University of Nairobi

School of Engineering

USE OF REMOTE SENSING IN ANALYSIS OF EFFECTS OF URBAN SPRAWL ON AGRICULTURAL LAND.

CASE STUDY: KIAMBAA SUB-COUNTY

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Declaration

I, Mungai, Teresiah Wakonyo 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 is submitted for examination with my approval as university supervisor.

DR. DAVID NYIKA

………………………………………… ………………………………….

Name of supervisor Date

Dedication

This project is dedicated to my sons: Christopher, Kevin and Brian who were very supportive and understanding during my time of study.

Acknowledgement

My sincere thanks go to my dedicated supervisor Dr David Nyika for his commitment and guidance in all stages of this project. His patience and efforts during our discussions were remarkable. May God bless you.

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ACRONYMS

ETM+ -	Enhanced Thematic Mapper plus
GIS -	Geographical Information Systems
GPS -	Global Positioning Systems
KeNHA	-Kenya National Highways Authority
MSS -	Multispectral Scanner
NDBI -	Normalised Difference of Built up Index
NDVI -	Normalized Difference Vegetation Index
NDWI -	Normalised Difference Water Index
OLI-TIRS -	Operational Land Imager- Thermal Infrared Sensors
RCMRD	-Regional Centre for Mapping Resource For Development
RS -	Remote Sensing
SOK -	Survey of Kenya
TM -	Thematic Mapper
USGS -	United States Geological Surveys
WGS -	World Reference System

ABSTRACT

Urban Sprawl is the spreading out of a city and its suburbs over more and more rural land at the periphery of an urban area. This involves the conversion of rural land into built up, developed land over time. Sprawl is characterised by one or more existing patterns of development. Those most frequently mentioned are low-density, leapfrogging, distance to central facilities, dispersion of employment and residential development, and continuous strip development. Urban sprawl on agricultural lands has become a global phenomenon plaguing the entire world especially the developing countries due to increasing population at high rates and consequent depletion of resources.

Remote Sensing techniques are being used in this study to show how the technology can be utilized to solve this problem. Landsat TM (1988), ETM+ (2000) and OLI TIRS (2016) images were used to analyse the effects of urban sprawl on Agricultural land in Kiambaa sub-county. The study is limited to the change in spatial extent of urban areas and agricultural land in general. Supervised classification with maximum likelihood classifier was used to delineate land cover/use in Kiambaa Sub County. Post classification analysis was used for change detection.

The results show the agriculture land in Kiambaa Sub County had reduced with 11.4% from 1988 to 2000 and 14.1% from 2000 to 2016. The urban areas were found to have increased by more than 18 times in 2016 in the spatial extent more than in 1988.From the maps the urban sprawl was characterised by low density, leapfrogging and continuous strip developments. The direction of the sprawl was to the northern part of the sub county where most large and plantation farms are. The sprawl is also likely to flow to the neighbouring sub counties along the roads. The rate of change of agricultural land to urban reduced from 77 hectares per year between 1988-2000 to 72 hectares between 2000-2016.Although the sprawl was not at a high rate as expected, measures need to be taken early to avoid the issue getting out of control. Remote Sensing techniques proved to be an efficient and effective means of mapping and management of urban change.

For sustainability of agricultural activities measures need be taken on management and conservation of the existing land. The government should incorporate use of remote sensing and GIS in its entire sectors to enhance data sharing. County governments should also consider using Remote Sensing and GIS technologies to monitor Land cover/ use changes.

CHAPTER 1

INTRODUCTION

1.0 Background

History of urbanisation dates back from ancient times of origin of cities where people witnessed evolution. The evolution originated from ancestral form to small port/ rail based towns and to cities with skyscrapers. At the end of 20th century urban growth was rapidly pushing cities further out to form the current stretched form of cities with low density at peripheral (Bekele, 2005).

Although many factors may have helped to explain urban sprawl and its causes, the ultimate has always been population and land use issue. The increasing population make demand on urban functions and services including housing, factories commerce and other social amenities which have in turn put great pressure on cities to make land available for spatial growth. (Melessee et al 2014).

Africa's urbanisation soared from 15% in 1960 to 40% in 2010, and is projected to reach 60% in 2050 according to a report by UN Habitat, (2010). The Kenyan population has also increased over the years from 10.9 million persons in 1969 to 38.9 million persons in 2009, 32.3 % of it comprising of urban population which is estimated to be at 61.5% by 2030. (Kenya National Bureau of Statistics, 2009).

Kiambu County had a population of 1,623,282 people in 2009 census and its projected to be 2,032,464 people by the end of 2017 (Kiambu County, 2013-2017). The population growth has been influenced by the influx of people working in the city who prefer to stay in Kiambu and its environs where there is less congestion. Urban sprawl is listed as one of the key planning issue that Kiambu County is currently facing (Kiambu County, 2013).

There are many definitions of sprawl, however a central component of most definitions has been summarised as follows: "Sprawl is the spreading out of a city and its suburbs over more and more rural land at the periphery of an urban area. This involves the conversion of open space (rural land) into built up, developed land over time" (Jain, 2009) and (Hartman, 2006). Sprawl is characterised by one or more existing patterns of development. Those most frequently mentioned are low-density, leapfrogging, distance to central facilities, dispersion of employment and residential development, and continuous strip development.

Urban sprawl on agricultural lands has become a global phenomenon plaguing the entire world especially the developing countries due to increasing population at high rates and consequent depletion of resources (Tarawneh, 2014). Once agricultural land is paved and built for urban use, it is lost in favour of non-agricultural and other uses, it is expensive to reverse category (Rosenberger,et al,2002).

There are various factors that cause urban sprawl and some can be identified as:

- Lower land prices compared to urban areas of the main city.
- Availability of unbuilt agricultural land.
- High rate of urbanisation and rapid development activities.
- Less control on urban development being located outside urban limit.
- Influence of speculators on the agricultural land owners for developing land to developers.
- Results of failure to match demand of urban infrastructure and services.
- Physical terrain, where unsuitable terrain restricts sprawl resulting to leap frog development.
- Transportation routes open the access of the city to country side. It is responsible for linear branch development.

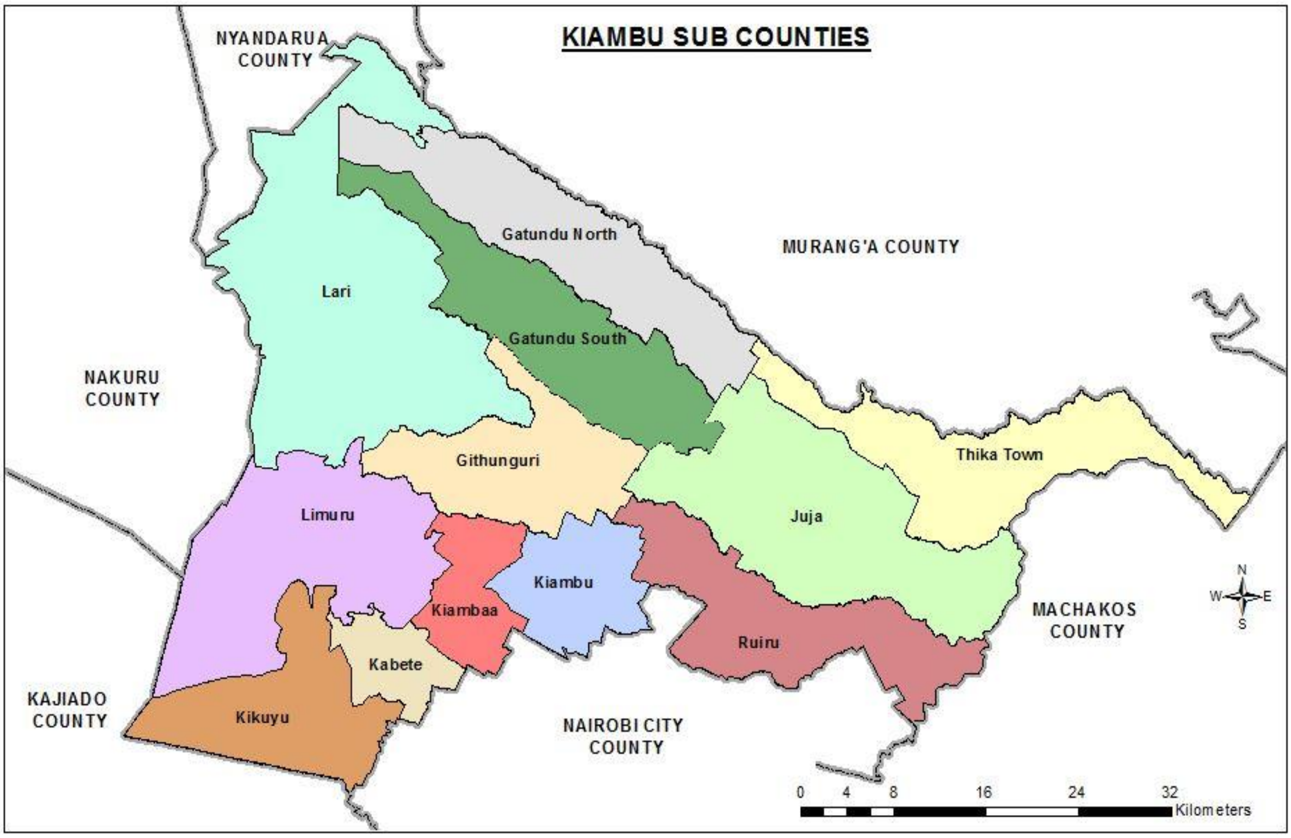
These lead to encroachment of built up areas on agricultural land rendering agricultural worker jobless or displaced to move to other areas for different occupation. Large areas become characterised by the initial scattered land uses such that balanced planning of the areas becomes impossible. Urban sprawl often takes place in either a radial direction around an established city or linearly along the highways over a given period of time.

'Agriculture land' means all land which is used for the purpose of agriculture, not being land which, under any law relating to town and country planning, is proposed for use for purposes other than agriculture. (Agriculture Act, 2012)

Agriculture is the predominant activity in the Kiambu County involving over 80% of the population. It is therefore a leading sector in terms of employment, food security, income generation and overall contribution to the social-economic well-being of Kiambu population (Kiambu(a), 2013).

Kiambu County being on the outskirts of Nairobi City has been suffering from urban sprawl. Urbanisation is over spilling onto the County's agricultural Land. Land is the most important resource in agricultural production but the limited availability of productive land is a major constraint to increased agricultural production. The average holding size of land in Kiambu County is approximately 0.36 Ha. on small scale and 69.5 Ha. on large scale (Kiambu(a), 2013). Increased population has laid pressure on the county and has led to sub-division of land to small uneconomical units.

