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Integrating GIS and Satellite Remote Sensing to Assess the Geospatial Dynamics of Urban Footprints in the Dormaa Central Municipality in Ghana

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Abstract:** Rapid urban expansion and changing land use in Dormaa Central Municipality, Ghana, pose challenges to sustainable development and agricultural preservation. Using GIS and Satellite Remote Sensing, this study analyzed urban changes and land use from 2001 to 2021. The findings revealed a 10% annual increase in urbanization, expanding the urban area by 20% (67,392.196 hectares) over two decades. Urgent, sustainable management and planning aligned with the UN's Sustainable Development Goals (SDGs) are crucial. Balancing urbanization with agriculture ensures food security (SDG 2) and biodiversity preservation (SDG 15). GIS and satellite sensing aid decision-making, contributing to resilient cities and communities (SDG 11). Efficient urban planning supports SDG 9 (Industry, Innovation, and Infrastructure) and SDG 13 (Climate Action) by mitigating environmental impacts. Promoting equitable access to resources reduces inequalities (SDG 10) and fosters inclusive, sustainable economic growth (SDG 8). The study highlights GIS and remote sensing as essential tools to monitor urban changes and advance sustainable urban development in line with the SDGs. By integrating sustainability, policymakers can create liveable, inclusive, and resilient cities in Dormaa Central Municipality while safeguarding agriculture and natural resources.

***Keywords:** Satellite Remote Sensing (RS), Urbanization, Land Use and Land Cover (LULC), Climate Change, Environmental Management.*

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1. INTRODUCTION

Urbanization has increased its footprint in various communities in the world (United Nations, 2018). This process of population migration from rural to urban areas has also resulted in increased urban growth and development in Ghanaian communities. The Dormaa Central Municipality in the Bono Region of Ghana has witnessed significant land use and land cover changes, particularly in peri-urban areas, where urban expansion clashes with the predominantly agricultural landscape (Puplampu and Boafo, 2021). This transformation, notably in Dormaa Ahenkro, has historically been an agriculturally shaped region. However, rapid urban development is converting agricultural spaces into built-up areas (Talema and Nigusie, 2023). Urbanization is driven by rural-to-urban migration due to improved infrastructure and amenities. This underscores the need for up-to-date geospatial information, particularly in fast-developing metropolitan regions in Ghana. Researchers have employed various methods, including census data, surveys, historical documents, and satellite imagery, to study the spatial patterns and dynamics of Urbanization (Harding et al., 2005; Walford, 2019; Seto et al., 2012; Fotheringham et al., 2000).

There have been different modern technologies which have been used to analyse urban footprints. Light Detection and Ranging (LiDAR) technology provides high-resolution elevation data for urban topography assessment (Batty, 2013). Spatial analysis methods including Cellular Automata Models, Agent-Based Models, and Spatial Econometric Models have been used by researchers to simulate urban growth and drivers (Clarke et al., 1997; Heppenstall et al., 2012; Xia et al., 2020; Hawelka et al., 2014). Big Data and social media data, like geotagged tweets and mobile phone data, have helped us understand urban activities, sentiment, and mobility (Mirzaee and Wang, 2020). Integrating Satellite Remote Sensing and GIS has enhanced the efficiency of urbanization assessment. GIS has evolved into a powerful tool for spatial analysis, while satellite remote sensing collects Earth surface data from orbiting satellites (Lillesand et al., 2015). Utilizing sensors that capture electromagnetic radiation from the surface and atmosphere of the earth, the integration of GIS and satellite remote sensing offers valuable insights into land cover, vegetation health, and urban dynamics. This combined approach enhances urbanization studies and informs planning decisions (Lillesand et al., 2015).

Multiple studies have leveraged satellite imagery and GIS to examine urban growth and land use changes in various regions. The researchers observed accelerated urbanization, declining agricultural land, and increased urban density. Additionally, the researchers employed techniques like image classification and spectral indices to analyse urban patterns, with results influenced by the approach and analyst expertise (Yin et al., 2010; Hegazy and Kaloop, 2015; Boori et al., 2015; Mansour et al., 2023; Yasin et al., 2022; Li et al., 2022; Tempa and Aryal, 2022).

Integrated GIS and satellite remote sensing is an effective technique to assess the geospatial dynamics of the urban footprint. This study seeks to integrate GIS and satellite remote sensing to identify and map the spatial dynamics of urban footprints in the Dormaa Central

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Municipality from 2001 to 2021. This will be done by finding the Normalized Difference Built-up Index (NDBI) for Dormaa Central Municipality and identifying the geospatial dynamics of urban footprints in the Dormaa Central Municipality from 2001 to 2021.

1.1 Study Area

Dormaa Central Municipality shown in Fig.1, situated in the Bono Region of Ghana, spans 1210.28 km^2 with Dormaa Ahenkro as its capital. Its population is 112,702, and 68% are involved in agriculture. The area features two forest reserves, undulating topography, and a wet semi-equatorial climate with a mean annual rainfall of 125-175 mm (Ghana Statistical Service, 2014).

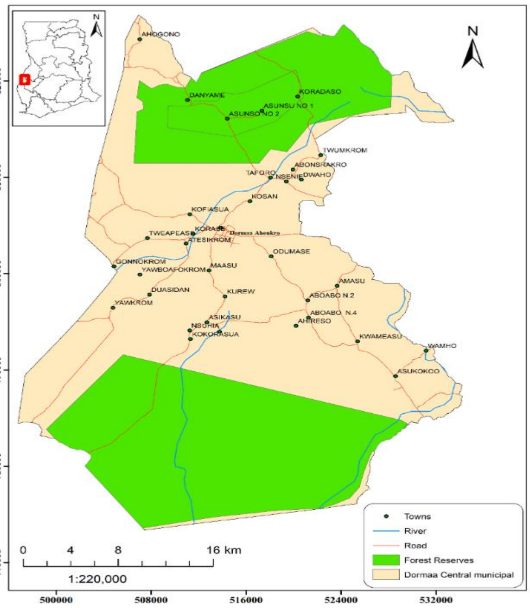

Fig. 1. A Map of Dormaa Central Municipality in the Bono Region of Ghana

1.2 Data Used

This study used Landsat images obtained from US Geological Survey (USGS) for Land use Land cover (LULC) classification. All the materials and data used for this study are shown in Table 1 with their sources.

