

SPATIAL DYNAMICS OF URBAN EXPANSION IN MAGELANG CITY AND ITS PERI-URBAN AREAS (2013-2031): A SHANNON ENTROPY AND CA-MARKOV APPROACH

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DOI: 10.21163/GT_2027.221.11

ABSTRACT

Built-up land is the land-use category undergoing the most rapid change and therefore requires attention. It is important to monitor and predict the future expansion of built-up land in order to minimize uncontrolled urban expansion. This study aims to monitor, identify patterns, and predict the future built-up land expansion. The results show that there was an increase in built-up land in Magelang City and its peri-urban areas during 2013 to 2025, from 2,674.35 ha to 3,483.81 ha, with the most dominant direction of expansion being towards the north-east and south. Identification of built-up land expansion patterns using Shannon Entropy indicates that the development of built-up land is dispersed, with values remaining relatively stable from year to year. Prediction of built-up land was carried out using driving factors, with the greatest influence coming from the distance to existing built-up land, while the smallest influence came from the distance to commercial facilities. The research results show that the area of built-up land in 2031 is estimated to reach 3,622.41 ha, representing an increase of 138.60 ha compared to 2025. The rate of increase in built-up land is 3.9 %, with an average annual growth rate of 0.66 %/year. The area projected to experience the greatest increase in built-up land area is Mertoyudan Sub-district. Meanwhile, North Magelang and Central Magelang Sub-districts are not projected to experience any increase in built-up land area. The direction of built-up land development is predicted to be predominantly southwards, with a constant Shannon entropy value.

Keywords: built-up land; expansion; Shannon entropy; prediction; cellular automata

1. INTRODUCTION

Built-up land is land that has undergone a process of paving or construction. Built-up land is the type of land use that undergoes the most rapid change. This is due to the conversion of non-built-up land into built-up land. The conversion of non-built-up land into built-up land causes the area of built-up land to continue to increase, a process known as the expansion of built-up land (Suharyadi, 2011). Built-up land expansion will continue in tandem with economic growth, and is therefore predicted to continue at a rapid pace in the future (Sunartono, 1995). The phenomenon of built-up land expansion is occurring in several cities in Indonesia, one of which is Magelang City. According to data from the Magelang City Environmental Agency, there was a reduction in agricultural land between 2013 and 2023, from an initial 210.7 ha to 105.54 ha (Environmental Agency, 2023). This phenomenon can occur due to the conversion of agricultural land into built-up land (Beckers et al., 2020).

The expansion of built-up land in Magelang City is driven by its promotion as a growth center and Regional Activity Center (PKW) in Purwomanggung, as stated in the 2011-2031 Magelang City Spatial Plan (RTRW) and Central Java Provincial Regulation No. 6 of 2010. Magelang City's strategic location at the intersection of the Semarang-Magelang-Yogyakarta-Purworejo transportation and economic routes, as well as the Kopeng-Borobudur-Yogyakarta and Dieng tourist routes, contributes to this development. However, the conversion of non-built-up land in the city center has limited land availability and driven the built-up land expansion to the outskirts (Suprayogi, 2022). Areas directly adjacent to Magelang City, namely the sub-districts of Mertoyudan, Secang, Tegalrejo, Bandongan, and Candimulyo, have the potential to experience built-up land expansion as a result of this expansion,

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as indicated by a decrease in agricultural land area of 518 hectares in 2009–2011 (Destianto & Pigawati, 2014).

The ongoing development of built-up land can cause challenges in spatial planning control, particularly because it has the potential to result in development that is inconsistent with spatial plans (Suryantoro, 2002). Therefore, monitoring and predicting built-up land expansion are necessary to support spatial planning and anticipate the negative impacts of urban development (Liu et al., 2021). Monitoring is also crucial for identifying fragmented development, as dispersed development patterns can lead to less efficient land use and infrastructure provision (Dewa et al., 2022) and encourage a shift in development from the city center to the outskirts (Malligai & Jegankumar, 2016). Monitoring and predicting changes can be conducted using remote sensing data, including Landsat imagery, to identify historical development patterns as a basis for future predictions (Zahrotunisa et al., 2017). In this study, Landsat imagery with a resolution of 30 m in the multispectral band and 15 m in the panchromatic band was pan-sharpened to produce 15 m multispectral imagery for multitemporal classification (Rokni, 2023).

Development patterns were then analyzed using the Shannon Entropy Index to measure the spatial concentration or dispersion of built-up land (Batty, 1974). This method is relatively simple and provides a quantitative measure of urban development fragmentation (Cho et al., 2021), with higher entropy values indicating a more dispersed development pattern (Jat et al., 2008). Predictions of built-up land expansion were performed using the Cellular Automata (CA) model, a dynamic model that represents space as a grid of cells with a set of states that change based on transition rules and the conditions of the surrounding cells (Batty, 2007). With its ability to represent spatial change processes based on historical development patterns, CA models are widely used to model urbanization processes from past conditions to predict future development. Prediction of built-up land expansion using cellular automata have been carried out in many previous studies, one of which is (Zhang et al., 2023) who conducted a simulation of built-up land expansion in Huizhou, China, and achieved a fairly high overall accuracy of 93%.

The Cellular Automata (CA) model requires two main inputs to predict built-up land expansion, a transition probability matrix and a transition potential map. The transition probability matrix indicates the probability of a land use class changing from one class to another within a given period and is constructed using a Markov chain model based on historical data (Eastman, 2006). Meanwhile, the transition potential map indicates the probability of each pixel undergoing change and, in this study, was generated using a Support Vector Machine (SVM). SVM with RBF kernel can capture the nonlinear relationship between socioeconomic and environmental factors and land use change, resulting in a more representative transition potential map for CA-Markov simulations.

Although Shannon Entropy, Markov Chain, CA, and SVM approaches have been widely used in urban development analysis and modeling, studying the growth dynamics of small and medium-sized cities remains crucial because their expansion characteristics can differ from those of metropolitan areas. Urbanization in small and medium-sized cities in Indonesia occurs not only within administrative boundaries but also extends into surrounding areas, forming peri-urban zones (Fahmi et al., 2014). In the context of Central Java, (Mardiansjah et al., 2021) specifically demonstrated that this process also occurs around Magelang, with urban growth expanding into the surrounding peri-urban areas. This highlights the need to understand how land expansion develops in small to medium-sized cities and how this process interacts with suburban areas. Therefore, this study fills this gap by integrating historical change monitoring, spatial pattern analysis using Shannon Entropy, and CA-Markov-based predictions that consider the potential transition of driving factors through SVM.

Overall, this integrated approach provides an overview of changes in the extent and direction of built-up land development, its distribution patterns, and locations with a higher potential for transition to built-up land. This approach is expected to provide information to support urban growth planning in Magelang and serve as a reference for other small and medium-sized cities facing expansion into peri-urban areas. Based on these things, this study aims to (1) monitor the expansion of built-up land, (2) identify the expansion pattern of built-up land using Shannon Entropy, and (3) predict the expansion of built-up land in the future using the CA-Markov model integrated with the SVM model.

2. STUDY AREA

This study covers the administrative area of Magelang City and five sub-districts in Magelang Regency, namely Secang in the north (51.39 km²), Mertoyudan in the south (46.25 km²), Tegalrejo (38.26 km²) and Candimulyo (49.28 km²) in the east, and Bandongan (48.56 km²) in the west, with a cumulative area of 252.29 km². Magelang City, with an area of 18.56 km², is an important center in Java located at the intersection of the Yogyakarta–Semarang–Temanggung–Purworejo corridor and has strategic access to Borobudur and the Dieng Plateau, with an altitude of around 370 meters above sea level and a slope of 5°–45° (Narotama et al., 2021). The surrounding areas have diverse characteristics, with Mertoyudan as the residential center (Magelang Regency Government, 2024), Bandongan and Candimulyo dominated by agriculture and hills (Sholikhah, 2021), Secang as a trading area (BPS Magelang Regency, 2024b), and Tegalrejo, which combines agriculture and small industry (BPS Magelang Regency, 2024a). A map of the study area is presented in Fig.1.

