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Using GlobeLand30 data and cellular automata modeling to predict urban expansion and sprawl in Kigali City

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Abstract

The growth and expansion of urban regions in various cities worldwide, especially in developing economies, leads to changes in land usage. Thus, the study assessed the changes in land use and land cover within Kigali City using the Land Change Modeler of the TerrSet software system. The study focused on 2010 to 2020, using classified GlobeLand30 maps to identify significant land cover transitions, which were then classified into submodels. An enhanced multi-layer perceptron neural network was also used to analyze these transitions. Urban expansion was predicted using five key variables: elevation, slope, distance from rivers, roads, and built-up areas. The multi-layer perceptron neural network achieved an accuracy of 81.90% in predicting land use and land cover changes. The Cellular Automata-Markov chain model in the Land Change Modeler was implemented to forecast land use and land cover patterns for 2030. Results indicated that (1) over the past decade (2010-2020), urban areas expanded by 20.89 km^2, while forests, grasslands, shrublands, and wetlands decreased by 1.31 km^2, 8.63 km^2, 0.15 km^2, and 0.05 km^2, respectively. The study also predicts that (2) from 2020 to 2030, urban areas and artificial surfaces will expand by 15.83%, with a considerable decrease in grassland and cultivated land. The study further predicts a slight decrease in wetland areas and for land use and land cover in Kigali City, highlighting the expansion of urban areas and their potential impact on other land uses. It serves as a critical tool to support sustainable urban planning and policies aimed at ensuring the long-term ecological and environmental sustainability of Kigali City.

1. Introduction

Cities worldwide are experiencing rapid population growth, a significant factor driving changes in land use and land cover (LULC) [1]. The alteration of LULC poses a critical environmental challenge worldwide [2]. The urbanization phenomenon is driven by socioeconomic and political developments, leading to large cities' expansion and LULC transformations [3,4]. Urban sprawl is a global occurrence that attracts the attention of urban planners due to its impact on the environmental efficiency of cities [5]. It is "a land-use pattern in urban areas characterized by low density, continuity, concentration, clustering, centrality, nuclearity, mixed-use, and proximity" [6]. The impacts of urban development on the structure and function of urban ecosystems are multifaceted [7]. Urbanization creates both opportunities and challenges for human life. According to some urban planners, urban sprawl improves the quality of life and supports economic growth. However, high human activity in cities adds to LULC changes, which negatively affect affected urban areas [8]. The worldwide urban population has grown unparalleled since the mid-twentieth century. In 1950, 30% of the world's population lived in cities; by 2050, this proportion is expected to rise to 66% [9]. The ongoing phenomenon of urbanization requires land conversion to make way for new urban constructions. According to estimates, over 5.87 million square kilometers of land are expected to be turned into urban areas globally by 2030 [10]. Thus, monitoring spatial and temporal patterns of urban expansion is critical to ensuring well-managed urban development. Such monitoring activities are efficient with satellite data. The combination of remote sensing (RS) and geographic information systems (GIS) has proven to be the most effective tool for controlling LULC change and natural resource research. Scientists, ecologists, farmers, lawmakers, and urban planners benefit from analyzing and tracking regional and temporal fluctuations in LULC [11].

RS and GIS techniques contribute to the efficient management of natural resources by facilitating land preparation and long-term tracking of change dynamics [12]. Several spatio-temporal prediction models, such as the Markov chain (MC) model, cellular automata (CA) model, and conversion of LULC and its effects (CLUE) model, have been created in recent years to forecast LULC changes and detect their impacts [13,14]. Future LULC changes can be predicted by combining LULC models with RS and GIS data. Different studies on LULC detection and prediction have been conducted using LULC models with RS and GIS [15], conducted a classification analysis of LULC change detection with temporal Landsat images in the seven-county Twin Cities Metropolitan Area, Minnesota. Another study [16] used a hybrid classification and post-classification approach using Land-sat images to assess land cover change in Samsun, Türkiye, between 1980 and 1999 [17] used Landsat data for intermediate change detection analysis in residential areas between 1975 and 2001 to study urban expansion in Isfahan, Iran, from 1956 to 2006. In the case of East Africa, some studies have been done as well, such as the use of multi-sensor satellite data for LULC monitoring in Nakuru, Kenya, by [18], and [19], analyzed urban expansion and LULC in the Post-Genocide Period in Kigali City, Rwanda. Furthermore, [20] used multitemporal Landsat data and landscape metrics to study the spatiotemporal analysis of urban land cover changes in Kigali, Rwanda.

Despite numerous studies on understanding urban growth and LULC change in Kigali City over the years, none of these studies have utilized the GlobeLand30 data. This global dataset proves valuable for Rwanda. Effective modeling of urban LULC changes in Kigali requires robust methods capable of capturing the urban environment's growth, complexity, and dynamic aspects. Thus, this study aims to assess LULC changes from 2010 to 2020 and forecast urban growth using the GlobeLand30 dataset and modeling tools such as Cellular Automata. Furthermore, analyzing LULC changes and predicting future urban growth can significantly contribute to the decision-making process regarding LULC and the sustainable development of Kigali City.

