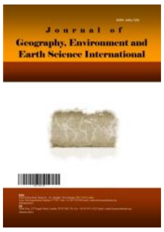

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Assessment of Urban Sprawl, Land Use and Land Cover Changes in Voi Town, Kenya Using Remote Sensing and Landscape Metrics

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Rapid and uncontrolled urbanization is a major issue in both developing and developed countries. Uncontrolled urbanization has resulted to unplanned expansion of residential and commercial areas, informal settlements, housing shortages, and unplanned land use. Understanding and quantifying urban sprawl spatiotemporal patterns is critical for informing the development of appropriate policies for effective and sustainable land use management. Using image classification and spatial metrics, this study examines the changes in Voi town's urban land use/land cover (LULC) between 1999 and 2019. The LULC was mapped using Landsat Thematic Mapper (TM):Landsat Enhanced Thematic Mapper Plus (ETM+):and Landsat Operational Land Imager (OLI) datasets using supervised maximum likelihood classification. A post classification approach was used to detect and assess LULC changes in the study area, while selected spatial metric indices quantified urban sprawl. The results of the change detection analysis revealed that Voi town has been rapidly expanding, with an urban expansion of 187.96 percent from 1999 to 2011, 183.40 percent from 2011 to 2019, and 716.1 percent from 1999 to 2019. In 1999, the built-up area comprised 1.29 percent of the total study area, 3.72 percent in 2011, and 10.53 percent in 2019. Based on spatial metrics analysis, the number of built-up area patches in 1999, 2011, and 2019 was 154, 278, and 526, respectively. An increase in the number of patches indicated fragmentation and the emergence of new built-up areas.

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As a result, city planners will need to plan ahead of time and implement additional measures to deal with the city's future rapid and unprecedented growth.

Keywords: Land use/ land cover; supervised classification; change detection; spatial metrics.

1. INTRODUCTION

The rapid growth of urban areas around the world has had a significant impact on society [1]. According to UN statistics, 55 percent of the world's population lives in urbanized areas, with the number expected to rise to 65 percent by 2050, accounting for roughly two-thirds of the global population [2]. Despite the fact that urban areas are rapidly expanding, cities still occupy only about 2% of the world's total land area [3]. According to World Population Prospects 2019, Africa's population will grow from 1.3 billion to 4.3 billion between 2020 and 2100, with Sub-Saharan Africa (SSA) leading the way. According to the 2019 Kenya census figures, Kenya has a population of approximately 47.5 million people, with rapid population growth expected [4]. [5] identified factors contributing to urban growth as increased urban population, migration from rural to urban areas, and conversion of rural settlements into towns or cities through increased and improved infrastructure. [6] reported that the end result of this urbanization process is the inevitable spatial extension of cities beyond their boundaries and into the outskirts in order to accommodate the growing urban population. The development of informal settlements is one of the major challenges confronting urban areas [7]. These increased informal settlements have posed a challenge to planners, particularly in developing countries, leading to the adoption of the Sustainable Development Goals (SDGs):particularly the Goal 11, which focuses on the sustainable growth of formal and informal settlements to ensure city sustainability [3,8]. For sound land use management policies and strategies, it is necessary to assess LULC changes over a set period of time [9]. Geographical information systems (GIS) and remote sensing (RS) are current technologies that provide a cost-effective and accurate tool for understanding the dynamics of landscapes [1]. International scholars have made extensive research efforts to quantify urban patterns and address the challenges of urban LULC [10–14]. Uncontrolled growth has resulted in issues such as urban sprawl, environmental pollution, insufficient water supply, insufficient electricity, poor housing, poor drainage and sewage system, garbage disposal, and other associated problems in urban areas [15,16]. The incorporation of landscape metrics into the use of RS is required to understand the urban process [17,18]. The spatial metrics tool is useful for quantitatively describing urban built-up and comparing the results using multi-date thematic maps [19]. These metrics enable a thorough understanding of the characteristics of the urban landscape in order to manage urban environments in a sustainable manner [20]. Extensive research has been conducted on the use of landscape metrics to measure and assess urban patterns in various landscapes. [21] described the spatial characteristics of land cover objects in the Santa Barbara South Coast using twenty-two spatial metrics. According to the study, combining RS and spatial metrics provides an efficient method for analyzing urban growth patterns. [22] conducted a study to assess the change in urban growth and land policies in Ankara, Turkey. Their findings revealed that the amount of urban land increased from 1.95 percent to 7.49 percent of the total area between 1984 and 2018. These findings clearly show that the proportion of Ankara's urban footprint in the landscape has increased. Mandal et al. [19] used temporal RS data and spatial metrics to conduct a spatiotemporal analysis of urban growth patterns in Howrah City, India. Class Area (CA):Number of Patches (NP):Patch Density (PD):Edge Density (ED):Largest Patch Index (LPI):Area-Weighted Mean Patch Fractal Density (AWMPFD): Contagion (CONTAG):and Shannon's Diversity Index (SHDI) were the eight spatial metrics used in the study. The study's findings revealed a gradual expansion of urban built-up areas in and around Howrah City from 1996 to 2016. Using the spatial metrics chosen, the types of urban growth identified were infilling, edge expansion, and outlying growth. [23] used the FRAGSTATS software to assess the forest fragmentation of the Chitteri Hills in the Eastern Ghats for different classes using specific metrics. The study concluded that monitoring the spatial metrics for forest ecosystems aids in analyzing changes in the composition and configuration of the ecosystem. Spatial metrics are an important tool in forest management for biodiversity conservation and sustainable forest management. It provides data for determining and evaluating LULC as well as the direction of the urban growth pattern [24]. However, the majority of existing urban growth studies are primarily focused on megacities or large cities. There has been less research on the urban growth of small and medium-sized cities such as Voi in Kenya. The purpose of this study was to examine urban growth patterns and LULC dynamics in Voi town in Kenya by combining the use of spatial metrics and RS. With the current population growth in Voi, it is critical to understand the spatio-temporal patterns of urban expansion for the town's future development. The findings of this study will provide a clear understanding of the changes in urban regions as well as the spatial growth pattern of Voi settlement. This study is relevant to the Taita Taveta County Government, specifically the Voi Sub-County, in terms of planning and controlling development. The study's findings will be useful to urban planners, developers, and administrators for future development and policy formulation in order to ensure Voi's sustainability.

