Recent land-cover/use change associated with land degradation in the Lake Baringo catchment, Kenya, East Africa: evidence from Landsat TM and ETM+

L. M. Kiage a,b; K. -B. Liu b; N. D. Walker a,c; N. Lam d; O. K. Huh a,c

a Coastal Studies Institute Earth Scan Laboratory, Louisiana State University, Howe/Russell Geoscience Complex, Baton Rouge, LA 70803 b Department of Oceanography and Coastal Sciences, Louisiana State University, 1000Y Energy, Coast, and Environment Building, Baton Rouge, LA 70803 c Department of Oceanography and Coastal Sciences, Howe/Russell Geoscience Complex, Baton Rouge, LA 70803 d Department of Environment Studies, Louisiana State University, 1285 Energy, Coast, and Environment (ECE) Building, Baton Rouge, LA 70803

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Recent land-cover/use change associated with land degradation in the Lake Baringo catchment, Kenya, East Africa: evidence from Landsat TM and ETM+

L. M. KIAGE*†‡, K.-B. LIU‡, N. D. WALKER†§, N. LAM¶ and O. K. HUH‡§

†Coastal Studies Institute Earth Scan Laboratory, Louisiana State University, Howe/Russell Geoscience Complex, Baton Rouge, LA 70803, USA
‡Department of Oceanography and Coastal Sciences, Louisiana State University, 1000 Y Energy, Coast, and Environment Building, Baton Rouge, LA 70803, USA
§Department of Oceanography and Coastal Sciences, Howe/Russell Geoscience Complex, Baton Rouge, LA 70803, USA
¶Department of Environment Studies, Louisiana State University, 1285 Energy, Coast, and Environment (ECE) Building, Baton Rouge, LA 70803, USA

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Many parts of East Africa are experiencing dramatic changes in land-cover/use at a variety of spatial and temporal scales, due to both climatic variability and human activities. Information about such changes is often required for planning, management, and conservation of natural resources. Several methods for land cover/change detection using Landsat TM/ETM+ imagery were employed for Lake Baringo catchment in Kenya, East Africa. The Lake Baringo catchment presents a good example of environments experiencing remarkable land cover change due to multiple causes. Both the NDVI differencing and post-classification comparison effectively depicted the hotspots of land degradation and land cover/use change in the Lake Baringo catchment. Change-detection analysis showed that the forest cover was the most affected, in some sections recording reductions of over 40% in a 14-year period. Deforestation and subsequent land degradation have increased the sediment yield in the lake resulting in reduction in lake surface area by over 10% and increased turbidity confirmed by the statistically significant increase ($t=−84.699$, $p<0.001$) in the albedo between 1986 and 2000. Although climatic variations may account for some of the changes in the lake catchment, most of the changes in land cover are inherently linked to mounting human and livestock population in the Lake Baringo catchment.

1. Introduction

Most of East Africa’s land-cover is in a state of permanent flux at a variety of spatial and temporal scales, due to both climatic variability and human activities. The fluxes are most pronounced in the transitional zone between forest and savannah particularly in the semi-arid environments. The Lake Baringo ecosystem in East Africa (figure 1) presents a good example of environments experiencing remarkable land cover change due to multiple causes. Changes that are of great interest to

*Corresponding author. Email: lkiage1@lsu.edu
ecologists and resource managers are those that are ultimately linked to human activities such as deforestation, and land clearing for agriculture or pastoralism. Satellite remote sensing can play a crucial role in providing information on land-cover/use modifications on local, regional, and even global scales, especially where aerial photographs are missing or outdated. The ability of any remote sensing system to detect and monitor such fluxes in land-cover depends on its capability to adequately deal with the reference database while simultaneously accounting for both short-term variability (e.g. seasonal) and longer-term secular change.

Figure 1. Map of East Africa showing the approximate location of the Lake Baringo catchment.

Satellite remote-sensing techniques have been applied extensively for monitoring change in a variety of natural environments (e.g. Skole and Tucker 1993, Boyd et al. 1996, Collins and Woodcock 1999, Gemmell et al. 2001, Townsend 2002, Wilson and Sader 2002, Cohen et al. 2003, Dowson et al. 2003, Jin and Sader 2005, Wulder et al. 2006). These techniques have proven useful for monitoring and assessing such

This article examines the land-use/cover change in the Lake Baringo catchment over a 14-year period using Landsat Thematic Mapper/Enhanced Thematic Mapper Plus (TM/ETM+) imagery. Our focus was largely on the changes in the forest and bare ground cover, which are linked to different forms of soil erosion, a proxy for land degradation. Change-related images are generated from change-detection techniques including post-classification image differencing, Kauth–Thomas tasselled cap transforms, and the Normalized Difference Vegetation Index (NDVI) differencing. Although land use and land cover are often used interchangeably, the two concepts are not identical. The latter measures the physical attributes or characteristics of the Earth surface, while the former describes how land cover is utilized (cf. Seto et al. 2002). Without additional information, remote sensing detects land cover, not land use, though in most cases one can derive land use from land cover. However, most remote-sensing change-detection studies use the two concepts interchangeably (e.g. Dimyati et al. 1996, Heikkonen and Varfis 1998, Muttitanon and Tripathi 2005) because land use often corresponds to land cover. For instance, in pastoral environments, pasture could describe land use type, while at the same time it is a form of land cover. In such scenarios, the two concepts could be considered synonymous. In this article, the two terms are used interchangeably unless otherwise specified.

