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Modelling Land Use/Land Cover Change of River Rwizi Catchment, South-Western Uganda Using GIS and Markov Chain Model

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Abstract

Analysis of catchment Land use/Land cover (LULC) change is a vital tool in ensuring sustainable catchment management. The study analyzed land use/ land cover changes in the Rwizi catchment, south western Uganda from 1989-2019 and projected the trend by 2040. Landsat images, field observations, key informant interviews and focus group discussions were used to collect data. Changes in cropland, forestland, built up area, grazing land, wetland and open water bodies were analyzed in ArcGIS version 10.2.2 and ERDAS IMAGINE 14 software and a Markov chain model. All the LULC classes increased in area except grazing land. Forest land and builtup area between 2009-2019 increased by 370.03% and 229.53% respectively. Projections revealed an increase in forest land and builtup area by 2030 and only built up area by 2040. LULCC in the catchment results from population pressure, reduced soil fertility and high value of agricultural products.

Keywords

Land Cover, River Catchment, Geographic Information System, Markov Model, Sustainable Land Management

1. Introduction

Land use/land cover change (LULCC) involves the inter-conversions of the land cover types by humans [1] [2] [3] influenced by biophysical and human factors. Agricultural land is the most vulnerable to these changes [4] [5] thus analysis of LULCC is vital for sustainable development [6] [7] Assessing past rates and trends of land cover change enhances better understanding of the current and accurate prediction of future trends which is a precursor for proper planning and practices for land and water resources' management [8]. The world's water resources are strongly influenced by changes in land cover as it affects evaporation, infiltration, and overland runoff; all of which control availability of water for human and other ecological services [9] [10]. The cross-cutting nature of land and water resources gives credence to the relevance of land use/land cover change analysis in agriculture and industrial development in both time and space. This can best be understood by using a modelling approach [11]. These models enable the interpretation of the causes and likely consequences of observed land use trends which is relevant for well thought out management policies and decisions [12]. A detailed analysis of land use/land cover changes in Uganda [13], established that population increase and distribution in an area are the key leading drivers of these land cover inter-conversions and their impacts are peculiar to individual sites. River Rwizi covering a catchment of about 8346 km^2 supports livelihoods of more than five million people but has dried up by about 80% due to catchment-based degradation [14] [15] [16]. The degradation of the river is a cross cutting challenge to river systems country wide and is attributed to the land management systems on the river banks and buffer zones [17] [18]. The high inflow of untreated effluent and increased river pollution plus unsustainable agricultural and other economic activities are causing a deterioration in water quality and quantity. This is exacerbated by the rapid population growth in the catchment districts from 1,878,491 (1992) to 2,451,111 (2002) and 3,366,153 (2014) [19], hence increased demand for water from the river and other resources like sand and cultivation along the river banks causing the observed drying up [20] [21] [22]. The catchment population is projected to grow to 7,910,456 by 2040 [23], which is likely to worsen the situation. These coupled with the effects of climate variability has negatively affected human livelihoods, increased poverty and frustrated industries in the region due to water shortage and rationing. For example, the Nile Breweries plant in Mbarara City receives only 10% of its water demand from river Rwizi [24] [25]. Previous analyses of Land use/land cover change in the Rwizi catchment reveal two knowledge gaps; disregarding the impact of the changes on the entire catchment and downscaling the analysis to the level of the district, since individual district local governments draw budgets every financial year based on their priorities and threats. This study thus analyzed LULCC for the entire catchment and also scaled it down to the district level. The results provide baseline data and justification for the incorporation of the district level as a vital unit in catchment management planning. The study analyzed Rwizi catchment LULCC rate and trend between 1989-2019 in three ten-year intervals, analyzed river flow for the same period and evaluated land management practices in the catchment. The status of the catchment land cover by 2040 was predicted using a Markov chain model. This is due to its effectiveness in modelling probability of spatio-temporal change in land cover along with GIS [26] [27]. A soil water assessment tool (SWAT) model was used to model river flow [28] [29] [30], and sustainable catchment land management options were designed according to [31] [32]. The overall aim of this research was to analyze the spatio- temporal land use/land cover changes of the Rwizi catchment and use the findings to contribute to sustainable catchment land management policy and practices so as to improve and sustain the use, flow and ecological value of the river.

2. Materials and Methods

2.1. Area of Study

Rwizi catchment lies in South- western Uganda between 29˚55'E 0˚55'S and 30˚55' 0˚16'S. River Rwizi originates from Buhweju hills (S00˚21.983', E030˚26.363') and Ntungamo hills (S00˚45.151', E030˚20.139'). It then flows downstream through Sheema (S00˚35.907', E030˚21.726') and Mbarara (S00˚37.095', E030˚38.630') and continues draining into lakes Nakivale in Isingiro and lake Kakyera in Lyantonde then to Lake Victoria through river Kagera, as shown in **Figure 1**. The catchment lies between 1300 - 2170 meters above sea level with annual precipitation of 690 mm - 1300 mm per year, experiencing two rainy and two dry seasons.

2.2. Data Acquisition

Satellite images for the years 1989, 1999, 2009 and 2019 (**Table 1**), with a 30 m spatial resolution were processed and analyzed for LULCC of the catchment. Landsat data were downloaded from U.S Geological Survey (USGS) center for Earth Resources Observation and Science (EROS) (http://earthexplorer.usgs.gov/). ASTER GDEM measuring 30 m per cell was also obtained from Aster Global Digital Elevation Map (http://gdex.cr.usgs.gov/gdex/), Rwizi flow data was obtained from the Directorate of Water Resource Management (DWRM), rainfall and temperature data was obtained from Uganda National Meteorology Authority (UNMA), population, production and other district specific data was obtained from Uganda Bureau of Statistics (UBOS) and Ministry of Agriculture Animal Industry and Fisheries (MAAIF), soil data was obtained from FAO, and district statistical abstracts were also used to obtain supplementary district specific data. Primary data was obtained from field visits/observations, key informant interviews and focus group discussions.

Table 1. Features of the satellite images for the years 1989, 1999, 2009 and 2019.

Agency	Satellite image	Path/row	Sensor	Resolution/scale (cm)	No. of bands	Date of acquisition	Cloud cover
SPOT	SPOTX	P173-R61, P173-R60, P173-R60, P172-R61	SPOTX	30	3	5th April, 1989	0
USGS	LANDSAT (AFRICOVER)	P173-R61, P173-R60, P173-R60, P172-R61	LANDSAT	30	3	9th April, 1999	0
USGS	LANDSAT 5	P173-R61, P173-R60, P173-R60, P172-R61	LANDSAT	30	5	4th April, 2009	0
USGS	LANDSAT 8		LANDSAT	30	6	1st April, 2019	0

