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RESEARCH ARTICLE

Integrating Machine Learning and Deep Learning to Predict Settlement Land Use Change and Carrying Capacity: A Case Study of Metro City, Indonesia

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Abstract. Rapid population growth and urban expansion in Metro City, Lampung Province, Indonesia, have intensified pressure on land resources and environmental sustainability. Therefore, this study aimed to integrate machine learning (Support Vector Machine, SVM) and deep learning (Cellular Automata–Artificial Neural Network, CA–ANN) to analyze as well as predict settlement land-use changes and assess land carrying capacity through 2038. SPOT satellite imagery from 2013, 2018, and 2023 was used for land cover classification. The results showed that settlement areas expanded from 1,087.16 ha in 2013 to 2,700.23 ha in 2023 and are projected to reach 4,336.22 ha by 2038, primarily driven by population growth and improved accessibility. The land carrying-capacity index ranged from 3.15 to 11.09, indicating that all districts remain above the minimum threshold (DDPm > 1), suggesting sufficient land availability to support projected settlement demand through 2038. Overall, the integration of SVM and CA–ANN proved effective for modeling complex urban dynamics and predicting future settlement changes. In conclusion, the results provide a scientific foundation for policymakers and urban planners to design data-driven and sustainable spatial development strategies in rapidly growing secondary cities.

1. Introduction

Urbanization has become a dominant demographic phenomenon worldwide in recent decades. In 2018, around 55% of the global population resided in urban areas, and this figure is expected to increase to 68% by 2050, largely due to population expansion as well as changes in land use and cover (Angel, Parent, Civco, Blei, & Potere, 2011; Ledent, 1982). The most significant population growth is expected to occur in low and middle-income countries (Cohen, 2004). According to the United Nations (2022), nearly 97% of global population growth between 2020 and 2050 is expected to occur in developing countries, including Indonesia (Department of Economic, 2024). By 2050, Indonesia is projected to remain the world fourth most populous country (United Nations, 2014).

One of the regions significantly affected by rapid population growth is Metro City, located in Lampung Province, Indonesia. Covering an area of 296 km² and consisting of five sub-districts, the proximity of Metro City to the provincial capital has stimulated economic, social, and infrastructure development. The city population reached 165,193 in 2018 and continues to increase annually (Risky, Malik, & Saraswati, 2023). This rapid population growth exerts growing pressure on the availability of land for residential development.

Settlements are living environments outside protected areas that serve as residential spaces and have direct implications for LULC change (Akhmad & Meisandy, 2021). In spatial planning, residential land comprises not only housing units but also supporting infrastructure, including transportation networks, clean water systems, and social facilities (Hanafi, 2025). Bintarto (1984) described settlements as the manifestation of continuous human–environment interaction (Bintarto, 1984). Consequently, the sustainable management of residential land is essential to balance spatial demand with environmental conservation. The imbalance between rapid population growth and limited residential land has increasingly driven the transformation of agricultural land and green spaces into urban housing, thereby threatening food security and environmental stability (Firman, 2004; Rondhi, Pratiwi, Handini, Sunartomo, & Budiman, 2018; UN-Habitat, 2020). This condition inevitably increases pressure on land carrying capacity, which refers to a region ability to provide a safe, comfortable, and sustainable living environment for its inhabitants. Predicting residential land carrying capacity is crucial for anticipating spatial crises and potential land-use conflicts. Therefore, land carrying capacity serves both as a predictive and regulatory tool for assessing the risks of excessive population density, the reduction of open spaces, and the heightened vulnerability to disasters resulting from inappropriate LULC management (Wang, 2022). This approach is also crucial for determining whether a region can sustainably accommodate future population growth without compromising environmental integrity or diminishing residents quality of life.

Accurate **monitoring and prediction of LULC change** are fundamental to evaluating and managing residential land carrying capacity. Continuous observation of spatial change helps prevent uncontrolled expansion, while future projections support LULC planning and policymaking (Verburg, Schot, Dijst, & Veldkamp, 2004). The development of land-use change models relies on data from both past and present land conditions (Sohl & Sleeter, 2012), where historical and future land cover conditions are evaluated through modeling. Since the 1990s, several studies have investigated residential land-use modeling (Sohl & Sleeter, 2012). Remote sensing data has increasingly been used as a primary source for detecting land cover, such as residential areas, at local, regional, national, and global scales (Lu, Mausel, Brondizio, & Moran, 2004). Generally, methods for predicting LULC change are based on multivariate analysis using image regression (Yuan & Elvidge, 1998). However, a limitation of this model is the inability to directly measure changes, as it primarily focuses on temporal analysis (Lambin, 1999). The estimation of present and future LULC distribution can be carried out using internationally recognized models (Singh, Srivastava, Gupta, Thakur, & Mukherjee, 2014), including Cellular Automata–Artificial Neural Network (CA-ANN) (Singh et al., 2014), ANN-Markov Chain (Patel, Singh, Kansara, Kalubarme, & Panchal, 2016), and CLUE-S (M. H. Saputra & Lee, 2019), which experts recommend for analyzing and predicting LULC changes.

Among these models, deep learning–based prediction techniques, such as CA-ANN, have proven to be highly effective in modeling the spatial and temporal dynamics of LULC changes, including the prediction of residential area development. The main advantage of CA-ANN lies in the ability to combine the strengths of CA, capable of capturing spatial patterns and interactions between neighboring cells, with the capabilities of ANN, which adaptively learn non-linear relationships from historical data (D. Das, Prodhan, Hoque, Haque, & Kabir, 2025). CA is used to model spatial transition rules based on surrounding environmental conditions. At the same time, ANN learns complex parameters from LULC change driving factors such as distance to roads, elevation, and population density. This model enhances prediction accuracy and represents realistic urbanization patterns, especially in the context of dynamic urban spatial planning (Zhang & Liao, 2024). ANN, when combined with CA models, can effectively simulate LULC systems (X. Li & Yeh, 2002).

Accurate mapping of LULC depends on selecting suitable classification algorithms. Classification methods are generally divided into parametric and non-parametric approaches (Wrigley et al., 2007). Parametric classification requires statistical parameters from training data that are normally distributed, while non-parametric or machine learning algorithms, such as Decision Trees (Pal & Mather, 2003), Random Forests (RF) (Belgiu & Drăguț, 2016), and SVM (Mountrakis, Im, & Ogole, 2011), can effectively handle high spectral heterogeneity without strict statistical assumptions (Langford & Bell, 1997; Schelhas & Sánchez-Azofeifa, 2006). In recent decades, these various algorithms have been widely used to map LULC changes. Among these machine learning algorithms, for high-dimensional data classification, the SVM algorithm has shown superior performance with limited training samples (Mountrakis et al., 2011). It has also outperformed several conventional classification methods (Huang, Davis, & Townshend, 2002; Kavzoglu & Colkesen, 2009; Keuchel, Naumann, Heiler, & Siegmund, 2003), including pattern recognition techniques such as neural networks (Foody & Mathur, 2004; Huang et al., 2002).

