University of Nairobi

School of Engineering

USE OF GIS AND REMOTE SENSING TECHNIQUES TO ESTIMATE COCONUT CULTIVATION AREA: CASE STUDY OF KALOLENI SUB-COUNTY

BY

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F56/82295/2012

A Project submitted in partial fulfillment for the Degree of Master of Science in GIS, in the Department of Geospatial and Space Technology of the University of Nairobi

MAY 2014

Declaration

I, Rhoda Rehema Chai, hereby declare that this project is my original work. To the best of my knowledge, the work presented here has not been presented for a degree in any other Institution of Higher Learning.

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Name of student Date

This project has been submitted for examination with our approval as university supervisor(s).

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Name of supervisor Date

Dedication

This project is dedicated to my family; my father Daniel, my mother Gladys, my sister Rita and my brother David, who remained patient and supportive throughout my study period. Thank you for providing a platform to further my ambition.

Acknowledgement

First of all I would like to thank the Almighty God for His blessing in my life and throughout the study period.

I would like to express my thanks and gratitude to the University of Nairobi and more to the Department of Geospatial and Space Technology for granting me an opportunity to further my studies.

My supervisor Dr.-Ing. S.M. Musyoka provided guidance throughout this research. The research benefitted from his efforts to refine my ideas and to evaluate the structure and contents of this project through discussions.

To my classmates, your support is greatly appreciated.

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List of Abbreviations

ABD – Agricultural Business Development

ASPS – Agricultural Sector Program Support

CDA – Coast Development Authority.

COGENT – International Coconut Genetic Reserve Network

DANIDA – Danish International Development Agency

FAO – Food and Agricultural Organization

GIS – Geographic Information Systems

GPS - Global Positioning System

KCDA – Kenya Coconut Development Authority

LU/LC- Land use/ Land cover

NEMA- National Environmental Management Authority

NDVI – Normalized Difference Vegetation Index

SOK – Survey of Kenya

Abstract

This study was aimed at estimating area under coconut cultivation in Kaloleni Sub-County by employing the use of GIS and remote sensing techniques. The viability of high resolution satellite imagery (GeoEye) was tested to locate the distribution of the coconut trees in the study area. After image pre-processing, the image was subjected to maximum likelihood classification to produce a land cover map showing the distribution of coconut palm trees and other land-cover types.

The classifier was trained and the accuracy of the results assessed using ground truth data of the coconut palm trees and other land-cover types that were collected. Ground truth data, in the form of field mappings, high resolution reference data and expert knowledge were used to gain further insights and produce reliable results. Results of the supervised classification showed an overall classification accuracy of 76.67%. A total of 303.82 hectares of coconut palms were detected from the image analysis.

INTRODUCTION

1.1 Background

The coconut palm tree was introduced in Kenya by the Portuguese in the 16^{th} century. Its cultivation spread rapidly and since then; it has grown to become a key source of livelihood for many in the coastal region. It is considered as “the tree of life” this is because it is widely used both as a cash and food crop (Waijenberg, 1993).

The study focuses on the use of GIS and remote sensing in estimating the area under coconut cultivation in Kenya specifically in Kaloleni Sub-County. Basic information on the geographical distribution and changes in areas that are under coconut cultivation is unreliable with general fear on the ground that coconut trees are being cut down. In 1997 the Government of Kenya de-listed the coconut tree as a protected crop (ASPS-ABD/KCDA, 2009). This made the situation worse and consequently making the crop invincible.

Coconut farming is a central part that affects the livelihood of most coastal communities; it is deeply entrenched in their cultures and practices and will continue to be so in the future. Integrating the coconut sector into the market as an important cash crop will greatly improve the livelihood of many, ignoring the crop will mean wasted opportunities. The development of the coconut sector should be spearheaded in order to reduce poverty levels in the county. The current trend shows the market expansion that goes beyond the coastal population. This is a positive aspect that only needs to be propelled further.

A generalized map of coconut growing areas with estimated acreage is important in guiding those who are concerned with the coconut industry, especially in key areas like planning, monitoring and evaluation, management of development projects and action programs. Areas under coconut cultivation are usually affected by socio-economic conditions. Land use conversion, urbanisation, cutting down trees and environmental concerns is vital in understanding the coconut production status.

Up-to-date information of major land use, acreage and distribution of crops is a basic need in agriculture throughout the world. In both the developed and developing countries these data are essential for efficient management of agricultural resources and sustainability.

Land is one of the most important natural resources on which all of man's activities are depended upon, and a thorough knowledge of it, which includes the land use/land cover, is very much essential for a number of planning and management activities. The term "land use" (LU) relates to the human activity or economic function associated with a specific piece of land whereas the term "land cover" (LC) relates to the type of feature present on the surface of the earth.

Coastal areas are most vulnerable for land use changes, especially with rapid industrialization and urbanization. It is therefore necessary to evaluate land use- land cover changes for efficient management. GIS and remote sensing is increasingly being used to monitor Land use/Land cover changes and to analyze the distribution patterns of the coconut trees (Mas, 1999). GIS is an appropriate technology for analysis of spatial data, visual communication and map manipulation.

Literatures pertaining to the location, extent and distribution of coconut palm trees are indicative of using conventional field survey mapping methods (ABD-DANIDA/CDA, 2007).This situation opens up several opportunities for the adoption of existing remote sensing-based techniques as starting point for mapping of the coconut palm tree in remote sensing images, which could lessen logistical and practical difficulties that are often encountered when using conventional field surveys, especially in inaccessible areas.

Remote sensing plays a key role in gathering information about an object, area or phenomenon using a device that is not actually in contact with it (Lillesand and Keifer, 1994). Recently, remotely sensed data have been integrated in GIS databases, such as to facilitate temporal analysis for resources monitoring. Furthermore, remote sensing is often the most cost-effective source of information for updating a GIS and it is a valuable source of current land use/land cover data (Silapathong and Blasco, 1992).

Remote sensing is an advanced tool for inventory and analysis of land use pattern. Satellite imageries have been available for the past few years, with different spatial and spectral resolution. This has contributed greatly in the monitoring of Land use/Land cover making it easier and reliable (Gregorio and Jansen, 1998).

1.2 Problem Statement

Coconut farmers in many parts of the world are facing difficulties in sustaining their livelihood from coconut farming. In Kenya, coconut farmers have not benefited from the industry through the years and are ranked among the poorest in Kenya (ABD-DANIDA/CDA, 2007).

The magnitude of the coconut sector in Kenya has generally been understated probably as a result of estimation errors in the absence of comprehensive surveys like the use of qualitative and quantitative approaches which have been used extensively in the past to conduct survey of coconut trees. The reason for the understatement has been due to failure to recognize the importance of the coconut tree.

In order to ensure growth in the coconut sector, information on the distribution of coconut cultivation is required, this will bring to light the magnitude of the coconut distribution in the Sub-County. This study looks at the application of GIS and remote sensing technology in determining area under coconut plantation.

1.3 Objectives of the study

The main objective of this study is to demonstrate the use of GIS and remote sensing techniques in area estimation of coconut cultivation areas.

The specific objectives of the study are to identify the different land uses/land cover types and calculate the area under coconut cultivation.

1.4 Justification for the Study

Basic information that is available on coconut cultivation areas is generally unreliable. This study will work towards filling the information dissemination gap on coconut distribution in the study area. The need for reliable information is critical for effective planning and development of the coconut sub-sector.

1.5 Scope of work

The project will focus on the distribution of the coconut trees and calculation of the area under coconut cultivation in the study area. The study will involve some image analysis that include; processing, image enhancement and the two types of classification on the image to produce a land use/land cover map. The study will also include results of statistics on the area under coconut cultivation. The study will not give an estimate on the numbers of coconut trees, change detection or health monitoring.

LITERATURE REVIEW

2.1 Introduction

The coconut palm, *cocos nucifera,* is the primary member of the family Arecaceae (palm family). It is the only species in the genus *cocos* and is a large palm growing to a height of up to 30m tall with pinnate leaves 4-6m long, the older leaves break away cleanly leaving the trunk smooth.

The coconut tree is ranked the most important perennial crop in Kilifi district (Muniu et al, 2002). Kilifi County grows a variety of food crops that include maize, beans, cassava, cashew nuts, millet and sugarcane. The distribution of coconut trees in Kilifi County is not even, with constituencies like Kaloleni, Malindi and Bahari having a higher concentration of coconut trees than Ganze and Magharini constituencies.

2.2 Historical background

In Kenya, the coconut tree (*coco nucifera*) has been grown for a longer period than other countries in Africa (Herlehy, 1984). The english name coconut was first mentioned in an english print in 1555 (Werth, 1993) it comes from the Spanish and Portuguese word '*cocos*' meaning monkey face. This was due to the resemblance of the markings or 'eyes' found at the base of the coconut to a monkey.

Coconuts received the name from Portuguese explorers, the sailors of Vasco Da Gama in India, who first brought them from Europe. When coconuts arrived in England, they retained the coco name and nut was added. Origins of the plant are still subject for debate with most authors claiming it is a native to South Asia. On the Nicobar Islands of the Indian Ocean, whole coconuts were used as currency for the purchase of goods until the early part of the 20th century.

