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Using Remote Sensing to Analyse the Role of Urbanization in the Transformation of Land-Use and Land Cover in Likasi Town (Haut-Katanga, DR Congo)

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Abstract

Environmental change is characterized as an alteration in the environment caused primarily by human activities and ecological processes that are natural. Given the fact that the southern part of the province of Haut-Katanga in the Democratic Republic of the Congo (DRC) is part of the African Copperbelt and has been a region of intense mining for decades, humans have affected the physical environment in various ways: such as overpopulation, suburbanization, wastage, deforestation. It is therefore important to track and control the changes in the area's mining activities. This study aimed to analyze these changes using remote sensing techniques. Landsat satellite images from 2002 and 2022 were processed and classified to quantify changes in built-up area, agricultural land, and vegetation cover over the 20-year period. The classification results revealed sizable differences between the two time points, indicating considerable expansion of built-up land and declines in agricultural land and vegetation cover from 2002 to 2022 in Likasi. These findings provide evidence that urban growth has transformed the landscape in Likasi, likely at the expense of farmland and ecosystems. Further analysis of the remote sensing data could quantify the changes and model future trends to support sustainable land use planning. The land cover and land use analysis were performed with the assistance of the ERDAS 16.6.13 software by mapping LANDSAT data from two different years 2002 and 2022.

Keywords

Urban Growth, Change Detection, Likasi, Urban Planning, Remote Sensing,

Democratic Republic of Congo

1. Introduction

In line with Awojobi & Tetteh (2021), the migration of the population from rural to urban areas is referred to as urbanization. In essence, the proportion of people living in urban areas is steadily increasing; this generally happens when a country is still economically growing (Moyer & Hedden, 2020). Globally, there has recently been unparalleled increases in the density of populations in cities, which have led to shifts in the relation between human activities and global environmental. Such transitions are also controlled by numerous socio-economic and biophysical processes associated with the transfer from non-urban to urban environments and the resulting heterogeneity of the landscape (Stucki & Petré, 2021).

According to the United Nation's Department of Social Affairs and Economic, studies have shown that currently 55% of the world's population lives in urban areas, a proportion projected to grow to 68% by 2050. In 2030, 54% - 60% of the sub-Saharan population is expected to live in urban areas (Pesantez, 2018). However, urbanization and urban development changes in Democratic Republic of Congo differ considerably from other nations on the African continent. Most sub-Saharan urban areas have undergone natural growth over time, with development forms and design mostly dictated by physical infrastructure, geological factors and topography (Munanura et al., 2021; Potts, 1995).

Therefore, over decades, the growing world population has had a major effect on the connectivity between urban and rural areas; leading to raised questions over the balance between supply and demand in terms of energy and land use. This insight calls into doubt the recent discussions around the stresses that people continue to place on the land that bring about changes in its physical environment and its use (Ramankutty et al., 2002).

The urbanization process contributes to changes in land cover, jeopardize biodiversity, impacts habitats through deforestation, interferes with hydrological processes, influences the effects of climate change, destroys agricultural land, leads to human encroachment, poor living conditions and increased traffic congestion (Stucki & Petré, 2021; Cowgill, 2004). For the purpose of this research, the emphasis was on comprehending the significance of the urbanization process has in contributing to the transformation of land use in South-eastern of Democratic Republic of Congo (DRC) using Likasi town as case study. The land around Likasi in DRC was selected as an instance study since it represents constraints like a rapid increase in population, lack of effective land use planning as well as the above-mentioned challenges. The typical size of its focal city, as measured by urban population, also played a part in the choice of the city.

However, in Sub-Saharan Africa—with the exception of cities containing a population of less than 300,000—the currently predominant city types are medium-sized cities (1,000,000 - 5,000,000 inhabitants) and they are the second most represented city class (Andre, 2007). According to the United Nation estimation, Likasi was supposed to have a population of 568,000 inhabitants in 2022. Therefore, monitoring and identifying of urban growth is essential to the creation of successful sustainable urban planning approaches to regulate urban development; greater attention needs to be paid to land management in relation to the growing population of urban scenery (Van Huyssteen et al., 2019; Andre, 2007).

2. Study Area

The study area is located in the Haut-Katanga province of the DRC (**Figure 1**). It is located along the Likasi River, 138 km north-west of Lubumbashi, and is accessible by road and rail. In 1892 Belgians discovered 24 km northwest of Likasi copper deposits and in Kambove as well. Opened in 1917, Likasi was declared an urban district in 1943. It is now one of the country's most significate mineral processing hubs, with copper and co-finishing plants (McKenna, 2020).

The increase in settlement rates has increased the demand for land. Between 1999 and 2011, there was a net increase of 1,045,627 informal dwellings and

