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Spatio-Temporal Pattern and Driving Forces Of Land Use Dynamics Around Yogyakarta International Airport

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ABSTRACT

A spatial and temporal analysis of the driving factors of land use dynamics is a mechanism for achieving sustainable land management. However, the majority of driving factor analysis studies are conducted on medium to low scale maps and only consider a limited number of factors. The objective of this study is to analyse the driving factors of land use dynamics using more detailed data and more comprehensive variables around the Yogyakarta International Airport (YIA) area, Indonesia. The land use map was created by visual interpretation of Pleiades imagery from 2014, 2018, and 2022, and the driving factors consist of aspects such as physical, location, socio-economic, land policy, and land right. The accuracy of land use was determined through the implementation of a confusion matrix, while driving factor analysis was conducted via spatial regression. The results demonstrated an increase in built-up land from 2014 to 2018, encompassing an area of 79.02 hectares, while from 2018 to 2022, it covered an area of 615.14 hectares. The factors that exert a significant influence on the location aspect include industry, distance to the city, distance to the airport, and road accessibility. Social factors comprise the occupation of the population, physical factors: relative relief, and land policy and land rights. The latter include protected areas and land rights status. The present study offers a comprehensive understanding of the drivers of land use dynamics in terms of its spatial and temporal dimensions, as a basis for formulating land use planning and control policies. Policies grounded in rigorous research are expected to facilitate sustainable land use and utilisation

INTRODUCTION

Land, which is in short supply, plays a crucial role in balancing social, economic, and environmental needs (Lambin and Geist 2006; Zhou et al. 2023). However, high pressure on land, particularly to meet economic needs, has led to environmental degradation, increased global warming, and more frequent disasters (Beillouin et al., 2022; Festus et al., 2020; Zhang et al., 2023). Increased built-up areas and uncontrolled urban expansion drive reduced vegetation cover, reduced agricultural land, and declining environmental quality (Ghimire et al., 2021; Wang et al., 2022). Therefore, efforts are needed to control built-up areas and urban expansion, including monitoring land-use changes (Koroso, 2023; Mosammam et al., 2017) and directing policies for sustainable land use and utilization (Abdullah et al., 2021; Nguyen et al., 2020).

A comprehensive assessment of the drivers of spatiotemporal land-use change is an effective strategy for controlling land-use change. Previous research by (Adebayo et al., 2019; Umarhadi et al., 2023; Suwanlee et al., 2023) has examined multi-temporal land-use dynamics to control land use. However, these studies have not yet examined the factors influencing land-use dynamics. Furthermore (Li et al., 2021; Mekonnen et al., 2022; Xu and Wu, 2023; Xie and Zhang, 2023) have successfully studied drivers through biophysical, socio-economic, and spatial policy variables in a multi-temporal manner. Although these studies found that drivers are highly dynamic in each period, they were conducted over large areas using low-resolution imagery. Low-resolution satellite imagery is feared to reduce the accuracy of multi-temporal land use analysis.

Theoretically, several studies (Li et al., 2021; Mekonnen et al., 2022; Xu and Wu, 2023; Xie and Zhang, 2023) have utilized socioeconomic, biophysical, and spatial policy factors, but have not yet incorporated important variables, as proposed (Lambin, and Geist, 2006) namely land policy and land rights. Conceptually, these two variables are important drivers of land-use change: land rights status influences legal certainty and land-use guidelines, while agricultural land protection limits land conversion. The limited use of variables driving land-use change is feared to result in inaccurate information and implications for inaccurate land management control efforts and policies

Land-use dynamics are often driven by proximate factors, including large-scale development (Lambin and Geist 2006). This phenomenon is also evident in the study area, where the construction of Yogyakarta International Airport as an economic corridor is expected to trigger massive land-use changes. A study of land-use dynamics around Yogyakarta International Airport (Muwahhid et al., 2025) found that road access significantly influenced these changes. Furthermore (Kinanthi et al., 2025) found that changes around the airport depended on population dynamics. These studies identified road and population variables as influential factors in the study area. However, both studies are limited in scope because they use a single variable, omit analysis of the multitemporal relationship between driving factors, and exclude the airport as a significant factor. This oversight of airport-driving factors in aerotropolis areas contrasts with studies (Kamruzzaman et al., 2021) that emphasise the pivotal role of airports in driving the expansion of built-up land in aerotropolis areas. Although (Ragab et al., 2022) did not specifically examine the drivers of built-up land growth, they found that the presence of airports and aerotropolis development significantly affects the socio-economic aspects of the surrounding area and influences built-up land growth patterns. Airports, along with road accessibility and centres of economic growth, exert a substantial influence on land-use dynamics.

A review of several previous studies on land use change and its key drivers, as described above, reveals a significant research gap. This study aims to address this research gap by offering a novel perspective on the drivers of land use change. To this end, this study utilises high-resolution Pleiades satellite imagery in a multitemporal analysis, covering periods before 2014, 2018, and after the airport's construction in 2022. Furthermore, this study also aims to address the research gaps identified (Liu, 2020; Zhou et al., 2020; Bamrungkhul and Tanaka, 2022; Muwahhid et al., 2025) by incorporating a more comprehensive set of factors that drive land use dynamics, namely physical, socio-economic, and location variables, including the addition of land use policy and property rights variables. The present study also investigates whether the growth of built-up land between periods (before, during, and after airport construction) is driven by fixed or dynamic factors. Using high-resolution satellite imagery, a more comprehensive set of factors, and an assessment of the factors driving built-up land growth over time is expected to yield more precise findings on land-use dynamics theory. The results of this study are expected to inform the formulation of more appropriate policies to control built-up land growth. Efforts to regulate and control land use near airports sustainably are expected to yield favourable outcomes.

RESEARCH METHODS

Study Area

The present study was conducted in a developing area located in a rural environment, where land use is dominated by agriculture (rice fields, fields, and swamps). The geographical location of the study site is specified by its coordinates, which are recorded at 7° 51' 35" - 7° 54' 59" South Latitude and 110° 02' 11" - 110° 08' 36" East Longitude. The site covers 8,260.70 hectares. This location was selected based on a comprehensive evaluation of villages directly and indirectly affected by the construction of the Yogyakarta International Airport area, as well as regions undergoing substantial land-use transformation. The construction of the YIA airport is one of the National Strategic Projects and covers a total area of 587 hectares. The construction of the building was carried out from 2015 to 2019. The study area encompasses 26 villages: 8 in Wates District, 15 in Temon District, and 3 in Panjatan District, all located in Kulon Progo Regency, Yogyakarta Special Region, Indonesia **(Figure 1).**