2. METHODOLOGY

2.1 Study Area

Voi is a historical town in Taita Taveta County that became a township in 1932 (Fig. 1). It is located at 3°23'45.78"S, longitude 38° 33' 21.92"E, at 600 m a.s.l., and has a land area of 55.31 km^2. Infrastructure such as the Kenya–Uganda railway, Standard-gauge railway (SGR):airstrips, the Voi–Tanzania highway, and the Mombasa–Nairobi highway account for the town's rapid growth. The town is close to ranching plains, national parks, and mining operations. Voi, as a commercial and tourist center, has drawn a large population from the surrounding areas, and it has the highest population growth rate among the towns in Taita Taveta County.

Voi town began as a settlement location in 1897, when the railway line between Kenya and Uganda reached the town, making it a resting place for the workers; however, as shown in the table 1 below, there was significant growth between the 1999 and 2009 censuses. Voi's population grew from 16,273 in 1989 to 52,472 in 2019 [4,25–27].

2.2 Image Pre-processing

Three images captured after the rainy season were obtained from the U.S. Geological Survey (USGS) for use in this study. Landsat 7 ETM+ image (October 1999):Landsat 5 TM image (July 2011) and Landsat 8 (OLI) of July 2019. The remotely sensed data were cropped to the study area and geometrically corrected to the UTM (Universal Transverse Mercator) projection zone 37 south. In order to analyze remotely sensed images, the bands of the individual Landsat images were stacked to create a band set using QGIS 2.18.15 Software to show different combinations of Red Green Blue (RGB) for better interpretation of the land use classes.

Table 1. Population of Voi town from 1989-2019 [4, 25–27]

Year	Population	% Increase
1989	16,273	-
1999	24,040	47.7
2009	45,483	89.2
2019	52,472	15

2.3 Image Classification

To carry out the land use/land cover classification, supervised classification method with maximum likelihood algorithm was applied in the ArcGIS 10.5 software. The images were classified into three macro-classes: built-up, bare land, and vegetation cover, using the maximum likelihood classification algorithm in the supervised classification technique. Water was excluded from the analysis since the study focused on land areas.

2.4 Accuracy Assessment

Following the image classification, the LULC classes were evaluated using independent data. The data's accuracy was assessed by generating randomly chosen points and comparing the land cover map generated from classification results to ground reference data collected from the same LULC classes [28]. Ground truth field data were collected using hand-held consumer-grade GPS. Aerial photographs, topographic maps from the Taita Taveta Planning offices, and Google Earth images were used as additional reference data for accuracy assessment. To determine the accuracy of the classification, each classified land cover map was compared to the reference data. The study used producer's accuracy, user's accuracy, overall accuracy, and the Kappa coefficient to assess classification accuracy [29–31].

2.5 Change Detection

The post classification comparison technique was used, which consists of an initial, independent classification of each image, followed by a thematic overlay of the classified maps in ArcGIS software [32]. The resulting maps depicted the newly built-up area in Voi town from 1990 to 2011 and again from 2011 to 2019.

