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# Study on Built-Up Land Development in the Mebidangro Metropolitan Area

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**Abstract**: Spatial planning serves as an essential regulatory framework for area development, ensuring that growth is managed and controlled. Unplanned expansion of built-up land that strays from the spatial plan can lead to increased urban growth, often referred to as urban sprawl. This study aims to analyze built-up land development over three periods since the establishment of the Mebidangro Spatial Plan, aligning it with the National Strategic Spatial Plan for Metropolitan Mebidangro. Previous research has primarily focused on either image analysis or policy review, while this study integrates both approaches. We address a gap in prior studies that have examined spatial development without connecting it to policy. The research divides the timeframes into three distinct periods: the pre-enactment period, the early enactment period, and the mid-enactment period. This study utilizes spatio-temporal data from Landsat imagery, processes it using Google Earth Engine, and verifies the image data in ArcGIS Pro. The results indicate a significant increase in built-up land from the early enactment to the mid-enactment period, revealing a centroid pattern of development. In terms of spatial planning, the expansion of built-up areas, which increased by 41.55%, aligns with the designated spatial structure of the National Strategic Area (NSA). However, continuous monitoring and periodic reviews are necessary to anticipate potential urban sprawl.

*Keywords: Built-up Land Development, Landsat, Google Earth Engine, Spatial Pattern Plan*

## INTRODUCTION

The expansion of an area visually illustrates regional growth and increasing urbanization trends (Himayah et al., 2023). Satellite imagery and spectral transformation indices, such as the Normalized Difference Built-up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Vegetation Index (NDVI), are commonly used to identify built-up areas. These indices effectively distinguish hard surfaces from vegetation and water bodies (Hidayati et al., 2018; Widiastuti et al., 2025). Previous studies have conducted similar studies (Hidayati et al., 2018; Widiastuti et al., 2025; Zhao et al., 2021), but they tend to focus on optimizing technical extraction algorithms and monitoring physical landscape dynamics without explicitly integrating these findings with regulatory frameworks. Therefore, this study fills this gap by using satellite imagery and linking it to spatial planning. Monitoring spatial changes in built-up areas is crucial for understanding pressures on green open spaces, the conversion of non-built-up regions, and ecological risks such as increased flood potential and environmental damage (Mardalena, 2024; Nugroho et al., 2020). This study uses spatial analysis in the National Strategic Area (NSA) Mebidangro region for the first time. It combines this with a temporally synchronized policy approach to directly evaluate the effectiveness of National Spatial Planning regulations.

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A metropolitan area consists of one central city and several surrounding regions interconnected by function and activity, all characterized by a large population, high density, and a comprehensive infrastructure network (Kusuma, 2019). In Indonesia, the government defines a metropolitan area as an area with at least one million people, consisting of a core city and its surrounding areas that form a single urban system (Pigawati, 2023). This area usually forms as the city expands and merges with neighboring areas, creating a conurbation (Silitonga, 2010). Beyond being residential centers, metropolitan areas are also centers of economic growth and play an essential role in supporting sustainable development (Kusuma, 2019; Suharsih & Winarti, 2021).

The development of built-up land in the Mebidangro Metropolitan Area is a key indicator of urbanization occurring alongside the implementation of regional spatial planning policies. This physical transformation, identified through satellite imagery and spatial analysis, reflects the development direction shaped by government regulations (Ramadhan et al., 2022). These policies are not only top-down but also result from interactions among various stakeholders, including the community and the private sector (Nugroho, 2023; Widodo, 2021). Therefore, monitoring built-up land dynamics plays a crucial role in evaluating the effectiveness of regional development policies. This analysis identifies the policy's impact on spatial change in real time and provides a basis for developing sustainable, adaptive development strategies (Mardalena, 2024; Widiastuti et al., 2025). To identify temporal land development, this study divides the determination period into three distinct stages. The year 2003 serves as the baseline before the enactment of Government Regulation no. 26 of 2008. 2015 marks the initial implementation period following Presidential Regulation No. 62 of 2011. Finally, 2023 marks the middle period, coinciding with Ministry of Agrarian Affairs and Spatial Planning / National Land Agency (ATR/BPN) Decree No. 1085/SK-TR.04.01/VIII/2022, which highlights the need to review the NSA Mebidangro spatial plan.

Previous studies on urban expansion in the Mebidangro National Strategic Area have mainly mapped land growth without linking these changes to the spatial planning policy. This leaves it unclear whether observed development patterns reflect effective policy implementation or a mismatch between land-use regulation and actual growth. Accordingly, this study aims to analyze built-up land development over three periods related to the establishment of the Spatial Plan, aligned with the National Strategic Spatial Plan of Mebidangro Metropolitan Area. This research activity also relates to the determination and revision period of the Regional Spatial Planning document. It highlights the need to revise it so policymakers can use it to evaluate policy implementation.

