



Prediction of Built-up Land Changes until 2032 Using the Cellular Automata-Artificial Neural Network (CA-ANN) and Logistic Regression Approaches (Case Study: Gerbangkertosusila)

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Received : 26 February 2025

Accepted : 8 June 2026

Available Online : 31 August 2026

Abstract: Urban areas are highly vulnerable to land cover changes, particularly the conversion of non-built-up land into built-up areas due to increasing population growth and urban activities. As the second-largest metropolitan agglomeration in Indonesia after Jabodetabek, Gerbangkertosusila has experienced rapid urbanization driven by migration and regional development. Understanding land-cover dynamics in this region is important for supporting sustainable urban planning and future land management. Therefore, this study aims to analyze built-up land expansion in Gerbangkertosusila from 2012 to 2022 and predict future growth in 2027 and 2032 using Cellular Automata-Artificial Neural Network (CA-ANN) and Logistic Regression models. The modeling process incorporated driving factors including proximity to roads, buildings, rivers, and Digital Elevation Model (DEM). The results indicate that built-up land increased from 41,417.50 hectares in 2012 to 63,928.06 hectares in 2022. The ANN model demonstrated higher accuracy (94.01% correctness, kappa 0.64) than Logistic Regression (93.09% correctness, kappa 0.58). Future projections show continued expansion, with the ANN model estimating 64,017.43 hectares in 2027 and 89,237.90 hectares in 2032,

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How to Cite

Wulandari, P., Wahyuningrum, D., & Susetyo, D. B. (2026). Prediction of Built-up Land Changes until 2032 Using the Cellular Automata-Artificial Neural Network (CA-ANN) and Logistic Regression Approaches (Case Study: Gerbangkertosusila). *Jurnal Wilayah dan Lingkungan*, 14(2), 161-179. <https://doi.org/10.14710/jwl.14.2.161-179>

while the Logistic Regression model predicts 62,662.39 hectares in 2027 and 84,438.57 hectares in 2032. These findings indicate that Gerbangkertosusila will continue to experience significant urban expansion in the coming years. The projected spatial patterns for 2027 and 2032 can support urban spatial planning, infrastructure development, and strategies to mitigate uncontrolled urban expansion in Gerbangkertosusila.

Keywords: CA-ANN, Changes in Built Land, Logistic Regression

Introduction

Land demand is directly proportional to regional development, economic growth, and population growth, all of which are manifestations of human activities in development (Roy et al., 2017). Land has a limited capacity, while human activities continuously evolve to fulfill various needs, leading to an increasing land demand and resulting in land cover changes, particularly the conversion of non-built-up land into built-up land (Adininggar et al., 2016). Urban areas are predominantly characterized by high-density built-up land, where land cover types are closely interconnected (Sulistiowati et al., 2012). Population growth and increasing human activities in a particular area contribute to land cover changes, particularly the expansion of built-up land to accommodate housing and accessibility needs (Mosammam et al., 2016). According to Cohen (2006), approximately 50% of the global population resides in urban centers, and future population growth is projected to occur primarily in urban areas, indicating the strong attractiveness of cities for surrounding populations. Without proper monitoring and prediction, rapid built-up land expansion may lead to uncontrolled land conversion and challenges for future urban development management.

Gerbangkertosusila encompasses seven regions, namely Gresik Regency, Bangkalan Regency, Mojokerto Regency, Mojokerto City, Surabaya City, Sidoarjo Regency, and Lamongan Regency, forming a metropolitan agglomeration in East Java Province. Centered in Surabaya, Gerbangkertosusila is the second-largest metropolitan region and the second most populous metropolitan area in Indonesia after Jabodetabek. This region is highly susceptible to land cover changes, particularly built-up land expansion, due to increasing population growth and urban activities. According to data from the Central Statistics Agency (BPS), the population of Gerbangkertosusila was recorded at 9,940,220 in 2020 and increased to 10,049,351 in 2022. As the population grows and human activities intensify, the demand for housing and accessibility will continue to increase in the future (Ariyani et al., 2021). Therefore, Gerbangkertosusila represents an important case study for analyzing and predicting built-up land expansion in rapidly growing metropolitan regions in Indonesia.

Given these circumstances, monitoring built-up land changes through spatial modeling is essential to understand future urban development patterns. Advances in computer technology, particularly Geographic Information Systems (GIS), facilitate the analysis of built-up land change modeling by incorporating driving factors influencing land transformation. One of the approaches commonly used for land-use and land-cover prediction is Cellular Automata (CA), which is capable of simulating dynamic spatial and temporal changes over time (Wijaya & Susilo, 2013). CA is widely used in land-use change prediction because of its ability to model complex spatial dynamics, although the model has limitations in explaining the causal relationships between driving variables and land-cover changes (Pravitasari et al., 2020). Therefore, CA is often integrated with transition potential modeling approaches such as Artificial Neural Network (ANN) and Logistic Regression (LR) to improve prediction performance. ANN is a machine learning-based approach capable of

recognizing complex and non-linear relationships between variables (Astuti, 2016), while LR is a statistical approach commonly used to model the probability of land-use change through binary regression analysis (Roseana et al., 2019).

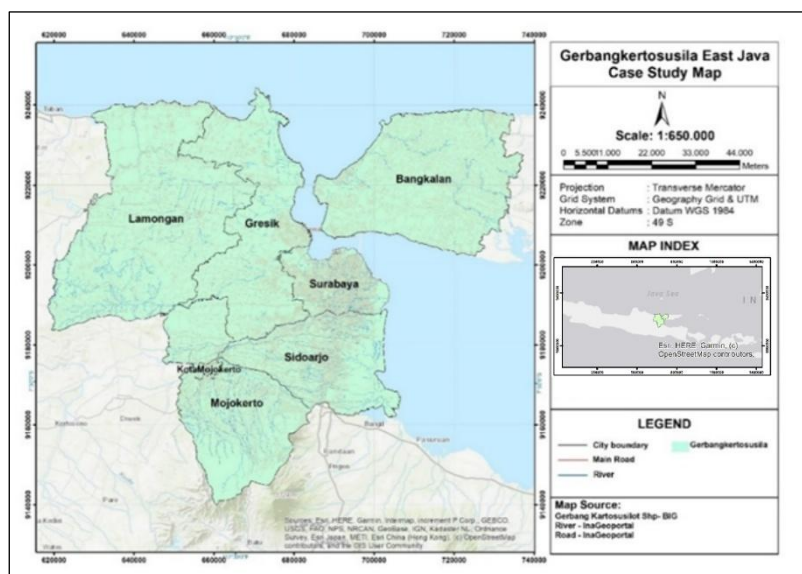
Previous studies have demonstrated the capability of CA-ANN and CA-LR in predicting land-use and land-cover changes with relatively high accuracy. Nabila (2023) reported that CA-ANN achieved a kappa index of 0.95 and a correctness value of 97.14% in land-use change prediction. Saputra et al. (2022) also showed that ANN produced higher accuracy than Multi Criteria Evaluation (MCE) in land-cover change modeling. In addition, Ricky et al. (2017) found that both ANN and LR produced good prediction performance, although ANN showed better results in terms of false alarm and misses. However, studies comparing the performance of CA-ANN and CA-LR for predicting built-up land expansion in rapidly growing metropolitan areas such as Gerbangkertosusila remain limited. Comparing these approaches is important because ANN represents a machine learning-based approach, whereas LR represents a statistical-based approach, both of which employ fundamentally different mathematical logics that may yield distinct spatial patterns and accuracy levels in spatial land-change modeling.

