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EARTH OBSERVATION BASED MONITORING OF URBAN DEVELOPMENT AND ENVIRONMENTAL IMPACT OF MUHANGA SATELLITE CITY, RWANDA.

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ABSTRACT

By 2050, the number of people who live in urban areas is projected to reach 68%. About 90% of the increase will come from Asia and Africa. However, rapid urbanization in the form of urban expansion, specifically when unplanned, leads to undesirable consequences. Rwanda is also under similar scenario and this leads to expressing how important it would be for identifying and evaluating the environmental impact of Rwanda's rapid urbanization. This study objectives are (1) to monitor Urban development of Muhanga satellite City, (2) to analyze the land use/land cover change in Muhanga Satellite City and (3) to evaluate the environmental impact resulting from the Urban development of Muhanga Satellite City. Three satellite imagery data from Landsat acquired in 2003, 2013, and 2023 have been used. Five LULC classes such as Built-up area, Cropland, Bare land, Forest, and Marshland were analyzed, yielding good overall accuracies of 91.0224%, 89.2421%, and 86.5000%, and Kappa Coefficient of 0.8878, 0.8655, and 0.8313. The results indicated that the Built-up area is very expanding over past 20 years. The landscape metrics analysis showed that every 10 years, the built-up area is doubled in Muhanga satellite city. In 2003 Built-up area were 2,168,100 pixels, in 2013 were 4,697,100 pixels, and in January 2023 Built-up area reached 8,832,600 pixels. Therefore, this study recommends local community, government officials, policy makers and urban planners to give more considerations on newly created urban areas and existing ones under rapid expansion so as to reduce the environmental related impacts.

Key words: Urban development, Earth observation, Land cover, Environmental impact, Muhanga, Satellite city, Rwanda.

Contribution/Originality:

The contribution of his Study titled Earth Observation Based Monitoring of Urban Development and Environmental Impact of Muhanga Satelite City, Rwanda, is to alert local community, government officials, policy makers and urban planners to give more considerations on newly created urban areas and existing ones under rapid expansion so as to reduce the environmental related impacts and give special consideration on food security for future generations.

1. INTRODUCTION

Urbanization is one of the demographic mega-trends that play a significant role in terms of shaping the built environment in the world. In 2018, 55.2% of the global population lives in urban areas. There have been worries that the trend of people moving from rural to urban areas is likely to continue given the world's present high population growth. By 2050, the number of people who live in urban areas is projected to reach 68% [1]. About 90% of the increase will come from Asia and Africa [2]. Therefore, urbanization can largely contribute to economic growth, poverty reduction, and human development when properly planned and managed [2]. Nevertheless, rapid urbanization in the form of urban expansion, specifically when unplanned, leads to undesirable consequences [3]. Rapid urbanization in developing countries often results in uncontrolled urban growth [4]. Urbanization is therefore, the fastest-moving and most irreversible of all human-induced changes to land use and land cover [5]. Even though metropolitan areas make up less than 0.5% of the world's land area [6], these areas are where more than half of the world's population lives and relies [7]. Rapid urbanization is also a global trend that is affecting society more and more [6].

Urban growth is frequently quick and unplanned in developing nations, which can have unanticipated and negative effects. The most productive agricultural fields are frequently where cities are located, therefore any growth of built-up regions quickly depletes natural resources, jeopardizing not only the supply of food but also the provision of ecosystem goods and services that are drawn from these landscapes such as climate regulation, water infiltration, etc. [8].

Urbanization is a significant global challenge, but experts have been particularly interested in what is causing the cities in developing nations to grow so quickly [1]. The challenges of urbanization include loss of biodiversity, air and water pollution, storm water runoff, urban heat islands, and exponential population growth, which damagingly affects both nature and cities themselves [9].

The study of Urbanization and urban land use efficiency, in 2021 revealed that Ethiopia has experienced rapid urbanization over the past three decades. Several cities expanded rapidly and many satellite towns sprung up around the major cities. The high rate of urbanization and urban growth resulted in high demand for urban land, mainly for industrial, commercial, and residential purposes. In order to meet the demand, an enormous amount of land has been made available for urban use, mainly through land conversion [1].

Urbanization in emerging nations has grown quickly and unpredictably in recent years, partly as a result of industrialization and changes in the global economy. Only 16 cities in the globe had populations of over a million at the start of the 20th century, the vast majority of which were in industrialized nations [10]. Around 400 cities in the world had a million or more residents at the start of the twenty-first century, and 75% of those cities were located in low- and middle-income nations. Most of the population growth in urban areas is taking place in low- and middle-income Latin American, East Asian, Pacific, South Asian, Central Asian, Middle Eastern, and North African emerging nations [11].

The visible outcome of land use change in the wake of urbanization is the spatial expansion of built-up areas (which implies a significant alteration of land cover features), accompanied by changes in the urban spatial structure and the urban form [12].

In Rwanda, Rapid expansion of built-up areas has coincided with urban population growth, particularly in Kigali's peripheral and fringe areas. It is feasible to assess changes in Rwanda's "built-up" land, such as land covered in artificial, impermeable surfaces and other infrastructure, using satellite photography [3]. This serves as a decent stand-in for urban growth. In order to measure and assess the geographical patterns and trajectories of urban landscape change, it is crucial to monitor urbanization progress based on comparable indicators [13]. Understanding how urban land cover change dynamics are affecting Ecosystem Services and their related value may be possible by analyzing links between landscape metrics (LM) and Ecosystem Services [14]. Muhanga District is located in fifty kilometers (50 km) from Kigali, Rwanda's capital. It is among the areas that supply Kigali in food especially vegetables, fruit and meat of small livestock, mainly the meat of pigs. The District of Muhanga as a recognized Secondary City identified in EDPRS 2, the direction of the district is to become a Green Secondary City with an Essential focus in Mining, Quarry and Commercial Businesses, reinforced by a National Roadmap for Green Secondary City Development which is a green growth policy that Global Green Growth Institute (GGGI) helped to develop with focus on Rwanda’s Secondary cities. GGGI continued to give support in the Elaboration of Muhanga District Development Strategy (DDS) by developing sustainable strategies with focus on Green Urbanization [15].

