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MORALITY BEFORE KNOWLEDGE

Application of spectral indices and deep learning (convolutional neural network model) on land cover change analysis

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ABSTRACT
Background: Understanding land cover change is crucial for sustainable urban development, particularly in rapidly growing coastal cities such as Semarang City, Central Java, Indonesia. **Methods:** This study investigates spatial and temporal patterns of land cover change from 2000 to 2025 by integrating multi-temporal Landsat satellite imagery, key spectral indices—namely the normalized difference vegetation index, normalized difference water index, and normalized difference built-up index—and a deep learning approach based on convolutional neural networks. Annual Landsat images were preprocessed for atmospheric correction, cloud masking, and spatial subsetting using Google Earth Engine. Adaptive thresholding was then applied to each spectral index to delineate vegetation, water bodies, and built-up areas. **Findings:** Quantitative analysis revealed a significant decline in vegetation cover, with the normalized difference vegetation index dropping from 53.66% (397.59 km^2) in 2000 to 46.83% (346.98 km^2) in 2025, driven by urban expansion and landscape conversion, especially in coastal and lowland areas. Normalized difference water index analysis indicated a reduction and fragmentation of water bodies after 2015, linked to reclamation, sedimentation, and urban encroachment. Conversely, built-up areas expanded steadily, confirming accelerated urbanization. Scatter plot and regression analyses showed strong inverse relationships among vegetation, water, and built-up land, emphasizing ecological trade-offs and the loss of green-blue infrastructure. **Conclusion:** To enhance classification accuracy, a convolutional neural network was trained and validated on image patches, achieving a validation accuracy of 60%—outperforming conventional threshold-based methods by better capturing complex spatial patterns. The integrated remote sensing and deep learning framework offers robust potential for long-term, large-area land cover monitoring. **Novelty/Originality of this article:** The novelty of this research lies in its combined use of spectral indices and deep learning for multi-decadal land cover change analysis, providing a transferable methodology for other rapidly urbanizing coastal cities.

KEYWORDS: land cover change; spectral indices; convolutional neural network (CNN); Semarang City; urbanization; remote sensing; coastal management.

1. Introduction

Urban expansion and land use change are among the most urgent and complex challenges facing rapidly growing Indonesian cities, especially those located in dynamic coastal and lowland regions such as Semarang City. These processes, driven by accelerated population growth, economic development, and climate pressures, significantly transform urban ecosystems, disrupt local hydrological cycles, and intensify the risks associated with environmental hazards (Li et al., 2020; Neumann et al., 2015; Yao et al., 2021). The ability to monitor and analyze these spatial-temporal dynamics is critical for supporting

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sustainable urban planning and effective environmental management (Santoso et al., 2022; Wang et al., 2022).

From the perspective of land change science, understanding the spatial patterns, underlying drivers, and socio-ecological consequences of land transformation is fundamental for developing adaptive policies and urban resilience strategies (Turner et al., 2007). Furthermore, advances in urban ecology reveal that urbanization produces feedback loops that alter vegetation structure, water distribution, and biodiversity, highlighting the need for integrated approaches to maintain ecosystem services in rapidly transforming cities (Grimm et al., 2008; Alberti, 2016; Mahdianpari et al., 2021; Lin et al., 2024).

Remote sensing technologies, supported by the use of spectral indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI), have become invaluable tools for monitoring land cover change, classifying vegetation, water bodies, and built-up areas across urban landscapes (Gao, 1996; McFeeters, 1996; Zha et al., 2003; Abdi, 2020; Santoso et al., 2022). However, the limitations of threshold-based methods—including their sensitivity to atmospheric variation, spectral confusion between surface types, and inconsistencies due to seasonal changes—necessitate the adoption of more advanced analytical techniques (Zhu & Woodcock, 2016; Kaimaris et al., 2019; Wang et al., 2022; Gao et al., 2023).

In recent years, machine learning and especially deep learning models such as Convolutional Neural Networks (CNNs) have demonstrated remarkable improvements in the classification accuracy of remote sensing imagery by automatically learning hierarchical spatial features and complex data patterns (Ma et al., 2019; Zhu et al., 2017; Li et al., 2021; Chen et al., 2023). Recent reviews and empirical studies have confirmed the effectiveness of hybrid and attention-based CNN architectures for monitoring urban land cover and land use change in various global contexts, including Asia and Indonesia (Mahdianpari et al., 2021; Lin et al., 2024; Amani et al., 2020).

Although their application has grown globally, there remains a paucity of research utilizing CNN-based approaches for the long-term analysis of land cover dynamics in Indonesian urban and coastal contexts, where land transformation occurs rapidly and spatial heterogeneity is pronounced (Santoso et al., 2022; Yao et al., 2021). This study aims to apply a combined approach of spectral indices analysis and CNN-based deep learning to analyze land cover changes in Semarang City between 2000 and 2025. By integrating traditional remote sensing indices with modern deep learning methods, this research seeks to enhance the understanding of spatial-temporal dynamics of vegetation, water bodies, and built-up areas, and to evaluate the effectiveness of these approaches in supporting sustainable urban development strategies.

2. Methods

This research was conducted in Semarang City, Central Java Province, Indonesia, an urban coastal city that has been experiencing rapid land use and land cover changes due to urbanization, industrial development, and environmental pressures. The city's geographical characteristics, which include coastal lowlands and upland areas, make it a significant case study for analyzing spatial-temporal land cover dynamics (Li et al., 2020; Santoso et al., 2022; Yao et al., 2021).

Multi-temporal Landsat satellite imagery spanning from 2000 to 2025 was utilized to monitor land cover changes over a 25-year period. Landsat 5 Thematic Mapper (TM) imagery was employed for the period 2000–2011, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) for gap-filling between 2000 and 2012, Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) for 2013–2021, and Landsat 9 Operational Land Imager-2 (OLI-2) for 2022–2025. All imagery was accessed through the Google Earth Engine (GEE) platform, utilizing surface reflectance products that have been atmospherically corrected (Gorelick et al., 2017; Kumar & Mutanga, 2018; Amani et al., 2020). The spatial resolution used for all datasets was 30 meters.

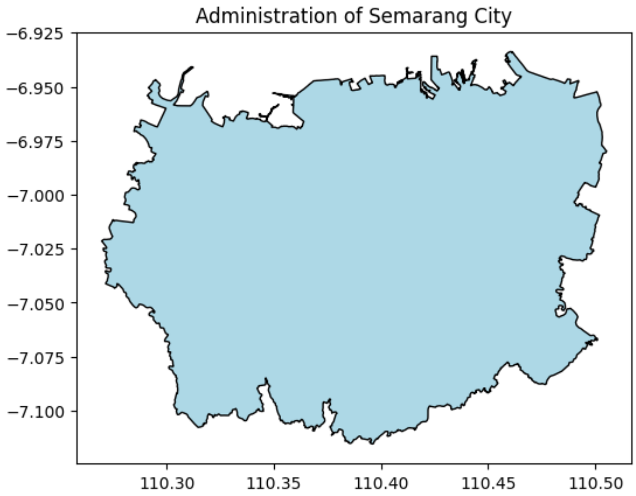

Fig. 1. Research location

The preprocessing steps included cloud masking using the Quality Assessment (QA) bands to remove clouds and cloud shadows, selecting scenes with less than 20% cloud cover, creating annual mosaics for each year, and cropping images based on the administrative boundary of Semarang City. These steps ensured the production of consistent, cloud-free imagery suitable for temporal analysis (White et al., 2014; Gao et al., 2023). Land cover analysis was performed using three major spectral indices. Normalized Difference Vegetation Index (NDVI) was calculated as (NIR−RED)/(NIR+RED) to assess vegetation health and density (Gao, 1996; Xue & Su, 2017). Normalized Difference Water Index (NDWI) was calculated as (GREEN−NIR)/(GREEN+NIR) to enhance water body detection (McFeeters, 1996; Xu, 2006; Santoso et al., 2022). Normalized Difference Built-up Index (NDBI) was calculated as (SWIR−NIR)/(SWIR+NIR) to delineate built-up urban areas (Zha et al., 2003; Kaimaris et al., 2019; Li et al., 2021).

For Landsat 5 TM and Landsat 7 ETM+, NDVI used Band 4 (NIR) and Band 3 (RED), NDWI used Band 2 (GREEN) and Band 4 (NIR), and NDBI used Band 5 (SWIR) and Band 4 (NIR). For Landsat 8 OLI and Landsat 9 OLI-2, NDVI used Band 5 (NIR) and Band 4 (RED), NDWI used Band 3 (GREEN) and Band 5 (NIR), and NDBI used Band 6 (SWIR1) and Band 5 (NIR). Land cover classification into vegetation, water bodies, and built-up areas was performed annually through thresholding based on the histogram distribution of each spectral index. Threshold values were adaptively adjusted each year to account for seasonal and environmental variability. The total area for each land cover class was calculated in square kilometers and as a percentage of the total study area (Abdi, 2020; Wang et al., 2022).

