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ASSESSMENT OF THE EFFECTS OF CLIMATE CHANGE ON LAND USE AND LAND COVER USING REMOTE SENSING: A Case Study from Kenya

Mwaniki W. Mercy (Bamberg University; JKUAT)
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Mwaniki W. Mercy
Bamberg University and
Jomo Kenyatta University of Agriculture and Technology (JKUAT)

ABSTRACT

This working paper presents a study on the combined effect of land-use land-cover (LULC) changes and the effects of climate variability for a specific study area in Kenya. The study was run between the years 1995 and 2010. LULC changes revealed competing land uses, which increased base and rock cover. The loss of green cover had a net effect of increasing both maximum and minimum temperature. Extreme weather effect negatively impacted crop and grassland cover, leading to forest area encroachment.

***Keywords**: land-use land-cover (LULC), change detection, climate variables, knowledge based classification, Landsat, image enhancement*

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1. INTRODUCTION

Environmental studies, such as on land degradation and on land-use land-cover (LULC), require monitoring of earth resources, and benefit greatly from remotely sensed products that have the capability to collect huge amounts of data cheaply and regularly for vast areas compared to field methods (van Lynden and Mantel 2001). These tools are essential in order to investigate the effects of climate change, whereby land use plays a critical role by influencing the surface-energy budgets as well as the carbon-cycle effects (Pielke Sr. et al. 2002). Changes in LULC driven by the need for more energy, food, and other resources to support a growing population, result in changing the physical properties of the land surface (Foley et al. 2005). These changes, in turn, affect the surface albedo properties, which affect the amount of reflected or absorbed energy to the atmosphere. In particular, shrinking forest cover undermines the ability of ecosystems to maintain freshwater resources, regulate climate and air quality, while decreasing carbon sink areas, which through carbon sequestration helps to revert the effects of climate change (Foley et al. 2005; Pielke Sr. et al. 2002).

Known detrimental effects of climate change include: unpredictable weather patterns, extreme temperatures, increased meteorological hazards (e.g. floods, tsunamis, El Niño, heat waves), prolonged droughts (La Niña), increased infectious diseases, and rising sea level (Parry et.al. 2007). Although there are natural drivers of climate change, human activities have substantially contributed to increased greenhouse gases (e.g. carbon dioxide, methane, halocarbons), which trap heat in the atmosphere, thereby altering the energy balance of the climate system (IPCC 2007). Therefore, there is a need to undertake studies that qualitatively and quantitatively measure the anthropogenic effects in order to campaign for sustainable use of resources that can help to slow or reverse climate change (Roseland 2012; Stone 2009). Hence, scientists have emphasised the importance of incorporating LULC studies in investigating climate change (e.g. Feddema et al. 2005; Foley et al. 2005; Pielke Sr. 2005).

Multispectral or hyperspectral data are mostly preferred for their ability to differentiate various land-cover types owing to imaging in several spectral bands, despite the fact that most have medium spatial resolution (e.g. Landsat and ASTER satellites) (Govender et al. 2007). This necessitates the use of various techniques to improve image classification and accuracy as suggested by Lu and Weng (2007) and Stehman and Foody (2009), among which include: image pre-processing and enhancement to improve feature extraction, image fusion, the use of non-parametric classifiers aiding multisource data classification, and the integration of remote sensing and Geographic Information System (GIS).

The choice of a classifier depends on the study area landscape complexity, the type of remotely sensed data (passive or microwave), and the need to obtain high classification accuracy (Mather and Tso 2009). Jensen et al. (2009) recommended the use of auxiliary data

in classifications to improve classification accuracy. Environmental data (e.g. slope, elevation, soil, precipitation, drainage) or processed image bands (e.g. band ratios, spectral indices) provide a basis for setting classification rules for use in a non-parametric classifier, such as knowledge-based or neural network (Weng 2009).

This working paper describes the research conducted to apply knowledge-based classification to map various land-cover units in the central highlands of Kenya. The main aim of the study was to perform land-use land-cover change in the study area and relate the changes to the climate variables of rainfall and temperature over the LULC classification period (1995–2010). The following environmental variables were used to define the land-cover units: slope, elevation, enhanced components from Principal Components (PCs), and Normalised Difference Vegetation Index (NDVI). Landsat multispectral medium resolution satellite data was chosen due to its availability and the utility of its bands through the spectral curve to differentiate land-cover types as discussed by Campbell (2002) and Song et al. (2011).

2. REGIONAL SETTINGS OF THE STUDY AREA

The research study area geographical extents were: longitudes 35°34´00"E to 38°15´00"E and latitudes 0°53´00"N to 2°10´00"S (Figure 1). Within the study area there are three of the most important Kenya’s water catchment areas, namely: Mt. Kenya, the Aberdare ranges, and part of the Mau catchment area. This makes the research significant because these catchment areas are supporting the ecosystem around the central highlands and the livelihoods of other people relying on the water resources from these regions in the lowlands. The altitude of the study area ranges from 450 m to 5199 m above mean sea level, while the climate varies from highland to savanna and semi-arid climatic conditions. The rainfall seasons are in March to May (long rain season) and October to December (short rain season), and most of the year is relatively dry, but cloudy especially in high altitude areas. Temperature in the highland regions vary from 5 °C to 25°C, while in the semi-arid area, the range varies between 15°C and 32°C in the year.