One of the principal goals of this study was to use satellite measurements to study vegetational change associated with land degradation in the Lake Baringo ecosystem, Kenya, and link these changes to sedimentation rates in the lake. The Lake Baringo ecosystem, a critical habitat for more than 500 avifaunal species and a source of livelihood for humans, is threatened by land degradation as a result of mounting population pressure. A combination of natural and anthropogenic factors, including deforestation in the lake catchment, increased sediment yield from soil erosion, evaporation, damming, and diversion of inflowing rivers, has reduced the depth of the lake from a maximum of 9 m and a mean of 5.6 m in 1972 to the current maximum of 4 m and a mean of 2.5 m (Alloo 2002, Johansson and Svensson 2002, Hickley et al. 2004). Reports have recently appeared in the media in East Africa quoting the United Nations Development Programme (UNDP) authorities that project the lake to fill up with sediments in the next 15 years (Kurgat 2003). These environmental problems are ultimately linked to land-cover/use changes. It is therefore important to investigate land-cover/use changes in order to monitor environmental change and develop sustainable resource management plans for fragile ecosystems such as Lake Baringo.

2. Study site

The focus of this study is the main catchment for Lake Baringo estimated to be 8655 km² (Hickley et al. 2004), and the immediate vicinity of the lake (figures 1 and 2). The entire catchment lies within the eastern fork of the Gregorian Rift Valley in East
Africa. It extends from approximately 0° 43' N to 0° 40' S, and 35° 18' E to 36° 20' E. A variety of environmental gradients are represented in the catchment ranging from semi-arid areas with bare or sparsely vegetated ground on the lowlands to evergreen forests on the highlands and upper reaches of the catchment. These variations are mainly related to altitude, which ranges from <900 m in the central and northern parts of the catchment around Lake Baringo to well above 2200 m at the Tugen Hills and the highlands on the western and southern regions (figure 2).

The inhabitants of the savannah and semi-arid lower reaches of the catchment are nomadic pastoralists with livestock under communal grazing arrangements. Both large- and small-scale agriculture are practised in the lush environments that characterize the upper reaches of the catchment. The spatial distribution of rainfall in the catchment correlates well with the topography: less than 600 mm yr⁻¹ in the lowlands and over 1200 mm yr⁻¹ in the highlands. The major land covers in the catchment are forest (deciduous and evergreen), water (mainly the lake), bushland/woodland/scrub (dominated by different Acacia species), wetland, bare ground (little or no vegetation), and pasture/farmland.
3. Data

A crucial requirement for change detection is availability of relatively cloud-free satellite image at each date. However, obtaining anniversary cloud-free images from the tropics is a daunting task because the region tends to be cloudy throughout the year. One has to take advantage of cloud-free windows such as the dry season. Two anniversary (27 January 1986 and 28 January 2000) satellite images were acquired using the Landsat 5 TM and Landsat 7 ETM+ sensors, thereby limiting exogenous effects. The effects of acquiring both images during the dry season are that phonomological differences are minimized, and the wetland system around the Lake Baringo stood out because it had dense green vegetation. These may have promoted classification accuracy (cf. Munyati 2000). However, the deciduous woodland/bushland vegetation was largely senescent during the dry season, making differentiation from pasture and farmland categories difficult, especially in the savannah landscapes of the Lake Baringo catchment. Obtaining many GPS points in the field and familiarity with the area helped minimize potential classification error. The steps involved in the methodology for this study are summarized in figure 3.

Table 1 provides the characteristics of the images used. Although slight differences in spectral band width, position, and calibration exist between TM and ETM+

![Figure 3. Summary of the change-detection procedure.](image-url)
sensors (Teillet et al. 2001, Vogelmann et al. 2001), they are not significant enough to affect the outcome of the analyses used in this study (cf. Cohen et al. 2003). The scene location was based on the Landsat worldwide reference system Path 169 and Row 60, covering the entire Lake Baringo catchment.

Rainfall data from two representative weather stations within the Lake Baringo catchment were obtained from the Kenya Meteorological Department in Nairobi to assist in the interpretation of the results. The two weather stations, i.e. Marigat (970 m above sea level) and Nakuru (1915 m above sea level), are situated less than 5 km and 120 km south of Lake Baringo, respectively. We also acquired seven 1:50 000 Universal Transverse Mercator (UTM) topographic maps (Clarke 1880 spheroid, UTM 37) prepared by the Kenya Ministry of Lands, Department of Survey. These maps were used mainly in the georeferencing the images and accuracy assessment. In addition, a series of global positioning system (GPS) points and photographs were acquired during fieldwork for use in accuracy assessment and discussion of our results.

4. Methods

4.1 Change-detection techniques

In almost all studies involving the use of satellite imagery for monitoring environmental change, imagery from one date is compared with another image from a different date. Within this paradigm of analysing images as end-points, numerous methods have been developed (Hobbs 1990, Coppin and Bauer 1994, Kasischke et al. 2004, Yang and Liu 2005). Some methods are suited for measuring specific kinds of change while others are more general in their applicability. Kasischke et al. (2004) identified three broad steps involved in change detection: (1) radiometric preprocessing, (2) data transformation, and (3) mapping change. However, not all the steps are necessary for change detection studies, and generally the relative importance of the first two steps is dependent on the method recruited.