Previous studies in Indonesia have widely applied LULC modeling approaches such as CLUE-S, CA-Markov, and ANN-based simulations to analyze urban expansion and land-use dynamics, including Saputra and Lee (2019) in North Sumatra (M. H. Saputra & Lee, 2019). However, most existing studies primarily focus on predicting land-use change patterns without explicitly integrating residential land carrying capacity assessment into the modeling framework. Limited studies have combined high-accuracy machine learning classification using Support Vector Machine (SVM) with deep learning-based CA–ANN simulation to evaluate the sustainability implications of future residential expansion at the city scale. Therefore, this study advances previous investigations by integrating SVM-

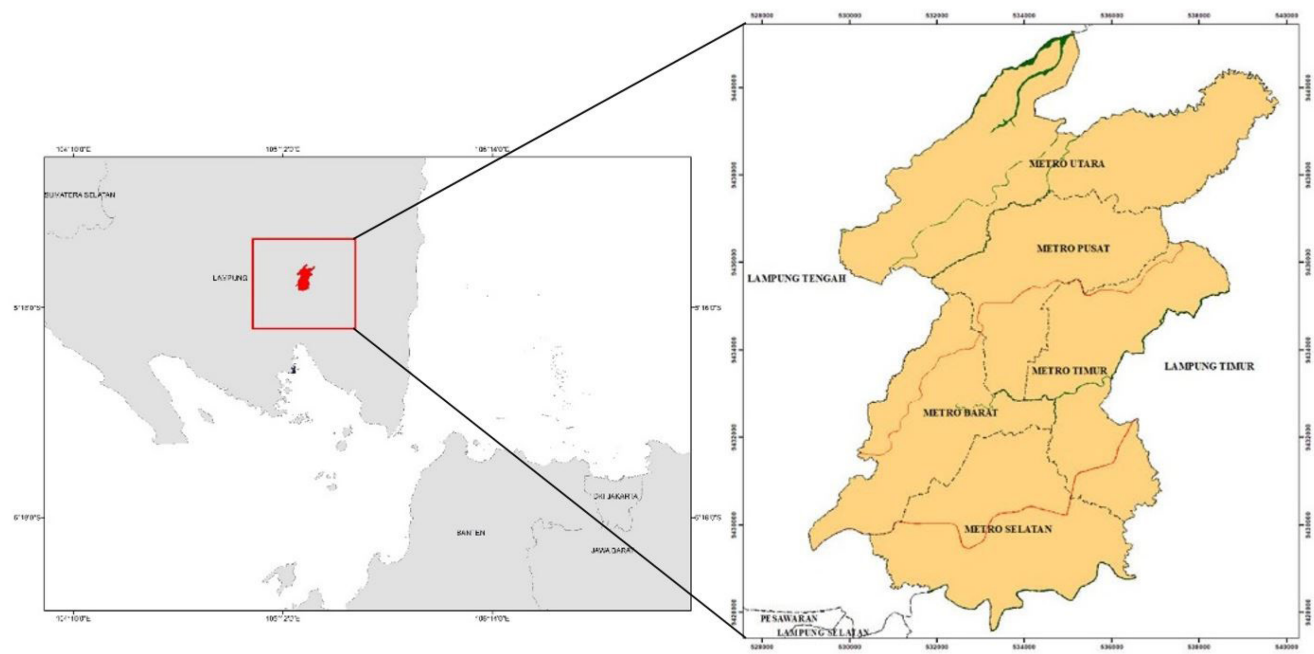

Figure 1. Study Location

based LULC classification and CA–ANN spatial prediction to assess future residential land carrying capacity in Metro City, Indonesia, providing a more comprehensive framework for sustainable urban spatial planning. Considering the strengths of machine learning (SVM) and deep learning (CA–ANN) approaches, this study integrates both methods to predict LULC changes and evaluate residential land carrying capacity in Metro City, Indonesia. The integration of high-accuracy SVM classification with CA–ANN spatial simulation is expected to provide more reliable projections of future settlement expansion and the implications for sustainable urban planning and land management.

2. Methods

Study Location

The location of this study is Metro City, one of the cities in Lampung Province that lies near the provincial capital. The city consists of five sub-districts, including Metro Pusat, Metro Selatan, Metro Timur, Metro Barat, Metro Utara, and 22 villages, with a population density of approximately 2,400 people per km^2, reflecting its status as one of the most densely populated urban centers in the province.

General methods

Figure 1 shows the methodological framework that integrates machine learning (SVM) and deep learning (CA–ANN) for LULC prediction and analysis. Spot satellite imagery from 2013, 2018, and 2023 was classified using the SVM algorithm, which is widely recognized for the accuracy in LULC classification (Mountrakis et al., 2011; Pal & Mather, 2003). The classification results were cross-checked using visual interpretation of Google Earth imagery and existing land-use maps to support class identification and interpretation. Quantitative accuracy assessment was subsequently conducted using confusion matrices, Overall Accuracy, User Accuracy, Producer Accuracy, and Kappa statistics. The 2013 and 2018 LULC maps were then used to construct a transition probability matrix with predictor variables including slope, population density, as well as distance to roads and rivers (Darmawan et al., 2020; X. Li & Yeh, 2002). An ANN learning process was employed to model land change dynamics, which were subsequently simulated using CA for 2023 and validated against actual 2023 LULC data (Aburas, Ho, Ramli, & Ash'aari, 2017). Finally, the validated model was applied to predict the LULC map for 2038. Settlement areas were extracted and analyzed to calculate land carrying capacity (Arfanuzzaman & Dahiya, 2019; Rahman, Aldosary, & Mortoja, 2017).

Data Collections

The primary data used in this study were LULC data from the years 2013, 2018, and 2023, processed from SPOT satellite imagery obtained from the National Research and Innovation Agency (BRIN) (Table 1). These data were used to predict LULC in the year 2038. Additionally, secondary data used to support the analysis include administrative boundaries, river networks, road networks, slope, and settlement data.

Classification

The classification process aimed to predict previously unknown land-cover classes using an SVM algorithm. In this study, SVM was applied to SPOT 4 (2013), SPOT 7 (2018), and SPOT 7 (2023) imagery to produce LULC maps.

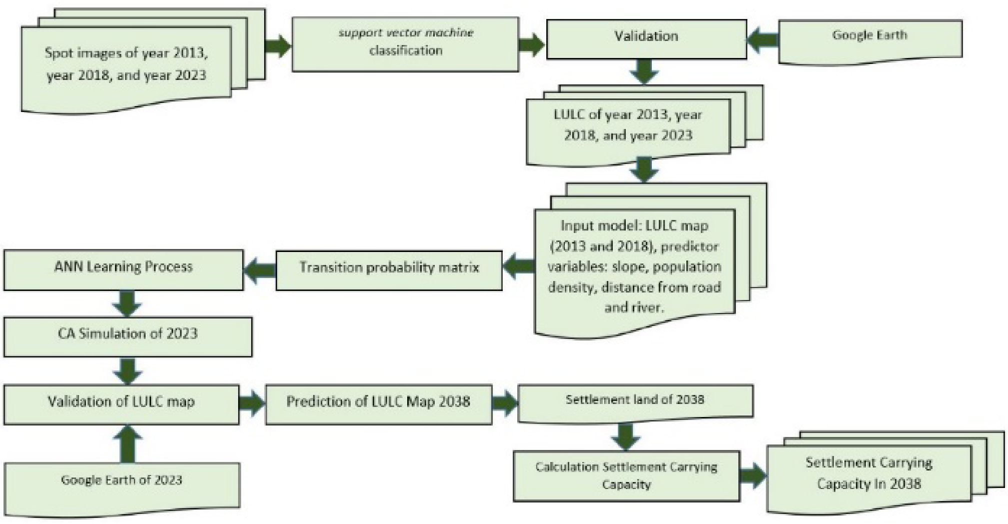

Figure 1. Study methodology framework illustrating the workflow

Table 1. Data used in this study

Dataset	Sources
SPOT 4 imagery (2013)	
SPOT 7 imagery (2018)	BRIN
SPOT 7 imagery (2023)	
Metro City administrative boundary map	BIG
River network map, settlement map	BIG
Road network map	Department of Public Works and Spatial Planning (PUPR) of Metro City
Slope	Regional Development Planning Agency (BAPPEDA) of Metro City

