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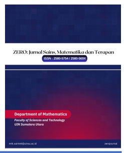

Drivers and Impacts of Agricultural Land Conversion: Regression Modelling with Spatial Dependence in West Bandung and Purwakarta Regencies, Indonesia

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ABSTRACT

The rapid conversion of farmland to non-agricultural uses in West Java threatens food security, farmer livelihoods, and environmental sustainability. This study investigates the causes and consequences of land conversion in West Bandung and Purwakarta Regencies using a mixed-source data, including geotagging, CAPI, and secondary data from satellite images, focusing on landowners who converted farmland between 2013 and 2021. Multiple linear regression and spatial models, including Spatial Lag Model (SLM), were applied to assess key determinants. The results revealed economic pressures as the main driver, with rice fields most affected and various geographic and infrastructure factors influencing outcomes. The findings underscore the need for targeted policies to balance development with sustainable land and food system management.

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1. INTRODUCTION

Agricultural land, particularly paddy fields. has been increasingly subjected to conversion for non-agricultural purposes in Indonesia [1]. Java, the nation's largest rice-producing island [2], [3], [4] has experienced significant paddy field conversion. Between 1994 and 2014, approximately 1.2 million hectares of paddy fields in Java were converted, averaging around 60.000 hectares per year [5]. Factors such as economic growth, infrastructure development, and population increase have significantly influenced this trend. The conversion of paddy fields poses a substantial threat to Indonesia's food security and rice self-sufficiency, necessitating effective land-use policies and sustainable agricultural practices to mitigate further loss of vital agricultural land [6]. The agricultural workforce is predominantly composed of individuals over the age of 40, with declining interest among younger generations in pursuing farming or agribusiness ventures [7]. Land conversion refers to the process of altering the function of a specific land area, either partially or entirely, for purposes other than agriculture. The demand for non-agricultural land continues to rise in parallel with urbanization, infrastructure expansion, and economic development, leading to shifts in land ownership and usage. However, uncontrolled agricultural land conversion poses critical challenges. including threats to food supply capacity and agricultural sustainability [8]. Managing land conversion is particularly challenging due to the increasing demand for land, necessitating strategic policies to balance development needs with food security concerns.

West Java Province, particularly West Bandung Regency and Purwakarta Regency, has been experiencing significant rates of agricultural land conversion, primarily due to its proximity to the capital city and substantial investment inflows. This trend poses a threat to agricultural output and food security in the region. Recent studies have highlighted the implications of this issue. For instance, a spatial analysis in Purwakarta Regency revealed a reduction in paddy fields by 195.55 hectares (1%) during the 2013–2017 period, primarily due to conversion into industrial areas, roads, and settlements [9]. This reduction in paddy fields has contributed to decreased food production, impacting food security in the region. Similarly, other research in West Java identified that agricultural land has been the primary target for urbanization. The construction of infrastructure has accelerated the shift from farmland to developed areas, raising concerns about future rice deficits if the trend continues [6].

This study aims to achieve two key objectives: (1) to analyze the characteristics of agricultural land conversion and the motivations of land-owning farmers in West Bandung and Purwakarta Regencies, and (2) to identify the key factors influencing farmers' decisions to convert agricultural land in these regions. The findings of this study are expected to serve as a critical reference for policymakers in formulating sustainable land management and regulatory frameworks to address agricultural land conversion.

2. RESEARCH METHOD

2.1 Study Area and Data Collection

Purwakarta and West Bandung Regencies in West Java Province are selected as the case study area due to their rapid agricultural land conversion inline with the urbanization and industrial expansion. Between 2013 and 2017, Purwakarta lost 195.55 hectares of paddy fields, primarily converted for industrial, residential, and infrastructure development [9]. The data utilized in this study were classified into primary and secondary sources. Primary data were obtained through geotagging and interviews conducted via Computer-Assisted Personal Interviews (CAPI). Geotagging involved the integration of precise spatial coordinates—latitude, longitude, and altitude—into GPS data, enhancing the spatial accuracy of the study [10]. CAPI, implemented using mobile devices enabled real-time collection, minimized input errors, and improved efficiency through automated data management. Secondary data were acquired from the Statistics Indonesia (BPS) and served as a foundation for identifying suitable study locations. These datasets encompassed key agricultural indicators, including the number of farmers from the 2013 Agricultural Census (ST2013), regional typology, geographical attributes, and land ownership records obtained from village administrations.

This study investigates the characteristics and drivers of agricultural land conversion by analyzing data from land-owning farmers who converted land between 2013 and 2021. It captures demographic details (age, education, household size, farming experience, occupation changes) and land-specific information (size, origin, price, former use). Motivations for conversion were explored across economic, social, demographic, policy, technical, and environmental dimensions. Broader regional influences were examined using 2014 and 2021 Village Potential Survey (Podes) data and satellite imagery, focusing on factors such as population growth, infrastructure, access to services, elevation, and environmental accessibility. The study targeted farmers in West Bandung and Purwakarta who transitioned agricultural land to non-agricultural uses, using land parcels and individual farmers as units of analysis. Landowners who permanently converted land formed the sampling unit, identified through records from village heads and local administrative offices.

Given the challenges in accessing a well-defined sampling frame, the study employed a non-probability sampling technique known as snowball sampling. This approach facilitated the identification of key informants with substantial knowledge of land conversion dynamics by leveraging initial respondents to refer others meeting the study criteria. The process continued iteratively until data saturation was achieved. Snowball sampling was particularly suitable due to the inherent difficulties in reaching respondents in the field. The final sample size was determined based on the workload of field enumerators and the available timeframe for data collection, ensuring feasibility while maintaining data reliability. Our previous internal studies [11], [12] provided preliminary insights into this phenomenon, however primarily relied on limited analysis of early survey data. This study builds upon those initial findings by incorporating advanced statistical modeling and a deeper investigation to better understand the socio-economic and environmental determinants of land use change.

