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CELLULAR AUTOMATA SPATIAL MODELLING FOR AGRICULTURE LAND COVER CHANGE IN KARAWANG REGENCY

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Abstract

Rapid urbanization in Karawang Regency poses a significant threat to agricultural sustainability. This study analyses land cover changes from 2009 to 2017 and predicts future transitions for 2021, 2026, and 2031 using Cellular Automata (CA) modelling in IDRISI TerrSet. The model was validated using a Kappa Index of Agreement (KIA) by comparing the 2021 simulation with official SPOT 7 satellite imagery, yielding a high accuracy of 0.9328. Results indicate a consistent decline in paddy fields, which are projected to decrease to 105,416.28 ha by 2031. Conversely, settlements and built-up land show a sharp upward trend, nearly doubling from 20,153.09 ha in 2009 to a projected 38,016.63 ha in 2031. These findings highlight the increasing pressure of urban expansion on productive agricultural land, necessitating stricter spatial planning policies to safeguard regional food security in alignment with the 2011–2031 Spatial Plan (RTRW).

Keywords: Land use change, Cellular Automata, Karawang, agriculture land conversion, Spatial modeling

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INTRODUCTION

Agricultural land conversion is a global phenomenon driven by rapid population growth and the structural transformation of economies from agrarian to industrial bases (Araza et al., 2026; Sofue & Kohsaka, 2024). In developing nations, particularly within Southeast Asia, this shift often occurs at the expense of highly productive "rice bowls"—fertile regions that are critical for national food security. Indonesia, as one of the world's largest rice consumers, faces a significant challenge in balancing its industrial ambitions with the preservation of its agricultural heritage (Prayitno et al., 2021).

Karawang Regency, located in the West Java Province, serves as a primary example of this tension. Historically recognized as a national "rice granary," Karawang has undergone a dramatic landscape transformation over the last two decades. Its strategic position along the Jakarta-Bandung industrial corridor has made it a magnet for large-scale industrial estates and residential expansion (Rustiadi et al., 2021). This rapid urbanization often results in the "leakage" of spatial plans, where paddy fields (sawah) are converted into built-up land despite existing protection policies (Marendraputra & Afifah, 2025; Pratika & Hudalah, 2024).

While the government has introduced the Sustainable Food Agricultural Land (LP2B) framework to mitigate these losses, empirical data on the long-term effectiveness of these policies remains limited. Previous studies have utilized remote sensing to document historical changes; however, there is a pressing need for predictive modelling that aligns with official planning horizons (Ambarwulan et al., 2016). Understanding the future trajectory of land use is essential for policymakers to anticipate spatial conflicts and adjust regional strategies before the loss of agricultural land becomes irreversible.

This study aims to bridge this gap by simulating land use and land cover (LULC) changes in Karawang Regency up to the year 2031—the final year of the current Regional Spatial Plan (RTRW). By utilizing Landsat 7 TM and SPOT 7 satellite imagery and employing a Cellular Automata (CA) modelling approach in IDRISI TerrSet, this research identifies the patterns of conversion and predicts the future extent of key land categories. The findings provide a quantitative basis for evaluating the sustainability of Karawang's spatial development and offer insights into the protection of agricultural zones under the pressure of industrialization.

LITERATURE REVIEW

Land Use and Land Cover Change (LULC) Dynamics

Land Use and Land Cover Change (LULC) is a fundamental indicator of the interaction between human activities and the natural environment. Rapid urbanization and industrialization are the primary drivers of the conversion of

fertile agricultural land into built-up areas (Najnin et al., 2023; Zhao et al., 2026). In Southeast Asia (Pichler et al., 2021), this phenomenon is particularly prevalent in peri-urban regions where industrial corridors expand into traditional "rice bowls." Such conversions are often irreversible and pose a significant threat to regional ecological balance and local livelihoods.

Cellular Automata in Spatial Modelling

Predicting future land-use patterns requires robust computational models that can handle spatial complexity. Cellular Automata (CA) has emerged as a powerful tool in geographical information science for simulating urban growth. The strength of the CA model lies in its ability to represent complex systems through simple local rules, where the state of a specific cell at time is determined by its state and the state of its neighbours at time. Beyene & Sewnet (2023); Wangyel et al. (2021); and Yue et al. (2024) have demonstrated that integrating CA with Markov Chains or using software like IDRISI TerrSet allows researchers to incorporate "driving factors" (such as distance to roads and population density) and "constraints" (such as protected zones). This hybrid approach provides a high degree of spatial accuracy, often validated through the Kappa Index of Agreement (KIA).

Agricultural Land Conversion and Food Security

The conversion of paddy fields (sawah) to non-agricultural use is a critical issue for food security. In Indonesia, the government has addressed this through the Sustainable Food Agricultural Land (LP2B) policy. However, Kavhu et al. (2025); Shan et al. (2025); and Zhang et al. (2025) suggest that legal designations often clash with economic pressures. As land values rise due to industrial demand, the opportunity cost of farming increases, leading to "land abandonment" or conversion. Studies specifically focused on West Java have noted that Karawang Regency serves as a critical case study due to its dual role as a national industrial hub and a primary rice producer.

Remote Sensing and Image Interpretation

The reliability of land-use analysis depends heavily on the quality of the source data. Landsat satellite imagery (e.g., Landsat 7 TM) has been the gold standard for long-term LULC studies due to its multi-spectral capabilities and historical availability. For validation, high-resolution imagery such as SPOT 7 and Google Earth Pro provides the necessary "ground truth" to verify classification results (Dong et al., 2026; Li et al., 2025; Y. Zhang, 2025). Techniques such as Supervised Classification using the Maximum Likelihood algorithm remain the most widely accepted methods for categorizing land cover with high statistical confidence.

RESEARCH METHODOLOGY

Study Area

The research was conducted in Karawang Regency, West Java, Indonesia. The area is strategically located between the metropolises of Jakarta and Bandung, making it a focal point for industrial expansion and agricultural preservation efforts.