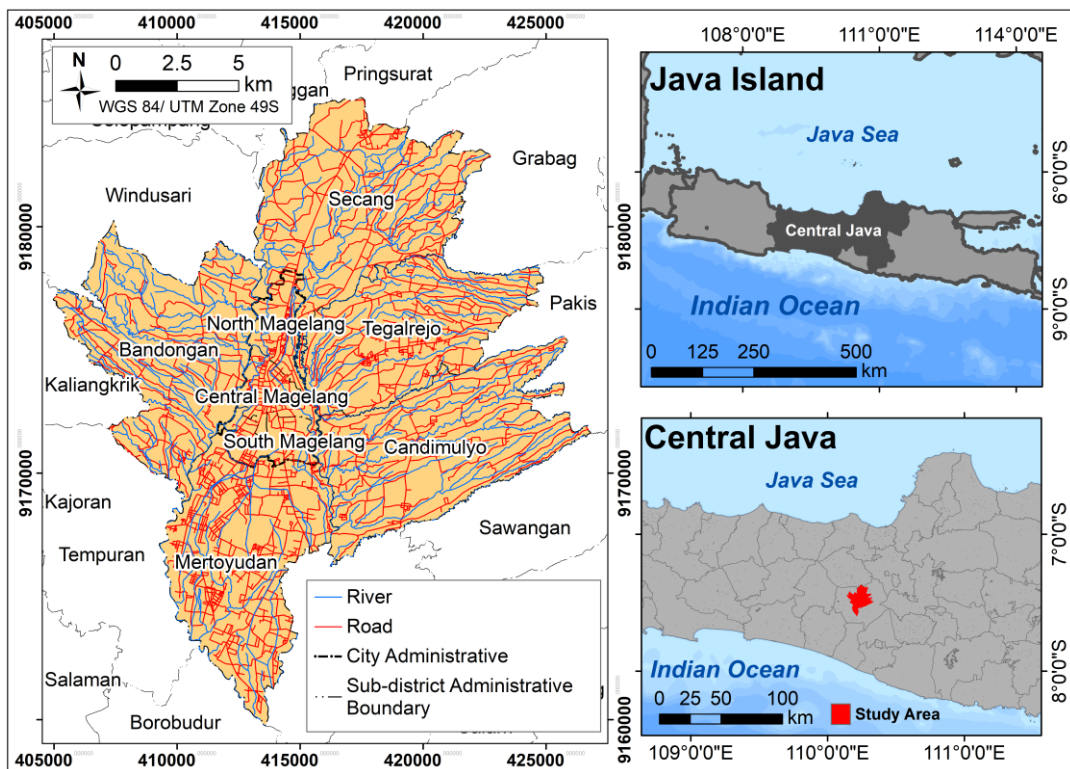


Fig. 1. Location of the study area in Magelang City and its surrounding districts.

3. DATA AND METHODS

3.1. Data Collection

The research data includes built-up land data from 2013, 2019, and 2025, the results of Random Forest multispectral classification from Landsat 8 OLI and Landsat 9 OLI-2 images, as well as driving factors such as educational facilities, health facilities, industrial areas, commercial facilities, population density, roads, rivers, and DEM. The data sources are presented in Table 1. Distance-based factors are calculated using Euclidean Distance, a feature that calculates the shortest straight-line distance from each raster pixel to the nearest source, which can be a point, line, or polygon, with the result being a raster whose pixel value indicates the distance to the nearest source in units according to the raster projection system (ESRI, 2025). Population density is converted from vectors

to rasters, while elevation and slope are obtained from DEMNAS. Other data used included disaster-prone areas, which encompassed a combination of floods, earthquakes, landslides, and volcanic eruptions. This data was obtained by converting vector data into raster data. All data are then standardized in raster format with a spatial resolution of 15 meters.

Table 1.

Specifications of the data used in the research.

No	Data	Type	Source
1	Built-Up Land 2013	Raster	Landsat 8 OLI (12 September 2013)
2	Built-Up Land 2019	Raster	Landsat 8 OLI (13 September 2019)
3	Built-Up Land 2025	Raster	Landsat 9 OLI-2 (13 September 2019)
4	Educational Facilities	Vector	Public Works and Spatial Planning Agency
5	Health Facilities	Vector	Public Works and Spatial Planning Agency
6	Industrial Areas	Vector	Public Works and Spatial Planning Agency
7	Commercial Facilities	Vector	Public Works and Spatial Planning Agency
8	Road	Vector	Public Works and Spatial Planning Agency
9	River	Vector	Public Works and Spatial Planning Agency
10	Population Density	Vector	Central Statistics Agency
11	DEMNAS	Raster	tanahair.indonesia.go.id
12	Disaster Prone Areas	Vector	Public Works and Spatial Planning Agency

3.2. LULC Classification and Transition Map

Land-use classification was carried out using pan-sharpened Landsat imagery from 2013, 2019 and 2025, employing the random forest method. Classification using the random forest method involved the formation of trees. The training sample was used to build the trees in the random forest. The trees were then trained to recognise the distinctive spectral value patterns of each land-use class from the data sample that had been collected. Next, the trained random forest model was used to predict the land-use class of each pixel in the imagery. For each pixel, the reflectance values of the object in each band were fed into all the trees; each tree then provided a prediction. The land-use class was determined based on the majority vote produced by these trees (Marlina, 2022). Random forest classification in this study was performed using 1,000 trees with a training set of 280 samples. Classification was carried out using seven classes, namely residential buildings, non-residential buildings, bare land, agriculture land, agroforestry land, shrubland, and water bodies. The results were then generalised into two classes, consist of built-up land and non-built-up land. Subsequently, a map of built-up land transitions was created, identifying classes that had changed and classes that had remained unchanged.

3.3. Shannon Entropy Index Calculation

Shannon entropy calculations were carried out using eight zones based on compass directions, comprising east (E), south-east (SE), south (S), south-west (SW), west (W), north-west (NW), north (N) and north-east (NE), with the centre of Magelang City as the reference point. The creation of zones based on directions was carried out to capture patterns of built-up land expansion in Magelang City and its surrounding areas, where development is influenced by transport corridors, existing built-up land, and physical landscape conditions. In each year of observation, the proportion of built-up land in each zone compared to the total area of built-up land was calculated. Subsequently, the Shannon entropy was calculated using the following formula (Effat & El Shobaky, 2015).

$$H = - \sum_{i=1}^n P_i \ln(P_i) \quad (1)$$

where:

H = entropy value

P_i = proportion of built-up land area in zone i

n = total number of zones

The resulting entropy values range from 0 to $\ln(n)$, where values approaching 0 indicate a compact and concentrated urban form, while values approaching $\ln(n)$ indicate a more dispersed spatial distribution associated with urban sprawl (Jat et al., 2008). This approach was applied to the results of the built-up land classification for 2013, 2019 and 2025. The same procedure was then applied to the results of the built-up land expansion prediction for 2031.

3.4. Driving Factors Selection

The map of factors driving built-up land expansion consists of 10 variables, namely distance to roads, rivers, educational facilities, health facilities, industrial areas, commercial facilities, existing built-up land, population density, elevation, and slope. The variables used represent physical characteristics, accessibility, and socio-economic conditions that potentially influence land conversion into built-up areas. Elevation and slope reflect topographic conditions, while distance to roads and facilities illustrates the level of accessibility that can increase the attractiveness of a location for development (Yang et al., 2023). Meanwhile, population density is used to represent socio-economic pressures that can drive built-up land expansion (Kamusoko & Gamba, 2015).

