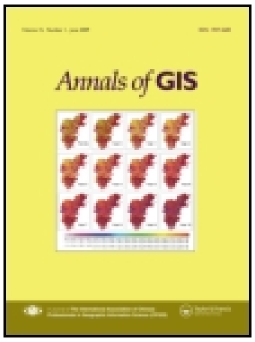

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Magnitude and transition potential of land-use/cover changes in the trans-boundary river Sio catchment using remote sensing and GIS

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The multiplicity of land-use/cover changes in reducing the areas covered by vegetation is of growing concern in Uganda today. Consequently, the study intended to determine the magnitude and transition potential of land-use/cover changes in a trans-boundary river Sio catchment. The magnitude of land-use/cover changes was determined by an application of unsupervised image classification on the ortho-rectified Landsat TM/ETM images of 1986 and 2000 using ILWIS 3.3 software; whereas an ArcGIS 9.2-based Land Change Modeler was used for both change analysis and transition potential modeling. The results showed that in the period of 1986 to 2000, wetlands and bushlands largely reduced by 21% and 5%, respectively, whereas small-scale farming and grasslands increased by 14% and 12%, respectively. The multilayer perceptron attained an accuracy of 97.03%, which is a higher percentage for the possible occurrences of land-use/cover changes in Sio catchment. The major drivers of land-use/cover changes are land ownership and household size. The study therefore recommends that the awareness of land-use/cover changes is extremely important for the Sio catchment's planning and management of the natural resources.

Keywords: Land Change Modeler; multilayer perceptron; land-use/cover changes; Sio catchment

Introduction

Land is a fundamental resource for of crop production, and through much of the course of human history, it has been tightly coupled to economic growth (Richards 1990). As a result, control over land and its use is generally associated with intense human interactions (Sivrikaya *et al*. 2007). Land-use/cover change plays a pivotal role in global environmental change. It contributes significantly to earth–atmosphere interactions and biodiversity loss and is a major factor in sustainable development and an indicator of human responses to global change (Meyer and Turner 1994, Lambin *et al*. 2001). One estimate, for example, holds that the global expansion of croplands since 1850 has converted some 6 million km^2 of forests/woodlands and 4.7 million km^2 of savannas/grasslands/steppes. Within these categories, respectively, 1.5 and 0.6 million km^2 of cropland has been abandoned (Lambin *et al*. 2001).

The magnitude of land-use/cover changes vary from one continent to another; for instance, in the Mediterranean Basin about 50,000 fires sweep from 700,000 to 1,000,000 hectares of land cover each year, causing enormous economic and ecological damage (Mostafa 1992). Most of these fires are human-caused, whereas several others are related to climate dynamics. However, in Africa, massive land-cover clearances affect an estimated 320 million ha, or about one quarter of Africa's dry lands triggering secondary effects such as soil erosion (UNEP 1997). Uganda still has considerable land-cover resources (NEMA 2007). However, this resource is being heavily 'mined' through rapid expansion of agricultural land. The conversion of natural resources into consumable products (mainly sawn timber, charcoal, and firewood) was estimated in 1995 to be 20 million tons and at an estimated growth rate of 3.6%, the consumption of wood products would almost be tripled from 20 (the 1995 level) to about 60 million tons by the year 2025 (National Biomass Study 2003). Agricultural activities in the Lake Victoria Basin are mainly responsible for presence of isolated pockets of natural vegetative land cover (Obando *et al.* 2007, Makalle *et al.* 2008).

The changes in land-use/cover due to natural and human activities can be detected using current and archived remotely sensed data at very high spatial, spectral, and temporal resolutions (Gete and Hans 2001, Mwavu and Witkowski 2008). Remote sensing and geographical information system tools including multilayer perceptron (MLP) facilitate synoptic analyses of Earth system function, patterning, and change at local, regional, and global scales over time. Such information is an important link between intensive, localized ecological research, and

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regional, national, and international conservation and management of biological diversity (Wilkie and Finn 1996).

