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Analysis and Effectiveness of Flood Hazard Based Settlement Prediction Models in Tegal Regency

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ABSTRACT

Annual flooding in Tegal Regency reflects a mismatch between settlement expansion and environmental vulnerability, particularly within high-risk flood zones. This issue requires predictive approaches capable of directing settlement growth adaptively. This study aims to develop a Cellular Automata (CA)–based settlement growth prediction model integrated with flood hazard maps and evaluate its effectiveness in supporting disaster-resilient spatial planning. The Analytical Hierarchy Process (AHP) was applied to determine settlement-driving factors based on expert interviews. The novelty of this research lies in the direct integration of flood-hazard zoning constraints into CA transition rules, combined with field-based sample-point validation to assess spatial accuracy. The model was simulated for 2023–2043 at five-year intervals. Results indicate that proximity to existing settlements is the dominant driver, while hazard-based zoning effectively restricts expansion into high-risk areas. Field validation confirms high model accuracy, reinforcing the reliability of the predictions. Overall, the integrated CA model provides a scientific and operational basis for local governments to guide settlement development toward safer zones and enhance the resilience of spatial planning.

Keywords: *Disaster resilient spatial planning, land Cover simulation, Analytical Hierarchy Process (AHP)*

ABSTRAK

Banjir tahunan di Kabupaten Tegal menunjukkan adanya ketidaksesuaian perkembangan permukiman dengan kondisi kerentanan lingkungan, terutama pada kawasan rawan banjir. Permasalahan ini menuntut pendekatan prediktif yang mampu mengarahkan pertumbuhan permukiman secara adaptif. Penelitian ini bertujuan mengembangkan model prediksi perkembangan permukiman berbasis Cellular Automata (CA) yang diintegrasikan dengan peta bahaya banjir, serta mengevaluasi efektivitasnya untuk mendukung penataan ruang yang berketahanan bencana. Metode Analytical Hierarchy Process (AHP) digunakan untuk menentukan faktor pendorong perkembangan permukiman melalui wawancara pakar. Kebaruan penelitian terletak pada integrasi langsung antara kendala zonasi bahaya banjir dan proses transisi CA, yang dikombinasikan dengan validasi lapangan berbasis titik sampel untuk menilai kesesuaian spasial hasil simulasi. Model disimulasikan untuk periode 2023–2043 dengan interval lima tahunan. Hasilnya menunjukkan bahwa kedekatan terhadap permukiman eksisting merupakan faktor dominan, sementara penerapan zonasi bahaya secara efektif membatasi ekspansi menuju area berisiko. Validasi lapangan mengonfirmasi akurasi tinggi model, memperkuat reliabilitas prediksi yang dihasilkan. Secara keseluruhan, model CA terintegrasi ini memberikan dasar ilmiah dan operasional bagi pemerintah daerah dalam mengarahkan perkembangan permukiman ke zona aman serta meningkatkan ketangguhan rencana tata ruang.

Kata Kunci: Perencanaan Tangguh Bencana, Simulasi Penggunaan Lahan, *Analytical Hierarchy Process* (AHP)

1. INTRODUCTION

Indonesia, located in the tropical region between two continents and two oceans, experiences highly dynamic weather and climate patterns, making it vulnerable to heavy rainfall that can trigger annual flooding (Khomariyah et al., 2022). Flooding results from a combination of natural processes and human activities, including climate change, increased surface runoff, land-use conversion, and settlement expansion (Hirabayashi et al., 2021). When rivers or drainage channels exceed their capacity, water overflows into surrounding land areas, causing infrastructure damage, economic losses, and risks to public safety (Rahmawaty & Hasan, 2023).

Tegal Regency, situated along the northern coast of Central Java, is one of the areas highly prone to annual flooding due to overflow from rivers such as Cacaban, Rambut, and Siwarak (Sejati et al., 2023). Population growth and rapid economic development continue to drive settlement expansion, often without considering the availability of safe land, thereby increasing flood vulnerability (Handayani et al., 2019; Insani et al., 2022). Flooding is further intensified by deforestation and land-use changes in upstream areas, which accelerate runoff toward downstream regions, especially when river and drainage capacity is insufficient (Meng et al., 2019). Therefore, spatial planning is needed to maintain water-absorption functions in upstream zones and guide development in downstream areas away from flood-prone zones through an integrated upstream–downstream approach (Awaliyah et al., 2020; Cilliers, 2019; Eldi, 2020; Ningrum & Ginting, 2020).