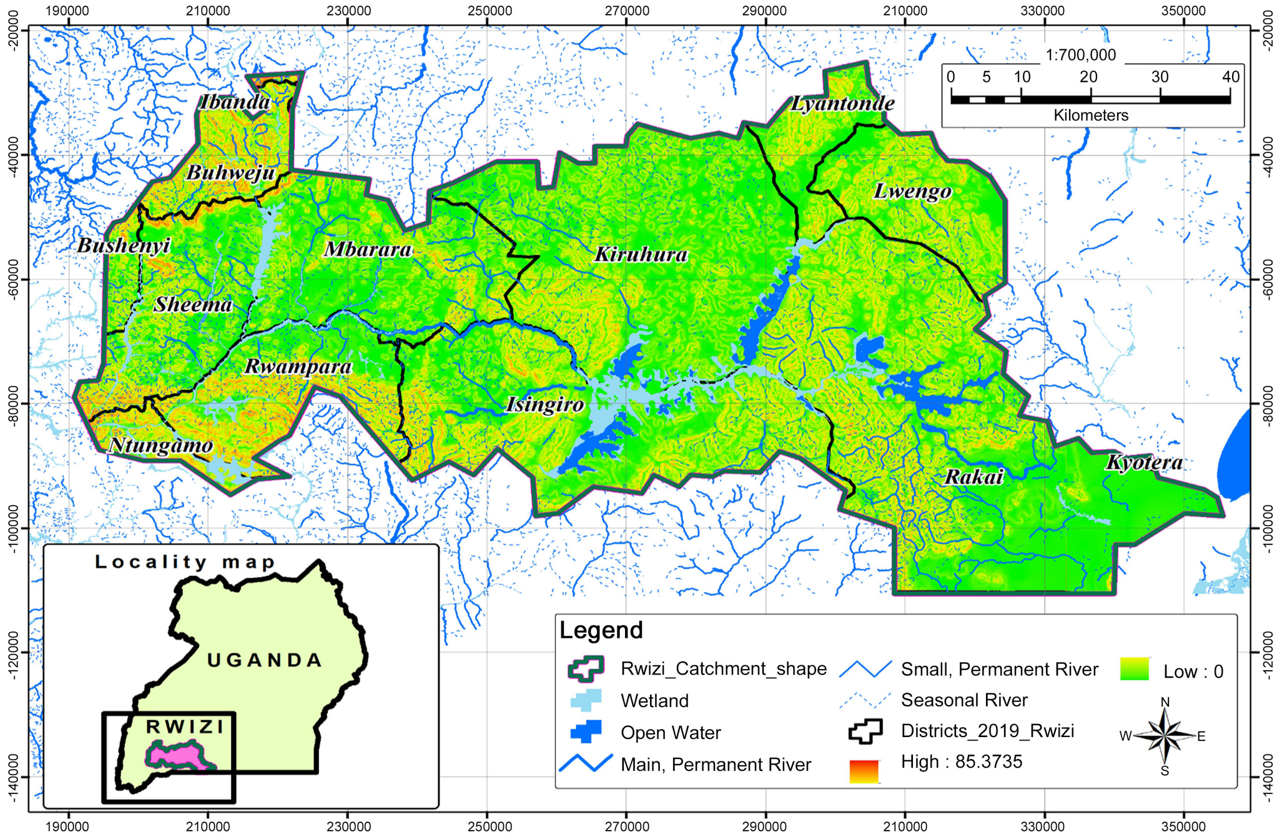


Figure 1. Map of the Rwizi catchment.

2.3. Data Preparation and Image Pre-Processing

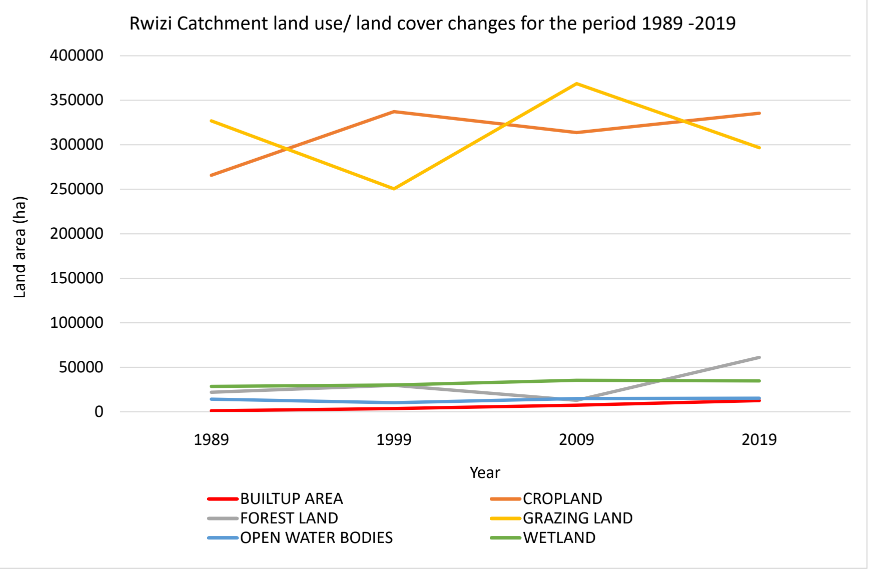
Data preparation involved unzipping of the downloaded images and combining selected bands (2, 3, 4, 5, 6, and 7) and stacking them to create multi-band images. Landsat image synthesis and classification was done in QGIS using random forest classifier algorithm. This clipped out the area of interest from the composite image which was then classified into different land use/cover categories (Table 2).

2.4. Image Classification

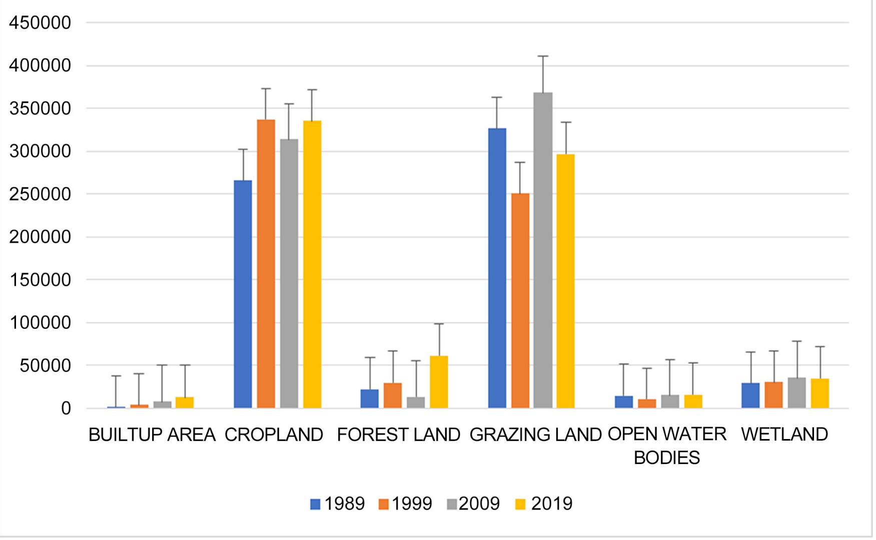
The software used for image processing was ArcGIS 10.2.2 and ERDAS IMAGINE 14. Before georeferencing to a datum in which river Rwizi falls, the images were first converted into Universal Transfer Mercator and image quality was improved by applying histogram equalizations. Thereafter, classification of the Rwizi catchment land cover classes was done followed by detection of change between 1989-2019 as well as between each ten year interval and catchment land cover maps for the four satellite years drawn as shown in Figure 3. Supervised image classification was used because of prior knowledge about activities and features of the catchment. The classification was done using Random Forest Classifier algorithm due to its robustness and high level accuracy when handling large data quantities [33] [34]. The obtained land cover classes are described in Table 2 below.

Table 2. Description of the Rwizi catchment Land use/cover types.

S/No.	Class	Features
1	Built up area (BA)	Land allotted for buildings and construction sites.
2	Crop land (CL)	Land allotted for annual and perennial crop cultivation.
3	Wetlands/swamps (WL)	Valley land with flowing water seasonally or permanently, with vegetation being predominantly papyrus, sedges and grass.
4	Grazing land (GL)	Area with grass mainly savannah grassland, shrubs, thickets supporting animal farms/herds and other abandoned previously cropland.
5	Open water bodies (OWB)	Lakes, rivers, valley tanks, ponds, open streams
6	Forest land (FL)	Natural and artificial plantation forests

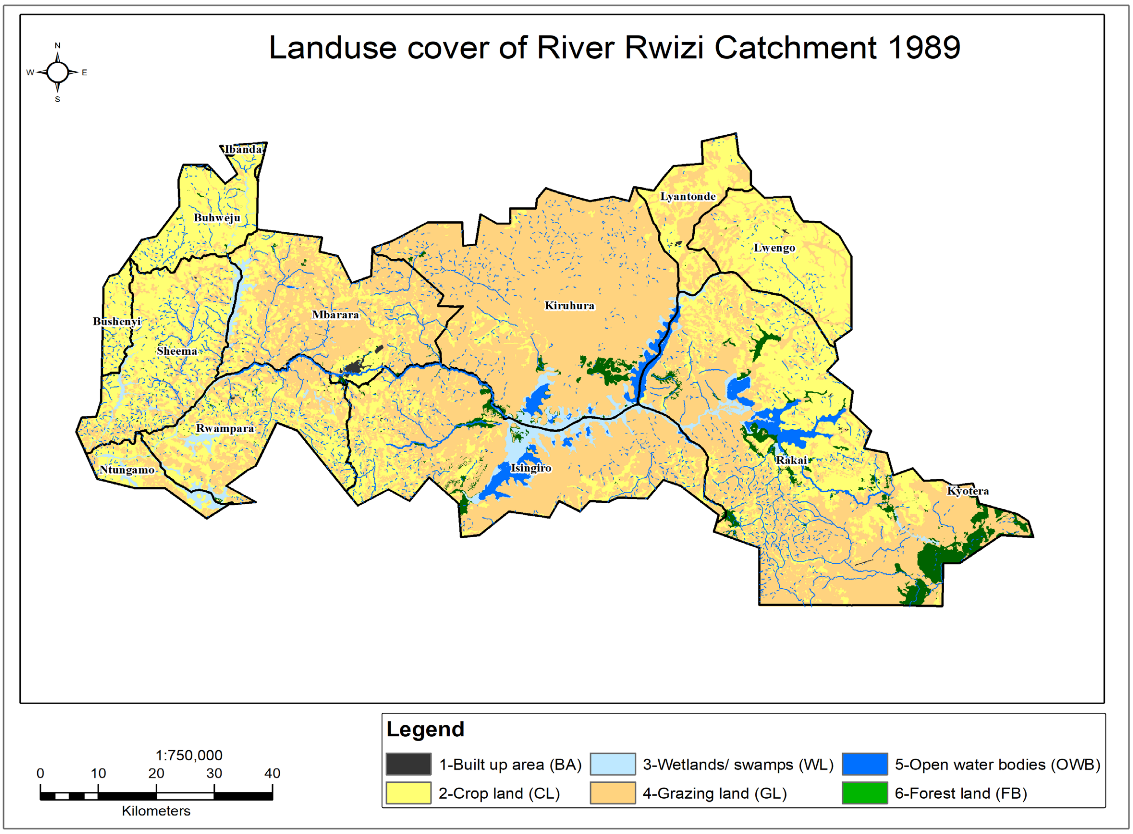


(a)

