

Evaluating the Driving Forces Behind Urban Land Transition in a Coastal Region: Integration of Geospatial and Local Knowledge Approach

Riska Ayu Purnamasari

Department of Soil Science, Faculty of Agriculture, Gadjah Mada University, Yogyakarta 55281, Indonesia
Innovation Centre for Tropical Science (ICTS), Bogor 16113, West Java, Indonesia

*Corresponding author: riska.ayupurnamasari@ugm.ac.id

ABSTRACT

Agricultural land transition in rapidly urbanizing coastal regions poses significant challenges for sustainable land use planning and long-term food security. This study examines the driving forces behind agricultural land conversion in Cilegon City, Banten Province, Indonesia as one of Southeast Asia's most industrialized coastal cities by integrating Remote Sensing (RS), Geographic Information Systems (GIS), and the Analytical Hierarchy Process (AHP) with structured local knowledge elicitation. Land cover classification was performed using Random Forest machine learning applied to multi-temporal Landsat imagery (2011 and 2023), revealing substantial encroachment of non-agricultural land uses. Through pairwise comparison interviews with six domain experts, AHP weighting assigned the highest influence to rainfall (18%), soil quality (15%), and road accessibility (14%) as transition drivers. The resulting transitional suitability map, validated against observed land cover change, achieved an overall accuracy of 88.70% and a Kappa coefficient of 0.86, demonstrating the model's strong predictive capacity. The findings underscore that environmental, infrastructural, and socio-economic factors collectively govern land conversion dynamics. This study contributes a replicable, participatory spatial framework that bridges objective geospatial data with community-embedded knowledge, supporting more inclusive, evidence-based urban planning and agricultural land management in fast-growing coastal cities.

Keywords: analytical hierarchy process, coastal city, land use change, local knowledge, remote sensing

Introduction

Rapid urbanization is one of the defining phenomena of the twenty-first century, fundamentally reshaping land use patterns across the globe. As cities expand to accommodate growing populations and diversifying economic activities, agricultural and peri-urban land is increasingly absorbed into urban and industrial landscapes. This process, while

indicative of economic growth, carries substantial environmental and food security risks, particularly in coastal and low-lying regions where agricultural land is both ecologically sensitive and spatially limited. Doydee (2005) identified residential expansion as one of the most pervasive drivers of farmland loss, often occurring faster than planning institutions can respond.

In this context, the ability to accurately monitor, analyze, and forecast land cover transitions has become a foundational requirement for sustainable urban governance. Remote Sensing (RS) and Geographic Information Systems (GIS) have emerged as indispensable tools for this purpose, enabling spatial analysis at scales and resolutions previously unattainable through conventional field surveys (Jensen & Im, 2007; Li et al., 2023; Purnamasari et al., 2026). High-resolution satellite imagery, in particular, offers consistent and temporally comparable data on land use dynamics, allowing planners and researchers to identify vulnerable agricultural zones and track the trajectory of land transformation (Tassi et al., 2022).

Machine learning-based classification methods have further enhanced the utility of RS data. Among these, the Random Forest (RF) algorithm has demonstrated superior accuracy and robustness in land cover classification tasks, owing to its ensemble approach and ability to handle high-dimensional feature spaces (Breiman, 2001). Recent studies have applied RF classifiers to multi-temporal Landsat datasets to produce reliable land use change maps across diverse geographic settings (Gandharum et al., 2021; Purnamasari et al., 2019a; Purnamasari et al., 2019b).

However, purely spatial and algorithmic approaches carry an inherent limitation: they capture the biophysical and structural dimensions of land conversion but often fail to account for the socio-cultural, institutional, and perceptual factors that fundamentally shape land use decisions at the local level (Yu et al., 2022). Farmers, local government officials, and community leaders hold contextual knowledge about land tenure, agricultural productivity, livelihood strategies, and development aspirations that no satellite sensor can directly measure. Without incorporating these perspectives, land use models risk producing outputs that are technically accurate but contextually

misaligned with the realities faced by communities on the ground.

The Analytical Hierarchy Process (AHP), a structured multicriteria decision-making method developed by Saaty (1980), provides a systematic framework for eliciting and quantifying expert and stakeholder judgments. When integrated with RS and GIS, AHP enables a participatory weighting of spatial criteria that reflects both scientific analysis and lived experience. This combined approach has been applied successfully in land suitability assessment, conservation planning, and urban growth modeling, demonstrating its versatility across socio-environmental contexts (Long et al., 2007; Tu & Long, 2017).