In Rwanda, the few studies have investigated impact of urban development of land cover dynamics, and the environmental impact of newly occupied area using satellite-based landscape metrics and the concept of ecosystem services in secondary cities [13].

Urban expansion is said to be related to population density. It has a positive relationship with urban growth throughout the entire region, thus as population density rises, so does the proportion of that area that is built-up. An area that is becoming more inhabited may also result in the development of new settlement sites and other built-up areas, such as new towns, new industrial land, etc. [16].

Land conversion, particularly the conversion of vegetated areas to built-up space, results from increased demand for such land. Environmental degradation brought on by unchecked changes in land use and land cover can result in environmental issues and even anthropogenic disasters like floods and landslides [17]. An increase in anthropogenic catastrophes could come from a decline in environmental quality caused by the discrepancy between land use and land capacity in respect to environmental carrying capacity. Reduced environmental carrying capacity, or the capacity of the environment to support human life and other forms of life, can be brought on by rapid growth in the built-up area as well as unchecked changes in land use and land cover, such as turning vegetated lands into built-up area or protected areas into cultivation areas. Disasters and environmental issues including floods, landslides, forest fires, land droughts, and an increase in critical land can result from the loss of environmental carrying capacity [16].

In order to create land-cover/use maps from optical remote sensing data, a variety of classification techniques are available, including algorithms based on parametric and nonparametric statistics, nonmetric techniques, supervised or unsupervised classification logic, hard or fuzzy set classification logic, per-pixel or object-oriented classification logic, and hybrid approaches [18]. All classifiers are susceptible to a three-way compromise between the spectral information content of the imagery, the method of determining class decisions, and the desired information classes. As a result, none of them are inherently better than the others [19].

As harmful effects of fragmentation on biodiversity and ecosystem services are typically evident at intermediate (regional) spatial scales, this is also a crucial extent for assessing environmental impact [20].

Land use and land cover can be thought of as the interface between anthropogenic influence and natural conditions across the majority of the planet. Indicators that represent landscape conditions, stresses, and associated societal responses are sought.

Together with areal statistics, landscape metrics are used to characterize the structure and composition of the landscape. Landscape metrics are based on the quantity, size, form, and arrangement of patches of various land-use/land-cover types [21].

This study contributed to advance a better understanding of these land cover dynamics, and satellite-based monitoring as a promising tool because it is regularly taking image of the same location and it can help in tracing the spatial-temporal land cover change. The general objective of this study was to investigate the extent of Urban development and its related environmental impact in Muhanga satellite City, Rwanda. The specific objectives of this study were to monitor Urban development of Muhanga satellite City, to analyze the land use land cover change in Muhanga satellite City and to evaluate the environmental impact resulting from the Urban development of Muhanga satellite City.

2. MATERIALS AND METHODS

2.1. Description of the study area

2.1.1. Location

Muhanga Satellite City is laid in Muhanga District which is located in the southern province of Rwanda, West of city of Kigali, it's also one of the eight districts comprising the Southern Province. Muhanga District is subdivided into twelve sectors which are Nyabinoni, Rongi, Kibangu, Kiyumba, Rugendabari, Kabacuzi, Mushishiro, Muhamga, Cyeza, Nyarusange, Shyogwe and Nyamabuye which is the study area. Muhanga satellite city is located in fifty kilometers (50 km) from Kigali, Rwanda's Capital City. It is among the areas that supply Kigali in food especially vegetables, fruit and meat of small livestock, mainly the meat of pigs [14] (Muhanga district, 2018).

Major towns of Southern Province connected to Muhanga Satellite City are Ruhango, Nyanza, Huye and Nyamagabe, while those of the Western Province are Ngororero and Karongi. It is also connected to the Mayaga, region rich in agricultural production. This strategic location makes Muhanga Satellite City an economic pole that strives for development in trade and other businesses in the Southern part of the country by supplying goods and services but also a transit point for the supply of food in City of Kigali [14].

2.1.2. Topography

One part of Muhanga District is located in the "central plateau" of the country with topography of hills type. With high and low peaks, this part constitutes one of the best elements of the central "plateau" of the country. Muhanga satellite city is surrounded by peaks prancing beyond 2,000 meters such as Saruheshyi, Kanyarira, Mukingi and Samba [14].

2.1.3. Soil

Muhanga soils are generally constituted by humic Kaoli soils derived from granitic rocks. However, the soil characteristics vary from one to another ecological type, which is observed from a variety of soils depending on the altitude (high and low hills or lower slopes). In addition, the district has lateritic and granite soils spread over most of the area of the district. Swamps and lowlands are characterized by clay soils rich in silt and covered in places by alluvium and colluviums. The balance soil - plant is very fragile. This fragility is a consequence of erosion during the great rain season which corresponds to the period of torrential rain and which outweigh the fields and other infrastructure [22].

2.1.4. Environment and Climate

Muhanga District is located in an area well-watered, between 1100 mm and 1200 mm of altitude. This region enjoys a climate of four seasons of which two rainy seasons and two dry seasons: a short rainy season, which extends from October to December, a short dry season that runs from January to February, and a long rainy season from March to June and a long dry season from June to August or early September. The district is located mainly in the Agro-bio-climatic region called "Granite Ridge" [22].

2.1.5. Fauna and flora

The district Natural plants or ecosystems have disappeared, leaving room for crops and artificial forests. The crops consist of large banana with the combination of avocado, sweet potatoes, cassava, etc. The majority of the current afforested consists of Eucalyptus, Pinus and few grevilleas especially on the conservation tillage. The main use is the construction of houses, the firewood and the construction of bridges. This imposes the rehabilitation of damaged forests and agroforestry. However, the District has a natural forest of 40 ha called Busaga in Ndiza Mountain. Wildlife no longer exists in the region for a long time except for some birds, small mammals and reptiles encountered in the less frequented places [22].