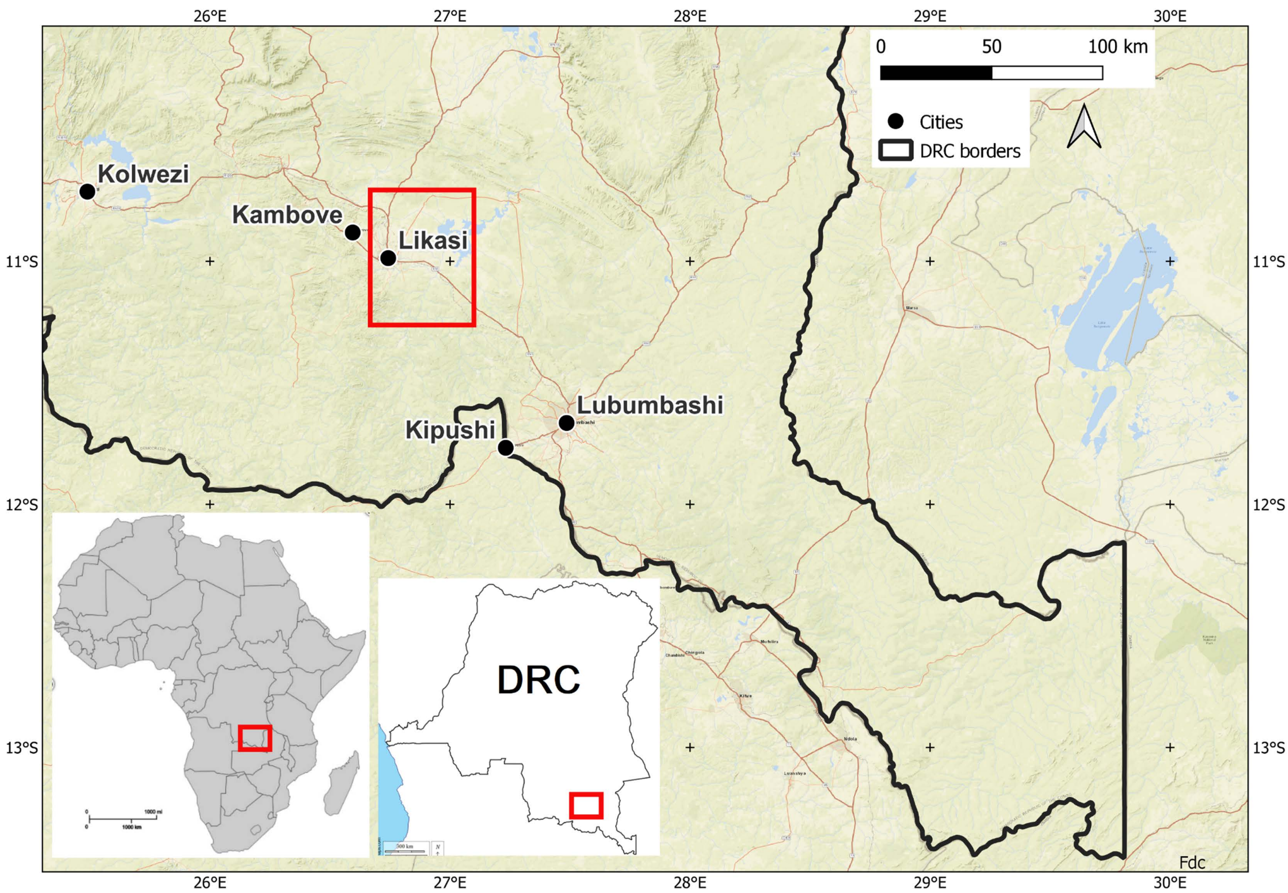

Figure 1. Map of the Democratic Republic of Congo showing the study area.

1,043,843 formal dwellings. One of the significant variables causing the growing urban sprawl is the expansion of gated developments in outlying green spaces catering to middle-class residents (O'Connor & Kuyler, 2009). Although almost no official studies have been carried out on the ecosystems of Likasi and its larger areas, this particular study seeked to examine the town from a holistic perspective in order to understand how the LULC has transformed between 2002 and 2022.

Due to the fact that the Haut-Katanga province in the DRC is part of the African Copper belt, it has been a region of intense mining for decades (Lubaba et al., 2018). As the main mineralizations in the Lufilien arc of Katanga, with regard to the stratigraphic positions, copper-cobalt mineralization is more economically important and is classically located in the Mines sub-group and exceptionally in the lower Mwashya at Tilwizembe and Shituru; and Iron deposits are observed in the lower Mwashya (Oosterbosch, 1962; Mashala, 2007).

3. Methodology

There is a range of factors that need to be considered particularly in regards with the way the data collection process is approached and implemented. The objective is to present a thorough account of all the techniques and materials used in the process of carrying out this analysis. In order to accomplish this, we will first illustrate the precise groups of land cover that have been used for this research effort (Kercival, 2015). A workflow, as shown in **Figure 2**, is used to accomplish this.

With the wide range of information and data generated, the remote sensing method has improved in speed, cost-effectiveness, and most importantly, a source of reliable information to determine changes or transformations in LULC (Alphan, 2003). Nevertheless, divide the act of mapping these changes demands that the land concerned into different groups of land cover (Thompson, 1996; Lillesand et al., 2014). To achieve this, LULC studies need a generic classification of the LULC Scheme that will help deliver the necessary consistency for LULC analysis and mapping (Thompson, 1996; Lillesand et al., 2014).

There is currently no single widely accepted LULC classification scheme because classification schemes tend to vary by region, organization and also by the preferences of the researcher. However, in the mid-1970s, the United States Geological Survey (USGS) invented one of the most widely used ground cover classification schemes (Lillesand et al., 2014; Alphan, 2003). The USGS Land Cover systems of classification is recognized as the fundamental structure of various land cover classification schemes; except for those classification schemes, which in recent studies have been able, to provide a more comprehensive and specialized mapping of land classes (Lillesand et al., 2014).

In the broad variety of different satellite images, we have chosen to use Landsat image in order to conduct this research; it has the highest spectral bands and ground resolution for monitoring land cover and land. Remotely sensed images

