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Research Paper

Past and future land use/land cover changes from multi-temporal Landsat imagery in Mpologoma catchment, eastern Uganda

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ABSTRACT

Land use/cover (LULC) change is a major concern in Africa's river basins and policy makers, environmentalists and other stakeholders tackling biodiversity and sustainable development issues in these watersheds require accurate information on past, present and future LULC projections to develop management strategies for the concerned watersheds. This study assessed the historical, current and future LULC changes in Mpologoma catchment. Remote sensing and supervised classification were used to analyze 33-year multitemporal LULC changes in Mpologoma catchment while future patterns for the next two decades were predicted using the Cellular Automata-Markov modelling technique in TerrSet's Land Change Modeler. Initially, in 1986, the catchment was dominated by grassland (32.08%). However, most grassland (92.77%) was gradually converted to subsistence farming (75%) and built-up (15.7%). Grassland, woodland and wetland annually declined at a rate of 5.52%, 2.47% and 0.63% respectively while farmland and built-up expanded at 9.32% and 6.22% respectively and by 2019 subsistence farming was the dominant class (53.16%). Prediction results showed that by 2039, woodland, grassland, wetland and open water will decrease while there will be major increases in built-up and commercial farming from 11.61% to 27.91% and 0.18% to 0.34% respectively. Subsistence farming will continue to be the dominant land use by 2039 attributed to gains from woodland (4.7%), grassland (3.7%) and wetland (4.9%). These LULC changes indicate an intensifying land use pressure in Mpologoma catchment and provide useful information for land use planners, environmentalists and policymakers in this catchment to consider when planning for sustainable management of the watershed.

1. Introduction

Land use/cover (LULC) change has continued to be a major environmental concern at global and local scales mainly due to its gross impact on ecological sustainability (Vitousek et al., 2008; Yirsaw et al., 2017). These LULC changes largely stem from an intricate interaction of various underlying socio-economic factors including technological capacity, urbanization and the increasing demand to provide food, fiber and shelter for the growing human population (MEA, 2005; Verburg et al., 2004; Vitousek et al., 2008). The aforementioned factors have accelerated LULC conversion in various landscapes thereby compromising the ecological capacity of the concerned ecosystems to provide their ecosystem services (ESs) (Defries et al., 2009; Foley et al., 2005). For instance, LULC conversion into construction and agricultural land has affected climate regulation (Portela and Rademacher, 2001), water availability and soil fertility (Temesgen et al., 2013) leaving catastrophic impacts on human wellbeing (MEA, 2005). In addition, about one million aquatic and terrestrial species are currently threatened with extinction due to habitat destruction by human activities and the threat is projected to increase in the near future (IPBES, 2019; Pimm and Raven, 2000). Therefore, evaluating and documenting past LULC changes and making predictions of plausible future LULC dynamics is essential for sustainable land use planning,

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management and monitoring of the concerned landscapes (You et al., 2017).

Landsat data has been used in land use/cover monitoring for nearly five decades (since 1972). The medium spatial resolution of Landsat satellite sensors coupled with a temporal resolution of 16 days have ensured that essential multispectral data are continuously available for tracking LULC changes and trends across multiple time scales (Carter and Engman, 1984; Hansen and Loveland, 2012). Advances in remote sensing and geographical information systems (GIS) such as the use of digital image processing algorithms coupled with rigorous validation protocols have increased the use of Landsat data in studies concerned with detecting, quantifying and monitoring LULC extent and change across multiple spatial–temporal scales (Hansen and Loveland, 2012). Key areas of interest in these studies have included marine and freshwater watersheds (Ballanti et al., 2017; Berihun et al., 2019; Butt et al., 2015; Elagouz et al., 2020; Matlhodi et al., 2019; Vanderstraete et al., 2006), urban areas (Dou and Chen, 2017; Kaya and Görgün, 2020; Singh et al., 2015; Somvanshi et al., 2020), drylands (Egeru et al., 2014; Garedew et al., 2009; Osaliya et al., 2019), rift valleys (Akinyemi, 2017) and protected areas (Gambo et al., 2018) among others. The aforesaid and other studies (Defries et al., 2010; Mohamed et al., 2020) continually highlight that human and natural factors play a key role in driving LULC change at all spatial and temporal scales. Hansen et al. (2008) particularly observed that a small forest portion below one percent (<1%) had been lost in the Congo Basin between 1990 and 2000 mainly due to settlement, agriculture and hunting. In another study, Mucova et al. (2018) detected a reduction in effective Quirimbas National Park area, Mozambique, between 1979 and 2017 and largely attributed the change to human settlement and agricultural intensification. Similarly, Uganda has experienced tremendous LULC changes in the past decades. Related studies (Egeru et al., 2014; Kiggundu et al., 2018; Nakakaawa et al., 2011) have mainly focused on quantifying these LULC changes in the country to gain an understanding of their magnitude and past trends. A few studies (Li et al., 2016; Mwanjalolo et al., 2018) have predicted future LULC changes in Uganda and none has focused on the increasingly threatened watersheds in the country (Uganda Bureau of Statistics, 2016).

Land use pressure is continuing to increase globally and due to the nexus between ecosystems and human livelihood, there will likely be more adverse LULC changes in the near future. It is, therefore, important to understand future LULC patterns and trends in order to guide responsible natural resource use tendencies in the present and future times. Predicting future LULC patterns requires building models based on educated assumptions of future actions of the driving factors (Munthali et al., 2020; Oyana et al., 2014; Verburg et al., 2004). Importantly, LULC modeling does not only provide checks into current land use policies, it also helps natural resource planners and managers to mitigate or prevent negative consequences of undesirable future LULC changes (Dezhkam et al., 2017; Omar et al., 2014; Theobald and Hobbs, 2002). The aim of LULC modeling, therefore, is to ensure that a continuous supply of natural resources is available for the current and future generations (Verburg et al., 2004). A variety of models have been used in diverse LULC predictions across the world including agent-based, Markov and cellular automata models (Li et al., 2016; Mwanjalolo et al., 2018; Sohl and Claggett, 2013). However, integrated models such as the cellular automata (CA)-Markov model have been found to give a better output when predicting long-term spatial and temporal LULC variations (Liping et al., 2018; Munthali et al., 2020; Singh et al., 2015; Yang et al., 2012). The CA-Markov model is robust and can be used in different land use planning scenarios (Fitawok et al., 2020; Fu et al., 2018; Kamusoko et al., 2009). The model gives accurate and consistent results (Arsanjani et al., 2012; Wang and Zhang, 2001).