The coconut palm trees are native to Malaysia, Polynesia, Southern Asia, India and in South America. Intercropping the coconut tree with other food crops and tree crops is common for most coconut farmers; this is because intercropping with short term crops has no adverse effects on the yield or growth of coconut trees (Denamany et al., 1979).

2.3 Coconut products

In Kenya, existing literature indicates that coconut is mainly used for making copra. Copra is the principal product of the coconut palm (J.G. Ohler, 1984) that is further processed into oil, mainly used in the soap industry, cosmetics, candle manufacture and also refined to edible quality. A study conducted showed that about 90% of copra produced in Kenya was dried through sun-drying (UNIDO, 1984). The study indicated that sun drying was the oldest method of drying copra and was still widely practiced in Kenya at the time. Copra is the dried meat or kernel of the coconut (wikipedia).

Other important coconut products in Kenya are palm wine (also known as Toddy), *madafu* from immature nuts, brooms and *makuti*. Products that are developed for both domestic and export market include desiccated coconut and coconut cream. Another product that can be exploited is the husk. Coir fibre is a by-product of the husk that can be spun into yarn for making mats and ropes. It can also be made for upholstery and stuffing mattresses, brushes and brooms.

2.4 Agronomy

The ecological requirements can be summarized as follows:

i. The coconut palm is a sun-loving tree. It needs at least 2000 hrs of sunshine per annum. When the palm is shaded it does not grow well and becomes excessively long and thin.
ii. The optimum temperature ranges from 24-35°C.
iii. The palm needs high air humidity of at least more than 60% and preferably 80-90%.
iv. The moisture requirements are high. In general, a well distributed annual rainfall of 1000-1400 mm is regarded as optimal.
v. The coconut palm grows at an altitude of 0-750 metres.

2.5 Legislation

During the pre-independence period, the development of the coconut industry was governed by two Acts of Parliament; Cap 331-"the Coconut Industry Act" and Cap 332 "Coconut Preservation Act". In post independence the Minister of Agriculture never gazetted coconut as a special crop, which would have facilitated the establishment of a Board to oversee the development of the coconut sector in the country.

In August 2007 the Kenya Coconut Development Authority (KCDA) was established through a Legal Notice No. 165 under the State Corporation Act Cap 446. It was established to regulate the coconut industry by providing a conducive environment to enhance development of coconut through research. Changes have been noted since then, but a lot remains to be done in terms of coconut research and the use of GIS technology is key.

2.6 Current research on coconut in Kenya

Research on coconut development in Kenya has been slow as compared to other countries such as Tanzania and Mozambique. Kenya has not been actively participating in important network organizations created for the coconut industry like the International Coconut Genetic Reserve Network (COGENT). Low priority given to the sub-sector has limited the ability to undertake research and development activities with a view to introducing drought tolerant varieties, improvement on crop husbandry, processing and marketing of the products and by – products.

Kenya has been ranked 7th among the eight coconut producing countries[1] in Africa (FAO, 2005). Over 14 billion worth of vegetable oil is imported annually into the country, while coconut has the potential to substitute by 30% especially coconut oil for soap making. Research has shown that Kenya could be earning approximately of Shs 25 billion far from the Shs 6 million earned each year from the local coconut industry. If developed this sector shows the potential that is far from being exploited.

In 2006 the Danish International Development Agency (DANIDA) in collaboration with the Coast Development Authority (CDA) commissioned a survey of coconut trees in the then four districts of Coast province- Kwale, Kilifi, Malindi and Mombasa. Out of the four districts, Kilifi

[1] *Ghana, Benin, Mozambique, Nigeria, Madagascar, Tanzania, Cote d' Ivoire, and Kenya*

district had the most coconut farmers. Using both qualitative and quantitative approaches, the exercise was carried out in the months of January through mid March in 2007. Data collections were done by a team of over 400 enumerators and in total 63,223 farmers were interviewed in 1,723 villages.

Table 1 shows the results of the survey done on coconut trees in Kenya. It was noted that the total size of land owned by coconut farmers in which certain portions are planted with coconut had other crops. The general approach used in calculating the acreage for the coconut tree was by estimating the number of trees there were and determining the size of land they would occupy, if they were planted using the recommended spacing dimensions.

Table 1: Size of land under coconut production (in hectares)

District	**Number of trees**	**Number of farmers**	**Total land under coconut (ha)**	**Size of land per farmer (ha)**	**Trees per hectare**
Kwale	2,895,427	26,201	86,596	3.30	33
Kilifi	2,831,978	28,739	56,448	1.96	50
Malindi	986,997	14,013	27,314	1.95	36
Lamu	434,105	6,768	22,661	3.36	19
Tana River	140,414	1,841	4,856	2.66	28
Mombasa	136,938	3,784	4,451	1.20	30

Source: ABD-DANIDA/CDA Coconut tree survey, 2007

It was noted that the coconut sector had been understated as a result of estimation errors in absence of comprehensive surveys. Information from the survey showed a population of coconut trees at 7.4 million, 3 million higher than the 4.4 million coconut trees that were thought to exist in the past. The survey conducted also showed that a small percentage (around 25%) of the coconut subsector is currently exploited.

The distribution of coconut trees in the coast region is in such a way that there are clearly identifiable production clusters, they are defined areas with concentration of coconut trees with a radius of 5-7 kilometres. Kilifi and Kwale County have the largest number of developed production clusters. It was also noted that all basic information on the geographical and age distribution, and holding per farmer looked outdated and unreliable for planning purposes. There was an obvious gap in terms of reliable information to many stakeholders.

2.7 Coconut Acreage in Kilifi County

As is the case with other tree crops cultivated by smallholders in Kenya, acreage under coconut cultivation is not a straightforward issue. This is because coconut farming among smallholders is hardly ever done in pure stand and trees are generally scattered across the farm sometimes in a manner in which seedlings sprout on their own but many cases following certain pattern of portions of the farm that are suitable for the crop i.e. sandy sections or along valleys/rivers.

In most of the cases, coconut trees will be found intercropped with other trees crops – mangos, cashew, citrus, bixa and even some forestry crops. It is therefore difficult to estimate the exact acreage under coconut cultivation as some portions of land will have no trees at all while, even where there are trees, these are intermixed with other crops. During the coconut survey conducted by DANIDA it came out clearly that farmers generally know the total size of land they own but have difficulties in telling the exact size they have planted with coconut.

Results of the survey also showed that Kenya's total land under coconut cultivation currently stands at slightly over 200,000 hectares (Table 1). It is however important to note that this is the total size of land owned by coconut farmers in which certain portions are planted with coconut, generally mixed with other crops.

In a recent interview (Mwambingu, 2013) a KCDA official stated that plans are underway to invest Shs 400 million per year in coconuts projects, in a bid to boost production in the country. One million seedlings were to be distributed to needy farmers. GIS technology can be used in identifying areas with low productivity and suitable areas to introduce the crop. Satellite images are also helpful in identifying characteristics of coconut plantation like vacant patches which are key in understanding coconut productivity.

2.8 Remote sensing

Remote sensing can be defined as "the science of collecting information about objects without coming into physical contact with them" (Hill 2000).Although satellite data has been available since the 1960s, civilian remote sensing of the earth's surface from space only began in the 1972 with the launch of the first series of Earth Resource Satellites i.e. Landsat.

Remote sensed data and techniques used have improved over time, moving from a traditional remote sensing approach to a more advance one. Traditional approach includes the use of aerial photograph and some high resolution systems. Aerial photography is sometimes preferred in developing countries because it is most cost effective and more readily accessible.

High resolution systems include Landsat, SPOT and ASTER (Jensen, 2000). Manual mapping methods take a relatively long time and are costly. Pressing needs for land use inventory has lead to the use of GIS and remote sensing techniques which provides up-to-date information (Luney and Dill Jr., 1970).

Digital imagery captured from sensors on earth observing satellite such as Landsat offer several advantages that include the following:

1) Covers both small and large geographic areas.
2) Satellite images are sufficiently accurate and reliable.
3) Changes over time can be identified.
4) A digital format that is compatible with geographic information systems.
5) Land cover maps generated at considerably less cost.

Remote sensing imagery generally offers imperative coverage, mapping and classification of land cover features namely vegetation, soil, water and forests. It can also be a source of useful information in many agricultural applications (Nualchawee, 1984). Some of the most promising agricultural applications include:

1) Crop identification and area estimation.
2) Crop condition assessment.
3) Yield forecast and estimation.
4) Soil survey and mapping

2.9 Image classification

Image classification is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixel into classes that match by comparing pixels to one another and to those of known identity. The success or failure of a classification project depends in large part upon the type of classifier used (and the training data employed). A number of different classification algorithms have been employed; such methods can be categorized as supervised, unsupervised, or hybrids of the two (Lillesand and Kiefer 1994).

Unsupervised classification is a largely automated procedure, involving little input from the user. Classification is performed automatically by the computer algorithm, and pixels are grouped into classes according to the natural spectral groupings existing in the data (Richards & Jia 1999), that is, the user does not have to identify or have knowledge about the classes. Instead, the algorithm identifies pixels that are similar, and groups them to form classes. Unsupervised classification has the benefit that it is quick and easy. It is often used for familiarization purposes (i.e. to get to know the data). However, since classes are selected automatically, it is of limited use for identifying ‘specific’ classes of interest.