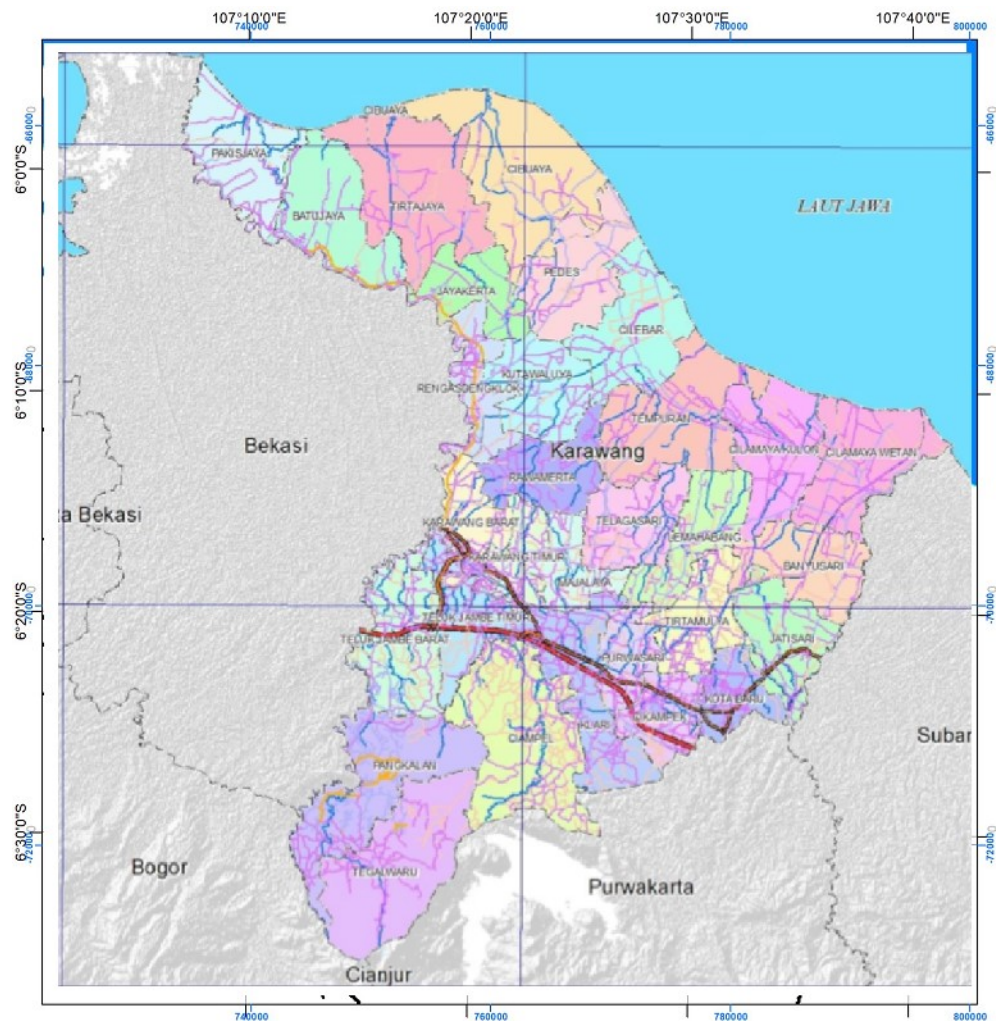


Figure 4: Research Location
 Source: Authors (2026)

Data Collection and Preparation

The study utilized a combination of multi-temporal satellite imagery and thematic maps. Primary datasets include:

- Landsat 7 ETM+ Imagery (2009 and 2017): Obtained from the USGS EarthExplorer for historical land cover analysis.
- SPOT 7 Satellite Imagery (2021): Used as a high-resolution reference for model validation, sourced via the Department of Public Works and Spatial Planning (PUPR).
- Administrative and Planning Maps: Including the 2011–2031 Karawang Regency Spatial Plan (RTRW) and the Sustainable Food Agricultural Land (LP2B) draft.

Image Processing and Classification

The satellite data underwent several preprocessing stages, including radiometric correction and layer stacking (band composition). Land cover classification was executed using the Maximum Likelihood Classification (MLC) algorithm—a supervised classification technique that categorizes pixels based on the probability of their belonging to a specific class. Ten distinct land cover classes were identified: Water Bodies, Plantation Forest, Open Land, Plantation, Settlement/Built-up Land, Mining, Dryland Agriculture, Paddy Field, Scrub/Shrubland, and Aquaculture Ponds. All spatial data were projected to the WGS 1984 UTM Zone 48N coordinate system with a standardized spatial resolution of 30 m x 30 m.

Research Framework

The research was conducted through a systematic framework divided into four primary phases: Data Acquisition, Image Processing, Model Validation, and Predictive Simulation.

Phase I: Data Acquisition and Pre-processing

The initial phase involved the collection of multi-temporal satellite data and auxiliary thematic maps. Landsat 7 ETM+ images for 2009 and 2017 were corrected for atmospheric and geometric distortions. All datasets were harmonized into a uniform spatial reference system (WGS 1984 UTM Zone 48N) and resampled to a 30-meter resolution to ensure pixel-to-pixel consistency across the time series.

Phase II: LULC Classification and Change Detection

A supervised classification was performed using the Maximum Likelihood Classification (MLC) algorithm. Training samples were established through

manual digitization of 10 land cover classes. The classification results from 2009 and 2017 were then subjected to a change detection analysis to identify transition patterns, specifically the conversion of paddy fields to built-up land.

Phase III: Model Parameterization and Validation

The transition probability matrix was calculated using Markov Chain analysis based on the 2009–2017 change patterns. This was then integrated into the Cellular Automata (CA) framework. To validate the model's predictive capability, a simulation for the year 2021 was executed. The reliability of the framework was confirmed by comparing this simulation with the official 2021 SPOT-7 based land cover map using the Kappa Index of Agreement (KIA).

ANALYSIS AND DISCUSSION

The prediction analysis of land-use change in this study was conducted through several analytical stages, utilizing specific software as supporting tools. The details regarding the analytical stages and the software employed are presented in Table 1.

Table 1: Analytical Stages and Software Utilization

ArcMap 10.8	Google Earth Pro	Terrset 10.3.1	ArcMap 10.8
Land Cover Classification	Land cover validity	Land cover prediction	Agriculture land cover change prediction

Source: Authors (2026)

The datasets utilized in this analytical process are outlined in below:

Table 2: Research Datasets and Sources

No	Data Type	Data Source
1	Landsat 7 Satellite Imagery (2009)	earthexplorer.usgs.gov
2	Landsat 7 Satellite Imagery (2017)	earthexplorer.usgs.gov
3	Google Earth Pro Imagery (2009)	Google Earth Pro
4	Google Earth Pro Imagery (2017)	Google Earth Pro
5	Existing Land Cover Map (2021)	Department of Public Works and Spatial Planning (PUPR)
6	Spatial Planning Map (RTRW) of Karawang Regency 2011-2031	Bappeda (Regional Development Planning Agency)
7	Draft Map of Sustainable Food Agriculture Land (LP2B) Karawang Regency	Department of Agriculture / Bappeda

Source: Authors (2026)

Land Cover Classification

Land cover classification analysis for Karawang Regency was conducted to identify spatial distribution and changes in land cover patterns between 2009 and 2017. The primary data sources consisted of Landsat 7 TM satellite imagery acquired from the USGS EarthExplorer (earthexplorer.usgs.gov).