In this study, CA-Markov modeling was executed using the Land Change Modeler (LCM) of TerrSet Geospatial Monitoring and Modeling system (Eastman, 2016). LCM's multi-layer perceptron (MLP) neural network technique is robust for modeling complex nonlinear relationships among variables and running multiple transitions (Eastman, 2009, 2016). Furthermore, because it is automatic, MLP monitors the LULC changing process from the start to the end thus giving an accurate prediction (Eastman, 2016). Moreover, LCM maximizes modeling accuracy by masking out any transition potentials that do not match the specific from transition case (Eastman, 2016). Thus, the LCM of TerrSet was chosen for this study due to its efficient analysis and accurate prediction of future LULC scenarios. Precisely, the study intended to (i) analyze LULC changes in Mpologoma catchment from 1986 to 2019 and (ii) predict LULC patterns for the years 2029 and 2039. Since the prediction is in connection with Uganda's Vision 2040 and SDGs 6 & 15 that call for protection and restoration of fragile ecosystems, this study is timely in exploiting remote sensing and GIS techniques to influence strategic land use planning and policy making geared towards taking immediate action on adverse human activities in Uganda's fragile ecosystems. In particular, the use of the Land Change Modeler to give accurate future LULC change scenarios is of utmost importance to future management of Mpologoma catchment and similarly affected catchments in the country.

2. Materials and methods

2.1. Study area

Mpologoma catchment (Fig. 1) is an approximately 12,195 Km^2 watershed found in eastern Uganda within the Kyoga water management zone (DWRM, 2017). Mpologoma River, from which the

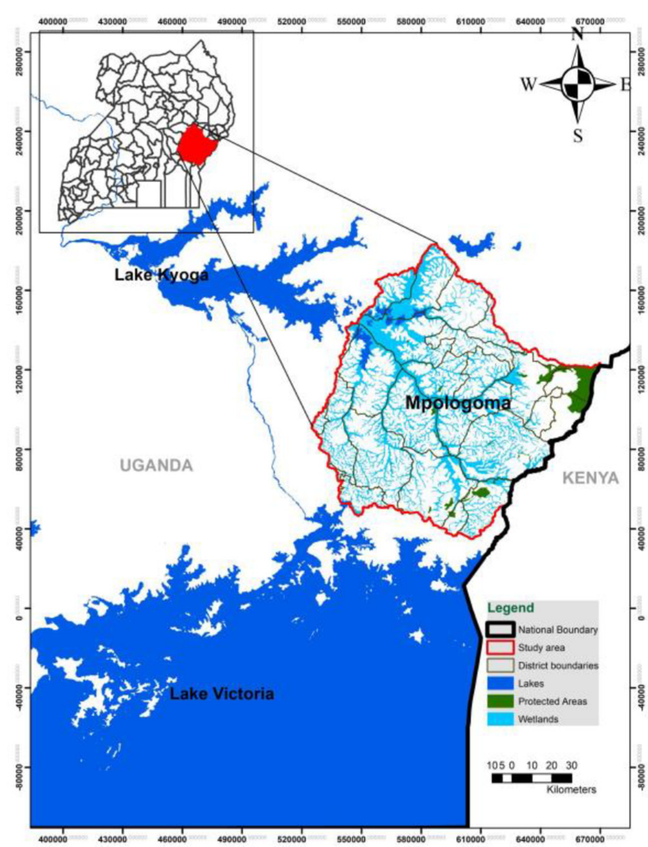

Fig. 1. Location of Mpologoma catchment in Uganda.

catchment is named, literally originates from Mt. Elgon (4,320 m asl), flows along the common Uganda-Kenya border, meanders severally and empties into Lake Kyoga 6.1x10^8 m^3 of water per annum (Muli, 2011). The catchment is a major drinking water reservoir for residents of eastern Uganda (NEMA, 2006). The climate has a bimodal rainfall pattern (March - May and August – November). On average, the area receives 1215–1238 mm of rainfall per annum while temperature ranges between 24 °C and 36 °C (Chombo et al., 2018). The people in this catchment are mainly subsistence farmers who grow crops on sandy-loams. However, encroachment on the region's natural resources has increased. Wetlands continue to be drained for farming leading to disappearance of several reptile and bird species (Tajuba, 2017). Fruit and hardwood trees especially Mvule, *Milicia excelsa* (Welw.) C.C. Berg. are increasingly felled for timber and charcoal. The rainfall pattern has also become unpredictable (Uganda Bureau of Statistics, 2016).

2.2. Data collection

This study used both ancillary and satellite data. Ancillary data included aerial images and ground truth data (reference data points collected using Geographical Positioning System (GPS). GPS data points were collected from July to November 2019 for 2019 image classification and assessment of overall classification accuracy. The satellite data consisted of multispectral data acquired by Landsat 4–5 TM (Thematic Mapper), Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) and Landsat 8 OLI/TIRS (Operational Land Imager/Thermal InfraRed Sensor). The satellite images were preliminarily screened and only those with a maximum cloud cover of 10% were selected and downloaded from the US Geological Survey Global Visualization Viewer (USGS Glovis) portal to a local workstation and analyzed. Table 1 summarizes the image details and the procedure followed in this study is shown in Fig. 2.

2.3. Image processing and classification

All the Landsat images used in this study were L1T (Level 1 Terrain-corrected data), implying they were already geometrically corrected (Hansen and Loveland, 2012; Zhu, 2017; Zhu and Woodcock, 2014). Nonetheless, to remove atmospheric influence that would encumber image analysis, images were atmospherically corrected Top of Atmosphere (TOA) and visualization enhanced using majority filtering method. The images were registered for WGS 84/ UTM zone 36 N, processed by RGB color composition, mosaicked and the study area clipped. Images were classified in ArcGIS 10.7 using the maximum likelihood algorithm of supervised classification where training samples were selected by delimiting polygons around representative class pixels. The delineated predetermined classes were subsistence farming, built-up, commercial farming, woodland, rice scheme, grassland, wetland, and open water (Table 2). Visual analysis and local knowledge tremendously improved supervised classification results.