MLP is a powerful tool that uses a machine learning approach to quantify and model complex behavior and patterns that involve multiple agents and factors. MLP has been used for pattern recognition in a variety of disciplines, such as economics (Fishman *et al.* 1991), medicine (Babaian *et al.* 1997), landscape classification, image analysis (Fukushima *et al.* 1983), pattern classification (Ritter *et al.* 1988), climate forecasting, and remote sensing (Atkinson and Tatnall 1997). The MLP consists of three layers: input, hidden, and output and thus can identify relationships that are nonlinear in nature (Rumelhart *et al.* 1986). Therefore, this article intended to determine the extent and pattern of land-use/cover changes and their drivers in Sio subcatchment.

This study's aim was to analyze this magnitude of change characterized by the complex behavior and patterns of underlying causes of land-use change. It is the characterization using the MLP that contributes to the discourse and understanding of land-use change (Bakker and Veldkamp 2010). This information is also necessary to understand the current catchment behavior (processes, status), to predict future trends, and to plan for catchment rehabilitation and people livelihood enhancement.

Materials and methods

Description of the study area

The study was conducted in the trans-boundary river Sio catchment. The river flows between Kenya and Uganda. In Uganda, Sio River is located in the eastern part of the country whereas in Kenya it is found in the western countryside. The catchment lies between latitudes 33°5”E and 34°1”E, and longitudes 0°10”N and 0°35”N. River Sio has its source from the footsteps of Mt. Elgon and has a catchment area of about 1500 km^2. It originates from Kaujai and Luucho Hills in Bungoma district, Kenya, at an altitude of 1800 m. The river flows through the Bungoma, Teso, and Busia districts into Berkeley Bay in Lake Victoria in Uganda (Figure 1). The Sio catchment forms an important subcatchment of the Lake Victoria and Nile basin. It is an important source of livelihood for a big proportion of small-scale farmers engaged in mixed farming, depending on agriculture and livestock keeping as well as a large population depending on fishing within and around it. The area is characterized by a high population density and is highly overgrazed (Busia 2004). The population density exceeds 300 persons per square kilometer and cattle densities of 38 have been noted within the basin, putting increasing pressure on already fragile heavy demand on the watershed resources including water, soil, and vegetation (MAAIF 1993).

The climate of river Sio catchment is humid to subhumid and is affected by the movement of the Inter-Tropical Convergence Zone but the effects are appreciably modified by the presence of Lake Victoria and local topography. The catchment receives a mean annual rainfall of 1514 mm and receives it twice a year with the first rains (short season) extending from March to May and a longer rainy season extending from August to November. The highest annual maximum rainfall in the catchment area is experienced around the lakeshore and on the slopes of Mt. Elgon. The mean annual maximum temperature of the catchment is 28.7°C whereas the mean annual minimum is 16.2°C (Uganda Water Development Report 2005).

Sio catchment soils are dominantly ferrallitic which characteristically represents almost the final stage in tropical weathering. The catchment also lies on Pre-Cambrian rocks, which include a variety of granites, gneisses, quartz, and smaller area of other kinds of strongly metamorphic rocks. Meanwhile, the observed vegetation in river Sio catchment has undergone considerable changes as a result of continuous cultivation, burning, or clearing for other purposes. What is seen today can therefore be considered as the remnants of the original vegetation types. There are also dense settlements and rain-fed cultivation throughout on both sides of the river. The crops grown include maize, sweet potatoes, beans, paddy rice, cassava, and sorghum whereas cattle, goats, pigs and sheep are the main livestock kept (Busia 2004).

Methods

Image classification system

For image classification, the study adopted a land use/cover classification system as set by the National Biomass Study (2003). The land-use and vegetative cover type descriptions are as follows:

(1) *Grasslands*. These were open areas where short grasses were the dominant vegetation and had few scattered trees.
(2) *Small-scale farming*. This comprised of areas under continuous cultivation where the plots were covered by mixed cropping such as maize with cassava and sweet potatoes and large-scale sugarcane growing together. This also comprised of plots left under fallow.
(3) *Wetlands*. These are designated areas which are shallow seasonally or permanently waterlogged and normally support hydrophytic vegetation. This class comprised of *Papyrus reeds*, *Echnochloa*, *Miscanthidium*, *Phragmites*, and *Pistia*.
(4) *Bushlands*. These are areas comprising of sparse flora (shrubs) and fauna (primary and secondary). The bushlands comprised of scattered tree plants like *Lantana Camara*, *Acacia*, and *Ficus*.

