IMPLICATION OF HUMAN ACTIVITIES ON LAND USE LAND COVER DYNAMICS IN KAGERA CATCHMENT, EAST AFRICA

By

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TITLE: IMPLICATION OF HUMAN ACTIVITIES ON LAND USE LAND COVER DYNAMICS IN KAGERA CATCHMENT, EAST AFRICA

MAJOR PROFESSOR: Dr. Tonny J. Oyana

The Kagera basin in East Africa has experienced major land surface loss in tropical forests, woodlands, and savannas due to the conversion of land for agricultural purposes. This has resulted in soil degradation, siltation, eutrophication, desertification, biodiversity loss, and climate change. Damages in the Kagera have also led to pollution and sedimentation in Victoria Lake which receives water from the basin. These environmental changes have an effect on people in this region who largely depend on the natural resources. It has been indicated that these problems are mainly due to population growth as this region has the highest population growth and density when compared to sub-Saharan countries. However, previous studies conducted in this region have not investigated the spatial relationship between population growth and LULC changes. The aim of this study was to quantify LULC changes that occurred from 1984 to 2011, and predict future scenarios. Another goal of this study was to investigate the spatial relationship between population growth/density and LULC changes, and its socioeconomic influences. A post classification change detection method and Markov chain model of LULC change were used to analyze the past and future LULC dynamics. Administrative level census data of Kagera was used to calculate population growth and density, and these were overlaid to LULC change. The assessment of change for the period of 1984-2011 overall showed a major expansion of agriculture at the expense of woodland savanna. This was mainly attributed to demographic and socioeconomic/political changes prior to and during the study period. Population growth and density were linked to transitions to agriculture, and agriculture dominance during the study period. In addition, the oil price shocks of the 1970's that led to the adoption of Structural Adjustment Program were implicated as the major global macroeconomic influence in the use of resources, mainly in the agriculture sector. Internal policies such as Tanzania's "Ujama" villagization of production, and biophysical factors such as precipitation and proximity to water bodies were also implicated to the LULC changes. The findings in this study imply that understanding inter-relationship of factors is critically important, and the issue of LULC change must be approached in a holistic manner.

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CHAPTER 1

INTRODUCTION

Land use and land cover (LULC) describes the economic use of land and surface features, respectively (Campbell, 2007). Humans play a major role as forces of change in the environment, inflicting environmental change at all levels ranging from the local to the global scale (Gamble et al., 2003). The various uses of land for economic purposes have greatly transformed land cover at a global scale (Turner et al., 1994). Over the last 10,000 years, almost half of the ice-free earth surface has changed and most of the result was due to the use of land by humans (Lambin et al., 2003; Turner et al., 2007). The production of agricultural and forest goods specifically have caused agriculture and forestry to become the most transformative events globally; with agricultural land rivaling forest cover and occupying 35% of the ice free land surface in 2000 (Foley et al., 2007). In using land to yield goods and services, humans alter ecosystems and their interactions with the atmosphere, aquatic systems, and surrounding land (Vitousek et al, 1997).

LULC is one of the environmental issues mostly tightly linked to climate change in a complex manner, and changes in both can have profound effect on an ecosystem's ability to provide goods and services to society (Loveland et al., 2003). Land use and cover plays a key role in climate changes through the exchange of greenhouse gases, sensible heat, and local evapotranspiration (Vitousek et al., 1997; Foley et al., 2005; Loveland et al., 2007). Approximately 35% of the CO_2 emissions to the atmosphere were from land use (Foley et al., 2005). In addition to climate change, growth of human population and land cover changes have an effect on the biogeochemical cycles, habitat availability, biodiversity, soil erosion, water quality, water flow, and sediment flows (Vitousek et al., 1997; Dale 1997; Turner et al., 1994).

Africa occupies one-fifth of the global land area and many of the continent's resources such as forests, water, biodiversity, marine eco-systems have experienced changes due to both human and climate change drivers (Mosha, 2011). The deforestation of tropical rain forests of central Africa in general was higher in the 1980's than in the 1990's, and cropland expansion by small holders is a more prevalent form of land cover conversion in Africa (Lambin et al., 2003; Justices et al., 2001; Brink and Eva., 2009).

The Kagera basin in east Africa has been one of the major locations around the world experiencing change in tropical forests, woodlands and savannas due to agricultural land use. Some of the consequences of these changes include soil degradation, siltation, eutrophication, desertification, biodiversity loss, and climate change. These changes have likewise been implicated with population growth, economic, and policy changes arising from the bordering countries of Burundi, Uganda, Tanzania, and Rwanda (Wasige et al., 2013). The population is projected to increase rapidly and the consequences of LULC changes remain a threat (NBI, 2008).

1.1. Rationale and problem statement

In Kagera, the resources and ecosystems are under pressure due to fast population growth, agricultural expansion and intensification (progressive reduction of farm sizes), and unsustainable use of land (FAO, 2013). This has caused persistence in land degradation accompanied by a serious loss of biodiversity. The impacts on the agro-ecosystems are also affecting the livelihoods of the local populous since they largely depend upon natural resources for their living (FAO, 2013). Moreover, degradation in water quality, the loss of wetlands, sedimentation of aquatic systems, and reduced ground and surface water supply are being observed. Off site, the Kagera basin is also a major contributor of inflow to Victoria Lake (the second largest fresh water lake in the world). The changes in the Kagera basin have contributed to the pollution and sedimentation of Victoria Lake (Tamatamah, 2004).

The above mentioned problems have been related to population growth, as well as economic and policy changes arising from the bordering countries of Burundi, Uganda, Tanzania and Rwanda (Wasige et al., 2013; Tolo et al., 2012). Kagera is a heavily populated basin in the east African Rift Valley Lakes sub-region (NBI, 2008). The total population is around 15 million which accounts for 40% of the total Lake Victoria basin population (NBI, 2008). The population density of Kagera basin is 248 km^2, more than 8 times the average of sub-Saharan Africa (NBI, 2008). The future population is projected to increase at rates of 3.4% (Rwanda), 2.3% (Tanzania) and 3.2% (Uganda), which are relatively higher compared to the average rate of other sub-Saharan countries (2.5%) (NBI, 2008).

For these reasons, the Kagera basin was selected for a visual study of the physical LULC changes at a regional level. Regional studies provide adequate spatial and temporal resolution and account for variations in cause to cover relationships that are not explained at the global level (Turner et al., 1994). Past studies have attributed population growth/density as a key driver, but none have tried to link them together. This study links population to land cover transitions with an explicit spatial component. It is also clear that causes of environmental degradation or change cannot be discussed in isolation from socioeconomic and political dynamics of the country; especially for the agriculture sector of Sub-Saharan Africa, which most of the population relies on. Usually the formulation and implementation of economic reforms does not take into consideration the effects on natural resource use. Thus, this study aims to assess the socioeconomic/political and demographic factors' effect on the LULC changes of the Kagera basin.

1.2. Aim of the study

Projections of the consequences of current and future LULC change necessitates the reconstruction of past land cover changes (Love land et al., 2003). Good change detection research should provide change, spatial distribution of changed types, and change trajectories of land cove types (Lu et al., 2011). This study's general aim was to investigate the LULC changes in the Kagera basin, while also looking at the implication of human activities on the observed LULC dynamics. Specifically, this study aimed to:

- Identify LULC changes for the duration of 28 years (1984-2011) using Land Sat images
- Quantify LULC changes using IDRSI's Land Change Modeler
- To predict future LULC changes using the Markov chain model
- Investigate the spatial relationship between population growth/density and LULC changes
- Qualitatively assess the implication of socioeconomic factors on LULC changes

1.3. Research questions

To complement the above objectives, the study was guided by 3 specific research questions;

i. What is the magnitude and dynamics of land cover change?

ii. What will future land cover types be like?

iii. What are the major factors that have driven the changes of LULC?

CHAPTER 2

LITERATURE REVIEW

This chapter presents the literature review in two sections: (1) Human-environment interactions (2) LULC. The human-environment interaction section investigates how humans drive environmental changes and how environmental changes affect them in return. The next section focuses on environmental change (LULC change) in terms of causes and assessment methods.

2.1 Human-environment Interaction

The human dimension of geography and the environment study how technological, socioeconomic, and cultural drivers affect the environment and in turn the adaptation of the society (Gamble et al., 2003). This is one of the main components in the study of environmental changes (Gamble et al., 2003); namely, interactions between changes in the atmosphere, climate, the carbon cycle, the water cycle, and LULC. The DPSIR (Driving forces, Pressure, State, Impacts and Responses) model (Figure 2.1) shows the relationship between environmental indicators (Smeets E. and Weterings R., 1999).

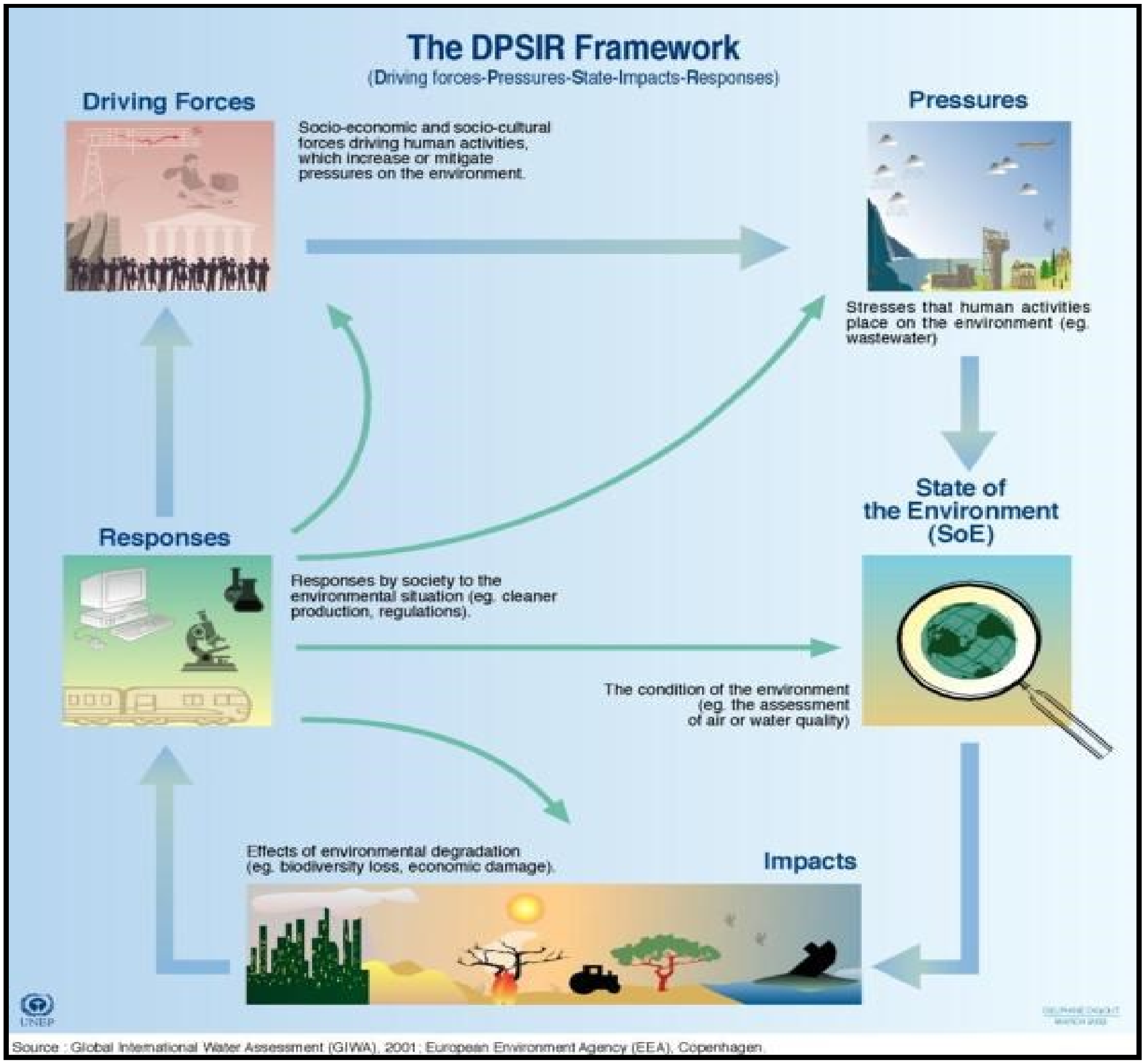

Figure 2.1 DPSIR framework

Source: Global International waters Assessment (GIWA), 2001; European Environment protection Agency (EEA); Copenhagen

Figure (2.1) illustrates the relationship between the environment and human activities. Smeets E. and Weterings R., (1999) describe the process as follows: Socioeconomic development puts pressure on the environment and will change the state of the environment (e.g. the presence of pollutants in water which indicate the status of water quality). As a consequence, these changes will be manifested as impacts on human health, ecosystems, and materials. Society will then respond (e.g. regulation, conservation etc.) in a way that feeds back on the driving forces or the state of the environment or impacts. Though the real world is much more complex than can be expressed in simple causal relationships, the communication necessitates simplicity to provide critical information about the phenomena (Smeets E. and Weterings R., 1999).Gabrielsen and Bosch (2003) describe the DPSIR indicators as follows (Table 2.1):

Table 2.1 DPSIR frame work elements

Indicator type	**Description of indicator type**
Driving forces	Describes the social, demographic and economic developments in societies, corresponding life style, and levels of consumption and production patterns.
Pressure	Describes the pressure exerted by society through the release of substances (emission), physical and biological agents, use of resources and the use of land by human activities.
State	Gives a description of the quantity and quality of physical phenomena, biological phenomena and chemical phenomena (e.g. CO_2 concentration)
Impact	Pressure changes the state of the environment which in turn has impacts on the function of the environment as human and ecosystem health, resources availability, biodiversity, etc.
Response	Describes the responses by groups (individuals) in society and government in attempt to prevent, ameliorate, or adapt to changes.

The dynamics of the DPSIR are expressed when the relationships between the elements (“in-between” indicators) are introduced (Figure 2.2). Smeets E. and Weterings R., (1999) explains as follows: Eco-efficiency indicators indicate whether or not there is technological progress (i.e. they indicate technologies' degree of efficiency). The pathways and dispersion patterns are useful for modeling current and future changes in the state of the environment and impacts by indicating the time of delay in natural processes and time bombs in the environment. Similarly, the dose response indicators between impact and state help quantify the consequences or act as early warnings. The costs and benefits to society in responding are governed by the degree of impact, which requires economic data. There is little information available in regards to the policy effectiveness indicator explaining the relationship of response with other elements (Gabrielsen and Bosch, 2003)

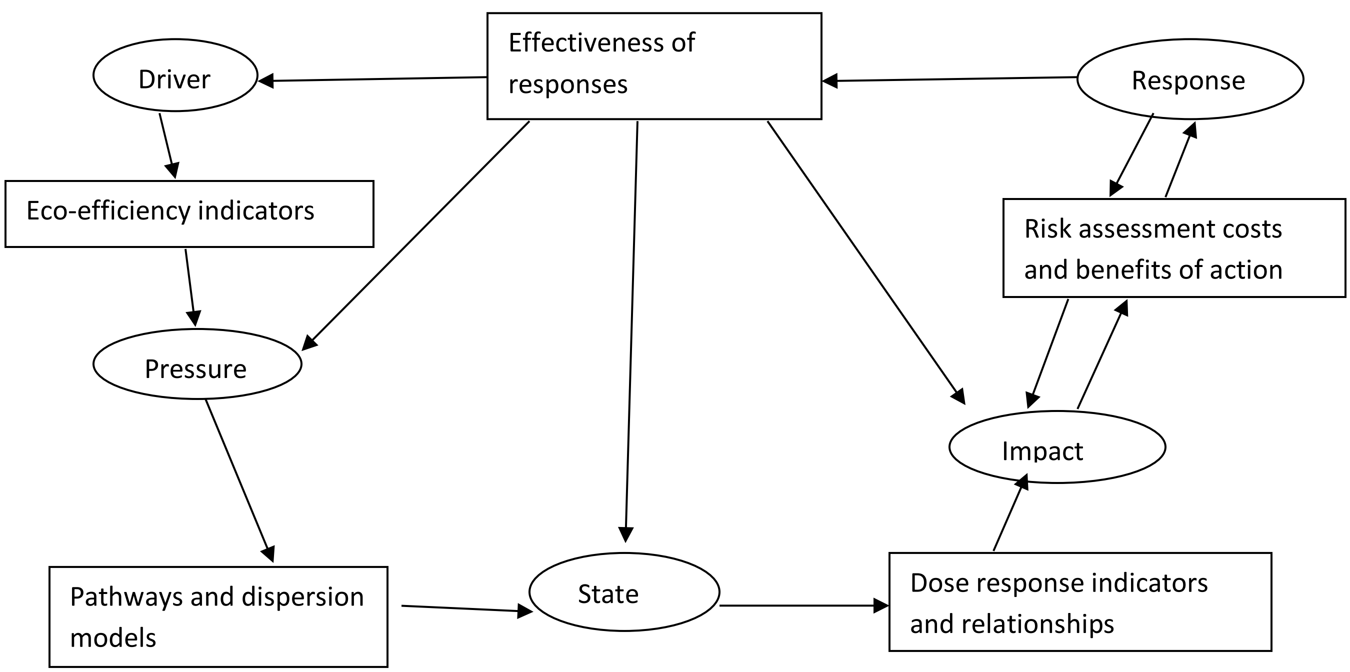

Figure 2.2 Indicators and their relationship

Source (Gabrielsen and Bosch, 2003)

2.2. Land use and Land cover

This section reviews the causes of LULC change and the methods involved in assessing the dynamics of LULC. Additionally, the LULC dynamics of the Kagera basin from previous studies are reviewed.

2.2.1. Causes of land use land cover change

LULC change is most important in understanding environmental change; necessitating the investigation of cause to cover relationship (Tuner et al., 1994). LULC changes are manifested through conversion and modification, which are caused by interactions between climatic and anthropogenic forces owing to its inherently complex nature (Lambin et al., 2003; Turner et al., 1994). Even though LULC change is affected by climatic change, it is primarily LULC change which drives environmental and climatic changes (Gamble et al., 2003; Loveland et al., 2003). LULC change and its relation to cause is very important as it has the greatest implications on the environment (Turner et al., 1994). Understanding the causes of land cover changes involves looking at proximate or direct causes at the local level and the decisions formed as a result of complex social, economic, political, demographic, technological, cultural, and biophysical factors at a regional/global level (Lambin et al., 2003). Turner et al. (1994) indicates there are variations in the observed cause to cover relationships at different levels as a result of different socioeconomic characteristics, politics, levels of affluence, and technological development as well as culture in different parts of the world. An individual look at the regional and local levels provides greater details in order to identify and account for these variations. As a result, the simplistic assumption that LULC is driven by only a few forces has moved to a complicated understanding that involves interactions among a large number of factors at different spatio-temporal scales (Lambin et al. 2003). Lambin et al. (2003) and Dale et al (1997) further indicate that the complexity of these factors can be simplified to themes that relate various drivers to particular LULC changes (i.e., limited paths ways), but the problem is finding a dominant path way or primary cause of land use change. This is because the importance of these factors depends on the situation and spatial scale of study. Nevertheless, the past understanding of these forces acting from a local to a global level becomes very important as this improves our ability to predict LULC changes and its consequences. These predictions are crucial in order to propose successful management options for a given biophysical/socioeconomical/political situation (Loveland et al., 2003). Lambin et al. (2003) describes the main drivers of LULC changes which are summarized in Table 2.2.

Table 2.2 Factors that influence land management decision of land use and land cover change

Drivers (factors)	**Description**
Multiple causes	A mix of driving forces that varies in time and space and acts on different levels. They are specific to human environmental conditions. They are biophysical and socioeconomic factors which can be slow and/or fast in nature. Usually, land use change occurs through a combination of both natures.
Natural variability	Natural environments interact with human causes of land use change. This could be in a synchronous or independent manner which leads to socioeconomic unsustainability. Usually, climatic driven ecosystem conditions amplify the pressure due to demands on the resources
Economic and technological factors	Land use change is predominantly the result of society responding to the opportunities and constraints created by markets and policies which in turn are influenced by global factors. This works on a decadal time scale. Access to technology for efficient land management is determined by distribution of wealth as a result it has an impact on geographical differences of economic opportunities and constraints.

Table 2.2 (Continued)

Demographic factors	This also is another factor which has a great impact on land use change over a longer time scale. It is a shift in rates of fertility and mortality, but it also means associated development of households life cycle. The life cycle is related to labor availability, migration, urbanization, and the breakdown of extended families into several families. This life cycle is mainly a response to economic opportunities and constraints which affect land use change and which in turn affect household economy. Migration, on the other hand, is also a significant driver coupled with non-demographic factors (e.g. government polices) and some policies could trigger migration.
Institutional factors	Local and national policies and institutions (political, legal, economic, and traditional) affect decision making as they usually constrain the access to land, labor, capital, technology, and information and thus determine the land managers capabilities to participate and define institutions. e.g. decision making systems(decentralization, inclusion of local communities in decision making) and institution control over distribution of resources. Ill-defined policies and weak institutional enforcement are causes of land use change. Some policies that influence land use change are policies of self-sufficiency, price control on agricultural inputs and outputs, structural adjustments, landholding consolidation, as well as investments in monitoring and guarding natural resources.
Cultural factors	The individual land managers' beliefs, attitudes, motives, collective memories, knowledge, skills, individual perceptions, and personal histories influence land use decisions. Cultural factors can be linked to political and economic inequalities (e.g. status of women and ethnic minorities affects access to land use).
Globalization	This is the process that underlies the other drivers and it amplifies or attenuates their impact by removing regional barriers, weakening national connections, and increasing the interdependency among people and between nations. The most effect is from economic/trade liberalization and reforms to open up the agro-industrial sector.