Table 1 Materials and data used with their sources

	Data	Source
1	Level 2 Landsat 7 ETM+ & 8 OLI images	https://earthexplorer.usgs.gov/
2	Administrative Boundary Layer	http://biogeo.ucdavis.edu/data/diva/adm/GHA_adm.zip
3	Towns and community layer	http://131.220.109.2/geonetwork
4	Ground Validation Points	https://earth.google.com
5	QGIS 3.16.3	https://www.qgis.org/en/site/forusers/download.html

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2. METHODS

When it comes to mapping surface phenomena across vast regions, like the Dormaa Central Municipal, satellite remote sensing has shown to be the most effective method (Li et al., 2022). In RS, many methods are employed to analyse urban patterns. Image classification is the most used approach (supervised classification and unsupervised classification). The image analyst and approach used by the analyst determine the accuracy of the image classification procedure. This study used a satellite remote sensing spectral index to delineate the urban footprints to analyse their dynamics in the municipality.

Satellite Remote Sensing and Geographic Information System (GIS) in Urban Footprint Mapping

Satellite Remote Sensing and GIS are instrumental in the assessment of urban footprint dynamics in Dormaa Central Municipality, Ghana, contributing to the advancement of Sustainable Development Goal 11 - "Sustainable Cities and Communities." Here, we explore how these technologies are harnessed to gain valuable insights into urbanization patterns, plan for sustainable growth, and promote the well-being of the residents.

Geographic Information system: GIS is a crucial tool for urban footprint assessment in Dormaa Central Municipality. It manages diverse geospatial data, detects changes, creates growth models, and aids in visualization. Integrating Satellite Remote Sensing and GIS aligns with SDG 11, promoting sustainable and inclusive urban development (Teng et al., 2017).

The Normalised Difference Built-up Index (NDBI)

NDBI is a remote sensing index used to assess and monitor urban and built-up areas within satellite imagery. NDBI is calculated based on the difference in reflectance values between the shortwave infrared (SWIR) and the near-infrared (NIR) bands of the satellite data (Kebede et al., 2022). Compared to many different algorithms used in image classification, the NDBI calculation is simple and easy to utilize for the extraction of urban signatures. NDBI is calculated by using the following formula:

$$NDBI = (SWIR - NIR) / (SWIR + NIR) \quad (1)$$

Where SWIR represents the reflectance in the shortwave infrared band
and NIR represents the reflectance in the near-infrared band.
For Landsat 7 ETM+ data: NDBI = (Band 5 – Band 4) / (Band 5 + Band 4)
For Landsat 8 OLI data: NDBI = (Band 6 – Band 5) / (Band 6 + Band 5)
NDBI values vary from -1 to 1, signifying urban or non-urban areas. Positive values denote urban regions, with higher values indicating denser development. Negative values represent non-urban features. NDBI aids in urban analysis, land use mapping, and environmental monitoring, facilitating urban growth assessment and urban heat island studies for urban planning and policy decisions (Abulibdeh, 2021).
In this study, Eq. (1) was used to compute the NDBI using Landsat 7 ETM+ Level 2 and Landsat 8 OLI Level 2 (L2) images with Landsat 7 ETM+ L2 images acquired in 2001 and 2011, and one Landsat 8 OLI L2 image acquired in 2021.
In QGIS 3.16.3, Landsat 7 ETM+ L2 images from 2001 and 2011 underwent scan-line error

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correction using the "fillnodata" tool. NDBI was calculated, and in the Dormaa Central Municipality, values were classified as Urban or Vegetation based on a chosen threshold, typically positive, to distinguish built-up from non-built-up areas.

Table 2 Classes for LULC classification

Class Code	LULC class	Description
1	Vegetation	grooves of evergreen thick vegetation stand and deciduous trees forming a dense canopy, grooves of evergreen and deciduous trees forming a less dense canopy and less thick vegetation stands
2	Urban	Settlements, Bare lands, exposed rocks, roads and Areas without vegetation cover (Bald soil patches)

Accuracy Assessment

Accuracy assessment in satellite image classification validates classification results by comparing them with reference data (Mas et al., 2014). Thematic map accuracy is evaluated through statistical analysis and a confusion matrix. Various sampling methods can be employed to select reference sites, and the matrix helps measure classification correctness, essential for land use and land cover classification (Congalton and Green, 2009; Rwanga, 2017).

Confusion matrix

The confusion matrix represents classification accuracy by comparing classification results with reference data. It highlights correct classifications along the main diagonal and identifies errors of omission and commission (Osei et al., 2023). Accuracy indices like overall accuracy, user accuracy, and producer accuracy are essential for evaluating classification quality (Rwanga, 2017). The three accuracy indices and their calculation methods are described in detail below:

Overall Accuracy (OA)

Overall accuracy is the percentage of all reference pixels correctly classified (in the scene) that the classification assignment and the reference classification agree on. It is calculated by dividing the total number of correctly classified pixels (the sum of the elements along the main diagonal) by the total number of reference pixels (Rwanga, 2017). According to the confusion matrix, the overall accuracy is calculated using Eq. (2).