The land cover mainly comprises forest areas, agricultural areas, grassland-dominated wildlife reserve areas, urban areas, and water bodies (Mwaniki and Moeller 2015). Some of the problems that arise from changes in LULC in the study area are drought, desertification, food scarcity, and river water shortage (Aeschbacher et al. 2005; Baldyga et al. 2008; Grace et al. 2014; Justus and Yu 2014; Muriithi et al. 2013; Otieno 2013; Rarieya and Fortun 2009; Were et al. 2013). Uncontrolled agricultural activities and increased population and infrastructure have been attributed to the changes in LULC (Kiage et al. 2007; Makokha and Shisanya 2010; Mundia and Aniya 2005; Ngetich et al. 2008).

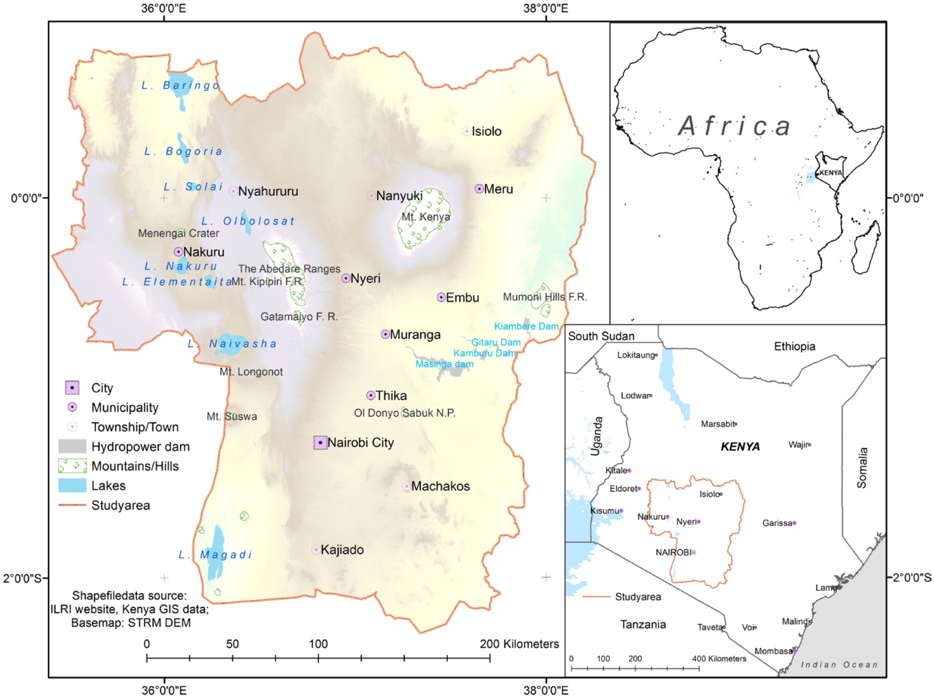

Figure 1: Map of the Study Area

3. DATA DESCRIPTION AND IMAGE ENHANCEMENT

The data required to carry out the LULC classification were multispectral, multitemporal resolution satellite imageries and meteorological climate data of the study area. The choice of Landsat Thematic Mapper (TM) data set was guided by its availability, which is multispectral, medium spatial resolution imagery. Landsat TM data sets paths 168/169 and rows 060/061, 30 m spatial resolution for the years 1995, 2002, and 2010 were downloaded from the USGS website and pre-processed to reduce the effect of haze before mosaicing and subsetting the study area. It can be noted that due to high relief mountain features in the study area, it was almost impossible to obtain 100% cloud-free data. Thus, image patching with data sets taken in January and February for the epoch years was necessary. A Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) 30 m spatial resolution was also downloaded and mosaiced and subset with the study area boundary. Slope variable was computed from the elevation model while NDVI spectral index was computed for each Landsat data set.

Table 1: Factor Loading for Principal Components 1–5 for the years 1995, 2002, and 2010

	1995					2002					2010				
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**
Band 1	0.3826	-0.2510	0.6291	0.5503	-0.1188	0.3793	-0.1308	-0.4106	-0.2121	-0.4672	0.3796	-0.1622	0.6769	0.4409	-0.3297
Band 2	0.1947	-0.0650	0.3023	-0.0152	0.1279	0.3149	-0.1060	-0.4131	-0.2039	-0.3039	0.2013	-0.0422	0.3322	-0.0520	0.1457
Band 3	0.2459	0.1636	0.4318	-0.6099	0.5325	0.3775	0.2634	-0.5042	0.1302	0.7154	0.2516	0.1553	0.4048	-0.5129	0.6164
Band 4	0.4245	-0.7656	-0.2958	-0.3534	-0.1421	0.3321	-0.8277	0.1615	0.3851	0.1741	0.4251	-0.8084	-0.2811	-0.2884	-0.0454
Band 5	0.6882	0.3762	-0.4697	0.2913	0.2816	0.5828	0.1321	0.5814	-0.5310	0.1513	0.6792	0.3487	-0.4326	0.4040	0.2582
Band 7	0.3184	0.4223	0.1354	-0.3393	-0.7678	0.4058	0.4470	0.2063	0.6829	-0.3527	0.3317	0.4155	-0.0372	-0.5417	-0.6492
Eigen val %	94.172	4.438	1.035	0.196	0.148	95.04	3.27	1.33	0.24	0.11	92.785	4.799	1.905	0.336	0.151