The driving factors were then statistically tested to identify variables associated with the transition to built-up land. The method used was Cramer's V, which measures the strength of the association between two variables based on the Chi-square (X^2) value, with values ranging from 0 to 1; values closer to 1 indicate a stronger association (Megahed et al., 2015). The evaluation was conducted using the Testing and Selection of Explanatory Variables procedure in the Land Change Modeler (LCM) in TerrSet, with Cramer's V as the initial measure of the association between each variable and the observed land-use transition. Categorical variables used their original categories, while continuous variables were automatically discretized into 256 categories by TerrSet before calculating Cramer's V. Variables with Cramer's V values >0.15 were selected as driving factors for modeling, following the criteria applied by Leta et al. (2021). These thresholds are used as operational criteria for variable selection and are not intended as universal limits indicating causal relationships.

The selected driving factors are then tested for multicollinearity to ensure there are no strong correlations between the independent variables that could affect model stability. Testing is performed using the Variance Inflation Factor (VIF) and tolerance values, with the VIF calculated based on the coefficient of determination (R^2) from the regression of each variable against the other explanatory variables. A VIF value close to 1 indicates a low correlation between the variables, while a value above 5 indicates potential multicollinearity. Conversely, a tolerance value, the inverse of the VIF, can indicate multicollinearity if it falls below the range of 0.1–0.2 (Kim, 2019).

3.5. Transition Potential Map

The creation of transition potential maps was carried out using a Support Vector Machine (SVM) model. The basic principle of SVM is to project data into a high-dimensional space via a kernel to separate classes with the maximum distance or margin using a hyperplane. The SVM used in this study utilised a radial basis function kernel. The kernel in SVM is a method of calculating the similarity between data points in a high-dimensional space without calculating the coordinates of that space. The RBF kernel calculates the proximity of data using the following formula (Fremmuzar & Baita, 2023).

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (2)$$

where:

x_i, x_j = two data points

$\|x_i - x_j\|^2$ = euclidean squared distance between two points

γ = parameters that regulate the width of influence

The RBF kernel works by calculating a value K for each pair of data points that indicates their proximity in space. Subsequently, this kernel value effectively projects the data into an infinite-dimensional space where linear separation occurs. The SVM then uses this kernel value to determine a hyperplane that maximises the distance between classes. The trained SVM model is then used to calculate the probability of change for each pixel in the image. This probability indicates the likelihood of each pixel changing from non-built-up land to built-up land. The result is a raster map of potential transitions showing the probability value for each pixel. The SVM calculates the probability by converting the margin into a probability, a process known as Platt scaling. This method adapts the logistic function to the margin results using the following equation (Lin et al., 2007)

$$P(x) = \frac{1}{1 + \exp(Af(x) + B)} \quad (3)$$

where:

$f(x)$ = the margin value from the SVM

A and B = parameters estimated from the validation data

The SVM model in this study used a sample size of 400, with samples selected using stratified random sampling and divided equally into 200 samples each from the changed and unchanged classes. This was done to ensure a balanced representation between changed and unchanged pixels, while all predictor variables were standardized through centering and scaling prior to model training. Model training and validation were performed using five-fold cross-validation, and hyperparameter tuning identified optimal cost (C) and sigma parameters of 0.5 and 0.252574, respectively (equivalent to $\gamma \approx 7.84$); the resulting model was then applied to all valid pixels of the predictor raster layer to generate a spatial probability map illustrating the potential for transition to built-up land by 2031.

3.6. Transition Probability Matrix

The transition probability matrix for built-up and non-built-up land classes was constructed using a Markov chain. A Markov chain can calculate the probability of a land use class changing to another class within a specific time period based on two land use maps from different time periods. In this study, a Markov chain was used to calculate the probability of non-built-up land changing to built-up land by 2031 based on land use maps from 2019 and 2025. The probability matrix represents the likelihood of land-use changes over a 6-year period, namely from 2019 to 2025, and is used to model changes over the subsequent 6-year period, namely from 2025 to 2031. Subsequently, the probability matrix and the number of pixels in each class in 2025 are used to predict the number of pixels in each class in 2031 using the following equation (Kumar et al., 2014).

$$S_{t+1} = S_t \times P \quad (4)$$

where:

$S_{(t+1)}$ = predicted number of pixels for each class in the future, i.e. $t+1$

P = transition probability matrix

S_t = number of pixels in each class at time t

3.7. Built-Up Land Expansion Prediction

Spatial modelling of built-up land expansion was carried out using cellular automata within the Land Change Modeler feature in Idrisi Terrset. Before predicting future built-up land expansion, the CA-Markov model combined with SVM was calibrated using built-up land maps from 2013 and 2019 to simulate built-up land expansion in 2025. Then, the results of the built-up land expansion simulation were validated with the actual built-up land map in 2025. The validation metrics used included overall accuracy, kappa value, and Figure of Merit. Overall accuracy and kappa value were used to test the accuracy of the quantity of change, while Figure of Merit was used to test the accuracy

of the location of the change. Figure of Merit consists of hits, misses, and false alarms. FOM is calculated using the following equation (Pontius et al., 2008).

$$FOM = \frac{Hits}{Hits+Misses+False\ alarms} \quad (5)$$

where :

Hits = number of pixels predicted to change and actually change

Misses = number of pixels predicted not to change but actually change

False alarms = number of pixels predicted to change but do not actually change

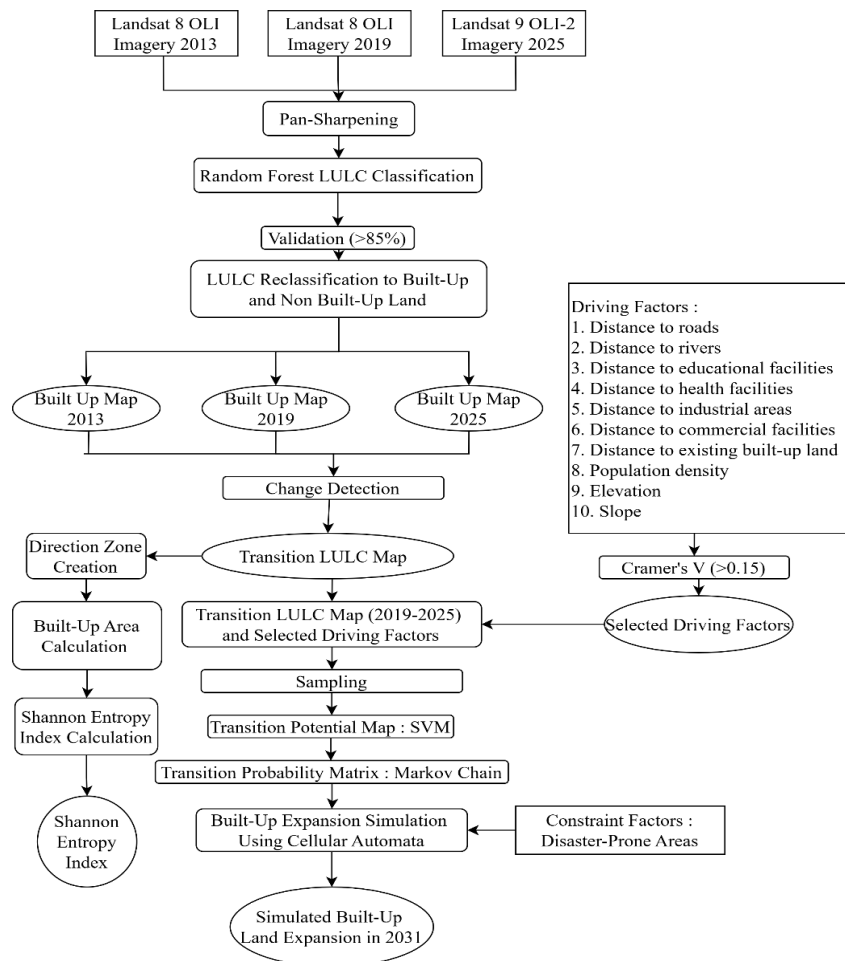


Fig. 2. Flow chart for monitoring and predicting built-up land expansion

Spatial modeling of built-up land expansion in 2031 uses 2019 and 2025 built-up land maps with a resolution of 15×15 meters. The CA-Markov simulation utilizes a 3×3 Moore neighborhood filter, a transition probability matrix from a Markov chain, and a transition potential map from an SVM model. Constraint factors in the form of areas prone to earthquakes, landslides, floods, and volcanic activity are applied as binary rasters, with a value of 1 indicating an absolute exclusion, therefore preventing prediction of built-up land expansion in that area, while a value of 0 indicates an area that can be considered for development. These constraint factors are used to direct the simulation to produce safer development patterns and support sustainable development. A flowchart of the monitoring and prediction method for built-up land expansion is presented in **Fig.2.**

