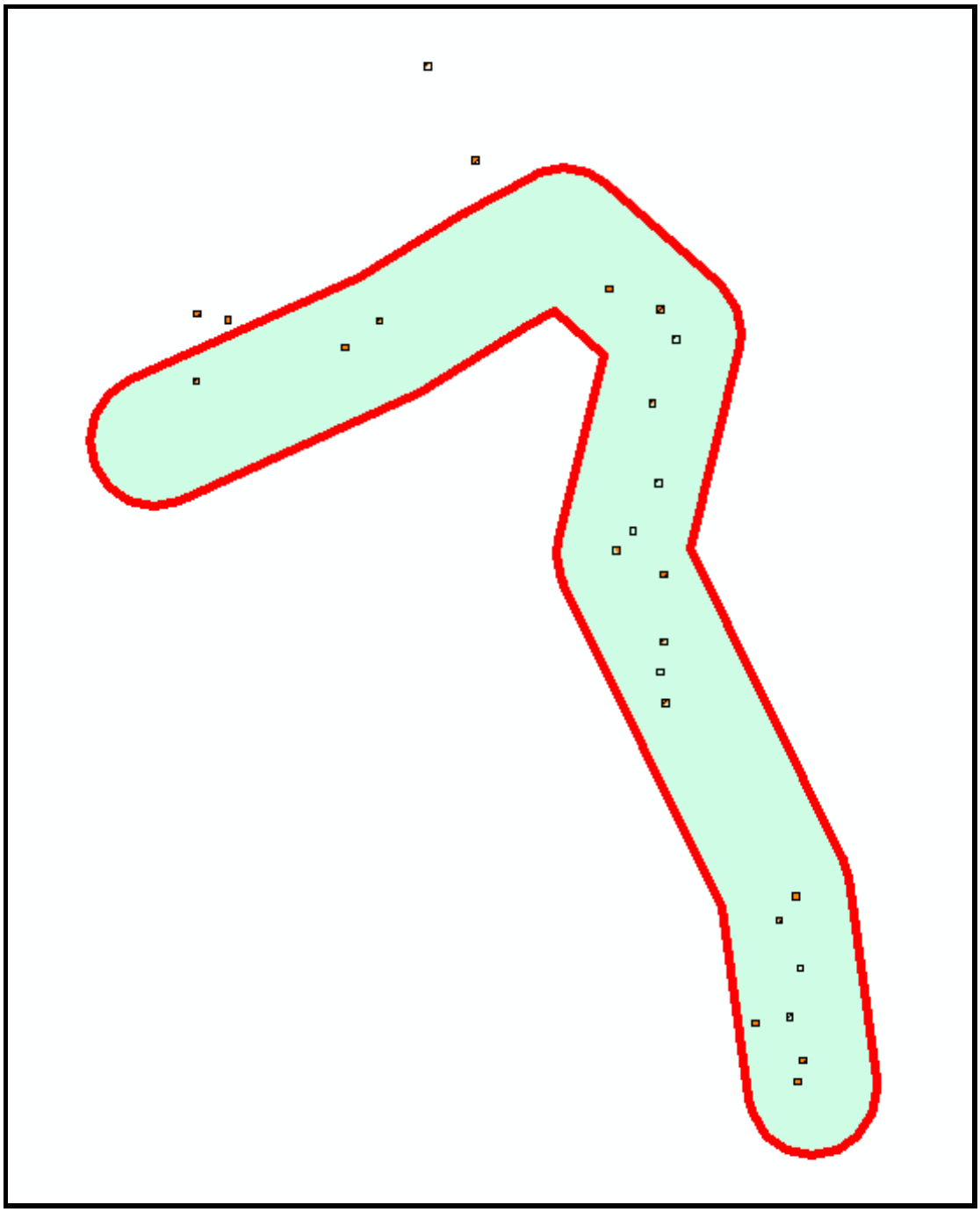
APPENDIX I: SELECTED PLOTS ON TRANSECT AREA

