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Spatial Analysis of Agricultural Poverty in Indonesia and Its Determinants in 2024

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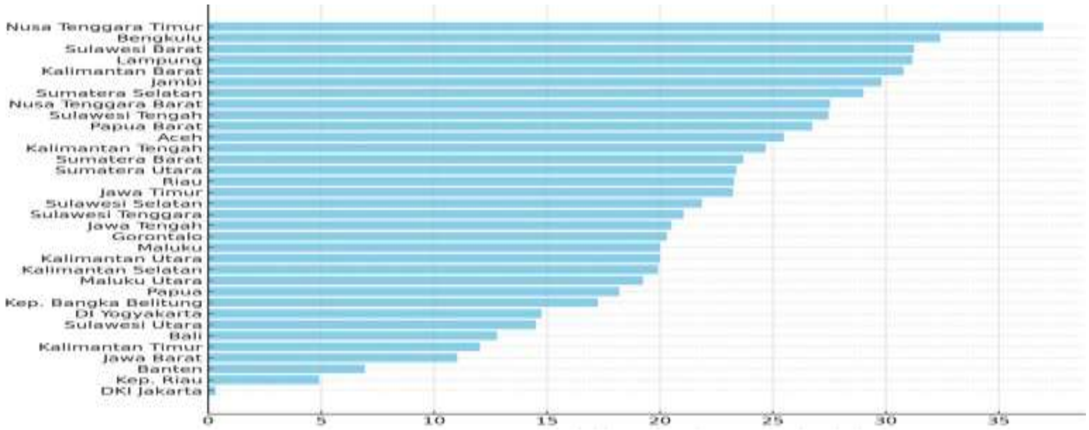
ABSTRACT: This study examines the spatial dynamics and determinants of agricultural poverty in Indonesia by combining descriptive spatial analysis and spatial regression modeling. Using Moran's I and Local Indicators of Spatial Association (LISA), the results reveal strong spatial clustering of agricultural poverty, particularly in provinces with weak infrastructure and limited access to markets and technology. The regression analysis shows that agricultural GDRP exerts a positive and significant effect on poverty, indicating that sectoral growth tends to benefit large enterprises rather than smallholder farmers, thereby intensifying inequality. Similarly, the Farmer's Terms of Trade (FTT) has a positive and insignificant impact, reflecting structural distortions and unequal benefit distribution across regions. In contrast, education demonstrates a negative and significant relationship with poverty, highlighting its role as a key driver in enhancing productivity and reducing vulnerability. Meanwhile, the age of the agricultural labor force shows a positive but statistically insignificant effect, suggesting that experience alone is insufficient for poverty alleviation without adequate education and adaptive capacity. Overall, the findings underscore that agricultural poverty in Indonesia is shaped by structural and spatial factors, requiring inclusive and pro-poor development strategies that focus on human capital investment, equitable resource allocation, and rural infrastructure development to ensure that agricultural growth contributes effectively to poverty reduction.

KEYWORDS: agricultural poverty, spatial analysis, GDP, Farmer's Terms of Trade, education, Indonesia

I. INTRODUCTION

Poverty remains one of the most persistent structural problems and continues to pose a significant challenge to Indonesia's national development affecting not only economic growth but also social stability and human well-being. Despite the implementation of various poverty alleviation programs and policies by the government since the New Order era through to the reform period, poverty rates continue to exhibit complex and multidimensional dynamics that are shaped by an interplay of social, economic, geographical, and political factors (Ardiansyah et al., 2020). According to Statistics Indonesia (BPS, 2024), although the national poverty rate shows a general downward trend, substantial regional disparities and inequalities in the distribution of welfare persist, particularly in rural areas and the eastern provinces of the country. This enduring inequality suggests that poverty is not merely a reflection of insufficient income, but also encompasses broader dimensions such as restricted access to essential services, including quality education, healthcare, decent employment opportunities, and social protection mechanisms. Empirical evidence, such as studies conducted by (Suryahadi et al., 2012), further highlights that poor households are disproportionately vulnerable to economic shocks, including global financial crises and pandemics, and that limited inclusivity in social protection systems exacerbates their precarious conditions. In addition, poverty in Indonesia's agricultural sector exhibits distinct spatial characteristics, reflecting the fact that the socio-economic well-being of farming households is closely tied to the geographical, infrastructural, and environmental contexts in which they operate.

Consequently, poverty is not uniformly distributed across the country but forms complex, interconnected spatial patterns, with clusters of high vulnerability often concentrated in remote and underdeveloped regions. This spatial dimension of poverty underscores the necessity for region-specific and context-sensitive policy interventions that address both structural constraints and local development disparities to achieve sustainable and inclusive rural development (Santi et al., 2020).



Data On Agriculture Poverty Rates Sector In Indonesia 2024 Source: BPS, 2024

The 2024 data on poverty rates in the agricultural sector reveals significant spatial variations across regions in Indonesia. The highest levels of poverty are recorded in East Nusa Tenggara (36.96%), Bengkulu (32.41%), West Sulawesi (31.25%), Lampung (31.18%), and West Kalimantan (30.78%), generally characterized by limited infrastructure, restricted market access, and the dominance of subsistence farming. Conversely, the lowest poverty rates are found in Jakarta (0.32%), Riau Islands (4.91%), Banten (6.94%), West Java (11.04%), and East Kalimantan (12.03%), which are relatively more economically advanced and benefit from diversified non-agricultural employment opportunities. Although several regions in Java, such as Central Java (20.51%) and East Java (23.24%), continue to face relatively high agricultural poverty rates, their conditions are comparatively better than regions outside Java, where geographical challenges are more severe. Overall, this phenomenon underscores that poverty in the agricultural sector is shaped by spatial factors, including geographical disparities, infrastructure gaps, and interregional linkages. Consequently, poverty alleviation policies need to take into account provincial disparities and the local rural context. Poverty is most prevalent in Indonesia, as well as in many other developing countries, among households engaged in the agricultural sector (Romadhon et al., 2022).