SVM, originally developed by Boser, Guyon, and Vapnik (1992) (Vapnik, 1997), is a supervised classification method designed for binary data and subsequently expanded for multi-class applications (Talukdar et al., 2020). In recent years, various fields have adopted the SVM algorithm due to the ability to provide higher classification accuracy compared to conventional methods (Mantero, Moser, & Serpico, 2005). The algorithm requires a kernel function to construct the hyperplane and minimize classification errors accurately. It uses four primary types of kernel functions, namely linear, polynomial, sigmoid, and radial basis function (RBF) (Hsu, Chang, & Lin, 2003). RBF is the most effective and widely used in various classification tasks because it helps reduce overfitting and is robust to outliers (Hsu et al., 2003). Therefore, the kernel was used in this study.

$$K\ (xi, xj) = \exp\ (-\gamma \parallel xi - xj \parallel 2) \qquad (1)$$

where

K (xi, xj) = Kernel value between two feature vectors xix_ixi and xjx_jxj

$\|xi-xj\|^2$ = Squared Euclidean distance between two data points

Γ = Kernel parameter controlling the influence of each training sample

Exp = Exponential function e^x

The performance of the SVM model using the RBF kernel is highly influenced by two parameters, namely C and γ (Huang et al., 2015). The hyperparameter values were adopted from a previous study on coffee plantation mapping (Tridawati et al., 2025). Based on the tuning results reported in the referenced study, the optimal hyperparameters were a regularization parameter of C = 100 and a kernel bandwidth of γ = 0.005. These parameter values were applied in the present study to improve classification performance and model generalization.

Determination of Classes and Classification Samples

A sample is defined as a subset of the population that serves as the primary source of data in a study. The sampling technique plays an essential role in guaranteeing that the data used for analysis are representative. Training samples were collected using a stratified sampling approach to ensure representative spectral variability across all LULC classes in the heterogeneous urban environment of Metro City. A total of 100 training ROIs were distributed among the seven LULC classes. Each ROI consisted of multiple homogeneous pixels used in the SVM classification process (Table 2). This classification scheme was adopted to maintain analytical consistency and to allow comparability with earlier studies.

Accuracy Assessment

At this stage, the LULCC classification map generated using the SVM algorithm was evaluated for accuracy against reference data through an error (confusion) matrix. Accuracy assessment was conducted using independently selected reference samples distributed across the seven LULC classes through a stratified sampling approach. The reference data consisted of visual interpretation of high-resolution Google Earth imagery, SPOT imagery interpretation, and existing land-use maps corresponding to the classification years (2013, 2018, and 2023). The confusion matrix is a standard tool for identifying classification deviations, where ideally all off-diagonal elements should be zero, indicating perfect classification (Carper, Lillesand, & Kiefer, 1990). Accuracy was assessed using the confusion matrix and kappa coefficient, two widely applied metrics in remote sensing and land-cover mapping (Congalton & Green, 2019).

$$\text{Kappa statistics} = \frac{N\sum_{i=1}^{n} Xii - \sum_{i=1}^{n} Xi + (X+i)}{N^2 - \sum_{i=1}^{n} Xi + (X+i)} \text{x } 100\% \qquad (2)$$

$$\text{Overall Accuracy} = \frac{\sum_{i=1}^{n} Xii}{N} \text{ x } 100\% \qquad (3)$$

$$\text{Users Accuracy} = \frac{Xii}{X+i} \text{ x } 100\% \qquad (4)$$

$$\text{Producer Accuracy} = \frac{\sum_{i=1}^{n} Xii}{Xi+} \text{ x } 100\% \qquad (5)$$

Where: N represents the total number of pixels included in the accuracy assessment, **R** denotes the number of rows or columns in the error matrix, corresponding to the number of land-cover classes, **Xii** refers to the diagonal element of the contingency matrix located at the i-th row and i-th column, **X+i** indicates the total number of pixels in the i-th column, and **Xi+1** indicates the total number of pixels in the i-th row.

Cellular Automata (CA)

CA is a mathematical model that demonstrates how different elements change over time under the influence of the nearest neighbors. Each cell in the system has a state that is continuously updated based on local rules, the given time

Table 2. LULC Descriptions

Class	Definition
Settlement (1)	Areas designated for human habitation.
Rice Field (2)	Agricultural land specifically used for rice cultivation, typically flooded during the planting season.
Shrubland (3)	Areas dominated by low vegetation such as shrubs, bushes, and wild plants.
Water Body (4)	Areas covered by water either permanently or seasonally.
Horticulture (5)	Agricultural land used for cultivating horticultural crops, including vegetables, fruits, and ornamental plants.
Bare Land (6)	Areas without vegetation cover or built-up structures, often consisting of vacant or bare land.
Non-Residential Building (7)	Buildings not used for housing but serving other functions, such as offices, factories, schools, hospitals, religious facilities, warehouses, and other public infrastructure.

step, its own condition, and the conditions of the neighboring cells in the previous step (Darmawan, Claudia, & Tridawati, 2022). Moreover, CA illustrates the interaction between cells by representing the spatial distribution and changes of values across different cells (Arsanjani, Helbich, Kainz, & Boloorani, 2013; Von Neumann, 2017).

The reliability of the CA model has made it a popular and effective tool for simulating LULC changes by integrating spatial and temporal dynamics within a dynamic modeling framework (C. Li, 2014; D. Liu, Zheng, & Wang, 2020). This model can adapt by combining conditional and statistical rules, thereby enabling the prediction of LULC transitions at calibrated spatial and temporal scales. In practice, modelers can use influencing factors derived from historical LULC changes. Finally, the CA model must address the sensitivity to calibration, classification schemes, parameter values, as well as the selected spatial and temporal scales. Additionally, the performance should be evaluated in terms of the ability to simulate LULC changes, including both the extent and spatial distribution of transitions (D. Liu et al., 2020).

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) represent computational models inspired by the structure and function of the human brain, designed to emulate the learning mechanisms. The term "artificial" refers to the implementation through computer algorithms capable of performing complex computations during the training process (Wuryandari & Afrianto, 2012). An ANN consists of multiple artificial neurons that are generally simulated with computer software. The fundamental concept of ANN is grounded in the ability to mimic the cognitive mechanisms of the human brain. According to Nabila (2023), ANN can be applied to model LULC changes through several stages, including (1) defining inputs and network architecture, (2) training the network, (3) testing the network, and (4) using the trained network to predict LULC changes. The CA–ANN approach is particularly effective for predicting LULC change, especially in simulating urban expansion and agricultural land conversion, as it represents both the statistical and spatial aspects of transitions (Xu, Wang, Liu, & Liang, 2021).

Validation

The Kappa Index of Agreement (KIA) was used to assess the agreement between LULC maps and simulation (prediction) results. In this stage, validation was conducted by comparing the predicted LULC maps for 2023 with the corresponding actual LULC maps. The validation test was measured using KIA after the model was declared valid. KIA consists of several indices, including **Kno, Klocation, KlocationStrata,** and **Kstandard.** Kno (Kappa for no ability) measures the overall level of agreement, while Klocation (Kappa for location) assesses the agreement level for specific locations. KlocationStrata measures agreement based on quantity (G. R. Pontius & Malanson, 2005), and Kstandard (standard Kappa index) evaluates the model ability to achieve perfect classification (R. G. Pontius, 2000).