Recurring floods in Tegal Regency reflect the region's hydrological vulnerabilities. In 2021–2023, flooding affected multiple sub-districts with water depths ranging from 20–150 cm, 16 recorded events in 2022, and renewed inundation in 2023 (BPBD Tegal Regency, 2023). These repeated incidents highlight the need for more adaptive spatial planning to reduce flood risk and to steer settlement growth toward safer areas.

Over the past decade, international studies have advanced *Cellular Automata* (CA) models integrated with flood hazards to simulate urban growth under environmental constraints (Liu et al., 2023; Szwagrzyk et al., 2018). CA–GIS approaches are widely recognized for their ability to capture spatial dynamics realistically. However, recent literature emphasizes the need for models that incorporate more dynamic hazard constraints and field-based validation to improve prediction reliability (Heiland, 2017; Mansour et al., 2024; Pérez-Molina et al., 2017).

In Indonesia, several studies have applied Cellular Automata (CA) to constrain settlement expansion in flood-prone areas (Sadewo & Buchori, 2018; Septawicaksono & Pratomoatmojo, 2020), However, the evaluation of model effectiveness in these studies has generally been limited to verification using satellite imagery without field checks. To date, no research has explicitly integrated flood-hazard zoning constraints with field-based sample-point validation to assess predictive accuracy within an adaptive planning context. The incorporation of field verification in this study represents an important advancement, as it enhances the model's ability to accurately capture the correspondence between predicted outcomes and actual on-ground conditions.

Therefore, this study aims to develop a settlement development prediction model that is integrated with flood-hazard maps in Tegal Regency and to evaluate its effectiveness through quantitative analysis. This objective is formulated into two research questions: "How can a settlement development prediction model that accounts for flood hazards be constructed in Tegal Regency?" and "Can the developed model effectively avoid areas with high flood risk?" In line with these questions, the study proposes the hypothesis that integrating flood-hazard maps as zoning constraints within a Cellular Automata (CA) model can guide future settlement growth away from high-risk areas. The explicit application of hazard constraints is expected to improve the predictive accuracy of the model and produce safer settlement development patterns that align with the principles of disaster resilient spatial planning.

2. METHOD

Study Area

The scope of the area in this analysis is Tegal Regency, which is one of the regencies in Central Java Province with its capital in Slawi. This regency is located between coordinates 108° 57' 6" to 109° 21' 30" E and 6° 50' 41" to 7° 15' 30" S. The area of Tegal Regency is 98,411.21 ha.

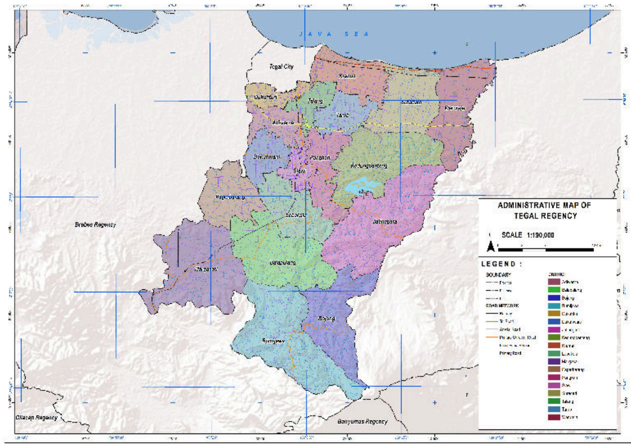

Figure 1. Administrative Map of Tegal Regency
Source: Authors, 2025

Data Collection

In this study, data were collected from both primary and secondary sources. Primary data were obtained through purposive interviews with respondents, including planning experts, academics, and local government agencies directly involved in spatial planning in Tegal Regency (Lenaini, 2021; Rusmawan, 2018; Sadewo & Buchori, 2018), as well as through field observations to validate actual conditions. Secondary data were obtained from BPBD and the Department of Public Works and Spatial Planning, including flood hazard maps, land-cover data, and contingency planning documents. Spatial analysis was conducted using ArcGIS 10.8 and QGIS 3.16 to process data and identify land-cover change patterns, while land-cover change simulations were performed using LanduseSim 2.3.1 with a Cellular Automata (CA) model to predict land-use development based on historical data and driving factors.