An unsupervised classification approach puts less burden on the image analyst, at least at the beginning of the classification process, because the computer programs search the image and then assign each pixel in the dataset to categories or clusters that are similar on the basis of multispectral reflectance characteristics. Then the image analyst must label each cluster class into descriptive land cover units e.g., hardwood forest, softwood forest, water, urban, etc. (Lillesand and Kiefer 1994).

Supervised classification is more complex and generally a more accurate method of classification. Supervised classification, however, does require prior knowledge of the ground cover in the study area. In supervised classification, the burden is on the image analyst to locate a full range of vegetation types in the image by drawing polygons around homogeneous stands or "training areas."

The classification routine develops statistics for each training area and then executes a decision rule to assign each pixel in the output dataset to one of the training area categories that is closest to the pixel in spectral statistical space. In this case, the classes are labeled *a priori* into land cover categories of interest (Lillesand and Kiefer 1994).

The general objective of image classification is to categorize each cell or pixel into land cover types using a series of computer processing routines. A generic classification system was developed by a practitioner named Anderson in 1976 (Table 2). This is perhaps the most well-known and widely used land cover classification system. One does not have to feel restricted to the Anderson’s system, and can adapt or alter Anderson’s classes, or even add entirely new classes.

It was always Anderson’s intention for Levels 1 and 2 to be broadly generic and contributions encouraged for Level 3 and 4. One of the main constraints of crop identification on satellite imagery is the relatively low spatial resolution. Besides the small fields sizes, tropical countries often face problems due to high cloud coverage (Reichert, 1984).

Table 2: Land use and land cover classification system for use with remote sensed data.

Level I	Level II
1 Urban or Built-up Land	11 Residential
	12 Commercial and Services
	13 Industrial
	14 Transportation, Communications, and Utilities
	15 Industrial and Commercial Complexes
	16 Mixed Urban or Built-up Land
	17 Other Urban or Built-up Land
2 Agricultural Land	21 Cropland and Pasture
	22 Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas
	23 Confined Feeding Operations
	24 Other Agricultural Land
3 Rangeland	31 Herbaceous Rangeland
	32 Shrub
	33 Mixed Rangeland and Brush Rangeland
4 Forest Land	41 Deciduous Forest Land
	42 Evergreen Forest Land
	43 Mixed Forest Land
5 Water	51 Streams and Canals
	52 Lakes
	53 Reservoirs
	54 Bays and Estuaries
6 Wetland	61 Forested Wetland
	62 Nonforested Wetland
7 Barren Land	71 Dry Salt Flats
	72 Beaches
	73 Sandy Areas other than Beaches
	74 Bare Exposed Rock
	75 Strip Mines Quarries, and Gravel Pits
	76 Transitional Areas
	77 Mixed Barren Land
8 Tundra	81 Shrub and Brush Tundra
	82 Herbaceous Tundra
	83 Bare Ground Tundra
	84 Wet Tundra
	85 Mixed Tundra
9 Perennial Snow or Ice	91 Perennial Snowfields
	92 Glaciers

Source: Anderson (1976)

2.10 Improved classifiers

It is very common that the same vegetation type on ground may have different spectral features in remote sensed images. Also, different vegetation types may possess a similar spectrum, which makes it very hard to obtain accurate classification results either using the traditional unsupervised classification or supervised classification. Searching for improved classification methods is always a hot research topic (Gad and Kusky, 2006).

However, strictly speaking, all classification methods are derived from the traditional methods as aforementioned, which provide the basic principles and techniques for image classification. Thus, improved methods usually focus on and expand on specific techniques or spectral features, which can lead to better classification results and thus deserve special attention. Great progress has been made in developing more powerful classifiers to extract vegetation covers from remote sensing images.

2.11 Mapping distribution of sago palms

A study on the distribution of the sago palm in the Philippines was conducted using remote sensing techniques. The sago palm had gained interest for its commercial utilization as a significant source of starch that can be converted into flour, lactic acid, ethanol and biodegradable plastics. Information on its present location and distribution was missing, and it could not be ascertained whether there was enough supply of sago to drive and sustain a large scale sago starch industry (Santillan *et al*, 2012).

The sago palms had been reported to exist in marshlands and wetlands of northeastern Mindanao which were difficult to access and would be costly if mapped using conventional field mapping techniques. Therefore, the use of remote sensing data and techniques would be appropriate for this purpose.

3.0 MATERIALS AND METHODS

3.1 Study area

3.1.1 Introduction

The area of study is located at the eastern part of Kaloleni Sub-County in the larger Kilifi County between 39˚37’42”E and 39˚38’59”E Longitude and 3˚48’12”S and 3˚50’45”S Latitude (Figure 2). The area of study is roughly 1,103 hectares. Kilifi County formerly known as Kilifi District is one of the main coconut growing areas in the Coast region.

It extends between 39˚15’E and 40˚15’ E Longitude and 2˚20’ S and 4˚00’ S Latitude. It has a total area of 12,245.9 km^2. Kilifi County is located north of Mombasa and has five Sub-Counties namely Bahari, Kaloleni, Ganze, Malindi and Magarini. Figure 1 shows the location of Kilifi County. Kilifi district has a population of 1,109,735 and has a total of 28,739 farmers (Census, 2009).

3.1.2 Economic activities

Tourism and fishing are the major economic activities due to the proximity to the Indian Ocean. The County has some of the cleanest beaches and popular resorts and hotels. The county has a strong industrial sector with the Mabati Rolling Mills and the Athi River Cement Factory contributing heavily to the region’s economy both in employment provision and income generation.

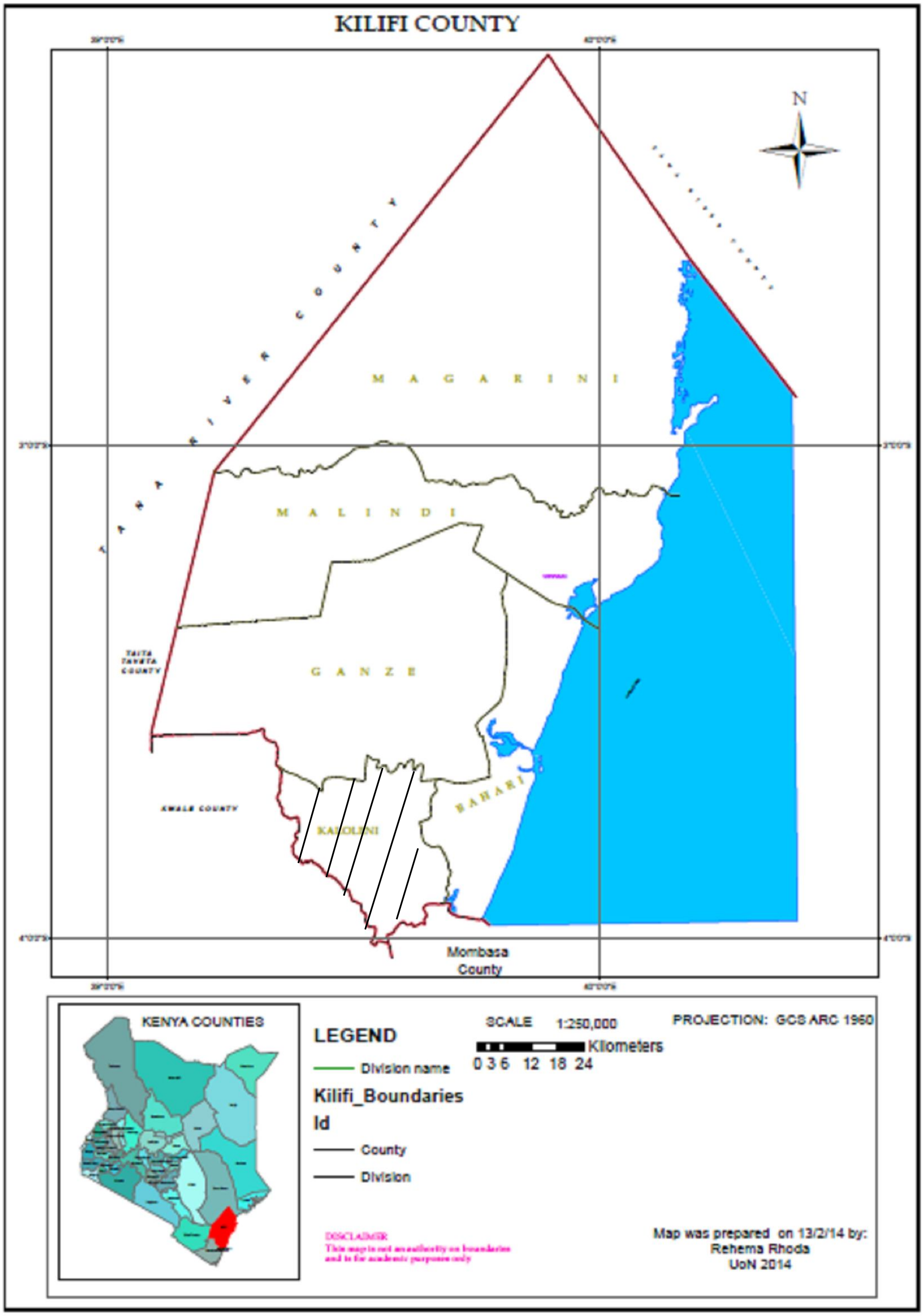


Figure 1: Map of Kilifi County (Source: SOK)