Overall Accuracy (OA) = (Number of features correctly classified / Total Number of Features) x 100 (2)

Producer's Accuracy (PA)

The probability that a pixel of class I in the reference classification is correctly classified is estimated by producer accuracy. It is calculated by dividing the reference pixels of class I by the pixels in class I where classification and reference classification agree. Eq. (3) is used to

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calculate the producer's accuracy. The accuracy of the producer indicates how well the classification agrees with the reference classification (Rwanga 2017).
Producer's Accuracy (PA) = (Number of features of specific class correctly classified / Row Total) x 100 (3)

User's Accuracy (UA)
The user's accuracy is calculated by dividing the number of pixels in class I classification results by the number of pixels in class I that agree with the reference data. Eq. (4) is used to calculate it. The accuracy of the user predicts the likelihood that a pixel classified as class I belongs to class I (Rwanga, 2017).
User's Accuracy (UA) = (Number of features of specific class correctly classified / Column Total) x 100 (4)

Kappa Statistics
The kappa analysis is a discrete multivariate technique used in accuracy assessment to determine whether one error matrix is statistically significantly different from another. KHAT statistics (actually K, an estimate of kappa) are the result of kappa analysis, which is another measure of agreement or accuracy (Osei et al., 2023). This agreement metric is based on the difference between the actual agreement in the confusion matrix (i.e., the agreement between the remotely sensed classification and the reference data as indicated by a major diagonal in the matrix) and the chance agreement (as indicated by the row and column totals) (i.e. marginal of the error matrix) (Rwanga, 2017). Kappa is calculated by Eq. (5).
Kappa (K) = (Total Number of Features * Number of Correct Features) -(Sum of all row totals * Column Totals) / (Total Number of Features squared) - (Sum of all row totals*Column totals) x 100 (5)

For this study, twenty (20) points (10 points from urban areas, and 10 from vegetated areas) were sampled from Google Earth for 2001, 2011, and 2021 to perform an accuracy assessment to validate the classified images from the NDBI raster.

Quantification of LULC
The LULC is quantified by using the pixel counts generated from the classified satellite imagery. LULC of the same class has the same pixel. All these pixel values are summed together to produce the pixel count after classification. The area for each LULC class is computed using Eq. (6). The percentage of the LULC (coverage) is also computed using Eq. (7).
Area (m^2) = Pixel count x Resolution of satellite image (6)
Percentage = (Area/Total Area)100% (7)
Where image resolution for the Landsat image used in the classification = 30m x 30m.
The coverage of urban footprints in the municipality was computed for 2001-2011 and 2011-2021 using Eq. (6) and Eq. (7). This was performed to estimate the change in areas of urban footprints from 2001 to 2021, at a 10-year epoch. The developed methodology in this study was applied sequentially to study the dynamics of urban footprints in the Dormaa

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Municipality to support Sustainable Cities and Communities in Ghana. The applicability of the derived results is to foster a more sustainable and resilient urban future for all. The Conceptual Framework of each step used for this study is illustrated in Fig. 2.

Change Detection Analysis for the dynamics of urban footprints

Change detection analysis is a powerful technique used in satellite remote sensing and GIS applications to study urban dynamics and monitor land cover changes over time. It allows researchers to identify and quantify changes in the landscape, particularly in urban areas, which are rapidly evolving due to urbanization and human activities. One effective method for conducting change detection analysis in this context is by employing the image difference equation.

Image Difference Equation Method

The image difference equation method is based on comparing two or more images acquired at different time periods. This study used the image difference method. The key steps involved in this method during the analysis using QGIS 3.16 software are as follows:

Image Registration

Before applying the image difference equation, it is crucial to register the images to ensure that corresponding pixels from different time periods align correctly. Image registration removes any spatial discrepancies caused by changes in satellite positions or sensor parameters.

Calculation of Image Difference

Once the images are registered, the image difference equation (Eq. 8) is applied to compute the pixel-wise difference between corresponding pixels in the two images. The equation is typically represented as:

$$\text{Image Difference (ID)} = \text{Image2} - \text{Image1} \tag{8}$$

Thresholding and Classification

The resulting image difference values represent the magnitude and direction of change between the two images. Thresholding is applied to categorize the changes as positive (increase), negative (decrease), or no change. The classified change map provides valuable insights into the spatial distribution and extent of urban dynamics. The coverage area, in hectares (ha), for urban footprints for each year was computed using Eq. 6. A spatial intersection was performed for 2001 and 2011, and 2011 and 2021. The change in urban footprint was detected using Eq. 8 to analyse the dynamics of urbanisation for two decades in the municipality.

