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Spatial Spillover Effects on Poverty in Indonesia: Evidence from Panel Data Analysis

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Abstract

Poverty in Indonesia remains a persistent issue characterized by uneven distribution and strong regional disparities. This study analyzes the determinants of poverty across 34 provinces in Indonesia from 2015 to 2024 by incorporating spatial dimensions to capture interregional linkages. Using a quantitative approach with panel spatial econometric models, this research evaluates the effects of economic growth, unemployment, population density, human development, infrastructure access, inequality, and household expenditure on poverty rates. The findings indicate significant spatial dependence, confirming that poverty conditions in one region are influenced by those in neighboring regions. Structurally, the Human Development Index (HDI), access to safe drinking water, proper sanitation, and per capita expenditure show a significant negative effect on poverty. Meanwhile, macroeconomic indicators such as Gross Regional Domestic Product (GRDP) growth and unemployment rates do not show a significant impact on poverty reduction, suggesting that economic growth has not been fully inclusive. The results also indicate that the Spatial Durbin Model provides the best model fit in explaining regional poverty dynamics. These findings highlight the importance of regionally integrated development strategies that prioritize human development and basic infrastructure rather than relying solely on aggregate economic growth.

Keywords: GRDP, Human Capital, Poverty Reduction, Regional Disparity, Spatial Econometrics

JEL Classification: I32, R12, and C33

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Introduction

Poverty remains a major development issue in Indonesia. Although nationally poverty rates are showing a downward trend, distribution across provinces remains uneven and tends to be persistent over time. Therefore, poverty alleviation is a top priority for national development. This is mandated by the constitution, with Law No. 13 of 2011 emphasizing the state's responsibility to promote public welfare, educate the nation, and care for the poor in order to meet their basic needs. This commitment is also in line with the global agenda of the Sustainable Development Goals (SDGs), which make reducing poverty and hunger a benchmark for the progress of countries around the world.

The trajectory of poverty alleviation policies in Indonesia represents a paradigmatic transformation that has adapted to socio-political dynamics, beginning with the Old Order era which emphasized national sovereignty through the Pembangunan Nasional Semesta Berencana Delapan Tahun (Penasbede) 1961–1969, to the New Order era which focused on economic stability through the Rencana Pembangunan Lima Tahun (REPELITA), before eventually transitioning into an emergency response via the Jaring Pengaman Sosial (JPS) following the 1998 crisis. The strengthening of this social protection system was subsequently institutionalized through the Undang-Undang Sistem Jaminan Sosial Nasional (UU SJSN) 2004 and the Program Keluarga Harapan (PKH) scheme in 2007, which was

further expanded during President Joko Widodo's administration through the digitalization of the "Kartu Sakti" ecosystem, comprising the Kartu Indonesia Sehat (KIS), Kartu Indonesia Pintar (KIP), and Kartu Keluarga Sejahtera (KKS) as well as the transformation of Bantuan Pangan Non-Tunai (BPNT) to enhance targeting accuracy.

Presidential Instruction (Inpres) No. 4 and No. 8 of 2025 marks a significant reform in poverty alleviation governance through the consolidation of the Data Tunggal Sosial Ekonomi Nasional (DTSEN) to enhance cross-sectoral targeting accuracy. The government is implementing a redesign of the Program Keluarga Harapan (PKH) with a maximum participation limit of five years and intensive mentoring to foster economic independence among beneficiaries. This policy also introduces regionalized assistance indices based on local living costs, while maintaining sustainable cash assistance for the elderly and persons with disabilities. All strategies are integrated into the Rencana Pembangunan Jangka Menengah Nasional (RPJMN) 2025–2029 with an ambitious target of reducing the poverty rate to 4.5%–5% by 2029. However, achieving this vision remains a significant challenge as, despite the implementation of various policy instruments, data from the Badan Pusat Statistik (BPS) as of September 2024 indicates that the national poverty rate remains at 8.53%, highlighting the need for accelerated regionalized assistance indices to more precisely address residual poverty.

Current poverty alleviation efforts tend to be global and uniform across Indonesia, without taking local characteristics into account. In fact, the determinants of poverty vary from region to region. For example, the determinants of poverty in West Java are dominated by factors such as gross regional domestic product (GRDP) and unemployment (Susanti, 2013), while in Papua they are more influenced by basic infrastructure such as irrigation and electricity (Wahyuni & Damayanti, 2014), and in Aceh they are influenced by education levels (Agustina et al., 2018). Rustiadi et al. (2011) and Hakim and Zuber (2008) emphasize that neglecting spatial elements in policy can lead to program failure.