Standard covariance PCA image enhanced method was applied to the Landsat bands (1–5, 7) and the information present on each component investigated using PC Factor loading (Table 1). From Table 1, information in PC1 was positively correlated although it had the highest Eigen value, most information from band 5 (soil information), and lower values from visible bands (containing water information). Thus, it was possible to discriminate water cover from other covers although there was a need to explore other PCs to distinguish other land covers. PC2 had the highest information from band 4 (vegetation information) and was negatively correlated with bands 5 and 7 (i.e. soil and geologic information). Similarly, using PC2 it was possible to differentiate: rocks from clear water as bands 1 and 2 were negatively correlated with bands 5 and 7, clear and turbid water (positive and negative correlation among visible bands). PC3 provided further differentiation between water and geologic/soil information, while PC4 and PC5 differentiated soil and geologic information. However, since the first three PCs contained the most information (over 99.4% Eigen value), PCs 4 and 5 were not considered and PC7 was not presented as it had the least information (< 0.01% Eigen value).

FCC using PCs 1, 2, 3 (Figure 2a) and individual bands contributing to most information in PCs 1, 2, 3 formed the basis for land-cover classes identification. Thus, bands 5, 7, and 4 contributed the most information but to increase the FCC contrast, band 3 in the visible region was chosen resulting to FCC bands 5, 7, 3 (Figure 2b), which were further enhanced by decorrelation stretch. Having obtained the enhanced image components and environmental variables of slope and elevation, knowledge-based classification followed as in the next section.

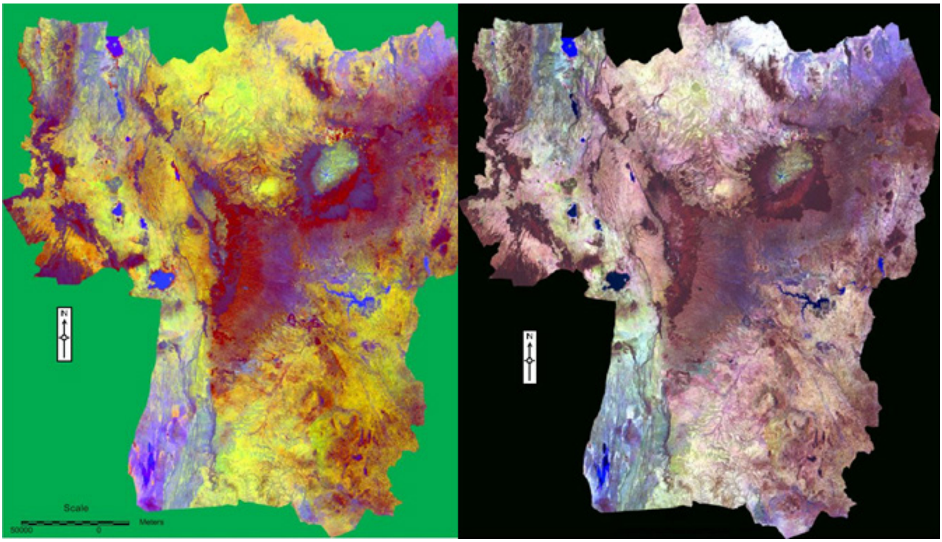

Figure 2: (a) FCC PCs 1, 2, 3 (b) Decorrelated FCC bands 5, 7, 3 Landsat TM, Year 1995