4. RESULTS AND DISCUSSIONS

4.1. LULC Classification in 2013, 2019, and 2025

The LULC classification maps for 2013, 2019 and 2025, generated using the Random Forest method, reveal differences in spatial distribution between the urban and peri-urban areas of Magelang City (see **Fig.3.**). Residential and non-residential buildings are concentrated in the central area, particularly in Magelang City itself, while agricultural land, agroforestry and scrubland are more prevalent in the peri-urban areas. Agricultural land is mainly distributed in the western part, including Bandongan Sub-district, whilst agroforestry land is predominantly found in the south-eastern part, particularly in Candimulyo Sub-district. This pattern indicates that the Magelang City area is dominated by built-up land, while the surrounding areas are still dominated by non-built-up land, which has the potential to become an area for the expansion of built-up land.

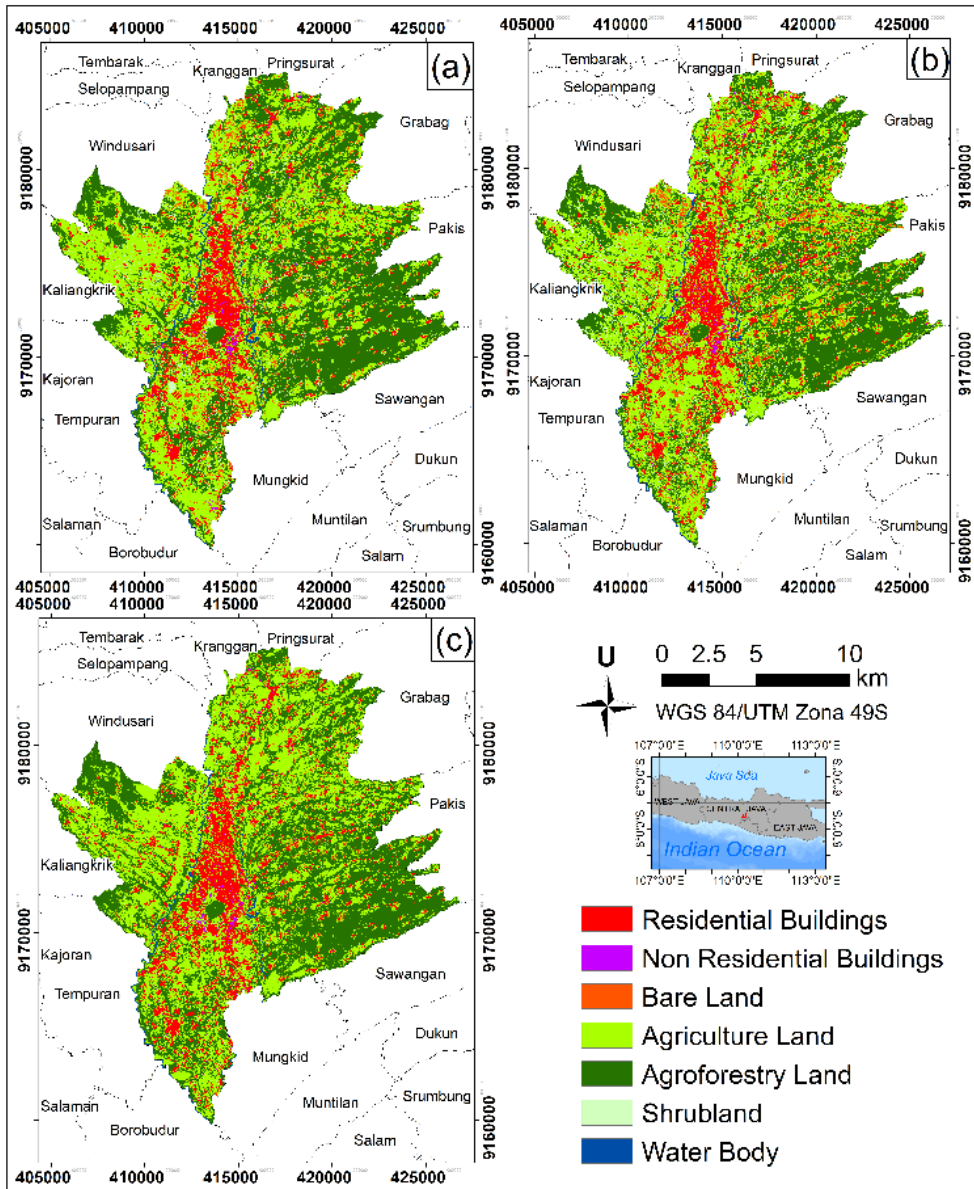


Fig. 3. LULC Classification of (a) 2013, (b) 2019, and (c) 2025.

Accuracy testing was conducted using a 70:30 split between training and validation data using a stratified random sampling method, with a different distribution of validation points from the training samples (**Table 2**). Based on 120 validation samples, overall accuracy increased from 90.83% in 2013 to 91.67% in 2019 and 93.33% in 2025, while the Kappa coefficient increased from 0.88 to 0.89 and 0.91 (**Table 3**). All values exceeded the minimum threshold of 85% for further analysis (Anderson, 1971), therefore the LULC map was deemed suitable for analyzing and modeling built-up land development. In general, the building and airspace classes had high UA and PA, some reaching 100%, while variations in accuracy were mainly found in vacant land and shrubs. These results indicate that Random Forest is capable of producing accurate and consistent LULC classifications in the third observation period.

Table 2.**Spatial distribution of training and validation samples in 2013, 2019, and 2025.**

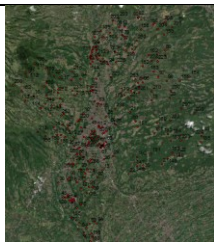
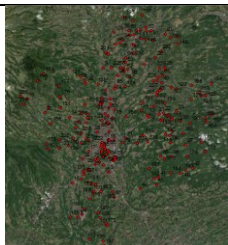
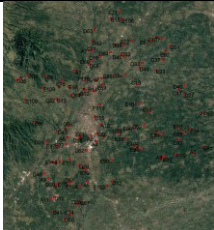
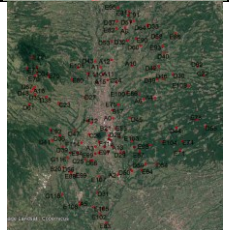
Sample	2013	2019	2025
Training			
Validation			

Table 3.**User Accuracy, Producer Accuracy, Overall Accuracy, and Kappa Value of LULC Classification in 2013, 2019, and 2025.**

LULC	2013		2019		2025	
	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Residential Buildings	100	87.50	100	88.89	100	100
Non-Residential Buildings	80.00	100	100	100	100	100
Bare Land	71.43	83.33	80	100	80	80
Agriculture Land	82.50	91.67	90.48	86.36	93.02	88.89
Agroforestry Land	97.62	89.13	90.24	94.87	92.50	94.87
Shrubland	100	100	83.33	100	80	100
Water Body	100	100	100	100	100	100
Overall Accuracy (%)	90.83		91.67		93.33	
Kappa Values (%)	0.88		0.89		0.91	

4.2. Built-Up Land Expansion in 2013, 2019, and 2025

The results of the study indicate that the built-up area in Magelang City and its peri-urban areas increased from 2,674.35 ha in 2013 to 3,231.29 ha in 2019 and 3,483.81 ha in 2025, or an increase of 809.46 ha. This result is in line with Nurhayati (2024) and in line with the development pattern in Makassar City and its surroundings (Arifin et al., 2023), which experienced an increase in built-up land from 4,017.2 ha in 2001 to 9,392.5 ha in 2016 with approximately 5,615.4 ha of built-up land

not converted into built-up land. Compared to Makassar, the expansion in Magelang occurred at a lower intensity, which may be influenced by differences in scale, urban characteristics, and regional development pressures. In Magelang, growth also occurred more significantly around the city, at 710.62 ha, compared to 98.84 ha within the city, indicating a shift in development due to limited land in the city center. A graph of changes in built-up land area is presented in **Fig.4**, while a map of built-up land for 2013, 2019, and 2025 is presented in **Fig.5**.

