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Detection of Urban Landscape Changes in Surabaya for the Years 2014-2024 Based on NDVI and NDBI Analysis of Landsat 8 OLI Imagery

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ABSTRACT
This study investigates urban landscape changes in Surabaya from 2014 to 2024 using NDVI and NDBI indices derived from Landsat 8 OLI imagery. The Earth Engine platform was employed to generate cloud-free composite images, enabling detailed analysis of vegetation and built-up area changes. The methodology included a bivariate geovisualization technique to display areas of change, comparing NDVI and NDBI values over a decade to assess changes at a granular level. Results indicate that the 'Vegetation Stable - Built-up Area Stable' category dominates, covering 2422 km², suggesting consistent land use in established areas. This dominance indicates well-established land use patterns across much of the city. Significant urbanization is observed in the 'Vegetation Decreased - Built-up Area Increased' (70 km²) and 'Vegetation Stable - Built-up Area Increased' (177 km²) categories, reflecting ongoing development pressures. These areas highlight zones of active development and environmental intervention. Additionally, a 75 km² increase in vegetation, particularly in coastal mangrove regions, highlights successful environmental management efforts. The study achieved an overall accuracy of 71%, demonstrating the effectiveness of NDVI and NDBI in capturing urban dynamics. While some classes require improved detection accuracy, particularly those involving decreased built-up areas, the model reliably identifies increases in vegetation and built-up areas.

INTRODUCTION

The rapid urban development in Indonesia, especially in major cities such as Surabaya, requires serious attention in monitoring the physical conditions of urban areas (Katherina & Indraprahasta, 2019; Marwasta, 2019). Rapid population growth and urbanization often lead to significant changes in the physical landscape of cities, including a decline in environmental quality and the loss of green open spaces (Alwedyan, 2023; Surya et al., 2021). Some challenges include land use changes, an increase in the number of buildings, and the degradation of air and water quality (Ali et al., 2021; Grimmond, 2007; Long et al., 2014). Monitoring urban physical conditions has which become crucial for sustainable spatial planning and effective environmental management (Katherina & Indraprahasta, 2019; Trubina et al., 2019). It is essential to develop and employ efficient monitoring methods to inform sustainable urban planning and management strategies, enabling authorities to respond promptly to the negative impacts of unchecked urbanization.

Field observation survey methods for monitoring urban physical conditions are often time-consuming and labor-intensive, and they have been unable to capture rapid changes over the years. In contrast, remote sensing offers significant potential for monitoring urban physical conditions (Kadhim et al., 2016; Toth & Jóźków, 2016). This technology enables data collection on a large scale and over a relatively short time, which is impossible with field observation survey methods (Anderson et al., 1976; Jensen, 2014). Remote sensing data can provide detailed information on various physical aspects of urban areas, such as land use, building density, and vegetation changes (Abrams & Dekker, n.d.; Levin et al., 2020). Previous research has shown that remote sensing data can assist in mapping urban physical dynamics, including identifying areas experiencing rapid growth and areas requiring environmental intervention in Surabaya (Purwono et al., 2024). This advantage makes remote sensing a very useful tool in urban management, as it provides a holistic view of the dynamics occurring within the city.

Among the various remote sensing tools available, the Landsat 8 Operational Land Imager (OLI) stands out due to its comprehensive spectral range, including visible, near-infrared, and mid-infrared channels, and its accessibility through free data (Anua & Wong, 2022; Wulder et al., 2022). These features make Landsat 8 OLI highly effective in monitoring changes in vegetation and built-up areas, key indicators of urban environmental conditions (Chávez et al., 2020; Hemati et al., 2021). Changes in vegetation conditions and built-up areas can be mapped through spectral transformations such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) based on Landsat 8 OLI (Yasin et al., 2022; Zheng et al., 2021). Masood et al (2024) It noted that NDVI and NDBI have proven to be simple and quick techniques for mapping land cover conditions, requiring only threshold value determination between classes. NDVI and NDBI allow rapid monitoring of physical changes in urban areas, making them more efficient than conventional survey methods (Chaves et al., 2020; Chen et al., 2013; Surya et al., 2021). Although simple and relatively old methods, the use of NDVI and NDBI is still very relevant because they are widely used for research on land change and urban growth, and they have even been linked to the urban heat island phenomenon in various studies (Drešković et al., 2024; Masood et al., 2024; Zheng et al., 2021).

This study introduces a novel approach by integrating NDVI and NDBI analysis over a decade (2014-2024) using Landsat 8 OLI imagery processed through the Earth Engine platform. The innovation lies in applying bivariate geovisualization techniques to simultaneously analyze vegetation and built-up area dynamics, providing a more nuanced understanding of urban landscape changes. This method allows for the visualization of two variables on a single map, categorizing them into several combination classes and enabling the display of complex landscape changes resulting from variations in NDVI and NDBI (Calka, 2021; Strode et al., 2019; Trumbo, 1981; Trumbo et al., 2021). This comprehensive approach offers new insights into Surabaya's intricate urban growth patterns and environmental change.

