

Urban Growth Dynamics of Special Region of Yogyakarta, Indonesia (1994–2024): Population Trends and Expansion Prediction

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Abstract

The urban area of Yogyakarta (Indonesia) is observed to have experienced quite rapid development due to the changes in built-up land over the past three decades. The growth is motivated by population growth as well as increased educational activities and equitable access to infrastructure. Therefore, this study aims to understand the complex changes through two main objectives which include analyzing patterns of built-up land change from 1994 to 2025 and predicting the direction of urban development using Cellular Automata-Markov Chain (CA-Markov) method. Random Forest (RF) analysis was used to analyze the variations in land use and land cover (LULC) based on Landsat 5 TM, 7 ETM+, 8 OLI, and 9 OLI-2. These imageries were adopted to observe changes in LULC and the direction of urban development every 5 years. The results showed that NE direction experienced the most rapid development from 986 ha in 1994 to 7,648 ha in 2024. Logistic regression analysis further identified population as the main factor of land conversion ($\beta = 1.673$). Meanwhile, educational facilities had a large contribution to the pressure of vegetation change ($\beta = -118.898$), which may reflect the increasing demand for educational infrastructure accompanying population growth and urban expansion. The transportation network also showed that the city center and areas with high connectivity had reached a saturation point and the trend led to the tendency of new development shifting to peri-urban areas. Shannon entropy value reflected a change in urban development patterns with the growth observed to be concentrated at the start identified to have spread and become increasingly fragmented after 2014. Moreover, the simulations conducted using CA-Markov showed the possibility of future urban development continuing to move toward peri-urban areas in a northeast–northwest (NE-NW) direction. The combination of multitemporal Landsat, RF classification, regression analysis, and CA-Markov models produced a more comprehensive picture of urban development dynamics in Yogyakarta and also provides a scientific basis for policymakers regarding spatial utilization.

Keywords: Shannon's Entropy, Urban Growth, Urban Remote Sensing

1. Introduction

Urbanization is a global process with a significant impact on urban development, increasing built-up areas. In recent decades, the world has experienced rapid development and growth, which has led to a reduction in open and green urban spaces due to the transformation into built-up areas [1]. This horizontal expansion is known as urban sprawl and is defined as the condition in which urban areas expand through dispersed and low-density development patterns [2]. The phenomenon has attracted the attention of several previous studies. Empirical results showed that urban sprawl had

occurred in several metropolitan cities in Indonesia and around the world [3]. The concept could be theoretically explained through the demographic and urban economic transition [4]. It suggests that increased industrialization and the concentration of economic growth centers often motivate migration from rural to urban areas. Furthermore, urban expansion tended to occur radially from the city center to the suburbs, along with population growth and increasing population density in the area. The trend shows that the phenomenon is motivated by the growth in the number of educators, migration

from rural to urban areas, economic development, and the expansion of urban infrastructure [5].

Yogyakarta Province has experienced quite intensive urbanization along the northern and northeastern corridors particularly in the last three decades. This direction has developed into a center for residential growth, service and trade areas, higher education centers, and improved healthcare facilities. The changes have led to uneven LULC conversion which makes the monitoring of urban development over time very important. A major impact of urbanization and urban expansion is land-use change. Significant urban expansion has increasingly pressured agricultural land, shrinkage of green open spaces, the occurrence of land fragmentation, decline in biodiversity, and direct impact on microclimates. The conditions can disrupt ecosystems, reduce biodiversity, and increase vulnerability to environmental stress [6] and [7].

Land-use change needs to be understood in a complex and comprehensive manner. The urbanization of a region is often influenced by several driving factors such as population size, educational facilities, transportation networks, and the availability of healthcare facilities [8]. Therefore, statistical models such as logistic regression are important for identifying the significance and influence of the factors on land-use change. The model provides a more quantitative representation of the determinants for land-use change. The prediction of urban development in 2030 shows the need for a dynamic model that is capable of integrating the probability of change and the spatial interactions among the pixels. Cellular Automata (CA) is a spatial and dynamic model often applied to LULC change to predict possible spatial distribution [9] and [10]. It functions as a dynamic modeling between cells that represent land cover or use with a regular grid interacting with each other [11] and [12]. The components of CA include pixels or cells, environments, states, and transition rules or functions. The presence of the components determines land cover or use changes depending on the rules used [13]. Furthermore, the model is generated from several probability matrices that motivate the changes [14][15] and [16]. It became popular for geographic simulations after a study in 1979 [17]. Nevertheless, CA models are often criticized for their strong dependence on local neighborhood interactions, which may limit their ability to represent broader-scale urbanization processes and regional development trends [18].

The model was initially theoretical but applied practically for spatial modeling and analysis in the 1990s. The integration of different methods and technological advances has changed the model into

a robust framework for simulating diverse environments particularly in relation to land-use change. CA often did not directly consider land-use change in setting the simulation scale before 2000. It was designed for [19] and had excelled in analyzing complex spatial systems such as urban landscapes. CA is different from other conventional models that depend on specific equations. The basic structure requires a rational introduction of several algorithms for geographic simulation with specific equations and known as CA methodological framework.

CA has been used for several urban development studies. An example is the combination of the model with weighted regression [20][21][22] and [23] and another study about the flexibility of CA in addressing complex urban challenges [21][24] and [25]. CA was also widely used with Markov Chains to project urban development. However, the complexity of Urban Cellular Automata (UCA) from data collection and processing to output interpretation presents some challenges [26]. Land-use change is significant spatio-temporal data and CA generally considers temporality but is limited in terms of time. Several other methods have different advantages such as the long-term relationships of deep learning (DL) models. Moreover, CA [27] and [28], SLEUTH [29][30] and [31], and CLUE-S [32][33] and [34] are popular and familiar methods in the world of spatial modeling for LULC change prediction. CA is generally based on predetermined rules and depends significantly on interpreter expertise because it requires accurate sample training and the ability to connect factors to LULC dynamics that are often non-linear. The interesting aspect of the model is the complexity of decisions in LULC modeling. Furthermore, Artificial Neural Network (ANN)-based models have been applied in several methods specifically those related to urban growth including the provision of solutions for LULC simulations [20][25] and [35].

