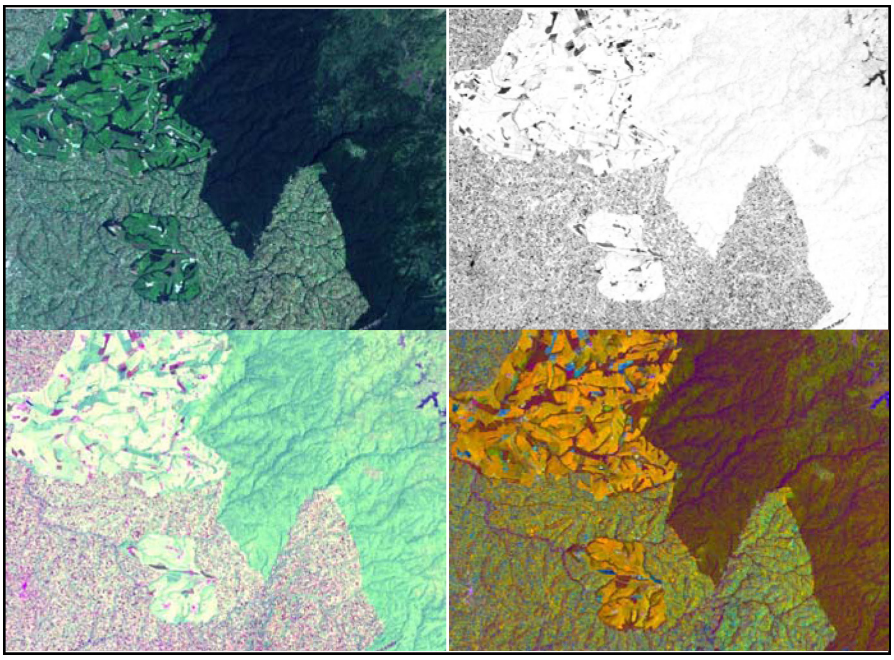
Department of Physical Geography and Quaternary Geology

Stockholm University

# Investigation of deforestation in East Africa on regional scales



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Master's thesis
Geography, 30 HECs

GA 10
2011

# Preface

This Master's thesis is Yi-Hua Wu's degree project in Geography, at the Department of Physical Geography and Quaternary Geology, Stockholm University. The Master's thesis comprises 30 HECs (one term of full-time studies).

Supervisor has been Ian Brown, at the Department of Physical Geography and Quaternary Geology, Stockholm University. Examiner has been Karin Holmgren, at the Department of Physical Geography and Quaternary Geology, Stockholm University.

The author is responsible for the contents of this thesis.

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# Abstract

Tropical forests contain abundant natural resources and play an important role in the balance of the ecosystems and environment. Depletion of forests could destroy habitats of endangered plants and animals and cause biodiversity loss. Rapid deforestation is a major problem in East Africa and seriously affects desertification and climate change in East Africa. More monitoring of the deforestation in East Africa are emergent. Therefore, this study was conducted to identify and evaluate the spatial and temporal distributions and determinants of deforestation in East Africa. Two kinds of satellite image datasets, including Landsat images and GIMMS data were used to map the deforestation in Kenya, Tanzania and Uganda. Possible drivers of deforestation were analyzed, including population statistics, economic and climate data. The analysis of Landsat images was focus on the forests, including Mount Kenya, Mao forest, Aberdares forest as well as Mount Kilimanjaro in Tanzania and its surroundings. Supervised classification was carried out on the images comprising PCA component images and Tassel Cap transformed images to identify forest area and non forest area. High Kappa coefficient of the classification indicated that using the images that comprising the enhancement images transformed from original images would be a better approach to mapping forest areas. The obvious deforestation was observed in Mau forest, Mountain Kilimanjaro and Aberdares forest close to Nairobi city from 1980s to 2000s. The analysis using the GIMMS NDVI dataset did not show a significant decline of NDVI values during the study period. The results indicate that the GIMMS NDVI is not a good proxy of total forest areas because of the coarse resolution of GIMMS dataset and the characteristics of NDVI. Future studies should use higher resolution satellite images and collect enough information to monitor deforestation.

**Keywords: Deforestation, Landsat, GIMMS NDVI, Supervised Classification, PCA, Tasseled Cap Transformation, Kenya, Tanzania, Uganda.**

# Acknowledgements

I would like to thank my supervisor, Ian Brown, for giving me this opportunity to carry out this project. Thank you so much for leading me into the field of remote sensing, helping me to deal with image processing, and providing all the assistance and valuable comments to bring out this study. My special thanks to my examiner, Karin Holmgren, for her substantial opinions and detailed suggestions for my thesis.

Furthermore, I would like to thank my family and friends in Taiwan for supporting and encouraging me. Special thanks to Hong-Mao Lin for his understanding and company.

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# 1. Introduction

Forests, especially tropical forests, contain abundant natural resources and influence the balance of the ecosystems and environment. Depletion of forests could destroy habitats of endangered plants and animals and cause biodiversity loss (Boahene, 1998). Kiage et al. (2007) indicated soil erosion and increases in sediment transport caused by deforestation affecting Lake ecosystems as well as the biodiversity. Forest loss changes the balance of hydrological cycle and decreases rainfall (Boahene, 1998). Meanwhile, forests play an important role in earth's carbon cycle and act as massive carbon stores. Removing forests releases carbon into atmosphere and exacerbates the global warming. Research has estimated that deforestation caused about 0.5 gigatonnes of carbon to be released from forests each year in last decade (FAO, 2010). At the same time, climate change enhances the occurrence of extreme weather events, such as storms, droughts and floods, which would also seriously damage forest ecosystems (FAO, 2010). Hence, adequate forest management to reduce and control deforestation is urgent. More assessments that completely monitoring the distribution of deforestation are needed to provide enough information for policy makers.

## 1.1 Background

In the last decade forest areas lost about 13 million hectares per year due to overpopulation, agricultural expansion, logging and so on (Boahene, 1998, FAO, 2010). Deforestation mostly occurs in developing countries. In Africa, over 50% of new agricultural land came from forests. In East Africa, farmland increased 50% since 1980 (Gibbs et al., 2010). Meanwhile, forests are a major source of fuelwood in East Africa (FAO, 2001). Rapid deforestation is a major problem in East Africa and seriously affects desertification and climate change in East Africa (FAO, 2001). More monitoring of the distribution of deforestation in East Africa are needed. Nevertheless, a comprehensive field study of deforestation is very time and cost consuming. A more efficient way is to use remote sensing data to identify deforestation.

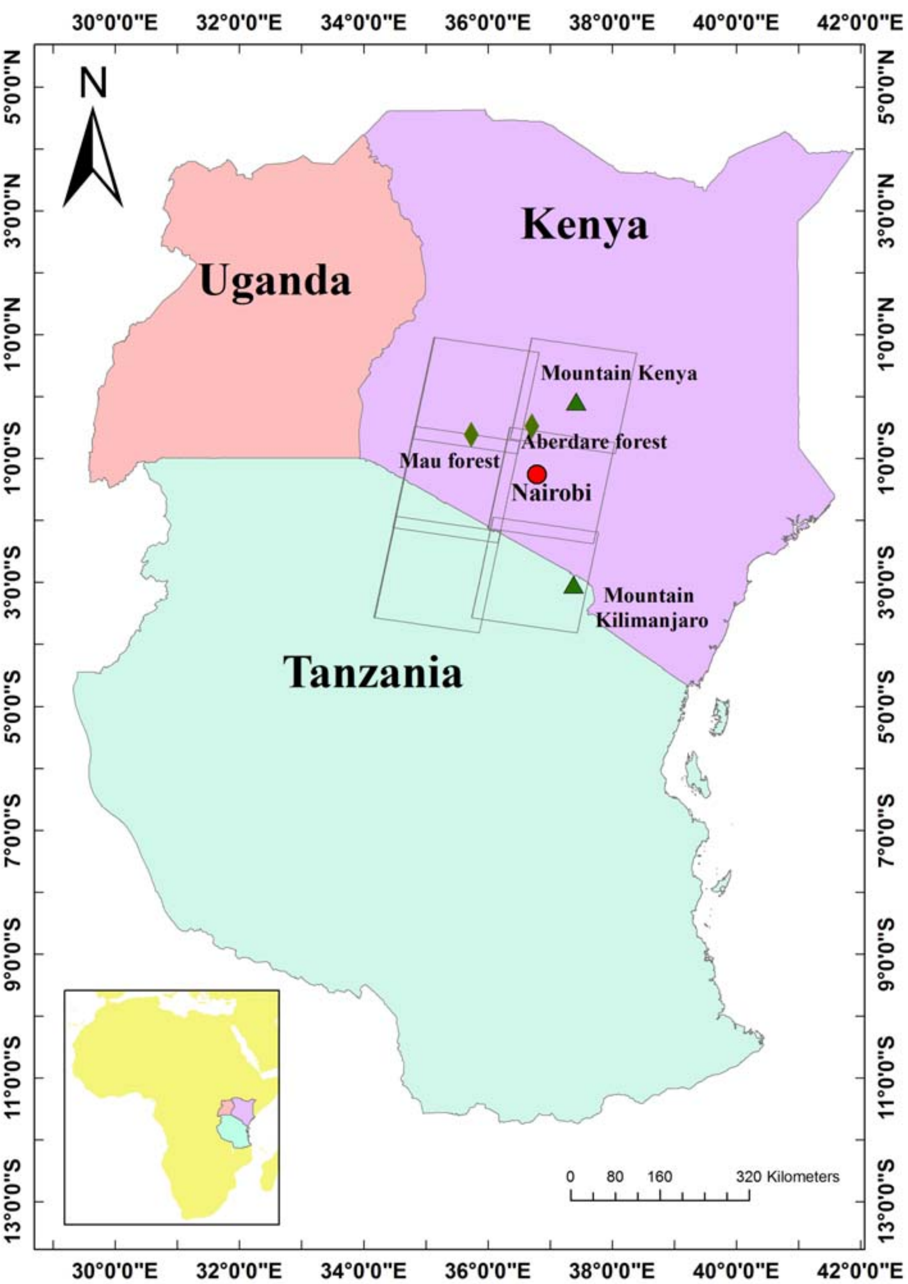


Fig. 1 The location of the study area

Remote sensing provides a useful mean to map and monitor the change of forest area. Methods include visual interpretation of deforestation with aerial photos or satellite images (Roy et al., 2002). Such methods can collect data in different scales, including local, regional and global scale, during a short time or over an inaccessible area. More and more research uses satellite images to investigate deforestation. For example, Global Forest Resources Assessment carried out by the Food and Agriculture Organization (FAO) (2010) used Landsat satellite images to map the pattern of deforestation over times at a global scale. Classification is performed on the satellite images to distinguish the forest area. In addition, vegetation indices calculated by satellite images are also a good proxy to identify the presence of forest. Based on different reflectance properties of vegetation types within different spectral bands, researchers can use vegetation indices to recognize the forest area (Campbell, 2002d). Therefore, a longitudinal study in this project was implemented to monitor deforestation in East Africa using high resolution satellite images.

## 1.2 Literature review

### 1.2.1 Deforestation in Africa

Numerous investigations have addressed deforestation on local, regional and global levels. One global forest resources assessment has been conducted by FAO since 1946 (FAO, 2010). This assessment used remote sensing data, such as Landsat images, to identify forest areas and estimate the change of forest areas over time. FAO reported that there are about 4 billion hectares of total forest area in the world and these are decreasing at about 13 million hectares per year. Highest rate of deforestation majorly occurred in developing countries and tropical zone, especially in South America and Africa.