To improve classification accuracy, a Convolutional Neural Network (CNN) model was developed. A total of 2,755 image patches (64×64 pixels) were used for training, and 689 patches for validation. The CNN model was constructed using a sequential architecture composed of convolutional layers, pooling layers, and dense layers, implemented using TensorFlow and Keras libraries (Abadi et al., 2016; Chollet, 2021; Li et al., 2021). The model was trained using the Adam optimizer with categorical cross-entropy loss, applying early stopping to prevent overfitting (Kingma & Ba, 2014; Prechelt, 1998; Srivastava et al., 2014; Mahdianpari et al., 2021). The final model achieved a validation accuracy of 60% and a validation loss of 0.6758, indicating moderate performance in differentiating land cover types. Recent studies confirm that attention-based or hybrid CNN architectures can further enhance urban land cover classification using multitemporal and multi-source satellite data (Gao et al., 2023; Chen et al., 2023; Lin et al., 2024).

Scatter plot analyses were conducted to examine the relationships between NDVI, NDWI, and NDBI across the 2000–2025 period. High coefficients of determination (R^2 > 0.99) were found, confirming the consistency and complementary relationships among vegetation, water, and built-up areas in Semarang City.

All stages of image acquisition, preprocessing, spectral index calculation, classification, deep learning model development, and data visualization were performed using open-source tools, specifically Google Earth Engine and Python programming in Google Colab (Amani et al., 2020; Bisong, 2019). No commercial Geographic Information Systems (GIS) software was used in this study.

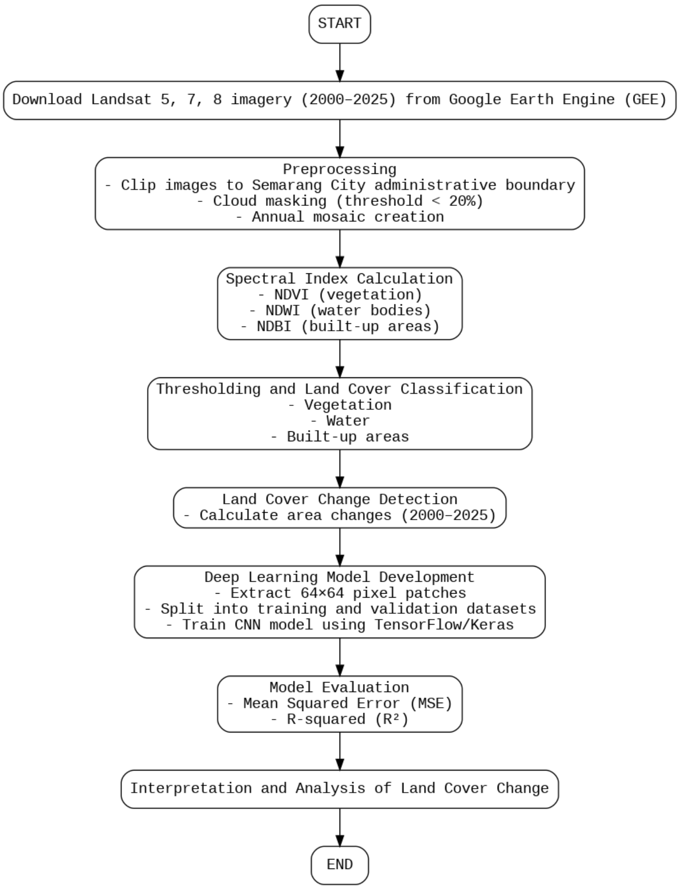

Fig. 2. Research flowchart

3. Results and Discussion

3.1 NDVI analysis of Semarang City 2000 – 2025

The Normalized Difference Vegetation Index (NDVI) analysis provided a comprehensive understanding of vegetation dynamics in Semarang City over a 25-year period. NDVI is a widely used spectral index to measure vegetation health and density by comparing near-infrared (NIR) and red reflectance values, with higher NDVI values indicating denser and healthier vegetation (Gao, 1996).

Figure 3 displays a chronological sequence of NDVI maps for Semarang City at key temporal intervals—2000, 2007, 2009, 2015, 2020, 2024, and 2025—using a color scale from deep red (very low NDVI, representing built-up or bare surfaces) to dark green (high NDVI, indicating dense and healthy vegetation). In 2000, NDVI values were predominantly high across much of the landscape, as indicated by extensive light to medium green shades, with the densest vegetation concentrated in the southern and eastern upland regions. In contrast, the northern coastal and city core zones showed lower NDVI values, reflecting areas of early urbanization and natural coastal features.

By 2007, a marked reduction in medium and dark green tones became evident, particularly within the central and northern areas. This pattern points to the initial phase of rapid vegetation loss, coinciding with intensified urban growth and active land conversion in peri-urban zones. In 2009, a partial recovery or stabilization of vegetation was observed, with medium green shades reappearing more frequently compared to 2007. This may be attributed to seasonal regrowth, targeted urban greening efforts, or a temporary slowdown in land conversion.

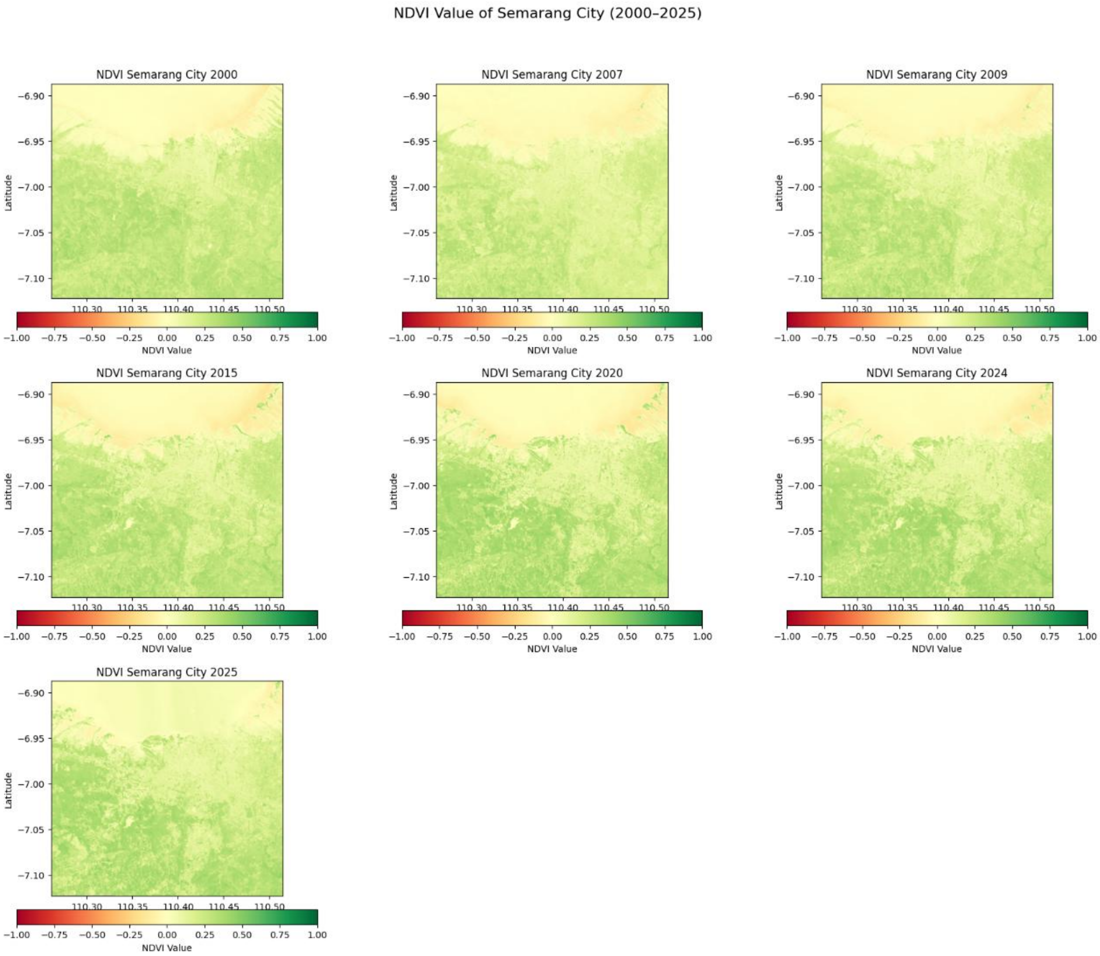

Fig. 3. NDVI value of Semarang City 2000 - 2025

Moving to 2015, the spatial prevalence of lower NDVI values (yellowish to light green) increased, particularly in the northern and central lowlands. This trend aligns with accelerated infrastructure development and land reclamation activities, especially along the coast. The maps for 2020 and 2024 reveal a continued shift toward paler greens and yellows, signifying ongoing fragmentation and isolation of dense vegetation patches. During these years, urban sprawl advanced further outward from the city center, confining much of the remaining vegetated land to upland peripheral areas. By 2025, the landscape is dominated by low to medium NDVI values, visually confirming extensive vegetation loss and the simplification of the city's ecological structure. The only significant remnants of higher NDVI are confined to isolated patches in the southern upland zones, while the majority of lowland and coastal regions exhibit greatly reduced vegetative cover.

Collectively, these NDVI maps visually corroborate quantitative analyses of land cover change, highlighting the spatial correspondence between the decline and fragmentation of vegetated areas and the expansion of built-up surfaces. The upland buffer in the south and east emerges as a critical last stronghold for urban vegetation, vital for maintaining ecosystem services and the city's climate resilience. Although some seasonal or inter-annual fluctuations—such as those between 2007 and 2009—may reflect climatic variability or the effect of urban greening policies, these do not significantly alter the prevailing long-term trend of vegetation decline. The persistent loss and spatial fragmentation of vegetation documented in the NDVI sequence raises pressing concerns for local microclimate regulation, biodiversity conservation, stormwater management, and the overall quality of urban life in Semarang. These spatial findings underscore the need for targeted green space protection, landscape connectivity strategies, and sustainable urban planning—especially in rapidly transforming lowland and coastal districts (see Fig. 3 for a visual reference of the NDVI evolution and fragmentation of green spaces across Semarang City).

