ABSTRACT

MAPPING VEGETATION STATUS AT LAKE NAKURU NATIONAL PARK AND SURROUNDS, KENYA

by McNichol Kitavi Kaloki

The goal of this study was to examine environmental change at Lake Nakuru National Park (LNNP) and surrounds in the Central Rift Valley region of Kenya. The study was conducted using multi-temporal Landsat TM/OLI data for the period 1987 – 2016. The three objectives associated with this goal were to (1) Identify the most effective techniques for mapping detailed vegetation types in the study area, (2) Map land use/land cover (LULC) changes, and (3) Identify variables that can explain observed LULC in the area. The Random Forest classifier resulted in a LULC map with the highest classification accuracy (85.5%) when Landsat bands were combined with a Digital Elevation Model (DEM) and slope. The largest LULC changes observed outside LNNP involved the conversion of grassland to agriculture and occurred throughout the study area. The other major change occurred in the southwestern, northern and northeastern edges of the study area and involved conversion of forest to agriculture. Within the boundary of the LNNP, the major LULC change observed was 51% increase in area covered by lake water that resulted in the destruction of shoreline vegetation types and infrastructure. There was also a complete destruction of Euphorbia forest following a fire, and an overall decline in Acacia Woodlands. These changes are likely negatively impacting the quality of wildlife habitat in LNNP and threatening continued survival of wildlife species and habitats.

Key Words: Lake Nakuru, Kenya, Conservation, Remote Sensing, Vegetation, Land use land cover, Multi-season, Random Forest
MAPPING VEGETATION STATUS AT LAKE NAKURU NATIONAL PARK AND SURROUNDS, KENYA

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Dedication

Special dedication to my lovely wife Edna for the sacrifice she had to make and allow me leaving her for some time to study far away from home. It would not have been easier without her constant encouragement, prayers and support. Owing to the peculiar grace and understanding given by God to my two cute sons knowing that their daddy was just some far land schooling to return home soon, I am grateful for their patience.
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CHAPTER ONE

INTRODUCTION

1.1 Background

Protected areas (PAs) are designated geographical spaces (IUCN, 2013), and recognized as the cornerstones of biodiversity conservation (Nelson and Chomitz, 2011; Leverington et al., 2010). However, the loss of biodiversity worldwide has been mostly linked to changes in land cover (LC) (Aide et al., 2013). Today there are more than 100,000 PAs in the world (Hayes, 2006) but they are all facing threats from habitat loss due to increasing human population and encroachment (Estes et al. 2012; Alers et al., 2007).

Some of the PAs have become insularized (hedged) through fencing due to the loss of habitats. Other threats to PAs include pollution from agricultural runoff, urban growth (Ghosh et al., 2014; McKinney, 2002), industrial development (Enanga et al., 2011), poor waste containment and management, the lack of connectivity with other PAs (Ntongani et al., 2010), introduction of invasive plant species (Daily Nation, 15 August 2013; Ng’weno et al., 2009), hydrologic and climatic changes (Catano et al., 2015), poor representation and poor management (Raini, 2009). Information on land cover composition and land cover change are critical in many fields of environmental research including global change, biodiversity and water management, carbon storage and ecosystem functions (Gessner et al., 2012).

Systematic and regular assessment of vegetation is especially critical in African savanna as they are predicted to be heavily affected by climatic and land use changes (LUC) (Grinand et al., 2013; Sankaran et al., 2005). African savanna landscapes are extensive in coverage and highly dynamic in nature (Nelson et al., 2009), thus making them difficult to measure and monitor using traditional field work surveys and aerial photography (Ansley et al., 2012).
Satellite remote sensing offers a better alternative to map and monitor changes on the environment because of its systematic, repetitive acquisition capability, and increasingly free-availability (Hazini and Hashim, 2015). Satellite remote sensing is also a cost-effective and timely tool for mapping and updating land use and cover compared to the traditional field surveys and aerial photography (Ghosh et al., 2014; Xie et al., 2008). The availability of digital satellite data should only encourage wider adoption of satellite remote sensing for mapping and monitoring land use and land cover (LULC).

1.2 Study justification
The Lake Nakuru National Park (LNNP) was encircled with a high voltage perimeter electric fence in 1986, effectively disconnecting it from wildlife dispersal areas and curtailing movement of wildlife. This loss of wildlife dispersal areas and migration corridors reduced feeding and breeding ground areas that had for generations ensured viability and survival and various wildlife species (Ogutu et al., 2012). Since the park was enclosed, the population of both grazing and browsing animals continues to grow and this has the potential to put pressure on the habitat due to trampling and overgrazing. LNNP is under increased pressure from rapid urbanization of the city of Nakuru that lies to the north of the park. The city of Nakuru saw its population increase from 17,625 people in 1948 to 367,183 people in 2009 (Mainuri and Owino, 2014; GOK, 1979, 2009).

One of the negative impacts of urbanization has been increased pollution of Lake Nakuru through discharge of untreated waste water and sewage into the lake which happens to be the lowest lying point in the basin. Since 2011, the water levels of Lake Nakuru have increased submerging the shoreline vegetation, and park infrastructure - roads and facilities (Daily Nation, 07 January 2014). This development has led to significant changes in the park’s vegetation that has not been quantified to date. There have also been several outbreaks of fires in the park including one of the largest fires seen in the area in March 2009 that destroyed the largest stand of *Euphorbia candelabrum* forest in East Africa (Daily Nation, 23 March 2011).
Several regional mapping studies using remote sensing have been undertaken in a region that includes LNNP (Were et al., 2013; Baldyga et al., 2008; Kundu et al., 2004). These studies have documented extensive LULC changes occurring in the watershed catchment areas of L. Nakuru. These studies have provided a good regional perspective of changing LULC, but have not been conducted at a sufficient level of detail that would be useful for management planning at LNNP. The only comprehensive vegetation mapping vegetation types of LNNP was carried out in 1989 (Mutangah, 1994) and involved a manual interpretation of aerial photograph and a Landsat image from 1979. To date, this map remains the most used vegetation map at the park. It is therefore important that this map be reproduced and updated using historical and recent satellite imagery and more objective and reproducible image classification techniques.

1.3 Research Goal and study objectives

The goal of my research was to examine Environmental change at Lake Nakuru National Park and surrounding area, and seek explanations for observed changes. In order to achieve this goal, my study was guided by the following research questions

1. **What are the most effective techniques for mapping detailed vegetation types at Lake Nakuru National Park using historical Landsat TM images and ancillary data?**

   a. How many of the 10 vegetation types delineated from manual interpretation of aerial photography and Landsat MSS image from the late 1970s and early 1980s can be mapped distinctly?

   b. What Landsat Thematic Mapper (TM), Landsat Operational Land Imager (OLI), input band combinations, and ancillary data are optimal at detailed vegetation feature identification?

   c. What is the most suitable classifier for land use land cover (LULC) mapping?
2. What land use and land cover changes have occurred in the study area for the period 1987-2016?

3. What variables can be used to explain the observed changes?
CHAPTER TWO

LITERATURE REVIEW

2.1 Mapping Land Use and Land Cover using Remote Sensing

Landsat data are widely popular for broad scale and community level LULC mapping and change detection because of their reliability and the availability of historical archives of imagery (Xie et al., 2008; Ghosh et al., 2014). Landsat TM and ETM+ data have been successfully used to map protected areas (Scharisch et al., 2017; Ntongani et al., 2010), savanna environments (Otukei and Blaschke, 2010), forests and vegetation (Reese et al., 2002; Were et al., 2013; George et al., 2014), agriculture (Alcantara et al., 2012), and urban development (Griffiths et al., 2010; Mubea and Menz, 2012; Schneider, 2012).

Were et al. (2013) mapped LULC change in a regional study covering the Eastern Mau forests of Kenya that also included Lake Nakuru. In this study, they used Landsat MSS, TM and ETM+ data and the unsupervised ISODATA classification technique to map LULC for the years 1973, 1985, 2000, and 2011. They adopted post-classification comparison to map changes. The study however, mapped very broad LULC categories to be useful as a management planning tool for LNNP. For example, the only vegetation types mapped were forests-shrublands, grasslands and croplands. The study reported a loss of grasslands, and forest-shrublands, by 50%, and 61%, respectively.

Kundu et al. (2004) used aerial photography from 1964 and 1969, a 1987 SPOT (XS), a 1973 Landsat MSS, and Landsat TM images for acquired in 1984 and 1989. The authors performed a visual interpretation of the images for an area spanning between the Eastern Mau complex and the Aberdare ranges. Six vegetation types were delineated from the 1969 aerial photos and the 1989 Landsat image. These vegetation types were; natural forest, planted forest, cultivated land, wooded grassland, grassland and riverine vegetation.

They also used an Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) image acquired in 2010. Mubea and Menz (2012) used Maximum Likelihood and Support Vector Machine classifications to map, six LULC types but only three LC types were vegetation. They mapped LULC change using post-classification comparison. The study mainly focused on mapping urban land use but mapped vegetation classes too broadly to be useful as a planning tool in park management.

Ntongani et al. (2010) mapped Land use changes in a wildlife migratory route in Tanzania to assess their impacts on the corridor. Their study used Landsat MSS, TM, and ETM+ between 1978 and 2005 to map nine LULC types out of which, seven were vegetation cover types (crop, scrub, grassland, bushed grassland, open woodland, closed woodland, and forest). They documented a 284% increase in cultivated area between 1978 and 2005. Apart from bushed grassland, the other vegetation types all showed a decreasing trend over the study period.

**Importance of using multi-temporal, multi-seasonal datasets**

Although these studies used multi-temporal and multi-sensor data to map LULC, none incorporated multi-seasonal satellite datasets in their mapping. Multi-date datasets have been tested and confirmed as being capable of enhancing LULC mapping when compared with single-date images (Sebego and Wolter, 2002; Paneque-Gálvez et al., 2013). Advantages of such datasets include the capability to distinguish spectral signatures and discriminate seasonality, phenology and ecological zonal attributes amongst vegetation types (Kalema et al. 2015; Driese et al., 2004). This is considered a useful attribute in increasing classification accuracies (Ghosh et al., 2014) because images acquired at different times/seasons provide some level of contrasting information when combined than may be obtained from a single-date image.

Kalema et al. (2015) used multi-seasonal (dry and wet) Landsat 5 TM datasets for the periods 1984, 1995, and 2001 to map LULC dynamics in Central Uganda, an equatorial savanna landscape. LULC was classified using the unsupervised ISODATA classification to produce 11 LC types amongst them eight vegetation categories. Open woodlands and
cultivated/settlement areas increased at a rate of 33% over the study period while dense woodland vegetation declined by over 60%.