2. Material and Method

2.1. Study Area

Our study area (Kigali City) is in the Central-East African area of Rwanda and serves as the country's capital and largest city (Figure 1). The province of Kigali is the most urbanized in Rwanda, with 86.9% of its population living in urban areas. Covering an area of 730 km^2, Kigali serves as a vital business center and main port of entry with a current population of 1,745,555, according to the Fifth Rwanda Population and Housing Census, 2022 [21]. The city comprises the districts of Nyarugenge, Gasabo, and Kicukiro. [20]. The land cover in the study area includes constructed areas with diverse urban functions, green spaces consisting of forests, open vegetated lands, agriculture, and wetlands [7]. Additionally, scattered bare lands, under construction or uncovered soil, and water bodies such as fishponds, streams, and part of Lake Muhazi in the extreme north are significant land cover classes. Kigali's historical development dates to its establishment as Germany's colonial administrative outpost in 1907, expanding over time to become a metropolitan area [22]. With a 4.1% annual urban growth rate, Kigali remains a vital hub for Rwanda's secondary and tertiary activities [23]. However, accelerated urbanization has resulted in the uncontrolled growth of informal settlements and environmental degradation. The study aims to predict land-use change paths in Kigali to inform sustainable urban dynamics and land-use management decision-making.

2.2. Data

The study utilized a variety of data sources, including remotely sensed and geospatial data (Table 1). These included LULC data obtained from GlobeLand30, administrative boundaries obtained from an updated source, SRTM 1 DEM, and additional data related to roads, rivers, and built-up areas received from the Centre for GIS and Remote Sensing (CGIS) at the University of Rwanda. The GlobeLand30 dataset, developed by the National Geomatics Centre of China, offers high-resolution imagery covering the period from 2000 to 2010 [24]. It is created using more than 10,000 Landsat satellite images and a "pixel-object-knowledge" method. For this study, GlobeLand30 data for 2000, 2010, and 2020 were obtained from [25]. The dataset classifies land cover into ten types: cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surfaces, bare land, and permanent snow and ice [26]. However, only seven of these land cover types are applicable in Rwanda. These seven land cover types are Cultivated land, Forest, Grassland, Shrubland, Wetland, Water bodies, and Artificial surfaces. The accuracy of GlobeLand30 has been evaluated and confirmed by Arowolo and Deng [27]. An overall accuracy of 79.6%, 83.5%, and 85.69% were respectively reported in 2000, 2010, and 2020. Kappa coefficient was 0.81 in 2000 and 0.78 in 2010 [28]. Their findings suggest that GlobeLand30 is suitable for data analysis in developing countries like Rwanda.

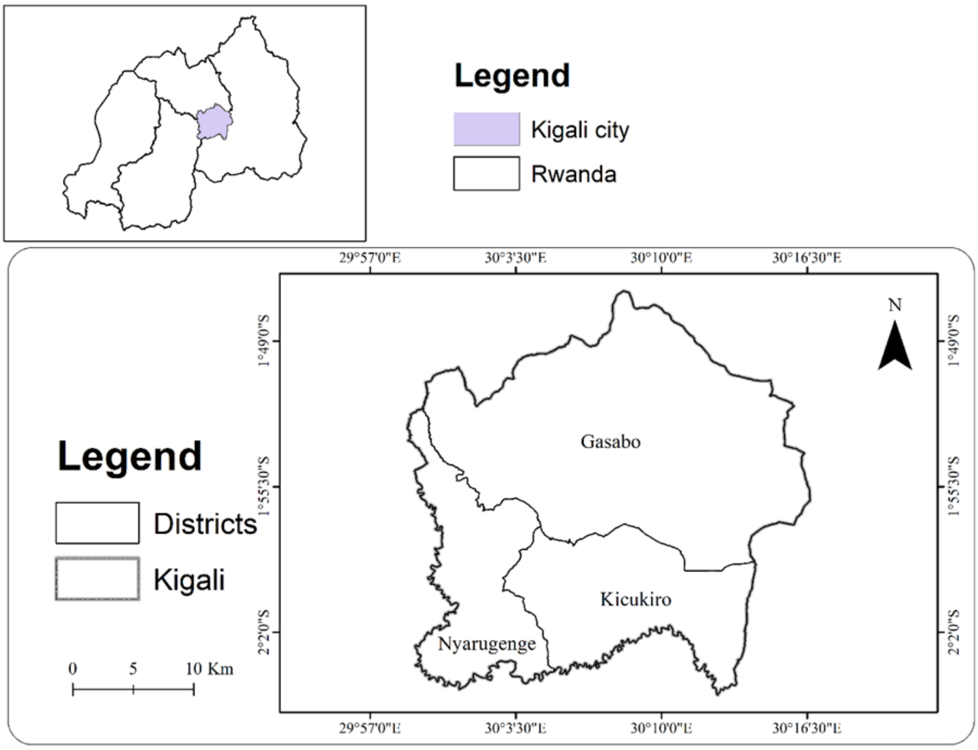

Figure 1. Kigali city location map.