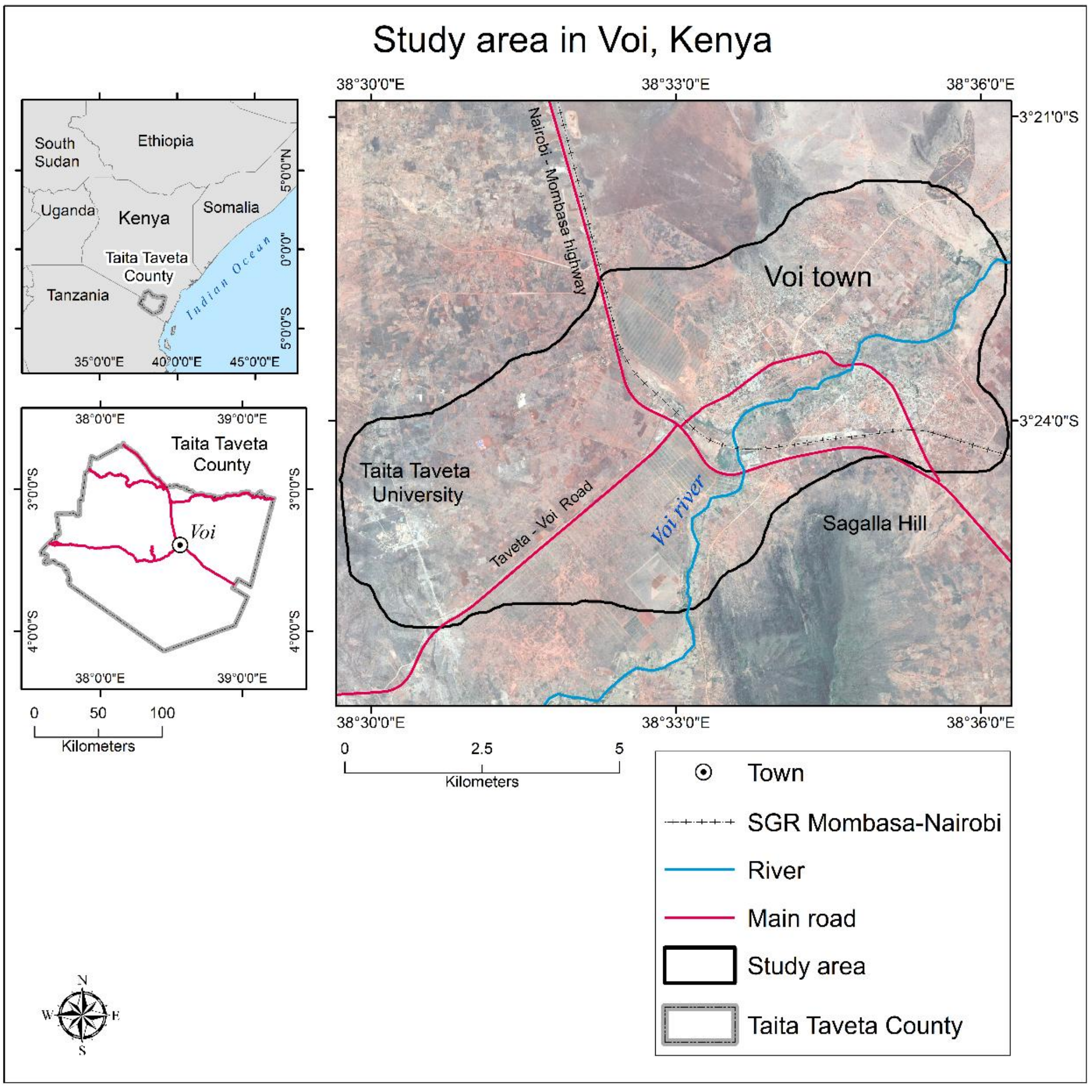

Fig. 1. Study Area of Voi Town

Source: Google Earth Pro 7.3.2.5776, October 10, 2020. Voi 03°23'13.40''S, 38°33'51.07''W, Eye alt 28.0 km Image@2022 CNES, Airbus; Image Image@2022 Maxar Technologies viewed May 4, 2022. http://www.google.com/earth/index)

Table 2. Land cover classification scheme

Land use types	Description
Built-up	Residential, commercial, industrial, transport networks, Other urban/ built-up land
Bare land	Parks, ranches, playground, air strip, grave, mixed barren lands
Vegetation Cover	Forest lands, vegetation, grass lands, bushes, sisal plantation

2.6 Quantifying LULC Using Spatial Metrics

Each map's landscape metrics were calculated for the years 1999, 2011 and 2019. To better understand the urban LULC in Voi, ten spatial metrics were computed using the FRAGSTATS software product [33]. The selected metrics were: Class Area (CA):Edge Density (ED):Number of Patches (NP):Largest Patch Index (LPI):Percentage of Landscape (PLAND):Landscape Shape Index (LSI):Aggregation Index (AI):Perimeter-Area Fractal Dimension (PAFRAC) Simpson's Diversity Index (SIDI):Shannon's Evenness Index (SHEI).