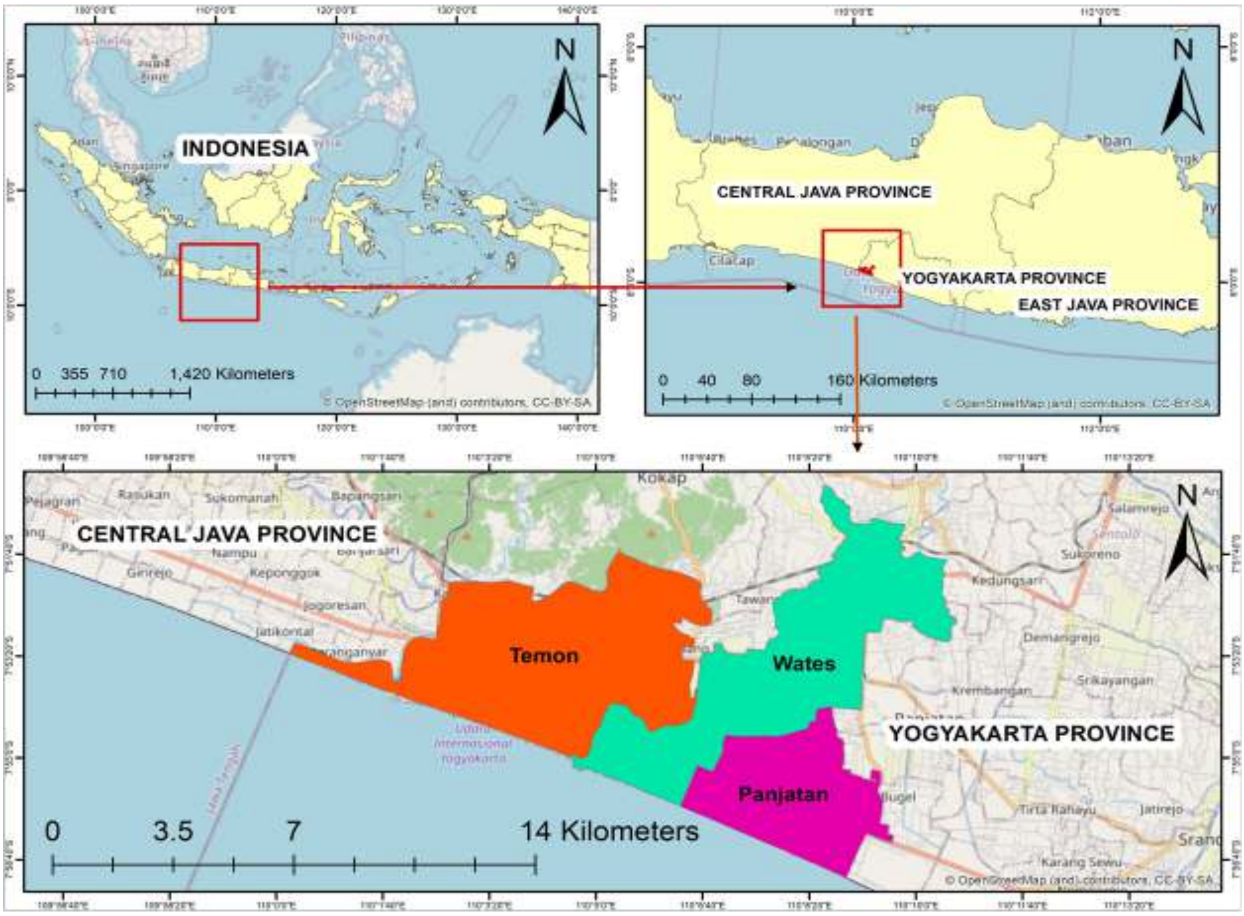


Figure 1. Research Location (Source: Data Processing, 2024)

Data, Sources, and Method

The land use map data presented in this study are spatiotemporal maps: First, the 2014 land use map was created before airport construction, when extensive agricultural land and rice paddies dominated the landscape. Second, the 2018 land use map reflects ongoing airport construction, with land clearing and construction underway. Thirdly, the 2022 land use map provides spatial information on the post-development land use conditions. This study uses village-level analysis units and Pleiades data sourced from Airbus Defence and Space in collaboration with the French National Space Agency, with a spatial resolution of up to 50 centimeters (James et al., 2020). The imagery is characterised by great detail in its land-use representation. The capacity of Pleiades imagery to distinguish between built-up and unbuilt land has been well documented (Özcihan et al., 2023), making it a highly suitable tool for urban and developing areas.

The Pleiades satellite imagery used in this study includes imagery from 2014, 2018, and 2022, selected in August 2022, a month characterised by minimal cloud cover. Before analysis, this study applies geometric correction to position pixels according to accurate coordinates. This research uses Universal Transverse Mercator (UTM) coordinates. The image sharpening process uses the pansharpening method, while masking and cloud masking minimise cloud and haze interference, ensuring the resulting image is clean and accurate. Image interpretation is conducted visually, using nine distinct interpretation keys: hue/color, texture, pattern, shadow, shape, size, site, association, and evidence convergence. Land-use classification is derived from the Thematic Mapping of the Ministry of Agrarian Affairs and Spatial Planning/National Land Agency, modified by the Indonesian National Standard/SNI Geospatial Information Agency. The digitisation scale employed in this study is 1:10,000, which enables the separate interpretation of objects measuring 50 x 50 m. This study classifies land use into two categories—built-up land and non-built-up land—based on SNI guidelines; **Table 1** presents the classification.

Table 1. Land Use Classification

Land Use (LU)	LU Reclassification
Pond, Sand field, Open field, Mangrove, Green belt, Rice field, Field, Tillage, Mixed farm, Sports field, Plantation, Square	Non-built-up area
Trade & Services, Warehousing, Industry, Livestock, Tourist Areas, Cemeteries, Health Centres/Clinics, Places of Worship, Stadiums, Sports Halls, Railway Stations, Colleges, Schools, Hospitals, Bus Terminals, Ports, Airports, Offices, Housing Estates, Hotels	Built-up area

(Source: Data Analysis, 2024)

As shown in **Table 1**, the classification of built-up areas from Pleiades image interpretation is characterised by high detail and clarity. This is evident in its ability to distinguish between open (non-built) land and built-up areas, including cemeteries, sports stadiums, livestock pens, and airports. The Pleiades satellite's 50 cm spatial resolution provides greater clarity and separation between pixels, facilitating the identification of objects on the Earth's surface.

Visual interpretation of Pleiades satellite imagery in this study yielded 3,900 land use polygons, and an accuracy test was conducted by determining the sample using the Slovin formula with a significance level of 5%, resulting in a land use sample of 441 points. This study used stratified random sampling. The confusion matrix analysis yielded an inaccuracy of 33 samples between the interpretation results and the field samples. The calculation yielded a very high accuracy of 92.5% for the land use map, which was produced from visual interpretation of Pleiades imagery. This result shows that the land use map meets the accuracy-testing standard, enabling further analysis.

The visual interpretation of Pleiades satellite imagery yielded 3,900 land use polygons. To ensure data accuracy, we conducted accuracy testing by determining sample points using the area plot method.

The calculation resulted in 441 land use sample points. We used stratified random sampling, with 294 built-up land samples and 147 unbuilt-up land samples. We then analyzed the field sample test results using a confusion matrix. In this study, 33 of the 441 samples were inaccurate. The analysis showed a user accuracy of 92%, a producer accuracy of 90%, and an overall accuracy of 92.5%. The kappa index was also calculated using the following algorithm.

$$Kappa\ (k) = \frac{N \sum_i^r X_{ii} - \sum_i^r X_{i+}X_{+i}}{N^2 - \sum_i^r X_{i+}X_{+i}}\ x\ 100\%$$

……….…..(1)

$$\text{Kappa (k)} = \frac{(441 \text{ x } 398) - 14{,}340}{(441^2) - 14{,}340} \text{ x } 100\ \%$$

$$\text{Kappa (k)} = \frac{161{,}178}{180{,}141} \text{ x } 100\ \% = 89\ \%$$

The kappa index calculation yielded an accuracy of 89%, indicating a reliable interpretation.

The independent variables in this study were determined by considering the socio-economic and geographical circumstances of the research area, changes in spatial planning policies, and the availability of data at the detailed/village unit level. The factors found to drive land use dynamics in the study were as follows: Location-related factors, namely: distance to the airport, distance to the city centre, distance to industry, and road accessibility. Physical-related factors, including: relative relief and vulnerability to flooding. Socio-economic factors, including: population and employment in the agricultural sector.

Spatial and spatial planning policy aspects, including: land rights status, land value, protected areas, and agricultural cultivation areas. **Table 2** and **Figure 2** explain the data types, analysis stages, processing techniques, and data analysis processes, including research sources.

Table 2. Research Stages

No	Variable	Symbol	Definition	Unit	Sources	Processing technique
1	Relative relief	R.Relief	The percentage of relative relief (high/steep) area limits the dynamics of LU	M	DEMNAS 8.1 m	Interpretation and analysis of hillshade slope, contours
2	Flood disaster	Flood.D	The percentage of flood-prone areas limits the dynamics of LU	Ha	Regional Disaster Management Agency	Disaster vulnerability analysis, (calculate geometry)
3	Road Access	Road.A	The longer the access road, the more it triggers the dynamics of LU.	Km	Ina-Geoportal Kulon Progo Regency RBI 1 :25.000, 2023	Road length analysis (calculate geometry)
4	Number of Industry	N.Industry	Industry drives the pace of LU dynamics	Unit	Department of Industry Kulon Progo Regency	Industry data analysis
5	Distance to Airport	D.Airport	The closer the airport is to triggering LU dynamics	Km	Ina-Geoportal Kulon Progo Regency RBI 1 :25.000, Year 2023	Distance analysis from Airport to Village Center (calculate geometry)
6	Distance to City	D. City	Getting closer to the city dynamic land use	Km	Ina-Geoportal Kulon Progo Regency, 1 :25.000, 2023	Analysis of the distance from the city (calculate geometry)
7	Total Population	T. Polutation	Population size triggers the rate of LU dynamics	P	Central Bureau of Statistics Kulon Progo Regency, Year 2024	Population analysis
8	Employment in Agricultural	Employme nt. AS	The more % of workers in the agricultural sector the limited LU dynamics	Person	Central Bureau of Statistics Kulon Progo Regency, Year 2024	Percentage analysis of the number of workers in the

						agricultural sector
9	Land Value Zone	Land Value.Z	The higher the land price, the lower the LU dynamics rate	IDR	National Land Agency Kulon Progo Regency, Year 2024	Analysis of average land prices per village (calculate geometry)
10	Land Title Status	Land Title.S	The higher the % area of non-ownership land, the lower the rate of LU dynamics	Ha	National Land Agency Kulon Progo Regency, Year 2024	Percentage analysis of land rights status (calculate geometry)
11	Protected Area	Protected.A	The higher the % protected area, the lower the LU dynamics	Ha	Land And Spatial Planning Service Kulon Progo Regency, Year 2024	Analysis of the percentage of protected areas in each village (calculate geometry)
12	Agricultual cultivation area	Agricultual. CA	The higher the % of protected agricultural land area, the lower the LU dynamics	HA	Land And Spatial Planning Service Kulon Progo Regency, Year 2024	Analysis of the percentage of protected agricultural land area in each village (calculate geometry)