Based on the research of FAO, the forest in Africa covers about 675 million hectares and around 3.5 million hectares per year has been lost in last decade, with annual deforestation rate of about 0.5%. The Tropical Ecosystem Environment observation by Satellite (TREES) II projects also used Landsat satellite data to map the forest area in 1990s (Achard et al., 2002, Mayaux et al., 2005), but this project focused on humid tropical forests. The results were similar to the results of FAO and showed that the forest loss in tropical forest was about 4.9 million hectares per year. Average deforestation rate in Africa was 0.43%.

Hansen and DeFries (2004) used Advanced Very High Resolution Radiometer (AVHRR) Data with resolution of 8 km to examine the long term change of global forest cover. Their results revealed that the tree cover of the world decreased between 1984 and 1997 and the annual deforestation rate in tropical Africa was about 0.09%. The deforestation rate in the study of Hansen and DeFries was lower than the studies of FAO and TREES II which could be due to the difference of resolution and sensors. The patchy distribution of deforestation in Africa could increase the difficulties to define the deforestation in Africa (Hansen and DeFries, 2004). All these research indicate that deforestation in tropical forests is difficult to map and remote sensing is a useful tool for forest monitoring.

### 1.2.2 Possible drivers of deforestation

There are many reasons for deforestation, such as agriculture expansion, population growth, industrialization and so on. Agriculture expansion was indicated as the main cause for loss of forest areas (FAO, 2010). In Africa, forest is the major source for new agriculture land (Gibbs et al., 2010). Excessive population growth increases the demand for resources. Hence, more nature resources, such as forests, are required to meet people's needs. Economic development also plays an important role in deforestation. In developing countries, people overexploit natural resources to improve financial incomes. In East Africa, fuelwood use and population growth are important contributors to deforestation (FAO, 2001). Rudel et al. (2009) use a Meta analysis to examine the possible reasons for deforestation in East Africa. They indicated that smallholders, increasing population, fuelwood use and forest products sold in urban markets were important drivers of deforestation in 1980s and 1990s. They also indicated that rural population, location of forest and economic growth were important drivers of deforestation in Uganda and Kenya. For Tanzania, population density and rural population growth were main causes (Rudel and Roper, 1996). These results showed that drivers of deforestation varied in different countries because of the difference of socioeconomic condition and environmental characteristics.

### 1.2.3 Previous studies in East Africa

The report of FAO (2010) indicated that in 2010 there were about 73 million hectares of forest in East Africa and the annual loss of forests was around 0.7 million hectares. Kenya still remained a deforestation rate of about 0.3 % per year. Large loss of forest area was indicated in Tanzania and Uganda about 1.2% and 2.7% per year, respectively. At the same time, several research projects have been carried out to map the distribution pattern of deforestation in East Africa. Remote sensing data were frequently used as a main source of data. Landsat satellite images acquired from several periods were used in studies conducted in Kenya (Kiage et al., 2007, Ochego, 2003), Tanzania (Halperin and Shear, 2005, Strömquist and Backéus, 2009) and Uganda (Malinverni and

Fangi, 2010, Mwavu and Witkowski, 2008) to identify forest areas and land cover change. These researchers classified satellite images into different classes to identify forest areas. Vegetation indices were also used in some of these studies as an auxiliary data to determine changes in forest (Kiage et al., 2007, Malinverni and Fangi, 2010, Ochego, 2003). The results all showed that forest loss has been severe in these countries during the last decades. Kiage et al. (2007) indicated that soil erosion caused by deforestation in Lake Baringo catchment of Kenya damaged the Lake ecosystem and affected the biodiversity in this area. Agriculture expansion, population growth and logging for charcoal were indicated as important reasons for deforestation (Kiage et al., 2007, Mwavu and Witkowski, 2008, Strömquist and Backéus, 2009).

According to these studies, remote sensing data is a good tool that can successfully map the pattern of deforestation in East Africa. However, the process and possible drivers of deforestation in East Africa are very complex. Information about forest resources is still lacking for East Africa to establish well forest management (FAO, 2001). More research using remote sensing data covering more areas and acquired over longer periods are required to completely monitor the spatiotemporal distribution of deforestation and further clarify the interrelations between deforestation and possible drivers. Therefore, a longitudinal study was implemented in this study to monitor deforestation in East Africa using high resolution satellite images.

## 1.3 Aim and objectives

The research question of this study is “how does the long term pattern of deforestation change in different forests and countries of East Africa?”, as well as “what are the possible factors of the deforestation in East Africa? and how do these factors affect the deforestation in East Africa?”.

Therefore, the main goal is to use remote sensing data to identify and evaluate the spatial and temporal distributions and determinants of deforestation in East Africa.

The objectives include:

A. To identify and map deforestation in East Africa using two kinds of satellite images datasets, including Landsat images and Global Inventory Modeling and Mapping Studies (GIMMS) data.
B. To examine the temporal and spatial patterns of deforestation in East Africa.
C. To analyze possible drivers of deforestation, including population statistics,

economic and climate data.

## 2. Method

This study includes two parts since two kinds of satellite images datasets were used to identify and map deforestation, including Landsat images and Global Inventory Modeling and Mapping Studies (GIMMS) data. GIMMS dataset with coarse spatial resolution was used to compare the deforestation in different countries in East Africa, and Landsat images with high resolution was used to analyze the deforestation in several major forests in East Africa.

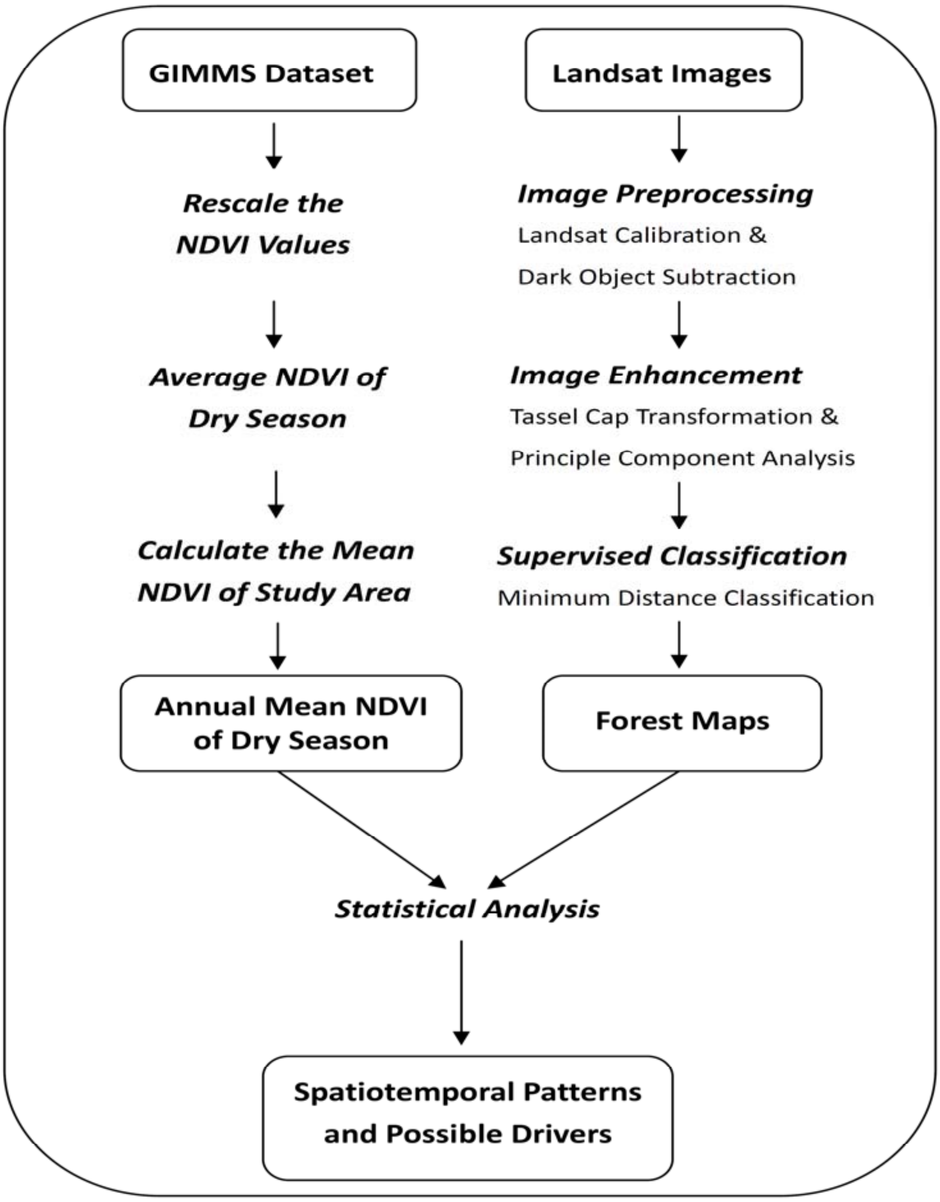


Fig. 2 Flow chart illustrating the image processing and method used in this study

## 2.1 GIMMS dataset

### 2.1.1 Study area

The focus of this study is deforestation in East Africa, including Kenya, Tanzania and Uganda. Kenya is located at the equator, between latitudes 5° south and 5° north, and longitude 34° and 42° east. The total area of Kenya is about 580,000 km$^2$ and the forest area covers about 3.5 million hectares (FAO, 2010). The mean annual temperature of Kenya is 23.9 °C. The two rain seasons in Kenya occur in March to May and October to December (McSweeney et al., 2008a).

Tanzania lies between latitude 1° and 12° south, and longitude 29° and 41° east with area of 947,300 km$^2$. There are about 33 million hectares of forest area (FAO, 2010). It has a tropical climate with a mean annual temperature 22.2 °C. The two rain seasons in Tanzania occur in March to May and October to December (McSweeney et al., 2008b).

Uganda is situated between latitude 1˚30 south and 4˚ north and longitude 29˚30 and 35˚ west with area about 241,500 km$^2$ (Obua and Agea, 2010, UNEMA, 2007). Forest area is about 3 million hectares. Uganda has a tropical climate with a mean temperature of 22.0 °C. Uganda has two wet seasons, October to December and March to May (McSweeney et al., 2008c).

### 2.1.2 Analysis of GIMMS dataset

The GIMMS dataset comprises the Normalized Difference Vegetation Index (NDVI) data averaged over 15-day periods using cloud free daily images collected by the Advanced Very High Resolution Radiometer (AVHRR) on board the National Oceanic and Atmospheric Administration (NOAA) satellite series. The data are resampled to a spatial resolution of 8 km (Tucker et al., 2005).

The NDVI is calculated by the reflectance of the near-infrared and visible red bands as NDVI= (NIR-R) / (NIR+R), where NIR and R are the spectral reflectance in the near-infrared and visible red regions by the AVHRR, respectively. Radiometric calibration, atmospheric correction and solar zenith angle correction were carried out to prevent the error by sensors, sun elevation, atmospheric scattering and volcanic eruption (Tucker et al., 2005).

The original values in GIMMS data does not range from -1 to 1, and then rescale must be done by dividing with 1000. The NDVI of dry season could be a good indicator to detect deforestation since only forest remains green during dry season (Hudak and Wessman, 2000, Prins and Kikula, 1996). In this study, the mean NDVI values during dry season of three countries were calculated from GIMMS NDVI data between 1981 and 2006. The calculation and analysis of GIMMS dataset was processed with ENVI software.

