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Impact of agricultural land acquisition for urbanization on agricultural activities of affected households in Bumbogo sector

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ABSTRACT:
The procedure by which the government obtains agricultural land for urbanization involves acquisition of agricultural land from multiple users, transferring it into non-farming land, and then developing and establishing infrastructure such as roads, buildings, residential areas, parks, and other infrastructure on the acquired agricultural land Agricultural. Land acquisition for urbanization had a substantial influence on agriculture in the Bumbogo sector. 2002, 2012, and 2022 are the most recent 20 years. In this study, conduction of surveys in a range of communities to find out how much agricultural land has changed. Spatial data obtained from not only primary data such as observation, interviews, and field data collection, but also secondary data such as satellite data, primarily Landsat images, of 2002, 2012, and 2022 was downloaded free of cost from the USGS Earth Explorer and classified using ERDAS Imagine 2014, By comparing before and after ALAFU, this study demonstrates the various effects of ALAFU on each type of agriculture practiced by impacted households. Agricultural activity has decreased as a consequence of urbanization as well as a farmland purchase, which caused decline of productive land. The research revealed that, 1376.6 hectares which is equal to 35.74 % of the entire agriculture area have been changed to other LULC and 648.27 hectares which is equal to 47.09 % of agriculture land has been changed to built-up area. vertical agriculture should be adopted due to its advantageous associated with urban dwellers as a good consumer market and upgrading infrastructure should be enhanced without affecting the environment. Plantations and livestock breeding have declined significantly. Regardless of whether they are diminishing or rising, all agricultural activities confront difficulties due to gaps in the development plans and distribution of agricultural land.

KEYWORDS: agricultural land acquisition, urban agriculture, urbanization, GIS, household and vertical farming.

I. INTRODUCTION

Agricultural land acquisition for urbanization is the procedure by which the government obtains agricultural land for urbanization involves purchasing agricultural land from multiple users, transferring it into non-farming land(Schneider, 2012).

As the average wage for urban labour is established, the more rural migrant workers move to urban areas, the higher the rate of urbanization, and the more remittances are sent back to the farmers who are left behind. Remittances from migrant workers help remaining peasants get around credit and insurance restrictions(Taylor et al, 2003).

By 2030, there will be approximately 5 billion urban dwellers worldwide, the urban population is expected to increase by 1.35 billion(Noresah, 2010).

Large-scale changes in land use and land cover (LULC) are brought about by the vast movements of capital, products, and people that are moving to urban centres(Seto et al., 2011).

Cities are growing at an alarming rate around the world, and built-up regions have expanded, displacing a lot of nearby agriculture and resulting in an approaching land shortage(Lambin et al., 2011).3.7% of the world's farmland is predicted to disappear owing to urbanization by the year 030(Kochar, 2020).

This led to challenges to food security due to a loss of world agriculture. The Kigali City Master Plan, which was approved for implementation in 2013 and specifies how land

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should be used in accordance with certain zoning restrictions, is being updated every ten years.

This caused a process of land use change owing to urbanization. With a significant change from agriculture to non-farming zones. Which reduced the aspects of agricultural activities in Bumbogo Sector?

II. II.STUDY AREA DESCRIPTION

According to(RPHC4, 2013) has enumerated 35,381 residents in Bumbogo sector with sum of households of 9,624 and landscape or surface area is 6007.33 Hectares, 17,722 are men and 17,659 are women Bumbogo sector represent 6.7 % of the total resident population of Gasabo district. It is bounded by 6 sectors namely Rutunga (north-east) Kinyinya (southwest), Ndera (south-east), Gikomero (east), Kimironko (north) and Nduba sector (west). Bumbogo sector consists of seven (7) cells which are Nyagasozi, Nkuzuzu, Mvuzo, Ngara, Nyabikenke, Kinyaga and Musave cells; all with the temperature in the range of an average low of 160c and an average of high 28.20c. It has an approximately 1669 meter of elevation and altitude of 16.16 kilometres. Bumbogo involves numerous economic activities such as commerce, farming, pottery, forestry, quarrying.

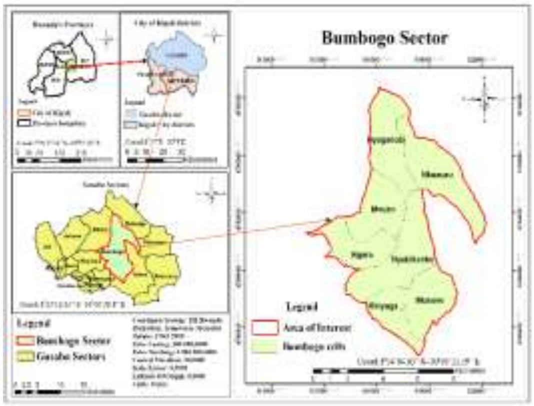

Figure 2.1: Study area description

III. III.METHODOLOGY

This part shows the materials and methods used by researcher to accomplish the project.