Figure 1. Percentage distribution of poverty in Indonesia (2024)

Source: Badan Pusat Statistik (BPS)

Spatially, the data shows that poverty levels in Indonesia have a non-random distribution pattern. Figure 1 shows that poverty tends to be high in some provinces in eastern Indonesia and is similar between neighboring regions. This phenomenon is consistent with Tobler's First Law, which states that everything is related, but things that are closer together have a greater influence than those that are farther apart (Prihandini & Sunaryo, 2011). Hyman et al. (2005) and Harmes et al. (2017) reinforce this view with their findings that poor people tend to be concentrated in areas with similar characteristics, where the dynamics of poverty in one area are closely related to those in neighboring areas. Therefore, poverty analysis requires an approach that involves spatial or regional elements.

Although the phenomenon of poverty in Indonesia exhibits strong spatial characteristics, most previous studies have still used conventional regression approaches. This approach assumes that each region is independent, when in fact the poverty conditions of one region are influenced by its neighboring regions. Ignoring this spatial element risks causing estimation bias and misinterpretation. Based on these issues, this study aims to analyze the factors that influence poverty by considering spatial

aspects. The application of the Spatial Regression approach in this study is expected to reveal comprehensive inter-regional relationships, identify the influence of neighbors, and determine the dominant socioeconomic factors more accurately.

Literature Review

Economic development theory states that increased output has the potential to reduce poverty through job creation and increased income. However, the effectiveness of this mechanism is highly dependent on the distribution of growth outcomes (Todaro & Smith, 2009; World Bank, 2019). Empirical evidence in Indonesia shows mixed results. A number of studies have found that high economic growth is not always followed by a significant reduction in poverty, especially when income inequality remains high (Pangiuk, 2018; Andiny & Mandasari, 2017). These findings indicate that economic growth needs to be analyzed in conjunction with distribution and regional structure factors.

The labor market plays an important role in explaining the relationship between economic growth and poverty. High unemployment rates reflect the failure of the economy to absorb productive labor. The dominance of the informal sector and low-wage jobs increases households' vulnerability to poverty (Setyanti et al., 2024; Borjas, 2016). Regional studies show that low labor quality and limited access to formal employment contribute significantly to high poverty rates, particularly in the Nusa Tenggara region (Holivil, 2024). In the regional context, labor market disparities between regions drive spatial linkages through labor mobility and regional economic interactions. Regional disparities have been shown to influence regional economic performance spatially through interregional spillovers, while differences in employment opportunities drive labor migration and strengthen regional economic ties (Panzeria & Postiglione, 2022; Susilo & Trisilia, 2024).

Demographic pressures also contribute to poverty dynamics. High population density increases pressure on the labor market, housing, and public infrastructure. If not balanced with adequate economic capacity and infrastructure investment, these conditions increase congestion costs and poverty vulnerability (Rodríguez-Pose & Storper, 2019; Granda et al., 2025). In Indonesia, urbanization patterns show a strong link between core and buffer zones, which reinforces the spatial dimension of poverty. The quality of human resources is a key factor in long-term poverty reduction. The Human Development Index reflects access to education, health, and decent living standards. Regions with low HDI tend to have lower labor productivity and limited economic opportunities (UNDP, 2020; Mira et al., 2024; Yusuf et al., 2024; Matashu & Skhephe, 2022; Sari & Prasetyani, 2024). HDI disparities between provinces in Indonesia reinforce regional disparities and form relatively stable spatial patterns of poverty.

Access to basic services, particularly safe drinking water and sanitation, plays an important role in determining community welfare. Limited access increases the risk of disease, reduces labor productivity, and adds to the burden of poor households' expenses (Andrés et al., 2021; Van Minh & Hung, 2011). Areas with underdeveloped basic infrastructure tend to experience more persistent poverty, especially in areas with geographical limitations (Taluku & Sutiyo, 2025).

Income inequality is a structural factor that weakens the impact of economic growth on poverty reduction. A high Gini ratio indicates an uneven distribution of income, meaning that the benefits of development are only enjoyed by certain groups within society (Anas et al., 2020; Rohmah et al., 2025). Per capita expenditure reflects the purchasing power and economic welfare of households. Regions with low per capita expenditure have limited consumption and savings, making them more vulnerable to economic shocks (Adnyani & Sugiharti, 2019; Harun et al., 2025). Differences in purchasing power between regions in Indonesia form consistent and interrelated geographical patterns (Purwono et al., 2020; Muttaqin, 2025).