This study adopted Random Forest (RF) for LULC analysis while CA was applied to predict built-up areas due to the ability to combine spatial and temporal dimensions. CA simulates land-use change through transition rules based on local neighborhood interactions, enabling the representation of urban growth patterns over time. The model has been widely adopted and applied in the earth sciences such as land-use change. The focus of this study has a very strong correlation with Sustainable Development Goal (SDG) 11 by understanding the spatial distribution of urban growth and identifying urban development pressures. The analysis from a scientific perspective

led to the determination of several new things which included identifying and predicting the dynamics of urban expansion in Yogyakarta from 1994 to 2024. First, the integrative method allowed for a more descriptive and predictive understanding of urban development. Second, the factors motivating urban expansion were measured by combining social variables and public facilities rarely used simultaneously in Yogyakarta urbanization studies. Third, the directional analysis provided a new perspective on the dominant growth corridors specifically in Northeast (NE) and Northwest (NW) directions which had not been comprehensively analyzed in previous studies. Therefore, this study mapped land-use change and provided theoretical and methodological contributions to existing literature on urban dynamics. The aims were to (1) analyze the pattern of changes in urban built-up areas from 1994 to 2024 in Yogyakarta City using CA method as well as (2) examine the prediction and direction of urban development. The period 1994–2024 was selected because it encompasses three decades of rapid urban growth in the Special Region of Yogyakarta, marked by population increase, infrastructure expansion, and the conversion of non-built-up land into urban areas.

2. Methods

2.1 Study Area

The study area is the Special Region of Yogyakarta (Figure 1) (Daerah Istimewa Yogyakarta, DIY), a province located in the southern part of Java Island, Indonesia. The province covers approximately 3,185 km² and consists of four regencies Sleman

Regency, Bantul Regency, Kulon Progo Regency, and Gunungkidul Regency and one municipality, Yogyakarta, which serves as the provincial capital. The province is bordered by Central Java to the north, east, and west, and the Indian Ocean to the south. The topography varies considerably, ranging from the volcanic slopes of Mount Merapi in the north to extensive limestone hills in the southern part of Gunungkidul and lowland plains in the central region. These diverse physical and administrative characteristics make the Special Region of Yogyakarta a representative area for analyzing regional spatial development and LULC dynamics.

2.2 Datasets

Landsat imagery published by U.S. Geological Survey (USGS) in 1994, 1999, 2004, 2009, 2019, and 2024 were used in this study. These were Landsat Collection 2 Level-2 imagery that had been radiometrically corrected to surface reflectance and geometrically corrected for accurate spatial positioning. This study utilized multi-temporal Landsat imagery acquired between 1994 and 2024 to analyze land use/land cover (LULC) change and urban expansion. The imagery was obtained from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI/TIRS, and Landsat 9 OLI-2/TIRS-2, providing consistent medium-resolution observations suitable for long-term urban growth monitoring. These sensors include visible, near-infrared, shortwave infrared, and thermal infrared bands that are widely used for LULC classification and urban studies.

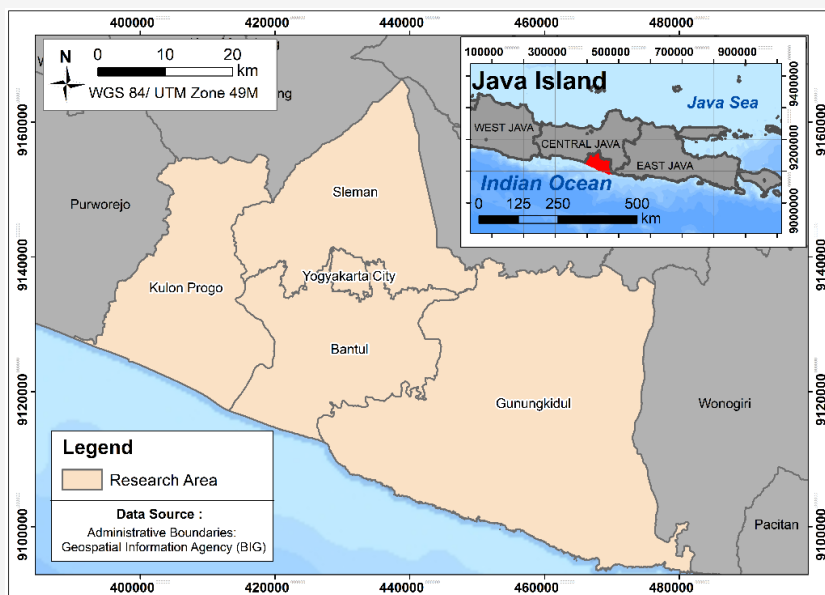


Figure 1: Special region of Yogyakarta, Indonesia

Table 1: Specification of Landsat imagery data

Year	Satellite	Sensor	Spectral Bands Used
1994	Landsat 5	TM	Visible, NIR, SWIR
1999	Landsat 7	ETM+	Visible, NIR, SWIR
2004	Landsat 5	TM	Visible, NIR, SWIR
2009	Landsat 5/7	TM / ETM+	Visible, NIR, SWIR
2014	Landsat 8	OLI/TIRS	Visible, NIR, SWIR
2019	Landsat 8	OLI/TIRS	Visible, NIR, SWIR
2024	Landsat 9	OLI-2/TIRS-2	Visible, NIR, SWIR

Data Source: <https://earthexplorer.usgs.gov/>

Although Landsat 7 has experienced Scan Line Corrector (SLC-off) data gaps since 2003, it remains a valuable source for land cover analysis when appropriate preprocessing procedures are applied. In this study, multispectral bands were used as input variables for the Random Forest classification to distinguish built-up and non-built-up areas. To ensure data quality, candidate Landsat scenes were evaluated based on both overall cloud cover (<15%) and the spatial distribution of clouds, ensuring minimal cloud contamination within the study area. A summary of the Landsat datasets used in this study is presented in Table 1.