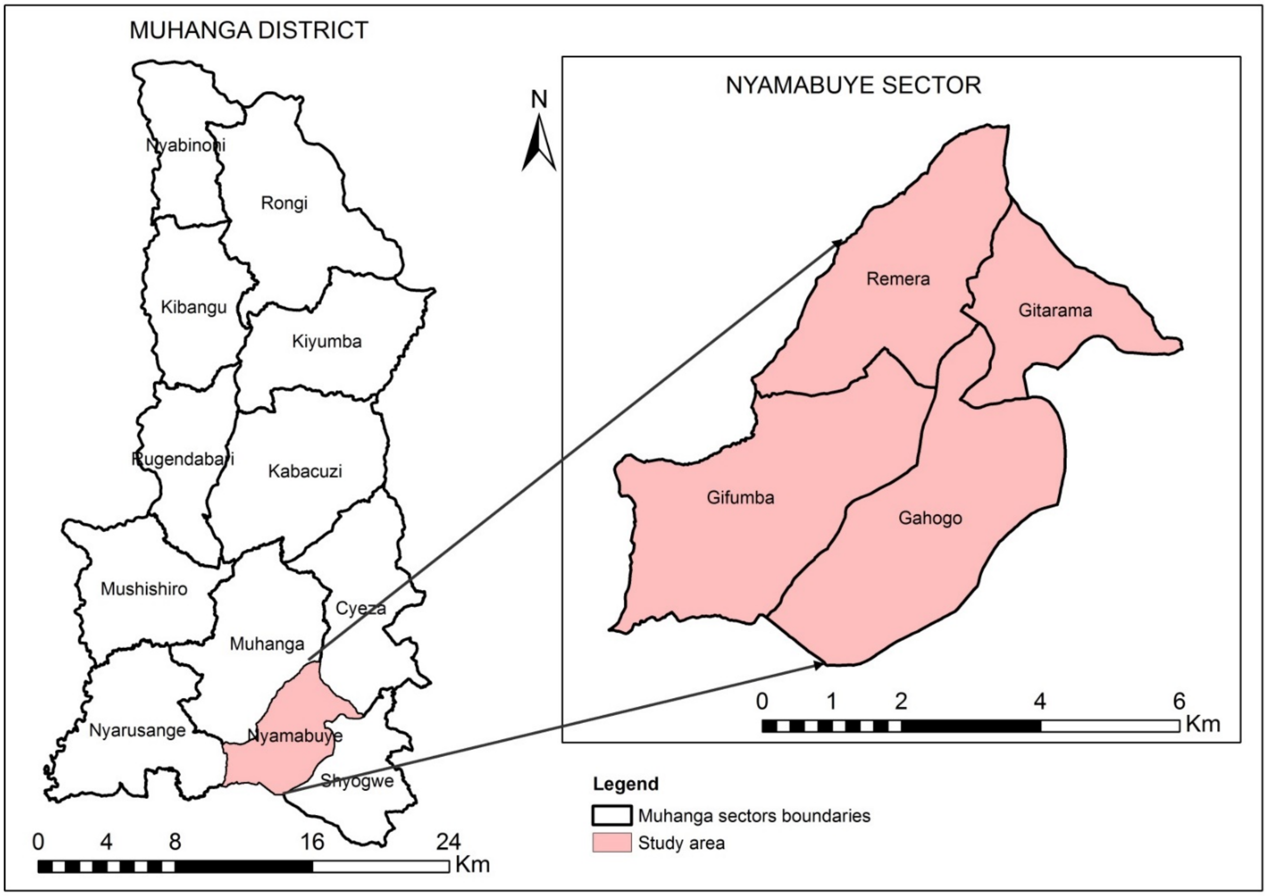

Figure 1: **Location of Study Area**

The figure 1 illustrates the location of study area which is Nyamabuye sector, a densely urban part of Muhanga satellite city, laid in Muhanga district, Southern Province of Rwanda. The population of Nyamabuye sector of Muhanga district increased over 3% in the past ten years [23].

Table 1: Population of Nyamabuye sector

Description	Area (Km2)	Population		
		Census 18/08/2012	Census 18/08/2022	Change [2012 - 2022]
Total Population	29.71	44,645	59,961	3.00%

Source: NSIR, 2023.

The table 1 presents the population change between two consecutive censuses of 2012 and 2022 in the study area.

2.2. Research design

The methodology of this study is concerned by firstly the classification of images based on remote sensing and analysis of land change using GIS applications. Landsat images collected between years 2003 and 2023 were processed in order to map land classes using a stratified image classification technique in conjunction with a GIS-based spatial reclassification procedure. This study analyzed Landsat imagery acquired from United States Geological Survey (USGS) from 2003, 2013, and 2023, then supervised classification were performed for analysis of land use land cover. In a supervised classification, the identity and location of the land-cover types such as built-up area, cropland, bare land, forest and marshland, are known a priori and the analysts attempt to locate specific sites in the remotely sensed data that represent homogeneous examples of these known land-cover types known as training sites because they are used to train the classification algorithm for eventual land-cover mapping of the remainder of the image. The algorithms based on supervised classification logic have been used. That is “Support Vector Machine Classification”. Thereafter, GIS-based activities facilitated the post-classification change detection technique to assess land cover changes and stratification. Landscape measurements were also used to investigate the scope, distribution, and kind of land changes.

2.3. Data Collection and Analysis

To perform this study, the authors proceeded by use of several methodological steps ranging from acquisition, pre-processing and analysis of satellite imagery data to the last stage of production of land use and land cover maps based on classification results. The general approach in this work was to process the satellite imagery dataset, run classification model, assess classification data accuracy, and measuring landscape metrics for detecting and illustrating the changes within considered land use land cover classes.

The Landscape Metrics approach involved applying one (or more) of the six metrics methodologies, namely edge-area, shape, core area, contrast, aggregation, and diversity metrics, to derive indices on land cover maps. Metrics indicators for measuring landscape structure will be created in this study utilizing the spatial pattern analysis application FRAGSTATS. In order to geographically characterize the study area, the landscape patterns were computed and examined at the class and landscape levels.