Calculation of Settlement Carrying Capacity

a. Population Projection

The 2038 settlement carrying capacity was estimated using projected population data derived through the arithmetic method, which adds the average annual population increase to the baseline population (Statistics Indonesia, 2013; Wiratna, 2014). This approach, widely used for regions with relatively stable growth rates, provides a practical basis for calculating settlement carrying capacity as the ratio between projected population and available land area. However, the arithmetic method assumes a constant absolute growth rate and may not fully capture non-linear urban growth dynamics in rapidly developing areas. Alternative approaches such as geometric and exponential models may produce different estimates due to the assumption of proportional or compounding growth patterns (Smith, Tayman, & Swanson, 2002). Therefore, the projected population values in this study should be interpreted as baseline estimates under relatively stable growth assumptions.

b. Settlement Carrying Capacity

According to Nuryanti (2020), environmental carrying capacity refers to the maximum population that can be supported by available ecosystem resources and services (Nuryanti, 2020). The calculation of land carrying capacity, following the Ministry of Public Housing Regulation (PERMEN No. 11 of 2008), evaluates whether the existing settlement land can meet residential needs based on population size and land area (Berman, Kurniyaningrum, Yuwono, & Pontan, 2024). Law No. 32 of 2009 on Environmental Protection further defines concepts of carrying and assimilative capacity (Hidup, 2009). The calculation of land carrying capacity is expressed as follows:

$$DDPm = \frac{\frac{LPm}{JP}}{\alpha} \tag{6}$$

where *DDPm* is the settlement carrying capacity, *JP* is the total population, α is the per capita space requirement (m^2/capita) assigned a value of 26, and *LPm* is the suitable residential land area (m^2). A DDPm value greater than 1 indicates that the available residential land is still capable of supporting the existing or projected population, while values below 1 suggest the land carrying capacity has exceeded sustainable limits and may experience increasing spatial pressure.

In accordance with PERMEN No. 11 of 2008, disaster-prone zones and protected forests must be excluded from calculations to ensure a realistic and sustainable estimate of land availability. In this study, disaster-prone and protected areas were obtained from BPBD and Bappeda of Metro City, respectively. Excluding these ecologically sensitive zones defines the effective land available for residential development, as the areas are crucial for flood prevention, landslide protection, and biodiversity conservation (Verburg et al., 2004; Wei, Huang, Lam, & Yuan, 2015).

3. Result and Discussion

LULC maps for 2013, 2018, and 2023 in Metro City, Lampung Province

LULC classification was derived from SPOT imagery for the years 2013, 2018, and 2023 using the SVM algorithm in Metro City, Lampung Province. The LULC was categorized into seven classes, including settlement, rice field, water body, bare land, shrubland, horticulture, and non-residential buildings. The land use of Metro City is predominantly characterized by rice fields and settlements, where most changes have occurred. Population growth has been identified as the primary driver of these changes, particularly the conversion of rice fields into settlements due to increasing land demand. As shown in Figure 2, during the 2013–2023 period, settlement areas expanded significantly. The accuracy assessment of the classification results for each year is shown in Tables 3–5.

The confusion matrix (Tables 3–5) presents the accuracy assessment of LULC classifications for 2013, 2018, and 2023. The results indicate that classification accuracy remained consistently high throughout the study period, with overall accuracies exceeding 90% and Kappa coefficients above 0.80, reaffirming the robustness of the SVM algorithm in handling high-dimensional multispectral datasets, particularly under conditions where training samples are limited or non-normally distributed (Foody & Mathur, 2004; Huang et al., 2002; Lu et al., 2004).

The strong performance observed across the three temporal datasets demonstrates the model reliability and stability over time. The 2018 classification achieved the highest overall accuracy, suggesting optimal spectral separability among classes during the year. In contrast, a slight decline observed in 2023 was possibly caused by the increasingly dynamic nature of urban land transformation and the spectral overlap between settlement, bare land, and agricultural surfaces, a phenomenon frequently reported in urban remote sensing studies (Alqurashi & Kumar, 2013; Lu et al., 2004). A closer examination showed that in 2013, settlement, water bodies, and non-residential buildings achieved the highest user accuracies (100%), while bare land recorded the lowest user accuracy (80%), and non-residential buildings had the lowest producer accuracy (75%). These variations indicate generally strong classification performance, although minor misclassifications occurred among spectrally similar classes, such as bare land and rice fields. By 2018, classification accuracy reached the peak, with settlement, shrubland, horticulture, bare land, and non-residential buildings all achieving 100% user accuracy, reflecting clear spectral separability and well-distributed training samples. However, shrubland demonstrated the lowest producer accuracy (86%), possibly due to the spectral similarity with adjacent vegetation or transitional land-use types. In 2023, water bodies and non-residential buildings achieved 100% user accuracy, confirming the model consistency in identifying spectrally distinct classes.

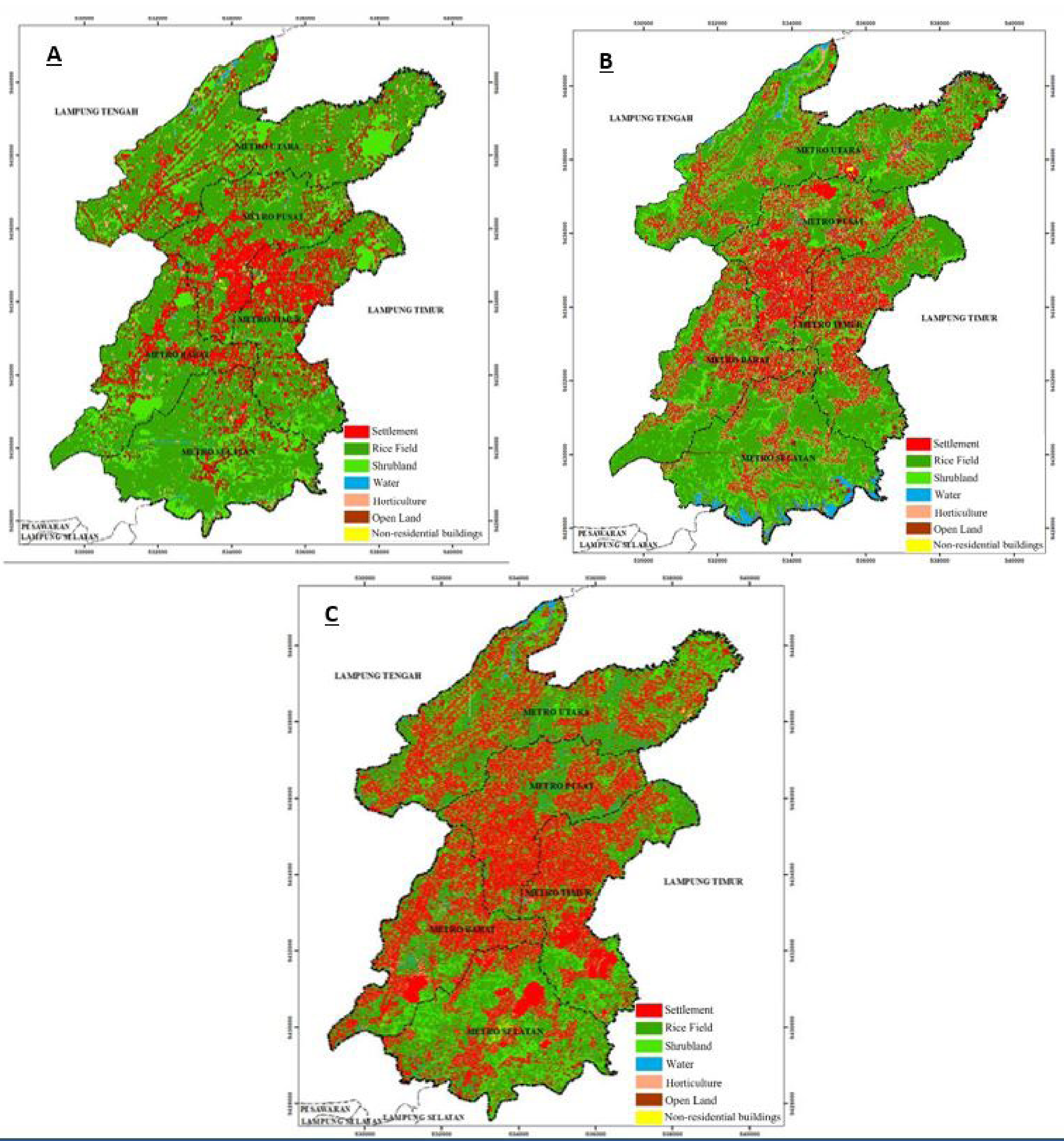

Figure 2. LULC maps for A) 2013, B) 2018, and C) 2023 in Metro City, Lampung Province