2.3 LULC Random Forest Classification

RF is an ensemble classifier that generates multiple decision trees from randomly selected training samples and variables and has been widely adopted in remote sensing due to its high classification accuracy, ability to handle high-dimensional data, and resistance to overfitting [36]. The model consists of a set of tree-based structures with each trained using a bagging method in the form of bootstrap aggregation which randomly samples the training data. During the training phase, each branch in the tree was formed by randomly selecting several features. The training of all trees was followed by the contribution of each to the prediction of the output variable. The final decision was determined through the majority vote of all trees. RF was selected in this study due to the robust ability to model nonlinear relationships, robustness to multicollinearity, and ability to handle imbalanced and heterogeneous data which led to the high suitability for LULC classification [37] and [38]. Several previous comparative studies have reported the effectiveness of RF in modeling complex LULC analysis. The advantages of RF include higher predictive accuracy, robustness to noisy data and outliers, and a lower risk of overfitting. Furthermore, the model is also capable of evaluating the relative importance of each input variable or feature importance used [39][40][41] and [42]. It has been widely used in several modeling studies including predicting the

occurrence, frequency, and severity of phenomena such as traffic accidents. The two main parameters required to be determined during the application are the number of trees to be formed and the number of randomly selected variables in each splitting process.

2.4 Field Validation

Field validation was carried out to test the accuracy of the LULC classification results against actual conditions on the ground. An accuracy test using field surveys was conducted for the 2024 classification results. Meanwhile, accuracy testing for the 1994–2019 LULC classification results were carried out using high-resolution imagery on the Google Earth platform. Validation was carried out by comparing the LULC classes in the classification results for each year with the actual LULC classes on the ground in that year.

2.5 Accuracy in Random Forest Analysis

Accuracy was tested using the confusion matrix method which compared the classification results from digital interpretation with reference data on LULC from field observations. The minimum acceptable level of accuracy in the process of identifying LULC is 85% [43]. The confusion matrix method is also considered effective due to its ability to comprehensively explain each category including the omission and commission errors in the process of classifying accuracy [44]. The main parameters include overall accuracy, precision of the producer and user, as well as the kappa coefficient. Overall accuracy could be calculated by comparing the number of correctly classified pixels with the total reference. Producer accuracy is often determined by calculating the ratio between the number of correctly classified pixels in a category and the total reference in the category. Meanwhile, user accuracy can be obtained by comparing the number of correctly classified pixels in a category with the total number of pixels classified in the category [45]. The confusion matrix method generally provides a comprehensive quantitative measure to determine the accuracy of LULC

classification results based on remote sensing data. However, it should be noted that the confusion matrix evaluates thematic classification accuracy only and does not explicitly account for the spatial arrangement or neighborhood relationships among pixels.

2.6 Shannon Entropy

Shannon entropy was defined by as a quantitative measure of the diversity and information content of a signal [46]. The concept is included in both communication and information theories. The initial aim of the concept was to calculate the information lost when sending a certain message through a communication channel but currently applied in several fields. The definition shows the possibility of using Shannon entropy to measure the evenness of a probability distribution [20] such as the expansion of urban areas [47][48][49] and [50]. It can also be applied to evaluate the level of concentration or spatial dispersion of a geographic variable (x) among "n" concentric circles [51].

2.7 Logistic Regression

Logistic regression is a statistical technique used to model the relationship between one or more explanatory variables and a categorical response variable. By fitting the training data to a logistic function, the model estimates the probability that a particular event will occur [52]. In this study, the likelihood of LULC change was estimated using binary logistic regression, a statistical classification technique designed for response variables with two possible outcomes. The model distinguishes between pixels that experienced LULC conversion and those that remained unchanged by relating these outcomes to a set of explanatory variables representing the driving factors of land transformation. The estimated relationships are then used to generate a transition potential map, where each pixel is assigned a probability of conversion. In addition, the regression coefficients obtained from the model quantify the relative contribution of each driving factor to the occurrence of LULC change. The probability of conversion is calculated using Equation 1:

$$p = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$$

Equation 1

Where:

p = probability of a grid cell having a LULC change

α = constant value

β_p = coefficient of driving factor x_p

2.8 Cellular Automata and Markov Chain

CA-Markov integration is a spatial modeling method often used in LULC analysis. This model provides a comprehensive framework for LULC prediction using historical change patterns, spatial dynamics between cells, and the driving factors. Furthermore, the CA-Markov model was employed to simulate future LULC changes by combining transition probabilities from the Markov chain with the spatial allocation capabilities of Cellular Automata. The components of CA were pixels or cells, environments, states, and transition rules or functions [53] which exist based on the rules used. CA model was generated from different probability matrices driving land-use change.

3. Data Presentation and Analysis

3.1 Population Projection of Yogyakarta in 2030

The population of the Special Region of Yogyakarta increased from 3,292,348 in 2005 to 3,426,637 in 2009, an average annual growth rate of about 1.0%. During 2009–2014, the growth rate increased to 1.15%, accompanied by a population increase of about 204,000 people over the five-year period. Population growth remained positive during 2014–2019, with annual growth rates ranging from approximately 1.0% to 1.1%. A different pattern was observed during 2019–2024, when population growth slowed considerably, with the average annual growth rate declining to approximately 0.61%. An anomalous decrease was recorded in 2020, which may be associated with demographic and mobility disruptions during the COVID-19 pandemic, followed by a return to positive growth after 2021. Overall, the results indicate continued population growth throughout the study period, with a noticeable deceleration in the most recent years. These demographic trends reflect changes in the balance between births and deaths, together with migration dynamics, which collectively influence population growth over time. The current population of Yogyakarta is projected to be 3,899,518 using the geometric method with a growth rate of 0.0061 and based on the data from 2005 to 2024. The geometric method projects future growth by multiplying the base-year population with an exponential growth factor. In theory, this projection is consistent with the demographic pattern from 2005 to 2024 which reflects positive but slow population growth due to declining fertility, increasing life expectancy, improvements in healthy lifestyles, and changes in family behavior.