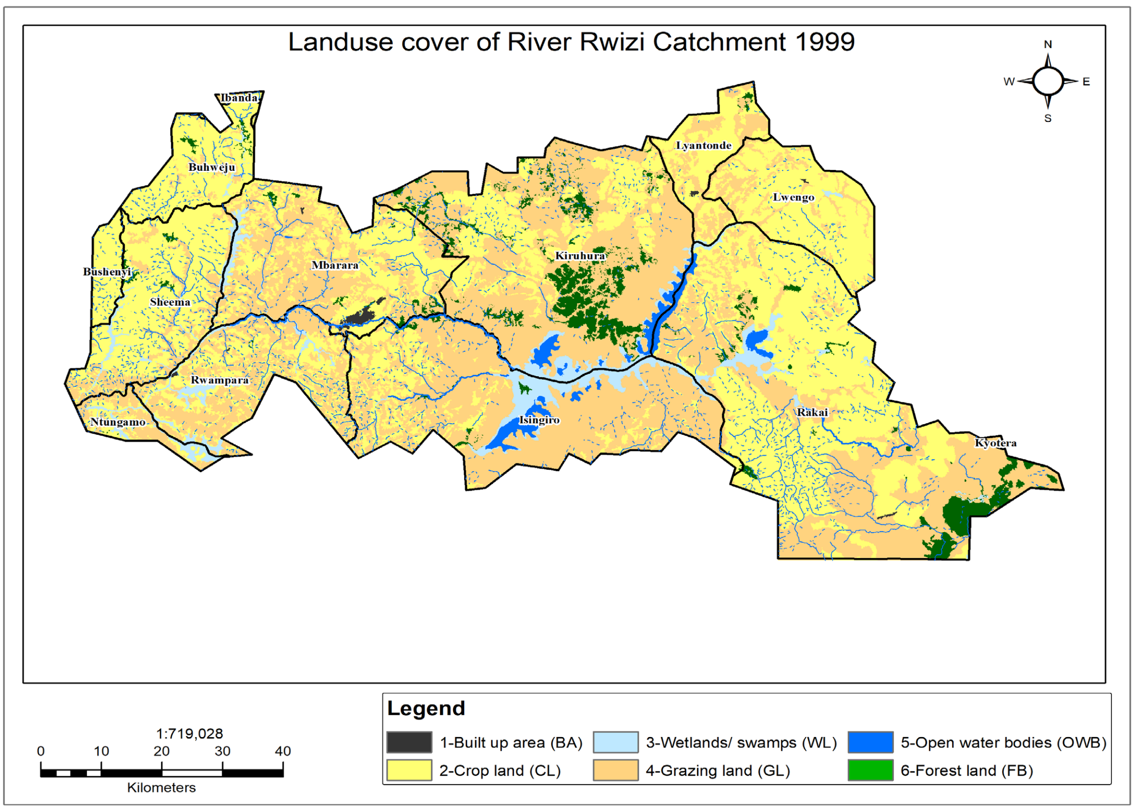


(b)

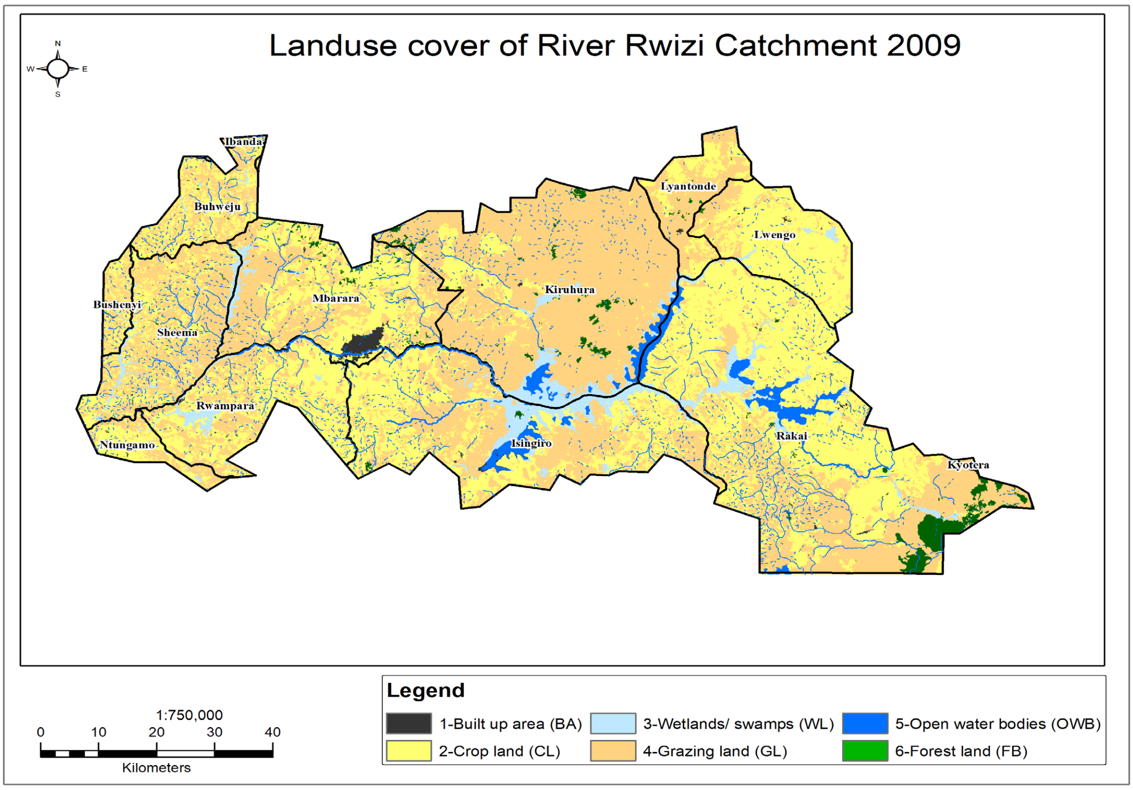
Figure 2. (a) Graph showing Rwizi catchment land use/land cover change trend through 1989, 1999, 2009 and 2019. (b) Graph showing Rwizi catchment land use/land cover change trend through 1989, 1999, 2009 and 2019.


Landuse cover of River Rwizi Catchment 1989
N
W
E
S
Ibanda
Buhweju
Lyantonde
Lwengo
Bushenyi
Sheema
Mbarara
Kiruhura
Rwampara
Ntungamo
Isingiro
Rakai
Kyotera
1:750,000
0
10
20
30
40
Kilometers
Legend
1-Built up area (BA)
2-Crop land (CL)
3-Wetlands/ swamps (WL)
4-Grazing land (GL)
5-Open water bodies (OWB)
6-Forest land (FB)