Detecting urban landscape changes, particularly in cities like Surabaya, is crucial for the early identification of environmental degradation and guiding sustainable urban planning. However, current studies are still exploring the use of effective techniques and methods to monitor and validate annual changes. Therefore, the main objective of this research is to monitor the urban landscape changes in Surabaya based on NDVI and NDBI analysis from Landsat 8 OLI imagery. The urban landscape observed in this study focuses specifically on changes in built-up areas and vegetation. This research also validates the results of the detected urban landscape changes. The validation aims to illustrate the model's accuracy, considering how far the model can be further developed and applied.

Surabaya was chosen as the study area because it is the second-largest metropolitan city after Jakarta, with rapid economic growth that also impacts surrounding areas (Katherina & Indraprahasta, 2019). The development of Surabaya has significantly influenced the landscape dynamics, as reflected in land cover changes, particularly vegetation and built-up areas, making this , in a region suitable for this study (Safitri et al., 2023; Yusroni et al., 2021). Utilizing

NDVI and NDBI analysis from Landsat 8 OLI imagery is expected to provide an understanding of the dynamics of urban physical changes in Surabaya. It is anticipated that the research results can serve as a scientific reference for better and more sustainable urban planning and management in Surabaya.

RESEARCH METHODS

Study Area

This research was conducted in the urban area of Surabaya, East Java. The study area includes the city's administrative boundaries and considers the physical urban area. Therefore, besides Surabaya, this research also covers parts of the surrounding districts (Sidoarjo, Gresik, and Bangkalan). The study area is a square with an area of 3248 km² and is located between two coordinate points: 112.42°E —7.55°S and 113.017°E —113.017°S (Figure 1)

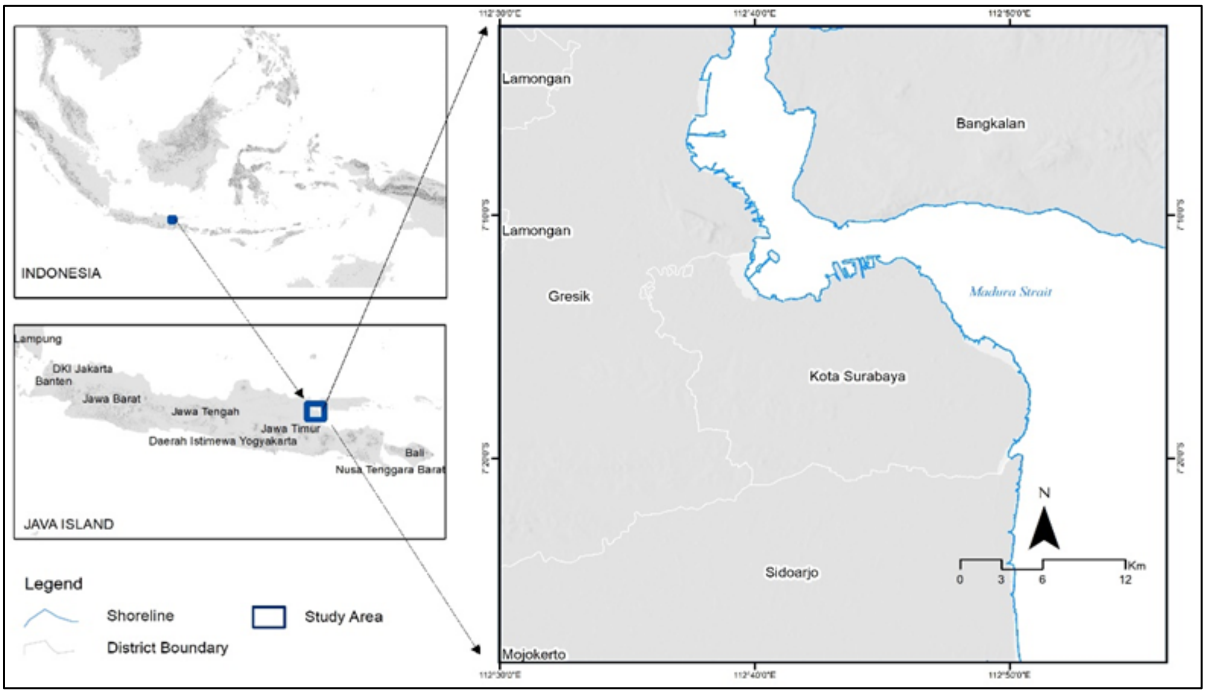


Figure 1. Study Area (Source: Data Processing, 2024)

Research Framework

This research employs a remote sensing-based approach to analyze urban landscape changes using Landsat 8 OLI imagery (Figure 2). The framework begins with input data from the Landsat 8 Level Top of Atmospheric Dataset. This data will then undergo NDVI and NDBI extraction for 2014 and 2024. Subsequently, date filtering, cloud masking, and mean composite image creation are performed to produce cloud-free NDVI and NDBI images for both years.

The next stage involves change analysis using a unit grid-based approach with bivariate mapping. The result of this analysis is the detection of urban physical changes between 2014-2024. As a final step, an accuracy assessment is conducted to validate the change detection results. This process enables comprehensive monitoring and analysis of urban landscape changes, leveraging the temporal and spectral advantages of Landsat 8 OLI imagery.

