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Urban Sprawl Mapping Based on Land Use and Land Cover (LULC) Time-Series in District II of Davao City, Philippines

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ABSTRACT

Urban sprawl, driven by rapid industrial and residential growth, significantly impacts land use and the environment. This study analyzes its effects on land use and land cover (LULC) in Davao City's District II from 2013 to 2023 using Geographic Information System (GIS) technology and remote sensing data. Vegetation areas, which accounted for 80.32% of the land in 2013, declined to 68.49% by 2023, Four key categories were assessed: built-up areas, vegetation, water bodies, and barren land. Landsat 8 images from 2013, 2017, 2020, and 2023 were processed using the maximum likelihood classification method, with accuracy assessments conducted to ensure reliable results. Additionally, the Normalized Difference Vegetation Index (NDVI) was used to monitor changes in vegetation and track urban expansion. The findings reveal a significant reduction in vegetated land and a corresponding increase in built-up areas, underscoring the negative impact of urban development on the local environment. This study highlights the need for continued monitoring of LULC changes to support sustainable urban growth and protect valuable natural resources.

Keywords: Built-up areas, environmental impact, urban sprawl, Geographic Information System (GIS), Spatial Analysis

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INTRODUCTION

Urban sprawl is one of the problems modern cities are dealing with. Cities have defined specific boundaries in recent decades, but excessive growth has yet to reach their areas today. This excessive, unregulated growth is known as "Urban Sprawl,". When the ratio of urban development is high, cities tend to grow, and planned growth occurs. However, when growth is above average, unplanned expansion stresses infrastructure, public services, and environmental resources (Habibi et al., 2011).

Urban sprawl, according to Burchell et al. (2002), occurs on a micro-scale in almost all major cities around the world as a result of rising wealth and a growing reliance on private transportation. Because of the increasing concentration of people, resources, and productive activity in cities, it is essential to thoroughly understand all relevant factors, especially those relating to the demographic, geographic, and economic aspects. Although urban sprawl is a global phenomenon, various theories exist on how and why it developed (Barnes et al., 2002).

Rapid urbanization is a significant obstacle for local governmental bodies and urban planners in tiny communities, primarily attributable to the need for more comprehensive data and a better understanding of the chaotic urban sprawl. (Das and Angadi, 2022). The estimate of the global urban area varies depending on the definition of urban land, ranging from less than 1% to 3% of the Earth's geographical surface. (Liu et al., 2014). Although urban areas occupy a small fraction of the Earth's surface, rapid urbanization has substantially influenced land use and land cover (LULC) categories. Several remote sensing methods, including unsupervised classification, supervised classification, Normalized Difference Vegetation Index (NDVI), and image differencing, have been effectively used in recent research to assess urban expansion across several spatial and temporal dimensions (Grimm et al., 2008). The impacts mentioned are significant in developing countries due to their capacity constraint to mitigate the repercussions on the environment and society associated with the fast urbanization process (Cohen, 2006).

For the past 25 years, Ismail (2014) reported that the population and geographic size of cities in the Southeast Asian area have progressed, rising from 760 million individuals in 1985 to 1.6 billion people in 2010, as observed at the regional level. However, rapid unplanned urbanization has adverse effects on the environment, an increase in environmental pollution and a decline in people's standard of living. However, rapid urbanization has advantages, including increased job opportunities and land value. As a result, rapid urbanization deserves better and more proactive attention (Mundhe and Jaybhaye, 2014).

Urban Sprawl in Southeast Asia has led to various environmental, social, and economic effects some of which include: Environmental Degradation: Urban sprawl has significantly reduced green spaces in cities like Jakarta, Metro Manila, and Kuala Lumpur, with green areas decreasing from 45% to 20% over two decades. This loss leads to habitat destruction, biodiversity loss, and worsened urban heat island effects, Increased Inequality: The development of private and exclusive residential areas has contributed to urban segregation and displacement of lower-income communities. This trend exacerbates socio-economic divides and marginalizes vulnerable populations. (Monash University, 2024). Infrastructure Strain: Unplanned urban expansion often overwhelms infrastructure, leading to traffic congestion, inadequate public transportation, and strained utilities, particularly in peri-urban areas, Flood Risk and Water Management Issues: Expanding urban areas reduce natural water absorption due to increased impervious surfaces, exacerbating flood risks in cities prone to heavy rainfall. (Douglas, 2005)

The findings on urban sprawl in Southeast Asia provide critical insights that can inform the study of Davao City's urban expansion. Similar to the rapid growth observed in Jakarta, Metro Manila, and Kuala Lumpur, Davao City faces potential challenges such as environmental degradation, social inequality, and infrastructure strain. The reduction in green spaces and increased flood risks due to unchecked development in other Southeast Asian cities highlight the environmental vulnerabilities that Davao City must address through sustainable urban planning, (Monash University, 2024). Furthermore, the socio-economic divides caused by exclusive urban developments in these cities suggest that Davao needs policies promoting equitable growth to avoid marginalizing low-income communities. By drawing from these regional patterns, the study of Davao City can contribute to broader strategies for managing urban sprawl in fast-developing regions.

Davao City, being one of the fastest-growing urban areas in the Philippines, has experienced significant urban expansion and land use changes over recent decades. District 2 of Davao City is an ideal candidate for studying urban sprawl due to its mix of urban and rural areas, vast land availability, and ongoing infrastructure development. Globalization has increased the mobility of goods, people, and other factors of production, resulting in massive urbanization as people flock to cities with better opportunities and higher pay (Dumayas, 2015). Its proximity to the city center makes it an attractive area for suburbanization, driven by population growth and demand for affordable housing and commercial spaces. The district's rapid urban expansion offers a unique opportunity to explore how sprawl impacts agricultural land, ecosystems, and rural livelihoods. Additionally, as a key area for economic development and agro-industrial activities, District 2 highlights the interplay between urbanization, environmental sustainability, and local economic priorities.

This study evaluates these changes between 2013 and 2023 using GIS, remote sensing techniques, unsupervised classification, supervised classification, Normalized Difference Vegetation Index (NDVI), and image differencing, which have been effectively used in recent research to assess urban expansion across several spatial and temporal dimensions (Grimm et al., 2008). Focusing on LULC and NDVI methods, which are regarded as precise and efficient (Lu et al., 2004). The research aims to produce LULC maps for the 2nd District of Davao City for 2013, 2017, 2020, and 2023, detecting changes in built-up areas and their impact on the district. By assessing the extent of urban expansion and tracking land cover variations, the study provides baseline data to support sustainable urban planning. This localized analysis contributes to understanding the dynamics of urban sprawl in rapidly developing regions and highlights the importance of balancing urbanization with environmental sustainability. The result s of this study can guide policies on sustainable development, environmental conservation, and urban planning in Davao City.