Table 2: Expert Knowledge Classification Criteria

Class Names	1995	2002	2010
Clear Water	PC1 <= 45, NDVI < 0.200 , PC3 >10 Elevation < 2 600 m, Slope < 20	PC1 <= 60, NDVI < 0, Slope < 20, Elevation < 2 600 m	PC1 < 50, Slope < 20, NDVI < 0, Elevation < 2 600 m
Glacier	PC3 >= 18, Elevation > 4 000 m	PC1 <= 85, NDVI < 0.400, Elevation > 4 000 m	PC1<= 30, PC2 < -25, Elevation > 4 000 m
Turbid Water	PC3 >= 35, Elevation < 2 600 m 70 < PC1 < 175, PC3 < 35, Elev. < 610 m, NDVI < 0.200	100 < PC1 < 280, Elevation < 2 600 m, NDVI < -0.340, Slope < 20	70 < PC1 < 110, PC2 < -15 NDVI < 0.1, Elev. < 2 600 m 110 < PC1 < 190, PC2 < -25, Elevation < 2 600m
Muddy/ Salty Water	45 < PC1 < 70, NDVI < 0.485 Elevation > 2 600 m	60 < PC1 < 100, Slope < 20 Elevation > 2 600 m, 0 < NDVI < -0.750	50 < PC1 < 70, PC2 < -15 Elevation < 2 600 m, NDVI < 0 PC1 < 70, PC2 < 7, NDVI < 0.280, Elev. < 1 910 m
Rocks	70 < PC1 < 140, 0.200 < NDVI < 0.485 PC2 > -15, Elevation < 4 000 m PC1 < 70, NDVI < 0.485 Slope > 20, Elevation < 2 600 m 90 < PC1 > 70, -15 < PC2 > -20, 0.485 < NDVI > 0.200, Elevation < 2 900 m Elevation >3 400 m, PC3< 18	85 < PC1 < 180, -0.280 < NDVI < 0.05 Elevation > 3 000 m 60< PC1< 180, NDVI< 0.2 Elevation < 3 000 m PC1 < 180, Slope > 20	70 < PC1 < 145, PC2 > -25, NDVI < 0.350 110< PC1< 190, PC2< -25, Elevation < 2 600 m, 0.2< NDVI< 0.28 Elevation > 3 250 m, PC1 > 245
Dense Forest	0.485 < NDVI < 0.650 Elevation < 4000 m	0.28 < NDVI < 0.465 Elevation < 4 000 m	0.5 < NDVI < 0.680 Elevation < 4 000 m PC1< 70, PC2 > -15, 1 910 m< Elevation < 3 250 m
Light Dense Forest	NDVI > 0.650, Elevation < 4 000 m NDVI > 0.650, Elevation < 4 000 m	NDVI > 0.465, Elevation < 4 000 m	NDVI > 0.680, Elevation < 4 000 m 2 900 m < Elevation < 4 000 m 0.280 < NDVI < 0.500, PC1 < 190
Grass-land	120 < PC1 < 175, Elevation < 3 500 m	180 < PC1 < 260, Elevation < 3 500 m, -0.29 < NDVI < 0	145 < PC1 < 190, NDVI < 0.280, PC2 < -25, Elevation < 3 500 m
Bare Soil	175 < PC1 < 195, Elevation < 3 500m	260 < PC1 < 330	190 < PC1 < 225, Elev. < 3 500 m 145 < PC1 < 170, Elev. > 3 500 m
Silt, Sand Deposits	236 < PC1 > 195	330 < PC1 < 420	225 < PC1 < 250, Elev. < 3 500 m 170 < PC1 < 250, Elev. > 3 500 m
Crop, Young Vegeta-tion	0.200 < NDVI < 0.485, Elevation < 2 900 m, 90 < PC1< 175, PC2< -15 90 < PC1 > 70, Elevation < 2 900 m, PC2 < -20, 0.485 < NDVI > 0.200	0 < NDVI < 0.280, Elevation < 2 900 m 60 < PC1 < 260	50 < PC1< 225, 0.280 < NDVI < 0.500, Elevation < 2 900 m PC1< 70, PC2 < -15 1 910 m < Elevation < 2 900 m

Field data obtained from Nairobi meteorological department for rainfall and temperature spanned between the years 1994–2010 and retrieved for 13 meteorological stations within the study area, at the interval of monthly data, minimum and maximum for the temperature were analysed for trends on yearly basis. Although the raster rainfall data from the Tropical Rainfall Measuring Mission (TRMM) satellite was available with 0.25^0 spatial resolution, it was limited to the duration 1997–2010, thus only station vector data was considered.

4. KNOWLEDGE-BASED CLASSIFICATION WITH IMAGE-ENHANCED COMPONENTS

Knowledge-based classification rules were set using histogram density slicing of the enhanced components i.e. PCs and NDVI spectral index. This was performed using Erdas Imagine remote sensing software beginning with visualising the FCC of the first three PCs. Image enquiry guided by colour was the basis for assigning possible classification classes and determining the range of each class interval. Further, NDVI data was helpful in distinguishing vegetation greenness covers of crops, dense forest, and relatively light dense forest. Elevation data was useful in distinguishing grassland and exposed weathering volcanic rocks at mountain tops, while slope controlled water covers. Thus, the following classes were mapped: clear water, turbid water, salty/muddy water, rocks, dense forest, light dense forest, grassland, bare soils, silts and salt deposits, and crop/agriculture areas (Table 2). It can be noted that each year had different histogram range values for NDVI and PC components. Therefore, it was not possible to have the land-cover class boundaries uniform although elevation and slope environmental variables were maintained uniform across classes in different years.

5. CLASSIFICATION RESULTS AND CROSS-TABULATION CHANGE ANALYSIS

LULC classification results obtained after running the knowledge-based classification rules (Table 2) are presented in Figures 3, 4, and 5 for the years 1995, 2002, and 2010 respectively. From visual comparison of the LULC maps, there were notable changes among the green cover, bare lands, rocks, and grassland. This was analysed by regrouping the LULC classes into: water, forest cover, grass, bare soil/rocks, and crops (Table 3) to visualise the trend of vegetation cover versus exposed land and agriculture areas as in Figure 6.

In general from the year 1995, water cover remained almost constant, with the only changes occurring in its turbidity forms. Forest cover instead had a significant decrease of 27.3% in the year 2002 and increase of 5.4% by the year 2010. Grass cover sensibly increased by 25% in 2002 and decreased slightly by 4% in 2010. Similarly, crop cover increased 10.4% and decreased 11.3% by the year 2010. Rock and bare land covers decreased by 4.09% by the year 2002 and increased by 10.03% by the year 2010.