2.4. Accuracy assessment

Accuracy assessment is important for verifying the quality of image output (Butt et al., 2015). A combination of reference earth-observation data and ground truth data was used for accuracy assessment (García et al., 2016). A stratified random sample of about 220 Google earth reference data pixels proportionally distributed among the eight LULC classes was routinely used for accuracy assessment. A Kappa test was carried out to measure the extent of classification accuracy; Kappa coefficient, K, being a coefficient of agreement. It reflects the difference between actual agreement of classification with reference data and the agreement expected by chance. In this study, Kappa coefficient was calculated using equation (1) (Congalton, 1991).

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad (1)$$

where,

K = Kappa Coefficient, r = number of rows/columns in the error matrix, N = total number of samples, x_{ii} = sum of correctly classified samples, x_{i+} =row *i* total, while x_{+i} = column *i* total.

2.5. Land use/cover change detection

The post-classification comparison (PCC) technique for change detection was performed in ArcGIS 10.7 (Manandhar et al., 2009). PCC method allows consecutive and independently classified images to be compared through overlay to detect which LULC type at the initial date actually changed to another class at the final date (Gatrell and Jensen, 2008; Kiggundu et al., 2018). The rows of the transition matrix produced (Table 4) represent LULC categories at time 1 (t_1), 1986, while columns display LULC categories at time 2 (t_2), 2019. Row vectors show how LULC type changed between the times (t_1-t_2) while column vectors show the land use type at time t_1 from which another land use type developed at time t_2. The main diagonal data in bold highlight areas of LULC persistence. Changes for each of the 8 LULC types were calculated from 8x8 transition matrices.

Table 1
Landsat image characteristics for this study.

Image recording time	Sensor	Path/Row	Spatial resolution (m)	RGB band composition
18/10/1986	Landsat 5 TM	170/059	30	3,2,1
18/10/1986	Landsat 5 TM	170/060	30	3,2,1
28/12/1986	Landsat 5 TM	171/059	30	3,2,1
27/02/1989	Landsat 4 TM	171/060	30	3,2,1
02/04/1995	Landsat 5 TM	170/059	30	3,2,1
02/04/1995	Landsat 5 TM	170/060	30	3,2,1
19/01/1995	Landsat 5 TM	171/059	30	3,2,1
19/01/1995	Landsat 5 TM	171/060	30	3,2,1
02/01/2006	Landsat 7 ETM+	170/059	30	3,2,1
03/02/2006	Landsat 7 ETM+	170/060	30	3,2,1
10/02/2006	Landsat 7 ETM+	171/059	30	3,2,1
10/02/2006	Landsat 7 ETM+	171/060	30	3,2,1
30/01/2019	Landsat 8 OLI/TIRS	170/059	30	4,3,2
19/03/2019	Landsat 8 OLI/TIRS	170/060	30	4,3,2
05/01/2019	Landsat 8 OLI/TIRS	171/059	30	4,3,2
05/01/2019	Landsat 8 OLI/TIRS	171/060	30	4,3,2

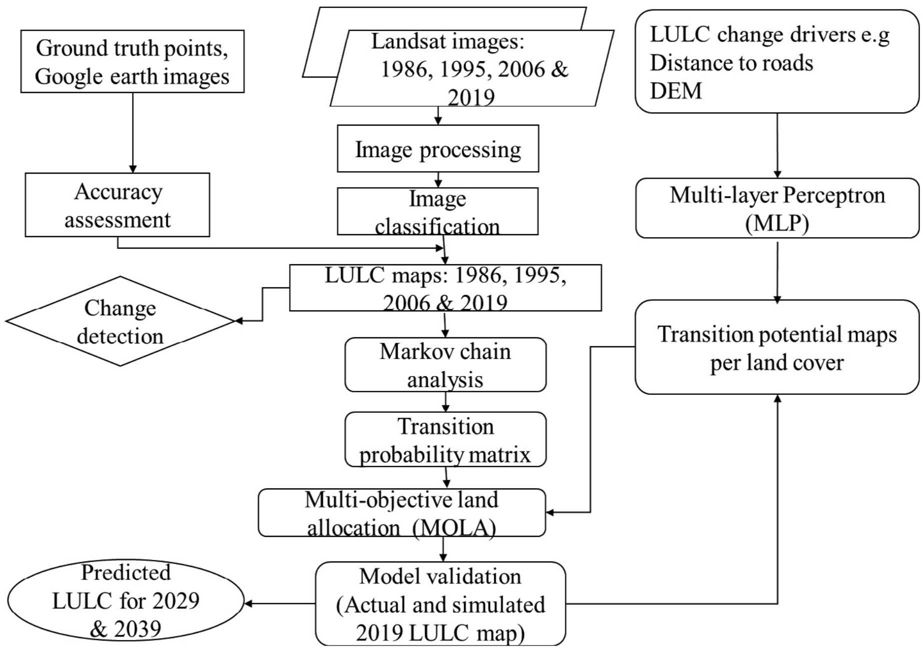

Fig. 2. Flow chart for LULC Change Detection and Prediction in this study.

Table 2
Delineated LULC classes.

Class name	Description
Subsistence farming	Smallholder rice paddies and crop fields in drained areas.
Commercial farming	Kibimba largescale commercial. Plots 45.84 ha –103.4 ha.
Woodland	Protected forests, woodlots (trees ≥ 8 m tall).
Grassland	Shrubs (≤2 m tall) and grasses, thicket, bush
Built-up	Constructed areas
Wetland	Vegetated areas at river, lakes and stream edges
Open water	Rivers, lakes, dam, ponds
Rice Scheme	Doho rice scheme (DRS). Plots 0.1–0.4 ha.

2.6. Annual rate of land use/cover change

Annual rate of LULC change is a measure of the extent of LULC change in a specific class per annum. It is useful in identifying threatened LULC. In this study, annual rate of change (r) in different LULC class areas (A_2, A_1) at specific times (t_2, t_1) was computed using the following standard equation introduced by (Puyravaud, 2003),

$$r = \frac{1}{(t_2 - t_1)} x\ln\left(\frac{A_2}{A_1}\right) \tag{2}$$

This formula is suitable when comparing LULC changes that are insensitive to differing time lengths between study dates as in this study.