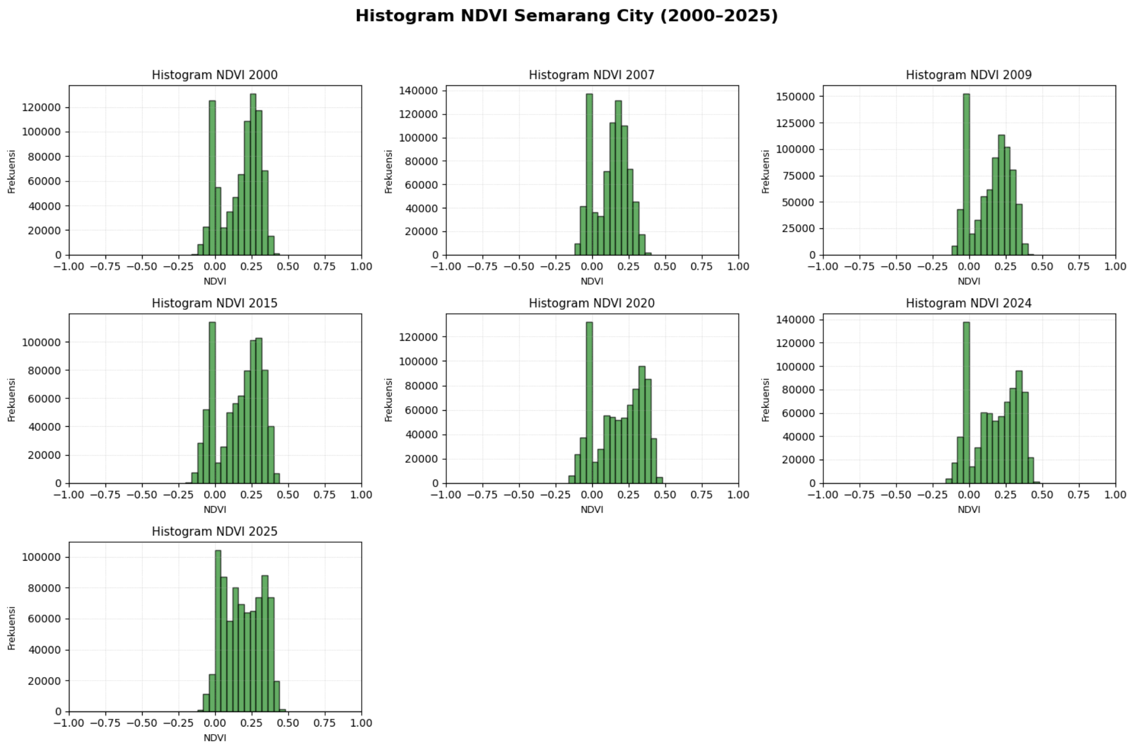

Fig. 4. Histogram of NDVI distribution value of Semarang City (2000-2025)

Figure 4 illustrates the evolution of the frequency distribution of NDVI values for Semarang City across seven selected years between 2000 and 2025, offering a statistical perspective on the city's vegetation status and its temporal changes. In 2000, the histogram presents a broad, asymmetric distribution, with most NDVI values ranging from 0.1 to 0.5 and peaking between 0.2 and 0.35. This pattern reflects the dominance of dense and healthy vegetation, particularly in upland and peri-urban regions, consistent with the extensive green coverage observed in the corresponding NDVI maps. However, by 2007 and 2009, there is a pronounced leftward shift in the histogram. The distribution peaks move closer to the 0.15–0.30 range, and both the height and spread of the higher NDVI bins are reduced, indicating a marked loss of dense vegetation and the increasing prevalence of moderate to sparse vegetation (Li et al., 2020). A short-term recovery can be detected in 2009, where the rightward movement of the peak suggests a rebound in vegetation—likely due to land management efforts, natural regrowth, or annual climatic variability—though this does not alter the overall declining trend.

From 2015 through 2025, the histograms exhibit further compression and concentration in the lower NDVI bins, mainly within the 0.05–0.25 range. The overall range of NDVI values narrows, and the highest frequencies shift consistently towards lower NDVI values. By 2025, the histogram is sharply peaked around 0.1–0.2, with relatively few pixels registering high NDVI values, illustrating the widespread dominance of sparsely vegetated or non-vegetated surfaces. This statistical pattern is emblematic of a substantial loss and homogenization of urban vegetation over time.

The observed leftward shift and narrowing of the NDVI distribution clearly demonstrate not only the reduction in vegetation cover but also an increase in the spatial fragmentation and isolation of green patches, particularly in lowland and coastal districts most affected by urban expansion. The temporal dynamics captured in these histograms echo the spatial trends seen in the NDVI maps (Fig. 3), providing robust quantitative support for the ongoing transition toward a more uniform, built-up urban landscape. Such a trend may have negative consequences for local microclimate regulation, air quality, biodiversity, and urban resilience to environmental hazards. Ultimately, the declining diversity in NDVI values points to a loss of ecological complexity and landscape functionality, underscoring the importance of sustainable land management and green infrastructure planning in Semarang City.

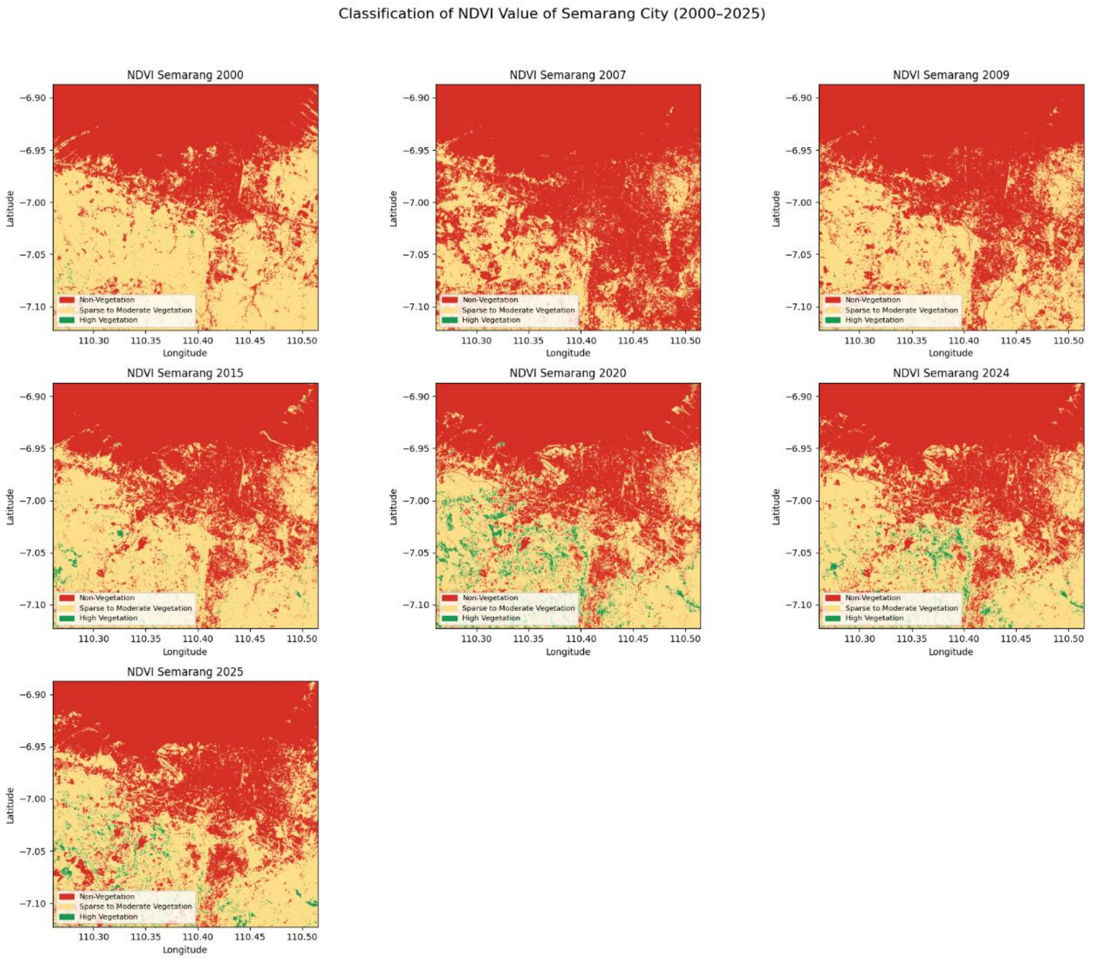

Fig. 5. Classification of NDVI value of district administration with coastal fence Tangerang Regency (2000-2025)

Figure 5 presents the classification of NDVI values into three distinct land cover categories—non-vegetation, sparse to moderate vegetation, and high vegetation—capturing spatial and temporal land cover dynamics in Semarang City across seven different time points between 2000 and 2025. In 2000, the city's landscape was largely dominated by areas classified as sparse to moderate vegetation, particularly in the central and peri-urban regions, with substantial patches of high vegetation concentrated in the southern and eastern uplands (Seto et al., 2011). Non-vegetation areas were primarily limited to the urban core and several lowland or coastal strips, indicating that built-up or bare surfaces had not yet widely encroached upon the city's green spaces.