Poverty in Indonesia is influenced not only by local economic conditions but also by regional interconnections, making it crucial to study spatial aspects. As Liu et al. (2023) highlight, understanding the spatial dynamics of regional poverty is essential, as poverty patterns are often shaped by spatial dependence, where neighboring regions interact through geographical proximity and shared socio-economic conditions. In Indonesia, with its significant regional disparities and diverse geographical and economic contexts, comprehending these spatial dynamics is critical for effective poverty reduction. Several studies in Indonesia have examined spatial aspects of poverty, revealing significant spatial clustering and dependence across regions. In West Java, spatial analysis using Global Moran's I and LISA demonstrated positive spatial autocorrelation in poverty rates, indicating that high-poverty areas are

often surrounded by similarly poor regions. This highlights the need for region-based and spatially integrated poverty alleviation policies (Lillah & Wijayaningrum, 2025). In Central Java, research using Global Moran's I, LISA, and the Spatial Autoregressive Model (SAR) identified high concentrations of poverty, unemployment, and population in the southern part of the province. The study found that poverty in neighboring areas was positively correlated, emphasizing the importance of spatial interdependence in poverty dynamics (Anwar, 2022). Similarly, a study in South Kalimantan (Novitasari & Iskandar, 2022) found spatial autocorrelation in poverty, with significant poverty clustering in agriculture-based regions. Using the Spatial Durbin Model, the study revealed that government expenditure on education, health, and social protection significantly reduced poverty, while spending on housing and public facilities had no significant effect. Additionally, education spending had an indirect spatial spillover effect, benefiting neighboring regions (Novitasari & Iskandar, 2022).

Miranti (2021) explored regional poverty convergence at the district level in Indonesia, incorporating variables such as poverty rate, poverty gap index, GDP growth, and unemployment rate. However, like other studies, Miranti's analysis was limited to a specific geographical scale (districts) and focused on a relatively short time period (2010-2018), potentially overlooking long-term spatial dynamics and regional heterogeneity. This study builds upon such existing research by utilizing provincial-level data from 2010 to 2024, offering a broader and more comprehensive analysis of how spatial dependence in poverty evolves over time across Indonesia's diverse regions.

Although these studies highlight spatial dependence, many are limited by their focus on specific regions or short time periods, and often consider only a narrow range of variables. This study aims to fill this gap by analyzing how spatial dependence operates over time and across broader geographic scales, offering insights into the spatial complexities of poverty in Indonesia. This study further distinguishes itself by incorporating a broader set of variables, including poverty rate, GDRP growth rate, unemployment rate, and access to basic infrastructure. By using a Spatial Error Model within a fixed-effects panel data framework, the study not only captures regional heterogeneity but also accounts for spatial correlations in the residuals caused by unobserved factors, offering a more nuanced and comprehensive perspective on poverty dynamics.

Research Method

Research Type and Design

This study uses a quantitative approach with an explanatory design. The purpose of the study is to analyze the factors that influence poverty levels and identify the existence of spatial effects between regions. The unit of analysis covers 34 provinces in Indonesia with an observation period from 2010 to 2024. The data used is in panel form, allowing for simultaneous analysis of variations between provinces and over time. The period from 2010 to 2024 was selected to capture long-term trends and the impact of various economic policies and external events, including the COVID-19 pandemic, which have influenced poverty dynamics in Indonesia. This timeframe ensures a comprehensive understanding of the evolution of poverty and spatial dependencies over a significant period.

Research Data and Variables

The study used annual secondary data sourced from the Central Statistics Agency and official publications from relevant government agencies. All data were compiled at the provincial level with consistent definitions and units of measurement throughout the study period. The dependent variable used was the poverty rate, measured using the percentage of poor people per province per year. The independent variables included GDRP growth rate, unemployment rate, population density, human development index, access to safe drinking water, access to proper sanitation, Gini ratio, and per capita expenditure. All variables were selected to represent economic, social, and basic welfare dimensions relevant to regional poverty dynamics.