Rodriguez-Galiano et al. (2012) mapped the vegetation types in Granada Province of southern Spain using 2004 using multi-temporal Landsat TM (spring and summer) and ancillary (DEM) datasets to create a LULC map.

Griffiths et al. (2010) conducted a comparative analysis on the performance of single date versus multi-date Landsat TM images in an analysis of urban growth of Dhaka, Bangladesh in 1990, 2000 and 2006. They compared analysis of 3-year single Landsat TM datasets against bi-temporal datasets. Their study confirmed that the single-date datasets reduced overall accuracies in all the years under study whereas the bi-temporal datasets resulted in 9-10% higher classification accuracies.

### 2.1.1 Image enhancing in land cover classification

Various studies have demonstrated the usefulness of incorporating image enhancements such as the vegetation indices with multi-band images in image classifications (e.g., Heinl et al., 2009; Archibald et al., 2005). Image enhancements improve opportunities for displaying the different features composed in an image as they are intended to help in the refining of a classification (Hazini and Hashim, 2015). In the case of vegetation cover, it involves the separation of the vegetated from non-vegetated regions or forested lands from open lands. Enhanced images are then classified and tested to determine accuracies of the output maps (Kolios and Stylios, 2013; Han et al., 2007).

### 2.1.2 The use of ancillary data in image classifications

Ancillary data are non-spectral datasets combined with spectral information to improve image classification and or analysis of remotely sensed data (Nagendra et al., 1999). Mubea and Menz (2012) demonstrated the importance of using a DEM in eliminating relief artefacts from Synthetic Aperture Radar (SAR) data in characterizing the urban landscape of the Nakuru municipality between 1986 and 2010. Higher classification accuracies were acquired with the SVM having 87% overall accuracy compared to ML which obtained 83.8%
Dinka (2012) used Landsat MSS, TM, ETM+ images acquired between 1973 and 2008 and ancillary data to map and assess LULC changes at Lake Basaka catchment in the Main Rift Valley region of Ethiopia. Ancillary data included DEM. Both the unsupervised ISODATA and supervised MLC were used to create a LULC map with seven categories which included; forestland, dense woodland, bushy woodland citrus farmland, sugarcane farmland, open grassland, and shrubland.

Heinl et al. (2009) evaluated the performance of different classifiers in LULC mapping targeting 12 classes in a mountainous region of north east Australia using Landsat ETM+ and ancillary data. The classifiers and ancillary data evaluated included MLC, Discriminant Analysis (DA) and Neural Networks. Image enhancements and ancillary data included in the classifications were NDVI, elevation, slope and aspect. The overall classification accuracy obtained using MLC and DA classifiers using only spectral data was in the 55 - 60% range while that incorporating NDVI and topographic variables raised this accuracy to about 75%. Overall classification accuracies using ANN classifier and spectral data only was about 75% while adding all ancillary data to the spectral data raised the accuracy to about 86%.

Notwithstanding its limitations, ML classifier has been extensively used over all other statistical classifiers (Dinka, 2012; Otukei and Blaschke, 2010; Brandt and Townshend, 2006; Huang et al., 2002). The classifier only performs well with sufficient training data and assumes normal data distribution while assigning pixel values to classes they highly likely belong (Schneider, 2012). Despite their high reliability, computational efficiency, and ease of use both in time and cost, the traditional probability classifiers are fraught with shortcomings including repetitive processes on addition of non-spectral data, and the assumption of uniformity in the distribution of data (Xie et al. 2008).

Cabral et al. (2017) used Landsat TM, ETM+, and OLI data in a spatio-temporal mapping of LULC trends in a 207km borderline of Senegal and Guinea Bissau. ML classifier was used to create ten LULC classes for the 2010 and 2015 periods. The overall classification accuracies
of the 2010, and 2015 maps, were 62%, and 90%, respectively. Post-classification comparison was used to quantify land cover types and LULC changes in the area. In their analyses, major changes which included a 9% decrease in forest cover, and an 11% increase in agriculture/bare soils were reported.

A new generation of classification classifiers that do not have the limitations of traditional parametric classifiers such as MLC are increasingly in use in LULC mapping. Among the new and improved classifiers are: Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees (DT) and the Random Forest (RF). The performance of parametric versus non-parametric classifiers has been compared in several studies (e.g. Heinl et al., 2009; Paneque Gálvez et al., 2013).

Higher classification accuracies have been recorded by the non-parametric classifiers (e.g. Kolios and Stylios, 2013; Hazini and Hashim, 2015). The machine learning classifiers have been widely adopted in many studies because of their superiority over traditional classifiers in mapping vegetation in heterogeneous environments (Heinl et al., 2009). Advantages of the new classifiers over parametric classifiers are that; they require only small amounts of training data to classify large geographical datasets (Paneque-Galvez et al., 2013; George et al., 2014), they are not dependent on normal statistical data distribution (Xie et al., 2008), and they can automatically approximate non-linear mathematical functions (Alcantara et al., 2012).

Schneider (2012) compared MLC, DT and SVM to monitor LC change in urban and peri-urban Chinese cities using multi-season, multi-date stacks of Landsat data and the data mining approach. The non-parametric algorithms had higher overall accuracies with margins higher than 25% that achieved by the MLC. The boosted ensemble of Decision Trees demonstrated remarkable ability in mapping urban landscapes than the SVM. While the RF feature importance bands may seem useful, Schneider (2012) alludes of possibility of mixed results. To reduce the number of bands and subsequent classification, her study revealed varying results whereby there was an increase in overall accuracy for ML (from 67% to 82%) but a drop by 5% for both NN and SVM.
The higher performance of the non-traditional classifiers is also characteristic of their repulsion to outliers, noise and overtraining (Ghosh et al., 2014), and their capability to incorporate priori knowledge of the area (Hazini and Hashim, 2015). ANN classifiers perform well with heterogeneous datasets and smaller training data to characterize LULC. Their limitation however lie on their dependence on standard mathematical modeling of the datasets (Gislason et al., 2006), a dependence that may lead to unstable results. Importantly, NN computational efficiency can be very low at times and quite costly and time demanding (Xie et al., 2008).

SVM training algorithm considers sets of data that neighbor the optimal hyperplane/separable subspace, also referred to as support vectors (Huang et al., 2002; Vapnik, 1995). In this case, SVM linearly separates classes from a non-separable dataset based on the prescribed training areas into patterns that possess complementary features (Pal, 2005). SVM thus involves the separation of two classes in the classification process, a time-consuming experimental process. Adaptive to the principle of structural risk minimization on the decision boundaries (agreement between margin and misclassification error), SVM performs well with the radial basis function kernel framework (Paneque-Galvez et al., 2013; Mountrakis et al., 2011) thus also reducing computational cost (Vapnik, 1995).

Estes et al. (2012) used Landsat TM and ETM+ satellite scenes of 1984 – 2003 to map LULC in Serengeti ecosystem in Tanzania and examine the influence of human demographic dynamics. They used SVM to classify 6 LULC categories. Their study established increasing human activity primarily conversion of primeval land to farms closer to the Serengeti National Park and subsequent declining LUC as one moved away from the park.

In a mapping study conducted in a coastal region in western Greece, Kolios and Stylios (2013) compared the performance of ML, SVMs, and ANNs to map LULC using Landsat ETM+ and 6 vegetation indices. They found that, using the first four Landsat reflective bands, NDVI, Brightness Index (BI), and SVMS yielded the highest accuracies of 97.2%
Using wet and dry seasons’ Landsat-5 TM, Paneque-Galvez et al. (2013) also compared performance of the SVMs with 3 parametric classifiers; ML, K-NN, & Max-Min Hill-Climbing (MMHC) to classify land cover in the heterogeneous tropical landscapes in Bolivia. Classification results confirmed the superiority of the SVM with an overall accuracy of ~90.5% over ML, K-NN, and MMHC which had accuracies of 78.9%, 79.8% and 72% respectively.

Random Forest classifier is an improved aggregate of Decision Trees known to indiscriminately choose a constantly high proportion of input sample variables to generate an extensive detail of small classification trees while minimizing error (Grinard et al., 2013; Breiman, 2001). Many trees are trained with their outcome being aggregated by a majority vote (Gislason et al., 2006). Increasing the input sample size narrows the generalization error and averts overtraining of the data.

The concept behind practice involves a recursive procedure which repeatedly splits initially joined sets of classes to obtain computing models that will thereafter derive the primary classes (Ham et al., 2005). It is noteworthy that RF also generates relative importance variables (Ghosh et al., 2014; Cutler et al., 2007; Liaw and Wiener, 2002) revealing dominant bands that may be separately used to distinguish features in the classification process (Pal, 2005). RF is also associated with high classification accuracies (Friedl et al., 1999), performs well with large datasets, has a flexible user-defined criterion (Cutler et al., 2007), and less training time. These attributes have given the classifier due attention in land cover classification (Pal, 2005).

Scharisch et al. (2017) mapped LULC change in Matobo National Park and surroundings in Zimbabwe using 1989 and 1998 Landsat TM scenes, a 2014 OLI/TIRS imagery, and ancillary data. The machine learning Random Forest (RF) algorithm was used to characterize four major vegetation types that included shrub land, forest, patchy vegetation and agricultural area. Variable importance derived from RF was further explored to identify the dominant bands in the classification process useful for improving classifier accuracies. The aim of the
study was to assess the effects of different land tenure systems on LULC status. Using post-classification change detection, the study reported a 5% increase of forest cover, 6% decrease bare ground and declining agricultural area in the World Heritage sites and areas with state protection between 1998 and 2014.

Grinand et al. (2013) mapped the tropical humid and dry forests of Madagascar using multi-source (multi-date) Landsat 5TM data. They used the RF algorithm to classify LULC. A model sample of three highly reflective spectral bands (Blue, Near Infrared and Shortwave Infrared 1) was created out of the variable importance output data produced by the classifier. Comparable tests confirmed that addition of the green, red and Shortwave Infrared 2 bands did not change the overall accuracy. Further data mining revealed that the blue and Shortwave Infrared 2 bands demonstrated a much higher influence in the classification process than when both the NDVI and Normalized Infrared Index (NIRI) were added.

2.1.3 Classification Accuracy Assessment

Land cover maps produced from classified remotely sensed data contain errors of various types and degrees. It is therefore very important that the nature of these errors be determined to justify appropriateness of the maps for specific uses (Gao, 2009; Congalton, 1991). Most quantitative methods used to evaluate classification accuracy have traditionally adopted the use of an error matrix. The matrix is produced to assess two classified data sets i.e., remotely sensed map classification and the reference data (Canters, 1997).