Therefore, this study aims to identify built-up land changes in Gerbangkertosusila from 2012 to 2022 and to analyze future built-up land changes for 2027 and 2032 using Cellular Automata simulations with the Artificial Neural Network and Logistic Regression methods. These simulations are conducted using the MOLUSCE (Modules for Land Use Change Simulations) plugin in the QGIS software, which supports multi-temporal land-cover modeling and provides several prediction approaches, including ANN and LR (Hakim et al., 2019). Satellite imagery data used for land cover classification include Landsat 7 for 2012 and Landsat 8 for 2017 and 2022. The driving factor variables used in the modeling and prediction of built-up land changes include distance to roads, distance to rivers, distance to buildings, and Digital Elevation Model (DEM).

Research Method

Study Area

This study was conducted in the Gerbangkertosusila region, a metropolitan agglomeration in East Java Province consisting of Gresik Regency, Bangkalan Regency, Mojokerto Regency, Mojokerto City, Surabaya City, Sidoarjo Regency, and Lamongan Regency. Also known as Surabaya Raya, the region represents one of the most densely populated urban areas in Indonesia. Gerbangkertosusila was selected as the study area because it is the second-largest metropolitan agglomeration after Jabodetabek and has experienced rapid urban growth and population increase, resulting in a high potential for built-up land expansion. Therefore, the region provides an appropriate case for analyzing and predicting spatial patterns of built-up land change in rapidly developing metropolitan areas. Figure 1 illustrates the research location map of Gerbangkertosusila.



Source: Author's Analysis, 2023

Figure 1. Study Area

Data Collection and Preparation

This study utilized both primary and secondary spatial data obtained from various institutions. The primary data consisted of Landsat imagery and land-cover maps, while the secondary data included road networks, rivers, buildings, and Digital Elevation Model (DEM) data used as driving factors in the modeling process. A literature review was also conducted to support the research framework and methodological approach through relevant journals, books, articles, and official documents. Previous studies have demonstrated that Cellular Automata integrated with Artificial Neural Network (CA-ANN) and Logistic Regression (CA-LR) can effectively model and predict land-cover changes with relatively high accuracy in urban and metropolitan regions.

Land Cover Classification

Land cover classification was conducted using Google Earth Engine (GEE). Landsat 7 Surface Reflectance imagery was used for 2012 while Landsat 8 Tier 1 Surface Reflectance imagery was used for 2017 and 2022. The classification process applied a supervised classification approach using the Support Vector Machine (SVM) algorithm to classify land cover into two categories: built-up land and non-built-up land. The SVM algorithm was selected because it provides a mathematically robust classification framework and is capable of handling both linear and non-linear classification problems through optimal hyperplane separation. Classification accuracy was evaluated using 50 sample points.

Driving Factors Preparation

Driving factors were incorporated into the modeling process because they influence land-cover transformation and urban expansion. The selected driving factors consisted of road networks, rivers, buildings, and elevation. These variables were selected based on previous studies indicating that accessibility and physical environmental conditions significantly influence urban development and land-cover changes. Proximity to roads and buildings represents accessibility and urban activity intensity, whereas rivers and elevation represent physical constraints affecting land development patterns.

All driving factor variables were initially prepared as vector spatial data and subsequently converted into raster format with a spatial resolution of 30 m to match the Landsat imagery resolution. Euclidean distance analysis was conducted in ArcGIS 10.3 to calculate the straight-line distance from each object, followed by the Extract by Mask process to ensure uniform spatial coverage across the Gerbangkertosusila region.

Land Cover Change Modeling

Land-cover change modeling was conducted using the MOLUSCE (Modules for Land Use Change Simulation) plugin in QGIS. MOLUSCE was selected because it supports multi-temporal land-cover simulation and provides several transition potential modeling approaches, including Artificial Neural Network (ANN) and Logistic Regression (LR). Cellular Automata (CA) was employed as the primary simulation framework because of its capability to model dynamic spatial-temporal changes. However, CA has limitations in explaining the relationships between driving variables and land-cover transitions. Therefore, CA was integrated with ANN and LR approaches to improve prediction performance.

ANN was selected because of its capability to recognize complex and non-linear relationships between variables, whereas LR was employed as a statistical-based approach for modeling land-cover transition probabilities. These two methods may produce different prediction results because ANN and LR apply different computational approaches in modeling transition potential. ANN identifies complex and non-linear relationships iteratively, while LR models transition probabilities through statistical regression analysis. Consequently, the two approaches may generate different spatial prediction patterns despite using the same input data.

The modeling process used land-cover maps from 2012 and 2017 as input data and consisted of several stages:

1. Inputs Preparation

Land-cover maps from 2012 and 2017 were assigned as the initial and final states, respectively, while rasterized driving factors were incorporated into the model. The driving factors included roads, rivers, buildings, and elevation. Geometry checking was conducted to ensure spatial consistency among all datasets.

2. Correlation Evaluation

This stage involved analyzing the correlation between driving factors and land cover using Pearson's Correlation. Pearson's correlation coefficient was employed to measure the degree of association between each driving factor and the respective land cover classes, with values ranging from 0 to 1. A value of 0 indicates no correlation, whereas a value of 1 signifies a strong correlation between the driving factor and land cover change (Kusniawati, 2020).

3. Area Changes

The Area Changes stage provided information on land cover transitions through a transition matrix, which illustrated the probability of land cover change. The results were presented in tabular format, displaying the extent of land cover change along with transition matrices.

4. Transition Potential Modeling

This stage determines the method to be used in modeling land cover predictions. Transition Potential Modeling assessed the likelihood of one land cover type transitioning into another. In this study, Artificial Neural Network (ANN) and Logistic Regression (LR) methods are employed to process the potential land cover changes into a different form.

5. Cellular Automata Simulation

The Cellular Automata Simulation stage involved generating a land cover model based on a defined time frame. The predicted year was determined by adding a specific time interval to the latest dataset. In this study, the 2012 land cover map served as the baseline, while the target year was set to 2022, with a time interval of five years. Therefore, the final predicted year was $2022 + 5 = 2027$. Using the Cellular Automata simulation process, a predictive land cover model for 2022 was generated based on data from 2012 and 2017.