The following indices were classified as indicators of landscape composition: Landscape portion (LP), Number of patches (NP), Greatest patch area (GPA), Landscape division (LD) and Splitting Index (SI). Therefore, the computer applications have been used such as Internet browsers, MS office, ENVI 5.3, and ArcGIS 10.3.in data processing, analysis and results presentation.

3. RESULTS

3.1. Introduction

This chapter is designed for the presentation, analysis, interpretation and discussions of the study results. The data analysis and interpretation of the findings were based on the objectives specified by the researcher such as

- To monitor Urban development of Muhanga Satellite City.
- To analyze the land use/land cover change in Muhanga Satellite City.
- To evaluate the environmental impact resulting from the Urban development of Muhanga Satellite City.

3.2. Monitoring of Urban development of Muhanga Satellite City

This study used three satellite imagery data from Landsat 7,8 and 9 acquired by satellite sensors in 2003, 2013, and 2023. The following are the images processed for monitoring the urban growth in the study for the period of 20 years ago.

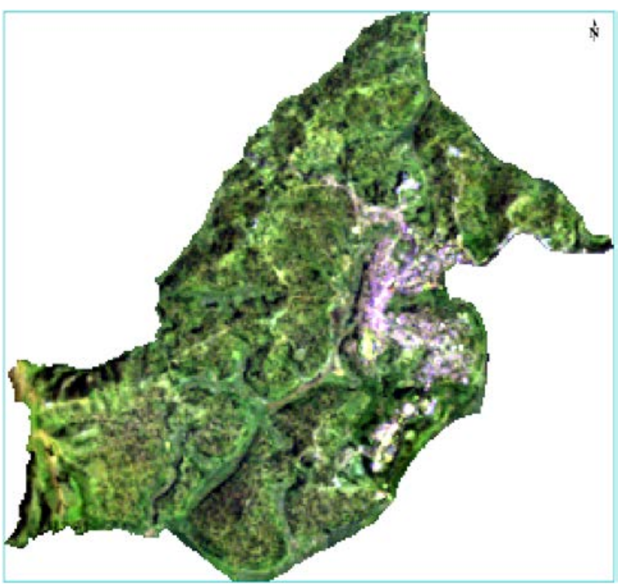

Figure 2 : 2003 Landsat 7 Image

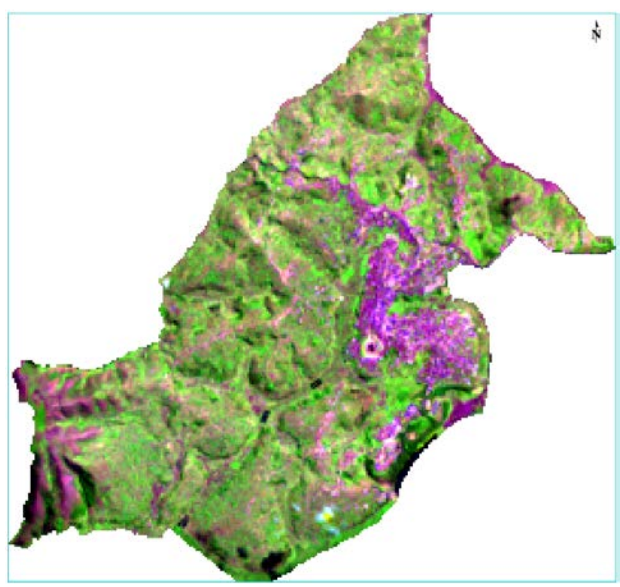

Figure 3 : 2013 Landsat 8 Image

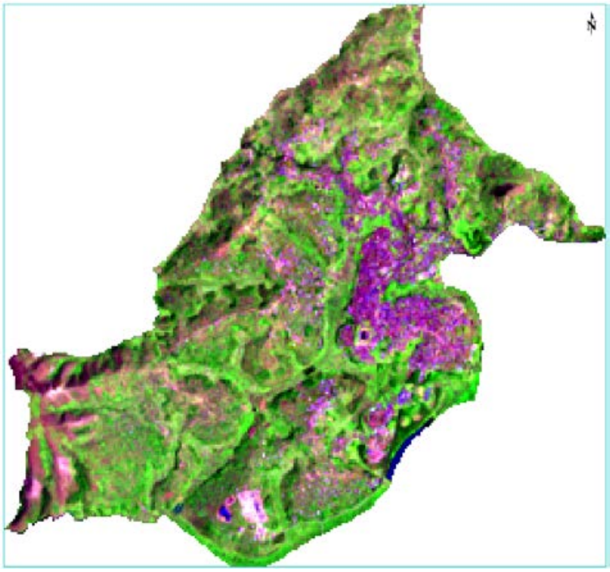

Figure 4: 2023 Landsat 9 Image

The figures 2,3 and 4 illustrate the extent of urban development in Nyamabuye sector, a densely urban part of Muhanga satellite city, in Muhanga district from 2003 to 2023.

3.3. Analysis of Land Use /Land cover change in Muhanga Satellite City

The land use / land cover in the study area have been acquired throughout remote sensing applications and processes performed by the authors. The land use land cover classes analyzed in this study are Built-up area, Cropland, Bare land, Forest, and marshland. Ta three satellite imagery data (2003, 2013, and 2023) 20 samples known as training areas are taken for supervised classification process. The results of Region of Interests (ROIs) Separability analysis indicated that the ROI pairs have a good separability as the values were close to 2.0 i.e. (1.74 to 1.99), then the accuracy assessment for Satellite image subsets have been performed, and the LULC maps have been produced.

3.3.1. Support Vector Machines classification

In order to identify the land cover classes in the study area a Support Vector Machines (SVM) classifier were employed on 7 bands of Landsat imagery datasets. The more frequent misclassifications were then fixed using urban and rural masks. The table 2 summarizes the number of training areas used to perform the process of supervised classification.

Table 2: Regions of Interests (ROIs) and Training Data Samples in the study area imagery subset.

Imagery Data acquired by satellites in 2003, 2013, and 2023		
No.	**Training Information**	**Number of Samples for training areas**
1)	Built-up area	20
2)	Cropland	20
3)	Bare land	20
4)	Forest	20
5)	Marshland	20

Source: Authors, 2023.