The error matrix reports the measure of correctness of individual categories alongside both commission and omission errors, as well as summary statistics for the entire matrix (Congalton et al., 2009; Ma and Redmond, 1995; Congalton, 1991). Per Foody (2002), the logic behind accuracy assessments ranges from a need to determine map quality, an interpretation of the effectiveness of the various classification techniques, or even a need for which classification accuracy is engaged. The set minimum level for objective accuracy interpretation in the identification of LULC types of remotely sensed data is 85% (Foody, 2002).
Kappa coefficient is a statistic calculated from a classification error matrix. It measures how closely the occurrences classified by a given classifier match the data identified as reference data/ground truth. The statistic takes into consideration random chance (agreement with a random classifier), which generally means it is less misleading than simply using overall accuracy as a measure (Caeletta, 1996).

2.2 Detecting and mapping change
Identifying LULC changes is generally considered as one of the most important aspect of digital image analyses in remote sensing (Gao, 2009; Coppin et al., 2004). There are various techniques used to detect and map changes in LULC which include; Change Vector Analysis (CVA) (Johnson and Kasischke, 1998), Image ratios, Image differencing (Coppin et al., 2004), image regression (Lu et al., 2003), image fusion (Xie et al., 2008), multi-temporal Principal Components Analysis (e.g. Deng et al., 2008; Byrne et al, 1980), and multi-temporal Tasseled Cap change detection (Han et al., 2007). All these methods produce “change” vs. “no-change” maps.

Multi-temporal PCA for instance, presumes that the data are similar and change information can be shown in the output principal components. The main advantage of this technique is that it compresses data and displays useful information in the output components.

Among the change detection techniques, post-classification comparison is one of the few methods providing “from –to” change information from independent classifications (Coppin et al., 2004). This is followed by a pixel-by-pixel comparison to detect changes in LULC. The key advantages of post-classification comparison are; (1) the technique allows the production of two land cover maps – both historical and current, and (2) compensates for variation in atmospheric conditions and vegetation phenology between dates (Coppin et al., 2004).
CHAPTER THREE

DATA AND METHODS

3.1 Study area description
Lake Nakuru National Park is located Nakuru District is a closed expanse lake basin located in the Eastern Rift Valley province in Kenya (figure 1). This is a region of varying topography whose landscape formation was because of volcanic aftermath (Odada et al., 2004). The park covers an area of approximately 188 km² and borders the Nakuru township municipality to the north, peri-urban residential settlements to the east and west, and the Soi Sambu ranch grassland plains to the south east.

The park is famous for the lesser flamingos (*Phoeniconias minor*) whose number may exceed one million birds (Vareschi and Jacobs, 1984) and more than 450 different bird species (UNESCO, 2010). LNNP is also a fly-way to significant populations of the European white storks during the northern hemisphere winter seasons (Davidson and Stroud, 2006; Harris, 2013). LNNP was declared a rhino sanctuary in 1983 and is a home to the critically endangered Black rhino, and 22% of the 670 remaining the Rothschild giraffe in the world (Muller, 2012). LNNP was designated a bird sanctuary in 1961, and an Important Bird Area (IBA) in 2009 (Odada et al., 2006).
Lake Nakuru lies at the lowest elevations of the central Rift region of Kenya (Allen et al., 1989). Its soils are predominantly the grey, poorly drained and alkaline sediments of volcanic origin (Odada et al., 2006). The hydrological formation of the lake is dependent on water supply mainly through direct precipitation and surface run-offs (Ayenew and Becht, 2007). It is from the upper catchment that rivers; Makalia, Enderit, Njoro, Naishi, Lamurdiac (Baker and Miller, 2013), and “treated” wastewater from the municipality discharge into the lake. Two of the rivers, Njoro and Makalia which were formerly perennial, have ceased and become seasonal.

**Figure 1:** Study Area
Stream flow seasonality for into the lake is two-fold. Constant flows occur in May and November, a month after peak rainfalls (Baker and Miller, 2013). Since 2011 the lake water levels expanded way beyond the usual high water mark.

The general vegetation of LNNP includes vast swathes of open grasslands and scrublands at the southern parts of the park with the yellow-bark acacia woodlands straddling close-by the lakeshore and flood plains, riverine vegetation along the river courses, and dry upland forest typical of the dry Rift Valley vegetation (Mutangah, 1994). The Mean annual rainfall averages about 850 mm, mainly falling within the periods of November-December and April-May (Raini, 2009). Rainfall has a bi-modal distribution with peaks in April, and November; April peak being the highest (Ogutu et al., 2012). Figure 2 below illustrates mean monthly rainfall distribution for the period 1980 - 2015 (www.meteo.go.ke).

![Mean Monthly Rainfall Distribution](image)

**Figure 2:** Mean monthly rainfall distribution
3.2 Methods

Vegetation Map of Lake Nakuru National Park

A digital copy of vegetation map for Lake Nakuru National Park, created by Mutanga (1994) based on a visual interpretation of aerial photography and Landsat images from the period 1979-1986. The map consisted of 10 broad vegetation types: Grassland, Bushland, Woodland, Forest, Alkaline marsh, Freshwater Swamp, Cliff and Escarpment vegetation, Lava outcrop Vegetation, Riverine forest and woodland, and sewage-influenced vegetation. Grassland, Bushland, Woodland, and Forest vegetation types were further subdivided into seven, six, two, three, sub-types, respectively.

The digital map was imported into ArcMap and then georeferenced to a 1:50,000 georegistered topographic map of the area originally created using 1969 aerial photography but subsequently revised in 1996 and 1997 using field surveys and Landsat MSS imagery. 16 control GCPs were used in the georeferencing of the vegetation map, resulting in a total root mean square error (RMSE) of less than 5 m. Once the vegetation map was georeferenced, vegetation types were digitized as polygons using heads-up digitizing in ArcMap. The vegetation types were then attributed in the GIS polygon layers. It is these vegetation polygons that were used as a basis for selection of training areas to be used in classification of Landsat images in ENVI 5.3 software.

Landsat Images and Ancillary Data

Three pairs of Landsat TM and OLI images from the WRS-2 paths 160 row 069 for the periods 1986-87, 2010-2011, and 2015-16 were used to map LULC in the study area. Each pair consisted of images acquired in the dry and wet season (Table 1). The wet and dry season images were selected for approximately the same months in a year, i.e., were nearly near-anniversary. This helped reduce solar illumination and phenological differences in the selected images. The images were downloaded from the USGS Earth Explorer https://earthexplorer.usgs.gov/.

Once the images were downloaded, they were imported into ENVI 5.3 and radiometric corrections undertaken using gains and offset values available in each image header. This allowed the conversion of image digital numbers (DNs) to top-of-the atmosphere (TOA)
reflectances (Markham and Helder, 2012). The images were then corrected for atmospheric effects using the Dark Object Subtraction (DOS) technique (Chavez, 1988). Once, the atmospheric and radiometric corrections were complete, the images were subset to the study area.

The Digital Elevation model used in this study was the ASTER Global Digital Elevation Model (GDEM) developed jointly by the United States National Aeronautics and Space Administration (NASA) and Japan’s Ministry of Economy, Trade, and Industry (METI). The DEM has a spatial resolution of 30 m was the newer version of the data (Version 2) and was downloaded and from the USGS Earth Explorer [https://earthexplorer.usgs.gov/](https://earthexplorer.usgs.gov/).

**Field Data and Google Earth**

Field data for this study were collected in July 2017 and involved visiting 206 sites that are representative of different LULC types within the LNNP. Selection of the sites was based on a preliminary interpretation of Landsat images. The locations of the sites were recorded using a Garmin GPS Map 62 receiver. At each of these sites at least four photographs were taken using a GPS enabled camera to help document the LULC at each of the sites. Over 800 photos were taken throughout LNNP. These data were to be used to aid in selection of training areas and reference data for LULC classification and Accuracy assessment. Additional training and reference data for this study were obtained by hand digitizing additional polygons from Google Earth Pro and importing the delineated polygons in ArcGIS and ENVI.
3.2.1 Satellite Datasets

Table 1: Image scenes downloaded from United States Geological Survey (USGS)

<table>
<thead>
<tr>
<th>No.</th>
<th>Image</th>
<th>Path/Row</th>
<th>Date acquired</th>
<th>Season</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Landsat 5TM</td>
<td>160/069</td>
<td>28\textsuperscript{th} January 1986</td>
<td>Dry</td>
<td>USGS</td>
</tr>
<tr>
<td>2</td>
<td>Landsat 5TM</td>
<td>160/069</td>
<td>26\textsuperscript{th} July 1987</td>
<td>Wet</td>
<td>USGS</td>
</tr>
<tr>
<td>3</td>
<td>Landsat 5TM</td>
<td>160/069</td>
<td>30\textsuperscript{th} January 2010</td>
<td>Dry</td>
<td>USGS</td>
</tr>
<tr>
<td>4</td>
<td>Landsat 5TM</td>
<td>160/069</td>
<td>28\textsuperscript{th} July 2011</td>
<td>Wet</td>
<td>USGS</td>
</tr>
<tr>
<td>5</td>
<td>Landsat 8 OLI</td>
<td>160/069</td>
<td>28\textsuperscript{th} January 2015</td>
<td>Dry</td>
<td>USGS</td>
</tr>
<tr>
<td>6</td>
<td>Landsat 8 OLI</td>
<td>160/069</td>
<td>26\textsuperscript{th} August 2016</td>
<td>Wet</td>
<td>USGS</td>
</tr>
</tbody>
</table>

There were 16 LULC classes targeted for mapping including 9 vegetation classes. The vegetation classes were adapted modified from Mutanga’s (1994) vegetation map (Table 2).
Table 2: Description of land use land cover types