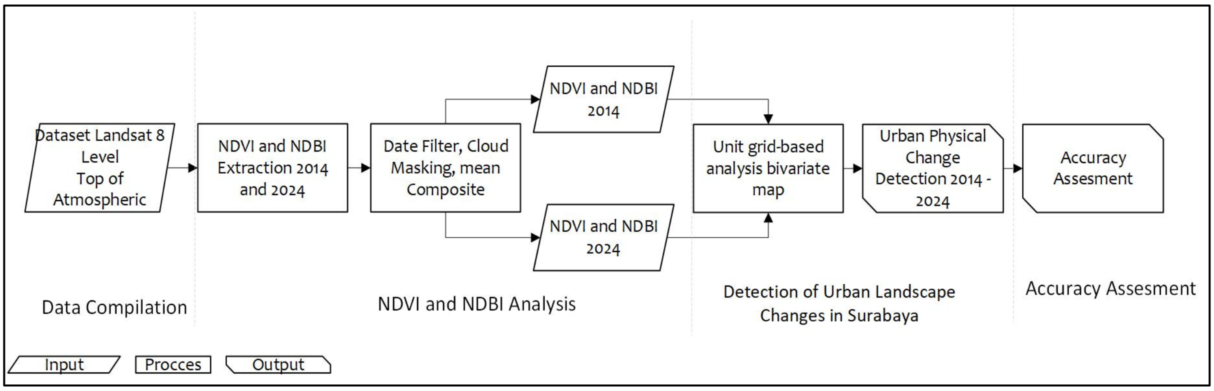


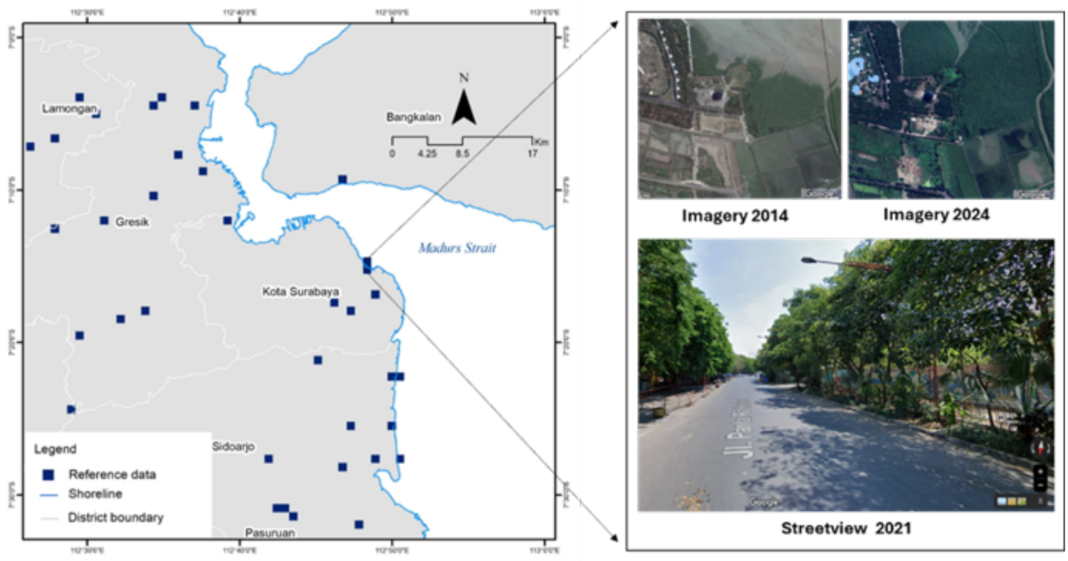
Figure 2. Flow of research (Source: Data Processing, 2024)

Data Compilation

Landsat 8 OLI imagery serves as the primary data used in the landscape change analysis for this research. The Landsat 8 OLI images were obtained with the assistance of the Earth Engine platform to create cloud-free composite images representing the landscape conditions in the years 2014 and 2024. The Earth Engine platform was chosen due to its advantages in retrieving Landsat images according to specific needs based on metadata information and processing the images for analysis (Amani et al., 2020; Kamal et al., 2020; Purwono et al., 2024).

The algorithm for acquiring Landsat 8 OLI data includes searching for the Landsat 8 OLI dataset at top-of-atmosphere reflectance, filtering the area of interest, specifying the time range (i.e., the years 2014 and 2024), and masking cloud cover. Earth Engine makes it easier to collect imagery because all processing is done via cloud computing, requiring only a browser and an internet connection (Amani et al., 2020). One limitation of Landsat 8 OLI is its 16-day temporal resolution, which can be restrictive for studies needing frequent, short-term observations, particularly in areas with persistent cloud cover. However, for this study, focused on changes over a multi-year period, the 16-day revisit cycle is adequate, as the analysis is conducted annually (Chaves et al., 2020). Thus, while the temporal resolution may limit studies requiring high-frequency data, it does not significantly impact the scope of this research.