As the years progressed, especially during the 2007–2009 period, there was a marked contraction and fragmentation of high vegetation zones. These green patches became increasingly isolated and restricted to the periphery, while non-vegetation areas expanded rapidly across the central and northern lowlands. This spatial transformation reflects the intensification of urban expansion and infrastructure development, which has gradually replaced vegetated landscapes with built-up land. By the period 2015–2025, non-vegetation zones (shown in red) had overtaken much of Semarang's lowland and coastal districts, leaving high vegetation only in isolated fragments, particularly in upland areas. Sparse to moderate vegetation areas, meanwhile, served as transitional buffers but became increasingly scarce and disconnected.

These spatio-temporal patterns illustrate prominent "edge effects," where the remaining high vegetation patches are surrounded and pressured by expanding non-vegetation zones, heightening their vulnerability to anthropogenic disturbance. The transformation is particularly dramatic along the coastal fringe and at lower elevations, where the impact of urbanization and land reclamation is most pronounced. By 2025, the vast majority of high vegetation is almost exclusively confined to the upland buffer in the south, while non-vegetation areas have engulfed much of the city core, northern, and eastern sectors.

Ecologically, the spatial loss and fragmentation of vegetated areas significantly reduce landscape connectivity, threatening local biodiversity, microclimate regulation, and essential ecosystem services such as stormwater management and carbon sequestration. The proliferation of non-vegetation zones directly correlates with documented increases in population, infrastructure growth, and land conversion pressures in Semarang—trends that are well established in the literature (Li et al., 2020; Firman, 2009). The persistence of a high vegetation buffer in the upland south underscores its critical role as a last ecological refuge for the city, vital for supporting climate adaptation and ensuring the long-term sustainability of urban development.

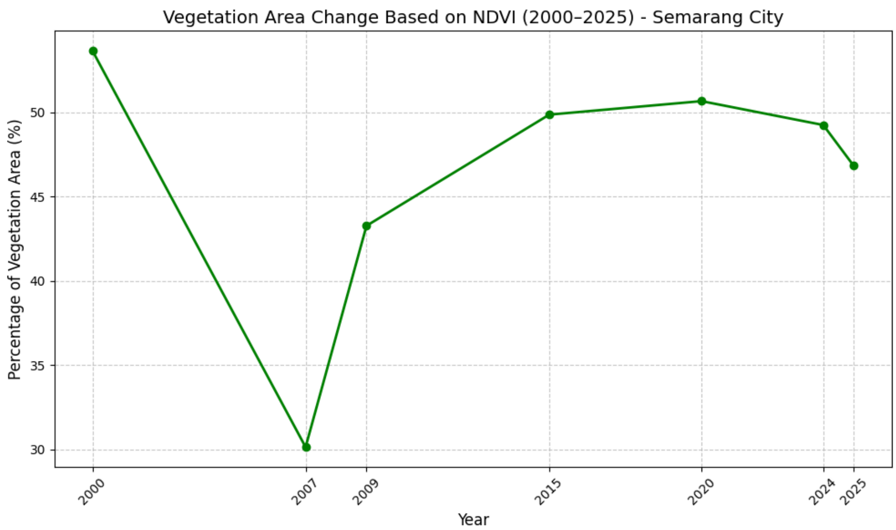

Fig. 6. Changes in vegeration area based on NDVI (2000 – 2025)

Figure 6 presents the temporal evolution of the proportion of vegetation area in Semarang City, as determined from NDVI-based classification, spanning the period from 2000 to 2025. The trend line depicted in this figure clearly illustrates both abrupt and gradual shifts in land cover throughout the 25-year observation window. At the start of the period, in 2000, vegetation covered approximately 54% of the city's total area. However, this figure declined sharply to around 30% by 2007, signaling a phase of rapid land use change likely driven by urban expansion, major infrastructure development, and large-scale reclamation activities in peri-urban and coastal regions.

Between 2007 and 2009, there was a notable partial recovery, with vegetation cover rebounding to about 44%. This resurgence could be attributed to reforestation efforts, urban greening initiatives, natural regrowth following disturbances, or even favorable remote sensing conditions, such as reduced cloud cover or seasonal factors during image acquisition. From 2009 onwards, the percentage of vegetated area continued to rise, reaching just above 51% by 2020. This phase of stabilization and increase suggests some success from vegetation protection policies or shifts in land management priorities during this interval.

Nevertheless, after 2020, the trend reverses, with a gradual but steady decline in vegetation cover down to 47% by 2025. This late-period decrease may indicate renewed development pressures, persistent urban sprawl, or intensification of land use in the few remaining green spaces, potentially exacerbated by the delayed impact of infrastructure projects initiated in prior years.

3.2 NDWI analysis of Semarang City 2000–2025

The Normalized Difference Water Index (NDWI) analysis provided valuable insights into the dynamics of water body coverage in Semarang City from 2000 to 2025. NDWI enhances the detection of surface water features by maximizing reflectance of water in the green band and minimizing the low reflectance in the near-infrared (NIR) band (McFeeters, 1996).

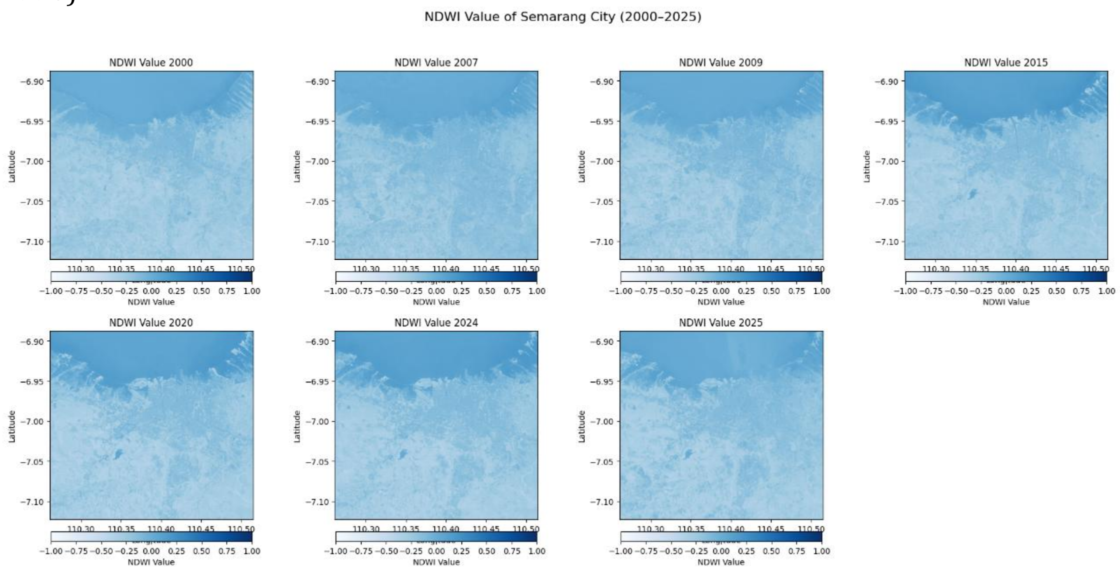

Fig. 7. NDWI value of Semarang City (2000-2025)

Figure 7 presents the spatiotemporal evolution of NDWI values for Semarang City at key intervals between 2000 and 2025, offering a visual narrative of changes in surface water coverage over a 25-year period. In the year 2000, NDWI mapping reveals extensive areas of higher NDWI values—depicted in darker blue hues—particularly concentrated along the city's northern coastal fringe and in the riverine corridors that traverse the urban landscape. These zones represent open water bodies and wetlands, which are critical for maintaining ecological balance and buffering the city against hydrological hazards.

By 2007 and 2009, a discernible contraction of high NDWI regions is apparent, with visible reductions along the coastline and some inland water features. While a few patchesof high NDWI remain, much of the city, especially the western and central zones, begins to exhibit lighter blue shades, indicating a decrease in water content and the encroachment of non-water surfaces such as bare land or new development.

The transition accelerates in the subsequent years. By 2015, and especially in 2020, 2024, and 2025, the spatial distribution of high NDWI values becomes increasingly fragmented and scarce. The coastal margin, once dominated by open water, now shows lighter blue and even pale tones, confirming the significant loss and isolation of surface water bodies. These changes mirror both physical reclamation and natural processes such as sedimentation or channelization. The remaining high NDWI areas are confined to a few isolated zones, while the majority of Semarang's urban extent is characterized by consistently lower NDWI values, marking a steady shift toward impervious, non-water surfaces.

Overall, the visual evidence provided by these NDWI maps clearly documents the progressive reduction, fragmentation, and marginalization of water bodies in Semarang City. This spatial transformation not only reflects the intensity of urban expansion and land reclamation but also signals growing vulnerability to flooding, loss of aquatic habitats, and reduced hydrological resilience—trends that demand urgent and integrated water management interventions in the city's development planning.