Figure 1.1: Kiambu Sub-Counties



Source: Survey of Kenya (2015)

Fig. 1.1 above shows Kiambu's 12 Sub-counties where small land holdings are mostly found in upper parts of Gatundu North, Gatundu South, Kiambaa, Limuru and Kikuyu sub-counties. The large land holdings are found in the lower parts of the county in Juja sub-county and upper highlands in Limuru and Lari Sub-county (Kiambu County, 2013).

The county is covered by three broad categories of soil which are: high level uplands soils, plateau soils and volcanic footbridges soil. These soils are of varying fertility level with soils from high-level uplands of volcanic rock origin being very fertile. These types of soils are found in the highlands, mostly in Gatundu North, Gatundu South, Githunguri, Kiambu, Kiambaa, Lari, Kikuyu, Kabete and Limuru sub-counties. Kiambu's Agriculture is mainly rain-fed and is entirely dependent on the bimodal rainfall. In humid, high altitude areas productivity as well as predictability of good crop is high (Kiambu County, 2013). However the population density in these areas has increased and land has been subdivided into small sizes that are becoming uneconomical for farm enterprises.

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation. This is done by sensing and recording reflected or emitted energy and processing, analysing, and applying that information. (Lillesand, 2004). Different objects have different reflectance hence the final image will have different digital values depending on the amount of light that has been reflected. These digital values together with other visual characteristics in an image assist in interpretation of the image.

Remote Sensing offers multiple advantages of wider coverage, long time series of data acquisition which facilitates monitoring and relatively low cost per square kilometre compared to other means of acquiring data (Hastings, 2002). Direct observation and/or interviews with the users in the field represent the most accurate means of collecting detailed information on land cover/use. However, this approach is costly especially when the region of interest is large (Hastings, 2002). Landsat Remote sensing images will be used in this project to monitor how urban developments have been affecting agricultural land in Kiambaa sub-county.

1.1 Problem Statement

As the country's population increases it calls for more food production in order to feed the increasing number of people. Unfortunately land is not increasing so we need to utilize the available land in a sustainable manner.

In Kiambaa sub-county, encroachment of urban settlements on agricultural land is increasing at an alarming rate. This is due to its proximity to the City of Nairobi, tracts of land that were previously under coffee plantations and other crops are now characterised by residential estates posing a threat to agricultural production. Multi billions real estate projects are being built while uprooting coffee which once used to be the biggest economic crop.

Those with medium pieces of land are converting from agricultural to residential or commercial use and subdividing them into small portions taking advantage of the increased land prices. Majority of middle class Kenyans prefer to buy this land and build homes away from the noisy and polluted city into the outskirts. This has resulted to subdivision of Agricultural land into small size plots that are uneconomical for farming.

There is need to analyse the Urban Sprawl in Kiambaa sub-county and develop strategies on how mitigation measures can be carried out.

1.2 Objectives

General Objective

1. To analyse the effects of urban sprawl on agricultural land in Kiambaa sub-county.

Specific Objectives

1. To use Satellite Remote Sensing Technology to delineate Land cover/ use in Kiambaa Sub-county.
2. To map urban development in the sub county.
3. To determine size, rate and direction of the urban development in the sub-county.

1.3 Justification for the Study

This project will be useful to the policy makers in making decisions especially concerning, zoning in land use planning and protecting of agricultural land. It will also generate knowledge to the general public in terms of investing and future trends in property markets.

1.4 Scope of Work

The project aims at using Landsat satellite imagery to analyse effects of urban sprawl on Agricultural land in Kiambaa sub-county. Landsat images, Geographic information system (GIS) and Global positioning System (GPS) will be used to acquire, process analyse and present data. Landsat images of three epochs taken in 1988, 2000 and 2016 will be used to analyse the trends of urban development. Most of the developments in the sub-county occurred from 1990s, hence there is need to study the area before and after the developments.

The project will be limited to the change in spatial extent of urban areas and agricultural land in general. This is especially because with 30m resolution Landsat imagery it may not be possible discriminate small land use activities.

1.5 Organization of the Study

The study is organized in five chapters, with chapter one being the introduction which contains the background, problem statement, objectives, justification for the study and scope and limitations of the study.

Chapter two contains the literature review where the study reviewed diverse projects that have been done before and are related to this project. Emphasis was made on recent advances in change detection, methodology used and results achieved in those projects.

Chapter three gives the methodology used to achieve the project's objective. This starts by identifying the study area, data collection, data preprocessing, image classification, accuracy assessment, change detection and GIS analysis.

Chapter four gives light on the results achieved from the methodology and brief analysis of the achieved results are discussed

Conclusions and recommendations of the project results are discussed in chapter five.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

Studies of Land Cover changes are fundamental for better understanding of interactions between human and the natural environment. Remote sensing technology has played a key role in the studies of land cover/ use changes. Availability of Multi-temporal satellite datasets provides the capability for mapping and monitoring of Land cover/use changes. Landsat have been exploited in several studies to evaluate built-up expansion and to assess urban morphology changes (Masek et al., 2000).

The physical expressions and patterns of sprawl on landscapes can be detected, mapped and analysed using remote sensing and geographical information system (GIS) technologies in conjunction with the secondary and ground truth data. Urban sprawl Mapping and monitoring is one of the operational applications of satellite remote sensing data. From the earliest Landsat-MSS-1973 which had 70metres resolution to the present high spatial resolution data have been proved efficient and more accurate in detecting the changes in urban sprawl.

An urban environment is constantly under transition with new constructions being put up now and then. The rate at which this change takes place can be overwhelming when they have to be monitored by field survey techniques. Remotely sensed data due to its frequency of acquisition can be exploited to alleviate this shortcoming (Karanja, 2002).

Remote Sensing data has become a major source for change detection studies because of its high temporal frequency, digital format suitable for computation, synoptic view and wider selection of spatial and spectral resolutions. (Chen. G., 2012)

Image interpretation algorithm methods may be grouped into statistical pattern recognition and image analysis techniques. Statistical pattern recognition which is mostly used consists of maximum likelihood, minimum distance classifiers among others.

The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. An assumption is made that the distribution of the cloud of points forming the category training data is normally distributed. The probability density functions are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. (Lillesand, 2004)

Minimum distance is done by first calculating the mean of the spectral value of each band for each category. A pixel of unknown identity is classified by computing the distance between the value of unknown pixel to each of the category means. The unknown pixel is assigned to the 'closest' class. Minimum distance to means strategy is mathematically simple and computationally efficient, but it has certain limitations. One of its limitations it that it is insensitive to different degrees of variance in the spectral response data. (Lillesand, 2004)

2.1 Change Detection Using Remote Sensing

Ideally a change detection procedure involves use multi-temporal datasets to discriminate areas of Land cover/use change between dates of Imaging (Lillesand, 2004). Urban sprawl development is a long time phenomena, hence requires a long time interval to realize the change.

Singh, (1989) defined change detection as "the process of identifying differences in the state of an object or phenomenon by observing it at different times".

Ochengo (2003), used post classification change detection method in a study on application of remote sensing in deforestation monitoring. False colour composites of bands 2, 3, 4 were used for two epochs. The results indicated 30% reduction in forest cover from year 1987 to 2000. Post classification change detection method requires accurate and complete training datasets. Its final accuracy depends mostly on classification accuracy of individual method (Ochego, 2003).

Atu et al.. (2012) used two multi-sensor, multi-spatial images. Landsat image 1980 and Spot XP 2005 were used to assess the influence of urban sprawl on farm sizes and densities in Calabar, Nigeria. The limitation of this approach is that different spatial and spectral resolution needs developing fusion strategies, but it allows one to take advantage of different sensors to detect different objects. In time series analysis it's helpful when one of the sensors may not be available. In the same study the researcher derived the rate of agricultural land loss and the urban sprawl from getting the difference of areas in the two epochs and later dividing the results by the number of years.

In a report by Shalaby (2012), a researcher in Egypt noted that urban sprawl is one of the dominant degradation processes in the Nile Delta. Nile delta is one of the oldest agricultural areas in the world that has been under continuous cultivation, encroachment of urban settlements on the agricultural lands is posing dire consequences. He concluded that considerable increase in urban settlements had taken place on the expense of the most fertile land in the area. These results are similar to another research by Saeed et al (2012) who reported that expansion and sprawl of Tehran and Karaj cities is in the expenses of fertile agricultural land.

Sometimes the conventional multispectral classification may not produce satisfactory accuracy, normally less than 80 percent, due to spectral confusion of the heterogeneous urban built-up land class. Therefore, many studies have not only used a single classification method to extract the urban built-up lands but also combined different methods to improve the extraction. Masek et al. (2000)

Zaha and others (Zaha et al., 2003) used Normalised Difference of Built-up Index in computer mapping urban regions from Landsat images that cover the city of Nanjing in eastern China, and the index has achieved accuracy in determining spatial regions of urban areas, reaching 92.6% accuracy.

The index is used in several studies of two cities in southeast China, including the Hanqui study (Hanqui, 2007) of mapping urban areas from Landsat images using the technology of the NDBI, the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Water Index (NDWI).

Alwan (2011), has highlighted the application of the NDBI in the study of changes in agricultural and urban areas in the Albramon village of the Dakahlia Governorate in Egypt. In this study, the author depended on the employment of the spectral index to detect and analyse the change in the area of agricultural land through the monitoring of rural building infringement on agricultural land.

Aziz (2012) has studied the growth of urban spread in the city of Fayoum, in which he used the NDBI with Landsat images (Landsat 5 & 7) from 1972 to 2009. A series of digital maps have been produced and modelled with Geographical Information Systems (GIS). These results have been made into the form of animated maps that show the urban growth of cities during the previous period. The NDBI has contributed to properly drawing the sprawl of the city.

The Change detection frameworks use multi-temporal datasets to qualitatively analyse the temporal effects of phenomena and quantify the changes. The general objectives of change detection in remote sensing include identifying the geographical location and type of changes, quantifying the changes, and assessing the accuracy of change detection results (Jensen, 2005). The change detection from remote sensing data is affected by various elements including spatial, spectral, thematic and temporal constraints, radiometric resolution, atmospheric conditions and soil moisture conditions (Jensen, 2005).

In this study, the focus is on change resulting from Urban Sprawl to agricultural land. Different change detection techniques have been developed in the past, depending on the requirements and conditions (Lu et al., 2004). They fall into two main categories namely change enhancement and nature of change detection (Karanja, 2002).