4.1.1 Image preprocessing. The ETM+ image was georeferenced to the 1:50 000 Universal Transverse Mercator (UTM) topographic maps that were obtained from the Kenya Ministry of Lands, Department of Survey. Polynomial transformation model in ERDAS-Imagine 9.0 (ERDAS 2005) was then used in the image-to-image registration with the already georectified ETM+ image as the reference. Radiometric calibration (discussed later in this section) was performed before the images were subset using the Lake Baringo catchment (drainage basin) as the area of interest (figure 2).
The quality of information derived from Landsat imagery depends on such factors as image quality, analysis techniques, and an array of temporal/phenological considerations. Even cloud-free Landsat TM/ETM+ data often contain noise from atmospheric interference with propagation of electromagnetic energy, changes in illumination geometry, and some noise from the instrument. It is often helpful to remove exogenous effects from multiday imagery to eliminate error and facilitate effective mapping of vegetational or environmental change (Kasischke et al. 2004, Muttitanon and Tripathi 2005, Varjo 1996). Radiometric preprocessing of TM/ETM+ data is one of the most effective ways of doing so. Teillet et al. (2001) and Vogelmann et al. (2001) provide a good summary of the significance and issues involved in the calibration of TM and ETM+ data.

Kasischke et al. (2004) and Olsson (1995) group radiometric preprocessing techniques for change detection into two broad categories; relative and absolute correction. The former involves an attempt to match the dates of image acquisition so that such factors as sun angle and the atmosphere are constant between the dates. Usually, one date (the subject image) is calibrated against the other date (the master image) using unchanging features within the image. The effect of this calibration is that the two dates appear as if they were acquired under the same illumination and atmospheric conditions. These corrections are relative because the effects are not actually removed from the imagery. The effects of relative corrections are very similar to choosing ‘anniversary’ images. In absolute radiometric calibration, the original brightness values in the images are converted into surface reflectance using a number of atmospheric correction and calibration equations (Vermote et al. 1997, Lillisand and Kiefer 2004). Reliable and accurate conversion factors have been developed for a number of satellite sensors including TM and ETM+ (Huang et al. 2001, Masek et al. 2001). Commonly used radiative transfer codes for atmospheric corrections include MODTRAN and 6S (Vermote et al. 1997).

The anniversary images used in this study enabled us to largely sidestep the effects of sun angle and phenology. However, to further minimize errors, we also performed radiometric calibrations, by converting the original brightness values into surface reflectance, thereby enabling us to compare the TM and ETM+ images.

4.1.2 Data-transformation methods. Transformation techniques provide an intermediate step in the change detection processes; the results from this step were used for mapping change. The primary goal of data transformation is to help reveal changes in surface reflectance. A number of different techniques were used in this study, including post-classification image differencing, Tasseled Cap transformation, and NDVI differencing.

Image differencing is where one image (usually from an earlier date) is simply subtracted from the other (usually the most recent date) to produce a difference image. The net effect of differencing is a product where the no-change pixels are centred on the value of zero. Thus, when the change image is displayed in greyscale, areas that exhibit the brightest tones are associated with greater change. In its rudimentary form, this technique may not require atmospheric correction, since while atmospheric and other exogenous effects shift the mean away from zero, they do not affect the image content (Kasischke et al. 2004). However, Nielsen et al. (1998) note that differencing non-transformed Landsat data may provide spurious results due to data noise and variable sensitivity of individual sensors.

Simple differencing of NDVI images was incorporated in this study to circumvent the errors that may accrue from differencing of individual standardized spectral
bands. The NDVI is a technique that separates green vegetation from other surfaces, since the chlorophyll of healthy green vegetation absorbs red light for photosynthesis and reflects in the near-infrared (NIR) wavelengths due to scattering caused by internal leaf structure (Wilson and Sader 2002). Dense vegetation shows up very strongly in the imagery, and areas with little or no vegetation are also clearly identified. Thus, NDVI is an excellent tool for change-detection studies. The index is calculated using equation (1):

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}},
\]

where NIR is the reflectance radiated in the near-infrared waveband (760–900 nm), and RED is the reflectance radiated in the visible red waveband (630–690 nm) of the satellite radiometer. NDVI values range between −1 and 1, with values above 0.6 indicating dense vegetation and values below 0 indicating no vegetation. Bare grounds have values of 0–0.1, grasslands have values of 0.2–0.3, while negative values correspond with water and ice surfaces. The simplicity of utilizing NDVI in detecting vegetation or the lack of it, plus the ease in calculation from various satellite data and in interpretation, makes it the most widely used vegetation index (Wilson and Sader 2002, Kasischke et al. 2004, Muttitanon and Tripathi 2005).

Tasselled Cap Transformation (TCT), also known as Kauth–Thomas tasselled cap (TC), was initially developed for crop-development surveys (Kauth and Thomas 1976). It is basically a guided and scaled principal-components analysis (PCA) that transforms the six Landsat ETM/TM bands into three orthogonal planes or components of known characteristics (Fung 1990, Collins and Woodcock 1994, Huang et al. 2002). TC-component one (BI) is a measure of brightness or albedo derived from the responses of all Landsat bands except the thermal band (Armenakis et al. 2003). TC-component two (GI) is a measure of greenness obtained by comparing the NIR with the visible bands. TC-component three (WI) contrasts the sum of the visible and NIR bands with the longer infrared bands to determine the amount of moisture being held by the vegetation or soil (Crist and Cicone 1984, Cohen et al. 1998). It is referred to as the wetness index because it is sensitive to soil and plant moisture (Crist and Cicone 1984, Wilson and Sader 2002). The different components of TC for this study were calculated by using the following formula adopted from Price et al. (2002) (cf. Crist and Kauth 1986, Jensen 1996):