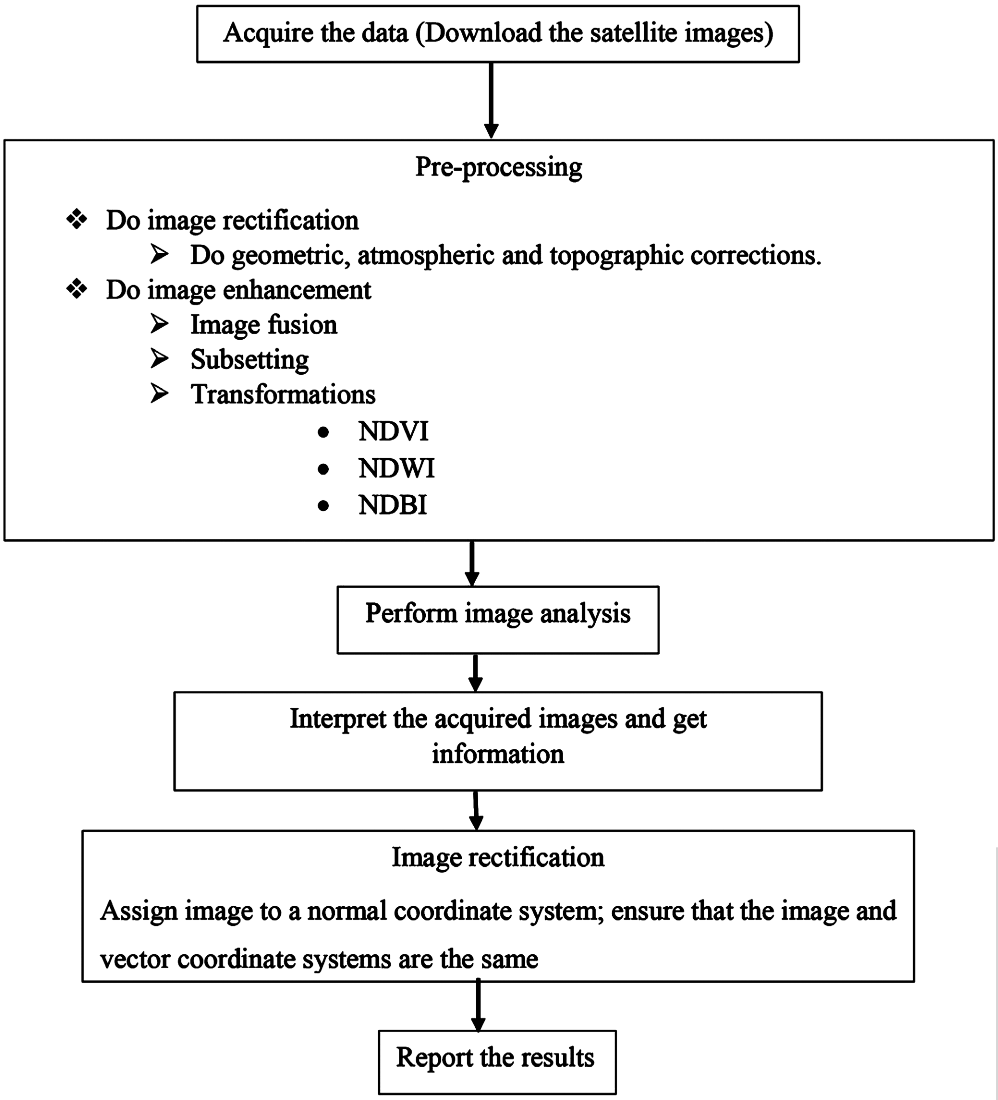

Figure 2. The methodology flowchart.

of Likasi was collected from Earth Explorer between 2002 and 2022. It allowed collecting two non-pre-processed images and then classifying them using the most accurate and suitable classifier algorithm to identify the LULC transformations (Lillesand et al., 2014).

To monitor changes in LULC, it is imperative to have comparison data of at least two time periods. Remote sensing approach typically includes the use of two or multiple-date satellite images to measure land-use and land-cover modifications in any area (Ahmad, 2015). The LULC information can be obtained via the image analysis and classification process from the multiband raster imagery. Image classification "supervised or unmonitored" is intended to automatically categorize pixels with a typical reflection range into different LULC groups (Lillesand, 1994).

Supervised classification is a user-focused method involving the collection of training sites as a categorization guide. Many methods are available to implement the supervised classification such as parallelepiped classification, K-nearest neighbour, minimum distance classification, etc. (Zhu et al., 2006). For this study, we typically use ERDAS 16.6.13 Image program to implement maximum likelihood classifier for LULC classification. The maximum likelihood algorithm measures the covariance and variance of the spectral response patterns quantitatively and assigns each pixel to the class for which it has the highest possible association (Tateishi & Shalaby, 2007). In addition, for vegetation modelling the Normalised Difference Vegetation Index (NDVI) was applied; for water in the town the Normalised Difference Water Index (NDWI) was applied and for built-areas analysis the Normalised Difference Built-up Index (NDBI) was applied.

4. Results and Discussion

Land-Use Land-Cover maps of an area offer users insight into the existing landscape. It displays the surface of the earth's biophysical covering (ISRO, 2015). The sophistication of image classification approaches may range from the basic predefined threshold value for a single spectral band to complicated statistically dependent decision-making rules that apply to multivariate data (Kumar & Kiran, 2017). The goal of the classification process is to assign each pixel in a digital image to one of several categories of land cover. Many different approaches are frequently used to create land-cover maps that have been developed (Lillesand et al., 2014). From non-parametric to parametric to non-metric, unsupervised to supervised, soft and hard classification, or sub-pixel, per pixel, and pre-field classification, they differ in their logic (Keuchel et al., 2003; Lillesand et al., 2014). However, there are three primary methods for classifying images. These are the three classification methods used in the remote sensing approach: unsupervised classification, supervised classification; and object-based classification (Keuchel et al., 2003). In hybrid methodologies, these procedures are frequently paired with more than one approach as a replacement technique (Keuchel et al., 2003; Richards & Jia, 2006). To map the land cover changes in Likasi Town that have taken place over the past 20 years. Using ERDAS 16.6.13 software, a supervised and unsupervised classification were performed.

4.1. Unsupervised Classification

Unsupervised classification is a method of classification based on pixels and is an automatic computer classification. We specified the necessary number of classes for this identification, and the software's computer algorithms then divided similar-looking pixels into the required classes (Kumar & Kiran, 2017). We determined the number of groups needed then the classification algorithm scanned and analysed the satellite image, grouping pixels into clusters that it considered uniquely representative of the content of the image, and we named the land cover types post classification in reference using ground reference data (Kumar & Kiran, 2017; Lillesand et al., 2014). **Figure 3** & **Figure 4** show maps of an unsupervised classification that were ran on Likasi town.

