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PREDICTION OF BUILT-UP LAND CHANGES IN BANDAR LAMPUNG CITY

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Abstract
Rapid population growth in Bandar Lampung City has driven the conversion of non-built-up land, highlighting the need to study future land changes to anticipate emerging challenges. This study aims to (1) map built-up land in Bandar Lampung City and analyze its changes from 2013 to 2023, (2) identify the most influential determinant variables affecting built-up land changes, and (3) predict the extent of built-up land up to 2045 through spatial modeling using multi-temporal imagery and physical-environmental and socio-demographic determinant data. A quantitative research method was employed, where built-up land was derived from Landsat 8 imagery using the Normalized Difference Built-up Index (NDBI) algorithm. The built-up land prediction model was developed using an integrated Markov Chain-Multilayer Perceptron-Cellular Automata (MC-MLP-CA) approach. The analysis revealed that built-up land in Bandar Lampung City increased from 9,410 ha (53%) in 2013 to 12,400 ha (70%) in 2023, marking an expansion of 2,990 ha (17%). The most influential variable in this change was proximity to roads. Model validation yielded an overall kappa value of 0.877, indicating high accuracy. Projections indicate that Bandar Lampung City's built-up land will expand to 16,010 ha (90.04%) by 2045. These findings highlight the importance of predictive spatial modeling in supporting proactive and sustainable urban planning strategies.

Keywords: Built-Up Land, Prediction Model, Spatial Modeling, Cellular Automata, Markov Chain, Multilayer Perceptron.

1 Introduction

The population of Bandar Lampung City which is the capital of Lampung province kept growing over time. According to the Central Statistics Agency (BPS) report in 2013, the city's population grew from 942,000 to more than 1.2 million in 2023. An overview of built-up of land changes in bandar lampung over the last ten years also reveals significant changes.

This trend is supported by previous research. Research indicates a significant decrease in vegetation density in Bandar Lampung (Luvi et al. 2021), , with the most significant land-cover change shifting from vegetated regions to urbanized areas (Miswar et al. 2023). The city's close proximity to forest and hill areas, mixed with access to recreational areas, has led to steady urban growth, increasing the probability of green spaces being repurposed for alternative purposes (Rizaldi et al. 2022). Furthermore, external factors, such as the development of ITERA (Sumatran Institute of Technology), elevated highways, hospitals, development of recent urban area called "Kota Baru", and the further development of UIN Raden Intan University, among other projects have contributed to increased population growth and land conversion to urban area. (Gazi 2017; Sari 2018).

The determinants of built-up land-cover changes refers to factors which affects the conversion of undeveloped land into built-up areas (Aini et al. 2022; Behradfar and Castanho 2025; Mshelia, Onywere, and Letema 2024; Suni et al. 2023; Zhao and Feng 2019). These determinants that includes physical, environmental, and social and demographic factors that can directly or indirectly affect urbanization cores and changes in land use. In this study, physical and environmental determinants consisted of elevation, slope gradient, accessibility to roads, distance to public facilities, distance to river networks, and unstable zones caused by changes in land use. Meanwhile, population density is the main social and demographic determinant, while previous research mostly ignored social and demographic variables (Fransiska and Pratomoatmojo 2020; Liang et al. 2025; Sang et al. 2011; Syafitri and Susetyo 2019; Wijaya and Susilo 2013). These determinants may trigger changes in land use or serve as limitations of development (Basse et al. 2014; Liang et al. 2025; Liu et al. 2023; Renwick et al. 2022).

The expansion of built-up zones reduces accessible land, vegetation cover, and groundwater supplies to runoff and generally has a negative impact on environmental quality, which can be seen by the increasing risk of flooding during rainy seasons and landslides on hilly region. Furthermore, the loss of vegetation affects air quality, leading to pollution and rising temperatures in cities (Dewi 2014; Fahmi 2021; Jain 2024; Kumar et al. 2025; Sumaryana, Buchori, and Sejati 2022).

To mitigate these consequences, evaluation of land usage is essential, using spatial modeling as a crucial tool for gathering information about future changes in land use (Amin Lasaiba 2024; Maharany Shandra Ayu Hapsary, Sawitri Subiyanto, and Hana Sugiastu Firdaus 2021; Syafitri and Susetyo 2019).