Research is a process of inquiry that is carried out in pondered, organized, and strategic manner. In order to obtain high quality results, it is is important to understand methodology.

Research methodology refers to how your project will be designed, what you will observe or measure, and how you will collect and analysedata. The methods you choose must be appropriate for your field and for specific research questions you are setting out to answer.

A strong understanding of methodology will help you: apply appropriate research techniques, design effective data collection instruments, analyse and interpret your data and develop well-founded conclusions.

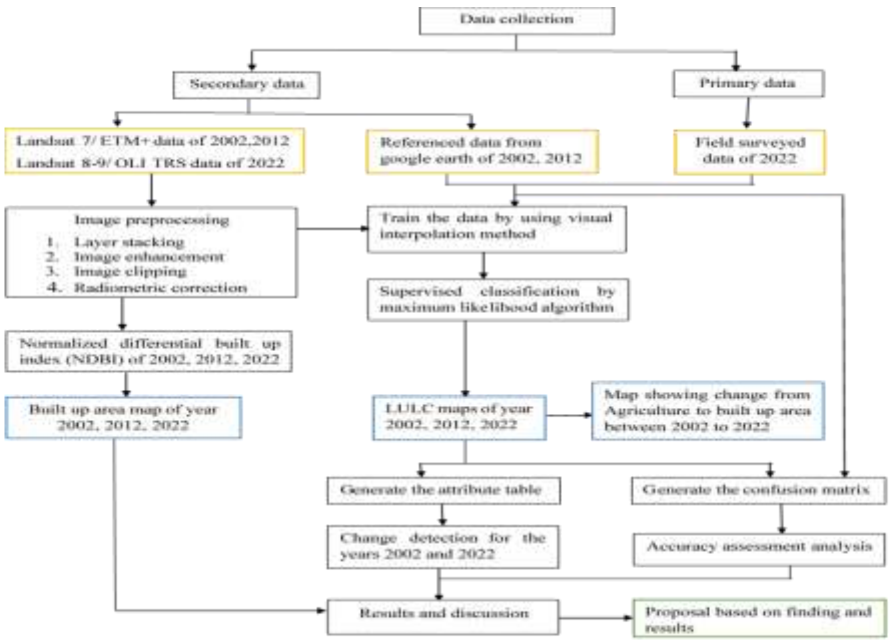

Figure 3.1: Flowchart of methodology

Data source

Analysing the modifications and effects of ALAFU on agricultural activities, several types of data have been used to express and quantifying the level and Impact of ALAFU within three decades from 2002 to 2022 by considering 10 years of interval. To obtain the required data, the study used both primary data (field surveyed data and interviews) and secondary data sources. Secondary data included remote sensing data, Demographic and settlement data, Aerial photography and google earth image, administrative boundary data.

Data collection techniques

The ways of obtaining quantitative and qualitative data, both primary and secondary sources of data are used.

Primary data

Primary data were collected using field observations and interview guides. The interviews were administered to sampled people in Bumbogo sector and professionals who work in some key institutions directly concerned with planning of the city.

Field observation and interviews was conducted in order to observe the current state of agriculture areas in Bumbogo sector and to collect the valuable qualitative data to compliment to the field surveyed data, satellite image classification and other further analysis. Household surveys, focus groups, in long interviews, village walks, and site visits to observation study areas were the project's main methods for gathering data.

From the list of affected families taken into consideration for the study, 31 of the more than 143 affected households whose land was reduced according to the interviews and LULC map analysis of the total previous agricultural land region as a consequence of ALA were randomly selected to participate in the household surveys. As part of the research, 15 members of the impacted communities took part in group discussions to identify and classify the causes of the changes, challenges, and opportunities for each agricultural activity. The study's participants were required to make a list of all the causes and evaluate the importance of each one using a few comparisons. Based on this, we identified ALAFU's causes as well as its issues and prospects.

Secondary data

The following material such as Landsat satellite data of past two decades have been downloaded from USGS Earth Explorer website used in the project. All the data were pre-processed and projected to the Universal Transverse Mercator (UTM) projection system and ERDAS imagine2014 and GIS software are the appropriate software used.