2.1.1 Change Enhancement Techniques

These techniques involve direct combination of the raw data sets at pixel level of two images taken at two different epochs. The algorithms include image differencing, rationing, vector analysis and principal component analysis. However they are hampered by the inability to comprehensively address variations in atmospheric and ground conditions, differences in illumination effects and sensor calibration at the two epochs in question (Karanja, 2002).

More complex change detection at pixel level is the direct multi-date change classification. The data source could originate from the same sensor or different sensors. The temporal data set is classified as a single set i.e. when six Landsat TM channels are in use for each epoch, the complete set will consist of twelve channels. The assumption is that like phenomena i.e. where no change has taken place will have statistically similar properties as opposed to those where change has taken place (Serpico and Bruzzone, 1999). The advantage of this method is that the classification is done in one step; however it has proved to be a very complex procedure particularly in situations where the data is from different sensor sources. It introduces information redundancy and also labelling of the cluster is a difficult endeavour (Karanja, 2002).

2.1.2 Nature of Change Detection Techniques

Some applications require more information to the type of changes. This involves comparing extracted land use classes at the two epochs i.e. post classification comparisons. The advantage of such change detection techniques is that they avoid the problems encountered at pixel level through independent classification of images taken at the two different epochs. Thus the comparison is at a higher level of abstraction whereby the pixels contain not only the digital number but an additional attribute of the land use class assigned through interpretation (Karanja, 2002).

Regardless of the technique used, the success of change detection from imagery will depend on both the nature of change involved and the success of the image pre-processing and the classification procedures. If the nature of the change within a particular scene is either abrupt or at a scale appropriate to the imagery collected then the change should be relatively easy to detect. Problems occur only if spatial change is subtly distributed and hence not obvious within any image pixel (Milne, 1988).

CHAPTER 3
METHODOLOGY

3.0 Study Area

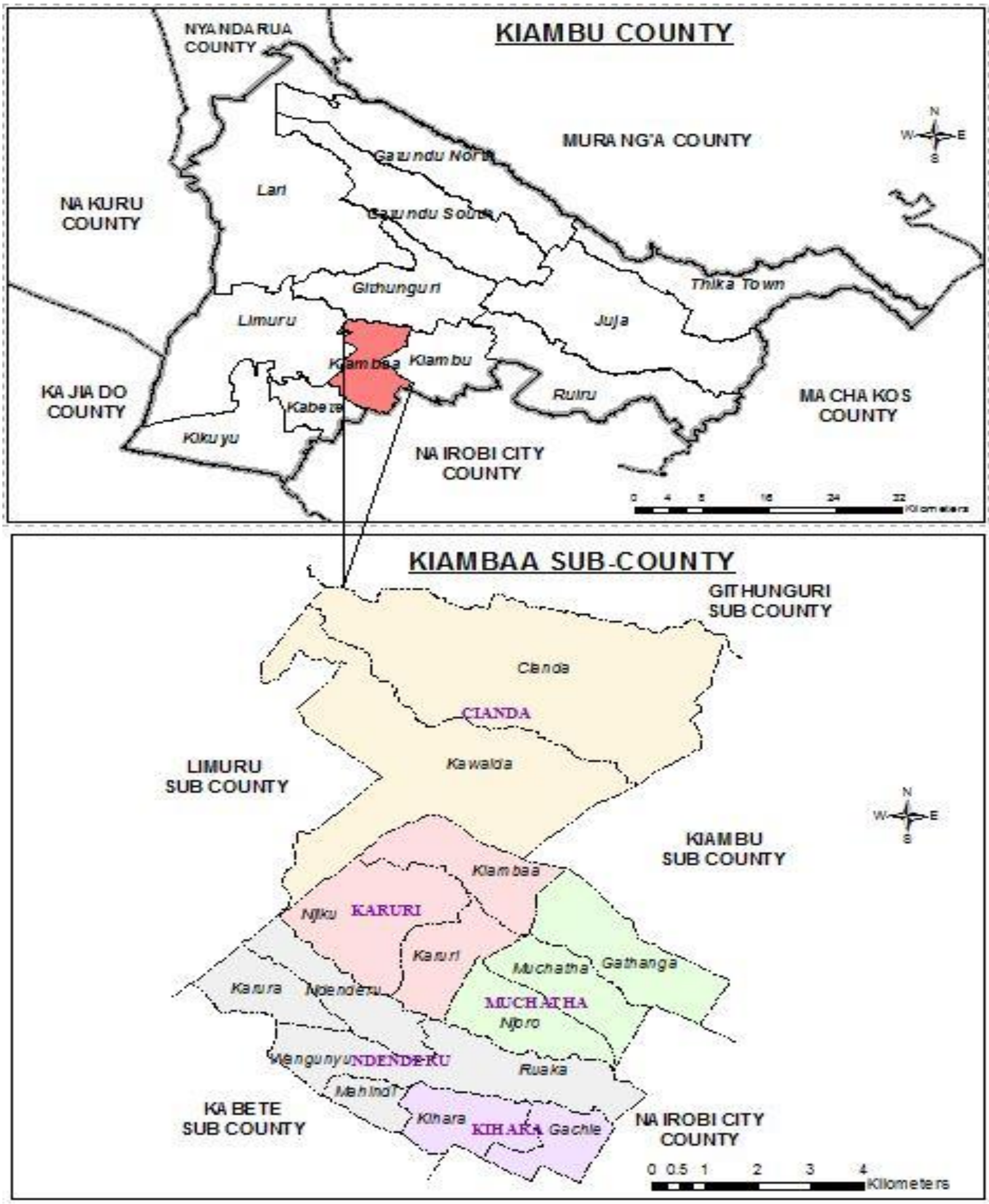
Fig. 3.1 below shows the location area of the Kiambaa sub-county which is within Kiambu county, central Kenya region. The sub-county covers an area of approximately 83 km². It neighbours Githunguri sub-county to the North, Kiambu sub-county to the East, Limuru sub-county to the west, Kabete sub-county to south west and Nairobi City County to the south east. The sub-county lies between latitudes 1º06'30" and 1º13'35"south of the Equator and longitude 36º42'45" and 36º42'45" East.

Five administrative wards make up the study area namely; Cianda, Kihara, Muchatha, Karuri and Ndenderu wards. Kiambaa sub-county had a population of 145,053 persons according to 2009 census. Kiambaa sub-county consists of 20 sub locations.

Kiambaa Sub County is the second highest in population density among the other sub counties in Kiambu County. Kabete Sub County had the highest population density which was 2329 persons/km² according to 2009 census. Kiambaa was the second with a population density of 1979 persons/km². The least densely populated sub county was Lari with 307 persons/km², this is mainly due to the fact that that a considerable part of the sub county is covered by forests.

The study area was chosen due to the currently mushrooming estates in the area. The Sub County is found in the environs of the Nairobi City. This area together with other sub counties neighboring Nairobi City County are more likely to suffer from urban sprawl.

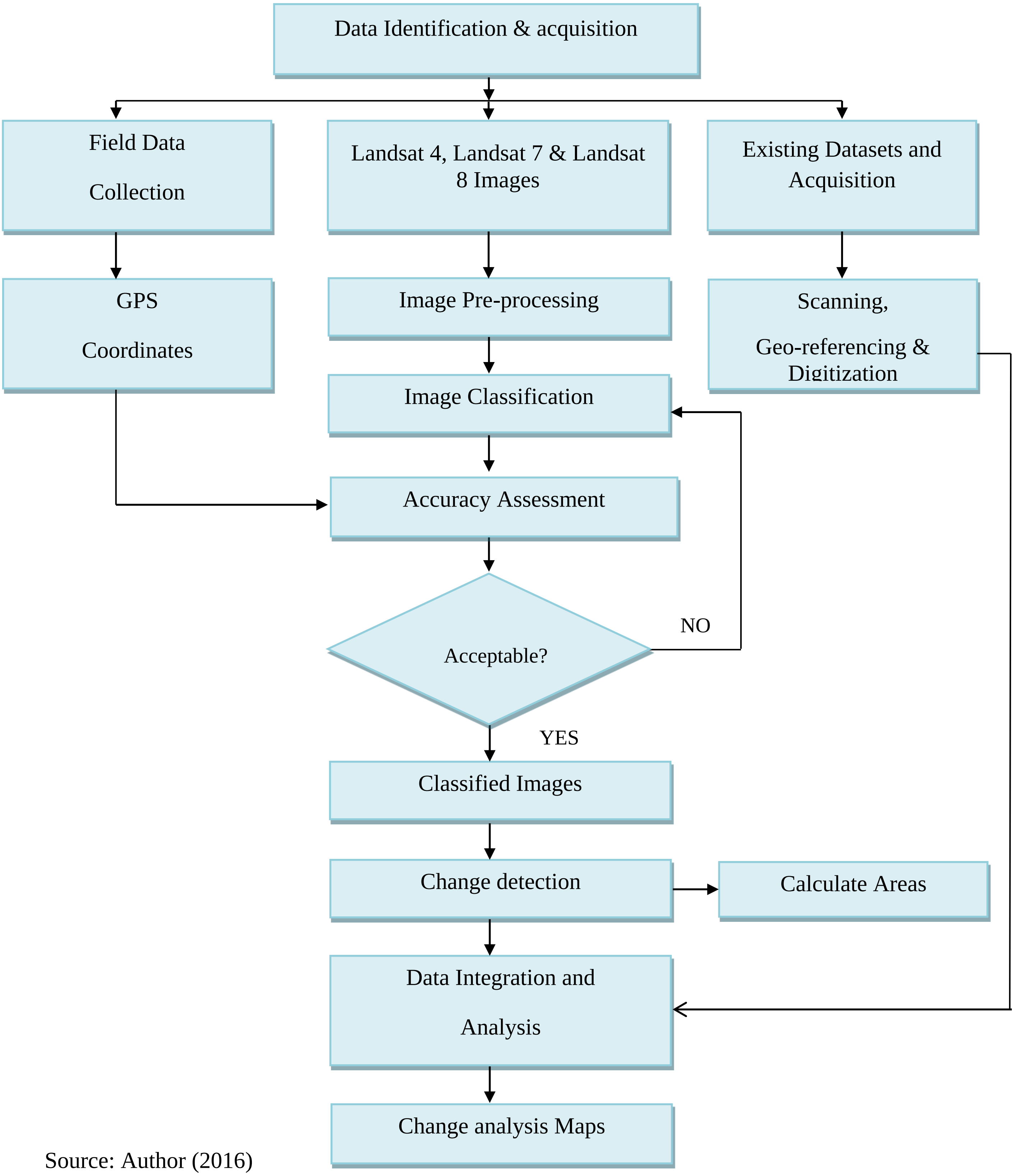
Figure 3.1: Location Map



Source: Survey of Kenya (2015)

3.1 Flow Diagram of Methodology

Figure 3.2 Flow Diagram



Source: Author (2016)

3.2 Data Collection

Landsat imageries were in bands in zipped files which were obtained from Regional Centre for Mapping of Resources for Development (RCMRD). Images of three epochs were obtained i.e. 1988, 2000, and 2016, the selection was done ensuring that the imageries were free of clouds. Also sufficient gap was observed so as to appreciate the sprawl.