Despite growing recognition of the value of integrating local knowledge with spatial technologies, this approach remains underutilized in the context of Indonesian coastal industrial cities, which are experiencing some of the most intense and rapid land use transformations in Southeast Asia. Cilegon City in Banten Province exemplifies this challenge: originally an agriculture-based settlement (Purnamasari et al., 2024), Cilegon has undergone dramatic industrial and residential expansion since the establishment of its steel manufacturing sector, placing persistent pressure on remaining agricultural land (Moon, 2009; Purnamasari et al., 2025).

This study addresses this gap by developing an integrated spatial-social framework for evaluating agricultural land transition in Cilegon City. Specifically, it aims to: (1) map and quantify land cover change between 2011 and 2023 using multi-temporal Landsat imagery and RF classification, (2) identify and weight the driving forces of agricultural land conversion through AHP-based expert interviews, (3) construct a transitional suitability map using weighted overlay analysis, and (4) validate the suitability model against observed land cover change. By combining quantitative geospatial

analysis with qualitative local insights, this research contributes a replicable, inclusive methodology for supporting sustainable land management decisions in rapidly urbanizing coastal regions.

Materials and Methods

Research Framework

The research was structured around three sequential analytical stages (Figure 1). In the first stage, land cover classification was performed for 2011 and 2023 using machine learning-based supervised classification of Landsat satellite imagery. Change detection analysis was subsequently applied to quantify spatial transitions in land use across the twelve-year period. In the second stage,

structured pairwise comparison interviews using AHP were conducted with local experts to determine the relative importance of environmental, infrastructural, and socio-economic factors driving land cover change. In the third stage, the AHP-derived weights were applied through Weighted Overlay analysis in ArcGIS to produce a transitional suitability map, which was then validated against the observed land cover change map.

Study Area

Cilegon City is located in Banten Province, at the westernmost tip of Java Island, Indonesia, positioned between 5°52'24"–6°04'07" S latitude and 105°54'05"–106°05'11" E longitude