2.7. Predicting future LULC dynamics in Mpologoma catchment

A hybrid cellular automata and Markov (CA-Markov) model (Clarke and Gaydos, 1998; Guan et al., 2011) was used to predict future LULC scenarios of Mpologoma catchment for the years 2029 and 2039 using the Land Change Modeler in TerrSet Geospatial Monitoring and Modeling system (Eastman, 2016). The prediction was based on the business-as-usual (BAU) assumption. It was assumed that future LULC trends will continue to occur in ways similar to the historical and recent LULC trends driven by same influencing factors (Samie et al., 2017). This meant that the communities in the catchment would keep on carrying out their routine socio-economic activities under the prevailing political situation and government policies and priorities. The driving factors, thus, included slope obtained from the digital elevation model (DEM) downloaded from the USGS Earth Explorer website, population density data by sub-county from the recent national census (Uganda Bureau of Statistics, 2016), and national roads layer from Uganda National Roads Authority. All the input datasets including drivers and LULC maps were prepared in ArcGIS 10.7 and then imported into TerrSet Geospatial Monitoring and Modeling System for transformation and modelling. The multi-layer perceptron (MLP) neural network classifier in TerrSet's Land Change Modeler (LCM), which consists of a set of three units, that is, the input layer, hidden layer of computation nodes and output layer was then used to model the transitions (Eastman, 2009). MLP units are interlinked by a network of connections which work as weights (Mwanjalolo et al., 2018). For each transition from one LULC to another, a map of change potential was produced as a transition submodel. Multiple transitions are possible under the same underlying driver variables and depend on the vulnerability of the LULC to change to other land uses in which case the submodels are aggregated into one composite change potential (or transition suitability) map for that land use (Eastman, 2016). Markov module was used to simulate the LULC of 2019 using the land cover image of 2006 as a reference and transition probabilities matrix. To spatially allocate the Markov transitions, the multi-objective land allocation (MOLA) and cellular automata built in the LCM were used. Markov model validation was achieved by comparing simulated LULC map of 2019 with the actual LULC map of 2019 basing on the Kappa variations (Singh et al., 2015). Kappa variations were generated from VALIDATE module. The validated LULC map of 2019 was then used as a basis to predict LULC changes for 2029 and 2039 under the CA-Markov prediction module in the LCM of TerrSet using Markovian transition areas, transition suitability images and a standard 5x5 cellular automata filter.

3. Results and discussion

The LULC map of Mpologoma catchment of the four years is shown in Fig. 3. Overall classification accuracies and kappa statistics for 1986, 1995, 2006 and 2019 were 85.0%, 86.7%, 90.4%, 91.0% and 0.824, 0.844, 0.888, 0.906 respectively. Initially, the catchment predominantly comprised grassland, wetland, subsistence farmland and woodland (Table 3, Fig. 4). However, several changes occurred in the 1986 LULC composition; grassland experiencing the greatest net losses followed by wetland and woodland (Fig. 5). Grassland, woodland and wetland were lost per annum at rates of 5.52%, 2.47% and 0.63% (Table 3) accounting for respective total areal losses of 3279.03 km^2, 948.8 km^2, and 601.94 km^2. Net gains were observed in subsistence farming (3552.38 km^2), largescale commercial farming (15.83 km^2) and built-up (1234.24 km^2) at annual rates of 2.41%, 3.77% and 6.22% respectively. Thus, by 2019, Mpologoma catchment typically comprised expanded subsistence farming, wetland and built-up at 53.16%, 21.49% and 11.61% respectively (Fig. 4). These changes are largely attributed to the return to a more politically stable climate in Uganda that provided a peaceful environment for the communities to engage in several economic activities including agriculture. Political instability diminishes the productive and transactional capacities of the economy and increases social unrests, thus creates a fragile sociopolitical environment (Aisen and Veiga, 2013; Dalyop, 2018). Therefore, the normalcy created by political stability opened up avenues for the affected communities to resume their activities as had been the case prior to the insurgence that ravaged the region and country at large. Consequently, population increased and this could have largely impacted on the land use and land cover situation of the catchment. As revealed in the most recent national census (Uganda Bureau of Statistics, 2016) during the 33-year period considered in this study, Uganda's population nearly quadrupled from about 9 million people in 1970s to just above 34 million people in 2014 largely attributed to the enabling environment created by a politically stable climate in the country. The census report particularly shows that eastern Uganda experienced an average annual population growth rate and a population density of 3.55% and 567 persons per square kilometer respectively which are higher than the national averages. The high population growth rates and density, therefore, could have accelerated the rate of conversion of grassland, woodland and wetland ecosystems in the catchment into farmlands (Table 4) to produce food for the families and the expanding urban markets.

Results from the cross-tabulation matrices (Table 4) showed that grassland experienced highest conversion (92.77%) to subsistence farming (75%) and built-up (15.7%). Most woodland (61.86%) was converted to subsistence farming (34.7%), grassland (14.3%) and built-up (12.7%) while wetlands (483.24 km^2) were converted mainly to subsistence farming. Large-scale commercial farmland gained 15.36 km^2 from neighboring wetland and small proportions of subsistence farmland (0.17 km^2) to expand production. To predict the future LULC changes in the study area, CA-Markov model was used. The model was validated using simulated and actual LULC map of 2019. The results are shown in Fig. 6 and Table 5. Commercial farming, wetland and open water prediction showed a strong agreement between simulated and actual LULC image of 2019 (Table 5) despite some overestimations in wetland and commercial farming by 1.63% and 1.35% respectively and underestimation in open water by 2.29%. Weak agreements were shown in overestimating built-up (55.46%) and woodland (17.38%) and underestimating grassland by 16.78%. Overall, however, agreement between actual and simulated LULC maps of 2019 was high at 92.3% while error of simulation was 0.078 resulting from allocation and quantity disagreements of 0.033 and 0.045 respectively (Table 6). Other researchers have also reported varying values for the quantity and allocation disagreement. Munthali et al. (2020), for example obtained 0.01 and 0.02 for quantity and allocation disagreement while Hyandye and Martz (2017) obtained 2.24% and 6.33% respectively for the same errors. Quantity and