3. RESULTS AND DISCUSSION

3.1 Land Use/ Land Cover Change Analysis

The results of the analysis of multi-temporal satellite imagery are depicted in Figs. 2–5.

Overall data accuracy for supervised image classification was 81 percent in 1999, 75 percent in 2011, and 87 percent in 2019, all of which were within acceptable limits. Any accuracy assessment value greater than 75%, according to [34], is considered acceptable. Table 3 depicts the effects of the change in LULC. The result shows that built-up area increased by 187.96 percent between 1999 and 2011, 183.40 percent between 2011 and 2019, and 716.1 percent between 1999 and 2019. In general, the most change has occurred in the last twenty years, indicating a significant expansion of the city and its surrounding areas. Some of the possible causes of urban sprawl in Voi town include population growth, land tenure, transportation, and utilities such as water and electricity provision. Population growth leads to an increase in demand for housing and infrastructure, which leads to the conversion of more land to urban use. Unregulated land sales, low land values on the outskirts, and speculation that land prices will soon rise or residential development will arrive sooner are all causes of land tenure. All of this leads to the easy acquisition of land for construction. Finally, people tend to relocate to areas with accessible road networks and other forms of transportation. A steady supply of water and electricity is also a driving force behind urban sprawl. Between 1999 and 2011, the area covered by bare land increased by 21%, then decreased by 7% from 2011 to 2019. The decrease in bare land can be attributed to urbanization, where people are utilizing open space to build residential and commercial properties. During the twenty-year study period, the amount of vegetation decreased steadily. This implies that these two groups are the primary contributors to the built-up area. Vegetation areas have shrunk primarily as a result of climatic conditions and development (construction of buildings, roads, and houses).

Land use/land cover changes are complex and interconnected, so a change in one type of land use/land cover occurs at the expense of another [35]. The findings of this study agree with those of [36]. According to their change detection analysis, built-up area increased by more than 30% from 28 to 255 km^2, while agricultural land decreased by 33%. A similar study [37] found a 454% increase in built-up area from 1978 to 2018 in the Ananthapur district of Andhra Pradesh state, South India.

Figs. 6 and 7 show how Voi town has grown over the 20-year study period. The town is clearly expanding outwards and in all directions. Fig. 7 depicts a zoomed-in view of linear settlement over a twenty-year period, as it primarily occurred along major roads. This is evident on the Voi-Mwatate road and the standard gauge railway. Much of these developments occurred between 2011 and 2019, during a period of significant infrastructural improvement in the region. Another type of sprawl pattern observed is clustered settlement, which can be found in some parts of the town. This pattern is observed as a result of increased population and the growth of the central business district, industries, and the Taita Taveta University in the Voi area. With population growth between 1999 and 2019, there has been an increase in population concentration within Voi town.

Table 3. Change in percent in time series analysis from 1999–2019

Land-use	Change in 1999-2011		Change in 2011-2019		Change in 1999-2019	
	Area(ha)	%	Area(ha)	%	Area(ha)	%
Built-up	141.93	187.96	398.79	183.40	540.72	716.1
Bare land	806.94	21.64	-348.48	-7.69	458.46	12.30
Vegetation	-948.87	-46.20	-50.31	-4.55	-999.18	-48.65