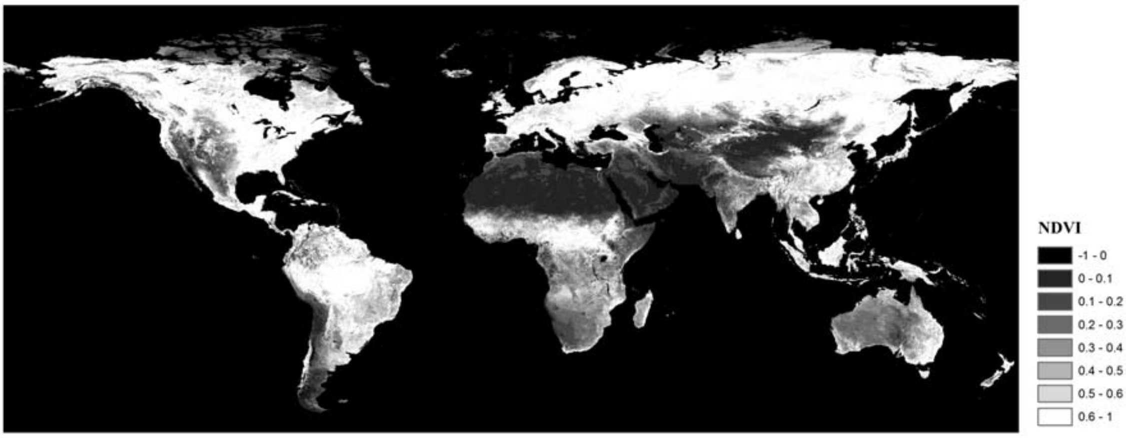


Fig. 3 An example of the GIMMS data: mean monthly NDVI of July in 1981

## 2.2 Landsat images

### 2.2.1 Study area

The analysis of Landsat images in this study was focus on the forests, including Mount Kenya, Mao forest, Aberdares forest nearby Nairobi in Kenya, the largest and populous city of East Africa, as well as Mount Kilimanjaro in Tanzania, the highest mountain in East Africa and its surroundings.

Mount Kilimanjaro is located in Tanzania, close to the border with Kenya. It is an area with significant natural resources, such as fertile soil, water and forest. It contains several types of forests: about 1200 species of vascular plants, 130 species of trees, and 170 species of shrubs grow on Mount Kilimanjaro (Hemp, 2006, Lambrechts et al., 2002). It is also an important habitat with high biodiversity and many endemic species, including about 140 species of mammals (Lambrechts et al., 2002). Moreover, Mount Kilimanjaro is an important water catchment for both Kenya and Tanzania. It contributes to water supply for agriculture, irrigation, industry and so on (Lambrechts et al., 2002, William, 2003).

Mau forest is a forest complex in Kenya. It is a large montane forest in Kenya and also the largest water catchment area in Kenya. Rivers in Mau forest are the major source for surface and groundwater reserves, supporting important water supply for agriculture and power generation (Baldyga et al., 2007, Kinyanjui, 2010, Ngigi and Tateishi, 2004). The forest on Mount Kenya is a large continuous indigenous forest in Kenya. Mount Kenya forest is an important catchment in Kenya, providing water supply for agriculture, irrigation and power generation (Ndegwa, 2005, Ngigi and Tateishi, 2004). Aberdares forest is close to Nairobi city. Like Mau forest and Mount Kenya, it is one of the important catchments in Kenya (Ochego, 2003). These forests provide various resources and services in Kenya, such as fuelwood for local people. They all are important habitats for numerous endangered species and they have high biodiversity of fauna and flora.

### 2.2.2 Image preprocessing

Seventeen Landsat images were acquired (Table 1) by Landsat 2 Multi-Spectral Scanner (MSS), Landsat 3 MSS, Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+). These images were chosen in the dry season for getting better identification between forest and non forest areas.

For these Landsat satellite images, general calibration and dark object subtraction were conducted to reduce bias caused by differences of sensors, sun elevation and atmospheric scattering.

Table 1. Data of Landsat images used in this study

| Image date | Satellite/Sensor | Path/ Row | Spatial Resolution |
|---|---|---|---|
| 1976.01.24 | Landsat 2/ MSS | 180/ 062 | 79 m |
| 1976.02.12 | Landsat 2/ MSS | 181/ 061 | 79 m |
| 1976.01.25 | Landsat 2/ MSS | 181/ 062 | 79 m |
| 1980.02.17 | Landsat 3/ MSS | 180/ 060 | 75m |
| 1980.02.17 | Landsat 3/ MSS | 180/ 061 | 75m |
| 1978.12.31 | Landsat 3/ MSS | 181/ 060 | 75m |
| 1984.12.17 | Landsat 5/ TM | 168/ 061 | 30m |
| 1987.02.25 | Landsat 5/ TM | 168/ 062 | 30m |
| 1986.01.28 | Landsat 5/ TM | 169/ 060 | 30m |
| 1986.01.28 | Landsat 5/ TM | 169/ 061 | 30m |
| 1987.02.16 | Landsat 5/ TM | 169/ 062 | 30m |
| 2000.02.21 | Landsat 7/ ETM+ | 168/ 060 | 30m |
| 2002.02.10 | Landsat 7/ ETM+ | 168/ 061 | 30m |
| 2000.02.21 | Landsat 7/ ETM+ | 168/ 062 | 30m |
| 2003.02.04 | Landsat 7/ ETM+ | 169/ 060 | 30m |
| 2003.03.08 | Landsat 7/ ETM+ | 169/ 061 | 30m |
| 2003.02.04 | Landsat 7/ ETM+ | 169/ 062 | 30m |

### 2.2.3 Image enhancement

In order to clearly distinguish between forest and non forest areas, several kinds of image enhancement methods were used here, such as NDVI and the Tasseled Cap transformation. NDVI is a ratio of the red and near infrared reflectance and related with the fraction of photosynthetically active radiation absorbed by the vegetation (Rees, 2001). The value varies from -1 to 1. Higher value presents the pixels covered by denser green biomass (Campbell, 2002d). It presents tropical forest where values approach 1.

Tasseled Cap transformation converts the bands of original image into new bands representing proxies of vegetation characteristics. Because of the difference of sensors in Landsat images, there are several kinds of calculations.

In Landsat MSS images (Campbell, 2002d):

Brightness =0.433 (Band 1) + 0.632 (Band 2) +0.586 (Band 3) + 0.264 (Band 4)

Greenness =-0.290 (Band 1) -0.562 (Band 2) + 0.600 (Band 3) + 0.491 (Band 4)

Yellowness=-0.829 (Band 1) + 0.522 (Band 2) -0.039 (Band 3) + 0.194 (Band 4)

In Landsat 5 TM images (Crist et al., 1986):

Brightness = 0.2909(Band 1) + 0.2493(Band 2) + 0.4806(Band 3) + 0.5568(Band 4) + 0.4438(Band 5) + 0.1706(Band 7) +10.3695

Greenness = -0.2728(Band 1) - 0.2174(Band 2) - 0.5508(Band 3) + 0.7220(Band 4) + 0.0733(Band 5) - 0.1648(Band 7)-0.7310

Wetness = 0.1446(Band 1) + 0.1761(Band 2) + 0.3322(Band 3) + 0.3396(Band 4) - 0.6210(Band 5) + 0.4186(Band 7)-3.3828

In Landsat ETM+ images (Huang et al., 2002):

Brightness= 0.3561(Band 1) + 0.3972(Band 2) + 0.3904(Band 3) + 0.6966(Band 4) + 0.2286(Band 5) + 0.1596(Band 7)

Greenness= -0.3344(Band 1) -0.3544(Band 2) -0.4556(Band 3) + 0.6966(Band 4) - 0.0242(Band 5) -0.2630(Band 6)

Wetness= 0.2626(Band 1) + 0.2141(Band 2) + 0.0926(Band 3) + 0.0656(Band 4) - 0.7629(Band 5) -0.5388(Band 6)

The first new band represents the index of “brightness” which shows the soil moisture of the image. The second new band is “greenness” which presents the amount of green vegetation. The third new band is “wetness”, which shows soil and surface moisture in TM and ETM+ images, or “yellowness”, which presents the amount of dried vegetation in MSS images (Campbell, 2002d, Rees, 2001). With the growing of vegetation, the greenness index will increase. Meanwhile, the brightness would decrease due to the increase in ground cover by vegetation.

Principal component analysis (PCA) was applied on Landsat images. PCA, similar to Tasseled Cap transformation, transforms the original images with many bands into few components images that are orthogonal to each other (Campbell, 2002b, Rees, 2001). In the original image some bands would correlate with each other. With PCA, these interrelated bands could be combined and converted into fewer less relevant components. It condenses the information, reduces the redundancy of the original data as well as highlights the similarity and difference between bands. The majority of total variance will be presented in the first few component images. Using PCA on remote sensing data can filter out the noise of satellite images and enhance image features (Byrne et al., 1980, Campbell, 2002b).

### 2.2.4 Image classification

The resulting component images were combined in a band stacking process to create a multi-band multi-proxy vegetation mapping dataset to allow supervised classification for the separation of forest areas and non forest areas. There are several approaches for supervised classification. In this study, minimum distance classification was used. Training areas were selected in forest and non forest areas. The unclassified pixels will be assigned to the class that is spectrally closest (Campbell, 2002c). Then the total area of forest could be calculated by the pixel numbers of forest class.

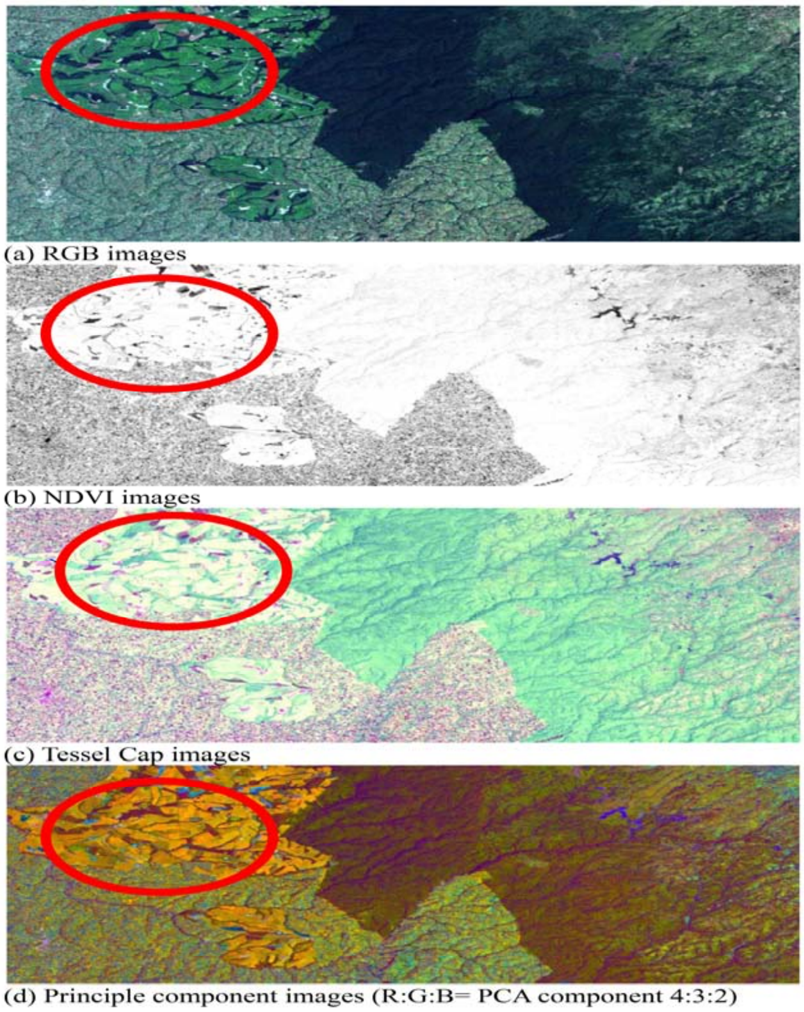


Fig. 4 Different image processing in Mau forest

### 2.2.5 Accuracy assessment

Accuracy assessment is performed by comparing the classification map with the ground truth image. However, the ground truth data is lacking in this study. Ground truth regions of interest (ROI) were used in this study to define the correct classes. Ground truth ROIs were randomly chosen in the forest and not forest area which were visually identified in Landsat images. For each classification image, user and producer accuracies as well as overall classification accuracies and kappa coefficient were calculated by establishing a confusion matrix (Campbell, 2002a).