Table 1. Remote sensed and geospatial data.

Data Type	Dataset	Resolution	Source
LULC	GlobeLand30	30 m	National Geomatics Centre of China. http://www.globallandcover.com
Administrative boundary	Vector data	-	Updated administrative boundary obtained from the link: https://www.diva-gis.org/gdata

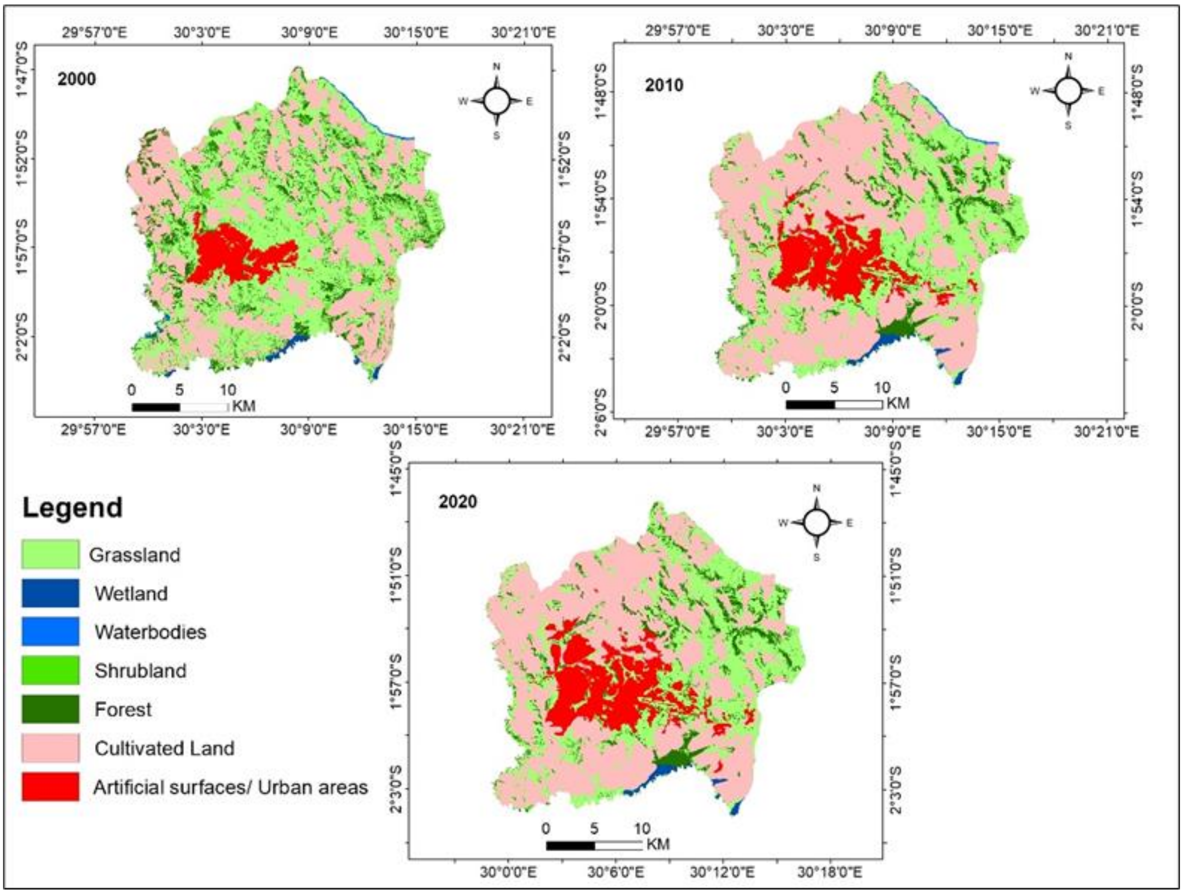

Figure 2. LULC classified maps.