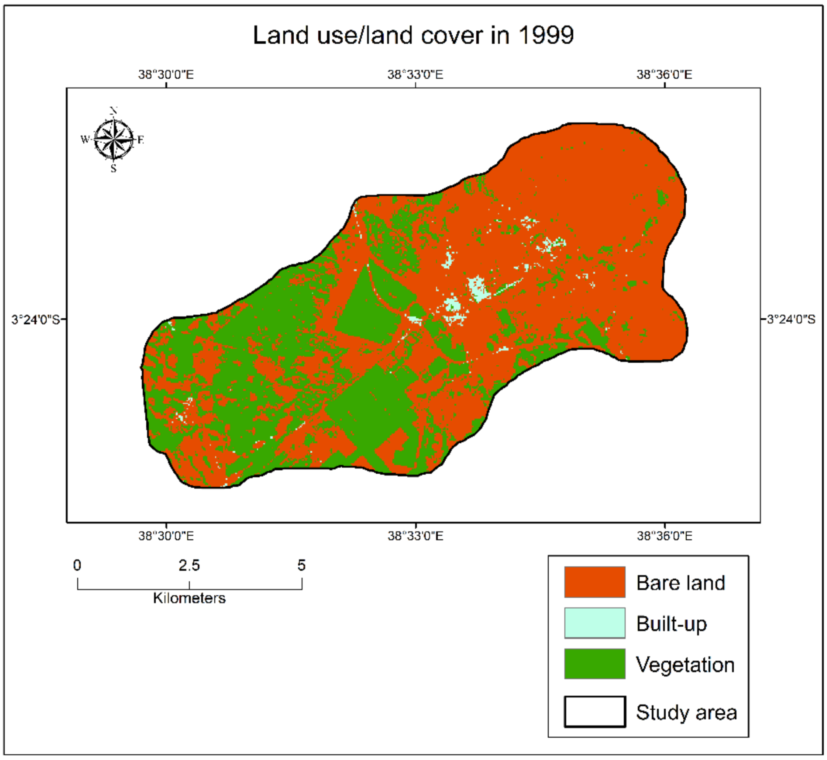

Fig. 2. Land use/ land cover map of 1999

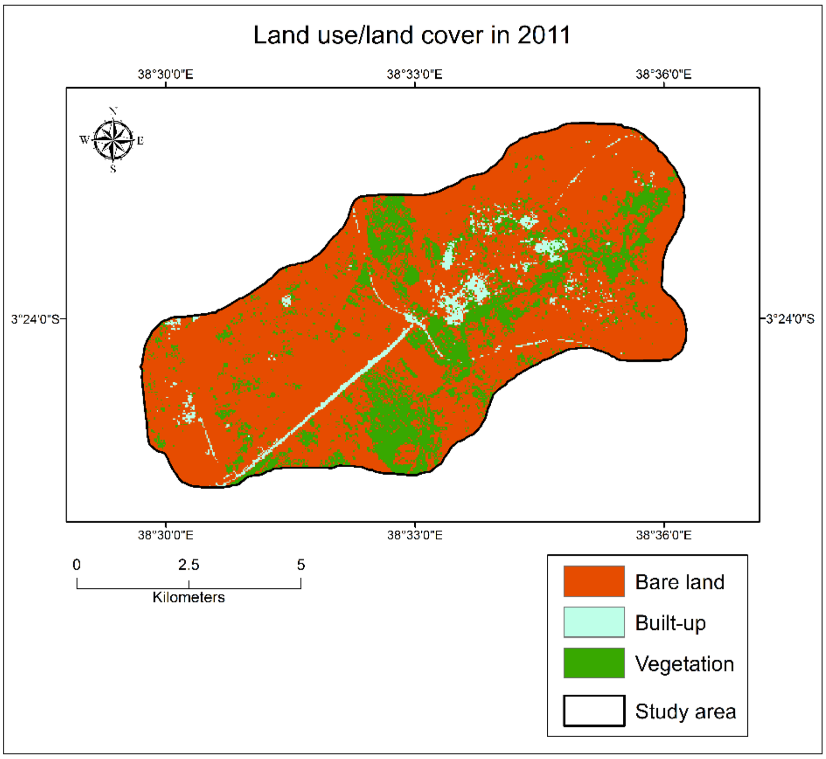

Fig. 3. Land use/ land cover map of 2011

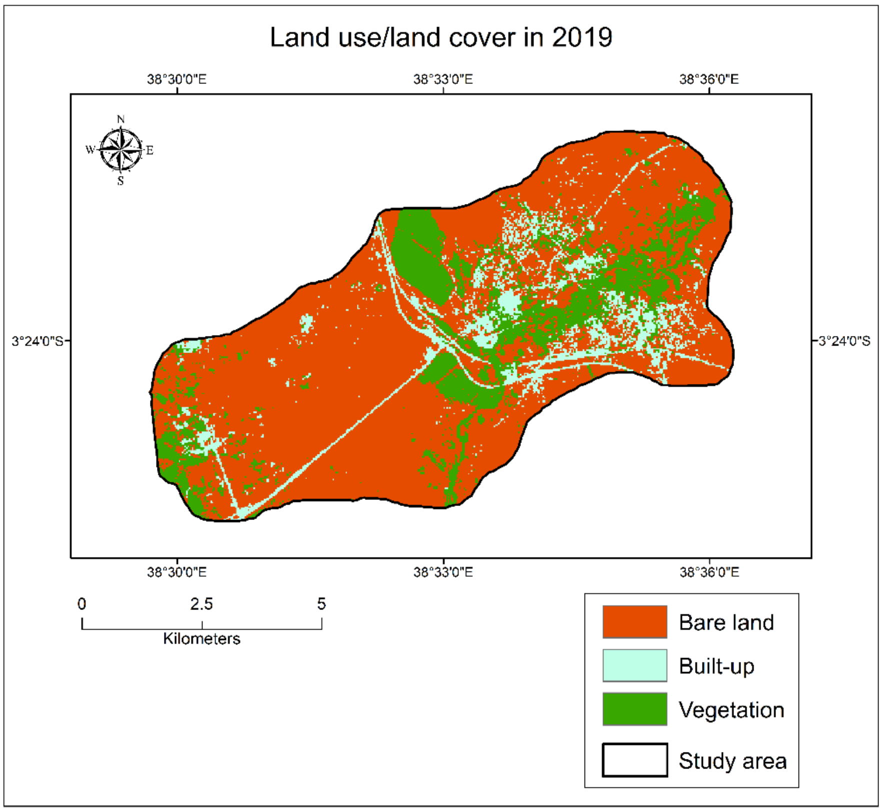

Fig. 4. Land use/ land cover map of 2019

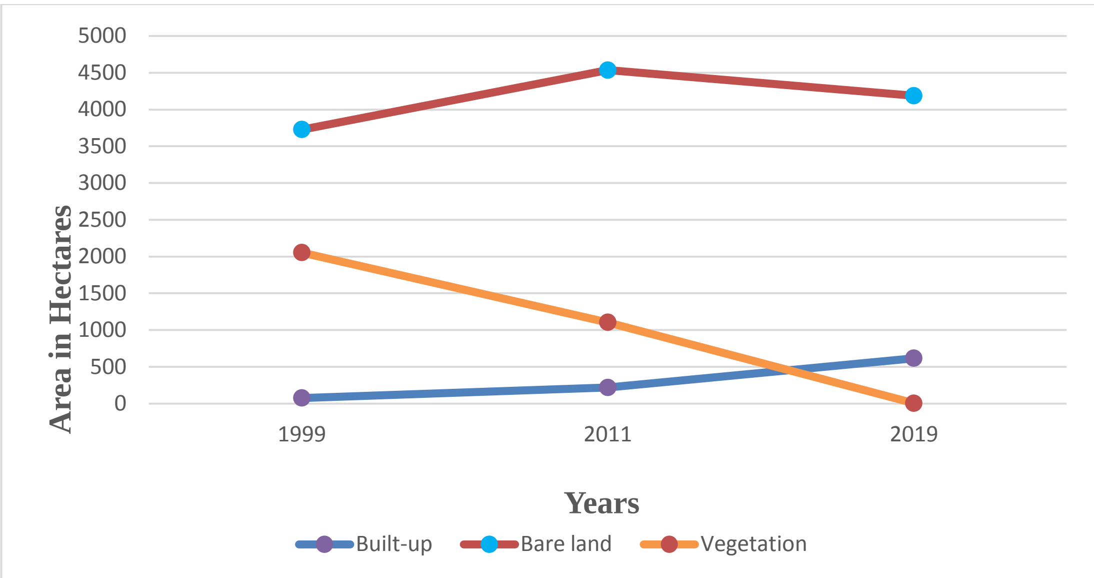

Fig. 5. Graph of total area for all land-use types from 1999–2019

3.2 Change in Urban Areas Using Landscape Metrics

Land use/land cover maps from three different years were used to compute spatial metrics for the analysis using the FRAGSTATS software. The temporal urban growth patterns of the spatial metrics are depicted in Table 4. The majority of the landscape metrics show a positive trend, while a few of these indices show a negative trend. CA, PLAND, and NP have increased from 1999 to 2019, indicating a higher urbanization rate between 2011 and 2019. The NP has steadily increased since 1999, rising from 154 in 1999 to 526 in 2019. Similar findings were reported by [38], where NP increased between 1995 and 2015 in the Greater Changsha metropolitan region. In contrast, the number of patches in Greater Noida, India, decreased due to a lower degree of fragmentation of urban patches [39]. In a study conducted in Kathmandu Valley (Nepal):the ED nearly doubled over the course of the study [40]. From 1999 to 2019, the values of PAFRAC increased from 1.5135 to 1.5509, indicating that urban patches were becoming more complex and irregular in shape. PAFRAC in Greater Noida decreased between 1977 and 2011, indicating that there was little change in the shape of the built-up area during the study period [39]. The Landscape Shape Index (LSI) increased from 14.4483 to 32.4639 between 1999 and 2019, indicating that built-up area in 2019 was more dispersed than in 1999. This is in contrast to a study conducted in the Chinese city of Yancheng's urban coastal wetland, where the LSI decreased during the study period [41]. The AI values in this study increased from 51.8519 to 61.3912, indicating that the built-up area is merging into a single patch. The AI was also used to quantify and measure the degree of aggregation or disaggregation in the urban sprawl pattern. The largest patch index (LPI) increased from 0.2628, 0.8729, and 2.239 in 1999, 2011, and 2019, respectively, indicating the centralization of urban growth. This result is similar to the findings of [42] in Kampala City (Uganda):where LPI gradually increased. According to Abebe, the LPI increased because urban areas became more aggregated and integrated with urban cores. However, [43] found a decrease in LPI values, indicating greater fragmentation of the urban landscape and rural landscape dominance.