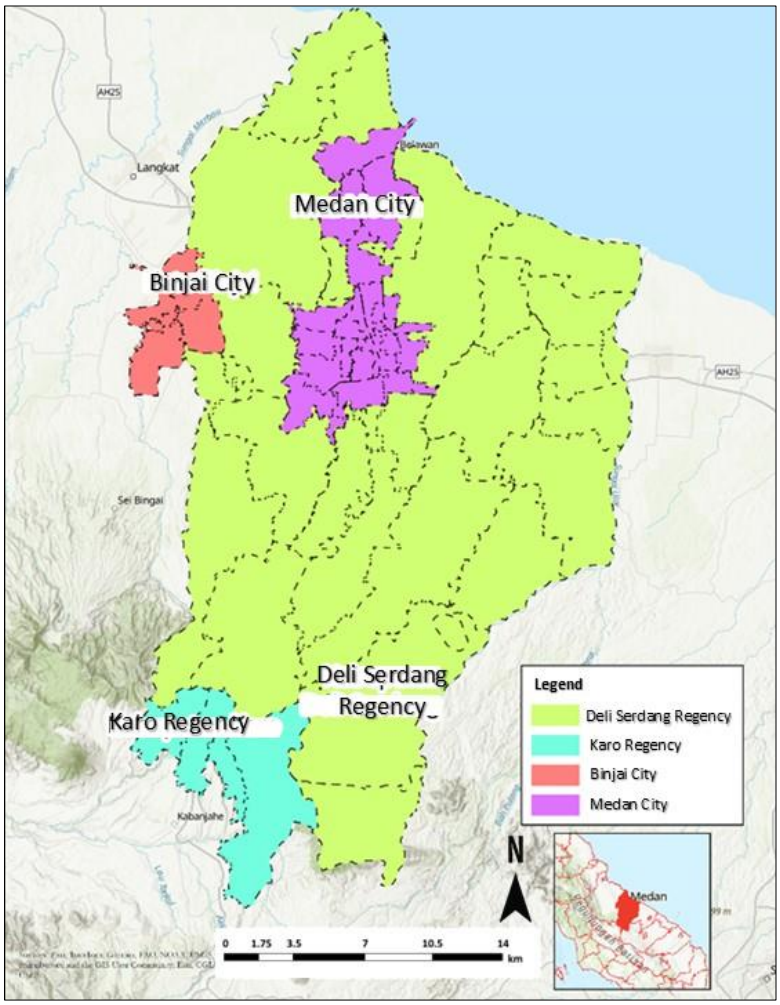
This study contributes by examining built-up land development in the Mebidangro Metropolitan Area and linking land cover changes to the prevailing spatial plan. Previous studies have discussed built-up land extraction and monitored urban development (Hidayati et al., 2018; Ramadhan et al., 2022; Widiastuti et al., 2025). This research builds on those studies by examining built-up land changes in 2003, 2015, and 2023 and comparing the development patterns with the designated spatial plan. To conduct the analysis, this study processes Landsat imagery through Google Earth Engine and performs spatial analysis using ArcGIS Pro. These two methods help identify built-up land development over time and simultaneously assess its alignment with the planned spatial allocation. Ultimately, this study aims to provide insights into current spatial plan implementation and guide future spatial planning in the Mebidangro Metropolitan Area.

## METHOD

### Study Area

The research area is located in the Mebidangro National Strategic Area (NSA), comprising Medan City, Binjai City, Deli Serdang Regency, and Karo Regency, with 52 sub-districts in total.

This NSA is located in North Sumatra Province and aims to develop spatial planning for an urban area, centering sustainable national activities in the northern part of Sumatra Island.




*Source: Analysis, 2025*

**Figure 1. Map of Research Area**

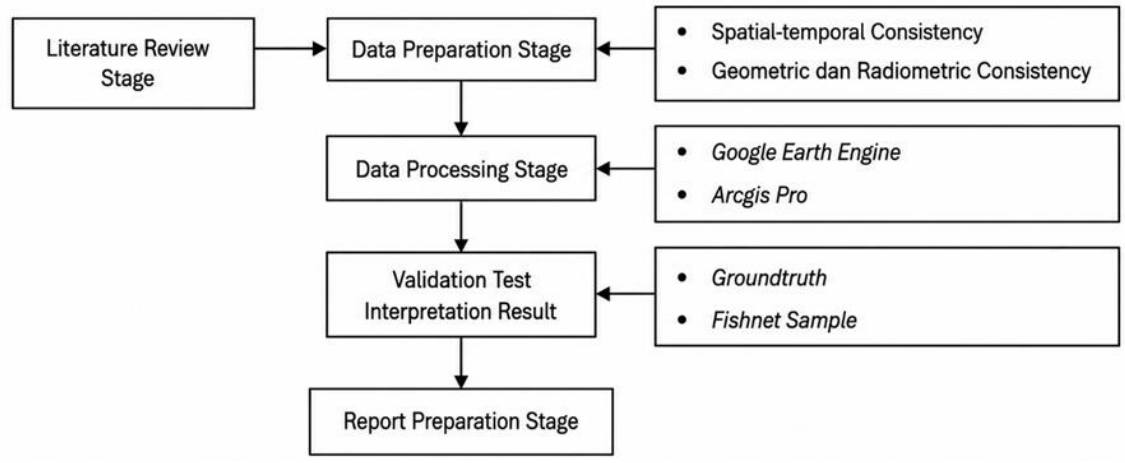
**Research Approach**

This research approach uses quantitative descriptive methods interpreted spatially. Scholars generally describe a literature review as a systematic method for identifying, evaluating, and synthesizing previous research relevant to a study topic. A literature review is generally described as a systematic method for compiling and synthesizing previous research (Snyder, 2019). The data criteria used in the analysis include spatial-temporal consistency, such as resolution, projection, period, and geometric and radiometric consistency (Congalton & Green, 2019).

This study used Landsat 4, Landsat 5, Landsat 7, Landsat 8, and Landsat 9 satellite imagery to ensure consistent temporal coverage from 2003 to 2023. We selected Landsat imagery because it provides the longest continuous record of Earth's surface reflectance at moderate spatial resolution (30 m), which is critical for monitoring multi-decadal urban expansion. We processed this multi-temporal dataset using the GEE cloud computing platform. We selected GEE because it enables rapid processing of large-scale datasets and reduces desktop computing hardware limitations. In addition, GEE supports rigorous pre-processing steps, including cloud masking and radiometric correction, ensuring comparability across years and sensors. Jensen (2009) stated that multi-temporal satellite imagery (Landsat, Sentinel) provides consistent data for secondary land-use change analysis.