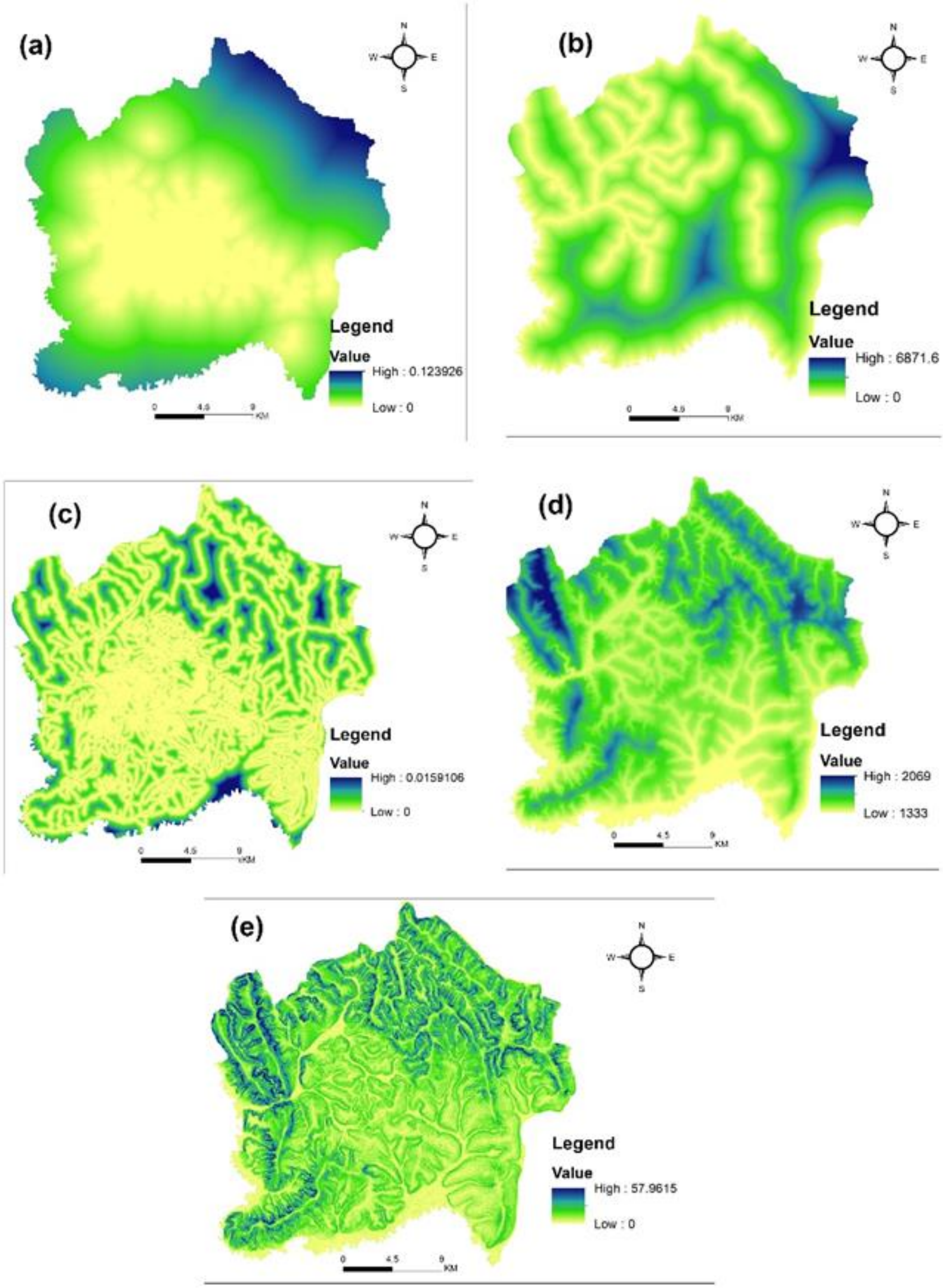

Figure 3. Variables used in the study: (a) built-up area; (b)Distance from rivers; (c) Distance from roads; (d) Elevation; (e) Slope.

2.3. Data processing

The LULC classified maps for the study area in the years 2000 and 2010 are depicted in Figure 2. These maps were generated using Esri software (ArcGIS 10.8), facilitating the analysis of the GlobeLand30 data. The reference system used for the maps was the Universal Transverse Mercator (UTM) projection in zone 31 North, and the World Geodetic System (WGS) 1984 was utilized with a spatial resolution of 30 meters. Also, the TerrSet software system's LCM module was used to make a prediction map. Furthermore, significant land cover transitions were carefully selected and categorized into submodels in this study. Each transition was then analyzed using an enhanced multilayer perceptron (MLP) neural network [29]. This study considered five factors (Elevation, slope, distance from rivers, roads, and Built-up area) (Figure 3) that were chosen and assessed based on their impact on urban expansion. Among these factors were static variables such as height, slope, and distance from water bodies and dynamic variables, including distance from major roadways and existing artificial surfaces. It is important to note that dynamic variables can be modified and recalculated during the prediction process, while static variables remain unchanged over time [3,29]. The sub-modeling in this study focused on two main variables: critical LULC transitions and driving forces.

In Figure 3, the units used for measurement are as follows: kilometers (km) for distance from roads and built-up areas, meters (m) for distance from rivers and elevation, and percentages (%) for slope. According to [30], topography and high population pressure significantly contributed to LULC variations in the study conducted in Rwanda. Our research used data on elevation (DEM) and slope to analyze the impact of topographical factors. In addition, we incorporated data on built-up area density as an indicator of high population density. In addition, we considered other urban drivers, predominantly human disturbance factors, such as distance to roads [31–33] and distance to aquatic bodies [34,35], which are essential urban expansion determinants. Roads were selected explicitly as, since 2000, the construction and enhancement of economic infrastructures such as roads have been constructed to attract investors and stimulate economic growth and as the top priority in urban planning regarding socioeconomic factors [19].