Though these are the general factors influencing land use change, Lambin et al., (2003) specifies the most frequent causes of land use change such as resource scarcity (which causes pressure on resources), market opportunities, outside policy interventions, loss of capacity and increased vulnerability, changes in social organization, changes in resource access, and changes in attitude.

Generally, in sub-Saharan countries, the most important drivers of forest degradation have been identified as the extraction of fuel wood, where 80% of the population uses wood as its main source of energy, and agriculture, which represents the primary source of income for 70% of the population. Additionally, forest policy, persistent conflict and war, demography and population movement, low economic growth and poverty, debt and dependence on development assistance, constraints arising from globalization, predominance of the informal sector, and inadequate investment also are underlying drivers (Henry et al., 2011). Several studies have been done in Africa at the watershed, regional, and local level to look into LULC dynamics, and required looking at the population growth and socioeconomic influence in cause-cover relationships. Dale (1997) indicates that the effects of population growth modified by the local situation can be considered as an ultimate cause of LULC changes. Cadjoe (2007) points out that most of the studies in developing countries place a majority of their emphases on the local level, where direct causes of the land use /cover changes are observed. In studying cause-cover relationship, Cadjoe (2007) further indicates that linking people to the appropriate level to describe LULC changes is a challenge. However, population data can be linked easily at the regional, national, and district or municipal level and smaller (i.e., village level that makes the linkage difficult as it needs household survey data).

A study on land cover change was done on the Sub-Saharan Africa region for a 25-year period by Brink and Eva (2009). This region shows a wide range of climatic and ecological diversity with differences in land cover types, population, and land management techniques. The study showed that agriculture increased at the expense of forests and natural vegetation and concluded that population increase (with the majority living in rural areas) was the main driving force. At a smaller scale, Mundia and Aniya (2006) studied Kenya's Nairobi city as it had experienced rapid growth in population and spatial extent compared to other major cities in the region, and was showing disappearance of vegetation giving way to urban sprawl and agriculture. They found that rapid economic development and urban population growth were the main reasons for the observed changes. Southern Burkina Faso has also experienced rapid increased population density and growth especially at the district level due to immigration of peasants from other regions of the country. As a result, there was an expansion of agriculture at the expense of open woodland and dense forest cover. The study by Ouedraogo et al., (2010) of these districts showed that there was a highly significant Pearson Product Moment Correlation between area of cropland and population density. At the municipality level in Tanzania, Musamba et al. (2011) assessed the impact of such socioeconomic activities as fishing, tourism, crop production and livestock on LULC changes. The results showed that there was a strong relationship between the LULC changes and anthropogenic activities. Another study in South Africa (Giannecchini et al., 2007) involved three villages (at the local and household level) to see the relationship between land cover change and socioeconomics. The villages consistently showed an exponential increase in human settlement as a result of refugees in the mid 80's and a decrease in vegetation. In addition, weakening of institutional control at the local level over natural resources was observed in each village during times of political change. As a result, population growth, the weakening of control of property, and increased dependency of household livelihood on cash income enabled individuals to harvest live wood without impunity. Other studies using watersheds to assess the land cover changes and its drivers were also completed in Africa. These studies were employed on the Kagera basin (Wasige et al., 2013; Tolo et al., 2012), Malagarasi catchment in Tanzania (Kashaigili and Majaliwa, 2010), and the Barekese catchment in Ghana (Boakye et al., 2008). Their findings indicated that land use was influenced by policy changes, lack of education, population growth, and socioeconomic issues.

2.2.2. Land use and land cover detection

Land use and cover data is collected through the combination of direct observation and remote sensing, with the latter being the most widely used method (Campbell, 2007). Data has been mapped at different scales using panchromatic, medium-scale aerial photographs since the 1940's and more recently by using small-scale aerial photographs and satellite images (Lillesand et al., 2008). Satellite data has been valuable in partnership with socioeconomic surveys and census data for a better understanding of land use/cover dynamics and the factors that drive them (Codjoe, 2007).

2.2.2.1. Image classification

Image classification is an important part of remote sensing, one which assigns pixels to classes to produce land cover information. It involves image selection, preprocessing, algorithm selection, and training data (Lu et al., 2011; Campbell, 2007). Lu et al. (2011) indicate there are different classification approaches such as Supervised, Unsupervised and Hybrid; Parametric and

Non parametric; Hard and Soft (Fuzzy) classification; and Per pixel, Sub-pixel, and Per field. The techniques used, however, are typically influenced by users' needs, the spatial resolution of satellite images, the complexity of the study area's landscape, available image processing and classification algorithms, and time constraints (Lu et al., 2011). .

Medium resolution images (e.g. Land sat) are most commonly used in LULC classification even though they have low time frequency, and rarely have cloud-free images (Henry et al., 2011). As spectral information is important for medium resolution image data, parametric classification algorithms such as maximum likelihood are often used, but Per pixel classifiers have repeated difficulties in dealing with mixed pixel problems (Lu et al., 2011). Lillesand et al. (2008) mention that the minimum distance classifier or algorithm has limitations where you have close spectral classes in measurement space and have high variance. In other words, it is insensitive to different degrees of variance in the spectral response of the data. The coarse resolution satellite images are not readily adapted; especially in estimation of deforestation at a national level (Henry et al., 2011). Lu et al. (2011), on the other hand, indicate that high resolution images such as QuickBird and IKONOS bring about high spectral variation within land cover class and as a result, Per pixel classifiers perform poorly. In such cases, Per field or object-oriented algorithms are appropriate (Lu et al., 2011)

In classification, three methods are used: (1) Supervised (2) Unsupervised (3) Hybrid classification. Unsupervised classification is used to aggregate initially unknown pixels based on image values which are later compared to reference values to determine identity (Lillesand et al., 2008). The most commonly used clustering algorithm in unsupervised classification is ISODATA. In a supervised classification method, pixels categorization is done by image analyst who specifies samples of known cover types to numerical interpretation that distinguishes each class's spectral attribute (Lillesand et al., 2008). This classification may include classifier algorithms such as minimum distance or Gaussian maximum likelihood. Lillesand et al. (2008) mention that hybrid classification is very effective where land cover types' spectral responses are highly variable, especially in vegetation species mapping. This method uses a combination of supervised and unsupervised approaches to improve the accuracy of purely supervised or unsupervised LULC classification (Lillesand et al., 2008). The unsupervised method is used to identify spectral classes present in the image which are later differentiated in supervised classification.

Different studies have used different techniques in LULC mapping. Mundia and Aniya (2006) used unsupervised classification method using ERDAS because it allowed spectral clusters to be identified with a high degree of objectivity. As a result of mixed pixels and same spectral responses (from moderate resolution images), the clusters were spectrally confused. They were then reclassified based on visual interpretation (local knowledge) and removed using the majority filter. A minimum distance algorithm was used during the classification. It showed an overall accuracy greater than 85% for each image classified. They used different images (ETM, TM and MSS) and used a modified version of Anderson's classification scheme. Brink and Eva (2009) also used an unsupervised method using sampled images from TM and MSS images to assess a 25 year land cover change for continental Africa. This study had an issue with incompatibility of the images in terms of radiometric and spatial resolutions. In another study in Ghana, Boakye et al. (2008) used TM data in assessing the LULC changes using the unsupervised classification method.

Ouedraogo et al. (2010) also used a combination of satellite images (land sat scenes and ASTER) in studying the land cover dynamics of Sissili province of Burkina Faso. They classified the images using training data supported by topographic maps and ground-truthing to assign pixels to identified categories. A Maximum Likelihood algorithm was used on a tasseled cap transformed image, and the overall accuracy of the classified images ranged from 87.6% to 94.4% for all land sat images and 92.5% to 94.8% for ASTER images. Others also used the supervised method and the maximum likelihood classifier in assessing the land use and cover dynamics. Wasige et al. (2013) validated their classified maps against aerial photograph topographic maps and field observation. They had an overall classification accuracy > 85%. In a similar study in Angola, Cabral et al. (2010) achieved an accuracy of 80%. The classification included ancillary data from Google Earth high resolution photography, visual interpretation of satellite images, vegetation maps and expert local knowledge. In both studies, Wasige et al. (2013) and Cabral et al. (2010) used a mosaic of TM/ETM images to encompass the study area, and the maps were made with images dated as closely to each other as possible.

Studies have also used hybrid classification, which is the combination of both supervised and unsupervised classification. It is a valuable approach, although there is complex variability in the spectral response patterns for individual cover types present. This arises from different cover types or conditions (Lillesand et al., 2008). Were et al. (2013) conducted land cover change detection for the Nakuru drainage basin in Kenya. They utilized TM, ETM and MSS images for different years and used supporting data from Google Earth imagery, thematic layers (Africover), field data, and topographic maps. They achieved an overall accuracy of 80% and above for the image classified and the change detection maps were above 70%. They attributed some of the classification errors they encountered to spectral confusion between croplands and grasslands and among forests, shrub lands, and croplands. Similar studies which employed hybrid classification also generated successful classification performance (Paiboonvorachat and Oyana, 2010; Torahi and Rai, 2011).

2.2.2.2. Change detection

Change detection involves quantitatively identifying the differences between multi-temporal data sets to see the dynamics of the phenomena of interest. The repetitive and synoptic data acquired from remote sensing has been a major source for change detection in past decades (Lu et al., 2011). Lu et al. (2011) point out that change detection gives an in-depth understanding of the relationships between human and natural phenomena for better management of resources. Accordingly, studies should involve the following information: change and rate of change, spatial distribution of change, and change trajectories of land cover types.

Many change detection algorithms are available: those giving change or no change information as image differencing, image rationing, Principal Components Analysis (PCA), as well as those giving detailed '*from-to*' information as hybrid change detection and post-classification methods (Singh,1989; Lu et al.,2011; Lillesand et al.,2008; Campbell, 2007). The pitfall of implementing the detailed '*from to*' change detection is that accuracy of such procedures depends upon the accuracy of each of the independent classifications used in the analysis (Lillesand et al., 2008). That is to say accuracies arising from the classification images will affect the change detection results (Singh, 1989). As a result, the accurate classification of images is a critical step in image classification (Lu et al., 2011). Nevertheless, post-classification change detection is widely used, as it circumvents problems associated with multi-date images such as radiometric and atmospheric differences and registration errors (Singh, 1989). This method further provides useful information using matrices of *from-to* changes than those methods which provide only change or no change information such as image differencing (Campbell, 2007).

Different studies have used different change detection methods. In assessing land cover changes and its effects on soil erosion in the Nan watershed in Thailand, Paiboonvorachat and Oyana (2010) used the post classification method for change detection. They used IDRISI to generate the cross tabulation matrices (cross tabulation) and cross classification to observe the '*from-to*' change. Shalaby and Tateishi (2007) in Egypt used the same technique in (post classification change detection) IDRISI to produce cross-tabulation and assess the changes that occurred in the north western coast. In studying the land cover and forest change in the mountainous area of Dehdez, Iran, Torahi and Rai (2011) used the post classification change method in INVI. Other studies in Africa which sought to quantify LULC dynamics also applied the post classification detection technique (Were et al., 2013; Kashaigili and Majaliwa, 2010; Boakye et al., 2008; Mundia and Aniya, 2006; Wasige et al., 2013; Shiferaw, 2011).

Researchers have used a variety of other methods in their studies as well. In assessing the potential of high resolution land satellite data for the horn of Africa, Brink and Eva (2011) overlaid two grid images and used the change or no change method using 7x7 gird boxes(300mby 300m) and visual interpretation. In Mozambique, Jansen et al. (2008) used object-oriented GIS overlay between images to assess the change that had occurred in the Manica province. Giannecchini et al. (2007) used raster images of cover (derived from aerial photographs) to compare the relative frequency of cover between the years of the study period.

2.2.3. Land cover changes in Kagera

Studies of LULC changes in the Kagera basin have previously been performed. Tolo et al. (2012) assessed the degradation of natural resources of the Kagera basin and sub-basin (Uganda) for the period between 1984 and 2002. In their studies for the Kagera basin, they identified and mapped 8 major land use and cover types; urban areas, forest, water bodies, woodlands of different types, cultivated land with different crops, bush land of different types, open land, and grassland with different types. This was done using Landsat, aerial photography, and ground-truthing. The results indicate that there are variations in the dynamics observed for woodland areas and bush land. The forest, cultivated land, and urban areas showed increases in areal coverage whereas water bodies showed a loss or decrease in areal coverage for the study period.

A similar study of the Kagera basin was done by Wasige et al. (2013). The researchers examined LULC dynamics for the period between 1901 and 2010 using historical thematic maps, topographic sheets, interviews, ground truthing, literature review, and satellite images. They identified the land cover classes as dense forest, degraded forest, woodlands, savannas, tea, plantation forest, bamboo, water bodies, farmlands, urban and built up areas, and permanent wetlands. Their findings show that the dominant LUCC change was by farm land, which increased to 60% of the total watershed area. They also found there was a decrease in dense forest (from 7% to 2.6%), woodlands (from 51% to 6.9%), and savannas (from 35% to 19.6%). As for the water bodies and wetlands, their study showed no change for the study period.

CHAPTER 3

DATA AND METHODOLOGY

3.1. Study area

The Kagera river basin is located in Eastern Africa. It is located between $29^0 1'37''$ E and $31^0\ 40'19''$ and between $3^0 57'\ 21''$ S and $0^0 39'\ 32''$ S and covers an area of 63,500 km^2 (6,350,400 ha) (Figure 3.1a). The watershed spans across four countries; Burundi (23%), Rwanda (36%), Uganda (7%), and Tanzania (35%) (NBI, 2008).

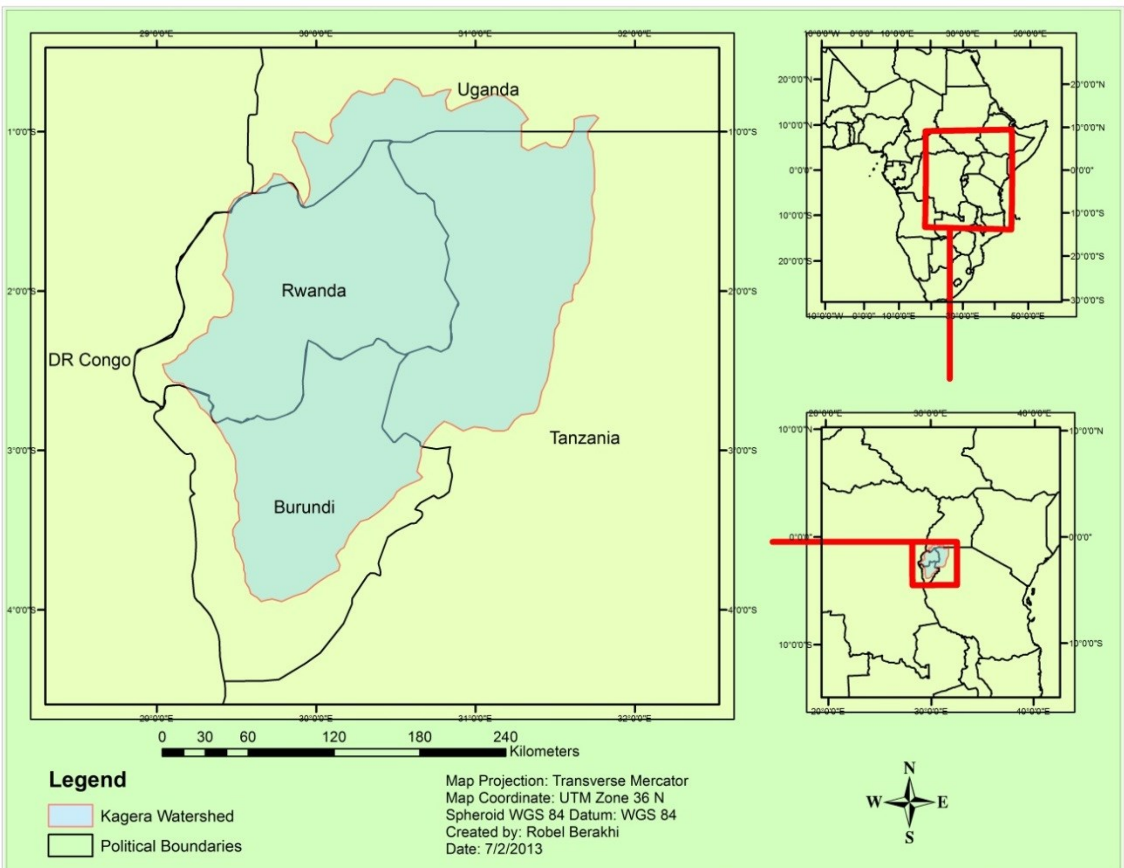

Figure 3.1a Map of Kagera basin showing neighboring countries: Uganda, Tanzania, Democratic Republic of Congo, and Burundi

Approximately 15 million people live in Kagera and 90% of the population consists of subsistence farmers who live in rural areas and depend directly on farming, herding, and fishing activities (FAO, 2013; NBI, 2008). The mean annual growth rate (2.7%) and fertility rate (6.34) of this region is higher compared to other sub-Saharan countries (NBI, 2008).

The climate of the Kagera basin is characterized by humid, sub-humid, and semi-arid climates with two dry seasons (June to September and December to February) and two rainy seasons per year, the wettest months being in April and November (FAO, 2013). Being a tropical location, temperatures are very constant. The average annual temperature is lower in the western and north western areas (15 to 18 ^{0} C), with an average of 22 ^{0} C in the central part of the watershed (NBI, 2008). The mean minimum temperature is 14.5 ^{0} C and the mean maximum temperature is 27.5 ^{0} C (NBI, 2008). The pattern of rainfall is distributed in such a way that the western parts of Rwanda and Burundi receive higher rainfall (over 1800 mm), with most of the eastern part receiving less than 1000 mm; with the exception of an area near Lake Victoria (NBI, 2008).

Kagera basin has an important river called Kagera River running through it, forming part of Tanzania's border with Rwanda and Uganda. This basin is part of the Lake Victoria basin and drains into Victoria Lake, contributing up to almost one-fourth of the inflow (FAO, 2013). Water from Lake Victoria eventually flows to the Mediterranean.

The Kagera has two major topographical zones; the West Rift Zone Scarp and Lake Victoria Basin. The West Rift Zone is on the eastern side of the Western Rift valley which forms the boundary between Rwanda and the Democratic Republic of Congo. The Nile Basin Initiative (2008) indicates that there are four hydro-geographical zones based on shared similarity in geology, landforms, relief, climate and stream flow. These zones are the Congo Nile Divide, Hills and Mountain Foot Ridges, Swamp and Lake Terrain, and West Victoria Lake region (Figure 3.1.b). The Congo Nile Divide encompasses the western part of the basin along the border with the DR Congo and is characterized by a heavily dissected mountainous area with steep slopes. The hill and mountain foot ridges are located mostly in Burundi. The majority of the Swamp and Lake Terrain region is located in the central part of the watershed. This is characterized by plain, plateaus mixed with some mountain and hills. Lastly, the West Victoria Lake region is in the eastern part of the basin (mostly in Tanzania) and is characterized by alluvial plains and plateaus.

The basin has a general elevation of 1200 to 1600 m. The west part of the basin has a higher general elevation of 2500 m with peaks in the north western corner reaching up to 4500 m in elevation. The eastern portion has an elevation lower than 1300 m (Shahin, 1985; NBI, 2008).

Most of the Kagera area is cultivated agricultural lands. Natural vegetation follows with only 2% of Kagera being covered by closed forest, the largest of which is Nyungwe forest. Nyungwe forest is one of the largest mountainous rain forests remaining in Africa (GWP, 2011). Natural vegetation types include forests and woodlands, savannas, shrub lands, pasture lands, and aquatic vegetation in wetlands (NBI, 2008).

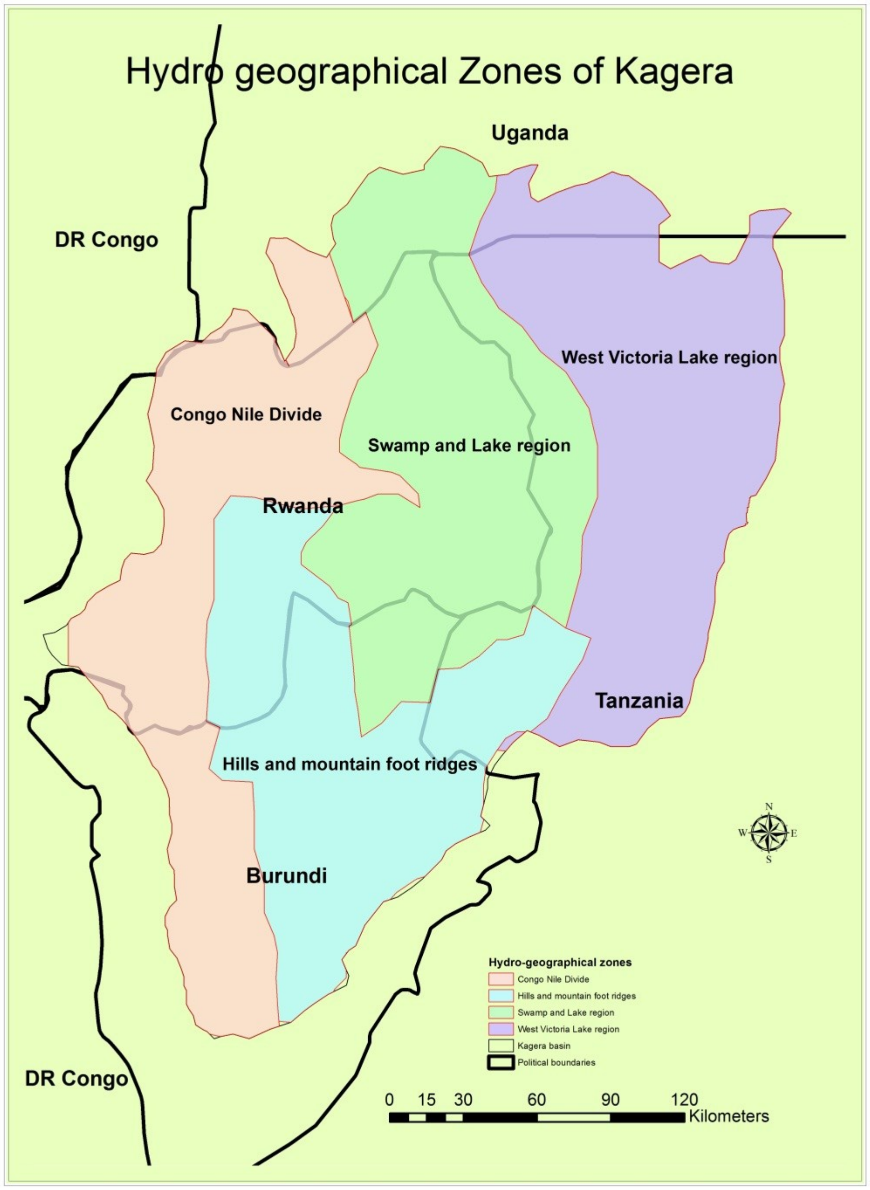

Figure 3.1.b Hydro geographical zones of Kagera (Source: NBI, 2008)

3.2. Data description and collection

In this study Landsat images, ancillary data (reference maps and Google photography), and administrative level census data from the four countries (Uganda, Burundi, Rwanda and Tanzania) were used.