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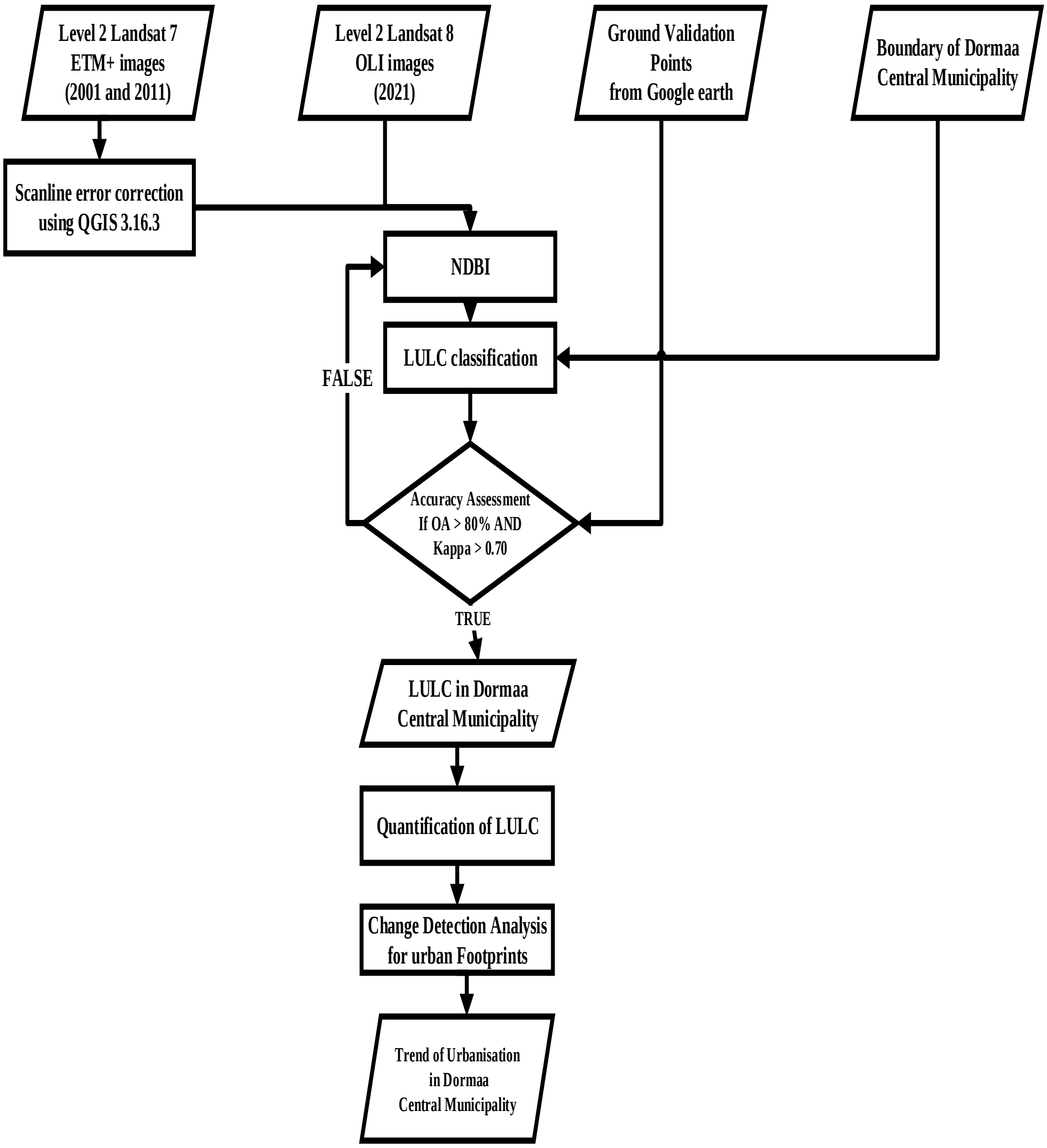

Fig. 2. Conceptual Framework of the study

3. RESULTS AND DISCUSSION

The study utilized satellite remote sensing and GIS techniques to assess the urban footprint dynamics in Dormaa Central Municipality, Ghana, over a specified time period (2001-2021). The following are the key results obtained from the analysis.

3.1 Urbanization Trends in Dormaa Central Municipality

The NDBI analysis allowed for the identification of trends in urbanization and provided a basis for understanding the historical growth patterns of urban areas. This information is critical for predicting future urban expansion and planning accordingly. The results from the

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NDBI computation are shown in Fig. 3.

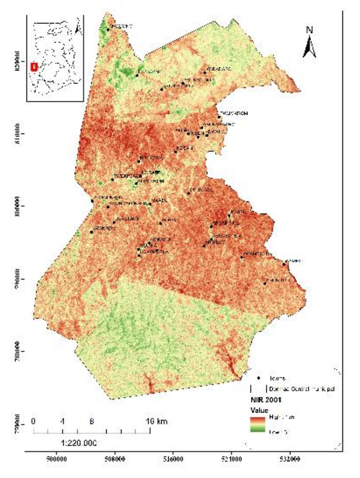
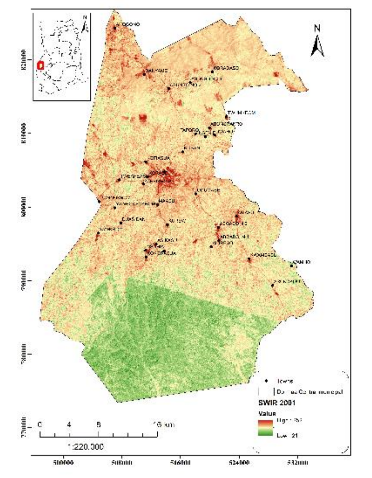
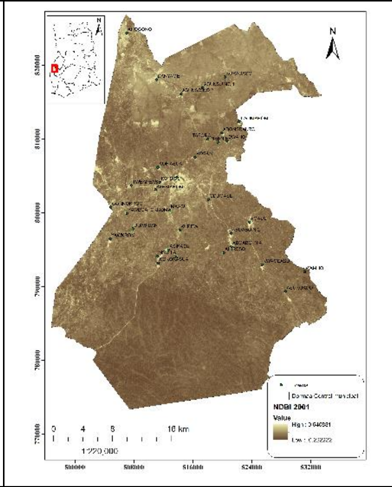
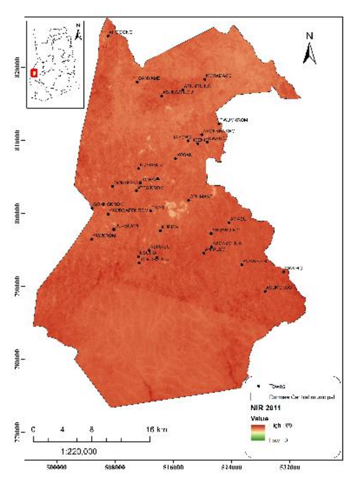
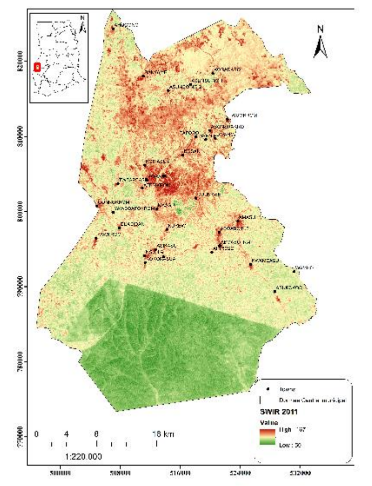
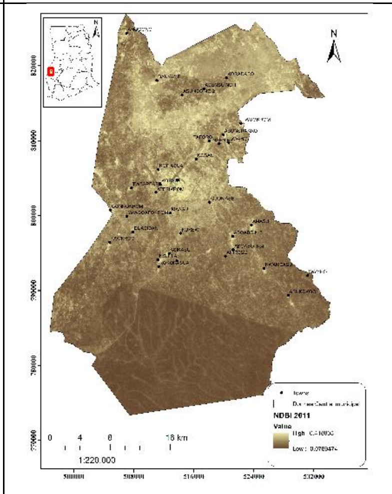
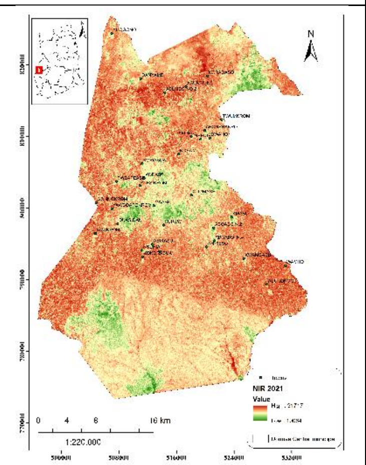
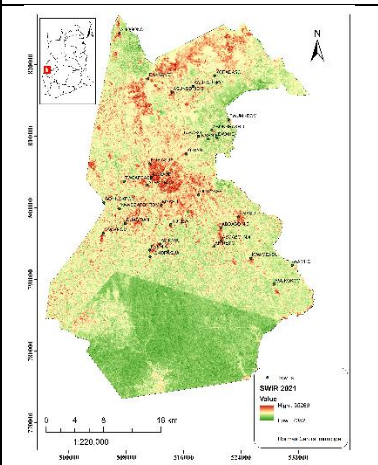
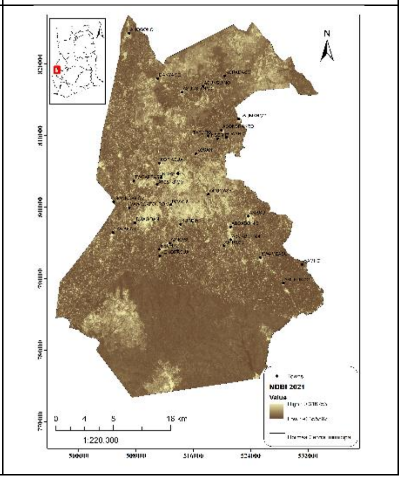
Year	NIR	SWIR	NDBI
2001			
2011			
2021			