We extracted built-up land using a multi-index thresholding approach. Although the Normalized Difference Built-up Index (NDBI) effectively highlights urban features, it often spectrally confuses built-up areas with bare land. To address this limitation, this study integrates the Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Difference Water Index (MNDWI) as masking filters. This combination isolates built-up pixels by systematically excluding vegetation (high NDVI) and water bodies (high MNDWI) from the final classification. Radiometric consistency is further ensured by applying Dark Object Subtraction (DOS) to reduce atmospheric scattering, a crucial step for accurate spectral index calculation in multi-temporal studies. To ensure temporal consistency, we transform raw data into formats ready for analysis in Google Earth Engine and ArcGIS Pro, including radiometric, geometric, and masking corrections for multi-sensor data (Roy et al., 2016). Reinforcing this, Lillesand et al. (2015) added that atmospheric and geometric corrections are critical steps before further analysis.

Validating interpretation results is critical to ensuring the accuracy and reliability of research findings. This stage typically involves field validation (ground truth) using random sampling and secondary data to compare image classification results with actual conditions at the research site (Thenkabail & Prasad, 2015). To validate the classification results, this study used a systematic sampling method using a "Fishnet" grid generated in ArcGIS Pro. We chose the Fishnet technique to ensure a uniform spatial distribution of sample points across the ±316,716.78 hectares study area, thus avoiding the spatial bias often found in simple random sampling. We established 515 validation points, with each grid cell representing approximately 609 hectares. This sample size met the statistical requirements for regional spatial studies and exceeded the minimum threshold of 50–100 points recommended in the remote sensing literature. We verified field data using high-resolution imagery and Google Street View. Finally, we quantified accuracy using a Confusion Matrix and the Kappa Coefficient, standard metrics for measuring agreement between classification results and reference data beyond chance. In addition, statistical tests such as the confusion matrix, overall accuracy, and Kappa coefficient were used to measure agreement between the interpretation results and the reference data (Foody, 2020). The report-writing stage systematically records all research activities clearly and in a structured way. Writing begins with developing a report framework that includes an introduction, methodology, results (main findings in the form of tables, graphs, or maps), discussion (interpretation of the results and comparison with previous studies), and conclusions (Leavy, 2022).




*Source: Analysis, 2025*

**Figure 2. Research Method Diagram**

**Method of Analysis**

This study used a remote sensing-based approach to identify and analyze changes in built-up areas by processing Landsat satellite imagery. Google Earth Engine (GEE) served as the cloud-based platform for satellite image processing, while ArcGIS Pro was used to assess classification accuracy. Landsat imagery from 2003, 2015, and 2023 was used as the primary data source. For 2003, we considered Landsat 4, Landsat 5, and Landsat 7 imagery acquired by the Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors, whereas for 2015 and 2023 we used Landsat 8 and Landsat 9 imagery acquired by the Operational Land Imager (OLI) sensor. We selected satellite imagery based on sensor availability and the need to maintain temporal consistency in surface reflectance observations.

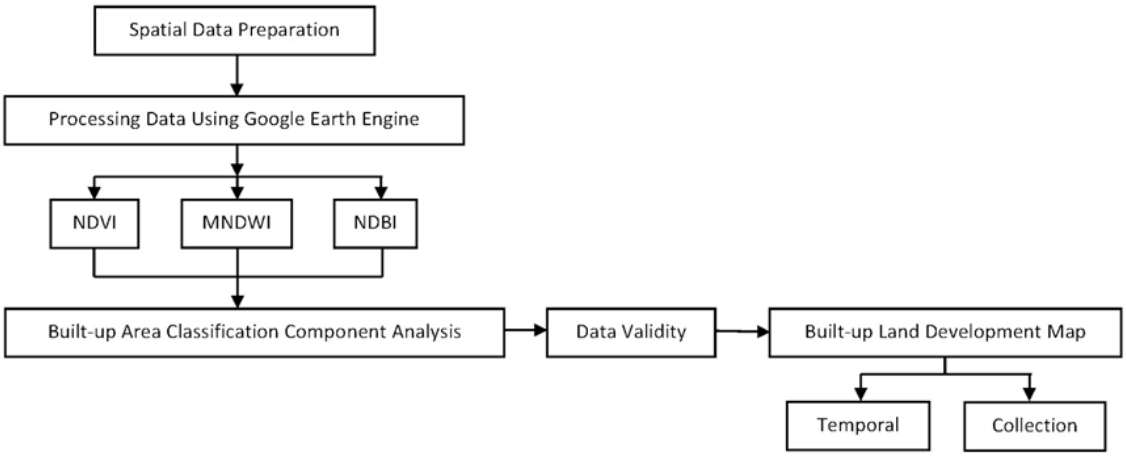
Image pre-processing involved several steps. First, we filtered the imagery to the region of interest and the annual observation period from January 1 to December 31. Second, we performed sensor-specific cloud masking using the QA_PIXEL band to remove cloud-contaminated pixels, cloud shadows, and other flagged pixels. This procedure reduced atmospheric interference and improved the reliability of subsequent land cover classification (Zhu & Woodcock, 2012). Finally, we applied the Dark Object Subtraction (DOS) method for atmospheric correction by estimating atmospheric path radiance from the 1% percentile of pixel values in each band. We then subtracted these values from the corresponding bands to reduce atmospheric scattering and improve surface reflectance representation for land cover mapping (Chander et al., 2009).

After pre-processing, we generated an annual composite image by calculating the median pixel value from all filtered, cloud-masked images acquired within each year. We then used the resulting composite images to calculate three spectral indices to identify built-up areas and distinguish them from vegetation and water bodies. These indices included the Normalized Difference Built-up Index (NDBI) to identify built-up surfaces, the Normalized Difference Vegetation Index (NDVI) to detect vegetation, and the Modified Normalized Difference Water Index (MNDWI) to identify water bodies (Xu, 2008). The indices were derived from near-infrared (NIR), shortwave infrared (SWIR), and other relevant spectral bands, depending on each index's formulation. A validity test was conducted using a systematic rectangular sampling grid created in ArcGIS Pro to evaluate land cover classification accuracy. This grid included 515 sample points, adjusted to the size of the study area. The fishnet provides a systematic framework for evenly distributing validation sample points across the study area.