To identify the change in agricultural area to built-up area under the impact of Agricultural Land Acquisition for Urbanization were analysed using Landsat images in a series of 2002, 2012, and 2022 years with a sensor resolution (30m). Demographic data uploaded by National Institute of Statistics of Rwanda (NISR) are used to analyse the impacts of population and housing strategies in the study. The region of interest was made using a base map of Rwanda, and to develop the critical thinking and theoretical consideration, other data sources, such as books from websites, scientific articles, and daily publications relevant to the research issues, were employed as reference materials.

Classification

Image classification is the procedure of classifying and labelling sets of pixels or vectors within an image in accordance with predetermined rules(Redko et al.,2019).

It makes use of the spectral data encoded in digital numbers in one or more spectral bands and makes an effort to categorize each individual pixel using this spectral data(Anand, 2018). Each image has been classified into five classes which determined by spectral characterization. To identify the change of agricultural area to built-up area under the impact of ALAFU in Bumbogo sector, Landsat ETM+ data 2002, 2012 and Landsat OLI_TIRS 2022 were used and the images were classified using a supervised classification technique (maximum likelihood classifier algorithm). Post classification change detection matrices were cross-tabulated in two interval steps: 2002- 2012, and 2012-2022 Pixel-by-pixel analysis was used to emphasize the spatial-temporal LULC changes and distribution in the post classification change detection approach.

Flow Chart/steps of classification

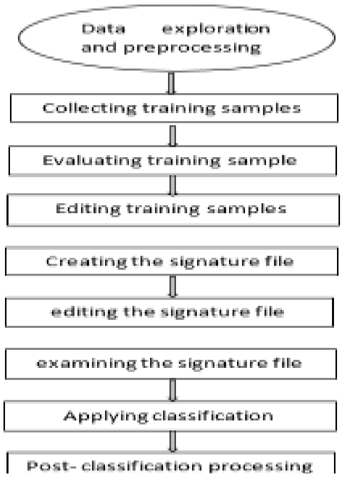

Figure 3.2: Flow Chart/steps of classification

Data Pre-processing

Remote Sensing data are always very hard to interpret them as the reason why the following process of pre-processing is performed to improve visualization of the image during classification. Since the process involve to remove errors from RS data, It alludes to the routinely carried out operations that enhance the geometrical and radiometric properties of the images and probable the process might have three different steps as follow (i) radiometric correction to compensate the effects of atmosphere (ii) geometric correction or registration of the image to enable it to be used with additional maps or pictures from the adopted reference system and (iii) noise removal to reduce unwanted noise of any kind due to the limitations of recording and transmission processes(Das, 2009).

In the research, Radiometric correction was performed because radiometric correction is obligatory whenever image differencing is used for change detection analysis and also is required while analysing built up area in raw remotely sensed radiance data. While geometric correction was not adopted simply because, the research does not require to know the position of the remotely sensed data and only the essential was to have Remote Sensed data covering the entire area of study.

Image enhancement

There are no special materials that can interpret images in easy way. Image enhancement refers to the process applied in a particular application to make the image more interpretable by human eyes by applying some technique to make more important features of row remote sensing data to be viewed and interpreted by naked eye(Wang et al, 2008).Choosing the appropriate technique for image enhancement will depend upon; data, objective, background, and expectations. Despite the possibility of performing radiometric corrections for illumination, atmospheric influences, and sensor characteristics before data distribution to the user, the image might still not be suitable for visual interpretation(Sergey, 2010)To make images more appealing for human visual analysis, a variety of image enhancement algorithms are applied to remotely sensed data. However, there is no such thing as the ideal or best image enhancement because the results are ultimately assessed by humans, who make subjective decisions about whether a given image enhancement is useful. In the research, removing noise, brighten an image were performed for making it easier to identify key features

Supervised Classification

The maximum likelihood classification algorithm, a supervised classification that is one of the most popular methods for identifying medium resolution satellite images, was used to categorize the Landsat images. A pixel is assigned to a class according to its feature vector by comparing it to predefined clusters in the feature space, which is the basis of image classification. A classified image is produced by doing this for each and every pixel. Comparing an image to predefined clusters, which requires the definition of the clusters and methods for comparison, is the crux of image classification. In the course of the "training process," the clusters are defined in an interactive manner. Using "classification algorithms," the clusters and the individual pixels are compared(Tempfli et al., n.d.).

The user of the image processing program was in charge of locating the pertinent land cover classes during the study, which used supervised classification. The user defines training samples which are either a group of pixels chosen to represent a prospective class or places in the map known to be representative of a specific land cover type. Different band combinations for both Landsat 7/ETM+ and Landsat 9/OLI_TIRS have been used to facilitate the identification of the features of interest.