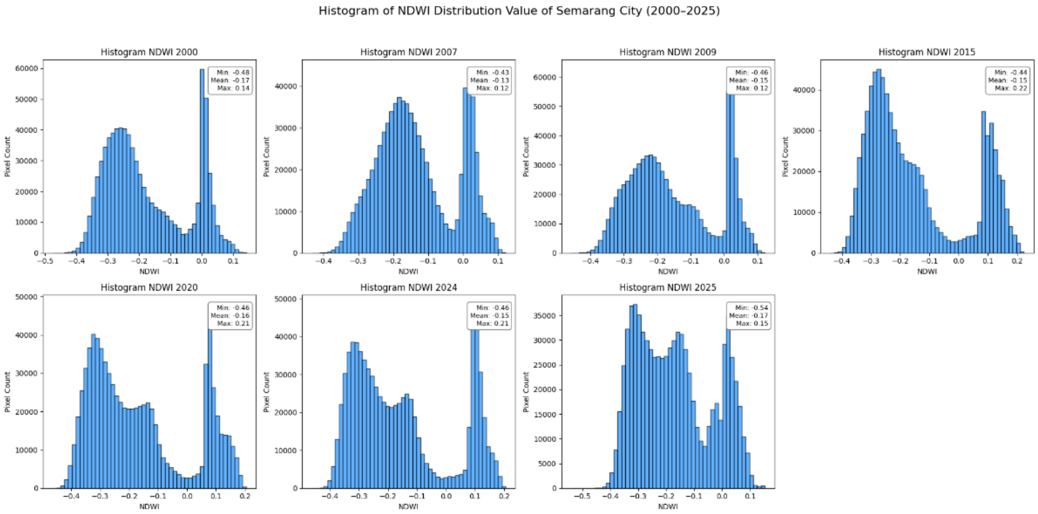

Fig. 8. Histogram of NDWI distribution value of Semarang City (2000-2025)

Figure 8 presents the temporal progression of NDWI value distributions for Semarang City over selected years between 2000 and 2025, providing statistical insight into the dynamics of surface water features. In 2000, the histogram reveals a bimodal pattern with a significant peak in the positive NDWI range, notably between 0.0 and 0.15, reflecting the widespread presence of open water bodies and moist surfaces. Another peak at negative values indicates the dominance of non-water surfaces such as dry soils and built-up areas, but the positive NDWI peak is both high and broad, underscoring the abundance of water features in the city's landscape at the beginning of the observation period.

As the years progress, the positive NDWI peak gradually contracts and shifts leftward, while the negative peak becomes increasingly prominent. By 2007 and 2009, the distribution shows reduced frequency in high NDWI bins, signaling a decline in water bodies and an expanding prevalence of non-water or impervious surfaces. In 2015, the positive NDWI peak becomes narrower and further diminishes in height, highlighting the continuing reduction in open water extent. The years 2020, 2024, and 2025 exhibit a persistent and pronounced dominance of the negative NDWI range, with the positive tail of the distribution nearly vanishing. This change corresponds to the widespread transformation of the urban landscape, where previously water-rich zones have been converted to built-up or barren land, and the presence of surface water becomes increasingly rare and fragmented.

The histogram analysis thus quantitatively supports the spatial evidence provided by the NDWI maps, confirming a long-term trend of water loss and landscape aridification. The clear leftward shift and narrowing of the positive NDWI peak over time reflect not only physical reduction of water bodies, but also the homogenization of the city's hydrological landscape—where urban expansion and reclamation activities have increasingly dominated. This trajectory highlights the pressing need for integrated and adaptive water resource management policies to prevent further decline in surface water, protect remaining aquatic ecosystems, and safeguard the city's resilience to hydrological hazards.

Figure 9 provides a series of binary classification maps illustrating the spatial distribution of water and non-water surfaces in Semarang City across the years 2000 to 2025, as identified by NDWI thresholding. In the year 2000, the classification map shows extensive contiguous water bodies (blue) along the northern coastal fringe and within major riverine corridors, indicating a landscape still strongly influenced by natural hydrological features. As time progresses, however, these water zones contract and become increasingly fragmented. By 2007 and 2009, the once broad coastal water belt narrows, and isolated water patches become visible in inland regions, reflecting the initial impacts of urban encroachment and reclamation activities.

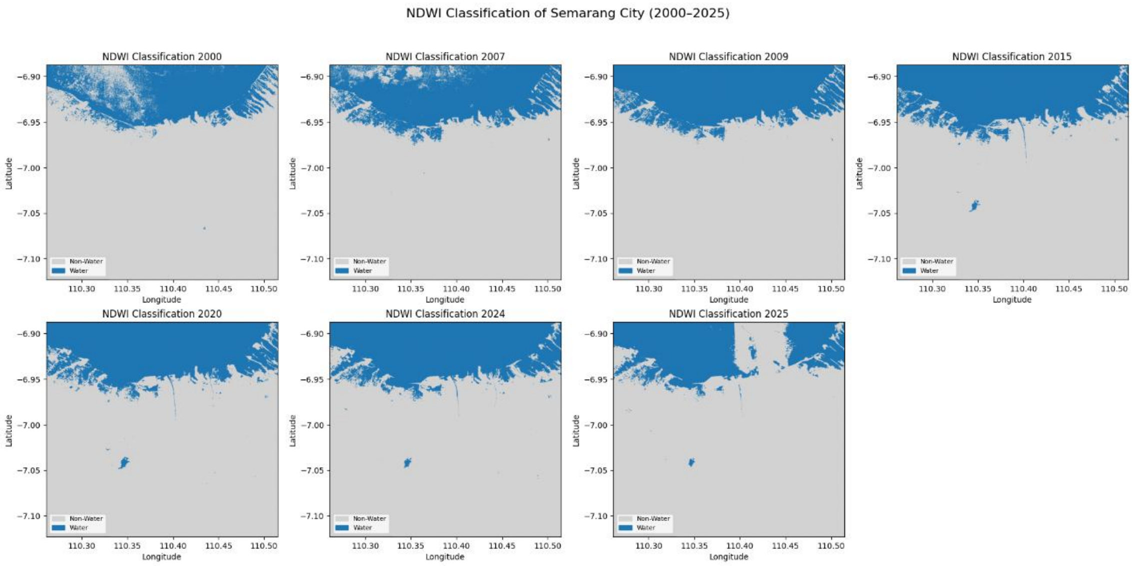

Fig. 9. NDWI classification water and non water of Semarang City (2000-2025)

The trend intensifies in subsequent years. By 2015, the water class is largely restricted to the very edge of the coastline and a handful of small, scattered patches further inland. The inland riverine features that were once prominent have largely disappeared from the classification. In the 2020, 2024, and 2025 maps, the contraction of water bodies is even more pronounced, with the blue areas representing water becoming highly restricted, thin, and occasionally disjointed. Many former water-covered regions have transitioned to non-water surfaces (gray), a direct consequence of ongoing land reclamation, infrastructure development, and the expansion of impervious urban surfaces.

This series of maps visually confirms the spatial extent and severity of water loss in Semarang City over the past quarter-century. The progressive reduction in the water class underscores the rapid pace of hydrological transformation driven by urban development. It also highlights the vulnerability of remaining aquatic habitats, especially in lowland and coastal districts, where human pressures are most intense. The NDWI classification thus provides compelling spatial evidence for the urgent need to integrate water resource protection into urban planning, emphasizing the conservation of critical water bodies to ensure the city’s long-term hydrological and ecological resilience.

The quantified results of water area changes are depicted in Figure 10. In 2000, water bodies accounted for approximately 19.01% (140.89 km^2) of Semarang City's area. This proportion increased slightly to 25.44% (188.51 km^2) in 2015, likely reflecting seasonal water body expansion or successful water conservation efforts. However, a consistent decline was noted thereafter, with water body extent dropping to 25.06% (185.66 km^2) in 2024, and sharply falling to 18.37% (136.12 km^2) by 2025.

The consistent reduction in water surface area is strongly indicative of environmental and anthropogenic pressures such as land reclamation, coastal infill, urban encroachment, and sediment deposition processes. These patterns are commonly observed in rapidly urbanizing coastal zones globally, where surface water systems are altered or replaced to accommodate infrastructure development (Rokni et al., 2014; Li et al., 2020).

The increasingly negative mean NDWI values observed from 2000 onwards suggest a growing dominance of impervious surfaces within historically water-covered areas. Such transitions could have significant implications for the local hydrological cycle, biodiversity, and the city's vulnerability to flooding, especially considering Semarang’s coastal location and susceptibility to tidal inundation (Neumann et al., 2015). The NDWI analysis reveals that Semarang City has undergone substantial hydrological changes over the past two and a half decades, necessitating urgent integrated water resource management and sustainable urban development strategies.