6. Model Validation

Model validation was conducted to assess the accuracy of the simulation results. The Validation Map compared three datasets: the initial land cover map, the reference land cover map, and the simulated land cover map. Model validation is a crucial step in determining the reliability of land cover change predictions. According to Altman (1991), as cited by Subiyanto & Suprayogi (2019), the Kappa accuracy value provides an indication of the model agreement level. A Kappa value between 0.81% and 1.00% indicates excellent agreement, between 0.61% and 0.80% is considered good, between 0.41% and 0.60% is moderate, between 0.21% and 0.40% is below average, and a value <0 to 0.20% is considered poor. In this study, the kappa coefficient obtained was 0.64012 for the ANN method, indicating moderate to good agreement, while the LR method yielded a kappa coefficient of 0.58565, representing moderate agreement. These results suggest that both methods are suitable for predicting future built-up land expansion.

7. Prediction of Future Built-up Land Changes

Future built-up land prediction was performed by iterating the Cellular Automata Simulation process. To determine the iteration, trial and error were performed to achieve optimal future predictions. The author tested several iterations, starting with iteration 1, but the results were not optimal. A subsequent test with iteration 12 also did not yield satisfactory results. After several attempts, the author predicted the land change for 2027 using iteration 3 and for 2032 with iteration 6, which produced the desired predicted future built-up land changes.

Result and Discussion

Land Cover in 2012, 2017, and 2022

The land cover classification of the Gerbangkertosusila region was derived from Landsat 7 and Landsat 8 imagery using the Support Vector Machine (SVM) method, implemented on the Google Earth Engine platform. This classification categorized land cover into two classes: built-up land and non-built-up land. The Support Vector Machine is a machine learning algorithm designed to identify a hyperplane that optimally separates datasets from different classes. One of the key advantages of SVM is its ability to measure distances using support vectors, enabling faster computational processes. Additionally, SVM classification has high accuracy and strong performance in high-dimensional spaces (Vapnik, 1995).

Table 1 indicates a continuous increase in built-up land within the Gerbangkertosusila region during the 2012–2022 period. Built-up areas expanded from 41,417.497 hectares in 2012 to 63,928.055 hectares in 2022, while non-built-up land gradually decreased over the same period. This trend reflects the rapid urbanization process occurring in the Gerbangkertosusila metropolitan area, which is strongly influenced by population growth, increasing economic activities, and the expansion of residential and infrastructure development centered around Surabaya.

Table 1. Land Cover Area in 2012, 2017, and 2022 in Gerbangkertosusila Region

Land Cover	2012 (Ha)	2017 (Ha)	2022 (Ha)	Deviation (Ha)
Built up land	41417,497359	55933,122805	63928,055353	536820,564811
Non-built-up land	572560,151163	54627,774486	550049,8657	77138,059949

Source: Analysis Results, 2023

Land Cover Accuracy Assessment

The accuracy assessment of the land cover classification was conducted using a confusion matrix. Given the extensive study area, a representative sampling strategy was applied across the Gerbangkertosusila region. According to Walpole & Myers (1993, as cited in Saidatuningtyas et al., 2022), the central limit theorem states that the sample mean is generally reliable when the sample size is ≥ 30 . To streamline the sampling process while ensuring representativeness, 50 sample points were selected.

Based on Anderson's rule, land cover classification accuracy should ideally be at least 85%. The accuracy assessment results indicate that the classification achieved an accuracy of 99% in 2012, 91% in 2017, and 99% in 2022, demonstrating acceptable accuracy levels. The detailed classification accuracy results are presented in Table 2.

Table 2. Land Cover Accuracy Test 2012, 2017, and 2022

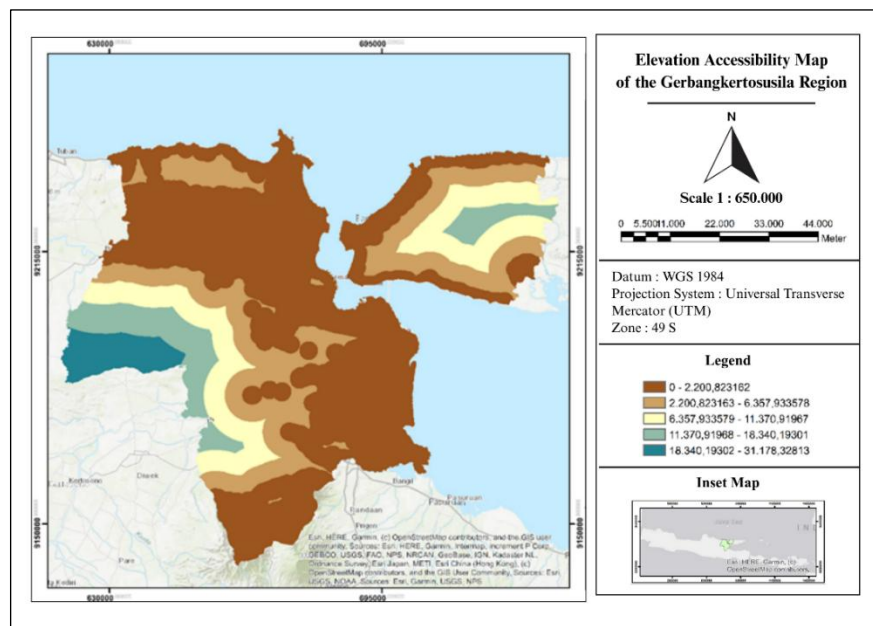
Year	2012	2017	2022
Overall Accuracy (%)	0.99	0.91	0.99

Source: Analysis Results, 2023

Factors Driving Built-Up Land Changes

a. Elevation

The Gerbangkertosusila region exhibits diverse elevation levels (Figure 2), ranging from 0 to 31.178 meters above sea level (MASL). Built-up land is predominantly located in lower elevation areas, whereas non-built-up land is generally found at higher elevations. The elevation gradually increases from west to east, with areas such as Lamongan, Mojokerto, Kota Mojokerto, and Bangkalan having relatively higher elevations, ranging from 6.357 to 31.178 MASL. In contrast, Surabaya and Sidoarjo are situated at lower elevations, ranging from 0 to 2.200 MASL. Elevation serves as a critical variable in analyzing areas susceptible to built-up land expansion.