Stages And Processes

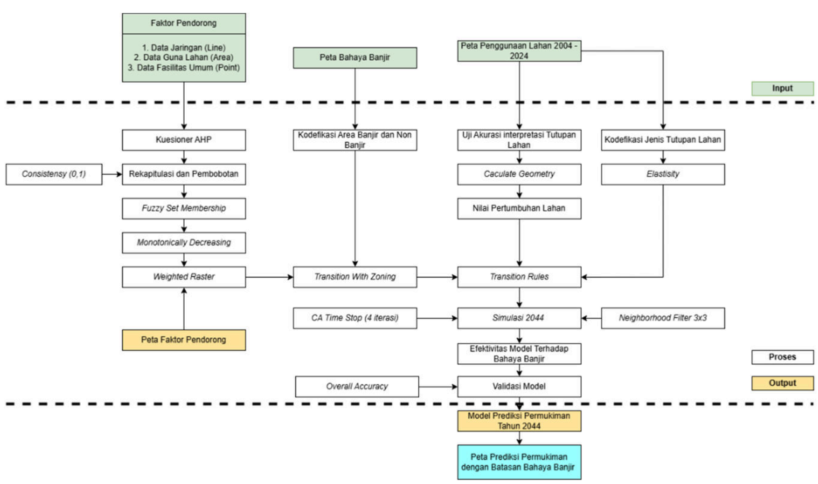

Figure 2. Stages And Processes
Source: Authors, 2025

Settlement Land Simulation Analysis

The methodology for the settlement land-use change simulation in this study adopts a quantitative spatial approach developed by Septawicaksono & Pratomoatmojo (2020), with adjustments made to the context of Tegal Regency. This approach integrates land-change dynamics analysis, weighting of driving factors using the Analytical Hierarchy Process (AHP), fuzzy set standardization, and the application of Cellular Automata (CA) to predict future settlement growth. The use of CA is supported by previous studies by (Burhan et al., 2020; Sadewo & Buchori, 2018; Septawicaksono & Pratomoatmojo, 2020), which achieved an accuracy of around 85%, demonstrating that CA can reliably represent spatial growth patterns influenced by neighborhood effects. Since settlement expansion typically follows the outward growth of existing built-up areas, CA is an appropriate and well-tested method for modeling such development.

1. Land Change Values 2003 – 2023

Land change is analyzed to identify change trends that occurred during a 20-year period in Tegal Regency. The analysis was conducted by collecting land cover data from 2023, then tracing back to 2003. Land cover data was obtained through digitization of Google Earth satellite imagery and Peta Rupa Bumi Indonesia (RBI), which was then overlaid to identify patterns and dynamics of land cover changes over the past two decades.

2. Formation of Land Cover Growth Transition Maps

The land change potential transition map illustrates the possible direction of development that can be simulated in land use. The transition map was obtained using the Analysis Hierarchy Process (AHP) technique with several driving factors for settlement land growth obtained from literature review. Weight determination was obtained from experts directly involved in spatial planning using the Analysis Hierarchy Process (AHP). The calculations in creating land use change transition maps are as follows (Pratomoatmojo, 2018).

$$TP_{i_{x,y}} = \sum_{z=0}^{n} \left(N_{i_{(z \to n)x,y}} \, . \, ITP_{i_{(z \to n)x,y}} \right)$$

Where:

$TP_{i_{x,y}}$	=	Transition potential change value from land use i at a specific cell (x, y) calculated through filter summation operations.
$N_{i_{(z \to n)x,y}}$	=	Neighborhood filter potential applied to a specific filter and accumulated at the center cell (x, y), while n includes total cells in the neighborhood, both with or without center cell
$max.S_i$	=	Initial transition potential map value for specific land use (i), or can be represented by suitability maps for specific land use that is developing

Each driving-factor map for settlement land-change modeling was standardized using fuzzy sets in LanduseSim, with values ranging from 0 to 1, consisting of both monotonically increasing and monotonically decreasing types (Burhan et al., 2020).. In this study, a monotonically decreasing fuzzy set was applied, meaning that the closer a location is to a driving factor, the higher the potential for settlement growth as indicated by the model. The fuzzy equations used follow the LanduseSim framework as formulated by (Pratomoatmojo, 2018).

Linear Monotonically Increasing

$$S_{std_{x,y}} = \frac{S_{i_{x,y}}}{max.S_i}$$

Linear Monotonically Decreasing

$$S_{std_{x,y}} = -\left(\frac{S_{i_{x,y}}}{max.S_i} - 1\right)$$

Where:

$S_{std_{x,y}}$	=	Standardized value at a specific cell (x, y)
$S_{i_{x,y}}$	=	Suitability number/distance value at a specific cell (x, y)
$max.S_i$	=	Maximum value of suitability number/distance value, after which each distance map and its relevant weights are overlaid to produce land use growth maps

3. Neighborhood Filter

Neighborhood Filter determines the extent of interaction between land use and dynamics determined in modeling. In this research, a 3x3 neighborhood filter size is used with weights on each cell of 1 and SUM mechanism. The cellular automata process with 3x3 filter produces more compact modeling compared to other filters, such as 5x5 or 7x7 (Pratomoatmojo, 2018). Therefore, this research uses the SUM 3x3 mechanism.