The initial processing stage involved layer stacking (band composition). This technique integrates individual spectral bands from the satellite sensor to produce a composite image that represents Earth's surface features in appropriate color visualizations (e.g., natural or false-color composites).

Following the band composition, supervised classification was performed within the ArcMap environment using remote sensing techniques. The composite raster imagery (.TIF) of Karawang Regency was processed using the Create Signature tool, utilizing training samples (.SHP) generated through manual digitization. These samples represent 10 distinct land cover classes. The resulting signature file (.GSG) was then used as the input for the Maximum Likelihood Classification (MLC) algorithm, applied to the composite imagery to generate the final land cover maps for Karawang Regency.

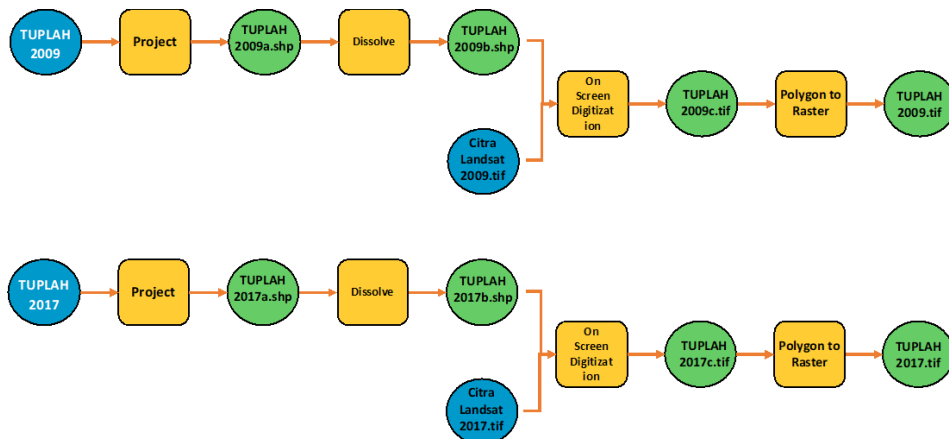


Figure 5: Land Cover Classification Model Builder in ArcMap

Source: Authors (2026)

During the "Project" stage, the coordinate system was standardized to WGS 1984 UTM Zone 48N. This study utilized raster data analysis, where all spatial information was processed in grid cells. In accordance with established literature, a spatial resolution of 30 m × 30 m was applied, representing a ground

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area of 900 m² per cell. The raster grid consists of 2,076 columns and 2,415 rows, resulting in a total of 5,013,540 cells.

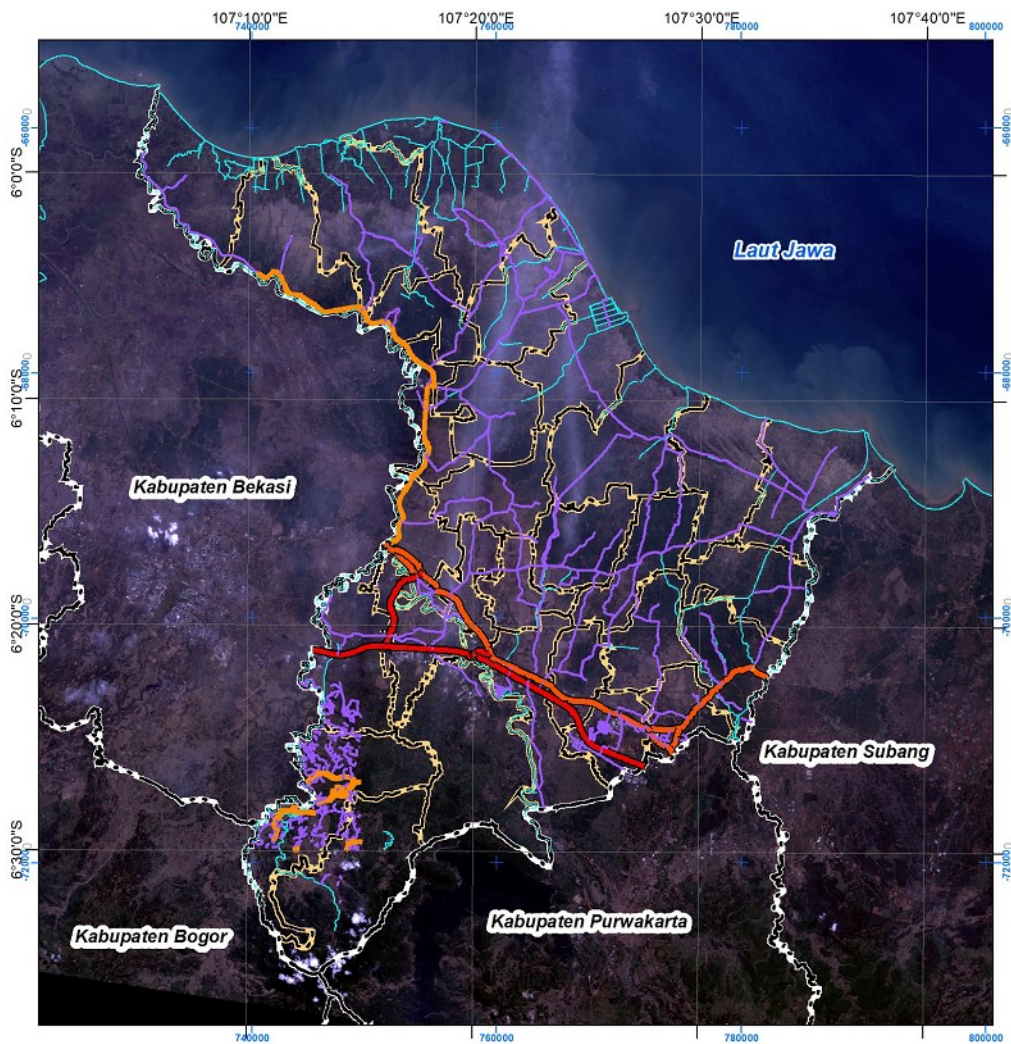


Figure 6: Landsat TM 7 Satellite Imagery 2009

Source: Authors (2026)