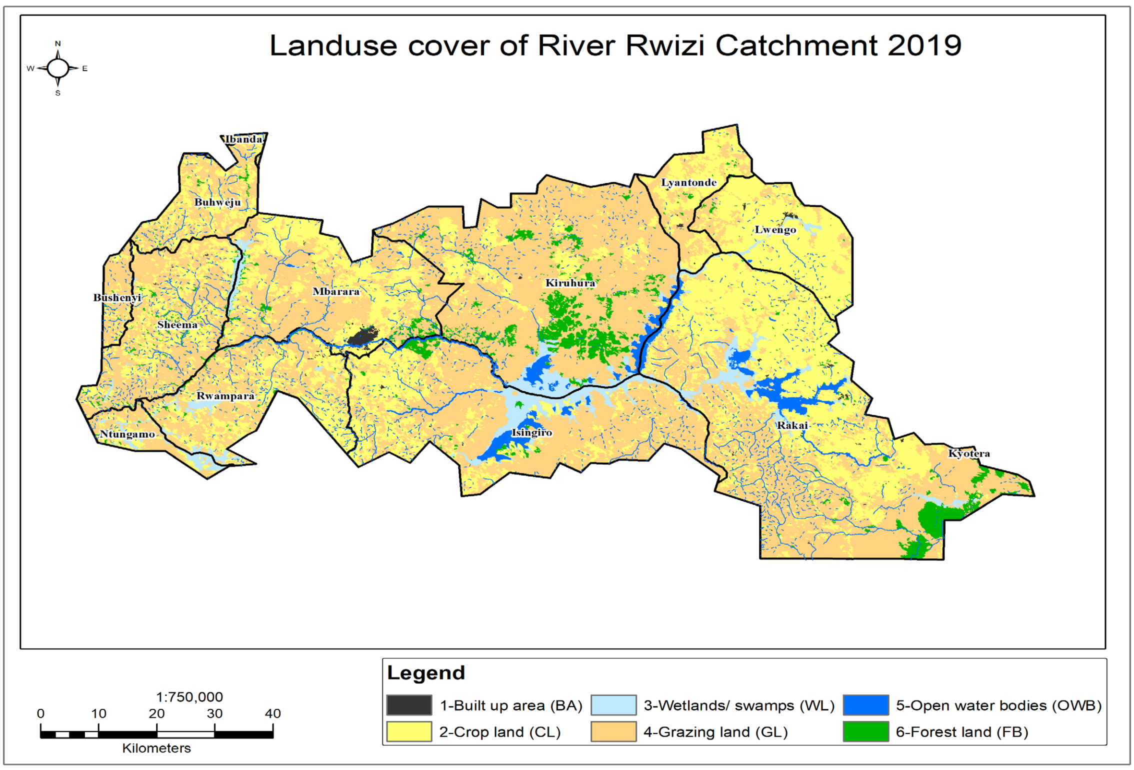
(a)


Landuse cover of River Rwizi Catchment 1999
N
W
E
S
Ibanda
Buhweju
Lyantonde
Lwengo
Bushenyi
Sheema
Mbarara
Kiruhura
Rwampara
Ntungamo
Isingiro
Rakai
Kyotera
1:719,028
0
10
20
30
40
Kilometers
Legend
1-Built up area (BA)
2-Crop land (CL)
3-Wetlands/ swamps (WL)
4-Grazing land (GL)
5-Open water bodies (OWB)
6-Forest land (FB)

(b)



(c)



(d)

Figure 3. (a) Rwizi catchment land use/land cover map of 1989. (b) Rwizi catchment land use/land cover map of 1999. (c) Rwizi catchment land use/land cover map of 2009. (d) Rwizi catchment land use/land cover map of 2019.

2.5. Validation

This process was done to identify the segments that were not classified correctly. Due to the fact that training samples were not picked from every segment, there were some segments that had wrong classes. The methods used to perform validation involved integrating a number of satellite imagery from ESA-Sentinel-2 images for 2019 land cover and other sources such as Google Maps, Bing maps and also the use of expert judgement based on the experiences about the subject area. The final LULC map obtained in ERDAS IMAGINE was fine-tuned by the Clump and Eliminate process. This process was important as it removes sliver polygons.

2.6. Accuracy Assessment

This was done to ascertain the reality on the ground and measure precision of the classified maps, and used randomly sampled reference data for LULC for the years 1989, 1999, 2009 and 2019. Accuracy was assessed using producer accuracy, user accuracy, overall accuracy and kappa coefficients [35] [36] [37]. Overall accuracy was calculated using Equation (1) while kappa coefficient was calculated using Equation (2).

$$\text{Overall accuracy} = \frac{1}{N}\sum_{i=1}^{n} x_{ii} \quad (1)$$

where, x = individual cell values, x_{ii} = the total number of observations in row i and column i, n = total number of classes, N = total number of samples.

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

where, K is Kappa coefficient, r is the number of rows in the matrix, x_{ii} is the number of observations in row i and column i, x_{i+} are the marginal totals of row i, x_{+i} are the marginal totals column i, and N is the total number of observations. The computed overall accuracy of the maps was 84.46% (1989), 89.69% (1999), 90.64% (2009) and 90.76% (2019); and kappa coefficients of 0.80 (1989), 0.83(1999), 0.84 (2009) and 0.85(2019) (**Table 3**). All overall accuracy values (84.46% - 90.76%) and kappa indices (0.8 - 0.85) fell in the range that indicates very good representation of ground truth by the images *i.e.* above 85% and (0.70 – 0.85) [38], thus the validation data set reveals very good accuracy of the classified maps.

The formula used to calculate overall accuracy has limitations; when the degree of variation between sensitivity and specificity rises and/or when the prevalence moves away from 50%, overall accuracy presents significant challenges as a validity indicator. The overall accuracy and either sensitivity or specificity deviate more and more in both cases.

Limitations of using Equation (2) and kappa coefficient for accuracy assessment

One statistical metric that is frequently used to evaluate the precision of image classification is the kappa coefficient. When analyzing the results, one should

Table 3. Accuracy assessment of the 1989, 1999, 2009 and 2019 classified images.

Land cover category	1989		1999		2009		2019	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Built up area	87.0	85.0	89.0	88.5	96.35	86.27	94.8	85.72
Cropland	80.95	97.14	82.75	95.5	96.49	74.85	94.95	86.91
Forest land	79.08	74.0	87.8	84.0	91.78	93.5	90.08	96.35
Grazing land	90.48	82.61	89.95	88.3	82.48	94.61	89.9	82.06
Open water bodies	95.0	92.5	92.4	95.65	100	95.0	95.59	97.1
Wetland	79.74	70.0	92.68	89.74	86.27	90.0	88.83	84.68
Overall accuracy	84.46		89.69		90.64		90.76	
Kappa coefficient	0.80		0.83		0.84		0.85	

keep in mind that it has certain limits. A research paper [39] claims that the kappa coefficient measures the degree of agreement between a classification and a reference dataset over and beyond what would be predicted by chance, rather than the quality of an image classification. The kappa coefficient's sensitivity to the prevalence of various classes in the dataset is one of its primary drawbacks. Furthermore, because the kappa coefficient's magnitude might have a large range of values that don't always correlate to different levels of accuracy, it can be challenging to interpret.

In conclusion, the kappa coefficient should be utilized cautiously and its limits should be considered when interpreting its results, even if it might be a valuable indicator of agreement between an image classification and a reference dataset.

2.7. Change Analysis

The aim of this was to quantify the rate and trend of land use/land cover from the remotely sensed data at different times. Markov chain model in Idrisi software and Land Change Modeler, incorporating Random Forest Classifier Algorithm were used to compute the extent of change in each land cover class, obtained from Landsat photos of the catchment for the years: 1989, 1999, 2009 and 2019. The Land Change Modeler is a robust tool in analyzing spatial change, net change and its drivers as well as change trends and forecasts.

Transition Potentials

This parameter facilitated computation of the area of change. If the underlying sources of change for each transition were common, their transitions were grouped together into sub-models and the changes in land cover influenced by the same variables were also grouped into a sub-model. This process involved deciding transitions to be modelled based on similarity of driver variables followed by collecting transition potential maps. The variables input in the model were either static if they didn't change over time for example elevation or slope or were dynamic if they changed over time taking an example of infrastructure and proximity to existing developments. This transition was run by using the process embedded in the Multi-Layer Perceptron (MLP).

2.8. Change Prediction

The Land Change Modeler (LCM) incorporating Markov chain were used for land cover prediction. The LCM based on artificial neural network, Markov chain matrices and transition suitability maps predicts changes from the thematic raster images having the same number of classes in the same sequential order. This model was used to forecast the future land cover changes in the Rwizi catchment for the years 2030 and 2040. In complimenting the LCM, Markov chain model represents a stochastic approach to LULCC modeling. It projects future land use/cover by using transition probability matrix and transition area matrix from time t =1 to time t + 1. The product matrix is a measure of the degree of chance that a land cover class converts to another one during the stated interval. Transition probability maps are estimates of the probability of converting each pixel into a different land cover class or remain unchanged over annual time steps.

The model was constructed by considering factors and constraints; where factors favour conversion to another class and constraints hinder conversion to a given class [40] [41], among these were: suitability for conversion to another class, distance to towns, distance to major roads, elevation, slope and proximity to water bodies (**Table 4**). The suitability for conversion was measured on a scale from 0 (no likelihood of conversion) to 1 (high likelihood of conversion). The ranks were arrived at by synthesising data from key informant expert opinions, Focus Group Discussions and desk review of several secondary documents. It was observed that conversion to cropland and built up area had slope as a key

Table 4. Factor/constraint rankings for land use conversions.