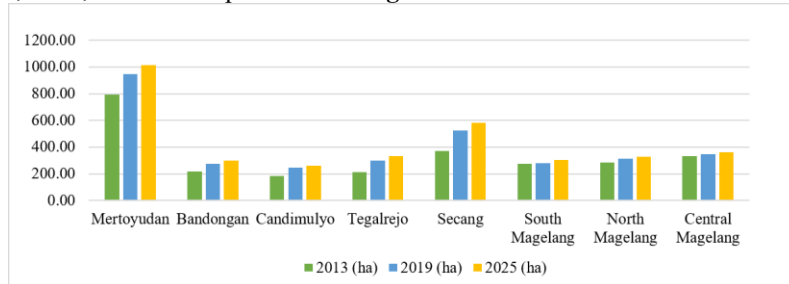


Fig. 4. Changes in the Area of Built-up Land by Sub-district.

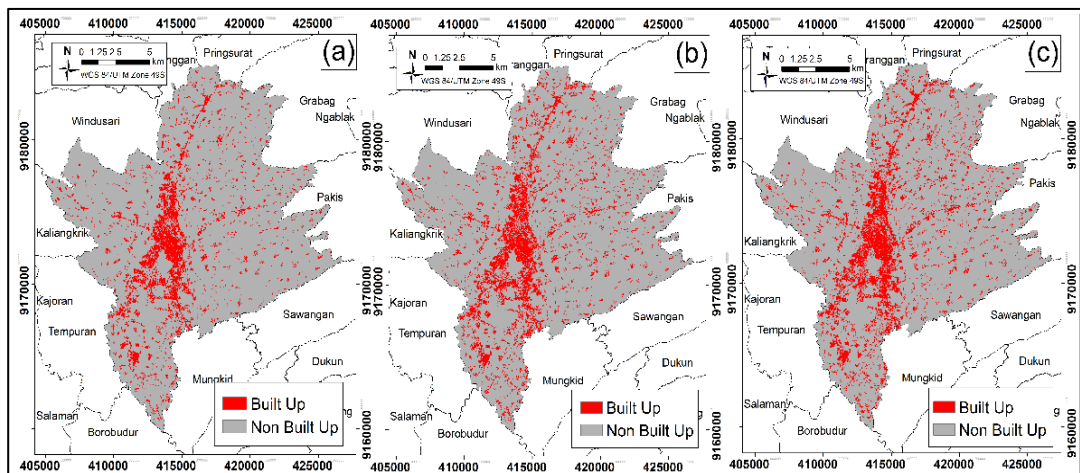


Fig. 5. Built-up Land in (a) 2013, (b) 2019 and (c) 2025.

The average annual growth rate of land area decreased from 3.47% in 2013-2019 to 1.30% in 2019-2025, indicating slower expansion in the second period. This slowdown coincided with the COVID-19 pandemic and changing socioeconomic conditions, as Magelang City's economic growth declined from 5.44% in 2019 to 2.45% in 2020, before recovering to 5.77% in 2022 (BPS Magelang City, 2022). Magelang Regency also experienced a 1.67% contraction in 2020 before recovering to 5.46% in 2022 (BPS Magelang Regency, 2025). This condition could theoretically affect development activity and land demand, but the direct relationship has not been empirically tested, so COVID-19 is seen as a potential factor, not a definitive cause of the slowdown.

The dominant direction of development also changes between periods, with increases in built-up land area in each direction presented in **Table 4**. In 2013-2019, the largest expansion occurred to the north-east, driven by housing development and urban activities due to good accessibility and relatively large land availability. In 2019-2025, the dominant direction shifted south, particularly along the Magelang-Yogyakarta corridor, which offers high accessibility and has seen development of housing, commerce, and urban support facilities, particularly in Mertoyudan. This condition encourages land conversion to built-up areas in the southern region of Magelang City. A map of built-up land area based on development direction is presented in **Fig.6**.

Table 4.
The increase in built-up land area in each direction.

Direction	2013-2019 (ha)	2019-2025 (ha)
SW	43.8525	22.68
S	111.5325	68.6025
SE	41.175	19.035
W	25.6725	11.1375
E	87.39	32.8275
NE	118.035	44.91
NW	19.8675	6.9975
N	109.4175	46.3275

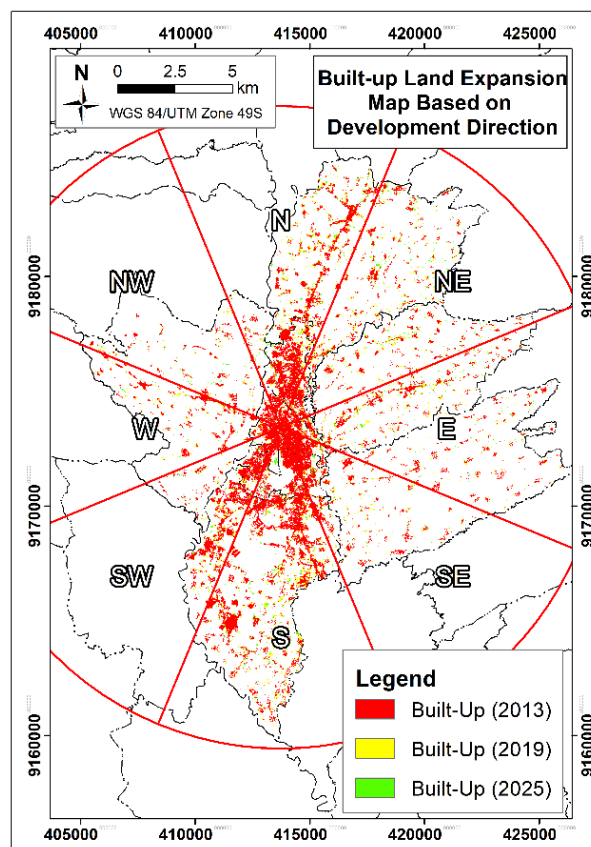


Fig. 6. Built-Up Land Expansion Map Based on Development Direction.

4.3. Shannon Entropy Index

The Shannon entropy calculation yielded a value of 1.925 in 2013, increasing to 1.934 in 2019, and then decreasing slightly to 1.932 in 2025. With a maximum value of $\ln(8) = 2.079$, the normalized entropies were 0.926, 0.930, and 0.929, respectively. Values close to 1 indicate that built-up land is relatively evenly distributed across the eight directional sectors, so that built-up land development in Magelang City and its surroundings is not concentrated in any particular direction. These results are consistent with Dewa et al. (2022), who obtained entropy values close to 1 (0.98 and 0.96) in the southeastern peri-urban area of Semarang, indicating a tendency for built-up land distribution to spread to the outskirts.

The very small change in entropy values indicates that the balance of the directional distribution of built-up land remains relatively stable even though the built-up land area increases from 2,674.35 ha in 2013 to 3,483.81 ha in 2025. The increase in entropy in 2013–2019 indicates a slight increase in the distribution balance, while the decrease in 2025 does not substantially change the condition. Overall, the normalized entropy values consistently above 0.92 indicate that the level of balance in the distribution of built-up land in the eight directional sectors remains high, so that the increase in built-up land area does not cause significant changes in the spatial distribution pattern during 2013–2025.