The table 2 presents the number of Samples for training areas taken on satellite images for performing supervised classification and accuracy assessment using Support Vector Machines (SVM) classifier.

3.3.2. Post Classification Analysis

This part presents the confusion matrix for the accuracy assessment on output raster data of land use land cover performed using ENVI 5.3. After that the classifications have been completed, the authors performed the accuracy assessments by using random sample vector points for verification of each land cover/use category. Overall accuracy, Kappa coefficient, and user's and producer's accuracies were calculated and used as accuracy measures.

3.3.2.1. Landsat Image acquired in 2003

Table 4: Confusion matrix of 2003 Landsat Image

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**71**	0	3	0	0	74
Cropland	2	**69**	2	0	9	82
Bare land	6	4	**74**	0	0	84
Forest	0	0	1	**80**	0	81
Marshland	2	**7**	0	0	**71**	80
Total	81	80	80	80	80	401

Source: Authors, 2023

The data presented in the table 4 is the number of pixels of each class from region of interests (ROIs) for 2003 satellite image. Built-up area 71 pixels, Cropland 69 pixels, Bare land 74 pixels, Forest 80 pixels, and Marshland 71 pixels. The total pixels are 401 pixels.

Table 5: The confusion matrix using Ground Truth (Percent)

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**87.65**	0.00	3.75	0.00	0.00	18.45
Cropland	2.47	**86.25**	2.50	0.00	11.25	20.45
Bare land	7.41	5.00	**92.50**	0.00	0.00	20.95
Forest	0.00	0.00	1.25	**100.00**	0.00	20.20
Marshland	2.47	8.75	0.00	0.00	**88.75**	19.95
Total	100.00	100.00	100.00	100.00	100.00	100.00

Source: Researcher, 2023.

The data presented in the table 5 is the percentage of each class from region of interests (ROIs) for 2003 satellite image. Built-up area (87.65%), Cropland (86.25%), Bare land (92.50%), Forest (100%), and Marshland (88.75%).

Table 6: Commission error, Omission error, Producer Accuracy, and User Accuracy

Class	**Commission (%)**	**Omission (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**
Built-up Area	4.05	12.35	87.65	95.95
Cropland	15.85	13.75	86.25	84.15
Bare land	11.90	7.50	92.50	88.10
Forest	1.23	0.00	100.00	98.77
Marshland	11.25	11.25	88.75	88.75

Source: Authors, 2023.

The table 6 presents the results of analysis of Commission error, Omission error, Producer Accuracy, and User Accuracy during classification process of Landsat image of 2003.

Table 7: The overall Accuracy and Kappa Coefficient

	Landsat 7 Image of 2003
Overall Accuracy	91.0224%
Kappa Coefficient	0.8878

Source: Authors, 2023.

The table 7 presents the overall Accuracy and Kappa Coefficient performed during land use land cover classification process of Landsat 7 Image of 2003.

Table 8: Statistics of classified land use land cover in 2003

Class	Pixel Count	Percent
Built-up Area	2,409	3.333
Cropland	42,957	59.431
Bare land	11,963	16.551
Forest	3,745	5.181
Marshland	11,206	15.504

Source: Authors, 2023.

The table 13 presents basic statistics of class information in pixels and percentage from the study area image of 2003. Built-up area was (3.333%), Cropland (59.431%), Bare land (16.551%), Forest (5.181%), and Marshland (15.504%).

3.3.2.2. Landsat Image acquired in 2013

Table 9: Confusion matrix of 2013 Landsat Image

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**79**	0	6	0	0	85
Cropland	0	**74**	0	2	13	89
Bare land	10	0	**74**	0	0	84
Forest	0	0	0	**75**	4	79
Marshland	0	**6**	0	3	**63**	72
Total	89	80	80	80	80	409

Source: Authors, 2023

The data presented in the table 9 is the number of pixels of each class from region of interests (ROIs) for 2013 satellite image. Built-up area 79 pixels, Cropland 74 pixels, Bare land 74 pixels, Forest 75 pixels, and Marshland 63 pixels. The total pixels are 409 pixels.

Table 10: The confusion matrix using Ground Truth (Percent)

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**88.76**	0.00	7.50	0.00	0.00	20.78
Cropland	0.00	**92.50**	0.00	2.50	16.25	21.76
Bare land	11.24	0.00	**92.50**	0.00	0.00	20.54
Forest	0.00	0.00	0.00	**93.75**	5.00	19.32
Marshland	0.00	7.50	0.00	3.75	**78.75**	17.60
Total	100.00	100.00	100.00	100.00	100.00	100.00

Source: Researcher, 2023.

The data presented in the table 10 is the percentage of each class from region of interests (ROIs) for 2013 satellite image. Built-up area (88.76%), Cropland (92.50%), Bare land (92.50%), Forest (93.75%), and Marshland (78.75%).

Table 11: Commission error, Omission error, Producer Accuracy, and User Accuracy

Class	Commission (%)	Omission (%)	Producer Accuracy (%)	User Accuracy (%)
Built-up Area	7.06	11.24	88.76	92.94
Cropland	16.85	7.50	92.50	83.15
Bare land	11.90	7.50	92.50	88.10
Forest	5.06	6.25	93.75	94.94
Marshland	12.50	21.25	78.75	87.50

Source: Authors, 2023.

The table 11 presents the results of analysis of Commission error, Omission error, Producer Accuracy, and User Accuracy during classification process of Landsat image of 2013.

Table 12: The overall Accuracy and Kappa Coefficient

	Landsat 8 Image 2013
Overall Accuracy	89.2421%
Kappa Coefficient	0.8655

Source: Authors, 2023.

The table 12 presents the overall Accuracy and Kappa Coefficient performed during land use land cover classification process of Landsat 8 Image of 2013.

Table 13: Statistics of classified land use land cover 2013

Class	Pixel Count	Percent
Built-up Area	3,151	4.359
Cropland	39,022	53.987
Bare land	6,041	8.358
Forest	2,519	3.485
Marshland	21,547	29.810

Source: Researcher, 2023.

