Semi-Unsupervised Threshold-Based and Jenks Optimization Classification for Analyzing Urban Expansion in BSD City Using Multi-Temporal Landsat Data

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A B S T R A K

Penelitian ini menganalisis perubahan tutupan lahan di BSD City dari tahun 2002 hingga 2023 menggunakan metode Semi-Unsupervised Threshold-Based and Jenks Optimization Classification (SUT-JOC). Lima kelas tutupan lahan dipetakan untuk tahun 2002, 2013, dan 2023, yaitu kawasan terbangun, tanah terbuka, vegetasi lebat, vegetasi rendah, dan tubuh air. Hasil penelitian menunjukkan ekspansi kawasan terbangun yang signifikan dari tahun 2002 hingga 2023, di mana luas kawasan terbangun meningkat dari 2.202 hektar menjadi 4.498 hektar. Transisi tutupan lahan mengikuti pola yang jelas, dari vegetasi menjadi tanah terbuka, lalu berubah menjadi kawasan terbangun, dengan arah pembangunan bergeser dari timur ke barat. Akurasi klasifikasi berkisar antara 88% pada tahun 2002 hingga 96% pada tahun 2023, dengan nilai Kappa mendekati 0,95. Integrasi NDVI, MNDWI, dan NDBI dengan klasifikasi berbasis aturan mampu mengurangi intervensi manual dan meningkatkan keandalan. Temuan ini menyoroti dinamika pertumbuhan peri-urban, dampak lingkungan seperti efek pulau panas perkotaan, serta memberikan wawasan penting bagi perencanaan kota berkelanjutan. Metode SUT-JOC bersifat skalabel dan mudah diinterpretasikan.

Keywords:
Land Cover Change
Urban Expansion
SUT-JOC Classification
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A B S T R A C T

This study analyzes land cover changes in BSD City from 2002 to 2023 using the Semi-Unsupervised Threshold-Based and Jenks Optimization Classification (SUT-JOC) method. Five land cover types were mapped for 2002, 2013, and 2023: built-up area, bare soil, vegetated area, sparsely vegetated area, and water bodies. The results show significant urban expansion from 2002 to 2023, with built-up areas increasing from 2,202 hectares to 4,498 hectares. Land transitions followed a clear pattern, starting from vegetated areas to bare soil, then to built-up land, with spatial development shifting from east to west. Classification accuracy ranged from 88% in 2002 to 96% in 2023, with Kappa values approaching 0.95. The integration of NDVI, MNDWI, and NDBI with rule-based classification reduced manual intervention and improved reliability. These findings highlight the dynamics of peri-urban growth, environmental impacts such as urban heat island effects, and offer insights for sustainable urban planning. SUT-JOC provides a scalable and interpretable framework for multi-temporal urban land monitoring.

Introduction

Urbanization is a dominant driver of land transformation in the 21st century, reshaping landscapes, altering ecological systems, and redefining global spatial planning paradigms (Barau & Ludin, 2012; Gao & O'Neill, 2020; Nickayin, 2022). As of the early 2020s, more than 56 percent of the global population resides in urban areas (Gu, Andreev, & Dupre, 2021), projected to rise steadily in the coming decades. Southeast Asia has emerged as one of the most dynamic regions of urban expansion, characterized by rapid socio-economic development and significant land conversion (Das & Paul, 2021). In Indonesia, urban growth is most concentrated in Greater Jakarta (Jabodetabek), where rapid expansion continues to transform surrounding peri-urban landscapes (Firmansyah, Jatayu, & Imaduddin, 2024; Kurnia et al., 2022). These spatial transitions bring opportunities and challenges in managing land resources, mitigating environmental degradation, and promoting sustainable urban development.