The selection of variables in this study is based on theoretical considerations and empirical findings in the poverty literature. Poverty is a multidimensional phenomenon influenced by economic performance, labor market conditions, income distribution, human development, and access to basic services. Therefore, this study incorporates variables representing these dimensions to capture the structural determinants of poverty across regions. Economic growth is represented by the GDRP growth rate. Higher economic growth is expected to increase production and income opportunities, which can

reduce poverty levels through job creation and improved economic activity. However, the impact of growth on poverty depends on the inclusiveness of the growth process. The unemployment rate reflects labor market conditions and the ability of the economy to absorb the workforce. High unemployment reduces household income and increases vulnerability to poverty, particularly in regions with limited employment opportunities. Population density is included to represent demographic pressure and regional development disparities. High population concentration can increase competition for resources, employment, and public services, which may influence poverty dynamics across provinces.

Table 1. Summary of Research Variables

Variable	Definition	Measurement Unit	Expected Effect	Data Source
Poverty Rate	Percentage of population living below the poverty line in each province	Percent (%)	Dependent Variable	BPS
GDRP Growth Rate	Annual growth rate of Gross Regional Domestic Product	Percent (%)	Negative	BPS
Unemployment Rate	Percentage of unemployed individuals in the labor force	Percent (%)	Positive	BPS
Population Density	Number of people per square kilometer in each province	People per km ²	Positive	BPS
Human Development Index	Composite index measuring education, health, and living standards	Index (0–100)	Negative	BPS
Access to Safe Drinking Water	Percentage of households with access to safe drinking water	Percent (%)	Negative	BPS
Access to Proper Sanitation	Percentage of households with access to proper sanitation facilities	Percent (%)	Negative	BPS
Gini Ratio	Measure of income inequality within a province	Index (0–1)	Positive	BPS
Per Capita Expenditure	Average household expenditure per capita per year	Rupiah	Negative	BPS

The Human Development Index is used to capture the quality of human capital through education, health, and living standards. Regions with higher human development tend to have better productivity and income opportunities, which contribute to poverty reduction. Access to safe drinking water and proper sanitation represents the availability of basic public services and infrastructure. Limited access to these services is often associated with poor living conditions, health risks, and persistent poverty. Income inequality is measured using the Gini ratio. High income inequality can weaken the poverty reduction effect of economic growth because the benefits of growth are not evenly distributed among the population. Per capita expenditure is used as a proxy for household welfare and purchasing power. Higher expenditure levels generally indicate better economic conditions and lower vulnerability to poverty. The variables used in this study are summarized in Table 1.

Before the model estimation, several variables were transformed into natural logarithmic form to reduce data skewness, stabilize variance, and improve the linear relationship between variables. Logarithmic transformation also facilitates the interpretation of coefficients as elasticities in the regression model. The variables transformed into natural logarithmic form include population density and per capita expenditure.

Data Analysis

Spatial regression is an analytical technique used to evaluate the relationship between one variable and another, specifically taking into account spatial or regional influences. Referring to [Anselin \(1988\)](#) the stages of spatial integration analysis conducted in this study are as follows:

Selection of The Best Panel Model

The best model from the static panel was selected using the Hausman test. Decision making:

H_0 = The Random Effects (RE) model is better because it is more efficient and there is no correlation between individual effects and independent variables.

H_1 = The Fixed Effects (FE) model is better because there is a correlation between individual effects and independent variables. If the probability is < 0.05 , then H_0 is rejected, and vice versa.

Spatial Weighting Matrix

This study employs a spatial weighting matrix based on the inverse distance matrix approach. This method is constructed using the geographical distance between regions, where closer regions receive greater weights while more distant regions receive smaller weights. The distance between provinces is calculated using the latitude and longitude coordinates of the centroid of each observed region. Measuring spatial dependence based on interprovincial distance is considered an appropriate approach because geographically closer regions tend to have stronger economic interactions, social linkages, and population mobility compared to regions that are farther apart. This approach is also consistent with Tobler's First Law of Geography, which states that everything is related to everything else, but near things are more related than distant things. Furthermore, the inverse distance matrix is more suitable for countries with an archipelagic structure such as Indonesia. Contiguity based spatial weighting methods are often less appropriate because many provinces are separated by seas and therefore do not share direct administrative boundaries. By using geographical distance, spatial relationships between provinces can still be captured even when regions are not directly adjacent.

Spatial Effect Testing (Spatial Dependency)

Spatial effect testing was conducted to determine the spatial effects in a data cluster. The cross-section dependence (inter-province) effect examination used was Pesaran's Cross-section Dependence Test (CD Test). The testing was conducted by calculating the average correlation between the residuals of the regression of each location. This means that after predicting a variable in each location, it is observed whether the "prediction errors" are interrelated between locations ([Pesaran, 2020](#)).