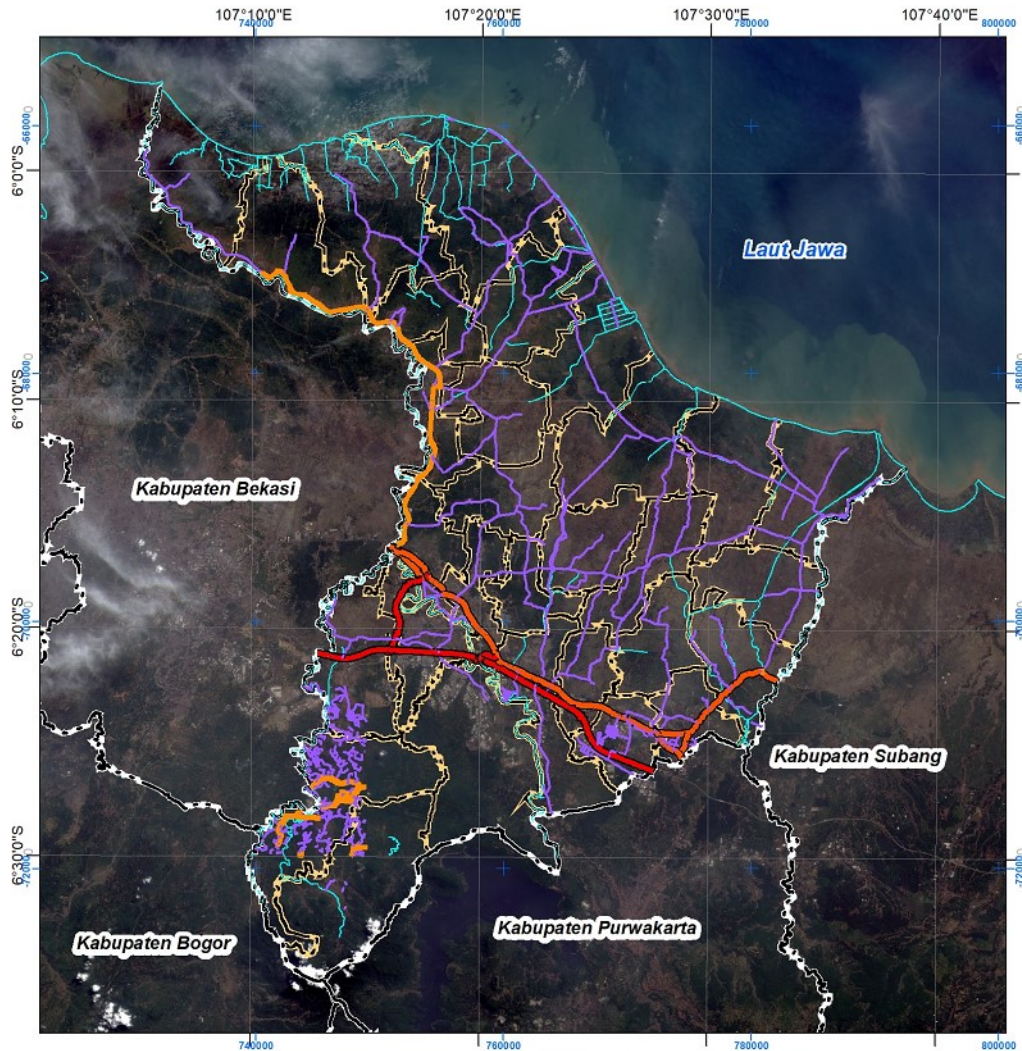


Figure 7: Landsat TM 7 Satellite Imagery 2017
Source: Authors (2026)

Based on the satellite imagery interpretation, paddy fields dominated the land cover in 2009, accounting for 113,575.61 ha (approximately 59%) of the total area of Karawang Regency. Other prominent land cover types included settlements and built-up land at 20,153.09 ha, followed by aquaculture ponds (tambak) at 18,610.89 ha.

By 2017, the interpretation results showed that the paddy field area had decreased by 3,453.37 ha to a total of 110,122.24 ha. Conversely, settlements and

built-up land increased significantly by 6,370.31 ha, reaching a total area of 26,523.40 ha

Table 3: Land Use/Cover Areas Based on Satellite Imagery Interpretation (2009 and 2017).

No	Land Cover Category	2009 Area (ha)	2017 Area (ha)
1	Water Bodies	1,185.53	1,135.25
2	Plantation Forest	6,476.85	4,366.52
3	Open Land	99.44	1,126.04
4	Plantation	1,467.64	571.42
5	Settlement/Built-up Land	20,153.09	26,523.40
6	Mining	-	11.16
7	Dryland Agriculture	19,419.38	13,057.77
8	Paddy Field	113,575.61	110,122.24
9	Scrub/Shrubland	101.72	61.01
10	Aquaculture Ponds	18,610.89	18,329.79
Total		192,314.69	192,314.69

Source: Authors

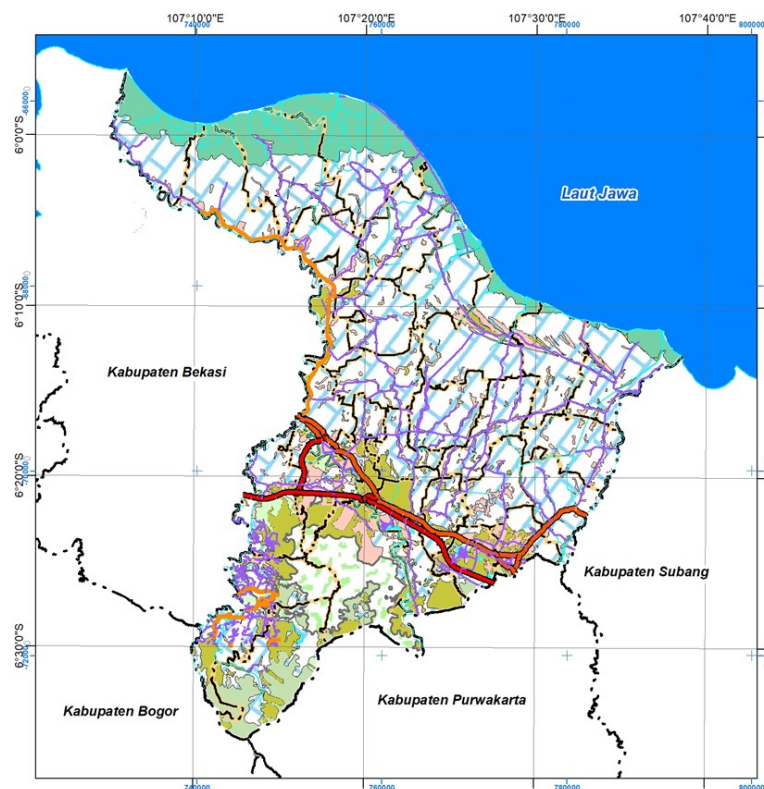


Figure 8: Land Cover Map from Satellite Image Interpretation in 2009

Source: Authors (2026)