By drawing polygons around the elements and regions that each LULC type considers to be representative, training samples for each type of land cover were gathered. To capture the spectral variability within each type of land cover, the polygons were generated at random throughout the image. Google Earth and the researcher's personal knowledge and experience of the study area were both used to gather the training sample data. In order to calculate the mean and variance of the classes in relation to all of the input bands or layers, the software analyses the spectral signature of the pixels contained within each training area. The class that each pixel in the image most closely resembles is then determined based on its spectral signature.

The accuracy is determined by contrasting the classified maps with the corresponding AOI that is produced from reference data. For each LULC class, topographic maps, satellite images, and Google Earth were used to gather a minimum of 85 AOIs. The differences in the LULC maps produced were quantified, identified, and described using the post-classification change detection technique, with a focus on understanding how much the agricultural land of impacted households changed as a result of ALAFU.

Table3.2: Classes of classification based in reflectance

Land use land cover classes	Description
Agriculture area	Wetlands, crops
Built up	Residential areas, commercial units, transportation facilities (paved roads)
Forestry	Forests, parks
Other LULC	gardens, grassland, bare land, roadside trees, all other areas which are not fall into agriculture area, built up and forestry.

Change detection

Change information about the ground object is obtained through the comparison and analysis of two (or more) remote sensing images taken at various times in the same region. This process is known as remote sensing image change detection (CD) (Yang et al., 2022). Since the main objective of the study was to determine the Impact of ALAFU, the use of change detection technique was a helpful because it helps in evaluation of the changes considerably as surface component alterations. Land-cover (LC) and land-use (LU) change information is important because of its practical methodology to quantify the changes on the study area from 2002-2012-2022 and to determine spatial distribution of changes with scientific accuracies.

Built-up area

After ALAFU, agricultural operations and their participation to household income gradually decreased under the push of urbanization, along with a rise in issues and obstacles. To reveal the level, do which urbanization affected agricultural land and its impact, NDBI approach have been used. The NDBI strategy was employed in the study as an effective method for autonomously mapping built-up urban areas using Landsat images. This index identifies urban regions where the shortwave-infrared (SWIR) reflectance is typically higher than the near-infrared (NIR) reflectance.(Haas et al., 2006). Built-up areas are indicated on the NDBI image by positive values, while other land covers are indicated by values ranging from 0 to -1(Haas et al., 2006).

The research used data from satellite imagery to delineate the built-up area in Bumbogo sector for 10 reference years from 2002 to 2022. To avoid incorrectly classifying those non-built-up pixels as built-up, a further step of subtracting the recoded NDVI image from the recoded NDBI image was made, resulting in only built-up pixels having positive values while all other land covers have a value of 0 or -1 and allowing built-up areas to be automatically mapped. To calculate the Normalized Difference Built-up Index (NDBI) from a multiband raster object and returns a raster object with the index values, the Raster Calculator is used to perform Raster Calculations on remotely sensed imagery and the following formula are used

$$\mathrm{NDBI} = \frac{\mathrm{Band\ 6\ (SWIR)} - \mathrm{Band\ 5\ (NIR)}}{\mathrm{Band\ 6\ (SWIR)} + \mathrm{Band\ 5\ (NIR)}} \text{For landsat 9} / \text{OLI TIRS data}$$

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$$\mathrm{NDBI} = \frac{\mathrm{Band\ 5\ (SWIR)} - \mathrm{Band\ 4\ (NIR)}}{\mathrm{Band\ 5\ (SWIR)} + \mathrm{Band\ 4\ (NIR)}} \text{For landsat 7/ ETM + data.}$$

IV. IV.RESULTS AND DISCUSSION

Introduction

This section presents the findings obtained from the classification of satellite image, field observations, and interviews. It also highlights the researcher's analysis and interpretation of the data. Finally, this section gives alternative solutions to identified challenges associated with ALAFU.