\[
\text{BI} = 0.2909 (\text{TM1}) + 0.2493 (\text{TM2}) + 0.4806 (\text{TM3}) + 0.5568 (\text{TM4}) + 0.4438 (\text{TM5}) + 0.1706 (\text{TM7})
\]

\[
\text{GI} = -0.2728 (\text{TM1}) - 0.2174 (\text{TM2}) - 0.5508 (\text{TM3}) + 0.7221 (\text{TM4}) + 0.0733 (\text{TM5}) - 0.1648 (\text{TM7})
\]

\[
\text{WI} = 0.1446 (\text{TM1}) + 0.1761 (\text{TM2}) + 0.3322 (\text{TM3}) + 0.3396 (\text{TM4}) - 0.6210 (\text{TM5}) - 0.4186 (\text{TM7}).
\]

The TC components were used in this study because a number of studies (e.g. Collins and Woodcock 1994, Huang et al. 2002, Parmenter et al. 2003) have shown that they can account for over 97% of spectral variability present in any given scene.
We specifically used the TC-BI (Brightness Index) components to calculate albedo change in the Lake Baringo waters as a proxy for increased sediment yield and turbidity. Clear waters appear dark in satellite imagery and have low reflectance values, while turbid waters are characterized by strong reflectance signals. The strength of the reflectance signal is dependent on sediment concentration with stronger signals corresponding to higher sediment concentrations (cf., Walker and Hammack 2000, Doxaran et al. 2003). The low reflectance of clear waters results in low TC-BI values, and the opposite is true for turbid water and/or high sediment concentrations. Thus, high TC-brightness values in lakes and coastal waters are consistent with high levels of turbidity and sediment concentrations. This makes the TC-brightness index a useful proxy for assessing turbidity and/or sediment concentrations in coastal and inland water bodies.

The different techniques of data transformation, i.e. post-classification image differencing, TC transformation, and NDVI differencing, were applied in this study because each uniquely contributed to identifying the hotspots of change in the Lake Baringo ecosystem. Both post-classification image differencing and NDVI image differencing have proven useful for highlighting vegetational changes, while the TC-brightness index is excellent for illuminating changes in albedo (cf., Huang et al. 2002, Parmenter et al. 2003, Kasischke et al. 2004, Muttitanon and Tripathi 2005).

4.1.3 Classification. Image classification has been used in many ways and for a variety of purposes in monitoring landscape changes (e.g. Asner and Lobell 2000, Seto et al. 2002, Muttitanon and Tripathi 2005, Yang and Liu 2005). We displayed the images using false-colour composites by assigning the red, blue, and green colour guns to bands 5, 4, and 3, respectively. Supervised classification was found to be inadequate in this study because of the complexity of vegetation and topography in the study area. We used the unsupervised classification by applying the Interactive Self-Organizing Data Analysis (ISODATA) algorithm in ERDAS-imagine 9.0 (ERDAS 2005) to identify and classify land-cover/use classes in the satellite images. The ISODATA algorithm was implemented without assigning predefined signature sets as starting clusters, which enabled us to avoid the impacts of sampling characteristics. Each image was grouped into 70 spectral clusters when the convergence reached 0.99.

The output of the ISODATA clustering was disintegrated into five broad land-cover classes in order to simplify the interpretation of change in the landscape. Each spectral cluster was assigned to one of the six land-cover/use classes using visual inspection of original images, reference data, and familiarity of the study area. These six classes were forest, water, bushland/woodland/scrub, wetland, bare ground, and pasture/farmland. Table 2 provides a descriptive summary of the land-cover/use classes. The classification and determination of the land-cover classes were done independently for each image (figure 4). The reference data included seven 1:50 000 topographic maps covering the catchment, and groundtruthing in the Lake Baringo catchment, involving the collection of global positioning system (GPS) points and description of the associated land-cover/use types. Fieldwork was conducted during the months of December 2003/2004 and, again in January 2004/2005, coinciding seasonally with the acquired images. A total of 150 GPS points covering the catchment were collected.

To label the spectral clusters and assign classes, we made the ISODATA output largely transparent and overlaid it on the original image in false-colour composite. This was done by assigning the targeted spectral cluster an opacity value of 1 and a
bright colour (yellow), while the rest of the clusters were assigned a zero value, thereby making the overlaid ISODATA output transparent except for the cluster being examined. Although individual image colour was used in determining class assignment, in some cases image elements such as association and site were used to eliminate possible classification error. Before the final land-cover/use products were assessed, they were subjected to $8 \times 8$ ha clump and $2 \times 2$ ha eliminate filters to reduce noise in the classification.

Table 2. Land-cover types used in the classification of satellite-derived land cover.