Land category	Factors	Factor weight	Consistency ratio	Constraint and classes considered
Cropland	• Suitable areas for conversion to cropland • Proximity to urban centers • Proximity to water bodies • Elevation	0.5544 0.2835 0.1112 0.0509	0.02	Slope (>13" -58")
Forest land	• Suitable forest land • Proximity to developed land • Elevation	0.6942 0.2103 0.0955	0.01	Slope
Grazing land	• Suitable grazing land • Proximity to developed land • Elevation	0.6370 0.2583 0.1047	0.03	Slope
Wetland	• Proximity to developed land • Elevation	0.2970 0.1634	0.02	Slope
Built up area	• Suitable built up area • Proximity to towns • Proximity to major roads • Elevation	0.4312 0.2703 0.1724 0.0794 0.0467	0.04	Slope (>13" - 58")
Open water bodies	• Suitable areas for conversion to open water bodies • Distance to towns • Elevation	0.5396 0.2970 0.1657	0.04	Slope

Model validation

For any modeling activity, model validation is a vital step [2] [42] [43] [44]. To ascertain the suitability of the Markov model in predicting future land changes, model validation was done [45] [46] [47] by simulating the 2019 LULC status with the help of the 1999 and 2009 processed images. There after the simulated and actual land cover maps for the year 2019 were compared using the VALIDATE tool of IDRISI module. Furthermore, kappa indices namely: $K_{location} = 0.9554$, $K_{standard} = 0.9275$, $K_{location\ strata} = 0.9345$ and $K_{no} = 0.9421$, were applied to validate the predictive accuracy of the model.

2.9. Detection of Land Cover Change and Its Interpretation

LULCC analysis is key in exhibiting patterns of change that informs the need and direction for sustainable land management practices, policies and decision making. This required at least two satellite imagery years [48] [49], from which computed land area for the different categories was analyzed to compute the percentage land cover change [50] as well as the annual rate of land cover change per decade and for the entire thirty year period using Equations (3) and (4) respectively. Furthermore, rate and trend of LULC change was projected for the periods 2019-2030 and 2030-2040 and interpreted accordingly. The named changes can be determined by using the following ways [51].

Total LULC change in hectares calculated as: Total LULCC = Area of a final year − Area of initial year. Positive values denote an increase while negative values denote a decrease.

Percentage LULC change calculated using the following equation:

$$\text{Percentage of LULCC} = \frac{\text{Area of a Final Year} - \text{Area of Initial Year}}{\text{Area of Initial Year}} * 100\% \quad (3)$$

- An annual rate of LULC change: computed as:

$$r = \frac{Q2 - Q1}{t} \quad (4)$$

where r = the rate of change, $Q2$ = recent year LULC in ha, $Q1$ = initial year LULC in ha, and t = interval year between initial and recent year.

Drivers of LULC changes, were assessed using key informant interviews with district and catchment management experts and focus group discussions with farmers and large-scale landlords.

3. Results

3.1. Land Use/Land Cover Change Rate and Trend for the Period 1989-2019

Land use land cover (LULC) change rate and trend for the period 1989-2019 in the Rwizi catchment, showed a total increase of 947.19% for built up area, 171.80% for forestland, 25.74%, for cropland 21.47% wetland and 4.43% open water bodies, with a decrease registered only in grazing land (−29.73%), (**Table 5**). Maps of the Rwizi catchment showing the extent of different land use/land cover classes in the four satellite years (1989, 1999, 2009 and 2019) were drawn as shown by **Figures 3(a)-(d)** respectively. However, each land use/land cover showed varying trends of change in each of the three decades (**Table 5**). Built up area increased continuously from 0.18% of the total catchment area in 1989 to 1.67 % by 2019. During the periods 1989-1999, 1999-2009 and 2009-2019 built up area increased by 28.82%, 146.68% and 229.53% respectively, and increased by 381.819 ha/year (**Table 6**).

Built up area registered highest percentage increase of 229.53% between 2009-2019, attributed to elevation of several administrative units to Town council, Municipality and City stati, as mentioned by majority of the respondents, and Mbarara District showed the highest rate of increase across all decades. Cropland area showed cyclic changes (**Table 5**), with 1989-1999 showing the highest rate of increase, with an annual rate of change of 2288.35 ha/year. Forestland area increased highest between 2009-2019 and overall change rate was 1287.43 ha/year. The sharp decline in the period 1999-2009 was due to pressure for fuel wood for many upcoming small scale industries, human settlement, more land for crop cultivation and clearing forests for construction materials owing to the anticipated elevation of administrative units attracting peri- urban settings. From interviews and focus group discussions, the highest percentage increase (370.03%) (2009-2019) was as a reversal to the drastic impacts of deforestation in the previous decade, where all district local governments embarked on a large-scale re-afforestation campaign. Grazing land changed cyclically (**Table 5**). The decade percentage change was only positive in the 1999-2009 period, though overall change rate was −4183.183 ha/year. The decline in grazing area in the last decade was attributed to the shift to zero grazing, food security at household level and commercial crop husbandry which required less land area than traditional grazing. Open water bodies area decreased only between 1989-1999, (**Table 5**), and overall change rate was 21.66 ha/year, while Wetland area only decreased between 2009-2019 (**Table 5**), and the overall change rate was 204.15 ha/year. According to key informants and focus group discussants,

Table 5. Land use/land cover area and percentage for the years 1989, 1999, 2009 and 2019.

Year	1989		1999		2009		2019	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Builtup area	1208.7	0.16	1557.09	0.21	3841.02	0.51	12657.42	1.67
Cropland	266701.9	35.29	340136.55	45.01	317059.56	41.96	335352.33	44.37
Forest land	22482.09	2.97	29793.24	3.94	13000.32	1.72	61105.86	8.09
Grazing land	422155.2	55.86	342804.69	45.35	370445.58	49.02	296659.71	39.25
Open water bodies	14663.79	1.94	10191.6	1.35	15002.1	1.99	15313.59	2.03
Wetland	28527.75	3.78	31256.19	4.14	36297.9	4.80	34652.25	4.59
TOTAL	755739.43	100	755739.36	100	755646.48	100	755741.16	100

Table 6. Percentage change between 1989-1999, 1999-2009, 2009-2019 and 1989 to 2019.

Land use/land cover	Percentage change			
	1989-1999	1999-2009	2009-2019	1989-2019
Built up area	28.82%	146.68%	229.53%	947.19%
Cropland	27.53%	−6.78%	5.77%	25.74%
Forest land	32.52%	−56.36%	370.03%	171.80%
Grazing land	−18.80%	8.06%	−19.92%	−29.73%
Open water bodies	−30.50%	47.20%	2.08%	4.43%
wetland	9.56%	16.13%	−4.53%	21.47%

the observed decline in wetland cover in 2009-2019 was attributed to encroachment for industrial parks, prolonged drought, a rise in population and increased demand for food that led to increased shortage of land for cultivation and loss of soil fertility in the available arable land but with no financial capacity to rejuvenate it, and people across the divide resorted to encroachment on wetlands for cultivation of seasonal crops.

An analysis of the annual rate of land cover change in hectares per year (**Table 7**) established that grazing land showed the highest rate (1999-2009) followed by cropland (1989-1999) and forest land (2009-2019). The three major land cover types showing maximum annual rate of increase in different decades point to a shift in policy that promote different priority investments inconsistently. Builtup area and wetland area showed the highest Pearson correlation coefficients between inter-decade annual rates of change and the highest R^2 values all showing that builtup area and wetland area changes are largely explained by a change in time in years, while other land cover changes are explained by other factors not largely time series.

These research findings conform to results from previous studies; [52] [53] [54] [55] [56], all in the upper Rwizi catchment, where cropland, built up area and forestland increased overall while grazing land and wetland area decreased. Further investigations by [57] [58], in the Mt. Elgon catchment, [59], in somodo watershed south western, Ethiopia, [60], in Tana River Basin, Kenya, [44], in Kilombero catchment in Tanzania, [61], in the Gaborone dam catchment, Botswana , [56] [62], in the uMngeni river catchment, South Africa and [63], in the Andassa watershed in the Upper Blue Nile basin of Ethiopia, all reported a positive change in cropland and built up area while grazing land registered a negative change, forest cover increased in some and decreased in others in their respective analysis periods. The observed trends point to a high degree of universality in both proximate and underlying drivers of land cover changes across different spatial distributions in Africa.