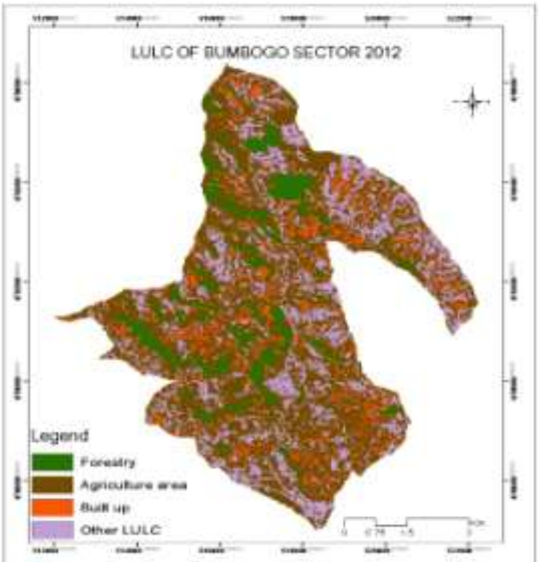
4.1. General characteristics of land use land covers in Bumbogo sector

The findings of field observations, research and image classification of the study area, indicated that the land use land cover of Bumbogo sector is mostly made up of agriculture area, forestry and built up area. In 2002 the built up are in Bumbogo sector were almost zero, and large part of sector were forest, agriculture area and other LULC such as gardens, bare soil, grassland, bare land, roadside trees, all other areas which are not fall into agriculture area and forestry. From 2002 to 2022, urban parts had developed in the Bumbogo sector, with an urbanization rate of about 19.13%. This number is anticipated to rise further as vast tracts of agricultural land are turned into cities.

4.2. Land use/cover analysis

There are some changes occurred among the classes, and the results from analysis showed that there were both decrease and an increase to the different defined classes with respect to period of time and from the classification of Landsat image, the results showed a decrease of farmland.

Figure 4.1: LULC of Bumbogo sector 2002



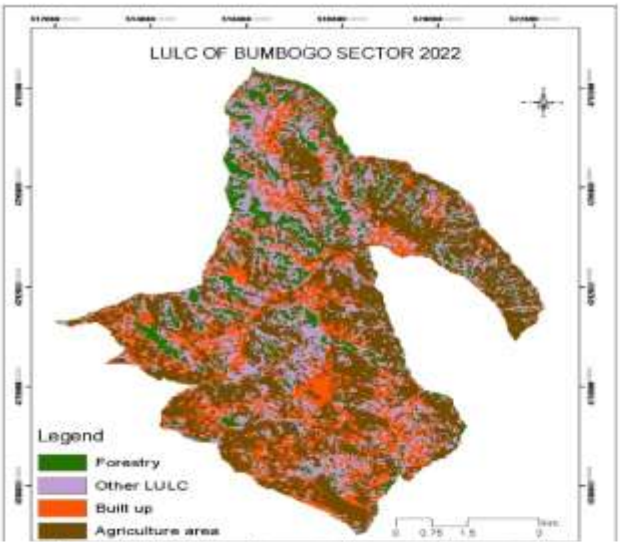


Figure 4.2: LULC of Bumbogo sector 2012Figure 4.1: LULC of Bumbogo sector 2022

Table 4.1: Changes in LULC in Bumbogo sector over period between 2002 and 2022

Sector name and location	**LULC of years from 2002 to 2022**	**SIZE in hectare**					
		Year 2002	**Year 2012**	**Changes**	**Year 2012**	**Year 2022**	**Changes**
Bumbogo sector In Gasabo district	Agriculture area	3840.83	3442.39	**394.44 (decreases)**	3442.39	2464.23	**978.16 (decreases)**
	Built-up Area	0	534.914	**534.914 (increases)**	534.914	1149.43	**614.516 (increases)**
	Forestry	812.81	620.49	**192.32 (decreases)**	620.49	687.73	**67.24 (increases)**
	Other LULC	1361.12	1417.72	**56.6 (increases)**	1417.72	1713.53	**295.81 (increases)**

The research revealed that, 1376.6 hectares which is equal to 35.74 % of the entire agriculture area have been changed to other LULC and 648.27 hectares which is equal to 47.09 % of agriculture land has been changed to built-up area. This decrease is simply explained to be caused by urbanization, inexistence and or poor implementation of policies and strategies related to promoting and protecting agriculture land, during that period.

Accuracy assessment: The classification of satellite Landsat images revealed change in LULC, specifically the decrease of agriculture areas under the impact of ALAFU. Based on image quality and possible author-induced errors, the images were classified at different overall accuracy and overall kappa values

Table4.2: Accuracy assessment

Table4.2: Accuracy assessment **Classified image**	**Year 2002**	**Year 2012**	**Year 2022**
CLASSES	**USER ACCURACY**	**USER ACCURACY**	**USER ACCURACY**
Built Up	**-**	**88.8**	**87.5**
Forestry	**70.9**	**72.2**	**78.2**
Other LULC	**73.3**	**73.8**	**81.7**
Agriculture area	**67.8**	**74.1**	**76.2**
	PRODUCER ACCURACY	**PRODUCER ACCURACY**	**PRODUCER ACCURACY**
Built Up	**-**	**74.4**	**78.6**
Forestry	**69.2**	**78.2**	**85.8**
Other LULC	**64.8**	**84.3**	**81.1**
Agriculture area	**75.5**	**74.7**	**77.5**
OVERALL ACCURACY	**70.26**	**77.09**	**80.68**
KAPPA COEFFICIENT	**0.55**	**0.69**	**0.78**