This is driven by various structural factors, including low productivity, limited access to markets and technology, and high vulnerability to climate and economic shocks. Data indicate that the majority of the rural poor depend on agriculture for their livelihoods. Research conducted by (Bellon et al., 2020) highlights that approximately 80% of the rural extreme poor rely on agriculture as their primary source of income. In Indonesia, Statistics Indonesia (BPS) also records that the majority of poor households originate from the agricultural sector, with more than 46% of the total poor households working as farmers or agricultural laborers. Another study published by International Scholars Journals further confirms that smallholder farming households and agricultural laborers account for the largest proportion of the rural poor (Wang, 2022). According to data from BPS 2024, agriculture remains the leading source of income among poor households in Indonesia, contributing as much as 49.1%. The distribution of primary income sources among poor households indicates that the agricultural sector remains the dominant livelihood base for the majority of low-income families, accounting for 49.1%. In comparison, the industrial sector contributes 18.04% of poor households' primary income, suggesting that a segment of industrial workers also experiences economic vulnerability due to low wages and precarious employment conditions. Consequently, poverty within the agricultural sector continues to represent a central development challenge in Indonesia, particularly in rural areas where most poor households rely on agriculture as their main source of livelihood.

According to (Suryahadi et al., 2012), growth in the agricultural sector contributes the largest share to poverty reduction, accounting for approximately 66 (Udi et al., 2023) percent at the national level and as much as 74 percent in rural areas. This finding underscores that improvements in agricultural productivity, expanded access to technology, and stronger market integration exert a direct impact on enhancing the welfare of poor households. Poverty in the agricultural sector is not solely shaped by low productivity and limited market access, but also by macroeconomic dynamics and the socio-demographic characteristics of farmers. Agricultural Gross Domestic Regional Product (GDRP) plays a pivotal role, as increases in output and value added have been empirically shown to contribute to poverty reduction in rural area. Furthermore, the Farmer's Terms of Trade (NTP) serves as a critical indicator of welfare, a low NTP reflects an imbalance between the prices farmers receive for their produce and the production costs they incur, thereby weakening their purchasing power (Suparman et al., 2024).

According to (Makower & Nurkse, 1953) argues that poverty is the outcome of interrelated factors that mutually reinforce one another, ultimately trapping a country in a persistent state of deprivation. His well-known assertion, "a poor country is poor because it is poor", emphasizes the cyclical and self-perpetuating nature of poverty. According to Nurkse, poverty is not only a consequence of the absence of past development, but also the result of structural barriers that hinder future growth. The essence of his vicious circle of poverty lies in the limited capacity for capital accumulation, which depends both on low savings and weak incentives for investment. In the agricultural sector, poverty emerges from a reinforcing cycle between low income and low productivity. Within this study, the Gross Domestic Ragional Product (GDRP) of agriculture reflects production capacity and its contribution to the economy a low GDRP indicates limited output, resulting in persistently low farmer incomes. The Farmers' Term of Trade (FTT) represents purchasing power; when low, it reveals that farmers' incomes are insufficient to meet living costs or agricultural inputs, thereby constraining investment in technology or productivity improvements. Education is another crucial factor, as limited schooling restricts farmers' access to innovation, skills, and opportunities in modern sectors, leaving them reliant on traditional, low-yield practices. Low education levels limit farmers' ability to access innovations, skills, and opportunities in modern sectors, leaving them dependent on traditional practices with low productivity. Research shows that literacy and education play a crucial role in the adoption of agricultural technology and the improvement of farmers' welfare(Dzulfian, 2025). Furthermore, labor age structure influences this dynamic older workers tend to be less adaptive to new technologies, while younger workers if not equipped with adequate education and skills are similarly unable to drive productivity growth. Older agricultural workers often struggle to adapt to modern technologies that could enhance crop yields, while younger workers with limited education are unable to capitalize on innovation opportunities to escape the poverty trap. Consequently, an aging labor force and the lack of skills among younger generations have become critical factors hindering productivity growth and poverty reduction in rural areas (Ngadi et al., 2023).

Demographic factors are also highly relevant, with the predominance of elderly farmers in Indonesia indicating both reduced labor productivity and slower adoption of new technologies (Ngadi et al., 2023). In addition, education functions as a key determinant, since low levels of educational attainment restrict farmers' access to market information, technological innovations, and empowerment programs that could enhance their well-being (Fatwa et al., 2022). Thus, agricultural poverty is multidimensional, reflecting not only resource constraints but also structural challenges rooted in macroeconomic conditions, welfare indicators, and socio-demographic factors. The issue of agricultural poverty constitutes a critical area of inquiry due to the complexity of its underlying determinants and the substantial contribution of the agricultural sector to the livelihoods of poor households in Indonesia. The high proportion of farmers living under vulnerable conditions indicates that improving productivity and market access alone is insufficient to achieve significant poverty reduction. Macroeconomic variables, such as agricultural GDRP growth and the Farmer's Terms of Trade, along with socio-demographic factors, including farmers' age and educational attainment, create multidimensional dynamics that require comprehensive analysis. Rigorous research in this area is essential not only to identify the root causes of poverty in agriculture, but also to design more targeted, inclusive, and sustainable policy strategies aimed at enhancing farmers' welfare and reducing regional disparities (Corral et al., 2017).