Fig.3. Spatial dynamics of Urbanisation in the Dormaa Central Municipality from 2001 to 2021 using NDBI

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Table 3 NDBI values for urban Areas in Dormaa Central Municipality

Year	NDBI value range in Dormaa Central Municipality	NDBI value range for only urban areas
2001	-0.222 – 0.541	0.224 – 0.541
2011	-0.079 – 0.419	0.220 – 0.419
2021	-0.356 – 0.316	0.200 – 0.316

Fig. 3 and Table 3 provide the value ranges for Dormaa Central Municipality in three different years (2001, 2011, and 2021). The results present NDBI value ranges for Dormaa Central Municipality in 2001, 2011, and 2021, indicating increased urbanization over time (20years). Higher NDBI values in later years suggests significant urban growth and infrastructure development. This information is vital for urban planning and highlights the importance of sustainable development practices for resilient and eco-friendly cities.

3.2 Spatial Distribution of Urban Areas in Dormaa Central Municipality

The study identified the spatial distribution of urban areas, highlighting concentrated growth in specific regions while also capturing peripheral expansion into previously rural or agricultural lands. The NDBI-derived binary maps (Fig. 3) provided a clear visualization of the spatial extent and distribution of urban growth in Dormaa Central Municipality. This information offered insights into the patterns of urbanization and the expansion of built-up areas over time by producing LULC maps as shown in Fig. 4. The outcome of the accuracy assessment of the LULC is shown in Table 4.

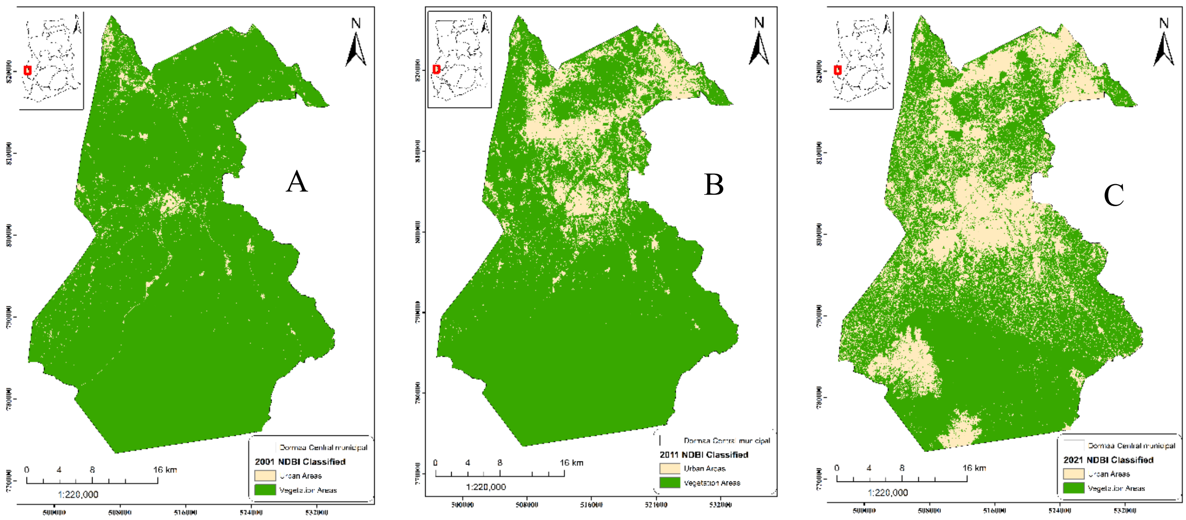

Fig. 4. Spatial Distribution of Urban Areas in the Dormaa Central Municipality A)2001 (B) 2011 (C) 2021