MATERIALS AND METHODS

Description of the study area

With a geographical area of 2,444 km^2, Davao City is the largest city in the Philippines. There are three congressional districts and eleven administrative districts located within this region. Agdao, Buhangin, Bunawan, and Paquibato municipalities comprise District II. According to the 2020 Census, Davao City has 1,776,949 residents or an average of four people per household. The population increased by 1.55% between 2015 and 2020. The city's population surpassed one million in the 20th century due to significant migration from other regions of the country, which is still a trend today (PSA, 2020). Also, District II is bordered by mountainous terrain ssto the west, including parts of the Davao River Basin. Some areas have higher elevation and feature forested hills, but also there are areas that are highly urbanized such as Buhangin and Agdao.

Data sources

This investigation utilized both primary and secondary data sources. Landsat 8 for the years 2013, 2017, 2020, and 2023 were the essential data extracted from the United States Geological Survey (USGS) Earth Explorer for the NDVI and 2013 Land Cover Map and ESRI Sentinel-2 was used for land-cover mapping for the years 2017, 2020, and 2023. To enhance the classification of various forms of mapping, the researchers used satellite images with minimal or no cloud cover.

Using the Landsat satellite record has shown to be an invaluable tool in comprehending the current anthropogenic effects (Wulder et al., 2022; Pesaresi et al., 2016). This resource has facilitated the acquisition of distinctive information regarding the socioeconomic factors driving these changes and the subsequent implications on the environment, ecosystem services, and humanity.

The spatial data utilized for GIS integration are the secondary data required for this investigation. The data was collected from the Davao City Local Government Unit, specifically the City Planning and Development Office (CPDO) and the Philippine Statistics Authority (PSA).

The study of Topaloğlu et al. (2016) utilized

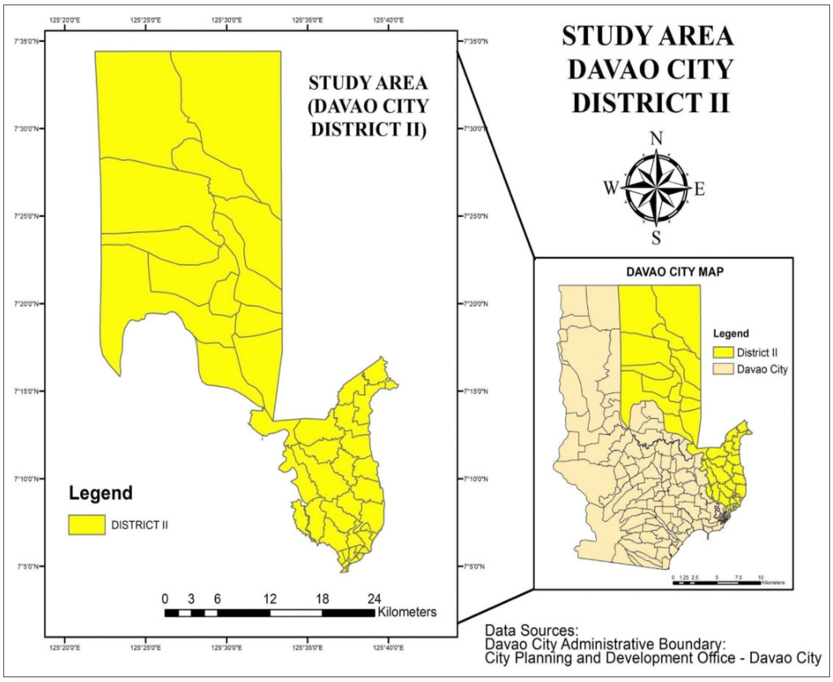

Figure 1. Map of the study area, District II of Davao City Region XI.

both satellite imagery from Landsat-8 and Sentinel-2. The integration of Landsat and Sentinel-2 imagery is crucial for accurately classifying urban sprawl because it combines Landsat's long-term, consistent global coverage with Sentinel-2's higher spatial and spectral resolution. Landsat offers a valuable historical record with a 30-meter resolution, enabling the detection of broad land cover changes over extended periods (Roy et al., 2014). Sentinel-2, on the other hand, provides finer spatial resolution (10 meters for select bands) and more spectral bands (13 compared to Landsat's 7), allowing for better differentiation of land cover types, especially urban and vegetation areas (Drusch et al., 2012). By integrating these datasets, researchers can leverage Landsat's temporal history for tracking urban expansion trends and Sentinel-2's frequent revisit time (every 5 days at the equator) for more up-to-date monitoring of urban growth (Bovolo et al., 2018). This combination enhances the accuracy of urban sprawl detection and helps mitigate the limitations of each system, providing a more comprehensive tool for sustainable urban planning and land management.

Table 1. Sources of data collection.

Data	Sensor	Date acquired	Data source	Projection	Scale/Resolution
Davao City Political Boundary	-		CPDO-Davao City	WGS 84 UTM 51N	-
Landsat 8	OLI/TIRS	2013 2017 2020 2023	USGS Earth Explorer	WGS 84 UTM 51N	30 m
Land Use Map, Davao City	-	2013-2023	USGS Earth Explorer	WGS 84 UTM 51N	30 m
Land Cover Map, District II	OLI/TIRS	2013	USGS Earth Explorer	WGS 84 UTM51N	30 m
Land Cover Map, District II	Sentinel-2	2017-2018 2020-2021 2022-2023	ESRI	WGS 84	10m

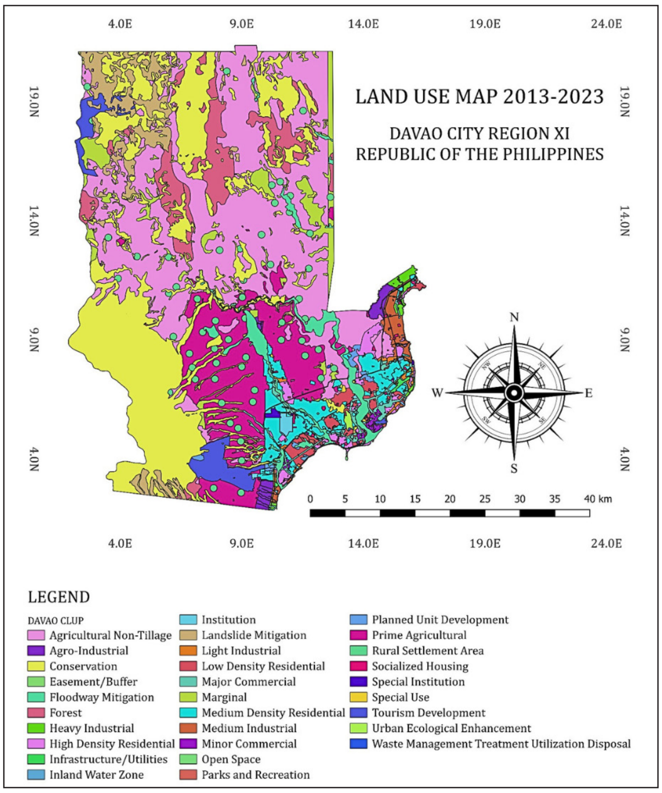

Figure 2. Land use Map of Davao City 2013-2023.