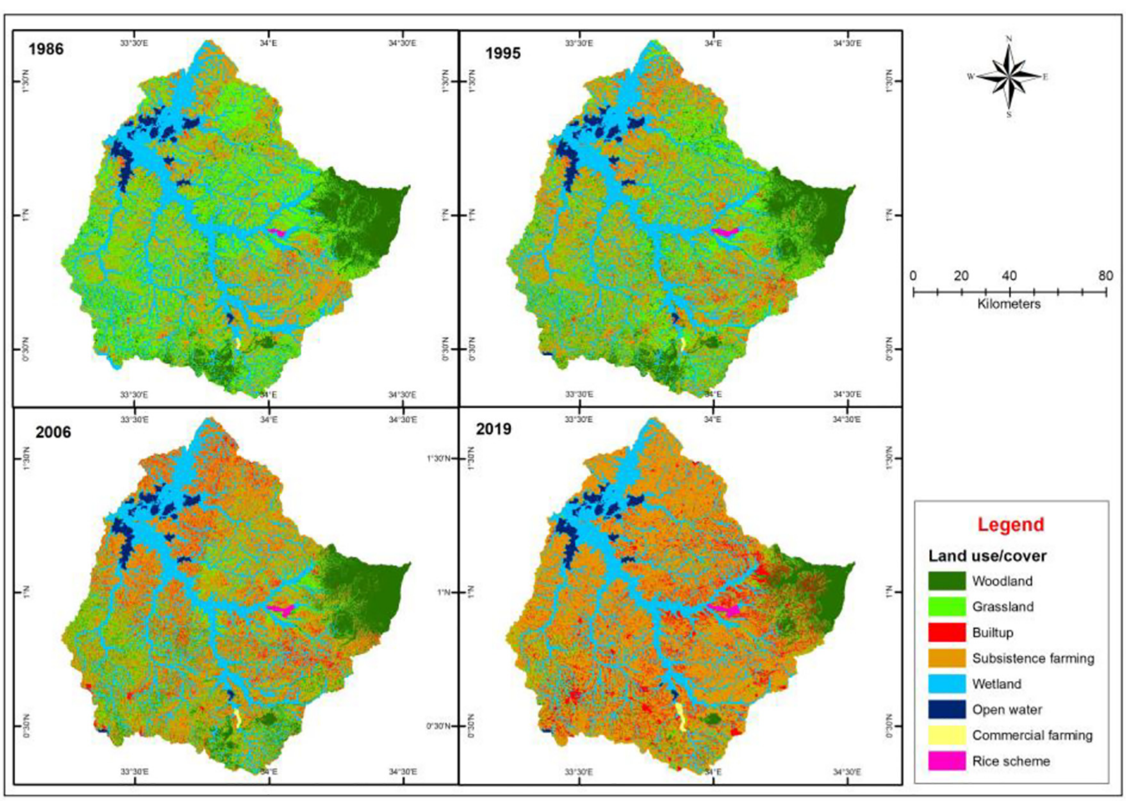

Fig. 3. LULC maps of Mpologoma catchment over the thirty-year period of investigation.

Table 3
LULC composition and change trend of Mpologoma catchment (1986–2019). Area in Km^2 and percentage (%). Change and annual change rate in percentage (%).

LULC type	1986		1995		2006		2019		Change detected (km^2)				Rate of change per annum (%)			
	km^2	%	km^2	%	km^2	%	km^2	%	1986–1995	1995–2006	2006–2019	1986–2019	1986–1995	1995–2006	2006–2019	1986–2019
Woodland	1703.77	13.97	1623.99	13.32	1538.70	12.62	754.97	6.19	9.78	−85.29	−783.73	−948.80	−0.48	−0.54	−5.48	−2.47
Grassland	3912.64	32.08	3279.93	26.90	1831.56	15.02	633.61	5.20	−632.71	−1448.37	−1197.95	−3279.03	−1.76	−5.83	−8.17	−5.52
Built-up	181.72	1.49	471.57	3.87	951.40	7.80	1415.96	11.61	289.85	479.83	464.56	1234.2	9.54	7.02	3.06	6.22
Subsistence farming	2931.24	24.04	3583.95	29.39	4789.39	39.27	6483.62	53.16	652.71	1205.44	1694.23	3552.38	2.01	2.90	2.33	2.41
Wetland	3222.26	26.42	2975.56	24.40	2815.39	23.09	2620.32	21.49	−246.70	−160.17	−195.07	−601.94	−0.80	−0.55	−0.55	−0.63
Open water	225.03	1.85	228.49	1.87	228.49	1.87	230.10	1.89	3.46	0.00	1.61	5.07	0.15	0.00	0.05	0.07
Commercial farming	6.42	0.05	7.56	0.06	12.25	0.10	22.25	0.18	1.14	4.69	10.00	15.83	1.63	4.83	4.59	3.77
Rice scheme	12.22	0.10	24.25	0.20	28.12	0.23	34.47	0.28	12.03	3.87	6.35	22.25	6.85	1.48	1.57	3.14
Total	**12195.30**	**100.00**	**12195.30**	**100.00**	**12195.30**	**100.00**	**12195.30**	**100.00**								

Table 4
Land use/cover transition matrix for 1986 – 2019 (area in Km^2).

LULC types	Woodland	Grassland	Built-up	Subsistence farming	Wetland	Open water	Commercial farming	Rice scheme	*Total 1986*
Woodland	**649.89**	244.43	216.98	591.66	–	–	0.14	0.67	1703.77
Grassland	78.61	**282.88**	613.94	2933.93	0.03	–	0.16	3.09	3912.64
Built-up	1.64	2.06	**47.7**	130.31	0.01	–	–	–	181.72
Subsistence farming	16.26	71.65	499.14	**2343.49**	0.14	–	0.17	0.39	2931.24
Wetland	8.22	31.51	37.88	483.24	**2618.53**	7.79	15.36	19.73	3222.26
Open water	0.16	0.44	0.02	0.49	1.61	**222.31**	–	–	225.03
Commercial farming	–	–	–	–	–	–	**6.42**	–	6.42
Rice scheme	0.19	0.64	0.3	0.5	–	–	–	**10.59**	12.22
Total 2019	754.97	633.61	1415.96	6483.62	2620.32	230.1	22.25	34.47	**12195.3**