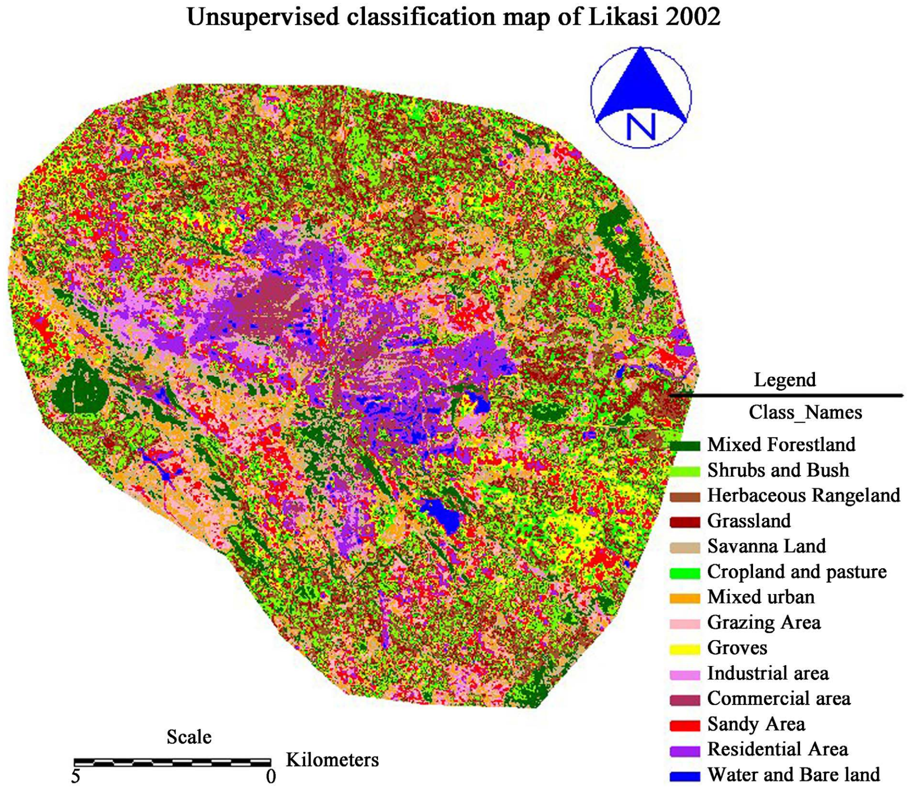

Figure 3. Unsupervised classification of Likasi 2002 using 14 classes.

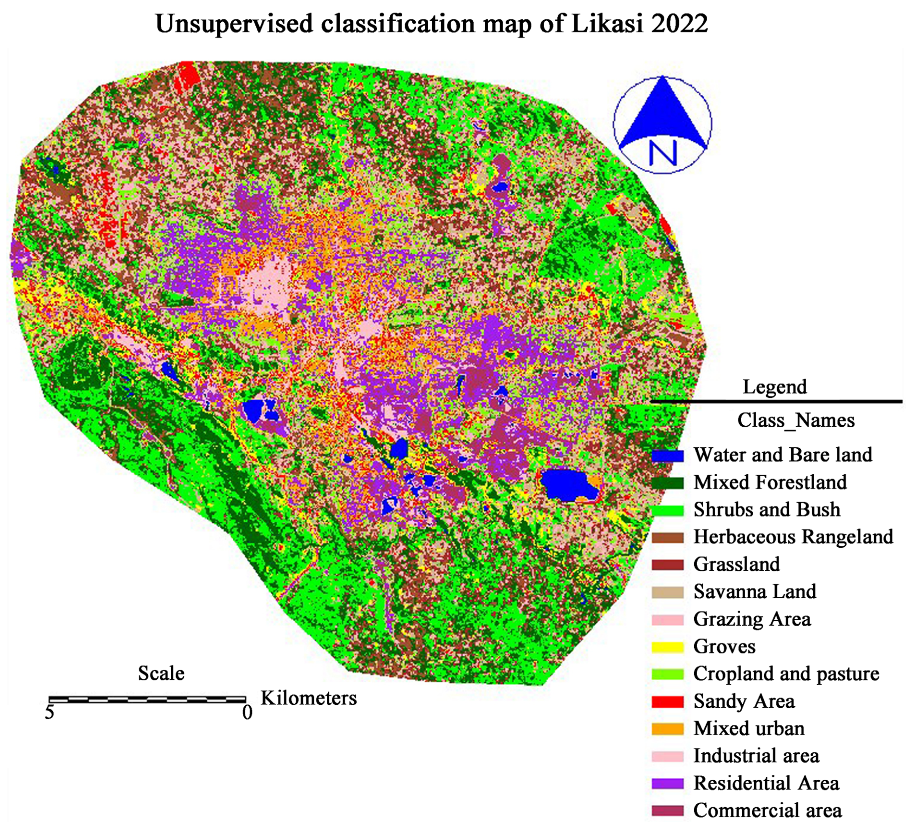

Figure 4. Unsupervised classification of Likasi 2022 using 14 classes.

4.2. Supervised Classification

Supervised classification is the most widely used methodology for quantitative remote sensing image processing (Kumar & Kiran, 2017). It is a method used to categorize pixels with unknown identities for samples with known identities. An image analyst must first choose the appropriate classification scheme before locating the training locations in the imagery that best represent each class (Al-Doski, 2013). The spectral signatures acquired from the sample training are used by supervised classification to identify the image (Lillesand et al., 2014). The study data pixels are then compared numerically using the signature file, and each pixel is given the land cover type that most closely resembles it (Lillesand et al., 2014). In **Figure 5** and **Figure 6**, the supervised images that were ran on Likasi town are shown.

The 2002 map in **Figure 5** demonstrates urban area covers much of the study area. The surface of Bare land in 2002 was just 5.32 square kilometre, representing 2.08 percent of the total area. Agriculture land occupied 75.15 square kilometre, which represented 29.34 percent of the total study area while the vegetation area occupied 18.57 square kilometre (7.25 percent of the total study area). The area of water body was 1.07 square kilometre, just 0.42 percent of the total study area.