Remote Sensing (RS) and Geographic Information Systems (GIS) combined with the MC-MLP-CA (Markov Chain-Multilayer Perceptron-Cellular Automata) method, are highly effective at monitoring and predicting changes in land use (Amin, Nazeer, and Sing Wong 2025; Hossain et al. 2024; Kumar et al. 2025; Zhao and Feng 2019). The Normalized Difference Built-up Index (NDBI) algorithm is a commonly used approach for mapping built-up land cover and serves as a key parameter for land-use change modeling (Aldzahabi, Abrari, and Wibowo 2024; Badapalli, Gugulothu, and Nakkala 2025; Binangkit et al. 2023; Kumar et al. 2025; Syahputra et al. 2021). Furthermore, Cellular Automata (CA) is becoming popular for simulating land-use dynamics (Amin et al. 2025; Behradfar and Castanho 2025; Gui, Bhardwaj, and Sam 2025; Jain 2024; Omwoyo et al. 2024; Tahir et al. 2025). CA simplifies the comprehensive simulations of change in land use by representing built-up areas as discrete cells and implementing transition rules that reflect the urbanization processes (Ahmad et al. 2022; Amin et al. 2025; Jain 2024; Omwoyo et al. 2024; Shorabeh et al. 2022; Tahir et al. 2025). CA are commonly used for evaluations of mangrove ecosystem change, wildlife movement simulations, and disease spread simulations following urban expansion (Cole and Cheshire 1996; Hasan, Sentinuwo, and Sambul 2017; Jain 2024; Tahir et al. 2025). However, the MC-MLP-CA hybrid model performs better than the traditional MC-CA because it can capture complex patterns of change in land use by using Multilayer Perceptron (MLP) that can identifies nonlinear relationships between driving factors and significantly increases prediction accuracy. (Astou Sambou et al. 2023; Badshah et al. 2024; Ozturk 2015; Sajan et al. 2022). this study offers an innovative approach that is distinct from previous studies by combining sociodemographic and physical-environmental factors such as population density, into a hybrid spatial prediction model that combines Markov Chain, Multilayer Perceptron, and Cellular Automata (MC-MLP-CA) (Astou Sambou et al. 2023; Hossain et al. 2024). This hybrid method increases the spatial accuracy and predictive capability of urban expansion simulations by recognizing complex, non-linear interactions among land-use determinants, when compared to conventional models that usually disregard sociodemographic factors or depends on linear assumptions (Hossain et al. 2024).

This study uses environmental physics and social demographic factors and also multi-temporal remote sensing data (Landsat 8 imagery from 2013, 2018, and 2023) as the model inputs to predict changes in land use in Bandar Lampung City by 2045. The findings are expected to provide valuable insights into land-use dynamics and support sustainable urban planning in Bandar Lampung, contributing to Indonesia's Golden Vision (Visi Indonesia Emas) development goals.

2. Materials and Methods

2.1. Materials.

This study was conducted in Bandar Lampung City, Lampung Province, Indonesia (Figure 1), located between 5°20' to 5°30' South Latitude and 105°28' to 105°37' East Longitude. The city comprises 20 districts: Kedaton, Kemiling, Langkapura, Tanjung Karang Barat (West Tanjung Karang), Tanjung Karang Pusat (Central Tanjung Karang), Tanjung Karang Timur (East Tanjung Karang), Tanjung Karang Utara (North Tanjung Karang), Enggal, Teluk Betung Barat (West Teluk Betung), Teluk Betung Selatan (South Teluk Betung), Teluk Betung Timur (East Teluk Betung), Teluk Betung Utara (North Teluk Betung), Bumi Waras, Panjang, Kedamaian, Rajabasa, Way Halim, Sukarame, Labuhan Ratu, and Sukabumi.

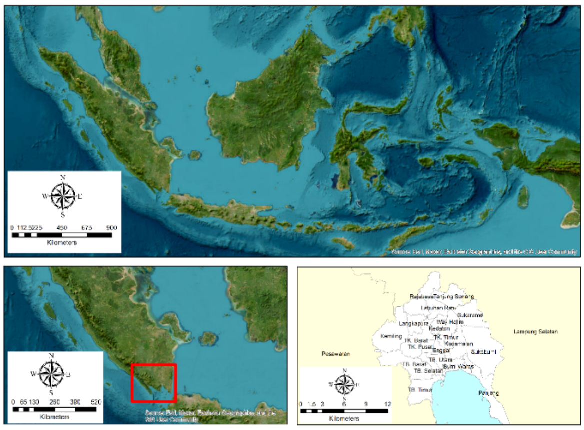

Figure 1. Study area map
(Source: ESRI Imagery)

2.2. Methods

The research methodology flowchart is presented in Figure 2.

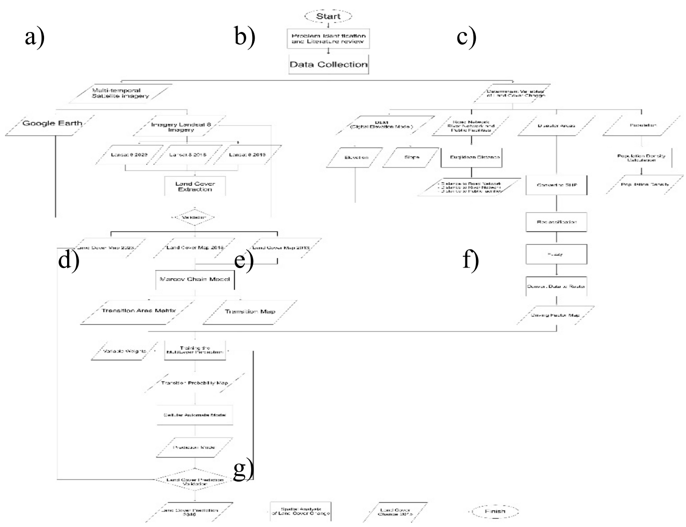

Figure 2. Research workflow

2.2.1. Problem identification and literature review

This initial phase focused on formulating the research problems based on observed phenomena and conducting a comprehensive review of relevant literature.