2.4. Transitional modeling and accuracy

During this phase, it is essential to identify significant LULC transitions and develop transition potential maps with sufficient precision for the transition models. These transition maps are generated by incorporating LULC transitions and static and dynamic variables into an MLP neural network, a prevalent type of artificial neural network. The MLP neural network uses a supervised "backpropagation" training algorithm to modify model parameters and reduce errors, enhancing accuracy. For an accurate LULC classification, a success rate from 79% is considered acceptable [36]. After conducting 10,000 iterations, the MLP achieved an accuracy of 81.90% in detecting LULC changes between 2010 and 2020. The resulting transition potential maps were then utilized to predict LULC changes. Furthermore, the assessment of the reliability of the LULC classification was obtained by the Equation 1:

$$GA = 100\frac{\sum_{i=1}^{m} Pii}{n} \tag{1}$$

The CA-Markov model LULC utilizes Equation (1) to determine the overall accuracy of a land use map generated by the model. This equation calculates the sum of the conditional accuracy of each land use type, divided by the total number of cells in the map [37].

2.5. Predicting future LULC changes

This study applied the CA-Markov chain model implemented in the Land Change Modeler (LCM) module of TerrSet software version 18.3 to forecast future LULC patterns of Kigali city using GlobeLand30 maps from 2010 and 2020. A CA model consists of interconnected cells capable of simulating the spatiotemporal properties of complex systems. CA assumes that the present LULC condition and changes in neighboring cells determine the LULC change for a specific location [38]. Markov chains are commonly used to represent LULC changes, as they capture the probabilities of transition between two-time intervals based on historical trends. The transition probability matrix derived from Markov chain analysis offers insight into upcoming LULC adjustments. In this study, the MLP neural network played a crucial role in determining the transition weights for incorporation into the probability matrices of the Markov chain, allowing for the prediction of future LULC changes. The resulting matrix quantifies the anticipated change quantity for each weighted transition until the anticipated end dates. The transition probability matrix for LULC variations between 2010 and 2020 was quantified in detail. Using the CA Markov chain approach, a prediction for 2030 was conducted, leading to the identification of prospective LULC alterations.

3. Results

3.1. Land use land cover proportions

Table 2 shows the distribution of LULC in the study area between 2010 and 2020. It displays the areas in km^2 and the changes in each LULC category. In 2010, the category with the largest LULC area was Cultivated Land, which covered 367.53 km² and accounted for 51.28 % of the total area. The area covered by Forest was 56.32 km² (7.86%), while Grassland was 213.08 km² (29.73%). Other categories, including Shrubland, Wetland, Waterbodies, and Artificial surfaces/Urban areas, had lesser areas ranging from 1.30 km² to 70.48 km², comprising less than 10% of the total area. There were minor variations in the distribution of LULC categories from 2010 to 2020. The cultivated land area decreased to 355.90 km² (49.66%), while forest and grassland areas also reduced marginally. Artificial surfaces/Urban areas, on the other hand, increased substantially by 91.37 km² (12.75%), indicating urbanization or increased development. The regions of Shrubland, Wetland, and Waterbodies remained relatively stable or underwent minor alterations. The table provides an overview of the composition and evolution of LULC over a decade. It emphasizes trends in various land cover categories, including the growth of urban areas and their prospective impact on other LULC classes.

Table 2. Land use Change statistics of 2010 and 2020.

Year	2010		2020	
LULC	Area (km²)	Area (%)	Area(km²)	Area (%)
Cultivated Land	367.53	51.28	355.90	49.66
Forest	56.32	7.86	55.01	7.68
Grassland	213.08	29.73	204.45	28.53
Shrubland	1.30	0.18	1.15	0.16
Wetland	5.74	0.80	5.79	0.81
Waterbodies	2.23	0.31	3.02	0.42
Artificial surfaces	70.48	9.83	91.37	12.75
Total	716.69	100	716.69	100

3.2. Land use change model analysis for LULC

The results from Table 3 indicate that between 2010 and 2020, 25,22 km² of agricultural land was lost, signifying a decline in agricultural areas. In addition, there were gains of 13,58 km², but the net consequence was a decrease of 11,63 km² in cultivated land. The forests lost 16.39 km² and gained 15.08 km², resulting in a small net reduction of 1.31 km². Grasslands lost 33.30 km² and gained 24.67 km² over the past decade, resulting in a net change of -8.63 km². Losses of 0.88 km² and gains of 0.73 km² resulted in a net change of -0.15 km² for shrublands. The wetland area decreased by 0.20 km² and increased by 0.25 km² for a net change of 0.05 km². The area of waterbodies decreased by 0.30 km² and increased by 1.10 km², resulting in a net change of 0.79 km². The net increase indicates an overall expansion of water bodies during the period. The category with the most significant growth was "Artificial surfaces/Urban areas," which grew by 23,69 km² over the decade. Significant urbanization and expansion of developed areas led to a net change of 20,89 km² for this category.

Table 3. Land use and land cover statistics from 2010 to 2020.