3.2 Urban Development from 1994 to 2024

Urban development in Yogyakarta between 1994 and 2024 was analyzed according to eight compass directions, consisting of north (N), northeast (NE), east (E), southeast (SE), south (S), southwest (SW), west (W), and northwest (NW). The directional analysis used the Yogyakarta Keraton as the central reference point, from which the directional sectors were delineated. The Yogyakarta Palace was chosen as the reference point because it represents the city's historical core and the starting point of its urban development. Built-up increase in each direction every 5 years is presented in Table 2. The result shows that Yogyakarta expanded to NW from 1994 to 1999 by covering an area of 296 ha. The smallest expansion occurred in the southern area at 26 ha which was already densely populated and had limited space for urban development. RF analysis of LULC also showed that the development for 1999–2004 tended towards NW with 201 ha. This showed the direction had the highest increase in built-up land in the first two intervals followed by the north (N) and NE. The pattern shows that the development in Yogyakarta has started shifting toward the southern part of Sleman Regency. The urban growth has also moved to Mlati, Ngaglik, and Depok Sub-districts which subsequently developed into medium- to high-density residential areas. The main influential factors were the expansion of campus areas, student boarding houses, and the role of road accessibility as observed in the presence of Jalan Kaliurang and Jalan Monjali. Meanwhile, south (S) and southwest (SW) directions showed negative values at the end of these periods. These decreases are likely attributable to classification uncertainty associated with the use of multi-temporal Landsat imagery, including spectral confusion between built-up surfaces and exposed land, as well as minor geometric misalignment between image dates, rather than indicating actual urban contraction.

From 2009 to 2014, Yogyakarta experienced a faster rate of increase in built-up land than in the two previous periods. The urban growth spread in approximately all directions with the highest identified in NW at 1,878 ha. This phase strongly represents the urban sprawl which is the horizontal spread of development without a planned pattern causing the city to expand beyond the administrative boundaries. The rapid growth is related to the increase in urban population, the availability of transportation infrastructure such as the north-west ring road, as well as the easy access to new residential areas in Sleman and Bantul. Furthermore, the development of higher education areas in Sleman and large-scale housing

developments on the outskirts are major factors accelerating the conversion of undeveloped land into built-up areas.

The 2014–2019 period shows a slowdown in built-up land growth, with negative values observed in the south (S) with –308 ha and NE with 241 ha. Since large-scale urban contraction is unlikely in the study area, these negative values are more likely attributable to uncertainties associated with multi-temporal image classification, including spectral confusion between built-up and non-built-up surfaces, as well as minor geometric inconsistencies between image dates, rather than actual losses of built-up land. However, the west (W) and SW directions showed positive growth at 420 ha and 192 ha respectively as a reflection of the shift in residential and economic activities to areas with better transportation access to Yogyakarta City and vice versa. Overall, the period is characterized by a slower rate of urban expansion compared with previous periods.

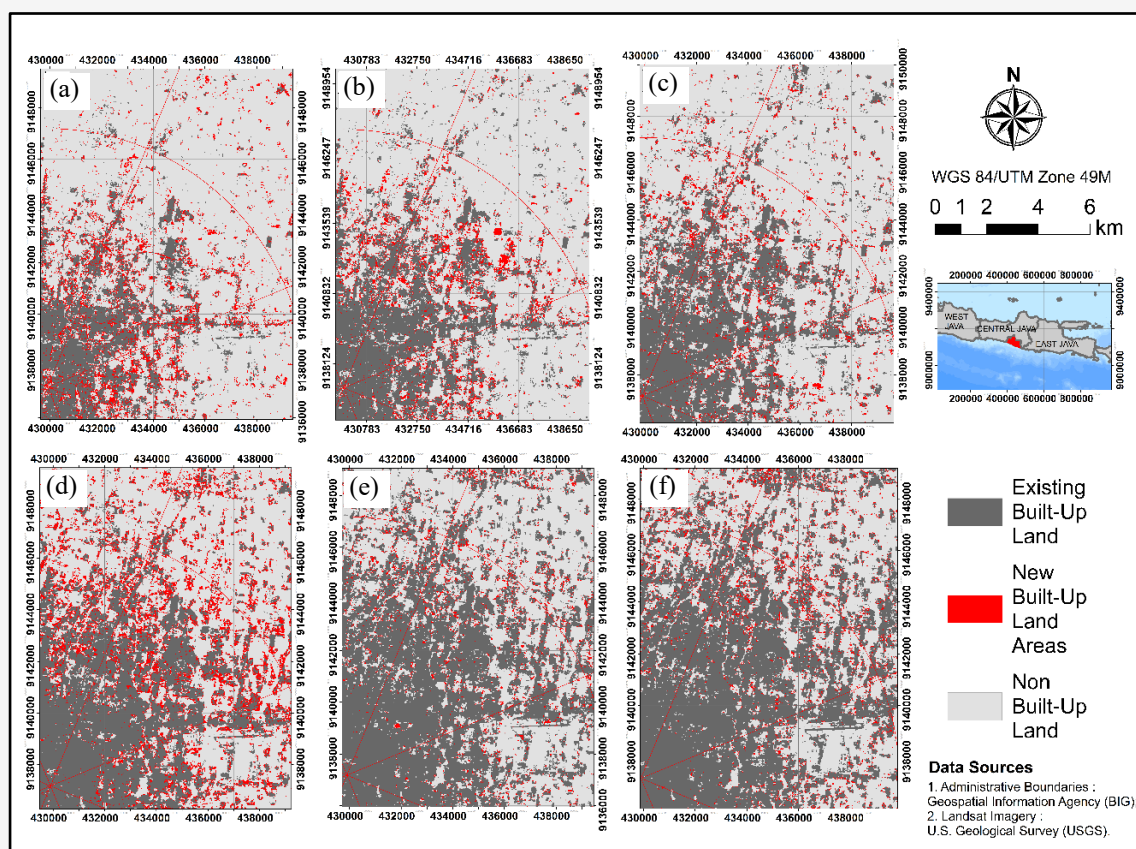
The data from the latest period of 2019 to 2024 showed a significantly different growth pattern compared to the previous. The highest growth occurred in NE with 4,696 ha and east (E) with 1,525 ha followed by N with 1,301 ha and S with 1,276 ha. This trend showed the reorientation of urban growth to the east and NE due to two main factors, including (1) the expansion of residential areas in eastern Sleman and West Prambanan due to limited land in the city center and (2) increased accessibility to the eastern region through the construction of a main road network connecting Yogyakarta with Klaten and Solo. The phenomenon also intersects with the expansion of economic activity in the service and education sectors which is developing along the eastern corridor particularly Caturtunggal–Condongcatur–Kalasan area. The spatial distribution of urban areas is shown in Figure 2.