We created the fishnet in ArcGIS Pro using a reference boundary of ±317,673.64 hectares for the Mebidangro area. Based on standard practices and references in the literature (Foody in Fonte, 2024), the minimum number of validation points is 50–100, with a uniform spatial distribution. However, in this study, the fishnet was designed to achieve optimal accuracy, with 515 sample points and a cell size of ±609 hectares per cell, for a total fishnet coverage area of ±317,673.64 hectares for the study area. Each cell is approximately 2,500 m x 2,500 m, a medium scale suitable for regional spatial studies in metropolitan areas. With this configuration, the fishnet can effectively cover almost the entire study area, with a difference of <1% of the total administrative area, thus remaining methodologically valid. Each fishnet cell is represented by a single central point, whose value is extracted from the land cover classification results. These point data are used to calculate classification accuracy and the Kappa coefficient.

Using the Spatial Join process, the fishnet points are then assigned reference class labels based on the reference land cover data. This method assigns each point a class attribute based on its overlap with the reference polygon layer containing ground truth information. The layer-to-layer method compares the analysis results with the 2023 NSA Mebidangro land use data. The values from the classified raster (in .tif format) are extracted into fishnet points using Extract Multi Values to Points. This process produces additional attributes at the points in the form of the resulting class values. The extraction method uses non-bilinear interpolation (nearest neighbor) because the raster is categorical (discrete classification), so interpolation should not affect the values.

Accuracy testing compares the reference class values and classification results at each point using the Compute Confusion Matrix. This process produces a confusion matrix table containing Producer Accuracy, User Accuracy, Overall Accuracy, and Kappa Value. Various studies recommend that an Overall Accuracy (OA) value of ≥85% is considered acceptable or satisfactory in land cover mapping evaluation, while the optimal Kappa coefficient (κ) value is above 0.70, with a range of 0.70–0.85 indicating substantial to strong agreement (Benkesmia & Bentekhici, 2025). Islami et al. (2022) agree with the quote above, reporting an OA of 85.3% and a Kappa of around 0.80, which they categorize as good and above the minimum threshold. Jasim et al. (2025) strengthened the Random Forest results, producing an OA of up to 93.1% with a Kappa of 0.90, while other methods achieved an OA of 86.2% (Kappa 0.83) and 82.5% (Kappa 0.76). Other studies have lower OA and Kappa results, such as Ursu et al. (2025), which compared four datasets, namely Dynamic World, CLC Backbone, ESRI Land Cover, and HRL, and produced an OA of 0.85% and Kappa of 0.50 for the CLC Backbone dataset, while the other datasets produced an OA of 0.62% - 0.67% and Kappa of 0.49-0.5