In addition to Landsat 8 OLI imagery, reference data were used in this research for accuracy assessment. Reference data were obtained by observing high spatial resolution multi-temporal imagery and field photos through the Google Earth and Google Street View platforms (Figure 3 b). Observations from Google Earth for 2014 and 2024 were carried out visually and classified according to the same classification scheme as the results of the change detection model from Landsat 8 OLI images before being compared. Google Street View is used to strengthen the results of interpretation from Google Earth; However, it is limited to street observations; in the study area, the information is available down to small streets.



(a) (b)

Figure 3. (a) Distribution of reference data for accuracy assessment (b) illustration of Surabaya's urban landscape for reference data accuracy assessment (Source: Google, 2024)

NDVI and NDBI Analysis

The urban landscape condition will be approached using NDVI and NDBI analysis to indicate the presence of vegetation and buildings in the Surabaya urban area. The NDVI formula (i) was developed to monitor vegetation based on Landsat data quantitatively (Huang et al., 2021; Rouse et al., 1974). In several studies, NDVI has accurately depicted vegetation conditions in urban areas (Chen et al., 2013; Yusroni et al., 2021). Meanwhile, NDBI (ii) was developed by. Observing land cover changes in urban and peri-urban areas, focusing on extracting built-up land. NDVI and NDBI are processed on the Earth Engine platform, using the average values for one year.

$$NDVI = \frac{\text{infrared}-\text{red}}{\text{infrared}+\text{red}} \text{ .... (i)}$$

$$NDBI = \frac{\text{Midle infrared} - \text{Infrared}}{\text{Midle infrared} + \text{Infrared}} \text{ .... (ii)}$$

Detection of Urban Landscape Changes in Surabaya

The analysis of urban landscape change detection is conducted using the approach of vegetation and built-up area changes. The technique used involves comparing NDVI and NDBI values from 2014 to 2024. The analysis was conducted over a decade to observe changes in urban landscapes over the past 10 years. By comparing NDVI/NDBI values from 2014 to 2024, the difference values between these two time periods are calculated at the landscape analysis unit, represented by a 1 x 1 km grid (Figure 4 a). The aggregation of analysis units within this grid adopts the concept that the smallest units in a landscape (NDVI and NDBI analysis pixels) do not stand alone and are connected and interact with surrounding units (Zha et al., 2003). Therefore, several biophysical and ecological aspects of modeling will be recommended using grid units of certain sizes as analysis units (Norvyani et al., 2018; Riqqi et al., 2011).

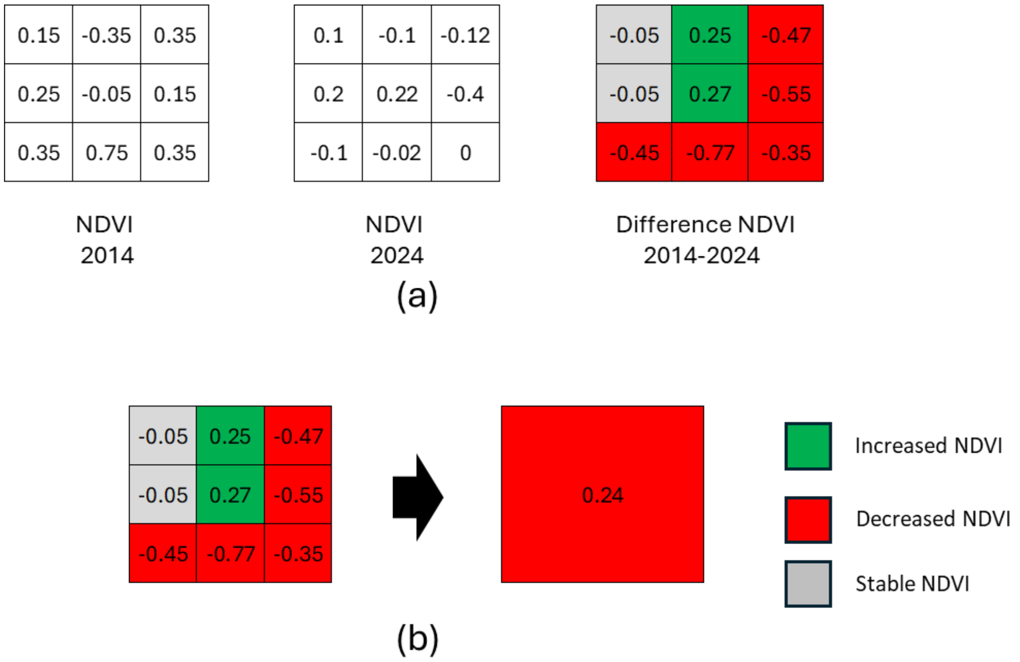


Figure 4. (a) Illustration of landscape change analysis based on NDVI and NDBI (b) Illustration of pixel aggregation based on 10 x 10 m to grid based on 1 x 1 km."