2.2.2. Data collection for modeling input

Primary datasets included multi-temporal satellite imagery and determinant variables influencing land use changes: elevation, slope gradient, distance to road networks, distance to river systems, proximity to public facilities, disaster-prone areas, and population density.

2.2.3. Data processing for modeling input

All collected data were standardized in terms of format and resolution to ensure modeling compatibility. Key processing steps included: Land cover extraction (classified as built-up and non-built-up areas) using the Normalized Difference Built-up Index (NDBI) algorithm . Accuracy assessment through confusion matrix analysis with higher-resolution reference data. Generation of land cover maps for 2013 (T1), 2018 (T2), and 2023 (for model validation). Processing of determinant variables using Euclidean Distance, Reclassify, and Fuzzy.

2.2.4. Prediction modeling using MC-MLP-CA integration

The modeling framework combined the multi-temporal land cover maps, determinant variable maps, transition area matrix, probability matrix, change probability maps, and neighborhood rules . Overlay methods were used to analyze the 2013 and 2018 land cover maps, providing a land cover visual change map for the 2013-2018 timeframe as well as a transition area matrix capturing changes between land cover classes at each periods. The Markov Chain (MC) simulation model processed this transition matrix as a vital input to generate a probability matrix that shows the probability of transitions between each land cover classes in the time period (Aghajani, Sarkari, and Fattahi Moghaddam 2024; dos Santos et al. 2024). By processing determinant variable maps through supervised training, the Multilayer Perceptron (MLP) model generated a raster-based probability map that quantified change likelihood for each individual pixel, thereby identifying locations with the highest probability of change (Basse et al. 2014). Then, using a combination of data sources, including the actual 2018 land cover map, transition probability matrices, change probability maps derived from MLP, and neighborhood rules applied through matrix filters, the Cellular Automata (CA) model projected the land cover for 2023 . The predictive model was properly tested to ensure its accuracy and reliability in predicting land cover changes .

2.2.5. Model Validation

Validation is necessary to verify the accuracy of the built-up land prediction model. The projected land cover estimates were validated using actual reference data from 2023. A validation accuracy of more than 80% correspondence with reference data indicates excellent model performance, making it ideal for future year estimates (Hardiyanti and Fitrianah 2021; Yeasmin et al. 2025). A confusion matrix approach was used for validation, which compares predictions with reference data to determine model accuracy (Kurniantoro 2021; Yeasmin et al. 2025). In this study, the 2023 prediction model was validated using actual 2023 sample data, with a validation criteria of a minimum of 80% (Yeasmin et al. 2025).

2.2.6. Model Simulation.

The validated built-up land prediction model was used to project future land cover conditions. Projections of land cover in 2030, 2035, 2040, and 2045 are the results of said simulation, of which can be analyzed further.

2.2.7. Change Analyis

Quantitative assessment of land cover changes across different time periods through comparative area calculations.

3. Results and Discussions

3.1. Land Cover in Bandar Lampung City (2013, 2018, 2023) and Its Changes

The Landsat 8 imagery extraction results for Bandar Lampung City revealed two distinct land cover classes: built-up areas and non-built-up areas. The classified maps demonstrated accuracy levels of 84% (2013), 90% (2018), and 96% (2023). Through overlay analysis of the 2013 (T1) and 2018 (T2) land cover maps, a change detection map was generated for the 2013-2018 period (T1 to T2). Figures 3-5 and Table 1 present the key findings: Figure 3 displays the land cover maps for 2013, 2018, and 2023. Figure 4 illustrates land cover changes during 2013-2018, 2018-2023, and 2013-2023 periods. Figure 5 provides the graphical representation of land cover changes, and Table 1 contains quantitative data on land cover areas.