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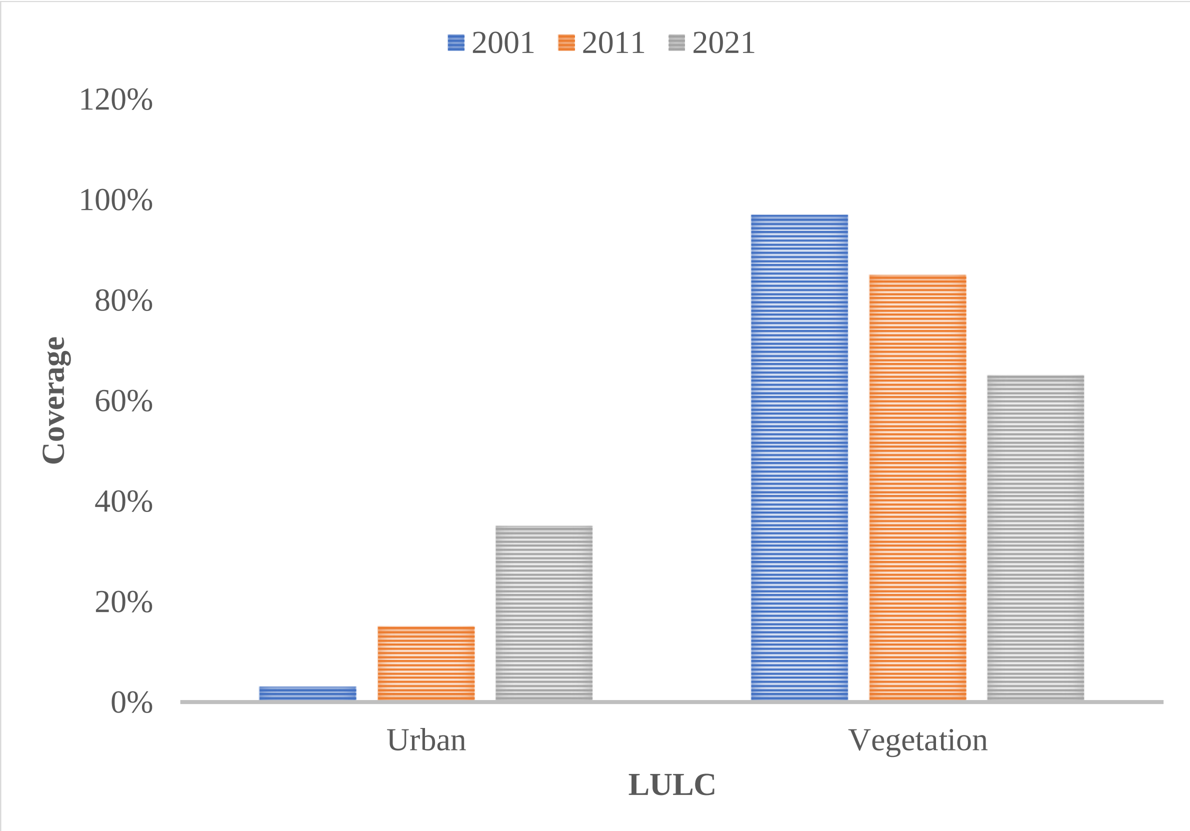

Fig. 5. Spatial Coverage of Urban and Vegetation Areas in the Dormaa Central Municipality from 2001 to 2021

Table 4 Confusion Matrix of the Accuracy Assessment for the Classified Images 2001, 2011 and 2021

2001 LULC	**Urban area**	**Vegetation area**	**Total**	**User Accuracy**
Urban area	8	2	10	80%
Vegetation area	2	27	29	93%
Total	10	29	39	
Producer Accuracy	80%	93%		
Kappa	0.731034			
Overall accuracy	90%			
2011 LULC	Urban area	Vegetation area	Total	User Accuracy
Urban area	8	2	10	80%
Vegetation area	1	25	26	96%
Total	9	27	36	
Producer Accuracy	89%	93%		
Kappa	0.785714			
Overall accuracy	92%			
2021 LULC	Urban area	Vegetation area	Total	User Accuracy

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Urban area	9	1	10	90%
Vegetation area	2	18	20	90%
Total	11	19	30	
Producer Accuracy	82%	95%		
Kappa	0.780488			
Overall accuracy	90%			

The confusion matrix (Table 4) provided valuable information about the accuracy of land use/land cover (LULC) classification for three different years: 2001, 2011, and 2021. The matrix presented the number of correctly classified pixels (diagonal elements) and the number of misclassifications (off-diagonal elements) for each land cover category.

3.2.1. 2001 LULC
The overall accuracy of 90% indicates that the LULC classification for 2001 was relatively accurate. The producer's accuracy for urban areas (80%) and vegetation areas (93%) demonstrates the percentage of correctly classified pixels for each class. The user's accuracy for urban areas (80%) indicates that 80% of the pixels classified as urban were correctly identified, while 20% were misclassified. Similarly, the user's accuracy for vegetation areas (93%) indicates a higher accuracy of correct classification. The Kappa coefficient (0.731034) suggests a substantial agreement between the LULC classification and the reference data, further confirming the reliability of the classification.

3.2.2. 2011 LULC
The overall accuracy of 92% for 2011 indicates a high level of accuracy in the LULC classification for this year. The producer's accuracy for both urban areas (89%) and vegetation areas (93%) highlights the precision in classifying these categories. The user's accuracy for urban areas (80%) indicates that 80% of the pixels classified as urban were correctly identified, while 20% were misclassified. The user's accuracy for vegetation areas (96%) demonstrates a higher accuracy of correct classification. The Kappa coefficient (0.785714) suggests a substantial agreement between the LULC classification and the reference data, similar to 2001.

3.2.3. 2021 LULC
The 2021 LULC classification achieved 90% overall accuracy, with precise classifications for urban (82%) and vegetation (95%) areas. The Kappa coefficient (0.780488) indicates substantial agreement. Urban coverage surged from 3% in 2001 to 35% in 2021, signalling rapid urbanization. Conversely, vegetation declined from 97% in 2001 to 65% in 2021, raising environmental concerns. Sustainable urban development and continuous monitoring are vital for informed decision-making and biodiversity preservation.