2.2 Method of Analysis

2.2.1. Multiple Linear Regression (MLR)

This study seeks to model a causal relationship between the variables that affect land conversion, such as population growth rate percentage, economic facility ratio, educational facility ratio, health facility ratio, altitude, area elevation variation, and accessibility of percentage rate of paddy field conversion rate. The inferential analysis method used is multiple linear regression (MLR) [13] and spatial regression using an area approach with regression model candidates in the form of spatial error models (SEM) and spatial lag models (SLM).

Multiple linear regression (MLR) is a statistical analysis technique used to model the relationship between a dependent variable and multiple independent variables. This method provides a framework for quantifying the extent to which independent variables influence the dependent variable, enabling a deeper understanding of underlying patterns and associations [14]. In this study, MLR is employed to estimate the key factors driving agricultural land conversion. One of the primary variables under investigation is population growth, which is hypothesized to significantly impact land conversion in West Bandung and Purwakarta Regencies. Population growth refers to the rate at which the population increases over time, leading to a higher demand for housing and infrastructure. As residential expansion intensifies, agricultural land is increasingly repurposed to accommodate urban development, resulting in a decline in arable land. Based on this premise, the study hypothesizes a positive correlation between population growth and the rate of agricultural land conversion. where higher population expansion accelerates the loss of farmland. The equation for the linear regression model is presented as follows.

$$Y_i = \beta_0 + \sum_{k=1}^{p-1} \beta_k X_{ik} + \varepsilon_i \quad ; \quad i = 1.2. \ldots . n \tag{1}$$

where:

Y_i	=	The dependent variable's value at the i-observation
β_0	=	Coefficient of intercept
k	=	Number of independent variables
p	=	Number of parameters
β_k	=	Coefficient of slope
X_{ik}	=	The independent variable’s value of the k-th at the i-observation
$\varepsilon_i \sim N(0. \sigma^2)$	=	Error at the i-observation

A regression model's accuracy and capabilities are examined in order to establish the extent to which the elements identified in the equation will effect land conversion. Finding the coefficient of determination. evaluating the whole (simultaneous) regression coefficient, and evaluating the partial regression coefficient comprise the regression model examination process.

2.2.2. Spatial Autocorrelation

Spatial correlation refers to the correlation a variable has with itself across space, and can also be understood as a measure of the similarity between spatially, temporally, or regionally related objects. It can be claimed that there is spatial autocorrelation if the object similarity measure demonstrates spatial interdependence and there is a systematic pattern in the distribution of variables. The existence of spatial autocorrelation suggests a relationship between attribute values in a given location and attribute values in nearby or adjacent areas. By contrasting the locations and characteristics of the points, spatial autocorrelation is used to examine the spatial pattern of the distribution of points. Clustered, diffused, and random spatial patterns are examples of the early stages of spatial randomness. Based on area data. autocorrelation might be either positive or negative. Positive spatial autocorrelation suggests that values from nearby areas tend to cluster and have commonalities. When there is a negative spatial autocorrelation, values at nearby sites differ and have a propensity to spread. The absence of spatial autocorrelation indicates a random location pattern [15]. The characteristics of spatial autocorrelation by Kmoch et al. [16] are as follows.

a. Spatial autocorrelation occurs when there is a structured or non-random pattern in the spatial distribution of a variable.
b. Positive spatial autocorrelation is observed when geographically proximate regions exhibit greater similarity in their attribute values.

2.2.3. Moran’s Index

Moran's Index is a measure of global autocorrelation which is an extension of the Pearson correlation coefficient [15]. Moran's Index is a technique in spatial analysis to calculate the spatial relationships that occur in a space [17]. The correlation (connection) between locations that are close to one another is measured by the Moran’s Index statistic. This statistic contrasts values that have been observed in various areas. Moran's Index is the most extensively used method to calculate global spatial autocorrelation. The formula below can be used to calculate spatial autocorrelation using the Moran’s Index.

$$I_{\mathrm{m}} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{\mathrm{ij}}(x_{\mathrm{i}} - \underline{x})(x_j - \underline{x})}{s_0(\sum_{i=1}^{n}(x_{\mathrm{i}} - \underline{x})^2} \text{ or } I_{\mathrm{m}} = \frac{n(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{\mathrm{ij}} z_{\mathrm{i}} z_{\mathrm{j}}}{s_0(\sum_{i=1}^{n} z_i^2)} \tag{2}$$

$$s_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{\mathrm{ij}} \quad . \quad z_i = (x_{\mathrm{i}} - \underline{x}) . \quad z_j = (x_j - \underline{x}) \tag{3}$$

where

I_m = Moran's Index
n = The number of incident locations
x_i = Value at the i-location
x_j = Value at the j-location
$\underline{x}$ = Average number of variables

The correlation coefficient, which has a range of -1 to 1, yields the same number when used to calculate the Moran's Index. The autocorrelation is high if the Moran's Index value is near to +1 or -1. When the value is negative, there is a negative spatial autocorrelation pattern, which suggests that nearby places are spread apart and have different values. When the value is positive, there is a positive spatial autocorrelation pattern, which means that values are comparable and tend to cluster together at nearby locations. Meanwhile, a value of zero indicates no autocorrelation.

2.2.4. Local Indicator of Spatial Association (LISA)

By identifying spatial correlation in each location. the Local Indicator of Spatial Association (LISA) locates local autocorrelation and provides precise information about spatial grouping in particular places. LISA is a statistic that fulfills two criteria [18], [19]. First, the LISA value in each area can be used to provide an indication that there is a significant spatial relationship grouping of the same values around the area. Second, the sum of the LISA values for all regions is proportional to the Moran's Index value.