Data pre-processing

Preprocessing of remotely sensed data is a crucial step that must be undertaken before any analytical procedures on a newly acquired time series. Initially, it is necessary to subject the images to pre-processing procedures such as cloud masking, mosaicking, and subsetting using Geographic Information System (GIS) software. Only after these steps have been completed can the specific area be chosen using the Area of Interest (AOI) technique, as described by Behera et al. (2012).

The main goals of preprocessing are to correct the data for radiometric and geometric aberrations that are unique to the sensor and platform. The innate variability in factors like scene illumination and viewing geometry, atmospheric conditions, sensor noise, and responses, necessitates the application of this correction technique to radiometric data (Tan et al., 2010). Furthermore, geometric correction involves satellite photos matching their points to the corresponding ground-based geographic coordinates, also known as georeferencing. Thus, it is essential to conduct georeferencing since it enables precise spatial data processing (Masancay and Jimenez, 2024). However, a portion of the satellite images acquired do not exhibit cloud-free conditions and possess a cloud coverage more than 10%. Hence, it is important to conduct a cloud masking to eliminate cloud formations present in the satellite image.

Cloud masking and image mosaicking techniques were employed on the Landsat platform to mitigate the presence of cloud cover in the image of the designated study area. In this study, the researchers observed and included the highest recorded values of cloud and cloud shadow into the C Function of Mask (CFMask) method, using the raster picture template. This procedure requires a minimum of two or more visual representations. For this study, data from two distinct temporal periods of Landsat imagery, specifically the years 2013, 2017, 2020. and 2023 were gathered. The focus of the analysis was on identifying the maximum value of cloud pixels within the obtained datasets. The CFMask function generates a temporary layer that is subsequently overlaid through mosaicking using the Blend parameters (Norzin and Daliman, 2022).

One of the primary objectives of the study was to generate a Land Use and Land

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Cover (LULC) map and a Normalized Difference Vegetation Index (NDVI) map with a high degree of accuracy. Consequently, it is imperative to utilize temporal satellite imagery that exhibits considerably low cloud cover. This study presents a cloud masking methodology that utilizes multi-temporal satellite imagery. The fundamental concept underlying this approach involves the identification of cloud and cloud shadow by the utilization of reflectance value discrepancies between uncontaminated pixels and those affected by cloud and cloud shadow (Candra et al., 2016).

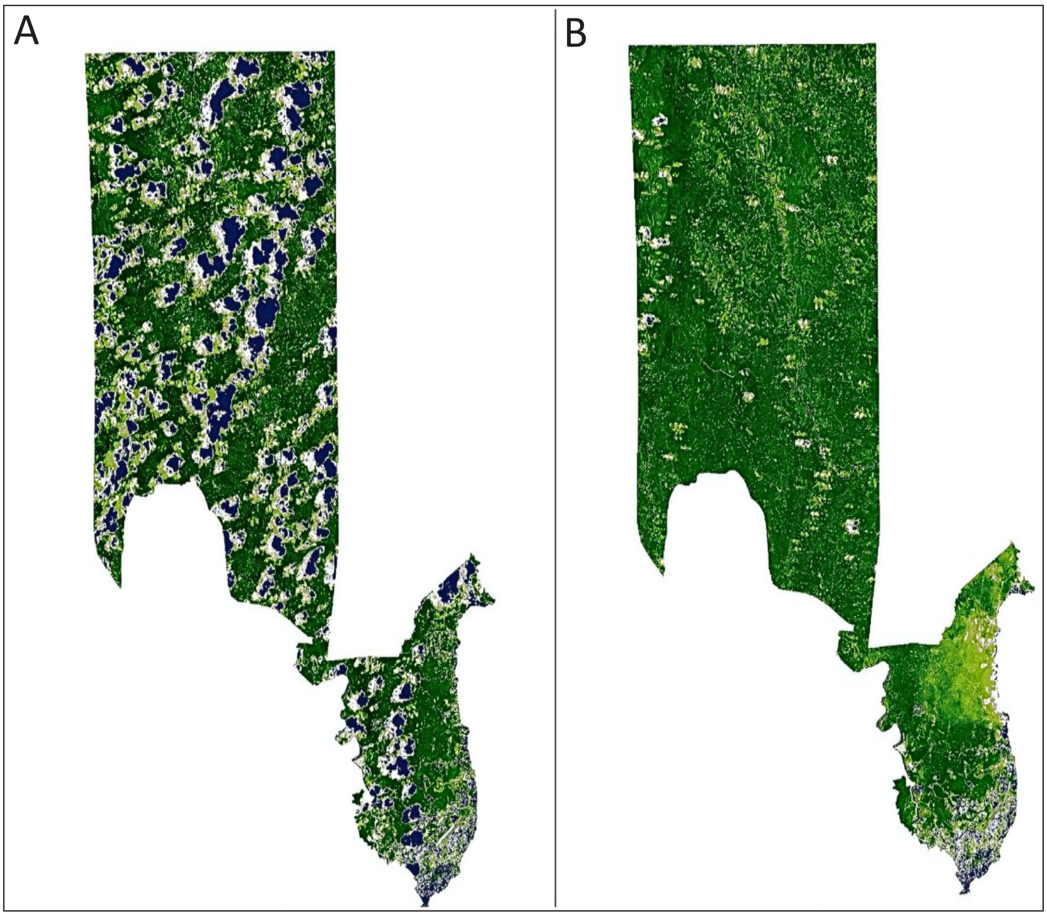

Figure 3. Satellite image. Before cloud masking (A); after cloud masking (B).

Image classification

Concerning mapping Land Use and Land Cover (LULC), false color composite (FCC) images were made using the band combinations 4-3-2 for the TMs images (representing Near-Infrared, Red, and Green), and 5-4-3 for the OLI image (representing Near-Infrared, Red, and Green). Based on field observations and spectral responses from the Landsat images, distinct LULC categories were found. To describe these LULC categories, Maximum Likelihood Classification (MLC) was employed to classify the supervised images classifier algorithm, a widely used remote sensing image classification technique (Chen and Stow, 2002).

The research area underwent a supervised maximum likelihood classification to classify the LULC categories. The study identified four distinct categories, including water bodies, vegetation, built-up areas, and barren land. The various types of water bodies encompass rivers, lakes, gravel beds, streams, canals, and reservoirs. The vegetation class encompasses both forested areas and agricultural lands. The built-up area encompasses several sectors of urban growth, including residential, industrial, commercial, administrative, cemetery, transportation, and sewage treatment facilities. It comprises all man-made structures resulting from urbanization. Finally, barren land refers to land cover that exhibits vegetation or other forms of cover on less than one-third of its surface. This particular land cover often displays characteristics such as a shallow layer of soil, predominantly composed of sand or rock.