One notable example of urban transformation in Indonesia is Bumi Serpong Damai (BSD City), a large-scale planned satellite city within Jabodetabek (Arifai & Arsyad, 2025; Risdollah, Mustafa, Mega, & Putri, 2025). Over the past two decades, BSD City has transitioned from predominantly rural and vegetated landscapes into a dense urban complex encompassing residential, commercial, and industrial zones (Arifai & Arsyad, 2025). BSD City, mainly driven by private investment, offers a clear example of how urban development unfolds in rapidly growing economies. Its well-organized spatial layout, combined with the availability of detailed satellite data, provides valuable opportunities to study changes in urban land use using geospatial methods.

Remote sensing has emerged as a powerful tool for monitoring land use and land cover (LULC) changes over large spatial extents and long timeframes (Mashala, Dube, Mudereri, Ayisi, & Ramudzuli, 2023). Satellite imagery, particularly from the Landsat program, offers a valuable and consistent record for observing temporal transformations in urban environments. Advances in classification methodologies have further enhanced the utility of remote sensing with machine learning and deep learning algorithms such as Support Vector Machines (Fragou et al., 2020), Random Forest (Amini, Saber, Rabiei-Dastjerdi, & Homayouni, 2022), and Convolutional Neural Networks (Barau & Ludin, 2012; Gao & O'Neill, 2020; Nickayin, 2022) demonstrating strong performance in LULC mapping tasks. However, the operational deployment of these algorithms often entails substantial challenges. These include the need for extensive labeled training data, high computational requirements, complex parameter tuning, and potential issues with interpretability. These constraints can limit the practical application of advanced classification techniques, particularly in settings with limited technical capacity or infrastructure.

Recognizing this methodological gap, this study proposes a novel yet practical approach for land cover classification: the Semi-Unsupervised Threshold-Based and Jenks Optimization Classification (SUT-JOC) framework. This method integrates remote sensing spectral indices with statistical classification, leveraging the strengths of both spectral thresholding and Jenks Natural Breaks Optimization. The SUT-JOC approach efficiently identifies key land cover classes, including water bodies, dense vegetation, sparse vegetation, bare soil, and built-up areas. It requires minimal manual labeling and is computationally lightweight, making it especially useful for applications with limited time, expertise, or computing resources. Unlike many black-box machine learning models, SUT-JOC remains transparent and interpretable, with classification boundaries defined by spectral logic and statistical separation rather than opaque learned parameters.

The core objective of this research is to evaluate the spatio-temporal dynamics of urban expansion in BSD City using a robust and replicable remote sensing framework. To achieve this, the study utilizes multi-temporal Landsat satellite imagery from 2002, 2013, and 2023, all processed on the cloud-based Google Earth Engine (GEE) platform. The specific goals of this research are threefold: (1) to develop and validate a semi-automated land cover classification methodology based on spectral index thresholding and statistical optimization, (2) to assess the effectiveness of the Jenks algorithm in enhancing land cover separability and classification accuracy, and (3) to conduct a detailed spatial analysis of urban growth patterns over 21 years within the study area.

The expected contributions of this study are both methodological and practical. From a methodological standpoint, it offers a replicable and scalable approach to land cover classification that bridges the gap between manual techniques and computationally intensive machine learning models. From a practical standpoint, it provides critical insights into urban expansion patterns and intensity in one of Indonesia's most strategically important urban growth zones. These findings directly affect urban planning, environmental monitoring, and land resource management. Researchers can also apply the proposed approach in other rapidly urbanizing regions where high-frequency land monitoring is essential, but analytical resources remain limited. In a broader context, this study aligns with global sustainability frameworks such as the United Nations Sustainable Development Goals (SDGs), particularly Goal 11 on Sustainable Cities and Communities, by contributing tools and knowledge for more informed urban decision-making.