Image classification procedure

The study utilized two sets of ortho-rectified Landsat TM/ETM images of 8 March 1986 (path 170/row 60) and

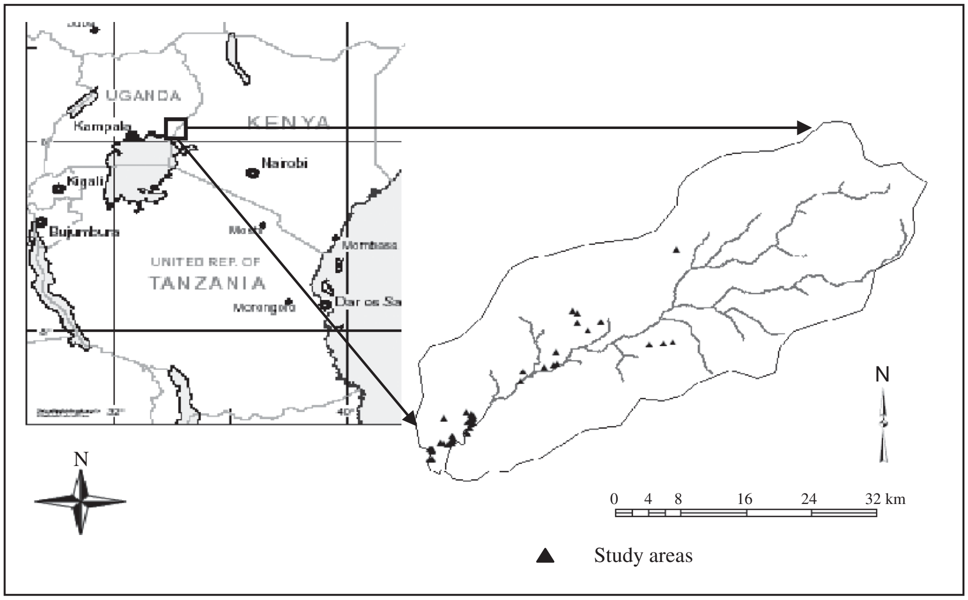

Figure 1. Location of study areas.

1 January 2000 (path 170/row 60) based on a 14 years lag time series with spatial resolution of 30 m. All images were registered to the UTM WGS84 projection, zone 36N using coordinate system projection. Images taken in the dry season (January–March) were utilized because of the highest contrast of spectral signatures of tree cover and that of undergrowth (grass, herbs) (Kiunsi and Meadow 2006).

Initial image clustering in which 15 clusters and pixels of similar spectral values were grouped together and assigned cover type class to each feature class was carried out in ILWIS 3.3 software. The unsupervised classification was used because of more information than in supervised classification (Jensen 1986). The preference for unsupervised classification is that it may not mistakenly separate pixels with slightly different spectral values and assign them to a unique cluster when they, in fact, represent a spectral continuum of a group of similar objects and thus yielding sufficient classification accuracy. The clustered images were re-classified into four spectral classes based on ground truth data. The color palette manipulations of each land-use/cover type were used for easy interpretations and differentiations in determining the size of land-use/cover changes.

A stratified random sampling design was used to select a total of 500 pixels from each land-use/cover map (1986 and 2000) for thematic accuracy assessment. The 1986 and 2000 land-use/cover maps were checked with reference to the 1970 aerial photographs and GPS points obtained during 2004 fieldwork as reference. The overall land-use/cover classification accuracy levels for the two dates range from 72 to 90% were assessed with Kappa statistical analysis (Anderson *et al.* 1976).

Change rate analysis

The change rates of single land-use/cover type were determined according to Peng *et al.* (2008) procedures: $K_1 = \frac{(U_b - U_a)}{U_a} \times \frac{100\%}{T}$ where K_1 is the land-use/cover dynamics degree, measuring the change rate of the target land-use/cover type, U_a and U_b are the area of the target land-use/cover type at the beginning and the end of the study period, respectively, and T is the study period, which is usually measured with the unit of year.