<table>
<thead>
<tr>
<th>Land cover</th>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>1</td>
<td>High density of trees with little or no undergrowth. Dominated by such tropical trees as Celtis spp., Urticaceae, Myrtaceae, Croton, Holoptelea, Prunus, Podocarpus, and Olea among others. Restricted mainly to the upper reaches (highlands) of the catchment.</td>
</tr>
<tr>
<td>Bushland/woodland/scrub</td>
<td>2</td>
<td>Common in the escarpments and lowland plains especially near the lake. Typically dominated by several Acacia and Commiphora species with little or no undergrowth.</td>
</tr>
<tr>
<td>Pasture/farmland</td>
<td>3</td>
<td>Environments dominated mostly by grasses and herbaceous plants. Some sections (i.e. farms) are characterized and distinguished by regular, linear and rectangular shaped features.</td>
</tr>
<tr>
<td>Water</td>
<td>4</td>
<td>Mainly the lake waters, dams, and rivers.</td>
</tr>
<tr>
<td>Bare ground</td>
<td>5</td>
<td>Exposed soil surfaces, cultivated areas, and in some instances very scantly vegetated areas.</td>
</tr>
<tr>
<td>Wetland</td>
<td>6</td>
<td>Dominated by swamps vegetation mainly papyrus (Cyperus papyrus) and Typha.</td>
</tr>
</tbody>
</table>

Figure 4. Land-cover maps generated from unsupervised classification of the 1986 TM and 2000 ETM+ images. Available in colour online.
4.2 Accuracy assessment

The method described by Congalton and Green (1999) was used in performing accuracy assessment once the final land cover/use classes were obtained. Classification accuracy assessment was performed on land-cover/use maps from both the 1986 and 2000 images. We used seven 1:50 000 topographic maps from the Kenya Department of Survey, as well as data and GPS points collected during fieldwork in Lake Baringo as the reference information for accuracy assessment. Ideally, ground reference materials should be collected at the time of image acquisition. However, that is not possible for most remote-sensing studies that involve the use of historical images (cf., Jensen 1996). Since it is impossible to go back in time to collect historical ground reference, we relied on information that was closest to the historical date. In the absence of aerial photographs, familiarity with the study area and topographic maps proved very helpful for assessing the accuracy of the classification of the 1986 image. The topographic maps that we used in this study were produced in 1984, and most of the land cover/use in the maps are comparable to those in 1986 image albeit with subtle differences. The topographic maps were also used to confirm the land-cover features described in association with the 150 GPS points for performing the accuracy assessment of the classification of the 2000 image.

The result of the accuracy assessment was a confusion matrix showing errors of omission (producer’s accuracy) and commission (user’s accuracy) and a Kappa coefficient (tables 3 and 4). The overall classification accuracy for each map was computed by dividing the sum of all the correctly classified pixels (diagonal of the confusion matrix) by the total number of pixels in the confusion matrix.

The user’s accuracy or reliability corresponds to a commission error, representing the probability that a pixel classified on the map actually represents that land cover type on the ground (Story and Congalton 1986). The producer’s accuracy corresponds to the omission error; the probability of a reference pixel being correctly classified. Overall classification accuracy makes use of the diagonal elements of the confusion matrix to measure agreement. Though simple to compute, it tends to overestimate classification accuracy, since it overlooks the proportion of random agreement between datasets (Congalton and Green 1999). That limitation is taken care of by the Kappa coefficient which attempts to control for chance agreement by incorporating the off-diagonal elements of the confusion matrix (cf. Verbyla 1995). The calculation of the Kappa coefficient is similar to the Chi-square

Table 3. Confusion matrix of the land-cover classification map derived from the 2000 Landsat-7 ETM+ image.

<table>
<thead>
<tr>
<th>Classified data (land-cover type)</th>
<th>Reference data</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Classified total</th>
<th>Producer’s accuracy</th>
<th>User’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Forest</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>35</td>
<td>93.9</td>
</tr>
<tr>
<td>2. Bushland/scrub</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>35</td>
<td>78.6</td>
</tr>
<tr>
<td>3. Pasture/Farmland</td>
<td>0</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td>3</td>
<td>35</td>
<td>87.9</td>
</tr>
<tr>
<td>4. Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>15</td>
<td>100</td>
</tr>
<tr>
<td>5. Bare Ground</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>0</td>
<td>15</td>
<td>100</td>
</tr>
<tr>
<td>6. Wetland</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>12</td>
<td>15</td>
<td>80</td>
</tr>
<tr>
<td>Reference total</td>
<td>33</td>
<td>42</td>
<td>33</td>
<td>15</td>
<td>12</td>
<td>15</td>
<td>150</td>
<td></td>
</tr>
</tbody>
</table>

Overall classification accuracy=88%
Overall Kappa statistics=0.85
and is computed using the following formula:

$$K = \frac{(\text{overall classification accuracy} - \text{expected classification accuracy})}{(1 - \text{expected classification accuracy})}. \quad (5)$$

The Kappa coefficient is basically the proportion of agreements after chance agreement has been excluded. Its upper limit is 1.00 (total agreement). Complete agreement at a chance level has a coefficient of zero.

5. Results and discussion

Table 3 presents the results of the confusion matrix for the 1986 land-cover/use classification accuracy assessment. The overall classification accuracy was 87.3%, with an overall Kappa statistic of 0.842. These results generally suggest that a good agreement exists between the classification and the actual land-cover categories with few misclassifications occurring across nearly all categories. For instance, although the producer’s accuracy for farmland and/or pasture class was 85.3%, the user’s accuracy is slightly lower (82.9%). However, the bare ground category had a perfect producer’s accuracy (100%) but a very low user’s accuracy (60%). This means that although 100% of the bare ground class was correctly identified, only 60% of the areas labelled bare were actually bare, implying a significant misclassification of pixels in that category.

The confusion matrix for the 2000 land-cover/use classification map (table 4) was a slight improvement on the 1986 classification. It had an overall classification accuracy of 88% and a Kappa coefficient of 0.85. In this classification, the reference data and the classified groups were largely in agreement probably because of the use of improved spatial accuracy due to improved methodology, i.e. the use of GPS (2000) vs. topographic maps (1986).