*Source: Analysis, 2025*

**Figure 3. Data Processing Stages Diagram**

## RESULT AND DISCUSSION

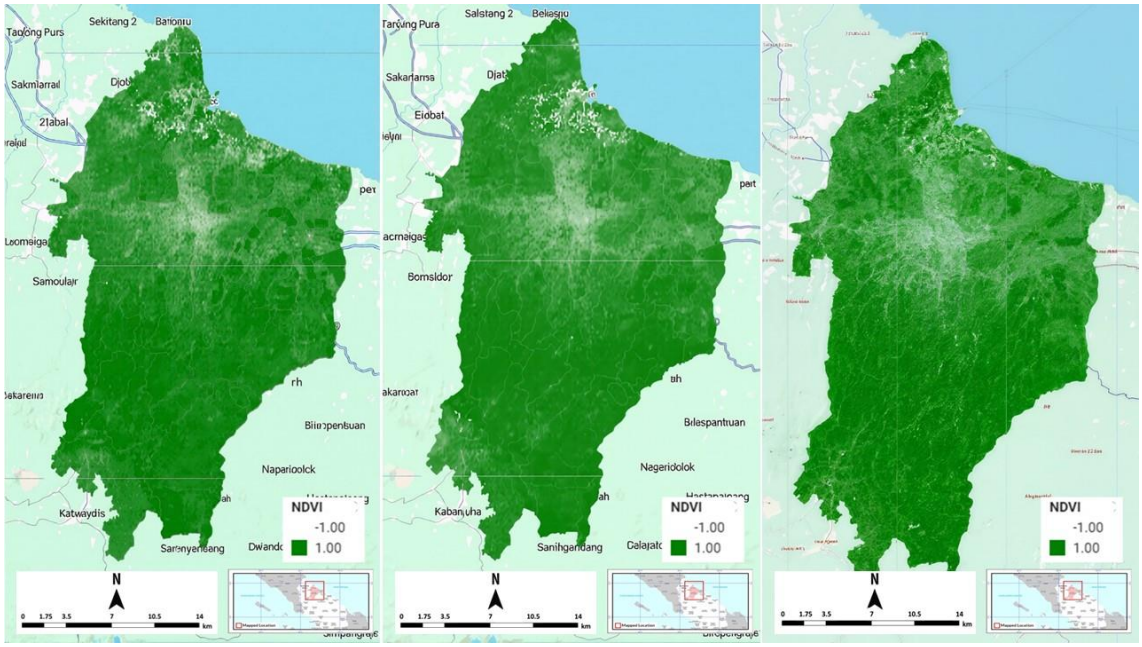
### Spatial Data Preparation

This study analyzed built-up land development through a series of multi-temporal Landsat satellite imagery processing stages. The data used to analyze 2003 and 2005 included Landsat 4, Landsat 5, and Landsat 7; for 2023, Landsat 8 and Landsat 9 images were used. We selected these years based on data availability and key periods of urban development in the study area. Researchers performed image acquisition and pre-processing. Each image was filtered based on the study area boundary, Region of Interest (ROI), and period (all calendar years) to ensure consistent temporal coverage. Radiometric correction was applied to improve analysis accuracy. The Dark Object Subtraction (DOS) method reduced the influence of atmospheric scattering by subtracting the minimum pixel value from each band. The next step was to mask clouds and cloud shadows to minimize interference in the analysis. This process utilizes the QA_PIXEL band with masking criteria tailored to each Landsat series. In Landsat 4-7, we masked clouds, dilated clouds, and cloud shadows. Meanwhile, in Landsat 8-9, we added masking for cirrus clouds to improve accuracy.

### Spatial Data Processing

To identify built-up areas, we calculated three leading spectral indices: NDVI to exclude vegetated areas, NDBI to indicate built-up areas, and MNDWI to distinguish built-up areas from water bodies.

**a. NDVI**

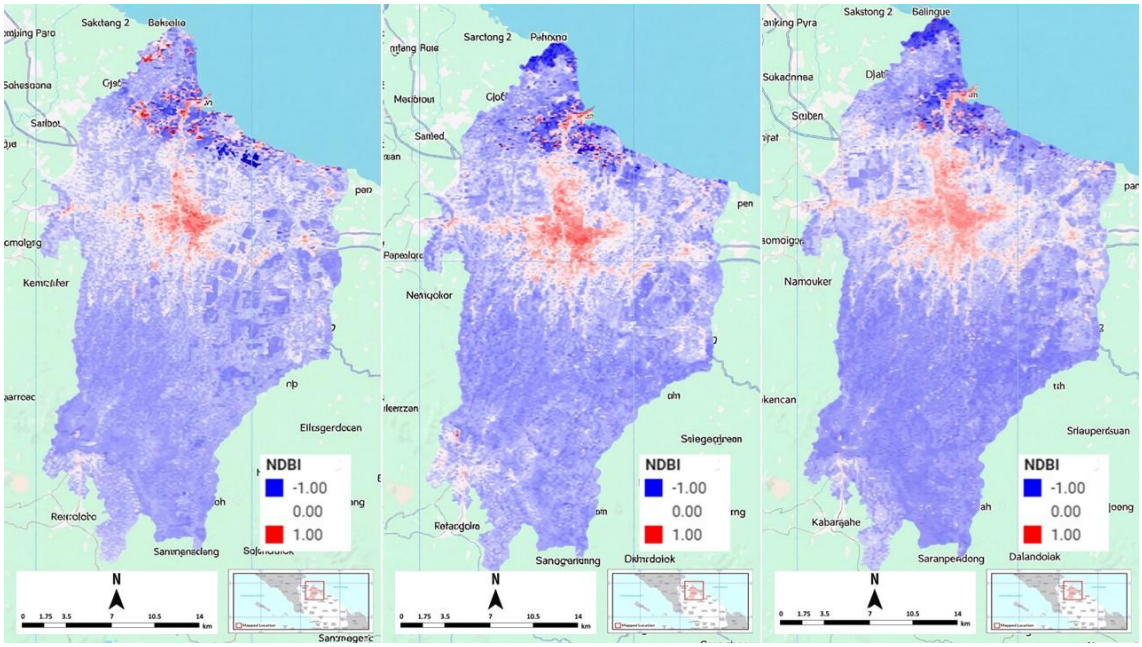



**(a) (b) (c)**

**Figure 4. NDVI of Mebidangro National Strategic Area in (a) 2003; (b) 2015; (c) 2023**

The vegetation index ranges from -1.00 (no vegetation, white) to 1.00 (vegetation, green). The index of -1.00 in the central to northern areas has increased each year. This indicates non-vegetated areas, or in this case, developed built-up areas. The analysis shows that the vegetation area decreased from 285,366 ha in 2003 to 278,243 ha in 202 (Figure 4).