4. Zoning Constraint Map

This step identifies land-use areas that will not experience growth and restricts zones that have potential for development within the model. The zoning map is designed specifically for flood-hazard areas by assigning a value of 0 to high-risk zones and a value of 1 to areas outside the hazard zone that can still be converted. This zoning constraint map is then used to update the Transition Map so that land-use changes occur only in areas suitable for development. (Rahmawati & Pratomoatmojo, 2020).

5. Land Change Simulation Using Cellular Automata

The use of Cellular Automata is intended to observe simulated land development changes. Simulations were conducted from 2023 to 2043. Iterations were performed 4 times to observe changes every 5 years, occurring in 2028, 2033, 2038, and 2043. The simulation equation used is as follows: (Pratomoatmojo, 2018)

$$LU_{x,y}^{t+1}=\left(LU_{x,y,}^{t}TP_{i_{x,y,}}G_{i_{x,y,}}C_{i_{x,y,}}E_{i_{x,y,}}Z_{i_{x,y,}}TS\right)$$

Where:

$LU_{x,y}^{t+1}$	=	New growth (changed state) of land use i at time t+1 at a specific cell (xy)
$LU_{x,y}^{t}$	=	Land use class state before simulation at a specific cell (x,y)
$TP_{i_{x,y}}$	=	Transition potential map of land use i at a specific cell (x,y)
$G_{i_{x,y}}$	=	Expected cell growth amount from land use i at time t+1
$C_{i_{x,y}}$	=	Land growth constraint that can be represented by specific land use that cannot be conserved by land use i or zones that need to be protected or conserved
$E_{i_{x,y}}$	=	*Elasticity of change for specific land use conserved to land use (i)*
$Z_{i_{x,y}}$	=	Zoning systems such as land use plans, disaster areas, promoted growth zones
TS	=	*Time-step of cellular automata iteration*

6. Model Validation

Simulation validation was conducted to assess the extent to which the predicted settlement growth has avoided flood-prone areas. Accuracy values were used to measure the agreement between the simulation results and field conditions.

Table 1. Accuracy Assessment Criteria

No.	Accuracy Values	Descriptions
1.	< 20%	Low
2.	21 – 40%	Fair
3.	41 – 60%	Moderate
4.	61 – 80%	Strong
5.	81 – 100%	Very Strong

Source: Anderson (Febianti et al., 2022)

Simulation were located in safe or flood-prone areas. If a sample point was in an area without a flood history, the prediction was considered appropriate; conversely, if it was in an area with a flood history, the prediction was considered inappropriate. This assessment was performed through spatial analysis by overlaying the simulation results onto the flood hazard map, as well as checking 70 random sample points in QGIS based on the 2043 prediction settlement, which were verified through field surveys. Field observations were then compared with the simulation outputs, providing an objective measure of the simulation's effectiveness in supporting flood-safe settlement planning (Congalton & Green, 2019).

3. RESULT AND DISCUSSIONS

Land Change Value

Land use growth values in Tegal Regency can be monitored through change patterns from 2003 to 2023 using ArcGIS and Microsoft Excel software. Data preparation requires land use data from 2003 and 2023 to be compared to determine the types of changes in the area of each land use.

Table 2. Land Change Value of Tegal Regency From 2003-2023

No.	Land Use Area	2003 -2013 (ha)	2013 – 2023 (ha)	Total Change (ha)
1.	Forest	0,00	0,00	0,00
2.	Industry	0,23	76,93	77,17
3.	Mixed Garden	-121,92	-68,20	-190,12
4.	Open Land	-31,34	-16,41	-47,75
5.	Land Sand	0,00	0,00	0,00
6.	Plantation	-0,43	-5,27	-5,70
7.	Settlement	530,01	322,14	852,15
8.	Rice Field	-347,76	-265,03	-612,80
9.	Shrubs	-10,67	-1,95	-12,62
10.	River	0,00	0,00	0,00
11.	Fishpond	-4,44	-5,84	-10,28
12.	Dry Land	-13,67	-36,36	-50,04
13.	Reseivor	0,00	0,00	0,00