In 2022, the trend of land use cover changed significantly with respect to 2002. An incredible decrease of over 9 per cent occurred in Agricultural land area. Urban area has risen from 152.402 kilometre square to 183.9137 kilometre square. This was followed by a decline from 18.57 square kilometre to 9.47 square kilometre in the vegetation area. With a total of 90 percent of the overall class, urban area and agricultural land held the largest classes in 2020. The water

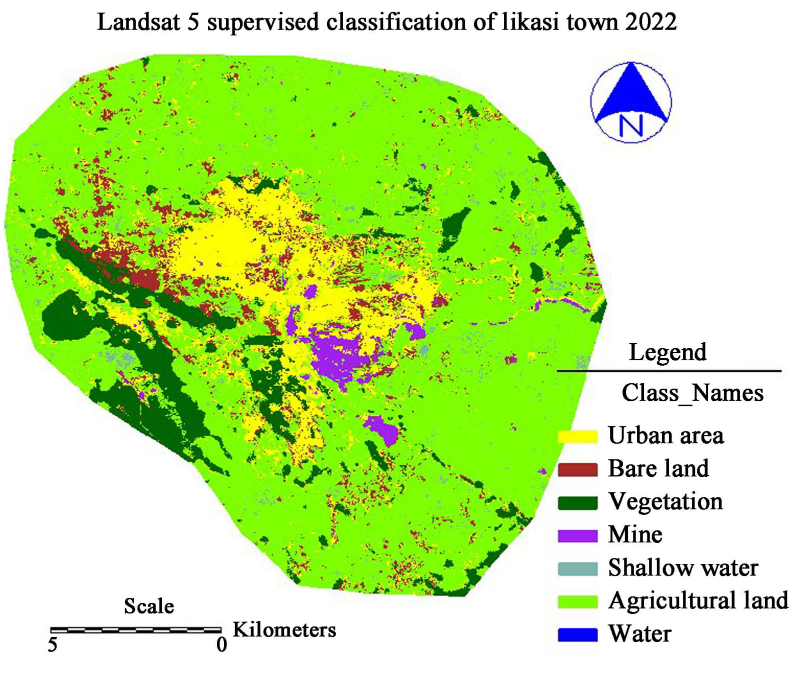

Figure 5. Supervised classification map of Likasi in 2002.

body takes up the minimum percentage of the total class. It is assumed that almost all the decrease in agricultural land and vegetation area is due to an increase in residential areas since urbanization process has taken place due to an increase in mining activities and related activities, as well as human pressure on firewood vegetation and livestock grazing in agricultural land.

In order to assess the LULC change that occurred in Likasi town, supervised and unsupervised classification were used to investigate the change in land cover. The outcome of the research showed that build up area had changed rapidly over the period from 2002 to 2022. Table 1 shows the LULC change that has

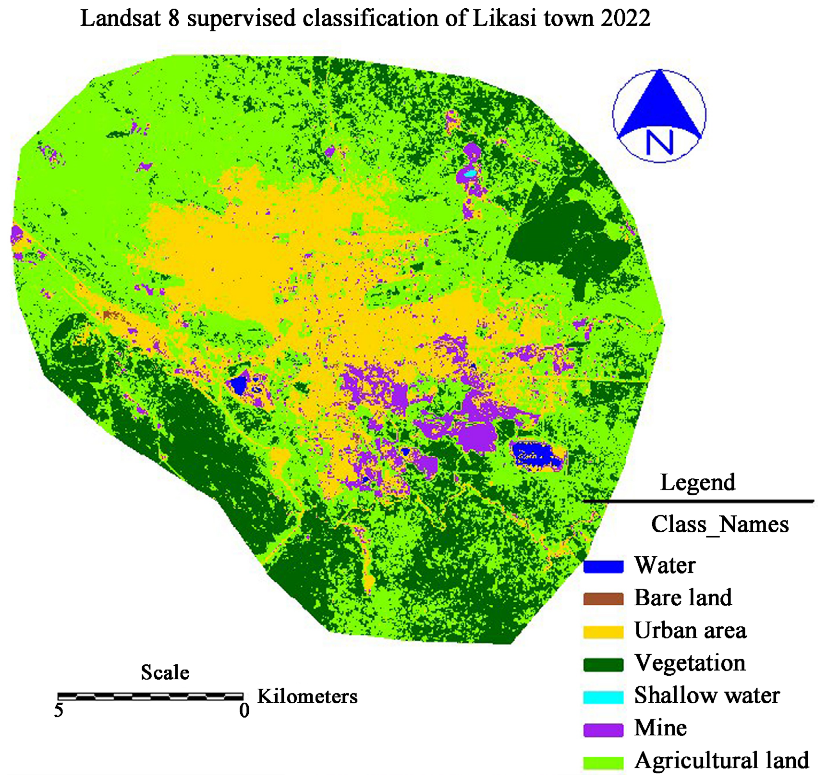

Figure 6. Supervised classification map of Likasi in 2022.

Table 1. Supervised Land use land cover mapping.

Land use/Land cover	2002		2022	
	Square km	%	Square km	%
Water	1.0727	0.4188	2.6054	1.0173
Mine	3.5897	1.4016	5.8764	2.2945
Bare land	5.3244	2.0789	4.268	1.6665
Vegetation	18.5689	7.2505	9.4689	3.6973
Urban area	152.402	59.5073	183.9137	71.8114
Agricultural Land	75.1487	29.3428	49.974	19.5118
Total	256.1064	100	256.1064	100

occurred in Likasi town.

Table 1 represents the area of each land use land cover group of the two different years.

Over the period from 2002 to 2022, the water body has increased by 1.53 square kilometre, with a percentage increase of 0.60. Bare land area decreased from 5.32 to 4.27 square kilometre during the same period. Vegetation area decreased from 18.57 to 9.47 square kilometre meanwhile urban area increased from 152.40 to183.91 square kilometre. The change in urban area was the greatest as compared to all groups. Agricultural Land decreased from 75.30 to 49.97 square kilometre during the period 2002-2022. There has been an increase in the urban area due to an increase in the area of settlement, and deforestation activities.

Supervised classification was used to investigate the change in land cover and not unsupervised classification. This is because supervised classification is reported to be more accurate than unsupervised classification (Hasmadi et al., 2009). The present research may be useful in identifying surrounding areas of Likasi that are at risk from mining activities. The limitation of this data is that no groundtruthing was performed; as a result, the data may contain classification errors.

4.3. Indices

Image indexes are images that are computed from existing multi-band images (Zha et al., 2003). Due to the fact that the derived layer is the calculated layer from the combined bands, it offers data that is frequently inaccessible from separate bands. The various spectral bands of the image are subjected to the spectral index, a mathematical equation, per pixel (Uddin, 2010). The development of Likasi town could be modelled by applying indices in the software. The Normalised Difference Vegetation Index (NDVI) was used for vegetation modelling; the Normalised Difference Built-up Index (NDBI) was applied to the built-up area of Likasi town and its surrounding, while the Normalised Difference Water Index (NDWI) was applied to the water in the reserve.