2. THEORITICAL FRAMEWORK AND EMPIRICAL STUDIES

2.1 Agricultural Poverty

The Vicious Circle of Poverty theory, as proposed by (Makower & Nurkse, 1953), conceptualizes poverty as a self-reinforcing and continuous cycle, lacking a clear point of origin or termination. According to Nurkse, poor countries remain impoverished due to low productivity, which leads to low income, limited savings, and minimal investment. This, in turn, results in capital scarcity, market imperfections, and underdevelopment, which further depress productivity, creating a cycle that is difficult to break. Breaking this cycle requires interventions that enhance productivity and investment, as well as improving access to capital and technology. According to (Chambers, 1983), rural poverty, particularly in the agricultural sector, is not merely characterized by income insufficiency but also encompasses vulnerability to risk and spatial isolation, which restricts farmers' access to basic services and economic opportunities. Meanwhile, (Todaro & Smith, 2012) emphasize that poverty in the agricultural sector is structural, driven by unequal resource distribution, weak development policies, and limited rural economic diversification. Consequently, the theory of agricultural poverty underscores that these conditions are not solely caused by individual factors but also by interacting institutional and spatial determinants, necessitating comprehensive and context-specific policy approaches. This is particularly relevant in the agricultural sector, where farmers' productivity and welfare levels are strongly influenced by external factors such as agroecological conditions, distance to market centers, and the quality of regional infrastructure.

2.2 Spatial Theory

Spatial theory constitutes a conceptual framework that emphasizes the interrelationship between space, location, and human as well as economic activities within a given territory. It is grounded in the assumption that space is not a neutral entity, but rather a determining factor that shapes the distribution of economic activities, patterns of interaction, and the level of growth across regions. Within regional economics, spatial theory is employed to explain why economic activities tend to concentrate in specific locations, why interregional disparities emerge, and how patterns of agglomeration or dispersion develop (Proost & Thisse, 2019). The intellectual foundation of spatial analysis dates back to the classical era. Johann Heinrich von Thünen, in his seminal work The Isolated State (1826), introduced the agricultural location theory, which explains how distance from the central market influences land use patterns, transportation costs, and agricultural returns. His framework highlights the critical role of spatial factors in determining efficiency and economic profitability (Rodriguez, 2021). Subsequently, (Christaller & Baskin, 1966) developed the Central Place Theory, which outlines the hierarchical organization of cities and service centers based on the concepts of threshold and range. This theory illustrates how spatially distributed growth centers emerge to serve surrounding areas.

August Lösch (1940) further extended Christaller's framework by incorporating general equilibrium principles, thereby stressing the systemic interdependencies of economic activities across space. Together, these contributions form the classical foundations of spatial theory Haggett in1967 (Renfrew, 1969). In its modern development, spatial theory has expanded beyond location and land-use studies into the domain of New Economic Geography (NEG). Within this paradigm, scholars such as Paul Krugman emphasize the roles of agglomeration, economic externalities, and transportation costs in explaining the spatial concentration of economic activities. NEG models demonstrate that economies of scale and the presence of large markets attract economic concentration, which in turn reinforces the spatial advantages of specific regions. However, these agglomeration dynamics also generate spatial inequalities, as regions with limited access to transportation, technology, or markets tend to lag behind in the development process (Fujita et al., 2001).

In the context of agricultural development, spatial theory is particularly relevant in explaining the disparities between rural and urban areas. Agriculture, as a land-based sector, is highly influenced by location, market accessibility, and the availability of transportation infrastructure. Rural regions that are distant from economic centers often face high distribution costs, limited access to technology, and weak integration into global value chains, thereby reinforcing cycles of poverty. Hence, a spatial perspective provides critical insights into why farmers' productivity and welfare remain low despite the sector's vital role in food security and employment. Conceptually, spatial theory also underpins regional development policies aimed at reducing spatial disparities. By improving connectivity, fostering the growth of new regional centers, and strengthening infrastructure in peripheral areas, spatial inequalities can be mitigated. Thus, spatial theory serves not only as an analytical framework to explain regional differences, but also as a foundation for designing inclusive and equitable development strategies.

3. METODOLOGY

This study employs two analytical approaches, namely descriptive and inferential analysis. The descriptive analysis is conducted through thematic map visualization to illustrate the spatial patterns of poverty in the agricultural sector at the provincial level in Indonesia in 2024. The study utilizes secondary data, sourced from the Ministry of Agriculture and statistic Indonesia (BPS) Meanwhile, the inferential analysis employs a spatial regression method to evaluate the influence of independent variables, such agricultural GDRP, Farmer's Terms of Trade (FTT), education, and the age of the agricultural labor force on agricultural poverty levels in Indonesia, while taking into account spatial effects across regions in the agricultural sector, taking into account spatial effects between regions. All hypothesis testing is conducted at a 5% significance level. The spatial regression analysis is performed using GeoDa software, which is designed to facilitate users in estimating spatial regression models, determining appropriate model specifications, interpreting estimation results, and conducting diagnostic tests to detect spatial autocorrelation in the data (Anselin, 2005). The implementation of the spatial regression procedure in this study follows several systematic stages.