The technique used in urban landscape change analysis is modifying the bivariate map geovisualization technique. Bivariate maps display two variables in one map to observe the relationship between those variables (Strode et al., 2019; Trumbo et al., 2021). In this study, the bivariate map coloring model used is the wedge model (Figure 5). The wedge model aims to detect urban physical changes based on the variation of changes between two variables, namely NDVI and NDBI (Calka, 2021; Strode et al., 2019). Determining the boundary where the NDVI and NDBI values are considered unchanged is +- 0.05; this boundary is employed to anticipate differences in pixel values in the image due to atmospheric conditions during image recording.

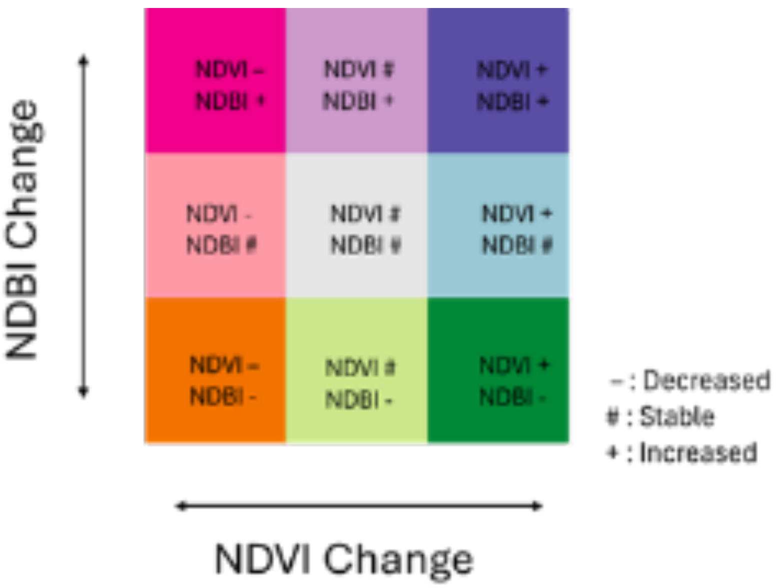


Figure 5. Illustration of geovisualization techniques for urban landscape change analysis

According to Table 1, the results of the changes in NDVI and NDBI from the bivariate analysis will be divided into at least eight classes. These nine classes will describe the results of the nine classes of urban landscape change, which are the main output of this study.

Table 1. Change detection classification

No	Class
1	Vegetation (-) - Built-up Area (-)
2	Vegetation (-) - Built-up Area (+)
3	Vegetation (-) - Built-up Area (#)
4	Vegetation (+) - Built-up Area (-)
5	Vegetation (+) - Built-up Area (-)
6	Vegetation (+) - Built-up Area (#)
7	Vegetation (#) - Built-up Area (-)
8	Vegetation (#) - Built-up Area (+)
9	Vegetation (3) - Built-up Area (#)

Note : (-) decreased, (+) increased, (#) stable
(Source: Data Analysis, 2024)

Accuracy Assessment

The results of urban landscape change detection in Surabaya will undergo an accuracy assessment to evaluate the performance of the detection model produced. This assessment is conducted by comparing the detection model results with reference data. The accuracy assessment calculation is performed using the confusion matrix (Table 1), commonly used to assess remote sensing data classification accurately (Congalton, 1991, 2001; Story & Congalton, 1986). The accuracy values are represented by overall, user, and producer accuracy, with the calculations shown in Table 2. Overall accuracy is calculated by dividing the total number of correct classifications by the total number of samples. In contrast, user and producer accuracies are derived from the confusion matrix rows and columns. This step helps identify specific strengths or weaknesses in classifying the landscape change class.

Data acquisition to accuracy assessment involves a series of interconnected stages. These include Landsat dataset compilation, NDVI and NDBI extraction for 2014 and 2024, unit grid-based analysis with bivariate map analysis, urban physical change detection, and accuracy assessment. Each stage builds on the previous one, ensuring that the analysis of urban physical changes is robust and accurate. This interconnected workflow ensures that insights drawn from earlier stages, such as grid-based analysis, directly inform the final detection and evaluation stages.

Table 1. Confusion matrix for accuracy assessment

		Reference			
		A	B	Total	Producer's Accuracy
Classification	A	AA	AB	AA+AB	AA/(AA+AB)
	B	BA	BB	BA+BB	BB/(BA+BB)
	Total	AA+BA	AB+BB	Total Sampel	
	User's Accuracy	AA/(AA+BA+CA)	BB/(AB+BB)		

Source: Congalton (1991)

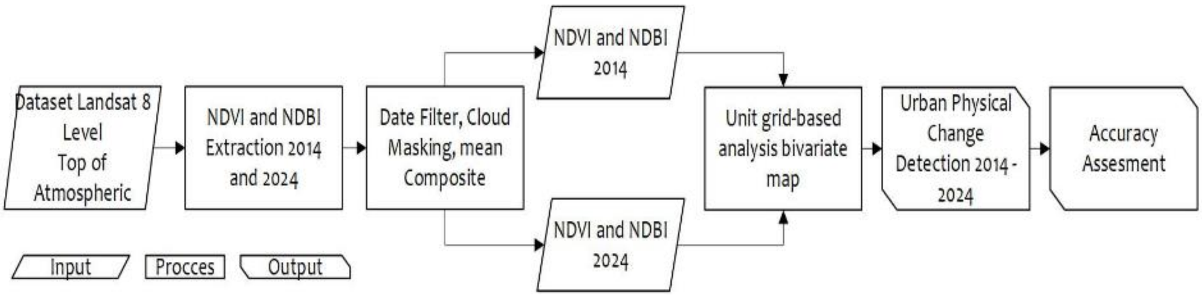


Figure 5. Flow of research (Source: Data Processing, 2024)