**b. NDBI**



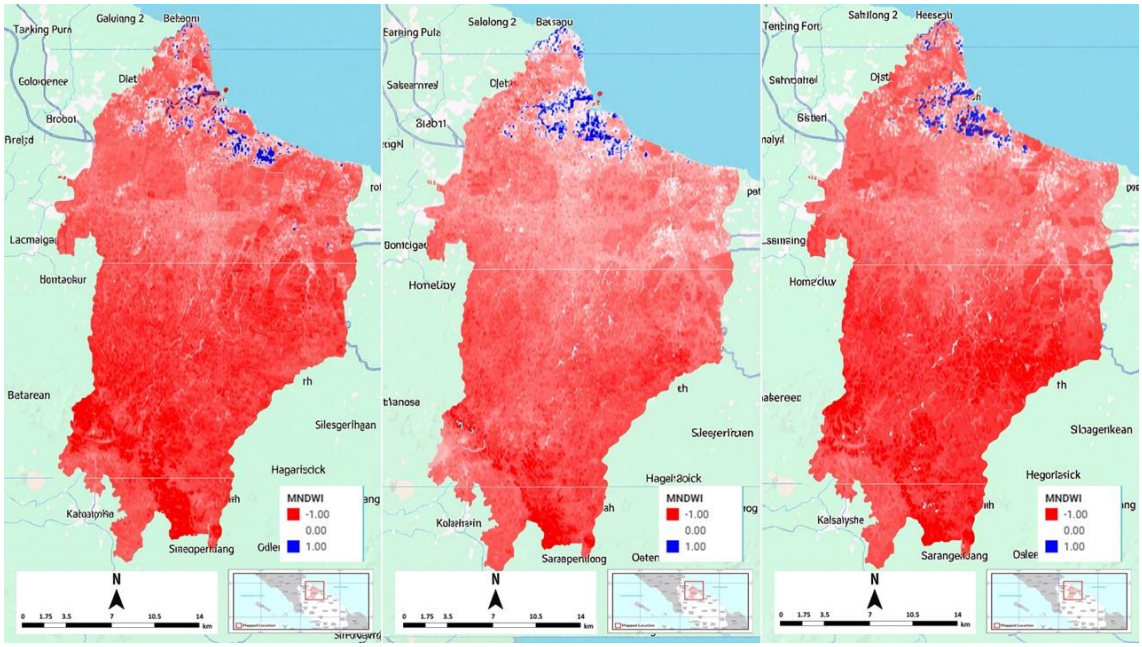

**(a) (b) (c)**

**Figure 5. NDBI of Mebidangro National Strategic Area in (a) 2003; (b) 2015; (c) 2023**

The built-up area index in the red areas (especially in the center and north) indicates a concentration of settlements that increased each year, forming a centroid pattern. The blue

areas dominate the south and west, indicating non-built-up land cover. The analysis shows that the built-up area increased from 21,009 Ha in 2003 to 29,738 ha in 2023 (Figure 5).

**c. MNDWI**




**(a) (b) (c)**

**Figure 6. NDBI of Mebidangro National Strategic Area in (a) 2003; (b) 2015; (c) 2023**

The index uses blue to indicate water areas in the north (near the coast), such as rivers or swamps, while red indicates dominant land and non-water areas. According to the analysis results, the water body area fluctuated from 7,993 ha in 2003 to 11,988 ha in 2015, then decreased to 5,899 ha in 2023 (Figure 6).

The analysis of built-up land development was conducted by comparing the classification results from the three years studied. The built-up land area was calculated in hectares using pixel area and visualized on a map with a different color palette for each period. Furthermore, combining the classification results to observe spatial changes over time created an urban expansion map.

In NDVI analysis, the reduction of approximately 7,123 hectares indicates a significant conversion of green open spaces into impermeable surfaces. The decline in NDVI values strongly correlates with the city's physical expansion, where vegetation is replaced by infrastructure that does not reflect NIR light. This inverse relationship between vegetation and urban expansion aligns with findings by Himayah et al. (2023), who noted that areal expansion visually represents regional growth at the cost of natural land functions. Monitoring this suppression of green space is also critical, as losing green areas increases ecological risks, including potential flooding and environmental degradation (Mardalena, 2024).

Meanwhile, the NDBI analysis shows that the increase of over 8,700 hectares confirms that the Mebidangro area is experiencing physical urbanization. The centroid pattern observed in the NDBI results highlights a specific type of urban sprawl where development densifies from the central city (Medan) and spreads radially outward, rather than developing randomly. This physical transformation reflects development driven by regional spatial planning policies (Ramadhan et al., 2022). The significant expansion in NDBI values confirms the presence of hard surfaces (concrete, asphalt, tiles), clearly distinguishing them from the surrounding rural landscape (Hidayati et al., 2018).

MNDWI is primarily used to identify water bodies; the observed fluctuations—particularly the rise in 2015—may reflect temporal variations during image acquisition, such as differences

in rainfall intensity, tide levels, or seasonal wetland flooding, rather than permanent land-use changes. However, MNDWI remains essential in this study as a masking filter. By accurately delineating water bodies, the method prevents spectral confusion that could otherwise misclassify wet surfaces as built-up land in the NDBI analysis, improving classification accuracy (Hidayati et al., 2018; Widiastuti et al., 2025).

**Spatial Data Validation**

The spatial data validation stage uses the fishnet method and several geotagging points taken through Google Earth Pro using the street view feature as a sampling medium. Researchers conducted four iterations to obtain the number of samples with optimal accuracy test results. Each cell is represented by a central point, and its value is extracted from land cover classification results and existing land use data as ground truth, then used to calculate accuracy and the Kappa coefficient in the Confusion Matrix test (Table 1).

**Table 1. Confusion Matrix Test Result**

| ClassValue | C_1 | C_2 | Total | U_Accuracy | *Kappa* |
|---|---|---|---|---|---|
| C_1 | 442 | 42 | 464 | 0.909483 | 0 |
| C_2 | 7 | 44 | 51 | 0.862745 | 0 |
| Total | 429 | 86 | 515 | 0 | 0 |
| P_Accuracy | 0.983683 | 0.511628 | 0 | 0.904854 | 0 |
| *Kappa* | 0 | 0 | 0 | 0 | 0.591554 |

*Source: Analysis, 2025*

The results show an accuracy of 90.49% and a Kappa of 0.59, categorized as Moderate according to Cohen's interpretation. We observed a clear Accuracy Paradox in our results. This happens because Class C_1 dominates approximately 84% of the region, leading to severe omission errors. The Kappa Index exposes this weakness, as it evaluates true performance across classes and actively penalizes the model for relying on chance agreement. Although several previous studies report similar figures, these test results are still worth using. Some studies report similar results; for example, Ursu et al. (2025) examined four satellite image datasets and reported OA of 0.85% and Kappa of 0.50 for the CLC Backbone dataset. Although the datasets differ, this dataset's accuracy results most closely match this study's test results.