3.3. Dynamics of Urban Footprint
Based on the LULC analysis of urban areas from 2001 to 2021, as well as the unchanged and added urban areas, the results on the dynamics of the urban footprint for this study are shown in Table 5 and Fig. 6.

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Table 5 Dynamics of Urban Footprints 2001 to 2021

2001 (ha)	2011 (ha)	2001-2011 unchanged (ha)	Addition 2001-2021 (ha)	Incremental rate
3655.440	17870.220	2321.387	15548.833	10%
2011 (ha)	2021 (ha)	2011-2021 unchanged (ha)	Addition 2011-2021 (ha)	Incremental rate
17870.220	42152.670	12521.496	29631.174	10%

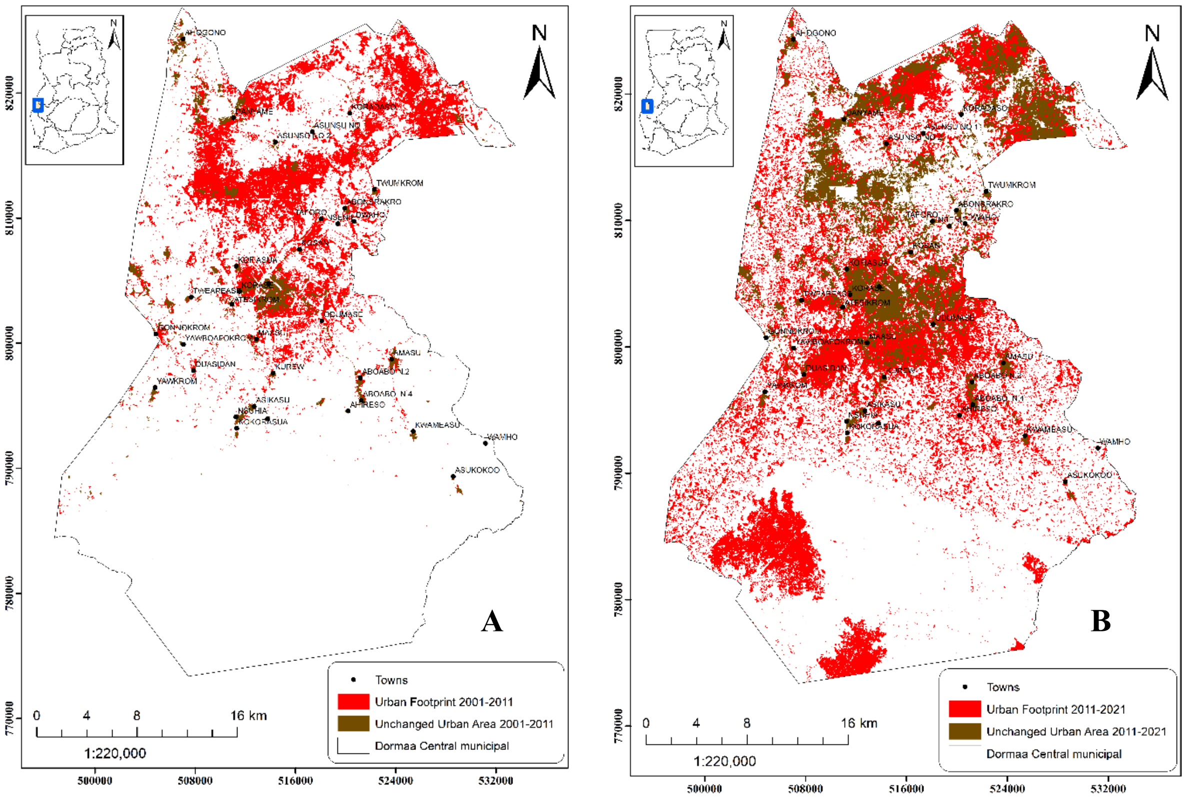

Fig. 6. Spatial distribution of Urban Footprints (red) Dynamics in the Dormaa Central Municipality (A) 2001-2011, (B) 2011-2021 (brown signifies unchanged urban areas)

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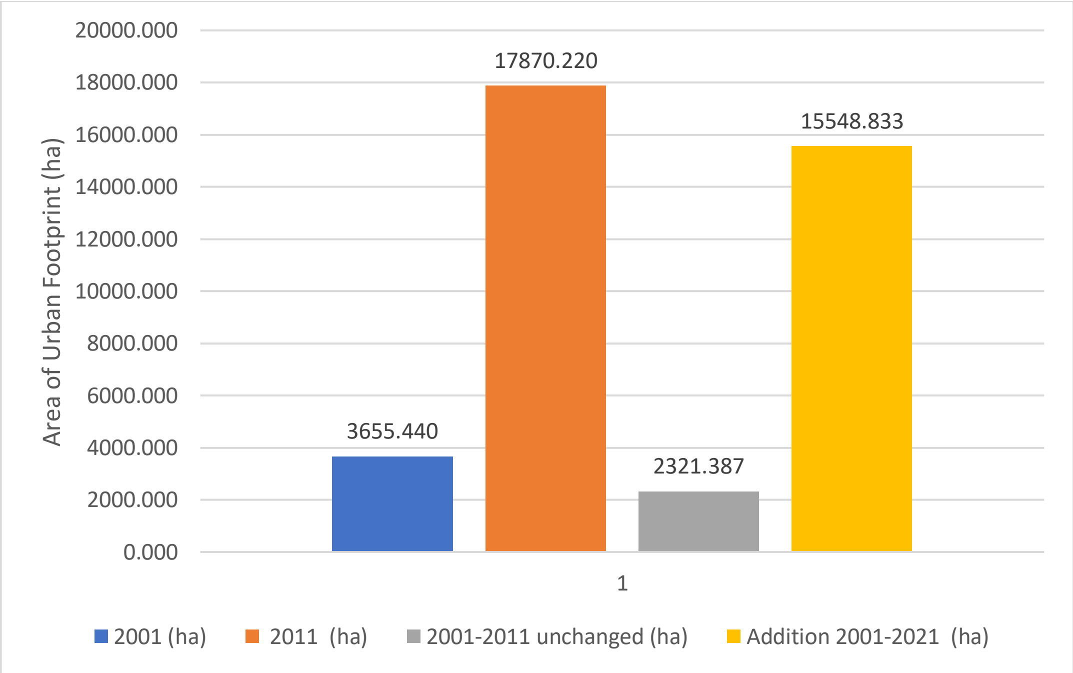