Methods

To assess the dynamics of urban expansion in BSD City, this study employed the SUT-JOC method using multi-temporal Landsat imagery for 2002, 2013, and 2023. The methodology integrated spectral index analysis with an automated thresholding approach based on Jenks Natural Breaks Optimization. This hybrid method classifies five dominant land cover categories, including water bodies, vegetated areas, sparsely vegetated areas, bare soil, and built-up areas, while minimizing reliance on manually labeled training data. The semi-unsupervised nature of the approach strikes a balance between interpretability and computational efficiency, providing a replicable model for land cover analysis in rapidly urbanizing regions.

Landsat data were sourced from the United States Geological Survey (USGS), specifically utilizing Landsat 5 Thematic Mapper (TM) for the year 2002 and Landsat 8 Operational Land Imager (OLI) for the years 2013 and 2023. This study processed all imagery within the GEE platform to facilitate efficient data handling and ensure methodological consistency across temporal datasets. Preprocessing included using surface reflectance products available via GEE for both TM and OLI data, along with cloud and shadow masking based on the FMask algorithm. The workflow continued by clipping the imagery to the administrative boundary of BSD City and resampling all datasets to a uniform 30-meter resolution for pixel-level analysis.

To enhance land cover class separability, three spectral indices were computed from each Landsat scene: the Normalized Difference Vegetation Index (NDVI) (Rouse, Haas, Schell, Deering, & Harlan, 1974), the Modified Normalized Difference Water Index (MNDWI) (Hanqiu Xu, 2006), and the Normalized Difference Built-up Index (NDBI) (Yong Zha, Gao Jay, & Shaoxiang Ni, 2003). NDVI was used to delineate vegetated and sparsely vegetated areas, while MNDWI was applied to identify surface water bodies. Built-up areas and bare soils were distinguished using NDBI due to their sensitivity to impervious surfaces and exposed soil. Each index was calculated using standard band combinations and mathematical formulations, with all indices normalized and exported for further analysis.

The core of the SUT-JOC framework lies in its thresholding mechanism, which applies the Jenks Natural Breaks Optimization algorithm to each spectral index. This statistical method partitions continuous index values into discrete, non-overlapping ranges that minimize within-class variance and maximize between-class variance. Doing so yields optimal threshold values corresponding to meaningful land cover categories without requiring manual labeling or subjective thresholding. For instance, NDVI values greater than 0.036 in 2002 were classified as vegetated areas, while values above 0.227 for MNDWI indicated water bodies. Similarly, NDBI thresholds such as 0.097 to 0.171 captured built-up areas, and values above 0.171 identified bare soil. Pixels that did not meet any of these thresholds but still exhibited low to intermediate NDVI values were assigned to the sparsely vegetated category.

Each classification was implemented using hierarchical decision-tree logic to ensure mutual exclusivity across land cover classes. Water bodies were extracted first using MNDWI thresholds, followed by vegetated areas based on upper NDVI breaks. Built-up areas and bare soils were derived from distinct threshold ranges within the NDBI index. In contrast, sparsely vegetated areas were assigned to pixels falling between vegetation and bare soil thresholds. Using Jenks-derived cutoffs for each year enabled adaptive thresholding that accounts for temporal variability in atmospheric and surface conditions, ensuring consistent classification performance across different epochs.

A stratified random sampling approach was employed to validate the accuracy of the resulting land cover classifications. Following recommendations from Russell G. Congalton and Kass Green (2019), 250 validation points were used for 2002 and 2013 and 375 points for 2023, reflecting the increasing spatial complexity of land cover in recent years. Sample points were distributed proportionally across all land cover classes to ensure representativeness. High-resolution imagery from Google Earth was used as the reference data for ground-truth validation. Standard accuracy metrics, including Producer's Accuracy (PA), User's Accuracy (UA), Overall Accuracy (OA), and the Kappa coefficient, were calculated based on confusion matrices constructed for each year to evaluate the reliability and consistency of the land cover classifications.