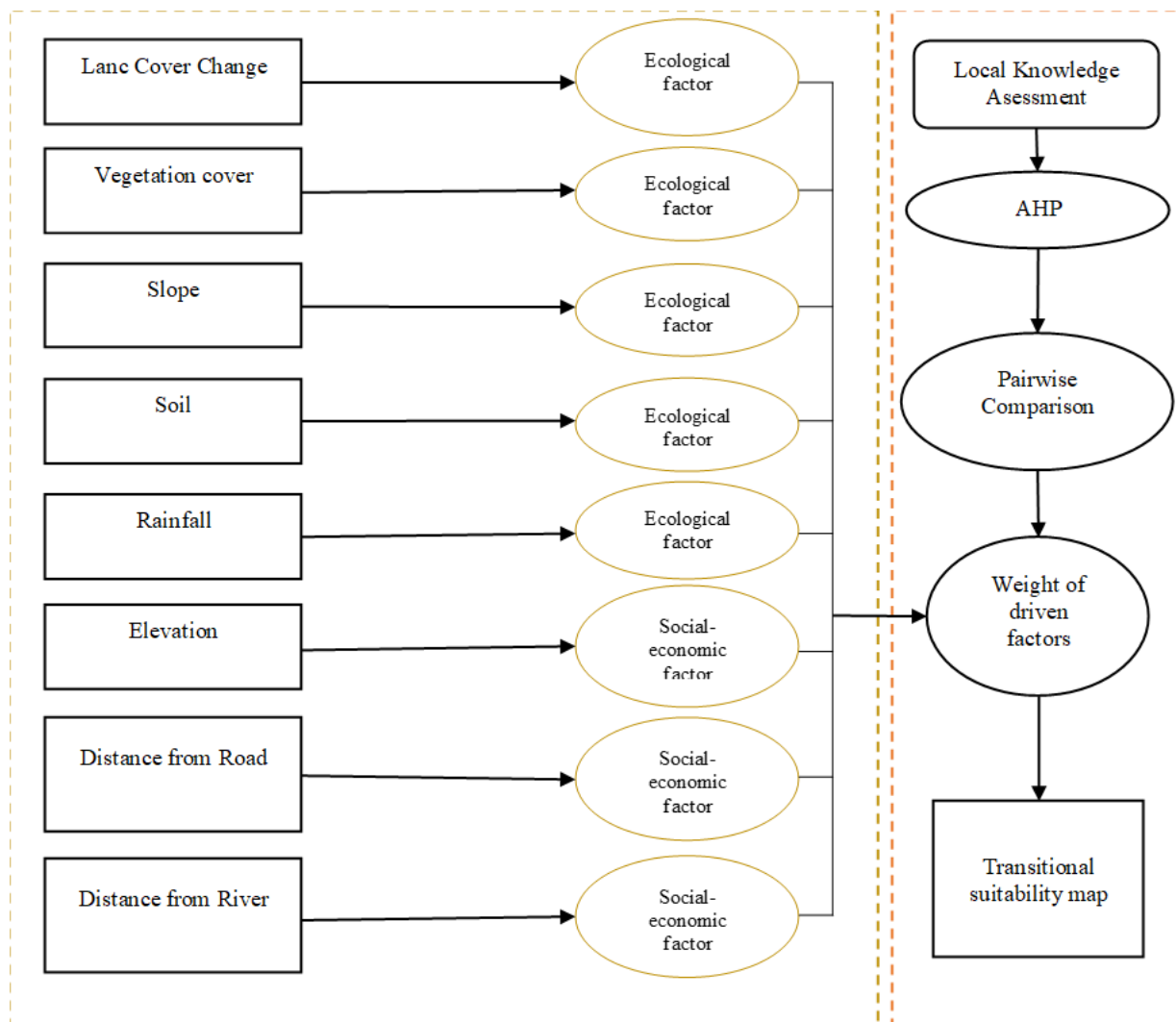


Fig. 1. Research framework illustrating the three-stage integration of Remote Sensing classification, AHP-based local knowledge analysis, and transitional suitability mapping.

(Figure 2). The city is administratively bordered by Serang Regency to the north, east, and south, and by the Sunda Strait to the west, giving it a distinctive coastal character. Its spatial configuration includes coastal zones in the north and west, rural agricultural areas in the south, and concentrated urban development in the central and northern districts.

Historically an agricultural settlement during the Sultanate of Banten era (c. 1651), Cilegon was transformed into an industrial hub following the establishment of the Trikora steel plant in 1962. Today, it hosts the largest integrated steel manufacturing complex in Southeast Asia and serves as a regional center for energy production, trade, and services (Moon, 2009). This industrial trajectory has driven sustained urbanization: Indonesia's national urbanization rate grew from 22.3% in 1980 to 56.7% in 2020, projected to reach 63.4% by 2030, while Cilegon's local urbanization rate of 1.49% between 2010 and 2020 exceeded the national average of 1.15%. The resulting land use pressures have progressively displaced agricultural activities toward peri-urban margins,

creating an urgent need for systematic land transition analysis.

Remote Sensing Data and Land Cover Classification

Multi-temporal Landsat satellite imagery was acquired from the United States Geological Survey (USGS) EarthExplorer platform, covering the years 2011 (Landsat 5 Thematic Mapper, TM) and 2023 (Landsat 9 Operational Land Imager-2, OLI-2). Images were selected from the same seasonal window to minimize phenological variation and ensure comparability of vegetation and agricultural reflectance signatures. Standard pre-processing steps, including radiometric calibration, atmospheric correction using the Dark Object Subtraction (DOS) method, and geometric co-registration, were applied to both scenes.

Land cover classification was carried out using the RF algorithm, an ensemble classifier that constructs multiple decision trees and aggregates their outputs to produce a final classification. RF was selected for its demonstrated accuracy and reduced susceptibility to overfitting,