3.1 Cross-Sectional Spatial Regression Method

The cross-sectional regression method is a statistical analysis approach employed to examine the relationship between a dependent variable (response) and one or more independent variables (predictors) based on data collected at a single point in time, while encompassing multiple observational units. Spatial weighting is a crucial element in spatial data analysis, serving to represent the spatial relationships among geographic locations or analytical units. A spatial weight matrix is employed to assign weights between observed locations based on their neighborhood relationships. The elements of the spatial weight matrix are structured as follows:

$$\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & w_{NN} \end{bmatrix}$$

The rows and columns of the spatial weight matrix represent the regions serving as analytical units. W_{ij} denotes the weight of the spatial relationship between region i and region j, where $W_{ij} \geq 0$, $W_{ij} = W_{ji}$, and $W_{ii} = 0$ for i=1,2,3,…,N. Spatial regression is an econometric approach employed when the data contains spatial elements, specifically the presence of dependence or influence among geographic locations. This method is an extension of the Ordinary Least Squares (OLS) regression, which theoretically assumes the absence of correlation among residuals (independence). However, in spatial data such as observations across administrative regions (villages, districts, provinces), this assumption is frequently violated due to spatial autocorrelation, meaning that the value of an observation is influenced by the values of geographically proximate observations. In general, there are two main models in spatial regression: the Spatial Lag Model (SLM) and the Spatial Error Model (SEM). The lag model is applied when spatial influence occurs on the dependent variable, whereas the error model is used when spatial influence is present in the residuals of the model.

Steps in Spatial Regression

1. Analysis Constructing the Spatial Weight Matrix (SWM)

Determine the relationships among regions, for example: contiguity (Queen/Rook) where regions sharing a direct border are considered neighbors, or distance-based criteria where regions within a certain radius are treated as neighbors. This matrix is used to calculate the spatial influence among observational units.

2. Testing Spatial Autocorrelation (Moran's I)

Assess whether there is a spatial pattern in the dependent variable. A significant Moran's I indicates the presence of spatial effects that need to be modeled.

3. Local Spatial Autocorrelation Test — Local Moran's I (LISA)

Local Moran's I, or LISA, is derived from the Global Moran's I and provides local information about the strength and pattern of spatial autocorrelation, rather than giving a general overview of the entire area. LISA helps identify clusters such as "High–High" (high values surrounded by high values), "Low–Low", and outliers like "High–Low" or "Low–High".

4. Lagrange Multiplier (LM) Test

Determine the most appropriate spatial model:

- LM-lag → use Spatial Lag Model (SLM) if spatial influence occurs in the dependent variable.
- LM-error → use Spatial Error Model (SEM) if spatial influence occurs in the error term.
- Robust LM → used when both LM-lag and LM-error are significant.

5. Estimating the Spatial Regression

Model Execute the SLM or SEM using spatial econometrics software, such as GeoDa.

6. Diagnostic Testing and Result

Interpretation Check model validity and the significance of explanatory variables. Interpret both direct and indirect (spillover) effects among regions.

4. RESULTS AND DISCUSSION

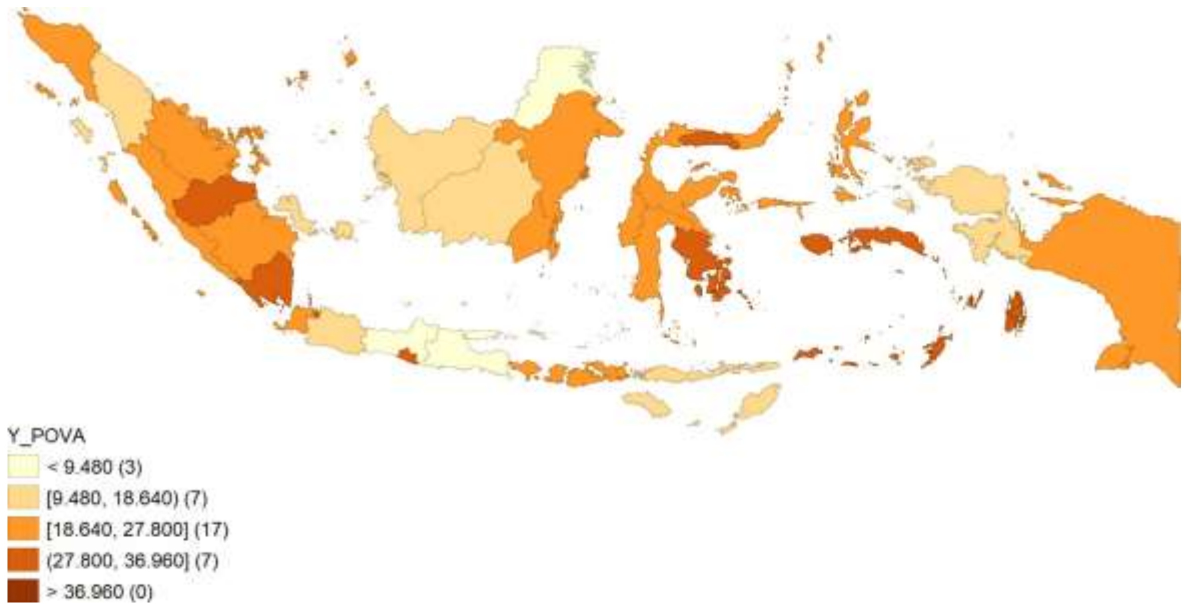


Figure 1. Spatial Distribution of Agricultural Poverty Across Indonesian Provinces in 2024

Source: Data Processed by Geoda

The thematic map presented in this study illustrates the spatial distribution of poverty among the agricultural population in Indonesia at the provincial level. The color gradient represents the intensity of poverty within this sector, ranging from light yellow (low poverty levels) to dark brown (higher poverty levels). According to the map legend, no region falls into the category of extreme poverty (>36,960), but several provinces are classified as high poverty (27,800–36,960), such as certain areas in Sulawesi and Sumatra. In contrast, regions with the lowest poverty levels (<9,480) are predominantly located in western Indonesia, including parts of Java and Kalimantan. This distribution pattern indicates that agricultural poverty is unevenly distributed and exhibits distinct spatial characteristics. For instance, geographically remote areas such as Papua, Maluku, and Nusa Tenggara, although not always in the highest poverty category, demonstrate significant vulnerability due to limited access to infrastructure, technology, and agricultural markets. Conversely, Java, as the national economic center, exhibits relatively lower poverty levels, reflecting a strong correlation between infrastructure development, industrialization, and poverty reduction in the agricultural sector.