Table 3.1. List of Satellite images collected for the study area.

Satellite Data	No. of Bands	Date Acquired	Spatial Resolution
Landsat 4 TM (Path 168 Row 061)	7 bands	17-10-1988	30M
Landsat 7 ETM+ (Path 168 Row 061)	8 bands	21-02-2000	30M 15M- Panchromatic
Landsat 8 OLI-TIRS (Path 168 Row 061)	11 bands	25-02-2016	30M 15M- Panchromatic

Source: Author (2016)

All the three satellite images above had a map projection of UTM WGS84 zone 37N. The bands to be used for the project had a resolution of 30 M Pixels. Band 6 of Landsat 4 TM was acquired at 120M resolution but products resampled to 30M pixels. In Landsat 7 ETM+, band 6 was acquired at 60M resolution and resampled to 30M pixels. For Landsat 8 OLI-TIRS, TIRS bands are acquired at 100M resolution but resampled to 30M in delivered data product. Landsat 7 ETM and Landsat 8 OLI-TIRS have a band 8 which is panchromatic and has a resolution of 15 M, it is used to sharpen the image definition.

Field data consisting of Eastings and Northings coordinates, heights, land use and description of the area were collected using a handheld GPS on March 2016. The data will be used as reference data during validation or accuracy assessment.

Table 3.2. Sample of GPS data collected.

Eastings	Northings	Altitude	Description	Comments
248829	9868401	1847 m	Built up area	Ndenderu
248496	9868516	1860 m	Built up area	
247905	9868981	1871 m	Built up area	
247415	9869368	1881 m	Built up area	Kianjogu
246578	9869910	1907 m	Built up area	
245988	9870385	1913 m	Green houses	
246377	9870590	1908 m	Agricultural	Tumaini SCh
247856	9869261	1858 m	Agricultural	mixed crops
247657	9869653	1877 m	Agricultural	mixed crops
247141	9870086	1900 m	Agricultural	mixed crops
246977	9870294	1905 m	Agricultural	mixed crops
249525	9869067	1862 m	Agricultural	mixed crops
249340	9869671	1898 m	Built up area	
249813	9870246	1936 m	Built up area	
250157	9870318	1908 m	Built up area	
250426	9870648	1904 m	Built up area	Banana Town
249932	9871193	1946 m	Built up area	
249565	9871405	1947 m	Forest	
248878	9871979	1983 m	Built up area	Raini
248881	9872111	1984 m	Built up area	
249746	9872637	1977 m	Agricultural	Nduota(Nazareth Junction)
249675	9872928	1991 m	Bareland	Kibubuti Farm
249531	9873220	1993 m	Agricultural	Flower Farms
250481	9874151	1953 m	Built up area	Kawaida Pri
251625	9874309	1897 m	Agricultural	Kibubuti Tea Farm
251681	9874500	1891 m	Agricultural	Cemetry
249583	9874254	1937 m	Water Body	Dam
249630	9875014	1929 m	River	Bridge
249999	9875103	1946 m	Agricultural	Coffee plantation
250169	9875332	1946 m	Agricultural	Coffee plantation
250269	9875480	1940 m	Agricultural	Dam
250559	9875317	1910 m	Agricultural	Fish ponds
251113	9875258	1925 m	Agricultural	Tea Plantation
250521	9875635	1934 m	Agricultural	Tea Plantation
249863	9876389	1974 m	Agricultural	Tea Plantation
249197	9876649	1991 m	Agricultural	Tea Plantation
248764	9876979	2001 m	Agricultural	Tea Plantation
248487	9877075	2005 m	Built up area	Ngorongo Tea Factory
251273	9875173	1928 m	Agricultural	plantation
253039	9866873	1767 m	Built up area	Ruaka

Source: Author (2016)

The above GPS data were acquired using UTM WGS 84 projection Zone 37 S.

Other data collected included roads data which contained attributes like class of the road, condition of the road, number of lanes, surface type and length of the road from Kenya National Highways Authority (KeNHA). Boundary data where there was constituency boundaries for Kenya, administrative wards boundary and sub location boundaries. Town centres data had the names and status of the towns. The boundary and towns data were collected from Survey of Kenya. These data are important since they provide general orientation of the study area and also enable verification of the interpreted details by supplementing it with information that cannot be obtained directly from the satellite imagery.

3.3 Image Pre-Processing

The first procedure was to layer stack the bands, which is a process of merging two or more registered bands together in order to enhance details contained across multiple exposures of the same scene. Since Landsat satellite images are acquired through bands with each sensor containing several bands, these bands need to be merged to form a scene image. Layer stacking brings all bands together for multi-layer or band operations. The layers to be layer stacked were done with consideration that there has been evolutions in Landsat 8 that were not there in Landsat 7 as shown in the table below.

Table 3.3.Comparison of Landsat-7 ETM and Landsat-8 OLI-TIRS.

Landsat-7 ETM+ Bands (μm)			Landsat-8 OLI and *TIRS* Bands (μm)		
			30 m Coastal/Aerosol	0.435 - 0.451	Band 1
Band 1	30 m Blue	0.441 - 0.514	30 m Blue	0.452 - 0.512	Band 2
Band 2	30 m Green	0.519 - 0.601	30 m Green	0.533 - 0.590	Band 3
Band 3	30 m Red	0.631 - 0.692	30 m Red	0.636 - 0.673	Band 4
Band 4	30 m NIR	0.772 - 0.898	30 m NIR	0.851 - 0.879	Band 5
Band 5	30 m SWIR-1	1.547 - 1.749	30 m SWIR-1	1.566 - 1.651	Band 6
Band 6	60 m TIR	10.31 - 12.36	*100 m TIR-1*	*10.60 – 11.19*	Band 10
			100 m TIR-2	*11.50 – 12.51*	Band 11
Band 7	30 m SWIR-2	2.064 - 2.345	30 m SWIR-2	2.107 - 2.294	Band 7
Band 8	15 m Pan	0.515 - 0.896	15 m Pan	0.503 - 0.676	Band 8
			30 m Cirrus	1.363 - 1.384	Band 9

Source: (Irons, 2016)

The above table shows comparison between Landsat 7 ETM+ bands and Landsat 8 OLI-TIRS. It helps to decide which bands to layer stack and in which order. This is especially necessary when doing a comparison or change detection between images with differing bands. The OLI collects data for two new bands, a coastal band (band 1) and a cirrus band (band 9). TIRS collects data for two more narrow spectral bands in the thermal region formerly covered by one wide spectral band on Landsats 4 and Landsat 7.

Layer stacking was done for six bands as shown in the table below.

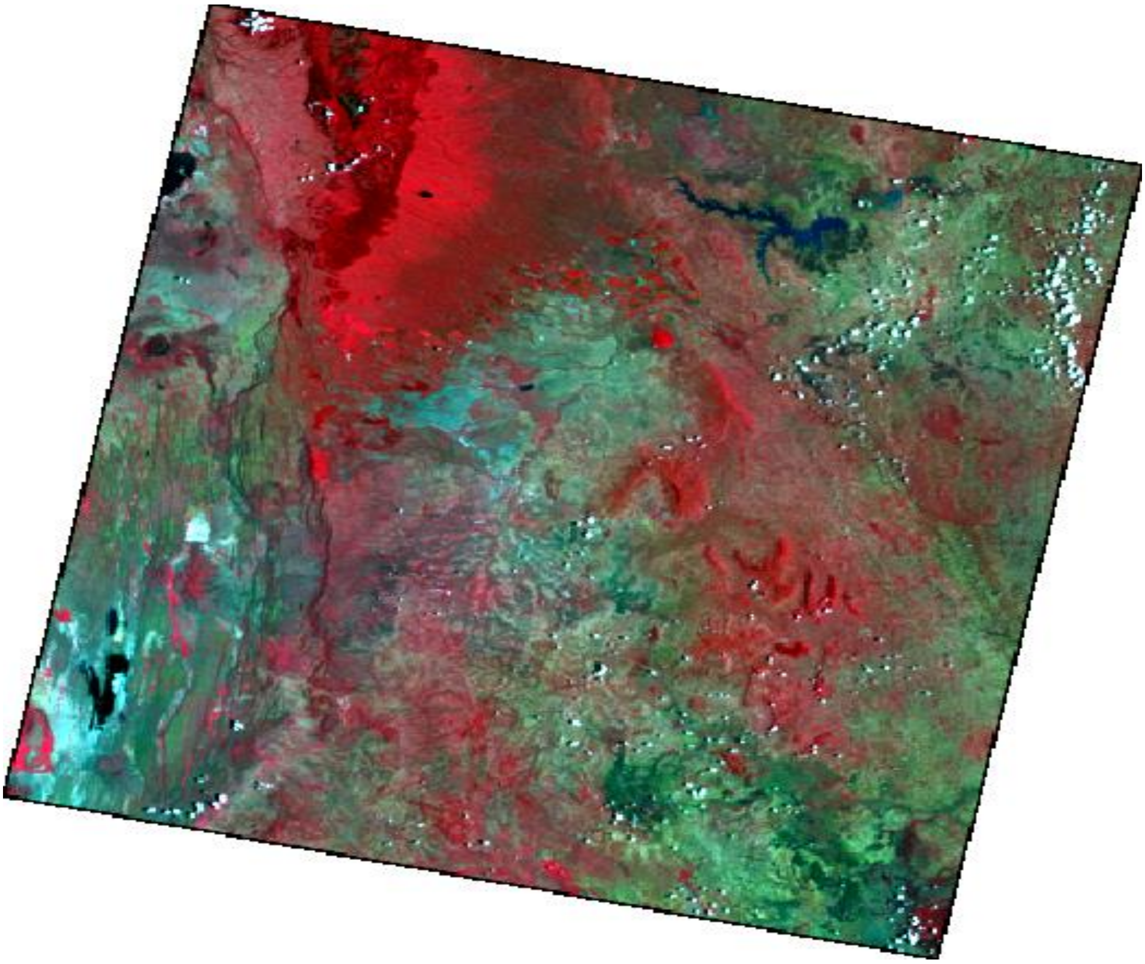
Table 3.4.Bands layer stacked for each scene.