Spatial Panel Regression Model Estimation

Spatial regression models are used in this study because poverty conditions across regions in Indonesia are not independent. Geographical proximity between provinces may create similarities in socio economic conditions, so poverty dynamics in one region can be related to those in neighboring regions. Therefore, a spatial approach is applied to capture potential interregional dependence that cannot be explained by conventional regression models which assume independence between observations. This approach is also consistent with Indonesia's development policy that emphasizes region based poverty alleviation, as reflected in Presidential Instruction No. 4 of 2025 and Presidential Instruction No. 8 of 2025 which promote policy interventions tailored to regional characteristics. Based on these considerations, spatial panel model estimation in this study was conducted using three main approaches, namely the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). The SAR model is used to identify the direct influence of dependent variables in neighboring regions through spatial lag effects, while the SEM model aims to capture spatial dependence in the error component that cannot be directly observed. In addition, the SDM is employed as a more comprehensive specification that extends the SAR model by incorporating spatially lagged independent variables.

Selection of The Best Spatial Panel Model

The selection of the best model between SAR, SEM, and SDM in this study was done by comparing the Akaike Information Criterion (AIC) values. The smaller the AIC value, the better the model is at explaining the dependent variable without causing overfitting.

Final Model Specifications and Estimation Techniques

Spatial econometric models allow the analysis to account for possible interactions between regions that cannot be captured by conventional regression models. In this framework, spatial dependence may arise either through the dependent variable or through the error component. Therefore, the general spatial

regression model can be expressed as follows. General Spatial Model:

$$Y = \rho WY_{it} + \beta_1 X_{it} + \beta_2 X_{it} + \dots + \mu_i + u_{it} \quad (1)$$

$$u_{it} = \lambda W\varepsilon_{it} + \varepsilon_{it} \quad (2)$$

To examine the robustness of the empirical findings, additional estimations were conducted using alternative spatial econometric specifications, namely the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). The SAR model assumes that spatial dependence occurs directly in the dependent variable. In this case, the poverty level in one province may be influenced by the poverty level in neighboring provinces. The SAR specification in this study is written as:

$$POV_{it} = \rho WPOV_{it} + \beta_1 GRDP_{it} + \beta_2 UNR_{it} + \beta_3 PD_{it} + \beta_4 HDI_{it} + \beta_5 ADW_{it} + \beta_6 SNT_{it} + \beta_7 GC_{it} + \beta_8 PCR_{it} + \mu_i + \varepsilon_{it} \quad (3)$$

The SEM model assumes that spatial dependence occurs in the error component rather than directly in the dependent variable. This implies that spatial correlation arises from unobserved factors that are spatially correlated across regions. The SEM specification is formulated as follows:

$$POV_{it} = \beta_1 GRDP_{it} + \beta_2 UNR_{it} + \beta_3 PD_{it} + \beta_4 HDI_{it} + \beta_5 ADW_{it} + \beta_6 SNT_{it} + \beta_7 GC_{it} + \beta_8 PCR_{it} + \mu_i + \varepsilon_{it} \quad (4)$$

$$u_{it} = \lambda W\varepsilon_{it} + \varepsilon_{it} \quad (5)$$

This study also estimates the SDM Model. The SDM extends the SAR model by incorporating spatially lagged explanatory variables, allowing the model to capture both spatial dependence and spatial spillover effects from neighboring regions. This specification enables the analysis to account not only for the influence of poverty in surrounding regions but also for the potential impact of neighboring regions' socioeconomic characteristics on local poverty levels. The SDM specification used in this study is expressed as follows:

$$POV_{it} = \rho WPOV_{it} + \beta_1 GRDP_{it} + \beta_2 UNR_{it} + \beta_3 PD_{it} + \beta_4 HDI_{it} + \beta_5 ADW_{it} + \beta_6 SNT_{it} + \beta_7 GC_{it} + \beta_8 PCR_{it} + \theta_1 WGRDP_{it} + \theta_2 WUNR_{it} + \theta_3 WPD_{it} + \theta_4 WHDI_{it} + \theta_5 WADW_{it} + \theta_6 WSNT_{it} + \theta_7 WGC_{it} + \theta_8 WPCR_{it} + \mu_i + \varepsilon_{it} \quad (6)$$

where *POV* represents Poverty, *GRDP* denotes Gross Regional Domestic Product, *UNR* refers to the Open Unemployment Rate, and *PD* stands for Population Density. *HDI* indicates the Human Development Index, while *ADW* and *SNT* represent Access to Safe Drinking Water and Access to Proper Sanitation, respectively. *GC* denotes the Gini Coefficient, and *PCR* refers to Per Capita Expenditure. The subscripts *i* and *t* indicate the province and time period, respectively. The term μ_i represents the fixed effect of the province, which captures unobserved heterogeneity and remains constant over time, while ρ is the spatial autoregressive coefficient, λ is the spatial error coefficient, θ denotes the coefficients of the spatially lagged explanatory variables, and *W* denotes the spatial weight matrix. Finally, u_{it} represents the random errors, which are assumed to be independent and identically distributed.