2.2.5. Moran's Scatter Plot

Moran's scatter plot is one way to interpret Moran's Index statistics which act as a tool to investigate the relationship between Z_{std} (standardized observed value) and WZ_{std} (standardized average neighboring area value calculated from a spatial weighting matrix) [15], [17]. A regression line that depicts the linear relationship between the observed values and the spatial value of the observations itself is called a Moran's scatter plot. In Moran's scatter plot, there are four quadrants.

1. Quadrant I (upper right), high-high (HH), indicates areas with high values surrounded by high values areas.
2. Quadrant II (upper left), low-high (LH), indicates areas with low values surrounded by high values areas.
3. Quadrant III (bottom left), low-low (LL), indicates areas with low values surrounded by low values areas.
4. Quadrant IV (lower right), high-low (HL), indicates areas with high values surrounded by low values areas.

Moran's scatter plot which places many observations in the HH and LL quadrants will tend to have positive spatial autocorrelation values (clusters). Contrarily, Moran's scatter plot, which concentrates a large number of observations in HL and LH quadrants, will typically have negative values for spatial autocorrelation.

2.2.6. Spatial Lag Model

According to Le Gallo (2021) [17], a spatial autoregressive (SAR) model or also called a spatial lag model (SLM) is a model that combines a simple regression model with a spatial lag in the dependent variable using cross sectional data. The dependent variable's observed values in the relevant spatial units and adjacent units are what lead to the model's creation. This model is formed when $\rho \neq 0$ and $\lambda = 0$. The general form of SLM is as follows.

$$y = \rho \boldsymbol{W} y + \beta X + u; \quad u = \lambda \boldsymbol{W} u + \varepsilon; \quad \varepsilon \sim N(0, \sigma^2 I) \tag{4}$$

where

y = Response variable
ρ = Response variable spatial lag coefficient parameter
$\boldsymbol{W}$ = Spatial weighting matrix
β = Regression coefficient parameters
X = The matrix of the predictor variable that measures $n \times 1(n \times (k+1))$
u = Error term
λ = Spatial lag error coefficient parameter
N = The number of observations or locations ($i = 1.2. \dots . n$)
$\varepsilon \sim N(0, \sigma^2 I)$ = Error at the observation

2.2.7. Spatial Error Model (SEM)

Spatial error model (SEM) arises when the error terms in one region are correlated with those in neighboring regions, indicating the presence of spatial dependence in the error structure [17], [18]. In SEM, the shape of the error in the i-th region is a function of the error in the j-th region where j is a region that lies around the i-th region. The general form of SEM is stated as follows.

$$y = \rho \boldsymbol{W} y + \beta X + u; \quad u = \lambda \boldsymbol{W} u + \varepsilon; \quad \varepsilon \sim N(0, \sigma^2 I) \tag{5}$$

where

y = Response variable that measures $n \times 1$
ρ = Response variable spatial lag coefficient parameter
$\boldsymbol{W}$ = Spatial weighting matrix of size $n \times n$ with zero diagonal elements
β = Regression coefficient parameter measures $(k + 1) \times 1$
X = The matrix of the predictor variable that measures $n \times 1(n \times (k+1))$
U = Error vector that measures $n \times 1$

I = Identity matrix of size $n \times n$
N = The number of observations or locations ($i = 1.2. \ldots . n$)

Inferential analysis assesses the impact of independent variables on the dependent variable using spatial and statistical modeling. The process begins with Ordinary Least Squares (OLS) regression, followed by classical assumption testing and a spatial autocorrelation test to determine model suitability. If no spatial autocorrelation is detected. OLS regression is used; otherwise, either a spatial lag model (SLM) or a spatial error model (SEM) is selected based on the significance of the lag or error component. The goodness-of-fit test ensures the optimal model choice, and final significance testing validates the robustness of the selected model.

3. RESULT AND ANALYSIS

3.1. Characteristics of Land-owning Farmers and Their Land Areas on Agricultural Land Conversion

Understanding the characteristics of farmers and their land areas is crucial in analyzing the underlying drivers of agricultural land conversion. The demographic composition, household size, and land ownership patterns provide valuable insights into how socio-economic factors influence land-use decisions and the sustainability of agricultural practices. **Table 1** presents a detailed overview and providing critical insights into the patterns and determinants of agricultural land conversion in West Bandung and Purwakarta Regencies.

Table 1. Characteristics of Land-owning Farmers and Their Land Areas on Agricultural Land Conversion in West Bandung and Purwakarta