A confusion matrix presents the pixel dispositions of the classification map and ground truth. Producer accuracy is calculated by dividing the numbers of the classified pixels which are assigned to the correct class by the total pixel numbers of the correct class. Producer accuracy shows the probability that the pixel of the correct class will be really assigned to the correct class. User accuracy is calculated by dividing the numbers of the classified pixels which are assigned to the correct class by the total pixel number of the assigned class. It presents the probability that the pixels of the assigned class actually represent the correct class.

Overall accuracy is calculated by dividing the total numbers of classified pixels which are assigned to the correct classes by total number of pixels. The kappa coefficient is to evaluate the difference of agreement between two maps. It is calculated by:

K= (observed- expected) / (1-expected)

"Observed" is the percentage of observed agreement and "Expected" shows the probability of chance agreement. The value of Kappa coefficient ranged from -1 to 1. Higher value indicates higher agreement (Campbell, 2002a, Monserud and Leemans, 1992).

## 2.3 Statistical analysis

SAS statistical package (v. 9.1, SAS Institute Inc., Cary, NC, USA) and SPSS Statistics (v.17.0, SPSS Inc., Chicago, IL, USA) were used to perform statistical analyses. Population and economic data was obtained from the World Bank and climate data was downloaded from NOAA, USA. Deforestation is defined by the decrease of dry season NDVI in the analysis of GIMMS and by the decrease of the forest area in the analysis of Landsat images. Correlation between forest area from Landsat images and mean NDVI values of dry season from GIMMS dataset of the same year were analyzed to examine the consistency between Landsat images and GIMMS dataset. Wilcoxon Signed Ranks Test was used to examine the differences of related samples for non-parametric statistics. Regressions models were developed for three countries to analyze the relationships between dry season NDVI and possible drivers, such as GDP, population, climate factors and so on

# 3. Results

## 3.1 Landsat images classification

Supervised classification was carried out on Landsat MSS, Landsat TM and Landsat ETM+ images. In total seventeen Landsat images were used in this study covering Nairobi, Kenya and nearby forests as well as Mountain Kilimanjaro in Tanzania, the highest mountain in East Africa and its surroundings. These areas were chosen because Nairobi is the largest and the most populous city of East Africa: many forests and mountains surrounding Nairobi, including Mau forest, and Mount Kenya, would be easily exploited due to urbanization and over population. Mountain Kilimanjaro also faces a similar situation now.

The forest area of each Landsat image was calculated by the sum of pixels in the forest class. In some images large plantations, such as tea plantations, have similar NDVI values with forests, as do dense agriculture areas and, in some cases, even urban areas could cause misclassification. Hence, several image processing methods were used to enhance the visual interpretation, to classify forest and non forest areas, and improve separation between classes. Methods including the NDVI transform, Tasseled cap transform and PCA analysis were used. Taking Mau forest (Path/ Row: 169/ 060) as an example, in the NDVI image (Fig. 4) the large plantation area nearby Mau forest is difficult to distinguish from forest area. In Tasseled Cap images and PCA component images, it is easier to identify forest areas. Therefore, supervised classification was carried out on stacked Tasseled Cap images and PCA component images.

An accuracy assessment of classification for Landsat images was performed and the results are summarized in Table 4. The Kappa coefficient of 0.75 or greater represents a very good reliability of the performance for classification (Jones and Vaughan, 2010, Monserud and Leemans, 1992). A value between 0.6 and 0.8 shows a substantial reliability (Landis and Koch, 1977). The classification maps in this study had overall accuracies all over 70%. All of the Kappa coefficients of classification map were greater than 0.68 and most of them were over 0.75. Most of the classification maps had a high producer accuracy and user accuracy for the forest class, ranging between 70% and 90%. Instead of using original Landsat images, in this study supervised classification was carried out on the images stacking Tasseled Cap images and PCA component images. The accuracy test of classification for the images using original Landsat data was also conducted to compare the performance of different images. The results showed that the accuracies of these two kinds of images are quiet similar, and most of them are greater than 0.75. However, the significant higher accuracies of classification using stacked Tasseled Cap images and PCA component images were still observed by Wilcoxon Signed Ranks Test.

The distribution of forest areas in seventeen Landsat images are presented in Fig. 5, Fig. 6 and Fig. 7. According to these figures, an obvious decrease in forest area occurred between the three different periods. The forest areas in each image were listed on the table 2. Because Landsat MSS images had different path and row with TM and ETM+ images, deforestation rate in Table 3 was only presented by comparing Landsat TM and ETM+ images. Wilcoxon Signed Ranks Test was used to examine the change of forest area in each two paired images in the same path and row between any two given periods (Table 3). The result indicated that the forest areas significantly decreased between 1980s and 2000s. It showed clearly significant deforestation during study period. The Gatamaiyo forest which is close to Nairobi city decreased 284.99 $km^2$ between 1980s and 2000s. In Mount Kilimanjaro, forest areas lost about 13.39 % in this period. The highest decreasing rate was observed in Mau forest area about 1.34 % per year during 1980s to 2000s.

The NDVI values from GIMMS data for the same area as the Landsat images and same year were also calculated to compare with forest areas (Table 2). The results showed the GIMMS NDVI in the dry season (July, August and September) and the forest area identified from the Landsat data, in the same areas and same years , have a significant positive relationship (correlation coefficient: 0.8) (Fig. 8). Therefore, in the analysis of GIMMS data, the NDVI values in dry season could be used as a proxy of total forest area.

Table 2. The results of classification of Landsat images

| Images number | Path/ Row | Date | Forest Area ($km^2$) | Dry season NDVI of GIMMS |
|---|---|---|---|---|
| L318006019800217 | 180/ 060 | 1980.02.17 | 4533.23 | - |
| L318006119800217 | 180/ 061 | 1980.02.17 | 1182.88 | - |
| L218006219760124 | 180/ 062 | 1976.01.24 | 2598.26 | - |
| L318106019781231 | 181/ 060 | 1978.12.31 | 11308.90 | - |
| L218106119760212 | 181/ 061 | 1976.02.12 | 5141.11 | - |
| L218106219760125 | 181/ 062 | 1976.01.25 | 4300.40 | - |
| L516806119841217 | 168/ 061 | 1984.12.17 | 1314.81 | 0.20 |
| L516806219870225 | 168/ 062 | 1987.02.25 | 2149.87 | 0.26 |
| L516906019860128 | 169/ 060 | 1986.01.28 | 5223.94 | 0.61 |
| L516906119860128 | 169/ 061 | 1986.01.28 | 4151.46 | 0.39 |
| L516906219870216 | 169/ 062 | 1987.02.16 | 1847.13 | 0.24 |
| L716806020000221 | 168/ 060 | 2000.02.21 | 3284.45 | 0.31 |
| L716806120020210 | 168/ 061 | 2002.02.10 | 1029.82 | 0.26 |
| L716806220000221 | 168/ 062 | 2000.02.21 | 1861.89 | 0.23 |
| L716906020030204 | 169/ 060 | 2003.02.04 | 4034.53 | 0.58 |
| L716906120030308 | 169/ 061 | 2003.03.08 | 4052.49 | 0.41 |
| L716906220030204 | 169/ 062 | 2003.02.04 | 1652.21 | 0.23 |

Table 3. The pattern of deforestation identified by Landsat images

| Path/Row | Landmarks | Forest ($km^2$) in 1980s | Forest ($km^2$) in 2000s | Decreasing area ($km^2$) | Decreasing Rate (% per year) | *P*-value [a] |
|---|---|---|---|---|---|---|
| 168/ 060 | Mountain Kenya; Aberdare Forest | - | 3284.45 | - | - | 0.043 |
| 168/ 061 | Gatamaiyo Forest; Nairobi city | 1314.81 | 1029.82 | 284.99 | 1.20 | |
| 168/ 062 | Mountain Kilimanjaro | 2149.87 | 1861.89 | 287.97 | 1.03 | |
| 169/ 060 | Mau forest | 5223.94 | 4034.53 | 1189.42 | 1.34 | |
| 169/ 061 | Shompole Conservancy | 4151.46 | 4052.49 | 98.97 | 0.14 | |
| 169/ 062 | Ngorongoro Conservation Area | 1847.13 | 1652.21 | 194.92 | 0.66 | |

[a] Wilcoxon Signed Ranks Test was used to examine the differences of forest area between the two periods