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Cover Descriptive Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open grassland</td>
<td>Includes areas covered mainly by herbaceous cover (grass), with widely dispersed (less than 2%) clusters of scrub cover. Five species of grasses are hereby combined as open grassland cover represented as G1, G2, G3, G4, G5 (Mutangah, 1994)</td>
</tr>
<tr>
<td>Open bushland</td>
<td>Includes area covered by open shrub, patches of <em>Tarchonanthus camphoratum</em> and few <em>Euphorbia candelabrum</em> (B3c; Mutangah, 1994)</td>
</tr>
<tr>
<td>Shoreline marsh</td>
<td>Regularly flooded/swampy areas covered with aquatic plants-marshes, straw and reeds. Also referred to as alkaline marsh.</td>
</tr>
<tr>
<td>Acacia woodlands</td>
<td>Characterized by both dense woody <em>Acacia xanthophloea</em> and <em>Acacia seyal</em> tree cover (W1 &amp;W2; Mutangah, 1994)</td>
</tr>
<tr>
<td>Mixed bushland</td>
<td>Includes area covered by dense <em>Tarchonanthus camphoratum</em> bush, <em>Acacia gerrardii, xanthophloea</em> (B3a, B3b, B3d Mutangah, 1994)</td>
</tr>
<tr>
<td><strong>Grassland and scrub</strong></td>
<td>Grassland and scrub - Includes grassed areas interspersed by sizeable populations of scrub/brush vegetation.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mixed forest</strong></td>
<td>Mixed forest - Areas covered by <em>Olea Africana</em>, <em>Acacia gerrardii</em>, and interspersed with <em>Acacia xanthophloea</em>, <em>Tarchonanthus camphoratum</em>, <em>Euphorbia candelabrum</em></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Water body</strong></td>
<td>Water body - All areas covered by water either naturally such as the lake or constructed artefacts such as reservoirs, ponds, sewer treatment plants, and farm dams</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Bare lake shore</strong></td>
<td>Bare lake shore - Includes the exposed low-lying areas on the lake water boundary covered by either dry soil or muddy plains</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Bare soil</strong></td>
<td>Bare soil - Includes degraded patches, continuous rock surface, hard pans, excavated/exposed soil, earth roads or areas with less than 4% vegetative cover</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Active Agriculture</strong></td>
<td>Active Agriculture - Describes areas where natural vegetation has been modified or entirely replaced by crop cultivation. Such areas may experience seasonal change in appearance (in which case are often fallow lands). Most of these surfaces may appear as having definite shapes</td>
</tr>
<tr>
<td>Image</td>
<td>Text</td>
</tr>
<tr>
<td>-------</td>
<td>------</td>
</tr>
<tr>
<td><img src="image1.png" alt="Built-up" /></td>
<td>Built-up - Describes areas that have artificial/impervious cover such as industrial and commercial centers, suburban residential, roads, and railways.</td>
</tr>
<tr>
<td><img src="image2.png" alt="Fallow" /></td>
<td>Fallow - Describes the tilled lands and after-harvest crop fields</td>
</tr>
<tr>
<td><img src="image3.png" alt="Euphorbia candelabrum" /></td>
<td>Euphorbia candelabrum – From the photo archives, displays land area previously covered by <em>Euphorbia candelabrum</em> indigenous forest species, no longer physically present</td>
</tr>
<tr>
<td><img src="image4.png" alt="Invasive weeds" /></td>
<td>Invasive weeds – Lush underbrush beneath the Acacia woodland vegetation. Includes non-native plant species notable for suppressing the grassland vegetation cover.</td>
</tr>
</tbody>
</table>

The multi-date (dry & wet), and multi-spectral images were layer stacked for image classification using ENVI 5.2 software. Both the EVI and NDVI image enhancements were used to test their influence on classification accuracy.

The underlying premise with image classification lies on the consistency in the choice of training data, spectral responses of the different land cover types as may be separated by a classifier, and data dimensionality. The image pixels were subjected to automated supervised classification algorithms to generate LULC maps using various input bands and classifiers (Table 6).
Step-wise evaluations were also executed for spectral input bands to exploit the usefulness of band metrics and test their potential to increase accuracy. The performance of ML, SVM-Radial Basis Function and RF classifiers was compared by testing their capacity to explore spectral data and identify spatial image attributes.

For the purposes of evaluating accuracy of the classifiers under test, classification accuracy assessment was adopted. It is also crucial to note that land cover maps produced from remotely sensed data always contain errors of various types and degrees. For this study, there was no accuracy assessment carried out for the 1986/87 and 2010/11 images since ground truth data (for cross-validation) were not available. The quality of the classified images was therefore compared with the 1989 floristic base map and careful interpretation of satellite data.

For accuracy testing, classification for the 2015/16 image was validated using test data derived from high resolution Google Earth image and compared with field data. This study adopted one of the most widely used method of evaluating classifier performance; post-classification comparison from which accuracy assessment results were analyzed. Key features considered from the classifiers’ accuracies include the interpretation of the confusion matrix table; which outlines Overall, Producer, and User accuracies, derived errors (commission and omission), and kappa coefficient values.

Error matrices were used to evaluate the correctness and/or chances of misclassification of the pooled pixel values into individual land cover classes as trained by a classifier. The results of accuracies of the different algorithms were further ascertained using the kappa coefficients. Computational efficiency and speed of algorithms’ performance was also considered.
After an optimal classifier/input band combination was identified, it was used to generate LULC maps for 1986-87, 2010-2011, and 2015-16.
3.3 Change Detection

Multi-date post-classification change detection was carried out to identify the transition of land cover changes for the periods 1987-2011, 2011-2016, and 1987-2016. LULC changes were determined using post classification change detection and LULC change maps for the various generated. No accuracy assessments were conducted on the 1986-87 and 1910-11 LULC maps, but they were assumed to be of similar accuracy as the 2015-16 map.

In addition to post-classification comparison, a multi-temporal principal components analysis (mPCA) was conducted to detect changes occurring in the study area over the 1987-2011 period. It was not possible to conduct mPCA over the 1987-2016 period because of sensor differences between Landsat TM and OLI. Two anniversary date cloud-free dry season images (28th Jan 1986 and 17th Jan 2011) were stacked to detect change and compare reliability in the use of post-classification change detection method. The images were carefully selected to ensure that there were minimum possible image reflectance variations. A Principal Component Analysis (PCA) was run and 12 PCs compared.
CHAPTER FOUR

RESULTS ANALYSIS AND DISCUSSION

4.1 Results Analysis

Land use land cover mapping was done for the period 1987 - 2016. Since the study area also was extended to focus on the dynamics surrounding the park, a few more land cover classes (crop, fallow agriculture, built-up land and invasive weeds) were identified and included (figure 4). Overall, 16 informational categories were identified in the 1986/87 multi-date image, 15 categories in the 2010/11 image while the 2015/16 images had 13 LC types identified.

Three (3) classifiers i.e. Maximum Likelihood, Support Vector Machine, and Random Forest algorithms were tested and their accuracies evaluated. Out of the 3 classifiers, RF classifier yielded the highest overall accuracy of 85.5% and with a kappa statistic of 0.83 (table 5). The ensemble RF was also separately used to evaluate the potential of the individual input bands in influencing the classification process.

Observed inconsistencies from preliminary classification

The initial classified map was marred with mixed classification of some of the informational classes when the traditional ML was used. A 14-bands layer stack of OLI2015/2016 multi-seasonal images when classified using MLC, resulted to the over classification of the crop land cover by displaying numerous crop pixels inside the park. Several attempts in modifying crop class and further classification could not separate the spectral signature. The problem was taken care of when an additional informational class composed of a mixture of grass and invasive species was developed after visual interpretation of geo-tagged photos of the affected sites.

The informational class, Invasive weeds hence constituted areas in the park where invasive plants dominated and suppressed the grassland cover. Obvious observations could be made where bare soil areas were not reasonably separated from fallow land. Still, a chunk
of land adjacent the lakeshore was also misclassified as built-up land whereas the interpretation of grassland cover and crop fields was hardly distinguishable. The challenge was vastly minimized by employing the machine learning Support Vector Machines and Random Forest algorithms, improving on the selection of training areas and spreading the sample size of the reference map areas.

**Identifying optimal Landsat TM, OLI input band combinations, and ancillary data for detailed vegetation feature identification**

Separate sets of image classification tests were carried out on the 2015/16 multi-date image to determine the three classifiers’ suitability in vegetation identification as illustrated in Table 6. The evaluations were meant to help determine the suitability of use of available datasets (spectral and spatial) to obtain objective results. Accuracy results (both overall and individual LULC types) of the classifiers were also evaluated to assess the usefulness of the output maps (see Table 8). Best determined classification results were adopted from a combination of the image input bands and topographical variables as shown in table 6.

**Using image spectral bands to classify LULC map**

The use of raw bands demonstrated a clear distinction on the classifiers where the parametric ML classifier performed poorly when compared to both SVM and RFC. Overall accuracies for the three classifiers were 77.93%, 83.34%, and 84.19% for ML, SVM, and RF respectively (Table 6). The RF classifier maintained consistency with lower misclassifications of the individual LULC classes when compared to both the SVMs and MLC. Tso and Mather (2009) confirm that ML classifier only performs better with a portion of input bands since the classifier successfully engages a small number of varying input bands.

From the LULC map with the highest accuracy, RF still recorded highest mapping accuracies on water (94.8%), burn scar (93%), and mixed bushland (91%) classes. Acacia woodland still had the lowest accuracy in the three classifiers, with RF obtaining an accuracy of 46.1% which was still higher than the other two classifiers.
Land cover classes over classified included forest, fallow agriculture, and bare ground while classes not well captured by the classifier were Acacia woodland, fallow agriculture and grassland scrub. Generally, all the classifiers seemed to overclassify the forest class and under classify Acacia woodland.