Source: Authors, 2025

Based on land use change data from 2003–2023, Tegal Regency experienced significant spatial transformation characterized by settlement expansion and the conversion of agricultural land. Settlement areas increased by 852.15 ha, with rapid growth occurring in 2003–2013 (530.01 ha) and continuing in 2013–2023 (322.14 ha), while industrial areas expanded by 77.17 ha, mostly within the last decade. Conversely, agricultural lands declined substantially, particularly rice fields (-612.80 ha) and mixed gardens (-190.12 ha), indicating strong conversion pressure driven by urbanization, alongside reductions in dry land, open land, shrubs, fishponds, and plantations. Natural land uses such as forests, rivers, land sand, and reservoirs remained unchanged, suggesting these areas are protected or unsuitable for conversion. Subsequently, cell development calculations were performed for each raster pixel sized 30 × 30 meters (900 m²), using the standard conversion that 1 hectare equals 10,000 m² to determine pixel values for land area measurements. The following is the calculation of hectare units converted to pixels.

$$Growth = \frac{Growth\ Area\ Settlement\ (ha)\ X\ 10000\ (m)}{30\ X\ 30\ m}$$

$$\frac{852{,}12\ X\ 10000}{900}$$

$$= \mathbf{9.468}\ \boldsymbol{Pixels}$$

The above calculation shows that the land use growth value from 2003-2023 produces growth of 9.468 pixels, meaning each pixel in raster data has a value of 900 meters because the pixel size used is 30 X 30 meters, which will be used in simulating land use change predictions 20 years ahead using growth tools.

Transition Map Formation and Zoning Constraint Map

Settlement development driving factors determine spatial variables that can influence settlement development through literature review in relevant articles or journals (Yohanes Paulus Goo Ado, Rieneke L. E. Sela, 2023) suggest that driving factor analysis can be conducted through literature review and weighting with Analysis Hierarchy Process (AHP). The standard inconsistency value is <0.1, then it can be accepted Saaty, 1980 in (Aristo & Hizbaron, 2023; Moghadas et al., 2019). he following is a recapitulation table of interview data processing results.

Table 1. AHP Weighting Recapitulation

No.	Variabel	Expert 1	Expert 2	Expert 3	Expert 4	Combination
1.	Road Network	0,238	0,247	0,298	0,228	0,274
2.	Energy Network	0,114	0,124	0,190	0,093	0,130
3.	Clean Water	0,134	0,088	0,190	0,102	0,129
4.	Existing Settlement	0,365	0,351	0,112	0,402	0,278
5.	Industrial Area	0,033	0,060	0,064	0,065	0,056
6.	Trading Center	0,029	0,033	0,042	0,031	0,036
7.	Education Center	0,049	0,048	0,047	0,041	0,049
8.	Health Center	0,039	0,049	0,056	0,038	0,048

Source: Authors, 2025

The weighting results show that the driving variable with the greatest influence on settlement development driving factors is existing settlements with a value of 0.278, while the driving variable with the smallest influence is trading centers with a weight value of 0.036 and an average inconsistency value of 0.07 or <0,1. The dominance of existing settlements reflects spatial inertia, as communities tend to choose locations near existing facilities, such as road access, electricity, and public services.

The fuzzy set process involves driving factor data with 8 variables, all data is then converted to raster with cell size 30 x 30 according to land development modeling (Parasdyo & Susilo, 2012), In the context of fuzzy set processes for driving factors using monotonically decreasing, meaning the closer to driving factors, the faster settlement land potentially grows.

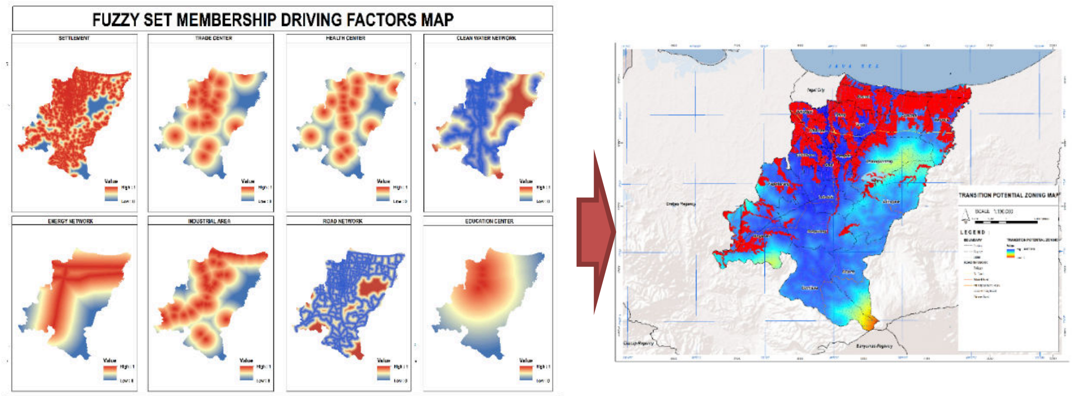

Figure 3. Fuzzy Set Membership Driving Factors Maps and Zoning Constraint Maps
Source: Authors, 2025