3.2.1. Image acquisition and preparation

The selection of remotely sensed data depends on factors such as the scale of study area, availability of image data, and cost/time. Landsat thematic mapper (TM) data is frequently used at a regional scale (Lu et al., 2011).The Landsat TM images used for this study were accessed for free from the Earth Resources Observation and Science Center (EROS) of the United States Geological Survey (http://glovis.usgs.gov/). The path and rows for the scenes covering the study area were identified (Table 3.1). Discrimination of change involved the use of multi-temporal images. Ideally all the images should be acquired from the same sensor, be recorded with the same spatial and radiometric resolution, viewing geometry, and time of day (Lillesand et al., 2008).

Different considerations were taken when selecting the study period such as the availability of images for the intended years, predominately cloud free images in each scene or study area, and availability and closeness (in terms of month) of each scene involved for a single year. Images were selected from the dry season; when cloud coverage is usually found to be at a minimum. However, complete Landsat TM data for the period of interest was not available, with available scenes containing cloud cover. Thus, it was not possible to compile a consistent dataset for the watershed. Henry et al. (2011) indicate the difficulty in obtaining cloud free images as one of the limitations inherent to Land Sat. Therefore, this study used scenes from those years closest to the year of interest (previous or next). In addition to image selection criteria, the time points 1984, 1994, and 2011 from TM 4 and 5 were selected to allow for adequate period gaps and range to detect land cover change. Also the years or time points chosen were meant to coincide with major socioeconomic and political changes for the study region in order to best capture change. Once the scenes were selected, the images were downloaded and 6 bands, excluding the thermal band (bands 1 through 5 and 7), were stacked to form multi-band images using ERDAS IMAGINE 2011.

Table 3.1 Predominantly cloud free Landsat scene chosen for the land cover classification. Source: USGS

Year	Sensor	Path / Row	Acquisition Date
1984	Landsat TM	173/61	19thJuly 1986
	Landsat TM	173/62	19th July 1986
	Landsat TM	172/61	6th June 1984
	Landsat TM	172/62	20th June 1984
	Landsat TM	172/63	20th June 1984
1994	Landsat TM	173/61	Jan 1st 1995
	Landsat TM	173/62	25th July 1994
	Landsat TM	172/61	4th Sept 1994

Table 3.1 (Continued)

1994	Landsat TM	172/62	3rd Aug 1994
	Landsat TM	172/63	3rd Aug 1994
2011	Landsat TM	173/61	8th July 2011
	Landsat TM	173/62	8th July 2011
	Landsat TM	172/61	25th June 2009
	Landsat TM	172/62	8th Feb 2011
	Landsat TM	172/63	1st July 2011

3.2.2. Population data

To estimate the population of Kagera, the districts (administrative regions) from the four sharing countries were selected by over-laying them on the watershed. Then population data was acquired for each district in the Kagera basin. These were collected from the different government websites of Tanzania (www.geohive.com), Uganda Bureau of Statistics (www.ubos.org), National Institute of Statistics of Rwanda (www.statistics.gov.rw), and United Nations development program Burundi (www.bi.undep.org) (See Appendix B). The national census is conducted at different times for each country so the population during the inter-census periods was estimated for each district in each country. Interpolation/extrapolation was done to fill the gaps and harmonize the data for the four countries' districts. The growth trend calculation was used to fill in a series of missing values (interpolate and extrapolate) using the series command in Microsoft Excel. This assumes that a population will increase or decrease exponentially (See appendix B).

Exponential growth estimation formula is shown below;

Growth rate $(r) = ((\frac{Pl}{Pb})^{1/n}) - 1$ where *Pl*= population at launch year; *Pb*= population at base year and *n* is period of time

$Pt = Pb*(1+r)^z$ Where *Pt*= is the population in the target year, and *z* is the number of years in the projection horizon.

3.2.3. Ancillary data

Ancillary data were used to support the classification. Thematic maps of the Kagera basin for the years 1985, 1995, and 2010 were scanned and geo referenced using ArcGIS 10 to Universal Transverse Mercator grid (zone 36 N, WGS 84 ellipsoid and datum). These data were prepared to support classification and assess the accuracy of the classified images. High resolution Google imagery and local knowledge were also used to support the classification.

3.3.3 Flow chart of the methodology

The figure below shows the methodology followed during this study. Two parallel procedures were followed for population data and satellite TM images.

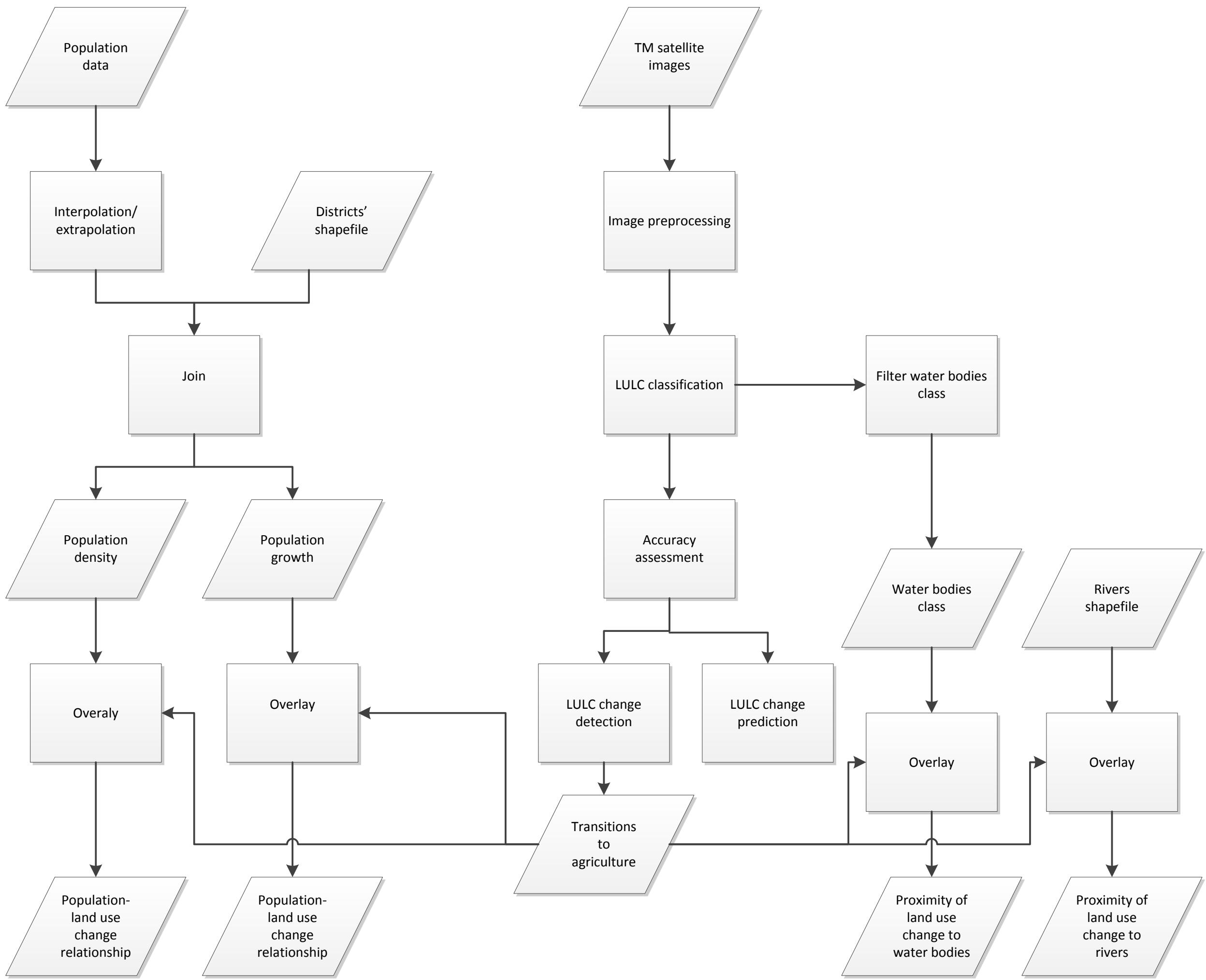

Figure 3.2 Flow chart of a methodology

3.3. Image preprocessing

Level 1T images were used, which are systematically processed for radiometric and geometric accuracy using ground control or elevation data. In addition, DEMs were used for topographic accuracy and to prevent distortions in the images (USGS, 2013). Radiometric correction was conducted on the mosaicked image by removing haze in ERDAS. Further correction was done using ATCOR software. ATCOR is one of the most popular commercially available atmospheric correction codes for land imagery (Lu et al., 2011). It removes the effects (e.g. bi-directional reflectance) of solar illumination and viewing geometry of different sensors by way of normalizing the data to nadir reflectance values with its sensor-specific atmospheric database look-up tables. ATCOR also removes the atmospheric and topographic effects using its physical model which is advantageous for multi-temporal data (Richter and Schlapfer, 2013). Figure 3.2 shows the image after atmospheric/radiometric correction. Though the image for 1994 shows some cloud coverage, it was the best mosaic available for this area and period. However the majority of cloud coverage was outside of the watershed.

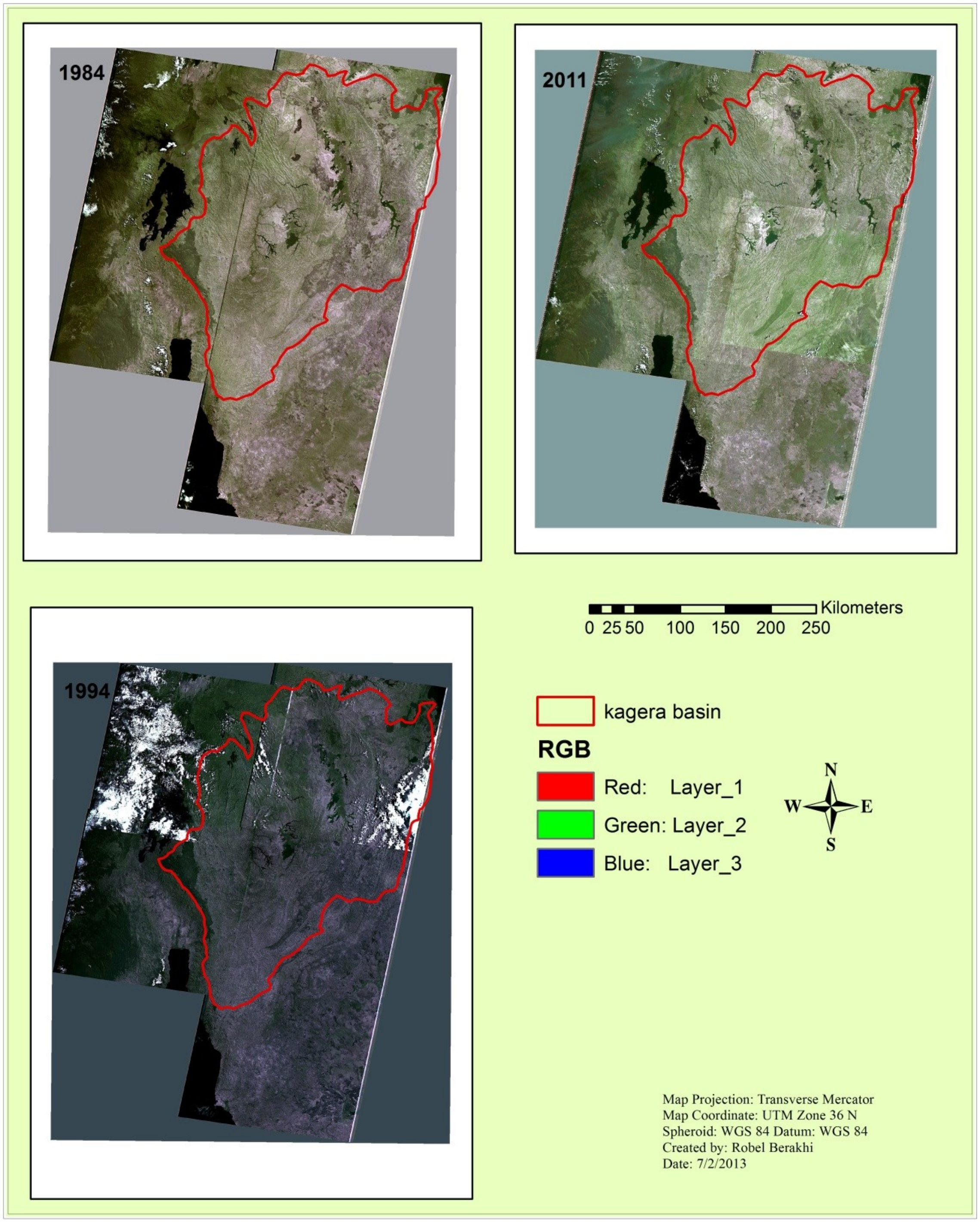

Figure 3.3 Mosaicked Landsat images after radiometric correction and haze reduction

3.4. Land use and Land cover classification and accuracy assessment

Classification of remotely sensed data uses image processing software, and for this study ERDAS IMAGINE 2011 version 11.0 was used. Once the images were classified, the newly classified maps were evaluated for classification performance using an error matrix.

3.4.1. Image classification

For this study, the USGS classification system was used. This is a widely used general-purpose LULC classification system (Campbell, 2007). The system is a reasonable and enduring classification scheme which allows interpretation of features from remotely sensed images (Lillesand et al, 2008). Having images with a resolution of 30, the more generalized level I classification system was used for this study. Anderson et al., (1976) mentions that this is more appropriate for nationwide information gathering and designed for use with Landsat satellite data. In other words, it is applicable to images having a resolution of 20 to 100 (Lillesand et al, 2008).

Based on the combination of ancillary data (a thematic reference map and high resolution Google earth photography), literature provided, close visual inspection of remotely sensed data, and the local knowledge of Dr. Oyana; five easily identifiable broad classes were identified (Table 3.2). Detailed land cover classes could not be completed due to limitations in the data. However, these broad classes give a general trend or dynamics of LULC at the scale of the study area. Also, urban areas could not be classified due to their very small size and spectral similarity with woodland savanna. As a result, they were not included in the interpretation of land cover dynamics. The woodland and savannas were categorized into one as it was difficult to differentiate between the two using the data provided.

Table 3.2 Land use and land cover classes

ID	Class Name
1	Forest
2	Water bodies
3	Wetland
4	Woodland Savanna
5	Agriculture

Different methods are available for classification and choosing a method depends on the resolution of the image and availability of classification software, among many factors (Lu et al., 2011). For this study a supervised approach was used. In supervised classification, known representative training areas are picked by the image analyst to describe the spectral attributes of each feature type of interest (Lille sand et al. 2008). A Minimum distance algorithm (a traditional Per pixel classifier) was used for the classification of the images. Lu et al (2011) mention that spectral information is important in medium resolution images as there is a loss of spatial information, and parametric classification algorithms are often used if imagery is spectral based.

Guided by the ancillary data, spectral signatures were acquired to train the classification through visual interpretation of the satellite images (notable classes as lakes, wetland and forest) and local/expert/interpreter knowledge of area. This information was coupled with temporally invariant land cover types (e.g. national parks) and high resolution Google imagery. The Area of Interest (AOI) tools (such as a polygon) and Seed Growing tool in ERDAS IMAGINE were used in acquiring the signatures.

After supervised classification of the images, the next step involved recoding of land use covers and further modification. Ancillary data (thematic map and Google high resolution photography), visual interpretation of the satellite image in comparison to thematic maps, and knowledge of the area were integrated to improve the accuracy of the land cover maps. Modification of land use cover is one of the processing roles after classification (Lu et al., 2011). The next step was the removal of the "salt and pepper effect". The salt and pepper effect is the result of a spectral signature-based, per pixel classification of a complex or heterogeneous landscape. Often a majority filter is used to reduce this effect (Lu et al., 2011; Lillesand et al., 2008).

The Kagera study area covers a large area with complex land forms and will inevitably have noise due to LULC cover and classification. A 15 x 15 thematic pixel aggregation tool in ERDAS IMAGINE was used to reduce this noise by down sampling so as to be comparable to the reference thematic map for accuracy assessment. Areas for each category for the three years were then calculated using ArcGIS 10.

3.4.2. Accuracy assessment

A quantitative approach to accuracy assessment based on sampling strategy was used in this study. Accuracy assessments measure how close an image of unknown quality is to a standard image assumed to be correct (Campbell, 2007). An error matrix is the most commonly used method, with its assessment elements including overall accuracy, omission error, commission error, and kappa coefficient. Generating this requires, among other things, the consideration of sampling size, sample unit, and the collection of reference data (Lu et al, 2011; Lillesand et al 2008). A random stratified distribution parameter was used to circumvent the problem of under sampling of smaller classes associated with random sampling (Lillesand et al, 2008). In total, 350 pixel samples were used in the accuracy assessment of the classified images of 1984, 1994 and 2011, and scanned thematic maps of 1985, 1995 and 2010 were used as reference data. Each of the 5 categories was used as stratum to generate the random sampling points. 50 random points were used for each forest, water body, and wetland as they represented smaller proportions of the watershed. 100 random points were generated for each woodland savanna, and agricultural area as these represented larger proportions of the watershed area. Lillesand et al. (2008) recommend as a general guideline that a minimum of 50 samples per category be used in error matrix, and 75 to 100 samples per category if an area is more than one million acre, or has a large amount of vegetation.

During the accuracy assessment, pixels that fell on or near the boundaries of the LULC class or watershed were removed to lessen the influence of potential registration errors. Using ERDAS IMAGINE 2011, the pixel class values for reference data were put in the accuracy assessment table and finally, an assessment report was generated.

3.5. Post-classification analysis

After the image was classified for each year, the change in LULC was assessed for the period of 1984-2011 and a future trajectory was computed in IDRISI. Since detailed land cover trajectory was one of the objectives, and geometric correction of the images was not possible, a post classification change detection method was used. Post classification change detection provides a complete matrix of change directions, and bypasses any registration, radiometric and atmospheric errors (Singh, 1989).

3.5.1. Past land cover change analysis

To analyze the changes that had occurred for the period of 1984-2011 in the Kagera basin, the change analysis tab of land change modeler and CROSS TAB GIS analysis operation of IDRISI Selva were used. Contributors to the change experienced by each category were investigated using the change analysis tab, the gain and losses by each category, and the net change experienced by each category. Furthermore, the change map option was used to provide spatial distribution of the changes (*from-to*). The CROSS TAB was also used also calculate the frequency of the pixels for each category by comparing two images to provide a *from-to* analysis. For ease of analysis, the frequency of pixels was converted to hectare units.

3.5.2 Major land cover transition

After the past land cover categories were analyzed, the dominant land cover transition for the period of study was chosen to map the land cover transition using IDRISI's Land Cover Modeler. Next, the raster images from IDRISI showing the transition were over laid with population maps (per district) of the watershed. This was done to see the relationship between population change and land use change (the dominant land use change of the watershed)

3.5.3. Land use and cover change prediction

In order to further estimate land cover transition, a Markov chain analysis in the Markov module of IDRISI Selva was implemented. The Markov model predicts the state system at time 2 based on state system 1 (Eastman, 2012). The predictive model in IDRISI (Markov module) considers previous land cover changes between two cover maps as input to produce a transition probability matrix showing the likelihood of each category to change or remain the same in the next period (Eastman, 2012). In turn, it uses the probability matrix to produce a transition area matrix which shows the quantity (in number of cells, hectares, etc.) that is expected to change. For this study, the classified images of 1984 and 1994 were used to predict LULC change in 2011 and this was compared to the actual land use calculated from the classified map to validate the prediction. Once it was validated, a prediction for the year 2020 was done using the transitions between 1994 classified image and 2011 classified image as well as the transitions between 1984 classified image and 2011 classified image.

3.5.4. Land cover-population relationship analysis

In this section, the population cover relationship was analyzed. In doing so, three transition maps were prepared for three periods (1984 to 1994, 1994 to 2011, and 1984 to 2011) using the IDRISI land cover change modeler. The population map was prepared by joining the population data to each district shapefile falling within the watershed. Selection by location and overlaying was used in the analysis of population-cover analysis.

CHAPTER 4

RESULTS

The results are organized in two sections. The first section shows the result of the classification after the Landsat images of the three years have been preprocessed. The second section presents the observed changes between the three temporal periods.

4.1. Image classification and accuracy assessment

The results of the classified images depicted and quantified the LULC categories in the Kagera watershed. Moreover it gave a generalized and preliminary view on the changes that occurred. The accuracy assessment showed an overall good classification for the classified images.