Year	**2010-2020**		
LULC	Loss (km²)	Gains (km²)	Net change (km²)
Cultivated Land	25.22	13.58	-11.63
Forest	16.39	15.08	-1.31
Grassland	33.30	24.67	-8.63
Shrubland	0.88	0.73	-0.15
Wetland	0.20	0.25	0.05
Waterbodies	0.30	1.10	0.79
Artificial surfaces	2.80	23.69	20.89

The category of Artificial surfaces/Urban areas with the most significant increase is depicted in Figure 4 as undergoing a substantial change. During the decade, it experienced a considerable increase of 23,69 km², resulting in a net change of 20,89 km². The category suffering the most significant loss is "Cultivated Land." Its area decreased by 25.22 km² over the past decade, resulting in a net change of -11.63 km². The loss of farmland was primarily caused by the urban expansion phenomenon between 2010 and 2010.

3.3. Markov chain transition matrix analysis

Using Markov chain analysis, Table 4 computes a transition probability matrix between 2010 and 2020, with a projection for 2030. The matrix comprises rows and columns representing various LULC classes. The diagonal values represent the likelihood that each LULC class will remain constant over time [39]. The outcomes disclose the probabilities of future transitions from diverse LULC classes to artificial surfaces. The probability of cultivated land becoming artificial surfaces is 3.54 %, while the probability of forest land becoming artificial surfaces is 1.05 %. In addition, the probabilities of grassland, shrubland, wetland, water bodies, and barren land becoming artificial surfaces are 4.62%, 17.54%, 0.00%, and 0.08%, respectively. These results suggest that shrubland, grassland, and cultivated land are more likely to be converted to artificial surfaces, indicating a potential conversion of vegetation into urban areas in the Kigali city area. In contrast, the study area's forest, water bodies, and wetland entities have a lower probability of transforming into artificial surfaces.

Table 4. Transition probability matrix for the period between 2010 and 2020.

LULC Class	Cultivated Land	Forest	Grassland	Shrubland	Wetland	Waterbodies	Artificial surfaces
Cultivated Land	0.9314	0.0062	0.0263	0.0001	0.0002	0.0003	0.0354
Forest	0.0434	0.709	0.2222	0.0044	0.0006	0.01	0.0105
Grassland	0.0482	0.0576	0.8437	0.0018	0.0006	0.0018	0.0462
Shrubland	0.0304	0.192	0.2486	0.3239	0.000	0.0297	0.1754
Wetland	0.0121	0.0116	0.0116	0.000	0.9646	0.0002	0.000
Waterbodies	0.0137	0.0444	0.065	0.0061	0.0052	0.8648	0.0008
Artificial surfaces	0.0102	0.0017	0.0275	0.0004	0.000	0.000	0.9602

3.4. Land use land cover prediction 2030

The corresponding area statistics and predicted extent of the various LULC classes for 2030 are presented in Table 5. In 2030, cultivated land is anticipated to comprise approximately 48.04 % of the total land area. This suggests that a substantial fraction of the city's land will continue to be used for agriculture. The projected forest area for the same year is approximately 7.63 % of the total land area, ensuring the preservation of significant forested areas within the metropolitan area, essential for maintaining biodiversity and ecological balance. The projected area of grassland is approximately 194,96 square kilometers, or approximately 27.25 % of the total land area. This indicates that Kigali City has an abundance of natural grasslands and open areas. The predicted wetland area in 2030 is 5,79 square kilometers, or approximately 0.81 % of the total land area. This is consistent with the government's efforts to relocate activities from wetland ecosystems, rehabilitate them, and preserve these ecosystems due to their vital role in maintaining biodiversity and water quality. Lakes, rivers, and reservoirs are anticipated to cover approximately 0.42 % of the total land area. These volumes of water play a vital role in urban water supply and serve as recreational areas. The predicted area of artificial surfaces, including urban and built-up areas, is approximately 113.43 square kilometers, or 15.85 % of the total land area. This demonstrates the development of urbanization and infrastructure in Kigali.

Table 5. 2030 predicted LULC area statistics.

LULC Classes	Area (km²)	Area (%)
Cultivated Land	343.78	48.04
Forest	54.57	7.63
Grassland	194.96	27.25
Wetland	5.79	0.81
Waterbodies	3.02	0.42
Artificial surfaces	113.43	15.85
Total area	715.54	100

In Kigali, the area designated as Artificial surfaces/Urban areas is projected to cover 113.43 square kilometers (15.85% of the total area) by 2030. This indicates a significant expansion of urban development in the city. Based on the research done by [3] in Lagos, the area designated as Artificial Surfaces is predicted to cover a much larger extent of 867.90 square kilometers (19.19% of the total area) by 2030. Kigali and Lagos are experiencing significant urban expansion, with the area of artificial surfaces/urban areas increasing in both cities. However, Lagos has a more considerable extent of urban expansion than Kigali. The expansion of artificial surfaces/urban areas in both cities signifies the challenges and opportunities associated with urban development, including the need for sustainable planning, infrastructure, and environmental conservation.