Results and Discussion

Descriptive Statistics

Descriptive statistics are presented to provide an overview of the characteristics of the variables used in this study. Table 2 reports the mean, standard deviation, minimum, and maximum values for each variable across 34 provinces during the observation period.

The results show that the average poverty rate in Indonesia is 10.63 percent, with values ranging from 3.45 percent to 28.47 percent, indicating substantial disparities in poverty levels across provinces. The average economic growth rate is 4.49 percent, although the minimum value reaches -15.74 percent, reflecting periods of economic contraction. The unemployment rate averages 4.97 percent with moderate variation across regions.

Population density shows the largest variation among the explanatory variables, with an average of 737.81 people per square kilometer and a maximum value of 16,165 people per square kilometer. This indicates a significant difference in population concentration between provinces. Meanwhile, the average Human Development Index is 71.01, suggesting a moderate level of human development across

regions. Access to basic services also varies considerably. Access to safe drinking water averages 80.24 percent and access to proper sanitation averages 74.89 percent. The Gini ratio averages 0.386, indicating moderate income inequality, while per capita expenditure averages 10,764.32 thousand rupiah per person per year. The variation across provinces reflects differences in economic structure and development levels, which justifies the use of spatial econometric analysis to capture regional interactions in poverty dynamics.

Table 2. Descriptive Statistics of Research Variables

Variable	Obs	Mean	Std. Dev	Min	Max
Poverty Rate (POV)	340	10.63368	5.524494	3.445	28.47
GRDP Growth (GRDP)	340	4.498882	3.687411	-15.74	22.94
Unemployment Rate (UNR)	340	4.973632	1.686476	1.14	10.015
Population Density (PD)	340	737.8059	2663.051	9	16165
Human Development Index (HDI)	340	71.00762	4.095268	57.25	83.08
Access to Safe Drinking Water (ADW)	340	80.24015	12.3918	37.35	99.96
Access to Proper Sanitation (SNT)	340	74.88603	14.58099	23.37	99.96
Gini Ratio (GC)	340	0.3861029	0.1140584	0.2395	0.851
Per Capita Expenditure (PCR)	340	10764.32	2241.661	6468.55	19953

Multicollinearity Test

The multicollinearity test results in Table 3 show that all Variance Inflation Factor (VIF) values are below the threshold of 10, with values ranging from 1.08 to 6.88 and an average of 3.15. These results indicate that multicollinearity is not a concern in the model. Therefore, all independent variables are considered reliable and suitable for further spatial regression analysis.

Table 3. Multicollinearity Test

Variable	VIF	1/VIF
GRDP Growth (GRDP)	6.88	0.145487
Unemployment Rate (UNR)	5.47	0.182597
Population Density (PD)	4.32	0.231724
Human Development Index (HDI)	3.14	0.318099
Access to Safe Drinking Water (ADW)	2.61	0.474038
Access to Proper Sanitation (SNT)	1.88	0.532616
Gini Ratio (GC)	1.16	0.861098
Per Capita Expenditure (PCR)	1.08	0.926159
Mean VIF	3.15	

Selection of Data Panel Models

To determine the most appropriate model, the Hausman test is usually used, which compares the estimation results between the FE and RE models (Hausman, 1978). Based on the results of the Hausman test, a Chi-square (X^2) value of 18.40 was obtained with a significance level (Prob > X^2) of 0.0184, so the null hypothesis (H_0) was rejected (Table 4). Therefore, the FE model is more appropriate to use in this study. This indicates that there is a correlation between individual effects and independent variables. In other words, each province has specific characteristics that cannot be ignored.

Table 4. Hausman Test: Fixed Effects (FE) vs Random Effects (RE) Model Comparison

Model Comparison	Chi ² Value	Prob > Chi ²
Fixed Effects (FE) vs. Random Effects (RE)	18.40	0.0184

Selection of Spatial Weighting Matrix

This study uses an inverse distance matrix, assuming that geographically close provinces tend to have stronger poverty correlations than distant provinces. The closer the distance between provinces, the greater the spatial weight given, reflecting a higher intensity of spatial influence (Firdaus, 2020). The distance between provinces is calculated based on the latitude and longitude coordinates of the center point or provincial capital. The coordinate data is sourced from the Directorate General of Population and Civil Registration (Dukcapil) in 2019, so that the formation of the spatial weighting matrix is based

on official and consistent data.