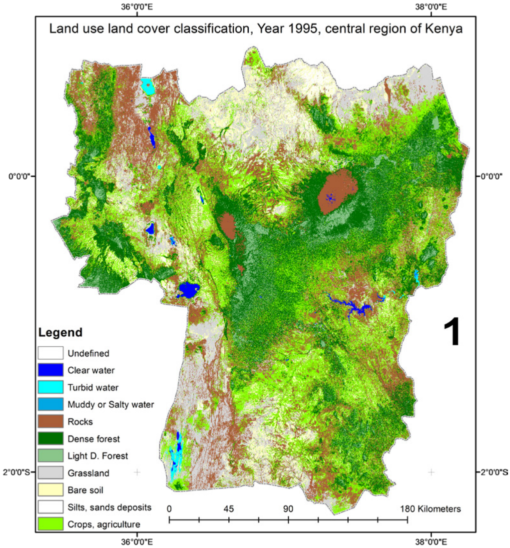

Figure 3: Land-Cover Land-Use Classification Map for Central Region Kenya, Year 1995

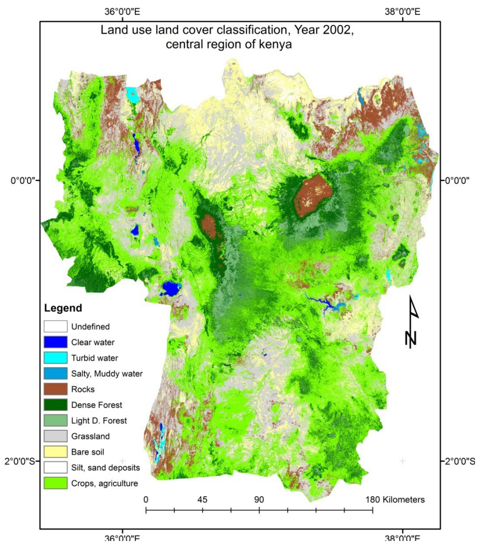

Figure 4: Land-Cover Land-Use Classification Map for Central Region Kenya, Year 2002

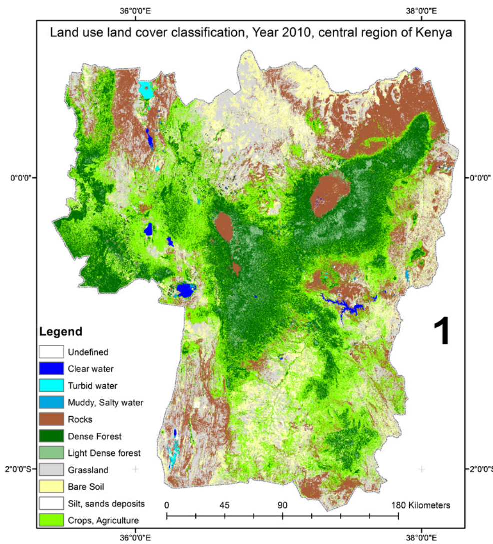

Figure 5: Land-Cover Land-Use Classification Map for Central Region Kenya, Year 2010

Table 3: Land-Cover Area Extent in Percentage for the Years 1995, 2002, and 2010

	Class	1995		2002		2010	
1	Clear Water	0.486	0.97	0.339	1.06	0.493	1.00
2	Turbid Water	0.412	0.97	0.357	1.06	0.277	1.00
3	Muddy Water	0.073	0.97	0.365	1.06	0.234	1.00
4	Dense Forest (D.F.)	22.311	44.35	13.281	17.34	19.784	22.68
5	Light Dense Forest (L.D.F.)	22.035	44.35	4.056	17.34	2.892	22.68
6	Grass	4.445	4.45	25.018	25.02	21.043	21.04
7	Rocks	14.925	23.51	7.944	19.42	17.444	29.45
8	Bare soil	7.325	23.51	10.105	19.42	10.502	29.45
9	Silts	1.261	23.51	1.372	19.42	1.501	29.45
10	Crops	26.727	26.73	37.164	37.16	25.830	25.83
		100%		**100%**		**100%**	

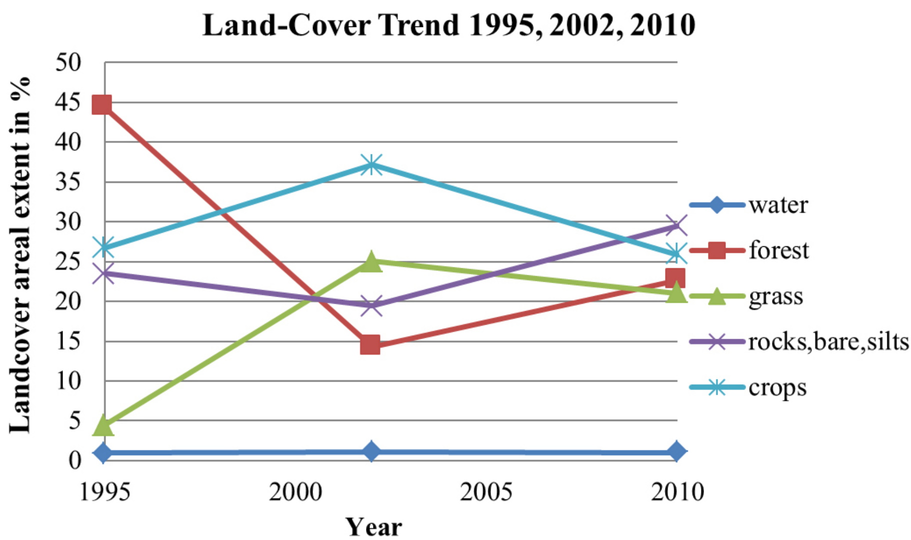

Figure 6: Regrouped Land-Cover Trend for the Years 1995, 2002, and 2010

The changes in land cover may be explained by the rainfall trend over the period 1995–2010 (Figure 7), where the rainfall pattern for selected stations within the study area (Figure 8) was characterised by sharp peaks and decreasing rainfall amounts. The rainfall pattern described heavy rainfall events (e.g. peaks representing the El Niño rains in 1997–1998), followed by low-peaks (e.g. La Niña drought, 1999–2000), and other rainfall peaks in the years 2001 and 2006. The La Niña drought had the effect of reducing green cover immensely given a rain-fed driven economy, especially around the highland regions and wood being the main energy source. This means that some forest cover areas were encroached and converted to agricultural lands, especially around the cooler mountain regions (Figure 4). On the other hand, the semi-arid areas responded to the heavy rains by reducing the bare lands and increasing grassland, which in turn increased livestock, whose increase had an overgrazing effect as highlighted by Otieno (2013).