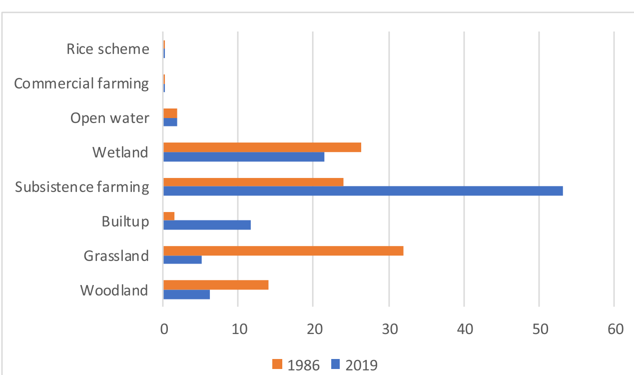

Fig. 4. Comparison of the LULC of 1986 and 2019.

allocation disagreements are absolute measures that are complements of the overall agreement (Pontius and Millones, 2011). In this study, the disagreement was more due to quantity than allocation discrepancy. Quantity disagreement results from a less than perfect match in the category totals between the actual and simulated 2019 LULC map. The allocation disagreement on the other hand, occurred because the distribution of spatial categories between the actual and simulated 2019 LULC map could have been less than the expected maximum for a perfect match (Pontius and Millones, 2011; Warrens, 2015). Researchers have asserted that the use of inadequate drivers, low quality suitability maps and validation method are key among other factors that could affect the accuracy of the LULC simulation (Hyandye and Martz, 2017; Munthali et al., 2020; Singh et al., 2015). In addition, these disagreements could also have stemmed from a less than perfect referencing of the map that was used for simulation. As such, a very accurate cell-by-cell agreement in terms of quantity and allocation of grid cells in each category could not be maximumly achieved. However, this does not mean that the model was imperfect. Results from the Kappa (K) accuracy coefficients revealed a reasonable prediction accuracy. The detailed validation results (Table 6), that is, $K_{no\_information}$, $K_{location}$, $K_{locationStrata}$, and $K_{Standard}$ of 91.29%, 95.1%, 95.1% and 89.09% showed a near perfect and thus satisfactory model accuracy. The Kappa variations, all above 80%, demonstrated a strong prediction agreement between simulated and actual LULC map of 2019(Araya and Cabral, 2010; Singh et al., 2015; Viera and Garrett, 2005). It follows that the model in this study has given a true image of how the LULC of Mpologoma catchment will be in the next two decades following its score on the Kappa coefficients. Nevertheless, for a more perfect model, conflict between the Kappa coefficients and the quantity and allocation errors should be infinitesimal. This can be achieved by maximizing cell-to-cell agreement in quantity and allocation using images with a slightly coarser resolution (Hyandye and Martz, 2017).

The modelled results have shown that the transition trend will continue through 2039 (Table 8). Subsistence farming which was the dominant LULC in 2019 is projected to also dominate in 2029 and 2039 though at comparatively reduced levels of 48.31% and 47.14% respectively (Table 7). The decrease in subsistence farming will largely be due to reduced land available for crop farming. Munthali et al. (2020) observed that agriculture in Dedza district, Malawi, would decrease over the same period due to population growth. Likewise, Kiggundu et al. (2018) asserted that high population growth in Murchison Bay catchment in Uganda had steered agriculture and other LULC changes in the catchment. However, population growth per se may not be the only problem. Efficient allocation of land resources to the competing land uses could be the major missing link (Metternicht, 2017). In particular, land use planning such as encouragement of vertical as opposed to horizontal construction is important in watersheds where development is in most cases unregulated (Appiah and Asomani-Boateng, 2020; Behera et al., 2012). Strategic land use planning will provide with dividends of sustainable utilization of ecosystem services, contribution to food security and biodiversity conservation (Bourgoin et al., 2012). Therefore, although the decline in

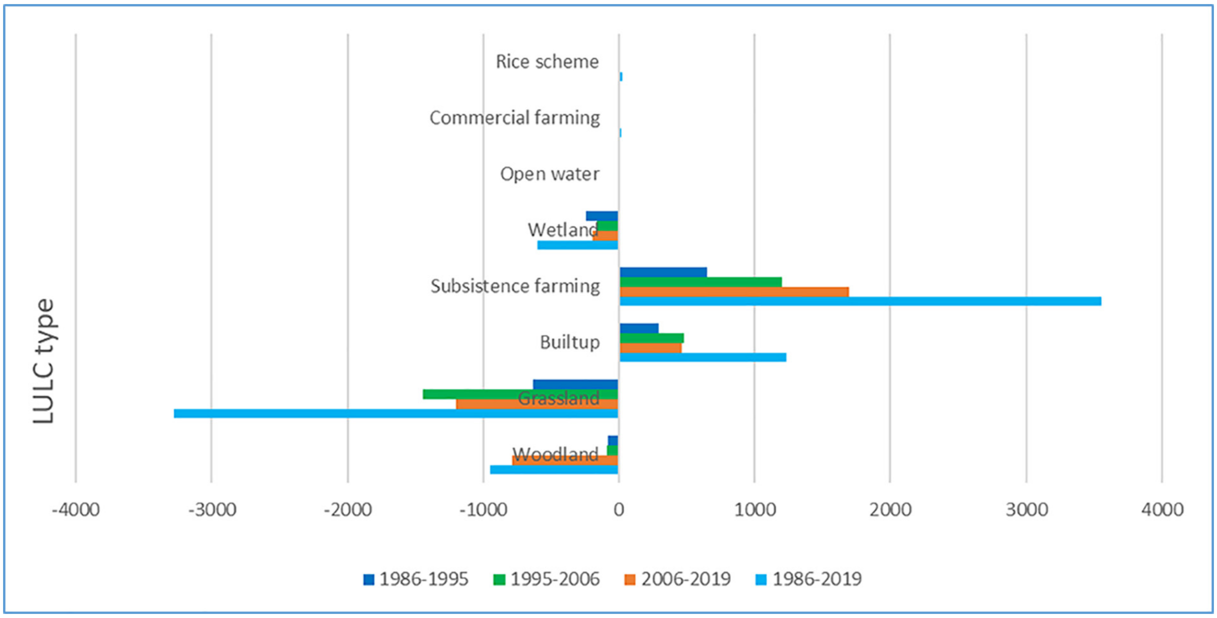

Fig. 5. Net change for each land use/cover category during the study period.