Acocording to Firdaus et al. (2016) emphasize that agricultural poverty is multidimensional, influenced by land access, productivity, agricultural commodity prices, and farmers' adaptive capacity to climate change and market fluctuations. Farmer poverty is also closely linked to land ownership structures and unequal access to production inputs, which remain skewed in many regions of Indonesia. Furthermore, the World Bank (2020) notes that spatial inequalities in development and access to basic services, such as education and healthcare, exacerbate farmers' welfare deficits in underdeveloped regions. Understanding this spatial distribution is critical for the formulation of targeted, regionally-informed policies. Policy interventions must consider spatial dimensions, particularly in the allocation of agricultural assistance programs, rural infrastructure development, and technical training and support for farmers in impoverished areas. Consequently, such mapping serves as an essential tool for data-driven, spatially-oriented development planning.

4.1. Spatial Approach to Agricultural Sector Poverty in Indonesia in 2024

Table 1. Results of Moran's I Test Indicating Spatial Autocorrelation in Model Residuals Source: Data Processed by Geoda

	TEST	MI/DF	VALUE	PROB	
	Moran's I (error)	0.0967	2.3200	0.02034	

The results of Moran's I test on the residuals indicate an index value of 0.0967, with a corresponding statistic of 2.3200 and a p-value of 0.02034. This result is significant at the 5% significance level, indicating that the null hypothesis of no spatial autocorrelation in the model residuals can be rejected. In other words, there exists significant spatial autocorrelation in the errors of the regression model employed. The positive Moran's I value suggests a positive spatial pattern, meaning that regions with high residual values tend to be located near other regions with similarly high residuals, and vice versa. This indicates the presence of spatial clustering in the residuals.

Figure 2. Local Moran's

Source: Data Processed by Geoda

Spatial Analysis of Agricultural Poverty in Indonesia and Its Determinants in 2024

The map presented represents the visualization of local spatial significance of agricultural sector poverty (Y_POVA) in Indonesia, likely derived from the Local Indicators of Spatial Association (LISA) or local Moran's I test. This map classifies provinces based on the p-values indicating the spatial significance of the relationship between regions for the variable Y_POVA, i.e., agricultural sector poverty. Provinces shaded in gray indicate that no significant spatial relationship exists between the poverty level in these provinces and their neighboring regions (not significant, totaling 25 provinces). Conversely, green shades with varying intensity represent different levels of spatial significance, ranging from weak ($p < 0.05$) to strong ($p < 0.001$). Provinces in Central and East Kalimantan dominate the high significance classification, particularly two provinces in the $p < 0.001$ category, indicating a very strong spatial cluster—meaning that agricultural poverty in these provinces is significantly correlated with the poverty levels of neighboring provinces. Additionally, some regions outside Kalimantan, such as West Papua, Bali, and parts of Sumatra, also show significant spatial relationships, albeit at lower significance levels ($p < 0.05$). Overall, this map demonstrates that agricultural poverty is not entirely randomly distributed geographically but exhibits local clustering patterns in certain regions of Indonesia, especially in Kalimantan, which should be considered in spatial policy planning. Both regional and central governments need to account for neighboring dynamics when designing poverty interventions, as spillover effects play a critical role in determining agricultural community welfare. A regionally based or clustering approach is therefore essential for addressing spatially concentrated poverty.

Figure 3. Local Moran's I

Source: Data Processed by Geoda

The displayed map represents the results of a Local Moran's I analysis (LISA cluster map) of agricultural sector poverty (Y_POVA) at the provincial level in Indonesia, identifying spatial clustering patterns, i.e., the relationship between the poverty level of a province and those of its neighboring regions. The map classifies provinces into five categories based on spatial significance and interregional relationships. Provinces shaded in dark red (High-High), such as in West Sumatra, West Kalimantan, Bali, and Southwest West Papua, constitute high-poverty clusters surrounded by provinces with similarly high poverty levels, indicating a pronounced spatial concentration of poverty. This finding is significant as it suggests that poverty in these provinces is not merely a local issue but is closely linked to surrounding conditions, necessitating regional or cross-administrative approaches for effective interventions.

Conversely, dark blue areas (Low-Low), encompassing much of Central Kalimantan, South Kalimantan, and East Kalimantan, represent provinces with low agricultural poverty levels that are also surrounded by provinces with similarly low poverty, reflecting positive clustering of relatively prosperous conditions. Additionally, one province, North Kalimantan, appears in light red (High-Low), indicating a spatial anomaly where high agricultural poverty exists amidst neighboring low-poverty regions. This may reflect local policy failures or unique structural characteristics that warrant further investigation. No Low-High clusters were observed, indicating the absence of provinces with low agricultural poverty surrounded by high-poverty areas. The remaining 25 provinces are shown in gray, indicating no significant spatial pattern. Overall, the map provides strong evidence that agricultural poverty in Indonesia is not randomly distributed but exhibits distinct spatial patterns, both in terms of concentrated poverty and relative prosperity. Consequently, poverty alleviation policies should consider interregional linkages, particularly when addressing High-High clusters and High-Low anomalies.