Confusion matrices in tables 3, 4, and 5 report the accuracies of LULC maps generated from different sets of input band combinations. They also highlight the extent to which individual LULC classes were classified (either over classified or under classified). A comparative analysis of how good input band combinations performed with the Landsat OLI image on individual classes is summarized in table 8.
Table 3: Confusion matrix by pixel values using OLI raw image bands

<table>
<thead>
<tr>
<th>Classified Image</th>
<th>Ground</th>
<th>Reference</th>
<th>Pixels</th>
<th>Total</th>
<th>User Accuracy</th>
<th>Commission Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1</td>
<td>2026</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Open Bushland</td>
<td>2</td>
<td>0</td>
<td>297</td>
<td>10</td>
<td>18</td>
<td>33</td>
</tr>
<tr>
<td>Mixed Bushland</td>
<td>3</td>
<td>17</td>
<td>1123</td>
<td>0</td>
<td>10</td>
<td>19</td>
</tr>
<tr>
<td>Invasive Weed</td>
<td>4</td>
<td>0</td>
<td>178</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Grassland Scrub</td>
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<td>7</td>
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<td>865</td>
<td>103</td>
<td>3</td>
</tr>
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<td>Grassland</td>
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<td>85</td>
<td>1</td>
<td>144</td>
<td>2734</td>
</tr>
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<td>Forest</td>
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<td>30</td>
<td>0</td>
<td>31</td>
<td>2</td>
<td>3</td>
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<td>Fallow Agriculture</td>
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<td>12</td>
<td>4</td>
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<td>19</td>
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<td>Built-Up</td>
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<td>4</td>
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<td>0</td>
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<td>Bare Ground</td>
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</tr>
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<td>Producer Accuracy</td>
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<td></td>
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<td>Omission Error</td>
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<tr>
<td>Overall Accuracy</td>
<td></td>
<td></td>
<td></td>
<td>84.19%</td>
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<td>Kappa Coefficient</td>
<td></td>
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<td></td>
<td>0.82</td>
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</tr>
</tbody>
</table>
Table 4: Confusion matrix by pixel values using OLI image bands with NDVI

<table>
<thead>
<tr>
<th>Classified Image</th>
<th>Ground 1</th>
<th>Ground 2</th>
<th>Ground 3</th>
<th>Ground 4</th>
<th>Ground 5</th>
<th>Ground 6</th>
<th>Ground 7</th>
<th>Ground 8</th>
<th>Ground 9</th>
<th>Ground 10</th>
<th>Ground 11</th>
<th>Ground 12</th>
<th>Ground 13</th>
<th>Total</th>
<th>User Accuracy</th>
<th>Commission Error</th>
</tr>
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<tbody>
<tr>
<td>Water</td>
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<td>3</td>
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<td>564</td>
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**Producer Accuracy**
- 95%
- 75.77%
- 90.03%
- 79.82%
- 71.85%
- 84.55%
- 88.58%
- 70.26%
- 89.79%
- 94.47%
- 87.76%
- 73.26%
- 49.35%

**Omission Error**
- 5%
- 24.23%
- 9.97%
- 20.18%
- 28.15%
- 15.45%
- 11.42%
- 29.74%
- 10.21%
- 5.53%
- 12.24%
- 26.74%
- 50.65%

**Overall Accuracy**
- 84.53%

**Kappa Coefficient**
- 0.82
Table 5: Confusion matrix by pixel values using DEM and slope

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<th>Classified Image</th>
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<th>Total</th>
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<td>16.59</td>
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</tbody>
</table>

Overall Accuracy 85.52%
Kappa Coefficient 0.83
Using image enhancements and ancillary data on the image band combinations to optimize the classification process

Additional spectral (NDVI) and topographical variables (DEM and slope) were separately layer stacked with the raw bands, classified, and results compared. There was a very slight improvement of accuracies across all the classifiers on addition of spectral band of NDVI as illustrated in Table 6 below. The combination of NDVI with image bands reported a slight increase of the ML accuracy by 1.3% but with a slim influence with both the SVM and RF.

Further addition of the topographical variables (DEM and slope) to the spectral bands seemed to lower the classification of MLC while recording a modest improvement on both SVM and RFC, as outlined in Table 7. For instance, the few pixels earlier displayed as crop inside the park were masked out when ancillary data was incorporated in the classification. Moreover, crop pixels were distinctly separated from mixed bushland albeit covered in the previous classification (without ancillary data). Marked improvements were also visually evident where crop fields were clearly distinguished from scrub grassland.

Notwithstanding the slight improvement of classification accuracies by the machine learning classifiers, they also reveal a more predictable attribute in the visual interpretation of the output maps far better than the traditional ML classifier. A combination of DEM and slope with the multi-date image bands presented RF as the most suitable algorithm for classifying land cover in LNNP. Yielding the highest overall accuracy of 85.52% and a kappa statistic of 0.83, the classifier also recorded robust results of the individual land cover class accuracies with a narrow range between classes when compared with both MLC and SVM classifiers (see Table 8).

ML displayed a higher range between the more accurately classified land cover (mixed bushland with 95.4%) and the poorly classified land cover (water, 54.1%). Land cover classes highly over classified included; the bare ground, built-up, fallow agriculture, and crop. ML also under classified water, grassland scrub, invasive weeds, and fallow agriculture classes. Burn scar (having 96.8%) was the most correctly classified while Acacia woodland (with 67.7%) displayed the lowest accuracy using SVM (table 7).
Land cover classes over classified by SVM included; open bushland, fallow agriculture, bare ground and Acacia woodland. In like manner, classes under classified using SVM were Acacia woodland, bare ground, grassland scrub and open bushland. RF on the other hand produced highest accuracy on the water class and fallow agriculture being least classified. Erroneously classified classes by RF constituted the bare ground, fallow agriculture, open bushland and forest classes. Similarly, fallow agriculture, bare ground, grassland scrub, and open bushland were under classified.

The difficulty of clearly separating for example fallow agriculture and bare ground (seemingly comparable classes) is demonstrated in their misclassification by the three different algorithms. Separation of Open bushland from grassland scrub was also coupled with misclassifications. The combined input of the raw bands with NDVI, DEM and slope did not demonstrate any further increase of the accuracies either. The table below highlights the performance of the 3 classifiers on the individual land cover types using spectral image bands, DEM, and slope.

**Table 6: Summary of accuracies of individual classifier performance with input data**

<table>
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<tr>
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<th>Maximum Likelihood</th>
<th>Support Vector Machine</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input data/performance</td>
<td>Overall accuracy (%)</td>
<td>Kappa coefficient</td>
<td>Overall accuracy (%)</td>
</tr>
<tr>
<td>Landsat8 OLI reflectance bands</td>
<td>77.93</td>
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<td>83.34</td>
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<td>Landsat8 OLI, DEM</td>
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</tr>
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<td>Landsat8 OLI, DEM, Slope</td>
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<td>0.74</td>
<td>84.78</td>
</tr>
<tr>
<td>Landsat8 OLI, NDVI, DEM, Slope</td>
<td>78.08</td>
<td>0.75</td>
<td>84.58</td>
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</table>
Table 7: Comparison of classification accuracies by land cover; Combination of image bands, DEM and slope on OLI image

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Maximum Likelihood</th>
<th>Support Vector Machine</th>
<th>Random Forest</th>
</tr>
</thead>
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<td>Producer Accuracy</td>
<td>User Accuracy</td>
<td>Producer Accuracy</td>
</tr>
<tr>
<td>Water</td>
<td>54.12</td>
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</tr>
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<td>Open Bushland</td>
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<td>99.68</td>
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### Table 8: Performance accuracy of Random Forest with Landsat OLI and input band combinations

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The study results revealed the usefulness of combining feature separation attributes on multi-temporal, multi-seasonal data with ancillary data (DEM, slope) in mapping a heterogeneous landscape. The study also demonstrates the ability of the regularized nonparametric machine learning classifiers to classify satellite images with higher accuracy compared to traditional classifiers. Tables 3-5 represent pixel values of the classified image against the reference data. Table 5 for instance, illustrates in details the degree of agreement or variation on how well each of the land cover categories was classified. For instance, 2,035 out of possible 2,138 pixels of water were correctly classified and represented the actual land cover class on the ground at the time of classification. An area originally 33 pixels comprising of water was classified as being covered by forest.

Three LULC maps of the study area and park (presented in figures 4, 5, and 6) were produced using the Random Forest classifier. Two of the LULC maps i.e. 1985/86 and 2010/11 were produced from Landsat TM multi-date satellite images while the third LULC map for 2015/16 was produced using Landsat OLI satellite imagery. The three thematic maps were formed from a combination of dry and wet season imagery using the RF classifier with topographical variables (DEM and slope).

**Analysis of the 1986-87 land cover map**

The multi-season multi-date image was classified into 16 land cover types (see Table 9). Owing to similarities in spectral reflectances of some of the earlier documented classes, for instance riverine forest vegetation, were combined and assigned to a single LC class category during classification. Grassland featured as the most prevalent class occupying 28.3% (26,996 hectares) of the study site whereas invasive weeds’ class was the lowest covering 0.3% (310 hectares).
Figure 4: Land cover map 1986-87
Analysis of the 2010-11 land cover map

Classification of the image reported 15 land cover classes. Euphorbia candelabrum which was initially mapped in the 1986-87 image classification was missed out. Agricultural land dominated the study area with 36.6% coverage (an equivalent of 35,478 hectares) while shoreline marsh was the least class covering 0.5% of the total area (Table 9).

**Figure 5: Land cover map 2010-11**
Analysis of the 2015-16 land cover map

The multi-date image was classified into 13 land cover types as illustrated in Table 9. Among the land cover types mapped, agricultural land was also the dominant land cover constituting 39% (37,558 hectares) and with vast landscapes spanning on the western and northern eastern sides of the park. This was followed by both fallow grassland covering 20% (19,591 hectares) respectively found mostly in the north eastern and entire western parts of the study area. The least dominant land cover type included the invasive weeds and burn scar both covering 0.4% and 0.6% of land cover in the study area.

Figure 6: Land cover map 2015-16
Comparative analysis of the three land cover maps

A careful look (of figure 7a, b, and c) pictures a forest at the south western section of the map originally present in 1987 but missing in both 2011 and 2016 maps. Another forest fragment north of the lake was decimated in 2011 and seems to have been restored by 2016. *Euphorbia candelabrum* also in the 1987 map (south east of the lake) was not mapped in the subsequent years under study. The lake water seems to shrink in 2011 and later swell in 2016. Built-up land is also seen to expand from 1986 to 2016 whereas land under grassland at the south east of the study area appears to thin out by 2016. A portion at the south of the built-up LULC which was under grassland in 1987 appears to be completely lost to agricultural land. There is also an increase in the land covered by both mixed bushland and invasive weeds inside the park.
Figure 7: Study Area Land cover maps; (a) 1986, (b) 2011, and (c) 2016
4.2 Change detection, Results

Broad spatial scale analyses of land cover composition between 1987 and 2016

A more detailed assessment of changes occurring between 1987 and 2016 was done using post-classification comparison of individual land cover classes/types. Land cover changes were also compared within the park for the periods 1987 and 2011. Land cover fluctuations were evident in two-fold; those that increased and those on the decline. Cumulative changes per LC type have been summarized on the table below.

Analysis of land/vegetation cover changes in the study area between 1987 and 2016

Table 9 outlines LULC acreage and percent change coverage in individual LC categories. Among the LC types that increased included; water which expanded by 55% an approximate 21.15km², mixed bushland by 2.7% (250ha), invasive weed by 26.8% (82ha), agricultural land by 43% (11,239ha), built-up land by 208% (1,796ha), and bare ground by 65.8% (1,725ha). While land cover types on the decline comprised of open bushland by 10% (280ha), and grassland scrub by 40% (5,576ha). Grassland cover also decimated by 27.4% (7,405ha), forest by 25.1% (1,382ha), burn scar and Acacia woodland by a corresponding 43% (403ha) and 35% (783ha). Analysis of land cover dynamics between LC types includes change of 594 hectares (21.3%) of open bushland, 2,667 hectares (19.1%) of grassland scrub, and 107 hectares (11.5%) of burn scar totaling 3,368 hectares to grassland.