3.2. Discussion

3.2.1. Reflection on Land Cover Conversions

Generally, cropland and grazing land dominated all the land cover classes in the

Table 7. Annual rate of land use/land cover change in hectares (ha/year).

Land use/land cover	Annual rate of change (ha/year)				Pearson	R^2
	1989-1999	1999-2009	2009-2019	1989-2019		
Built up area	248.041	377.054	520.361	381.819	0.992975	0.986
Cropland	7148.277	−2348.25	2167.746	2288.35	0.658703	0.43389
Forest land	774.072	−1679.26	4816.404	1287.43	−0.53849	0.289974
Grazing land	−7638.74	11814.67	−7200.62	−4183.183	0.348499	0.121451
Open water bodies	−400.149	468.207	43.991	21.66	0.134517	0.018095
wetland	156.996	530.172	−74.664	204.15	0.954198	0.910493

study period. However, the stable (undisturbed) area of both land cover classes diminished progressively for the periods 1989-1999, 1999-2009 and 2009-2019. Previous studies on the catchment and in other regions also reported the dominance of cropland and grazing land in land cover area and inter class conversions across the study periods. For example, a study on the upper Rwizi catchment [64], reported that cropland covered majority of the land cover and increased between 2000-2014, while grazing land reduced; all due to conversions from and to other land cover classes respectively. This is similar to findings by [65], on the Lake Mburo pastoral area, where farmland increased by conversion from wetland area during the 1987-2020 period [26], in the Mt. Elgon region (1978-2020), reported a similar conversion trend.

3.2.2. Drivers of Land Cover Conversions

The population of the Rwizi catchment districts grew by 30.5% between 1992-2022 and further by 37.3% between 2002-2014, and is projected to grow by 135% by 2040 [66]. The percentage increase in the population varied from one district to another; with Kiruhura district leading (80.6%) while Lwengo had the lowest (14%) between 1992-2002 and Mbarara district had the highest (105.9%) while Rwampara had the lowest (11.9%) between 2002-2014. The catchment districts are projected to increase their population by 135% by the year 2040. Information from primary respondents and other secondary sources cited population increase as the prime driver of land cover conversions. This is due to its consequent increase in demand for more land to serve the emergent human needs including: housing, infrastructure development, and fuel wood and agriculture land. The choice of enterprise in the catchment districts according to Focus Group respondents and interview respondents is influenced by economic value (78%), food security (39%), favourable soils and prestige (29.3%). Bananas ranked the most popular agricultural produce (49.4%), followed by milk (19.5%). Drought and reduced soil fertility were ranked as the leading drivers of wetland encroachment.

3.2.3. Model Validation

The comparison by visual inspection of the 2019 simulated and actual maps

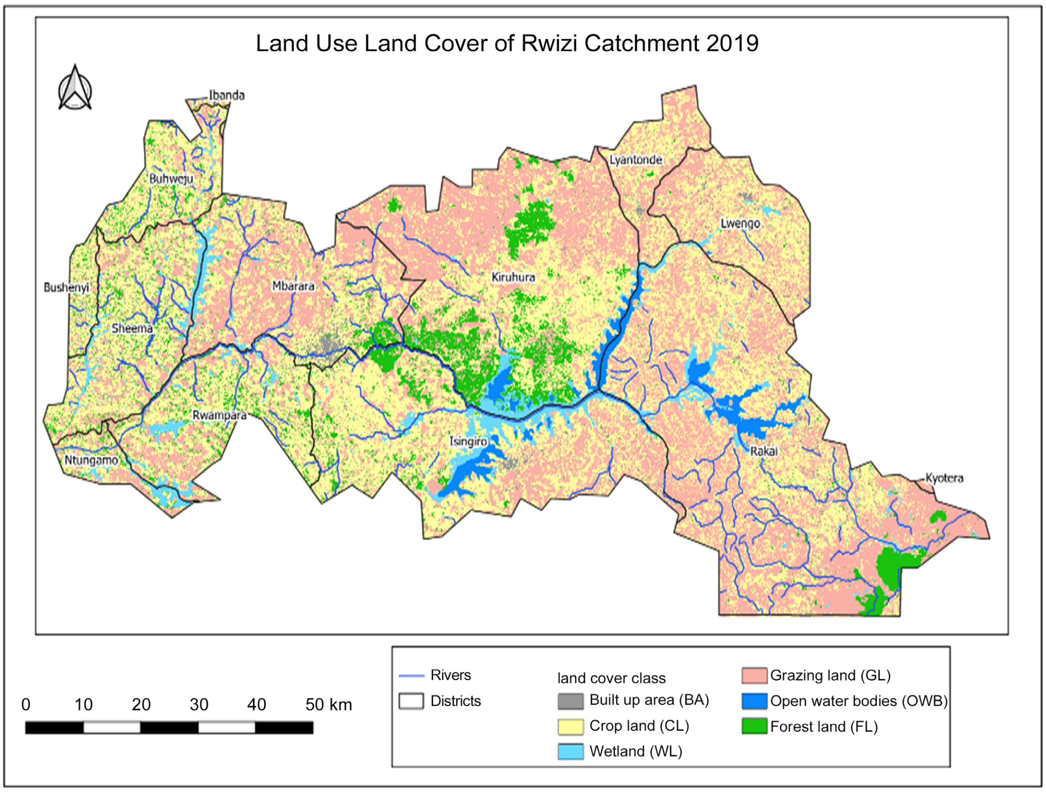
(**Figure 4(a)**, **Figure 4(b)**) reveals close similarity in area per land cover class (**Table 8**). For example cropland was 43.62% and 44.37% while grazing land was 40.50% and 39.25% in the simulated and actual maps respectively. The categories; forestland, builtup area, wetland and open water bodies all had a small difference in area of about 1% between the two map categories. Validations were done using Kappa statistics K_{no} (0.9421), $K_{location}$ (0.9554), $K_{location\ strata}$ (0.9345) and $K_{standard}$ (0.9275), all of which were above 0.80 (**Table 8**), confirming suitability of the model in simulating future land cover conditions [46].

3.2.4. Projected Land Use/Land Cover

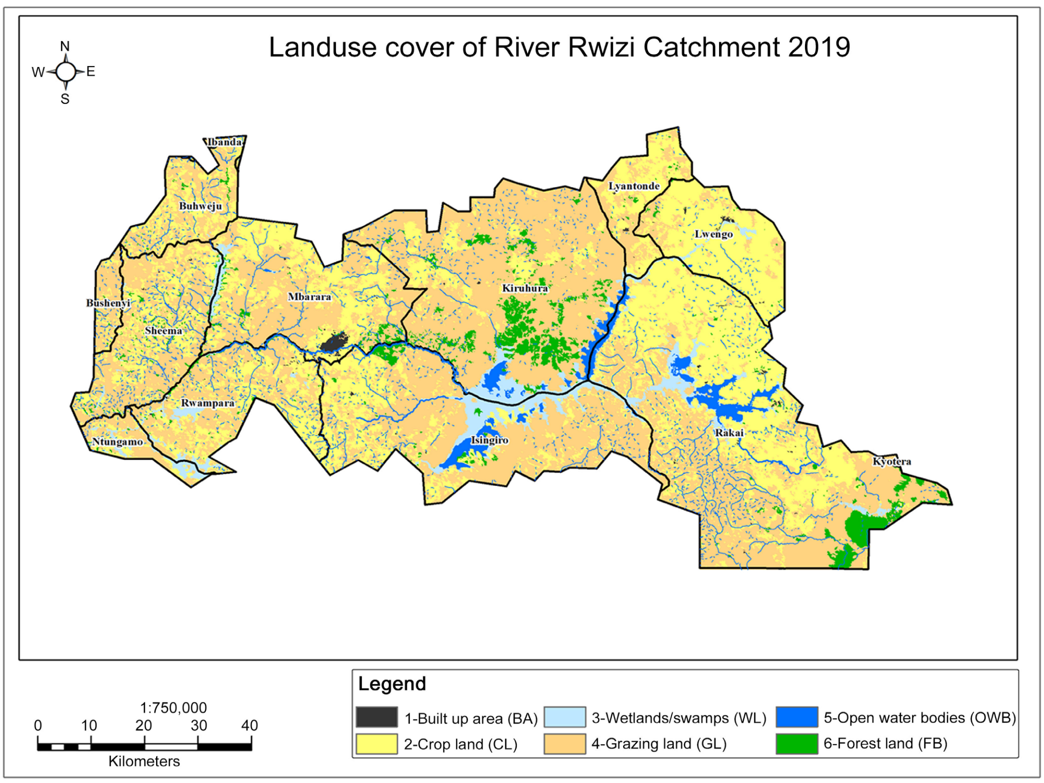
The status of the Rwizi catchment land cover as predicted for 2030 and 2040 are shown (**Figure 5(a)** and **Figure 5(b)**), with the respective land cover areas (**Table 9**) and percentage change and annual rate of change (ha/year) (**Table 9**) for the periods 2019-2030 and 2030-2040. The area of cropland is projected to decrease from 44.37% in 2019 to 43.23% in 2030 and then increase slightly to 43.98% in 2040. Built up area is projected to increase from 1.67% to 2.31% to 2.49% in 2019, 2030 and 2040 respectively. Forestland is projected to increase from 8.09% to 11.12% and decrease to 11.05% and Open water bodies from 2.03% to 2.1% and maintain the 2.1%, in 2019, 2030 and 2040 respectively. A decline in grazing land from 39.25% to 36.81% and to 35.97% then wetland cover from 4.59% to 4.43% and to 4.41% were observed in 2019, 2030 and 2040 respectively (**Table 9**). In general, an increase in built up area and forest land at the expense of grazing land and wetland cover will be observed through 2019, 2030 and 2040, while cropland will decrease between 2019-2030 and then increase between 2030-2040, as open water bodies increase between 2019-2030 and show no