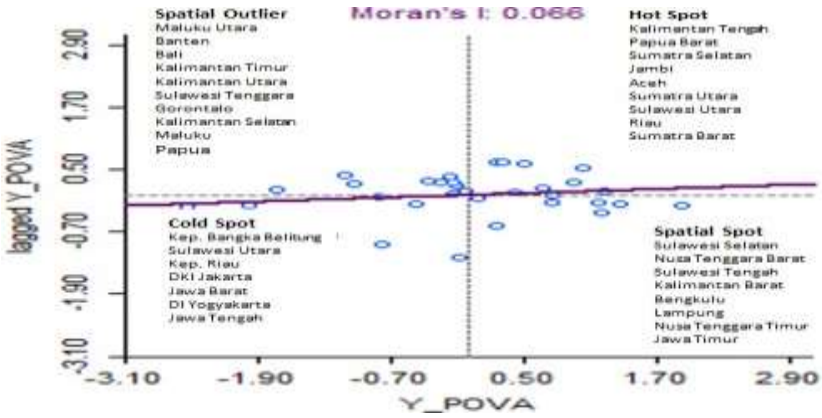


Figure 4. Moran Scatterplot Source: data processed by Geoda

The figure presents the results of a Moran's I scatter plot analysis, which measures spatial autocorrelation among provinces in Indonesia with respect to agricultural sector poverty. The Moran's I value of 0.066 indicates a weak yet positive spatial correlation, suggesting that there remains some degree of interregional linkage, albeit not strong. The scatter plot is divided into four quadrants, illustrating the spatial characteristics of regions. First, the Hot Spot (Quadrant I) includes provinces such as Central Kalimantan, West Papua, South Sumatra, Jambi, and Aceh. These regions exhibit high variable values surrounded by neighboring areas with similarly high values, indicating clusters of high-poverty regions. Second, the Cold Spot (Quadrant III) encompasses Bangka Belitung, North Sulawesi, Riau Islands, DKI Jakarta, West Java, Yogyakarta, and Central Java, representing provinces with low values surrounded by other low-value areas, reflecting clusters of relatively prosperous regions. Third, Spatial Outliers (Quadrant II), such as North Maluku, Banten, Bali, Papua, and East Kalimantan, represent areas with low values surrounded by high-value neighbors, or vice versa, indicating spatial anomalies. Lastly, Spatial Spots (Quadrant IV) include South Sulawesi, West Nusa Tenggara, West Kalimantan, Bengkulu, Lampung, and East Java, denoting provinces with high values located near regions with low values. Overall, this pattern reveals an imbalance in interregional development, where growth and welfare are unevenly distributed, resulting in concentrated pockets of poverty in certain areas, particularly in eastern Indonesia.

Tabel 2. Spatial Diagnostics Source: data processed by Geoda

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.0967	2.3200	0.02034
Lagrange Multiplier (lag)	1	5.9125	0.01503
Robust LM (lag)	1	7.4011	0.00652
Lagrange Multiplier (error)	1	0.9470	0.33049
Robust LM (error)	1	2.4355	0.11861
Lagrange Multiplier (SARMA)	2	8.3480	0.01539

The results of the spatial diagnostic tests indicate the presence of significant spatial autocorrelation, as evidenced by a Moran's I (error) value of 0.0967 with a p-value of 0.02034. This suggests that interregional values are not random but exhibit a specific spatial pattern. The Lagrange Multiplier (LM) tests and their robust variants indicate that the spatial lag model is more appropriate, with significant LM (lag) and Robust LM (lag) values, compared to the spatial error model, which is not significant. Although the LM SARMA test is also significant, the robust results confirm that the spatial lag model remains the most relevant approach for capturing spatial dependence in this dataset.

Tabel 3. Spatial Lag Model (SLM) – Estimation Source: data processed by Geoda

Variable	Coefficient	Std. Error	z-value	Probability
W_Y_POVA	0.28786	0.224104	1.28449	0.19897
CONSTANT	51.1076	10.3648	4.9309	0.00000
X1_GDPA	0.333114	0.0916796	3.63346	0.00028
X2_FER	0.0366999	0.0425851	0.861802	0.38880
X3_OLD	0.00722789	0.00588364	1.22847	0.21927

X4_EDU	-5.24307	0.968668	-5.41266	0.00000
R-Suared	0.714771			

The estimation results of the Spatial Lag Regression model indicate that the variables studied exert varying influences on agricultural sector poverty in Indonesia, taking into account the spatial effects from neighboring regions. The spatial lag coefficient (W_Y_POVA) is positive (0.28786), suggesting that agricultural poverty in a province tends to increase if neighboring provinces also experience high poverty levels. However, this effect is not statistically significant (p = 0.19897), implying that the spatial influence is not strong enough to draw definitive conclusions. The Gross Domestic Product (GDP) of the agricultural sector, conversely, exhibits a positive and significant relationship (p = 0.00028) with poverty, paradoxically indicating that increased agricultural economic output has not yet succeeded in reducing poverty, likely because the benefits of growth are captured primarily by large-scale enterprises rather than smallholder farmers. In contrast, farmers' education shows a negative and highly significant effect (coefficient = -5.24307, p = 0.00000), highlighting that improvements in education substantially reduce agricultural poverty by enhancing adaptive capacity, economic decision-making, and access to technology. Meanwhile, the farmer exchange rate and young farmers' age are not statistically significant, suggesting that these variables do not directly contribute to regional variations in poverty within this model. The R-squared value of 0.7148 indicates that approximately 71% of the variation in agricultural sector poverty can be explained by the model, reflecting reasonably strong explanatory power. Overall, these findings underscore the importance of policy interventions focused on human capital development in the agricultural sector, as well as the need to reassess the distribution of benefits from agricultural economic growth to ensure a more inclusive impact on poverty reduction.