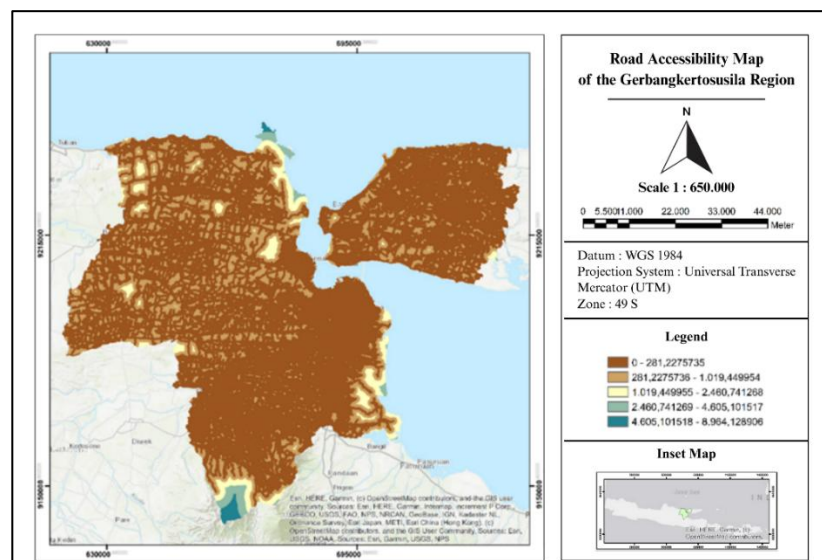


Source: Author's Analysis, 2023

Figure 2. Elevation Accessibility

b. Road Accessibility

Road networks play a crucial role as a primary factor in built-up areas. Developed areas tend to be located near roads to support activities. Consequently, built-up land is typically found around road infrastructure. Road accessibility is therefore a relevant driving factor in analyzing or predicting built-up area expansion. Based on Figure 3, nearly all districts in the Gerbangkertosusila region have high road accessibility, with an average accessibility range of 0 to 0.281 meters, and the farthest distance reaching 4.605 to 8.964 meters.

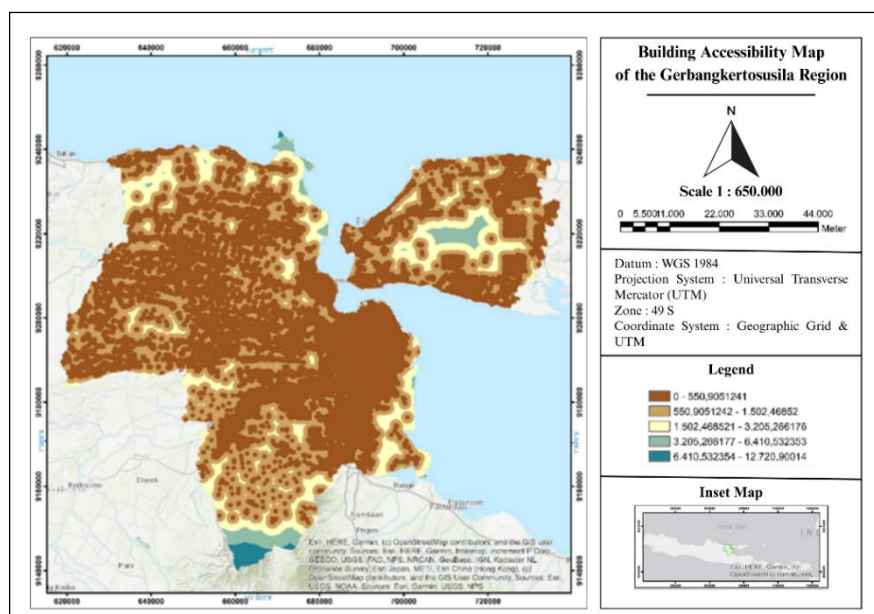


Source: Author's Analysis, 2023

Figure 3. Road Accessibility

c. Building Accessibility

Buildings play a significant role in built-up land expansion, as human settlements tend to drive further development in their vicinity. Areas located closer to existing settlements have a higher likelihood of being converted into built-up land. As a metropolitan region, Gerbangkertosusila has a high concentration of buildings, contributing to the widespread proximity to built-up areas. Figure 4 illustrates that most districts in the region are located near existing buildings, with an average accessibility range of 0 to 1.502 meters, while the farthest distances reach 6.410 to 12.720 meters.

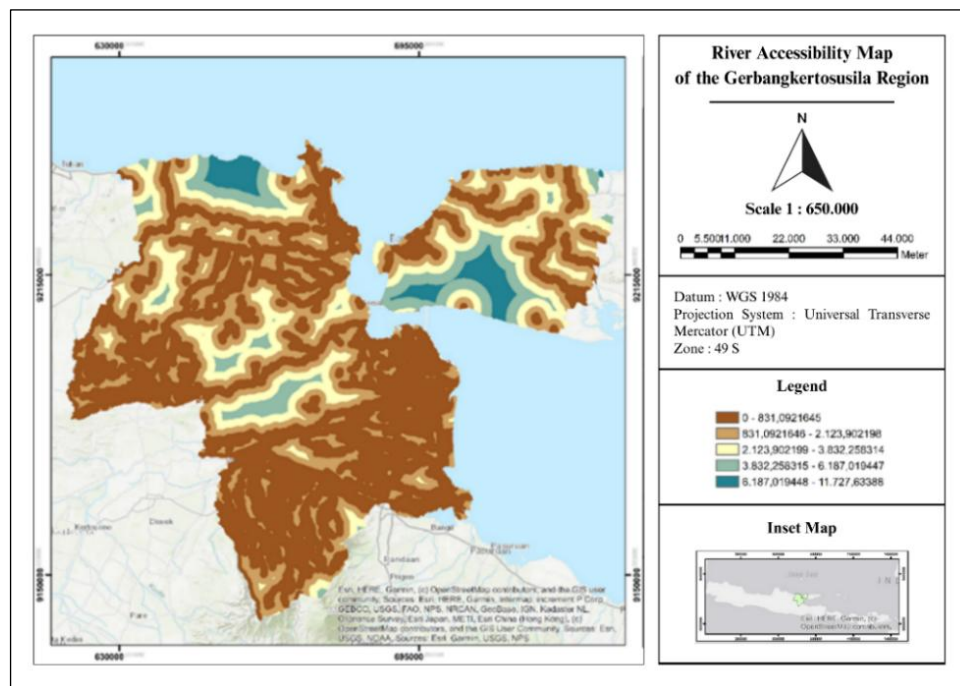


Source: Author's Analysis, 2023

Figure 4. Accessibility Building

d. River Accessibility

Historically, human settlements have been established near water sources, a trend that continues to influence urban expansion today. River accessibility significantly affects the distribution of built-up land, as proximity to water bodies often makes areas more attractive for development. However, despite the environmental risks associated with riverside construction, urban expansion near rivers remains prevalent. Figure 5 shows that the Gerbangkertosusila region generally has good river accessibility, with most rivers being reachable within 0 to 0.876 meters.