4.1.1. Land use and land cover

Based on the table (Table 4.1.), the largest LULC categories were agriculture and woodland; both covering almost 90% of the watershed in all the study years. Forest, water bodies, and wetland accounted for the rest of the land use and cover in the watershed. The dominancy of agriculture and woodland savanna is also evident from the classified images (Figure 4.1)

Looking at the pattern or distribution of the land use cover categories, the classified images show that woodland savanna is a major land cover type on the eastern part of the watershed along with the major permanent wetland. Agriculture was found to be consistently dominant in the central and western part of the watershed for the study period. The major dense forest (Nyungwe forest) found in the western lower part of the watershed and other smaller patches of dense forest are located in the northeastern part of the watershed

Change in LULC for the period of 1984-2011 is also visually evident. This also can be verified from the dynamics observed in terms of the proportion (area) of the land use categories shown in the table. The agriculture and the woodland savanna categories showed major changes. Specifically, agriculture increased at the expense of woodland savanna. Water and wetland showed insignificant change or fluctuation. The general change observed exhibited a southward pattern of agriculture expansion.

Table 4.1 The areas and proportions of each land use and land cover category of the Kagera basin for each study year.

Land cover classes	1984 (ha)	%	1994(ha)	%	2011(ha)	%
Forest	341556.75	5.37	364824	5.74	360713.25	5.67
Water bodies	109329.75	1.72	127190.25	2	105138	1.65
Wetland	255069	4.01	247900.5	3.9	254461.5	4
Woodland Savanna	2778219	43.7	2271969	35.74	1990332	31.31
Agriculture	2873434.5	45.2	3345725.25	52.63	3646964.25	57.36
Total	6357609	100	6357609	100	6357609	100

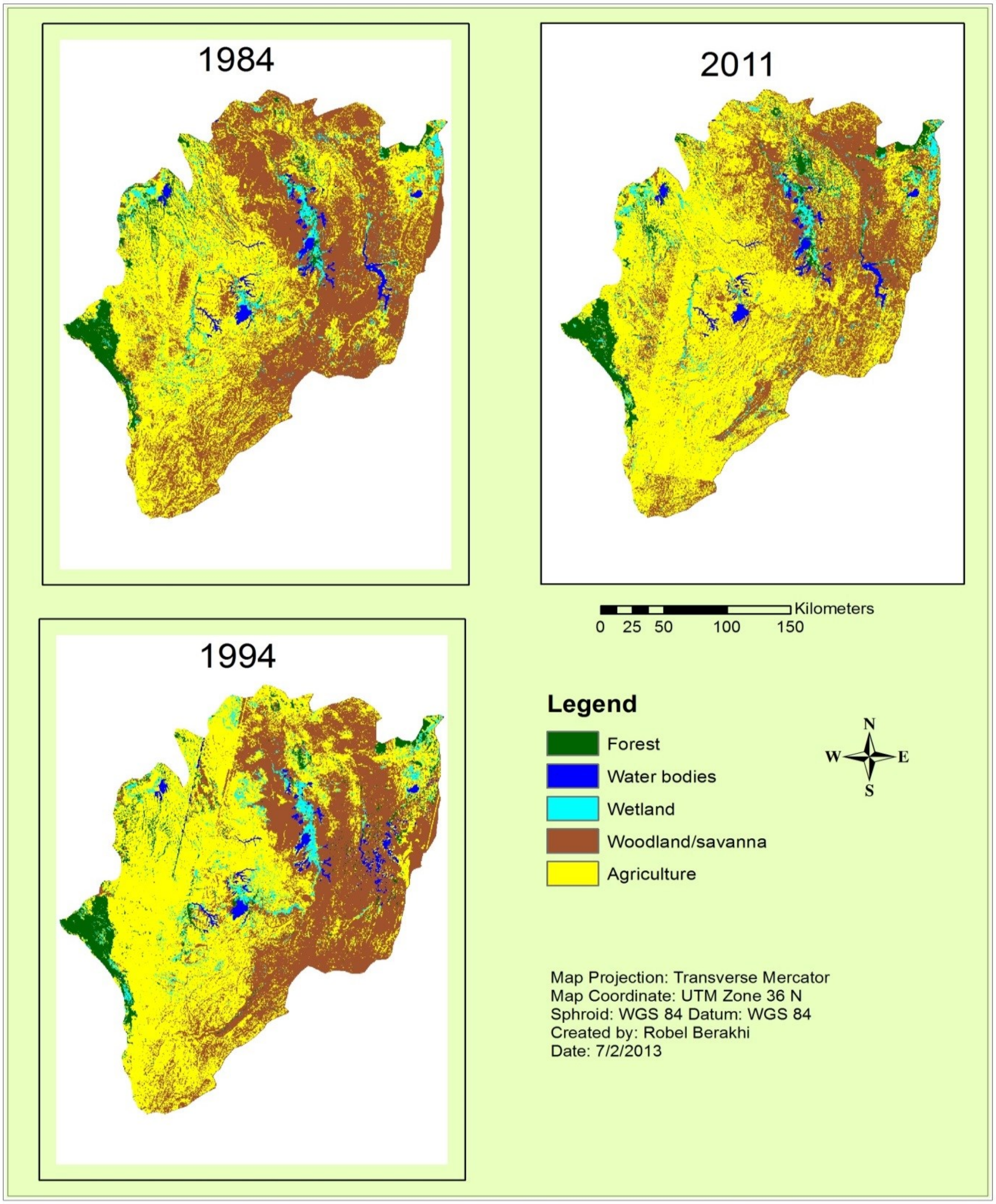

Figure 4.1 The land use and land cover classification of Kagera basin for the years 1984, 1994 and 2011.

4.1.2. Accuracy Assessment

This section presents the evaluation of classification performance for the classified images of 1984, 1994, and 2011. The error matrix for each year is shown along with measures of accuracy. For each class the producer's accuracy, user's accuracy, overall accuracy, kappa coefficient, and the overall kappa value is calculated. A stratified random sampling design and 350 pixel sample units were used during the accuracy assessment.

For the 1984 classified image, water bodies showed a100% accuracy in classification (Table 4.2). Forest, wetland, woodland, savanna, and agriculture all showed both commission and omission error. A number of pixels of forest and wetland were misclassified as wetland, agriculture and forest. As for woodland, savanna, and agriculture, the majority of the pixels were misclassified to one another. This is has to do with spectral similarity of agriculture, wetland and agriculture.

Table 4.2 Error matrix of 1984 classified image

	Reference Data						
	Class names	Forest	Water bodies	Wetland	Woodland savanna	Agriculture	Row total
Classified Data	Forest	**38**	0	8	0	4	50
	Water bodies	0	**50**	0	0	0	50
	Wetland	3	0	**38**	4	5	50
	Woodland savanna	0	0	1	**80**	19	100
	Agriculture	2	0	2	14	**82**	100
	Column total	43	50	49	98	110	350

Looking at the accuracy measurement for 1984 (Table 4. 3), an overall high classification accuracy of 82.29% and overall Kappa statistic of 0.77 (which is near the borderline of good classification performance) was achieved. The Kappa statistic indicates that the1984 classified image is almost as accurate as the other classified images. There was a slight difference in the Kappa value between the classified images, with 1984's being the smallest and 2011's being the highest.

A further look at the distribution of error among each category is examined from a producer's and user's perspective and Kappa value of each category. Forest, water bodies, and woodland savanna have a high producer's accuracy of 88.37%, 100% and 81.63% respectively, whereas, wetland and agriculture showed a moderate classification performance of 77.5% and 74.5%, respectively. On the other hand, the user's accuracy for water bodies, woodland savanna, and agriculture was high (100%, 80% and 82% respectively) whereas, forest and wetland showed moderate classification of 76% each. Generally, water bodies and woodland savanna showed good accuracy from both perspectives. The kappa value of water bodies showed good classification performance and moderate performance of the rest.

Table 4.3 Accuracy totals and Kappa Statistics result for 1984 classified image

Class name	Producers Accuracy (%)	Users Accuracy (%)	Kappa Statistic
Forest	88.37	76	0.73
Water bodies	100	100	1

Table 4.3 (Continued)

Wetland	77.55	76	0.72
Woodland Savanna	81.63	80	0.72
Agriculture	74.55	82	0.73

Overall classification accuracy = 82.29%   overall kappa statistics = 0.77

Table 4.4 shows the error matrix for the 1994 classified image. From the user and producer perspective, the majority of pixels were misclassified between woodland/savanna and agriculture. Generally, forest and wetland were also misclassified as wetland, agriculture and forest.

Table 4.4 Error matrix of 1994 classified image

	Reference Data						
	Class names	Forest	Water bodies	Wetland	Woodland savanna	Agriculture	Row total
Classified Data	Forest	**37**	0	9	2	2	50
	Water bodies	0	**40**	0	5	5	50
	Wetland	2	0	**41**	3	4	50
	Woodland savanna	0	0	1	**84**	15	100
	Agriculture	0	0	1	10	**89**	100
	Column total	39	40	52	104	115	350

For the 1994 classified image, the overall classification was also high (83.14%) (Table 4.5). The overall kappa statistic (0.78) was also near the border line of good classification performance. There was a slight improvement in both accuracy measurements from the previous year's classification. The producer's accuracy of forest, water bodies, and woodland savanna was high; 94.87%, 100%, and 80.77%, respectively. Wetland and agriculture also showed a 78.85% and 77.39% producer's accuracy, respectively. This is near the borderline of good classification. From the user's perspective, all the categories showed accuracy over 80% except for forest, which showed a moderate classification performance of 74%. In general, woodland/ savanna and water bodies showed a high user's and producer's accuracy measurement. The kappa value of each category also shows that all had a moderate classification performance except for agriculture which showed a high classification kappa value of 0.84. Even though the kappa values of the categories showed moderate performances, it was close enough to the threshold of good classification in the case of water bodies, wetland, and woodland savanna.

Table 4.5 Accuracy totals and Kappa Statistics result for 1994 classified image

Class name	Producers Accuracy (%)	Users Accuracy (%)	Kappa Statistic
Forest	94.87	74	0.71
Water bodies	100	80	0.77
Wetland	78.85	82	0.79
Woodland Savanna	80.77	84	0.77
Agriculture	77.39	89	0.84

Overall classification accuracy = 83.14% overall kappa statistics = 0.78

The classified image of 2011 generally showed a similar confusion among forest, wetland, and agriculture based on the results observed from other years (Table 4.6). Also, agriculture and woodland savanna both showed that the majority of pixels were confused between them.

Table 4.6 Error matrix of 2011 classified image

	Reference Data						
Classified Data	Class names	Forest	Water bodies	Wetland	Woodland savanna	Agriculture	Row total
	Forest	**38**	0	6	3	3	50
	Water bodies	0	**50**	0	0	0	50
	Wetland	4	0	**35**	5	6	50
	Woodland savanna	0	0	0	**82**	18	100
	Agriculture	1	0	0	9	**90**	100
	Column total	43	50	41	99	117	350

The overall classification and kappa values for 2011 were 84.29% and 0.79, respectively (Table 4.7). These values indicate an overall high classification performance (0.79 is near the border of good classification) and showed slight improvement from previous years' classification. A look at the producer's accuracy tells that all of the categories classification performances were high (over 80%) except for the agriculture, which showed a moderate classification performance of 76.92%. User's accuracy for water bodies, woodland savanna, and agriculture, on the other hand, had a high accuracy of over 80% compared with forest and wetland in which moderate classification performance was observed. In terms of kappa values, water bodies (1) and agriculture (0.85) had good classification performance. Forest, wetland, and woodland savanna had a moderate classification performance of 0.73, 0.66, and 0.75, respectively.

Table 4.7 Accuracy totals and Kappa Statistics result for 2011 classified image

Class name	Producers Accuracy (%)	Users Accuracy (%)	Kappa Statistic
Forest	88.37	76	0.73
Water bodies	100	100	1
Wetland	85.37	70	0.66
Woodland Savanna	82.83	82	0.75
Agriculture	76.92	90	0.85

Overall classification accuracy = 84.29%   overall kappa statistics = 0.79

Looking at the entire research period, there was overall consistency in the LULC classification of the three periods. Each period exhibited good classification performance. This was supported in terms of close values of overall classification and overall kappa values.

A further comparison of accuracy assessment of all categories between the three temporal periods reveals that generally, the producer's accuracy for all categories for the entire study period showed consistent accuracy measures except for forest and wetland. The inconsistency observed for forest had to do with 1994's accuracy measurement. In 1984 and 2011 it was 88.37% but in 1994 it was 94.87%. There was an increase in forest from 1984 to 1994 and a decrease in 2011. This indicates that forest might have been underestimated in 1984 and 2011 and as a result, part of the changes detected can also be attributed to the differences in accuracies.

In terms of the classification performance, producer's accuracies of over 80% were observed for forest, water bodies, and woodland savanna across all the years; hence it had good classification performance as it implies the omission error was smaller. Agriculture had moderate classification performance for the entire period according to its producer's accuracy (74.55%, 77.39%, and 76.92%, for 1984, 1994 and 2011 respectively). Also wetland showed moderate classification for 1984 and 1994 and good classification performance in 2011 (77.55%, 78.85%, and 85.37%, respectively).

Regarding the user's accuracy, all categories in all the periods showed consistency except for water bodies in 1994, agriculture in 1984, and wetland in all years. The accuracy in 1994 was 80% for water bodies and 100% in other years. Agriculture was 82% in 1984 and in the other two years it was 89% and 90%. Wetland showed moderate performance in 1984 (76%) and 2011 (70%) and good performance in 1994 (82%). It showed more variability of the accuracy's measurement throughout the study period.

Looking at the classification performance from a user's perspective, water bodies, agriculture, and woodland savanna all had user's accuracy of over 80%. This implies there was less commission error or more than 80% of the pixels were identified correctly in the classified images. Both forest and wetland showed a moderate classification performance.

4.2. Land use and land cover changes in Kagera basin

This section provides additional insight into the changes that had occurred in the past and also gives projections into what the future scenario would look like for the Kagera basin.

4.2.1. Past land use and land cover changes

The results from the Change analysis tab of the IDRISI LCM are presented here. The outputs are organized for each temporal period in three sections based on the options given in the tab. The first section shows the overall gains and losses by land cover category. This gives a rapid quantitative assessment (Eastman, 2012). Cross tabulation is also presented to show the results in hectares.

The second section shows the net change experienced by each category. This is a result of taking the earlier land cover areas, adding the gains, and then subtracting the losses. This indicates whether a class showed an overall increase or decrease. The last section shows the contributors to the net changes by each land cover classes. Selected land cover results are presented in this section (Please refer to appendix A for the rest of the figures).

For each section the results are shown using different units: percentage change and percentage of area.

Percentage change = (number of pixels changed for a class / area of a class in the later land cover image) x 100

Area of percentage= (number of pixels changed for a class / total area of the land cover map) x 100

Looking at the three periods (from 1984 to 1994, from 1994 to 2011, and from 1984 to 2011), woodland savanna and agriculture have experienced the greatest change as shown by their gain from and loss to other land cover types (Figure 4.2). The comparison between these two categories reveals that agriculture gained a greater percentage of the basin than woodland savanna, and vice versa when considering the loss. The tables (Table 4.8, Table 4.9 and Table 4.10) show the corresponding results in hectare for the three periods. On the other hand, percentage of change (loss and gain) each category from their previous amount (Figure 4.2) shows wetland had the greatest change followed by forest during the three periods. This was because the biggest proportions of wetland was lost to and gained from agriculture, and this was higher than the proportion that remained wetland (Table 4.8, Table 4.9 and Table 4.10). Even though spectral confusion had a role in the result, this indicated encroachment of agriculture into wetland. Water bodies' high gain and loss (from 1984 to1994 and from 1994 to 2011), on the other hand, was mainly due to misclassification that was visually evident in the 1994 classified image (Figure 4.1).

However the net percentage changes (both in terms of basin area and base year amount) indicate major dynamics were observed for agriculture and woodland/savanna because they showed the highest net increase and decrease, respectively. Water bodies' high net gain and loss was due to misclassification of cloud to water in 1994, which increased the apparent size of the water bodies. The entire period (from 1984 to 2011) in fact showed small loss. Forest showed a net loss after 1994 but gained in area overall for the entire period of study .Wetland, on the other hand, indicated net loss for the entire period.

The results (net change and gains/losses) point to the fact that woodland savanna and agriculture showed the greatest dynamics. Therefore, looking at the contributors to the net changes of these two categories indicates both contributed largely to the dynamics of the other for three periods. Agriculture gained from woodland savanna which contributed to agriculture's net increase. Agriculture at the same time was the biggest contributor to the net decrease of woodland savanna by net gaining from it. A look at the cross tabulation (Table 4.8, Table 4.9 and Table 4.10) reveals the amount (in hectare) gained by agriculture from woodland savanna was higher than which was lost to woodland savanna. The rest of the categories combined contributed very little to the changes. The wetland, though very small, contributed positively to the net change of woodland savanna whereas water and forest contributed negatively in 1984-1994 period (i.e. woodland savanna lost area to both water and forest). An opposite effect was observed in the 1994-2011 period. The entire period, however, shows that forest was the only contributor to woodland savanna's net loss. In agriculture, other classes' contribution to agriculture was very small. Overall, the contributions from forest, water bodies and wetland were negligible compared to the contribution made by the woodland savanna and agriculture to each other. For figures showing the contribution to net changes of other classes refer to Appendix A.

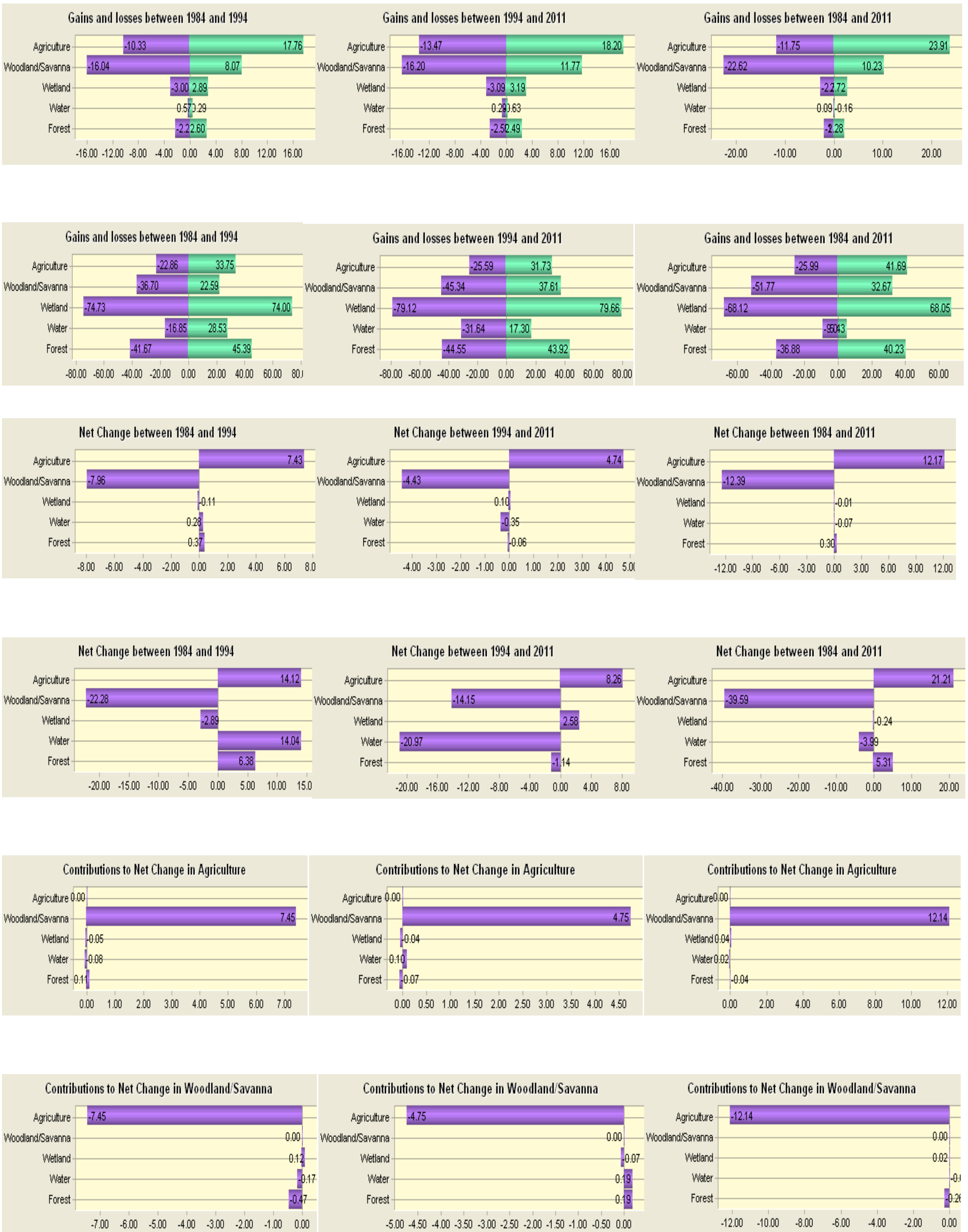

Figure 4.2 Gain and losses, net changes and contributors of each class for three periods

Table 4.8 Cross tabulation for the period between 1984 and 1994 showing gain and losses.

		1984						
	Class name	Forest	Water	Wetland	Woodland Savanna	Agriculture	**Total**	**Gain**
1994	Forest	**199240**	1802.25	38535.8	39244.5	86001.8	364824	**165584.3**
	Water	1518.75	**90902.3**	2835	22497.8	9436.5	127190.3	**36288**
	Wetland	38049.8	810	**64455.8**	33594.8	110990	247900.5	**183444.7**
	Woodland/ Savanna	9578.25	11745	41512.5	**1758713**	450421	2271969	**513256.5**
	Agriculture	93170.3	4070.25	107730	924170	**2216585**	3345725	**1129140**
	Total	341556.8	109329.8	255069	2778219	2873435	6357609	
	Loss	**142317**	**18427.5**	**190613.3**	**1019507**	**656849.3**		

Table 4.9 Cross tabulation for the period between 1994 and 2011 showing gain and losses.