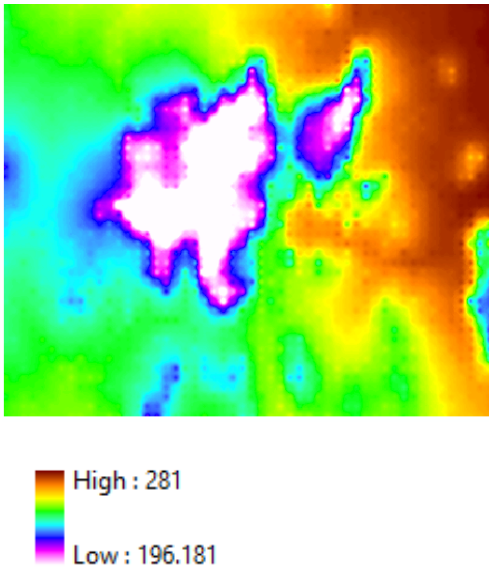


APPENDIX II: CROP DATA GPS COORDINATES

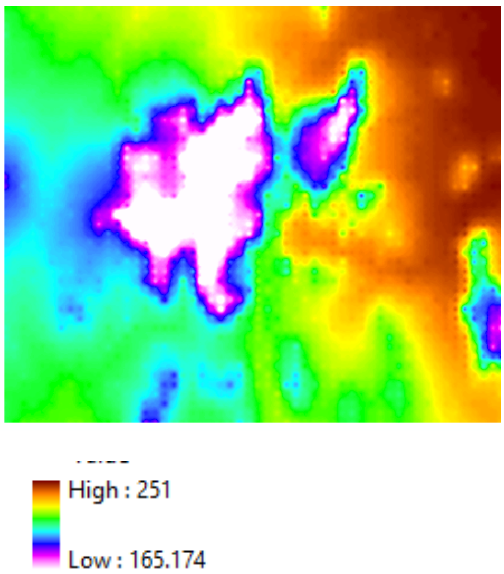
East (meters)	North (meters)	Crop (species)
428952	9619420	Avocado
426414	9626104	Avocado
426413	9625526	Avocado
426458	9625442	Avocado
426426	9625326	Avocado
424766	9624418	Avocado
423140	9624228	Avocado
429044	9623190	Avocado
429071	9623224	Avocado
429147	9623210	Avocado
429313	9622770	Avocado
429296	9622770	Avocado
429125	9622166	Avocado
428830	9622296	Avocado
428169	9622244	Avocado
426968	9622728	Avocado
431279	9615454	banana huge
426429	9625552	banana huge
426373	9625518	banana huge
423123	9624204	banana huge
429140	9623604	banana huge
429069	9623204	banana huge
429132	9622130	banana huge
428823	9622324	banana huge
426839	9622854	banana huge
426653	9623510	banana huge
425609	9625222	Eucalyptus
424698	9624206	Eucalyptus
427000	9622492	Eucalyptus
431248	9615470	maize
431200	9614800	maize
429080	9619442	maize
431168	9615722	mango
431254	9615712	mango
431248	9615246	mango
431167	9615048	mango
431229	9614604	mango
429039	9619168	mango

428907	9619306	mango
428826	9619380	mango
428899	9619388	mango
429176	9623212	mango
429161	9619044	Mango
429284	9618870	mango
429316	9618770	mango
429398	9618780	mango
429379	9618826	mango
429422	9618794	mango
429421	9618782	mango
429437	9618804	mango
429461	9618820	mango
429462	9618768	mango
429481	9618768	mango
429503	9618758	mango
429507	9618738	mango
429490	9618730	mango
429512	9618630	mango
429484	9618632	mango
429533	9618574	mango
429481	9618552	mango
429497	9618572	mango
429716	9618542	mango
429714	9618562	mango
429755	9618512	mango
429818	9618570	mango
429182	9619432	mango
429111	9619484	mango
429098	9619408	mango
429101	9619390	mango
429089	9619386	mango
429048	9619456	mango
429029	9619486	mango
429004	9619496	mango
428975	9619506	mango
429039	9619156	sugarcane
429021	9619452	sugarcane
431242	9615029	two mangoes