Through this semi-unsupervised approach, the study offers a computationally efficient yet statistically grounded methodology for land cover classification using freely available satellite data. The method balances automation and interpretability by leveraging index-based spectral features and Jenks optimization, making it suitable for large-scale and longitudinal urban studies in data-scarce regions

Results

Figure 1 presents the classified land cover maps of BSD City for 2002, 2013, and 2023, generated using the SUT-JOC method. The classification distinguishes five primary land cover types: built-up area, bare soil, vegetated area, sparsely vegetated area, and water bodies. These maps offer a spatiotemporal overview of land cover changes over two decades, highlighting patterns of urban expansion and transitional land dynamics.

In 2002 (Figure 1a), BSD City was characterized mainly by vegetated areas and bare soil, reflecting a semi-rural landscape in the early stages of development. Built-up areas were relatively limited, occupying approximately 2,202 hectares (around 29% of the total area), mainly in the northern and western regions. Bare soil was prominently located in the eastern part, indicating initial construction activity. By 2013, much of this eastern bare soil had been converted into built-up areas, while a significant portion of the vegetated and sparsely vegetated zones had transitioned into new areas of bare soil, particularly in the central part of the city.

In 2013 (Figure 1b), built-up areas expanded considerably, covering around 3,029 hectares (approximately 40% of the total area). This expansion coincided with a decline in vegetated cover, especially in the central and northeastern zones. At the same time, the spatial distribution of bare soil shifted from the east to the central region, primarily resulting from the conversion of green cover into cleared land for ongoing development. These central bare soil patches would later serve as the foundation for continued urban growth, as seen in the 2023 map.

The 2023 land cover map (Figure 1c) shows a continued surge in urbanization, with built-up areas increasing to approximately 4,498 hectares representing about 60% of the total area. This growth was primarily driven by the transformation of bare soil from 2013 into developed land. Meanwhile, new bare soil patches emerged in the western region, replacing previously vegetated and sparsely vegetated areas, demonstrating a consistent trend of vegetation loss preceding construction. The directional shift of bare soil, from east (2002) to central (2013) to west (2023), reflects the sequential nature of urban development in BSD City.

These spatial patterns illustrate a recurring land cover transition: vegetated and sparsely vegetated areas tend to degrade into bare soil, which subsequently converts into built-up land. The maps also show the persistence of water bodies across the three time points, indicating that hydrological features have been reliably maintained during classification. The SUT-JOC method effectively captures the complexity of urban growth and land cover change, clearly visualizing how BSD City has evolved through distinct phases of development from 2002 to 2023.

To evaluate the reliability of the classification results, an accuracy assessment was conducted using stratified random sampling and high-resolution Google Earth imagery as reference data. As described in the methodology, 250 validation points were used for 2002 and 2013, while 375 points were allocated for 2023 to reflect increasing land cover heterogeneity. The resulting confusion matrices, summarized in Table 1, show strong classification performance across all periods