		1994						
	Class name	Forest	Water	Wetland	Woodland Savanna	Agriculture	**Total**	**Gain**
2011	Forest	**202297.5**	3746.25	37077.75	23044.5	94547.25	360713.3	**158415.8**
	Water	1923.75	**86953.5**	708.75	11238.75	4313.25	105138	**18184.5**
	Wetland	35012.25	2389.5	**51759**	50847.75	114453	254461.5	**202702.5**
	Woodland/ Savanna	35437.5	23591.25	46696.5	**1241852**	642755.3	1990332	**748480.5**
	Agriculture	90153	10509.75	111658.5	944986.5	**2489657**	3646964	**1157308**
	Total	364824	127190.3	247900.5	2271969	3345725	6357609	
	Loss	**162526.5**	**40236.75**	**196141.5**	**1030118**	**856068.8**		

Table 4.10 Cross tabulation for the period between 1984 and 2011 showing gains and losses.

		1984						
	Class name	Forest	Water	Wetland	Woodland Savanna	Agriculture	**Total**	**Gain**
2011	Forest	**215601.8**	3564	36288	32035.5	73224	360713.3	**145111.5**
	Water	911.25	**99427.5**	870.75	2045.25	1883.25	105138	**5710.5**
	Wetland	38657.25	1944	**81303.75**	46554.75	86001.75	254461.5	**173157.75**
	Woodland/ Savanna	15531.75	1154.25	47911.5	**1340003**	585731.3	1990332	**650328.8**
	Agriculture	70854.75	3240	88695	1357580	**2126594**	3646964	**1520370**
	Total	341556.8	109329.8	255069	2778219	2873435	6357609	
	Loss	**125955**	**9902.25**	**173765.3**	**1438216**	**746840.3**		

4.2.2. Land use and cover change prediction

After the past land cover changes of Kagera were assessed, future land cover change was determined. First, prediction for the land cover change probability was done for 2011 from the land change transition of 1984 to 1994. The output tables show both the probability matrix and transition areas matrix calculated in hectares for 2011. The probability matrix (Table 4.11) shows the probability of a pixel from an earlier year changing or remaining the same for a given category (Eastman, 2012). This was used to predict the amount of each category expected in 2011. Results show that the probability of a pixel remaining the same is higher compared to the probability of a category changing. The exception to this case was for wetland. It showed a much higher probability (0.5) of changing to agriculture in 2011. The corresponding hectare value (127,595.3) in Table 4.12 shows that it is the greatest proportion of wetland that changed to agriculture. This change trend for wetland relates to the LULC change analysis (Table 4.8, Table

4.9 and Table 4.10) showing the highest proportion gain from and loss to agriculture. In the remaining categories, forest had a large probability of changing to agriculture, and woodland savanna had higher probability of changing to agriculture than agriculture to woodland savanna.

Table 4.11 The probability of change in 2011 based on the land transition between 1984 and 1994.

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Probability of change to	Forest	**0.4125**	0.0245	0.1501	0.0247	0.0447
	Water	0.0075	**0.7308**	0.0145	0.0119	0.0059
	Wetland	0.1107	0.0111	**0.1145**	0.0220	0.0445
	Woodland/ Savanna	0.0744	0.1525	0.2061	**0.4905**	0.2148
	Agriculture	0.3949	0.0811	0.5147	0.4509	**0.6901**

The prediction in terms of hectares (transition area matrix) for 2011 based on the transition between 1984 and 1994 was calculated from the transition probability matrix (Table 4.12). The transition area matrix predicts how much an area is expected to change (Eastman, 2012). The diagonals values show the amount in hectares of each category that did not change whereas the remaining numbers show the amounts lost to another category. The comparison between the amount that remained unchanged to the actual amount from the transition between 1994 and 2011(Table 4.9) shows that it was lower for all categories except for water. The transition from forest to water bodies and agriculture was overestimated, while the transition from forest to woodland savanna was underestimated. The conversion of water to wetland and the wetland that remained the same was considerably underestimated as well. Some extreme estimated values (over predictions) were observed for transition of woodland savanna to forest and agriculture, and also for transition of agriculture to forest and water. The estimations from agriculture to wetland and woodland savanna, and woodland savanna to water were higher than actual calculations. The remaining classes were fairly close to the actual values. Overall, the Markov chain model was effective.

Table 4.12 The amount expected to transition in 2011 based on the land transition between 1984 and 1994

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Expected to transition to	Forest	**150477.8**	3118.5	37219.5	56072.25	149607
	Water	2733.75	**92947.5**	3604.5	27114.75	19865.25
	Wetland	40398.75	1417.5	**28370.25**	49936.5	148736.3
	Woodland Savanna	27155.25	19399.5	51111	**1114398**	718672.5
	Agriculture	144058.5	10307.25	127595.3	1024468	**2308844**

The prediction for the year 2020 from two transition periods was also calculated (Table 4.13 and Table 4.14.). The results show the prediction based on the transition between the 1994 and 2011. For the year 2020, all categories can be expected to experience changes to other categories, but the greater proportions of forest, water bodies, woodland savanna, and agriculture will remain unchanged (Table 4.13). This is also supported by their calculated high probability to remain unchanged (Table 4.14). Wetland, on the other hand, has a low probability to remain unchanged and therefore will show changes. Looking at each categories transition, some forest will likely change to agriculture, to wetland, and a small amount to woodland savanna. Water bodies are likely to change to woodland savanna. The probability of wetland changing to agriculture is higher than the probability of wetland remaining the same. As a result, Table 4.15 shows a bigger proportion of the wetland will be lost to agriculture and some will be converted to forest. Both woodland savanna and agriculture will retain bigger areas, but will lose some area to each other. Only a few portions of agriculture will transition to forest and wetland.

Table 4.13 The amount expected to transition in 2020 based on the land transition between 1994 and 2011

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Expected to transition to	Forest	**251059.5**	2146.5	39912.75	2470.5	66440.25
	Water	1336.5	**85009.5**	425.25	7431.75	1397.25
	Wetland	36045	1478.25	**78185.25**	31752	109998
	Woodland Savanna	18589.5	14762.25	38353.5	**1310297**	533506.5
	Agriculture	53682.75	1741.5	97584.75	638381.3	**2935622**

Table 4.14 The probability of change in 2020 based on the land transition between 1994 and 2011

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Probability of change to	Forest	**0.6960**	0.0204	0.1568	0.0012	0.0182
	Water	0.0037	**0.8086**	0.0017	0.0037	0.0004
	Wetland	0.0999	0.0141	**0.3073**	0.0160	0.0302
	Woodland Savanna	0.0515	0.1404	0.1507	**0.6583**	0.1463
	Agriculture	0.1488	0.0165	0.3835	0.3207	**0.8050**

The next two tables show predictions for 2020 calculated from the transition of the entire period (1984-2011). The amount (in hectares) in Table 4.15 shows that most of the forest, water bodies, wetland, agriculture, and woodland savanna will remain essentially unchanged. That is shown in table (4.16) by their higher probabilities to remain unchanged. Few portions of the forest will change to wetland and agriculture. Wetland is also predicted to change to agriculture, woodland savanna, and forest. On the other hand, agriculture and woodland savanna will lose area to each other. There is also the possibility of agriculture changing to wetland and forest.

Table 4.15 The amount expected to transition in 2020 based on the land transition between 1984 and 2011

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Expected to transition to	Forest	**294880.5**	1478.25	32116.5	0	41411.25
	Water	344.25	**101817**	526.5	526.5	567
	Wetland	34769.25	1032.75	**131726.3**	10287	79197.75
	Woodland Savanna	0	141.75	37219.5	**1267832**	534762
	Agriculture	30719.25	648	52872.75	711666	**2991047**

Table 4.16 The probability of change in 2020 based on the land transition between 1984 and 2011

Class name		Given				
		Forest	Water	Wetland	Woodland Savanna	Agriculture
Probability of change to	Forest	**0.8175**	0.0141	0.1262	0.0000	0.0114
	Water	0.0010	**0.9684**	0.0020	0.0003	0.0002
	Wetland	0.0964	0.0098	**0.5176**	0.0052	0.0217
	Woodland Savanna	0.0000	0.0014	0.1463	**0.6370**	0.1466
	Agriculture	0.0852	0.0062	0.2078	0.3576	**0.8201**

4.3. Population growth

The figure below shows the population growth from 1984 to 2011 (Figure 4.3). This is the total population of the Kagera basin aggregated from each administrative region of the four countries. Obviously, the population of Kagera shows an increasing trend. A further look at the four individual countries' populations within the basin shows Rwanda and Burundi have higher populations compared to Tanzania and Uganda (Figure 4.4). This is because the highest numbers of districts in the watershed are found within Burundi and Rwanda. Generally, Rwanda's and Burundi's districts also have higher densities in the Kagera basin (Figure 4.7).

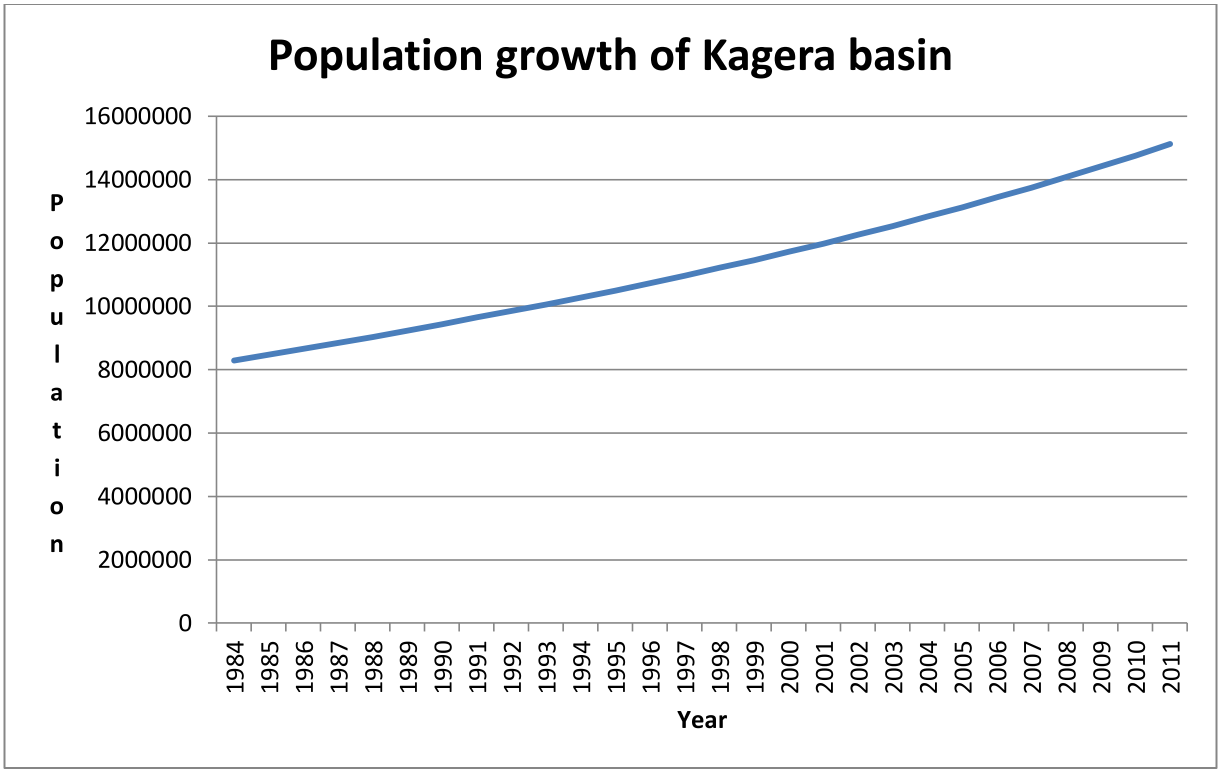

Figure 4.3 Total population of Kagera basin for the period between 1984 and 2011

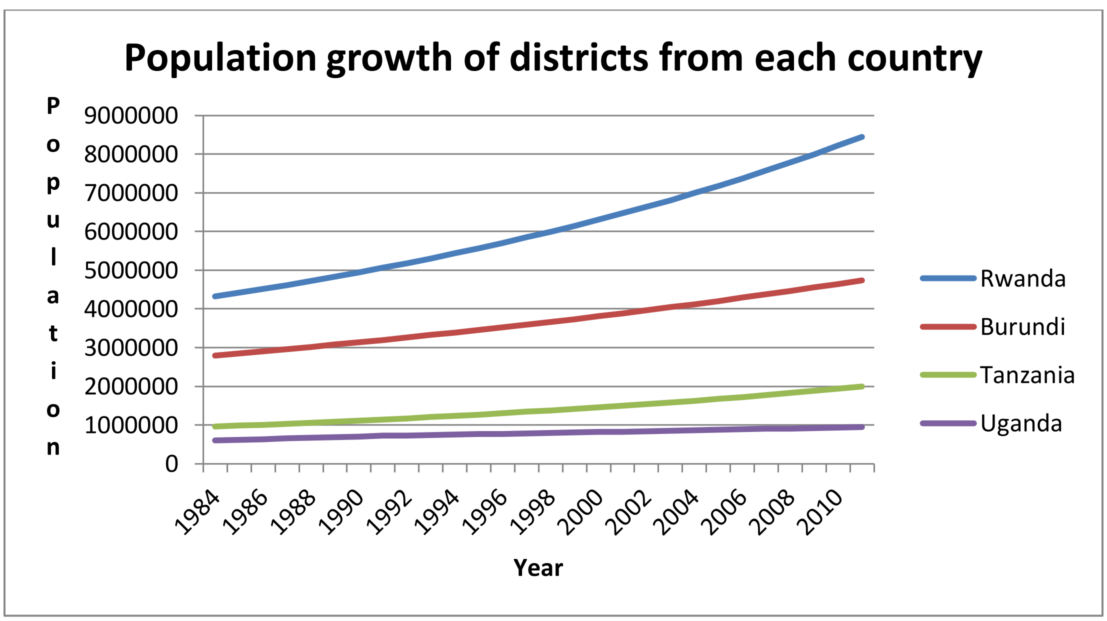

Figure 4.4 The population in each country in the basin

The population density shows that almost all areas of Rwanda and Burundi in the basin have higher densities. Uganda also shows some districts with higher densities. This is consistent throughout the study period and that also explains the dominancy of agriculture in this portion of the basin for the entire period of the study.

However the interpretation of the population should be taken with caution as this study was not focused on population. A rough estimate of the population was done with limited census data of the districts to obtain a general trend of the population growth in this region. The figures below (Figure 4.5. and 4.6.) show better modeling to predict the population

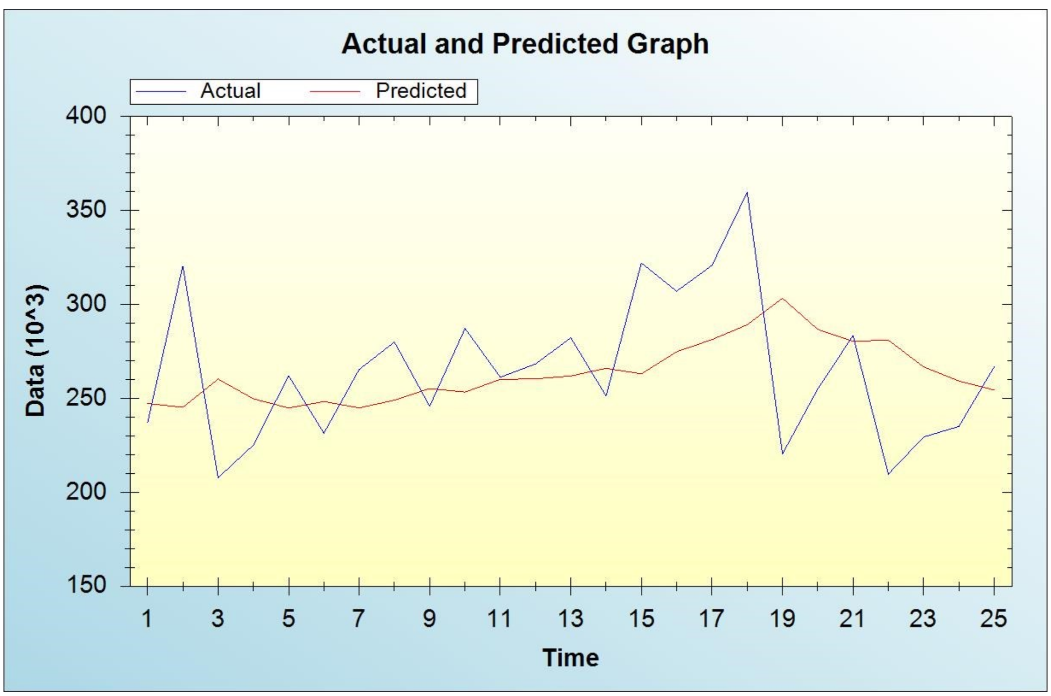

Figure 4.5 Actual and predicted population for the year 2002 for Rwanda

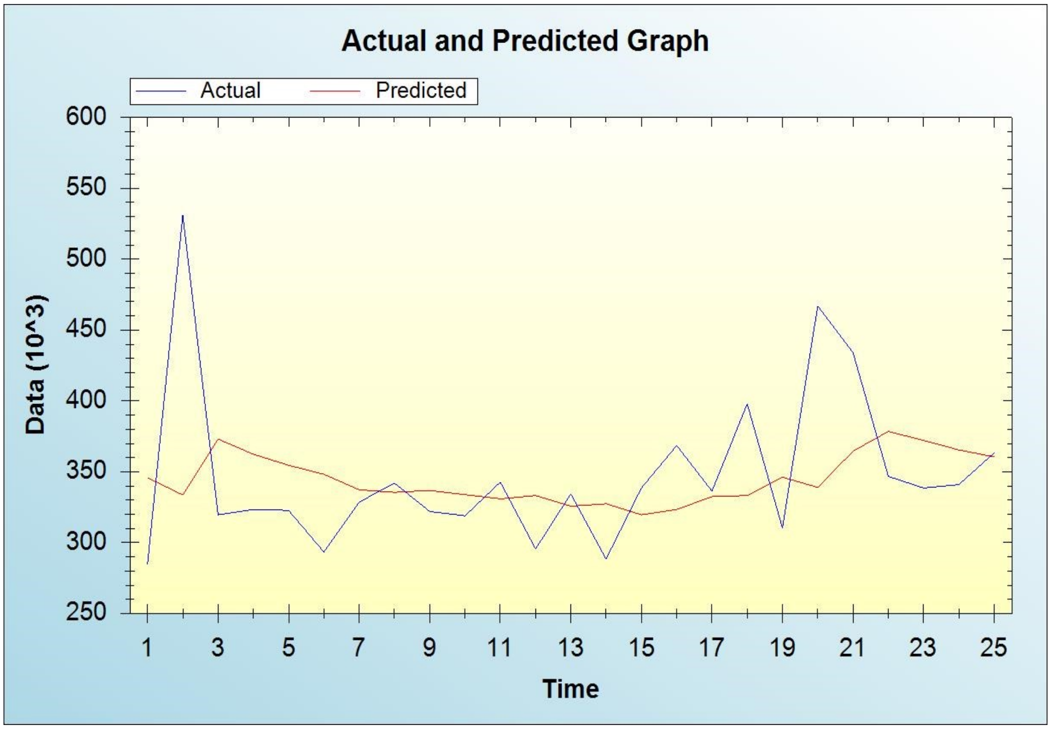

Figure 4.6 Actual and predicted for the year 2012 for Rwanda

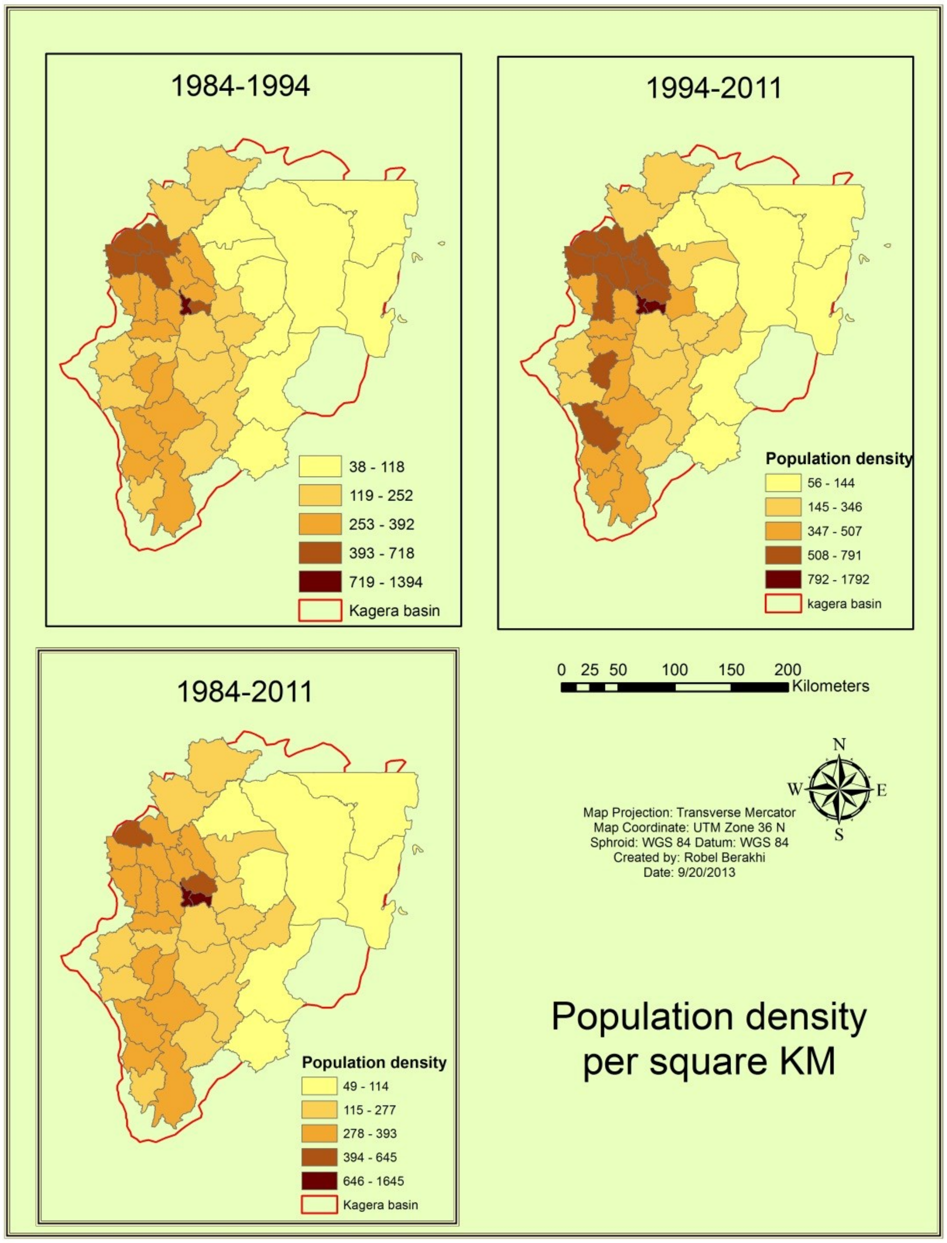

Figure 4.7 Population densities of the districts within the Kagera basin

4.4. Population change and Land use patterns

The three periods (1984, 1994, and 2011) LULC analysis showed that the major changes observed were between agriculture and woodland savanna. Both were the major contributors to the net changes of the other, more than the rest of LULC categories. Agriculture showed a net gain at the expense of woodland savanna (i.e. the net decrease of the woodland savanna was primarily due to its conversion to agriculture). Comparing the loss and gain between agriculture and woodland savanna, the gain of agriculture from woodland savanna was consistently much higher than woodland savanna's gain from agriculture. Therefore the transition to agriculture cover category was chosen to analyze its relationship with population change at an administrative/district level.