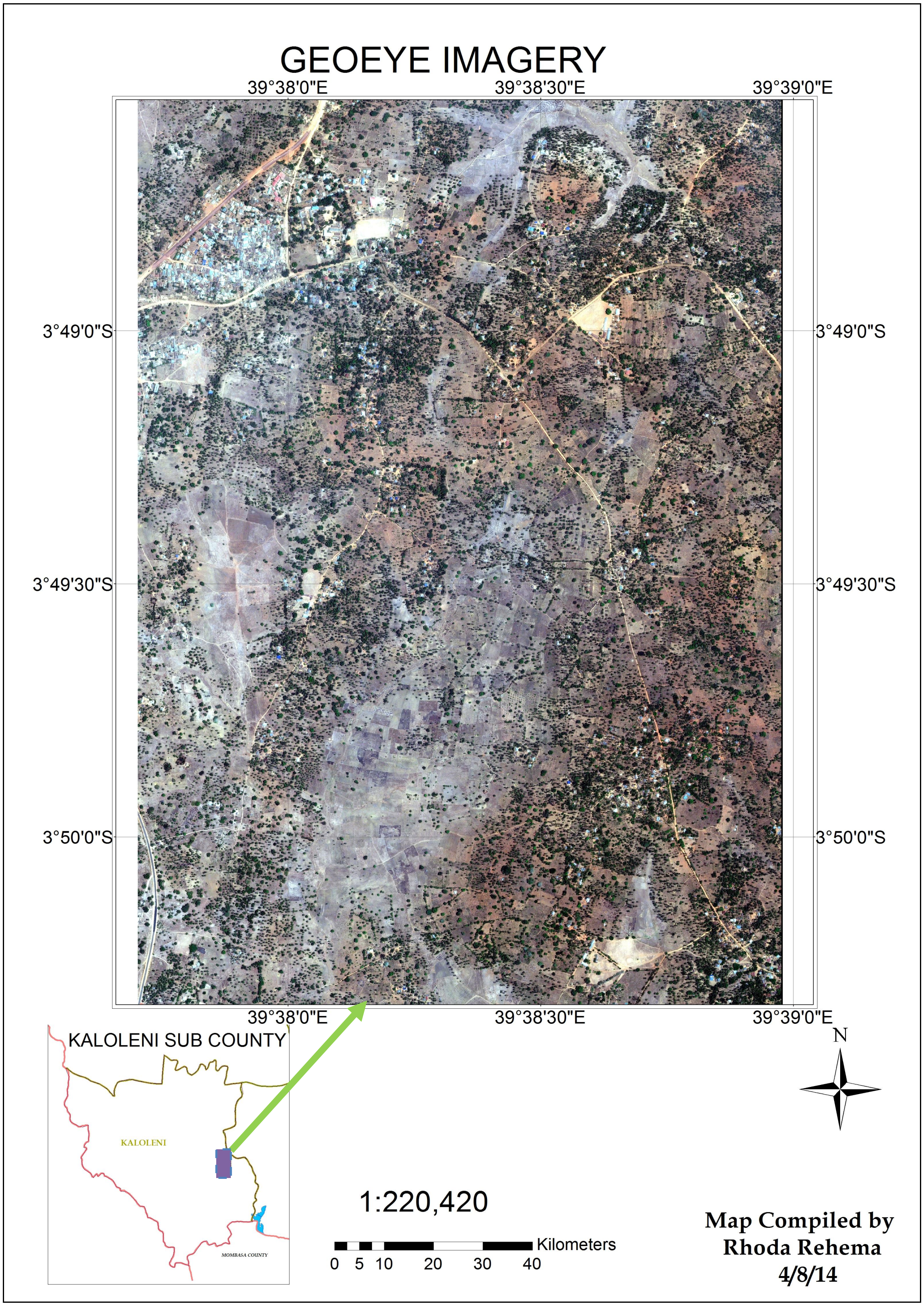


Figure 2: GeoEye image covering the study area.

3.2 Data and Tools

3.2.1 Remote Sensing data

In this study a three band GeoEye Satellite imagery of the year 2011 was used. It was obtained from the National Environmental Management Authority. Table 3 shows the specifications of a GeoEye image.

Table 3: GeoEye-1 Specifications

Imaging mode	**Multispectral**
Spatial Resolution	0.5m (pan-sharpened)
Spectral Range	Blue 450-520nm Green 520-600nm Red 625-695nm Near IR 760-900nm
Nominal Swath Width	15.2 km at Nadir

3.2.2 Ancillary data

The ancillary data consisted of digitised topographic maps and reference data from the internet which was mainly used to assist in interpretation of the images. Table 4 shows the datasets that were acquired and their sources.

Table 4: Sources of ancillary data

Data type	**Data source**	**Format**
Administrative boundaries	SOK	Digital
Reference data	Google earth (internet)	Digital

3.3 Software and Equipment

A number of software packages were used;

- ERDAS Imagine and ArcGIS these were used in image classification and processing.
- Google Earth for image interpretation.
- Mapsource was used to upload GPS ground truthing data.
- Garmin handheld GPS receiver
- Laptop
  Windows 8
  2 GB of RAM
  Hard disk space: 500GB

Figure 3 shows the sequence of the image analysis. The study involves two main steps. The first step involves classification of the satellite data for land use/land cover types. The second step is area estimation of the coconut cultivation areas.

3.4 Data identification and collection

All relevant data were identified and selected accordingly. A 3 band GeoEye image of the area of study was acquired as opposed to a Landsat image which was heavily contaminated by cloud cover and shadows, making it impossible to generate a more informative land-cover map. The GeoEye imagery is of a high resolution which enabled clear identification of the land cover.

3.5 Image Data Pre-Processing

Image processing is very important in most remote sensing operation. A spot check on the acquired satellite imagery indicates that it had undergone some of the processes and is free of geometric and radiometric errors like cloud cover. The image acquired was already georeferenced.

Image enhancement was performed to improve the image quality and increase the interpretability of the image. It was performed by employing a contrast method using the Histogram Equalization.

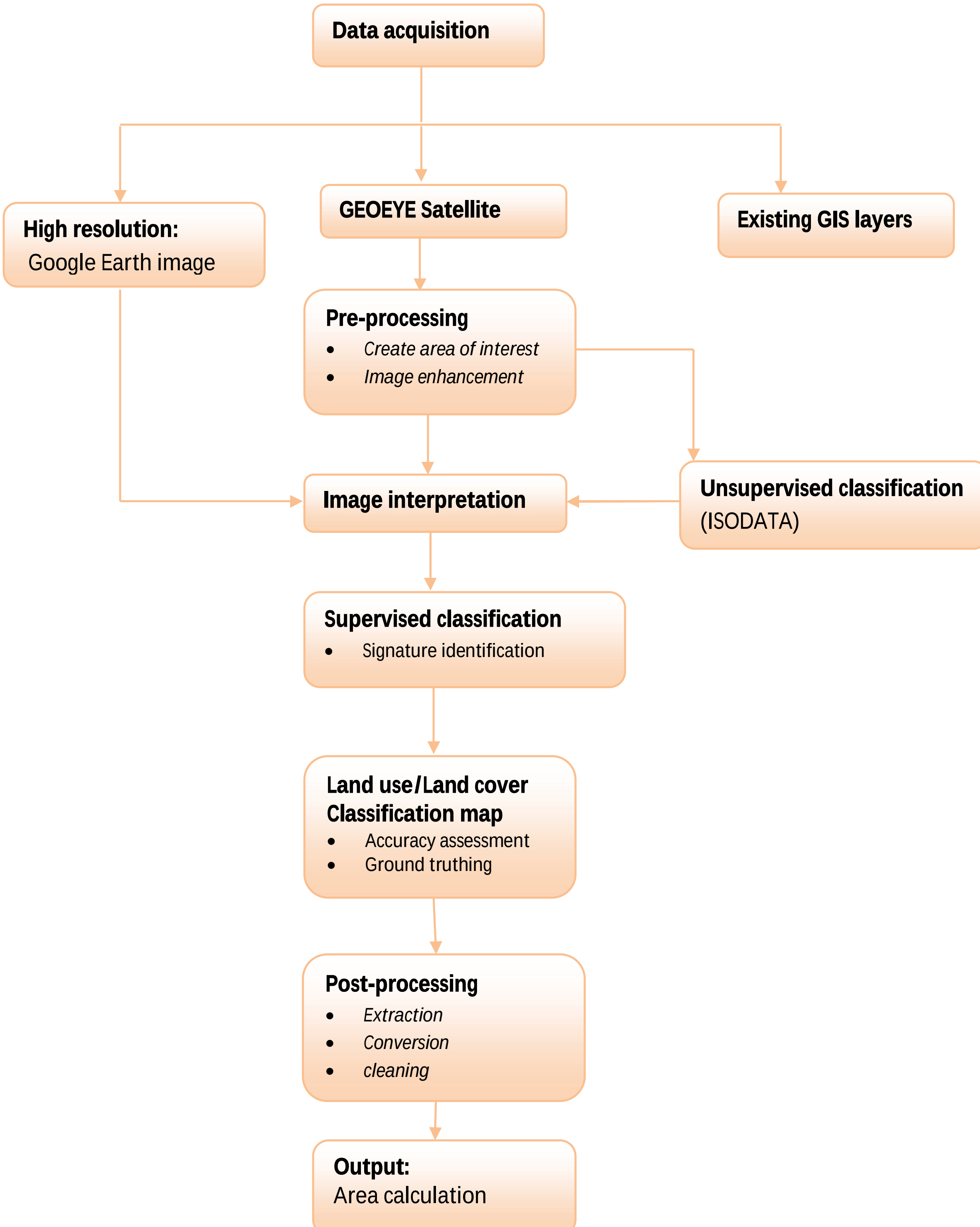


Figure 3: Flowchart of the methodology

3.6 Image interpretation

The pre-processed GeoEye image was visually interpreted to obtain information as to what land-cover types are present in the study area. Expert knowledge of the study area was applied because of the strong familiarity of the area and the ability to identify land cover features reliably. High resolution images provided by the Google Earth application were also used as references to aid in the interpretation.