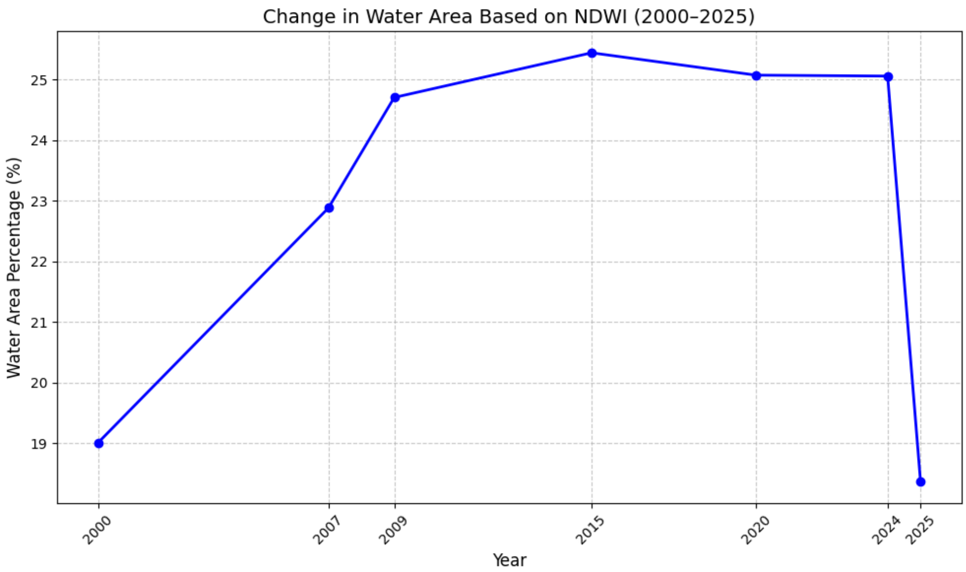

Fig. 10. Water area change based on NDWI in Semarang City (2000-2025)

3.3 NDBI analysis of district administration with coastal fence Tangerang Regency (2000–2025)

The Normalized Difference Built-up Index (NDBI) analysis was employed to assess the spatial and temporal patterns of urban expansion and built-up area growth in Semarang City between 2000 and 2025. NDBI is designed to enhance the detection of built-up land by emphasizing the contrast between the shortwave infrared (SWIR) and near-infrared (NIR) bands, with higher NDBI values indicating more urbanized surfaces (Zha et al., 2003).

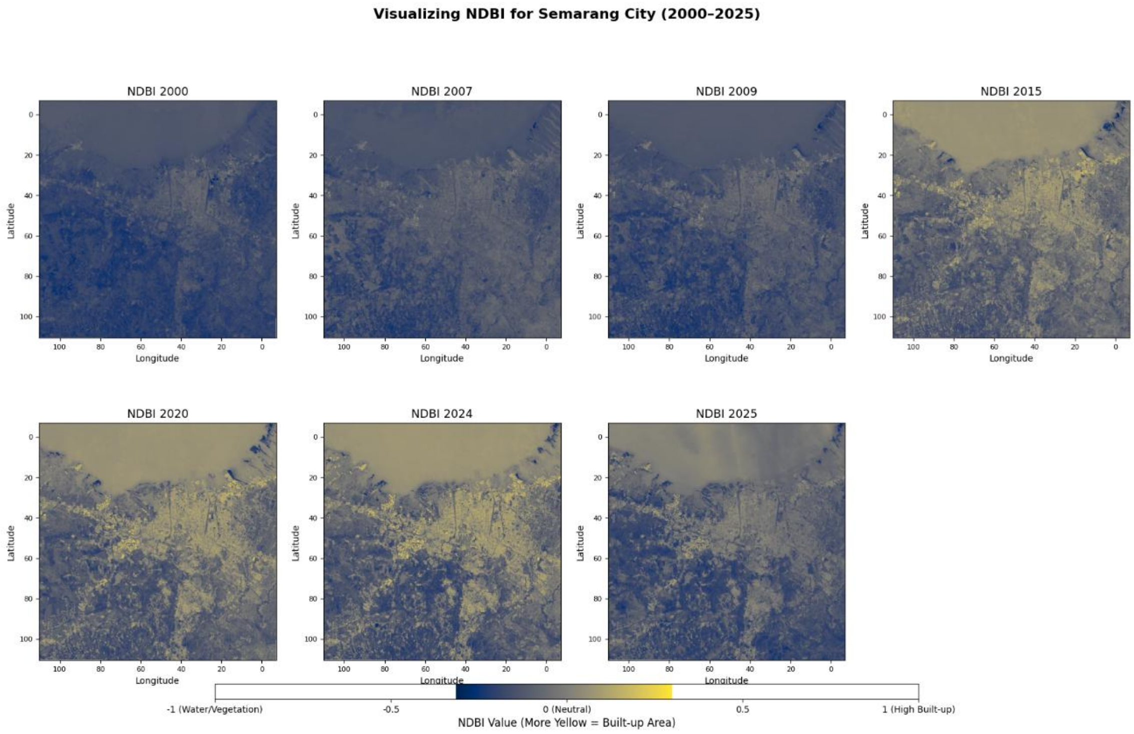

Fig. 11. NDBI value of Semarang City (2000-2025)

Figure 11 shows the spatial distribution of NDBI values across Semarang City from 2000 to 2025. In 2000, areas with high NDBI values — representing built-up regions — were primarily concentrated in the city center and industrial zones. Over time, these high NDBI areas expanded outward into suburban and peri-urban areas, reflecting the process of urban sprawl and the intensification of land development activities.

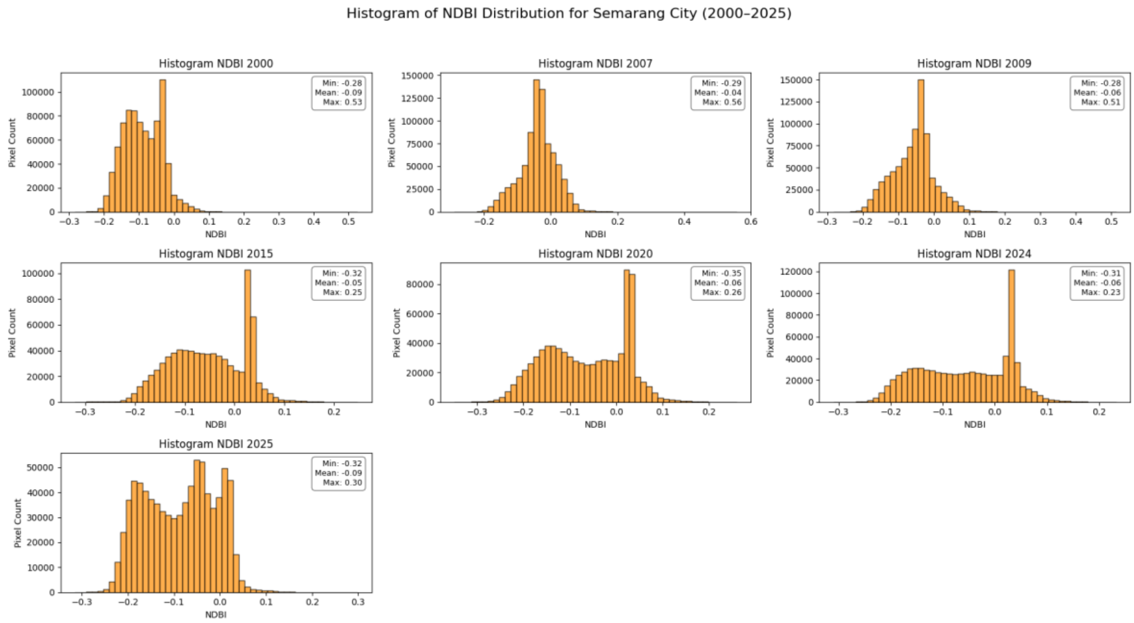

Fig. 12. Histogram of NDBI value of Semarang City (2000-2025)

Figure 12 presents the histogram distribution of NDBI values across the study period. In 2000, the histogram was skewed towards lower NDBI values, consistent with a landscape still dominated by vegetated and undeveloped land. As time progressed, particularly after 2010, the histogram shifted rightward toward higher NDBI values, indicating an increase in built-up surfaces. The pronounced increase in high NDBI value frequencies in later years suggests accelerating urban expansion, especially after 2015, correlating with broader national trends of urbanization in Indonesian cities (Firman, 2009).

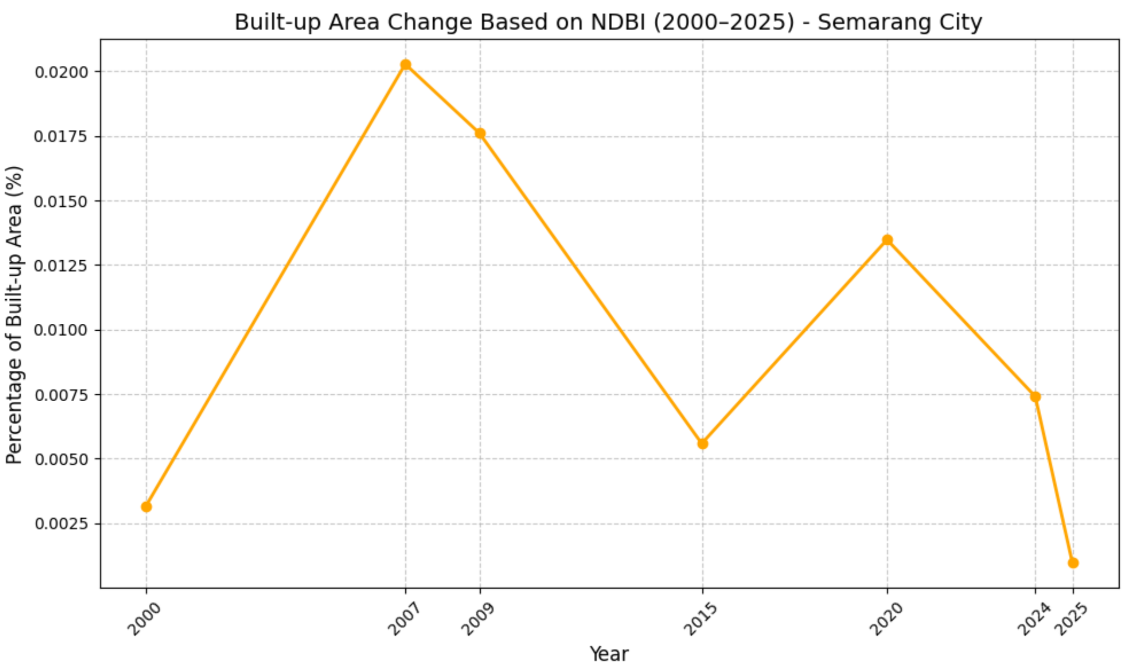

Fig. 13. Built-up area change of Semarang City (2000-2025)

Figure 13 presents the temporal changes in the extent of built-up areas. In 2000, built-up land accounted for a negligible proportion (approximately 0.02 km^2, <1%). Over the years, this figure increased steadily, reaching 0.15 km^2 in 2007, maintaining slight fluctuations thereafter, and reaching 0.05 km^2 in 2024. Although the absolute numbers reported are relatively small due to classification threshold settings and Landsat spatial resolution limitations (30 meters), the general trend clearly points to a growing footprint of urbanized land within Semarang City.