Figure 4.8 shows high and low population density districts. A similar spatial pattern is observed for the three time periods. The districts with low population density (20 percentile) are located in the western part whereas the districts with high population densities (80 percentile) are in the north western part of the watershed. Figure 4.7 also shows that higher population densities are located mainly in the Rwanda and Burundi portion of the watershed. Major conversion to agriculture had occurred in high population density districts from the beginning of the study period. Thus, most transitions occurred in the low population density districts which had primarily consisted of woodlands savanna.

Population change was analyzed for the three time points (Figure 4.9). Districts in the 20% percentile had population change ranging from 13% to 43% during the study period (1984-2011). Six of them were located in the northwest, one in the northeast, and another one in south of the Kagera Basin whereas the districts in the 80% percentile had population change ranging from 173% to 412%. The districts with high population change are found at the center of the watershed, mainly in Rwanda close to the border with Tanzania. A similar spatial pattern was also observed for the other two time periods (1984-1994 and 1994-2011). These two time periods are also shown. The highest population change range was from 45% to 83% and from 88% to 179% for the periods of 1984-1994, and 1994-2011, respectively. Their corresponding low population change range was from 2% to 15 % and from 8% to 25%. Notably, most transitions occurred within the districts where there was high population change as compared to those areas with low population change districts.

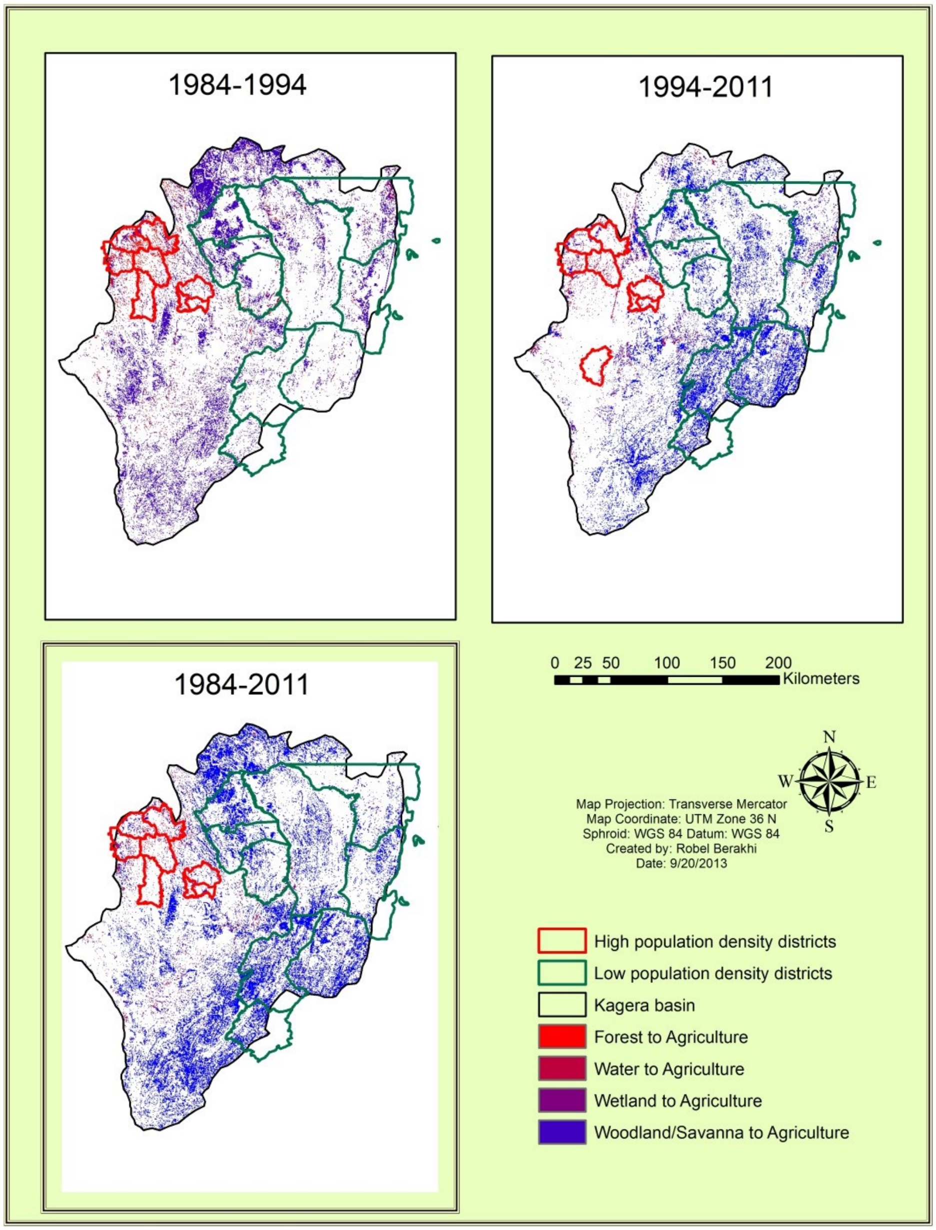

Figure 4.8 High and low population density districts and the Land use and cover transitions

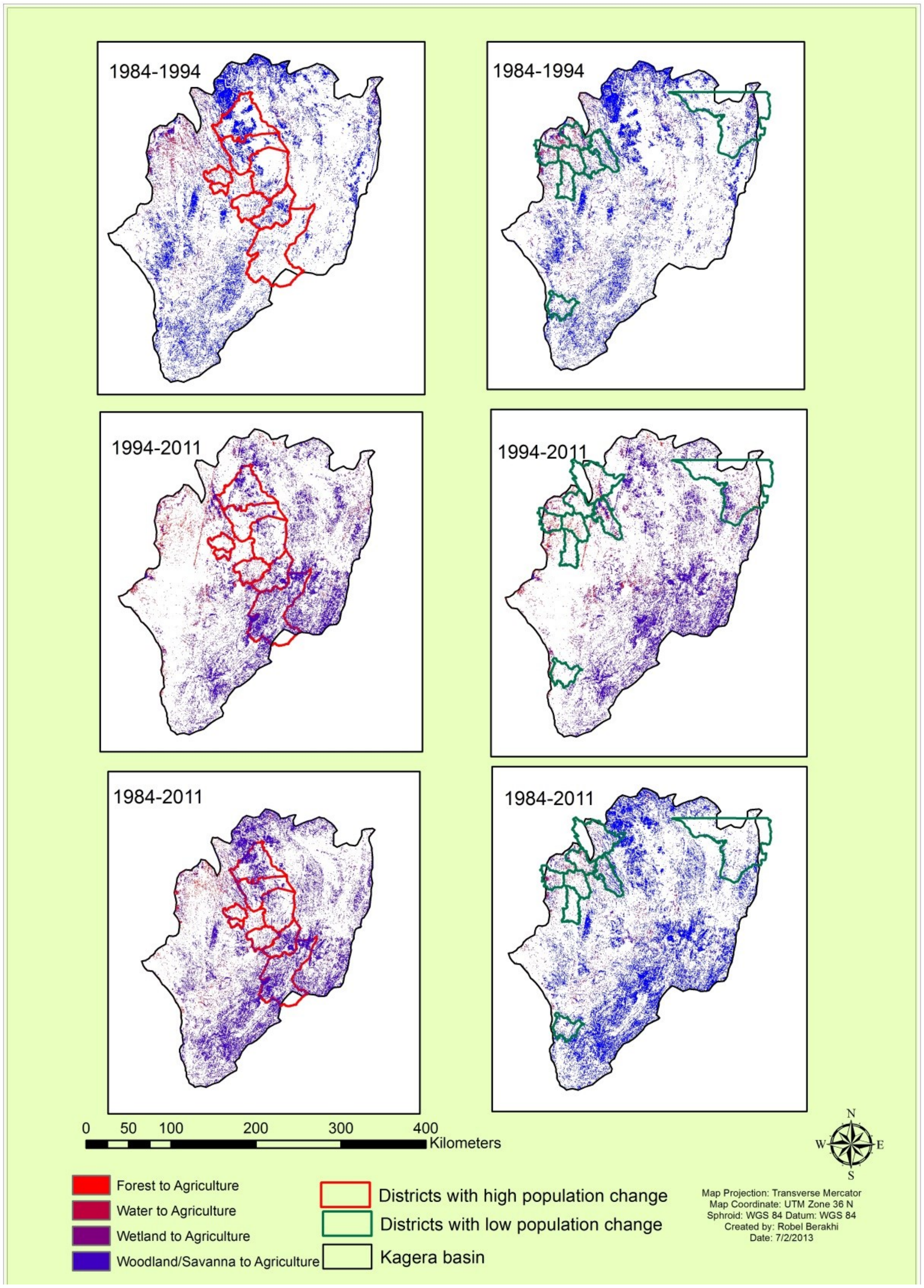

Figure 4.9 Land cover transitions for the three periods and districts with high and low population change

4.5. Land cover transitions and Hydro-geographical zones

The figure below (Figure 4.10) shows that transitions to agriculture in close proximity to water bodies. Woodland savanna cover in 2011 was dominant throughout the West Victoria Lake region, and Swamp and Lake Terrain region. The changes (transitions) during the study period are observed in the hydro geographical zone, Hill/Mountains Ridges, and Swamp and Lake Terrain region. Most transitions in the hydro-geographical zones are observed in close proximity to rivers. Agriculture has been dominant in the Congo Nile Divide and Hills and Mountains Foot Ridges (located mainly in Rwanda and some portion of Burundi) which will be further discussed in section 5.2.3.

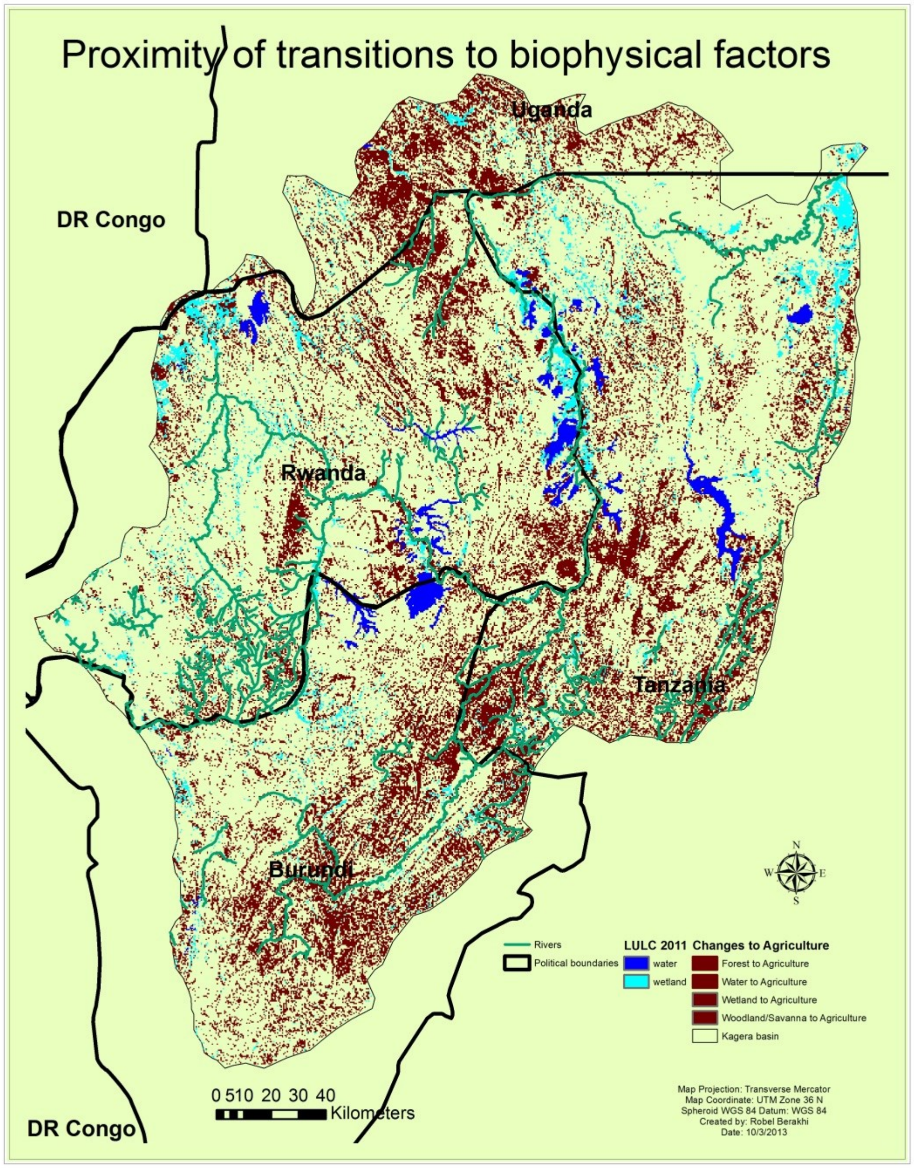

Figure 4.10 Hydro geographical zones of Kagera in relation to the land cover transition (Source: NBI, 2008)

CHAPTER 5

DISSCUSION AND CONCLUSION

5.1. Image Classification and analysis

Based on the availability of data and the rendered capability of discriminating cover types, five major classes were identified for the Kagera region for the study period between 1984 and 2011. The key findings from the image classification showed that agricultural activities were the dominant land use change followed by woodland savanna cover type. Both occupied nearly 90% of the watershed area for all three years under the study. The remaining 10% was occupied by the water bodies, wetland, and forest. Among these, forest was the dominant and water bodies occupied ≥ 2% of the watershed. These results are consistent with studies conducted in this region indicating a similar pattern (Wasige et al., 2013; Tolo et al., 2012). Features in the basin that were easily identified included Nyungwe Forest National Park (West), Ruvubu National Park (South East), Akagera National Park (North east). These parks were established in the early 1930's with Ruvubu being the earliest (1980). The lakes in the region that were consistently identifiable were the Rweru, Cyohoha Sud, Burera, and the Ruhondo. There has been a persistent dominancy of cultivation in the central and western part of the watershed since 1984 (beginning of the study period) where the Rwandan and Burundi lie. Throughout the study they showed an eastward pattern of expansion. This dominancy may be explained by the region's high population density, mild climate, good soil fertility, and predominance of farmers among residents. Brink and Eva (2009) showed that agricultural expansion was the main phenomena observed in Sub-Saharan countries at the continental level. This result, in conjunction with previous studies, reaffirms the dominancy of cultivation at the regional level.

The accuracy assessment of the classified images was good despite observed inconsistences. An overall accuracy (above 80%) was achieved for the classified maps of 1984, 1994 and 2011. These accuracy levels were 82.29%, 83.14 % and 84.29%, respectively. The overall kappa value was moderately good as it showed a near 0.8 Khat value. The values were 0.77, 0.78, and 0.79 for 1984, 1994 and 2011, respectively. Water bodies and woodland savanna consistently had good performance (over 80%) for both perspectives (users and producers) in all three years. The only inconsistency observed in water bodies was in 1994 which exhibited an 80% user's accuracy compared to 100% for other years. This implies there was an overestimation or commission error, likely due to lack of a data for the interiors of water bodies. They were therefore automatically classified to water. The presence of cloud shadows in 1994 with the same spectral value (no data) associated with water led to misclassification of cloud shadows to water bodies. This resulted in overestimations and played a role in the changes observed in 1994. The inconsistency is noteworthy when the classified image and amount of hectare of 1994 is compared with the other two years' amount and classified images (Table 4.1 and Figure 4.1). For this reason, it is assumed that there were small or insignificant changes in 1994 for water bodies based on the amount in 2011. This is further supported by Wasige et al. (2013), whose study indicates no change in water for the area. Tolo et al. (2012) did note a slight increase for the period 1984-2002. It is possible that this is due to the effect of seasonal variations rather than long term changes. The same conclusion was made for water bodies by Brink and Eva (2009) during their study of the land cover changes for sub-Saharan countries.

Wetland overall showed moderate performance in both perspectives except for user's accuracy in 1994 and producer's accuracy in 2011.There were inconsistencies in wetland areas when comparing both measures in all years. This may be explained in part by the changes or fluctuations observed for this category. Forest, on the other hand, had consistently good producer's accuracy (over 80%) and moderate user's accuracy in all years. Agriculture had inconsistent user's accuracy, but consistently moderate producer's accuracy. It is possible that all of the observed inconsistencies played a role in the observed changes in their respective categories.

The accuracy assessment (section 3.4.2) for forest, wetland, and agriculture categories showed inconsistencies but also exhibited moderate accuracy. This was due to the confusion arising from spectral similarity between classes. Misclassifications between these categories were pronounced and visually evident during classification. This is due to the Kagera basin having a complex tropical landscape (Lu et al, 2011). Spectral similarities between classes may also be a source of the inaccuracies observed (Paiboonvorachat and Oyana, 2008; Were et al., 2013; Cabral et al., 2010; and Mundia and Aniya, 2006).

Interestingly, the classified images show an agricultural and savanna dynamic with the conversion of savanna woodland to agriculture and vice versa. This also might have had a role in the classification error for woodland savanna or agriculture. Similar problems were noted by Were et al. (2013) between grassland and crop land. A possible explanation for this dynamic in the Kagera is the practice of fallow, where land is left unsown for a period to restore fertility.

5.2. Implications of human activities on land use and land cover changes in Kagera

The key observations of the land cover and population analysis are as follows:

1. During the 28 year period, the most dynamic LULC change was agriculture followed by woodland savanna.
2. Future scenarios indicate that:

   i) The greater proportion of forest, water bodies, and woodland savanna will remain the same. Woodland savanna and agriculture will lose area to each other, with woodland savanna loss being bigger.

   ii) Forest also will change mainly to agriculture.

   iii) Wetland, on the other hand, will lose the biggest proportion to agriculture.
3. Potential driver factors indicated in the study include population change and population density.
4. Identified policy drivers factors in the study include:

   i) Oil price shocks that happened in the 1970's.

   ii) National policies as Ujama (of Tanzania).

   iii) Outside policy intervention as SAP (Structural Adjustment Policy).
5. Potential biophysical factors indicated were precipitation and proximity to water bodies.

The discussion is divided based on endogenous (demography) causes and underlying factors (such as globalization and structural policy interventions). Discussion on the biophysical factors influencing the LULC transition is also included.

5.2.1. Demographic factor

The results show that the predominant past and future change is in agriculture with future change consisting of forests converted into agriculture. This result is consistent with Henry et al.'s (2011) findings as the Kagera is shared by sub-Saharan countries. The researchers indicated that agriculture in sub-Saharan countries is the main source of income where a large percentage of the population is directly dependent on agriculture causing it to be one of the drivers of forest degradation. Indeed, the majority of the population in Kagera lives in rural areas and are directly engaged in farming and other activities (FAO, 2013).

The primary endogenous cause is population growth. In Rwanda and Burundi, the most influential factor has been population growth which mounted even more pressure on the available arable land. Lambin et al. (2003) mentioned resource scarcity and natural population growth as major causes of land use change in tropic areas, taking their toll over a series of decades. The populations of the countries sharing the Kagera basin are among the highest of sub-Saharan countries (NBI, 2008) with Rwanda and Burundi generally having the highest population densities (Figure 4.7 and Figure 4.8). This is persistent throughout the study period and parallels the agriculture dominancy in this area. This further confirms that population pressure had a high impact on the agricultural expansion.

The REMA (2009) report for the Rwandan portion of the basin notes that farmers have multiple and tiny scattered plots. The owned land by each house hold ranged from 0.7 ha to 0.2 ha. As a result, intensive cultivation with no fallow is practiced. The report further indicates the land scarcity problem is exacerbated by the cultural (inheritance) practice of dividing land among sons. Lambin et al. (2003) mention breakdown of extended family as one of the main causes of the land use change in tropics. Figure 4.9 shows the link between the population change at the district level within the Kagera basin to the land cover transitions observed for the entire period of study (from 1984 to2011). Results showed the high population districts were significantly falling into transition of land cover to agriculture. This also affirms the connection of population to the land cover dynamics observed in this area.