Characteristics		West Bandung		Purwakarta	
		Frequency	(%)	Frequency	(%)
Age	Early Adult Group (18-40 years)	67	34.50	9	9.10
	Middle Adult Group (41-60 years)	73	37.60	55	55.60
	Late Adult Group (> 60 years)	54	27.80	35	35.40
Number of Household Members	Below Average (1-2)	33	17.00	24	24.20
	With the Average (3-4)	113	58.20	42	42.40
	Above Average (>4)	48	24.80	33	33.40
Education	Elementary Education	103	53.09	73	73.74
	Secondary Education	81	41.75	18	18.18
	Higher Education	10	5.15	8	8.08
Years of farming experience	<20 years	107	55.15	45	45.46
	21-40 years	44	22.69	34	34.34
	>40 years	43	22.16	20	20.20
Main Job After Land Conversion	Agriculture	103	53.09	49	49.50
	Other Sectors	64	32.99	34	34.34
	Stop Working	27	13.92	16	16.16
Factors Influencing Land Conversion by Land-Owning Farmers	Economy	142	73.95	50	50.51
	Social	2	1.03	0	0.00
	Demographic	7	3.61	7	7.07
	Policy	13	6.70	7	7.07
	Technical	3	1.55	2	2.02
	Environmental and Geographical	0	0.00	0	0.00
	Others	27	13.92	33	33.33
Area of Land Ownership	<1000 m2	127	65.46	48	48.48
	1000-2000 m2	25	12.89	21	21.21
	>2000 m2	42	21.65	30	30.30
Land Origin	Purchasing	74	38.14	46	46.46
	Inheritance	120	61.86	53	53.54
Area of Converted Land	Small (<700 m2)	159	81.96	57	57.58
	Moderate (700-1400 m2)	15	7.73	13	13.13
	Large (>1400 m2)	20	10.31	29	29.29
Land Convertion Mechanism	Ownership-Transfer-Based	53	27.32	55	55.56
	Non-Ownership-Transfer	141	72.68	44	44.44
	a. Housing Area	100	70.92	23	52.27
	b. Industrial Factory Land	7	4.96	1	2.27
	c. Tourism Place	2	1.42	0	0.00
	d. Public Facilities	10	7.09	4	9.09
	e. Others	22	15.60	16	36.36
Land Market Value	Low (<IDR 250K/m2)	115	59.28	77	77.78
	Medium (IDR 250K-500K/m2)	50	25.77	15	15.15
	High (>IDR 500K/m2)	29	14.95	7	7.07
Land Rental Price	Low (<IDR 50K/m2)	147	75.77	85	85.86
	Medium (IDR 50K-100K/m2)	21	10.82	7	7.07
	High (>IDR 100K/m2)	26	13.40	7	7.07
	Rice	136	70.10	86	86.87

Characteristics		West Bandung		Purwakarta	
		Frequency	(%)	Frequency	(%)
Main Agricultural Commodities	Other Foodcrops	37	19.07	7	7.07
	Horticulture	11	5.67	4	4.04
	Others	10	5.12	2	2.02

The demographic composition of land-owning farmers in West Bandung and Purwakarta Regencies reveals critical insights into agricultural land conversion patterns. In West Bandung. the majority of farmers (37.6%) belong to the Middle Adult Group (41–60 years), followed by the Early Adult Group (34.5%) and the Late Adult Group (>60 years) at 27.8%. In contrast, Purwakarta has a significantly higher proportion (55.6%) of Middle Adult Group farmers. with 35.4% in the Late Adult Group and only 9.1% in the Early Adult Group. This trend suggests that land conversion decisions are primarily influenced by experienced farmers who have been engaged in agriculture for decades. However, the lower proportion of younger farmers in Purwakarta signals a declining interest in farming among the next generation, which could accelerate land conversion in the long term.

Household size also plays a role in agricultural land conversion decisions. A considerable proportion of farmers in West Bandung (17%) and Purwakarta (24.2%) have smaller households (1–2 members), indicating a shift toward smaller family units. This trend may contribute to agricultural decline, as smaller households might lack the labor force needed to sustain farming operations. Consequently, economic pressures may drive farmers with limited land and labor resources to convert their agricultural land into non-agricultural uses, particularly for housing and infrastructure development. The analysis also highlights that land ownership size is predominantly below 1000 m², emphasizing the vulnerability of smallholder farmers to economic fluctuations. Since paddy fields represent the most frequently converted land type. their lower rental and sales values make them more susceptible to conversion. Unlike other agricultural land types, paddy fields require intensive irrigation and consistent maintenance, making them less financially viable compared to alternative land uses. This economic disadvantage further incentivizes farmers to shift their land toward non-agricultural functions. These findings underscore the need for strategic land-use policies that balance economic development with agricultural sustainability. The declining interest of younger farmers in Purwakarta suggests that targeted interventions, such as financial support for young farmers and knowledge transfer programs, are necessary to sustain agricultural productivity. Additionally, economic incentives for sustainable rice production and stronger land tenure security could help mitigate excessive land conversion. Without such policies, the increasing demand for non-agricultural land could threaten food security and long-term agricultural viability in West Bandung and Purwakarta Regencies.

Table 2. Area of Converted Land based on Land Origin

Regency	Land Origin	Area of Converted Land (m²)						Total	
		Small (<700)		Moderate (700-1400)		Large (>1400)			
		Amount	(%)	Amount	(%)	Amount	(%)	Amount	(%)
West Bandung	Purchasing	59	79.73	9	12.16	6	8.11	74	38.14
	Inheritance	100	83.33	6	5.00	14	11.67	120	61.86
Total		159	81.96	15	7.73	20	10.31	194	100.00
Purwakarta	Purchasing	26	56.52	7	15.22	13	28.26	46	46.46
	Inheritance	31	58.49	6	11.32	16	30.19	53	53.54
Total		57	57.58	13	13.13	29	29.29	99	100.00

In general. the converted paddy fields are predominantly inherited and have a relatively small conversion area. As shown in **Table 2**. in West Bandung Regency. 83.33% of converted land originates from inheritance and falls within the low conversion area category (1–700 m²). Similarly, in Purwakarta Regency. 58.49% of converted land shares the same characteristics. This trend suggests that landowners may have a stronger inclination to convert or sell inherited land, as it was acquired without direct financial investment. making it easier to repurpose for non-agricultural uses. The conversion of agricultural land with medium to large areas (>700 m²) is primarily conducted through sales transactions, while land areas of less than 700 m² are often converted without direct sales. Across both regencies, the average converted land area is 3,386.6 m², reflecting significant shifts in land use. In West Bandung Regency, non-transactional conversions are the predominant method. with most converted land measuring less than 700 m². Conversely, in Purwakarta Regency, land conversion is largely driven by sales transactions. However, smaller land areas (<700 m²) in Purwakarta are still frequently converted without sales transactions, whereas larger areas (>700 m²) are predominantly transferred through formal sales.