Table 2. Land use classes based on supervised maximum likelihood classification technique.

Land use class	Definition
Water bodies	Include all water bodies (river, lakes, gravels, stream, canals, and reservoirs).
Vegetation area	Include all forest field and agricultural lands.
Built-up area	Include all residential, industrial, commercial, administration, cemetery and transportation, and sewage treatment plant.
Barren land	Include land cover that has less than one-third of its surface covered by vegetation or another type of cover. This type of land cover often features thin soil, sand, or rocks.

Accuracy assessment

To guarantee correctness, integrity, and quality, an accuracy assessment of classified images from 2013 to 2023 is required. The quantification of estimation to classification conditions using remotely sensed datasets is known as accuracy assessment. It helped to assess the effectiveness of the classification technique and is crucial in identifying potential errors. The confusion matrix is a suggested format for evaluating the accuracy of the classifiers precision (Contalgon, 1991).

To comprehend and estimate the changes effectively, accuracy assessment is a vital and fundamental component of researching image classification and, consequently, LULC change detection. If the generated data are to be usable in change detection analysis, the accuracy for individual classification must be derived (Owojori and Xie, 2005).

Kappa tests, which can test any element's confusion matrix depending on the minimal requirement, are used to assess the accuracy of categorization (Halmy et al., 2015). Based on the assignment's producer and user ratings, the Kappa tests can be evaluated. According to Pontius and Millones (2011), the probability that a pixel in an image will represent a class on the ground can be used to explain user accuracy, whereas producer accuracy is the likelihood that a pixel will be correctly classified, which typically determines how good a certain area can be classified.

The accuracy assessment points were distributed randomly in all four categories in the study area using GIS software. Using 500 accuracy assessment points and Google Earth Pro for 2013, 2017, 2020, and 2023 was used to determine the accuracy assessment of all classes of LULC. The accuracy assessment for 2013, 2017, 2020, and 2023 have a kappa coefficient of 0.88, 0.88, 0.82, and 0.80, respectively. For accuracy assessment, identified classes of LULC should achieve a minimum kappa coefficient of 0.8 (Weng, 2010). The result shows that all the kappa coefficients meet the minimum criterion for reliability. Furthermore, the overall classification accuracy generated by the confusion matrix for 2013, 2017, 2020, and 2023 is 94.80%, 94.60%, 91.60%, and 93.40%, respectively (Table 3.1, Table 3.2, Table 3.3, Table 3.4). It is recommended that the LULC maps tested will have at least 85% overall accuracy before LULC analysis can proceed.

Table 3.1. Accuracy assessment of 2013 in Davao City 2nd District.

Class name (2023)	Water	Vegetation	Built-up land	Barren land	Total reference	User accuracy
Water	6	0	0	0	6	100.00%
Vegetation	0	346	10	11	367	94.28%
Built-up land	0	3	86	0	89	96.63%
Barren land	0	2	0	36	38	94.74%
Total reference	6	351	96	47	500	0
Producer accuracy	1	98.58%	89.58%	76.60%	0	94.80%

Overall classification accuracy = 94.80%; Kappa Coefficient = 0.88

Table 3.2. Accuracy assessment of 2017 in Davao City 2nd District.

Class name (2020)	Water	Vegetation	Built-up land	Barren land	Total reference	User accuracy
Water	7	0	0	1	8	87.50%
Vegetation	0	341	7	10	358	95.25%
Built-up Land	0	4	78	1	83	93.98%
Barren Land	2	2	0	47	51	92.16%
Total Reference	9	347	85	59	500	0
Producer Accuracy	77.78%	98.27%	91.76%	79.66%	0	94.60%

Overall classification accuracy = 94.60%; Kappa Coefficient = 0.88

Table 3.3. Accuracy assessment of 2020 in Davao City 2nd District.

Class name (2023)	Water	Vegetation	Built-up land	Barren land	Total reference	User accuracy
Water	11	0	0	2	13	84.62%
Vegetation	3	324	16	8	351	92.31%
Built-up land	0	4	67	3	74	90.54%
Barren land	1	4	1	56	62	90.32%
Total reference	15	332	84	69	500	0.00%
Producer accuracy	73.33%	97.59%	79.76%	81.16%	0	91.60%

Overall classification accuracy = 91.60%; Kappa Coefficient = 0.82

Table 3.4. Accuracy assessment of 2023 in Davao City 2nd District.

Class name (2023)	Water	Vegetation	Built-up land	Barren land	Total reference	User accuracy
Water	1	0	0	0	1	100.00%
Vegetation	3	389	14	8	414	93.96%
Built-up land	1	3	51	1	56	91.07%
Barren land	0	1	2	26	29	89.66%
Total reference	5	393	67	35	500	0
Producer accuracy	20.00%	98.98%	76.12%	74.29%	0	93.40%

Overall classification accuracy = 93.40%; Kappa Coefficient = 0.80

Detection change of land use/land cover

To analyze LULC change for the periods 2013–2017, 2017–2020, and 2020–2023, post-classification change detectiontechniques in Geographic Information Systems (GIS) utilized. Post-classification change detection is a GIS technique that analyzes and identifies changes in land cover or land use over time by comparing and contrasting classified images from various periods. This technique employs supervised or unsupervised classification techniques to build independent land cover maps for each period. It compares the categorized maps pixel by pixel to determine changes in land cover types such as built-up areas, forest areas, and agricultural lands. The utilization of this methodology enables the examination of urban expansion and the evaluation of alterations in land utilization through the provision of a visual depiction of the changes in land use (Lu et al., 2004).

$$Change\ (\%) = \left(\frac{{}^{A}final\ year - {}^{A}initial\ year}{{}^{A}initial\ year} \right) \times 100$$

The letter “A” is used to denote the spatial extent in Land Use and Land Cover (LULC) maps, specifically indicating alterations between two distinct time periods. It signifies the discrepancy in area between the initial and final years. A positive % value signifies an expansion in the area encompassed, while negative percentage values denote a reduction in the area covered.

LULC (Land Use/Land Cover)change detection is an effective method for quantifying urban sprawl by tracking the transformation of land over time. (Dumdumaya and Cabrera, 2023). Using satellite imagery, researchers can compare images from different years to identify changes in land cover, such as the conversion of agricultural or forest areas to urban uses. In the context of District II of Davao City, this method can be applied to assess urban expansion, particularly by quantifying the growth of residential and commercial areas.

In this study, LULC change detection aligns with key objectives, such as measuring the extent of urban expansion in District II and understanding how land use classes have shifted over time. The data will be instrumental in guiding sustainable urban planning and policy decisions. (Bhatta, 2010).