Sensor	**Bands Merged**
Landsat 4 TM	Bands 1,2,3,4,5 and 7
Landsat 7 ETM+	Bands 1,2,3,4,5 and 7
Landsat 8 OLI-TIRS	Bands 2,3,4,5,6 and 7

Source: Author (2016)

Band 1 in Landsat 8 was not used since it’s a coastal band which is not necessary for the project; thermal bands were also not used. The output of layer stacking is a composite image as shown below.

Figure 3.3. False Colour composite image for year 2016.

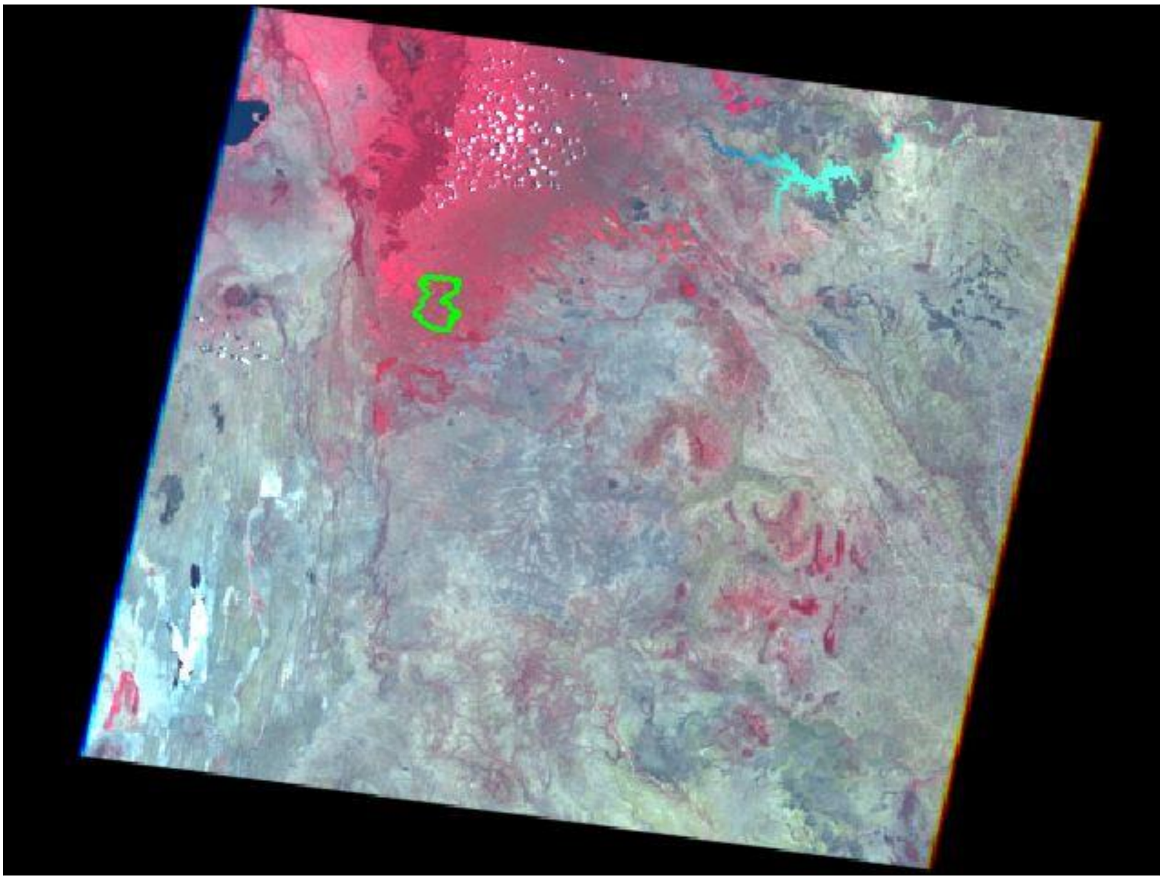


Source: Author (2016)

The above figure shows layer stacked bands producing a composite for 2016, false colors composite 4, 3, 2 are used to enhance feature interpretation. True colour composites were also used to enhance interpretation of the different scenes. The process was done for all the other scenes i.e. 1988 and 2000.

A subset is a section of a larger image, since satellite data downloads usually covers more area than is needed; it is possible to select a portion from the larger image. The project area of interest was clipped using the Kiambaa sub-county boundary shape file. Subset removes data outside the area of interest reducing the file size and improving the processing time for many operations.

Figure 3.4. False Colour composite image showing study area.



Source: Author (2016)

The above figure shows the boundary of the study area shown in light green. The study area is small compared to the entire scene. The processing time will be greatly reduced when we concentrate on just the area of interest which is Kiambaa sub-county.

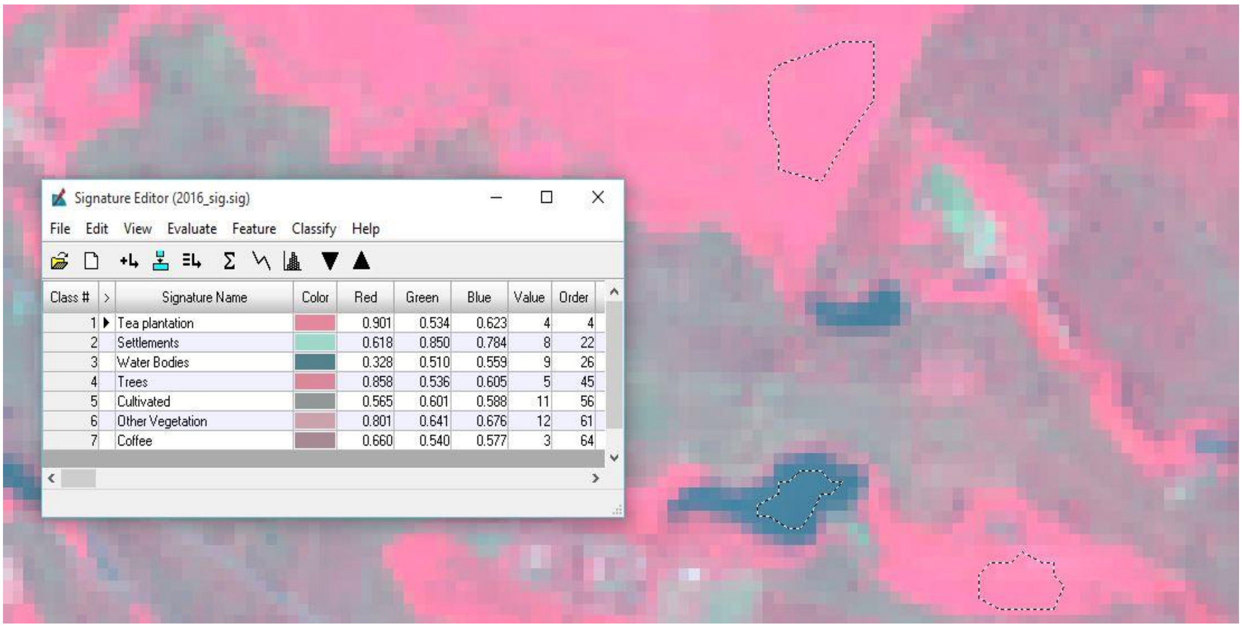
Image registration is an important step to avoid spurious results as image displacement will cause false change areas in the scene.

3.4 Image Classification

Image classification is defined as the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes (Lillesand, Keifer 1994). The overall objective of image classification is to automatically categorize all pixels in an image into a finite number of individual classes. Supervised classification will be used in this project where the operator determines the areas where a particular type of land cover is present and then the computer computes the spectral signatures.

The first and most important step in a supervised classification is the selection of training samples. The areas with known land cover are digitized, then the image processing software computes the spectral signatures of the land cover types. The training areas are established by viewing portions of full scene in an enlarged format on an interactive colour display device. Training sites were developed for the seven land use/ land cover classes based on goggle earth and familiarity with the study area. The classes include Coffee plantations, Tea Plantation, Forest, Cultivated Land, Other vegetation, Settlements and Water bodies.

Figure 3.5. Training Areas.



Source: Author (2016)

The above figure shows some of the training areas polygons delineated on a computer monitor. The signature editor shows the information classes given to the various training areas chosen. The information classes for the year 2016 scene were chosen based on the google image, the 1988 and 2000 scenes information classes were based on familiarity and knowledge of the land cover/ land use that existed then.

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The method is used in this project because it has some advantages in that: The classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. This is done by assuming that the distribution of the cloud of points forming the category training data is normally distributed. The probability density functions are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each class.

3.5 Classification Accuracy Assessment

Accuracy assessment is an important step in the process of analyzing remote sensing data. It determines the value of the resulting data to a particular user. Users with a variety of applications should be able to evaluate whether the accuracy of the map suits their objectives or not. There are different ways of accuracy assessment; confusion matrix or error matrix is the most common means of expressing classification accuracy. It compares, on a category-by-category basis, the relationship between known reference data and the corresponding results of an automated classification.

Ground truthing points were collected using a handheld GPS which were used to assess the accuracy of classified image for the year 2016. These points were later used to assess the accuracy of the classified images.

Instead of using the actual category names, codes were used at this stage. Recoding was done as shown in the table below.

Table 3.5.Recoding of Land use Cover classes

No.	Land use/ Land cover class	Code
1.	Coffee Plantations	1
2.	Tea Plantations	2
3.	Cultivated Land	3
4.	Forest	4
5.	Settlement	5
6.	Water Bodies	6
7.	Other Vegetation	7

Source: Author (2016)

Each Land use was given a code which will assist in its identification during and after accuracy assessment. The same codes were also given to the points to be used as reference data during accuracy assessment. The reference data which was in excel format was saved as text file and later imported in Erdas imagine.

3.6 Urban Sprawl on Agricultural Land Analysis

Change detection involves the use of multi-temporal datasets to discriminate areas of Land cover/use change between dates of Imaging. In this project post classification change detection method was used to analyse change in agricultural land to urban areas.

Reclassification of data entailed aggregating the different classes of land cover/use into those classes that represent urban or built up area and Agriculture land. At the end of the study, analysis of effects of urban sprawl on the agricultural land during the duration of study will be given.

Since the main interest of the project was to analyse effects of urban development on agricultural areas, the information classes were merged to have three main classes. The three classes were identified as:

1. Agriculture- This includes tea plantation, coffee plantation, other vegetation, forest and cultivated areas. Other vegetation consisted of maize, beans and all other crops and vegetation planted in small scale. Forests were also included in agriculture since they largely influence the food production in terms of rainfall and also due to the fact that in some areas it was not easy to delineate them.
2. Urban- This included all the built up areas and the roads.
3. Water bodies – Natural and man-made dams and rivers were classified in this class.