The major output of this study is the compilation of change-detection maps for the Lake Baringo catchment. Comparison of land-cover/use classification maps (figure 4) for 1986 and 2000 was the basis for the change-detection output (figure 5) obtained through simple image differencing. There were significant changes in land cover/use involving the bush/woodland and pasture/farmland classes, with the former showing a marked increase at the expense of the latter (figure 4). However, differentiating between the two classes was not straightforward in the field because bush/woodland areas were also used as pasture. The nomadic pastoralists that reside
within the lowland plains of the Lake Baringo catchment utilize the grazing and browsing resources equally between the two classes. Differentiation between the two land-cover/use classes is compounded by the fact that some areas that are used for farming are often left fallow for prolonged periods, thereby drifting into bush/woodland class and vice versa. Although the two land-cover types could be grouped together under one land cover class, there are some important differences between them that justify their separation. The bush/woodland class is dominated by *Acacia* and *Commiphora* species with little undergrowth, while the pasture class is dominated by grasses with scattered woody vegetation (table 2). Overall, the two classes complement one another, and change among them may not have direct

Figure 5. Change-detection map obtained by comparing the 1986 and the 2000 land covers. The sites labelled A–F represent areas that underwent significant change in land cover. More details are provided in table 5. Available in colour online.
implications on land degradation unless the change promotes the expansion bare land cover class or sheet erosion.

Table 5 is a summary of the change in land cover in the areas that could be described as hotspots of change in land cover within the catchment (labelled A, B, C, D, E, and F in figure 5). The change detection map (figure 5) shows that many areas in the catchment underwent change in land cover/use over the 14-year period. However, the bulk of the changes are confined to a few hotspots, the most important being the highlands that define the upper reaches of the catchment, the lake surface, and the central plains south of the lake.

There was a significant reduction in the total surface area of Lake Baringo between 1986 and 2000. The land-cover change-detection analysis revealed that approximately 1518 ha (~10.8%) of the lake surface was lost or converted to wetland over the 14-year period. Much of the change (represented in red) occurred in the shallower parts of the lake (southern and eastern shores) (figure 6). The reduction in the surface area of the lake may be attributed to one or a combination of three possible factors: (1) infilling by sediments brought in by rivers that feed the lake; (2) reduction in the volume of water in the lake as a result of a decrease in precipitation; and (3) an increase in evapotranspiration. The rainfall receipt in Baringo is consistent with the general East Africa rainfall pattern characterized by variations on annual and interannual timescales correlated to the phase of El Niño/South Oscillation (Ogallo 1988, Mutai and Ward 2000, McHugh 2006). Rainfall variability is most pronounced in the semi-arid environments such as those that define the Baringo lowlands where the long-term average shows a slight downward trend since the 1960s (cf. Johansson and Svensson 2002) in keeping with the downward trend of precipitation since the 1960s as recognized throughout East Africa (Nicholson 1996).

Despite heightened rainfall variability, records from two weather stations within the Lake Baringo catchment (figure 7) show no evidence of a dramatic reduction in precipitation for the period of interest, making it unlikely that the decrease in the lake surface area is an outcome of reduced precipitation. A more probable cause of the reduction in the surface area of Lake Baringo is infilling by sediments brought in by the rivers that feed the lake. Indeed, one of the lake’s most noticeable features is

<table>
<thead>
<tr>
<th>Site</th>
<th>Land-cover type</th>
<th>1986 (ha)</th>
<th>2000 (ha)</th>
<th>Change (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Lake</td>
<td>Water surface</td>
<td>14100</td>
<td>12582</td>
<td>-1518</td>
</tr>
<tr>
<td></td>
<td>Wetlands</td>
<td>1951</td>
<td>1230</td>
<td>-721</td>
</tr>
<tr>
<td>B. Njemps flats</td>
<td>Forest</td>
<td>751</td>
<td>453</td>
<td>-298</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>633</td>
<td>5492</td>
<td>4859</td>
</tr>
<tr>
<td>C. Tugen hills</td>
<td>Forest</td>
<td>30753</td>
<td>17835</td>
<td>-12918</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>3</td>
<td>79</td>
<td>76</td>
</tr>
<tr>
<td>D. Lembus and Londiani Forest</td>
<td>Forest</td>
<td>84529</td>
<td>72703</td>
<td>-11826</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>17</td>
<td>511</td>
<td>494</td>
</tr>
<tr>
<td>E. Mau forest complex Forest</td>
<td>Forest</td>
<td>86503</td>
<td>62789</td>
<td>-23714</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>39</td>
<td>1696</td>
<td>1657</td>
</tr>
<tr>
<td>F. Marmanet Forest</td>
<td>Forest</td>
<td>25386</td>
<td>17214</td>
<td>-8172</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>66</td>
<td>168</td>
<td>102</td>
</tr>
<tr>
<td>Entire catchment</td>
<td>Forest</td>
<td>227892</td>
<td>170994</td>
<td>-56898</td>
</tr>
<tr>
<td></td>
<td>Bare grounds</td>
<td>758</td>
<td>7946</td>
<td>7188</td>
</tr>
</tbody>
</table>
its extreme turbidity (figure 2). The brightness output from the Kauth–Thomas Tasseled Cap transformation revealed that the albedo of the lake increased significantly between 1986 and 2000 (figure 8), with the average brightness index values increasing from 0.248 and 0.316 for 1986 and 2000, respectively (figure 9). To test the significance of change in brightness values for 1986 and 2000, we used SPSS software to perform a $t$ test on readings from 100 randomly selected points throughout the lake. The results of the $t$ test revealed that the brightness values were significantly different ($t = -84.699, p < 0.001$) at the 0.05 significance level, indicating that the change in the TC-brightness index cannot be explained by chance.
High turbidity is further confirmed by Secchi disk readings from the lake that were approximately 3 cm in August 2003 (Hickley et al. 2004). The increased turbidity of the lake can probably be best explained by an increase in wind driven resuspension resulting from the decreasing depth of the lake (cf. Aloo 2002). Similar observations about sediment resuspension and turbidity have been made in the