Source: Author's Analysis, 2023

Figure 5. River Accessibility

Land Cover Change Modeling

1. Inputs

The input stage involves integrating the initial (2012) and final (2017) land cover maps with driving factors such as proximity to roads, rivers, buildings, and elevation contours.

2. Evaluating Correlation

Correlation analysis was conducted using Pearson's correlation coefficient to assess the relationship between driving factors and land cover change. As shown in Table 3, a strong correlation was observed between road-building (0.7249) and building-river (0.0898), indicating that land cover changes occur more rapidly in areas closer to settlements, roads, and rivers. Conversely, elevation exhibited a negative correlation with roads and buildings, suggesting minimal land cover change in higher-altitude areas. This is consistent with the Gerbangkertosusila region's topography, where most areas are relatively elevated, except for Surabaya and Sidoarjo.

Table 3. Correlation Test Results

	Elevation	Road	Building	River
Elevation	1	-0,1119	-0,0116	0,0002
Road		1	0,7249	-0,0422
Building			1	0,0898
River				1

Source: Analysis Results, 2023

3. Area Changes

This stage produces a land cover change table and a transition matrix, which illustrate the likelihood of land cover transformation. The results from the MOLUSCE processing are presented in Table 4.

Table 4. Land Cover Change

Land Cover	2012	2017	Devition
Built-up Land	6.73815961847	8.90164837518	2.1634887567
Non-Built-up Land	93.2618403815	91.0983516248	-2.1634887567

Source: Analysis Results, 2023

According to Table.4, the land cover type that increased in area was built-up land, which expanded by 2,163.49 hectares. Conversely, non-built-up land experienced a decrease of -2,163.49 hectares.

Table 5. Land Cover Change Opportunity Transition Matrix

Land Cover	Built-up Land	Non-Built-up Land
Built-up Land	0.957522	0.042478
Non-Built-up Land	0.266850	0.733150

Source: Analysis Results, 2023

This stage also generates a transition matrix (Table 5) that quantifies the probability of one land cover type transforming into another. The transition matrix values range from 0 to 1, where values between 0.01 and 0.99 indicate the likelihood of land cover change, while values of 0 or 1 signify land cover stability (i.e., no change). The diagonal component of the matrix shows that non-built-up land has the highest probability (0.957) of converting into built-up land. Meanwhile, the diagonal component for built-up land has a probability value of 0.266, indicating that built-up areas are more likely to remain unchanged.

4. Transition Potential Modeling

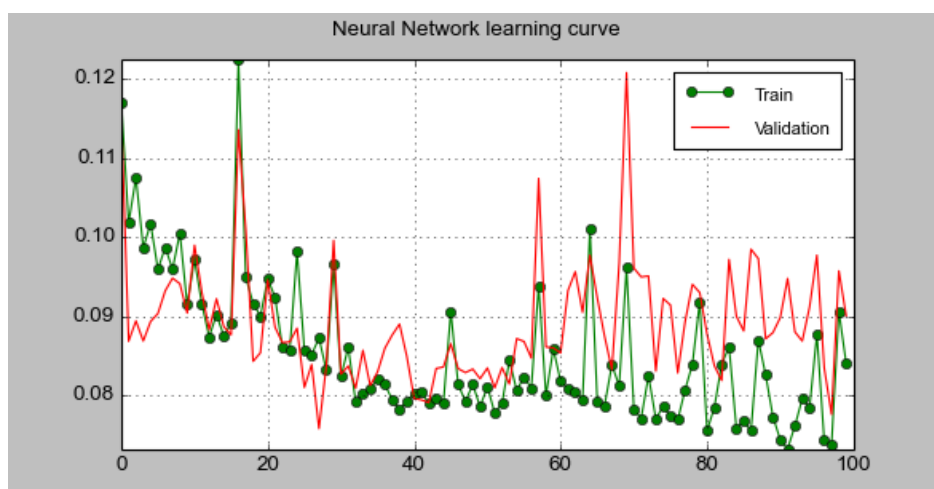
The network topology applied in the ANN modeling is 6-4-1, consisting of six nodes in the input layer, four nodes in the hidden layer, and one node in the output layer. The connections between nodes within each layer contain weights (W) represented in a matrix format, with dimensions based on the number of input, hidden, and output nodes. The results of the ANN modeling are presented in Table 6.

Table 6. ANN Modeling Results

Neighbourhood	1 px
Learning Rate	0,010
Maximum Iterations	100
Hidden Layers	6
Momentum	0,050
Δ Overall Accuracy	-0.01429
Min Validation Overall Error	0.07573
Current Validation Kappa	0.58693

Source: Analysis Results, 2023

The training and learning process of the network is performed iteratively by adjusting the magnitude of each parameter that influences the model. Based on the selected parameters, the obtained error value is 0.07575, which is considered acceptable for proceeding to the next stage. A high learning rate and a large number of iterations do not necessarily guarantee better results or accuracy. This suggests that other parameters, such as momentum, also play a crucial role in improving model performance. The momentum parameter determines the degree of weight adjustments during training.



Source: Author's Analysis, 2023

Figure 6. Neural Network Learning Curve

The training results are visualized in an ANN graph (Figure 6), which illustrates the relationship between RMS and the number of iterations, demonstrating the optimal parameter values for the ANN model. Multiple network simulations indicate that parameter variations significantly influence the results, particularly in terms of learning rate, hidden layers, momentum, and iteration count.

Table 7. Logistic Regression Modeling Results

Momentum Iteration	100
Neighbourhood	1
Pseudo R-squared	0.94800

Source: Analysis Results, 2023

According to Table 7, the logistic regression analysis produced a model with a Pseudo R-squared value of 0.94800. This value indicates a strong explanatory power of the independent variables (driving factors) in predicting the dependent variable (land cover). The obtained Pseudo R-squared value falls within the strong category, as per Clark and Hosing's theory, which states that a Pseudo R-squared value greater than 0.2 is considered relatively strong.

5. Cellular Automata Simulation

The Cellular Automata Simulation stage produced a land cover prediction model for 2022 based on data from 2012 and 2017, as shown in Figures 7 and 8. Furthermore, the predicted land cover maps for 2022, generated using the Artificial Neural Network (ANN) and Logistic Regression methods, were utilized to forecast built-up land changes in 2027 and 2032.

6. Validation

The 2022 land cover prediction model was validated against the existing land cover map to assess its accuracy. The validation results indicate that the ANN model achieved a correctness percentage of 94.01% with a kappa value of 0.64, while the Logistic Regression model obtained a correctness percentage of 93.09% with a kappa value of 0.58. These kappa values suggest that the model demonstrates moderate to strong agreement with actual land cover changes. The validation results are presented in Tables 8 and 9.