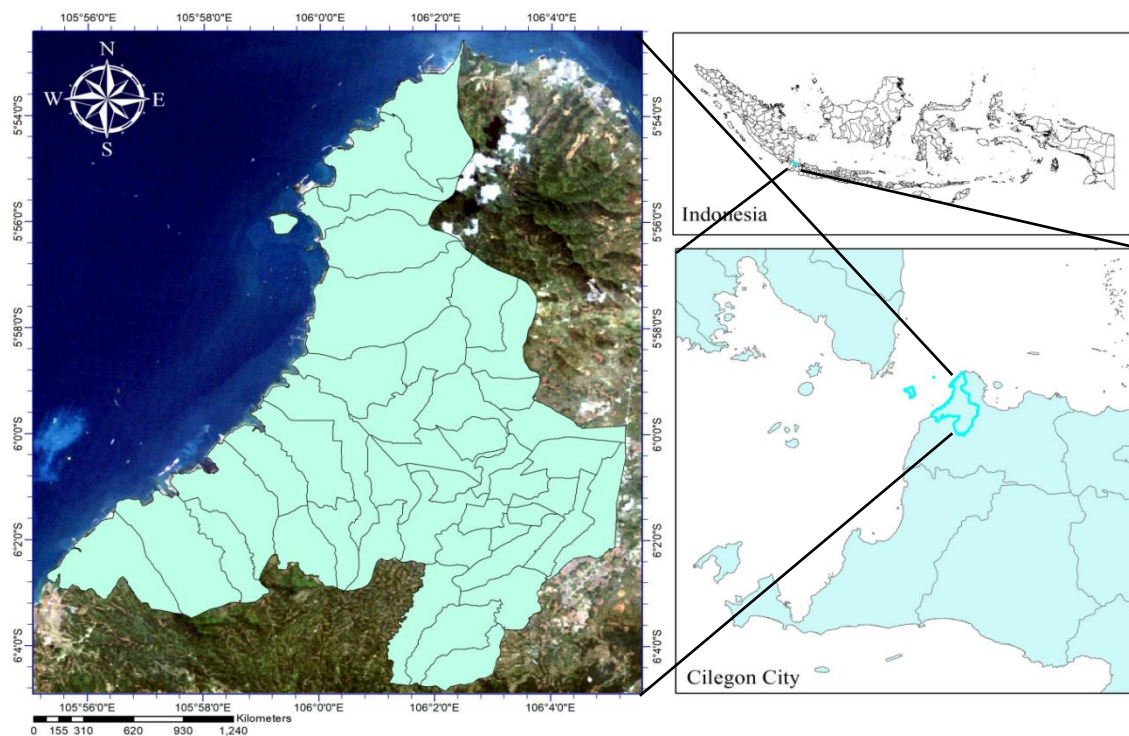


Fig. 2. Location of the study area in Cilegon City, Banten Province, Indonesia.

particularly in heterogeneous peri-urban landscapes. Training samples were delineated through a combination of field verification, high-resolution imagery cross-referencing, and ancillary map data. The classification was applied consistently to both the 2011 and 2023 datasets, and change detection was subsequently performed through post-classification comparison.

Local Knowledge Analysis and AHP Expert Interview Design

To complement the spatial analysis with community-grounded perspectives, structured interviews were conducted with six local experts representing two key stakeholder groups: local government representatives with authority over land use planning and spatial regulation, and community leaders with firsthand knowledge of agricultural land management and livelihood transitions. Because AHP does not rely on statistical sampling but rather on expert judgment, purposive selection was employed, targeting individuals with demonstrated expertise and institutional relevance to land use decision-making in Cilegon (Saaty, 1980).

Eight candidate driving factors, identified through literature review and reconnaissance fieldwork, were incorporated into the AHP framework: (1) rainfall, (2) soil quality, (3) distance from road, (4) distance from river, (5) land use/land cover, (6) vegetation cover (NDVI), (7) elevation, and (8) slope. Interviews were structured around pairwise comparison matrices at each hierarchical level, following Saaty's nine-point intensity scale. The consistency of expert judgments was assessed through the Consistency Ratio (CR), with $CR < 0.10$ considered acceptable (Figure 3).

AHP Computation

The AHP procedure involved three computational steps. First, pairwise comparison matrices were constructed for each criterion pair. The sum of each matrix column was computed as:

$$C_{ij} = \sum_{i=1}^n C_{ij} \quad (1)$$

Second, each matrix element was normalized by dividing by its column sum to obtain the normalized pairwise matrix:

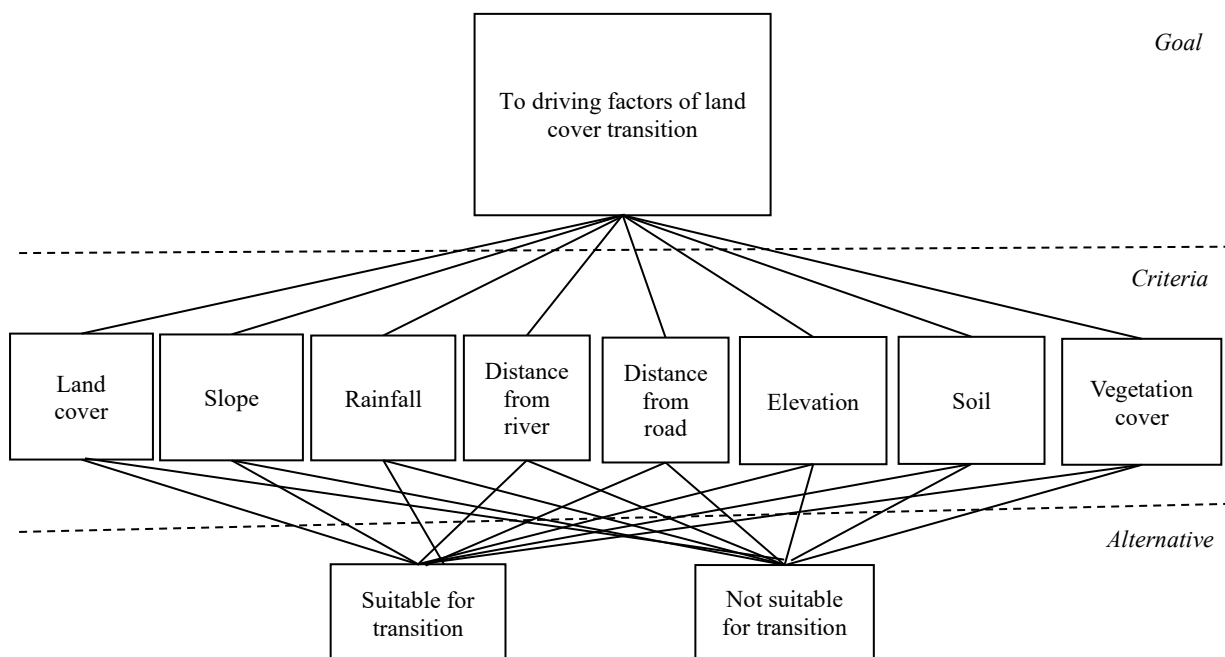


Fig. 3. The driving factors of land cover change.

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^n C_{ij}} \quad (2)$$

Third, criterion weights (priority vectors) were derived by averaging each row of the normalized matrix across n criteria:

$$W_{ij} = \frac{\sum_{j=1}^n X_{ij}}{n} \quad (3)$$

$$\lambda_{max} = \sum_i^n CV_{ij} \quad (4)$$

The assessments were additionally analyzed to compute the Consistency Index (CI), which was determined through the following procedure:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (5)$$

The principal eigenvalue (λ_{max}) was computed to assess consistency, and the CI and CR were derived as:

$$CR = \frac{CI}{RI} \quad (6)$$

where RI is the Random Index value corresponding to the matrix size, as tabulated by Saaty (1980). Expert panels with $CR < 0.10$ were retained; all six respondents in this study met this threshold.

Transitional Suitability Mapping

AHP-derived weights were applied to the eight spatial data layers (Table 1; Figure 4) using the Weighted Overlay tool in ArcGIS to generate a Transitional Suitability Map (TSM). The TSM represents the spatial probability of each pixel transitioning from an agricultural to a non-agricultural land cover class. Raster layers were reclassified to a common suitability scale (1–5) prior to overlay. The resulting composite suitability index was then compared with the land cover change detection map for 2011–2023 to validate model performance, with target accuracy set at $\geq 80\%$.

Table 1. Spatial data layers used as driving force criteria in weighted overlay analysis.

No.	Data layer	Year	Description	Source
1	Land Cover Map	2023	Scale 1:50,000	Indonesia Geospatial Agency (BIG)
2	Slope Map	2021	Scale 1:50,000	DEM SRTM
3	Rainfall Map	2023	Scale 1:50,000	BIG
4	Soil Map	2021	Scale 1:50,000	BIG
5	NDVI Map	2023	Derived from Landsat-9 OLI-2, 30 m resolution	USGS (Landsat-9 OLI-2)
6	Elevation Map	2023	Scale 1:50,000	BIG
7	Road Map	2021	Scale 1:50,000; distance calculated via Euclidean analysis	BIG

Results

AHP Criterion Weights: Local Expert Perspectives

Six local experts, comprising government planning officials (Experts A, B, and C) and community representatives (Experts D, E, and F), completed pairwise comparison matrices evaluating the eight candidate driving factors. All expert panels achieved CRs below 0.10, confirming adequate coherence in judgment (Table 2). Aggregated weights were computed as the arithmetic mean of individual expert weights.

Rainfall received the highest aggregate weight (18.1%), indicating that experts perceive water availability as the most decisive environmental factor in land use viability decisions. Areas with insufficient rainfall are widely regarded as unsuitable for rain-fed agriculture, rendering them more susceptible to conversion toward non-agricultural uses. Soil quality ranked second (14.9%), reflecting the primacy of land fertility in determining agricultural persistence. Distance from road ranked third (14.2%), highlighting the role of transport infrastructure in catalyzing urban and industrial expansion. Distance from river

(13.3%), land cover (12.2%), vegetation cover (11.2%), elevation (8.1%), and slope (7.7%) followed in descending order of influence.