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Built-up-area in Bumbogo sector

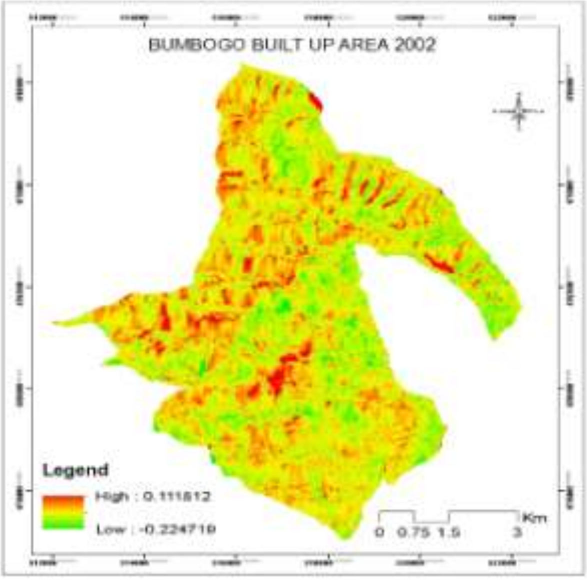

Figure 4.4: Bumbogo sector built-up-area in 2002

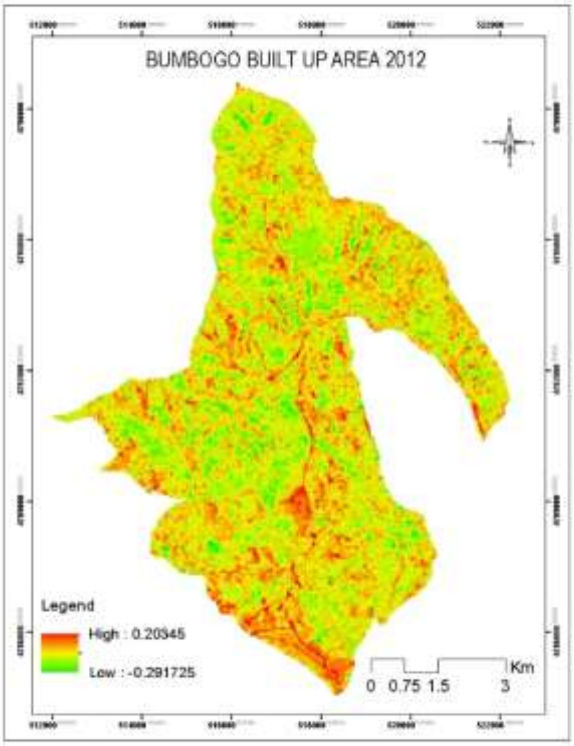

Figure 4.4: Bumbogo sector built-up-area in 2012

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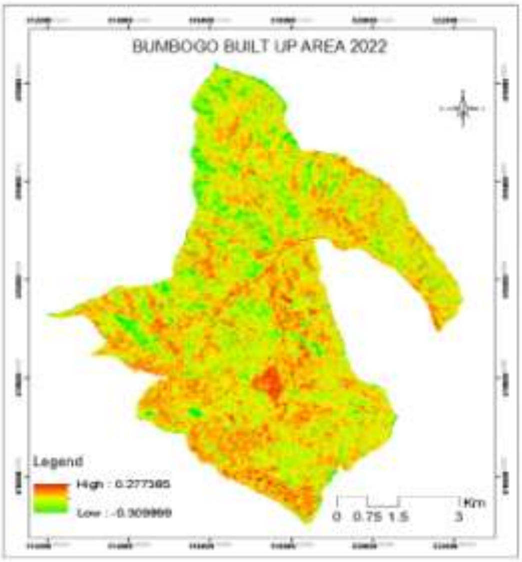

Figure 4.4: Bumbogo sector built-up-area in 2022

In order to successfully map urban built-up areas using Landsat imagery, the research used NDBI method. This index highlights urban areas where the reflectance in the shortwave-infrared (SWIR) region is typically higher than the reflectance in the near-infrared (NIR) region(Haas et al., 2006).Built-up areas are indicated on the NDBI image by positive values, while other land covers are indicated by values ranging from 0 to -1(Haas et al., 2006). The research used satellite data to delineate the built-up area in Bumbogo sector for 20 reference years from 2002 to 2022. The research revealed that 1149.43 hectares which is equal to 19.14 % of total area of Bumbogo sector were built. 10.8% which equal to 648.27 hectares before ALAFU were agriculture land.