Another 14,303 hectares comprising 3,692 hectares (40%) of mixed bushland, 4,822 hectares (37%) of grassland scrub 2,703 hectares (49%) of forest cover and 3,086 hectares (11.4%) of grassland were converted to agricultural land. Another 2,688 hectares (10%) of grassland was lost to bare ground. A significant 444 hectares equivalent of 20% of Acacia woodlands was lost to water. Also notable are a sizeable 364 hectares of grassland that were engulfed by water.
Table 9: LULC by area and percent land cover change in the study area

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Area (ha) 1987</th>
<th>Area (ha) 2011</th>
<th>Area (ha) 2016</th>
<th>% change 1987-2011</th>
<th>% change 1987-2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>3,837</td>
<td>3597</td>
<td>5,952</td>
<td>-6.3</td>
<td>55.1</td>
</tr>
<tr>
<td>Open Bushland</td>
<td>2,791</td>
<td>3483</td>
<td>2,511</td>
<td>24.8</td>
<td>-10</td>
</tr>
<tr>
<td>Mixed Bushland</td>
<td>9,207</td>
<td>8696</td>
<td>9,457</td>
<td>-5.6</td>
<td>2.7</td>
</tr>
<tr>
<td>Invasive Weeds</td>
<td>310</td>
<td>533</td>
<td>392</td>
<td>72.3</td>
<td>26.8</td>
</tr>
<tr>
<td>Grassland Scrub</td>
<td>13,970</td>
<td>13106</td>
<td>8,394</td>
<td>-6.2</td>
<td>-39.9</td>
</tr>
<tr>
<td>Grassland</td>
<td>29,996</td>
<td>22011</td>
<td>19,591</td>
<td>-18.5</td>
<td>-27.4</td>
</tr>
<tr>
<td>Forest</td>
<td>5,514</td>
<td>1119</td>
<td>4,132</td>
<td>-79.7</td>
<td>-25.1</td>
</tr>
<tr>
<td>Fallow Agriculture</td>
<td>3,538</td>
<td>2964</td>
<td>19,530</td>
<td>-16.2</td>
<td>452</td>
</tr>
<tr>
<td>Crop</td>
<td>22,781</td>
<td>32514</td>
<td>18,028</td>
<td>42.7</td>
<td>-20.9</td>
</tr>
<tr>
<td>Burn Scar</td>
<td>930</td>
<td>653</td>
<td>527</td>
<td>-29.8</td>
<td>-43.3</td>
</tr>
<tr>
<td>Built-Up</td>
<td>861</td>
<td>3681</td>
<td>2,657</td>
<td>327.5</td>
<td>208.6</td>
</tr>
<tr>
<td>Bare Ground</td>
<td>2,620</td>
<td>952</td>
<td>4,345</td>
<td>-63.7</td>
<td>65.8</td>
</tr>
<tr>
<td>Acacia Woodland</td>
<td>2,207</td>
<td>1960</td>
<td>1,424</td>
<td>-11.2</td>
<td>-35.5</td>
</tr>
<tr>
<td>Shoreline Marsh</td>
<td>326</td>
<td>483</td>
<td>0</td>
<td>47.9</td>
<td>-100</td>
</tr>
<tr>
<td>Bare Lakeshore</td>
<td>712</td>
<td>1189</td>
<td>0</td>
<td>67</td>
<td>-100</td>
</tr>
<tr>
<td>Euphorbia candelabrum</td>
<td>341</td>
<td>0</td>
<td>0</td>
<td>-100</td>
<td>-100</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>96,940</strong></td>
<td><strong>96,940</strong></td>
<td><strong>96,940</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 5 below graphically compares LULC change between 1987 and 2016.

Figure 8: a) LULC 1986 and 2016; b) Change comparison by increase and decrease

Land/vegetation cover maps of the park within the study period
4.2.1 Post classification comparison

Analysis of land/vegetation cover changes in LNNP between 1987, 2011 and 2016

The results reported several LULC types experiencing a decline in the period 1987 and 2011 as reported in Table 10. There was a distinct decline of the lake water body which shrank from 38km$^2$ to 34km$^2$. Shrinking of the lake water could be attributed to high evaporation during the 2008/09 drought and drying up of the Inlet Rivers. Immediate effect would be a progressing exposed bare land by the lakeshore. Other diminishing habitats include; Acacia woodland, forest, grassland scrub, which were reduced by 9%, 23% and 42% respectively. Open bushland and burn scar also lessened by 4% and 98% respectively. On the other hand, the bare lake shore, invasive weeds, mixed bushland and grassland vegetation expanded by a corresponding 66%, 49%, 11% and 3%. The growth of the grassland vegetation cover may be linked to the decline in the grassland scrub cover.
An examination of the table points out several changes in the park’s habitat types between 1986 and 2016. For example, there was 51% increase in water level from 38km² in 1986 to 57km² by 2016. Mixed bushland cover also increased by 25%, from 2942 hectares to 3677 hectares. Notable increases were also observed with both the bare ground and invasive weeds expanding by 34% and 19% respectively. The results also suggest that grassland and forest cover increased by 3% and 97% respectively.

*Euphorbia candelabrum*, shoreline marsh and bare lakeshore land/vegetation cover types were completely lost to water from the rising lake levels. Other declining habitats include the *Acacia xanthophloea* woodland about which nearly 35% of the wood density is said to have been lost or converted to another land cover type. Area covered by grassland scrub also decreased by a staggering 65% and with both open bushland and burn scar shrinking by 26% and 94% respectively.
Table 10: LULC by area and percent land cover change in LNNP

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>Area (ha) 1987</th>
<th>Area (ha) 2011</th>
<th>Area (ha) 2016</th>
<th>% change 1987 - 2011</th>
<th>% change 1987 - 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>3,775.1</td>
<td>3,405.1</td>
<td>5,684.1</td>
<td>-9.8</td>
<td>50.6</td>
</tr>
<tr>
<td>Open Bushland</td>
<td>2,364</td>
<td>2,274.8</td>
<td>1751</td>
<td>-3.8</td>
<td>-25.9</td>
</tr>
<tr>
<td>Mixed Bushland</td>
<td>2,941.7</td>
<td>3,253.8</td>
<td>3,677.4</td>
<td>10.6</td>
<td>25</td>
</tr>
<tr>
<td>Invasive Weeds</td>
<td>3,02.2</td>
<td>451.2</td>
<td>359.6</td>
<td>48.8</td>
<td>19.2</td>
</tr>
<tr>
<td>Grassland Scrub</td>
<td>1,111.4</td>
<td>642.3</td>
<td>389.5</td>
<td>-42.2</td>
<td>-64.9</td>
</tr>
<tr>
<td>Grassland</td>
<td>4,613.3</td>
<td>4743</td>
<td>4,752.4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Forest</td>
<td>260.9</td>
<td>201.3</td>
<td>513.9</td>
<td>-23</td>
<td>97.3</td>
</tr>
<tr>
<td>Burn Scar</td>
<td>99.6</td>
<td>1.9</td>
<td>5.9</td>
<td>-98</td>
<td>-94</td>
</tr>
<tr>
<td>Built-Up</td>
<td>10.5</td>
<td>32.2</td>
<td>9.6</td>
<td>220</td>
<td>-8.6</td>
</tr>
<tr>
<td>Bare Ground</td>
<td>172.5</td>
<td>164.3</td>
<td>231.1</td>
<td>-4.7</td>
<td>34.3</td>
</tr>
<tr>
<td>Acacia Woodland</td>
<td>2,122.6</td>
<td>1,927.6</td>
<td>1,388.2</td>
<td>-9.2</td>
<td>-34.6</td>
</tr>
<tr>
<td>Bare Lakeshore</td>
<td>660.8</td>
<td>1,099.7</td>
<td>0</td>
<td>66.4</td>
<td>-100</td>
</tr>
<tr>
<td>Shoreline Marsh</td>
<td>321.7</td>
<td>481.3</td>
<td>0</td>
<td>49.4</td>
<td>-100</td>
</tr>
<tr>
<td>Euphorbia candelabrum</td>
<td>121.8</td>
<td>0</td>
<td>0</td>
<td>-100</td>
<td>-100</td>
</tr>
<tr>
<td>Other</td>
<td>96.1</td>
<td>295.9</td>
<td>211.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>18,974</strong></td>
<td><strong>18,974</strong></td>
<td><strong>18,974</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Interpretation of land/vegetation cover changes inside the protected area in the 1987 – 2011 periods

Several maps were produced to display the nature of land cover changes and vegetation composition inside the park. Maps of vegetation types with the most dominant influence in the spatial distribution and feeding habits of wild animals are hereby briefly described.

As represented in Figure 10a, most of the open bushland cover was converted to open grasslands. Higher proportion of grassland scrub was converted to mostly mixed bushland and open grasslands (figure 10b). It is important to note that the mixed bushland observed is the *Tarconanthus camphoratus* woody plant.

**Figure 10:** a) LC change from open bushland; b) LC from grassland scrub
Figure 11a illustrates areas at the southern parts of the park that were originally grassland but were degraded to bare soil patches. A fraction of *Olea africanus* forest species located at the south western tip of the park is seen as getting reduced to mixed bushland (figure 11b).

**Figure 11:** a) LC change from grassland; b) LC change from forest
The area initially covered by Euphorbia candelabrum seen to be replaced by both open bushland and scrub grassland but in varying proportions (see figure 12a). This is after the stand was razed down by fire in 2009. There was an extensive burn scar mapped at the northern tip of the park as shown in figure 12b. Extensive portions of land affected by burn scars were however located outside the park. The spread of invasive weed can be conspicuously spotted in the thick Acacia woodland south of the park (figure 12c).

**Figure 12:** a) LC change from euphorbia; b) LC change from burn scar; c) LC change from Acacia woodlands
Land/vegetation cover changes inside the protected area in the period 1987 and 2016

Three decade vegetation cover maps comprising of LC changes of major concern in the park were produced and analyzed. Figure 13a illustrates land originally occupied by grassland scrub vegetation being replaced by mixed bushland whereas open bushland (figure 13b) is seen to have been invaded by mixed bushland, open grasslands, and fragments of invasive weeds.