Commodities covered in this study include rice, crops, horticulture, and others. Rice consists of paddy rice and field rice. Paddy rice is rice grown in paddy fields. Field rice is rice grown in fields, gardens, or huma. Corps consists of corn, soybeans, cassava, sweet potatoes, peanuts, and green beans. Meanwhile, horticulture consists of vegetables, fruits, biopharmaceuticals, and ornamental plants. The analysis of land selling prices by commodity type, shown in **Table 3**, reveals significant variations in agricultural land values across West Bandung and Purwakarta Regencies. In West Bandung, 54.41% of rice-farming land is sold at low prices (1–250 thousand rupiahs/m²), making it highly susceptible to conversion due to lower profitability and higher maintenance costs. In contrast, land used for horticulture is sold at higher prices, reflecting its greater economic returns and market demand. This disparity suggests that rice fields face greater financial pressure, increasing the likelihood of conversion to non-agricultural uses, while horticultural land remains more economically viable.

Table 3. Land Selling Price based on Types of Commodities Grown on the Land

Regency	Commodities	Land Selling Price (thousand rupiahs/m²)						Total	
		Low (1-250)		Medium (251-500)		High (>500)			
		Amount	(%)	Amount	(%)	Amount	(%)	Amount	(%)
West Bandung	Rice	74	54.41	38	27.94	24	17.65	136	70.10
	Corps	26	70.27	7	18.92	4	10.81	37	19.07
	Horticulture	4	36.36	5	45.45	2	18.18	11	5.67
	Others	10	100.00	0	0.00	0	0.00	10	5.15
Total		114	58.76	50	25.77	30	15.46	194	100.00
Purwakarta	Rice	66	76.74	13	15.12	7	8.14	86	86.87
	Corps	7	100.00	0	0.00	0	0.00	7	7.07
	Horticulture	2	50.00	2	50.00	0	0.00	4	4.04
	Others	2	100.00	0	0.00	0	0.00	2	2.02
Total		77	77.78	15	15.15	7	7.07	99	100.00

3.2 Factors Influencing Farmers to Convert Agricultural Land

Analyzing the factors influencing farmers to convert agricultural land in West Bandung and Purwakarta Regencies is essential to identify the socio-economic and environmental drivers of land-use change, mitigate the risks to food security and agricultural sustainability, and develop evidence-based policies that balance economic development with long-term land conservation. **Figure 1** illustrate the distribution of annual paddy field conversion rate (in percent) in West Bandung Regency and Purwakarta Regency from 2013 to 2021 by mapping of classification and conversion of agricultural land using satellite imagery in our previous study [12].

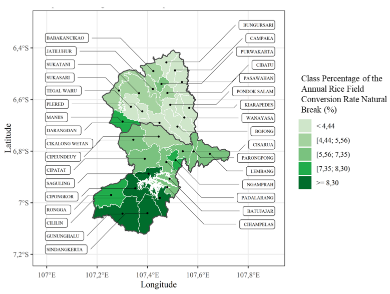
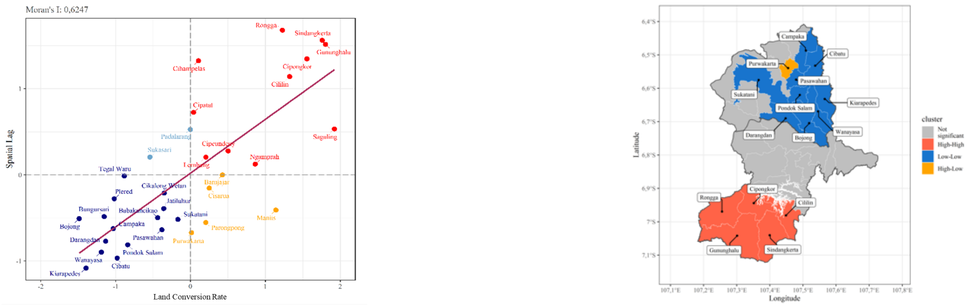


Figure 1. Percentage of Annual Paddy Field Conversion Rate

Satellite imagery analytics enables large-scale, high-resolution monitoring of land use and land cover changes by leveraging advanced remote sensing techniques to classify vegetation with precision [20], [21]. Its potential in agricultural statistics lies in its ability to provide real-time, and objective data on crop types enhancing decision-making for food security and sustainable agriculture [22]. This capability ensures supporting policy development [23]. The categorization class is created through a five-class natural break. The subdistricts of Cililin, Cipongkor, Gununghalu, Saguling, and Sindangkerta, all of which are in West Bandung Regency, have very high yearly land conversion rates, with paddy fields being changed into other (non-agricultural) land at a rate of more than 8.30 percent. On the other hand, subdistricts in Purwakarta Regency have very low annual land use change rates, with rice fields being converted to other (non-agricultural) land at less than 4.44 percent annually.

From **Figure 2**, as can be seen from the scatter plot Moran's I. quadrant I (High-High quadrant) and quadrant III (Low-Low quadrant) include the majority of the observations. This indicates a positive spatial autocorrelation value as evidenced by the Moran's I Index value of 0.625. Positive spatial autocorrelation values demonstrate a globally relationship between values in one location and values in adjacent areas. In other words, areas with a high percentage rate of annual paddy field conversion are close to other areas with a high percentage rate of annual paddy field conversion. On the other hand, areas with low annual paddy field conversion rates are close by areas with low annual paddy field conversion rates.