3.3 Urban Development Analysis Using Shannon Entropy

Shannon Entropy analysis was used as the quantitative indicator to understand the spatial dispersion of urban growth along eight cardinal directions over 30 years (1994–2024). The resulting entropy value provides an overview of the dominant direction of urban expansion, the level of spatial regularity, and the potential pattern of urban sprawl during the observation period. Theoretically, a higher Shannon Entropy value reflects the tendency toward dispersed development, while a lower value represents restrained, focused, or localized (compact) growth.

Table 2: Built-up land increase every 5 years by direction

Direction	1994 (ha)	1999 (ha)	2004 (ha)	2009 (ha)	2014 (ha)	2019 (ha)	2024 (ha)
SW	365	472	435	634	1,799	1,991	2,735
S	385	410	377	555	1,716	1,408	2,684
SE	326	456	462	688	1,818	1,577	2,586
E	409	419	578	865	1,754	1,793	3,318
W	867	1,029	1,166	1,261	2,483	2,903	4,344
NE	986	1,161	933	1,029	1,927	2,952	7,648
NW	1,103	1,399	1,600	2,017	3,894	3,744	4,608
N	792	971	1,147	1,442	2,893	2,924	4,225

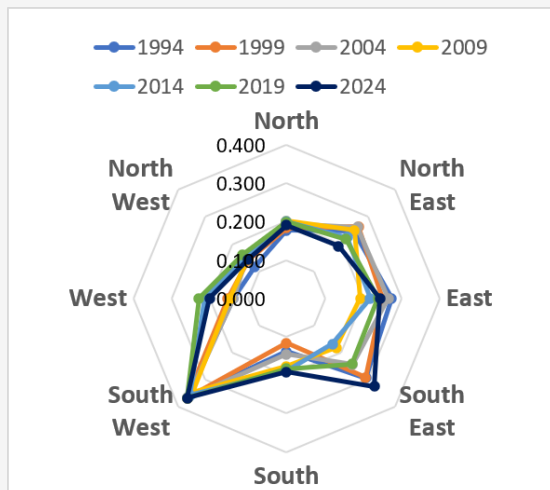
**Figure 2:** Map of Yogyakarta urban growth in the northeast direction over 5 years: (a) 1994-199, (b) 1999-2004, (c) 2004-2009, (d) 2009-2014, (e) 2014-2019, and (f) 2019-2024

This aligns with observations in [48] and [54] that entropy can detect spatial patterns of land-use change in dynamic urban systems. Table 3 and Figure 3 present Shannon Entropy Values by direction every 5 years. Results for the 1994-2024 period show highly heterogeneous spatial dynamics of urban growth across eight cardinal directions. This method has been widely used in land-use change studies because it measures the degree of disorder and the spatial distribution of urban growth

[46]. Entropy remains relatively stable in the SW direction, ranging from 0.367 in 1994 to 0.360 in 2024. The very small change of 0.007 recorded shows that the residential development in this direction is consistent and growing very slowly. SW's status as an urban area suggests limited development, but the high stability value indicates the corridor is experiencing the most intense urban expansion across residential, industrial, and supporting infrastructure.

Table 3: Shannon entropy every 5 years by direction

Direction	1994	1999	2004	2009	2014	2019	2024
SW	0.367	0.367	0.365	0.346	0.356	0.367	0.360
S	0.138	0.116	0.145	0.177	0.189	0.183	0.192
SE	0.293	0.292	0.243	0.183	0.169	0.242	0.324
E	0.274	0.250	0.266	0.192	0.218	0.239	0.244
W	0.139	0.153	0.139	0.148	0.213	0.228	0.201
NE	0.249	0.265	0.262	0.251	0.224	0.218	0.192
NW	0.117	0.142	0.147	0.144	0.152	0.161	0.143
N	0.178	0.183	0.196	0.202	0.200	0.199	0.191

**Figure 3:** Shannon entropy value by direction graph

The sustained growth in the southwest (SW) over three decades indicates its role as a primary axis of urban development. This pattern is associated with the presence of major transportation networks, access to economic zones, and stronger regional connectivity than in the other directions. The consistency of entropy values in this direction also reflects that the urbanization process tends to be progressive and does not stagnate despite increasing spatial pressure. The Shannon's entropy values in the southern (S) and southeast (SE) directions indicate changes in the spatial configuration of urban development rather than the magnitude of built-up land expansion.