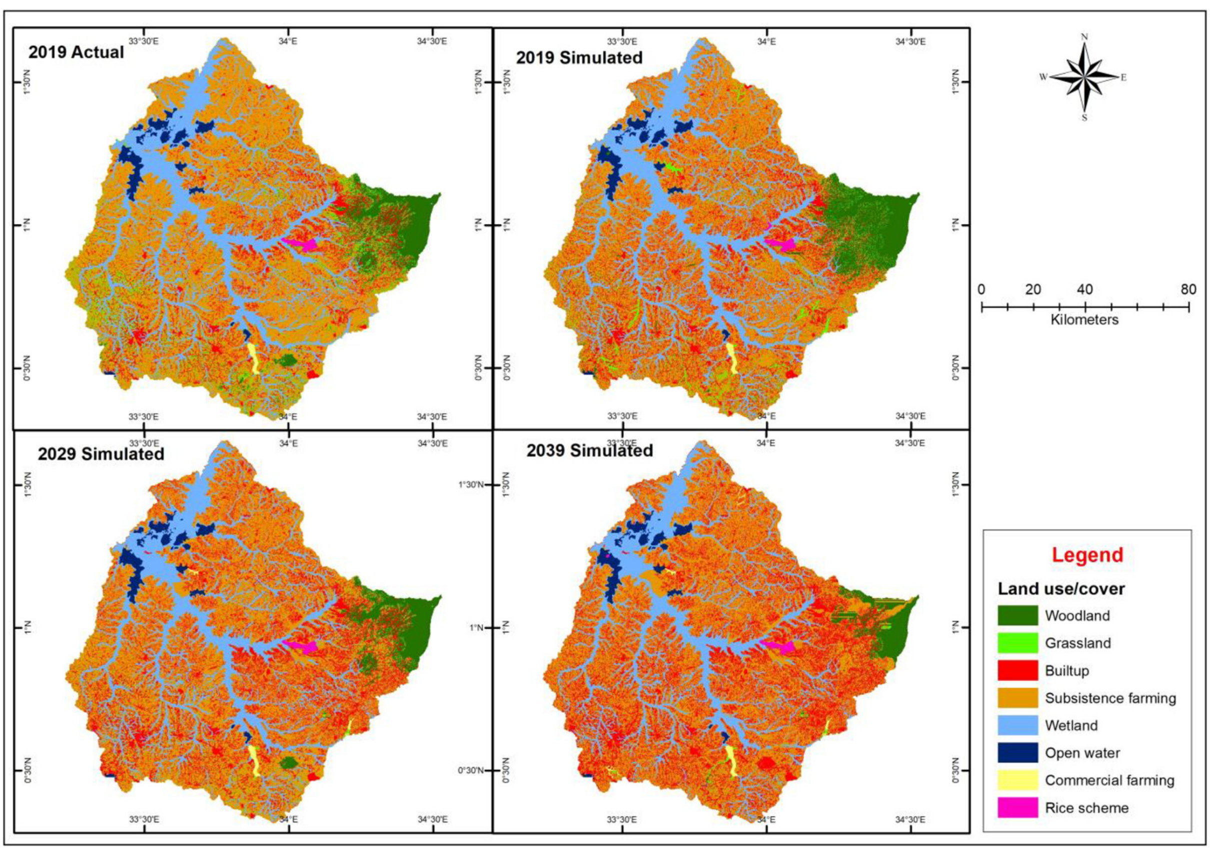

Fig. 6. Projected LULC maps of 2019, 2029 and 2039.

subsistence farmland will likely affect the feeding situation in the region, it will necessarily demand adoption of resilient smart agricultural technologies that increase food production and safeguard the environment. Radical strategies including farm redesign, conservation agriculture, use of push–pull integrated pest management technologies, agroforestry, high-yielding and climate resilient varieties will, therefore, be a means to achieving sustainable and environmentally healthy yields (Bharucha, 2020; Eyhorn et al., 2019; Pretty, 2018) A paradigm shift from subsistence to commercial farming will also bolster food and economic benefits for the farmers. These adjustments will be crucial in making progress on SDGs 1 & 2 of zero poverty and zero hunger respectively.

Table 5
Comparison of actual and predicted LULC types in 2019.

LULC type	Area (Km^2)		Extent of agreement*	
	Actual 2019	Predicted 2019	Change (Km^2)	Change (%)
Woodland	754.97	886.18	131.21	17.38
Grassland	633.61	527.27	−106.34	−16.78
Built-up	1415.96	2201.25	785.29	55.46
Subsistence farming	6483.62	5633.47	−850.15	−13.11
Wetland	2620.32	2662.92	42.6	1.63
Open water	230.1	224.84	−5.26	−2.29
Commercial farming	22.25	22.55	0.3	1.35
Rice scheme	34.47	36.82	2.35	6.82

* Difference between actual and predicted LULC proportions of each class.

Table 6
Classification agreement/disagreement.

Information of Allocation	Information of Quantity		
	No [n]	Medium [m]	Perfect [p]
Perfect [P(x)]	P(n) = 0.4765	P(m) = 0.9552	P(p) = 1.0000
Perfect Stratum [K(X)]	K(n) = 0.4765	K(m) = 0.9552	K(p) = 1.0000
Medium Grid [M(X)]	M(n) = 0.4554	M(m) = 0.9226	M(m) = 0.9031
Medium Stratum [H(x)]	H(n) = 0.1111	H(m) = 0.2915	H(m) = 0.3008
No [N(X)]	N(n) = 0.1111	N(m) = 0.2915	N(n) = 0.3008
Chance Agreement	0.1111		
Quantity Agreement	0.1804		
Allocation Agreement	0.6312		
Allocation Disagreement	0.0325		
Quantity Disagreement	0.0448		
Kappa no information	0.9129		
Kappa location	0.951		
Kappa location strata	0.951		
Kappa standard	0.8908		