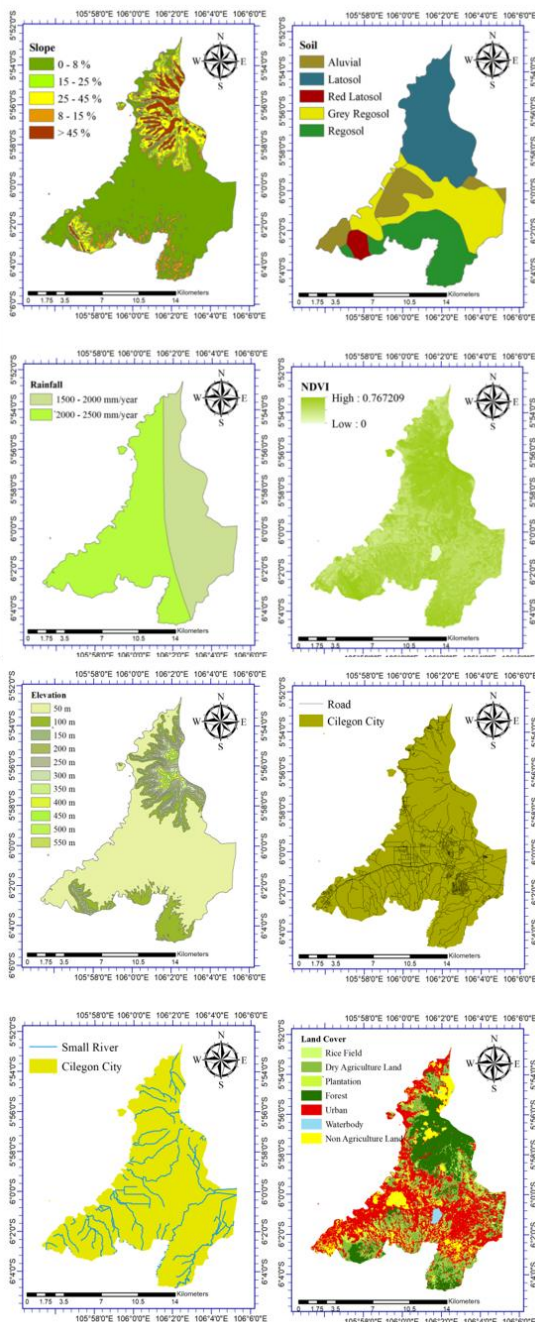


Fig. 4. Spatial criteria layers used as inputs for the weighted overlay transitional suitability analysis.

Transitional Suitability Map and Model Accuracy

The AHP weights were applied to the eight reclassified spatial raster layers via Weighted Overlay in ArcGIS, generating a TSM that classifies each pixel

according to its propensity to transition from agricultural to non-agricultural land use (Figure 5a). Areas classified as highly suitable for transition were concentrated along major road corridors and near existing industrial and residential zones, consistent with the high AHP weights assigned to distance-from-road and proximity effects (Purnamasari, 2024).

Accuracy assessment was performed by comparing the TSM with the independently derived land cover change detection map for 2011–2023 (Figure 5b), using overall accuracy (OA) and the Kappa coefficient as evaluation metrics (Carletta, 1996; Congalton, 1991). The model achieved an overall accuracy of 88.70% and a Kappa coefficient of 0.86, indicating 'almost perfect' agreement between predicted and observed land cover transitions (Landis & Koch, 1977). Both values exceed the widely accepted minimum thresholds of $OA \geq 80\%$ (Anderson et al., 1976) and $Kappa \geq 0.80$ (Carletta, 1996; Foody, 2002), confirming the model's suitability as a spatial prediction tool. These results validate the effectiveness of the AHP-weighted overlay approach and confirm that the locally identified driving forces meaningfully correspond to the observed spatial patterns of land cover change. The high predictive accuracy is particularly notable given the complexity of the study area, where simultaneous industrial, residential, and infrastructural pressures create a heterogeneous and rapidly evolving land use mosaic. The use of weighted overlay constrained to AHP-derived expert judgment thus proves effective not only as a decision-support tool but also as a spatially predictive framework for agricultural land transition in fast-growing coastal cities.

Discussion

The findings of this study illuminate the multidimensional nature of agricultural land transition in Cilegon City, a coastal

industrial center whose land use trajectory reflects broader patterns of urbanization-driven farmland loss observed across developing Asia (Bren d'Amour et al., 2017; Seto et al., 2011). The application of RF classification to multi-temporal Landsat imagery produced high-accuracy land cover maps for both 2011 and 2023, confirming a marked increase in built-up and non-agricultural surfaces over the study period. This trend aligns with documented patterns of urban encroachment on peri-urban agricultural land in Indonesian cities (Gandharum et al., 2021; Purnamasari et al., 2019).