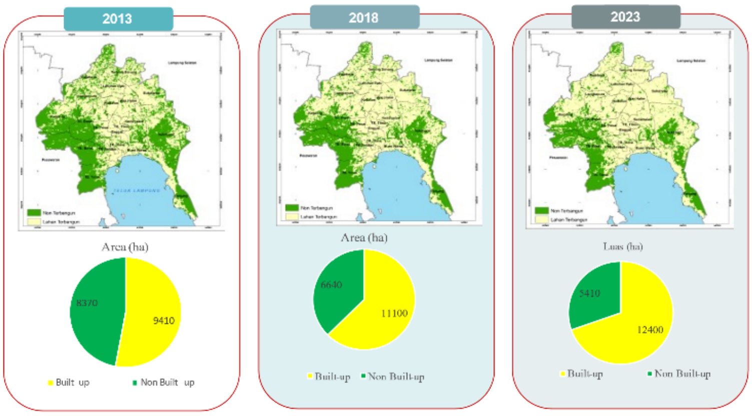

Figure 3. Land cover maps of 2013, 2018, and 2023

Figure 4. Land cover change maps for periods 2013-2018, 2018-2023, and 2013-2023

The graphical analysis highlights significant land conversion patterns in Bandar Lampung City. During the 2013-2018 period, approximately 1,690 hectares of non-built-up land converted to built-up areas. Between 2018 and 2023 period: an additional 1,300 hectares underwent similar conversion. Over the entire 10-year period from 2013 to 2023, a total conversion of 2,990 hectares from non-built-up to built-up areas.

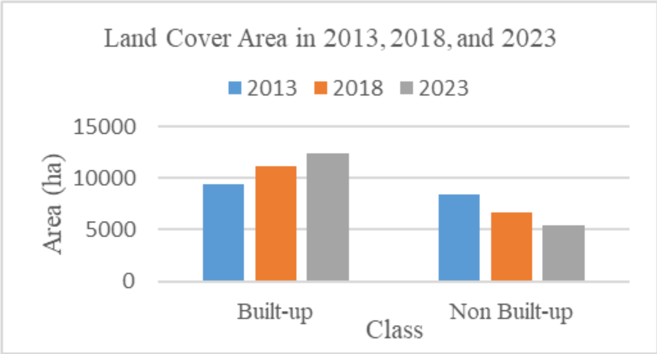

Figure 5. Land cover change graph for 2013, 2018, and 2023

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Table 1. Land cover area in Bandar Lampung City (2013, 2018, 2023)

Class		Area		
		2013	2018	2023
Built-up	(ha)	9.410	11.100	12.400
	(%)	53	62	70
Non-built-up	(ha)	8.370	6.680	5.380
	(%)	47	38	30
Total	(ha)	17.780	17.780	17.780
	(%)	100	100	100

The table demonstrates that: In 2013, built-up areas dominated at 9,410 ha (53% of total area), while non-built-up areas covered 8,370 ha (47%). By 2018, built-up areas expanded to 11,100 ha (62%), with non-built-up areas reduced to 6,680 ha (38%). In 2023, built-up areas further increased to 12,400 ha (70%), leaving only 5,380 ha (30%) as non-built-up land.

The land cover analysis from 2013 to 2023 indicates a consistent and substantial expansion of built-up areas in Bandar Lampung City, increasing by 2,990 hectares (31.7%) over the decade. Built-up land rose from 53% to 70% of the total area, while non-built-up land decreased to only 30%, reflecting a strong and ongoing urbanization trend. This pattern mirrors the dynamics observed in other rapidly urbanizing Indonesian cities, where infrastructure development, such as toll roads, universities, and commercial hubs, accelerates land conversion . According to Renwick et al. (2022), the expansion of built-up areas have an irreversible effects. As such, the aggressiveness of the expansion from undeveloped to built-up areas highlights the necessity of strategic land-use planning.

From an ecological point of view, the loss of vegetated areas in urban city might lead to increased flood and landslide risk, less groundwater supplies, and rising temperature in urban cities . These findings highlight the importance of creative urban development solution that focus on spatial monitoring and green infrastructure preservation in crowded urban cities. To support the accuracy of this result and reliability of the aerial land cover assessment, it must be at least within high accuracy levels (>84%) across all periods .

3.2. Determinant Variables Influencing Land Change

Land cover changes in Bandar Lampung are influenced by seven important variables that have been assessed: elevation, slope gradient, accessibility to roads, distance to public facilities, distance to river networks, population density, and unstable zones (Figure 6).