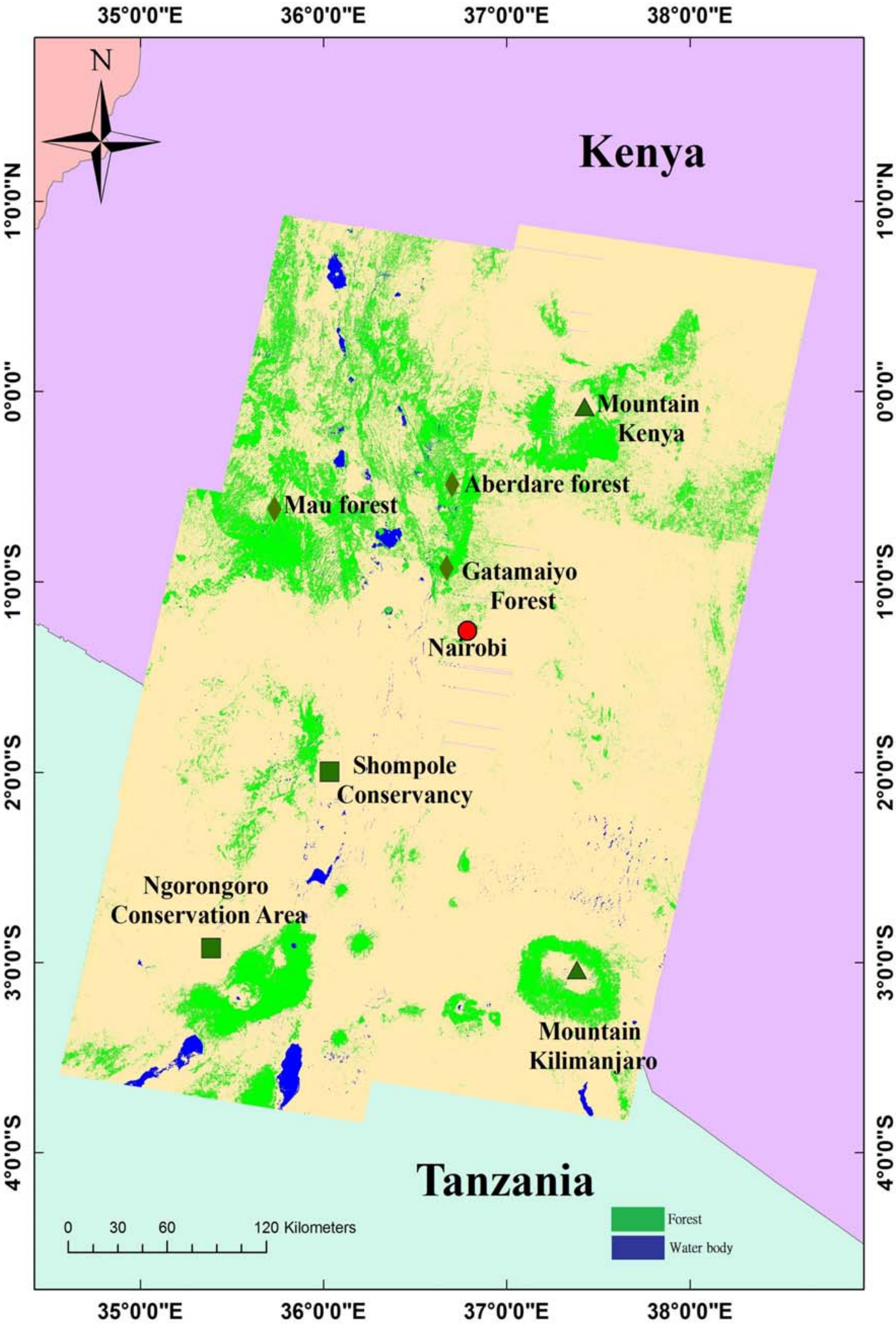


Fig. 5 Forest areas during 1976 to 1980

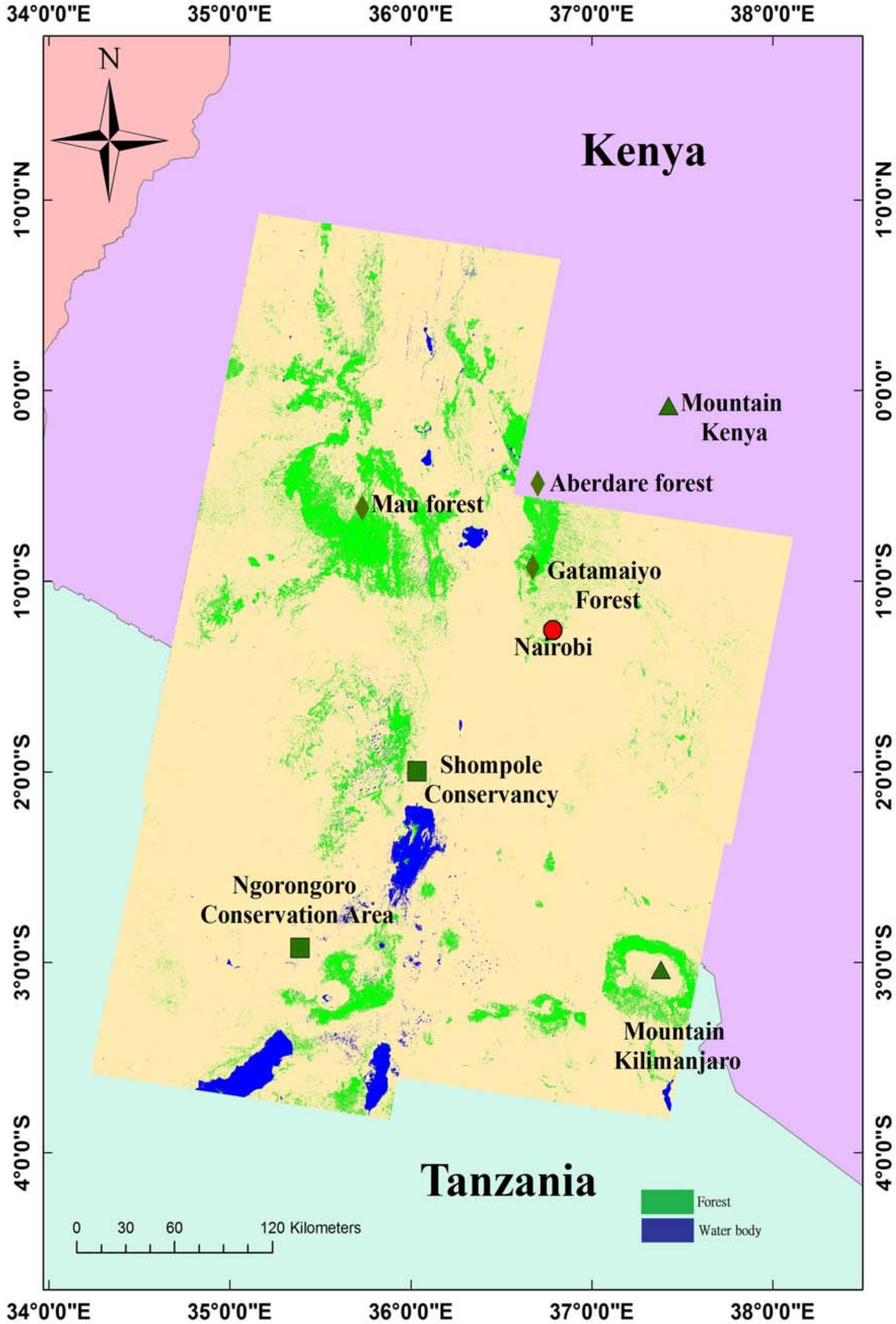


Fig. 6 Forest areas during in 1980s

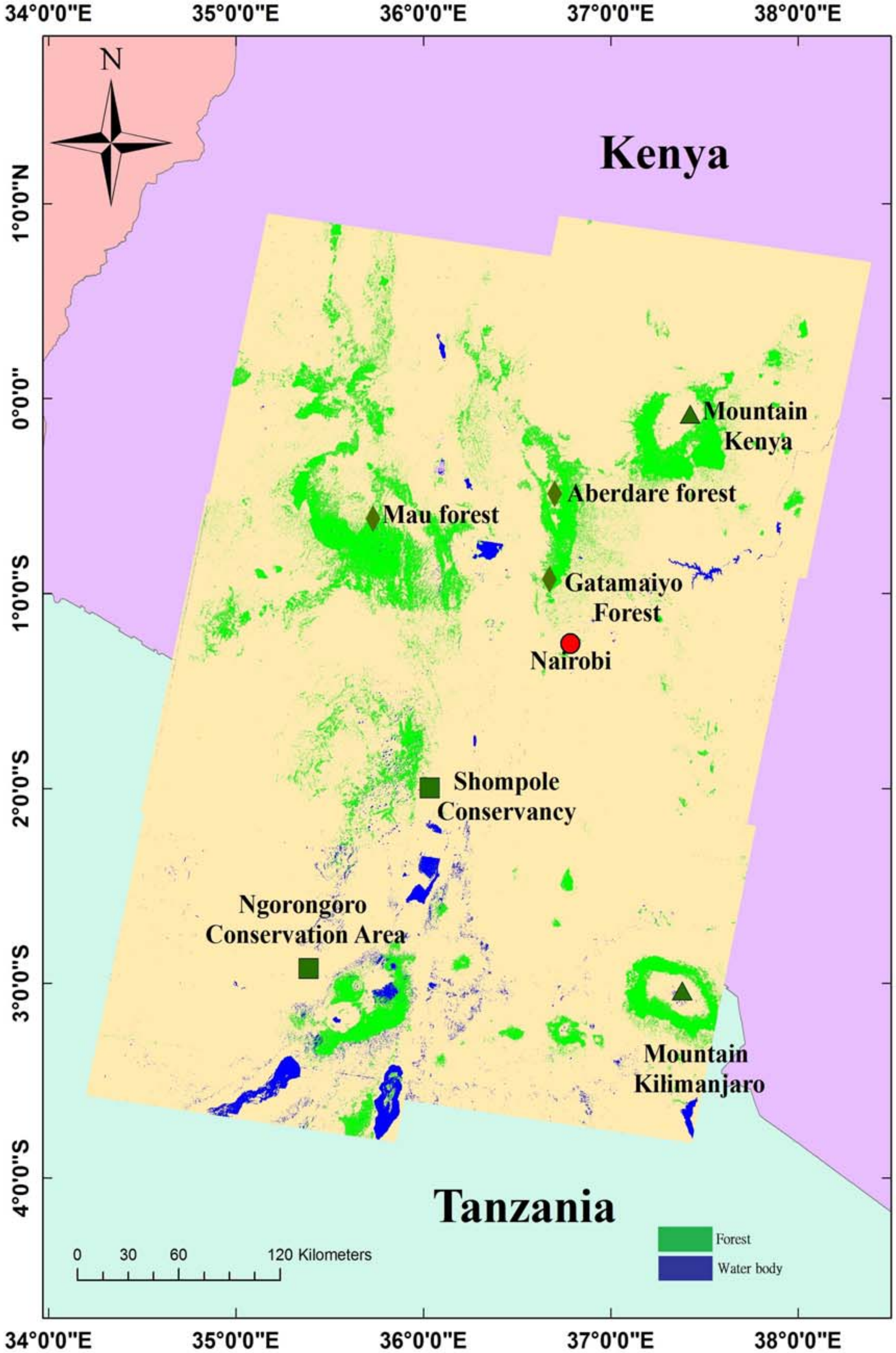


Fig. 7 Forest areas during in 2000s

Table 4. The accuracy of classification for Landsat images

| Images number | Path/ Row | Producer Accuracy (%)[a] | User Accuracy (%)[a] | Overall Accuracy (%)[a] | Kappa Coefficient [a] | Overall Accuracy (%)[b] | Kappa Coefficient [b] | *P*-value [c] |
|---|---|---|---|---|---|---|---|---|
| L318006019800217 | 180/ 060 | 92.39 | 80.97 | 81.1517 | 0.7637 | 81.1483 | 0.7636 | 0.002 |
| L318006119800217 | 180/ 061 | 86.20 | 78.67 | 76.1097 | 0.7012 | 76.1097 | 0.7012 | |
| L218006219760124 | 180/ 062 | 86.97 | 82.07 | 77.7605 | 0.7370 | 77.6048 | 0.7352 | |
| L318106019781231 | 181/ 060 | 78.34 | 81.23 | 84.4550 | 0.8133 | 84.4535 | 0.8133 | |
| L218106119760212 | 181/ 061 | 93.89 | 71.94 | 78.0276 | 0.7422 | 78.0264 | 0.7422 | |
| L218106219760125 | 181/ 062 | 99.59 | 99.19 | 84.6880 | 0.8083 | 84.6874 | 0.8083 | |
| L516806119841217 | 168/ 061 | 86.88 | 89.23 | 82.0519 | 0.7846 | 81.3516 | 0.7762 | |
| L516806219870225 | 168/ 062 | 96.08 | 73.24 | 76.7311 | 0.7339 | 76.1935 | 0.7278 | |
| L516906019860128 | 169/ 060 | 98.78 | 90.71 | 86.9843 | 0.8439 | 86.9347 | 0.8433 | |
| L516906119860128 | 169/ 061 | 99.45 | 87.24 | 73.4398 | 0.6897 | 73.2454 | 0.6874 | |
| L516906219870216 | 169/ 062 | 95.10 | 99.88 | 94.3214 | 0.9290 | 90.5831 | 0.8823 | |
| L716806020000221 | 168/ 060 | 96.74 | 94.38 | 84.6343 | 0.8097 | 84.6343 | 0.8097 | |
| L716806120020210 | 168/ 061 | 97.00 | 92.29 | 83.3074 | 0.7989 | 82.9365 | 0.7944 | |
| L716806220000221 | 168/ 062 | 94.88 | 86.42 | 86.3646 | 0.8408 | 86.2548 | 0.8395 | |
| L716906020030204 | 169/ 060 | 84.58 | 95.47 | 83.2444 | 0.7988 | 83.2225 | 0.7986 | |
| L716906120030308 | 169/ 061 | 99.86 | 93.51 | 81.2248 | 0.7749 | 80.9473 | 0.7716 | |
| L716906220030204 | 169/ 062 | 97.17 | 99.92 | 92.3835 | 0.9047 | 91.3520 | 0.8918 | |