Table 8. Kappa Accuracy Results of ANN Method

% of Correctness	94.01264
Kappa (Overall)	0.64012%
Kappa (histo)	0.85408%
Kappa (loc)	0.74949%

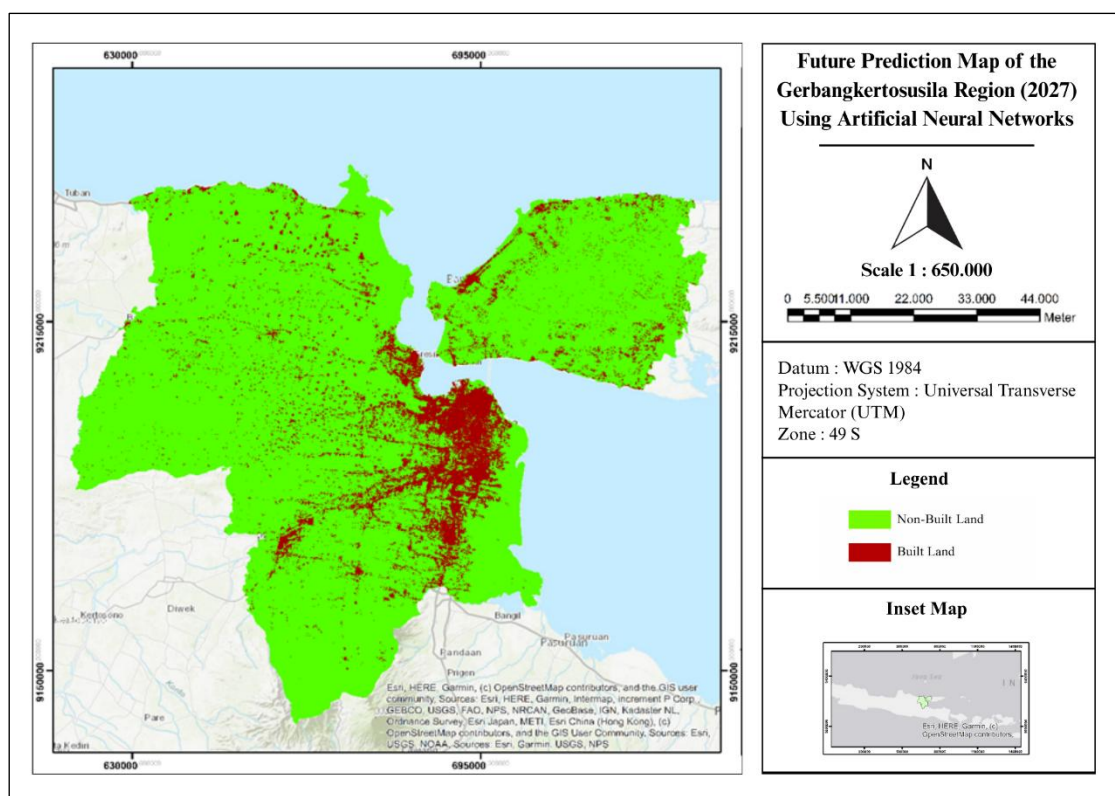
Source: Analysis Results, 2023

Table 9. Kappa Accuracy Results of LR Method

% of Correctness	92.35423
Kappa (Overall)	0.55931%
Kappa (histo)	0.91183%
Kappa (loc)	0.61339%

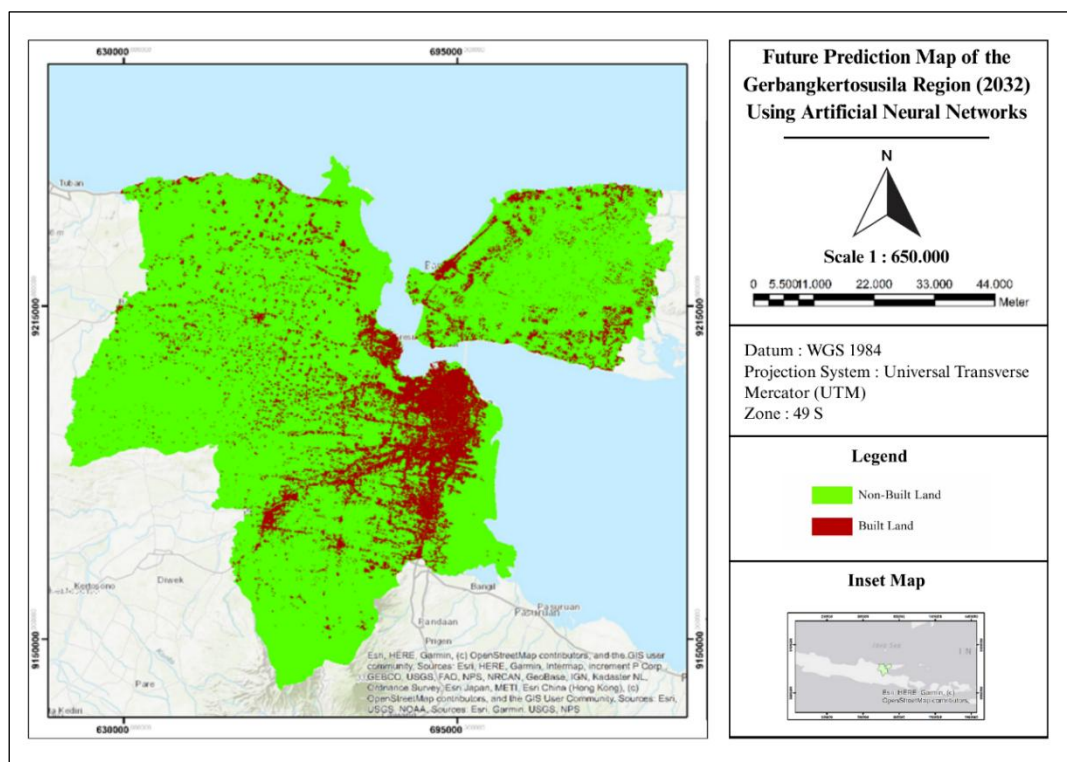
Source: Analysis Results, 2023

Development of Built-up Land in 2027-2032 Using the Artificial Neural Network Method



Source: Author's Analysis, 2023

Figure 7. Land Cover Prediction Map for 2027 Using Artificial Neural Network Method



Source: Author's Analysis, 2023

Figure 8. Land Cover Prediction Map for 2032 Using Artificial Neural Network Method

Table 10. Land Change Area Modeling and Prediction Results in the Future in 2027 and 2032 CA-ANN

Land Cover	Modeling 2022 (Ha)	2027 (Ha)	2032 (Ha)	Deviation (Ha)
Built-up Land	56215,860156	64017,433312	89237,897652	30995,395816
Non-Built-up Land	557742,782215	549941,209059	524720,744719	582963,246555

Source: Analysis Results, 2023

Based on Figures 7 and 8, the development of built-up land between 2027 and 2032 shows significant growth, both in terms of direction and intensity. This is evident from the increase in the built-up area, which expands from 64,017.43 hectares in 2032 to 89,237.90 hectares. The most rapid growth in built-up land during this period occurs in the Surabaya region. This can be attributed to the high level of development in Surabaya, which has a significant potential for rapid land cover change and serves as a major attraction for migrants (Rahmasari, 2023).