Table 8. Area (ha) of the 2019 actual and simulated Rwizi catchment land cover maps and Kappa indices.

Land use/land cover	Simulated		Actual	
	Area (ha)	Percent (%)	Area (ha)	Percent (%)
Built up area	11908.37	1.58	12657.42	1.67
Cropland	329623.3	43.62	335352.33	44.37
Forest land	59880.12	7.92	61105.86	8.09
Grazing land	306049.16	40.50	296659.71	39.25
Open water bodies	15208.65	2.02	15313.59	2.03
Wetland	32971.4	4.36	34652.25	4.59
Total	755641.0	100	755741.16	100
Kappa indices	**Markov chain model**			
$K_{standard}$	0.9275			
$K_{location}$	0.9554			
K_{no}	0.9421			
$K_{location\ strata}$	0.9345			

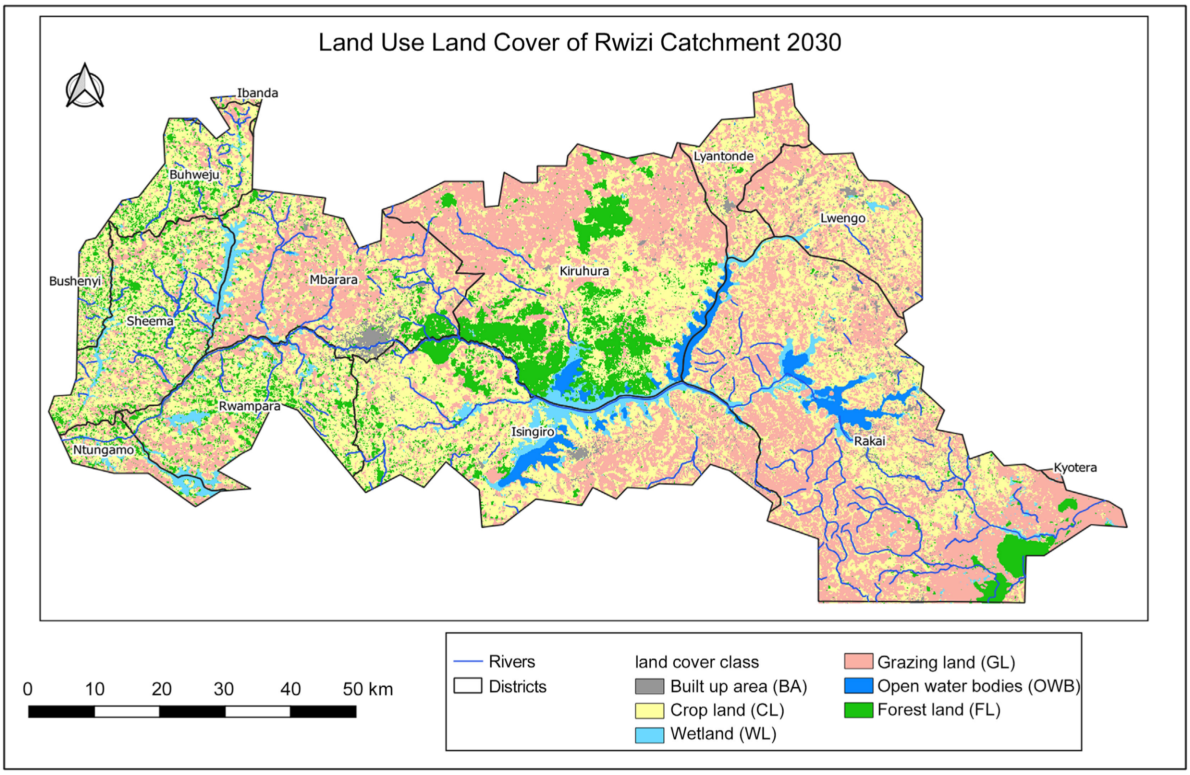


(a)

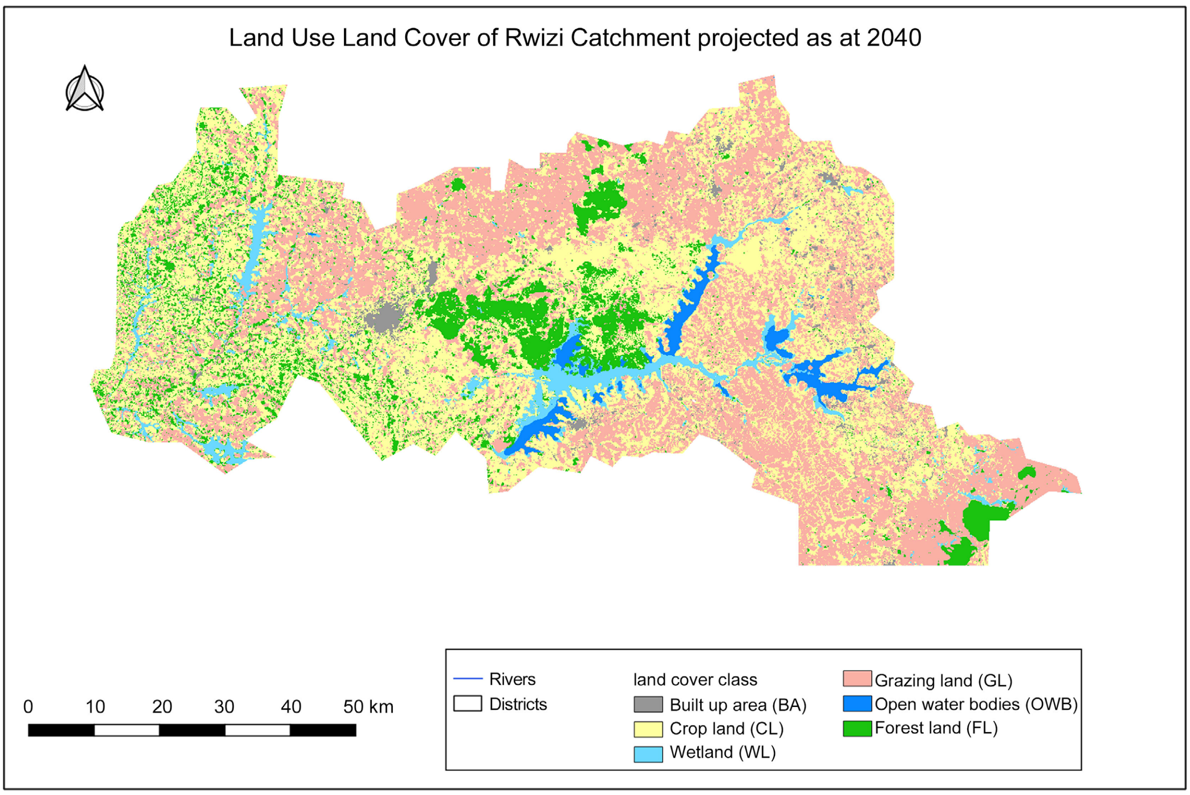


(b)

Figure 4. (a) Simulated 2019 Rwizi catchment land cover map. (b) Actual 2019 Rwizi catchment land cover map.



(a)



(b)

Figure 5. (a) Land use land cover of Rwizi catchment projected as at 2030. (b) Projected land use/land cover map of the Rwizi catchment for the year 2040.

Table 9. Rwizi catchment land cover area as projected in 2030 and 2040.