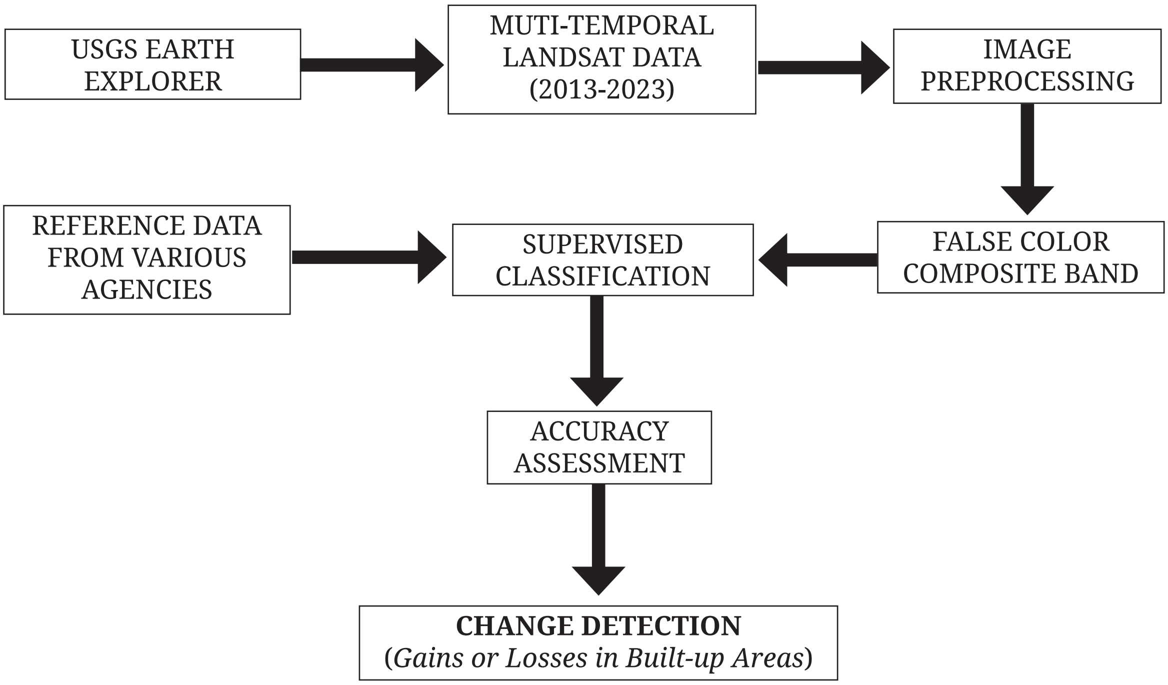

Figure 4. Methodology for Land Use and Land Cover (LULC) mapping and change detection.

Normalized Difference Vegetation Index (NDVI)

Through the utilization of remote sensing and satellite imagery, the NDVI calculates the amount and condition of vegetation of a particular study area. By monitoring the NDVI over time allows for the assessment and identification of land cover changes. This method can help with sustainable urban planning and management by allowing the identification of urban growth patterns and their effects on natural landscapes (Pettorelli et al., 2014). In addition, estimating the size of green spaces, monitoring vegetation loss, and research into the connection between urbanization and ecological changes have all been done using NDVI-based urban sprawl assessments (Bhandari et al., 2020).

The Normalized Difference Vegetation Index (NDVI) value goes from -1 to 1, although there is no clear-cut distinction between the various land cover types. For instance, a negative value indicates that the pixel is covered in water; however, when the value is close to +1, it indicates a strong likelihood that green leaves surround the area. However, if the NDVI value is near zero, it may denote an urbanized region where the land use implies no green leaves. NDVI can be solved using the equation (4) below.

$$NDVI = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}$$

where the averaged surface reflectance in red wavelength (0.6 m) and near-infrared, IR (0.8 m) denotes NIR - RED and NIR + RED. In other words, NDVI is a consistent method of evaluating the health of the vegetation. The vegetation in the study area is healthier when the NDVI value is higher (Yasin et al., 2019). NDVI was generated using QGIS software and adjusting its range value for each category based on table 3.

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Table 4. Normalized Difference Vegetation Index (NDVI) range identified for each class.

Class	NDVI Range
Water	-0.28 - 0.01
Built-up	0.015 - 0.1
Barren Land	0.14 - 0.18
Shrub and Grassland	0.18 - 0.27
Sparse Vegetation	0.27 - 0.36
Dense Vegetation	0.36 - 0.74

The study conducted by Shirazi and Kazmi in 2020 involved the analysis of five distinct classes, including built-up areas, vegetation, open areas, water bodies, and mixed class. The segmentation of vegetation into sparse and dense categories allowed for a more detailed analysis by further subdividing them into distinct vegetation classes.

RESULTS

LULC Changes Over Time (2013-2023)

Table 5 represents, the result showed the changes in the LULC density from 2013 to 2023 with the four determined classes: Water, Vegetation, Built-up land, and barren land. This study focused on the built-up land as it implied urban expansion and development in the study area. Based on Table 4, the built-up land in 2013, 2017, 2020, and 2023 has an area of 56.96 sq. km, 76.0 sq. km, 94.38 sq. km, and 100.98 sq. km, respectively. It showed that there is a significant increase in terms of built-up land, showing a sign of urbanization in the area. This trend indicates a higher demand for available land resources, which is an indicator of urban sprawl.

In contrast, the vegetation in the study area from 2013, 2017, 2020, and 2023 is 439.66 sq. km, 406.70 sq. km, 383.75 sq. km, and 374.88 sq. km, respectively. The decrease in vegetation cover over the same period signifies potential deforestation and loss of green spaces. Urban sprawl typically leads to various environmental impacts due to rapid urban development and urban expansion.

From 2013 to 2023, barren land saw a steady and notable increase, expanding from 43.300 sq. km (7.91%) in 2013 to 63.70 sq. km (11.64%) in 2023, reflecting an overall growth of approximately 20.4 sq. km. This trend suggests land degradation, urban sprawl, or deforestation, potentially driven by human activities or natural factors such as soil erosion and climate change. On the other hand, water bodies exhibited smaller fluctuations, with a slight decline from 7.455 sq. km (1.36%) in 2013 to 7.32 sq. km (1.34%) in 2020, followed by a modest recovery to 7.82 sq. km (1.43%) in 2023.

Table 5. Land Use and Land Cover (LULC) change from 2013-2023.