Cross-Section Unit Dependency Effect

The test results show a statistical value of 2.443 with a probability of 0.0146. Since the p-value is less than 0.05, the null hypothesis is rejected, indicating significant cross-sectional dependence or spatial dependence between units in the panel data. Thus, the use of conventional panel models such as OLS, Fixed Effects, or Random Effects is less appropriate because they are unable to capture this spatial correlation.

Table 5. Spatial Econometric Estimation Results

Variable	OLS FE	SAR	SEM	SDM
GRDP Growth (GRDP)	0.008 (0.011)	0.009 (0.010)	0.016 (0.011)	0.015 (0.010)
Unemployment Rate (UNR)	-0.035 (0.055)	0.001 (0.054)	-0.009 (0.052)	-0.001 (0.051)
Population Density (PD)	0.003*** (0.001)	0.003*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Human Development Index (HDI)	-0.132*** (0.039)	-0.151*** (0.037)	-0.148*** (0.034)	-0.157*** (0.033)
Access to Safe Drinking Water (ADW)	-0.003 (0.007)	-0.005 (0.007)	-0.037*** (0.009)	-0.045*** (0.009)
Access to Proper Sanitation (SNT)	-0.008 (0.007)	-0.105* (0.006)	-0.022*** (0.006)	-0.021*** (0.006)
Gini Ratio (GC)	-0.552* (0.321)	-0.661** (0.303)	0.925 (1.492)	0.592 (1.937)
Per Capita Expenditure (PCR)	-0.001 (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
W × GRDP				0.006 (0.021)
W × UNR				0.142 (0.216)
W × PD				0.005** (0.002)
W × HDI				-0.650*** (0.244)
W × ADW				0.060** (0.029)
W × SNT				0.035* (0.019)
W × GC				-1.563 (2.017)
W × PCR				0.002*** (0.000)
Number of observations	340	340	340	340
R2 within	0.646	0.664	0.613	0.721
R2 between	0.012	0.005	0.089	0.001
R2 overall	0.009	0.003	0.105	0.001
AIC		586.044	537.209	501.511
BIC		624.334	575.498	570.432
ρ (rho)		-0.271** (0.134)		0.471*** (0.131)
λ (lamda)			0.882*** (0.028)	

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard error in parentheses. W × denotes the spatially lagged explanatory variables (θ) in the SDM

Spatial Econometric Estimation Results

The estimation results show that population density has a positive and statistically significant effect on poverty across all model specifications. The coefficient remains relatively stable, ranging from 0.002 to 0.003 and significant at the 1 percent level. This finding suggests that regions with higher population density tend to experience higher poverty levels. High population concentration may increase pressure

on labor markets, infrastructure, and public services, which can contribute to a higher incidence of poverty in densely populated areas. The Human Development Index consistently exhibits a negative and statistically significant effect on poverty across all models. The estimated coefficient ranges from -0.132 to -0.157 and remains significant at the 1 percent level. This result indicates that improvements in education, health, and living standards play a crucial role in reducing poverty. Regions with higher human development levels tend to have better access to productive economic opportunities and stronger socioeconomic

The identification of spatial dependence in the data provides a strong justification for applying a spatial econometric approach. Conventional regression models are unable to capture interregional interactions that may influence poverty dynamics across regions. The selection of the preferred model was based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), where lower values indicate better model performance with a more efficient balance between model fit and parameter complexity (Kuha, 2004). In addition, models that produce smaller residual variation are considered more efficient in explaining the observed data (Ingdal et al., 2019). Based on the comparison of AIC and BIC values across the estimated spatial models, the Spatial Durbin Model (SDM) was identified as the most appropriate specification for analyzing poverty dynamics in Indonesia. The SDM model produced the lowest AIC value compared to the SAR and SEM models, indicating a better model fit and stronger explanatory capability.

The SDM estimation results presented in Table 5 indicate a spatial autoregressive coefficient (ρ) of 0.471, which is statistically significant at the 1 percent level. This result confirms the presence of spatial dependence in poverty across regions. The positive value of the spatial coefficient suggests that poverty conditions in one province are influenced by poverty levels in neighboring provinces. In other words, an increase in poverty in one region tends to be associated with an increase in poverty in surrounding regions, reflecting strong spatial interactions across provinces.