Following Surabaya, the Sidoarjo region also experiences notable growth. Sidoarjo is known as the main buffer zone for Surabaya and is located in a lowland area. The demand for land to support growing community activities continues to increase, in line with the population and economic growth. As available land in Surabaya becomes more limited, the growing demand leads many residents to migrate to Sidoarjo, which offers high accessibility to Surabaya, strategic locations, complete facilities, and utilities. As a result, Sidoarjo has become a prime residential area for Surabaya's residents, as detailed in the RP4D Kabupaten Sidoarjo 2010-2020. According to data from the Public Works and Spatial

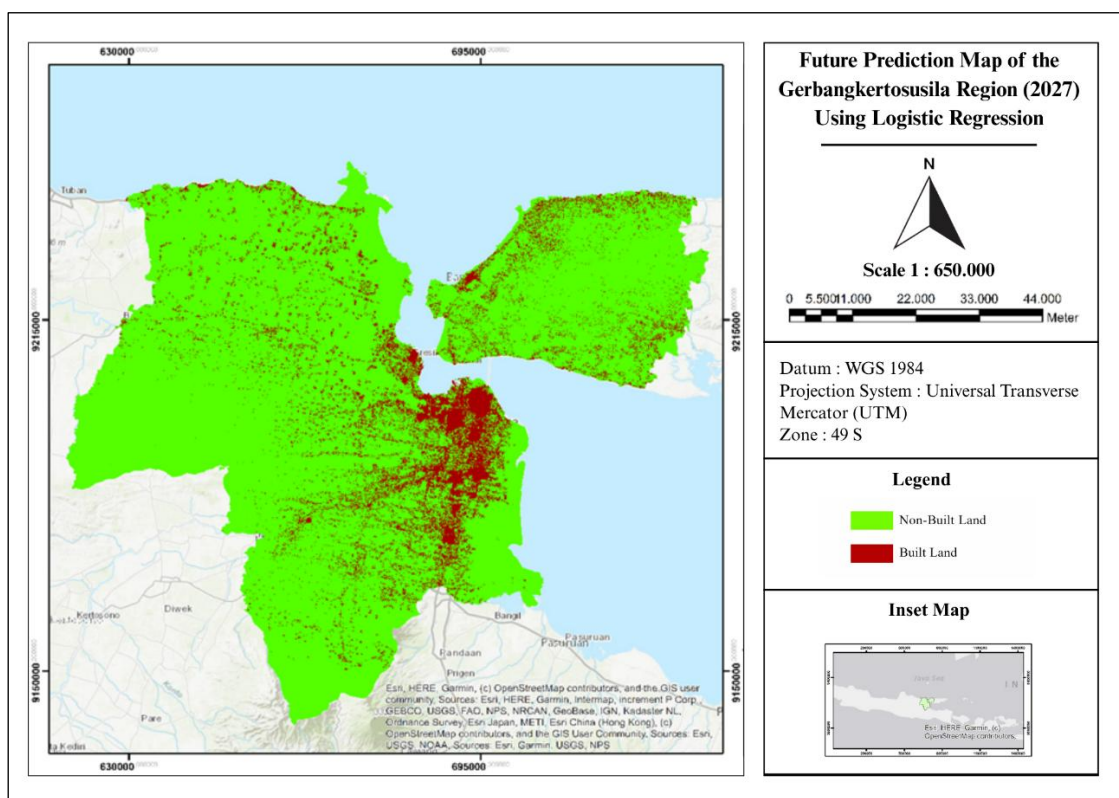
Planning Agency of Sidoarjo, between 2010 and 2015, residential land increased by 28%, and this growth is projected to continue significantly in the future.

The development of built-up land is also observed in Gresik Regency, which has substantial potential for rapid growth within the Surabaya Metropolitan Area. Furthermore, the rapid expansion of the industrial sector in Gresik and the development of the Java Integrated Industrial Port Estate (JIPE), an international-scale port, have spurred increased activity along the coastal areas, with industrial effects boosting housing, services, and transportation sectors. This heightened activity is likely to transform other land cover types into built-up land.

In Lamongan, the growth of built-up land is seen primarily along the coastal areas. Lamongan is located along the northern coast of East Java, with some of its coastal regions being hilly. The increasing population and economic growth in the area have spurred demand for land, particularly in regions that have already experienced development, where available land is limited. This has contributed to the rise in built-up areas along the coastal strip.

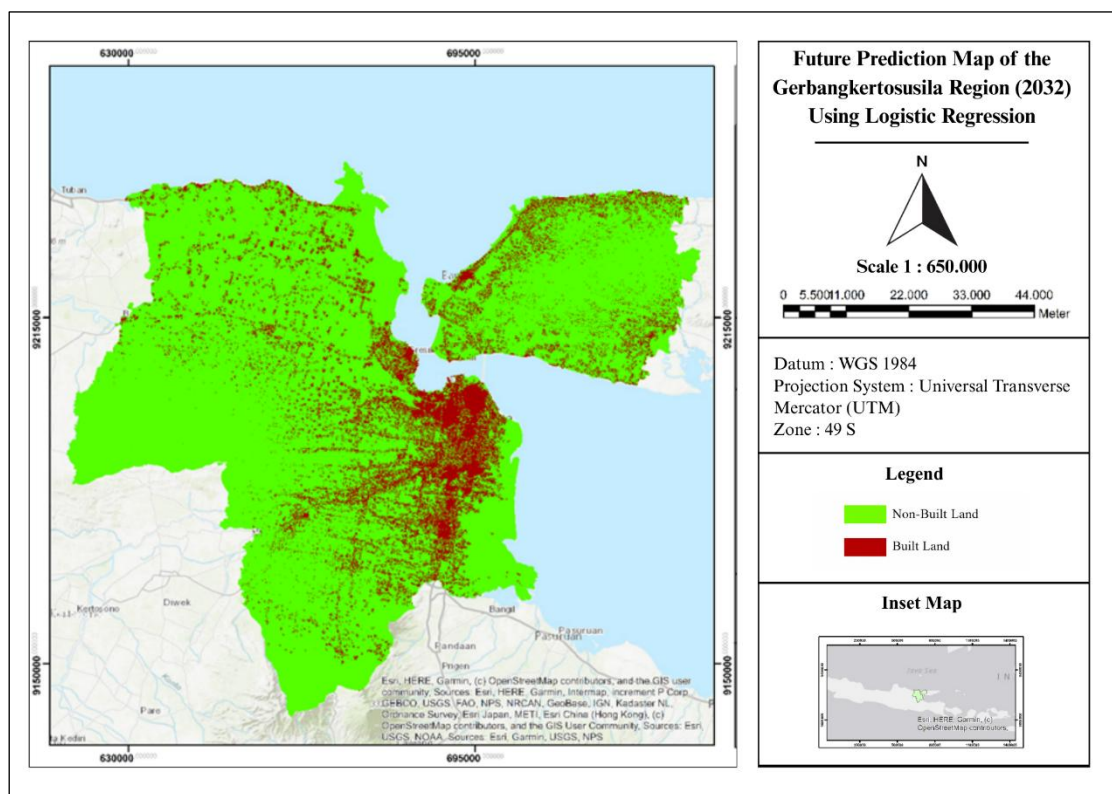
In Mojokerto, an increase in built-up land is also evident. Mojokerto ranks second in East Java for the highest population density, which leads to increased demand for land cover. This demand results in agricultural land conversion and may have environmental consequences. Similarly, in Bangkalan, built-up land also increased. The Madura Island has considerable potential in the agriculture, marine, and mining sectors. Consequently, infrastructure development on Madura Island is necessary to fully optimize these natural resources for the welfare of the local population (Habiby, 2020).