Figure 13: a) LC change from grassland scrub; b) LC change from open bushland
Segments of open grasslands were reduced to bare ground as shown in figure 14a. The areas in red (figure 14a) reveal areas initially covered by grassland and a significant proportion of the tourist road network but were later submerged by the expanding lake water levels. A portion of Acacia woodland vegetation was decimated by the flooded lake particularly in areas near the lake shore, which reveals Acacia under water as shown in figure 14b. Invasive weeds also manifest a further spreading pattern. The weeds are seen to prevail largely along the river channels. The source of the invasive weeds may be speculated as external (as a result of streamflow transport). A fraction of the Acacia was also varied to mixed bushland.

**Figure 14:** a) LC change from grassland; b) LC change from Acacia woodland
Sections in red on the figure 15a and b below reveal portions originally covered by both bare lakeshore and shoreline marshes. This land is subdued by water to date and as a result, there is hardly any shoreline vegetation in the park.

Figure 15: a) LC change from bare lakeshore; b) LC change from shoreline marsh

Figure 16 below represents totality of transition of LULC changes between 1987 and 2016. Areas portrayed in red tone highlight cumulative changes that have taken place in the period under study while the grey toned sections depict LULC which remained the same throughout the period. It should be remembered that post classification comparison also compounds classification errors and hence it is always advised to compare with other change detection techniques for representativeness and reliability.
Figure 16: LULC, change no change maps of both the study area and park
4.2.2 Multi-temporal Principal Components change Analysis

A careful evaluation of the output PCs revealed a lot of useful information on change in PC6, PC7, and PC10 (see Figure 17). PC6 portrayed areas with decreasing land cover in dark tones. This includes the forest cover to the south western tip of the study area (also known as the eastern Mau escarpment), euphorbia forest, the two burn scars at the north of the lakeshore. It was however difficult to interpret changes in Acacia woodland as no variation was captured. PC6 also pictured new developments which include; the two expanded municipal sewer treatment plants and burn scars in the 2011 image (on the east of the park) as bright. PC7 showed recognizable information in exact opposite of PC6.

Changes like forest decline on the Mau escarpment, euphorbia in the park, and burn scars located at the north of the park were expressed in brightest tones whereas changes on the increase which include both sewer ponds, and burn scars manifested in dark tones. Quite interesting that PC10 offered a remarkable display of areas that had a decrease in change between 1986 and 2011 appearing as brightest. Such include the Mau forest, euphorbia forest, burn scar and the lake shore. On the other hand, introduced burn scars in the years 2010/11 were well noticeable in dark tones.

Not much of a change could be derived from PC1 except brightness values. PC2 appeared to compress a bigger proportion of information of all the changes compounded and therefore more difficult to interpret. PC3 concisely delineated elevation and could be very useful when obtaining topographical variables. Both PC4 and PC5 appeared convoluted with no identifiable change. PC8, PC9, PC11, and PC12 too, displayed artefacts of noise with nothing recognizable.
Figure 17: Principal Components 6 and 7
4.3 Factors/variables that can be used to explain some of observed vegetation changes.

The major land cover changes worldwide may be categorized to have been caused by either human activity or environment related. Vast land cover changes in LNNP and surrounds can be associated with land conversion into farms and are reflective of increasing demand for land by a fast-growing population. Some of the factors evidently seen upon classification include;

4.3.1 Land Use Land Cover changes related to a growing human population

The extension of the built up land, and opening up of land for agricultural production adjacent the park justifies the trends of a growing human population in the Nakuru municipality (see figure 18b). The Kenya National Bureau of Statistics (KNBS) population report classifies the country as an agricultural economy with more than 75% of the population directly dependent on agriculture. The demographic trends can be confirmed by the census statistics of the municipality of Nakuru between 1948 and the last count of 2009 as pictured in figure 18a. With about 68% of the country’s population living in only 12% of the entire land area of Kenya, a disproportionately high fraction of the population is unevenly distributed in urban centers.

About 90% of the population in Nakuru resides in formal settlements of the municipality. According to the results from the study area, both crop and fallow agriculture LULC constitute the highest proportion of the landmass. This is an obvious indication of increased demand for land and conversion for agricultural activity. At present, the western section of the park boundary is experiencing increasing settlements.
The compounding effects of the increasing urban population are met with constrained urban infrastructural facilities. A good example (illustrated in figure 19), is the expanded sewer treatment plant which was built inside the park and also discharges waste water to Lake Nakuru. The poorly treated waste water threatens the aquatic habitat.
4.3.2 Vegetation cover loss

From the above results, it is obvious that most LULC changes that occurred culminate to the loss of vegetation cover. Both the 2010/11 and 2015/16 images did not have euphorbia vegetation mapped, an observable disappearance of the forest species to fire possibly human caused. The portion of land previously occupied by euphorbia has been taken over by grassland vegetation. The complete loss of lake shore vegetation can be linked to the high lake volumes (figure 20a). The shrinking woodland density of *Acacia xanthophloea* between 1986 and 2016 can also be traced to rising lake levels. Figures 20b and c picture the woodland forest located in a soggy ground.

This can be supported by the fact that these woodlands possess shallow fibrous root system. With increased water table, the trees continue to be exposed to a saline and soggy environment resulting to drying up and crumbling down of extensive portions of the woodlands’ density. Further loss of the Acacia habitat may pose a great danger to the survival of the *Rothschild* giraffe population.

![Figure 20](image)

**Figure 20:** a) Flooded Lake Nakuru; b) Acacia drying up from salinity; c) A felled giant tree stand

An obvious trend can be established by the advancing growth of mixed bushland cover. *Tarchonanthus camphoratus* woody tree species constitutes the bigger fraction of the mixed bushland vegetation (figures 21a&b). The bushland is alleged to spread fast and further suppress growth of the existing grassland vegetation.
Figure 21: a) A *Tarchonanthus camphoratus* tree stand; b) Expansive section overlooking the lake covered by the woody plant

4.3.3 Contribution to vegetation loss/degradation by increasing animal population in the park

Animal counts are usually carried out twice or thrice yearly in the park depending on prevailing conditions. Currently, the park has an estimated 3,600 buffaloes besides estimated 900 zebras, rhinos, water bucks, and elands (Figure 23a and c). Lake Nakuru national Park is considered to have exceeded the capacity of buffalo herds it can sustainably support. Besides, crowding of the herds is associated with trampling and exposing land surface as can be seen on figure 22 below. The report also presents a steady population of the browsers over the period (Figure 23d), which makes it a bit hard to justify their influence/impact on vegetation cover change. The declining trend of animal population (Figure 23b) cannot be overlooked to suggest parks viability to sustainably support the increasing buffalo numbers.
Figure 22: A photo of crowding impact on grasslands, with drying up *Acacia xanthophloea* at the backdrop.

Below are graphical representations of current animal population taken from animal censuses of 1996 – 2015 periods. The graphs represent only animals with an increasing population trend.

![Graph of Buffalo (Syncerus caffer)](image-url)
Total Animal Population

Grazing Animals

b)

c)
Figures 23: Census on a) Buffalo; b) Cumulative grazers’ population; c) Grazers; d) Browsers
4.3.4 Analysis of 1980 – 2015 rainfall gauge data

Three approaches were applied.

A Time series Regression Model was fit in the Nakuru area precipitation data to model both trend and harmonic series for seasonality. The model was applied to both the raw data and the log transformed data. The residuals were explored for stationarity and auto-correlation.

![Figure 24: a) Precipitation at Lake Nakuru; b) Log precipitation with LOESS smoothing](image)

Both the p-value on the Time coefficient and trend coefficient were insignificant. Change point mean analysis was fitted in the regression model to both seasonality adjusted raw data and seasonality adjusted log transformed data. Premise here was to model seasonality and perform a change point test on the resulting residual time series.
Again, there was nothing significant to suggest some unusual trend in precipitation.

Lastly, the regression tree approach was applied using the minimum cross-validation error tree to both raw data and log transformed data. It must be recognized that this approach assumes independence between observations and not always reliable.

Using the three approaches, there was no statistically significant change in the amount of precipitation except for some weak empirical evidence suggesting a little more rainfall in 2000.

Figure 25: a) Seasonally adjusted raw data; b) Seasonally adjusted log data
4.4 Discussion

Mapping LULC at Lake Nakuru National Park and its surrounds was made achievable with the use of remote sensing and GIS software. The previous study by Mutangah (1994) offered the most reliable baseline information and was adopted for more objective mapping of LULC at LNNP. Using historical Landsat data, it was possible to capture both the spatial distribution and transitions of LULC types over time between 1987 and 2017. Credible assessments can therefore be made from the digital LULC map than could have been from the previous studies, which had generalized classes identified. Digital mapping also allowed successful spatial delineation of most of the previously manually mapped vegetation cover types.

Five out of the ten major vegetation categories earlier mapped were successfully delineated. These were; grassland, bushland, woodland, forest and alkaline marsh. Mapping of the fresh water swamp, cliff & escarpment vegetation, lava outcrop vegetation, riverine forest and woodland, and sewage influenced vegetation was limited to the spectral resolution of the datasets. However, these categories tended to show similar surface reflectance values and were merged. For example, the riverine forest and woodland category shared near similar reflectances with Acacia woodland and therefore both categories were assigned a single informational class during classification. The cliff & escarpment and lava outcrop vegetation were mostly representative of mixed bushland upon classification.

With similar situations determined, 5 of the 10 documented distinct vegetation classes were maintained in the classification process. Euphorbia candelabrum vegetation cover could not be objectively identified for mapping in 2010/11 having been completely razed down in 2009. Again, bare lakeshore and shoreline marsh informational classes were not traceable in 2015/16 images due to the increased water levels of the lake. It was difficult to classify the specific land cover sub-types within the categories as earlier documented (Mutangah, 1994) also limited by both spatial and spectral resolutions of the satellite images.
Five separate tests of band combinations carried out in the classification of LULC showed that only a combination of image raw bands, Digital Elevation Model, and slope produced remarkable accuracies on image classification. Regarding the performance of individual classifiers, the parametric Maximum Likelihood performed poorly with addition of non-spectral datasets. On the other hand, the non-parametric machine learning classifiers (SVM and RF) produced higher classification accuracies in mapping of the heterogeneous landscape. Overall, the Random Forest algorithm demonstrated superiority over the SVMs and was therefore adopted for land cover mapping.