3.6.1 Ground truthing

Ground truthing on the study area was conducted in two days. The aim was to collect more data and information from the field. Table 5 shows a total of sixteen GPS coordinates of the sample sites that were taken during the site visit.

Table 5: GPS coordinates of the ground truth sites.

Point	Northing (m)	Easting (m)	Description
024	9579414	0569903	Coconut
025	9579430	0569885	Coconut
026	9379396	0569879	Agricultural
027	9579376	0569804	Grassland
028	9579390	0569796	Grassland
035	9578503	0569871	Bare ground
036	9578500	0570016	Bare ground
037	9578618	0570279	Bare ground
038	9578648	0570412	Bare ground
039	9578690	0570454	Built up
040	9578950	0570244	Bare ground
041	9578804	0570212	Built-up
042	9578797	0570115	Built up
043	9578797	0570029	Agricultural
044	9578638	0569961	Built up
045	9578657	0569821	Built up

3.6.2 Unsupervised classification

Results from the unsupervised classification were used in the image interpretation. in order to identify the numerous spectral classes that need to be defined before one can adequately represent the land cover information classes and perform a supervised classification.

An unsupervised classification with eight classes was carried out on the image. Below are the steps followed to perform the classification:

- Input raster file is opened; image to be classified.
- Output file was also set; new classified image to be created.
- Output signature file; spectral signatures for each class.
- A total of eight classes were set. This was determined from the image interpretation.
- Unsupervised classification is performed using the ISODATA which is by default (ERDAS IMAGINE 9.2).
- Colours are adjusted to satisfy the appearance of the classification.

3.7 Supervised Classification

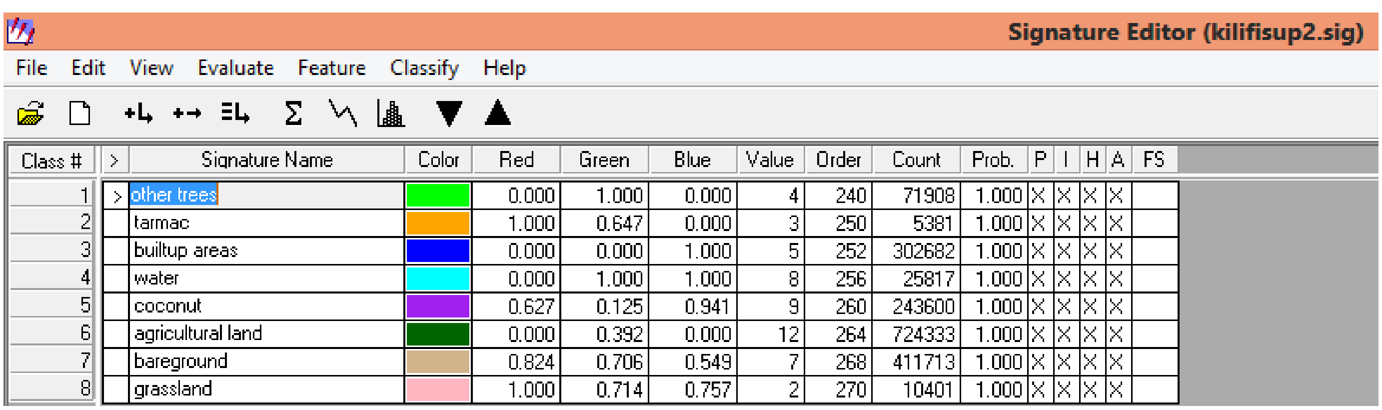
A supervised classification was adopted for this study. A clear picture was gained from the image interpretation, which included the unsupervised classification, familiarity of the area and use of patterns and texture. Table 6 summarises the land cover types that were identified during the image interpretation. These land cover types are then used in training of the classes. A Maximum Likelihood Classifier (MLC) was used for the supervised classification.

Table 6: Land-cover types

Land-cover type	**Description**
Agricultural land	Areas for agriculture and planting of crops (includes planted/unplanted)
Barren land	Bare exposed soils , unpaved roads
Built-up areas	Residential, commercial and industrial areas
Coconut	Tracts of lands planted with coconut trees
Grassland	Areas where vegetation is dominated by grass
Other trees	All other trees
Tarmac	Features such as roads
Water	Reservoirs

3.7.1 Class training

- Polygons around each training site were digitized and assigned a unique identifier for each of the land cover types.
- Pixels within the training site were digitized and spectral signatures created for the land cover types.



Class #	>	Signature Name	Color	Red	Green	Blue	Value	Order	Count	Prob.	P	I	H	A	FS
1	>	other trees		0.000	1.000	0.000	4	240	71908	1.000	X	X	X	X	
2		tarmac		1.000	0.647	0.000	3	250	5381	1.000	X	X	X	X	
3		builtup areas		0.000	0.000	1.000	5	252	302682	1.000	X	X	X	X	
4		water		0.000	1.000	1.000	8	256	25817	1.000	X	X	X	X	
5		coconut		0.627	0.125	0.941	9	260	243600	1.000	X	X	X	X	
6		agricultural land		0.000	0.392	0.000	12	264	724333	1.000	X	X	X	X	
7		bareground		0.824	0.706	0.549	7	268	411713	1.000	X	X	X	X	
8		grassland		1.000	0.714	0.757	2	270	10401	1.000	X	X	X	X	

Figure 4: Selected pixel colours for different classes using signature editor

3.7.2 Accuracy assessment

The classified image was subjected to different types of accuracy assessment. The first accuracy assessment was done by comparing high resolution satellite image. High resolution satellite image was available through the GIS software Google Earth on which coconut trees were distinguishable. One main problem when using these images as a ground truth reference is that, the acquisition dates of the scenes covering the study area differed from the date the analyzed image was taken and could only be used as an approximate representation of the study area.

Nevertheless, due to lack of other resources, the images were compared to the results in order to perform a rough qualitative assessment. It turned out that this is a good way to visualize the results, but that an objective accuracy assessment is needed.

The second accuracy assessment was performed using the error matrix. The accuracy assessment is done by generating random points in the study area. These points are used for verifying the true land cover type. A reference value is recorded for the true land cover class for each of these points. These values are then compared with the raster image of the classified image at the location examined.

A report is then generated from these values giving an error matrix which tabulates the relationship between true land cover classes and the classes as mapped. The report measures three levels of accuracy namely, the Overall Classification Accuracy (OCA as a percentage), Producer's Accuracy (PA) and User's Accuracy (UA).

3.8 Post processing

After classification, the features of interest (coconuts) are extracted from the resulting raster image to enable further analysis. In Arcmap the Spatial analyst tool is used to extract by attribute the feature of interest. A resulting raster image of the extracted features is produced. When overlaid with the original satellite image one is able to see the coconut features. The raster image of the extracted feature is then converted to polygon. This enables cleaning, since some mixed pixels existed.

3.9 Area calculation

Using the land use/land cover map, area calculation of the coconut cultivation areas was determined. Cleaning has been done by overlaying the extracted features with the original image to remove the mixed pixels. The attribute table of the polygons is displayed and a field is added to the table. The field is named Area_ha, the geometry of the field is calculated to get area of each polygon in hectares. The statistics of the field Area_ha is calculated to get the total area of the polygons, this give the total area of the coconut areas.

4.0 RESULTS AND DISCUSSIONS

The aim of this study was to demonstrate use of GIS and remote sensing in estimating coconut cultivation areas by performing land use/land cover classification and eventually calculating the area. The results of this study are in the forms of;

a) A classified raster image of the study area

b) Statistical analyses

4.1 Image enhancement

It was important to improve the quality of the image for better interpretation. A contrast was done using Histogram equalization.