Moodley et al. (2010) conducted a study in three towns of Rwanda to investigate the causes and effects of the 1994 genocide on land cover. They attributed overpopulation (land scarcity) along with poverty and unemployment as facilitators in the recruitment of militia and ethnic tension rather than as causes. After the genocide, the attempt by the government to resettle people by making land more available had negative effects on forests and woodlands in Nyngwe and Akagera national forests (Moodley et al., 2010). This is consistent with LULC changes observed in this period as it showed an increase of agriculture at the expense of woodlands. Looking at the Akagera National Forest Park also reveals the same trend. Moodley et al. (2010) further specify that after the genocide, forests were cleared for their needs and resettlement purposes (forests and woodlands decreased), wetlands were converted to agriculture due to scarcity of agricultural land (through drainage, irrigation and reclamation), and there was an increase in subsistence agriculture in areas surrounding houses and on the outskirts of cities.

The largest contributor to agricultural change during the entire study period (in terms of hectare area coverage) for the entire basin was woodland savanna (Figure 4.8).On the other hand, in terms of probability of future and amount expected to transition, wetland showed high contribution (Figure 4.6). This could be a result of spectral similarity between agriculture and wetland. Forest decreased during the study period (Figure 4.6) which can be attributed to the 1994 genocide and its consequences of displacement, overpopulation, and scarcity of land. REMA (2009) report indicates that cultivated land in Rwanda in general, increased from 64.5% to 74% between 1984 and 2002, and this increase was mainly at the expense of pasture, fallow, and woodlots.

Similarly, Uganda's economy is heavily dependent on the agricultural sector as is evident in its high land usage (4,450 Sq.Km) and employment of 89% of the population living in rural areas (FAO, 2013). Uganda has been showing an upward trend in population and has one of the highest population growths (3.4%) in the world (FAO, 2013). The unregulated expansion of agriculture at the expense of forests, savannas, and wetlands can be partially contributed to population growth and low agricultural productivity (IFRI, 2002). Specifically, smallholder farmlands have been the dominant cause of land conversion in Uganda since the 1960’s, but most of the forest areas were cleared prior to that (IFRI, 2002). In addition to projected increases in the population (NBI, 2008), all of these endogenous factors have impacted the land use change, with agriculture at the fore-front.

5.2.2. Global macro-economic influences/implications

Land use change is mainly due to society's response to economic factors (Lambin et al., 2003). Undoubtedly the influence of the economic reform funded by the International Monetary Fund and the World Bank has been and will be a dominant driving force in Africa's economic policy (Loxley, 1990). This economic reform, known as the Structural Adjustment Program (SAP), was geared toward sustained economic growth of the developing nations by implementing economic policies (more market oriented) acceptable to the institutions supporting them (Mohan et al., 2000). SAP originated as a result of two major global economic crises (Figure 5.1) that influenced these developed nation's institutions. These include two major oil price increases imposed by OPEC (1973 and 1979/80) which led to a global economic recession and increased interest rates between 1973-80 and 1980-1986 that were spurred by the adoption of neo-liberal economic policies in western industrial nations as deflationary measures in response to oil price shocks (Mohan et al., 2000). Such oil price crises bring about macro-economic and trade conditions, or rapid changes that lead to changes in prices as a result changes in market opportunities. These changes often result in changes in land use (Lambin et al. 2003). The outcome of these crises was an increased demand on raw materials (stemming from a price boom for raw commodities) that initially proved beneficial to many developing countries. The appearance of SAP coincided with a time when many developing nations were experiencing rapidly deteriorating economies which led many developing countries to accept the program. These outside policy interventions from the IMF and World Bank likely exacerbated changes in land use (Lambin et al., 2003).

Most developing nations had adopted SAP by the 1980's (Mohan et al., 2000) as a precondition to receiving financial assistance or low interest subsidies. African countries were in economic crises in early 1980's due to the global economy crises of late 1970's. This was a result of reliance on export earnings in a deteriorating global economy which left them unable to pay back their debts (Kingston et al.2011). They accepted SAP funds with the broad agenda of a minimized role of the state, reducing taxes on high incomes, cuts in social spending or subsides, currency devaluation, price liberalization and increased privatization (Mohan et al., 2000; Kingston et al., 2011).

It is important to discuss Tanzania's SAP to shed light on the implication of the SAP for Burundi and Uganda, and Rwanda's SAP is important to discuss due to its unique history of genocide. Tanzania experienced changes in its socioeconomic/political sector before and after the adoption of SAP which had an impact on agriculture. From 1961-1980, Tanzania attempted to reduce its dependency on external economies and withdraw from international markets (Wobst, 2001). In 1967 (after independence in 1961), Tanzania passed an economic declaration (also called Ujamaa policy) which followed self-reliance, a state controlled socialist economy, price controls, nationalization, and instituted villagization which resettled 17 million citizens from scattered villages to larger villages with better access to markets (Wobst, 2001). The agricultural policy of this time was geared towards satisfying national food requirements through self-sufficiency. This had a detrimental effect on the resources which resulted in environmental degradation. The villagization and political interference further led to declining agricultural production and increased debt. The extremely overvalued exchange rate decreased the country's competitiveness, diminishing agricultural export earnings. Consequently, the trade deficit increased, foreign capital inflows decreased, and overall indebtedness reached critical levels

(Wobst, 2001). Enforcement was also poor because staffing was limited and fines were continually eroded by inflation. Indeed, state polices to attain self-sufficiency, price controls on agricultural inputs and outputs, and nationalization are institution factors mentioned by Lambin et al. (2003) as influential in land use change. Though some positive economic performance was achieved, the advance was short-lived as a result of two oil price shocks in 1973-1974 and 1979. The breakup of the East African Community in 1977 and the 1978 war with Uganda also contributed to the countries collapse (Wobst, 2001). From 1979 to 1986, with no aid from the IMF and World Bank, and a failed Stand by Arrangement with the IMF, Tanzania turned to SAP (1981) which emphasized increasing agricultural production, particularly for exports, to alleviate both food and foreign exchange shortages (Wobst, 2001). However, this did not result in any significant changes in Tanzania's economic performance because the government was reluctant to implement the policy measures (Wobst, 2001) resulting in more political and economic transitions and eventual outside policy intervention.

New reforms were enacted in 1986 and again in 1996. These programs were based on a free market economy with its main internal changes as domestic tax system (less tax on higher producers), infrastructure investment (especially to give impetus to rural agricultural development), devaluation of exchange rate (shilling was depreciated by 40%), increase in agriculture producer price by 46-55% (for food and export crops), and privatization (by deregulating investment and taking government control) (Wobst, 2001).

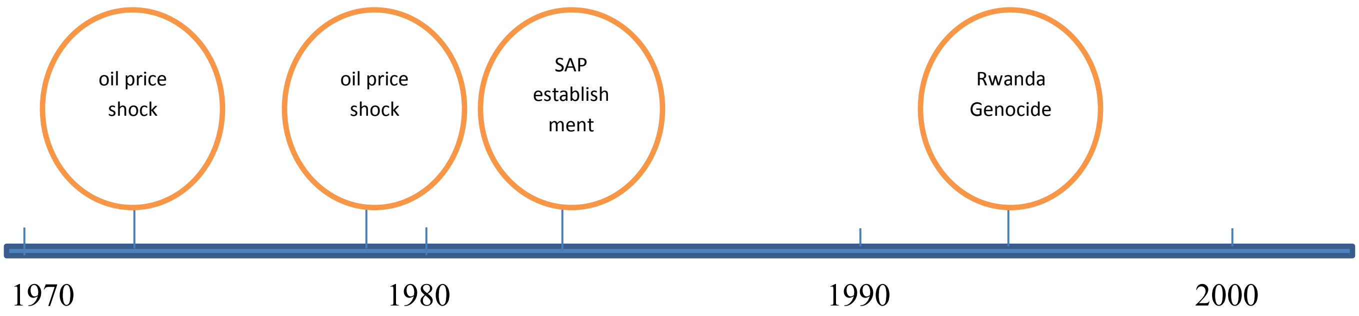

Figure 5.1 The major socioeconomic events

During the enactment of these new reforms, cultivated area increased in 47.5% of households due to either increased consumption or cash needs necessitating the clearing of more land and a shift in land area allocated from cash crops to food crops (Peters et al., 1994). This was due to SAP's favorable price and marketing system to food crops. Inputs were improved due to privatization, but availability was poor primarily because of high prices. In addition, marketing operations, after the partial abolition of state owned marketing boards, were also poor. This was due to poor organization stemming from the high cost of transportation and neglect of cooperatives under the SAP.

In Rwanda, the most important conflict occurred in 1994, leading to genocide. The cause of genocide was mainly due to socio-political factors. Colonial powers (Germany and Belgium) caused the division between the two ethnic groups in Rwanda serving as an underlying cause to the genocide (Moodley et al., 2010; Storey, 2001). This occurred through the manipulation of the hierarchal structure as a means to gain economic and political power (i.e. through a divide and rule strategy). Manipulation also continued through political powers after independence (Moodley et al., 2010). The implementation of SAP also deepened the situation (Storey, 2001 and Moodley et al., 2010). The support that Rwanda was receiving through SAP (from the World Bank and other entities) meant a discursive support for the Rwanda state, increasing available resources which led to repressive situation (Storey, 2001).

Rwanda received substantial aid from Canada and Belgium during the 1980's and it was in 1990 (post 1980 economic crisis) that SAP was adopted, but with it the same standard policy package (Storey, 2001). Following the genocide there were refugees returning to Rwanda and this led to increased competition on resources for survival (The ensued consequences are listed in section 5.2.1) (Moodley et al., 2010). In general, economic policy changes such as SAP have driven the expansion of agriculture. Forced population displacement and mounting pressure also drove change (Lambin et al., 2003).

Lambin et al. (2003) mention outside policy intervention as exogenous and as a major cause of most of land use changes mediated by local factors in tropics which cause land managers to respond in a manner further degrading the environment. This creates opportunities and constraints for new land use. This has implication on the expansion of agriculture and further degradation of the environment. Lambin et al. (2003) again mention opportunities and constraints as major cause in change that are created by markets and policies (influenced by global factors such as changes in global macroeconomics, leading to surges in energy prices). This is achieved by slowly increasing commercialization of the agro-industry and improving access by road construction. As a result, road construction and agriculture production are thought to cause substantial impediments to environmental sustainability and thus more prominent land degradation occurs (Lambin et al., 2003). Moreover, the impact of this structural adjustment can be more devastating as this implies borrower nations should export more to pay off debt, keep currencies stable, concentrate on cash crops and commodities, and earn foreign exchange. This forces them into the global market before they are economically and socially stable. This will keep the developing nations dependent on developed/donor nations, and poor. Lambin et al. (2003) suggest loss of adaptive capacity and increased vulnerability as major causes for land use change and mention impoverishment and dependence on external assistance to be slow factors leading to loss of capacity. Generally, Lambin et al. (2003) sees economic liberalization, globalization (trade liberalization) and reform to open agro industrial sectors as triggers to land degradation from unsustainable production methods. It also marginalizes the poor rural farmers to the forest frontier.

5.2.3. Bio-physical factors

Bio-physical factors include predisposing environmental conditions for land use change such as climate, soils, lithology, topography, relief, hydrology and vegetation (Geist et al., 2006). The variability of these factors interacts with human causes of land use change. The Nile Basin Initiative (2008) identified four hydro-geographical zones based on shared similarity in geology, landforms, relief, climate, and stream flow (Figure 3.1.b). The soil types in the Congo Nile Divide are limited in fertility whereas the Hill and Mountain Foot Ridges have little weathered recent soil which is favorable. The dominant soil type in the watershed is ferrasol which is limited in fertility (USDA, 2013: NBI, 2008). Despite its dominance, which necessitates the practice of shifting cultivation and the use of fertilizer, the area is mostly covered by agriculture.

This could be driven by a higher population density and high dependence on subsistence agriculture.

The Congo Nile Divide and mountain and Hills Ridges (which are in the western part of the watershed) receive the highest rainfall with an average annual rainfall of over 1400 mm (NBI, 2008). This likely contributes to the intensity of agriculture in this region of the watershed for the period of the study. Geist et al. (2006) indicate precipitation, topography, presence or proximity of water bodies, and soil conditions are prominent factors in cropland changes or in zones of intensified agricultural production. The central part of the watershed (Swamp and Lake Terrain hydro-geographical zone) is where the lakes and wetlands are concentrated (Figure 4.10). This region is found in Rwanda and a very small portion is found in Uganda. This figure (4.10) shows that most transitions occurred in close proximity to wetlands and lakes. Woodland savanna close to the wetland and lakes along Kagera river (forming the border between Rwanda and Tanzania), mostly remain unchanged because this is a reserved environment (Akagera National park found within Rwanda). Similar observations (transitions) are seen around Lake Rweru (a lake located at the center of the watershed) in Rwanda, and in the Uganda where there are wetlands. Looking at the Hills and Mountain Foot Ridges hydro-geographical zone (most of the south portion of the watershed), the transition is concentrated along the Ruvubu River (Runs to south towards Burundi and along the Ruvubu National park). The West Victoria Lake region zone (in Tanzania) also shows some transition in the North eastern corner close to Lake Victoria where there are wetlands. In addition, this area receives the highest precipitation in the basin, i.e. average annual rain fall is over 1400 mm (NBI, 2008). This could also contribute to the transition to cropland.

Through this general analysis, hydro-geographical zones seem to have transition to cropland mainly in regard to precipitation and proximity to rivers (in addition to population). A further local study might reveal the influences of soil and topography.

5.3. Limitations

Lack of data was the major obstacle during this research. Ground data, aerial photographs, and topo-sheets for image classification were not available which negatively affected the accuracy of the classified images. This limits both the classification accuracy as well as their location for use in accuracy, as reference data is itself another classification (Foody, 2010). In the preprocessing of the scenes from the land sat images, ATCOR software was used to substantially correct the atmospheric, topographic, and sensor effect. Radiometric relative calibration of the scenes could not be performed and this also might have had a negative effect on classification accuracy. The population data as mentioned in the result section was based on limited census data for the district. Better modeling and interpolation of the data should be done for improved accuracy. Lastly, during classification, major urban centers (the most notable being Kigali which is the Capital of Rwanda) could not be classified due to spectral similarity with the woodland savanna, and as result were not included.

5.4. Further studies

This study can be improved with better modeling of the population for the regions (districts) to observe the relationships between land cover and population dynamics. This study was based on LULC change in relation to human dimension factors. Land cover change is driven by not only human dimension, but also by biophysical factors. Both interact in the process of LULC change. Therefore, biophysical aspects should also be further investigated. Various biophysical factors such as geology, topography (elevation), soil, and climate (rainfall) can be used to thoroughly and accurately investigate its spatial relationship with the LULC transitions observed. Furthermore, urban/towns (both vector and raster) could be incorporated in the investigation as a land cover change by itself and its relation to transitions to agriculture.

In addition, studies linking the biomass dynamics to the indirect effect that land use cover has on carbon sequestration and other environment degradation (such as soil erosion and its subsequent effects off site) should be performed.

5.4. Conclusion

The overall result of the LULC change was consistent with the changes observed in the Kagera region. Agriculture was and is the dominant change in the Kagera basin, as most of the population heavily relies on this sector for survival and economy. Even though the drivers of the LULC are complex in nature, the study further affirms and shows that socioeconomic and politics play an important role in influencing decision making, especially in the agricultural sector as this is the main economy of the developing countries of east Africa. This study supports the idea that institutional and economic factors play a role at multiple levels (from local to global) and are interconnected in a complex ways. This implies that the need for addressing the issue of land use cover, which has been a global issue, cannot only be approached at the local level, but must also be addressed holistically by addressing the socio- economic/politics from a global perspective. This is critically important to the developing nations (where agriculture is the major means of survival) as these are the ones which are heavily affected as is evident by the structural adjustment policy and global crisis of this study period. Understanding the socioeconomic implications will help in better decision making with sound and sustainable outcomes. Furthermore, additional factors influencing land cover changes are related in a complex manner and this study provides a better understanding of the process.

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APPENDICES

APPENDIX A

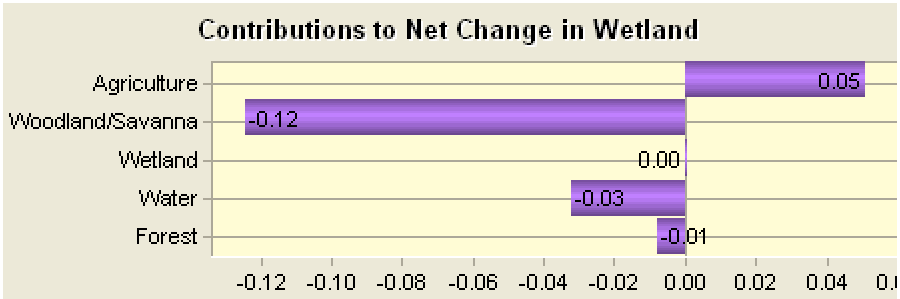

Figure 4.16. Contributors to net change experienced by wetland by percentage of the area for the period between 1984 and 1994

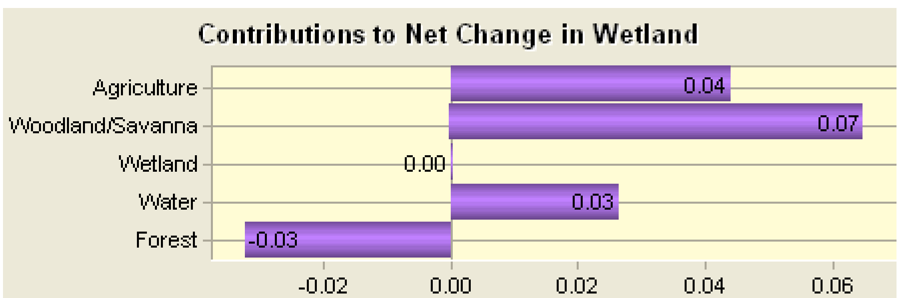

Figure 4.17. Contributors to net change experienced by wetland by percentage of the area for the period between 1994 and 2011

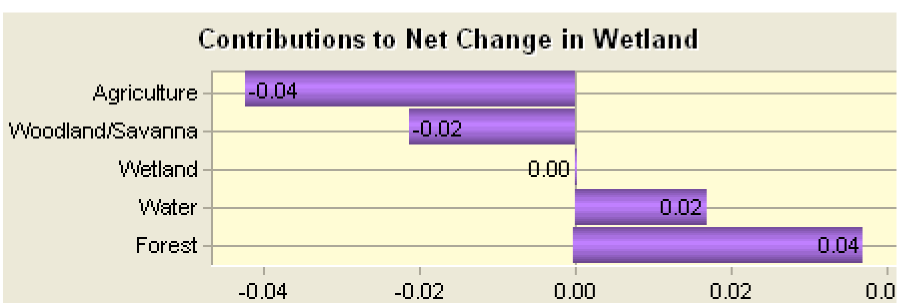

Figure 4.18 Contributors to net change experienced by wetland by percentage of the area for the period between 1984 and 2011

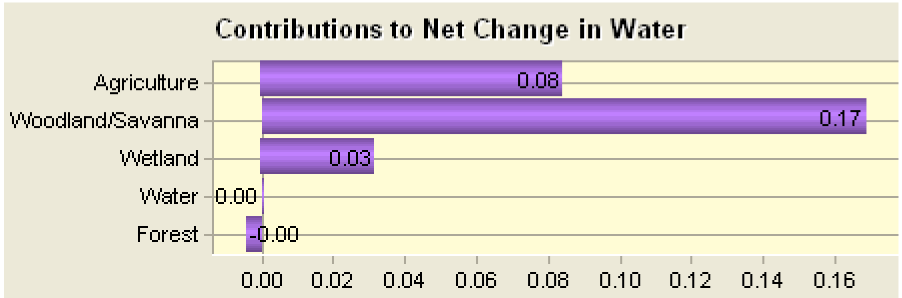

Figure 4.19 Contributors to net change experienced by water by percentage of the area for the period between 1984 and 1994

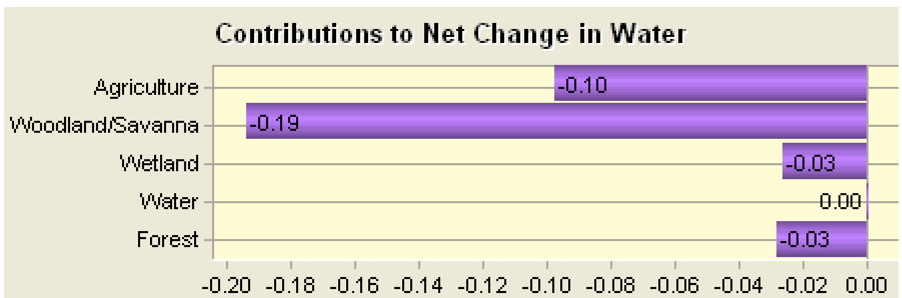

Figure 4.20 Contributors to net change experienced by water by percentage of the area for the period between 1994 and 2011

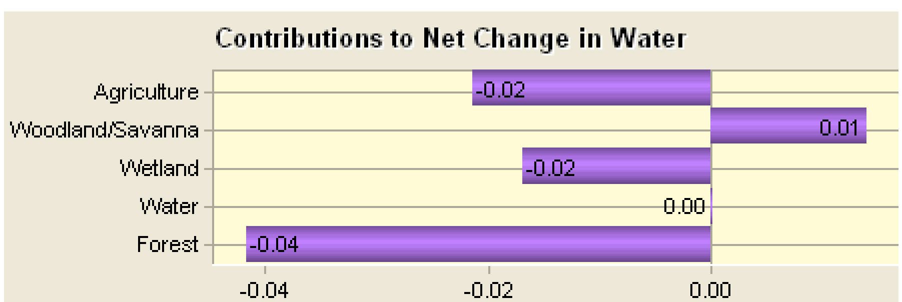

Figure 4.21 Contributors to net change experienced by water by percentage of the area for the period between 1984 and 2011