LULC density classes	2013		2017		2020		2023	
	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%
Water bodies	7.45	1.36	7.34	1.34	7.32	1.34	7.82	1.43
Vegetation area	439.66	80.32	406.69	74.30	383.75	70.11	374.85	68.49
Built-up area	56.96	10.41	75.100	13.88	94.375	17.24	100.98	18.45
Barren land	43.300	7.91	57.35	10.48	61.930	11.31	63.70	11.64

Table 5 shows that the vegetation consistently decreased over time as built-up land increased. This shift in LULC indicates a characteristic of urban sprawl, where vegetation covers such as forest and agricultural land are transformed into built-up areas to support the growing demand for residential, commercial, and industrial development. Due to land conversion and urbanization, land classes are dynamic and change over time depending on the demand of the population in the area. Furthermore, there is a slight increase in barren land which can bean indication of the preliminary stage of development that involves land clearing or land that remains under developed.

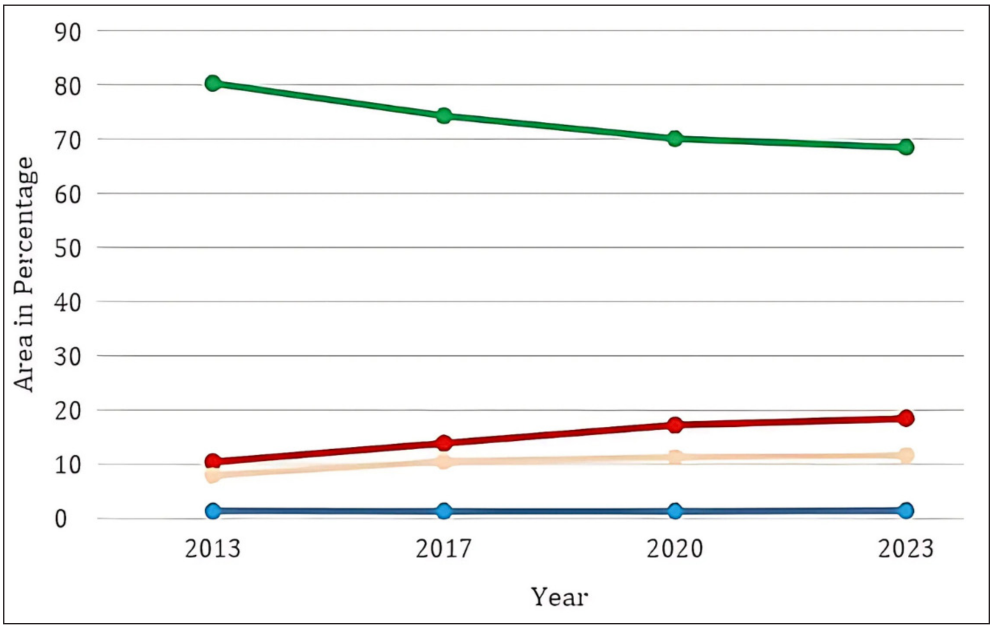

Figure 5. Shows the graphical representation of the percentage increase and decrease for water, vegetation, built-up, and barren land of Davao City District II.

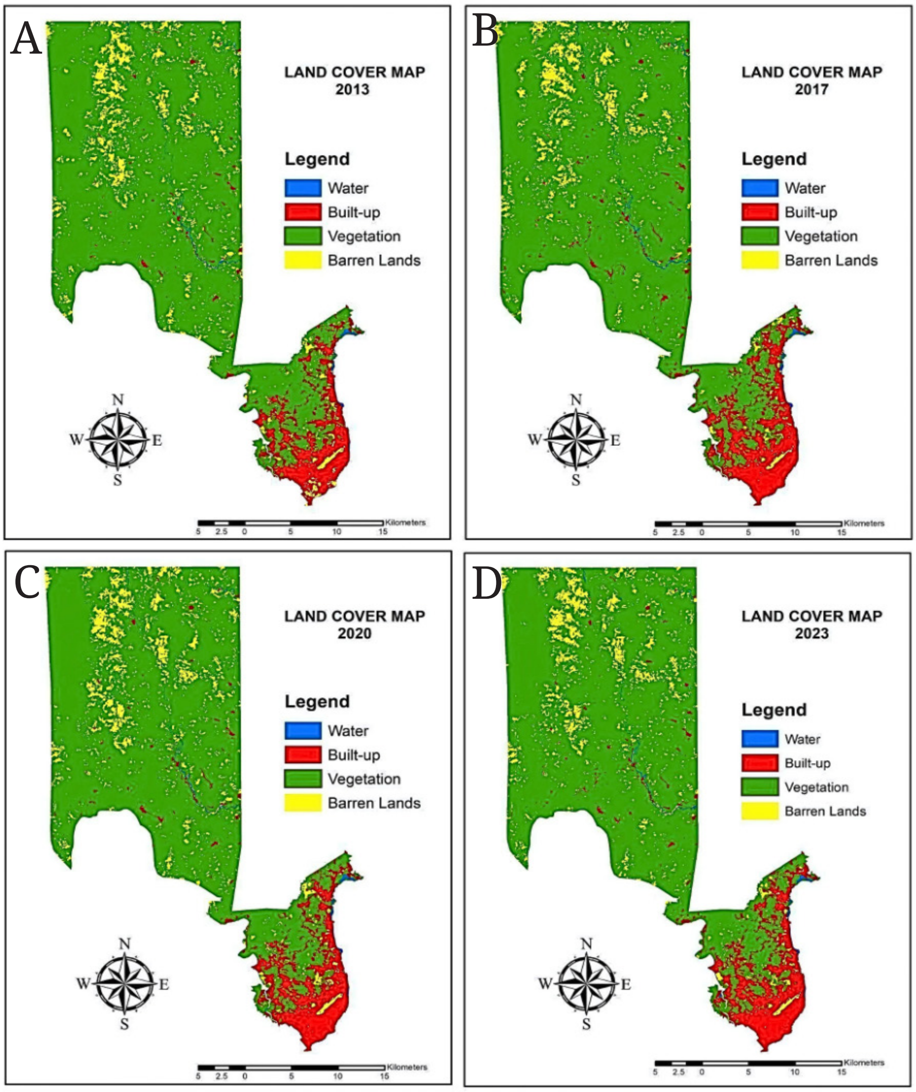

Figure 6. Land Cover Map of Davao City District II. 2013 (A); 2017 (B); 2020 (C); 2023 (D).