Table 3. Confusion Matrix of LULC Classification for 2013

	Classes	ROI Ground Check								
		1	2	3	4	5	6	7	Total	User Accuracy
Classification SVM	1	260	0	0	0	0	0	0	260	100%
	2	20	200	0	0	0	0	0	220	91%
	3	0	0	140	0	20	0	0	160	88%
	4	0	0	0	40	0	0	0	40	100%
	5	10	0	0	0	100	0	0	110	91%
	6	0	10	0	0	0	120	20	150	80%
	7	0	0	0	0	0	0	60	60	100%
	Total	290	210	140	40	120	120	80	1000	
	Producer Accuracy	90%	95%	100%	100%	83%	100%	75%	OA	92%
									Kappa	0,90

Table 4. Confusion Matrix of LULC Classification for 2018

	Classes	ROI Ground Check								
		1	2	3	4	5	6	7	Total	User Accuracy
Classification SVM	1	280	0	0	0	0	0	0	280	100%
	2	20	130	20	0	0	0	10	180	72%
	3	0	0	180	0	0	0	0	180	100%
	4	10	0	10	20	0	0	0	40	50%
	5	0	0	0	0	110	0	0	110	100%
	6	0	0	0	0	0	130	0	130	100%
	7	0	0	0	0	0	0	80	80	100%
	Total	310	130	210	20	110	130	90	1000	
	Producer Accuracy	90%	100%	86%	100%	100%	100%	89%	OA	93%
									Kappa	0,91

Table 5. Confusion Matrix of LULC Classification for 2023

	Classes	ROI Ground Check								
		1	2	3	4	5	6	7	Total	User Accuracy
Classification SVM	1	250	0	0	0	10	0	0	260	96
	2	30	160	0	0	0	0	20	210	76
	3	0	0	110	0	0	10	0	120	92
	4	0	0	0	70	0	0	0	70	100
	5	0	0	10	0	110	0	0	120	92
	6	10	0	0	0	10	70	0	90	78
	7	0	0	0	0	0	0	130	130	100
	Total	290	160	120	70	130	80	150	1000	
	Producer Accuracy	86%	100%	92%	100%	85%	88%	87%	OA	90%
									Kappa	0,88

Conversely, rice fields (76%) and bare land (78%) recorded lower accuracies, possibly due to rapid land-cover transitions, seasonal variations, and mixed-pixel effects associated with ongoing urban expansion. Overall, the temporal consistency of the SVM algorithm demonstrates effectiveness as a non-parametric classifier in heterogeneous urban environments, including Metro City, providing reliable performance for long-term land-cover monitoring and analysis.

LULC Change Classification

The SVM classification generated area estimates for each LULC class (settlement, rice field, water body, bare land, shrubland, horticulture, and non-residential buildings). Overall, the area of each LULC class in the years 2013, 2018, and 2023 is shown in Table 6.

The analysis of LULC change in Metro City from 2013 to 2023 shows substantial spatial and temporal transformations driven by rapid urbanization and population growth. In 2013, rice fields dominated the landscape (4,022.47 ha; 54.99%), followed by shrubland (1,352.53 ha; 18.49%) and settlements (1,087.16 ha; 14.86%). Over the decade, settlement areas expanded sharply to 2,700.23 ha (36.91%) in 2023, an increase of approximately 1,613 ha primarily at the expense of agricultural and bare land. Concurrently, rice fields declined to 2,848.68 ha (38.94%), while shrubland and bare land also decreased steadily, reflecting ongoing urban encroachment and the reduction of undeveloped spaces.

The substantial increase in mapped water bodies from 55.55 ha in 2013 to 236.77 ha in 2018 should be interpreted cautiously, as it may not entirely represent permanent expansion of aquatic areas. The pattern can be attributed to several factors, including seasonal hydrological variation, temporary inundation or flood events, spectral similarity between shallow water and saturated surfaces, and classification uncertainty commonly encountered in multi-temporal LULC mapping (Richards & Jia, 2006). In addition, differences in image acquisition timing and local hydrological conditions may have influenced the extent of detected water-covered areas. The 2018 imagery could have captured wetter environmental conditions, increasing the extent of temporarily inundated surfaces within low-lying urban and agricultural areas. The subsequent decline in water body extent in 2023 possibly reflects ongoing urban expansion, reclamation activities, drainage modification, and conversion of temporarily inundated land into built-up areas.

Non-residential buildings, including public and industrial facilities, increased from 15.79 ha to 107.26 ha, indicating growing investment in economic infrastructure. Spatially, settlement expansion was concentrated along major transportation corridors and near the provincial capital, with the eastern and southern districts experiencing the most intensive land conversion. These trends indicate largely unregulated urban growth driven by population pressure rather than proactive spatial management. The conversion of rice fields and shrubland into settlement areas has diminished natural buffers, heightened flood risks, and posed threats to local food security. Similar patterns have been observed in other medium-sized Indonesian cities (Rondhi et al., 2018; R. Saputra et al., 2022; UN-Habitat, 2020), underscoring the urgent need for integrated and sustainable spatial planning to balance urban expansion with environmental protection.

Prediction of LULC Change in the Year 2023

LULC prediction for 2023 was conducted using the CA-ANN model, which integrates the spatial dynamics of CA with the nonlinear learning capability of ANN. The model was developed within the MOLUSCE (Modules for Land Use Change Evaluation) framework, employing LULC maps from 2013 and 2018 as temporal inputs. Several spatial driving factors, namely distance to roads, existing settlements, rivers, and slope, were incorporated to simulate transition probabilities and spatial dependencies of LULC change (Hasbani, Wijesekara, & Marceau, 2011). These variables were selected based on data availability and the established influence on spatial patterns of land-use change, as supported by previous studies (Clarke, Hoppen, & Gaydos, 1997; Verburg et al., 2004). The ANN architecture was implemented as a multilayer perceptron (MLP) with a neighborhood size of one pixel, a learning rate of 0.001, a momentum of 0.05, and 1,000 training iterations. The model achieved a minimum validation error of 0.03161 and a Kappa coefficient of 0.77, indicating strong convergence and predictive stability (G. R. Pontius & Malanson, 2005; Tayyebi & Pijanowski, 2014). The learning curve (Figure 3) shows a steady improvement during training, confirming the model suitability for simulating urban growth patterns.