4. Discussion

4.1. Artificial surface expansion in Kigali City

Kigali has experienced a significant increase in artificial surfaces, especially in urban areas, due to population development and the repatriation of Rwandan refugees from nearby nations [7]. On the other hand, Kigali is a city that is rapidly modernizing and emphasizes sustainability, cleanliness, and creative urban planning [40]. However, Kigali has seen significant deforestation because of the influx of refugees [3]. Thus, managing urban growth while maintaining natural habitats and open areas wasn't easy. The susceptibility of their wetlands is another issue that Kigali has faced, while Kigali's wetlands have slightly changed during the study. Kigali's approach to urban development is unique due to its focus on sustainability and cleanliness [41]. The city has made significant progress in implementing eco-friendly policies, such as prohibiting plastic bags and encouraging green spaces [42].

Finally, Kigali represents its own set of difficulties and possibilities. While artificial surface growth has occurred, the patterns of land cover changes, particularly regarding vegetation and wetlands, have been distinct. Figure 5 shows a net increase in the area covered by artificial surfaces in Kigali. This indicates that the city has witnessed urbanization and the growth of built-up regions over this time. In addition, Kigali expanded outward in all directions, as seen by the rising MSI (Modified Sprawl Index) value [41,44]. Issuing horizontal building licenses, which made it easier for the city's built-up regions to expand, is to blame for the sprawl. Rural land on the periphery of current artificial surfaces has been developed to meet the growing demand for urban space. The demand for urban growth and the requirement to accommodate the expanding population and economic activity in these cities are reflected in the conversion of rural land to urban usage. While Kigali has seen the growth of artificial surfaces, it is vital to note that there might be variations in the scope, speed, and particular causes of these changes. Various variables, including population increase, economic development, urban planning regulations, and governance procedures, can influence each pattern of urban growth. Urban planners may control urban growth, protect natural ecosystems, and apply sustainable urban planning practices to secure a better future for its citizens and the environment.

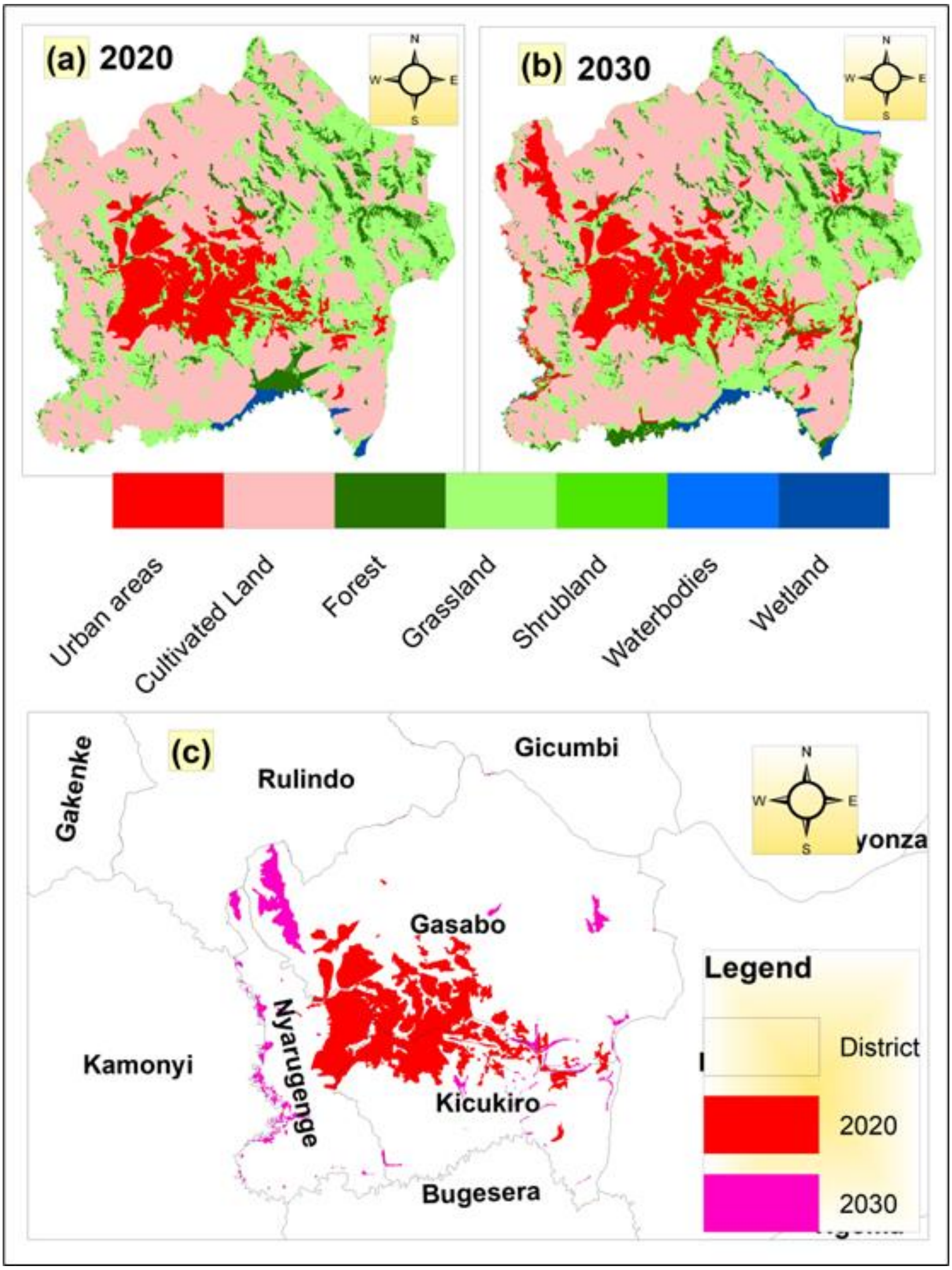

Figure 4. Maps showing: (a) LULC 2020, (b)predicted LULC 2030, and (c) Predicted urban expansion 2020-2030.