The table 13 presents basic statistics of class information in pixels and percentage from the study area image of 2013. Built-up area was (4.359%), Cropland (53.987%), Bare land (8.358%), Forest (3.485%), and Marshland (29.810%).

3.3.2.3. Landsat Image acquired in 2023

Table 14: Confusion matrix of 2023 Landsat Image

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**79**	0	3	0	0	82
Cropland	0	**67**	0	0	37	104
Bare land	1	0	**77**	0	0	78
Forest	0	0	0	**80**	0	80
Marshland	0	**13**	0	0	**43**	56
Total	80	80	80	80	80	400

Source: Authors, 2023

The data presented in the table 14 is the number of pixels of each class from region of interests (ROIs) for 2023 satellite image. Built-up area 79 pixels, Cropland 67 pixels, Bare land 77 pixels, Forest 80 pixels, and Marshland 43 pixels. The total pixels are 400 pixels.

Table 15: The confusion matrix using Ground Truth (Percent)

Class	Built-up area	Cropland	Bare land	Forest	Marshland	Total
Built-up area	**98.75**	0.00	3.75	0.00	0.00	20.50
Cropland	0.00	**83.75**	0.00	0.00	46.25	26.00
Bare land	1.25	0.00	**96.25**	0.00	0.00	19.50
Forest	0.00	0.00	0.00	**100.00**	0.00	20.00
Marshland	0.00	16.25	0.00	0.00	**53.75**	14.00
Total	100.00	100.00	100.00	100.00	100.00	100.00

Source: Authors, 2023

The data presented in the table 15 is the percentage of each class from region of interests (ROIs). Built-up area (98.75%), Cropland (83.75%), Bare land (96.25%), Forest (100.00%), and Marshland (53.75%).

Table 16: Commission error, Omission error, Producer Accuracy, and User Accuracy

Class	**Commission (%)**	**Omission (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**
Built-up Area	3.66	1.25	98.75	96.34
Agricultural land	35.58	16.25	83.75	64.42
Forest	1.28	3.75	96.25	98.72
Marshland	0.00	0.00	100.00	100.00
Water body	23.21	46.25	53.75	76.79

Source: Authors, 2023.

The table 16 presents the results of analysis of Commission error, Omission error, Producer Accuracy, and User Accuracy during classification process of Landsat 9 image of 2023.

Table 17: The overall Accuracy and Kappa Coefficient

	Landsat 9 Image 2023
Overall Accuracy	86.5000%
Kappa Coefficient	0.8313

Source: Authors, 2023.

The table 17 presents the overall Accuracy and Kappa Coefficient performed during land use land cover classification process of Landsat 9 Image of 2023.

Table 18: Statistics of classified land use/land cover 2023

Class	Pixel Count	Percent
Built-up Area	9,814	13.578
Cropland	40,562	56.118
Bare land	5,584	7.726
Forest	6,889	9.531
Marshland	9,431	13.048

Source: Authors, 2023.

The table 18 presents basic statistics of class information in pixels and percentage from the study area image of 2023. Built-up area was (13.578%), Cropland (56.118%), Bare land (7.726%), Forest (9.531%), and Marshland (13.048%).