4.5.the change in agricultural area to built-up area under the impact of ALAFU

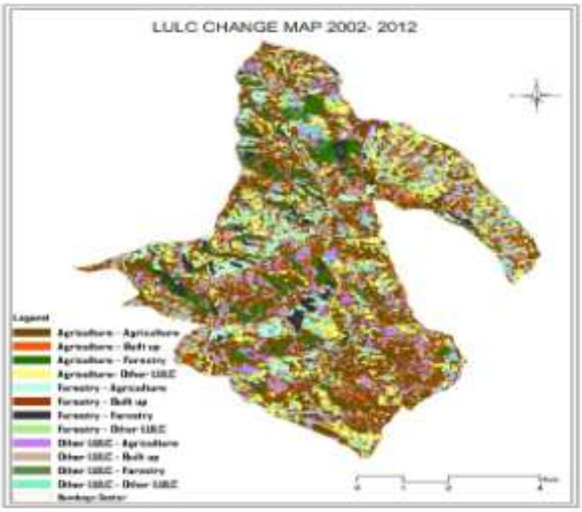

Figure 4.7: LULC change from 2002-2022

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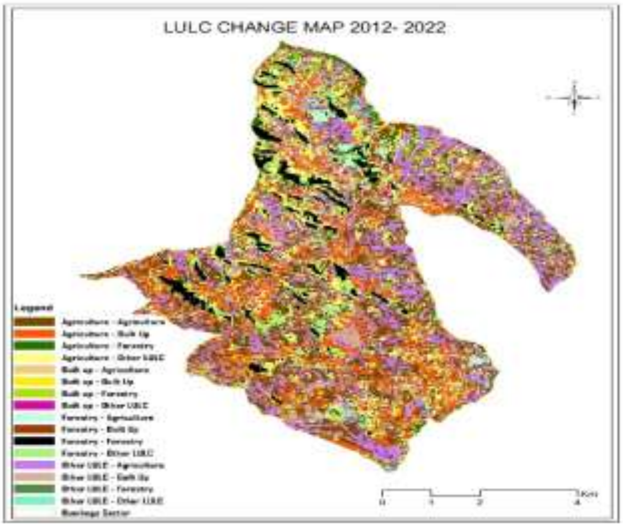