Since the entropy values in this study were calculated using eight spatial classes and were not normalized, they range theoretically from 0 to $\ln(8)$ (2.079), where values closer to 0 represent a compact distribution of built-up land, while values approaching the theoretical maximum indicate a more dispersed and fragmented urban pattern. The S direction exhibited an increase in entropy from 0.138 in 1994 to 0.192 in 2024, suggesting that urban development gradually became more spatially dispersed.

However, the entropy values remained far below the theoretical maximum throughout the study period, indicating that urban growth in this direction was still predominantly compact with only limited fragmentation. The relatively stable entropy observed after 2014 further suggests that the spatial pattern of development became more established, with little additional change in its degree of dispersion. In contrast, the SE direction experienced more pronounced temporal fluctuations, with entropy decreasing from 0.293 in 1994 to 0.169 in 2014, indicating that urban development became increasingly concentrated within this sector. The subsequent increase by 2024 suggests a renewed tendency toward a more dispersed distribution of built-up land. The rate increased significantly in 2024 made SE part of the most intensive and expansive urban developments in the last decade. This increase shows a shift in the growth orientation of the city toward SE corridor possibly due to the new infrastructure development, the opening of planned residential areas, or government policies designating the direction as a new growth zone. The phenomenon is in line with the position of peri-urban expansion theory that suburban areas develop gradually based on the dynamics of accessibility and land prices.

The eastward (E) movement to the urban city of Yogyakarta showed a relatively stable increase pattern from 0.274 in 1994 to 0.244 in 2024. This is not as high as SE direction but the trend is slightly upward after a significant decline in 2009. The situation is also different from NE direction which has a downward trend after experiencing a peak of 0.265 in 1999. Moreover, the 2024 entropy value of 0.192 shows that growth tends to be more controlled and concentrated in certain areas. NW trend also shows moderate growth ranging from 0.117 in 1994 to 0.161 in 2019. The stable growth since 2004 reflects gradual development in the direction without significant annual spikes to show consistency with the planned spatial pattern. Interestingly, the growth to N direction has a relatively stable entropy value of 0.178-0.202.

The significant increase up to 2014 reflects that N direction is a fairly attractive location for development.

4. Discussion

Landsat satellite imagery is very important in urban development analysis particularly for spatial analysis of the direction and for Shannon Entropy calculations [55]. The imagery has a 30 m spatial resolution with a long-time frame which dates back to 1972. In the context of mapping urban built-up areas, Landsat is highly useful due to the existence of spectral bands such as short-wave infrared (SWIR) and visible wavelengths in the form of blue, green, and red. The imagery can also be used to extract building indices and other data that support urban development analysis. It was successfully used for land-use change detection particularly for monitoring urban development in Yogyakarta over 30 years from 1994 to 2024 with 5-year intervals. The reliability of the LULC classification results was further evaluated through an accuracy assessment based on confusion matrix, including user accuracy, producer accuracy, and overall accuracy. The results are presented in Table 4.

The classification results achieved overall accuracy exceeding 85%, indicating that the generated LULC maps were sufficiently reliable to support subsequent analysis. The integration of RF method for built-up land analysis serves as the starting point for this study. RF was used to understand the dynamics of land-use change associated with urban expansion and predict urban development by 2030. The preference for the method was due to its advantages in addressing

image spectral variability and nonlinear issues between spectral bands. RF also offers strong generalization and is resistant to overfitting due to the ensemble-learning method that develops thousands of decision-making paths. It proved effective in identifying built-up land in the context of urban development despite highly heterogeneous land cover by producing relatively stable classification results over a long time span. The dynamics observed in RF analysis using Landsat imagery showed the evolutionary nature of the urban development in Yogyakarta. Early in the period 1994-2004, the growth of built-up land tended to be clustered and concentrated in Yogyakarta and Caturtunggal areas. This showed that the city was in the early growth phase where urban development typically remained concentrated in specific development centers.

Yogyakarta experienced accelerated urban expansion between from 2009 to 2014, characterized by a substantial increase in built-up land compared with the preceding period. This surge marked a major transformation in Sleman and northern Yogyakarta urban areas which developed into educational, economic, residential, and commercial service areas. Interestingly, Shannon Entropy value for SE direction decreased to 0.183 from 2009 to 2014 to show the focus on the formation of new urban clusters. This result is consistent with the theory that mid-sized urban growth is significantly influenced by transportation corridors, educational facilities such as the Islamic University of Indonesia (UII), and the development of new settlements around UII site.

Table 4: User accuracy, producer accuracy, and overall accuracy, for each LULC classification

Year		Built-Up Land	Vegetation	Water	Bare Land	Overall Accuracy (%)
1994	UA (%)	80.00	90.00	100.00	70.00	85.00
	PA (%)	72.73	90.00	100.00	77.78	
1999	UA (%)	90.00	90.00	100.00	70.00	87.50
	PA (%)	75.00	81.82	100.00	100.00	
2004	UA (%)	80.00	90.00	100.00	80.00	87.50
	PA (%)	80.00	81.82	100.00	88.89	
2009	UA (%)	80.00	90.00	100.00	90.00	90.00
	PA (%)	88.89	90.00	100.00	81.82	
2014	UA (%)	90.00	90.00	100.00	70.00	87.50
	PA (%)	75.00	81.82	100.00	100.00	
2019	UA (%)	100.00	90.00	100.00	80.00	92.50
	PA (%)	83.33	90.00	100.00	100.00	
2024	UA (%)	100.00	90.00	100.00	80.00	92.50
	PA (%)	90.91	90.00	100.00	88.89	