(a) (b)

Figure 2. (a) Scatter Plot Moran's I and (b) LISA Cluster Map Percentage of Annual Conversion Rate

The LISA cluster map displays the spatial autocorrelation distribution. The Subdistricts of Cililin, Cipongkor, Gununghalu, Rongga, and Sindangkerta, all located in West Bandung Regency, make up the High-High Cluster Region, or a collection of places with a high yearly percentage of rice fields. On the other side, the Low-Low Cluster region, which is made up of The Subdistricts of Bojong, Campaka, Cibatu, Darangdan, Kiarapedes, Pasawahan, Pondok Salam, Sukatani, and Wanayasa in Purwakarta Regency, has a low percentage rate of annual conversion of paddy fields. The High-Low Cluster in The Subdistrict of Purwakarta, Purwakarta Regency, is an unusual instance. The subdistrict has a high yearly paddy field conversion rate, although the areas around it have lower paddy field conversion rates.

Forming a global regression model using the Ordinary Least Squares (OLS) method, such as shown in **Table 4**, is essential to quantify the overall influence of independent variables on agricultural land conversion in West Bandung and Purwakarta Regencies, providing a comprehensive statistical framework to identify significant drivers. assess their magnitude, and establish a baseline for spatial analysis.

Table 4. OLS Global Regression Coefficient of Converted Land

Variable	Coefficient	p-value
Intercept	5.10463	0.00504
Percentage of Population Growth Rate	-0.629399	0.19444
Economic Facility Ratio	0.202764	0.14168
Educational Facilities Ratio	1.29203	0.03847
Health Facility Ratio	-4.30095	0.00941
Region Altitude	0.00374709	0.00069
Regional Altitude Variations	-0.0162564	0.00002
Accessibilities	0.615864	0.01752

The results of testing the classical assumptions demonstrate that the normality and multicollinearity assumptions have been met. To ascertain whether spatial effects are present in the data, spatial autocorrelation is identified and tested. The Global Moran's Index test is used in spatial autocorrelation testing. Based on specific observed variable data. spatial autocorrelation demonstrates the level of linkage between observation locations. In this study, the subdistricts in West Bandung Regency and Purwakarta Regency are compared in terms of their annual percentage rates of land conversion. This linkage can depend on the spatial autocorrelation test with the statistical values of the Global Moran's Index as follows (**Table 5**).

Table 5. Calculation Results of Global Moran's Index Statistics

Variable	Spatial Weighting	Moran's Index	p-value
Percentage rate of annual land conversion	Queen Contiguity	2.1257	0.03353

Table 5 shows the statistical calculation results of the Global Moran's Index. The percentage rate of annually land conversion in West Bandung Regency and Purwakarta Regency exhibits a spatial autocorrelation, according to the Moran I value (Error) with a probability of 0.03353 and a 95% confidence level. The Moran's index number demonstrates a positive spatial autocorrelation, which means that regions that are close to other areas geographically tend to share the same annually land conversion rate characteristic.

Lagrange multiplier statistics used to test the effect of spatial dependence. The spatial lag dependency test and the spatial dependency test on the error are both parts of the dependency test on the dependent variable. **Table 6** shows the outcomes of the Lagrange multiplier test.

Table 6. Calculation Results of Lagrange Multiplier Statistics

Lagrange Multiplier	Df	Value	p-value
LM (lag)	1	4.2231	0.03988
LM (error)	1	0.7260	0.39417

Based on **Table 6**. it can be seen that the probability lag is 0.03988, which is means that there is a dependency lag hence it can be continued to the spatial lag model. For a probability error value of 0.39417, it is more than an alpha of 5 percent, so it cannot be continued to the spatial error model. **Table 7** describes the findings from the calculation of the spatial lag model parameter percentage rate of annually land conversion rates in West Bandung Regency and Purwakarta Regency.

Table 7. Spatial Lag Model Regression Results

Variable	Coefficient	p-value
Intercept	3.940	0.00718
Spatial Lag *	0.321	0.02912
Percentage of Population Growth Rate	-0.685	0.07164
Economic Facility Ratio	0.124	0.27017
Educational Facilities Ratio *	1.010	0.02202
Health Facility Ratio *	-3.079	0.02202
Region Altitude *	0.003	0.00354
Regional Altitude Variations *	-0.013	0.00001
Accessibilities *	0.451	0.02812

* Significant variable

A model is regarded as good when it yields a lower Akaike Information Criterion (AIC) value, a higher log-likelihood, and an increased R-squared, indicating better fit and explanatory power. For a given dataset, the AIC estimates the prediction error and thus serves as a metric for evaluating the relative quality of statistical models. It assesses each model's performance in comparison to alternative models within the same dataset.

The R-Squared test was used to assess the model's capacity to account for how much the independent variables collectively influence the dependent variable. as shown by the R-squared value [24]. The R-Squared value is categorized as strong if it is more than 0.67 [24], [25]. The best modeling results of all candidate linear combination models are an R-Squared of 0.7755 and an AIC of 110.31, which are acquired from the findings of the spatial model. This is because the AIC is smaller and the R-Squared is strong. The spatial lag model may be seen to explain 77.55 percent of the variation in the annual conversion rate of paddy fields based on R-Squared. Because the statistical value of the likelihood ratio test indicates the number 4.24 with a probability of 0.039 or delivers a significant result for the spatial lag model, it indicates that the spatial lag model is superior to the ordinary least square model. A regression spatial lag model is used to continue the investigation, and the outcomes of estimating the regression coefficient are as follows.

$$\mathrm{Y} = 3.940 + 0.321 \sum_{i=1}^{33} \boldsymbol{w}_{ij} y_j{}^* - 0.685\, X_1 + 0.124\, X_2 + 1.010\, X_3^* - 3.079\, X_4^* + 0.003\, X_5^* -0.013\, X_6^* + 0.451\, X_7^* \quad (6)$$

where :