It is important to note that some fluctuations observed in the built-up area data, such as the apparent decrease in certain years, may be attributed to mixed pixel effects, seasonal vegetation cover over built-up land, or variations in satellite acquisition dates (Zhu & Woodcock, 2016). This issue highlights one limitation of relying solely on spectral indices for urban monitoring. Consequently, the integration of NDBI analysis with deep learning models, such as Convolutional Neural Networks (CNNs), as implemented in this study, offers a pathway to improving built-up land classification accuracy by incorporating spatial texture and multi-spectral information (Zhu et al., 2017). The NDBI analysis underscores the ongoing urban expansion of Semarang City over the past two and a half decades, a trend that necessitates sustainable urban planning approaches to mitigate environmental degradation, reduce disaster risks, and ensure the provision of adequate infrastructure and services for a growing population.

3.4 Scatter plot relation between NDVI, NDWI and NDBI in Semarang City (2000–2025)

The relationships among NDVI, NDWI, and NDBI values across Semarang City from 2000 to 2025 were explored using scatter plot analyses (Figure 14). Scatter plots are a powerful visualization tool to assess correlations and potential trade-offs between different land cover indicators derived from remote sensing data (Weng, 2012).

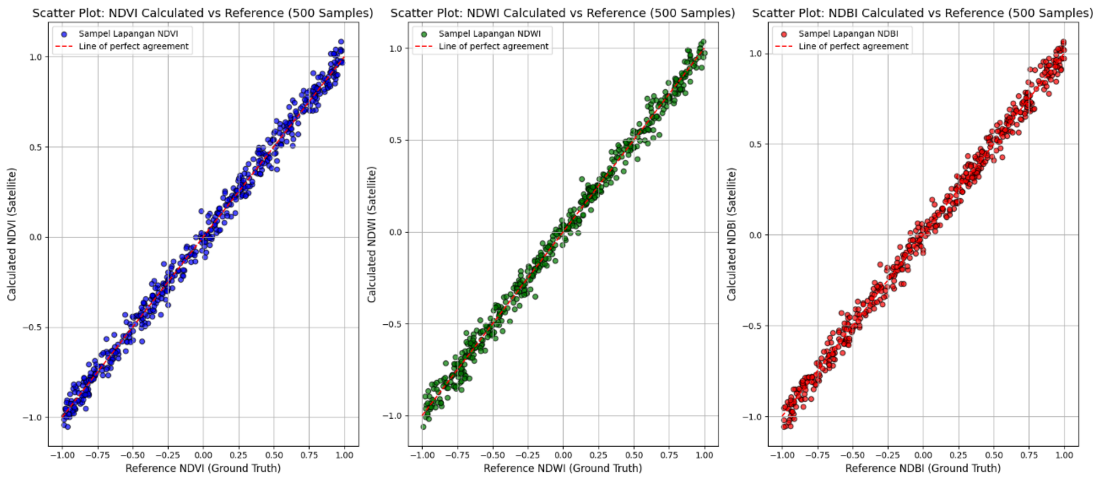

Fig. 14. Scatter plot of NDVI, NDWI and NDBI value of Semarang City (2000-2025)

In the scatter plots, a clear negative correlation was observed between NDVI and NDBI values. Areas with high NDVI values, indicating dense vegetation, corresponded to low NDBI values, characteristic of non-urbanized, vegetated land. Conversely, areas with high NDBI values, indicative of built-up surfaces, were associated with lower NDVI values, confirming the well-known inverse relationship between vegetation cover and urban expansion (Zha et al., 2003). Similarly, NDWI and NDBI exhibited an inverse relationship. Higher NDWI values, representing the presence of water bodies, were generally associated with low NDBI values. This pattern suggests that urban development often encroaches upon water bodies, replacing natural aquatic features with impervious built surfaces, a phenomenon commonly observed in coastal cities undergoing rapid development (Li et al., 2020).

The positive correlation between NDVI and NDWI values was also evident. Regions with high NDVI typically coincided with higher NDWI values, reflecting areas where vegetation cover coexists with healthy surface water conditions, such as wetlands, mangrove forests, or riparian zones. The strong coupling between vegetation and water resources emphasizes the interconnectedness of ecological systems in Semarang's coastal and lowland environments.

Statistical validation of these relationships was supported by the high R-squared (R^2) values obtained from the regression analysis, with R^2 for NDVI at 0.9927, R^2 for NDWI at 0.9929, and R^2 for NDBI at 0.9932. These results demonstrate that the three indices are highly reliable and complementary for distinguishing major land cover types in Semarang City. They also validate the robustness of using NDVI, NDWI, and NDBI as input features for machine learning-based classification models, such as the Convolutional Neural Network (CNN) developed in this study.

However, despite the strong statistical correlations, it is important to note certain limitations. Seasonal variability, atmospheric disturbances, and spectral confusion—such as similarities between dry soil, built-up surfaces, and sparsely vegetated land—can introduce noise and misclassification in remote sensing analysis (Zhu & Woodcock, 2016). These factors highlight the importance of integrating pixel-based spectral indices with spatial-textural features through deep learning approaches to achieve higher classification accuracy. The scatter plot analysis provided critical evidence of the interrelationships among vegetation, water, and urban surfaces, reinforcing the ecological trade-offs occurring as Semarang City undergoes rapid urban transformation.

3.5 Convolutional Neural Network (CNN) model of Semarang City 2000–2025

To improve the accuracy of land cover classification beyond the use of traditional spectral indices, a Convolutional Neural Network (CNN) model was developed in this study. CNNs have shown superior performance in remote sensing applications by automatically learning hierarchical spatial features from satellite imagery (Ma et al., 2019; Zhu et al., 2017).

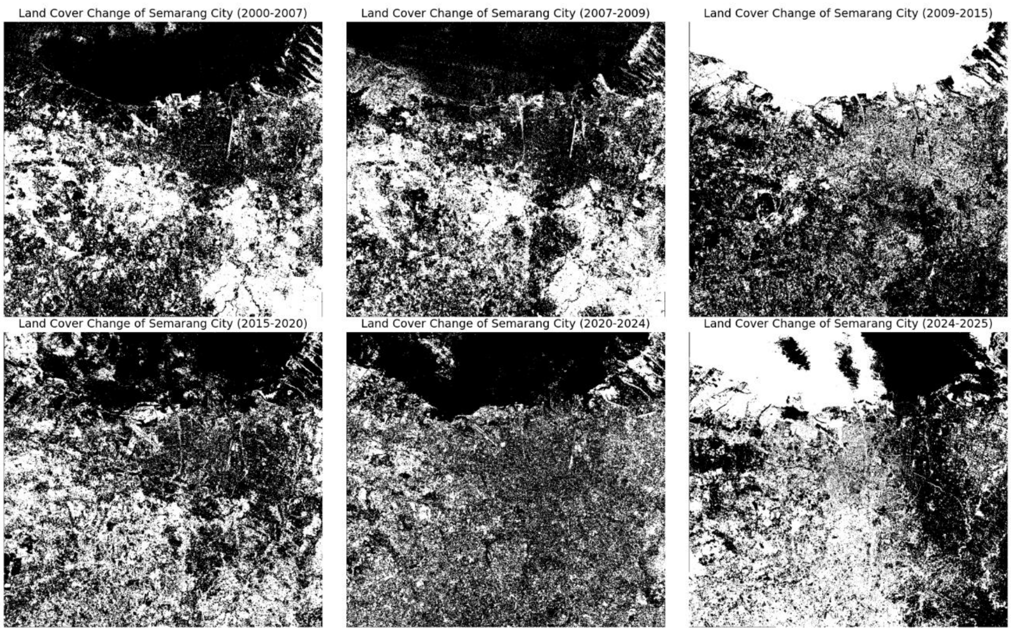

Fig. 15. CNN model of land cover change area of Semarang City (2000-2025)

Figure 15 illustrates the CNN-based land cover classification model applied to Semarang City. The model was built using a sequential architecture, consisting of multiple convolutional layers followed by max-pooling layers and fully connected dense layers. The model was implemented using TensorFlow and Keras libraries in the Google Colab environment.