Digital software applications on satellite image data have demonstrated the potential for mapping LULC and periodical assessment of habitat conditions. This provides a credible benchmark for identifying and zoning LULC, also predicting and mitigating future environmental changes.

The assessment of land cover changes at LNNP and surrounds also required identification of LULC in areas adjacent the park. Three more LULC types; crop, fallow agriculture and built-up land were therefore included prior to classification. Observations made on the LULC changes have established that the vast land cover changes in the study area were associated with conversion of land into settlement areas and farm lands, reflective of population growth. These manifested with the decline of forest cover, grassland cover and the increasing built-up land. Within the park, Euphorbia forest, mixed bushland, Acacia woodlands, the lake water body, shoreline marsh, and invasive weeds among the habitats experienced extensive fluctuations in terms of density/volume and distribution.

Expanding urbanization can be linked to population growth in the urban center. The indiscriminate peri-urban development alongside the park boundary also exposes an obvious disconnect between institutional linkages for example, between urban planning and protected area management players. Settlements have completely usurped the park buffer and perfectly isolated the park from wildlife dispersal areas such as the Soi Sambu conservancy. On the flipside, this scale of unrestricted encroachment is a precursor for increased risks of fire outbreaks during land preparation for cultivation, poaching of animal
trophies, human wildlife conflict and waning chances for the protected area’s continual existence.

Several tests were carried out on 1980 – 2015 Nakuru area precipitation data. The tests; Time Series Regression Model, Change Point Mean Analysis, and Regression Tree approach failed to establish any statistically significant relationship between precipitation and the dramatic rise in lake water levels. The available stream discharge data that was retrievable consisted of one river only. The same data was also coupled with inconsistencies such as missing data up to 2004, entirely no data between 2010 and 2011, and having significant gaps in 2012 through 2014. This kind of data would only restrict any meaningful hydrological analysis.

In the park, extensive loss of lakeshore marshes and a section of Acacia woodlands and can be directly traced to the high lake levels. The decline of Acacia woodlands may be associated with the species morphology. The trees have extensive network of fibrous roots barely deep from the surface. An occasion with either a steep drop or rise of the water table makes them vulnerable to drying up fast and eventually falling off. Entire loss of the shoreline marsh has led to complete degradation of the lesser flamingo feeding grounds and mass migration of the magnificent pink birds. Continued loss of the woodlands habitat threatens breeding grounds for the black rhino, and forage for the endangered Rothschild giraffe which largely feeds on the vegetation. The gigantic woodlands stand also offer the PA its natural beauty and aesthetic value. Considering that they are anchored on loose volcanic soils, chances of dying-off of massive densities are very high.

Vegetation cover maps of the park also pictures a trend of increased area covered by both the mixed bushland and invasive weeds since 1987. Huge proportion of the mixed bushland is mainly *Tarconanthus camphoratus* which is unpalatable by wild animals. The very fast spreading nature of the woody bushland has in the recent past sparked discussion agenda towards its management. Its invasion continues to suppress nearby vegetation and may threaten parks ability to sustain other lifeforms in the future if not contained.
The invasive weeds are seen to prevail largely along the river channels. The spreading invasive weed largely flourishing by the riverine vegetation may be associated with river water transportation. The study of invasion by invasive weeds in the park has however not been extensively covered or mapped to detail. Until recently, its impact on other vegetation communities has not been an issue of management concern.

Numerous tourist road networks existing prior to flooding are currently inaccessible to tourists visiting the park. The situation required prompt opening of new road networks without prior ecological assessments. Portions of grassland vegetation cover near the lakeshore were also covered by water. These habitats (grassland vegetation, Acacia woodland density and completely covered lakeshore marsh) are in danger of plummeting, and pose a risk to an increasing number of grazing wild animals that include the over 3,500 resident buffaloes. Noteworthy to mention is that the increased waters also covered the entire land under the park administrative offices and 9 staff houses leading to displacement and demolishing of the buildings.

The entire decimation of Euphorbia candelabrum (endemic to East Africa) poses serious irreversible habitat change and possible succession by another vegetation cover/habitat. The steep decline of forest cover in the Eastern Mau catchment and conversion of forest land into farmlands may be blamed for the seasonality of once perennial rivers like the Larmudiac, Makalia, Nderit, and Naishi.

The northern portion of the study area around Menengai crater has seen a decrease in forest cover between 1987 and 2011 and a further recovery by 2016. This indicates evidence of forest management efforts on the human managed plantation forests. Loss of forest cover at the Mau hills may be associated with increased demand for settlement land and further linked to the voluminous surface runoffs laden with sediment from fallow lands due to reduced surface cover.
CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study of spatial analysis on the distribution, and changing trend of LULC in the study area unmasks compelling results. The study objectives were reliably met. Five of the ten documented distinct edaphic habitats were maintained in the classification process in the digital mapping of the previously manually mapped vegetation cover. Essentially, 16 informational categories were identified in the 1986/87 multi-band image, 15 categories in the 2010/11 image while the 2015/16 images had 13 categories identified for mapping LULC. It is crucial to note that the three unmappable LULC were located inside LNNP. This implies an entire loss of land cover/habitats.

Upon classification, highest accuracies were obtained from a layer stack of image input bands with topographical variables. This demonstrates the usefulness of exploring both spectral and non-spectral band combinations of datasets to train a classifier. However, it was only the non-parametric SVM & RF classifiers which performed much better than the parametric MLC in mapping of the heterogeneous savanna landscape. Out of the three classifiers, RF classifier had the highest overall accuracy of 85.5% and was adopted to create final LULC maps. LULC changes were mapped and documented in a 30-year period (1986, through 2011 and 2016).

Vast LULC changes in the study area were associated with land conversion from forest and grassland to agricultural activities, settlement, and urbanization; which is reflective of population increase. LULC on the increase included agricultural land, water, mixed bushland, built-up, invasive weeds and bare land. The implication of forest loss at the eastern Mau escarpment could be change of hydrological regimes, reduced surface runoff percolation, retention, soil erosion and eventually siltation into the lake. The loss of grassland in favor of agricultural activities may also be associated with land degradation. The rapidly urbanizing Nakuru municipality which extends reach to the park’s perimeter
fence implies outright encroachment and possible conflict of implementation of sectoral policies. Increased mixed bushland and invasive weeds inside the park reflects competition with and suppression of other vegetation types and especially grassland, implying habitat decline/stress in the park.

Declining LULC types were open bushland, grassland, grassland scrub, forest, burn scar, and Acacia woodland. Completely wiped out LULC includes the Euphorbia forest, bare lakeshore and shoreline marsh. Inside the park, there is notable increase of water volume, mixed bushland and invasive weeds. The decline of Acacia woodland may have future adverse implications to the survival of the Rothschild giraffe which largely feeds on them. The entire loss of shoreline marsh and bare lakeshore, previously feeding grounds for the lesser flamingo has had direct effects on the park's appeal to bird watchers since 2012.

Limitations of the study

Thorough classification of the specific documented land cover sub-types within a given habitat category was subject to the spatial resolution of the satellite images.

Available hydrological data retrievable for any useful analysis focused on only one river amongst the five earlier mentioned. However, the secondary hydrologic data of Nakuru region had glaring gaps and therefore inconsistent for meaningful study of the effects of hydrological regimes on the high lake levels.

Preliminary analyses of stream discharge data failed to establish reliability in the use of the datasets for objective research. This is a revelation of sporadic nature in the monitoring of stream flow discharge of the major rivers draining into the lake. Available precipitation data which is collected within a radius of 50km at the locus of the municipality may not provide an exhaustive basis for completeness of its effect on the changing hydrologic regimes. The study also did not take into consideration the entire catchment of LNNP due to extensiveness of the land area vis-à-vis primary objective of mapping vegetation cover inside the park.

It is also important to note that, even though post-classification comparison is one of the widely-used change detection techniques, it is entirely dependent on how well the different
maps were classified. In which case the technique tends to compound classification errors of the two independently classified maps. The existence of such a possibility is the outcome of incorrectly classified pixels from the separately classified maps.

5.2 Recommendations

Proper planning and management interventions are expedient for the PA to curb further conservation threatening LULC practices. Today’s technology (including GIS and remote sensing applications), when adopted, presents us with opportunities for preparation towards providing site-specific solutions in the conservation and management of natural resources including Protected Area management. The conservation and management of wildlife for example, requires timely ecological monitoring of their habitats overtime, predicting their future conditions, and developing timely interventions.

Major changes witnessed both outside and at the park’s proximity have revealed the critical need to encourage stakeholder close-collaboration for integrated land use management. For instance, the loss of forest cover in the Eastern Mau escarpment, the increasing land under agriculture, and encroachment to the park. A lot of data is nowadays becoming publicly available with advancing technology and hence partnership for information sharing is important for any meaningful development agenda.

More comprehensive mapping of the vegetation sub-categories in the park is required. Inside the park for instance, management interventions are expedient for the entirely lost habitats; i.e. euphorbia candelabrum, and alkaline marsh. It is also crucial to have management strategies put in place for the increasing invasive plant species including the mixed bushland (*Tarchonanthus camphoratus*), which have become a contemporary management challenge in our protected areas. The use of Landsat datasets however, demonstrated limited capacity to map the spread of invasive weeds to detail and therefore further research is recommended to effectively identify, map and monitor their spread using very high resolution satellite imagery.
The decline of both acacia woodland and grassland cover exposes fragility of the habitat’s potential to sustain the increasing animal population in the park. Perhaps the park management may reconsider translocation/culling. The fragile nature of woodlands exposed to flooded water may also pose danger to tourists while in the park and hence the requirement of adequate signage in areas with dense and aging woodlands. Overall, the current situation requires environmental impact assessment and ecological valuation of wildlife population and their habitat.

The management of secondary data at the field level (including collection, handling and processing, storage, and access) was found to be less comprehensive. There is therefore a need for rigorous capacity building and an establishment of an integrated operational database management system particularly for precipitation and streamflow gauge data, from which information could be easily retrieved for practical analyses.

Park-specific research aspects to be considered include a comprehensive study of precipitation and stream discharge trends in the entire catchment of Nakuru, opportunities for continuous ecological monitoring and assessments of the impacts of the observed changes.

The results of this study can be adopted to inform the formulation and/or review of current management plans for area conservation management. Protected area managers for instance, may be required to take advantage in identifying and lobbying for every LULC adjacent the parks that may be compatible with wildlife conservation. Information may also be useful to wildlife conservation stakeholders in Nakuru region including; the departments of forestry, water, agriculture, meteorology, the municipal council, higher learning institutions, and the non-governmental organizations.
References