(Source: Data Analysis, 2024)

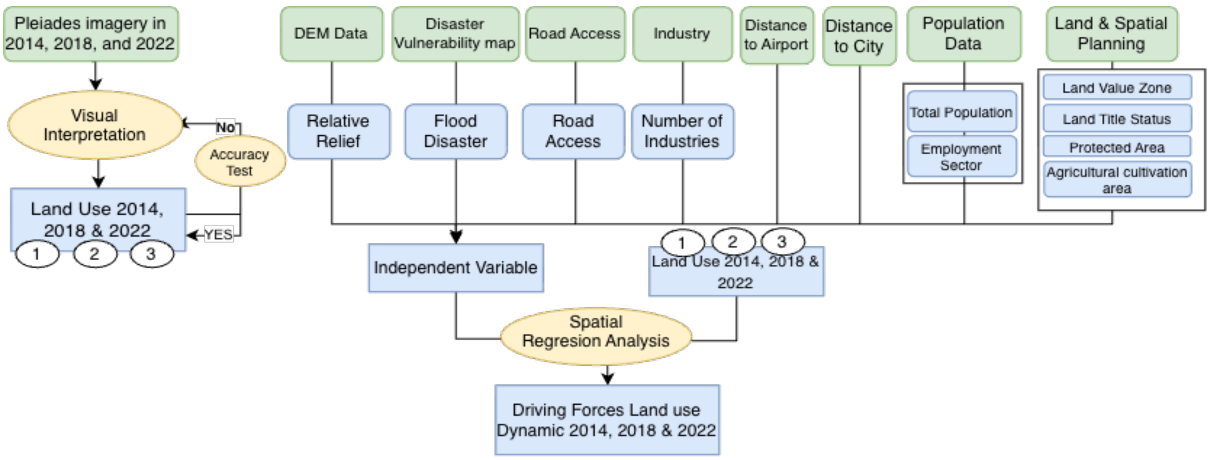


Figure 2. Research Flow Diagram (Source: Data Analysis, 2024)

Driving Forces Land Use Dynamics

This paper presents the study's findings, which analysed the triggering factors behind land-use dynamics. The study was conducted spatially and temporally in 2014, 2018, and 2022, so the triggering factors also used multi-temporal data. To assess the relationship between the dependent variable, built-up land use, and the independent variable, land use trigger factors, the study used spatial regression. The study incorporated spatial regression considerations because land use is spatially and temporally dependent, and because the land use trigger factors used are closely linked to spatial aspects. Spatial regression is a statistical analysis that considers spatial proximity, where proximity exerts a stronger influence than distance (Hasbi et al., 2014; Yang et al., 2023). The following formula is employed for the purpose of spatial regression analysis:

$$Y = a + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \beta_{n+1} \text{ autocov} \text{ ..(2)}$$

x_i (i= 1,2,3,…, n) = driving forces
$\beta_{i\,(i=1,2,3,\ldots,n)}$ = regression coefficient
n = amount of data
Y = dependent variable
$x_{1,\ldots,\ldots,n}$ = independent variable

$$\text{autocov}_j = \frac{\sum_{j=1}^{l_i} W_{kj} Y_j}{\sum_{j=1}^{l_i} W_{kj}} \ \ldots\ldots\ldots \ (3)$$

Autocov = weighted average of k pixels surrounded by neighbouring pixels
l_i (i = 1,2, … , n) = neighbouring pixel
W_{kj} (k = 1,2,.., n; j=1,2,..n) = the opposite of the Euclidean distance between K and neighbour J
y_i (i = 1,2, … , n) = the likelihood of the prediction resulting from the regression

Spatial regression analysis was carried out using Geoda software, where the connectivity between one village unit and another village unit is linked. In the spatial regression analysis, several models were generated: spatial lag, spatial error model (SEM), and spatial classic. The model used is determined by the highest R-squared value. R^2 is a measure of the strength and credibility of a method in analysing the relationship between dependent and independent variables. It is important to note that the R-squared value, which is indicative of the influence of the independent variable on the dependent variable, is maximised at a higher value. The remaining value is determined by other variables. The AIC value quantifies a model's fit to the available data. A smaller AIC value indicates a better fit. The formulas for R-squared and AIC are as follows.

$$\text{R-squared} = \frac{SS_{regression}}{SS_{total}} \ \ldots\ldots\ldots\ldots\ldots. \ (4)$$

Description:
SS Regression = regression effect sum of squares
SS Total = total sum of squares

$$\text{AIC} = AIC = -2Lm + 2m \ \ldots\ldots\ldots\ldots\ldots \ (5)$$

Lm = maksimum log – log–likelihood
m = number of parameters in the model

A statistical technique known as spatial regression analysis can be used to determine the level of significance between a dependent and independent variable. This significance is shown by the z-value, which is calculated using a special formula. The next part will explain this formula in more detail:

$$\text{z-value} = (x - \mu) / \sigma \ \ldots\ldots\ldots\ldots\ldots. \ (6)$$

x : data point values
μ : the average of the sample or data set
σ : standard deviation

RESULTS AND DISCUSSION

Dependent Variable Land Use in 2014, 2018, and 2022

The land use map from 2014, derived from the interpretation of Pleiades imagery (see Figure 3), shows that built-up land is more dominant in the city centre, specifically in the Wates sub-district. The built-up land use pattern in the study area has two distinct features. First, it exhibits an elongated, ribbon-like pattern that follows road accessibility. Second, it shows a clustering pattern, particularly evident in the city centre. Figure 5 also indicates that the southern section of the area is dominated by non-built-up land; this condition is influenced by the area's geographical location—bordering directly on the Indian Ocean—and the sandy nature of the terrain. The analysis shows that in 2014, the built-up area was 1,660.8 Ha.

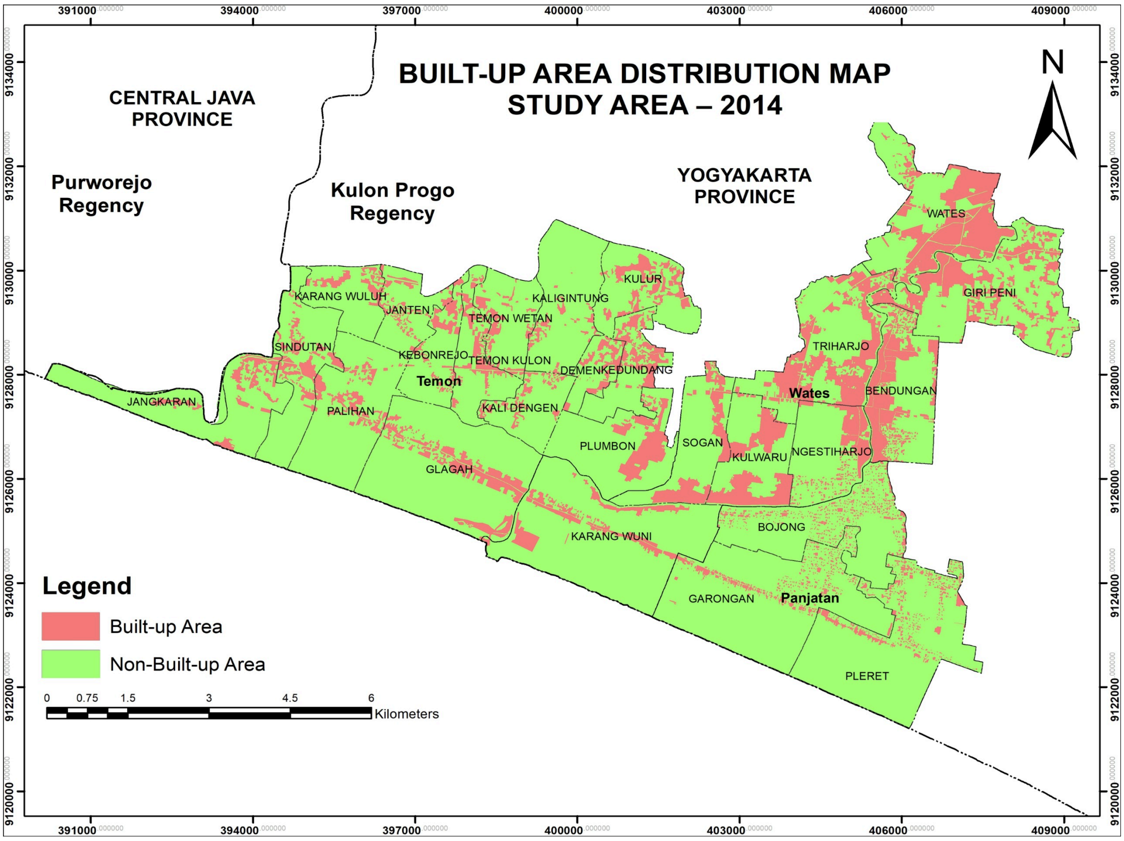


Figure 3. Map of Land Use in 2014 (Source: Data Analysis, 2024)