Development of Built-up Land from 2027-2032 Using the Logistic Regression Method



Source: Author's Analysis, 2023

Figure 9. Land Cover Prediction Map for 2027 using Logistic Regression Method



Source: Author's Analysis, 2023

Figure 10. Land Cover Prediction Map for 2032 using Logistic Regression Method

Table 11. Land Change Area Modeling in 2022 and Future Prediction Results in 2027 and 2032 Using LR Method

Land Cover	Modeling 2022 (Ha)	2027 (Ha)	2032 (Ha)	Devition (Ha)
Built-up Land	42098,436732	626623935,898	84438,56692	626581595,767812
Non-Built-up Land	571860,205639	5512962487,81	529520,075451	5513004827,94019

Source: Analysis Results, 2023

Based on Figures 9 and 10, the development of built-up land simulated by the Logistic Regression model for the period 2027 to 2032 shows an increase. This can be observed from the growth in built-up land area, which rises from 626,623.94 hectares in 2032 to 84,438.57 hectares. The regions experiencing the most significant growth in built-up land are Surabaya. Surabaya's population increased from 2.5 million in 2000 to 2.8 million in 2020. This population increase from 2000 to 2020 has been accompanied by the expansion of built-up land. With a population of approximately 3,016,653 people and a population density of 9,231 persons per square kilometer in 2016, Surabaya was officially classified as a Metropolitan City according to the Surabaya Central Statistics Agency in 2017. This situation indicates that activities within the city of Surabaya have become more intense. The population growth rate increased from 0.5% from 1990 to 2000 to 0.63% from 2000 to

2010, according to the Surabaya BPS 2017 report. The impact of Surabaya's development includes the conversion of agricultural land and the expansion of the built-up area.

The next area showing increased built-up land is Sidoarjo, which is part of the Surabaya Metropolitan Area (SMA). Sidoarjo has undergone rapid urbanization, accompanied by significant population growth. This population increase has made Sidoarjo one of the main destinations for residential development. Bangkalan Regency also experiences an increase in built-up land. Bangkalan serves as the main gateway from Madura Island to Surabaya. As the community develops, particularly landowners, there has been a trend of maximizing the use of agricultural land for non-agricultural purposes. This change is driven by the improved accessibility between Bangkalan and Surabaya following the construction of the Suramadu Bridge. The ease of access has triggered rapid land-use conversion in the administrative center of Bangkalan Regency. Rahmawati (2014) noted that urban development can lead to the shift of urban functions to suburban areas (urban fringe) in a process of urban sprawl. The accessibility improvements following the construction of the Suramadu Bridge have become a major driver of regional development, particularly in Bangkalan District. Significant changes in land-use from agricultural areas to residential developments and shopping malls occurred between 2009 and 2016.

Lamongan Regency also experienced an increase in built-up land during the study period. This expansion is associated with the development of coastal economic activities, particularly within the Minapolitan program area. The region has experienced rapid development characterized by the growth of fishery processing industries, aquaculture infrastructure, and fishery ports (Choirun et al., 2015). The concentration of fishing communities along the coastline has also encouraged the development of fish landing facilities and surrounding residential settlements.

The increase in built-up land in Lamongan supports previous studies stating that intensified human activities, infrastructure development, and economic growth contribute significantly to land-cover conversion, particularly from non-built-up land into built-up land (Mosammam et al., 2016). In addition, Setyawan et al. (2003) reported that coastal areas along the North Java Coast, including Lamongan, have experienced substantial land transformation due to aquaculture and other human activities. The ongoing expansion of built-up areas observed in this study extends these historical trends, demonstrating how coastal landscapes continue to transition to support intensifying regional economic functions. The findings of this study indicate that the expansion of fisheries-based economic activities and supporting infrastructure has become one of the important drivers of built-up land growth in the Gerbangkertosusila region.

Conclusion

This study demonstrates that the Gerbangkertosusila Region experienced substantial and continuous expansion of built-up land between 2012 and 2022, a trend that is projected to persist through 2027 and 2032. Supervised classification using the Support Vector Machine (SVM) algorithm successfully identified the historical trajectory of urban growth, where built-up land increased from approximately 41,417 hectares in 2012 to 63,928 hectares in 2022. Future spatial projections further indicate that rapid urbanization will continue to drive the conversion of non-built-up land into developed areas across the metropolitan agglomeration by 2032.

The findings contribute to the current body of knowledge by demonstrating the applicability of both statistical and machine learning-based approaches in regional urban growth modeling. Both the Cellular Automata–Artificial Neural Network (CA-ANN) and Cellular Automata–Logistic Regression (CA-LR) models produced reliable prediction performances, achieving validation accuracies of 94.01% and 93.09% correctness, respectively. Methodologically, this study highlights the integration of Google Earth Engine-

based land-cover classification and MOLUSCE-based spatial simulation as an effective framework for predicting future built-up land expansion in rapidly developing metropolitan regions.

From a practical perspective, the projected built-up land maps for 2027 and 2032 provide important spatial information for future monitoring and evaluation of urban growth in Gerbangkertosusila as a National Strategic Area. The findings indicate that continued urban expansion may increase pressure on environmental carrying capacity through the reduction of agricultural land, green open spaces, and water catchment areas. Therefore, the predicted spatial growth patterns generated in this study can serve as an empirical reference for spatial planning authorities in formulating land-use control strategies and sustainable urban development policies.

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