3.3.3. Land Use Land Cover output maps of study area

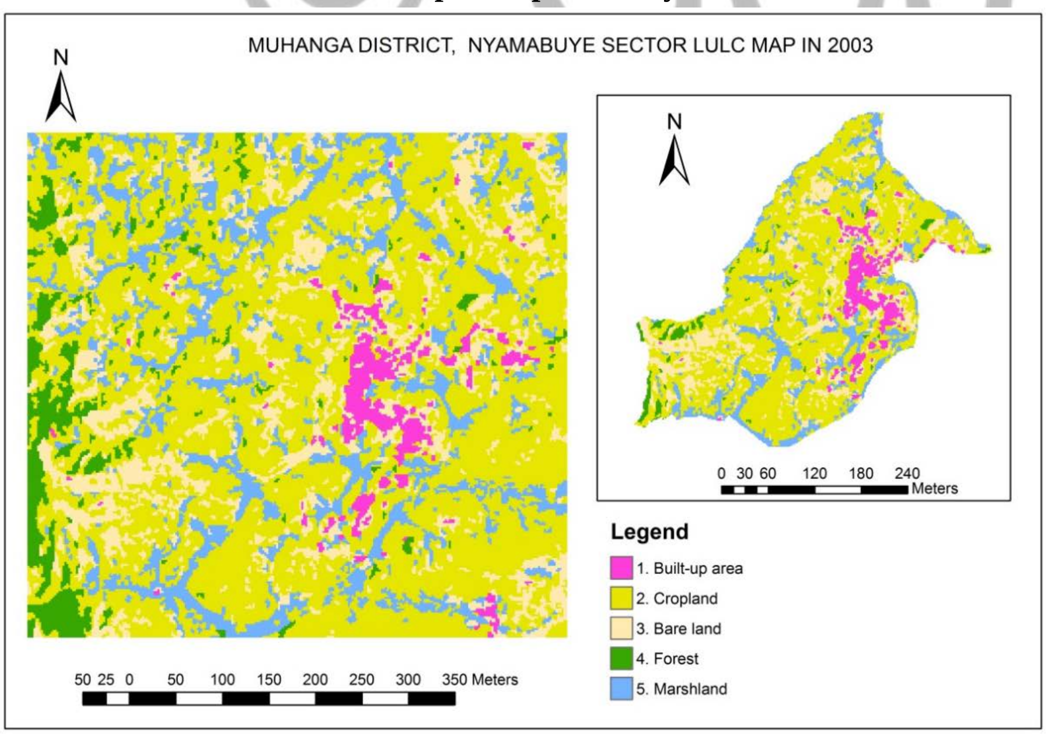

Figure 5: Land use land cover map of Nyamabuye sector in 2003

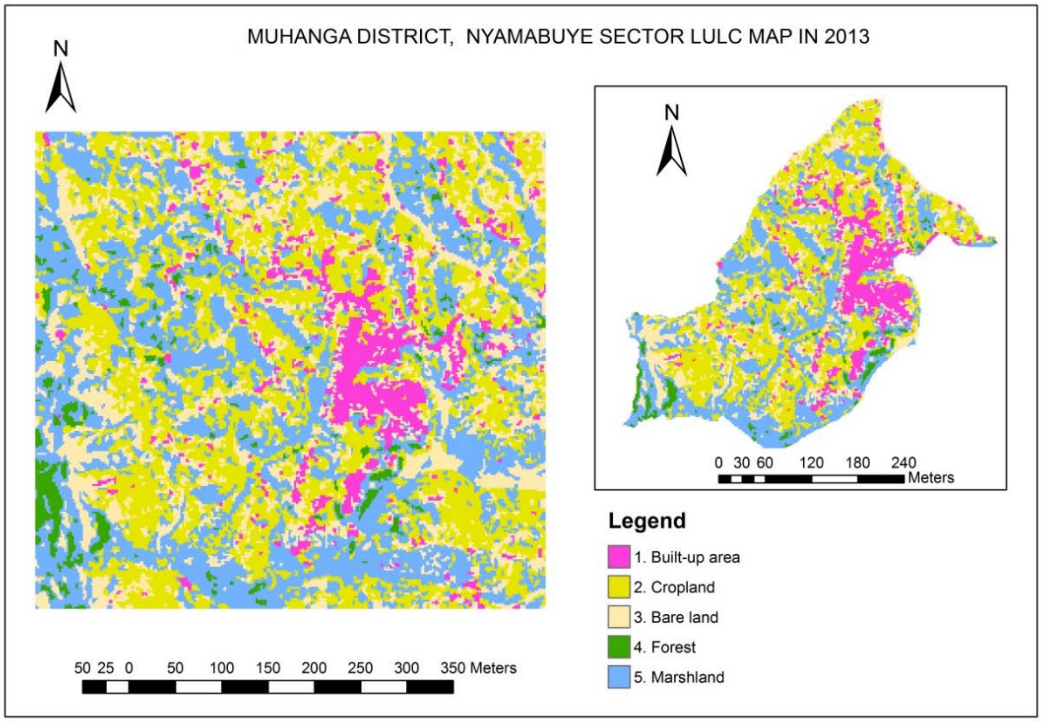

Figure 6: Land use land cover map of Nyamabuye sector in 2013

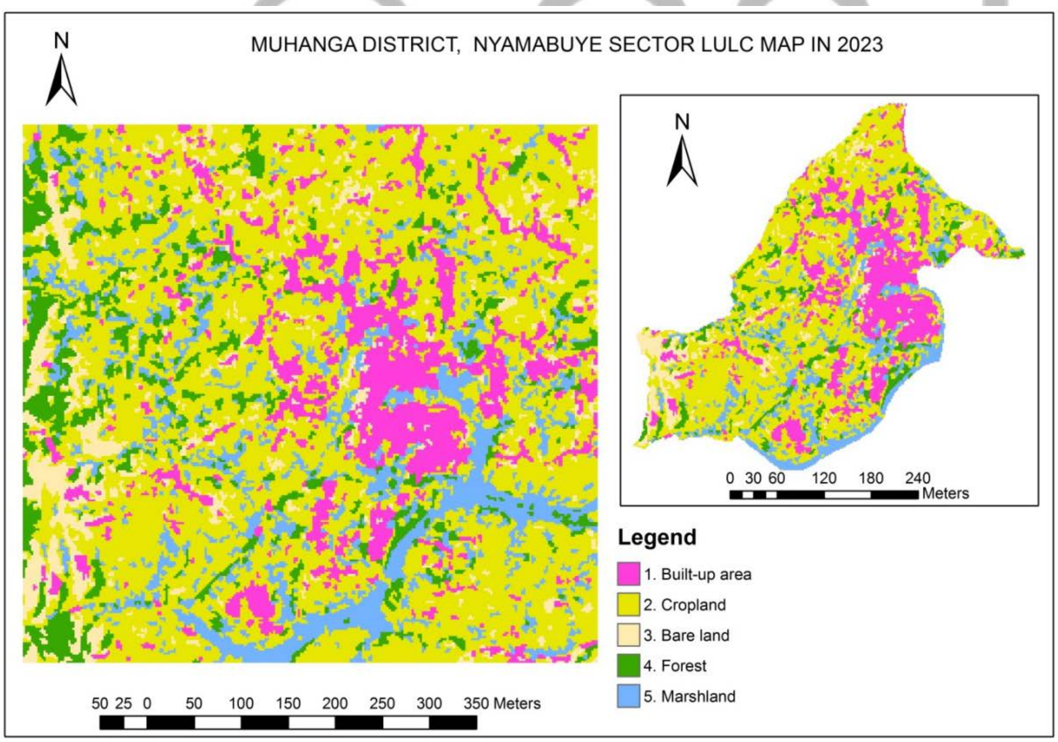

Figure 7: Land use land cover map of Nyamabuye sector in 2023

3.4. Evaluation of the environmental impact resulting from the Urban development of Muhanga satellite City.

This part presents the landscape metrics which geographically characterize the study area. The landscape patterns were computed and examined at the class and landscape levels. The indices that were classified as indicators of landscape composition are: Landscape portion (LP), Number of patches (NP), Greatest patch area (GPA), Landscape division (LD) and Splitting Index (SI).

Table 19: Landscape Ecology statistics of Landsat Image acquired in 2003

Class	Land cover	Landscape Proportion	Number of Patches	Greatest patch area	Landscape division	Splitting Index
Built-up area	2,168,100	0.033	72	1,065,600	1.000	3,570.39
Cropland	38,661,300	0.594	112	36,835,200	0.679	3.12
Bare land	10,766,700	0.166	378	1,050,300	0.999	1,545.07
Forest	3,370,500	0.052	106	1,107,900	1.000	2,583.26
Marshland	10,085,400	0.155	284	1,105,200	0.999	1,558.41

Source: Authors, 2023.