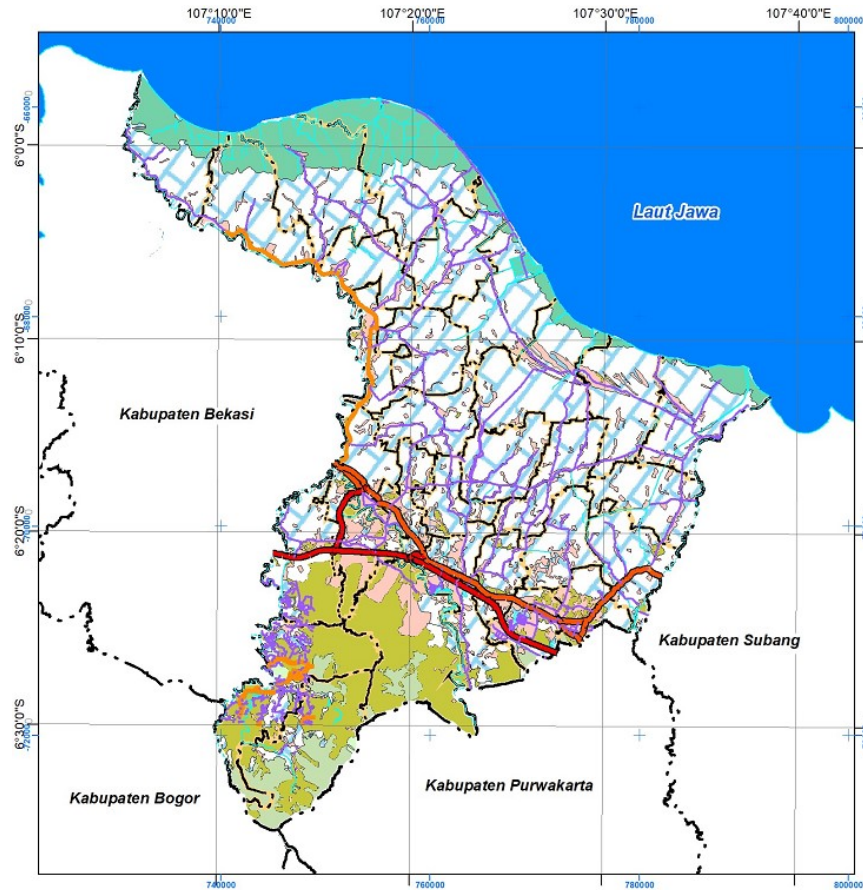


Figure 9: Land Cover Map from Satellite Image Interpretation in 2017
Source: Authors (2026)

Land cover validation was performed to assess the accuracy of the generated 2009 and 2017 land cover maps. This accuracy assessment involved comparing the classified data against reference points generated using the Create Random Points tool. These sample points represent terrestrial surface samples—measured or acquired data points assumed to accurately represent the actual land relief and cover.

The validation process was conducted by cross-referencing these sample points with high-resolution historical imagery from 2009 and 2017 within Google Earth Pro. This comparison serves as the "ground truth" to verify the level of agreement between the classification results and the actual conditions on the ground.

Accuracy Assessment and Prediction Modelling

A total of 42 sample points were tested, distributed evenly across the Karawang Regency. The accuracy assessment yielded an overall accuracy of 78.5% for 2009 and 80.9% for 2017.

Land Use Change Prediction Analysis

The land-use change prediction in this study was executed in three stages: projections for 2021, 2026, and 2031. The 2021 prediction served as a validation phase to evaluate the reliability of the Cellular Automata (CA) model. The model's performance was measured using the Kappa Index, which compared the 2021 simulated land cover results against the official 2021 Land Cover Map. The reference map was provided by the Karawang Regency Department of Public Works and Spatial Planning (PUPR), derived from SPOT 7 satellite imagery and validated by the Geospatial Information Agency (BIG). Furthermore, the 2031 prediction was aligned with the final planning year of the Karawang Regency Spatial Planning (RTRW) 2011–2031. These simulations were performed using IDRISI TerrSet 18.02 (or version 10.2).

In modelling these transitions, the integration of driving factors and constraints is essential. By identifying the variables that either promote or restrict land-use conversion, the study can estimate and predict spatial shifts as a proactive step in managing regional land-use dynamics.