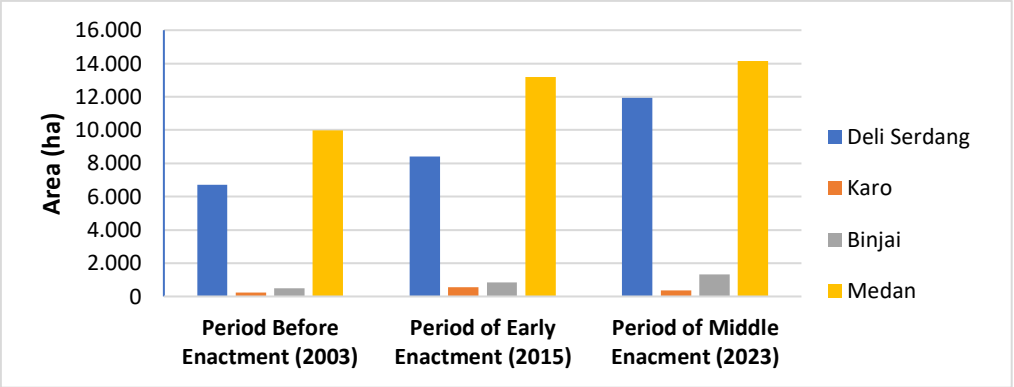
**Interpretation of Land Development Spatial Data**

Land development interpretation results using Landsat imagery show significant development from 2003 to 2023 (Table 2, Figure 7, Figure 8). In 2003, built-up land was concentrated in the city center and major settlements with a compact development pattern. Classification results show built-up areas spreading centrifugally from the city center. By 2015, built-up land expanded, with growth toward the suburbs and the emergence of a linear urban growth pattern following the road network.

**Table 2. Development of Built-Up Land Area**

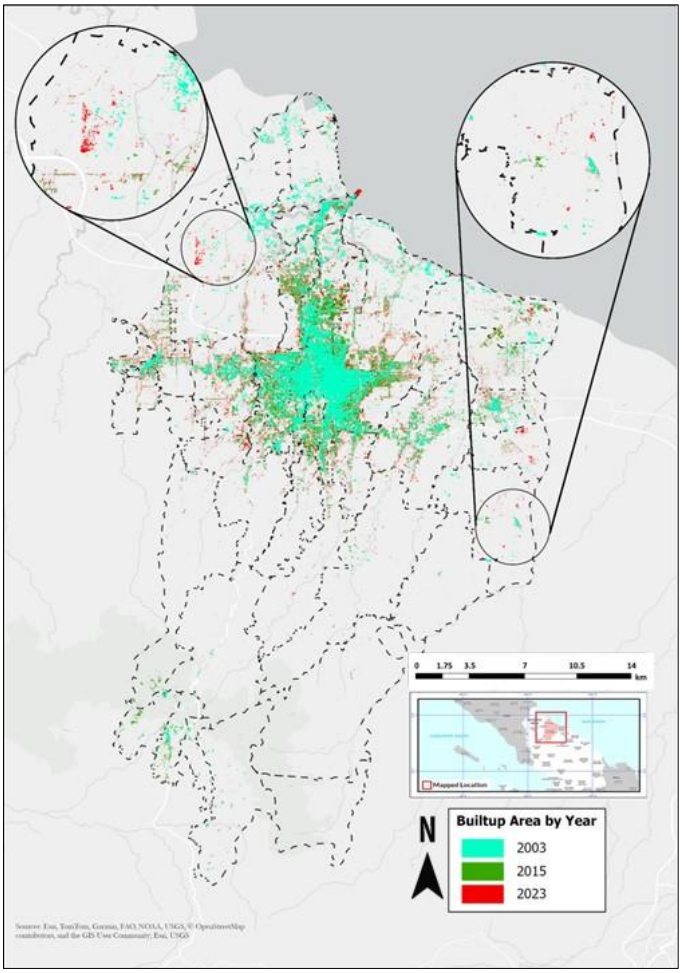
| City/Regency | Period Before Enactment | Period of Early Enactment | Period of Middle Enactment |
|---|---|---|---|
| | **Years 2003 (ha)** | **Years 2015 (ha)** | **Years 2023 (ha)** |
| Deli Serdang Regency | 6,700.00 | 8,422.00 | 11,940.00 |
| Karo Regency | 251.00 | 548.00 | 378.00 |
| Binjai City | 479.00 | 841.00 | 1,319.00 |
| Medan City | 9,981.00 | 13,199.00 | 14,159.00 |
| **Total** | **17,411.00** | **23,010.00** | **27,796.00** |