4.3.1. Normalised Difference Vegetation Index (NDVI)

The NDVI is an index of vegetation that compares the values of electromagnetic spectrum reflectance in the red and NIR regions (Extension, 2014). A vegetation index is defined as a single number that is used to quantify vegetation biomass from an image acquired by remote sensing in each pixel (Extension, 2014). NDVI is computed as follows: $\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$ where RED and NIR are the red or visible and near-infrared response bands, respectively. These bands are employed because healthy leaves exhibit a distinct NIR reflection, whereas unhealthy leaves exhibit a greater red light reflection than NIR (Lamchin et al., 2016). Figure 7 shows the NDVI images obtained from running Likasi Town 2000 and 2020 image.

To determine the change in vegetation biomass over the last 20 years, a change detection analysis was done using image difference on the ERDAS IMAGINE 16.6.13 software. Figure 9 shows the change detection results obtained. The images in Figure 7 and Figure 8 were compared with the data type set to float single; in this data type, the differences between bits is covered in that an 8-bit image will yield the same result as a 16-bit image.

4.3.2. Normalized Difference Built-Up Index (NDBI)

Areas that are heavily used make up a built-up area, and buildings cover most of the land (Lillesand et al., 2014). Examples of built-up are villages, cities and

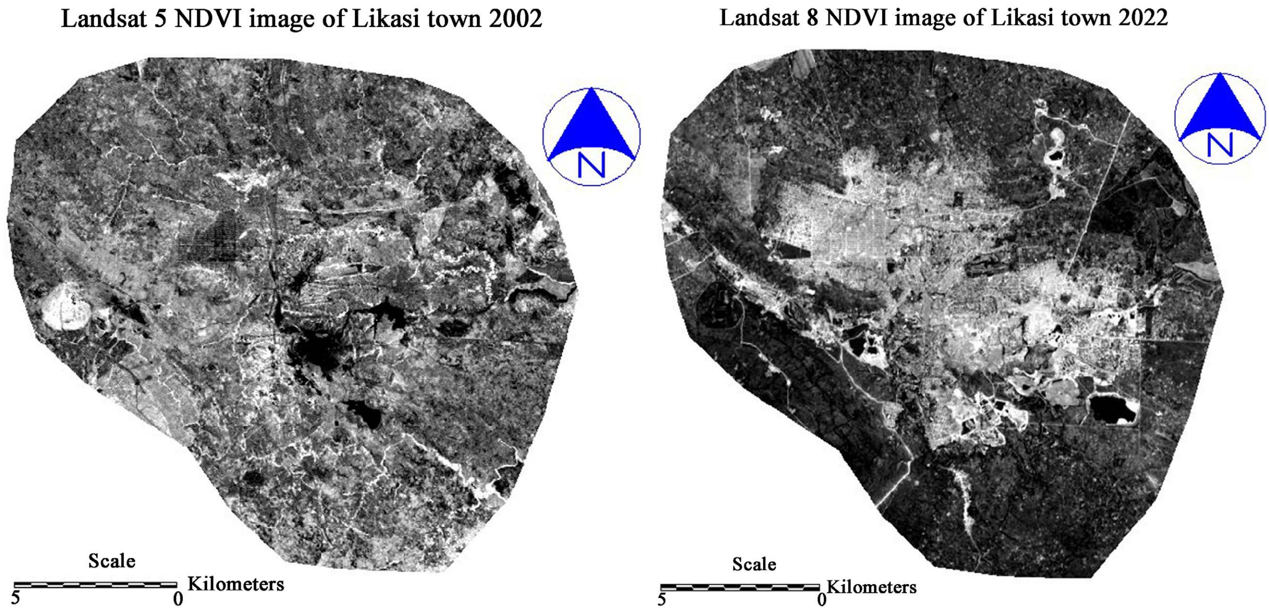

Figure 7. At left Landsat 5 NDVI image. The different shades correspond to the reflectance pixel values with darker shades, at right Landsat 8 NDVI image. The darker areas show higher biomass of vegetation and correspond to reflectance pixel

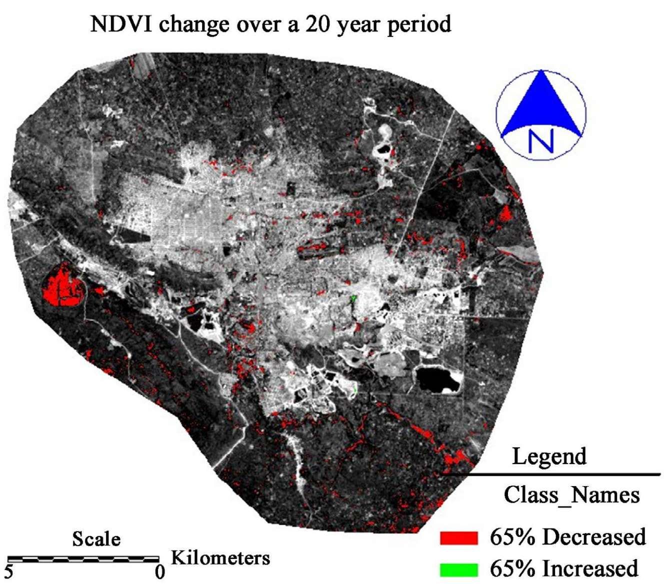

Figure 8. NDVI change over the last 20 years. The change is indicated by the red and green colours on the subset of Likasi town as a background image.

industrial areas (Lillesand et al., 2014). To get the spatial distribution and monitor the growth of urban areas, the NDBI is used. This index identifies urban areas where reflection in the short-wave infrared (SWIR) region is typically greater than in the near-infrared (NIR) region (Zha et al., 2003). It is calculated as follows: $\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}}$. The NDBI images of the study area are shown in Figure 9 with the change over the 20 years period shown in Figure 10.