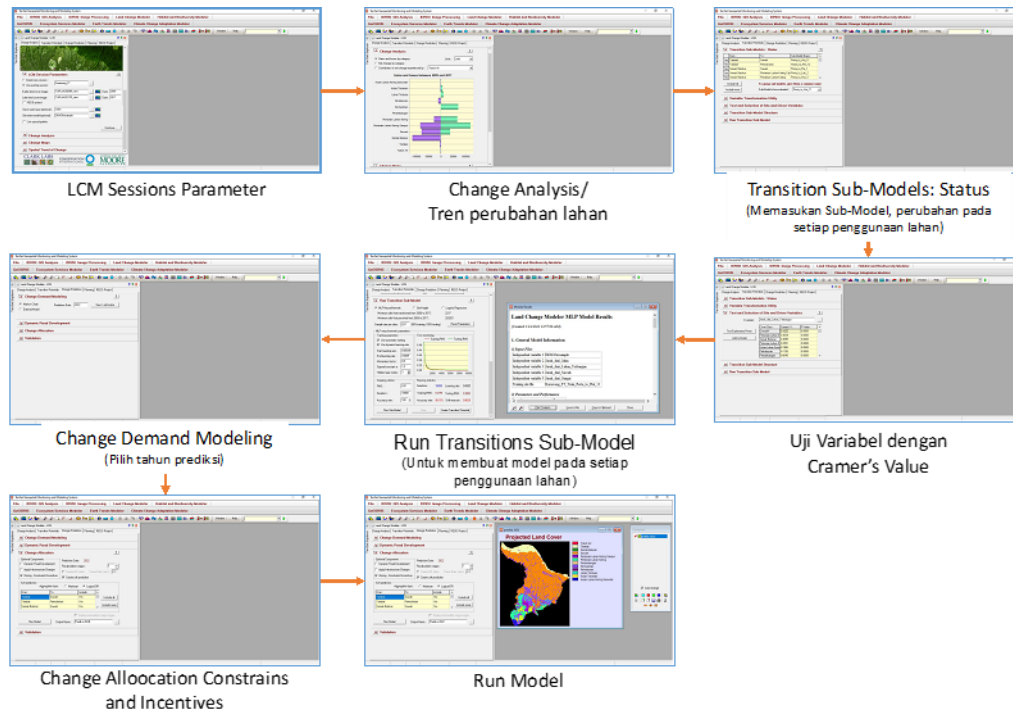


Figure 10: Flowchart of Land Cover Prediction Analysis Stages Using CA-Markov Method Using TerrSet Software
Source: Authors (2026)

Land Cover Prediction and Kappa Index Validation

The land cover prediction for 2021 was conducted to validate the Cellular Automata (CA) simulation process. The reliability of the model was assessed using the Kappa Index of Agreement (KIA), which measures the consistency between the simulated 2021 land cover and the official 2021 reference map. This reference data was obtained from the Karawang Regency Department of Public Works and Spatial Planning (PUPR), based on SPOT 7 satellite imagery validated by the Geospatial Information Agency (BIG).

The Kappa test evaluates both the total area per land class and the spatial distribution of those classes. The Kappa Index is categorized into five classification levels with 0.2 intervals. A value approaching 1.0 indicates that the simulation is highly accurate and closely reflects reality, thereby justifying its use for future projections. In many studies, a minimum Kappa value of 0.6 is considered the threshold for acceptable model performance. Consequently, models falling within the "Good" or "Very Good" categories are deemed scientifically valid for predicting future land cover changes.

Table 4 Kappa Index Classification

Index Kappa	Strength of Agreement
<0,2	Poor
0,21 - 0,4	Fair
0,41 - 0,6	Moderate
0,61 - 0,8	Good
0,81 - 1.00	Very Good

Source: Anang, 2019

Results of the Model Validation

The validation results for the predicted 2021 land cover of Karawang Regency yielded a Kappa coefficient of 0.9328. This value falls within the "Very Good" strength of agreement category, indicating that the simulation model exhibits high accuracy and high fidelity to observed conditions. Consequently, the model is considered scientifically robust and suitable for projecting future land-use and land-cover changes

Classification agreement/disagreement According to ability to specify accurately quantity and allocation			
Information of Allocation	Information of Quantity		
	No[n]	Medium[m]	Perfect[p]
Perfect[P(x)]	P(n) = 0.3389	P(m) = 0.9830	P(p) = 1.0000
PerfectStratum[K(x)]	K(n) = 0.3389	K(m) = 0.9830	K(p) = 1.0000
MediumGrid[M(x)]	M(n) = 0.3252	M(m) = 0.9595	M(p) = 0.9570
MediumStratum[H(x)]	H(n) = 0.0769	H(m) = 0.3973	H(p) = 0.3965
No[N(x)]	N(n) = 0.0769	N(m) = 0.3973	N(p) = 0.3965

AgreementChance = 0.0769
AgreementQuantity = 0.3203
AgreementStrata = 0.0000
AgreementGridcell = 0.5622
DisagreeGridcell = 0.0235
DisagreeStrata = 0.0000
DisagreeQuantity = 0.0170
Kno = 0.9561
Klocation = 0.9600
KlocationStrata = 0.9600
Kstandard = 0.9328
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Figure 11: Kappa Test Results on Land Cover Prediction in 2021

Source: Authors (2026)

Predicted Land Cover Analysis for 2021

Based on the results of the 2021 land cover prediction, paddy fields remain the most extensive land category, covering 107,888.87 ha. However, settlements and built-up land continue to expand, reaching a total area of 29,553.86 ha.

Furthermore, aquaculture ponds, which constitute the third-largest land cover category in Karawang Regency, account for 18,472.45 ha.

Table 5: Predicted Land Cover Analysis for 2021

No	Land Cover Category	Area (ha)
1	Water Bodies	1,147.71
2	Plantation Forest	4,349.70
3	Open Land	2,233.72
4	Plantation	579.64
5	Settlement / Built-up Land	29,553.86
6	Mining	15.69
7	Dryland Agriculture	11,731.30
8	Paddy Field	107,888.87
9	Scrub / Shrubland	62.88
10	Aquaculture Ponds	18,472.45
Total		192,314.69

Source: Authors

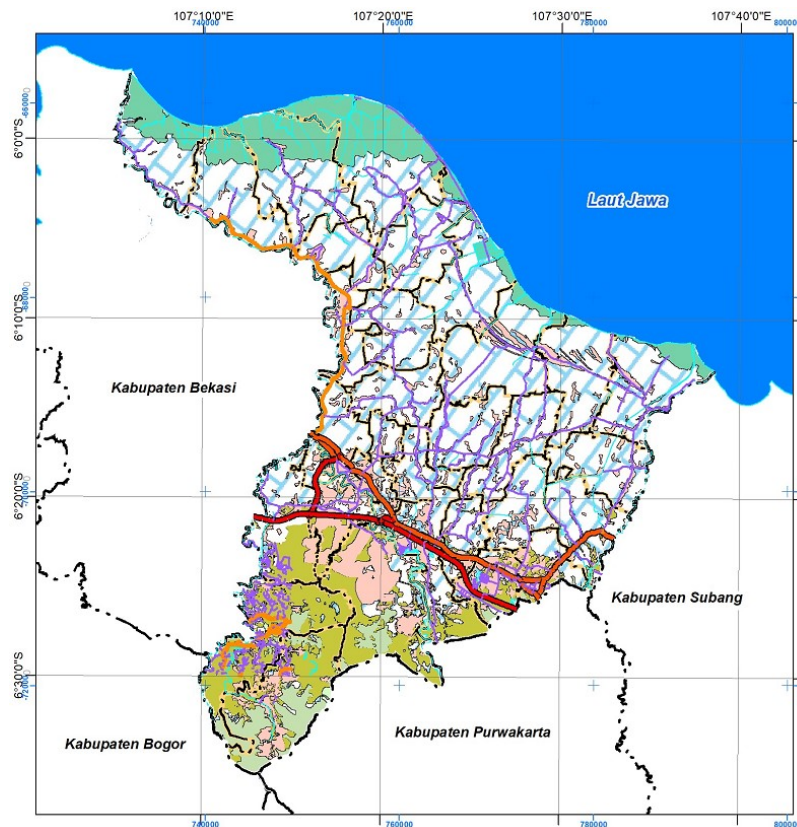


Figure 12: Land Cover Prediction Map for 2021

Source: Authors (2026)