[a]. The images for classification were stacking PCA component images and Tasseled Cap images

[b]. The images for classification were original Landsat images

[c]. Wilcoxon Signed Ranks Test was used to examine the differences of accuracy of classification using two kinds of images

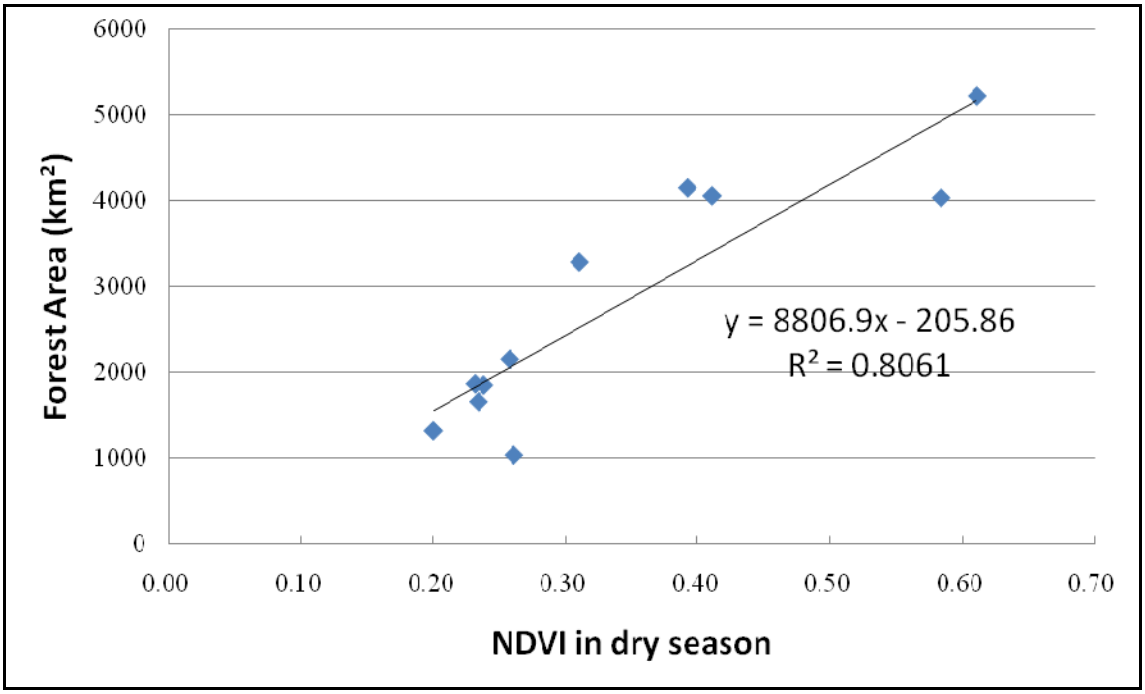


Fig. 8 The relationship between annual mean dry season NDVI of GIMMS and forest areas in Landsat images

### 3.2 NDVI of GIMMS

Using the GIMMS dataset, the annual mean dry season NDVI of three countries, Kenya, Tanzania, and Uganda, between 1981 and 2006 were calculated. Several related climate, economic and demographic indicators were also collected. Tables 5 to 7 summarize the descriptive statistics of the dry season NDVI values and related indicators of three countries during the study period. The dry season NDVI in three countries showed significant difference between each other ($p<0.01$). The NDVI had significantly higher values in Uganda (mean value: 0.56) and lowest in Kenya (mean value: 0.28). Comparing dry season NDVI among the three periods, 1980s, 1990s and 2000s, no significant differences were observed in any of three countries. However, the dry season NDVI still showed slowly decreasing pattern from 1981 to 2006 in Kenya and Uganda. In Tanzania, the dry season NDVI was more constant during the study period (Fig. 9). The spatial and temporal pattern of annual mean dry season NDVI were also presented in Fig.10. Based on the Fig. 10, it showed that Uganda had the most pixels with NDVI greater than 0.6, followed by Kenya and Tanzania. The greenness was slowly decreased in Uganda and Kenya from 1980s to 2000s. At the same time, the pixels with NDVI values greater than 0.4 were increased in Tanzania.

The annual mean dry season NDVI of Mau forest, Mount Kilimanjaro, Mount Kenya and Aberdars forest were also calculated. The distribution of dry season NDVI between 1981 and 2006 in these four forest areas is shown in Fig 11. The results were not consistent in these four forests. The dry season NDVI values in Mau forest had a slight decrease during study period. However, the NDVI in other three forest areas had a similar pattern with the NDVI of Tanzania.

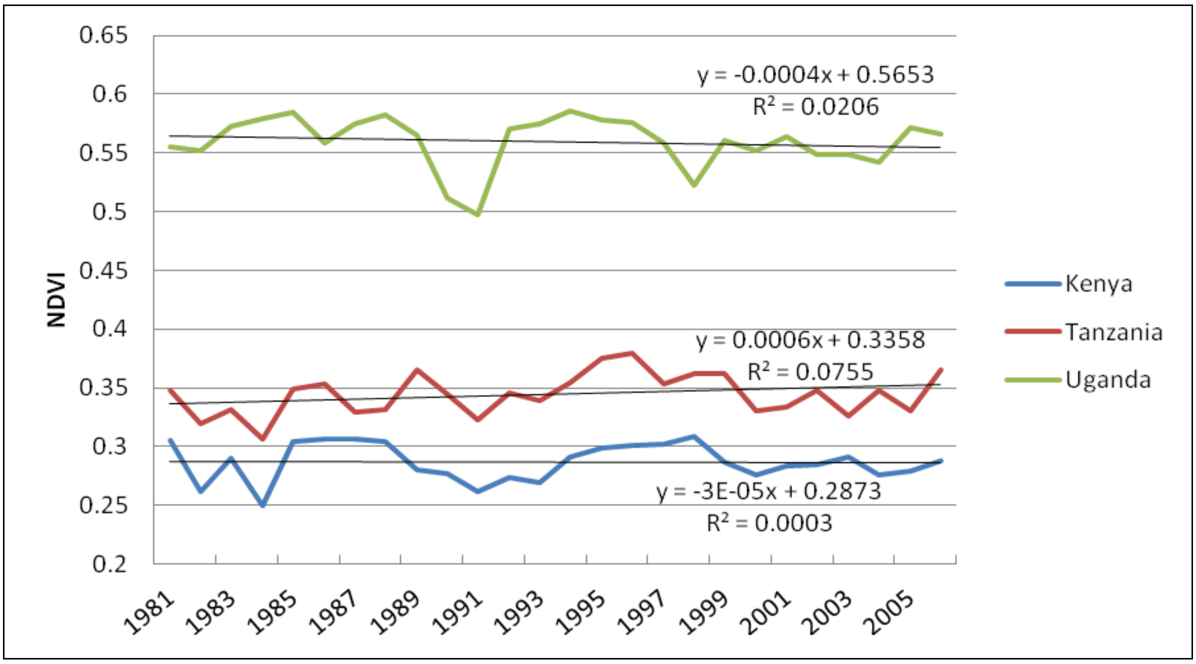


Fig. 9 The distribution of annual mean NDVI of dry season from 1981 to 2006 in Kenya, Tanzania and Uganda

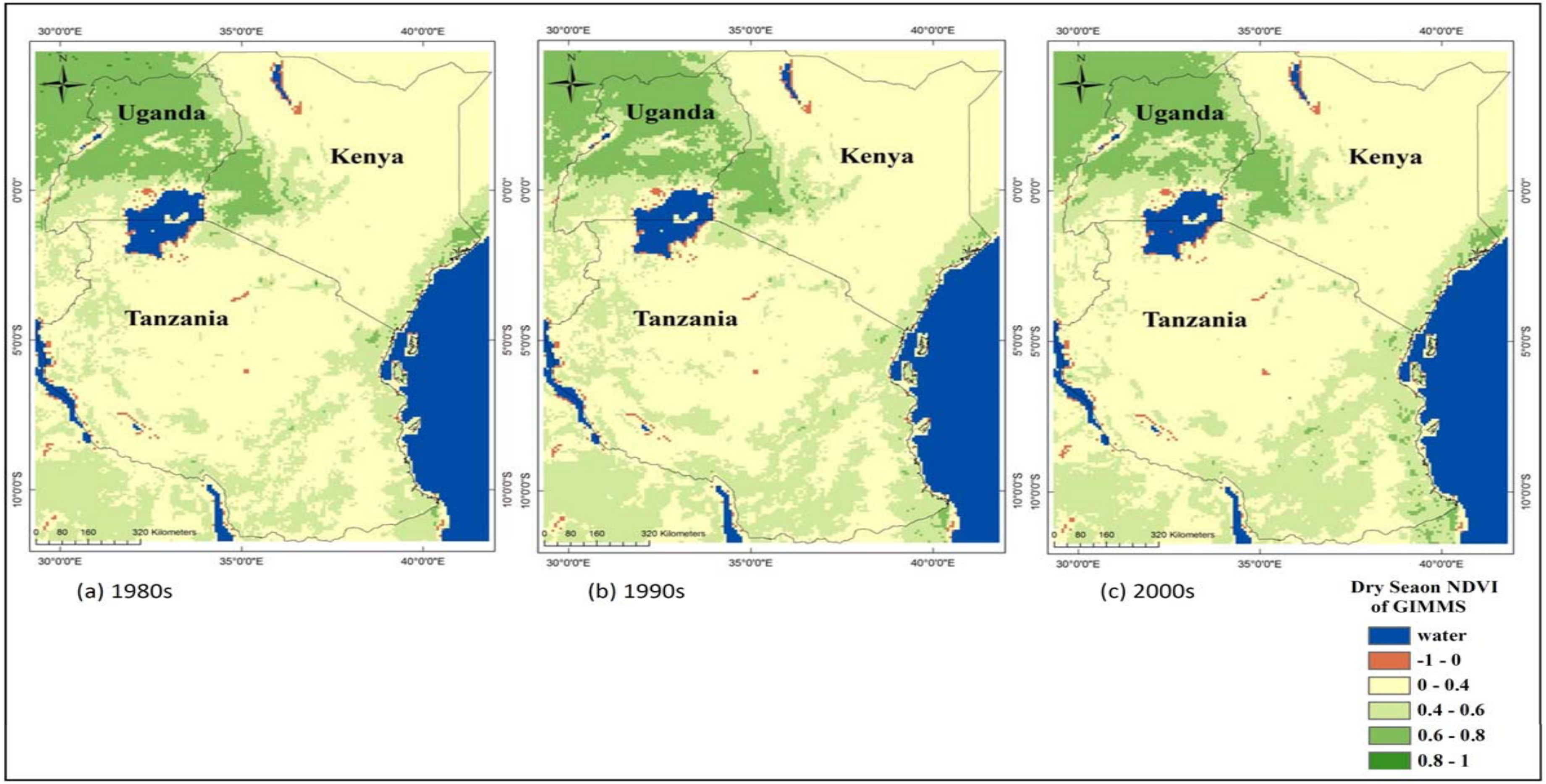


Fig. 10 The spatiotemporal pattern of annual mean NDVI of dry season in East Africa in 1980s, 1990s and 2000s.