The rainfall peaks in the years 2002 and 2006, followed by the gradual decrease in rainfall and longer dry spells, had the net effect of reducing agricultural cover, while increasing bare and rock cover. The slight increase in forest cover reflected the government action towards afforestation and evacuation of people from restricted forest lands, although it takes time to achieve given maturity age of trees. These land-cover changes were in harmony with the findings of Wandago (2002), which revealed that forest degradation and loss was a compounded effect from competing land use of agriculture, industry, human settlements, and other energy and infrastructural developments. On the other hand, the maximum annual temperature trend (Figure 9a) was more gradual with peaks in the years 2000, 2005, and 2009 just preceding the rainfall peak (years 2001, 2006, and 2010). This may be explained by the effect of reduced vegetation cover, especially the loss of forest cover, that has a cooling effect and instead the adoption of land uses that expose the land such as agriculture and overgrazing.

The minimum annual temperature trend (Figure 9b) had two patterns corresponding to the highland regions and the savanna and semi-arid areas. The highland regions had generally steady, less significant minimum temperature changes, compared to the savanna regions, which were characterised by more temperature peaks. In relation to the LULC changes, this implies that the changes in the LULC in the savanna and semi-arid regions were more drastic and had a significant effect in relation to the changes in minimum annual temperature. The minimum temperature remained more constant around the highland regions probably due to the non-complete loss of vegetation cover; instead it was mainly conversion from one form to another whose long-term effect was increased minimum temperature by the year 2010. Thus, although there were extreme weather events such as El Niño (1997–1998) and La Niña (1999–2000), the effects of temperature changes impacted the LULC more in the savanna and semi-arid regions compared to the highland regions. These findings support what Rarieya and Fortun (2009) reported. They also associated the changes in precipitation and temperature to environmental degradation and extreme weather events.

Cross-tabulation techniques were utilised for an in-depth analysis of the classes. This is presented in Tables 4 and 5, where the reference year is the column information and the classification year (whose change description was required) is the row information. The diagonal matrix represented the unchanged pixels for each class, while the column information tabulated the original classes that had changed by the target classification year. Thus, from Table 4, turbid water remained the most unchanged, muddy water was lost most to clear water and crop cover, dense forest was lost most to crops followed by exposed rocks, Light Dense Forest (LDF) was lost to crops followed by grass, grass was lost most to LDF, exposed rocks and bare lands were lost most to crop cover, while crop land was lost most to LDF and rocks. This emphasised the competing land uses between agricultural land use and the forest resources.

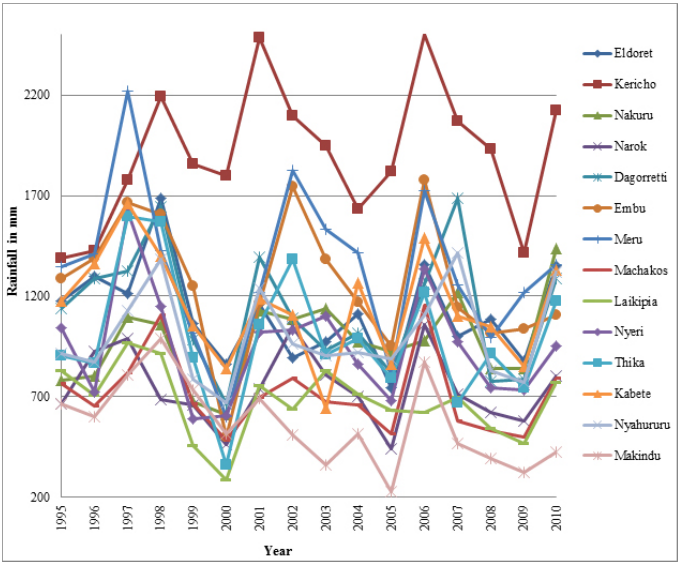

Figure 7: Total Annual Rainfall Trend (Years 1995 to 2010)