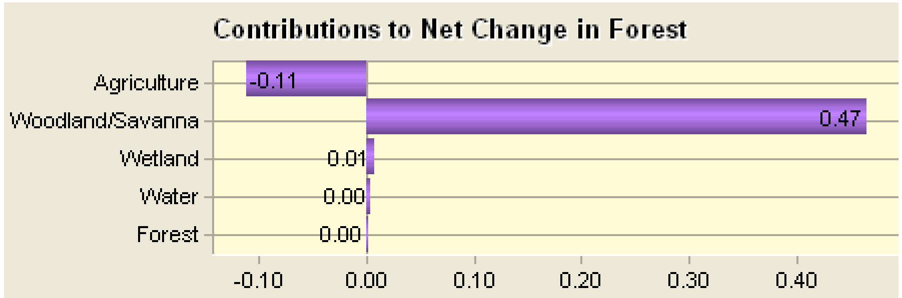

Figure 4.22 Contributors to net change experienced by forest by percentage of the area for the period between 1984 and 1994

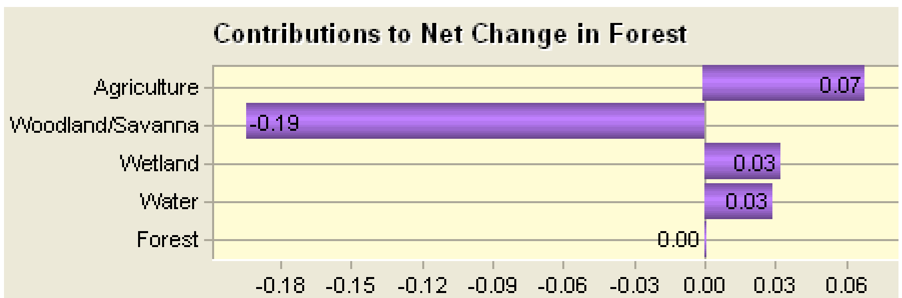

Figure 4.23 Contributors to the net change experienced by forest by percentage of the area for the period between 1994 and 2011

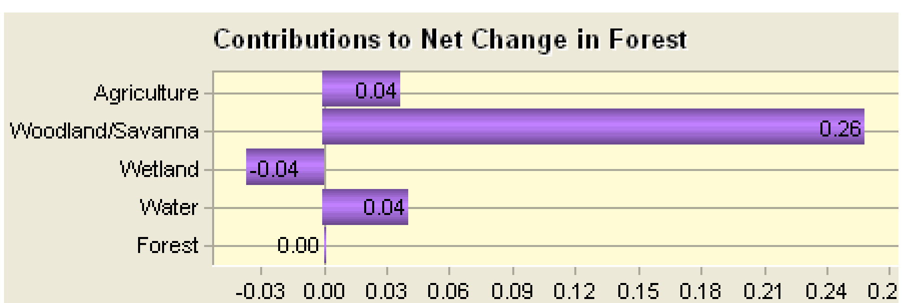

Figure 4.24 Contributors to the net change experienced by forest by percentage of the area for the period between 1984 and 2011

APPENDIX B

Population data

Burnidi districts within the watershed and its population

Province	1990	8/16/2008
Cankuzo	142,797	228873
Gitega	565,174	725223
Karuzi	287,905	436443
Kayanza	443,116	585412
Kirundo	401,103	628256
Muramvya	230,771	292589
Muyinga	373,382	632409
Mwaro	209,882	273143
Ngozi	482,246	660717

Rwanda districts within the watershed and its population

district	2002	2012
NYARUGENGE	236,990	284,860
GASABO	320,516	530,907
KICUKIRO	207,819	319,661
NYANZA	225,209	323,388
GISAGARA	262,128	322,803
NYARUGURU	231,496	293,424
HUYE	265,446	328,605
NYAMAGABE	280,007	342,112
RUHANGO	245,833	322,021
MUHANGA	287,219	318,965
KAMONYI	261,336	342,792
NYABIHU	268,367	295,580
NGORORERO	282,249	334,413
RULINDO	251,266	288,452
GAKENKE	322,043	338,586
MUSANZE	307,078	368,563
BURERA	320,759	336,455
GICUMBI	359,716	397,871
RWAMAGANA	220,502	310,238
NYAGATARE	255,104	466,944
GATSIBO	283,456	433,997
KAYONZA	209,723	346,751
KIREHE	229,468	338,562
NGOMA	235,109	340,983
BUGESERA	266,775	363,339

Tanzania districts within the watershed and its population

District	1988	2002
Ngara	159,546	334,409
Muleba	273,329	385,184
Karagwe	284,137	424,287
Bukoba Rural	340,800	394,020

Uganda districts within the watershed and its population

district	1980	1/12/1991	9/12/2002
Kabale	328,757	417,218	458,318
Ntungamo	213,161	305,199	379,987

Interpolation and extrapolation for missing years.

Burnidi

province(B)	1984	1985	1986	1987	1988	1989	1990
Cankuzo	122018.9426	125259.083	128585.264	131999.769	135504.944	139103.197	142797
Gitega	520098.6299	527353.445	534709.456	542168.076	549730.736	557398.887	565174
Karuzi	250624.255	256484.299	262481.36	268618.644	274899.429	281327.07	287905
Kayanza	403833.834	410130.27	416524.878	423019.188	429614.755	436313.158	443116
Kirundo	345378.7913	354097.102	363035.487	372199.502	381594.842	391227.345	401103
Muramvya	213217.237	216047.277	218914.881	221820.547	224764.779	227748.091	230771
Muyinga	313236.1107	322541.362	332123.043	341989.365	352148.784	362610.007	373382
Mwaro	192236.9646	195071.257	197947.338	200865.822	203827.337	206832.514	209882
Ngozi	434196.5333	441858.688	449656.055	457591.02	465666.011	473883.5	482246

province(B)	1991	1992	1993	1994	1995	1996	1997
Cankuzo	146588.9	150481.5	154477.42	158579.47	162790.5	167113.3	171550.9
Gitega	573057.6	581051.1	589156.14	597374.23	605707	614155.9	622722.7
Karuzi	294636.7	301525.9	308576.08	315791.14	323174.9	330731.3	338464.4
Kayanza	450024.9	457041.5	464167.57	471404.71	478754.7	486219.3	493800.2
Kirundo	411227.9	421608.5	432251.03	443162.23	454348.9	465817.9	477576.4
Muramvya	233834	236937.7	240082.6	243269.23	246498.2	249769.9	253085.1
Muyinga	384474	395895.5	407656.3	419766.47	432236.4	445076.8	458298.6
Mwaro	212976.4	216116.5	219302.88	222536.23	225817.2	229146.6	232525.1
Ngozi	490756.1	499416.3	508229.39	517197.98	526324.8	535612.8	545064.6

province(B)	1998	1999	2000	2001	2002	2003	2004
Cankuzo	176106.28	180782.68	185583.258	190511.311	195570.23	200763.48	206094.63
Gitega	631409.04	640216.51	649146.843	658201.741	667382.95	676692.22	686131.34
Karuzi	346378.31	354477.25	362765.564	371247.672	379928.11	388811.51	397902.62
Kayanza	501499.38	509318.59	517259.705	525324.637	533515.32	541833.7	550281.78
Kirundo	489631.75	501991.4	514663.045	527654.556	540974.01	554629.68	568630.06
Muramvya	256444.34	259848.14	263297.115	266791.867	270333.01	273921.15	277556.91
Muyinga	471913.19	485932.24	500367.74	515232.079	530537.99	546298.59	562527.39
Mwaro	235953.41	239432.24	242962.371	246544.546	250179.54	253868.12	257611.08
Ngozi	554683.2	564471.55	574432.634	584569.499	594885.25	605383.03	616066.07

province(B)	2005	2006	2007	8/16/2008	2009	2010	2011
Cankuzo	211567.35	217185.4	222952.626	228873	234950.59	241189.56	247594.2
Gitega	695702.14	705406.43	715246.089	725223	735339.08	745596.27	755996.53
Karuzi	407206.29	416727.5	426471.337	436443	446647.82	457091.24	467778.86
Kayanza	558861.58	567575.16	576424.589	585412	594539.54	603809.39	613223.78
Kirundo	582983.85	597699.96	612787.556	628256	644114.91	660374.14	677043.8
Muramvya	281240.94	284973.86	288756.326	292589	296472.54	300407.64	304394.96
Muyinga	579238.29	596445.62	614164.132	632409	651195.87	670540.83	690460.47
Mwaro	261409.24	265263.39	269174.362	273143	277170.15	281256.68	285403.45
Ngozi	626937.63	638001.04	649259.681	660717	672376.5	684241.76	696316.4

Rwanda

district®	1984	1985	1986	1987	1988	1989	1990	1991
NYARUGENGE	170179.57	173339.51	176558.12	179836.5	183175.76	186577.01	190041.43	193570.17
GASABO	129224.84	135913.58	142948.54	150347.64	158129.71	166314.59	174923.13	183977.24
KICUKIRO	95736.451	99948.842	104346.58	108937.81	113731.06	118735.21	123959.54	129413.75
NYANZA	117418.64	121744.93	126230.61	130881.57	135703.9	140703.9	145888.13	151263.37
GISAGARA	180197.99	183989.21	187860.2	191812.63	195848.21	199968.7	204175.88	208471.58
NYARUGURU	151087.88	154712.3	158423.67	162224.06	166115.63	170100.55	174181.06	178359.45
HUYE	180767.28	184667.14	188651.13	192721.08	196878.83	201126.27	205465.36	209898.05
NYAMAGABE	195240.51	199191.08	203221.58	207333.63	211528.9	215809.05	220175.8	224630.92
RUHANGO	151217.12	155355.04	159606.2	163973.69	168460.69	173070.47	177806.39	182671.91
MUHANGA	237826.04	240332.44	242865.25	245424.76	248011.24	250624.97	253266.25	255935.37
KAMONYI	160362.44	164772.9	169304.67	173961.07	178745.54	183661.6	188712.87	193903.06
NYABIHU	225541.48	227730.41	229940.58	232172.2	234425.47	236700.62	238997.85	241317.37
NGORORERO	207998.92	211556.39	215174.71	218854.91	222598.06	226405.23	230277.51	234216.02
RULINDO	195993.67	198717.46	201479.1	204279.12	207118.06	209996.45	212914.84	215873.79
GAKENKE	294275.85	295753.67	297238.9	298731.6	300231.79	301739.52	303254.81	304777.72
MUSANZE	221093.13	225165.35	229312.57	233536.17	237837.57	242218.19	246679.5	251222.98
BURERA	294328.42	295737.92	297154.17	298577.2	300007.05	301443.74	302887.32	304337.8
GICUMBI	300020.69	303060.58	306131.28	309233.09	312366.33	315531.31	318728.37	321957.82
RWAMAGANA	119262.55	123404.89	127691.09	132126.17	136715.29	141463.81	146377.25	151461.35
NYAGATARE	85927.408	91282.277	96970.854	103013.93	109433.61	116253.35	123498.09	131194.31
GATSIBO	131669.06	137399.08	143378.47	149618.07	156129.21	162923.7	170013.88	177412.61
KAYONZA	84835.392	89210.144	93810.49	98648.065	103735.1	109084.46	114709.68	120624.97
KIREHE	113939.2	118458.11	123156.23	128040.69	133118.87	138398.45	143887.42	149594.09
NGOMA	120402.36	124962.97	129696.33	134608.98	139707.72	144999.58	150491.89	156192.23
BUGESERA	152983.55	157783.44	162733.93	167839.74	173105.75	178536.98	184138.61	189916

district®	1992	1993	1994	1995	1996	1997	1998	1999
NYARUGENGE	197164.43	200825.435	204554.417	208352.64	212221.39	216161.97	220175.73	224264.01
GASABO	193500	203515.668	214049.75	225129.08	236781.88	249037.84	261928.18	275485.72
KICUKIRO	135107.93	141052.662	147258.96	153738.33	160502.8	167564.9	174937.73	182634.97
NYANZA	156836.66	162615.298	168606.85	174819.16	181260.36	187938.89	194863.49	202043.23
GISAGARA	212857.65	217336.005	221908.58	226577.36	231344.36	236211.66	241181.37	246255.63
NYARUGURU	182638.09	187019.359	191505.732	196099.73	200803.93	205620.98	210553.58	215604.51
HUYE	214426.37	219052.393	223778.212	228605.99	233537.91	238576.24	243723.27	248981.33
NYAMAGABE	229176.18	233813.408	238544.47	243371.26	248295.72	253319.82	258445.59	263675.07
RUHANGO	187670.57	192806.011	198081.981	203502.32	209070.99	214792.04	220669.63	226708.07
MUHANGA	258632.62	261358.295	264112.693	266896.12	269708.88	272551.28	275423.64	278326.27
KAMONYI	199235.99	204715.603	210345.918	216131.08	222075.36	228183.12	234458.87	240907.22
NYABIHU	243659.4	246024.168	248411.882	250822.77	253257.05	255714.96	258196.73	260702.58
NGORORERO	238221.89	242296.28	246440.352	250655.3	254942.34	259302.7	263737.64	268248.43
RULINDO	218873.86	221915.624	224999.661	228126.56	231296.91	234511.32	237770.4	241074.78
GAKENKE	306308.28	307846.517	309392.483	310946.21	312507.74	314077.12	315654.37	317239.55
MUSANZE	255850.15	260562.538	265361.723	270249.3	275226.9	280296.19	285458.84	290716.58
BURERA	305795.24	307259.648	308731.073	310209.54	311695.1	313187.76	314687.58	316194.57
GICUMBI	325219.99	328515.207	331843.818	335206.15	338602.56	342033.38	345498.96	348999.65
RWAMAGANA	156722.04	162165.446	167797.917	173626.02	179656.55	185896.54	192353.26	199034.24
NYAGATARE	139370.14	148055.481	157282.08	167083.67	177496.07	188557.37	200307.98	212790.88
GATSIBO	185133.32	193190.02	201597.339	210370.53	219525.52	229078.92	239048.06	249451.05
KAYONZA	126845.31	133386.405	140264.812	147497.92	155104.02	163102.35	171513.14	180357.65
KIREHE	155527.09	161695.397	168108.342	174775.63	181707.34	188913.98	196406.43	204196.04
NGOMA	162108.5	168248.859	174621.806	181236.15	188101.03	195225.94	202620.73	210295.61
BUGESERA	195874.65	202020.262	208358.69	214895.99	221638.39	228592.35	235764.48	243161.64

district®	2000	2001	2002	2003	2004	2005	2006
NYARUGENGE	228428.21	232669.725	236990	241390.5	245872.7	250438.13	255088.34
GASABO	289745.01	304742.37	320516	337106.08	354554.88	372906.83	392208.69
KICUKIRO	190670.88	199060.372	207819	216963.01	226509.35	236475.73	246880.63
NYANZA	209487.5	217206.054	225209	233506.81	242110.36	251030.9	260280.12
GISAGARA	251436.65	256726.677	262128	267642.96	273273.96	279023.42	284893.85
NYARUGURU	220776.61	226072.781	231496	237049.32	242735.85	248558.79	254521.43
HUYE	254352.84	259840.227	265446	271172.71	277022.97	282999.44	289104.85
NYAMAGABE	269010.36	274453.609	280007	285672.76	291453.16	297350.53	303367.22
RUHANGO	232911.74	239285.168	245833	252560.01	259471.09	266571.3	273865.79
MUHANGA	281259.5	284223.628	287219	290245.94	293304.78	296395.85	299519.51
KAMONYI	247532.91	254340.837	261336	268523.55	275908.78	283497.13	291294.18
NYABIHU	263232.75	265787.479	268367	270971.56	273601.39	276256.75	278937.87
NGORORERO	272836.37	277502.78	282249	287076.4	291986.36	296980.29	302059.65
RULINDO	244425.08	247821.935	251266	254757.93	258298.39	261888.05	265527.59
GAKENKE	318832.69	320433.822	322043	323660.26	325285.64	326919.18	328560.93
MUSANZE	296071.15	301524.357	307078	312733.93	318494.04	324360.24	330334.49
BURERA	317708.78	319230.249	320759	322295.07	323838.5	325389.32	326947.56
GICUMBI	352535.82	356107.813	359716	363360.75	367042.42	370761.4	374518.06
RWAMAGANA	205947.27	213100.411	220502	228160.67	236085.34	244285.26	252769.99
NYAGATARE	226051.69	240138.899	255104	271001.7	287890.13	305831.02	324889.95
GATSIBO	260306.76	271634.887	283456	295791.55	308663.92	322096.48	336113.6
KAYONZA	189658.25	199438.452	209723	220537.9	231910.49	243869.54	256445.29
KIREHE	212294.58	220714.326	229468	238568.85	248030.65	257867.7	268094.91
NGOMA	218261.21	226528.53	235109	244014.48	253257.29	262850.19	272806.46
BUGESERA	250790.89	258659.504	266775	275145.12	283777.86	292681.45	301864.39

district®	2007	2008	2009	2010	2011	2012
NYARUGENGE	259824.89	264649.386	269563.468	274568.8	279667.07	284860
GASABO	412509.62	433861.343	456318.242	479937.52	504779.35	530907
KICUKIRO	257743.34	269084.011	280923.67	293284.27	306188.74	319661
NYANZA	269870.13	279813.483	290123.196	300812.77	311896.2	323388
GISAGARA	290887.79	297007.833	303256.639	309636.92	316151.43	322803
NYARUGURU	260627.09	266879.23	273281.348	279837.04	286550	293424
HUYE	295341.98	301713.661	308222.808	314872.38	321665.42	328605
NYAMAGABE	309505.66	315768.308	322157.675	328676.33	335326.88	342112
RUHANGO	281359.89	289059.062	296968.914	305095.21	313443.88	322021
MUHANGA	302676.08	305865.916	309089.371	312346.8	315638.55	318965
KAMONYI	299305.68	307537.516	315995.753	324686.62	333616.51	342792
NYABIHU	281645.02	284378.443	287138.393	289925.13	292738.91	295580
NGORORERO	307225.87	312480.453	317824.908	323260.77	328789.6	334413
RULINDO	269217.72	272959.129	276752.534	280598.66	284498.23	288452
GAKENKE	330210.92	331869.196	333535.801	335210.78	336894.16	338586
MUSANZE	336418.77	342615.118	348925.593	355352.3	361897.37	368563
BURERA	328513.27	330086.477	331667.216	333255.53	334851.44	336455
GICUMBI	378312.79	382145.961	386017.974	389929.22	393880.09	397871
RWAMAGANA	261549.42	270633.783	280033.671	289760.04	299824.24	310238
NYAGATARE	345136.61	366645.017	389493.792	413766.47	439551.78	466944
GATSIBO	350740.72	366004.393	381932.315	398553.39	415897.8	433997
KAYONZA	269669.54	283575.729	298199.028	313576.41	329746.77	346751
KIREHE	278727.73	289782.249	301275.203	313223.97	325646.64	338562
NGOMA	283139.85	293864.644	304995.678	316548.33	328538.58	340983
BUGESERA	311335.45	321103.664	331178.359	341569.15	352285.95	363339

Tanzaina

District(tz)	1984	1985	1986	1987	1988	1989	1990	1991
Ngara	129139.66	136149.55	143539.94	151331.5	159546	168206.39	177336.88	186962.99
Muleba	247810.26	253957.41	260257.04	266712.95	273329	280109.17	287057.52	294178.24
Karagwe	253382.03	260743.69	268319.23	276114.87	284137	292392.2	300887.25	309629.1
Bukoba Rural	326959.72	330366.18	333808.14	337285.95	340800	344350.66	347938.31	351563.35

District(tz)	1992	1993	1994	1995	1996	1997	1998	1999
Ngara	197111.62	207811.12	219091.42	230984.02	243522.17	256740.92	270677.19	285369.95
Muleba	301475.59	308953.95	316617.83	324471.81	332520.62	340769.09	349222.17	357884.93
Karagwe	318624.94	327882.14	337408.3	347211.23	357298.96	367679.78	378362.2	389354.98
Bukoba Rural	355226.15	358927.11	362666.63	366445.11	370262.95	374120.58	378018.39	381956.82

District(tz)	2000	2001	2002	2003	2004	2005	2006	2007
Ngara	300860.25	317191.38	334409	352561.21	371698.75	391875.11	413146.67	435572.88
Muleba	366762.58	375860.45	385184	394738.83	404530.67	414565.41	424849.07	435387.83
Karagwe	400667.15	412307.97	424287	436614.06	449299.27	462353.03	475786.05	489609.35
Bukoba Rural	385936.27	389957.19	394020	398125.14	402273.05	406464.17	410698.96	414977.87

District(tz)	2008	2009	2010	2011	2012
Ngara	459216.41	484143.36	510423.37	538129.9	567340.38
Muleba	446188.01	457256.09	468598.73	480222.74	492135.09
Karagwe	503834.26	518472.46	533535.95	549037.09	564988.59
Bukoba Rural	419301.36	423669.9	428083.95	432543.98	437050.49

Uganda

district(ug)	1984	1985	1986	1987	1988	1989	1990	1991
Kabale	358,515	366,366	374,389	382,588	390,966	399,528	408,277	417,218
Ntungamo	242,879	250,934	259,257	267,856	276,740	285,918	295,401	305,199

district(ug)	1992	1993	1994	1995	1996	1997	1998	1999
Kabale	420,797	424,406	428,047	431,719	435,422	439,157	442,924	446,723
Ntungamo	311,341	317,607	323,998	330,519	337,170	343,956	350,878	357,939

district(ug)	2000	2001	2002	2003	2004	2005	2006	2007
Kabale	450,555	454,420	458,318	462,249	466,215	470,214	474,247	478,315
Ntungamo	365,142	372,491	379,987	387,634	395,435	403,393	411,511	419,793

district(ug)	2008	2009	2010	2011	2012
Kabale	482,418	486,556	490,730	494,939	499,185
Ntungamo	428,241	436,859	445,651	454,619	463,768

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