Predicted Land Cover Analysis for 2026

The land cover prediction for 2026 indicates a continued shift in the spatial landscape of Karawang Regency. The total area of paddy fields is projected to decrease to 107,643.69 ha, though it remains the dominant land cover class. In contrast, settlements and built-up land show significant growth, expanding to 35,181.36 ha. Meanwhile, aquaculture ponds continue to rank as the third most dominant land cover type, covering an area of 18,256.95 ha.

Table 6: Predicted Land Cover Analysis for 2026

No	Land Cover Category	Area (ha)
1	Water Bodies	1,141.20
2	Plantation Forest	7,070.13
3	Open Land	1,757.52
4	Plantation	159.57
5	Settlement / Built-up Land	35,181.36
6	Mining	25.83
7	Dryland Agriculture	20,043.90
8	Paddy Field	107,643.69
9	Scrub / Shrubland	56.25
10	Aquaculture Ponds	18,256.95
Total		192,314.69

Source: Authors

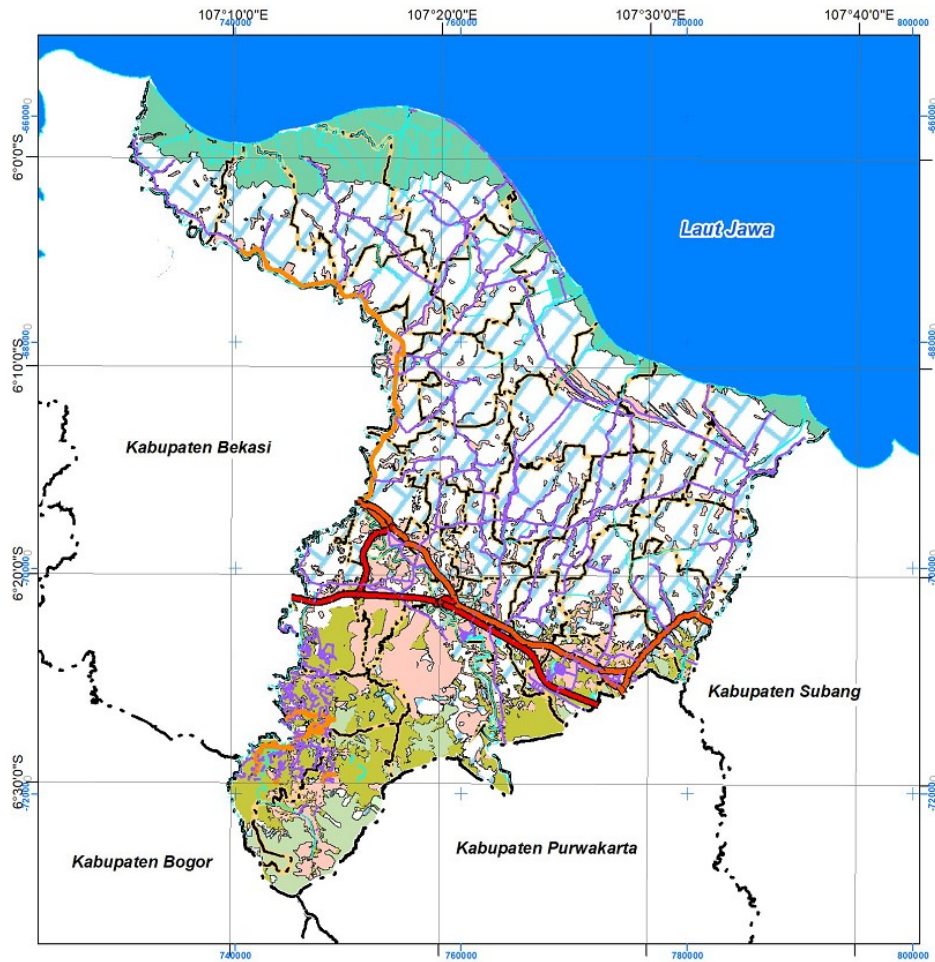


Figure 13: Land Cover Prediction Map for 2026
Source: Authors (2026)

Predicted Land Cover Analysis for 2031

The land cover prediction for 2031 was conducted to align with the final planning year of the Karawang Regency Spatial Plan (RTRW) 2011–2031. Based on the simulation results, the area of paddy fields is projected to decrease to 105,416.28 ha. Conversely, settlements and built-up land are expected to expand from the 2026 figures, reaching a total area of 38,016.63 ha. Furthermore, aquaculture ponds, which remain the third most dominant land cover type, are projected to encompass an area of 18,185.22 ha

Table 7: Predicted Land Cover Analysis for 2031

No	Land Cover Category	Area (ha)
1	Water Bodies	1,147.71
2	Plantation Forest	4,349.70
3	Open Land	2,233.72
4	Plantation	579.64
5	Settlement / Built-up Land	29,553.86
6	Mining	15.69
7	Dryland Agriculture	11,731.30
8	Paddy Field	107,888.87
9	Scrub / Shrubland	62.88
10	Aquaculture Ponds	18,472.45
Total		192,314.69