Table 6. LULC in the years 2013, 2018, and 2023

Class	2013		2018		2023	
	Area (in ha)	Percentages (%)	Area (in ha)	Percentages (%)	Area (in ha)	Percentages (%)
Settlement	1,087.16	14.86	1,441.84	19.71	2,700.23	36.91
Rice Field	4,022.47	54.99	3,542.11	48.42	2,848.68	38.94
Shrubland	1,352.53	18.49	1,275.18	17.43	1,122.74	15.35
Water	55.55	0.76	236.77	3.24	113.82	1.56
Horticulture	200.56	2.74	575.46	7.87	277.20	3.79
Bare Land	580.90	7.94	209.83	2.87	145.04	1.98
Non-Residential Building	15.79	0.22	33.77	0.46	107.26	1.47

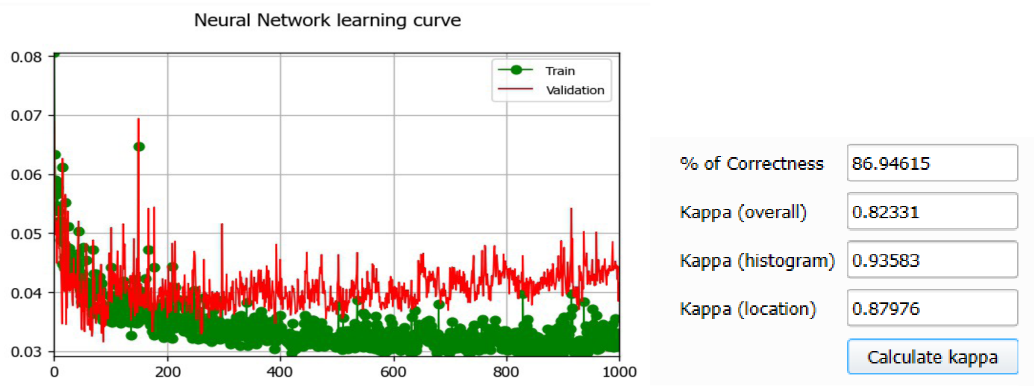

Figure 3. Neural Network Learning Curve

Validation of the predicted 2023 map was performed by comparing it with the actual 2023 LULC classification. The simulation achieved an overall accuracy of 86.94% and a Kappa coefficient of 0.82, signifying a high degree of agreement between the predicted and observed maps. The overall accuracy represents the proportion of correctly classified pixels, while the Kappa coefficient accounts for the possibility of random agreement. A Kappa value above 0.80 is generally considered to indicate excellent predictive accuracy in land-cover modeling (Mountrakis et al., 2011).

A quantitative comparison between the predicted and observed LULC (Table 7) shows that the CA–ANN model effectively reproduced the general spatial pattern of LULC change in Metro City. The predicted settlement area reached 1,800.9 ha (25%), compared to 2,700.23 ha (37%) in the observed 2023 map, an underestimation of approximately 899 ha. This suggests that although the model successfully captured the direction and clustering of urban expansion, it generalized the extent of settlement growth. In contrast, rice fields were overestimated (4,131.81 ha predicted versus 2,848.68 ha observed), reflecting the rapid and continuous conversion of agricultural land into built-up areas. Other land-cover types, including shrubland, horticulture, bare land, and water bodies, showed smaller discrepancies, demonstrating that the model effectively represented non-urban transition dynamics.

The deviations possibly stem from factors not explicitly modeled, such as socioeconomic drivers, land ownership, and infrastructure development, which strongly influence local land conversion. Overall, the CA–ANN model demonstrated a strong capability in simulating spatiotemporal LULC change and accurately capturing the dominant urbanization trends in Metro City. The high level of agreement between the predicted and observed maps underscores the robustness of the hybrid CA–ANN framework for modeling complex urban systems. However, discrepancies in the magnitude of settlement expansion indicate the need to integrate additional socioeconomic and policy-based variables to enhance model realism. These results are consistent with previous studies confirming the CA–ANN model effectiveness for urban growth prediction (Almeida, Gleriani, Castejon, & Soares-Filho, 2008; B. Das & Prasad, 2025) and align with population data from the Central Statistics Agency (Maulidya, 2025), which indicate continuous urban expansion driven by population and infrastructure growth.

To further understand this discrepancy, the observed underestimation of settlement expansion (approximately 33%) is influenced by several factors. First, the model incorporates a limited set of spatial drivers, which may not fully represent key determinants of urban expansion, particularly socioeconomic dynamics such as population growth, economic activity, and

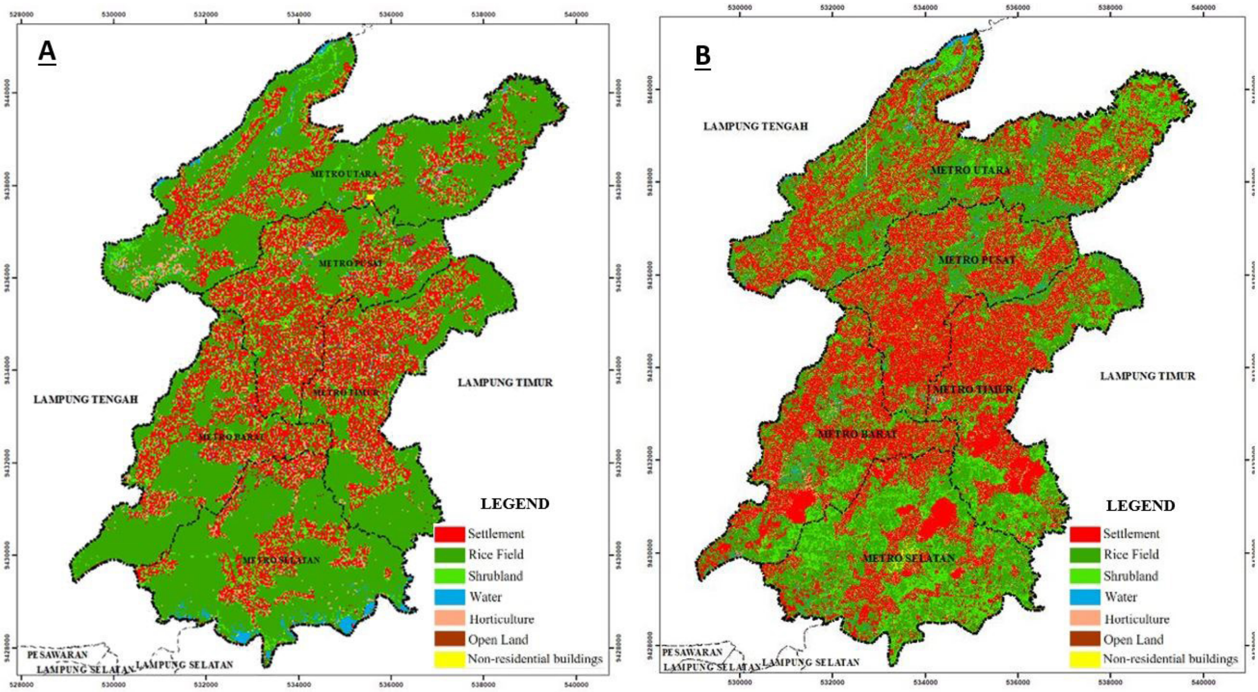

Figure 4. LULC map for A) Predicted LULC in 2023, B) Actual LULC in 2023

Table 7. The comparison between Predicted and Actual LULC in 2023.

LULC	Predicted LULC in 2023		Actual LULC in 2023	
	(Ha)	%	(Ha)	%
Settlement	1800.9	25%	2700.23	37%
Rice Field	4131.81	56%	2848.68	39%
Shrubland	782.1	11%	1122.74	15%
Water	152.64	2%	113.823	2%
Holticulture	379.26	5%	277.196	4%
Bare land	47.34	1%	145.036	2%
Non-Residential Building	20.61	0%	107.255	1%

policy interventions (Verburg et al., 2004). Second, the CA–ANN approach relies on transition rules derived from historical land-use patterns, which tend to produce a smoothing effect and may constrain the model ability to simulate rapid, non-linear, or policy-driven urban development (Clarke et al., 1997; X. Liu et al., 2017). Third, differences in input data characteristics and classification uncertainties possibly contribute to discrepancies between simulated and observed results (Foody & Mathur, 2004). Although each temporal dataset was classified independently using period-specific training samples, residual cross-sensor variability could still influence spectral signatures and contribute to uncertainty in temporal LULC comparisons. However, the consistently high classification accuracy obtained in this study suggests that sensor-related differences did not substantially affect overall classification performance.