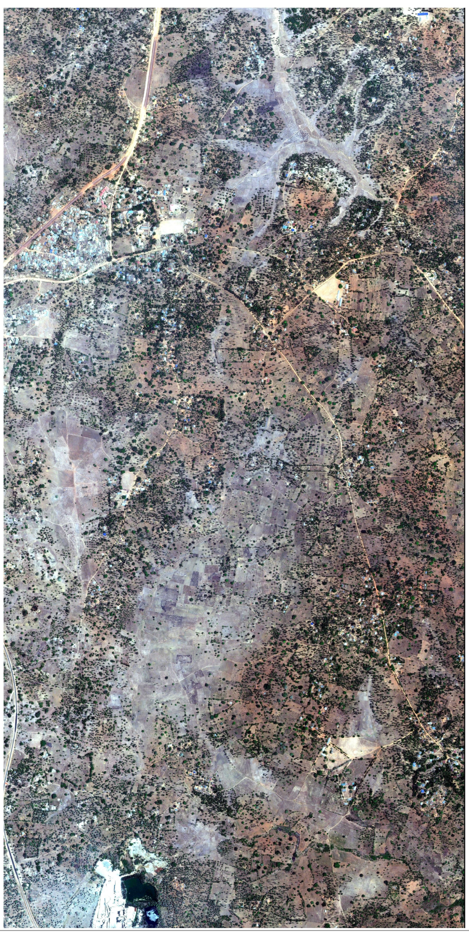


Figure 5: Image before enhancement **Figure 6: Image after enhancement**

(Displayed in true color)

The resulting image shows a true colour image of the study area. The visibility of the image has improved greatly, thus making it easier for image interpretation.

4.2 Image exploration

Use of texture and patterns will help one to separate coconut trees from natural forest and other land cover features. Figure 7 show how patterns and textures can be used to identify features in the image.

Figure 7: Image showing textures and patterns (part of)

4.3 Results from the classifications

In this study image classification was done in two stages, first by performing an unsupervised classification which was largely automated procedure and involved little input from the user. Classification was performed automatically by the computer algorithm (ISODATA). The second stage involved a supervised classification that was aimed at categorizing each cell or pixel into land cover types.

4.3.1 Results from unsupervised classification

The aim of the unsupervised classification was to pre-define land cover classes, though it was a little difficult to interpret this classification meaningfully since some of the classes derived may not have necessarily represented anything which one is familiar with.

Figure 8 shows the resulting raster image of the area of study after unsupervised classification has been done. A visual comparison of the results with high resolution satellite (Google Earth) indicated that a more differentiated classification was needed for this study.

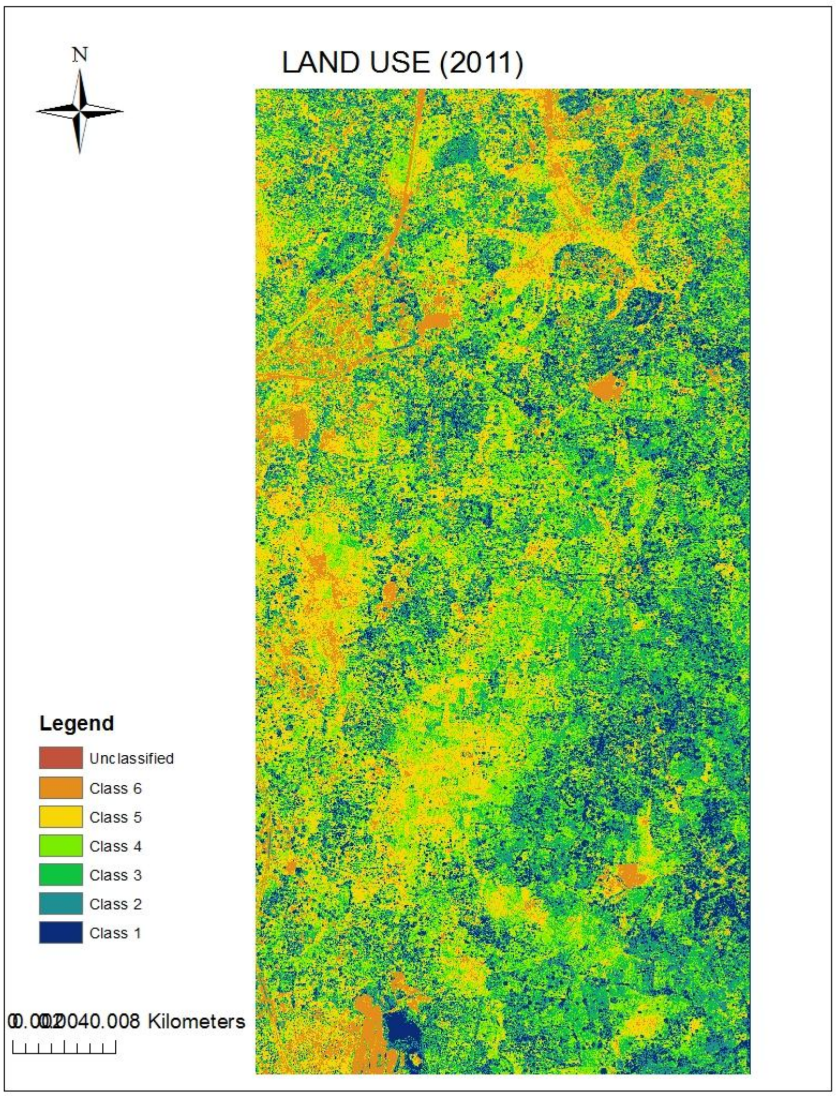


Figure 8: Unsupervised Classification

4.3.2 Results from the supervised classification

A Maximum Likelihood Classifier (MLC) was used during the supervised classification. It is a widely used algorithm and the most powerful classification method when accurate training data is used (Sohn and Rebello,2002). This is because it assumes the training data is normally distributed however this may not always be the case like in complex areas. It also has the ability to incorporate the statistics of the training samples before assigning the land covers to each pixel.

The classified image below depicts a clear picture of the land cover types that are in the study area. The land cover generated were water, tarmac, grassland, built up areas, bare ground, agricultural land, other trees and coconut.

The presence of the Athi River Mining Company in the area of study has greatly affected the vegetation of the surrounding area. Most of the plants are covered in dust and there is less vegetation in this area, this is clearly visible from the classified image. This shows the impact of environmental pollution that is common with mining plants.

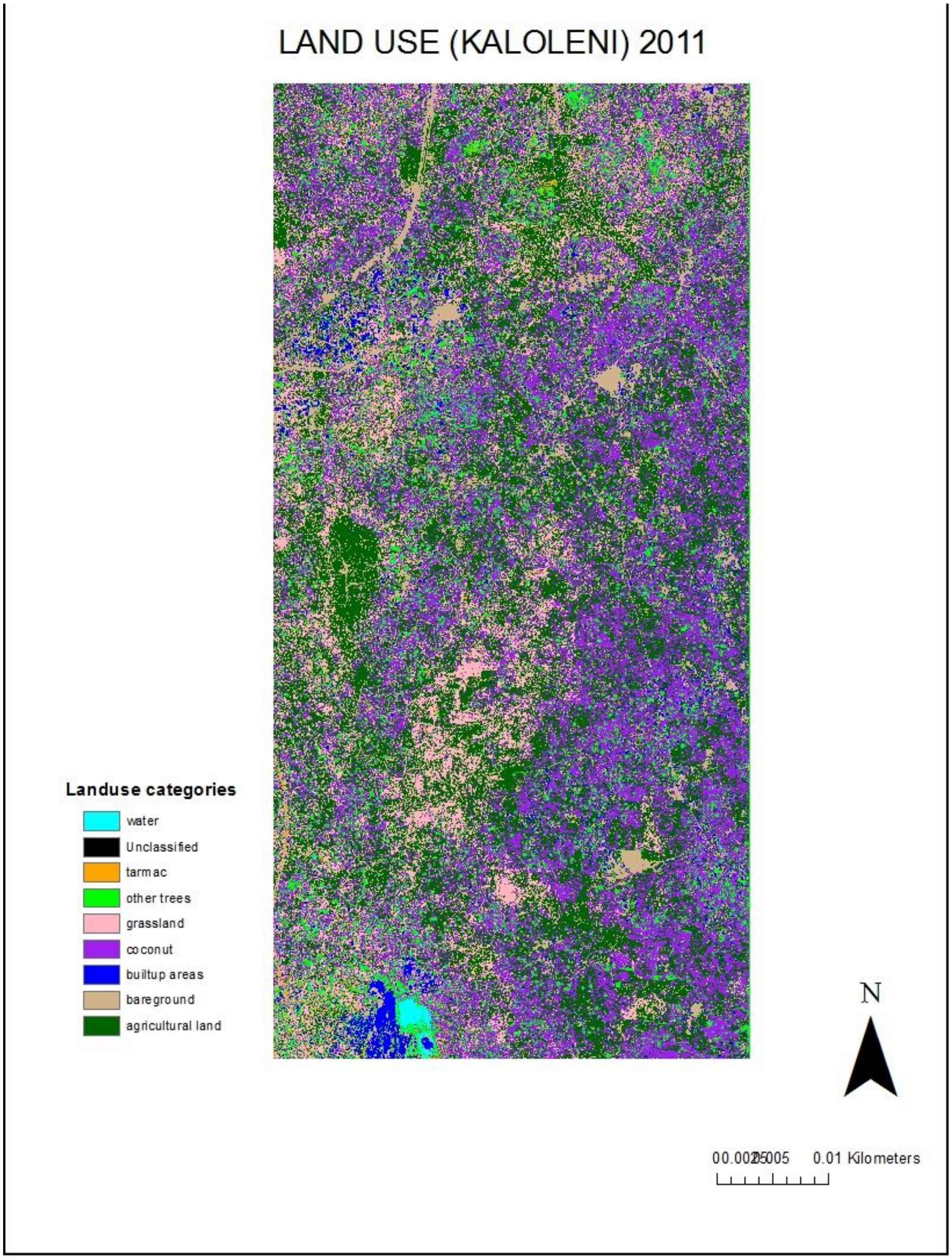


Figure 9: Land use/land cover map of the study area.