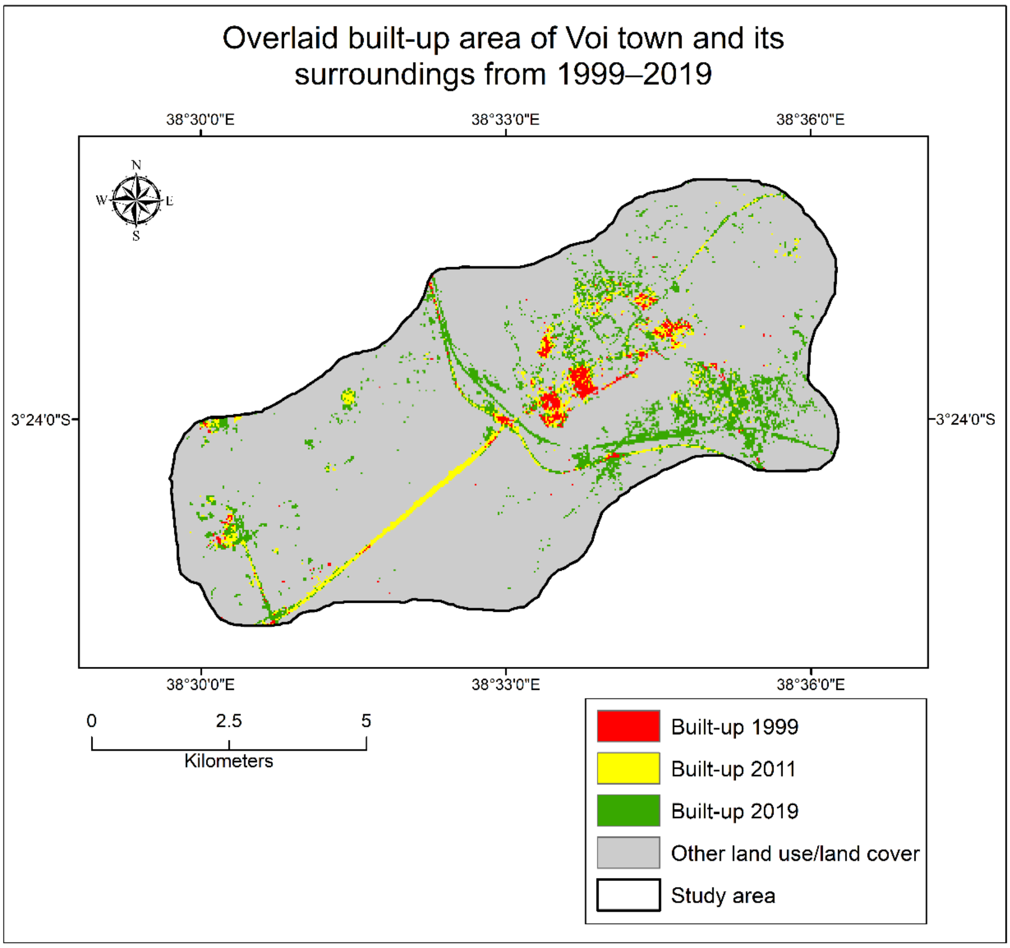

Fig. 6. Overlaid built-up area of Voi town and its surroundings from 1999–2019

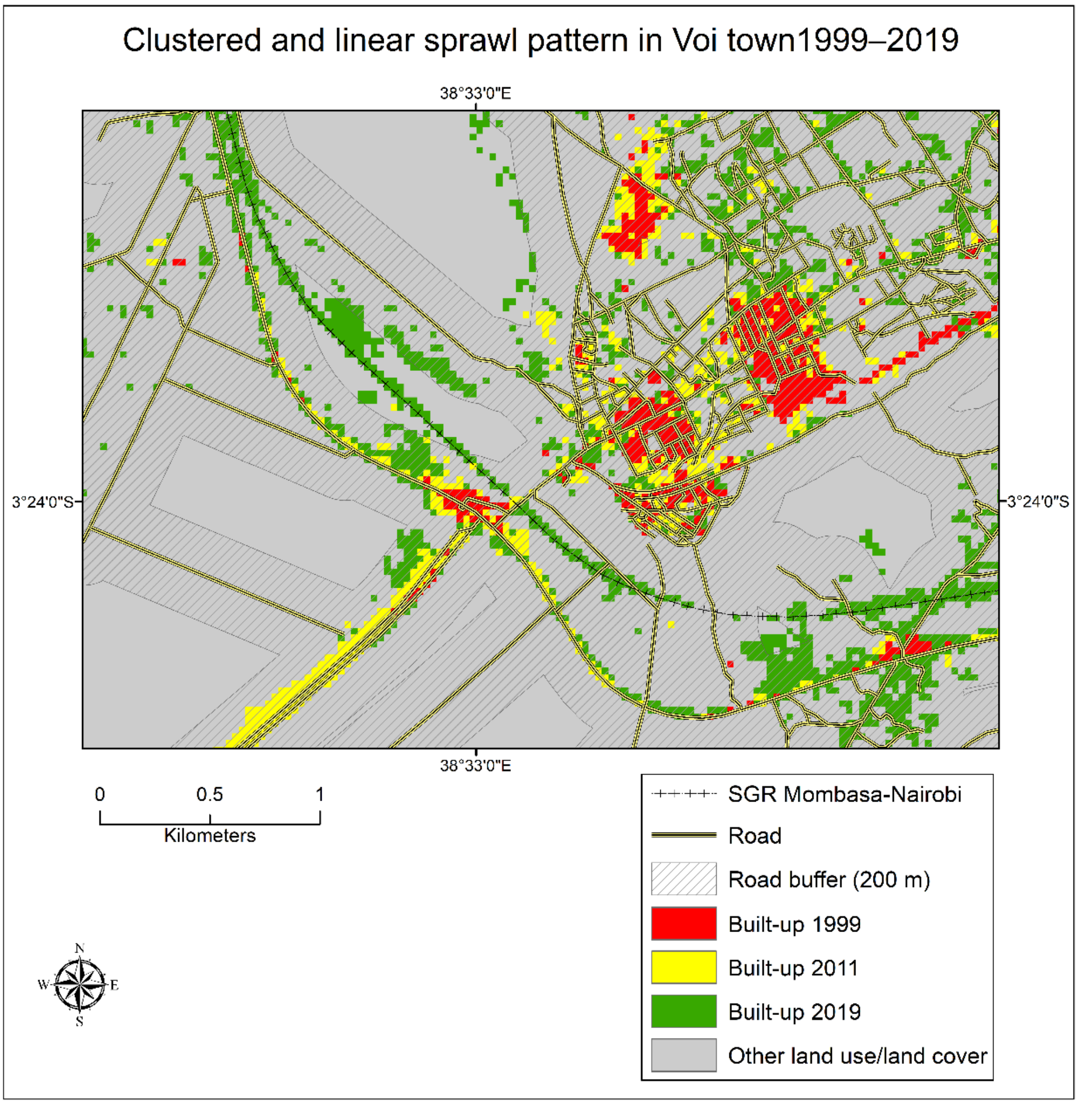

Fig. 7. Clustered and Linear Sprawl pattern

Table 4. Class metrics indices for built-up area from 1999–2019

Years					Class metrics			
	CA	PLAND	NP	LPI	ED	LSI	PAFRAC	AI
1999	75.51	1.2893	154	0.2628	8.539	14.4483	1.5135	51.8519
2011	217.44	3.7127	278	0.8729	20.8788	20.6768	1.5268	58.8422
2019	616.23	10.5219	526	2.239	54.9016	32.4639	1.5509	61.3912

4. CONCLUSION

Using multi-temporal Landsat data, GIS, RS, and spatial metrics indices, this study examined the LULCC and spatiotemporal pattern of urban growth in Voi. The results show that bare land is the most common LULC in the study area, which is due to the fact that Voi is a semi-desert region with an annual rainfall of 733 mm. As a result, the area is dry for the majority of the year. Due to climate change and clearing of vegetation to make room for settlement, bare land increased by 12.30 percent (458.46 ha) during the study period, while vegetation cover decreased by 48.65 percent (999.18 ha). During the study period, the area under built-up land increased by 716.1 percent (540.72 ha):owing primarily to urbanization. The results showed that there was an increase in urban areas over a 20-year period, which was clearly illustrated in the land cover maps. Thus, this study demonstrates that it is possible to detect changes in LULC and quantify spatial phenomena using GIS and RS techniques. The findings of this study can help urban planners, developers, and administrators plan future development and policy to ensure Voi's long-term viability. Future research could focus on the factors that fuel urban growth in Voi and its surroundings.

5. RECOMMENDATIONS

- Voi town is affected by poor housing, a poor drainage and sewage system, garbage, insufficient water supply, insufficient electricity, and disposal major traffic congestion, drinking water, sewerage disposal problems, and many other environmental and socioeconomic issues that cannot be resolved without taking into account the issues associated with urban sprawl.
- The output of LULCC from this study could be used as an input for predicting future LULCC in Voi town.
- Further research is needed to explain the factors influencing Voi town's growth and the consequences of that growth in greater detail.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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