The Effect of Agricultural Sector GDRP on Agricultural Sector Poverty

The Gross Domestic Regional Product (GDRP) of the agricultural sector exerts a positive and significant effect on agricultural sector poverty in Indonesia. This finding indicates that an increase in agricultural GDRP does not automatically translate into successful poverty alleviation; rather, it may contribute to an increase in the number of poor individuals within the sector. Theoretically, this phenomenon can be explained through structuralist perspectives, which view poverty as a result of unequal resource distribution and limited economic access. Smallholder farmers and agricultural laborers are often trapped within an exploitative economic structure due to limited land ownership, capital, technology, and market access. This view aligns with Todaro and Smith (2012), who assert that economic growth does not necessarily reduce poverty if resource distribution structures remain unequal. Furthermore, the dualistic economic theory proposed by Boeke and developed by (Lewis, 1954) is also relevant, where traditional agricultural sectors dominated by smallholders coexist alongside modern sectors such as large plantations or agribusinesses, yet without productive linkages. Consequently, productivity and output gains in modern subsectors are primarily enjoyed by large enterprises, while smallholder farmers remain as low-wage laborers without gaining added value from growth.

This finding is consistent with (Rosdiyanto & Sukartini, 2025) increase in GDRP per capita does not necessarily guarantee poverty reduction and, in some cases, may even exacerbate inequality and intensify poverty. Consequently, poor communities in underdeveloped regions remain trapped in poverty, as they lack access to opportunities generated by economic growth. This disparity can be further aggravated if the increase in GDRP is disproportionately captured by higher-income groups, while impoverished communities lack the capacity to benefit from such growth. Thus, despite the rise in per capita GRDP, widening economic inequality may cause poverty levels to remain high or even increase. Empirical evidence from the study conducted by (Berutu & Usman, 2018; S.Achmad, 2016; Takaredas et al., 2024) indicates that GDRP has a positive and statistically significant relationship with poverty levels. Therefore, based on empirical evidence, theoretical frameworks, and prior studies, it can be concluded that agricultural GDP growth without accompanying structural reforms, asset redistribution, and capacity building for smallholders will only widen inequalities and reinforce structural poverty. Inclusive and pro-poor policies, emphasizing resource redistribution, are thus essential to ensure that agricultural sector growth effectively reduces rural poverty.

The Effect of Farmer's Terms of Trade on Agricultural Sector Poverty

The Farmer's Terms of Trade (FTT) exerts positif and not significant effect on agricultural sector poverty in Indonesia. This finding an increase in the Farmer's Term of Trade (FTT) may paradoxically exert a positive influence on rural poverty levels, rather than reducing them. While the FTT is generally intended to capture improvements in farmers' purchasing power, its rise may also reflect structural distortions in agricultural markets. The results of the study indicate that the Farmer's Terms of Trade (FTT) has a positive but statistically insignificant effect on agricultural poverty in Indonesia. This implies that, although an increase in FTT can potentially raise farmers' income through improved output prices relative to input costs, the effect is not strong enough to significantly reduce poverty levels. The statistical insignificance of this relationship may be attributed to other influencing factors such as low education levels, limited access to capital, and the slow adoption of agricultural technology. Therefore, policies aimed at improving FTT should be complemented by efforts to enhance farmers' capacity and rural infrastructure to achieve a more effective impact on poverty reduction. According to structuralist and spatial theories of development, changes in relative prices can generate uneven effects across socio-economic groups and regions. For example, when agricultural output prices increase, farmers who are net consumers rather than net producers of food may face higher living costs, thereby worsening their poverty status despite an apparent increase in FTT. Similarly, higher terms of trade may disproportionately benefit larger and more capitalized farmers who are able to sell surplus production at favorable prices, while smallholders with limited marketable output remain excluded from these gains. In this case, the rise in FTT reinforces spatial inequality by concentrating benefits in areas with stronger market linkages and infrastructure, while peripheral rural regions experience little or no improvement. This interpretation aligns with the concept of cumulative causation Myrdal, 1957 in (Todaro & Smith, 2012) and the vicious circle of poverty (Nurkse, 1953), wherein structural constraints prevent certain groups from benefiting from macro- level improvements. Consequently, although FTT is often used as an indicator of rural welfare, in practice its positive movement can coincide with a simultaneous increase in rural poverty, particularly where access to markets, productive assets, and technology is unevenly distributed.

Empirical evidence demonstrates that the Farmer's Terms of Trade (FTT) has a positive statistically impact on poverty within Indonesia's agricultural sector. This finding implies that while improvements in FTT may enhance farmers' income through better relative price conditions, such effects are insufficient to produce a substantial reduction in poverty levels. The insignificance of this relationship suggests the presence of structural and institutional constraints, including limited access to productive assets, inadequate education, and low levels of technological adoption, which diminish the potential benefits of favorable trade conditions. Consistent with this, (Nurfajari, 2024) and (Rahmanto et al., 2020) emphasize that despite the generally positive association between FTT and farmers' welfare, its influence remains statistically weak due to persistent barriers in rural infrastructure and market efficiency. According to the structuralist view, improvements in relative agricultural prices do not benefit all farmers equally, as market structures and asset inequalities generate asymmetric outcomes (Myrdal, 1957; Nurkse, 1953). Larger, capital-intensive farmers are better positioned to capture the gains from rising FTT, whereas smallholders who are often net consumers and possess only limited surplus to sell face higher consumption and input costs. Thus, an increase in FTT does not automatically improve the welfare of marginal farmers but may instead exacerbate poverty among vulnerable groups. From the perspective of spatial development theory, the concentration of benefits in core regions with stronger infrastructure and market linkages further reinforces regional disparities, leaving peripheral areas increasingly disadvantaged (Proost & Thisse, 2019). Therefore, the positive and significant relationship between FTT and poverty can be interpreted as evidence of structural dualism within the agricultural economy, where aggregate improvements in trade indicators mask underlying distributional inequalities. This perspective highlights the importance of complementary policiessuch as expanding market access, enhancing smallholder productivity, and reducing transaction costs so that improvements in FTT genuinely contribute to poverty alleviation rather than intensifying it.