Fig. 7. Dynamics of Urban Footprints in the Dormaa Central Municipality 2001 to 2011

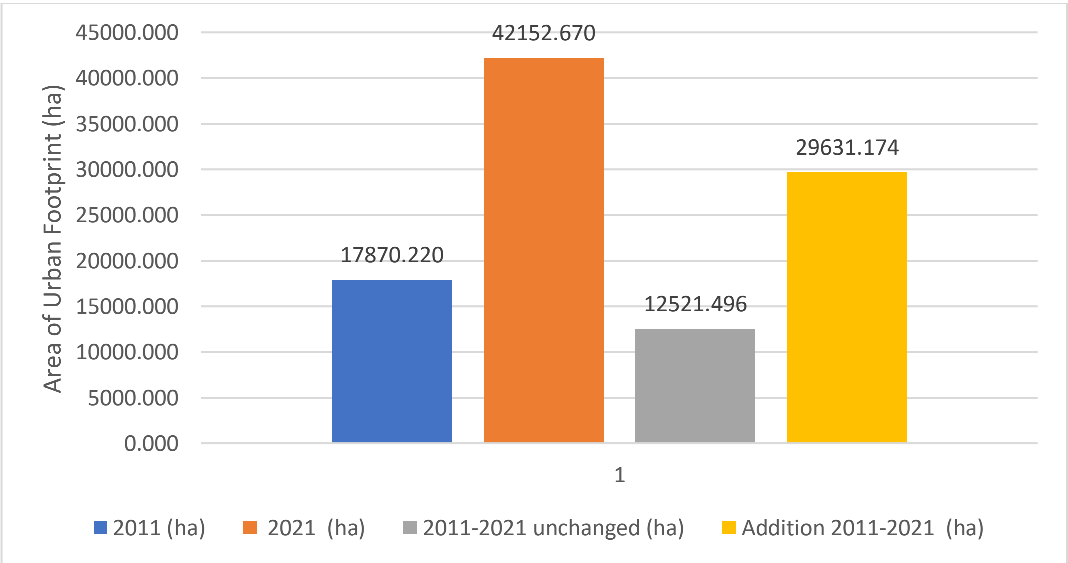

Fig. 8. Dynamics of Urban Footprints in the Dormaa Central Municipality 2011 to 2021

3.3.1. 2001-2011 Dynamics

The urban footprint in 2001 was 3655.44 hectares, which expanded significantly to 17870.22 hectares in 2011. This represents an increase of 14214.78 hectares over the decade. Out of the total urban footprint in 2011, 2321.39 hectares remained unchanged from 2001. This suggests that a considerable portion of the urban areas established in 2001 continued to persist without significant changes over the following decade. However, the addition of new urban areas from 2001 to 2021 was substantial, amounting to 15548.83 hectares as shown in Fig. 7 and

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Table 5. This indicates rapid urban expansion and development during this period. The incremental rate of urban growth from 2001 to 2011 is 10% as shown in Table 5. This rate measures the percentage increase in the urban footprint during this specific decade.

3.3.2. 2011-2021 Dynamics

Between 2011 and 2021, Dormaa Central Municipality witnessed substantial urban growth, with an additional 24282.45 hectares of urban areas, while 12521.50 hectares remained unchanged. The rate of urban expansion during this period matched that of the previous decade, emphasizing a consistent pattern of urban growth over two decades as shown in Fig. 8 and Table 5.

3.4. Discussion of Urban Footprint Dynamics

The results as shown in **Fig. 7 and Fig. 8** show a rapid and consistent urbanization trend in the study area over the past two decades. The urban footprint expanded substantially, nearly quadrupling from 2001 to 2021.

The unchanged urban areas from 2001 to 2021 and from 2011 to 2021 show that certain urban areas have remained relatively stable and resistant to changes over time, while others have experienced significant growth and development as shown in Fig. 6. The high incremental rate of 10% for both periods signifies steady and sustained urban growth, which may be influenced by population growth, economic activities, and urban planning policies. The dynamics of the urban footprint demonstrate the importance of proactive urban planning and sustainable development strategies to manage the challenges posed by rapid urbanization. Balancing urban growth with environmental preservation, green spaces, and infrastructure development is crucial to creating liveable and resilient cities. Long-term monitoring and analysis of urban dynamics are essential to inform decision-making, develop resilient urban policies, and ensure that urbanization aligns with sustainable development goals.

4. CONCLUSION

The NDBI trends for Dormaa Central Municipality and its urban areas provide valuable insights into urbanization patterns and the presence of built-up surfaces, guiding urban planning and sustainable development. The confusion matrix confirmed the accuracy of the LULC classification, supporting land cover change monitoring and environmental management. Integrated GIS and satellite remote sensing revealed significant urbanization and vegetation decline, emphasizing the need for sustainable urban development. The study showed a continuous 10% annual urban footprint increase over two decades, highlighting the urgency of effective urban planning and environmental conservation. Monitoring urban changes can lead to resilient, inclusive, and sustainable cities in alignment with the SDGs.

Declaration of Competing Interest

The authors declare no conflicts of interest in relevance to this manuscript.

Data Availability

All the data taken in the manuscript are based on the literature study carried out in conjunctive with the field survey and are available upon reasonable request.

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