RESULTS AND DISCUSSION

NDVI and NDBI Analysis

Figure 6 shows the NDVI and NDBI extraction results, and Table 3 shows the image statistics results. NDVI and NDBI analysis are commonly used methods in remote sensing to monitor land use and land cover changes (Chen et al., 2013; Drešković et al., 2024; Hidayati et al., 2017; Saini, 2021; Yasin et al., 2022; Zha et al., 2003; Zheng et al., 2021). NDVI is used to identify the presence and condition of vegetation, while NDBI is used to identify built-up areas. Based on the analysis results shown in Figure 6, we can observe significant changes in vegetation and built-up areas in the urban area of Surabaya over the last decade.

The increase in the average NDBI value from -0.35 in 2014 to -0.33 in 2024 indicates an increase in built-up areas. This change reflects the ongoing trend of urbanization in Surabaya, which is also supported by previous studies revealing a 10-12% increase in built-up areas from 2012 to 2022 (Purwono et al., 2024). The rise in the maximum NDBI value from 0.40 in 2014 to 0.52 in 2024 further emphasizes the intensification of development in some areas. The increase in standard deviation from 0.11 to 0.12 also indicates a greater variation in the distribution of built-up areas, suggesting uneven development across the region.

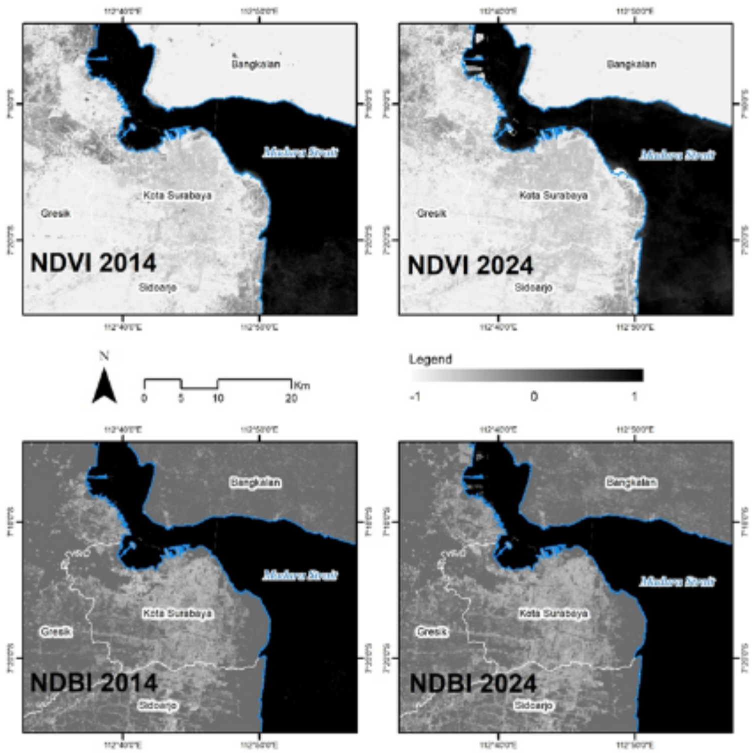


Figure 6 Results of NDVI and NDBI analysis in Surabaya urban area
(Source: Data Analysis, 2024)

On the other hand, NDVI analysis shows an average increase from 0.17 in 2014 to 0.18 in 2024. Although this increase appears small, it indicates increased vegetation density in some locations. The increase in the minimum NDVI value from -0.62 to -0.57 shows that although some areas have low vegetation, the overall vegetation condition is improving. The decrease in the maximum NDVI value from 0.83 in 2014 to 0.81 in 2024 may indicate that some areas have lost high-quality vegetation, although this is not significant. The slight decrease in the standard deviation from 0.38 to 0.36 indicates a more homogeneous distribution of NDVI values, suggesting more evenly distributed efforts to improve or maintain vegetation throughout the study area.

Table 3. NDVI and NDBI statistics for 2014 and 2024

	2014		2024	
	NDVI	NDBI	NDVI	NDBI
Min	-0.62	-0.87	-0.57	-0.79
Max	0.83	0.40	0.81	0.52
Mean	0.17	-0.35	0.18	-0.33
Std Dev	0.38	0.11	0.36	0.12

(Source: Data Analysis, 2024)

Surabaya Urban Landscape Change Detection

The results of urban landscape change detection in Surabaya based on NDVI and NDBI change analysis using bivariate map geovisualization techniques can be seen in Figure 7. Figure 7, No. 1 shows the development of industrial areas, marked by the densification of built-up land between 2014 and 2020. This is consistent with the change detection results showing an increase in NDBI while NDVI remains stable. On the other hand, Figure 7, No. 2 shows the development of mangrove areas observed in 2024, which were previously absent in 2014, and the development of built-up land. The bivariate map analysis supports these findings by showing increases in both NDVI and NDBI in those areas. The results of urban landscape change detection based on NDVI-NDBI change analysis with high spatial resolution imagery also show consistency, reinforcing the validity of this study's findings.