The identification of rainfall (18.1%), soil quality (14.9%), and road accessibility (14.2%) as the three most influential transition drivers offers important interpretive insights. The primacy of rainfall reflects the agro-climatic vulnerability of the study area: where rainfall is insufficient to sustain rain-fed cultivation, agricultural land is inherently less competitive against alternative uses. Consistent with studies on climate-sensitive seasonally dry regions, these results highlight how high rainfall variability creates a volatile environment (Lobell et al., 2015). The high weight assigned to soil quality similarly underscores the ecological foundation of land use decisions—low-fertility soils provide weaker economic justification for sustaining agricultural activity, making these areas natural targets for non-agricultural development.

Road accessibility, as the third-ranked driver, confirms the role of transportation infrastructure in catalyzing land conversion. Enhanced road connectivity reduces the transaction costs of urban development by improving market access, labor mobility, and logistics, thereby rendering proximate agricultural land more attractive to developers and industrial investors. This pattern has been consistently documented in rapidly urbanizing regions of East and Southeast Asia, where road network expansion frequently precedes and enables agricultural-to-urban transitions.

The integration of local expert perspectives via AHP was instrumental in contextualizing these spatial patterns. Government planning officials and community leaders brought distinct but complementary knowledge: officials emphasized regulatory and infrastructural factors, while community representatives highlighted ecological and livelihood dimensions. This divergence in perspective, captured and weighted through the AHP's pairwise comparison procedure, produced a more nuanced understanding of transition drivers than either source could have provided independently. Such integration aligns with calls in the land change science literature for epistemically plural approaches that combine objective spatial data with socially embedded knowledge (Ngongo et al., 2023; Yu et al., 2022).

The TSM's overall accuracy of 88.70% and Kappa coefficient of 0.86 demonstrate that the AHP-weighted

Table 2. AHP criterion weights derived from six local expert pairwise comparisons.

Criterion	Expert A	Expert B	Expert C	Expert D	Expert E	Expert F	Mean weight
Rainfall	0.155	0.216	0.210	0.143	0.081	0.042	0.181
Soil quality	0.187	0.182	0.095	0.134	0.226	0.115	0.149
Distance from road	0.161	0.060	0.212	0.134	0.085	0.115	0.142
Distance from river	0.100	0.182	0.108	0.143	0.243	0.155	0.133
Land cover	0.154	0.074	0.126	0.134	0.040	0.300	0.122
Vegetation cover (NDVI)	0.089	0.165	0.061	0.134	0.040	0.042	0.112
Elevation	0.058	0.055	0.076	0.134	0.226	0.115	0.081
Slope	0.096	0.060	0.112	0.040	0.057	0.115	0.077
Consistency ratio (CR)	0.095	0.024	0.096	0.004	0.028	0.051	≤ 0.10

overlay approach can serve as a reliable predictive tool for spatial land use forecasting (Congalton, 1991; Foody, 2002). A Kappa value above 0.80 is interpreted as indicating 'almost perfect' agreement, confirming that the model performs substantially better than chance (Landis & Koch, 1977). The model's capacity to replicate observed change patterns across a heterogeneous urban-industrial landscape supports its potential applicability in other fast-growing coastal cities in Indonesia and the broader region. However, several limitations merit acknowledgment. The AHP sample of six experts, while sufficient for the method's qualitative requirements, may not capture the full diversity of community perspectives, particularly those of smallholder farmers and women, who may hold distinct land use priorities. Future studies should consider expanding the expert panel and incorporating participatory GIS or collaborative mapping

approaches to deepen the representativeness of local knowledge integration.

It is also noteworthy that Cilegon's existing Spatial Plan (RTRW 2020–2040) designates the city primarily as an industrial zone, with agricultural land supply expected from surrounding regencies such as Serang and Pandeglang. While this planning orientation may normalize ongoing agricultural land reduction within Cilegon, it raises broader regional planning questions about inter-jurisdictional food system resilience and the cumulative impact of industrial land conversion across the Banten Province food production network.