4.4. Driving Factors Selection

The map of driving factors for built-up area expansion used in this study is presented in **Fig. 7**. Each factor has a different range and distribution of pixel values, thus varying its impact on land-use change. The selection of driving factors was conducted using Cramer's V analysis of the transition from non-built-up land to built-up land in 2019–2025. The Cramer's V values for each factor are presented in **Table 5**. The highest value, 0.5539, was obtained for distance from existing built-up land, indicating a strong relationship with the development of new built-up land. This pattern suggests that development tends to occur around previously built-up areas (Kim et al., 2023), and aligns with Wicaksono et al. (2023) in the Yogyakarta Urban Area, which found distance from existing organizations to be a dominant factor. Conversely, distance to commercial facilities had the lowest value, 0.0897, indicating a weak relationship with the transition from built-up land. Factors with Cramer's V values >0.15 were retained in the modeling, while distance to industrial areas, distance to commercial facilities, and elevation were excluded due to their values below this threshold. The low value of the third factor indicates a limited relationship with built-up land development during 2019–2025. This condition can be related to most of the areas around industrial areas and commercial facilities that have been developed previously, while new developments are starting to reach higher elevation areas because land at lower elevations has been widely developed.

Table 5.

Cramer's V Values for Each Driving Factors.

Driving Factors	Cramer's V
Distance to Road	0.2013
Distance to River	0.1821
Distance to Educational Facilities	0.2006
Distance to Health Facilities	0.1733
Distance to Commercial Facilities	0.0897
Distance to Industrial Areas	0.1075
Distance to Existing Built Up Areas	0.5539
Population Density	0.2053
Elevation	0.0996
Slope	0.1502

The seven selected driving factors were tested for multicollinearity using VIF and tolerance values. The results showed that all driving factors had VIF values close to 1 and tolerance values above 0.2 (**Table 6**). This indicates that there was no evidence of high correlation among the independent variables used. Therefore, each driving factor does not have a strong linear relationship with the others, meaning all factors can be included in the model. This condition suggests that each factor has the potential to provide distinct information in explaining patterns of built-up land expansion. Furthermore, the absence of significant multicollinearity minimizes information redundancy among variables and ensures that the inclusion of all explanatory factors does not introduce bias due to overly strong relationships between variables in the modeling process.

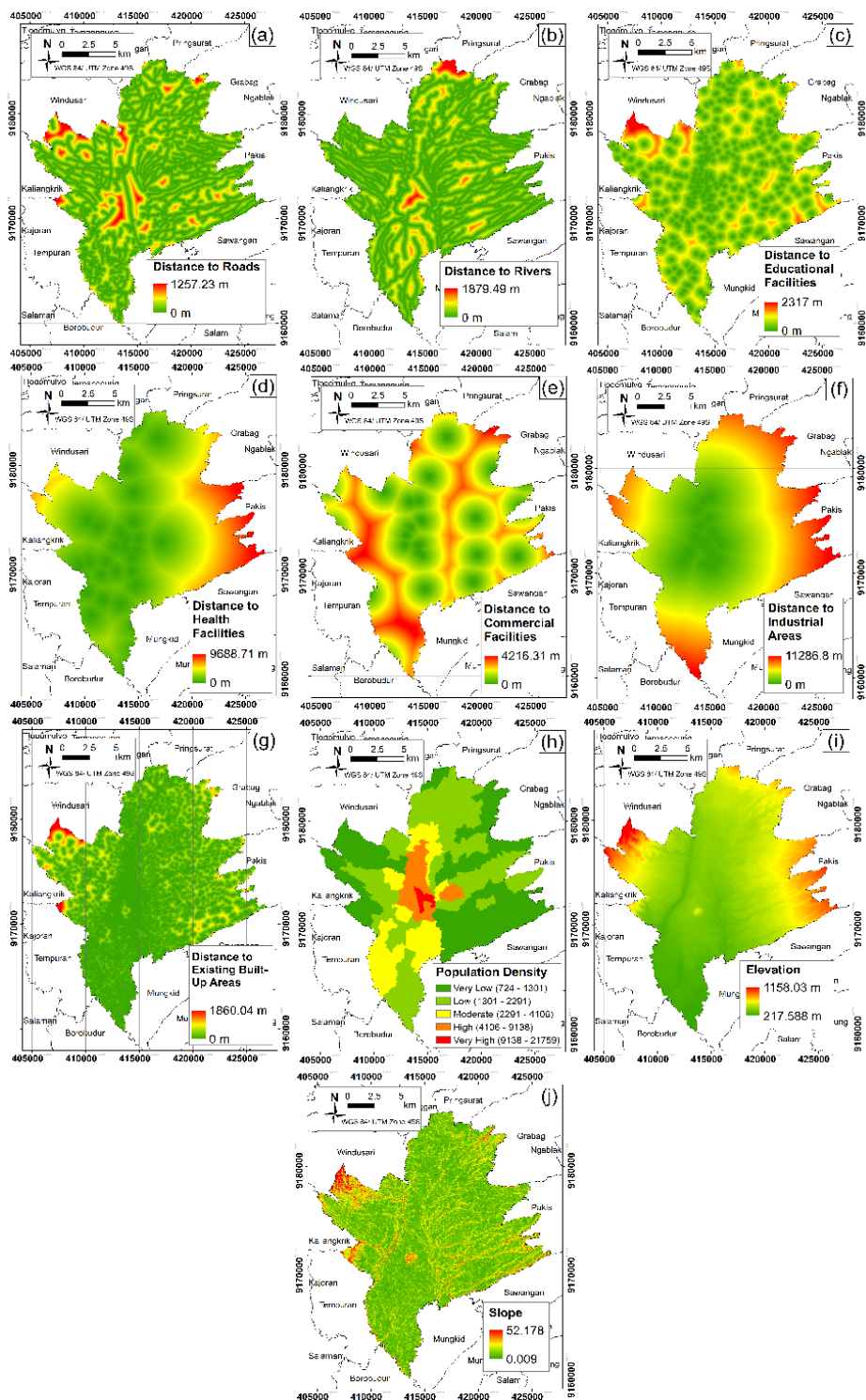


Fig. 7. Driving factors map: a) distance to roads; b) distance to rivers; c) distance to educational facilities; d) distance to health facilities; e) distance to commercial facilities; f) distance to industrial areas; g) distance to existing built-up areas; h) population density; i) elevation; j) slope

Table 6.

Multicollinearity Test Results for Each Driving Factors.

Driving Factor	Tolerance	VIF
Distance to Road	0.769	1.301
Distance to River	0.917	1.091
Slope	0.818	1.222
Population Density	0.752	1.329
Distance to Health Facilities	0.740	1.352
Distance to Existing Built Up Areas	0.573	1.746
Distance to Educational Facilities	0.810	1.234

4.5. Transition Potential Map

The transition potential map was generated using an SVM model with an RBF kernel and produces pixel probability values between 0 and 1, representing the likelihood of a change from built-up land to non-built-up land. The resulting transition potential map has a value range of 0.192106–0.749188 and is presented in **Fig.8**. High probability values are distributed primarily in Mertoyudan and Secang sub-districts, indicating a high potential for change in these two areas. This condition is likely influenced by the proximity to main roads, health facilities, and existing built-up land, as well as relatively low slope conditions that are more conducive to development. Conversely, low probability values are more common in Bandongan, Candimulyo, and Tegalrejo sub-districts, possibly related to their greater distance from health facilities and existing built-up land, relatively low population density, and steeper slope conditions. Meanwhile, areas of Magelang City surrounding the city center tend to have moderate to low transition potential because most of the land in these areas has been developed since the previous period, so land use changes during 2019–2025 are relatively limited. This pattern shows that limited land in the center of Magelang City is pushing the potential for built-up land development to shift to the peri-urban areas, especially to areas that still have available land and characteristics that support development.