*Source: Analysis, 2025*




*Source: Analysis, 2025*

**Figure 7. Built-Up Land Development Area in Mebidangro Chart**

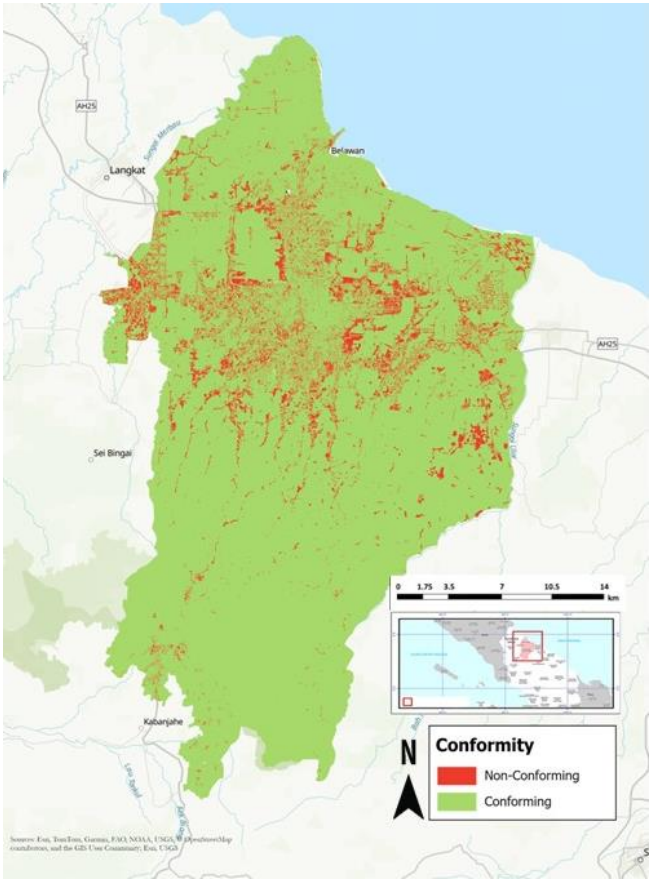



*Source: Analysis, 2025*

**Figure 8. Built-Up Land Development Map of Mebidangro National Strategic Area**

Urban sprawl is the uncontrolled, unstructured, and seemingly random expansion of built-up land in suburban areas. Unchecked population growth drives this (Ansar & De Vries, 2024). Key characteristics of urban sprawl include chaotic development, land development that follows the road network, extensive land-use changes, and traffic jams on city outskirts (Ansar & De Vries, 2024; Fatimah & Anwar, 2023). This development requires government attention to prevent uncontrolled built-up land development. Building on this, Setyono et al. (2017) explained that urban spatial planning in Indonesia focuses more on spatial planning, while city management receives less attention.

Mebidangro National Strategic Area experienced urban growth concentrated along its road network of 41.55%. This type of growth pattern occurs frequently in large cities in the world, such as in Chengdu, where a significant correlation was found between city expansion and road networks, with an urban/non-urban classification accuracy of 79% (Xianyuan & V, 2019), and Jakarta is experiencing toll road expansion, triggering sporadic urban sprawl within a 40–50 km radius of the city's center. Sprawl occurs along major road corridors, indicating that the road network structure significantly determines the city's growth patterns (Pratama et al., 2022). Before the designation, built-up land characteristics tended to be centered in Medan City and slightly to the north. However, after NSA Mebidangro was established, built-up land characteristics changed, following the road network and spreading in a centroid pattern. Based on the image-processing results, development after the designation followed the Residential Regulation No. 62 of 2011. This analysis is based on the distribution of built-up land, which is still in line with the applicable spatial pattern plan.




*Source: Analysis, 2025*

**Figure 9. Conformity in Mebidangro**

We use conformity analysis to align land-cover classifications from Landsat Collection imagery with spatial pattern plans. By overlaying observational data, the analysis categorizes into two distinct classifications. The quantitative data show that the vast majority of the study area adheres to the established spatial plans, with conforming zones accounting for 90.80% of the total mapped region (288,392.35 ha). However, a closer examination highlights important spatial deviations, with non-conforming areas accounting for 9.20%, which translates to 29,220.66 hectares. These non-conforming zones are not distributed uniformly. These red-colored zones indicate potential urban sprawl or agricultural encroachment that diverges from planned boundaries (Figure 9).

The observed built-up land in the Mebidangro National Strategic Area aligns with urban sprawl theories, which suggest physical expansion often relies heavily on transportation infrastructure. Previous research by Pratama et al. (2022) in the Jakarta Metropolitan Area and Xianyuan (2019) in Chengdu supports this finding, showing that road network structures strongly shape sporadic urban growth and sprawl patterns. Moreover, as Ansar & De Vries (2024) and Fatimah & Anwar (2023) define them, this ribbon-like development and centroid spread are classic symptoms of suburban sprawl that, if not properly managed, risk triggering extensive land-use conversion and uncontrolled growth on the city's urban fringe.

From a policy perspective, the 90.80% spatial plan conformity shows that regional development in Mebidangro largely reflects intended top-down regulatory frameworks, supporting Ramadhan et al.'s (2022) assertion that physical transformations mirror top-down spatial planning. However, the 9.20% non-conforming area highlights a critical gap between spatial planning and actual city management, a challenge previously identified by Setyono et al. (2017) in the Indonesian urban context. The continuous vegetation loss shown in the NDVI analysis further supports Himayah et al. (2023) and Mardalena (2024), who emphasize that while areal expansion signifies regional growth, it inherently increases ecological risks by sacrificing natural open spaces and escalating the potential for environmental degradation.

## CONCLUSION

NSA is entering the middle period of its establishment since the ratification of the Presidential Regulation no. 62 of 2011. The analysis results show that built-up land in this area expanded significantly, with a pattern initially centered around Medan City in 2003, then developing centroidally in 2015 and 2023. The development of the urban regions with a planned polycentric pattern cannot yet be implemented because there is no plan for an integrated public transportation network system, so the tendency for landed land development will become a trend for the next few years, and it is feared that the conurbation phenomenon will develop as the years go by. The early to mid-period of the determination showed the highest level of development. Therefore, spatial planning, especially Presidential Regulation No. 62 of 2011 on Spatial Planning, has proven effective in developing built-up land in the area. The development of built-up land does not violate spatial utilization regulations; rather, it reflects the efficient use of land, particularly the conversion of agricultural land into built-up land. Despite this, monitoring and review are needed to anticipate the spread of urban sprawl in the northern and western parts of the NSA to ensure more equitable growth in the Mebidangro Urban Area, particularly in the central and southern parts of the NSA. A limitation of this study is that accuracy testing used image-processing and land-use data from the Ministry of ATR/BPN, so researchers could improve accuracy by collecting field data directly. In the future, it is hoped that research like this can go directly to the field to collect samples of land-cover changes so accuracy can be improved.

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## AUTHOR CONTRIBUTIONS

M.F.R. was responsible for the overall manuscript preparation, GEE script creation, data processing, data analysis, and manuscript editing. D.A.R. contributed to data curation, the literature review, the creation of visual aids such as diagrams and tables, GEE script creation, and the drafting of the initial manuscript. N.D.A.P. contributed to data collection and curation,

the literature review, and manuscript editing. A.B.R. contributed to the development of the research concept, supervision, and validation.

## CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest, whether financial or personal, that could have influenced the research, its findings, or the preparation and publication of this manuscript.

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