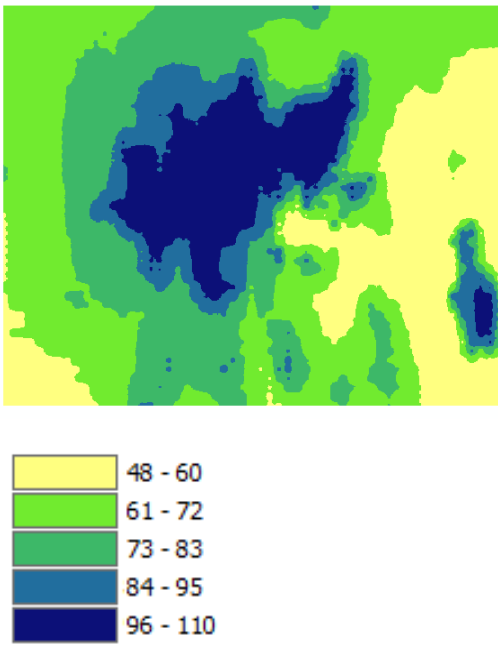
APPENDIX III: AGROCLIMATIC ZONES OF TAITA HILLS



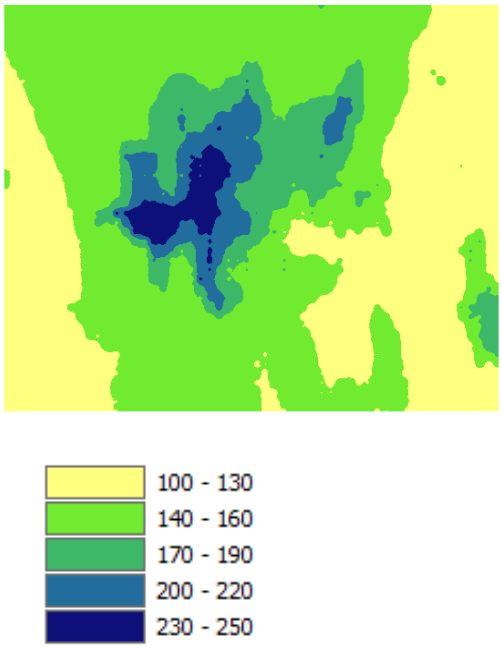
Current temperature 2010 (°C*0.1)



2050 future temperature(°C*0.1)