Change analysis

Change analysis and their net contributors to changes and transitional potential was conducted using an ArcGIS 9.2-based Land Change Modeler software developed by Idrisi 15 Andes. Clustered land-use/cover maps of 1986 (earlier map) and 2000 (later) were uploaded into the software for change analysis. The gains and losses of areas covered by land-use/cover types were set in hectare units.

The change map of all land uses (wetlands, bushlands, and grasslands) to small-scale farming was transformed by evidence likelihood transformation for MLP to solve cases of strong nonlinearities and to attain a higher accuracy. The transformation to small-scale farming was chosen because small-scale farming was gaining more land compared to the other land uses in the catchment. But also it is an indicator of the underlying dynamics of the landscape. The evidence likelihood-transformed map was evaluated to test the explanatory power of Cramer's V and P-values and then added to the model. Cramer's V is used as a post-test to determine strengths of association after chi-square has determined the significance.

V is calculated after chi-square determination, using the following expression:

$$V = \mathrm{SQRT}\left(\frac{c^2}{n(k-1)}\right)$$

where c^2 is chi-square and k is the number of rows or columns in the table.

Cramer's V varies between 0 and 1. A value close to 0 shows little association between variables whereas a value close to 1 indicates a strong association (Cramér 1999). For a higher accuracy assessment, wetlands, bushlands, and small-scale farming land-use/cover types were also calibrated and tested against grasslands.

In the analysis of the complex behavior and partners as well as likelihood for change, MLP was utilized which first creates a random sample of cells that experienced each of the transitions being modeled. MLP develops a multivariate function that can predict the potential for transition based on the values at any location for the explanatory variables. This was done by taking half the samples it was given to train on and reserving the other half to test how well it is doing. In addition, MLP constructs a network of neurons between the three input values from the explanatory variables and the three output classes (the transition and persistence classes), and a web of connections between the neurons that was applied as a set of (initially random) weights. Subsequently, with each pixel, MLP looks at the training data; it gauges its error and adjusts the weights (Eastman 2005).

Analysis of drivers of land-use/cover changes

The Participatory Rural Appraisal method was used to establish the underlying drivers of land-use/cover changes through community ranking. Focus group discussions (FGD) were conducted in 15 villages. In each village 8–15 households randomly selected were invited and the information acquired from them was related to the past and present land-use/cover changes, population trend and type of crops grown, and their perception on the causes of land-use/cover changes in river Sio catchment. The FGD method was adopted because they supplement on attitudinal data (Morgan 1996).

Results

Magnitude of land-use/cover changes

The image classification indicates that in 1986, wetlands (46%) and bushlands (40%) were the most predominant land-use/cover followed by small-scale farming (10%) and grasslands (4%) (Table 1 and Figure 2). By year 2000, bushlands (35%) and wetlands (25%) were still the most predominant land-use/cover types followed by

Table 1. Magnitude and change date computation for each land-use/cover type.

Year	1986		2000		Change		Change date computation
Land use	Area (ha)	%	Area (ha)	%	Area (ha)	%	%
Bushlands	586.2	40	503.1	35	83.1	5	12
Grasslands	53.8	4	234.6	16	180.7	12	13
Small-scale farming	144.5	10	347.1	24	202.7	14	10.8
Wetlands	665.7	46	365.4	25	300.3	21	3.5