$\hat{Y}$ = Percentage rate of annual land conversion
$\boldsymbol{w}_{ij} y_j$ = Spatial lag
X_1 = Percentage rate of population growth
X_2 = Economic facility ratio
X_3 = Educational facility ratio
X_4 = Health facility ratio
X_5 = Region altitude
X_6 = Regional altitude variations
X_7 = Accessibility

A significant variable is a variable with a probability value of less than 0.05. The significant variable in the output described above is educational facility ratio, health facility ratio, region altitude, regional altitude variation, and accessibility. The intercept value of 3.940 indicates that when all variables are constant, then the annual conversion rate of paddy fields is around 3.940 percent. In general, assuming all other factors remain constant. an increase in the educational facility ratio, region altitude, and accessibility will increase the percentage rate of annual land conversion, while an increase in the health facility ratio and regional altitude variations will decrease that rate. The variable coefficient of the educational facility ratio is 1.010, which means that, given that all other factors remain constant, each unit increase in the educational facility ratio will result in a 1.010 rise in the percentage rate of annual land conversion. Given that all other factors remain constant, each unit increase in the health facility ratio will result in a 3.079 reduce in the percentage rate of annual land conversion. Given that all other factors remain constant, each unit increase in the region altitude will result in a 0.003 rise in the percentage rate of annual land conversion. Given that all other factors remain constant, each unit increase in the regional altitude variations will result in a 0.013 reduce in the percentage rate of annual land conversion. Given that all other factors remain constant, each unit increase in the accessibility will result in a 0.451 rise in the percentage rate of annual land conversion.

The coefficient of $w_{ij}y_j$ in the form of ρ of 0.321 also appears to be a significant coefficient in addition to these five significant explanatory variables. The value of ρ indicates that the rate of annual land conversion in a subdistrict is influenced by the rate of annual land conversion in nearby subdistricts. The probability value for spatial lag ($w_{ij}y_j$) is also smaller than 0.05 which means that spatial influence or adjacent locations will have a significant effect on the percentage rate of annual land conversion in West Bandung Regency and Purwakarta Regency. This shows that the spatial lag model can use the dependence of the spatial lag to provide additional information. The spatial lag coefficient value is 0.321, meaning that the percentage rate of annual land conversion in each subdistrict will be affected by 0.321 times the average percentage rate of annual land conversion in neighboring subdistricts. According to the result of lag equation, if the number of lag variables in surrounding subdistricts rises by one unit, the percentage rate of annual land conversion in a subdistrict increases by 0.321 times the spatial weight of each subdistrict. In other words, if the percentage rate of annual land conversion in a subdistrict rises by one percent, the annual percentage rate of annual land conversion in the subdistricts nearby will also rise by 0.321 percent.

The regional altitude variations has a negative effects on the rate of annual land conversion. This is because the average area variation in West Bandung Regency and Purwakarta Regency is 145.2, indicating that the area heights of the two regions are quite varied. If the variation in the height of this area is greater, it will reduce the rate of annual land conversion. This is because the difference in perpendicularity between the high and low points on the Earth's surface causes the change in height of the area. There are hills, mountains, beaches, and other geographical features in the area if this variation is bigger or greater. Due to the relatively unstable soil conditions. the conversion process is frequently more challenging when agricultural land has a wide range of elevations. For instance, if a sloped piece of land is to be used for construction, the landowner will take the stability of the soil and the possibility of landslides into account. If the geographic conditions of the area are very diverse, it will lower the rate of annual land conversion because if the rice fields have good irrigation, people will hesitate to convert them because it is unlikely that they will find another source of income aside from farming.

Accessibility is calculated from the length of the road divided by the number of residents in the subdistrict. The average number of roads for 1000 residents is 3.079. Accessibility variable has a positive effects on the rate of annual land conversion. With higher accessibility it will make it easier to reach the area. Investors are more likely to purchase land, including agricultural land, in locations that are accessible and, in particular, those that are underdeveloped. As a result of the increase in land values and the ease of access to the land. farmers may decide to sell their agricultural land or develop structures like restaurants, hotels, and other businesses.

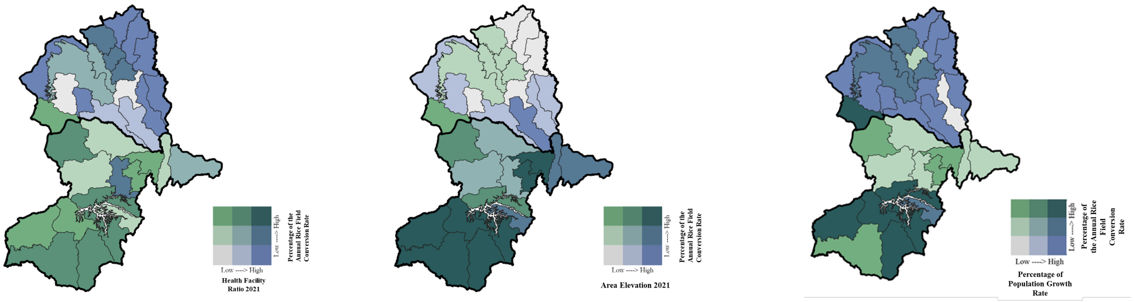
There are insignificant variables, or variables with a probability value of more than 0.05, based on the spatial model's output. The variables that are not significant to the model are the percentage rate of population growth and the economic facility ratio. According to the developed model. the percentage rate of annual land conversion is not significantly influenced by either the economic facility ratio or the percentage rate of population growth. The population is increasing over time, although the rate of population growth has decreased. As a result of population growth, there is an increasing need for land to accommodate basic needs like housing and public facilities, which has led to an increase in the need for land conversion. However, rather than converting land, requests for residential land are fulfilled through the reclamation process in a number of locations in West Bandung Regency. In addition, to accommodate their housing needs, people frequently convert land that is not paddy fields. This is in line with study conducted by Bay et al [26].