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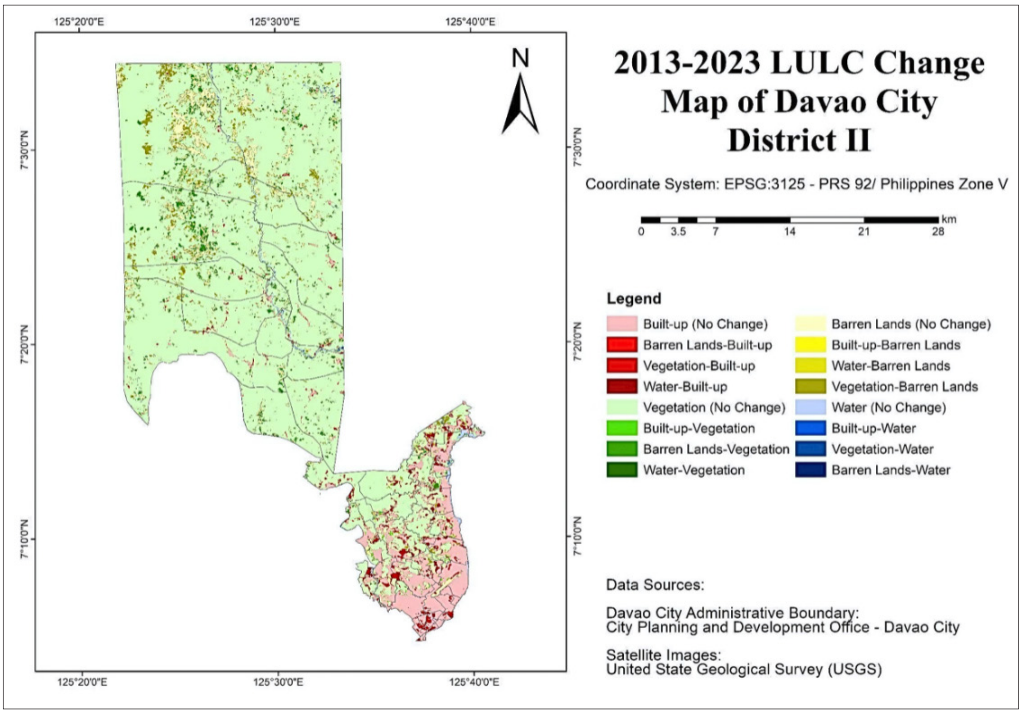

Figure 7. Land Use and Land Cover (LULC) Change Map of Davao City District II from 2013-2023.

Table 6. Difference of area (km²) in Land Use and Land Cover (LULC) from 2013 to 2023.

Land use class	2013-2017	2017-2020	2020-2023
Water Bodies	-0.11	-0.02	0.50
Vegetation Area	-32.97	-22.94	-8.88
Built-Up Area	19.03	18.38	6.61
Barren Land	14.05	4.58	1.77

Using the formula for change detection in LULC, Table 5 shows the rate of change of LULC from 2013, 2017, 2020, and 2023. The class for Water Bodies showed inconsistency and insignificant change in the area. As for vegetation, from 2013 to 2017, 2017 to 2020, and 2020 to 2023, its area decreased from 7.5%, 5.64%, and 2.31%, respectively. As for built-up land, its area increased constantly from 33.41%, 24.18%, and 7.00%, respectively. From 2013 to 2020, there was a significant increase in built-up land due to urban and population demand. This trend signifies a similar result from the discussion above which underscores a continuous pressure on vegetation cover as the demand for built-up areas increases. However, from 2020 to 2023.

Table 7. Rate of change in percentage for Land Use and Land Cover (LULC) from 2013 to 2023.

Lulc classes	2013-2017	2017-2020	2020-2023
Water bodies	-1.52	-0.25	6.79
Vegetation area	-7.50	-5.64	-2.31
Built-up area	33.41	24.18	7.00
Barren land	32.44	7.99	2.86

Normalized Difference Vegetation Index (NDVI) trends and implications

The findings of the study demonstrate a progressive decrease in the vegetation index from 2013 to 2023, as observed by the changes in vegetation index classes over 10 years. Based on Table 6, the vegetation, the sum of sparse and dense vegetation, for 2013, 2017, 2020, and 2023 is 493.05 sq. km, 486.52 sq. km, 475.91 sq. km, and 461.50 sq. km, respectively.

The result showed a consistent decline in the vegetation index. On the other hand, the built-up showed a consistent growth which implies urbanization in the area. The constant decrease in the vegetation index signifies an encroachment of built-up area in various land covers, especially in the vegetation cover. This encroachment can be an implication of an impending urban sprawl in the region. The consistent growth in built-up areas, as supported by the LULC and NDVI data, shows the pressure of rapid urban expansion in the region.

Table 8. Normalized Difference Vegetation Index (NDVI) change from 2013-2023.

NDVI density classes	2013		2017		2020		2023	
	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%
Water	2.02	0.37	3.57	0.65	2.87	0.52	3.20	0.58
Built-up land	16.27	2.97	25.20	4.60	28.02	5.12	33.05	6.04
Barren land	9.65	1.76	9.71	1.77	11.13	2.03	13.42	2.45
Shrub and grassland	26.38	4.82	22.39	4.09	29.44	5.38	36.21	6.61
Sparse vegetation	51.74	9.45	37.84	6.91	40.71	7.44	67.94	12.41
Dense vegetation	441.308	80.62	448.67	81.97	435.21	79.51	393.56	71.90

Therefore, the value is continuously fluctuating since most vegetation classes are susceptible to turning into built-up land, shrub and grassland, and barren land. The NDVI Density Data (see Figure 5), indicates that the predominant land use class in 2013 was the vegetation pattern. As the year goes on, other courses begin to appear in different parts of Davao City's 2nd district. As shown in Table 8 Dense Vegetation Cover declined from 80.62% to 71.90 from 2013 to 2023.