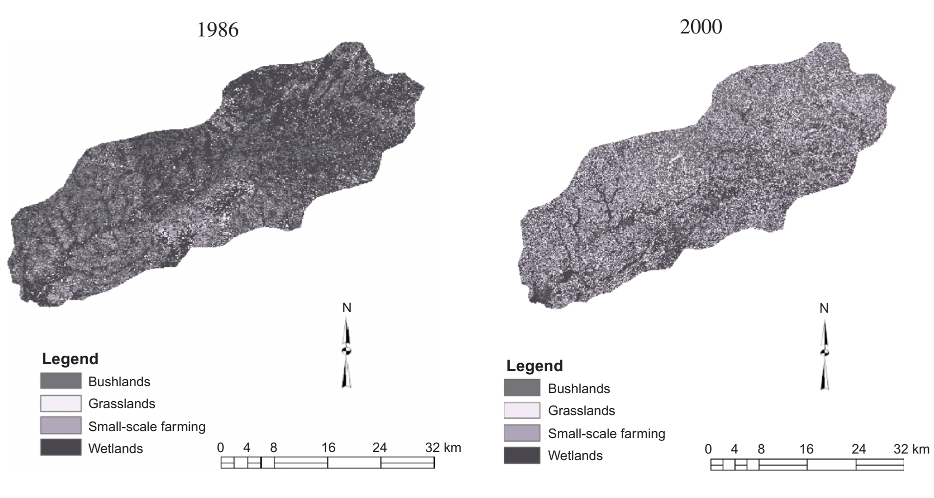

Figure 2. Land-use/cover maps for the Sio catchment.

small-scale farming (24%) and grasslands (16%) (Table 1 and Figure 2) but there were significant reductions in land-use/cover types of wetlands (21%) and bushlands (5%) whereas small-scale farming increased by 14% and grasslands by 12% (Table 1).

The rates of change differed between land-use and cover types. The index of K_1 measuring annual net increasing rates of land-use/cover types showed that grasslands had the highest change rate (13%) followed by bushlands (12%), small-scale farming (11%), and wetlands (3%). This also coincides with the findings from the FGD that grasslands are normally burnt during each dry season.

Change analysis

Analysis of the gains and losses of the land-use/cover classes indicates that the contributors to gains and losses depended on other land-use/cover types. Small-scale farming is the biggest contributor to the loss of bushlands ranging from 39% to 49% (Figure 3) and wetlands (34.2%) (Figure 3). However, wetlands (53%) and bushlands (41%) were the biggest contributors to net gain of grasslands (Figure 3). The findings from the FGD also collaborates with net gain of bushlands were participants indicated that bushlands were easier to clear than wetlands in the catchment.

Transition potential modeling

The overall Cramer's V (a measure of association that ranges from 0 to 1) is 0.0613; however, individual class values are more important because they have a strong predictive power to be added to the model. The Cramer's V shows a higher likelihood of bushlands and grasslands changing to small-scale farming compared to wetlands. Table 2 shows that all the pixels were independently sampled and had no spatial dependence in their values. Of the 13,253 cells that could have undergone transition in Sio catchment, MLP attained an accuracy of 97.03% as the RMS error declined with the training of 0.0993 by 10,000 iterations. This shows a higher percentage for the likelihood of land-use/cover changes to occur in Sio catchment (Figure 3). The validation of random data also yielded an accuracy of 87.44% and hence a higher accuracy still holds. This finding also indicates that Sio catchment is a highly dynamic landscape driven by the underlying factors.

Drivers of land-use/cover changes

The participatory appraisal method extracted household size and land ownership as the main drivers of land-use/cover changes in Sio catchment. Other drivers of land-use/cover change include weak institutional laws for managing catchments, decline in soil fertility, increased livestock activities, and use of fire in land management. Also, findings from the FGD indicated that land is scarce and cannot sustain enough crops to cater for the growing population food requirements. Also, when the indigenous trees are cut the farmers remove even the stumps and this reduces the chances of regeneration.

Discussion

The image classification and change analysis findings demonstrates that in the period of 1986–2000, the areas covered by bushlands and wetlands greatly reduced compared to small-scale farming and grasslands which increased. By 1986, bushlands (40%) and wetlands (46%) were the most predominant land-cover types compared to 2000 where they covered 35% and 25%, respectively. These reduced at a change range of 5–21% per hectare with an annual rate range of 4–12%. The reductions were largely attributed to the intensifications of small-scale farming for a livelihood which increased by 14% per hectare with an