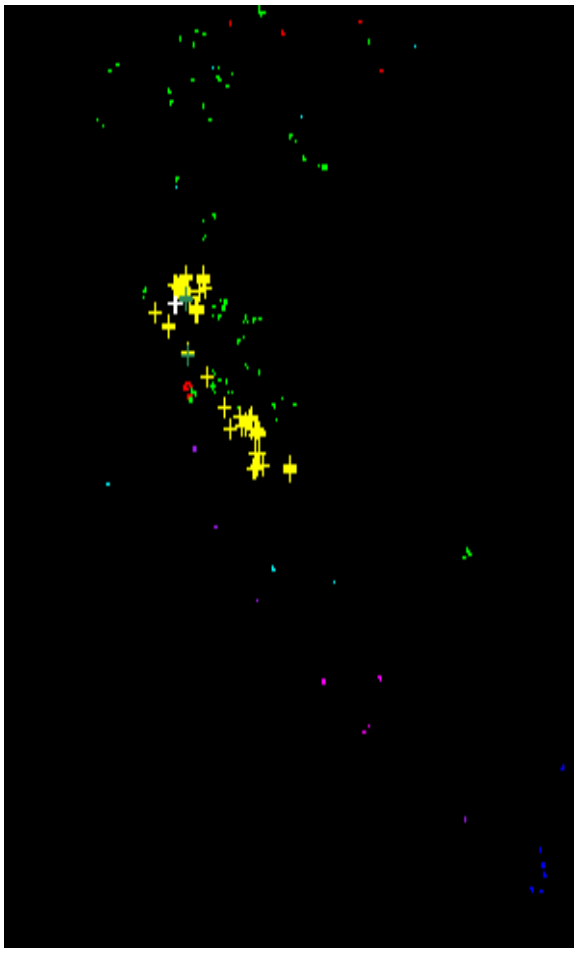


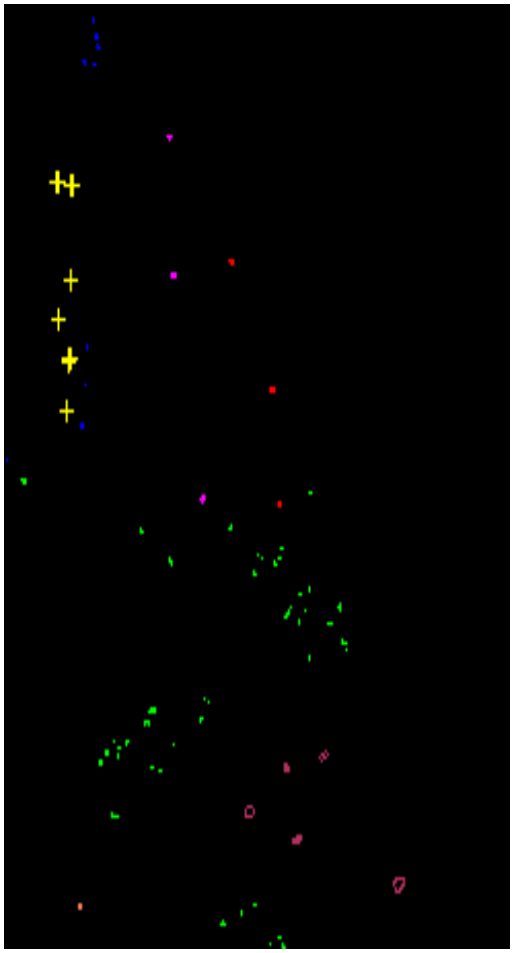
Current rainfall 2010 (mm/month)



2050 future rainfall (mm/month)

APPENDIX IV: TRAINING AREAS (SPECTRA)





APPENDIX V: PUBLICATIONS FROM THIS RESEARCH

I am responsible for writing, delineating the research questions, designing the methodologies and analyzing the results obtained in all the research papers listed below. Moreover, all co-authors contributed with corrections and suggestions before publishing the research papers. The following are the publications from this research.

I **Boitt, M. K., Mundia, C. N. & Pellikka, P.K.E.** (2014). Modelling the Impacts of Climate Change on Agro-Ecological Zones–a Case Study of Taita Hills, Kenya. *Universal Journal of Geoscience*, *2*(6), 172-179.

II **Boitt, M. K., Mundia, C. N. & Pellikka, P. K. E.** (2014). Using Hyperspectral Data to Identify Crops in a Cultivated Agricultural Landscape-A Case Study of Taita Hills, Kenya. *Journal of Earth Science and Climate Change,* 5: 232. doi: 10.4172/2157-7617.10002 32 Page 2 of 4 Volume 5 Issue 9.

III **Boitt, M. K., Mundia, C. N., Pellikka, P. K. E, & Kapoi, J. K.** (2015). Land Suitability Assessment For Effective Crop Production, a Case Study of Taita Hills, Kenya. *AGRÁRINFORMATIKA/JOURNAL OF AGRICULTURAL INFORMATICS*, *6*(2), 23-31.