Recoding was for the three classes. Agriculture was given code 1, Settlement code 2 and Water bodies' code 3. Change detection has to be carried out between different times, in this project change was analysed between 1988 to 2000 and 2000 and 2016.

Table 3.6. Change Detection Codes

	First Image			
Second image	Class Codes	1	2	3
	1	11	21	31
	2	12	22	32
	3	13	23	33

Source: Author (2016)

The shaded boxes on the table above shows where there was no change e.g. 11 means the land was agricultural in image 1 and still agricultural in image 2, hence no change. Other values shows change from one category to the other. This project will mainly be interested with the change areas from agricultural land to urban which is 12. After which the size, rate and direction of urban sprawl can be calculated.

3.7 GIS Analysis

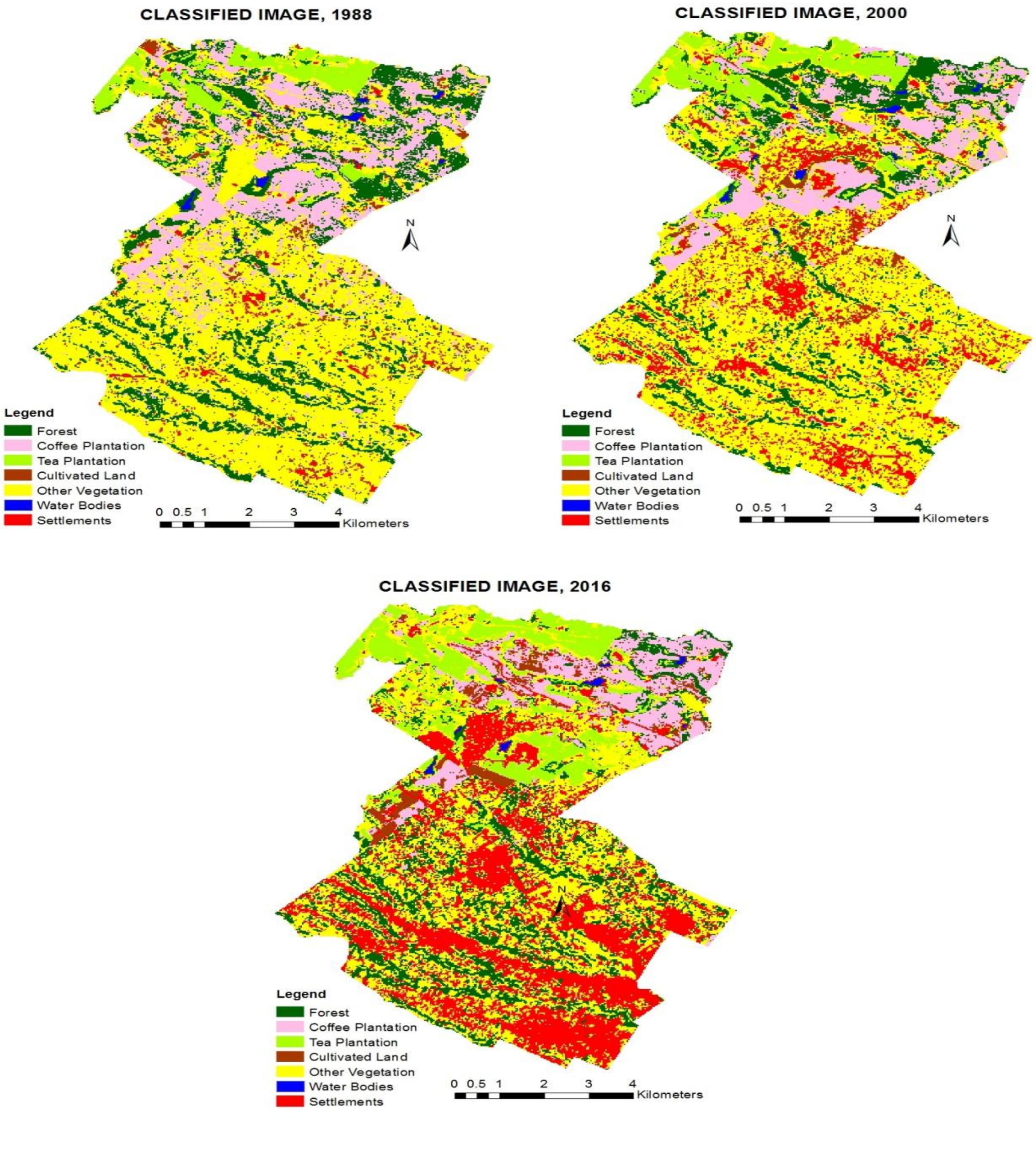
To assist in analysing the urban sprawl existing datasets covering the same geographical area were merged in a GIS environment. Roads and towns data when overlayed with urban development data enables one to understand why the settlements are found there. These data are important since they provide general orientation of the study area and also enable verification of the interpreted details by supplementing it with information that cannot be obtained directly from the satellite imagery.

CHAPTER 4
RESULTS AND ANALYSIS

4.0 Results

Three classification maps for the three scenes under investigation are produced as shown below. The Maps below shows the classified images for 1988,2000 and 2016.

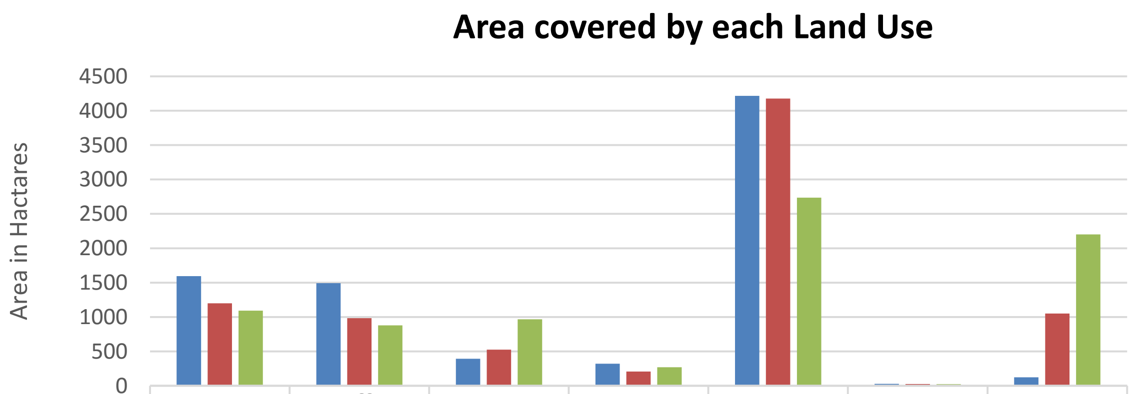
Figure 4.1 Classified Images



Source: Author (2016)

The classified images show that there are also two main cash crops grown in the sub county which are coffee and tea. These plantations are mainly in the upper area of the county, with settlements in the lower part of the sub county. Other crops grown in the area could not be delineated due to the resolution of the image. Maize, beans, potatoes are some of the crops grown in small scale.

Figure 4.2. Graph showing areas covered by each Land Use.



	Forest	Coffee Plantation	Tea Plantation	Cultivated Land	Other Veg	Water Bodies	Settlements
Area 1988	1595	1492	393	320	4217	27	122
Area 2000	1199	983	525	207	4177	26	1051
Area 2016	1093	879	966	270	2735	23	2202

Source: Author (2016)

Figure 4.2 above shows the different categories of land cover/use found in the Kiambaa sub county in tabular form. The total area under consideration was 8167 hectares approximately. Seven information classes were produced as shown above. It can be realized that forest cover has declined with approximately 396 hectares from 1988 to 2000 and 105 hectares from 2000 to 2016. This may have been brought about by the high population as they seek for land to cultivate.

Coffee plantation reduced by approximately 509 ha. from 1988 to 2000 and 104 hectares from 2000 to 2016. This confirmed a report by daily nation of December 14th 2015 which stated that the Kenya’s coffee production has reduced from 150,000 tonnes in 1980s to the current 35,000 tonnes. Coffee production is facing numerous challenges including: high cost of labour and inputs; erratic rains; high incidences of pests and diseases; competition from other farm enterprises; and poor governance of farmer’s organizations, (Gitonga, 2015).

Immediately from figure 4.1 an increase in tea plantations can be noted. This is also confirmed by figure 4.2 where the values of tea plantations have increased with approximately 131 hectares from 1988 to 2000 and 441 hectares from 2000 to 2016. From the ground and from classified images we note that most of the land that was under coffee has been converted to tea. The rate of increase may not be the same as the reduction for coffee since their suitability areas differs. Therefore in those areas that are not suitable for tea, farmers have opted to other crops and land use instead.

The spatial extent of water bodies reduced by 0.99 hectares from 1988 to 2000 and 3.2 hectares from 2000 to 2016. This may have been caused by degradation caused by the urban sprawl. Settlements increased by approximately 929 hectares from 1988 to 2000 and 1151 hectares from 2000 to 2016.

4.1. Classification Accuracy Assessment.

Table 4.1. Error Matrix Resulting from Classified Image, 2016.

	Reference Data							
Classified Data	Coffee	Tea	Cultivated	Forest	Settlement	Water Bodies	Other Vegetation	Row Total
Coffee	53	0	0	0	0	0	0	53
Tea	0	57	0	0	1	0	0	58
Cultivated	16	0	21	0	0	0	0	37
Forest	1	1	0	32	0	4	1	39
Settlements	7	0	3	0	162	2	1	175
Water Bodies	0	0	0	0	0	31	0	31
Other Vegetation	0	0	0	0	1	0	80	81
Column Total	77	58	24	32	164	37	82	474

Source: Author (2016)

The above table shows error matrix results for year 2016 classified image. The training set pixels that were classified into proper land use categories are located along the major diagonal of the error matrix indicated in blue colour. Omission errors are shown as non-diagonal column elements while commission errors correspond to the non-diagonal row elements.

From the table we can say that coffee had the highest value of omissions errors where we find that 16 pixels were classified as cultivated land, 7 as settlements and 1 as forest instead of being classified as coffee. Cultivated land had the highest number of commission errors with 16 coffee pixels being classified as cultivated land. This has been explained in figure 4.2 values and percentages.