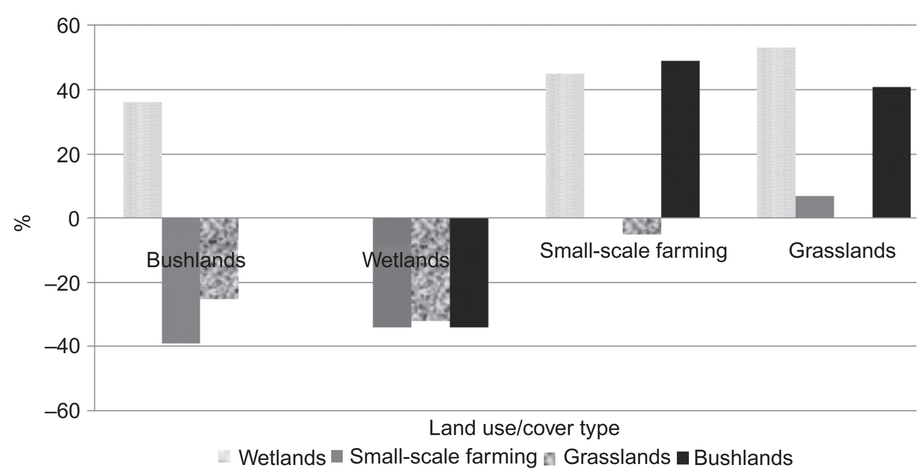

Figure 3. Land-use/cover classes contributing to net gains and losses of bushlands, wetlands, small-scale farming, and grasslands.

Table 2. Test and selection of site and driver variables.

Cover class	Cramer's V	P values
Overall V	0.0613	0.0000
Small-scale farming	0.1474	0.0000
Bushlands	0.1108	0.0000
Grasslands	0.0399	0.0000
Wetlands	0.0000	1.0000

annual rate of 10.8%. Similar observations were made by Isabirye (2008) in the Lake Victoria Basin. Elsewhere, Mertens and Lambin (2000) also observed that in tropical countries, mainly in Latin America, the socioeconomic factors most related to natural land-cover clearance are attributed to the expansion of the agricultural frontier and population increase (Agrawal 1995). It has also been established that building roads and other communication systems increases the rate of land-cover clearance (Mertens and Lambin 2000).

In addition, the duration taken by most households to clear one acre of land for cultivation was less than a week as per FGD. The main cropping method practiced by most farmers is single crop whereas few of them practice mixed cropping with cattle being the main livestock that is grazed along the river banks. The intensification of small-scale farming was also attributed to the decline in soil fertility as perceived by the households and this has led to land abandonment thus resulting in land-use/cover variations leaving only isolated pockets of vegetation cover standing. Elsewhere, anthropogenic factors, which favor arable land use, are also reported to be the drivers of change on the South Downs landscape, United Kingdom (Burnside *et al.* 2003).

Demographic pressure and the decreasing cultivatable land (subdivisions) contributed significantly to the encroachments on both wetlands and bushlands (Makalle *et al.* 2008). Similar observations were also noted by Woldeamlak (2002) in Chemoga Watershed, Blue Nile Basin, Ethiopia, that the increase in the areas covered by farmlands and settlement was also attributed to population increase. Place and Otsuka (2000) also revealed that population pressure, market access, and land tenure are also important factors affecting land use and resource management in east-central Uganda. In addition, the reductions of bushlands and wetlands were also accredited to charcoal burning, increased livestock activities, and timber harvesting. Almost all the households (98%) used firewood and charcoal for cooking. This is similar to the findings made by UBOS (2002) in the study area. This also corresponds to the findings of Geist and Lambin (2001) that agricultural expansion, overgrazing, charcoal burning, and timber harvesting contributes 37% of land-cover clearance, which is one-third of the causal factors for land-cover depletion worldwide. However, it disagrees with the findings of Lambin *et al.* (2003) who observed that most of Africa and Latin America increased their food production through both agricultural intensification and extensification.

The areas covered by wetlands (53%) and bushlands (41%) were the biggest contributors to the net gain in grasslands, which increased by 13% annually in the Sio catchment. Similar observations were made by Mugisha (2002) and Handa *et al*. (2002). This was attributed to man-made fires and drying up of wetlands. The presence of fires was associated with land-cover clearance in land management (Makalle *et al.* 2008). This is also in agreement with Mworia-Maitima (1997) that the remains of grass cuticles and grass phytoliths showed an expansion of grasslands and an increase in the diversity of grass types following the period of extensive fires in western Kenya. From a worldwide perspective, Jin-Ping *et al.* (2007) adds on that the gain in grasslands has been advantageous in accelerating vegetation restoration and improving the ecological environment.