The interpretation of Pleiades images reveals substantial land use in 2018, attributable to land acquisition for airport development, with a minimum land requirement of 587 Ha. The land acquisition process instigated considerable transformations in 2018, with five villages (namely Palihan, Kebonrejo, Sindutan, Glagah and Jangkaran) transitioning from residential to open areas as a consequence of the airport construction project. Although built-up area decreased in locations affected by land acquisition, the overall built-up area in the study area increased. This expansion is characterised by the emergence of residential areas, restaurants, hotels, and commercial and service areas, both near the airport and along arterial and connecting roads (see Figure 4). The airport's desirability as a transport hub contributes to increased economic activity and population movement in the surrounding area. The analysis indicates that the built-up area in 2014 was 1,660.79 hectares, while in 2018 it was 1,739.8 hectares (an increase of 79 hectares). **Figure 4** shows the spatial distribution of land use in the study area in 2018.

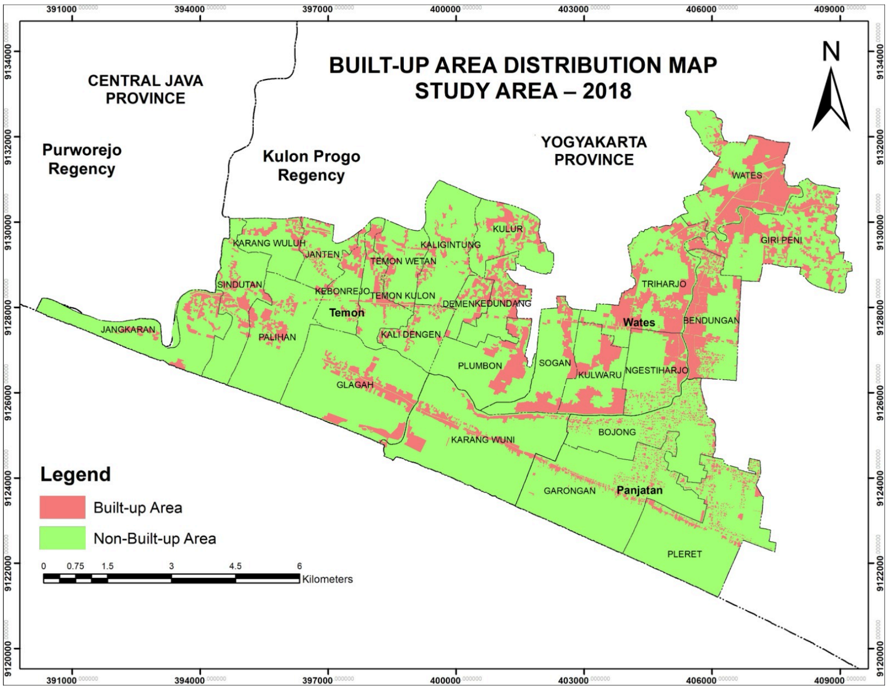


Figure 4. Map of Land Use in 2018 (Source: Data Analysis, 2024)

The transition from undeveloped to developed land continued in 2022. An analysis of the available data indicates that built-up land increased from 1,739.82 hectares in 2018 to 2,354.90 Ha in 2022, an increase of 615.14 hectares. The rapid growth in built-up land is closely linked to the large-scale development of the airport and its surrounding supporting facilities. As shown in Figure 5, built-up land growth in the study area is relatively uneven, with growth predominantly occurring around the city centre, around the airport, and along collector roads. The pattern of built-up land growth in 2022, as shown in **Figure 5**, persists in the study area and is expected to trigger multiple issues in the rural environs of the airport, particularly near arterial roads, resulting in land fragmentation.

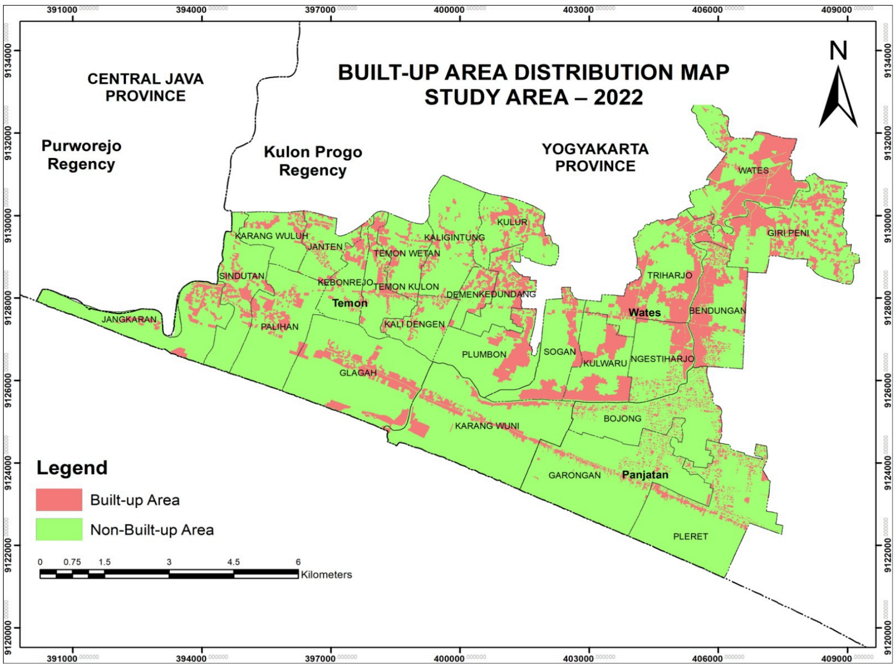


Figure 5. Map of Land Use in 2022 (Source: Data Analysis, 2024)

In this study, the data analysis unit is a village, and **Figure 6** shows multi-temporal land use in the form of built-up land in 26 villages. A thorough examination of the available data shows that the villages of Glagah and Palihan have the highest levels of built-up land growth. The substantial increase in built-up land in both villages is influenced by the presence of the YIA airport and the construction of various airport-supporting facilities (offices, hotels, warehouses, restaurants, etc.). The increase in built-up land in these two areas is also influenced by their location at the airport's main entrance and exit, as well as by arterial and collector roads leading to the center of Yogyakarta City.

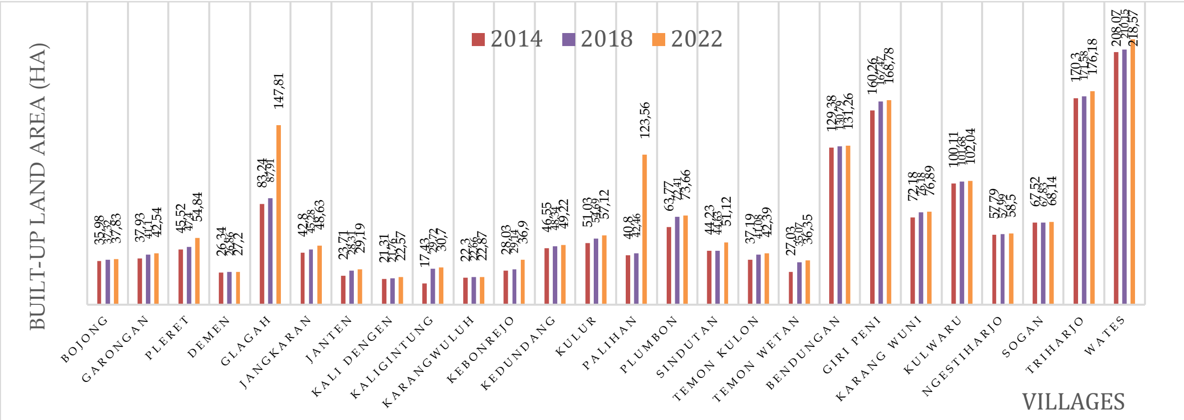


Figure 6. Built-up Land Area by Village in 2014, 2018, 2022 (Source: Data Analysis, 2024)