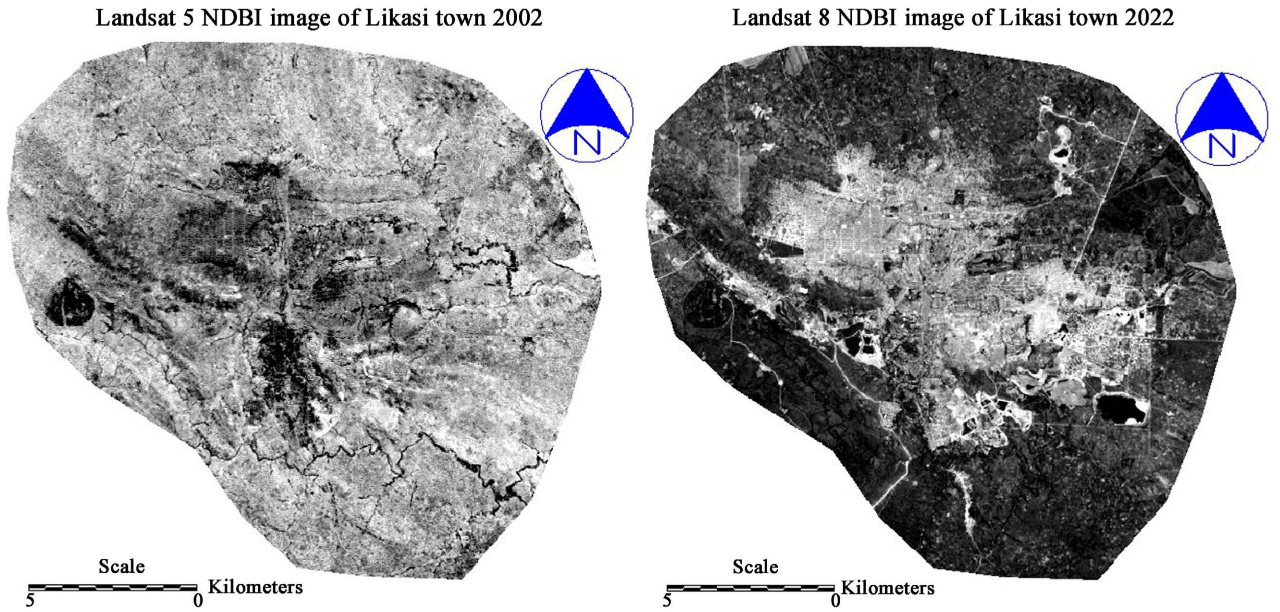

Figure 9. At left Landsat 5 NDBI image. The darker shades represent areas that have built-up features. At right Landsat 8 NDBI. The lighter shades correspond to areas with little or no built-up land.

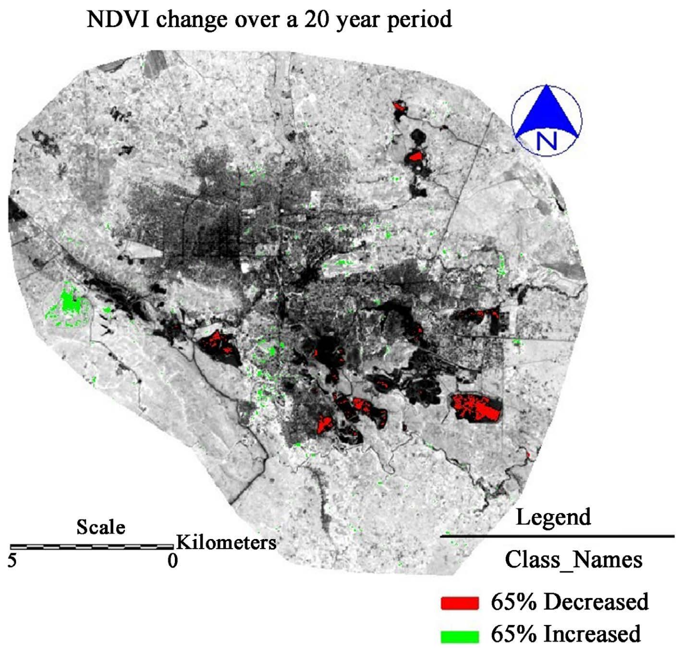

Figure 10. NDBI change over the past 20 years. The green shows areas where there was an increase in built-up areas in the specified period with the green showing the increase by 65%.

4.3.3. Normalized Difference Water Index (NDWI)

The important information of water content in vegetation can be determined using the Normalised Difference Water Index "NDWI" (Jensen, 2014). Its principles and formula are based on the NDVI formula (McFeeters, 1996). The NDWI can be used to see moisture content in soil and plants (Jensen, 2014). It is calculated by comparing it to the NDVI, as shown below: $NDWI = \frac{NIR - SWIR}{NIR + SWIR}$ where a portion of the spectrum of wavelengths in the range of 1.628 - 1.652 nm is NIR "near infrared" with wavelengths in the range of 0.841 - 0.876 nm and SWIR. With water not absorbed in the NIR range, NIR is used in the NDWI formula to make NDWI immune to atmospheric effects and to differentiate it from NDVI. The NDWI images obtained are shown in **Figure 11**. **Figure 12** shows the change observed over a period of 20 years; that is a change between when Landsat 5 image was recorded and when Landsat 8 image was recorded.

It is assumed that 65 percent change detection was done on the NDVI, NDWI and NDBI images as shown in **Figure 8**, **Figure 10** and **Figure 12** respectively. An Image Difference change detection tool in the ERDAS 16.6.13 software was used. This gives information about the changes that took place in Likasi Town in terms of the vegetation, built-up areas and the water bodies. In the change detection maps shown, the red colour corresponded to a 65 percent decrease of the variable over a period of 20 years from 2002 to 2022 and the green colour showed the increase thereof.