The small gains in bushlands ranging from 24% to 36%, on the other hand, were mainly attributed to the demarcation of Mt. Elgon National Park by the Kenyan government in the upstream. The demarcation was responsible for the emergency of secondary vegetation (thorny trees) in the previous wetland areas upon drying. In addition, the bushlands also emerged because of the subsequent lack of fire effects in the park. Elsewhere, Ferrier (2002) and Jeffrey *et al.* (2004) also pointed out that the establishment of protected areas is a vital component of most regional and national strategies to mitigate the ongoing loss of land cover. However, the limits to this, Chape *et al.* (2003) argued that the lower levels of investment into protected-area management and protection, as well as local communities living in conditions of poverty and vegetation dependence are responsible for land-cover depletion in the developing countries.

Furthermore, the increase in bushlands was attributed to the loss of land productivity caused by land overuse without external inputs and sheet erosion that has caused low-yielding fields to be abandoned. This is in line with the findings of Olson *et al.* (2004), who observed that the abandonment of cultivated lands and pastures has resulted in the recovery of bushlands at a rate determined by the local conditions. Elsewhere, in the Blue Nile Basin, Ethiopia, the increase in areas covered by bushlands is also attributed to increased tree planting at the household level, which has led to the formation of clustered plantations around homesteads (Woldeamlak 2002). However, this is disregarded by the findings of IPCC (2000) that the abandoned fields have been re-cultivated after an application of fertilizers and this has led to a shift from subsistence farming to commercial sugarcane growing.

Besides, small-scale farming and bushlands had strong predictive powers of the likelihood to change to other land uses over time if the nature of developments stayed the same in Sio catchment. The changes would arise from the increased demand of both agricultural and cultivation land. Guppy (1984) also noted that the spiraling population growth, rising consumption of timber and forest products, or demand for new agricultural land and war or pandemic could affect the trend, as could protectionism of land cover in the tropics.

The weak institutional laws and policies are responsible for land-use/cover alterations in Sio catchment. Similar observations were also made by SOER (2004) in the Lake Victoria Basin about the noncompliance by the communities with the basin laws. This is also related to the findings of Mwavu and Witkowski (2008) in northwestern Uganda that the weak laws are responsible for the clearance of land cover because they are highly violated and usually have lighter penalties. The inappropriate policy and weak legal and institutional frameworks have contributed toward unfavorable environment for land-cover conservation and sustainable use in the catchment. Land ownership which is majorly under customary land tenure was also responsible for land-use/cover changes. This is in conformity with the findings of Place and Ostuka (2000) and Makalle *et al.* (2008) in the Sio and Mara basins. This is because the tenure has generated little interest in the conservation of land-cover resources resulting in massive clearances while creating land for household livelihood activities. However, even if the institutional systems were strong enough and enforced, the likelihood of underlying forces such as drive for expansion of agriculture, poverty and population pressure would still drive change in land use/cover.

The effects of land-use/cover changes also vary from one catchment/ecosystem to another; for instance, Copeland *et al.* (1996) noted that significant changes in temperature, humidity, wind speed, and precipitation may have occurred in Colorado due to land-use changes. Baron *et al.* (1998) also agreed that land-cover change exerted a large influence on annual plant productivity and water fluxes when grasslands were converted to crops, whereas the effect of temperature change on productivity and water fluxes was stronger in the mountain vegetation in the South Platte Basin, USA.

Conclusion

Dynamic landscapes such as Sio are increasingly experiencing fast-paced land-use/cover changes. This is due to the underlying demographic forces that affect natural cover differently because of ease for transition to land use. Wetlands and bushlands reduced by 21% and 5%, respectively, at the expense of small-scale farming and grasslands which increased by 14% and 12%, respectively. Consequently, MLP attained an accuracy of 97.03%, which shows a high likelihood of land-use/cover changes in the catchment. Whereas the model validations test accuracy was 87.44%, which is much lower than the training accuracy of 97.3%. The main drivers of land-use/cover change in Sio catchment were household size and land ownership. To combat on the rapid clearances of Sio catchment land cover, there is need for a region-wide land-use/cover change detection analysis for conservation planning and environmental monitoring to address issues of habitat fragmentation, landscape dynamics, and plant species distributions in the catchment.

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