The analysis indicates that built-up land in the study area has undergone significant multi-temporal development. Sustained escalation in development and land demand has increased built-up land by 79.0 hectares from 2014 to 2018 and 615.14 hectares from 2018 to 2022. Tables 3 and 4 show the periodic land **use** change matrix**.**

Table 3. Land Use Change Matrix 2014-2018

Land Use 2014	**Land use 2018**	
	Built up Area	**Non Built Up Area**
Built up Area	1,660.79	19.7
Non Built Up Area	79.02	6,501.19

(Source: Data Analysis, 2024)

Table 4. Land Use Change Matrix 2018-2022

Land Use 2018	Land use 2022	
	Built up Area	Non Built Up Area
Built up Area	1,739.82	0
Non Built Up Area	615.14	5,905.74

(Source: Data Analysis, 2024)

Drivers of Built-up Land Growth

The driving factors behind built-up land use dynamics in this study include physical/geographical, socio-economic, location, spatial planning, and land policies. The selection of these 12 variables was based on the spatial regression analysis that produced the highest overall R-squared value. During this process, the researchers conducted a series of trials and eliminated several variables deemed less suitable to achieve the highest possible R-squared value. The R-squared value is pivotal in quantifying the extent to which independent variables explain the dependent variable. Additionally, R-square serves as a metric for evaluating the performance of different spatial models (classic, spatial error, or spatial lag). One physical factor examined in this study is relative relief. The digital elevation model (DEM) analysis classified the area into five classes, whose spatial distribution is shown in Figure 7. The highest relief values range from 102 to 181 metres, while the lowest relief values range from 6 to 25 metres. The relative relief classification results were then calculated as a percentage, dividing the area with high to very high relief by the area per village unit. The higher the percentage of areas with relatively high/very high relief, the greater the impact on land-use dynamics.

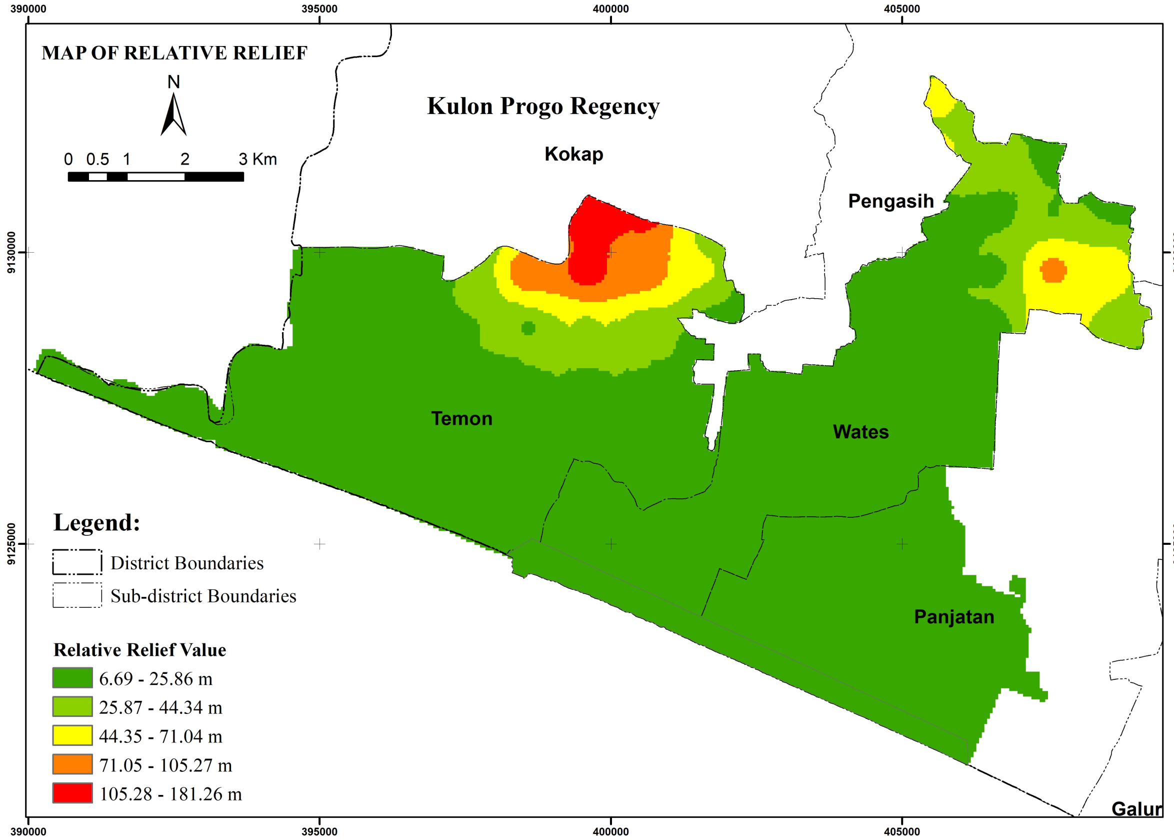


Figure 7. Relative Relief Map (Source: Data Analysis, 2024)

Figure 7 shows that most of the study area has relatively flat relief, with values of 6.7-25.9 m. The figure above shows that only a small part of the area has a relatively high relief, namely on the northern side (Kaligintung and Kulur villages), while several other villages have a low/flat relief. Relative relief is used as a triggering factor because locations with relatively high relief tend to have less built-up land growth than flat locations. Population is also correlated with built-up land growth; i.e., the higher the population, the greater the tendency for built-up land growth, and vice versa. Several previous studies, such as (Zhao et al., 2022), suggest that population is a key factor in the dynamics of built-up land growth. **Figure 8** presents population data for each village in the study area.

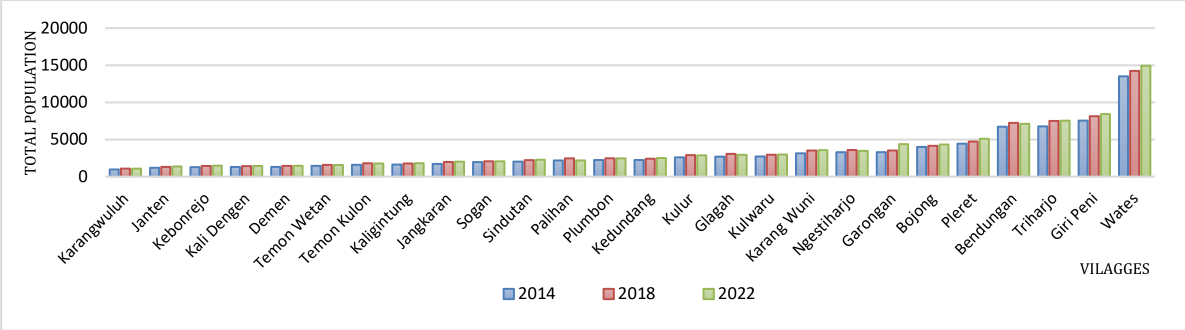
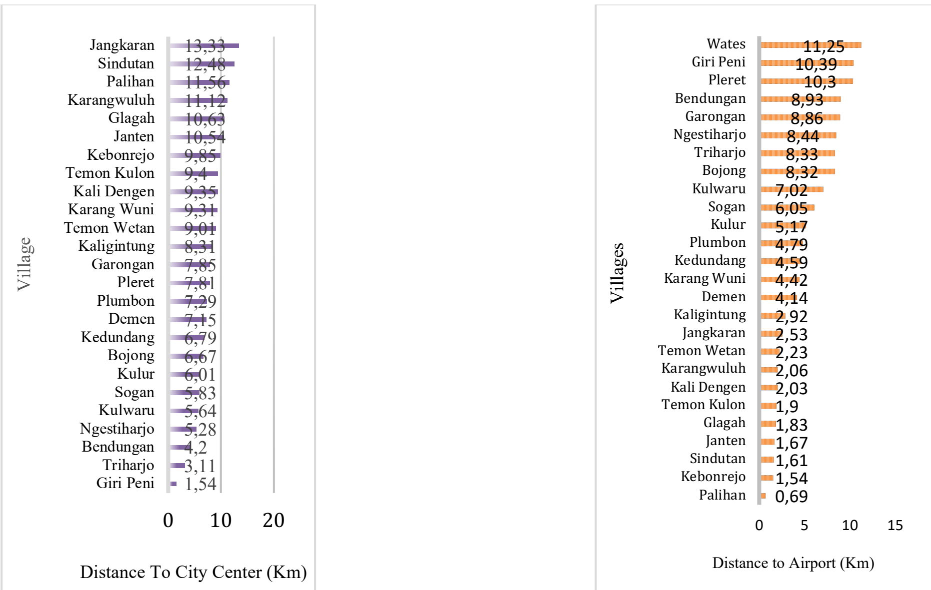