Table 4.2. Accuracy Totals for 2016 Classified Image.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Coffee	77	53	53	69%	100%
Tea	58	58	57	98%	98%
Cultivated	24	37	21	88%	57%
Forest	32	39	32	100%	82%
Settlement	164	175	162	99%	93%
Water Bodies	37	31	31	84%	100%
Other Vegetation	82	81	80	98%	99%
Totals	474	474	436		

Source: Author (2016)

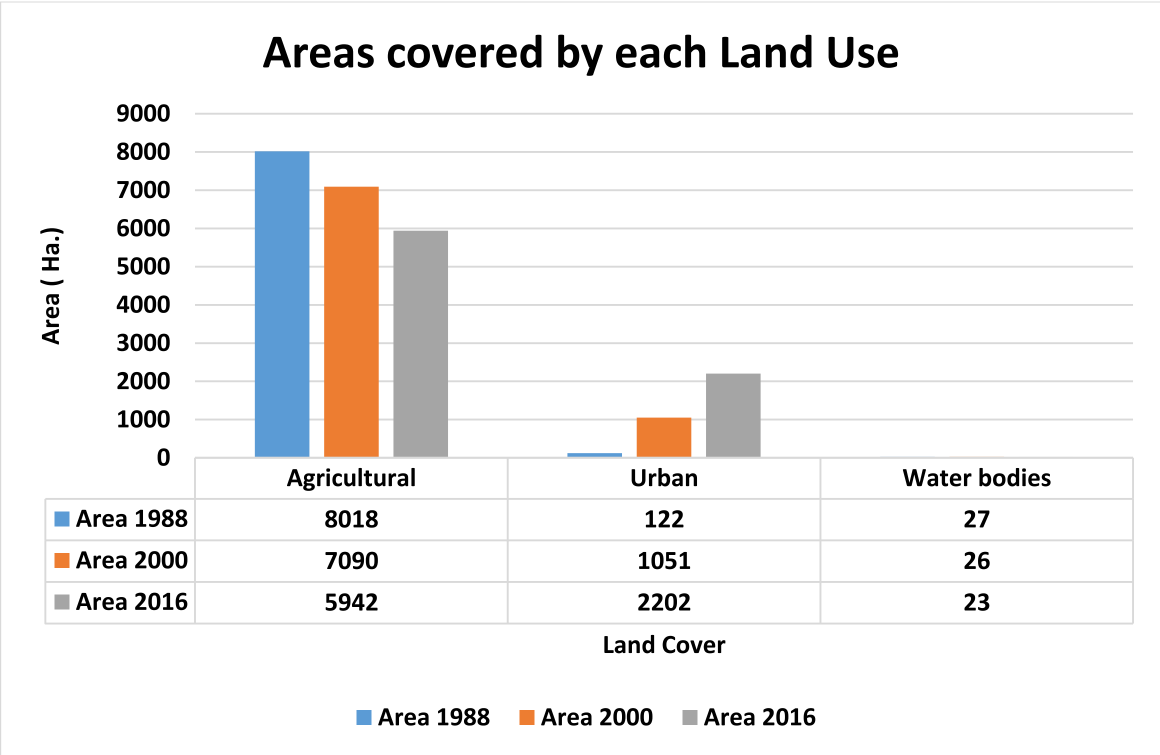
The user accuracy ranged between 57% and 100%, it measures the commission error. This indicates the probability that a pixel classified into a given category actually represents that category on the ground. The Producer's accuracies range from 69% to 100%, this indicates how well training set pixels of the given cover type are classified.

The overall classification accuracy for 2016 was 92%, which means the classification is acceptable and can be used for analysis.

4.2. Urban Sprawl on Agricultural Land Analysis

The areas for the three land use types in the three epochs considered are as shown in the figure below:

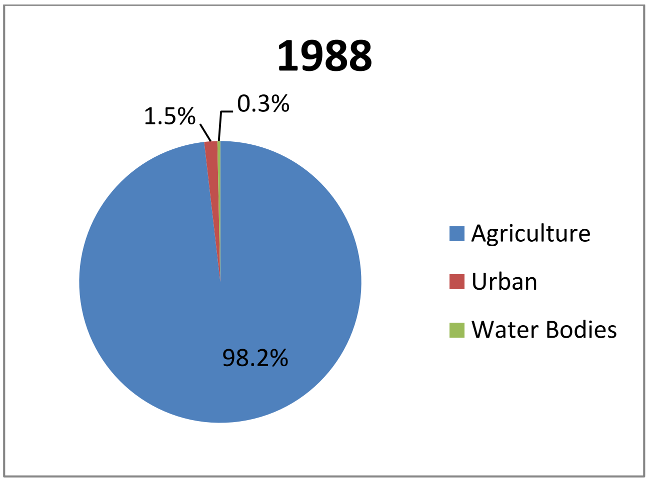
Figure 4.3 Land use coverage

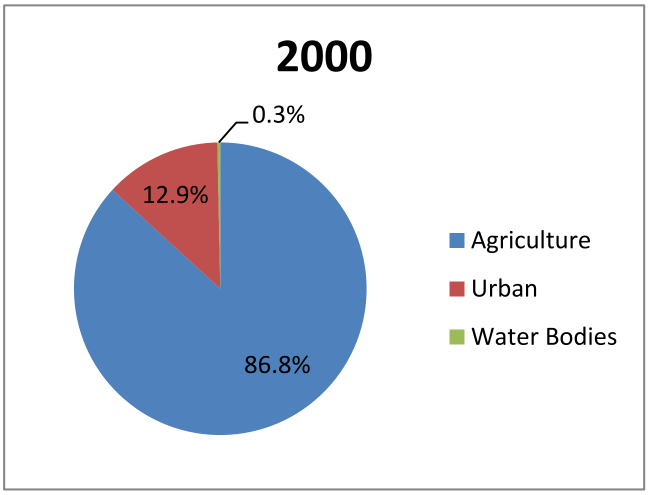


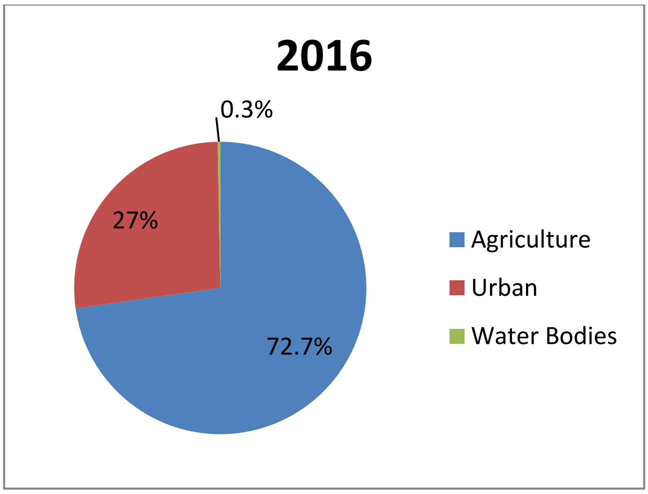
Source: Author (2016)

The above figure shows the area in hectares how agricultural land has been affected by the increased urban settlements. The Agricultural land reduced by approximately 928 hectares from 1988 to 2000 and 1148 hectares from 2000 to 2016. The reductions in agricultural land have been caused by urban development in the study area.

Figure 4.4. Trend of Land Cover/Use in percentage



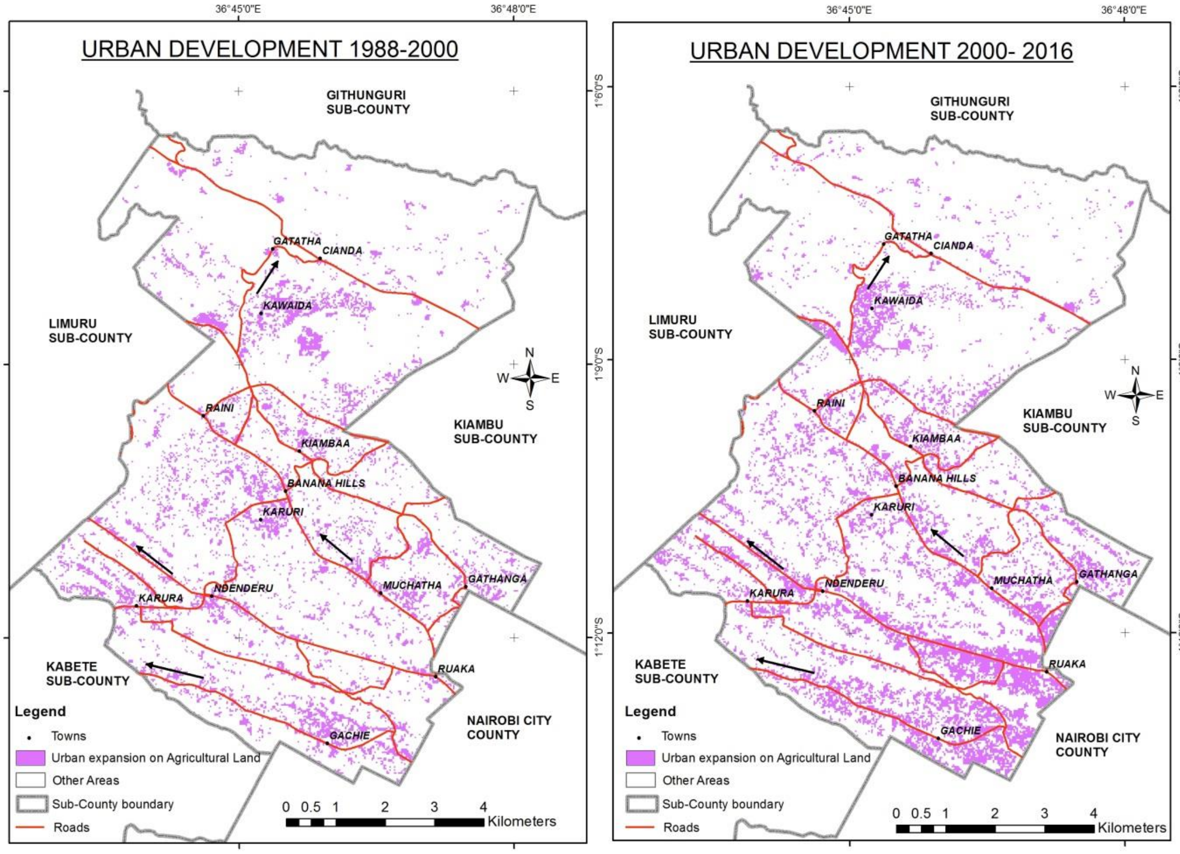




Source: Author (2016)

The figure above shows three pie charts for the three epochs in consideration. The area under each category land use is shown in percentage. Agriculture land reduced by 11.4% from 1988 to 2000 and 14.1% from 2000 to 2016. It can also be noted that the change in water bodies are minimal. Therefore it can be realised that the urban areas are expanding in expense of agricultural land.