4.3.3 Accuracy of the classification

This is useful in determining the level of error that might be contributed by the image.

a) Error matrix

Accuracy of the classification is expressed in the form of an error matrix (Congalton and Green, 1998). An error matrix is a square array of numbers in which the columns express the informational categories, and the rows show the classes in which those informational categories have been classified. The overall agreement of the classification is therefore expressed by the sum of main diagonal entries.

An omission error happens when a test area is not classified into its informational category. On the other hand, the commission error occurs when a test area is classified in a class different from its true informational categories. Information about these types of error is given by the user's and producer's accuracies respectively.

Traditional accuracy assessment is done by generating random set (Figure 10) of locations to visit the ground for verification of the true land cover type. A simple value file is then made to record the true land cover class (by integer index number) for each of these locations (Figure 11). This value file is then used with the vector file of point locations to create raster image of true classes found at the location examined. The raster image is then compared to the classified map using error matrix.

An error matrix tabulates the relationship between true land cover classes and the classes as mapped. It also tabulates error of omission and errors of commission as well as the overall proportional error. This information is used to assess the accuracy of the classification procedure that was under taken and is used for the results of all supervised classification.

Figure 10: Random points for error matrix

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Point #	Name	X	Y	Class	Reference
1	ID#1	39.630	-3.809		1
2	ID#2	39.645	-3.835		6
3	ID#3	39.647	-3.832		1
4	ID#4	39.633	-3.812		28
5	ID#5	39.629	-3.813		46
6	ID#6	39.646	-3.813		31
7	ID#7	39.640	-3.804		31
8	ID#8	39.629	-3.838		31
9	ID#9	39.630	-3.829		1
10	ID#10	39.646	-3.820		1
11	ID#11	39.636	-3.832		6
12	ID#12	39.642	-3.833		31
13	ID#13	39.643	-3.840		1
14	ID#14	39.640	-3.831		1
15	ID#15	39.638	-3.811		46
16	ID#16	39.648	-3.829		31
17	ID#17	39.649	-3.809		31
18	ID#18	39.649	-3.807		46
19	ID#19	39.649	-3.837		7
20	ID#20	39.630	-3.838		46
21	ID#21	39.636	-3.825		31
22	ID#22	39.632	-3.844		3
23	ID#23	39.635	-3.805		28
24	ID#24	39.644	-3.829		6
25	ID#25	39.648	-3.817		6
26	ID#26	39.632	-3.804		3
27	ID#27	39.646	-3.819		31
28	ID#28	39.645	-3.844		1
29	ID#29	39.644	-3.819		1

Figure 11: Reference values of random points.

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ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
agricultural la	56	68	52	92.86%	76.47%
builtup areas	5	3	3	60.00%	100.00%
grassland	39	26	22	56.41%	84.62%
water	1	1	1	100.00%	100.00%
tarmac road	3	4	3	100.00%	75.00%
bareground	13	11	9	69.23%	81.82%
coconut	36	54	36	100.00%	66.67%
other trees	27	13	12	44.44%	92.31%
Totals	180	180	138		

Overall Classification Accuracy = 76.67%

----- End of Accuracy Totals -----

Figure 12: Accuracy assessment

b) Ground truthing

This was achieved by overlaying the ground truth data points with the classified image then comparing the level of accuracy. Figure 13 shows a sample of the ground truth data that was collected on the site.

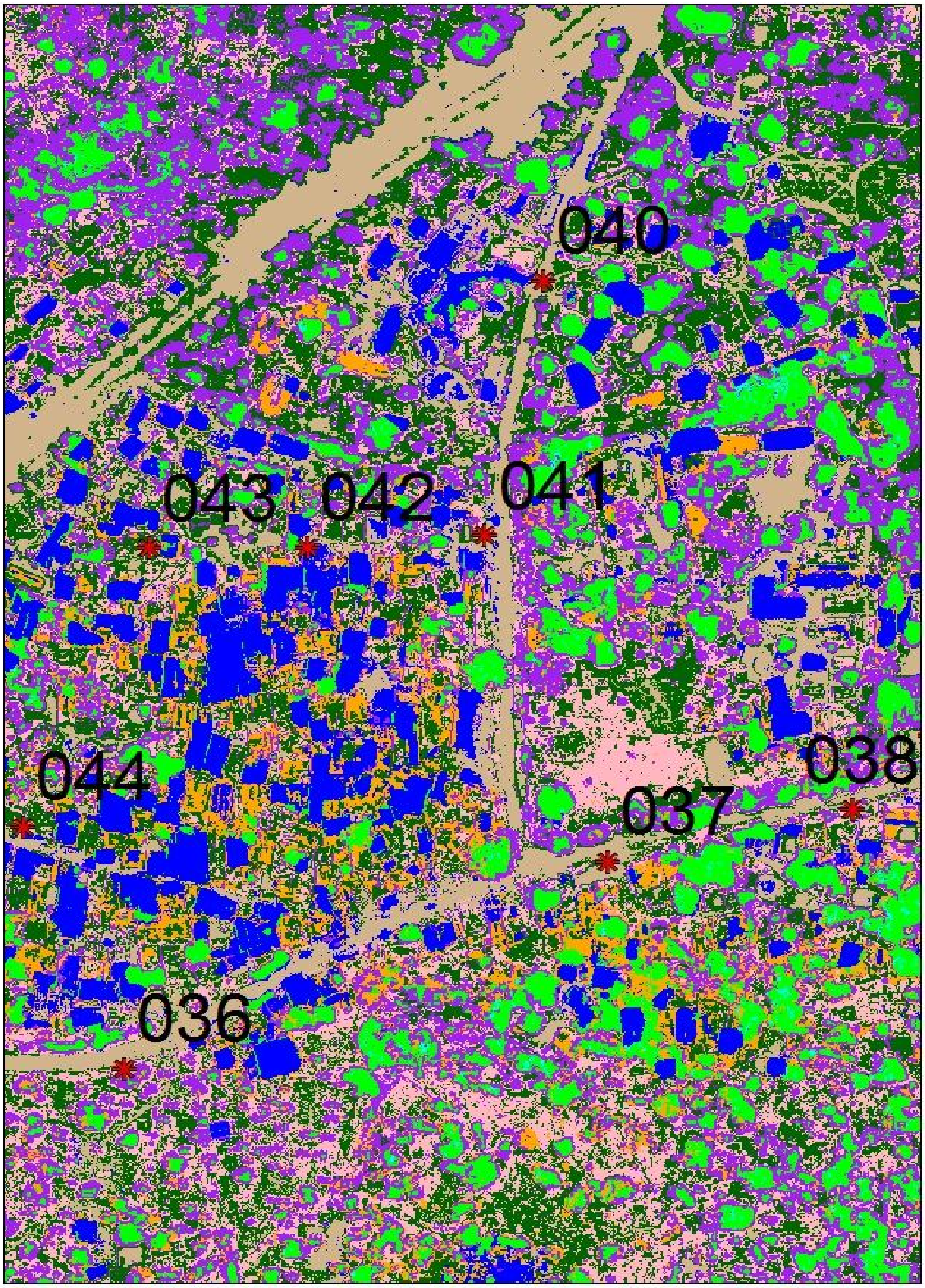

Figure 13: Ground truth data.

4.4 result of Feature Extraction

Once the accuracy has been determined, the feature of interest is extracted by the attribute name_coconut. Figure 14 show the extracted feature.