The NDVI change map in **Figure 8** showed both an increase and decrease in vegetation. The decrease affected mostly the area surrounding the town. With

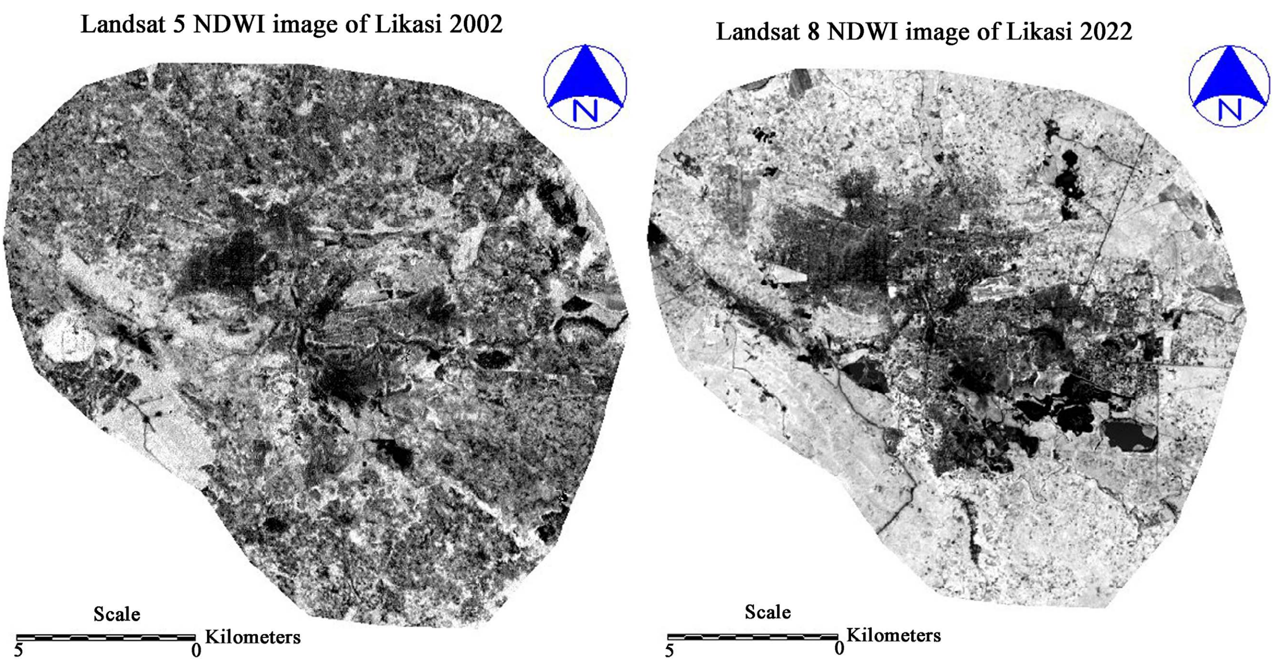

Figure 11. At left Landsat 5 NDWI image. The darker shades represent areas where there is high water content in the plants and a high biomass of vegetation. And at right Landsat 8 NDWI image. The shades correspond to water content and vegetation biomass whereby lighter shades indicate low water content in the plants and sparse vegetation.

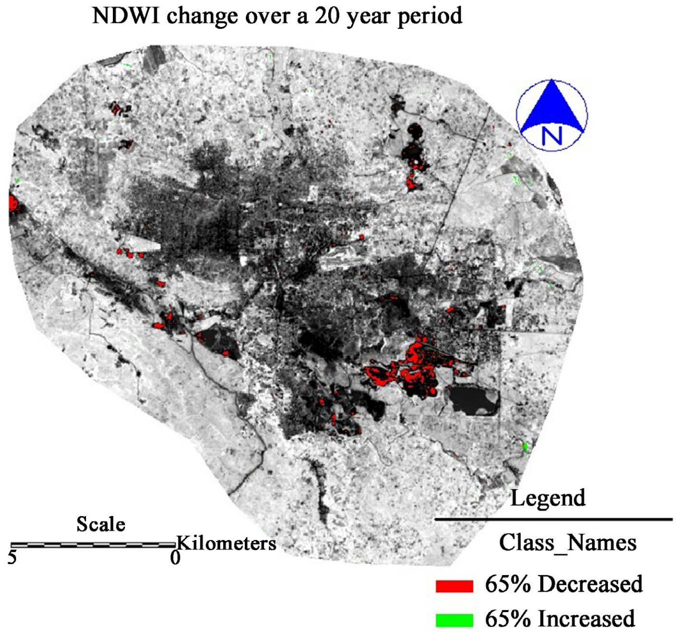

Figure 12. NDWI change over the past 20 years. The red regions indicate areas where the water content and vegetation biomass decreased by 65% in the specified period.

the water index, NDWI, there seemed to be a loss of water content in plantation around the mining area. There was over 65 percent decrease of water content in plants shown in Figure 10. The NDBI change shows in Figure 12 that there has been an increase in built-up land, as well as a decrease. It shows that vegetation area around Likasi town have been turned into Urban areas. The increase in built-up area can be attributed to urbanisation that occurred over the 20 years. Not only were new built-up features added, existing ones were decreased. This could be abandoned buildings or other NDBI-specific features. As a result, growth in the mining sector in the area can be connected to in an increase of the population migration into the region.

In order to compare images from different satellites, the Landsat 5 image has been converted to a 16-bit image to match the Landsat 8 image, and Google Earth has been used to match the pixels in the images to the images seen on Google Earth. The results for this particular show that vegetation area, and a large portion of Agricultural land have been turned into urban areas (formal and informal settlements, and roads) following the introduction of mining operations. Therefore, the growth in the mining sector of the region can justify the decrease in agricultural land and vegetation. Increased mining operations have increased the migration of populations into the region.

5. Conclusion

In order to assess the LULC change that occurred in the town of Likasi, Landsat images were collected, identified and analyzed. From studies previously performed in this particular area, remote sensing has the unique ability to track LULC changes over multiple time scales. The outcome of the work showed that the agricultural Land and vegetation in the area had changed rapidly over the period from 2002 to 2022. The present study may be useful in identifying vegetation areas that are threatened by mining operations. It has demonstrated that remote sensing technology provides a real option in fast-growing urban settings for the development of land-use monitoring and inventory systems. To make optimal urban land use decisions, these systems can be used. Although census-based literature has recorded a general increase in the urban population of the Democratic Republic of Congo during this time, this research attempted to fill the void in the literature on physical urban spatial patterns.

Conflicts of Interest

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

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Acronyms

DRC	Democratic Republic of Congo
LULC	Land Use and Land Cover
NDBI	Normalized Difference Built-Up Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalized Difference Water Index
UN	United Nation
USGS	United States Geological Survey