Figure 7. Rainfall data from two weather stations in the Lake Baringo catchment, i.e. Marigat station (970 m above sea level) situated less than 5 km south of the lake and Nakuru (1915 m above sea level) approximately 120 km south of Lake Baringo. The annual rainfall amount in the two stations between 1986 and 2000 does not deviate from the earlier period beginning 1960.

High turbidity is further confirmed by Secchi disk readings from the lake that were approximately 3 cm in August 2003 (Hickley et al. 2004). The increased turbidity of the lake can probably be best explained by an increase in wind driven resuspension resulting from the decreasing depth of the lake (cf. Aloo 2002). Similar observations about sediment resuspension and turbidity have been made in the

Figure 8. Tasselled cap brightness transform (proxy for albedo) images for Lake Baringo surface for 1986 (on the left) and 2000 (on the right) displayed in greyscale. The lake surface in the 1986 image is darker when compared with the 2000 image, which is consistent with the increased albedo of more turbid water in the latter.
Atchafalaya-Vermilion Bay region in Louisiana (Walker and Hammack 2000). Sediment cores collected from different parts of Lake Baringo under different depths show average sedimentation rates of up to 1 cm yr\(^{-1}\). A recent study by Onyando et al. (2005) on Perkerra River, which flows into Lake Baringo, confirms the presence of exceptionally high rates of soil erosion within the catchment. It was estimated that the catchment of River Perkerra alone generates a sediment yield of 1.47 million t yr\(^{-1}\). These phenomenal sedimentation rates suggest that land degradation, especially soil erosion in the catchment area, is responsible for the high turbidity in the lake.

The results of the change-detection procedure, NDVI analysis (figures 10 and 11), and BI provide evidence for land-cover change that may well indicate increased deforestation and land degradation in the Lake Baringo catchment (table 5). Figure 11 maps the changes in NDVI between 1986 and 2000 that had values greater than 0.3. The major changes in NDVI corresponded to areas that had lost forest cover and those that had recruited wetland vegetation at the expense of the lake surface. Considering that the primary objective of this study was to investigate changes related to land degradation, we focused on changes linked to forest loss or gain as well as increases in bare ground cover. Overall, there was an increase in the size of the land-cover class classified as bare. The bare ground class encompassed areas that were either entirely or nearly devoid of vegetation, as characterized by NDVI values below 0.1 (figure 10). The change-detection map (figure 5) revealed that the Njemps area (figure 6) in the plains immediately south of the lake was the most affected in terms of land degradation, as large areas that were classified as pasture/grassland or bushland in the 1986 image had been converted to the bare ground class in the 2000 image. These changes resulted in the bare ground class increasing from 633 ha to 5492 ha from 1986 to 2000.

Field surveys in the Njemps flats in December 2003 and January 2005 confirmed that most of the areas depicted as bare were indeed heavily degraded. Much of the area was not only bare or scantily vegetated but scarred by different forms of soil erosion, especially gully erosion (figure 12). Increasing human and livestock populations in the area subject the vegetation cover to intense pressure. For

Figure 9. Tasselled cap brightness values along a north–south transect in Lake Baringo. The TC brightness values obtained from the 1986 TM image were significantly different from those obtained from the 2000 ETM+ image ($t = -84.699$, $p < 0.001$).
instance, the population of Baringo District was 203,762 in 1979 and 220,922 in 1989. By 2004, the population was estimated at 302,245 and was growing at a rate of 2.65% per annum. The corresponding livestock numbers have been consistently large; approximately 900,000 goats, 200,000 sheep, and 300,000 cattle (Hickley et al. 2004, Kenya Ministry of Planning and National Development 2004). The inevitable outcome of such mounting human and livestock population is pressure on the limited vegetation resources in the catchment. Immense pressure on vegetation in the form of overgrazing, and deforestation coupled with the soil properties of the clay loams and silt (cf. Vrieling 2006) that characterize the area, steep slopes, and the high intensity and sporadic rainfall in the fragile semi-arid environment is a perfect recipe for soil erosion and land degradation.