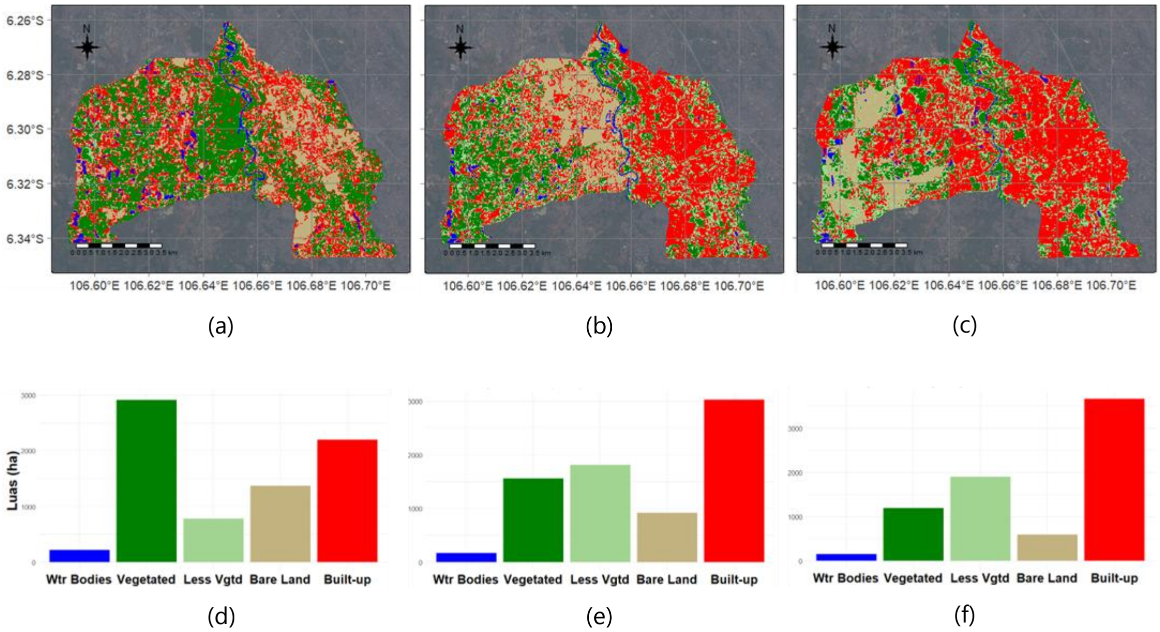


Figure 1. Land cover classification maps of BSD City generated using the SUT-JOC method for (a) 2002, (b) 2013, and (c) 2023, along with bar charts of land cover composition for (d) 2002, (e) 2013, and (f) 2023.

Table 1. Accuracy assessment results of land cover classification

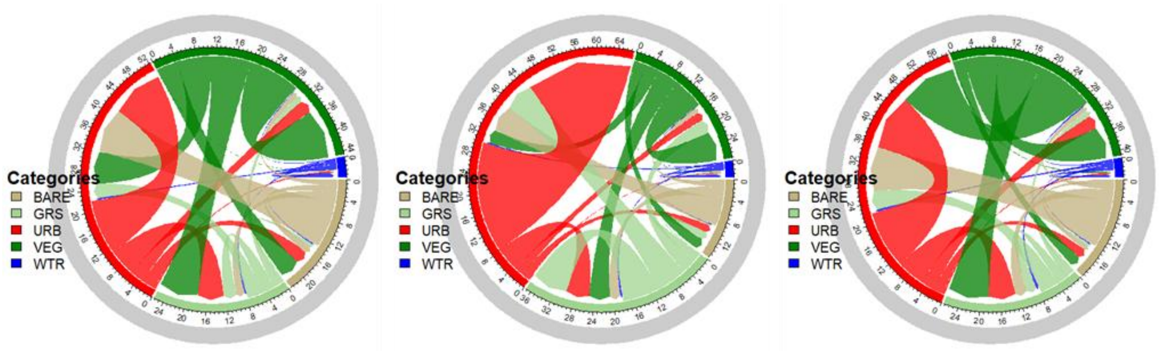
Year	Overall Accuracy	Kappa	User Accuracy (Built-up)	Producer Accuracy (Built-up)
2002	88.00%	0.848	91.70%	94.80%
2013	91.60%	0.893	93.40%	96.60%
2023	96.00%	0.949	97.40%	97.40%

The OA increased steadily over time, recorded at 88.00% in 2002, 91.60% in 2013, and 96.00% in 2023. Similarly, the Kappa coefficient rose from 0.848 to 0.893 and 0.949, respectively, indicating a transition from substantial to near-perfect agreement. The built-up class, which serves as a key focus of this study, showed marked improvements in both UA and PA. UA for built-up areas rose from 91.70% in 2002 to 97.40% in 2023, while PA improved from 94.80% to 97.40%. These results affirm the robustness of the SUT-JOC method in distinguishing urban features and capturing temporal land cover transformations with minimal manual input.