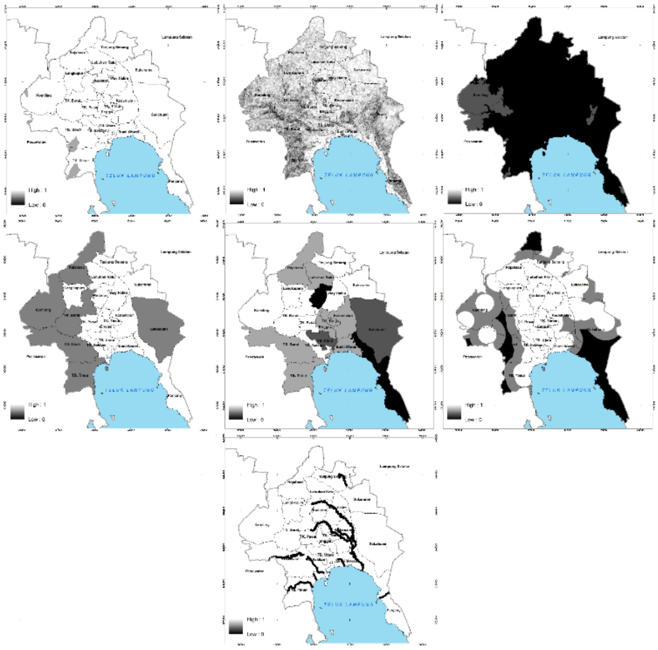

Figure 6. Maps of Determinant variables: a) distance to roads, b) slope gradient, c) elevation, d) population density, e) disaster risk, f) distance to public facilities, g) distance to river systems

According to the analysis of the determinant variables, the most significant variable affecting the high level of land conversion in Bandar Lampung City from 2013 to 2018 was the close proximity to roads. This finding is consistent with earlier studies which indicates that accessibility is a significant factor of urban growth, particularly in fast growing areas . Land conversion occurs more aggressively in areas close to transportation networks due to its strategic value for residential, commercial, and institutional development. Other physical-environmental factors, such as slope, elevation, and distance to public facilities, all played a part in changes in land use to some extent. Based on spatial suitability theory, Flatlands at lower elevations are often more suitable for urban development, while hilly and steep regions tend to slow expansion .

Notably, population density, introduced here as a socio-demographic determinant, proved to be a meaningful variable, although it is often underutilized in previous spatial models . Its inclusion enhances the explanatory power of the model by capturing the human-driven dimension of urbanization. These findings support the premise that both physical and demographic variables jointly shape land transformation processes. They also emphasize the importance of integrating diverse spatial factors into predictive models to improve their reliability and policy relevance in urban planning contexts.

3.3. Built-up Land Modeling Using MC-MLP-CA and Validation

The land cover development was modeled using an integrated MC-MLP-CA approach. The initial modeling step required a transition area matrix, generated by comparing land cover maps from two time periods: T1 (2013) and T2 (2018). The transition area matrix is presented in Table 2.

Table 1. Transition area matrix (hectares)

	Built-up area (ha)	Non-built-up area (ha)
Built-up area (ha)	9.410	0
Non-built-up area (ha)	1.690	6.680

Of Bandar Lampung City's total area, 9,410 hectares of built-up land in 2013 remained unchanged through 2018, with no observed conversion from built-up to non-built-up areas observed. During the same period, 1,690 hectares of previously non-built-up land were converted to built-up areas. The remaining 6,680 hectares of non-built-up land retained their original classification.

Based on the transition area matrix depicting these land cover changes, a transition probability matrix was derived to quantify the tendencies of land use change during the study period (Table 3). This probability matrix reveals:

Table 2. Transition probability matrix

	Built-up area	Non-built-up area
Built-up area	1	0
Non-built-up area	0.202	0.798

The transition probability matrix derived from the 2013-2018 land cover data indicates complete persistence of built-up areas, with all built-up land from 2013 remaining unchanged by 2018 (transition probability = 1.000). No conversion from built-up to non-built-up areas were observed (probability = 0.000). In contrast, approximately 20.2% (probability = 0.202) of non-built-up areas transitioned to built-up land, while the remaining 79.8% (probability = 0.798) maintained their original classification.

Following the transition probability matrix derivation, the Cellular Automata (CA) model required transition probability maps generated through a Multilayer Perceptron (MLP)-based approach to identify key determinants of land cover change. The MLP configuration consisted of 7 hidden layers, a learning rate of 0.0001, and 10,000 iterations, achieving 72.29% accuracy (Figure 7). This process produced transition probability maps (Figure 8) and identified distance to roads as the most influential determinant variable affecting land cover changes in Bandar Lampung City during the 2013–2018 period.