Conclusion

This study developed and validated an integrated spatial-social framework for evaluating the driving forces of agricultural land transition in Cilegon City, a rapidly industrializing coastal city in Banten

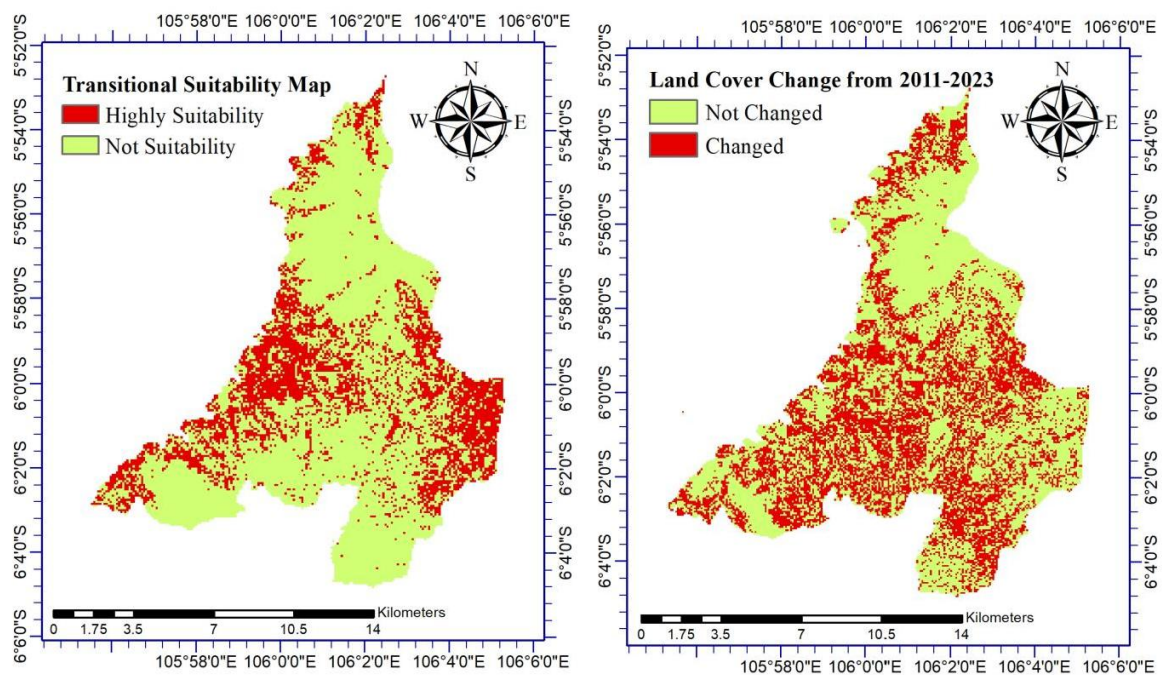


Fig. 5. Comparison of the AHP-derived transitional suitability map (a) and the observed land cover change detection map (b) for Cilegon City, Banten Province, Indonesia, 2011–2023. Areas of high transition suitability in (a) correspond spatially with observed agricultural-to-urban conversions in (b) OA = 88.70%, Kappa = 0.86, indicating 'almost perfect' agreement (Landis & Koch, 1977).

Province, Indonesia. By combining multi-temporal Landsat RS classification using RF with AHP-based local expert knowledge and Weighted Overlay analysis, we produced a Transitional Suitability Map that achieved 88.70% accuracy against observed land cover change data for 2011–2023.

The analysis identified rainfall, soil quality, and road accessibility as the three primary drivers of agricultural land conversion, reflecting an interplay of environmental, ecological, and infrastructural forces. These findings demonstrate that land use transitions in Cilegon are shaped not only by top-down planning decisions but also by underlying biophysical conditions and proximity to transportation infrastructure. The consistency of expert judgments (all CR < 0.10) and the high model accuracy (OA = 88.70%, Kappa = 0.86) validate the effectiveness of participatory AHP-weighted spatial modeling as a decision-support tool.

The proposed framework offers several practical contributions. For local governments, it provides a replicable methodology for identifying agricultural land most susceptible to conversion, enabling pre-emptive planning interventions to protect high-value farmland. For regional planners, it demonstrates the importance of accounting for both spatial and perceptual drivers in land use governance. For the research community, it establishes a transferable workflow for integrating community-embedded knowledge with geospatial technologies in data-sparse contexts.

Future research should expand the expert panel to include a broader cross-section of land use stakeholders, incorporate socio-economic datasets such as land price gradients and tenure security indicators, and apply the framework longitudinally to assess predictive accuracy under changing urban growth scenarios. The increasing availability of high-resolution satellite data and open-access

machine learning platforms will further strengthen the scalability and precision of this integrated approach.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Ethics Statement

Informed consent was obtained from all expert participants prior to interview. The study did not involve vulnerable populations or sensitive personal data. Participant confidentiality was maintained by anonymizing individual expert responses in the analysis.

Data Availability

The Landsat satellite imagery used in this study is publicly available through the USGS EarthExplorer platform (<https://earthexplorer.usgs.gov>). Spatial reference data were obtained from the Indonesia Geospatial Agency (Badan Informasi Geospasial/BIG). AHP interview data are available from the corresponding author upon reasonable request.

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