The presence of this underestimation has important implications for the 2038 projection, as it may influence the quantitative estimation of future settlement extent. Therefore, the projection results should be interpreted with caution, particularly regarding the quantitative magnitude. To provide context for this limitation, the model outputs should primarily be interpreted as representing spatial trends and expansion patterns rather than exact estimates of settlement area extent. Despite this limitation, the CA–ANN model demonstrates a consistent ability to capture the general spatial trends and directional expansion of settlements, which remain valuable for supporting spatial planning and land-use policy analysis (Arsanjani, Helbich, Kainz, & Boloorani, 2013)

Analysis of Predicted Settlement in Metro City by 2038

Building on the successful calibration of the CA–ANN model for 2023, a projection of future settlement land use in Metro City was simulated for the year 2038. The projected spatial distribution of settlement areas is presented in Figure 5, while the quantitative results for the predicted LULC areas

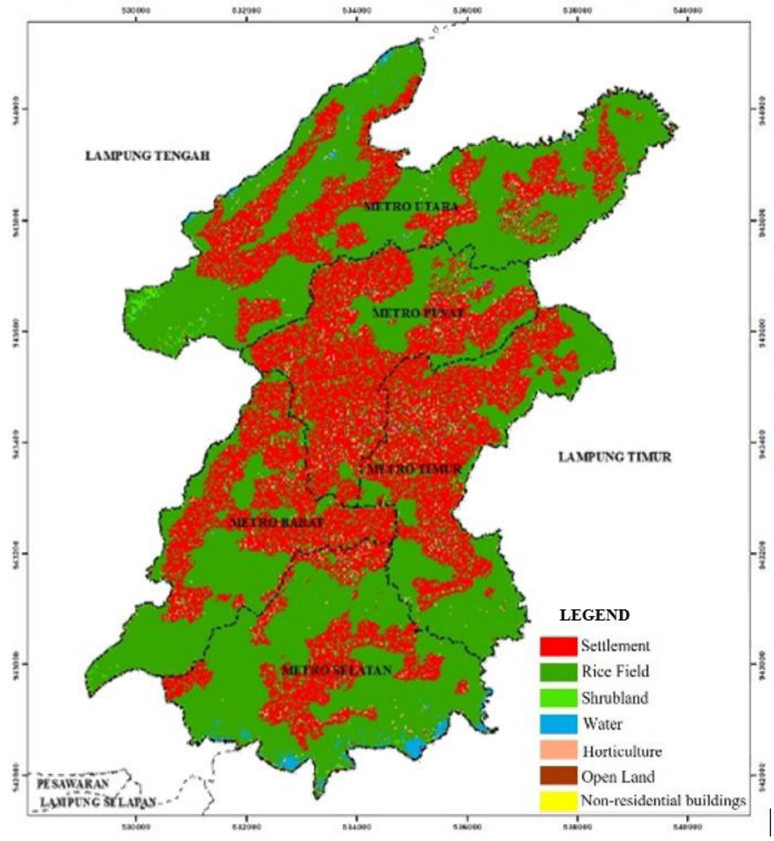

Figure 5. Projection map of settlement land use in Metro City for 2038

Table 8. The predicted LULC area in 2038

LULC	Predicted LULC in 2038	
	(Ha)	%
Settlement	4336.22	59.31
Rice Field	1387.72	18.98
Shrubland	641.09	8.77
Water	160.35	2.19
Holticulture	262.74	3.59
Bare land	24.93	0.34
Non-Residential Building	500.03	6.83
Total	7,313.08	100

in 2038 are summarized in Table 8. The analysis indicates that the total settlement area in Metro City is expected to reach 4,336.22 ha by 2038, representing a substantial increase of approximately 1,698.77 ha (63%) compared to the 2023 baseline of 2,700.23 ha**.**

The CA–ANN simulation results for 2038 (Figure 5 and Table 8) show significant spatial and quantitative transformations in Metro City land-use composition. Settlement areas are projected to expand markedly to 4,336.22 ha (59.31%), confirming the continued dominance of urban development over other land-cover types. This expansion reflects a pronounced urbanization trend, primarily at the expense of agricultural and open lands. Conversely, rice fields are projected to decline sharply to 1,387.72 ha (18.98%), underscoring the continuous conversion of productive agricultural land into residential and infrastructural zones. Vegetation-related classes, including shrubland and horticulture, are expected to decrease to 641.09 ha (8.77%) and 262.74 ha (3.59%), respectively, indicating reduced green space availability and potential ecological stress due to increasing impervious surfaces. The bare land category also decreases to 24.93 ha (0.34%), suggesting more efficient land utilization and a reduction in undeveloped areas as urbanization intensifies. Meanwhile, non-residential buildings, including public, commercial, and industrial facilities, are projected to expand to 500.03 ha (6.83%), reflecting growing investment in economic and service infrastructure. The water body class remains relatively stable at 160.35 ha (2.19%), implying minimal hydrological alteration under current development trajectories.

Overall, the CA–ANN projection depicts Metro City evolving into a highly urbanized landscape dominated by settlement areas, consistent with broader urban expansion patterns observed in medium-sized Indonesian cities (Rondhi et al., 2018; R. Saputra et al., 2022; UN-Habitat, 2020). This scenario underscores the urgent need for proactive land-use regulation, the preservation of remaining agricultural zones, and the integration of ecological considerations into future urban planning to maintain environmental sustainability and spatial resilience.

Interpretation of Settlement Change Dynamics

The dynamics of settlement change across the five administrative districts of Metro City (Table 9) show a consistent upward trend in residential land use from 2013 through the projected year 2038. All districts experienced a marked increase in settlement area, indicating that urban growth has been both widespread and sustained over the past decade and is expected to intensify over the next fifteen years. Metro Selatan recorded the most substantial increase, from 81.49 ha in 2013 to a projected 948.50 ha in 2038, representing an approximately eleven-fold expansion. This rapid growth suggests that the district relatively large proportion of undeveloped land and high accessibility along arterial corridors have made it a focal area for new housing development.

Metro Utara is projected to remain the district with the largest settlement area, expanding from 196.09 ha in 2013 to 980.17 ha by 2038. The continued dominance of this district underscores the strategic location near economic centers and major road networks, which facilitate both residential and industrial development. Metro Barat and Metro Timur also show substantial increases, reaching 868.84 ha and 780.45 ha, respectively, indicating a steady diffusion of settlement growth toward the western and eastern peripheries. In contrast, Metro Pusat, despite an increase from 308.19 ha in 2013 to 758.26 ha in 2038, shows comparatively slower expansion due to high spatial saturation and limited land availability for new development.