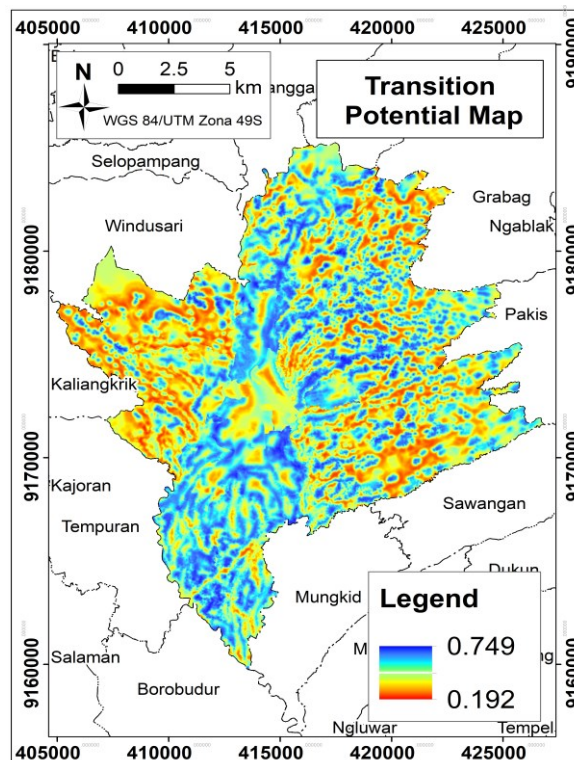


Fig. 8. Transition Potential Map.

4.6. Transition Probability Matrix

The transition probability matrix shows the probability of change between built-up and unbuilt land classes, with the change matrix for 2031 presented in **Table 7**. The results indicate that the probability of non-built-up land changing to built-up land is 1.3%, while 98.7% remains unbuilt. Conversely, the probability of built-up land changing to non-built-up land is only 0.55%, while 99.45% remains built-up. The low probability of built-up land changing to unbuilt land is likely related to image classification errors, given the relative stability of built-up land classes. Although the conversion probability is only 1.3%, the predominance of unbuilt land in 2025 still allows for an increase in built-up land in 2031, while the low probability of reversion suggests that most built-up land will remain intact. This condition indicates a development trajectory consistent with urbanization trends, namely an increase in built-up land and a decrease in non-built-up land.

Table 7.

Transition Probability Matrix.

	Built-Up Land	Non-Built-Up Land
Built-Up Land	0,9945	0,0055
Non-Built-Up Land	0,0130	0,9870

4.7. Temporal Model Validation

Temporal validation of the CA-Markov/SVM model was performed using a hindcasting procedure. Calibration of the model was based on the 2013 and 2019 built-up land maps to simulate conditions in 2025, then comparing it with the 2025 classification map as shown in **Fig.9**.

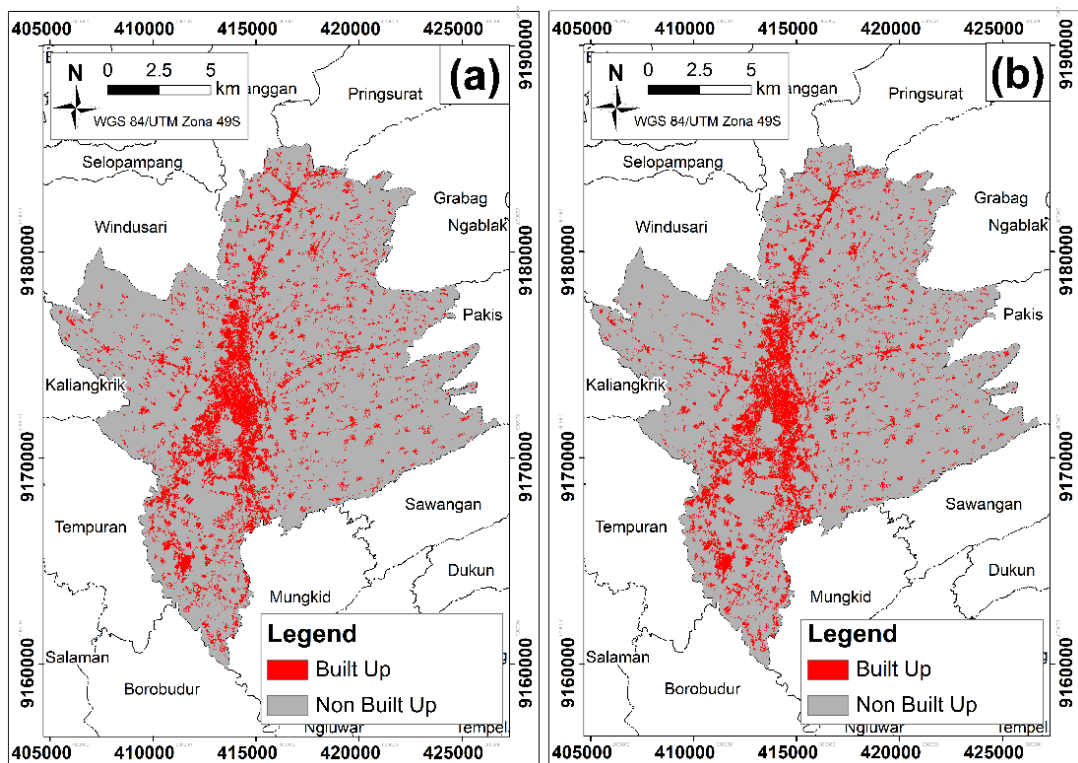


Fig. 9. Comparison of (a) Classified and (b) Simulated Built-Up Land Map in 2025.

The validation results showed an Overall Accuracy (OA) value of 98.46% and a Kappa value of 0.935, indicating a very high level of agreement between the simulated and observed maps overall. However, because OA and Kappa are also influenced by areas that have not experienced change, the model's ability to determine the specific locations of change was also evaluated using the Figure of Merit (FoM), which resulted in a value of 15.3% (0.153). This value indicates that the model is able to partially replicate the spatial pattern of change, although the suitability of the change locations is still more limited than the overall suitability of the map. Kappa values above 0.75 and FoM values above 0.15 are generally considered to indicate an acceptable level of accuracy (Ma et al., 2026). Therefore, the Kappa value of 0.935 and FoM of 0.153 meet the threshold, so that the CA-Markov/SVM model is considered to have a sufficient level of reliability to be used in predicting built-up land development patterns until 2031, although there are still limitations in determining the exact location of changes.

4.8. Built-Up Land Expansion Prediction

The prediction of built-up land expansion in Magelang City and its surrounding areas in 2031 was carried out using inputs in the form of transition probability matrices from a Markov chain and transition potential maps generated by an SVM model. The map showing the predicted development of built-up land and the distribution of land pixels predicted to undergo built-up land expansion in Magelang City and its surrounding areas in 2031 is presented in Fig.10.

The results indicate that by 2031, Magelang City and its surrounding areas are predicted to have 3,622.41 hectares of built-up land. Compared to 2025, built-up land is predicted to increase by 138.60 hectares.