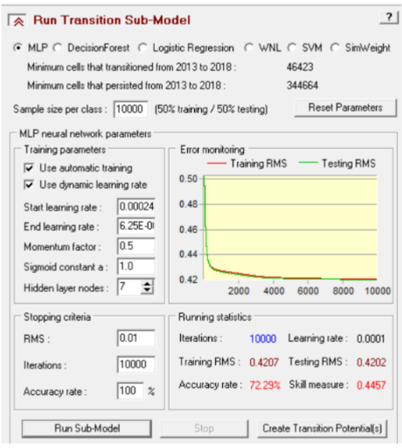

Figure 7. MLP neural network model execution process

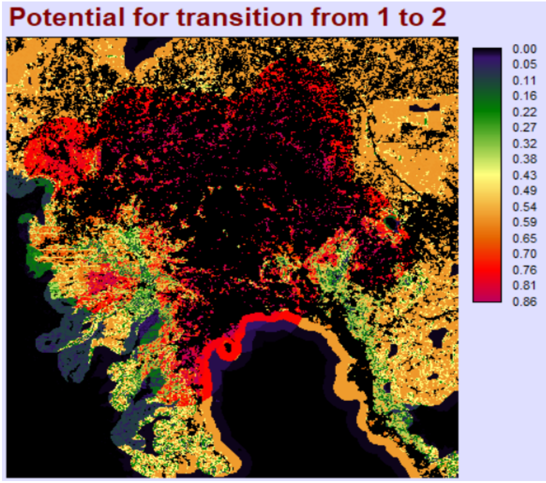

Figure 8. Transition probability map

The transition probability map illustrates the likelihood of land cover change for each pixel within the study area, with values ranging from 0 to 1. Probability values approaching 0 indicate areas with minimal change potential, while values nearing 1 represent high-probability change areas. The spatial distribution pattern of probability values facilitates identification of change-vulnerable locations.

Following the generation of transition area matrix, transition probability matrix, transition probability map, and neighborhood filter, the CA model was implemented to predict 2023 land cover. The CA integrated all MC and MLP outputs, producing a prediction map that follows the established spatial distribution patterns (Figure 9). The 2023 prediction results were subsequently validated against actual 2023 data.

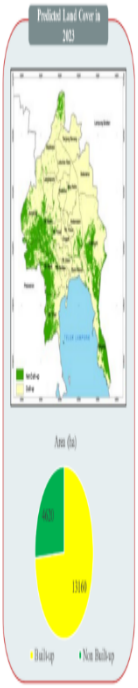

Figure 9. Predicted land cover map for 2023

This study combined Markov Chain (MC), Multilayer Perceptron (MLP), and Cellular Automata (CA) to create a reliable and accurate predictive model for land cover change. The MC component quantified transition probabilities based on previous land cover data, while MLP enabled the identification of complex, non-linear relationships between determinant variables, significantly increasing the model precision . The CA model uses neighborhood effects, and simulated spatial dynamics of urban expansion at high resolution . According to the MLP-derived probability surface data, proximity to roads was the most influential determinant that affects land changes in Bandar Lampung City. This finding supports previous projections in Section 3.2 and is consistent with the reports indicating accessibility as a primary urban growth catalyst .

The model validation with actual 2023 land cover data showed a Kappa coefficient of 0.877 and a total accuracy of more than 87%, which is considered excellent by the conventional remote sensing standards . This result shows that the model has a high reliability in projecting future land usage scenarios, which is powerful in spatial planning and urban management strategies. However, there are a slight difference in the model. The model slightly exaggerated built-up areas of (+760 ha) while undervaluing the undeveloped areas. This differences can be caused by unmeasured variables, for example, regulatory zoning restrictions or the real estate market price fluctuations, which are not directly detected by the prediction model.

Overall, the MC-MLP-CA combination performs better than conventional MC-CA models, in particular for the urban environments with various land usage variables . MC-MLP-CA's ability to integrate environmental and demographic variables makes it an effective tool to provide predictions of urban dynamics in complex social and ecological structures.

3.4. Model Validation

Model validation assessed the congruence between predicted and actual conditions. Figure 10 compares actual and predicted 2023 land cover maps, while Table 4 presents the validation matrix results.

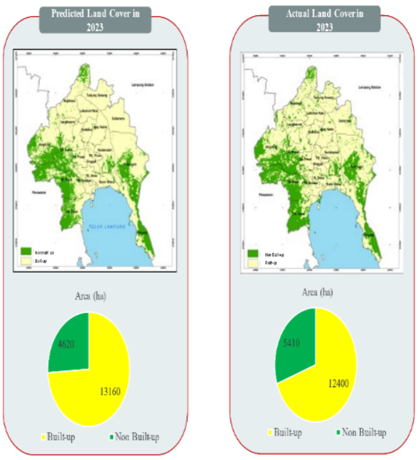

Figure 10. Comparison of actual and predicted 2023 land cover maps

Table 3. Validation matrix

	Predicted Results	Total	*Producer's*

		Built-up area	Non-built-up area		*Accuracy*
Actual Data	Built-up area	209.419	31.285	240.704	0.87
	Non-built-up area	27.024	204.920	231.944	0.88
	Total	236.205	236.443	472.648	
	User's Accuracy	0.87	0.88		

The validation matrix revealed that 204,920 pixels correctly predicted non-built-up areas when compared to actual data. However, 27,024 pixels were misclassified as built-up areas despite being non-built-up in reality. The model accurately predicted 209,419 pixels as built-up areas, while 31,285 pixels that should have been classified as built-up were incorrectly predicted as non-built-up areas. The overall accuracy, calculated by comparing correctly predicted pixels against the total evaluated pixels, demonstrated the model's performance.