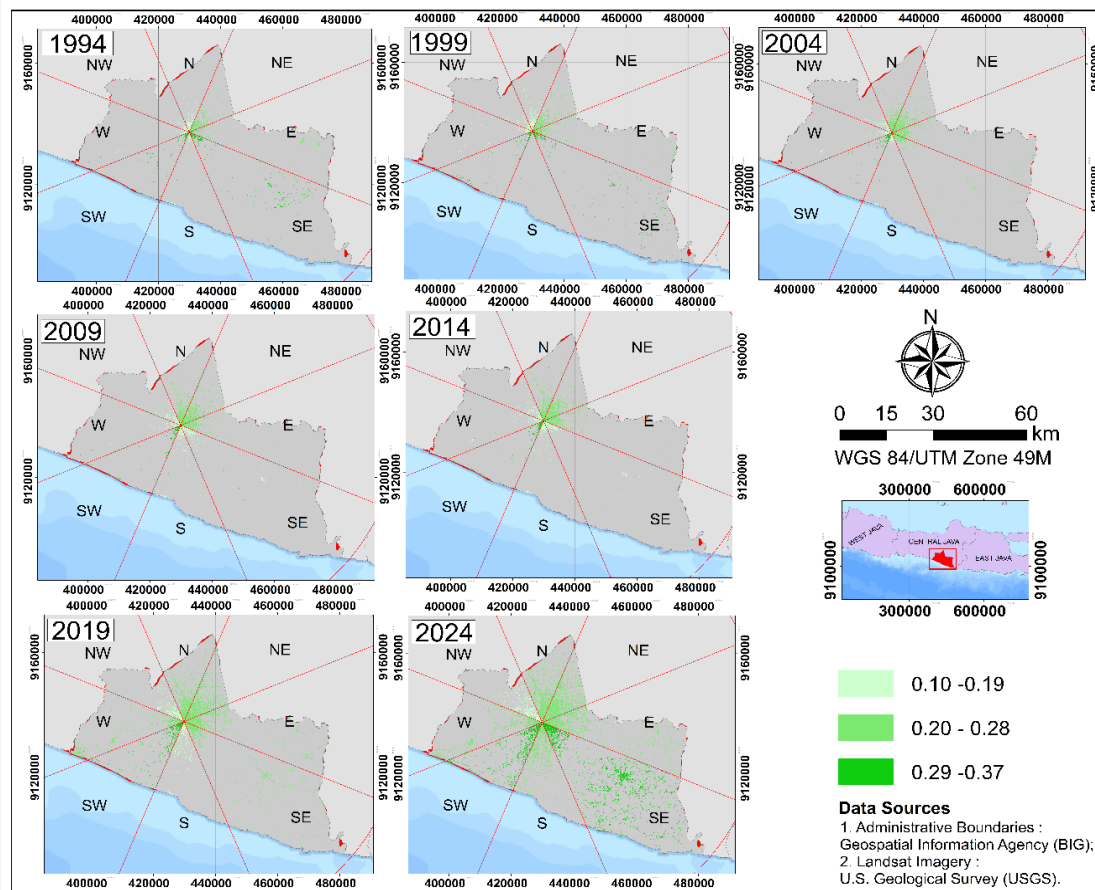


Figure 4: Shannon entropy index map by direction of Yogyakarta Province

The urban development expanded toward W and SE directions from 1994 to 2019 which reflected the increasing land fragmentation and the spread of built-up space particularly toward Kulon Progo. The period marked the development of residential areas and public facilities in the western part of Yogyakarta urban area. It also represented the transition into an urbanization phase that was not centralized but rather spread laterally. Meanwhile, the most recent period from 2019 to 2024 showed the most extreme phenomenon over the past 30 years with land shrinkage toward NE reaching 4,696 ha (Figure 4). This extensive expansion to NE is in line with the development of residential areas in Depok, Ngaglik, Ngemplak, and NE direction of Yogyakarta urban area. The observation was in line with the report of the previous study by [56] that developing cities tended to experience sporadic urbanization in the final stages due to population pressure, economic growth, and the growth of services and trade. Shannon Entropy pattern generally showed that urban growth during the 1994–2024 period was strongly toward S, SW, and

SE directions. SW direction remains the main center of urbanization while S and SE have developed into new corridors with a significant role over the last two decades. A contrasting observation was that E direction experienced controlled growth while NE, N, and NW were relatively stagnant. These results showed that urban growth dynamics did not occur evenly in all directions but followed specific patterns influenced by accessibility, physical land conditions, economic structure, and spatial planning policies.

Therefore, the entropy analysis results provided important insights for planning and controlling urban development particularly in preventing uncontrolled urban sprawl and promoting more sustainable development [47] and [48]. The integration of RF, CA, and MC in this analysis provides insight into land-use change dynamics and a spatial projection of urban development through 2030. There was a consistent upward trend in the change of population in Yogyakarta from 2005 to 2024.

Moreover, all the urban areas of Yogyakarta showed a significant increase between 1994 and 2024 but with different patterns of intensity as observed in the direction of built-up land development. Population growth was observed to have a direct contribution to the expansion of built-up land. This was because the increase in population led to the need for more housing. The trend was in line with Shannon Entropy values which showed the eastern areas of Yogyakarta including Depok, Condongcatur, Seturan, and surrounding areas had the highest population growth from 2010 to 2014. This subsequently translated to an increasing development of built-up land in NE and NW directions. The trend showed a strong relationship between population growth and changes in built-up land in the city. An increase in population led to the expansion of the residential land to areas with good accessibility and ample land availability particularly in NE, NW, and N directions.