The predicted results further showed that by 2029 and 2039 area under built-up will increase to 22.24% and 27.91% respectively (Table 7) mainly in previously woodland, subsistence farmland, and grassland areas (Table 8). This is partly attributed to the common tradition in eastern Uganda of parents allocating land inheritance to their male children to start marital life generation after generation. This cultural land use practice coupled with the high population growth rates in the region (Uganda Bureau of Statistics, 2016) risks further fragmentation of the limited land resource and will cause more catastrophic effects. Concerns have already emerged about the reducing bird and reptile species in the catchment (Tajuba, 2017) and will likely escalate in the near future. Therefore, national initiatives that strengthen family planning such as limiting the number of children produced per family and national housing subsidies will be paramount. Prediction results have also indicated that there will be reduced woodland and grassland cover by the end of the next two decades. This will interrupt the hydrological cycle thus exacerbate the climate conditions of this region. Reduced woodland cover will also imply low timber production for the region's construction needs, hence affected communities should start afforestation or prepare to use other construction alternatives. Similarly, reduced grassland cover will also have implications for livestock production in this region. The inadequate pasture will likely intensify land use conflicts among the people. Cattle farmers should therefore be helped to start alternative cattle farming practices such as paddocking if they are to keep in production. Given the multiple socio-economic and environmental challenges that Mpologoma catchment is likely to experience in the near future, an integrated multi-stakeholder land use management approach is recommended to help the

Table 7
LULC changes from 2019 to 2039.

LULC type	2019 Actual		2029 Predicted		2039 Predicted	
	Area(km^2)	Area (%)	Area(km^2)	Area (%)	Area(km^2)	Area (%)
Woodland	754.97	6.190664	542.72	4.450239	341.15	2.7973892
Grassland	633.61	5.195526	327.41	2.684723	158.92	1.303125
Built-up	1415.96	11.6107	2712.09	22.23881	3404.1	27.913212
Subsistence farming	6483.62	53.1649	5890.98	48.30533	5749.06	47.141604
Wetland	2620.32	21.48631	2424.88	19.88373	2229.39	18.280731
Open water	230.1	1.886792	229.5	1.881873	229.52	1.8820365
Commercial farming	22.25	0.182447	31.78	0.260592	41.25	0.3382451
Rice scheme	34.47	0.28265	35.94	0.294704	41.91	0.343657
Total	12195.3	100	12195.3	100	12195.3	100

Table 8
Transition matrix for observed 2019 and simulated 2039 LULC maps.

LULC type	Woodland	Grassland	Built-up	Subsistence farming	Wetland	Open water	Commercial farming	Rice scheme	*Total 2039*
Woodland	**328.24**	22.17	132.66	270.6	0.24	0.03	0.23	0.8	754.97
Grassland	7.45	**116.67**	293.89	214.4	0.67	0	0.12	0.41	633.61
Built-up			**1415.96**						1415.96
Subsistence farming	0.15	3.01	1492.03	**4979.83**	6.45	0	0.98	1.17	6483.62
Wetland	5.31	17	69.12	284.11	**2220.07**	1.48	17.71	5.52	2620.32
Open water	0	0.06	0.02	0.05	1.94	**228.01**	0	0.02	230.1
Commercial farming		0.01	0.01	0.02	0		**22.21**	0	22.25
Rice scheme	0	0	0.41	0.05	0.02			**33.99**	34.47
Total 2019	341.15	158.92	3404.1	5749.06	2229.39	229.52	41.25	41.91	**12195.3**

communities in Mpologoma catchment deal with environmental and livelihood challenges.

4. Conclusion

Knowledge of the historical LULC changes, patterns and future trends is important in enhancing environmental management in the concerned landscapes. This study has shown that Mpologoma catchment underwent multiple spatial–temporal LULC changes since 1986 dominated by subsistence farming. The study further predicted two-decade changes using the CA-Markov model in TerrSet's Land Change Modeler (LCM). Prediction results, continued to stress that subsistence farming and built-up will be major land use changes in Mpologoma catchment by the end of the next 20 years. Crop farming, mainly subsistence, is the mainstay of the people in Mpologoma catchment. Because the land is limited and population continues to grow higher, there is an increased risk of soil degradation including increased soil erosion, leaching, loss of soil fertility and reduced yields. The farmers should, therefore, be trained in soil conservation approaches including fallowing, use of farmyard manure, mulching and crop rotation among others. It will also be equally important to equip these subsistence farmers with skills of climate-smart agriculture and help them with agricultural inputs to increase production on their farms while reducing encroachment pressure on intact ecosystems. Besides, the government should motivate subsistence farmers with incentives to produce-for-market and reduce producing-for-the-stomach-only orientations. Furthermore, it is imperative to help farmers develop alternative sources of livelihood to crop farming. Crop farming has become a risky venture in the region due to prolonged droughts that often leave farmers without any meaningful harvests. Thus, ventures into animal husbandry including poultry should be encouraged to boost the economic power of the communities.

Furthermore, it is equally important to emphasize that since future LULC conversion will continue to reduce the amount of land cover (grassland, woodland and wetlands) and replace it with subsistence farming and built up, the communities in this catchment should prepare for adverse climatic conditions. These adverse conditions will continue to affect community livelihood. Therefore, local and central governments should put in place and monitor measures to curtail environmental degradation such as afforestation and wetland restoration among others. Local authorities should ensure that every home plants at least ten trees, the seedlings of which should be provided to the communities free of charge. Additionally, infrastructural development in the catchment, especially the growing urban centers, should be well planned with particular emphasis on retaining some green belts around urban centers and promoting green cities. It follows that urban farming will, therefore, also be an opportunity to exploit due to rapid emergence of urban centers in the catchment coupled with the associated demand. Implementation of a suit of pro-environmental policies will, therefore, reduce pressure on natural ecosystems thereby contributing to environmental sustainability.

The prediction of LULC change using the Land Change Modeler (LCM) of TerrSet Geospatial Monitoring and Modeling system is the first one of its kind in Mpologoma catchment. And, since the validation results (Kappa variations) for the simulated and actual LULC maps were in strong agreement, this model is recommended for LULC predictions in other catchments. Policy makers and land use planners could therefore take advantage of its predictive ability to shape future LULC policies in Uganda's catchments with similar LULC challenges as Mpologoma watershed. However, since this study used the BAU assumption, more research should be conducted on this catchment and similar ones in the country using other socioeconomic and environmental policy scenarios such that the best empirical scenario is adopted for sustainable management of watersheds in the country.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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