According to the developed model. the economic facility ratio variable has no significant effect on the agricultural land conversion. This shows that neither West Bandung Regency nor Purwakarta Regency need to convert large areas of land to build economic and industrial facilities, nor are any changes to paddy fields subject to disincentives by creating new paddy fields in other areas that are still part of the same subdistrict. This is in line with research conducted by Dewinta & Warlina [1].

3.3 Discussion

The relationship between health facility ratios. regional altitude, and population growth rates with the percentage rate of annual land conversion is essential to be invetigated. For instance, Indonesia's health facilities vary widely. with advanced hospitals in cities while rural areas face shortages in medical staff. infrastructure, and essential services. deepening regional health disparities [27]. A bivariate choropleth visualization can be used to analyze it. Since this method requires a correlation between two variables to be effectively visualized. only the independent variables that exhibit significant correlations with the dependent variable—the percentage rate of annual land conversion—are included in the visualization. This approach enhances the interpretability of spatial patterns and provides deeper insights into the underlying dynamics of land conversion. A Pearson correlation test between the health facility ratio (2021) and the percentage rate of annual land conversion reveals a correlation coefficient of -0.465 with a p-value of 0.006. This result. statistically significant at the 95% confidence level, indicates a moderate negative correlation between these variables. The findings suggest that areas with fewer healthcare facilities tend to experience higher rates of agricultural land conversion. likely driven by socio-economic disparities that make agricultural land more vulnerable to non-agricultural development.

The spatial distribution of these relationships is evident in **Figure 3a**. where Cipongkor, Ngamprah, and Rongga in West Bandung Regency, along with Maniis in Purwakarta Regency, exhibit high land conversion rates and low health facility ratios. It suggests that limited access to healthcare may contribute to economic pressures, prompting landowners to convert agricultural land to alternative uses. Conversely, Bungursari. Campaka, and Wanayasa in Purwakarta Regency demonstrate the opposite tren, with low land conversion rates and high health facility ratios. These findings highlight the potential role of social infrastructure in stabilizing agricultural land use, emphasizing the need for integrated spatial planning that aligns with equitable access to healthcare services.



(a) (b) (c)

Figure 3. Bivariate Choropleth Map Indicating Relationship Between the Percentage Rate of Annual Land Conversion with (a) Health Facility Ratios. (b) Regional Altitude, and (c) Population Growth Rates

The statistical analysis reveals a significant relationship between regional altitude and the percentage rate of annual land conversion. A Pearson correlation test yields a correlation coefficient of 0.505 with a p-value of 0.003, indicating a moderate positive correlation between these variables at a 95% confidence level. This result suggests that higher-altitude regions tend to experience higher rates of land conversion, potentially due to the expansion of infrastructure, tourism, or alternative land uses that provide greater economic incentives than traditional agriculture. The spatial distribution of this pattern, as illustrated in **Figure 3b**, shows that subdistricts such as Cililin, Cipongkor, and Sindangkerta in West Bandung Regency exhibit both high land conversion rates and high altitudes. In contrast, Bungursari, Plered, and Pondok Salam in Purwakarta are characterized by low-altitude regions with lower land conversion rates, indicating that elevation differences may influence land-use decisions.

Similarly, an inverse relationship is observed between population growth rates and agricultural land conversion. The Pearson correlation test produces a correlation coefficient of -0.452 with a p-value of 0.008. signifying a moderate negative correlation at the 95% confidence level. This suggests that areas with lower population growth rates tend to experience higher land conversion rates, potentially driven by aging farmer demographics, economic pressures, or declining agricultural viability. **Figure 3c** illustrates this spatial tren, where Cipeundeuy, Gununghalu, and Ngamprah in West Bandung Regency exhibit high land conversion rates despite lower population growth. Conversely, Bungursari, Bojong, and Tegalwaru in Purwakarta demonstrate higher population growth rates but lower rates of land conversion, suggesting that growing populations do not necessarily drive agricultural land conversion in the study area. The spatial regression analysis further refines these findings by identifying the significant factors influencing land conversion across West Bandung and Purwakarta Regencies.

4. CONCLUSION

The increasing conversion of farmland to non-agricultural areas, especially in West Jawa, Indonesia poses significant challenges to farmer livelihoods and food security. This study examines the drivers and impacts of land conversion in West Bandung and Purwakarta Regencies, West Java, Indonesia. Our finding using spatial regression model reveals that economic pressures drive agricultural land conversion in West Bandung and Purwakarta Regencies, with most converted land transitioning into housing areas. Farmers engaging in land conversion are predominantly middle-aged, possess small landholdings, and inherit much of their land. The spatial lag model explains 77.55% of the variation in annual land conversion rates, identifying educational facility ratio, health facility ratio, altitude, altitude variation, and accessibility as significant factors. While educational facility ratio, altitude, and accessibility positively correlate with land conversion, health facility ratio and altitude variation exhibit a negative correlation. Notably, economic facility ratios and population growth rates are not significant determinants. These findings provide critical insights into land-use dynamics, emphasizing the need for policy interventions that balance economic development. food security, and environmental sustainability.

Future research direction are still open for improving the insight by assessing the long-term impacts of agricultural land conversion on food security, water resources, and climate, while evaluating policy effectiveness in regulating land use. Advanced spatial analysis using remote sensing and machine learning could also improve predictive modeling of land conversion trends. Additionally, studying farmer decision-making in response to economic pressures and urban expansion would provide insights for sustainable land management strategies.

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