The Effect of Farmers' Age on Agricultural Sector Poverty

The age of the labor force in the agricultural sector in Indonesia exhibits a positive but statistically insignificant effect on agricultural sector poverty. This finding implies that while an increase in the average age of agricultural workers may tend to contribute to higher poverty levels, the effect is not strong enough to be considered decisive. Theoretically, age is often associated with accumulated experience and traditional farming knowledge. However, older workers generally face constraints in adapting to modern agricultural technologies, innovations, and alternative income-generating opportunities. Within the framework of modern labor economics, an aging workforce is considered less flexible and less adaptive, which can potentially reduce competitiveness in a sector that is increasingly technology-driven (Tong et al., 2024). In the Indonesian context, where agriculture is still dominated by labor-intensive and traditional practices, the rise in the proportion of older farmers may contribute to higher poverty rates. Nevertheless, the statistical insignificance of this effect suggests that other factors such as education, access to capital, and technology adoptionplay a more critical role in determining poverty reduction within the agricultural sector (Udi et al., 2023).

These findings are consistent with previous studies, such as (Sari & Falianto, 2020), which indicate that labor force age does not have a significant impact on poverty because farmers' productivity is more strongly influenced by factors such as education level, access to capital, and utilization of agricultural technologies. Therefore, based on empirical evidence, theoretical considerations, and prior research, it can be concluded that age is not a determining variable in alleviating poverty in the agricultural sector. The implication is that poverty reduction policies in this sector should focus on enhancing human capital through education, training, and technology adoption rather than relying solely on age as a benchmark for farmers' economic contribution. Furthermore, research by (Ngadi et al., 2023) highlights the challenges posed by an aging agricultural workforce in Indonesia. The study indicates that a significant portion of farmers are aged 45 and above, and the younger generation tends to migrate to urban areas for better employment opportunities. This demographic shift can lead to a decline in agricultural productivity and exacerbate poverty in rural areas. These studies suggest that while age may influence certain aspects of agricultural labor, it is not a decisive factor in determining poverty levels. Addressing poverty in the agricultural sector may require a more comprehensive approach, focusing on education, access to resources, and technological advancements rather than solely on the age of the labor force.

The Effect of Education on Agricultural Sector Poverty

Education exerts a negative and significant effect on agricultural sector poverty in Indonesia. This finding reflects that the higher an individual's level of education, the lower the likelihood of being in poverty. Theoretically, this phenomenon can be explained through the Human Capital theory proposed by Gary Becker, which emphasizes that education is a form of human capital investment capable of enhancing cognitive capacity, productivity, efficiency, and innovative capabilities of economic actors. In the context of agriculture, education plays a crucial role in improving farmers' ability to access market information, understand and adopt modern cultivation technologies, and manage their farms more effectively.

Consequently, education not only promotes income growth but also broadens opportunities for social mobility, diversifies income sources, and reduces vulnerability to economic shocks. Empirical findings from various studies support this argument. For instance, (Sari & Falianto, 2020) demonstrate that educational attainment significantly contributes to poverty reduction, while (Aini & Nugroho, 2023) highlight that education helps reduce poverty through increased income and decreased dependence on traditional agriculture. Similar results are reported by Sofira (2022) and (Purmini & Rambe, 2021), consistently showing that education has a negative and significant effect on agricultural sector poverty. Therefore, based on empirical evidence, theoretical frameworks, and previous studies, it can be concluded that education is a key determinant in alleviating poverty in the agricultural sector. The implication is that enhancing access to and quality of education in rural areas represents a fundamental strategy for breaking the cycle of structural poverty and promoting more inclusive and sustainable agricultural development.

CONCLUSION

Based on the results of spatial and regression analyses, this study confirms that poverty in Indonesia's agricultural sector is multidimensional and influenced by a combination of economic, demographic, and spatial factors. The growth of agricultural GDP was found to exert a positive and significant effect on poverty, indicating that increases in agricultural output do not automatically reduce poverty but may instead exacerbate inequality, as the benefits of growth are largely captured by large- scale enterprises rather than smallholder farmers. In contrast, education demonstrated a negative and significant effect on poverty, underscoring that improving human capital through access to education is a critical instrument in breaking the cycle of poverty. The Farmer's Terms of Trade (FTT) also plays a vital role as a welfare indicator; although its increase may paradoxically correlate positively with poverty due to structural distortions, the findings highlight the need for more inclusive market-based policies to ensure that smallholder farmers can benefit. The age of the agricultural labor force showed a positive but statistically insignificant effect on poverty, suggesting that experience and age alone are insufficient without complementary support in the form of modern skills, capital access, and agricultural technology adoption. These findings indicate that poverty alleviation policies in the agricultural sector cannot rely solely on economic growth, but must be accompanied by structural reforms, improvements in education, asset redistribution, enhanced market access, and the development of rural infrastructure. Therefore, spatially oriented, pro-poor, and inclusive development strategies should be prioritized as the foundation for policymaking to ensure that agricultural growth genuinely enhances farmers' welfare while simultaneously reducing regional disparities.

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