Figure 8. Total Population in 2014, 2018, 2022
(Source: Central Bureau of Statistics Kulon Progo, 2024)

As shown in **Figure 8**, several villages and regions, including Wates, Giripeni, Triharjo, and Bendungan, have higher population density. These villages' proximity to the city centre, economic growth centres, roads and industry has implications for their high population density. In addition to socio-economic and physical aspects, this study also considered location. Several geographical factors have been identified as potentially influencing land use dynamics, including distance to the city, the presence of industry, road accessibility, and distance to the airport. The correlation between proximity to urban areas or airports and the rate of built-up land expansion is statistically significant. The following villages are in close proximity to the city centre: Wates, Giripeni, Pleret, and Bendungan. The villages closest to the airport include Palihan, Kebonrejo, Sindutan, and Jangkaran. The distance between villages and the city centre is illustrated in **Figure 9**(a), while **Figure 9**(b) details the distance between villages and the airport. This study used a multifaceted approach, incorporating not only geographical distance from the city centre and the airport, but also road accessibility. The analysis results indicate that several villages with higher road accessibility are located in the districts of Wates, Triharjo, Bendungan, and Palihan. The analysis revealed two primary advantages. First, the property is well situated in terms of road access, and second, it is close to the city.



(a) (b)

Figure 9. (a) Distance to the City Centre; (b) Distance to the Airport (Source: Data Analysis, 2024)

The analysis of the triggering factors in this study also integrates aspects of spatial planning policy and land aspects, namely: the percentage of village area included in protected areas, the percentage of village area included in protected agricultural land areas, land rights status, and land value zones. The fundamental assumption of this study is that the greater the percentage of protected areas and protected agricultural land areas, the more negligible the dynamics of built-up land growth will be. Concurrently, the proportion of regions characterised by Non-Ownership land rights status (Building Use Rights/HGB, Management Rights/HPL, or Cultivation Rights/HGU) is associated with minimal land utilisation dynamics. In principle, and in accordance with land-rights regulations, ownership rights have the potential to offer greater flexibility in altering land use. Meanwhile, other rights are subject to limitations, since land use and utilisation must align with the rights inherent in the land. For instance, when Cultivation Rights are designated as plantations or livestock land, they last 30 years and can be extended in accordance with the regulations applicable in the given context. **Figure 10** shows the distribution of protected areas and agricultural land in each village. **Figure 11** presents the distribution of areas with non-ownership land rights status.

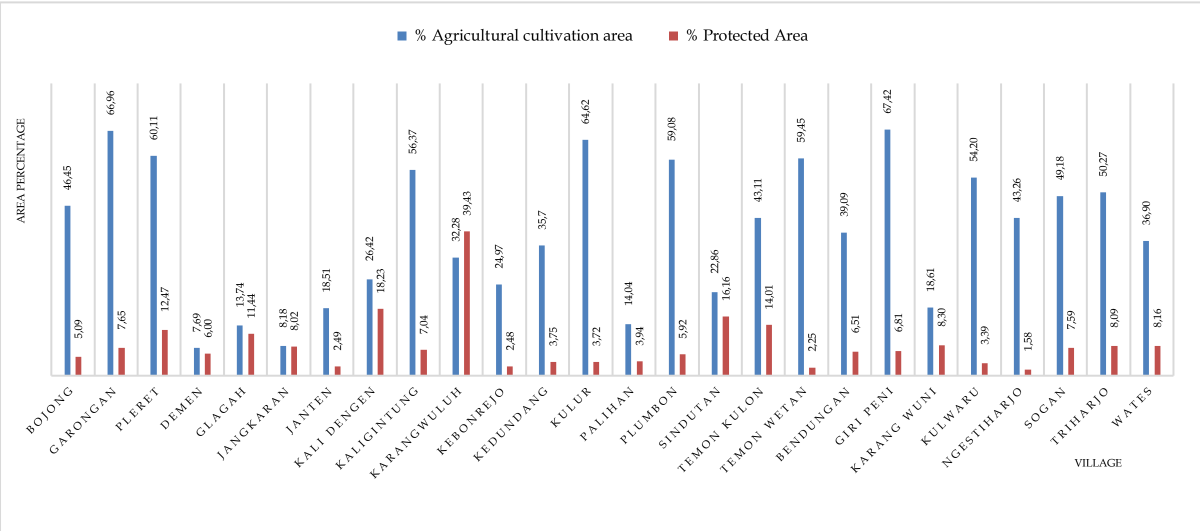


Figure 10. Percentage of Agricultural Cultivation Area and Protected Area by Village
(Source: Data Analysis, 2024)

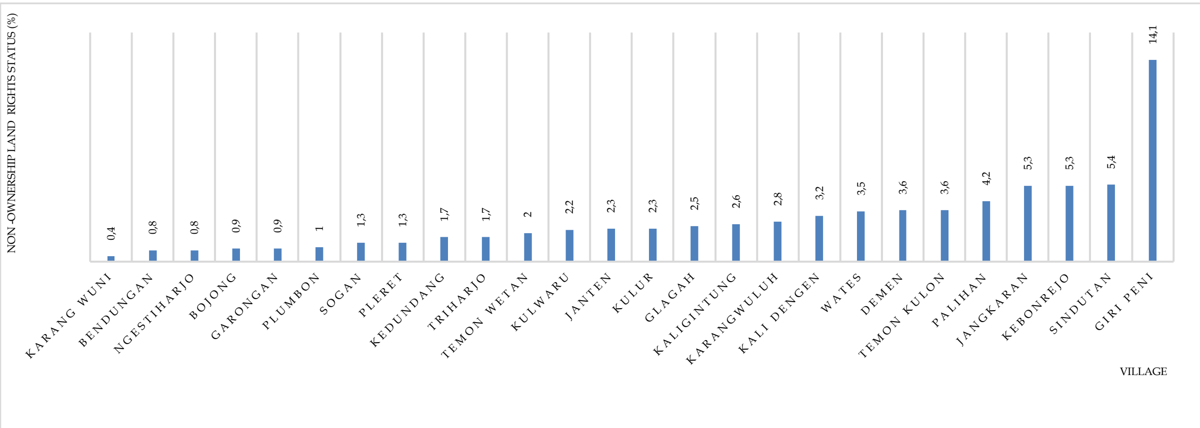


Figure 11. Percentage of Non-Owned Land Status by Village
(Source: Data Analysis, 2024)

As illustrated in Figure 10, 39% of the area is designated for agricultural use. The study area's rural location, the aerotropolis development plan's focus on agriculture, and the population's dependence on the agricultural sector contribute to the high level of protected agricultural land. This finding aligns with the conclusions of the study (Rijanta et al., 2022), which posits that socioeconomic and geographical factors significantly influence the trajectory of regional development. Moreover, the data indicate that 8% of the designated area is classified as protected. The topographical characteristics of the region, including its steep northern slopes, coastal southern expanse, and the presence of the major rivers Bogowonto and Serang, which traverse the area, collectively influence the necessity for designated protected area space. Spatial planning policies and land rights constrain built-up development and should therefore be considered when analysing the development rate.

Spatial Regression Analysis of the Drivers of Built-up

This study employs spatial regression. The rationale is to integrate spatial dimensions into the analysis of variable relationships, thereby minimising spatial autocorrelation. The determination of the most appropriate model is achieved through the use of the R-square value and the Akaike Information Criterion (AIC) value. Moreover, with reference to the spatial statistics concept of Hasbi et al., (2014), the range of lambda values that can be utilised is from $-1 < \lambda < 1$. **Table 5** presents the results of the 2014 spatial regression analysis. As shown in the table, the spatial error model, with a high R-square value (0.98) and a low AIC (197.43), is deemed suitable, as it indicates the model's ability to explain variation in the dependent variable.

Table 5. Spatial Regression Accuracy Test of Driving Forces of Land Use in 2014

Year	Model	R-square	AIC	Moran	Lagrange Lag	Lagrange Errorr	Lagrange SARMA
2014	Classic	0.978118	203.104	0.81194	0.24496	0.22735	0.38125
	Spatial Error	0.986154	197.43				
	Spatial Lag	0.979399	221.285				

(Source: Data Analysis, 2024)

Based on the data presented, the spatial error model is the most suitable for determining the relationship between the dependent and independent variables. As shown in Table 6, you can view the coefficient, z-value, and probability for each variable.