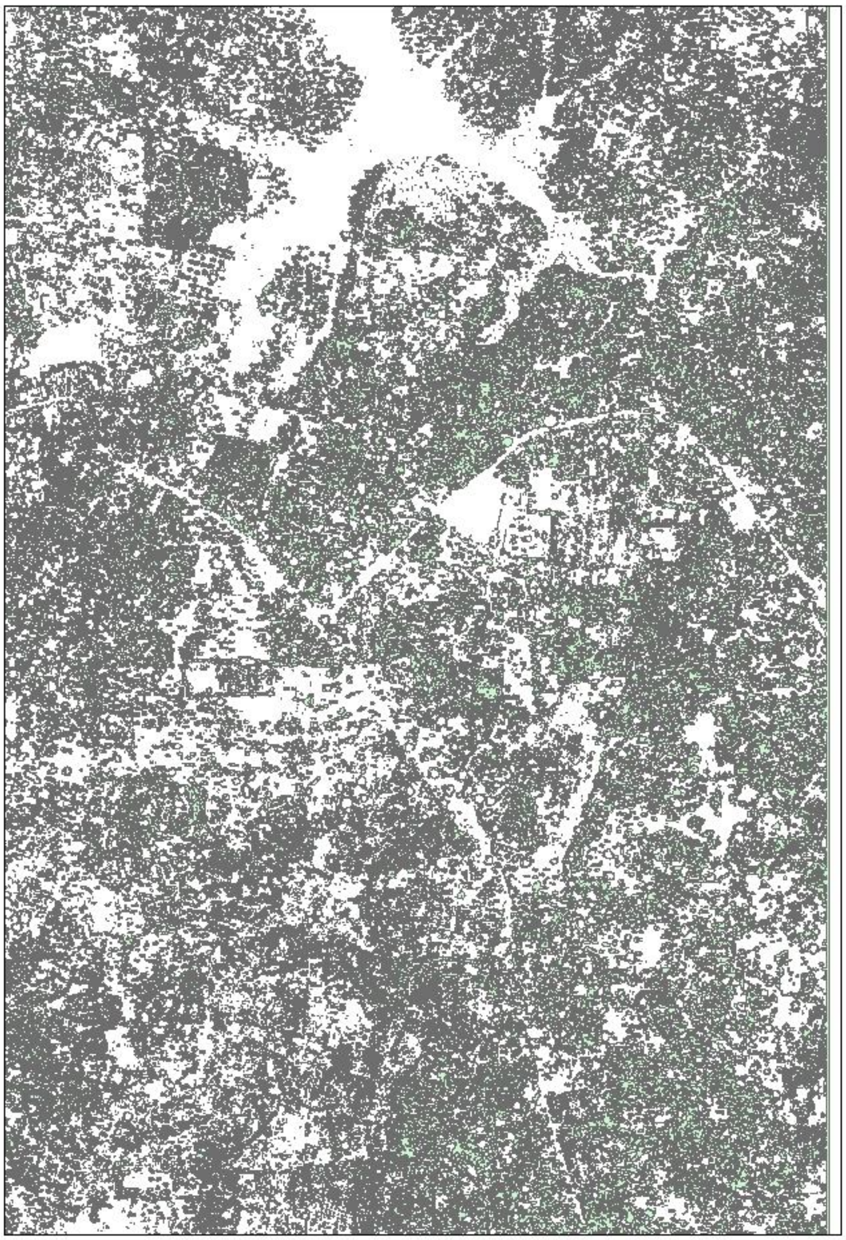

Figure 14: Extraction of coconuts feature.

4.5 Result of area calculation.

The attribute table of the resulting polygon is opened and a field is added to enable area calculation for each and every polygon. Figure 15 shows the area calculated for each polygon in hectares.

coconut_poly_utm

FID	Shape	ID	GRIDCODE	Area_Ha
0	Polygon	1	31	0.000006
1	Polygon	5	31	0.000006
2	Polygon	28	31	0.000012
3	Polygon	29	31	0.000018
4	Polygon	30	31	0.000006
5	Polygon	31	31	0.000006
6	Polygon	32	31	0.000006
7	Polygon	33	31	0.000006
8	Polygon	34	31	0.000012
9	Polygon	35	31	0.000018
10	Polygon	36	31	0.000018
11	Polygon	37	31	0.000006
12	Polygon	38	31	0.000012
13	Polygon	39	31	0.000012
14	Polygon	40	31	0.000012
15	Polygon	41	31	0.000006
16	Polygon	42	31	0.000018
17	Polygon	43	31	0.000012
18	Polygon	44	31	0.000006
19	Polygon	45	31	0.000006
20	Polygon	46	31	0.000012
21	Polygon	47	31	0.000028
22	Polygon	48	31	0.000028
23	Polygon	49	31	0.000022
24	Polygon	50	31	0.000065
25	Polygon	51	31	0.000006
26	Polygon	52	31	0.00002
27	Polygon	53	31	0.000031
28	Polygon	54	31	0.000058
29	Polygon	55	31	0.000024

Figure 15: Attribute table of polygons

A Statistics of the coconut features is run as shown in Figure 16 which gives the total area of coconut coverage.

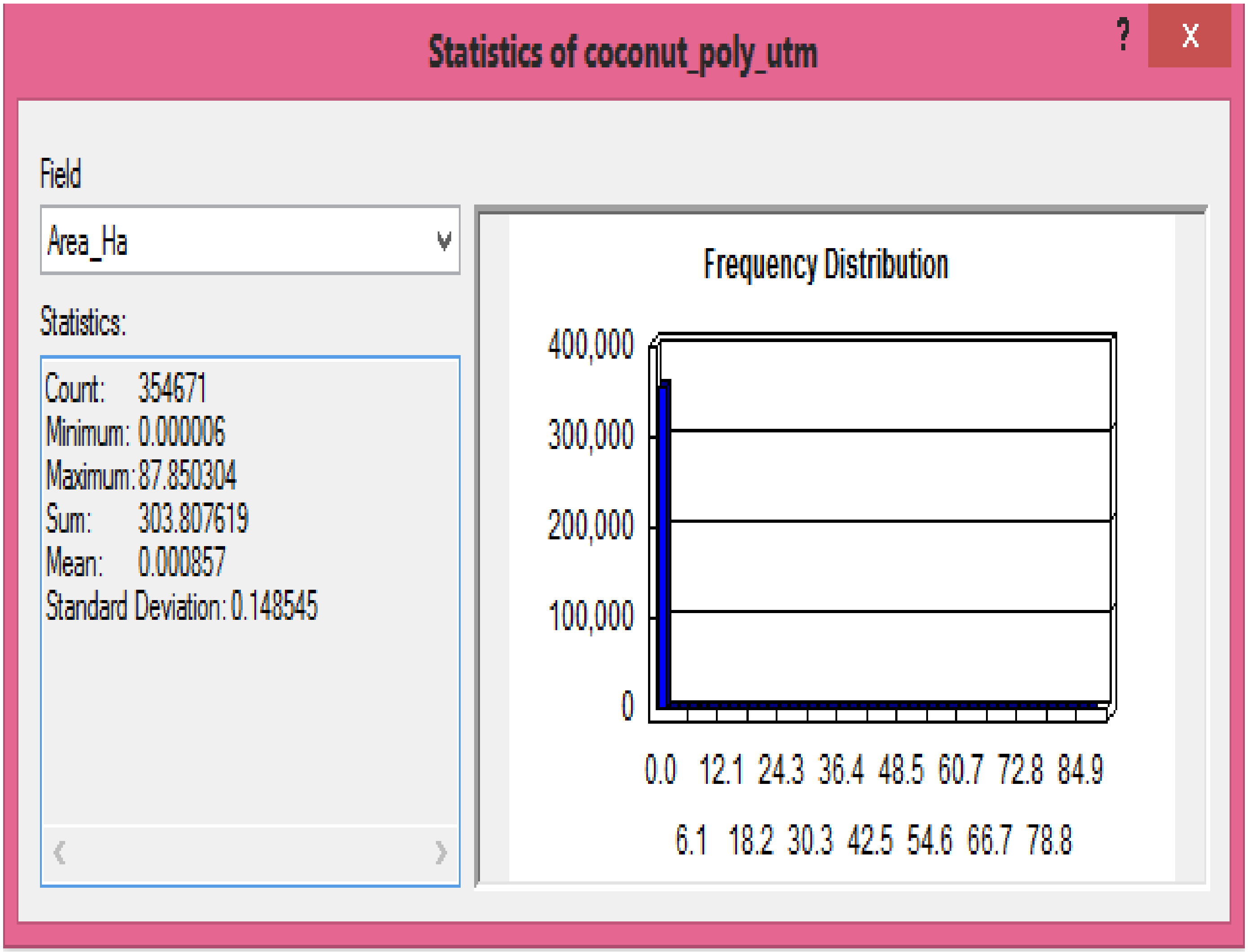

Figure 16: Statistic of coconut in hectares

The total area under coconut cultivation is approximately 303.82 hectares which is 27.5% of the area of study.

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

- In this study the integration of remote sensing and GIS has proven to be powerful tools for land use/cover evaluation based on the available natural resources. The contribution of these technologies is indispensable, especially when dealing with spatial information over a large geographic area.
- Remote sensing technology can play a role in providing accurate and reliable landscape details with lower cost and lesser time compared to the other methods.
- There is a gap in terms of reliable information with regards to the distribution of the coconut cultivation in the country.
- The high resolution image analysis demonstrated how GIS and remote sensing can be used to provide a spatial depiction of coconut distribution and coconut estimation in the area of study.
- The resultant land use land cover map represent spatial distribution of the coconut palm trees.

5.2. Recommendations

- The accuracy of the classification can be improved by increasing the number of ROIs during classifier training. The use and evaluation of other classification algorithms to detect the coconut trees may be a subject of future research.
- There is need of up-to-date information of major land use, acreage and distribution of the coconut crops. This will bring to light the magnitude of the coconut distribution in the Sub-County and the country.
- My hope is that different stakeholders will pick from here and draw the many possible conclusions and intervention areas necessary to move this important sub-sector forward. Stakeholders can provide funding to enable further research on coconut estimation in the country, this will assist in making informed decisions.
- Stakeholders can provide platforms to aid in information dissemination, through initiatives of regional organizations such as KCDA. The use of GIS and remote sensing technology and expertise can be useful.

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