Land use/land cover	2030		2040	
	Area (ha)	Percentage (%)	Area (ha)	Percentage (%)
Built up area	17434.08	2.31	18839.16	2.49
Cropland	326629.2	43.23	332256.3	43.98
Forest land	84006.09	11.12	83480.4	11.05
Grazing land	278091.2	36.81	271707.4	35.97
Open water bodies	15854.85	2.1	15855.03	2.1
Wetland	33527.07	4.43	33347.97	4.41
Total	755542.49	100	755486.26	100

change between 2030-2040 (Table 9). The period 2019-2030 projects forestland to have the highest rate of increase (2081.84 ha/year) with grazing land having the highest rate of decline (−1866.05 ha/year) while 2030-2040 has cropland with the highest rate of increase (562.71 ha/year) and grazing land with the highest rate of decline (−638.38 ha/year) (Table 10).

3.2.5. Conversion between 2019 and 2030

During this time, 18159.3, 639.99 and 196.47 ha of grazing land, wetland and built-up area respectively will be converted to cropland while cropland will be converted to 18399.33, 6753.96, 2885.13 and 58.05 ha of grazing land, forest land, built up area and wetland respectively (Table 11). During the same time a vast area of cropland (18399.33 ha) will be converted to grazing land as other classes will lose less than 70 ha each to grazing land; as grazing land will be converted to 18159.3, 13109.31, 2190.87 and 1659.69 ha of cropland, forestland, built up area and wetland respectively. Built up area will be converted mainly from cropland (2885.13 ha) and grazing land (2190.87 ha) while it will be converted to 365.85, 332.82, 196.47 and 32.52 ha of forestland, open water bodies, cropland and grazing land respectively. Similarly, 13109.31,6753.96, 1710.27, 365.85 and 5.67 ha of grazing land, cropland, wetland, built up area and open water bodies respectively will be converted to forest land as only 31.68 ha of forestland will be converted to grazing land (Table 10). Wetland will be converted mainly from grazing land (1659.69 ha) and converted largely to forest land (1710.27 ha). During the same period, open water bodies will be converted from wetland (491.76 ha) and built-up area (332.82 ha) while it will be converted to 61.11, 5.76 and 0.45 ha of grazing land, forestland and wetland respectively (Table 11).

3.2.6. Conversion between 2030 and 2040

The projection is that 19352.07, 660.06 and 143.01 ha of grazing land, wetland and built-up area respectively will be converted to cropland while cropland will be converted to 18877.95, 6901.38, 3397.41 and 59.58 ha of grazing land, forest land, built up area and wetland respectively, with grazing land constituting 96.02% of land converted to cropland and cropland constituting 64.57% of land

Table 10. Percentage change and Annual rate of LULC change for the period 2019-2040.

Land use/land cover	2019-2030		2030-2040	
	Percentage change	Rate of change (ha/year)	Percentage change	Rate of change (ha/year)
Built up area	37.74	434.24	8.06	140.51
Cropland	−2.60	−793.01	1.72	562.71
Forest land	37.48	2081.84	−0.63	−52.57
Grazing land	−6.26	−1688.05	−2.29	−638.38
Open water bodies	3.53	49.21	0.001	0.018
Wetland	−3.25	−102.29	−0.53	−17.91
Total				

Table 11. Transition Matrix for the period 2019-2030.

Row labels	Builtup area	Cropland	Wetland	Grazing land	Open water bodies	Forest land
Builtup area	16333.47	196.47	0	38.52	332.82	365.85
Cropland	2885.13	298464.57	58.05	18399.33	0	6753.96
Wetland	0	639.99	30671.46	13.5	491.76	1710.27
Grazing land	2190.87	18159.3	1659.69	242988.48	0	13109.31
Open water bodies	0	0	0.45	61.11	15934.14	5.67
Forest land	0	0	0	31.68	0	83976.84

converted to grazing land (**Table 12**). During the same time, 3397.41 and 2543.22 ha of cropland and grazing land will be converted to built up area; accounting for 55.6% and 41.6% of total land converted to built up area respectively. Forest land will gain 13910.31 ha (60.93%) and 6901.38 ha (30.23%) from grazing land and cropland respectively. Similarly, 1762.47 ha (59.43%) wetland will be converted to forestland and 507.96 ha (17.13%) of wetland will be converted to open water bodies, while 660.06 ha (22.23%) of wetland will be converted to cropland. On the other hand, 1769.67 ha of grazing land will be converted to wetland making up 96.72% of total land converted to wetland, as 19352.07 ha of grazing land was converted to cropland constituting 51.5% of the total converted grazing land followed by forestland (13910.31 ha) comprising 37.02% while 18877.95 ha of cropland was converted to grazing land making up 99.37% of total land converted to grazing land (**Table 12**).

Generally, cropland and grazing land accounted for the highest percentage of land use/land cover across the entire period. Built-up area increased from 1989 to 2040, forest land also increased across this period save for the year 2009. On the contrary grazing land declined from 1989 to 2040 also registering an increase only in 2009. Cropland on the other hand registered cyclic episodes from one decade to another across the entire period, wetland and open water bodies registered a narrow range of change in land cover variations across the entire period unlike other land use/cover classes (**Figure 6**). The observed variations in LULC

Table 12. Transition Matrix for the period 2030-2040.

Row labels	Builtup area	Cropland	Wetland	Grazing land	Open water bodies	Forest land
Builtup area	12236.76	143.01		24.57		249.21
Cropland	3397.41	305998.94	59.58	18877.95		6901.38
Wetland	21.06	660.06	31682.95	13.95	507.96	1762.47
Grazing land	2543.22	19352.07	1769.67	258967.87		13910.31
Open water bodies	6.03		0.45	58.5	15243.21	5.4
Forest land	142.38			22.95		60913.53

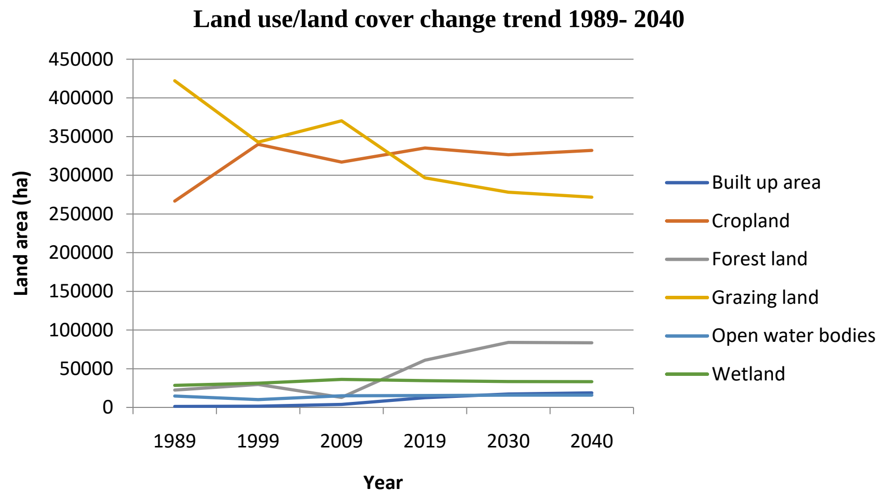


Figure 6. Land use/land cover change trend for the period 1989-2040.

trends especially for forestland, cropland and grazing land is attributed to changes in government led programmes that popularise different agricultural products at different times and price dynamics compounded by population pressure and reduced soil fertility that threaten forest cover and wetlands.

3.3. Conclusions

There were marked Land Use Land Cover conversions during 1989-2019 in the Rwizi catchment.

Only built-up area increased irreversibly throughout the entire period while Cropland, wetland and forestland showed cyclic falls and rises while grazing land showed a continuous decrease.

A trend of increase in built-up area, forestland and open water bodies is expected by 2030 and 2040 while wetland and grazing land are projected to decrease. In contrast, cropland is projected to decrease by 2030 and rise again by 2040. The projected trends threaten food security, river hydrology and soil quality in the catchment. Thus, management and planning should be oriented towards minimizing the likely adverse effects of this trend to the river and livelihood of catchment inhabitants. The major drivers of change in Land Use Land Cover were socio economic due to population pressure followed by hydro-climatic factors and Land Use Land Cover Change accounted for more variation in river flow than climate variability. Therefore the extent of enforcement of sustainable land management practices in the Rwizi catchment should be an area for further research.

3.4. Recommendations

There is need for catchment management planning and implementation to prioritise the cropland and grazing land, being the dominant land use/land cover types.

There is need for increased recurrent budget allocation at national, catchment and district levels for natural resources protection, management and education every financial year.

There is also a need for consistency in government's programmes of popularising agricultural production and environmental conservation.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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