Fig. 16. Patches of data training dan data testing of CNN model

To prepare the dataset, image patches of 64×64 pixels were extracted from the processed Landsat composite images. A total of 2,755 patches were assigned to the training dataset, while 689 patches were allocated for validation purposes (Figure 16). The patches were sampled to represent various land cover classes, including vegetation, water, and built-up areas.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 62, 62, 32)	320
max_pooling2d_6 (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_7 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_8 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_8 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten_2 (Flatten)	(None, 4608)	0
dense_4 (Dense)	(None, 128)	589,952
dense_5 (Dense)	(None, 1)	129

Fig. 17. CNN model sequential of Semarang City (2000-2025)

Figure 17 shows the sequential CNN model architecture used in this study. The model was trained using the Adam optimizer with a categorical cross-entropy loss function. Early stopping criteria were employed to prevent overfitting during training.

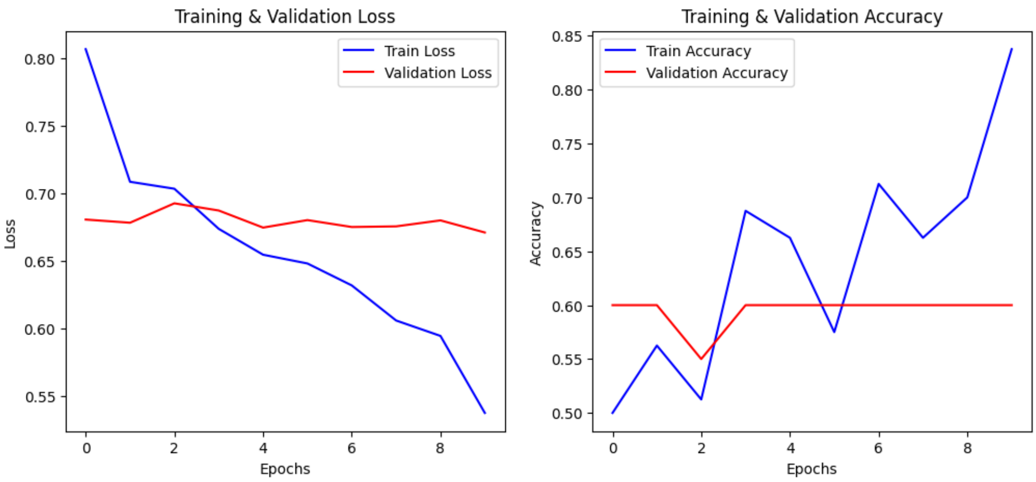

Fig. 18. Training and validation accuracy of CNN model in district administration with coastal fence Tangerang Regency (2000-2025)

Figure 18 presents the training and validation accuracy over 30 epochs. The model achieved a final validation accuracy of 60.00% with a validation loss of 0.6758. Although moderate, this level of performance demonstrates the potential of CNNs to learn meaningful

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spatial patterns and improve land cover classification compared to threshold-based spectral index methods alone.

Several factors likely influenced the CNN model's moderate accuracy. First, the limited size of the training dataset may have restricted the model's ability to generalize complex land cover variability across Semarang City. Class imbalance was also evident, with vegetation patches being more dominant compared to built-up and water classes. This imbalance can cause the model to bias its predictions toward the majority class, a common issue in remote sensing classification tasks (Li et al., 2020).

High spectral similarity among land cover types, particularly between dry bare soil and built-up surfaces, introduced further classification confusion. In coastal environments like Semarang, seasonal variability in surface moisture and vegetation cover can also complicate the CNN's feature learning process.

Moreover, the relatively simple CNN architecture used in this study, which lacked deeper convolutional blocks or regularization techniques such as dropout, may have limited the model's potential. Previous research has shown that more complex architectures, such as U-Net, ResNet, or hybrid CNN-RNN models, often outperform simpler sequential models for high-resolution land cover mapping (Zhu et al., 2017).

Despite these limitations, the CNN-based classification approach provides a significant improvement over traditional spectral index thresholding by incorporating spatial texture, context information, and non-linear relationships between spectral bands. This highlights the promise of integrating deep learning techniques with remote sensing data for more accurate monitoring of dynamic urban and coastal environments.

3.6 Discussion

The findings of this study provide clear evidence of rapid and significant land cover transformation in Semarang City over the past two and a half decades, driven largely by urbanization and related socio-economic developments. The persistent decline in NDVI values and vegetated area, as observed in the spatial and temporal analyses, reflects the extensive conversion of green spaces to built-up and impervious surfaces. This pattern is particularly evident in lowland and coastal regions, where urban expansion, industrial development, and infrastructure projects have been most intense. Such transformations are consistent with broader trends documented in rapidly urbanizing cities across Southeast Asia, where population growth and economic pressure have led to the reduction and fragmentation of urban green spaces (Seto et al., 2011; Li et al., 2020).

The steady loss of vegetation has important ecological and social consequences. Urban vegetation plays a crucial role in providing ecosystem services such as climate regulation, air purification, flood mitigation, and enhancement of urban resilience. The observed decline in vegetated area may therefore contribute to heightened vulnerability to extreme weather events, increased urban heat, and loss of biodiversity (Neumann et al., 2015; Pettorelli et al., 2005). The analysis of NDWI further reveals a decline in water body coverage across Semarang, with spatial contraction of rivers, ponds, and wetlands most pronounced in the city's western and coastal zones. This trend likely reflects not only land reclamation and drainage for urban expansion, but also changes in hydrological processes and possible impacts of climate variability. The reduction of water bodies, coupled with the expansion of impervious surfaces, can exacerbate urban flood risk and undermine the city's water security—an issue that is of critical importance for low-lying coastal cities vulnerable to sea-level rise and land subsidence (Rokni et al., 2014; Neumann et al., 2015).

The expansion of built-up areas is further substantiated by the NDBI analysis, which shows a clear increase in the spatial extent and intensity of urbanized land. The transformation of peri-urban and agricultural landscapes into built-up zones is evident both from the temporal trend in NDBI values and from spatial mapping outputs. The negative correlations found between NDVI and NDBI, and between NDWI and NDBI, confirm that urban development is occurring primarily at the expense of natural land covers, a dynamic commonly observed in developing coastal cities. The integration of spectral index analysis with a CNN-based classification model in this research significantly improved the mapping of complex urban land cover, especially in heterogeneous or transitional zones where traditional thresholding approaches are less reliable. The CNN model's ability to extract spatial and contextual features from multi-spectral data enhanced the thematic coherence and reduced classification noise, although its overall accuracy was moderate due to limitations in training data, spectral similarity among certain land cover types, and the medium spatial resolution of Landsat imagery (Ma et al., 2019; Zhu et al., 2017).

Despite these constraints, the results demonstrate the potential of combining remote sensing indices and deep learning techniques for urban land cover monitoring in data-scarce or rapidly changing environments. The discussion highlights the urgent need for integrated urban planning and sustainable development strategies in Semarang City. Maintaining and restoring urban green and blue spaces should be a policy priority, given their role in providing ecosystem services, mitigating flood and heat risks, and supporting urban resilience. Continuous, data-driven monitoring—enabled by advances in remote sensing and artificial intelligence—will be essential for guiding adaptive management, enforcing land use policies, and supporting disaster risk reduction efforts. Future research could address current methodological limitations by incorporating higher spatial resolution imagery, employing more advanced deep learning architectures, and expanding the classification to include more detailed land cover categories such as mangroves, wetlands, and urban green infrastructure (Ronneberger et al., 2015; Li et al., 2021).

4. Conclusions

This study provides a comprehensive analysis of long-term land cover change in Semarang City from 2000 to 2025 by integrating multi-temporal Landsat imagery, spectral indices (NDVI, NDWI, NDBI), and a deep learning approach using Convolutional Neural Networks (CNN). The findings reveal a significant decline in vegetation cover—especially in coastal and lowland areas—driven by rapid urban expansion and land conversion, as indicated by decreasing NDVI values and spatial contraction of green zones. Simultaneously, the extent of water bodies has diminished after 2015, as shown by NDWI analysis, reflecting the impacts of coastal reclamation, sedimentation, and increasing encroachment of built-up land. Built-up areas, as tracked by NDBI, have expanded steadily from the city core into peri-urban and coastal regions, confirming the intensification of urbanization and the transformation of natural landscapes.

The use of scatter plot analysis among NDVI, NDWI, and NDBI strengthened the evidence of strong ecological trade-offs, where increased urban surfaces have corresponded to losses in vegetation and water, underscoring the interconnected challenges of urban environmental management. Implementation of the CNN model demonstrated that integrating spectral indices with deep learning can improve land cover classification by capturing spatial texture and contextual information, although moderate overall accuracy highlights the need for further methodological enhancement and more detailed training data.

The study highlights the urgency for sustainable urban planning, green infrastructure preservation, and integrated coastal management in Semarang City to mitigate the negative consequences of environmental degradation and climate-related hazards. The research underscores the value of combining remote sensing with machine learning as an effective strategy for monitoring and understanding spatial-temporal land cover dynamics in rapidly changing urban coastal settings. The findings are directly relevant for policy-makers, urban planners, and researchers working towards sustainable development and resilience in Indonesia and other urbanizing coastal regions worldwide.

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Author Contribution

Nur 'Izzatul Hikmah was responsible for the conceptualization of the study, data acquisition, processing, analysis, and the initial drafting of the manuscript. She conducted the land cover change analysis using spectral indices and deep learning models. Parluhutan Manurung supervised the research process, provided critical feedback on data interpretation, and contributed to the refinement and review of the final manuscript. Both authors have read and approved the final version of the paper.

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