Settlement Land Simulation

The land use simulation process will involve modeling over a 20-year period, from 2023 to 2043, as a basis for evaluating spatial pattern policy planning in Tegal Regency. This process aims to provide an in-depth understanding of potential land use changes in the region. The simulation is carried out by generating land use predictions for the next 20 years, up to 2043. The simulation outcomes will be divided into four iterations, with each iteration representing a five-year interval. This approach enables gradual monitoring of the simulation model's development within measurable time intervals (Feng & Qi, 2018; Hanafi et al., 2021).

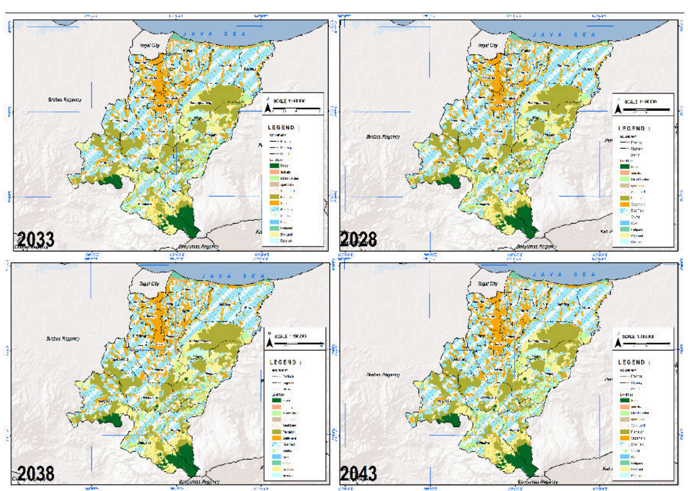

Figure 2. Map of Land Use Change Simulation Results for Tegal Regency From 2023 to 2043
Source: Authors, 2025

The simulation of settlement land-use change in Tegal Regency from 2023 to 2043, using a Cellular Automata model integrated with flood hazard maps, shows the projected expansion of built-up areas at five-year intervals. Several land types such as rivers, forests, fishponds, reservoirs, industrial zones, coastal sand areas, and existing settlements were designated as restricted zones where development is not allowed. These constraints were applied to prevent settlement growth in protected or flood-prone areas. The model focuses on how settlements expand based on road access, infrastructure, and proximity to existing built-up areas. Overall, the approach ensures that predicted development remains within safe and sustainable spatial boundaries.

Table 2. Land Use Forest From 2028 to 2043

No.	Land Use Area	Year			
		2028	2033	2038	2043
1.	Forest	3.951,09	3.951,09	3.951,09	3.951,09
2.	Industry	353,43	353,43	353,43	353,43
3.	Mixed Garden	4.611,87	4.594,05	4.581,9	4.568,49
4.	Open Land	161,55	156,51	150,84	149,49
5.	Land Sand	15,03	15,03	15,03	15,03
6.	Plantation	17.007,84	17.007,84	17.007,39	17.005,86
7.	Settlement	15.021,36	15.234,39	15.447,42	15.660,45
8.	Rice Field	45.788,04	45.598,32	45.404,55	45.208,98
9.	Shurbs	130,23	130,14	130,14	130,14
10.	River	215,91	215,91	215,91	215,91
11.	Fishpond	653,04	653,04	653,04	653,04
12.	Dry Land	9.826,83	9.826,47	9.825,48	9.824,31
13	Reservoir	676,8	676,8	676,8	676,8
Total Area (ha)		98.413,02	98.413,02	98.413,02	98.413,02

Source: Authors, 2025

The simulation results show a steady increase in settlement areas in Tegal Regency, growing from 15,021.36 hectares in 2028 to 15,660.45 hectares in 2043, an expansion of 639.09 hectares. This growth mainly occurs through the conversion of nearby agricultural and open lands—such as rice fields, mixed gardens, dry land, and vacant areas around existing settlements. The pattern reflects urban sprawl influenced by proximity to existing built-up areas, road networks, and infrastructure, consistent with the AHP results that identified existing settlements as the most dominant factor. Restricted zones including rivers, forests, reservoirs, fishponds, industrial areas, coastal sand dunes, and existing built-up zones remain unchanged, indicating that zoning constraints function effectively.