4.2. The future of Kigali City

According to the LULC change projection for Kigali City, there is a significant expected increase in artificial surfaces and urban areas. In contrast, cultivated land, forest, and grassland are expected to decrease. This trend is typical in rapidly developing cities worldwide. The projection shows a decrease of 12.12 km^2 in cultivated land, 0.44 km^2 in forest cover, and 9.49 km^2 in grassland cover. However, wetland and waterbody coverage are projected to remain stable over the same period. An increase of 22.06 km^2 in artificial surfaces is expected between 2020 and 2030.

Table 6. LULC changes between 2020 and 2030.

LULC Classes	Area (km^2)		
	2030	2020	Change
Cultivated Land	343.78	355.9	-12.12
Forest	54.57	55.01	-0.44
Grassland	194.96	204.45	-9.49
Wetland	5.79	5.79	0
Waterbodies	3.02	3.02	0
Artificial surfaces/Urban areas	113.43	91.37	22.06

This change represents a 1.69% reduction in Cultivated Land over the past ten years. Similarly, the Forest area is projected to decrease from 55.01 km^2 (7.68%) in 2020 to 54.57 km^2 (7.61%) in 2030, resulting in a net change of -0.07%. The Grassland area is anticipated to decrease from 204.45 km^2 (28.53%) to 194.96 km^2 (27.20%), resulting in a net change of -1.33%. [19,43] observed this trend over the past decade and reported that the rapid expansion of urban areas has put pressure on the natural environment, decreasing forest and open land areas. However, the Shrubland, Wetland, and Waterbodies categories are expected to remain unchanged over the next ten years and maintain their present proportions and territories. This prediction is primarily due to the initiatives the City of Kigali implemented to promote sustainable development [45]. These initiatives include the Sustainable Development Goals (SDGs) [46], 7 Years Government Programme National Strategy for Transformation [47], the City of Kigali Development Plan (CKDP), and the Kigali City Master Plan. Moreover, the city of Kigali has eradicated all infrastructures, facilities, and illicit activities from the wetland areas of Kigali [48]. On the other hand, the category of Artificial surfaces/Urban areas is expected to expand significantly. The area is projected to grow from 91.37 km^2 (12.75%) in 2020 to 113.43 km^2 (15.83%) in 2030, representing a net increase of 3.08%. This suggests that urban development and human-made structures will continue to increase over the past decade. The growth and expansion of metropolitan areas in 2030 are supported by [19], who argued that Kigali's residents will continue to increase exponentially (Figure 5). The districts where future urban area expansion is anticipated are primarily Gasabo, Nyarugenge, and Kicukiro, as illustrated in Figure 5. The same districts have shown some degree of dispersion over the past decade, with Gasabo's built-up area being marginally denser at 40.60 km^2 than those of Nyarugenge and Kicukiro, which are at 12.52 km^2 and 20.36 km^2, respectively [40].

5. Conclusion

Over the past decade, the city of Kigali underwent significant landscape transformations, as revealed by an analysis of land use and land cover changes between 2010 and 2020. While there were minor variations in the distribution of LULC categories, the growth of artificial surfaces/urban areas was substantial, indicating a need for sustainable urban planning and policies to preserve natural habitats and resources. The analysis further revealed that land cover categories such as Cultivated Land, Grassland, and Shrubland are at a greater risk of being transformed into urban areas, potentially leading to vegetation loss. On the other hand, forests, Wetlands, and water bodies had lower probabilities of transformation, highlighting the need for their conservation. The study also predicted that by 2030, artificial surfaces/urban areas will account for approximately 15.85% of the total land area. Cultivated land, Forests, and grassland will continue to constitute a significant portion of the land area. In addition, conservation efforts have helped maintain the expected area of wetland ecosystems, emphasizing the significance of preserving natural habitats and open spaces. The findings of this study underscore the importance of managing urban growth and preserving natural resources, especially in the context of rapid urbanization. The use of remote sensing and GIS techniques was effective in analyzing and tracing LULC changes in Kigali, and similar approaches can be used in other African cities better to understand the effects of population pressure and urbanization. By adopting sustainable urban planning and policies, we can ensure cities like Kigali's long-term ecological and environmental sustainability.

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Author contributions

Katabarwa Murenzi Gilbert: Conceptualization, methodology, formal analysis, visualization, and draft writing. **Yishao Shi:** Supervision, fund acquisition, draft review, and editing.

Conflicts of interest

The authors declare no conflicts of interest.

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