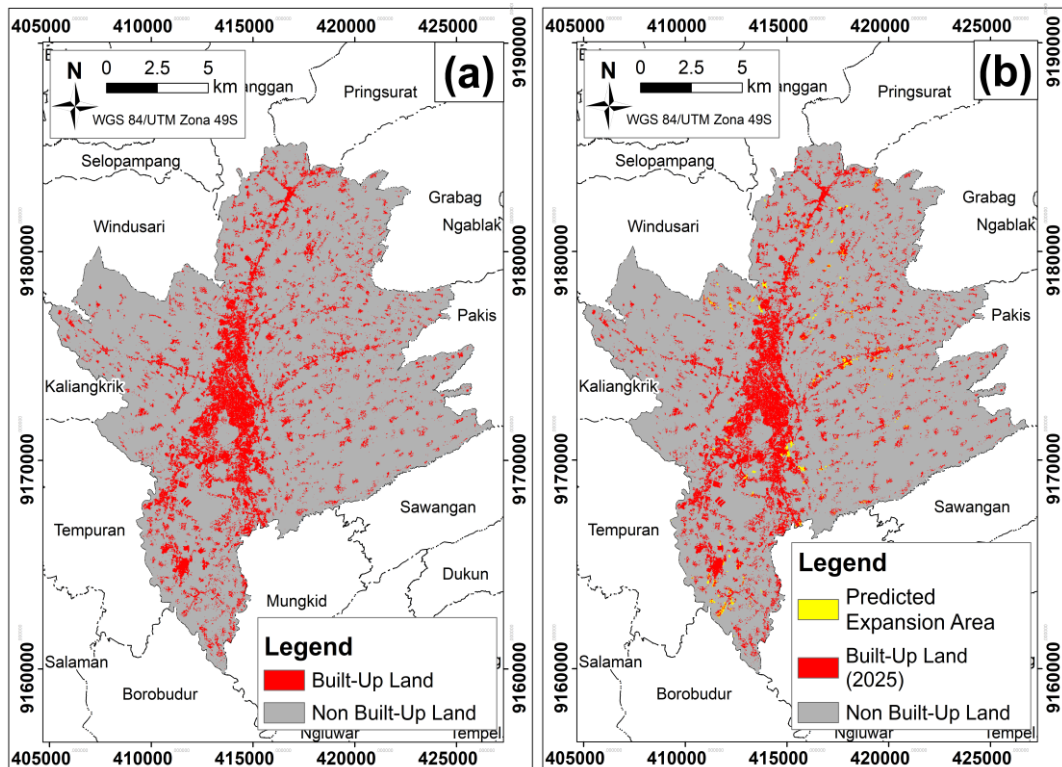


Fig. 10. Predicted Built-Up Map: a) Predicted Built-Up Land Map 2031, b) Predicted Built-Up Land Expansion Areas in 2031.

Based on growth rates, the growth rate of built-up land in Magelang City and its surrounding areas is estimated to reach 3.9% from 2025 to 2031, with an average annual growth rate of 0.66%. This rate is slower than the 2019 to 2025 period, likely influenced by limited space for horizontal expansion in Magelang City and the dominance of productive agricultural land and conservation areas in the peri-urban area. As a result, built-up land expansion is expected to occur locally and not spread widely. The increase in built-up land area for each sub-district is presented in **Table 8**. The largest increase in built-up land area is predicted to occur in Mertoyudan sub-district, at 47.79 hectares, followed by Tegalrejo at 33.41 hectares, and Secang at 31.14 hectares. This potential is supported by the presence of main roads and public facilities, relatively flat topography, and the availability of land that is still suitable for development. Mertoyudan offers strategic access via the Yogyakarta-Semarang route and various public facilities, while Tegalrejo and Secang enjoy strategic locations as intercity connecting routes and relatively favorable topography for development.

When viewed based on annual growth rates, Tegalrejo sub-district has the highest growth rate, at 1.66%. This high figure is influenced by, among other factors, the relatively small built-up area in 2025, allowing for a larger growth percentage, and the availability of non-built-up land. Conversely, North Magelang and Central Magelang sub-districts are not predicted to experience an increase in built-up area until 2031 due to limited vacant land suitable for horizontal development. This situation indicates that development in both sub-districts tends to be more directed toward densification through vertical development rather than horizontal expansion.

Table 8.**Increase in Area and Growth Rate of Built-up Land by Sub-district in 2031**

Sub-District	Area 2025 (ha)	Area 2031 (ha)	Increase in Area (ha)	Growth Rate (%/year)
Mertoyudan	1013.42	1061.21	47.79	0.79
Bandongan	297	306.36	9.36	0.53
Candimulyo	262.89	271.01	8.12	0.51
Tegalrejo	335.14	368.55	33.41	1.66
Secang	582.14	613.28	31.14	0.89
South Magelang	301.91	310.68	8.78	0.48
North Magelang	327.94	327.94	0	0
Central Magelang	363.38	363.38	0	0
TOTAL	3483.81	3622.41	138.6	

The prediction results indicate that built-up land development in 2031 will occur more around Magelang City than within the city. Within Magelang City, the increase in built-up land is only predicted to occur in the South Magelang sub-district, amounting to 8.78 ha, while the peri-urban area is projected to increase by 129.83 ha. This condition indicates that limited land in urban areas is driving a shift in development to areas surrounding Magelang Regency, while Magelang City is more suitable for vertical development. However, the projection results should be understood as scenarios based on model assumptions, not deterministic predictions, because the CA-Markov model assumes the continuation of historical transition patterns and does not fully capture changes in land use policies, infrastructure development, socioeconomic conditions, and land market dynamics. Furthermore, uncertainty in the results may be influenced by misclassification of the LULC input data, which remains limited in the predictions regarding the magnitude and location of actual changes in 2031.

The Shannon entropy value for 2031 is predicted to be 1.932, almost the same as 2013 (1.925), 2019 (1.934), and 2025 (1.932), with a maximum value of $\ln(8) = 2.079$. The normalized entropy is 0.926, 0.930, 0.929, and 0.929 in 2013, 2019, 2025, and 2031, respectively (see **Fig.11.**). The relatively constant value and close to 1 indicates that the distribution of built-up land in 2031 is expected to remain spread out and relatively even in various directions, so that the increase in built-up land area is not accompanied by significant changes in the spatial structure or distribution balance.

However, analysis of development direction shows that expansion remains predominantly to the south, especially following the Magelang-Yogyakarta corridor. This dominance is related to high accessibility and the development of residential, commercial, and service functions, particularly in Mertoyudan sub-district, which is increasingly integrated with the urban system of Magelang City. Therefore, the southern region is expected to remain the primary direction for built-up land development until 2031.

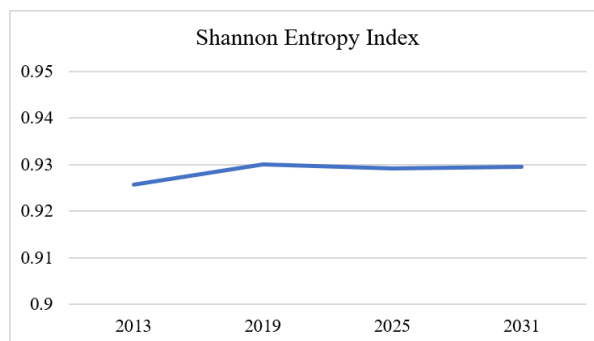


Fig. 11. Shannon Entropy Index in 2013, 2019, 2025, and 2031.

5. CONCLUSIONS

This study shows that the built-up area in Magelang City and its surrounding areas increased from 2,674.35 ha in 2013 to 3,483.81 ha in 2025, with greater expansion occurring in the peri-urban areas. The direction of expansion shifted from northeast in 2013–2019 to south in 2019–2025, while the distribution pattern remained relatively dispersed based on the Shannon Entropy value which approached the maximum value and tended to be stable. The strongest driving factor for built-up land expansion is distance from existing built-up land, while the weakest is distance to commercial facilities. Based on Cramer's V value, distance to commercial facilities, industrial areas, and altitude were excluded from the model. The 2031 prediction shows an increase in built-up land of 138.60 ha or an average growth rate of 0.66% per year, with the largest growth in Mertoyudan supported by adequate accessibility and facilities, while North Magelang and Central Magelang are not predicted to experience an increase due to land limitations. Expansion in 2031 is expected to remain predominantly southward with a relatively stable spatial distribution.

ACKNOWLEDGEMENTS

The author would like to express sincere gratitude to the Faculty of Geography, Universitas Gadjah Mada, for the academic guidance and research facilities provided throughout this study. Appreciation is also extended to the Department of Public Works and Spatial Planning (DPUPR) of Magelang City and Magelang Regency for providing the spatial datasets and supporting information used in this research. The author gratefully acknowledges the Final Assignment Recognition Program (Rekognisi Tugas Akhir/RTA) 2026 of Universitas Gadjah Mada for providing financial support for the implementation and completion of this study under Assignment Letter No. 5432/UN1.P2/Dit-Lit/PT.01.03/2026.

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