Model Effectiveness Analysis : Identification of Simulation Results With Flood Hazards

Land development identification against flood hazards aims to ensure the simulation model predicts settlements moving away from flood-prone areas. The results reveal relationships between variables, providing new data on spatial interactions (Larasati, 2017). This process compares existing land use and simulation results overlaid with flood hazard areas. In this way, settlement development directions relative to flood hazards can be monitored. The following is a map showing settlement development in relation to flood-prone areas.

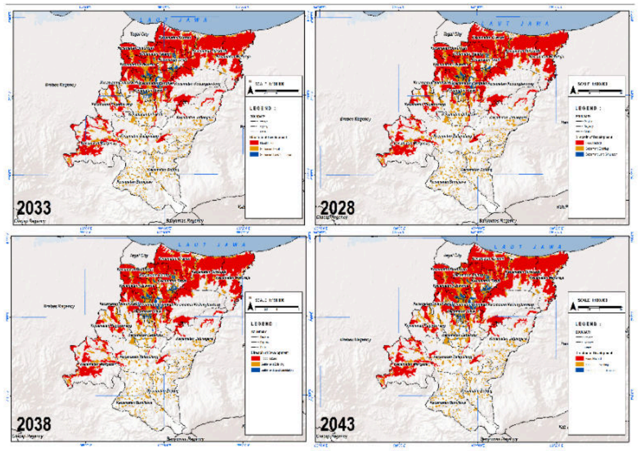

Figure 3. Map of Predicted Settlement Development Direction
Source: Authors, 2025

Based on the map analysis, it is clearly evident that the pattern of settlement development tends to avoid flood-prone areas, indicating the effectiveness of integrating flood hazard maps as zoning constraints in the prediction model. However, visual observations alone are insufficient to conclusively determine how effectively the model has restricted expansion into high-risk zones. Therefore, quantitative data is needed to systematically measure and compare the area of settlements developing in safe zones versus those in flood-prone areas. The following diagram provides a quantitative overview of settlement growth during the period 2028–2043.

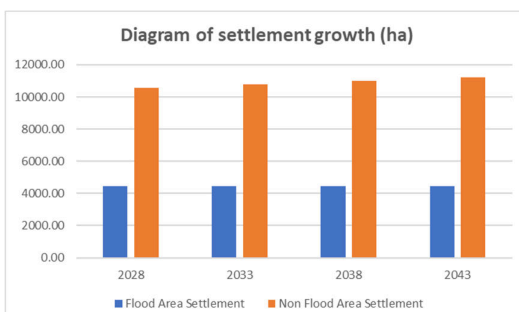

Figure 4. Diagram of Settlement Growth
Source: Authors, 2025

Overlay results between developing settlements and flood hazard areas show that settlement development tends to avoid flood-prone areas, but there is still settlement distribution to these areas. Evaluation table shows that settlement area in safe areas increased significantly from 6,048.63 ha (2028) to 9,584.95 ha (2043), while settlement area in flood hazard areas remained stable at 4,442.42 ha. This shows that this model has successfully limited settlement development in high-risk areas, although additional efforts are still needed to reduce risks in areas already affected.

The findings of this research are consistent with previous studies (Liu et al., 2023; Rahmawati & Pratomoatmojo, 2020; Sadewo & Buchori, 2018), which highlight the dominant role of neighborhood effects and infrastructure networks in driving settlement expansion as captured by Cellular Automata (CA) models. Unlike these studies, however, the present research incorporates flood-hazard zoning as a hard constraint within the CA transition rules and complements the evaluation with field-based validation using 70 sample points. This approach provides stronger empirical evidence that integrating hazard constraints can effectively steer spatial growth toward safer areas. Theoretically, the integration of CA-AHP modeling aligns with resilience-informed spatial planning, where risk reduction is achieved by controlling exposure through location-based development management and by providing scientific support for adaptive policy decisions.

Overall Accuracy Analysis

Overall Accuracy analysis aims to evaluate the accuracy of settlement prediction models against flood hazard areas (Nabila, 2023). A total of 70 random sample points were selected from areas identified as settlements based on model prediction results, represented by yellow color in. Each point is distributed throughout Tegal Regency, covering various locations considered potential for settlement development. Through field validation processes, each point is visited to verify whether the location is truly included in flood-prone areas based on physical conditions in the field. Observation results are then compared with model prediction results to calculate overall accuracy.