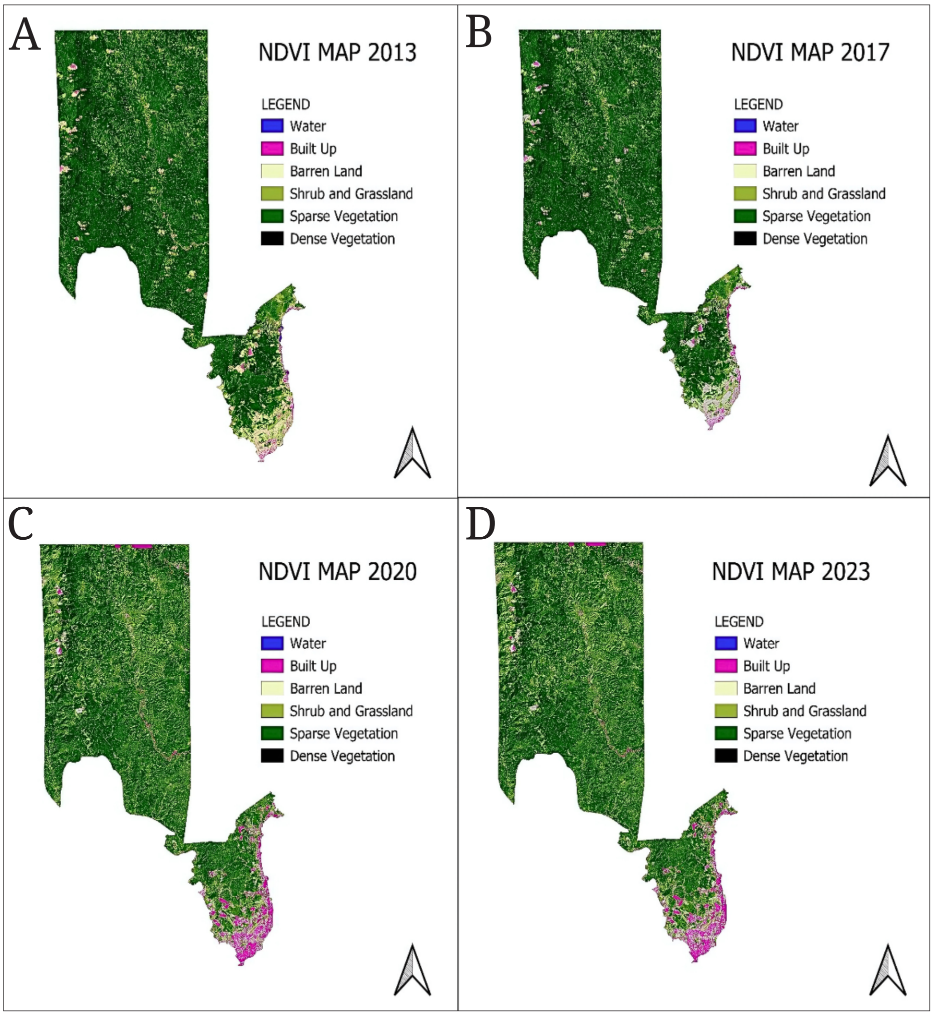

Figure 8. Normalized Difference Vegetation Index (NDVI) Map of Davao City District II. 2013 (A); 2017 (B); 2020 (C); 2023 (D).

The results show a significant increase in built-up land from 2013 to 2023, indicating urbanization and land conversion. This has resulted in a steady decline in vegetation, potentially leading to deforestation, biodiversity loss, and changes in land productivity.

DISCUSSIONS

The integration of Land Use and Land Cover (LULC) change analysis with the utilization of the Normalized Difference Vegetation Index (NDVI) techniques is regarded as a recent and innovative approach (Yasin et al., 2019). The NDVI is a mathematical formula that incorporates the measurement of infrared radiation reflected by vegetation. Among the characteristics of urban sprawl that have been previously identified in this study are the expansion of various land uses, the damage to the environment, and the decline in agricultural productivity.

Urban expansion has significant effects on natural areas, biodiversity, local communities, and resource availability. As cities grow, natural habitats like forests and wetlands are cleared, reducing biodiversity and fragmenting ecosystems, which makes it harder for species to survive (Seto et al., 2010). Local communities also suffer, as agricultural lands are lost, impacting food production and livelihoods, while urban sprawl can displace residents, creating social and economic challenges.

The COVID-19 pandemic has significantly impeded urban expansion and imposed restrictions on public life for a specific duration, with the primary objective of mitigating the transmission of the disease (Choi, 2021). The COVID-19 pandemic disrupted urban growth by halting construction activities, delaying permits, and exacerbating supply chain and labor shortages. These challenges slowed infrastructure development, while economic uncertainty redirected investments to healthcare, deprioritizing non-essential projects (Almeida, 2020). However, the crisis also inspired a shift toward sustainable urban planning. Cities expanded green spaces, promoted cycling and pedestrian-friendly infrastructure, and adapted remote work trends by converting office spaces into mixed-use developments. These strategies reflect a growing focus on resilience, sustainability, and equity in urban design (Fulton, 2021).

With its expansive land area and agricultural heritage, Davao City faces urban sprawl driven by rapid population growth and economic development. According to the research conducted by Masancay et al. (2024), the concentration of businesses, industries, and residential neighborhoods raises the number of people in danger and makes rescue and evacuation efforts more difficult. To reduce casualties and increase the efficiency of relief efforts, urban planners and disaster response teams must give priority to these areas. Unlike Manila, which struggles with high-density sprawl resulting in congestion and informal settlements, Davao's expansion is characterized by outward growth into rural and forested areas, threatening biodiversity and water resources. According to Tinoy et al. (2019), this pattern of sprawl poses risks to local ecosystems and highlights the need for proactive conservation measures.

While Manila and Cebu face challenges of higher population density and limited space for growth, specific metrics, such as Davao's lower population density of 604 persons per square kilometer compared to Manila's 20,785 persons per square kilometer (Philippine Statistics Authority, 2021), underscore Davao's potential to adopt more sustainable urban planning practices. Cebu, with a population density of 3,658 persons per square kilometer, has seen significant commercial and industrial growth, which has pushed urban development toward coastal areas, leading to land reclamation and environmental concerns. Southeast Asian cities like Jakarta and Bangkok, experiencing rapid urbanization, emphasize infrastructure expansion to meet growing demands, while Singapore stands out as a model of compact, well-planned urban development with a focus on green infrastructure and sustainable land use (Behnisch et al., 2022). These examples provide valuable insights for Davao in balancing urban growth with environmental preservation.

CONCLUSIONS

This study revealed significant increases in built-up areas and declines in vegetation in District II of Davao City from 2013 to 2023, driven by rapid urbanization and population growth. Using the Normalized Difference Vegetation Index (NDVI) and Maximum Likelihood Classification (MLC) on Landsat satellite images, the analysis of four LULC categories—vegetation, built-up areas, water bodies, and barren land—demonstrated a substantial transition from vegetation to developed land for residential, commercial, and industrial use. Barren land also showed a slight increase, while water bodies remained relatively stable. These findings underscore the critical role of urban sprawl and population expansion in reshaping land use patterns.

The study highlights that urbanization's adverse impacts on ecosystems can be mitigated through strategic urban planning and sustainable land-use policies. For instance, incorporating green infrastructure, such as urban parks and green corridors, can preserve biodiversity, reduce habitat fragmentation, and improve water quality by managing runoff and filtering pollutants. Furthermore, equitable access to green spaces for all residents, particularly marginalized communities, is essential for enhancing social well-being, public health, and economic benefits like increased property values and tourism potential.

Remote sensing and GIS tools proved effective in analyzing spatial and temporal urban growth, providing policymakers and urban planners with critical data for decision-making. By accurately mapping LULC and NDVI changes, this study supports the foundation for sustainable urban growth in rapidly developing areas like District II of Davao City. These findings stress the importance of aligning urban development with environmental conservation to achieve balanced and sustainable progress.

RECOMMENDATIONS

Future studies could integrate higher-resolution satellite data and socio-economic analyses to provide more detailed assessments of urban growth dynamics. Policymakers should leverage these insights to reform zoning regulations, promote green infrastructure, and develop equitable and sustainable urban development strategies. This approach will ensure that urban planning not only meets current needs but also preserves environmental and social resources for future generations.

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AUTHOR CONTRIBUTIONS

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CONFLICT OF INTEREST

No potential conflict of interest was reported by the authors.

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