The 2023 model validation achieved an accuracy of 87.7%, classifying it as excellent. This strong agreement between predicted and actual 2023 data confirms the model's reliability for forecasting future built-up land changes. Table 5 presents the comparative analysis between actual and predicted 2023 land cover areas in Bandar Lampung City.

Table 4. Comparison of actual and predicted 2023 land cover areas

Land Cover		Actual 2023	Predicted 2023
Built-up	Area (ha)	12.400	13.160
	(%)	69,75	74,02
Non-built-up	Area (ha)	5.380	4.620
	(%)	30,25	25,98
Total	Area (ha)	17.780	17.780
	(%)	100	100

Table 5 reveals discrepancies between predicted and actual 2023 land cover data across both classes. The model predicted built-up areas of 13,160 ha (74.02%), exceeding the actual recorded area of 12,400 ha (69.75%). Conversely, non-built-up areas were underpredicted at 4,620 ha (25.98%) compared to the actual 5,380 ha (30.25%). The total study area remained consistent at 17,780 ha (100%) for both datasets.

3.5. Land Cover Change Dynamics in Bandar Lampung City

Urban expansion in Bandar Lampung is projected to continue, particularly in high-accessibility zones with strong development potential, such as areas near major roads and economic centers. Figure 11 presents the 2045 built-up land prediction map.

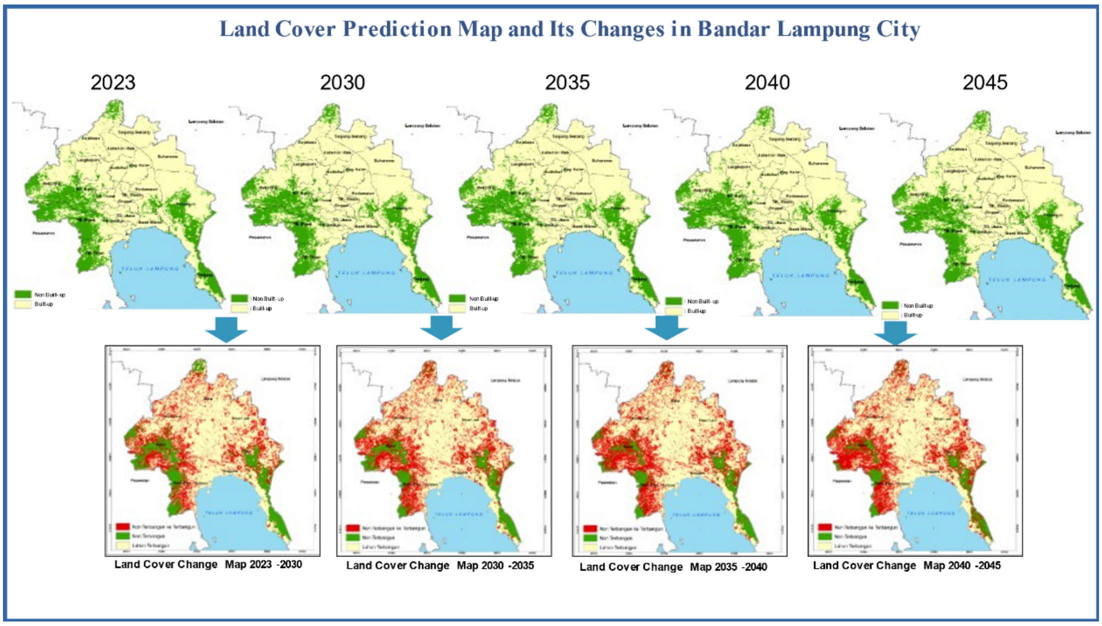

Figure 11. Predicted built-up land map of Bandar Lampung City (2045)

To better understand built-up land growth dynamics from 2013 to 2045, Figure 12 and Table 6 present the quantitative projections.

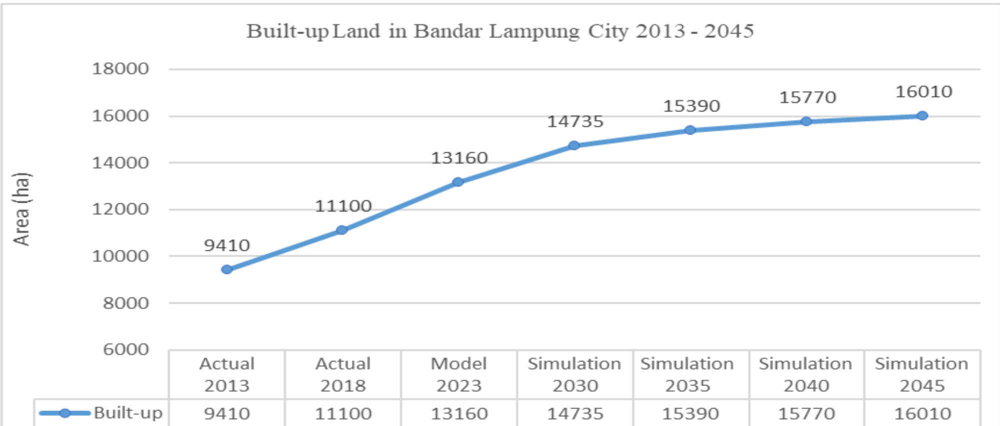

Figure 12. Built-up land area trends in Bandar Lampung City (2013-2045)