The logistic regression model used in CA-Markov analysis showed that population was the strongest driver of land-use conversion ($\beta = 1.6730$). This was because population growth led to an increasing need for housing, services, trade, and public service facilities which directly expanded into the physical peri-urban area. NE and NW directions experienced the greatest urban development in line with population growth. Meanwhile, the accessibility or transportation network had a large negative coefficient ($\beta = -41.5654$) to reflect that areas with high connectivity but already substantial built-up areas lacked open

land for residential development. The condition led to the expansion of urbanization toward areas with medium accessibility but quite extensive land availability such as Ngemplak, Kalasan, Ngaglik, and parts of Prambanan. This pattern shows the conditions of city centers and transportation corridors that have reached saturation or are already congested. The other influential factors including education and health facilities had negative coefficients in both regression models. This showed that areas developed as service centers tended to have a high intensity of built-up land development without green open spaces or open land to be further converted. However, the model signaled that the role of educational facilities was dominant ($\beta = -118.8982$). This value reflected that development pressure around educational areas such as Seturan, Babarsari, Pogong, and Condong Catur was very high specifically due to the demand for student housing or dormitories and commercial facilities. Another important observation is that the educational areas in Sleman Regency have experienced the most intensive changes compared to the others. CA-Markov analysis showed that pixels with high conversion probability values were located in existing residential areas but slightly away from the city center. This signals that the prediction model motivates the conversion of open land and vegetation into built-up areas specifically in the buffer zone. The trend observed shows that Yogyakarta city follows a fairly strong peripheral expansion pattern.

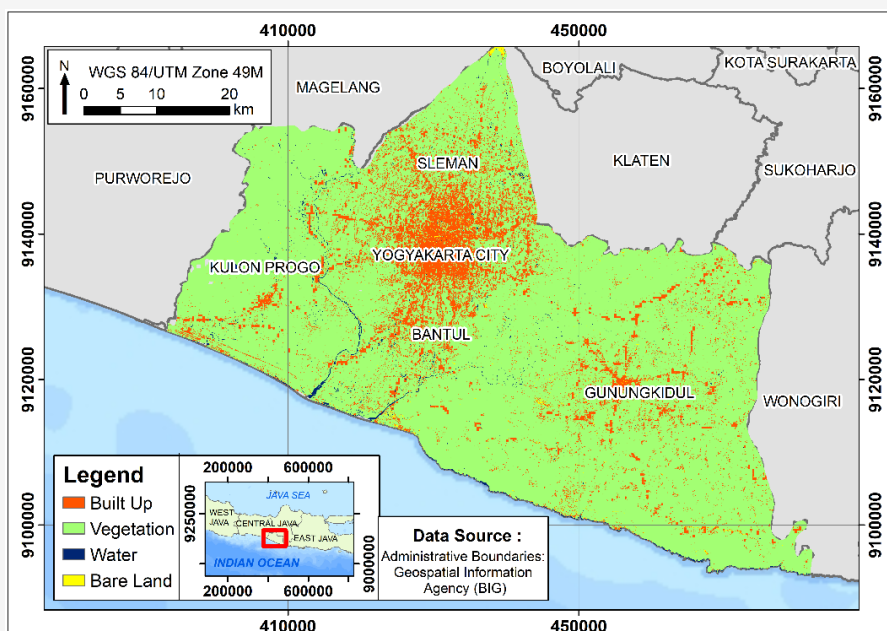


Figure 5: Simulated urban growth in Yogyakarta

The combination of the regression results from CA-Markov prediction NE as the most extensive urbanization direction by 2030 due to the influence of factors associated with urban development, including population growth, educational areas, accessibility, and proximity to the national road and ring road. This was further confirmed by the significant increase of 4,696 ha in built-up land between 2019 and 2024. Moreover, NW direction with stable and consistent growth is also projected as a corridor for further urban growth. The logistic regression showed that the population pressure in the direction was quite strong. CA-Markov analysis also projected a gradual growth pattern driven by accessibility and existing housing blocks. This model suggests that NW direction is not expected to experience the same level of rapid growth as NE but is capable of increasing consistently and sustainably. The direction is predicted to experience increased growth due to population migration from dense urban areas. Meanwhile, the regression model projects S and SE to initially have less development and the influential factor is population but the growth is not comparable to NE or NW. The prediction results projected S and SE to experience a slower rate of residential development. Simulated urban growth map of 2030 is presented in Figure 5.

The results generally show that Yogyakarta city is experiencing very rapid, complex, and multidirectional urbanization with diverse dynamics. The use of multitemporal Landsat imagery combined with RF analysis and Shannon Entropy allowed for comprehensive detection of land-use change. Moreover, the spatial analysis associated with demographic data and logistic regression to predict urban development in 2030 can provide an overview for the formulation of development control policies, the establishment of green open spaces, and other development strategies in Yogyakarta City and its surroundings.

5. Conclusions

The research results showed that multitemporal Landsat imagery can be used for spatiotemporal analysis and for predicting urban development. The Random Forest method consistently delivers excellent results for visualizing urban development. The spatial pattern of the Random Forest indicates the presence of two main urbanization pathways in the Yogyakarta Urban Area: urban development driven by population growth, resulting in new housing construction dispersed toward the N, NE, and NW directions; and urban development driven by educational and health facilities. These two patterns become interesting findings in this study. Shannon's entropy analysis shows that a settlement

development pattern occurred: in 1994–2004, the settlement development pattern tended to be clustered in specific locations, while in 2004–2014, a different pattern was found, namely settlement development beginning to expand toward peri-urban areas, and in 2014–2024, it became more dispersed. This dynamic indicates that Yogyakarta's urban development is not only in the same direction and form but also spatially adjusts to its driving factors, which are influenced by various aspects, including accessibility and educational facilities.

The logistic regression analysis in the study shows that population size is the strongest driver of the conversion of open land into urban built-up land. An interesting finding is that the transportation network has an adverse effect: areas with very high connectivity tend to become urban spaces that do not develop or are spatially saturated, leading to urban development shifting to peri-urban areas. Areas with comprehensive educational facilities also trigger rapid urban growth. The CA-Markov modeling results indicate that urban development will continue to shift along previous spatial patterns, especially toward the NE and NW directions, where the largest land conversions have occurred. Overall, this study confirms that Landsat data, combined with entropy analysis and CA-Markov prediction, is a practical approach for monitoring the direction and extent of urban development. However, this study focuses exclusively on horizontal urban expansion derived from satellite imagery and does not account for changes in urban density associated with vertical development, which should be considered in future research to provide a more comprehensive understanding of urban growth.

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