Table 6. Spatial Regression Analysis in 2014

Variable	Coefficient	Std.Error	z-value	Probability
Contant	19.8801	44.1382	0.450406	0.65242
T Population	0.00932029	0.00503123	1.85249	0.06396
Protect. A	0.390209	0.344852	1.13153	0.25783
Agriculture. CA	0.0113809	0.427833	0.0266014	0.97878
Road. A	0.00166351	0.000536623	3.09996	0.00194
Flood. D	-0.106388	0.0777571	-1.3682	0.17125
Land Title. S	3.28973	1.8392	1.78868	0.07367
R. Relief	-0.136848	0.0537051	-2.54813	0.01083
Land Value.S	3.82622e-05	7.861e-05	0.486735	0.62645
D. City	-9.71514	1.83079	-5.30653	0.00000
N. Industry	48.7206	17.9884	2.70845	0.00676

Employment. AS	1.80368	0.279018	6.46438	0.00000
LAMBDA	-0.634363	0.184483	-5.39001	0.00000

(Source: Data Analysis, 2024)

As shown in Table 6, the variables influencing land use dynamics with a significance value below 0.05 (as indicated by the probability/P-value) include the percentage of employment in the agricultural sector, the number of industries, distance to the city centre, road accessibility, and relative relief. This finding indicates that before the airport's construction (2014), location aspects (road accessibility, proximity to the city centre, and industry) varied more than social, physical, and spatial/land planning policy factors. **Table 7** shows the results of the spatial regression analysis of the factors driving land use dynamics in 2018. The 2018 spatial regression results indicate that the spatial error model was most appropriate, with an R-squared of 0.976521 and the lowest AIC of 202.376.

Table 7. Spatial Regression in 2018

Year	Model	R-square	AIC	Moran	Lagrange Lag	Lagrange Erorr	Lagrange SARMA
2018	Classic	0.966717	213.957	0.13835	0.56297	0.05611	0.12547
	Spatial Error	0.976521	202.376				
	Spatial Lag	0.967277	215.583				

(Source: Data Analysis, 2024)

The spatial regression analysis in 2018 showed that the spatial error model was the most suitable, with an R-squared of 0.976521 and the lowest AIC of 202.376. The statistical calculations for the spatial error model showed that the lambda value met the criteria for the spatial regression test. This analysis indicates that the variables significant for land use in 2018 were the percentage of protected areas, the status of land rights, relative relief, distance to cities and airports, and the percentage of employment in agriculture. Table 8 presents the data from the 2018 spatial regression analysis.

Table 8. Spatial Regression Analysis in 2018

Variable	Coefficient	Std.Error	z-value	Probability
Contant	55.036900	24.511900	2.245310	0.024750
Protect. A	1.000090	0.358502	2.789640	0.005280
Agriculture. CA	0.571956	0.317305	1.802540	0.071460
Road. A	-0.000222	0.000863	-0.266646	0.786200
Flood. D	-0.023157	0.060305	-0.384000	0.700980
Land Title. S	4.508490	2.033930	2.216640	0.026650
R. Relief	-0.185326	0.047917	-3.867660	0.000110
Land Value.Z	-1.59175E-05	1.50637E-05	-1.055280	0.291300
D. City	-11.191600	1.364430	-8.202410	0.000000
D. Aiport	-9.318100	1.785740	-5.218060	0.000000
N.Industry	15.776500	13.224000	1.193010	0.232860
T.Population	1.142040	0.271467	4.206940	0.000030
LAMBDA	0.020326	0.003096	6.565210	0.000000

(Source: Data Analysis, 2024)

Table 7 outlines the regression accuracy test results for the driving factors of built-up land in 2022 and shows that the most appropriate model, the spatial error model, is the same as the previous model. The high R-square value of 0.944986 and the lowest AIC value of 236.395 compared with other models indicate this model's strong ability to explain variation.

Table 7. Spatial Regression Accuracy Test in 2022

Model	R-square	AIC	Moran	Lagrange Lag	Lagrange Errorr	Lagrange SARMA
Classic	0.896291	247.103	0.23350	0.64545	0.04918	0.00647
Spatial Error	0.944986	236.395				
Spatial Lag	0.897673	248.831				

(Source: Data Analysis, 2024)

Table 8. Spatial Regression Analysis of Driving Forces of Land Use in 2022

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	39.155500	34.817400	1.124600	0.260760
T.Population	0.010876	0.005384	2.019930	0.043390
Road.A	0.002436	0.000995	2.448830	0.014330
Flood.D	-0.056276	0.084614	-0.665089	0.505990
Land Title.S	4.152780	2.754710	1.507520	0.131680
R.RELIEF	-0.218515	0.081936	-2.666900	0.007660
Land Value.Z	1.97091E-05	1.80122E-05	1.094210	0.273860
D.City	-12.478900	2.829390	-4.410450	0.000010
N.Industry	66.877700	25.240500	2.649610	0.008060
D.Airport	-7.563870	4.703730	-1.608060	0.007820
Employment.CA	3.146890	0.709369	4.436180	0.000010
Agricultural.CA	0.401596	0.307693	1.305180	0.191830
Protected.A	-0.739089	0.427739	-1.727900	0.054010

(Source: Data Analysis, 2024)

The findings from the spatial regression accuracy test of the relationship between driving factors and changes in built-up land use in 2022 are outlined in Table 7, which shows that the most appropriate model, the spatial error model, is the same as the previous model. The elevated R^2 value and the minimal AIC value in comparison to the rest are indicative of the findings of the spatial regression analysis presented in Table 8. These findings suggest that the factors driving land use dynamics in 2022 are intricate. The factors considered in this study include road accessibility, relative relief, distance to cities, industry, distance to airports, population, and the percentage of employment in the agricultural sector.

Drivers of Increased Built-up Land

The multitemporal spatial regression analysis reveals that the factors driving land use changes in 2014, 2018, and 2022 are not fixed but highly dynamic. The factors driving land use dynamics, particularly for built-up land, in a multitemporal manner are delineated in Table 9 below.

Table 9. Variable Analysis of Driving Forces of Land Use in 2014, 2018, and 2024

Year	2014	P-value/ α	2018	P-value/ α	2022	P-value/ α
Driving Force	Industry	0.00	% Protected Area	0.00	Population	0.04
	Distance to City	0.00	Land Title Status	0.02	Road Access	0.01
	Relative Relief	0.01	Relative Relief	0.00	Relative Relief	0.00
	Road Access	0.00	Distance to City	0.00	Distance to City	0.00
	% Employment in Agricultural	0.00	% Employment in Agricultural	0.00	% Employment in Agricultural	0.00
			Distance to Airport		Industry	0.00
			Population	0.00	Distance to Airport	0.00

(Source: Data Analysis, 2024)

The findings of this study confirm the research (Mekonnen et al., 2022; Xu and Wu, 2023; Xie and Zhang, 2023) that significant driving factors influencing the dynamics of built-up land use are very dynamic. As illustrated in **Table 9**, the study found that locational aspects, specifically distance from the city, physical aspects, including relative relief, and social aspects, notably employment in the agricultural sector, emerged as significant influential variables in 2014, 2018, and 2022. The city centre, which simultaneously functions as a centre of government, a centre of economic development, and a centre of population activity, supported by a variety of educational, health, and entertainment facilities, is a strong attraction for the dynamics of built-up land growth. A thorough analysis of the multitemporal built-up land use map in the study area reveals that built-up land growth is predominantly observed in areas in close proximity to the city centre or on the outskirts. This research finding corroborates the study's findings (Salem et al., 2020; Al-Dousari et al., 2023) that the limited availability of land in the city centre and the high cost of land in such areas have implications for the emergence of urban sprawl.

In addition to the distance from the city centre, social aspects, namely the percentage of people working in the agricultural sector, also have a significant influence on the low rate of built-up land growth. The higher the population that is still dependent on the agricultural sector, the more implications there are for this rate. This research finding is in accordance with the study of (Cai et al., 2024) which demonstrated that human activities significantly influence land use and utilisation in a region. The high number of people who are economically dependent on the agricultural sector in the study area has implications for the high level of community effort to maintain agricultural land and rice fields, thereby reducing the rate of built-up land growth. From a physical perspective, relative relief has been shown to have a significant influence on the development of built-up land. The findings of this study indicate that in areas characterised by steep relief conditions, the growth of built-up land is comparatively slow in comparison to areas exhibiting a flatter topography. The present study finds conceptual agreement with the research of (Liu et al., 2015; Zhang et al., 2023). The former research established that geographical factors of the region, including relief, are significant factors in the growth of built-up land. The present study corroborates earlier research that geographical factors in each region vary in their influence. This finding confirms that, in each region with diverse geographical and socio-economic conditions, there are implications for differences in factors influencing land use dynamics.