Quantitative analysis of land cover composition for each year is illustrated through comparative bar charts in Figure 1d to 1f. These visualizations highlight significant shifts in land cover proportions over the 21-year study period. Between 2002 and 2013, built-up areas expanded by 827 hectares, representing a 37.56% increase. From 2013 to 2023, built-up land further expanded by 1,469 hectares, marking a 48.48% increase. Overall, BSD City experienced a net gain of approximately 2,296 hectares in built-up area between 2002 and 2023, corresponding to a 104.29% increase. This rapid urban growth reflects ongoing residential, commercial, and industrial development, supported by strategic investments in infrastructure and the emergence of a central business district (CBD) comprising offices, educational facilities, apartments, and convention centers.

In contrast, vegetated areas showed a continuous decline throughout the study period. From 2002 to 2013, vegetation cover decreased by approximately 1,475 hectares, followed by an additional reduction of 1,310 hectares between 2013 and 2023. This trend underscores the conversion of green spaces into urban land uses. Sparsely vegetated and bare soil classes also exhibited temporal variability, particularly during land transition and pre-construction phases. Notably, bare soil area temporarily increased in 2013, reflecting land clearing and excavation associated with major development projects. Meanwhile, the extent of water bodies remained relatively stable over the two decades, indicating limited hydrological disturbance within the study area.

To further elucidate the dynamic patterns of land cover change in BSD City, chord diagrams were utilized to visualize class-to-class transitions across three temporal intervals: 2002–2013 (Figure 2a), 2013–2023 (Figure 2b), and the cumulative period of 2002–2023 (Figure 2c). These diagrams provide a comprehensive overview of the directionality and magnitude of conversions among land cover types, allowing for the identification of dominant transformation trajectories underpinning the city's urban growth.



(a) (c) (b)

Figure 2. Chord diagrams showing land cover transitions in BSD City for (a) 2002–2013, (b) 2013–2023, and (c) 2002–2023.

Between 2002 and 2013, the most prominent transitions into built-up areas originated from bare soil (47.9%) and vegetated areas (34.8%), with additional contributions from sparsely vegetated land (15.2%). These patterns suggest that early-phase urban development primarily capitalized on areas already cleared or partially disturbed, including construction sites and fallow agricultural fields, while also beginning to encroach into vegetated greenfields. The spatial evidence from this period, characterized by construction clusters in the eastern region, supports the interpretation that large-scale infrastructure projects were underway, leading to land preparation activities that converted vegetated zones into bare soil before final development.

During the 2013 to 2023 period, the transition dynamic shifted, with sparsely vegetated areas (41.3%) and bare soil (37.3%) emerging as the dominant precursors to built-up expansion and a reduced share of vegetated land (19.4%). This evolution reflects a spatial saturation of developable greenfields and a gradual reliance on land undergoing partial anthropogenic disturbance. The increasing conversion of sparsely vegetated land suggests that peri-urban zones, often characterized by fragmented vegetation, low-density settlements, or abandoned fields, were systematically targeted for intensification. Concurrently, the re-emergence of bare soil in the western sector indicates ongoing land preparation for westward urban sprawl.

Over the entire 21-year period, cumulative land cover transitions into built-up areas totaled 1,169.4 hectares from vegetated land, 925.2 hectares from bare soil, and 376.3 hectares from sparsely vegetated land, with minor contributions from water bodies (47.1 hectares). This trajectory underscores the sequential and spatially extensive nature of BSD City's urban transformation, which follows a clear progression: vegetated or semi-natural land → cleared (bare) land → built-up development. Such sequential degradation-to-development pathways are emblematic of master-planned urban growth, where pre-construction phases, including land clearing and infrastructure provisioning, are integral to the expansion process.