However, not all areas classified as bare ground (figure 6) depicted in low NDVI values are necessarily degraded. For instance, the Perkerra irrigation scheme near Marigat in the Njemps plains was classified as bare grounds because the land had been ploughed for irrigation farming. This was also true for most of the bare ground in the Tugen Hills, and the southern plains near Nakuru where rain-fed agriculture is practised. However, these misclassifications are of minor importance as the cultivated farms represent only a small proportion of the bare ground class and can easily be identified by their rectangular and linear shapes in the change detection map. Considering that agriculture in the ecosystem is limited largely to small-scale farming of maize, wheat, and millet, it was difficult to differentiate farmland from pasture during the dry season. The difficulty in differentiating farmland from pasture in the dry season imagery partly explains the two land-cover/use types were combined in our analyses. The only exception was land that had been cultivated and prepared for sowing, which was classified as bare in the satellite imagery. It was also noted during fieldwork that many parts of the Baringo plains classified as pasture

Figure 10. Map of classification based on NDVI values for 1986 and 2000 showing an increase in bare ground cover (brown) and pasture/farmland/other cover type. However, most of the change has values of less than 0.3. Available in colour online.
and bushland had suffered livestock-induced sheet erosion that did not appear in the change-detection map. Apparently, the network of acacia bushes there remained largely unchanged over the 14-year period preventing the land from more severe forms of soil erosion. The NDVI values also remained largely unchanged between 0.2 and 0.4 (figure 10).

Although forests constitute less than 10% of the total land cover in the Baringo catchment, they play a crucial role in the ecosystem. They are a biodiversity and genetic resource seen as key to poverty alleviation (Food and Agriculture Organization 2003). Forests are an important natural resource that provides both material goods and environmental services such as soil protection and erosion control. Deforestation is a proxy for land degradation because it is often accompanied by an increase in soil erosion and sediment delivery from river

Figure 11. Highlight of the NDVI difference between 1986 and 2000. Although changes in NDVI were observed throughout much of the catchment, only the formerly forested sites and the lake shore recorded values above 0.3. Available in colour online.
systems (cf. Kasai et al. 2005, King et al. 2005). Forest clearance in the Lake Baringo catchment between 1986 and 2000 has probably led to a large enough increase in fluvial input of sediments into Lake Baringo to significantly alter the albedo of the lake (figure 8).

The rate of sediment delivery in the Lake Baringo catchment must have increased following deforestation in the upper reaches of the catchment leading to increased surface flow coupled with increased riverbank erosion (figure 13). It is easy to identify areas of forest loss in satellite imagery because forest vegetation is associated with NDVI values above 0.56 (figure 11) while non-forest classes have lower values. Change in NDVI values often points to change in land cover/use. The changes in forest cover were most pronounced in Marmanet forest (table 5), which is the main catchment of Ol Arabel River, where over 32% of forest cover was lost between 1986 and 2000. Significant decreases in forest cover were also evident in the Mau (27.4%) and Lembus and Londiani (14%) forests (table 5), which are part of the highland chain that constitutes the main catchment for Molo and Perkerra Rivers, the only permanent rivers in the Lake Baringo catchment.

Figure 12. Large sections of the areas classified as bare in this study such as this picture of Njemps flats, the plains to the south of Lake Baringo (labelled B in figure 5), were also severely degraded. Available in colour online.

Figure 13. Picture of riverbank erosion on a section of (left) Endau and (right) Perkerra Rivers. The former dries out completely, while the latter undergoes a remarkably low discharge during the dry season. Most of the eroded sediments end up in Lake Baringo. Available in colour online.
The most significant forest-cover change was in the Tugen Hills (42%), another important catchment for the lake. The Tugen Hills are characterized by very steep slopes, some of which are severely eroded following deforestation but do not show up in the Landsat imagery, due to the limitation of the spatial resolution. Forest clearance in the Lake Baringo catchment is largely due to pressure to increase land for agriculture or pasture to accommodate the growing population. Although wood is the inhabitants’ primary energy source, its collection does not contribute to land degradation due to its abundance, especially in lowlands. A much more important contribution to land degradation is logging for charcoal which is then sold to urban residents. Charcoal stacks abound in roadsides throughout the Baringo plains that are most severely degraded. Informal interviews with some inhabitants of the lower reaches of the catchment gave the impression that seasonality of the ephemeral rivers has increased, and that the dry season flow in the permanent rivers has decreased remarkably in recent years. Forests enhance infiltration capacity and wetness of soils, which, coupled with a higher water table under forests, increase the ability of a forested catchment to support dry season flow in rivers (cf. Sandström 1995). Deforestation has increased overland flow and decreased infiltration in areas previously under forest cover leading to decrease in ground water recharge and dry season discharge.

6. Conclusion

This study shows that Landsat TM and ETM+ can be used to delineate land-cover change in ecosystems threatened by land degradation in semi-arid environments such as Lake Baringo. The different methodologies used in this study show that the nature of land cover/use and associated impacts influence geomorphic processes associated with land degradation. Our analysis revealed that the TC-brightness (albedo) index can be useful for measuring changes in turbidity. Both the NDVI differencing and post-classification comparison effectively depicted the hotspots of land degradation and land-cover/use change in the Lake Baringo catchment. Change-detection analysis showed that the forest cover was the most affected class, in some sections recording reductions of over 40% in a 14-year period. Deforestation and subsequent soil erosion or land degradation have increased the sediment yield in the lake. Land degradation coupled with the high evapotranspiration rates has led to a reduction in lake surface area and increased turbidity, as confirmed by the statistically significant increase in the albedo of Lake Baringo between 1986 and 2000.

Our results reveal that deforestation and land degradation are serious problems in the Lake Baringo catchment, which poses a threat to the rich biodiversity in this ecosystem. Although climatic variations may account for some of the changes in the lake catchment, most of the changes in land cover are inherently linked to mounting human and livestock populations in the Lake Baringo catchment. Urgent steps need to be undertaken to help prevent further damage to the Lake Baringo ecosystem and possible environmental catastrophe.

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