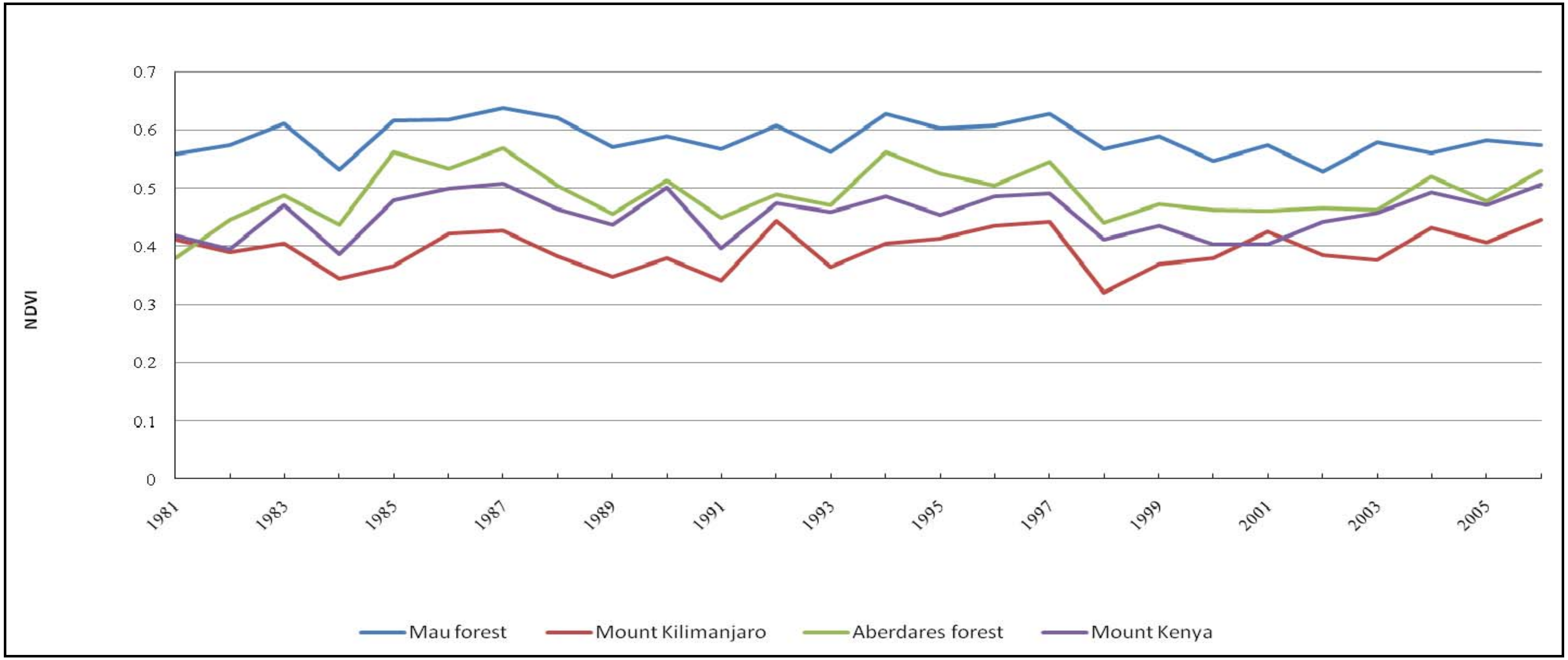


Fig. 11 The distribution of annual mean NDVI of dry season from 1981 to 2006 in four major forest areas

## 3.3 Relationships between deforestation and possible drivers

The dry season NDVI in this study was used as the indicator of deforestation. A decrease of the dry season NDVI would present the loss of forest areas. In the spearman correlation test, the results showed small, negative but not statistically significant correlations between dry season NDVI and population, birth rate, agricultural areas as well as agricultural population in Kenya (Table 5). Gross domestic product (GDP) growth and GDP per capita growth were significantly and positively related to dry season NDVI in Kenya with simple linear regression analysis (Table 8).

In Tanzania, population growth, GDP per capita, life expectancy and arable land per person also showed slightly negative but no significant correlations with dry season NDVI by spearman correlation analysis (Table 6). Using simple linear regression analysis, birth rate in Tanzania had a significant negative relationship with dry season NDVI. But Cereal production showed a significant positive correlation with dry season NDVI (Table 8).

The weak negative but non-significant relationships between dry season NDVI and population, cereal production, GDP, agricultural areas as well as agricultural population were also observed in Uganda by spearman correlation test (Table 7). With simple linear regression analysis, dry season NDVI was significant related to rainfall negatively (Table 8).

Multiple regression models were used to examine the possible drivers for deforestation. (decreasing of dry season NDVI) (Table 9). In multiple regression model analysis, rainfall was significantly associated with dry season NDVI both in Kenya and Uganda, yet had diverse effects on their values. Agriculture value added (% of GDP) showed significant positive relationships with dry season NDVI in Kenya and Uganda. GDP per capita growth (annual %) also had a significantly positive correlation with dry season NDVI in Kenya. For Tanzania, Cereal production and Life expectancy of people in Tanzania were significant predictors of dry season NDVI.

Table 5. Descriptive statistics for annual mean NDVI of dry season and related indicators in Kenya during study period

| **Kenya** | **1980s** | **1990s** | **2000s** | **Correlation Coefficient to Dry season NDVI[a]** |
|---|---|---|---|---|
| Dry season NDVI | 0.283±0.023 | 0.280±0.018 | 0.278±0.008 | - |
| Total population | 19,723,154±1,975,504 | 26,968,696±2,357,310 | 33,834,739±1,908,026 | -0.085 |
| Birth rate (per 1,000 people) | 47±2 | 39±1 | 39±0.3 | -0.135 |
| Cereal yield (kg per hectare) | 1677.77±183.89 | 1588.47±173.32 | 1599.31±136.33 | -0.002 |
| GDP per capita (current US$) | 357.69±30.24 | 362.08±80.94 | 462.57±79.53 | 0.227 |
| Agricultural land (% of land area) | 45.9±1.01 | 47.16±0.5 | 47.25±0.23 | -0.263 |
| Agricultural population | 15,941,222±1,450,585 | 20,946,200±1,502,406 | 25,042,857±1,069,010 | -0.085 |
| Temperature (℃) | 22.84±0.64 | 22.64±0.82 | 22.9±0.68 | 0.290 |
| Dew point temperature (℃) | 18.59±0.27 | 18.55±0.15 | 18.61±0.26 | -0.128 |
| Rainfall (mm) | 1,501.72±326.58 | 1,563.35±584.26 | 1,469.66±438.66 | 0.167 |

[a]. Correlation is analyzed by spearman correlation test

Table 6. Descriptive statistics for annual mean NDVI of dry season and related indicators in Tanzania during study period

| **Tanzania** | **1980s** | **1990s** | **2000s** | **Correlation Coefficient to Dry season NDVI**[a] |
|---|---|---|---|---|
| Dry season NDVI | 0.330±0.019 | 0.352±0.019 | 0.340±0.017 | - |
| Total population | 21,865,143±1,843,855 | 29,439,756±2,649,568 | 37,016,402±2,154,669 | 0.375 |
| Birth rate (per 1,000 people) | 45±1 | 43±1 | 42±0 | -0.370 |
| Life expectancy (years) | 50.91±0.28 | 50.21±0.33 | 52.37±1.31 | -0.326 |
| Cereal production (metric tons) | 3,527,870.11±637,074.84 | 3,959,030.6±590,146.48 | 5,193,234.57±1,156,208.66 | 0.424* |
| GDP per capita (current US$) | — | 209.92±54.32 | 333.57±29.13 | -0.110 |
| Agriculture value added (current US$) | — | 2428736345.1±561289041.93 | 3600610178.43±402846578.42 | -0.083 |
| Agricultural land (% of land area) | 37.88±0.59 | 38.38±0 | 38.93±0.38 | 0.184 |
| Agricultural population | 18,576,556±1,578,374 | 23,636,700±1,681,121 | 28,050,571±1,161,972 | 0.375 |
| Arable land (hectares per person) | 0.39±0.02 | 0.31±0.03 | 0.25±0.01 | -0.350 |
| Temperature (℃) | 23.66±0.52 | 23.77±0.51 | 23.9±0.17 | 0.177 |
| Dew point temperature (℃) | 17.19±0.21 | 16.8±0.98 | 17.13±0.62 | 0.013 |
| Rainfall (mm) | 903.47±261.49 | 708.96±339.52 | 761.85±209.65 | 0.117 |

[a]. Correlation is analyzed by spearman correlation test.

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7. Descriptive statistics for annual mean NDVI of dry season and related indicators in Uganda during study period

| **Uganda** | **1980s** | **1990s** | **2000s** | **Correlation Coefficient to Dry season NDVI[a]** |
|---|---|---|---|---|
| Dry season NDVI | 0.57±0.012 | 0.554±0.036 | 0.556±0.012 | - |
| Total population | 14,917,869±1,396,944 | 20,654,970±1,999,041 | 26,957,768±1,881,014 | -0.291 |
| Birth rate (per 1,000 people) | 49±0 | 49±1 | 47±0 | 0.206 |
| Cereal production (metric tons) | 1,231,520.56±211,937.79 | 1,822,080±229,600.27 | 2,369,571.43±153,534.86 | -0.238 |
| GDP per capita (current US$) | 252.26±101.64 | 231.01±52.93 | 273.02±43.25 | -0.032 |
| Agriculture value added (current US$) | 56.02±1.86 | 47.9±5.73 | 26.48±2.41 | 0.106 |
| Agricultural land (% of land area) | 58.24±2.17 | 61.46±0.43 | 63.34±0.98 | -0.291 |
| Agricultural population | 12,642,000±1,105,039 | 17,019,900±1,390,156 | 21,042,429±1,135,240 | -0.291 |
| Temperature (℃) | 22.7±0.68 | 23.24±0.54 | 22.96±1.44 | -0.238 |
| Dew point temperature (℃) | 16.99±1.28 | 17.32±0.67 | 16.38±1.31 | -0.429* |
| Rainfall (mm) | 986.07±523.91 | 1,440.45±1963.95 | 924.45±121.03 | -0.074 |

[a]. Correlation is analyzed by spearman correlation test

*. Correlation is significant at the 0.05 level.

Table 8. Univariate linear regression models for deforestation in three countries

| | β Coefficient | SE | *p*-value | $R^2$ |
|---|---|---|---|---|
| *Kenya* | | | | |
| 1. GDP growth (annual %) | 0.003 | 0.001 | 0.026 | 0.191 |
| 2. GDP per capita growth (annual %) | 0.004 | 0.001 | 0.021 | 0.203 |
| *Tanzania* | | | | |
| 1. Birth rate (per 1,000 people) | -0.006 | 0.002 | 0.014 | 0.228 |
| 2. Cereal production (metric tons) | 0.00000001 | 0.000000004 | 0.031 | 0.180 |
| *Uganda* | | | | |
| 1. Rainfall (mm) | -0.00001 | 0.000003 | 0.006 | 0.331 |

Table 9. Multiple regression models for deforestation in three countries

| | β Coefficient | SE | *p*-value | $R^2$ |
|---|---|---|---|---|
| *Kenya* | | | | 0.436 |
| Intercept | 0.151 | 0.050 | 0.006 | |
| GDP per capita growth (annual %) | 0.006 | 0.001 | 0.001 | |
| Agriculture value added (% of GDP) | 0.003 | 0.001 | 0.034 | |
| Rainfall (mm) | 0.00002 | 0.00001 | 0.018 | |
| *Tanzania* | | | | 0.382 |
| Intercept | 0.804 | 0.183 | 0.0002 | |
| Cereal production (metric tons) | 0.00000002 | 0.000000004 | 0.001 | |
| Life expectancy (years) | -0.01 | 0.004 | 0.012 | |
| *Uganda* | | | | 0.519 |
| Intercept | 0.542 | 0.013373929 | <.0001 | |
| Agriculture value added (% of GDP) | 0.001 | 0.000313971 | 0.016 | |
| Rainfall (mm) | -0.00001 | 0.000003 | 0.0007 | |

## 4. Discussion

In this study, two kinds of satellite images data, Landsat images and GIMMS dataset, were used to examine the spatiotemporal distribution of deforestation in East Africa. These two datasets have different spatial resolution. Landsat images with higher resolution can provide more detailed information and are helpful to further understand the local change of forest loss. The data with coarse resolution, such as GIMMS, can acquire data widely and is useful to examine the change at regional or global scales. Therefore, GIMMS was used in this study to investigate the deforestation of three East African countries. Landsat images were acquired to analyze tropical forest depletion of several important forests in East Africa.