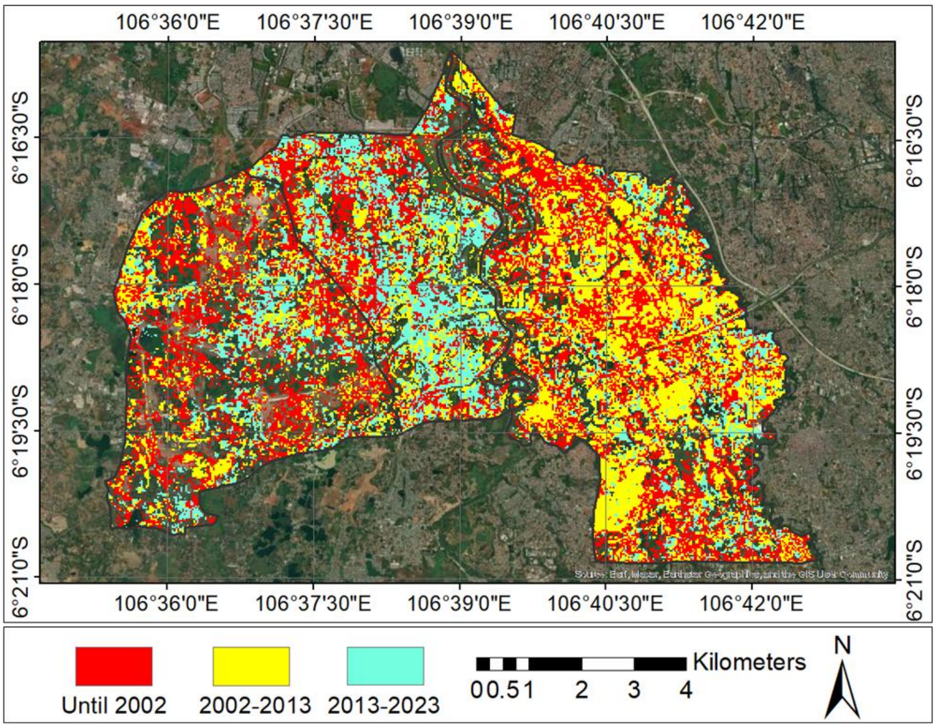


Figure 3. Urban expansion map of BSD City from 2002 to 2003

The directional movement of land transitions, particularly the observable shift of bare soil zones from east (2002) to central (2013) and west (2023), mirrors the phased roll-out of urban projects consistent with long-term development strategies. This pattern illustrates the internal logic of spatial planning in BSD City and provides a temporal fingerprint of how large-scale urban projects are staged over time. Moreover, the persistent transformation of green spaces into impervious surfaces raises important ecological sustainability considerations, including potential biodiversity losses, disruption of hydrological processes, and exacerbation of the urban heat island effect.

The land cover transition analysis reveals that BSD City's development is not merely a product of random urban encroachment but follows a structured and phased model of land conversion, deeply embedded within planning frameworks and market-driven land-use intensification. These findings provide critical inputs for urban planners, environmental managers, and policymakers seeking to anticipate future land cover changes, mitigate ecological degradation, and promote more resilient patterns of urbanization.

Figure 3 depicts the spatial overlay of built-up area expansion across three intervals: development since 2002 (core urban footprint), 2002–2013 (first major expansion), and 2013–2023 (latest expansion). The earliest developed areas (in red) are concentrated around BSD's urban core, comprising early residential estates, public facilities, and retail complexes. The 2002–2013 phase (in yellow) reveals outward expansion toward the west and southwest, aligned with the development of new residential clusters and secondary road networks. The most recent expansion from 2013 to 2023 (in cyan) is spatially more fragmented and distributed along peripheral zones, characterized by infill development and vertical urban growth, such as apartment complexes and mixed-use high-rise structures. This spatial trend suggests transitioning from initial horizontal sprawl to more compact and diversified land use planning.

Regarding spatial typology, urban growth has taken both concentric and leapfrogging forms. While core urban areas exhibit contiguous expansion, fringe zones show patchy development patterns, potentially driven by land availability, proximity to infrastructure, and policy incentives. The bare soil patches adjacent to urban edges confirm areas under transition or ongoing construction. These spatial insights are critical for understanding land demand pressures, ecological fragmentation, and potential hotspots for urban sprawl management.