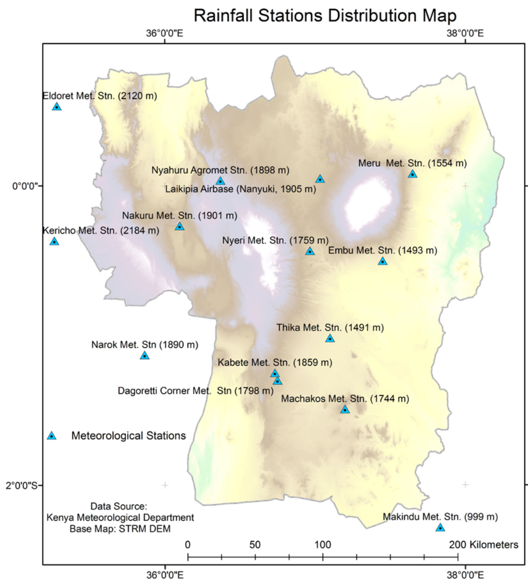

Figure 8: Distribution of the Meteorological Stations

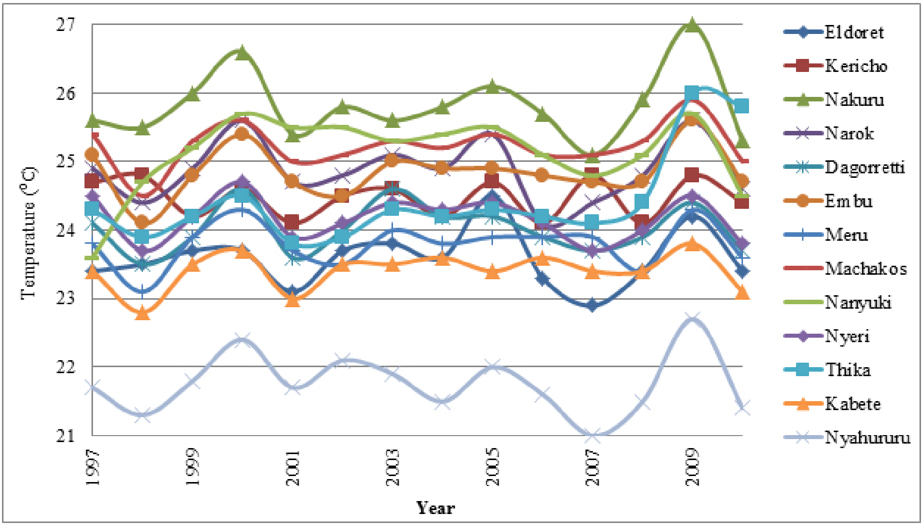

Figure 9 (a): Maximum Average Annual Temperature (Years 1997–2010) Reported By the Meteorological Stations Defined in Figure 8

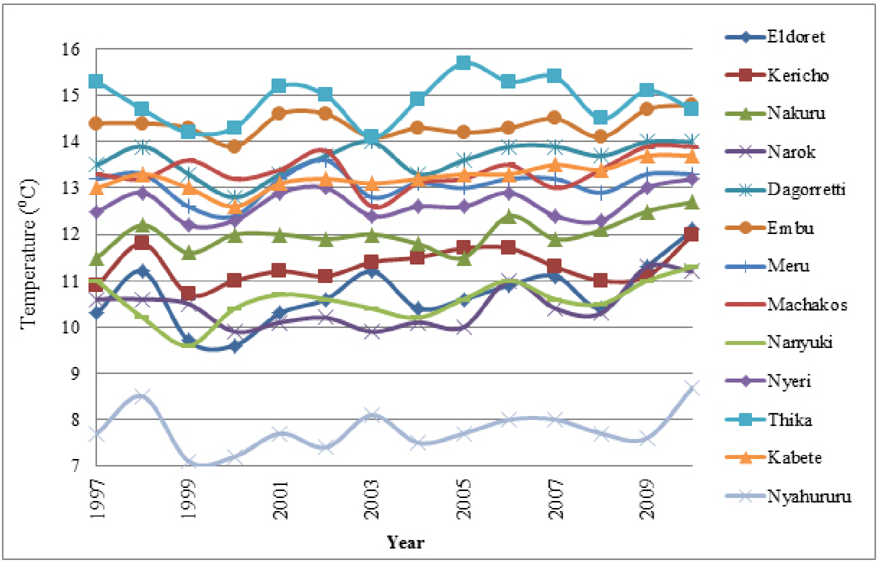

Figure 9 (b): Minimum Average Annual Temperature (Years 1997–2010) Reported By the Meteorological Stations Defined in Figure 8

Table 4: Cross-Tabulation of Classification 1995 (Columns) Against Classification 2002 (Rows)

		Reference Data (1995) *(no. of pixels)*										
	Classes	**Clear Water**	**Turbid Water**	**Muddy Water**	**Dense F.**	**LDF**	**Grass**	**Rocks**	**Bare**	**Silt**	**Crops**	**Row Total**
Classi-fication Data (2002) (no. of pixels)	Clear Water	580,652	7,340	387,246	27,920	25,186	7,850	13,004	4,234	6,480	34,370	1,094,282
	Turbid Water	165,286	446,640	43,948	139,999	860	8	109,638	66,640	58,770	123,318	1,155,107
	Muddy Water	220,938	69,840	209,064	247,766	36,742	828	68,673	23,571	13,468	288,519	1,179,409
	Dense Forest	163,876	81,752	273,612	15,507,149	193,136	230,330	4,567,929	380,990	153,527	4,129,242	25,681,543
	Light Dense Forest	120,406	22,724	53,703	2,615,851	17,165,258	3,197,127	1,915,453	659,189	108,334	17,074,114	42,932,159
	Grass	24,985	1,446	3,798	138,670	5,725,621	5,632,706	114,667	47,127	44,561	1,378,386	13,111,967
	Rocks	282,039	93,198	182,448	12,516,203	866,095	49,067	40,022,424	14,754,933	577,143	11,541,138	80,884,688
	Bare	136,291	61,644	66,778	1,049,616	133,206	28,707	9,468,064	17,662,305	1,791,142	2,273,305	32,671,058
	Silt	6,204	5,216	6,906	53,749	3,878	91	398,902	2,816,657	1,023,409	118,830	4,433,842
	Crops	431,362	96,752	401,574	21,662,701	6,610,308	668,950	27,833,629	9,282,025	566,921	52,593,972	120,148,194
	Column total	2,132,039	886,552	1,629,077	53,959,624	30,760,290	9,815,664	84,512,383	45,697,671	4,343,755	89,555,194	323,292,249