Table 5. Built-up land area projections

Class		Area						
		Actual 2013	**Actual 2018**	**Model 2023**	**Simulation 2030**	**Simulation 2035**	**Simulation 2040**	**Simulation 2045**
Non-built-up area	(ha)	8.370	6.680	4.620	3.045	2.390	2.010	1.770
	(%)	47	38	25.98	17.13	13.44	11.3	9.96
Built-up area	(ha)	9.410	11.100	13.160	14.735	15.390	15.770	16.010
	(%)	53	62	74.02	82.87	86.56	88.7	90.04
Total	(ha)	17.780	17.780	17.780	17.780	17.780	17.780	17.780
	(%)	100	100	100	100	100	100	100

Table 5 presents projected changes in non-built-up and built-up land areas from 2023 to 2045, alongside historical data from 2013-2023. In 2013, non-built-up areas covered 8,370 ha (47% of total area), while built-up areas accounted for 9,410 ha (53%). By 2018, this shifted to 6,680 ha (38%) non-built-up and 11,100 ha (62%) built-up. Actual 2023 data showed further conversion to 5,380 ha (30%) non-built-up and 12,400 ha (70%) built-up, though the model predicted more aggressive changes (4,620 ha non-built-up [25.98%] and 13,160 ha built-up [74.02%]). This 760 ha discrepancy (-760 ha non-built-up, +760 ha built-up) indicates the model overestimated conversion rates compared to actual observations.

Projections reveal continued urban expansion, with built-up areas increasing to 14,735 ha (82.87%) by 2030, while non-built-up areas decline to 3,045 ha (17.13%). This accelerating trend continues with built-up areas reaching 15,390 ha (86.56%) in 2035, 15,770 ha (88.7%) in 2040, and ultimately 16,010 ha (90.04%) by 2045, leaving only 1,770 ha (9.96%) as non-built-up land. The most rapid conversion occurs between 2023 and 2040, during which built-up areas from 74.02% to 90.04% of total area during the 2023-2045 projection period, illustrating near-complete urbanization of Bandar Lampung.

The simulation results indicate that urban expansion in Bandar Lampung City will continue intensively, with built-up areas projected to increase from 74.02% in 2023 to 90.04% in 2045. This pattern reflects a trajectory of near-complete urbanization, especially in areas with high accessibility, such as regions adjacent to major roads and economic centers . The result of agressive land conversion stimulates the concern about the sustainability of urban management, specifically the absence of vegetated area and green spaces that act as buffers against environmental hazards . The expected decrease in undeveloped areas to less than 10% of the overall city land presents major risks to urban sustainability, such as increased flood risk, reduced groundwater recharge, and the loss of biodiversity areas .

According to the model predictions, most agressive urban expansion will occur between 2023 and 2040, that could also coincide with increased national infrastructure availability and migration to urban areas. This points out the importance of applying predictive land-use modeling into governmental spatial planning to inform zoning regulations, green space allocation, and infrastructure investments . W Although the simulation delivers useful knowledge, the results should be handled with caution. Unplanned political decisions, economic shocks, and migration related to climate change can be challenging to measure and can have unpredictable consequences for future plans. Therefore, adaptive urban planning and management frameworks that incorporate dynamic feedback from updated land usage monitoring are essential for maintaining spatial stability and environmental sustainability over time .

4. Conclusions

The built-up land area in Bandar Lampung City increased by 2,990 hectares (31.7%) between 2013 and 2023, expanding from 9,410 hectares (53% of total area) to 12,400 hectares (70%). Projections for 2023-2045 indicate continued urban expansion, with built-up areas predicted to grow by an additional 2,850 hectares. By 2045, built-up land is predicted to reach 16,010 hectares, representing 90.04% of the city's total area. Distance to roads emerged as the most influential determinant variable driving land conversion patterns. Spatial model validation for 2023 built-up land predictions achieved an excellent overall kappa statistic of 0.877, confirming the model's high reliability .

Nonetheless, several limitations should be acknowledged. The model relies on static physical and demographic variables, without incorporating dynamic policy, economic, or informal development factors. In addition, the use of medium-resolution satellite imagery may limit the detection of detailed land-use transitions in complex urban environments. Despite these limitations, the model provides valuable foresight for urban planning. Its integration into spatial policy instruments—such as Regional Spatial Plan (RTRW) can help local governments anticipate land pressure, mitigate environmental risks, and guide more sustainable and adaptive urban development, in line with national long-term goals such as Visi Indonesia Emas.

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