The table 19 presents Landscape Ecology statistics of Landsat Image acquired in 2003.

Table 20: Landscape Ecology statistics of Landsat Image acquired in 2013

Class	Land cover	Landscape Proportion	Number of Patches	Greatest patch area	Landscape division	Splitting Index
Built-up area	4,697,100	0.072	175	1,907,100	0.999	1,112.15
Cropland	21,843,000	0.336	250	2,745,000	0.994	166.16
Bare land	13,884,300	0.213	517	1,112,400	0.999	1,458.81
Forest	1,821,600	0.028	107	438,300	1.000	17,854.11
Marshland	22,806,000	0.351	279	5,533,200	0.987	74.18

Source: Authors, 2023.

The table 20 presents Landscape Ecology statistics of Landsat Image acquired in 2013.

Table 21: Landscape Ecology statistics of Landsat Image acquired in 2023

Class	Land cover	Landscape Proportion	Number of Patches	Greatest patch area	Landscape division	Splitting Index
Built-up area	8,832,600	0.136	246	3,417,300	0.997	345.59
Cropland	36,505,800	0.561	135	29,493,000	0.790	4.76
Bare land	5,025,600	0.077	330	739,800	1.000	4,956.53
Forest	6,200,100	0.095	287	429,300	1.000	5,922.41
Marshland	8,487,900	0.130	387	1,352,700	0.999	1,263.12

Source: Authors, 2023.

The table 21 presents Landscape Ecology statistics of Landsat Image acquired in 2023.

4. DISCUSSION

By visual observation of three satellite imagery from Landsat 7, 8 and 9 acquired by satellite sensors in 2003, 2013, and 2023 used in this study, the built-up area is very expanding over past 20 years. This observation agrees with the study of Nesru H. Koroso et al., which stated that in 2018, 55.2% of the global population lives in urban areas, and that there have been worries that the trend of people moving from rural to urban areas is likely to continue given the world's present high population growth. The supporting results of Muhanga satellite city quick expansion are presented in basic statistics of class information from this the study, in analyzing satellite images of 2003, 2013, and 2023. The results showed that in 2003, Built-up area was 3.333%, increased in 2013 on 4.359%, and in 2023 on 13.578%. This proves the statement of Liu and Yang 2015 stating that Urbanization is the fastest-moving and most irreversible of all human-induced changes to land use and land cover. This rapid urban growing in Muhanga satellite city impacts negatively environment in the study area, such as deforestation and excessive land fragmentation. The basic statistics of this study results indicate that in 2003, forest was 5.181%, decreased in 2013 on 3.485 %, and after 10 years, in 2023 the forest increased at 9.531% thanks to Muhanga distict measures for environmental protection. These results are in line with Muhanga District Development Strategy (DDS): 2018-2024 stating that the district Natural plants or ecosystems have disappeared, leaving room for crops and artificial forests. In 2018 Muhanga District stated that the majority of the current afforested consists of Eucalyptus, Pinus and few grevilleas especially on the conservation tillage, which increased the forest in the study area. The Landscape Ecology Statistics in this study revealed the dynamics in land use land cover classes analyzed which are Built-up area, Cropland, Bare land, Forest, and Marshland, by the indices that were classified as indicators of landscape composition which are Landscape portion (LP), Number of patches (NP), Greatest patch area (GPA), Landscape division (LD) and Splitting Index (SI). The results showed that landscape fragmentation and changes in spatial pattern had an effect on the provision of Environmental Services (ES) in the study area throughout the previous 20 years, from 2003 to 2023. The amount of forest and cropland for agriculture that provided the regulating services (air quality, surface runoff, and erosion management) vary along with the size of the LULC that offered those services whereas built-up area is increasing considerably.

The results of this study in landscape analysis showed that every 10 years, the built-up area is more than doubled in Muhanga satellite city, as in 2003 built-up area were 2,168,100 pixels, in 2013 were 4,697,100 pixels, and finally in January 2023 built-up reached 8,832,600 pixels. These results emphasized the study of Foley et al., 2005 which revealed that Urban growth is frequently quick and unplanned in developing nations, which can have unanticipated and negative effects on natural environment. And that the most productive agricultural fields are frequently where cities are located, therefore any growth of built-up regions quickly depletes natural resources, jeopardizing not only the supply of food but also the provision of ecosystem goods and services that are drawn from these landscapes.

5. CONCLUSION

Based on Landsat imagery datasets, this study demonstrates the potential of employing a hybrid land cover monitoring system to assess the effects of urbanization development on the environment and natural resources stewardship. With the proposed hybrid technique, five LULC classes: Built-up area, Cropland, Bare land, Forest, and marshland were successfully mapped, yielding good overall accuracies ranging between 91.0224%, 89.2421%, and 86.5000% with the Kappa Coefficient ranging between 0.8878, 0.8655, and 0.8313 respectively. The results of this study revealed that the change in land cover showed that built-up area in the study area is more than double every 10 years from 2003. Landsat imagery and their texture measures were used for image analysis and the mapping of spatial-temporal patterns of urban expansion with high accuracy with the help of urban/rural masks. Indeed, the results showed that landscape fragmentation and changes in spatial pattern had an effect on the provision of Environmental Services (ES) in the study area throughout the previous 20 years, from 2003 to 2023.

Food provision, flood protection, local climate regulation, water provision, air purification, surface runoff and erosion control, recreation and aesthetic value, and habitat for biodiversity are the main services identified by the ES analysis. The majority of the ES are clustered in marshes, cropland, and forests. Therefore, this study recommends policy makers and urban planners to take care and give more consideration on newly created urban areas and existing ones under rapid expansion so as to reduce the environmental related impacts; and give special consideration on sustainable food security, with reference to rapid population growth projection, for future generations. Local leaders are recommended to give priority to environmental protection and conservation as well as stewardship of current natural resources.

The methodology adopted in this study can be used in future studies for monitoring Urban development of other two remaining Satellite Cities of Kigali namely Nyamata and Rwamagana, and Secondary Cities in Rwanda, to analyze the land use/land cover changes, and evaluate the environmental impact and plan for food security issues.

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