Overall, these results demonstrate a clear directional pattern of urban expansion radiating outward from the city center toward the peripheral districts, particularly along major transportation corridors. The pattern supports the classic monocentric urban growth model, in which accessibility and land availability act as primary drivers of settlement development (Rondhi et al., 2018; R. Saputra et al., 2022; UN-

Table 9. Historical and projected settlement area (Ha) of Metro City Districts, 2013–2038

District	2013 (ha)	2018 (ha)	2023 (ha)	Predicted 2038 (Ha)
Metro Selatan	81.49	154.53	406.852	948.5
Metro Barat	172.12	248.77	511.352	868.84
Metro Timur	329.27	332.22	546.712	780.45
Metro Pusat	308.19	429.33	580.192	758.26
Metro Utara	196.09	277	655.122	980.17
Total	1087.16	1441.85	2700.23	4336.22

Table 10. Projected land carrying capacity based on settlement area, population, and environmental factors in metro city, 2038

District	Predicted Settlement Area in 2038 (Ha)	Projected Population in 2038	Disaster-Prone Area (Ha)	Protected Forest (Ha)	Land Carrying Capacity (DDPm)
Metro Selatan	948.50	26,337	175.94	13.32	11.09
Metro Barat	868.84	27,375	154.88	9.48	9.90
Metro Timur	780.45	38,539	179.93	13.60	5.86
Metro Pusat	758.26	62,171	242.34	7.89	3.15
Metro Utara	980.17	49,284	357.74	39.26	4.55
Total	4,336.22	203,706	1,111.83	83.55	

Habitat, 2020). The significant growth in Metro Selatan and Metro Utara emphasizes the city continuous suburbanization process, while the slower expansion in Metro Pusat reflects urban consolidation and densification within the core. These spatial disparities underscore the need for balanced spatial planning, emphasizing compact growth strategies and effective land-use regulation to prevent uncontrolled urban sprawl and ensure sustainable urban development.

Land Carrying Capacity Analysis of Metro City in 2038

The assessment of residential land carrying capacity provides a critical framework for evaluating the spatial sustainability of urban growth in Metro City. In accordance with the Regulation of the Minister of Housing Affairs (PERMEN No. 11 of 2008), residential carrying capacity is defined as the ratio between suitable residential land and the total land required by the population (JP), adjusted by the standard coefficient of space requirement (α) (Maulidya, 2025). This metric serves as a key instrument in urban planning and sustainability analysis, enabling policymakers to anticipate potential imbalances between land supply and demographic growth (Verburg et al., 2004; Wei et al., 2015). Based on the CA–ANN modeling results, the total suitable residential land in Metro City by 2038 is estimated at 4,336.22 ha (equivalent to 43.36 million m²), accommodating a projected population of 203,706 inhabitants, derived from arithmetic projection methods.

As shown in Table 10, substantial spatial variation exists in carrying capacity across districts, with DDPm values ranging from 3.15 to 11.09 m² per capita. According to settlement carrying-capacity criteria, a DDPm value greater than 1 indicates that available land resources remain sufficient to support projected population demand, while a value equal to 1 represents a balanced condition, and values below 1 indicate land deficit conditions. Based on this threshold, all districts in Metro City show DDPm values above 1, suggesting that available land resources remain capable of accommodating projected settlement needs through 2038. However, variation among districts indicates differences in development pressure and land availability that should be considered in future spatial planning and resource allocation strategies.

Metro Selatan shows the highest carrying capacity value (DDPm = 11.09), followed by Metro Barat (9.90), indicating that these districts possess relatively greater land availability relative to projected population demand. These conditions suggest that the districts still have substantial capacity to accommodate future settlement expansion while maintaining favorable land availability conditions. The disparities are consistent with those of Verburg et al. (2004) and Wei et al. (2015), who emphasized that spatial heterogeneity in land resources should be incorporated into sustainability planning to minimize uneven development pressure and environmental impacts (Verburg et al., 2004; Wei et al., 2015).

Spatially, variation in DDPm values also reflects differing land-use pressures and environmental constraints among districts. In contrast, Metro Pusat records the lowest carrying-capacity value (DDPm = 3.15), followed by Metro Utara (4.55). These values remain within a favorable range, but indicate comparatively higher development pressure and more limited land availability relative to other districts. The lower carrying-capacity values are possibly associated with higher population concentration, more intensive urban development, and larger spatial constraints resulting from existing built-up areas and environmental limitations. In addition, Metro Pusat and Metro Utara contain relatively larger proportions of disaster-prone and environmentally sensitive areas, further reducing the land available for future settlement expansion. These spatial constraints may limit opportunities for horizontal development and increase pressure on remaining suitable land resources. The proximity of settlements to hazard-prone zones also represents an important planning concern, as expansion into flood-prone or unstable areas may increase urban vulnerability and environmental risks (Rondhi et al., 2018; R. Saputra et al., 2022; UN-Habitat, 2020). Meanwhile, Metro Selatan and Metro Barat still possess relatively undeveloped land with lower disaster exposure, providing opportunities for more controlled and sustainable urban expansion.

From a sustainability perspective, maintaining a favorable carrying-capacity index alone does not guarantee long-term urban resilience. Although DDPm is useful for assessing settlement carrying capacity, it focuses mainly on land–population relationships and does not account for infrastructure capacity, environmental services, or socioeconomic factors. Therefore, the results should be interpreted within a broader urban sustainability context. Effective governance, spatial regulation, and zoning policy enforcement remain essential to ensure that land use remains within ecological limits. Li and Yeh (2002) emphasized that integrating modeling tools such as CA–ANN with carrying-capacity assessments enhances policymakers ability to simulate future growth scenarios and evaluate long-term sustainability implications (X. Li & Yeh, 2002). In the case of Metro City, combining predictive modeling with carrying-capacity analysis indicates the need for proactive spatial management strategies, such as compact city development, promoting vertical housing, and protecting agricultural land, to balance population growth with environmental constraints. Ultimately, the sustainability of the urban future depends on the capacity to harmonize land demand with ecological resilience. Although aggregate land availability remains adequate to sustain projected population growth through 2038, uneven distribution of land resources across districts may generate unequal development pressure and spatial disparities in future urban growth. Embedding carrying-capacity assessments into regional and municipal planning frameworks is crucial for promoting equitable development, minimizing environmental risks, and ensuring long-term spatial sustainability (Rondhi et al., 2018; R. Saputra et al., 2022; UN-Habitat, 2020).

4. Conclusion

In conclusion, this study successfully analyzed and predicted settlement land use changes in Metro City, Lampung Province, Indonesia, using an integrated machine learning (SVM) and deep learning (CA–ANN) approach. The combined model achieved high accuracy (Kappa > 0.80), effectively capturing the spatial and temporal dynamics of urban growth. The results show that settlement areas expanded from 1,087.16 ha in 2013 to 2,700.23 ha in 2023 and are projected to reach 4,336.22 ha by 2038, primarily driven by population growth and proximity to major transportation networks. By 2038, Metro City is projected to maintain relatively favorable settlement carrying-capacity conditions, with DDPm values ranging from 3.15 to 11.09, although spatial disparities among districts remain evident. However, the uneven distribution of land resources and environmental constraints present continuous challenges to the achievement of spatially equitable growth. Although the CA–ANN model demonstrated acceptable spatial agreement in simulating urban growth patterns, the validation results indicated an underestimation of settlement expansion in 2023. This limitation suggests that the projected settlement distribution for 2038 should be interpreted cautiously, particularly regarding the magnitude of future urban expansion. The projected results are better understood as indicative spatial development scenarios rather than absolute predictions. Overall, this study demonstrates the effectiveness of integrating machine learning (SVM) and deep learning (CA–ANN) techniques for modeling complex urban dynamics in rapidly developing regions. It offers valuable insights for policymakers and urban planners in optimizing spatial planning, managing residential land allocation, and promoting environmental sustainability. Future studies are recommended to incorporate more detailed socioeconomic, environmental, and policy-related variables to improve urban growth prediction accuracy. Variables such as land price dynamics, transportation accessibility, infrastructure investment, formal zoning compliance, flood-risk distribution, and climate scenario-based population projections may improve the capability of CA–ANN models in capturing complex urban expansion processes and reducing uncertainty in future settlement projections.

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