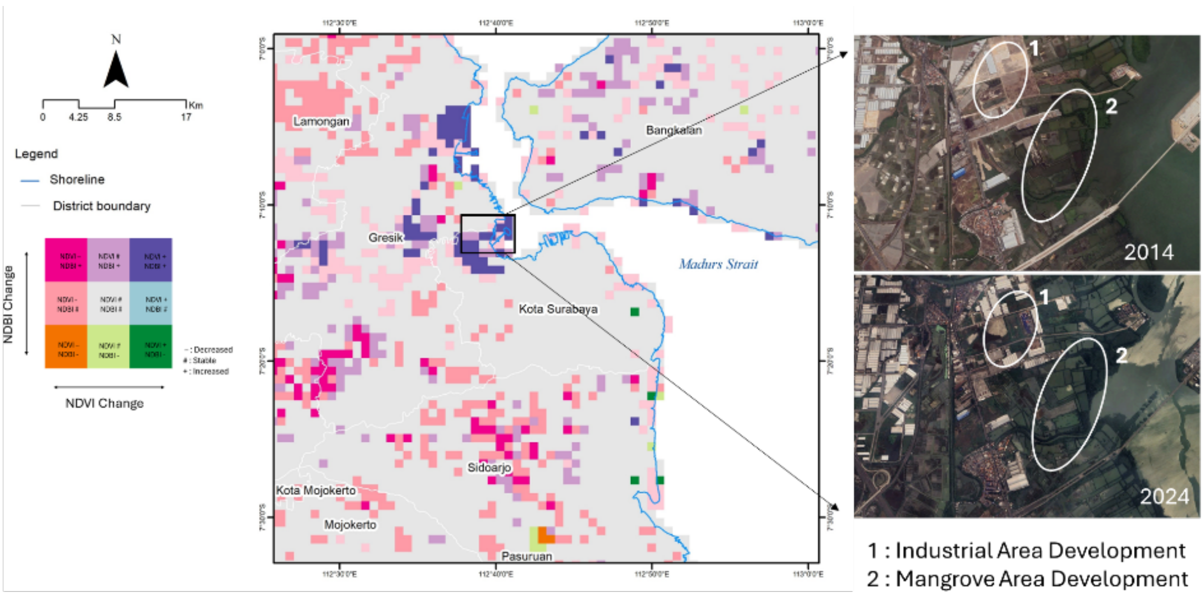


Figure 7. Results of NDVI and NDBI analysis in Surabaya urban area
(Source: Data Analysis, 2024)

If changes in NDVI values correspond to physical changes in vegetation and changes in NDBI values correspond to physical changes in built-up areas, then the dominant change observed in the study area is 'Vegetation Stable - Built-up Area Stable' covering an area of 2,422 km² and representing most of urban Surabaya (Table 4). This suggests that most urban areas have not undergone significant changes in vegetation or built-up areas. This condition may reflect stable land use in many parts of the city, likely in well-established areas or areas that have reached a saturation point, limiting further urban landscape development.

In the study area, significant changes were observed in the categories 'Vegetation Decreased - Built-up Area Increased,' covering an area of 70 km², constituting 2.2% of the total area. Similarly, the 'Vegetation Stable - Built-up Area Increased' category spans 177 km², accounting for 5.5% of the total. These increases in built-up areas highlight ongoing urbanization and expansion, where natural vegetation and green spaces are converted into residential, commercial, or other infrastructure areas. This trend indicates considerable pressure on the urban environment, potentially leading to environmental challenges such as increased air temperature due to the urban heat island effect, reduced air quality, and habitat loss for local biodiversity.

Conversely, the category 'Vegetation Increased - Built-up Area Increased,' which covers 75 km² or 2.3% of the total area, suggests efforts to increase vegetation alongside the development of new areas. This may point to initiatives aimed at mitigating the negative impacts of urbanization through greening programs and the enhancement of green open spaces. Notably, this class is prevalent in coastal areas, where the development of mangrove ecosystems is ongoing due to significant mangrove management and rehabilitation along the Surabaya coast (Amdani, 2022; Jeannyla, 2018). However, to ensure urban environmental sustainability, it is critical to maintain and expand these efforts, particularly with climate change and a growing population that continues to increase the demand for space and resources within the city.