The multitemporal analysis of factors driving built-up land in the study area reveals unique dynamics. In addition to three factors (distance from the city centre, employment in the agricultural sector, and relative relief) that significantly influence development from year to year, the findings indicate that in 2014 and 2022, two other significant driving variables were road access and industry. In principle, the concept of industry is associated with a considerable number of employees and exerts a significant influence on the increasing demand for residential land and a variety of economic activities that give rise to the expansion of built-up land. These findings corroborate the research (Debela et al., 2020) that the development of industrial (manufacturing) zones in developing countries can engender employment opportunities but also result in a decrease in non-built-up land (agricultural land and green open spaces). This research is consistent with studies (Tepe, and Guldmann, 2020); Xifeng et al., 2023) that have found that locational aspects, particularly road access, significantly influence the growth of built-up land. The existence of roads facilitates various activities, opens up business opportunities, and serves as an economic attraction (Msofe et al., 2019; Xie & Zhang, 2023; Zhang et al., 2022). Within the context of the study area, the significant influence of roads on built-up land is evidenced by the presence of a ribbon-shaped/elongated built-up land pattern.

The findings of this study indicate that the presence of an airport exerts a significant influence on the growth rate of built-up land. In 2018 and 2022, during and after the construction of the airport, the airport was a significant factor. The development of this mega-project has implications for increasing various government development projects and attracting speculators and investors to build various facilities (hotels, homestays, restaurants, offices, shops, warehouses, etc.) located near the airport. The present findings corroborate studies (Tveter, 2017; Peng et al., 2020; Ke and Baker, 2022; Lampropoulos et al., 2022) that the existence of an airport can trigger massive changes in the regional landscape and can trigger the formation of new cities/aerotropolis areas.

The present study offers a contribution to the examination of drivers of land use change, a field that has been limited to the analysis of physical and socioeconomic aspects. Additionally, it provides a contribution to the study (Alam et al., 2021) which has been restricted to the examination of physical, geographical, and social factors in analysing drivers of land use change. The incompleteness of the driving factors utilised in preceding studies may have ramifications for land use management policies. The present study provides a broader perspective on the matter, highlighting that, in addition to socioeconomic, geographical, and physical aspects, there are other factors that are often not utilised, namely land/spatial planning and land rights policies. The study revealed that land ownership status/ land right and protected area designation policies have significant influences on the outcomes. This finding corroborates studies (Huang et al., 2017; Ansah and Chigbu, 2020; Gud and Akhmedova, 2020; Gomes et al., 2024) that spatial planning and land policies are significant regulatory mechanisms in controlling and suppressing the rate of land use change. Gomes et al., (2024) study posited that spatial planning is endowed with legal force and functions as a regulatory instrument for long-term land use. The findings of this research indicate that, despite the development of large-scale airports, policies regarding spatial planning and the designation of protected areas are able to regulate the conversion of land. Moreover, from the standpoint of land rights, the primary conclusions of this study are in alignment with those (Boutthavong et al., 2016); Spalding, 2017) which assert that land rights have a discernible impact on the utilization and management of land within a specific region. The findings indicate a positive correlation between the percentage of land rights in the form of ownership and the tendency for built-up land to increase, and vice versa. This finding reinforces the concept of land management (Enemark et al., 2021) sustainable land management is all about owning and controlling land, as well as setting restrictions and responsibilities for how it's used.

Theoretically, this research provides a significant contribution by demonstrating that analysing the drivers of land use is a complex undertaking. The social, economic, locational, geographical/physical conditions of the land, policies, and proximity factors such as development or disasters are highly dynamic, and it is evident that they can influence land use. The fundamental theoretical finding of this research, from a social perspective, is that population, as in the study (Zhao et al., 2022; Koroso, 2023) is frequently a catalyst for land use dynamic. Nevertheless, the present study demonstrates that population is not the solitary social factor exerting influence, as the percentage of employment has also been found to be a significant factor. Furthermore, from the perspective of spatial planning and land rights policies, this factor is a significant factor that is often overlooked and has not been considered by previous researchers (Xu and Cheng, 2022; Zhao et al., 2022), while the findings of this research indicate that the establishment of protected areas and land rights are important factors that control land use dynamics. From a geographical and physical perspective, the findings of this research differ from the results of previous studies (Liu et al., 2023) in question was characterised by elevated levels of disaster vulnerability. In this study, relative relief is identified as a significant factor. Theoretically, the fundamental finding of this research confirms that proximity to the city centre, distance to the airport, road access, and industry are the main factors driving the growth of built-up land. The desirability of these location variables is a key factor in the decision-making process of individuals and organisations when selecting sites for residential development, various business and service establishments, and the establishment of these locations as centres of economic growth. This, in turn, has implications for increasing built-up land. The findings of this study demonstrate that various driving factors differ between periods, influenced by the conditions of large-scale development/land acquisition for airports, the increase in speculators and investors building various built-up areas around airports, the condition of the community and the geographical conditions of rural areas that depend on the agricultural sector, the existence of industrial development, and land policy/spatial planning that influences the direction of land use.

From a methodological perspective, the results of this study serve to simplify the complex phenomenon of land use dynamics in the field and accurately present multitemporal land use data, using high-resolution imagery. The spatial regression approach employed in this study yielded an effective model to explain the diversity of dependent variables. This study corroborates research (Hasbi et al., 2014; Liu et al., 2015) that spatial regression has the advantage of representing spatial connectivity and can produce more accurate models.

The research results indicate a substantial increase in built-up land surrounding Yogyakarta International Airport. This is feared to have implications for agricultural land pressure and threaten the availability of green open space. In this context, the valuable findings of this research are expected to be used as a consideration by the government in formulating policies to control and regulate built-up land. A range of strategies can be employed to this end, including spatial planning policies that focus on the designation of protected areas and the conservation of agricultural land. The efficacy of these measures in curbing urban expansion has been demonstrated by this research. In addition, control efforts are required, including the implementation of a policy on the Conformity of Spatial Utilisation Activities. This policy would establish the conformity of detailed spatial plans as a prerequisite for the approval of applications for land use change permits and business permits. In order to reduce the issue of land fragmentation, there is a necessity for the implementation of policies that are designed to control and restrict the process of land conversion, with a particular emphasis on the areas surrounding arterial and collector roads. In order to address the issue of land conversion in the area surrounding the airport, there is a necessity for the implementation of control measures. Such measures should include the use of incentive and disincentive policies, as well as the imposition of sanctions, in order to regulate land use.

Whilst the research findings have been found to make theoretical and empirical contributions to the study of land use dynamics, this study has several weaknesses, such as its limitation to 26 villages, which poses a potential risk of data bias and overfitting. Furthermore, the utilisation of units of analysis based on village administrative boundaries of varying sizes or shapes is also feared to give rise to the Modifiable Area Unit Problem (MAUP) in spatial statistical analysis. The utilisation of spatial regression is subject to certain limitations, namely the absence of a pure control area for causal comparison and the presence of reciprocal relationships between regions, which have implications for high statistical endogeneity. From a multitemporal perspective, the utilisation of panel data frequently exhibits deficiencies, namely the inability to capture the dynamic effects of change and the constrained degrees of freedom.

CONFLICTS OF INTEREST

The authors declare no conflict of interest, as they were all in agreement with the study methodology and the results presented and discussed.

AUTHOR CONTRIBUTION

WU was instrumental in the conceptualisation of the study, the design of the research, the collection and analysis of data, and the drafting of the manuscript. **CS & NR** contributed to the development of the theoretical framework and the supervision of the research process. **N & AM** contributed to the review and revision of the manuscript. It is evident that **RAPL & RBY** contributed to the analysis of spatial data and the subsequent visualisation of maps. **MNS & M** contributed to the revision and editing of the manuscript. All authors have read and approved the final version of this manuscript.

CONCLUSIONS

The infrastructure development of Yogyakarta International Airport, designated a National Strategic Project, has facilitated connectivity between regions and catalysed economic growth. However, the project has also resulted in increased land use changes. The research findings indicate a change in land use, with an increase of 79.02 hectares in the 2014-2018 period and 615.14 hectares in the 2018-2022 period. The present study demonstrates that the increase in built-up area is influenced by highly dynamic factors. The variables influencing land use dynamics include geographical factors such as location, including industry, city centres, airports, and road networks; social factors such as occupations and population; and physical factors such as relative relief. Research findings also indicate that land rights status and spatial planning (protected areas), often overlooked factors, also have a significant influence on the rate of built-up area growth. While this research makes a theoretical contribution to the study of land use dynamics around the airport area, it is limited by the following factors: the village administration-based analysis unit, the weakness of the use of package/multitemporal data, and the absence of control areas that can trigger the risk of overfitting, potential Modifiable Area Unit Problems, and statistical analysis bias. Further studies must analyse land use dynamics by adding control variables, employing the generalized method of moments, and incorporating instrumental variables in spatial regression.

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