Table 5: Cross-Tabulation of Classification 2002 (Columns) Against Classification 2010 (Rows)

		Reference Data (2002) *(no. of pixels)*										
	Classes	**Clear Water**	**Turbid Water**	**Muddy Water**	**Dense Forest**	**L. Dense Forest**	**Grass**	**Rocks**	**Bare**	**Silt**	**Crops**	**Row**
	Total	580,652	7,340	387,246	27,920	25,186	7,850	13,004	4,234	6,480	34,370	1,094,282
	Clear Water	852,552	52,862	348,463	110,361	17,816	2,077	70,274	43,372	7,987	80,791	1,586,555
	Turbid Water	11,311	505,364	37,105	42,812	22,471	2,297	78,747	104,166	1,380	89,430	895,083
	Muddy Water	98,787	110,383	58,830	104,230	48,563	5,354	78,620	31,575	1,749	218,840	756,931
Classi-fication Data (2010) (no. of pixels)	Dense Forest	34,925	247,393	471,647	18,768,091	2,643,944	109,791	14,715,124	927,846	28,488	18,450,916	56,398,165
	Light Dense Forest	44,987	2,476	39,432	363,343	27,897,161	7,206,858	1,800,614	479,977	30,222	26,100,213	63,965,283
	Grass	13,800	115	6,420	240,558	3056735	5,062,341	41,023	40,798	1,958	888,408	9,352,156
	Rocks	8,055	129,363	76,049	3,573,582	827622	50,821	35,605,515	11,474,780	348,518	15,938,505	68,032,810
	Bare	987	60,492	23,463	281,496	371166	30,944	9,665,922	14,259,484	2,591,604	6,670,443	33,956,001
	Silt	1,839	36,205	6,746	135,491	64242	9,086	715,788	1,901,621	1,341,452	639,836	4,852,306
	Crops	27,036	10,446	111,243	2,061,499	7985691	632,382	18,112,868	3,407,332	81,320	51,074,885	8,350,4702
	Column Total	1,094,279	1,155,099	1,179,398	25,681,463	42935411	13,111,951	80,884,495	32,670,951	4,434,678	12,015,2267	323,299,992

6. CONCLUSION

The knowledge-based classification used in this research helped to determine the changes in LULC from 1995 to 2010 for a selected study area in Kenya. The changes in LULC revealed competing land uses, particularly involving forest, crop, and grassland, which led to increased changes in exposed bare and rock covers. Comparing the LULC changes to rainfall and temperature trends, the loss of green cover had a net effect of varying maximum temperatures and slightly increased minimum annual temperatures by the year 2010 around the semi-arid regions. The rainfall trend depicted extreme weather effects (El Niño and La Niña) which had a negative impact on crop cover and grasslands, leading to encroachment of forested areas around the highland regions.

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Ammonstrasse 74, 01067 Dresden, Germany
Tel.: + 49-351 8921 9377
Fax: + 49-351 8921 9389
e-mail: flores@unu.edu

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In line with the general mission of UNU to foster sustainable development, UNU-FLORES aims to contribute to the resolution of pressing challenges to the sustainable use and integrated management of environmental resources, such as water, soil, and waste. UNU-FLORES strives to advance the development of integrated management strategies that take into consideration the impact of global change on the sustainable use of the environmental resources. To this end, the Institute engages in research, teaching, advanced training, capacity development, and dissemination of knowledge.

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The organisation of UNU-FLORES into five academic units – three core scientific units (Water Resources Management (WRM), Waste Management (WM), and Soil and Land Use Management (SLM)), supported by two cross-cutting units (System Flux Analysis Considering Global Change Assessment (SFA) and Capacity Development and Governance (CDG)) – supports the think tank function of the Institute.

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As a hub for initiatives on the Nexus Approach, UNU-FLORES is not only committed to strengthening its own network but also to providing an international platform to foster cooperation and networking amongst all actors working on or with the Nexus Approach to managing environmental resources. That platform is the biennial Dresden Nexus Conference (DNC).

Every two years UNU-FLORES organises a DNC, welcoming scholars, politicians, and practitioners from all regions of the world to meet and discuss the most recent and innovative initiatives on a Nexus Approach to the management of environmental resources.

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Building on the outcomes of the 2013 "International Kick-Off Workshop on Advancing a Nexus Approach to the Sustainable Management of Water, Soil and Waste", UNU-FLORES organised the inaugural Dresden Nexus Conference (DNC). From 25 to 27 March 2015 representatives from academia, politics, and civil society assembled in Dresden under the theme "Global Change, Sustainable Development Goals and Nexus Approach". Working together with co-organisers, TU Dresden and IOER, in 2014 UNU-FLORES solicited applications from numerous renowned academic institutions from around the world. Categorised under three key themes – climate change, urbanisation, and population growth – 18 sessions were selected for the first DNC. Comprising of a comprehensive selection of the diverse initiatives on the Nexus Approach, sessions were convened by UN entities, international research organisations, universities, and non-governmental organisations.

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