Source: Authors

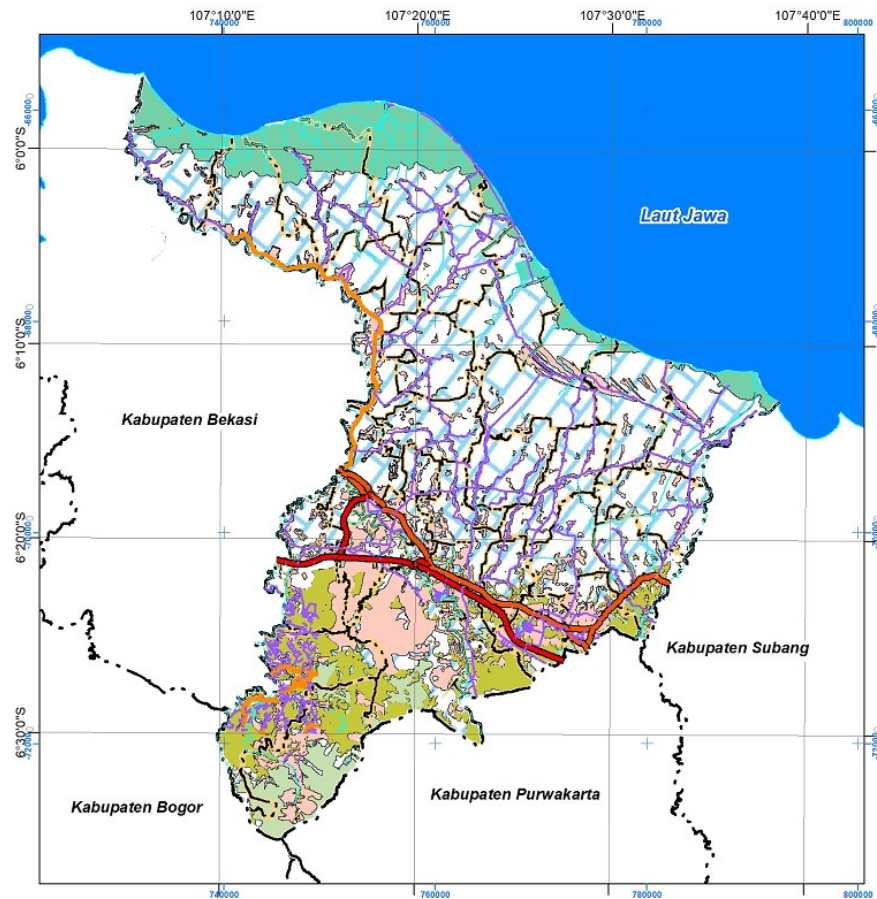


Figure 14: Land Cover Prediction Map for 2026

Source: Authors (2026)

Table 8: Predicted Land Cover Analysis Comparison

No	Land Cover Category	2021	2026	2031
1	Water Bodies	1,147.71	1,141.20	1,141.20
2	Plantation Forest	4,349.70	7,070.13	4,798.53
3	Open Land	2,233.72	1,757.52	2,054.25
4	Plantation	579.64	159.57	106.29
5	Settlement / Built-up Land	29,553.86	35,181.36	38,016.63
6	Mining	15.69	25.83	22.95
7	Dryland Agriculture	11,731.30	20,043.90	15,955.20
8	Paddy Field	107,888.87	107,643.69	105,416.28
9	Scrub / Shrubland	62.88	56.25	55.53
10	Aquaculture Ponds	18,472.45	18,256.95	18,185.22
Total		192,314.69		

Source: Authors

Model Performance and Spatial Accuracy

The validation of the Cellular Automata (CA) model produced a Kappa Index of 0.9328, indicating a "Very Good" level of agreement. This high degree of accuracy suggests that the driving factors (e.g., proximity to roads, existing built-up centers, and spatial constraints) used in the IDRISI TerrSet simulation were highly representative of the actual urban growth dynamics in Karawang Regency. The use of validated SPOT 7 imagery as a reference for the 2021 prediction further strengthens the empirical reliability of the 2026 and 2031 projections.

The Dynamics of Agricultural Land Conversion

The results highlight a significant and continuous reduction in paddy fields (sawah). From 2009 to 2031, the total area of paddy fields is projected to shrink from 113,575.61 ha to 105,416.28 ha. This loss of approximately 8,159 ha is a critical finding, given Karawang's status as a national "rice granary."

The expansion of settlements and built-up land, which is projected to reach 38,016.63 ha by 2031, appears to be the primary driver of this conversion. This suggests that the conversion is not merely random but is a systematic response to the massive industrial and residential demand in the region (Luo et al., 2025; Sun & Xu, 2025; Yu et al., 2025). The trend aligns with Karawang's strategic position as an industrial corridor, where the shift from a primary agricultural economy to a secondary industrial/service economy is reflected in its spatial footprint.

Implications for Spatial Planning and Food Security

The 2031 projection serves as a critical evaluation of the 2011–2031 Karawang Regency Spatial Plan (RTRW). Despite the existence of the Sustainable Food Agricultural Land (LP2B) draft maps and local regulations, the model predicts that built-up areas will continue to encroach upon productive lands.

The increase in "Dryland Agriculture" observed in the 2026 and 2031 periods suggests a possible fragmentation of large paddy field blocks. When irrigation systems are disrupted by settlement construction, the surrounding paddy fields often lose their productivity and are converted into dryland agriculture before eventually being sold for industrial or residential use (Ferreira et al., 2015; Heilemann et al., 2025; Whitesel et al., 2025).

Policy Recommendations

To mitigate the projected loss of agricultural land by 2031, local authorities must transition from passive spatial planning to active enforcement. This includes:

- **Stricter Zoning Enforcement:** Ensuring that areas designated as LP2B are legally protected from land-use permits for non-agricultural purposes.
- **Incentive Mechanisms:** Providing subsidies or infrastructure support to farmers in high-pressure conversion zones to prevent the sale of productive land.
- **Vertical Development:** Encouraging high-density residential development rather than horizontal urban sprawl to minimize the land footprint per capita.

CONCLUSION

This study demonstrates that Karawang Regency is undergoing a significant spatial transformation driven by the expansion of built-up areas. The Cellular Automata model utilized in this research proved highly reliable, as evidenced by a Kappa validation score of 0.9328, falling within the "Very Good" agreement category. The predictive analysis reveals that by the end of the 2031 planning period, approximately 8,159.33 ha of paddy fields will have been lost compared to 2009 levels, primarily due to the conversion into residential and industrial zones. Built-up land is projected to reach 38,016.63 ha, representing a nearly 89% increase from 2009. While paddy fields still dominate the landscape, the continuous rate of conversion presents a long-term risk to the Sustainable Food Agricultural Land (LP2B) program. These projections serve as a critical decision-support tool for local authorities to evaluate the effectiveness of current spatial regulations and to implement more robust conservation strategies for agricultural preservation.

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