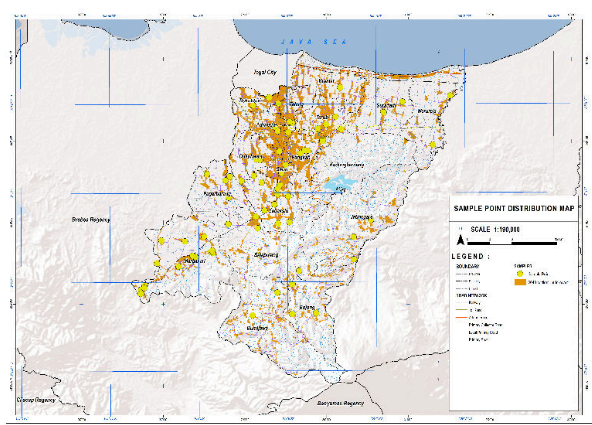

Figure 5. Map of Field Validation Using Overall Accuracy
Source: Authors, 2025

According to the land use classification framework by Anderson (Febianti et al., 2022), mapping results are considered to meet accuracy standards when their conformity level reaches at least 85%. Based on this criterion, the overall accuracy in this study was calculated as follows:

$$Overall\ Accuracy = \frac{N_{Correct}}{N\ Total}\ X\ 100\%$$

Substituting value:

$$Overall\ Accuracy = \frac{61}{70}\ X\ 100\%$$
$$= 87{,}14\%$$

The calculation shows that the model achieved an overall accuracy of 87.14%, which falls into the "Very Strong" category according to Anderson's land-cover classification standards. This value exceeds the minimum threshold of 85%, indicating that the flood hazard–based settlement prediction model demonstrates strong reliability. With 61 out of 70 field validation points matching actual conditions, the model effectively captures settlement growth tendencies and their spatial avoidance of flood-prone areas.

Despite its strong performance, the model still has several important limitations. The AHP process involved only four experts, which may introduce subjective bias in factor weighting. The use of a 30 × 30 m raster resolution and a 3 × 3 neighborhood filter also reduces sensitivity to micro scale land-use changes. In addition, uncertainties in the flood-hazard map and the absence of non-spatial variables such as socio-economic conditions or land-market dynamics limit the model's ability to fully represent the complexity of settlement development.

Considering these strengths and limitations, the prediction model can support disaster-resilient spatial planning, particularly in formulating spatial patterns that account for flood risk. The settlement prediction output may serve as one of the technical considerations for local governments in identifying growth corridors, directing development toward safer zones, and restricting permits in high-risk areas. The model can also be utilized in *what-if* policy simulations to evaluate alternative planning scenarios and can be integrated into routine monitoring mechanisms and multi-actor forums to strengthen evidence-based decision-making.

5. CONCLUSION

This study successfully developed a flood hazard–integrated settlement growth prediction model using Cellular Automata (CA) to analyze development patterns in Tegal Regency. The main scientific contribution lies in the methodological advancement of embedding flood-hazard zoning directly into CA transition rules and incorporating satellite image–based validation using 70 sample points, addressing the limitation of previous studies that relied solely on satellite-based verification without confirming whether the predicted areas actually fall within flood-prone zones. The model achieved an overall accuracy of 87.14%, exceeding the minimum threshold of 85%, demonstrating high reliability in predicting settlement expansion and its tendency to avoid high-risk flood zones.

The findings indicate that proximity to existing settlements is the dominant driving factor, supporting the neighborhood effect theory in CA-based modeling. The integration of flood-hazard maps as a hard constraint effectively redirects future settlement growth toward safer areas, enhancing the model's relevance for disaster-resilient spatial planning. Practically, the simulation outputs can assist local governments in shaping spatial patterns, identifying growth corridors, restricting development in high-risk zones, and conducting what-if policy evaluations. These insights can support revisions of the RTRW and the preparation of RDTR, contributing to evidence-based planning processes.

Despite its strong performance, the model has several limitations. The AHP process involved only four experts, raising the potential for subjective bias. The 30 × 30 m raster resolution may overlook micro-scale land-use changes, and uncertainties persist in the flood-hazard map. Moreover, socio-economic drivers and land-market dynamics were not incorporated, limiting the model's ability to fully represent the complexity of settlement development. Future research should integrate socio-economic variables, compare CA with alternative approaches such as Agent-Based Modeling or machine learning methods, and conduct sensitivity tests on spatial resolution and AHP weights to enhance predictive robustness under varying environmental and policy conditions.

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