Table 4. Physical Urban Landscape Change 2014-2024

No	Change Detection Classification	Area (Km2)
1	Vegetation (-) - Built-up Area (-)	3
2	Vegetation (-) - Built-up Area (+)	70
3	Vegetation (-) - Built-up Area (#)	287
4	Vegetation (+) - Built-up Area (-)	4
5	Vegetation (+) - Built-up Area (-)	75
6	Vegetation (+) - Built-up Area (#)	201
7	Vegetation (#) - Built-up Area (-)	9
8	Vegetation (#) - Built-up Area (+)	177
9	Vegetation (#) - Built-up Area (#)	2422
	Total	3248

Note : (-) decreased, (+) increased, (#) stable
(Source: Data Analysis, 2024)

Accuracy Assessment

The overall accuracy of 71% indicates that the model reliably detected urban landscape change in Surabaya in 71% of cases. Whether this is satisfactory depends on the context. For urban landscape monitoring, accuracy around this level can be considered moderate—often used in exploratory studies or initial assessments. This accuracy is relatively typical, compared to other studies, especially those relying on remote sensing with medium-resolution data such as Landsat. However, it may be lower than achieved with high-resolution imagery or more sophisticated models. Several studies using land use/land cover classifications have reported 69–95% accuracy for a single map-type (Chughtai et al., 2021). However, it is important to note that the landscape change maps in this study involved the analysis of two maps, which may have resulted in lower accuracy than a single-map assessment.

However, this model has weaknesses in certain change classes, particularly identifying areas with decreased built-up areas. The difficulty in detecting areas with decreased built-up areas may be due to small changes that occur in built-up areas not sufficiently detected by the resolution of the data used or because these changes occur in areas covered by vegetation, making them unrecorded. Additionally, NDBI still has issues distinguishing between buildings with asbestos roofs and dry open land (Hidayati et al., 2017), making misidentifying built-up areas highly possible. Nonetheless, these results can still be considered good, given the challenges in detecting changes on a landscape scale with complex land use variations.

Looking more at the confusion matrix, it shows that change classes such as 'Vegetation (-) - Built-up Area (-)' have low accuracy, namely 33%. This may be because areas experiencing decreases in vegetation and built-up areas are rare, or the changes occur on a very small scale. On the other hand, the classes 'Vegetation (+) - Built-up Area (+)' and 'Vegetation (-) - Built-up Area (+)' show higher accuracy, at 100% and 75%, respectively, indicating that this model is more reliable in detecting increases in vegetation and built-up areas. These findings are important for further model development, where improving data resolution and applying more complex analysis methods can be implemented to enhance the accuracy of urban landscape change detection. Further model development in subsequent research will provide more precise and detailed insights.

Several limitations could influence the accuracy of assessment results. The reference data used in this study is based on interpretations from Google Earth and Google Street View rather than field data, which may introduce inaccuracies. Additionally, NDBI has limitations in distinguishing between dry open land and built-up areas, which may result in some areas of open land being misclassified as increases in built-up area. Nevertheless, the results of this study are reliable enough to provide a general overview of urban landscape changes. To improve accuracy in the future, using higher-resolution images or more advanced classification methods could help capture these subtle changes better.

Table 3-3: Surabaya urban landscape change detection accuracy assessment results

	Class		Reference									Amount	Producer's Accuracy
			1	2	3	4	5	6	7	8	9		
Classification	1	Vegetation (-) – Built-up Area (-)	1								2	3	33%
	2	Vegetation (-) – Built-up Area (-)		4								4	100%
	3	Vegetation (-)- Built-up Area (#)		2	2							4	50%
	4	Vegetation (+) – Built-up Area (-)				4						4	100%

5	Vegetation (+) – Built-up Area (+)					4					4	100%
6	Vegetation (+) – Built-up Area (-)						3			1	4	75%
7	Vegetation (#) – Built-up Area (-)		1	1	1			0		1	4	0%
8	Vegetation (#) – Built-up Area (+)					1			3		4	75%
9	Vegetation (#) – Built-up Area (#)			1					2	11	14	79%
	Total	1	7	4	5	5	3	0	5	15	45	
	User's Accuracy	100%	57%	50%	80%	80%	100%	0%	60%	73%		
	Overall Accuracy						71%					

Note : (-) decreased, (+) increased, (#) stable
(Source: Data Analysis, 2024)

CONCLUSION

The findings show that most of Surabaya's urban area remains stable, with the 'Vegetation Stable - Built-up Area Stable' class covering 74.6% of the area (2422 km²). However, notable urbanization and expansion are evident, as 7.6% of the landscape (247 km²) falls under 'Vegetation Decreased - Built-up Area Increased' and 'Vegetation Stable - Built-up Area Increased,' indicating significant conversion of green spaces to built-up areas. Coastal areas also show positive changes, with 2.3% (75 km²) in the 'Vegetation Increased - Built-up Area Increased' class, largely due to mangrove rehabilitation efforts essential for coastal resilience and environmental sustainability.

Although the model achieves 71% accuracy in capturing urban landscape dynamics using NDVI and NDBI from Landsat 8 OLI imagery, detecting some change classes still needs improvement, particularly in identifying areas with decreased built-up areas. This challenge may stem from the subtle nature of urban decline or redevelopment, where small changes—such as removing a few buildings or temporary construction—are difficult to detect. Nevertheless, the results of this study are reliable enough to provide a general overview of urban landscape changes. To improve accuracy in the future, using higher-resolution images or more advanced classification methods could help capture these subtle changes better.

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