For Landsat images during 1970s to 2000s, the study areas focused on the forests near Nairobi area, the largest city in East Africa, as well as Mountain Kilimanjaro, the important habitat and intensively settled and cultivated area in Tanzania, and its surroundings. According to the results, obvious deforestation during study period occurred in Mau forest, located in northwest of Nairobi, the forest in Mountain Kilimanjaro and Gatamaiyo forest close to Nairobi city. In East Africa, the expansion of cultivation, and population growth were the major reasons for deforestation. With the increasing population, small farmers had to convert more forest area into arable lands (Rudel and Roper, 1996). Comparing to the report from FAO (FAO, 2010), the deforestation rate in Tanzania of 1.2 % per year was close to the result of this study in Mountain Kilimanjaro between 1980s and 2000s. However, the deforestation rate in Mau forest and Gatamaiyo forest was four times higher than the average annual deforestation in Kenya of 0.3 %. These results indicate that the forests near overpopulated city would face more serious deforestation in comparison of average levels.

Previous studies with aerial photos and Landsat images were conducted to examine the land use change in Mountain Kilimanjaro (Mbonile et al., 2003, Soini, 2002). Their results both revealed that large forest loss in Mountain Kilimanjaro was caused by the expansion of cultivation and increasing population pressure. Baldyga et al. (2007) using Landsat images indicated that significant forest loss in Mau forest was due to a large area in Mau forest converted to small-scale agricultural lands. Nkako et al. (2005) also pointed out that the main causes of deforestation in Mau forest was settlement and logging using an aerial survey.

Gatamaiyo forest is a part of Aberdares forest, but the image covering the major part of Aberdares forest in 1980s was not acquired in this study. Therefore, it was difficult to examine the deforestation in Aberdares forest between 1980s and 2000s. However, comparing with the images of Landsat MSS in 1970s, clear forest loss in Aberdares forest was still observed in this study. The forest area was declined about 37 % between 1978 and 2002. The research of Ochego (2003) also showed significant deforestation of 30 % in the Aberdares forest during 1987 to 2000 using Landsat images. United Nations Environment Programme conducted an aerial survey in Aberdares forest and confirmed that the depletion of Aberdares forest was mainly because of logging, producing charcoal, settlements, cultivation and grazing (Lambrechts et al., 2003).

For Mount Kenya forest, the result showed the forest loss was about 12.7 % between 1980 and 2000 by comparing the Landsat MSS image and ETM+ image. It was close to the study of Ndegwa (2005) that indicated 10.3 % of forest decrease in Mount Kenya from 1978 to 1987 and 7.2 % from 1987 to 2002. The results also suggested the forest destruction was mostly due to the development of plantation, especially between 1978 and 1987. Ngigi and Tateishi (2004) used Landsat images to investigate deforestation in similar study area in Kenya with this study (Mount Kenya forest, Mau forest, Aberdares forest and Eburu forest). Their results showed the forest in this area decreased totally at 2 % per year from 1987 to 2000. The results of this study also revealed similar pattern in Mau forest and Gatamaiyo forest during 1980s to 2000s.

The results of this study showed pattern of deforestation consistent with other research which used Landsat images or aerial photos. It proves that satellite images are a useful tool to identify forests in tropical region. However, misclassification could happen due to clouds, and the slope and aspect of topographic relief. The pixels that covered by clouds or mountain shadow could easily be misclassified. For example, some agriculture or urban areas located in the mountainside of Mount Kenya, Mount Kilimanjaro and Mau forest that covered by mountain shadow could be classified as forest and the forest area covered by shadow could be identified as non forest. Bias could occur in six images used in this study with cloud covering that some pixels in both forest and cloud to be classified as cloud. Meanwhile, the similarity of forest and other wooded areas in the dry region could make it more difficult to distinguish in the classification process (FAO, 2010). Baldyga et al. (2007) also pointed out the limitation of Landsat images to discriminate from similar land use types. These kinds of bias become unavoidable when using satellite images. Image enhancement which emphasizes the difference of features would be helpful to separate similar land use types in tropical and high relief landscapes, such as NDVI, Tasseled Cap transformations and PCA (Baldyga et al., 2007, Ndegwa, 2005).

PCA could decrease the noise of the original images and highlight the image features. The vegetation index derived from Tassel Cap transformation can help analysts to clearly identify different types of vegetation. Baldyga et al. (2007) used the images stacking original Landsat images, Tassel Cap image and NDVI image to perform image classification with Kappa Coefficient of 0.76. Similar method was also used by Ndegwa (2005) to conduct image classification on the images comprised Landsat images, PCA component images, Tasseled Cap images and NDVI images with high Kappa Coefficient, over 0.85. Therefore, in this study the images stacking Tasseled Cap images and PCA component images from Landsat images were used to decrease the occurrences of bias.

Most of the results presented a very good reliability of the performance for classification with Kappa Coefficient that over 0.75 for classification (Jones and Vaughan, 2010, Monserud and Leemans, 1992). Comparing the Kappa coefficient of the classification using original images, the results of this study showed that supervised classification using the images comprised Tasseled Cap images and PCA component images could have a better result than which using only original Landsat data. It also indicated that the images comprising Landsat enhancement images, such as Tasseled Cap images and PCA component images, would be a possible solution to reduce bias and improve the accuracies in classification process for forests in tropical region.

The second part of this study was to use GIMMS dataset to examine the deforestation in Kenya, Tanzania and Uganda. Annual mean NDVI of dry season was derived to be a proxy of total forest areas. NDVI in dry season might be helpful to represent forest area since only woody plant is still green in this period. In this study, the forest areas in Landsat images were compared with NDVI in dry season of the same location and year. According to the statistic analysis, annual mean NDVI of July, August and September showed the highest correlation with the forest areas of Landsat images, rather than the whole dry season (June to September). It showed a lag effect of vegetation for the coming of dry season. Due to the two dry seasons in these three countries, the dry season in winter was also analyzed. However, NDVI in second dry season (January and February) was much less correlated with forest areas of Landsat data ($R^2$= 0.06). Therefore, mean dry season NDVI was derived from NDVI in July, August and September.

A significant decrease in annual mean dry season NDVI was expected in all three countries. However, the results only showed a non significant and slow decrease of NDVI in Kenya and Uganda. NDVI in Tanzania were constant and slightly increased during the study period. The similar pattern was also found in the results of Pelkey et al. (2000). Pelkey et al. used NDVI values derived from Pathfinder AVHRR land (PAL) data from 1982 to 1994 with resolution of 8 km to map the change of vegetation cover in Tanzania. A vegetation map collected from Landsat images was used to define the area of various vegetation types. The result of Pelkey et al. showed the monthly NDVI over Tanzania and in forest areas increased from 1981 to 1994, likely due to the regeneration and protection. Other types of vegetation, such as swamp, had a significant decrease in NDVI values. In this study, annual mean dry season NDVI were also calculated in Mau forest, Mount

Kenya, Mount Kilimanjaro and Aberdares forest and showed similar results with Pelkey et al. The study of Kinyanjui (2010) also found that annual NDVI of different forest blocks of Mau forest varied smoothly during 1999 to 2009. Both studies of Pelkey et al. and Kinyanjui indicated that NDVI is useful to examine the resilience of forest and vegetation health.

In this study the results showed that the greenness showed no significant changes in the three countries between 1981 and 2006. However, large loss of forest area was indicated in Tanzania and Uganda and small scale of deforestation in Kenya (FAO, 2010).These results might indicate that the recovery ability of forest was slightly higher in Tanzania and a bit weak in Kenya and Uganda. Kinyanjui (2010) also confirmed the resilience of forest was slightly lower in Mau forest. But it is still needed to get further information to figure out the real situation. The consistent findings indicated that NDVI is more applicable to measure the greenness or density of vegetation types, rather than to monitor the change of forest area. NDVI values are correlated with the radiation of photosynthetically activity absorbed by the vegetation (Rees, 2001). NDVI could present the greenness of vegetation or biomass of green plant, but would be insufficient to define the accurate total area and range of forest area.

In statistical analysis, dry season NDVI was used as dependent variable to represent the total forest areas. Possible drivers, such as population statistics and economic indicators were applied to examine the relationships with deforestation. Significant negative correlations between the dry season NDVI and economic development and population growth were expected to be found out with statistical analysis. Unexpectedly, the results showed GDP growth in Kenya was a positive factor both in univariate and multiple regression models. Cereal production had a very small positive relationship with dry season NDVI in Tanzania in both univariate and multiple regression models. The possible driver in Uganda was rainfall, with a negative correlation. Meanwhile, the estimates of these relationships were very small, which indicated that even if they showed statistical significant correlations, the influence of these factors for the change of NDVI was quite small. The contradictory results of regression model analysis in this study could be because of the spatial resolution of GIMMS is too low to identify forest areas accurately and the characteristic of NDVI is not applicable as a proxy for total forest area. With this small range of NDVI values, varied from -1 to 1, it is difficult to use NDVI to quantify the loss of forest area. The coarse resolution of GIMMS made NDVI of GIMMS to be more unsuitable to detect the change of deforestation. Misclassification could occur in the mixed pixels that are both part of forest and non forest. Dent and Bai (2008) suggested that the study using NDVI should compare with fieldwork to get more information about ground truth and confirm the reliability and accuracy of NDVI data. Moreover, underestimation of total forest area might be occurred when using NDVI of dry season since some deciduous forest cloud lose their leaves or become yellowish in the dry season. It needs more information and field studies to verify the bias could be caused by the underestimation. Another possible reason for the ambiguous results could be few sample number for statistic analysis, since only 25 values of annual mean NDVI of the dry season for each countries. The correlation between possible drivers and dry season NDVI of GIMMS could be more complex. More information about the interactions as well as possible confounding and modifying factors are needed to be considered.

The spatial and temporal distribution of deforestation in East Africa was successfully identified by Landsat images in this study. But the possible drivers for deforestation in East Africa were still unclear in this study with NDVI of GIMMI dataset. For future studies, using high resolution satellite images and conducting a long term study to gather more information will be more helpful for further examine the pattern of deforestation and the possible drivers. At the same time, using Landsat images to study the deforestation in tropical areas, classification should be performed on the images that comprised enhancement images to improve the separability of classification.

# 5. Conclusion

Obvious deforestation was revealed in East Africa between 1970s and 2000s using Landsat satellite images, especially in Mau forest, Mount Kilimanjaro and Aberdares forest. The forests near overpopulated city faced more serious deforestation. In this study, it is shown that using the images that comprising enhancement images transformed from original images would be a better approach to mapping forest areas. The GIMMS NDVI dataset is not a good proxy of total forest areas probably because of the coarse resolution of GIMMS dataset and the characteristics of NDVI. More auxiliary information is needed to analyze the deforestation with GIMMS NDVI. Therefore, future studies of deforestation should use higher resolution satellite images and collect more detailed information.

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