Figure 4.5. Urban Development



Source: Author (2016)

The two maps above show the changes in urban development. Immediately from the first map we find that urban development or change in built up areas on agriculture land increased by substantial amount. The second map also shows the more expansion of urban land on agriculture land from 2000 to 2016. In 1988-2000 map the urban expansion had leapfrog developments and clustered patterns. The 2000- 2016 map can shows the urban development which has changed to linear settlements along the road and emanating from Nairobi City County.

The direction of the sprawl is as shown with arrows in figure 4.5. Since the flow is along the road and we can expect it to flow to the neghbouring sub counties which are Limuru and Kabete. It can also be noted from the map that more urban development is moving towards the upper part of the sub-county.

Table 4.3 Rate of change of Agricultural Land

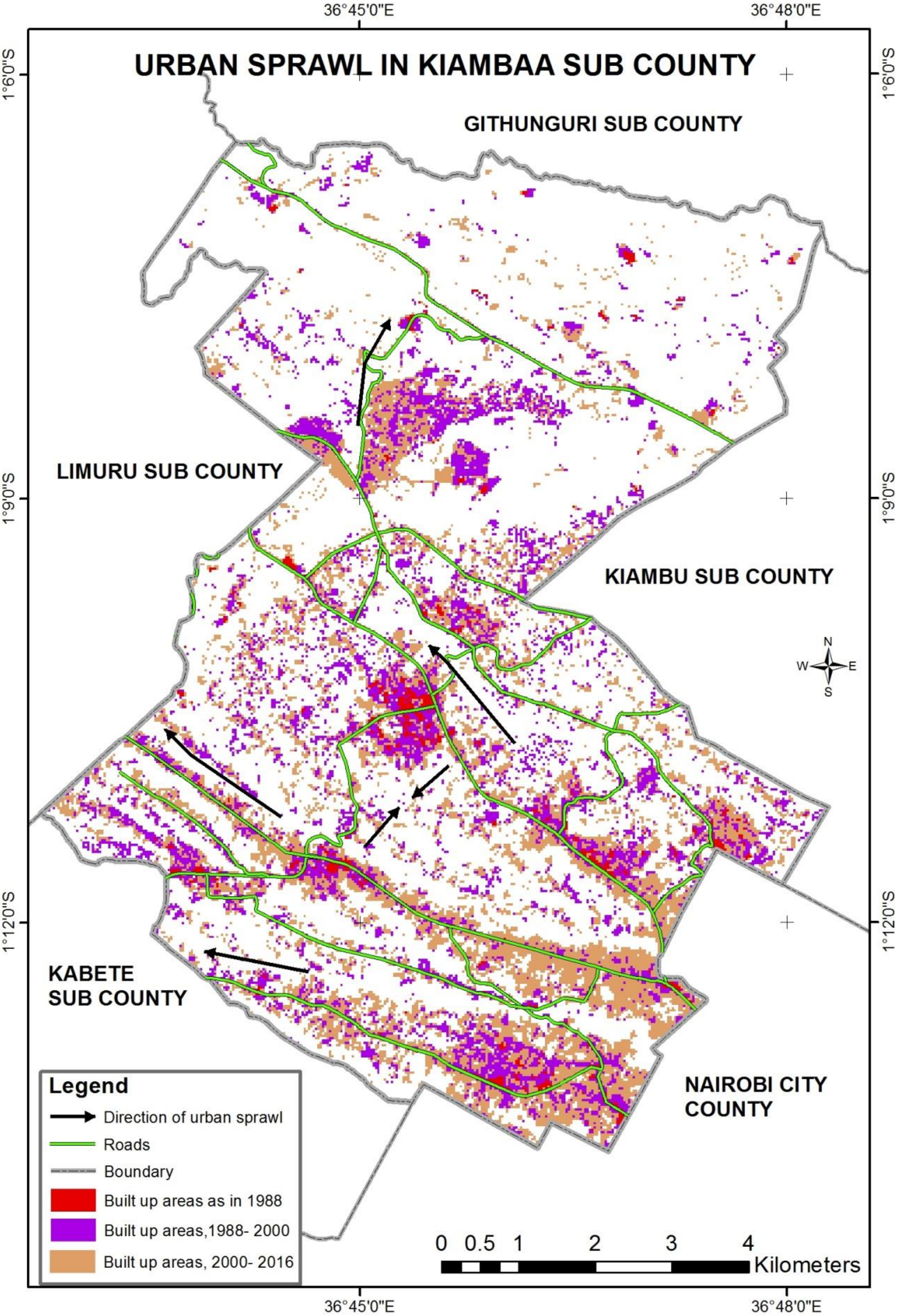
YEARS	AREAS (Ha.)	LOSS (Ha.)	No. OF YEARS	RATE OF CHANGE (Ha.)
1988	8018	-	-	-
2000	7090	928	12	77
2016	5942	1148	16	72

Source: Author (2016)

The table above shows the agricultural land in hectares that was lost to urban from 1988 to 2000 and from 2000 to 2016. Agricultural land reduced with 928 hectares from 1988 to 2000 and with 1148 hectares. From 2000 to 2016. The rate of change was calculated and it was found that approximately 77 hectares of agricultural land was lost to urban development between 1988 and 2000 and approximately 72 hectares from 2000 to 2016.

The result shows a reduction in rate of loss in agricultural land to urban, this may be due to several reasons: government initiative, increased land prices or lack of favorable land for building in terms of landscape, security etc.

Figure 4.6. Urban sprawl in Kiambaa sub- county



Source: Author (2016)

The figure above shows the trend of urban development where in year 1988, the built up areas were few as shown in colour red. In 2000 the built up areas increased as shown in purple and 2016 the built up areas increased further as shown in brown colour.

The direction of the urban sprawl is shown in figure 4.4. Most urban development is at the border of the Sub County and Nairobi City County. There are linear urban developments along the roads emanating from the City. One can predict that urban developments will continue along the roads to even the neighboring sub counties which are Limuru and Kabete sub counties. More urban developments are also spreading towards north of the sub county where there are large agricultural land.

4.3. Analysis of Results

In 1988 most of the study area was agricultural with few settlements in the lower part of the sub county, the upper portion had coffee, tea plantations and even forest cover. Classified image for 2016 shows increase in spatial extent of urban areas in lower and middle part of the sub county.

Classification accuracy assessment for 2016 was done image and had an overall accuracy of 92%. These good results may have been attributed by the quality of the image used which was clear and free from clouds.

Change analysis which was done using post classification change detection method compared three land use categories which are agricultural land, urban land and water bodies. Figure 4.4 shows the trend, how agriculture land reduced by 11.4% from 1988 to 2000 and 14.1% from 2000 to 2016. Agricultural land reduced by approximately 26 percent in spatial extent in 2016 compared to 1988. The urban areas were found to have increased by more than 18 times in 2016 in the spatial extent more than in 1988. Therefore urban land has affected the spatial extent of agricultural land. No significant change is seen on water bodies extent. This may be because the sub county have sufficient rainfall hence it does not really heavily on irrigation for farming.

The rate of change of agricultural land to urban reduced from 77 hectares per year from 1988-2000 to 72 hectares from 2000-2016. The rate of urban sprawl is not as high as one would have imagined due the huge developments on the ground. This reduction may have been caused by high prices of land in the area or inaccessibility to the remaining areas.

From figure 4.5 and 4.6 we find that the sprawl started with leapfrogged settlements where we had scattered settlements. The direction of the urban sprawl is now moving along the roads emanating from the Nairobi City County. Leapfrogging and continuous strip developments are some of the characteristics of urban sprawl realised in the study area. The sprawl is also spreading towards the upper part of the sub county where large farms are found.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.0. Conclusions

The main objective of the study was to analyse the effects of urban sprawl on agricultural land in Kiambaa Sub County and have been achieved. Availability of Landsat images on the USGS web site at low cost assisted in reducing the cost of the project. Satellite remote sensing technology was used to delineate land Cover/ Use in the sub county for three epochs. From these images it is possible to understand the major land cover/use in the sub county and detect any positive or negative change. For example, the classified images show spatial extent reduction in coffee plantations and increase in settlements or built up areas. These results are useful to the policy makers in making decisions.

Large area views on Landsat images are quite informative as they provide a complete spatial view which is virtually impossible to obtain with ground survey data. To obtain data using ground survey takes time and is costly. In remote sensing only training data and ground truth data are collected directly from the ground and it is possible to get them from other secondary sources.

The amount of urban sprawl increased by 2080 hectares from 1988 to 2016.In 1988 we had clustered settlements which are villages where the natives lived. These clustered settlements have increased radially, which may have been brought about by mainly population increase. Again there were no settlements along the roads before 1988, but we find linear settlements along the roads from 1988 to 2016. Considerable increase in urban settlements has taken place in the expense of agricultural land.

It was noted from the study that the direction of the sprawl was along the roads. These roads emanated from the Nairobi City and it was likely for it to flow to the neighbouring sub counties which are Limuru and Kabete. Another direction of urban sprawl was towards the upper part of the Sub County which currently has large plantations.

The rate of change was found to be 77 hectares per year between 1988 and 2000. The rate reduced to 72 hectares per year between 2000 and 2016. The rate of sprawl was not high as expected, the 2009 census showed Kiambaa sub county ranked second highest in population density. This combined with huge developments on the ground one would expect a high rate of sprawl. The reduction in the rate of sprawl may be due to lack of suitable area for settlement or due to the high increase in land prices in the study area.

Post classification change detection method proved to be an effective way of detecting change in urban sprawl. It was also noted that the final accuracy largely depends on the classification technique used. Remote sensing has proved to be efficient and effective way of collecting, processing and analysing data.

5.1. Recommendations

The government should incorporate use of remote sensing and GIS in its entire sectors to enhance data sharing. County governments should also consider using Remote Sensing and GIS technologies to monitor Land cover/ use changes.

There is need for an up to date zoning system for ensuring efficiency in granting construction permits and approving or rejecting construction proposal. Developing this system can be done using remote sensing and GIS technologies, by obtaining valuable information necessary for planning.

Low detailed image resolution prevents clear delineation of land use classes, therefore high resolution images though expensive will produce better results.

For sustainability of agricultural activities measures need be taken on management and conservation of the existing land.

5.2. Areas for Further Research

The issue of urban sprawl need to be studied further through multi-dimensional fields and socio economic factors in order to protect the precious and limited agricultural land and increase food production.

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