Figure 4.7: LULC change from 2002-2022

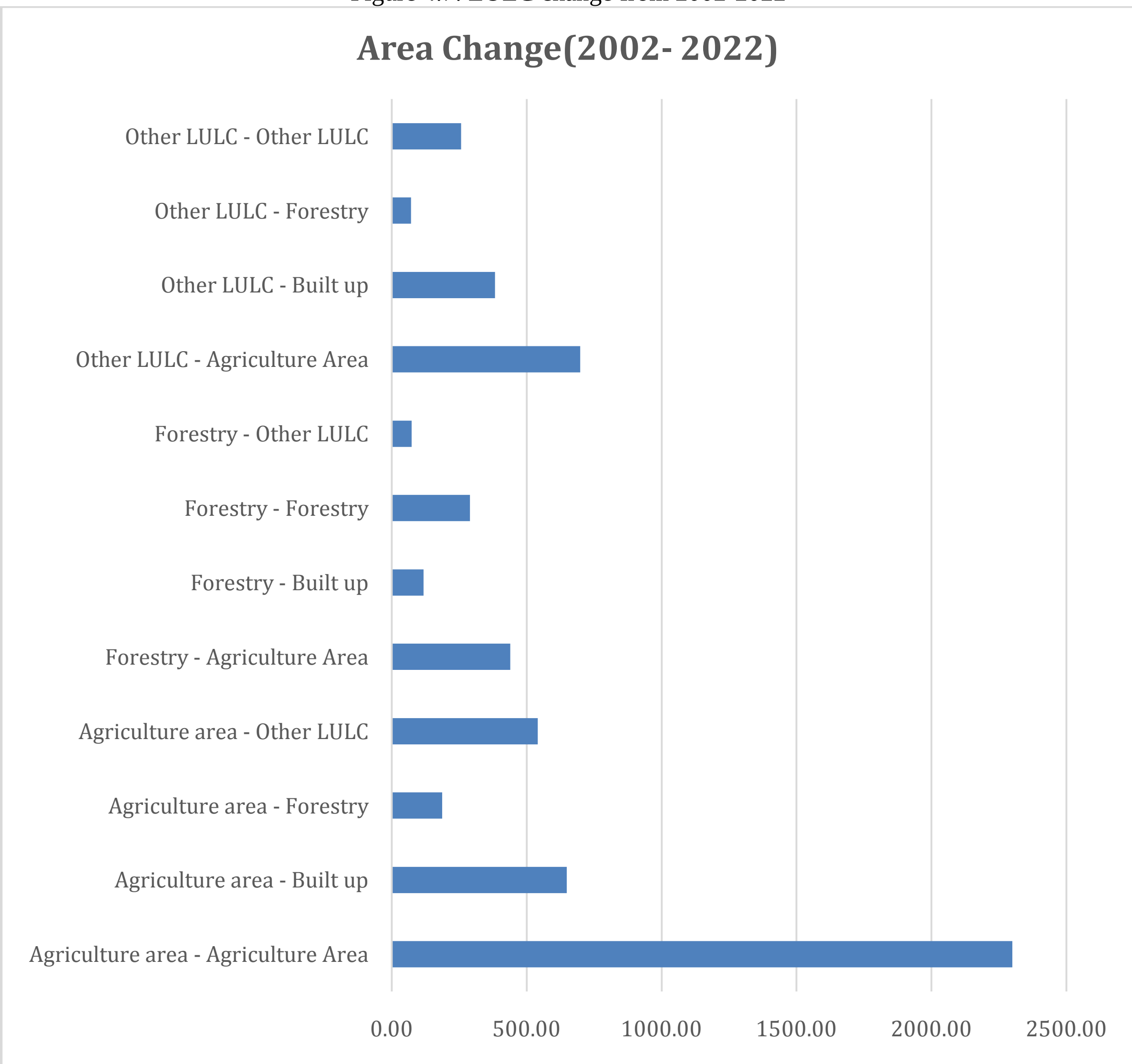

Figure 4.9: LULC change chart from 2002-2022

Using post-classification change detection technique in a GIS system and remote sensing integration, the change in LULC for the periods have been examined. This method enables to assess the temporal changes of the LULC types and to compute the extent of LULC conversion induced by the urbanization. The research revealed a decrease of 1376.6 hectares which is equal to 35.74 % of the entire area reserved for agriculture. And 648.27 hectares which is equal to 47.09 % of agriculture land has been changed to built-up area.

4.6. Sustainable solutions on the impacts of ALAFU

People invested in non-farming job such as commerce(trading), industrial activities, construction activities, self-employment, transportation activities (motorcycling activities, bicycle potters, car driving, house renting businesses).

Local communities started doing peri-urban agriculture where they are fertile soil and their production are growing day per day.

V. CONCLUSION

Urbanization is generally believed to have a negative impact on agriculture due to the loss of agricultural land as a result of urban growth and the bias in favour of urban regions when allocating social funds for infrastructure, services, and subsidies0. Nonetheless, the scale of urban poverty shows that for the majority of the urban population, there is little evidence of urban bias, and certainly, urban demand for agricultural products is fundamental to rural incomes. Agricultural producers and rural customers rely on urban-based firms for a variety of goods and services, including market access.

So, the crucial question is whether an expanding urban population and economy can support agricultural and rural prosperity and sustainability in the face of global losses in agricultural land area per person and water restrictions. The necessity to adapt to climate change consequences, which may disrupt urban demand, agriculture, and urban businesses that provide producer and consumer services to rural communities, has now been added. The majority of low- and middle-income countries are expected to continue growing economically, which would likely result in more urbanization worldwide. The most economically prosperous of these nations will also be the ones that tend to urbanize the most. Higher-income nations may no longer urbanize, but this is primarily because non-agricultural workers may live in rural areas or because industrial and service businesses are opening their doors there. Urbanization will be minimal in low- and middle-income countries with unsuccessful economies. They may de-urbanize during severe economic downturns by hiring more people in the fishing, forestry, and agricultural industries. Nevertheless, this is only likely in nations where some urban poor people still have connections to the rural world that enable them to reintegrate into rural livelihoods. Because the effects of climate change significantly rely on international agreements to quickly reduce the causes of greenhouse gas emissions, their effects are difficult to predict. Farmers who want to reduce their greenhouse gas emissions face a number of obstacles, as do better-off urban dwellers who want to adopt less carbon-intensive ways of life. If greenhouse gas emissions aren't reduced, there will very probably be more disasters, which will have serious effects on both rural and urban people. Several of the biggest cities in low-income nations are particularly vulnerable and presently unable to adapt.

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