Discussions

The land cover dynamics observed in BSD City from 2002 to 2023 reflect the spatial manifestation of rapid urban expansion within a peri-urban environment. As the area transformed from predominantly vegetated and bare lands into a dense built-up region, the landscape experienced substantial anthropogenic modification. The built-up area more than doubled within two decades, indicating an accelerated urban development process driven by infrastructure investments, real estate demand, and population growth. This pattern aligns with urbanization trends observed in other satellite cities around Jakarta and Southeast Asia, where rapid land conversion is often associated with economic modernization.

The spatial redistribution of bare land, transitioning from the eastern part of BSD in 2002 to the central region in 2013 and further westward by 2023, signifies a phased and directional development pattern. These sequential land transitions from vegetated to bare soil and eventually to built-up surfaces represent the stages of urban construction, from land clearing and grading to physical infrastructure development. Visualizing these dynamics using chord diagrams confirms the dominant transformation pathways and provides an effective means of communicating land conversion trends for urban planning and policy evaluation.

From a methodological standpoint, the SUT-JOC framework introduced in this study is a reliable and efficient approach for mapping multi-temporal land cover changes. The integration of normalized indices, such as NDVI, MNDWI, and NDBI, within a rule-based decision framework, followed by Jenks natural breaks optimization, facilitated clear class differentiation with minimal human intervention. The consistently high accuracy metrics across all three temporal analyses (88.00% in 2002, 91.00% in 2013, and 96.00% in 2023) and substantial Kappa values (all above 0.86) validate the robustness of this approach, particularly in environments with mixed land cover types or limited training data availability.

The model's capability to discriminate between bare land and built-up areas, often spectrally similar in conventional classifications, demonstrates the advantage of integrating multi-index logic and spatial rules. This hybrid approach bridges the gap between unsupervised objectivity and the interpretability of supervised classification, thus reducing potential bias in user-defined thresholding while maintaining transparency and reproducibility. Furthermore, the method's implementation on the GEE platform underscores its scalability and accessibility, which are essential for broader applications in data-driven urban management.

These findings have significant implications for sustainable urban planning. The rapid loss of vegetated areas and the dominant transition to built-up land suggest mounting pressure on ecosystem services, urban climate regulation, and biodiversity. If unchecked, such land transitions may exacerbate environmental degradation, contribute to urban heat islands, and reduce the resilience of urban systems. The insights derived from this study offer a scientific basis for revising spatial planning policies, emphasizing the importance of green infrastructure preservation, zoning controls, and strategic land conservation.

About prior studies on urban expansion in the Jabodetabek region, this study provides both methodological enhancement and local-scale granularity. While earlier research has often relied on conventional supervised classification or generalized trend analysis, the current work offers a semi-automated yet detailed and interpretable method readily adaptable to other urbanizing landscapes. The study advances analytical clarity and operational usability by pairing quantitative transition matrices with intuitive visualizations and an efficient classification strategy.

Conclusions

This study presents a novel approach for analyzing the spatiotemporal dynamics of land cover in BSD City, Indonesia, from 2002 to 2023 by applying the SUT-JOC classification framework. The method integrates key spectral indices, including the NDVI, MNDWI, and NDBI, and combines them with decision-rule logic and statistical optimization. It achieved high classification accuracy and temporal consistency using Landsat imagery. The results indicate that built-up areas more than doubled during the study period, accompanied by a significant decline in vegetated land, reflecting intensified urbanization pressure in the Jabodetabek peri-urban region. These findings emphasize the importance of adopting sustainable land-use strategies that promote green infrastructure and protect remaining ecological zones. The proposed methodology is robust and reproducible in data-limited environments and offers a scalable solution for continuous urban monitoring to support evidence-based planning and environmental governance.

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