The presence of significant spatial dependence implies that regional poverty dynamics are not solely determined by local socioeconomic characteristics but are also shaped by interactions between neighboring regions. Economic activities, labor markets, and the movement of goods and services often extend beyond administrative boundaries. As a result, economic shocks, employment opportunities, and income disparities in one province can influence socioeconomic conditions in adjacent provinces. Such spatial spillover effects may arise from several forms of regional economic interaction. Interregional trade flows, particularly in agricultural and basic commodities, can transmit economic shocks across provincial borders. Labor mobility is another important channel, as workers frequently migrate between regions in response to differences in employment opportunities and wage levels. Infrastructure connectivity and transportation networks further facilitate these interactions, strengthening the economic linkages between neighboring provinces.

Therefore, the significant spatial dependence captured by the SDM model indicates that poverty in Indonesia should not be analyzed as an isolated phenomenon at the provincial level. Instead, poverty dynamics should be understood as part of a broader spatial economic system in which regional conditions are closely interconnected. This finding highlights the importance of spatially coordinated development policies, as poverty reduction efforts implemented in one region may generate spillover effects that influence surrounding areas.

The spatially lagged explanatory variables (θ) in Table 5 show that poverty in a province is also related to the characteristics of its neighbors. The clearest result is for human development: the coefficient of $W \times \text{HDI}$ is -0.650 and significant at the 1 percent level, so higher human development in neighboring provinces is associated with lower poverty locally, in addition to the province's own HDI effect (-0.157). Neighboring per capita expenditure (0.002, 1 percent), population density (0.005, 5 percent), access to safe drinking water (0.060, 5 percent), and access to proper sanitation (0.035, 10 percent) carry positive signs. This may reflect the concentration of economic activity and basic infrastructure in neighboring core regions, which leaves adjacent provinces relatively worse off, although this interpretation requires further testing. The spatial lags of GRDP growth, unemployment, and the Gini ratio are not significant, in line with their insignificant own effects. Because the SDM also includes the spatial lag of poverty (ρ), these coefficients should be read as associations with neighbors' characteristics, not as marginal spillover effects.

The results of SDM estimation with fixed effects show that poverty dynamics between regions are more influenced by structural factors and quality of life than by macroeconomic indicators alone. The GRDP variable does not have a significant effect on poverty levels, suggesting that economic growth at

the provincial level is not necessarily inclusive. One key reason for this is the structure of economic growth in many Indonesian provinces, which relies heavily on capital-intensive sectors such as mining. According to the latest BPS data (2024), the mining sector contributes approximately 6.99% to Indonesia's total GDP. However, despite its significant contribution to GDP, the mining sector has limited capacity to absorb labor, especially for lower-skilled workers.

From 2019 to 2023, employment in the mining sector has steadily declined. In 2019, the sector employed 22,692 workers, while in 2023, it decreased to 18,126 workers, reflecting a 20% decline over the period. This decrease is consistent with the capital-intensive nature of mining, which requires less labor and tends to replace workers with technology and automation. Despite the sector's substantial contribution to GDP, its limited capacity for labor absorption means that the benefits of growth are not widely distributed across the population. These findings support the view that economic growth driven by sectors with limited labor absorption, such as mining, does not automatically reduce poverty. This aligns with studies such as those by [Efendi et al. \(2019\)](#), who found that while the coefficient of economic growth (GR) has a positive effect, it is not statistically significant in influencing poverty levels in Indonesia. Similarly, [Carter \(2024\)](#) highlight that growth concentrated in capital-intensive industries, with limited labor benefits, often fails to reduce poverty effectively.

A similar situation can be observed with the unemployment rate variable, which also shows no significant effect. These results suggest that poverty at the provincial level is not always synonymous with open unemployment. While the unemployment rate may appear to decrease, this does not necessarily correlate with a reduction in poverty. The key issue lies in the quality of available jobs, rather than the mere quantity. In Indonesia, a significant portion of the poor population is engaged in the informal sector and low-productivity jobs, such as those in agriculture and small-scale services, where wages are often below the poverty line.

A decline in the unemployment rate does not directly result in a reduction in poverty if the quality of employment remains poor. Many individuals may be employed, but in jobs that offer very low wages, lack social security, and provide limited job stability. This situation is particularly evident in agriculture, which remains a major employer in many provinces but offers low wages due to seasonal labor, informal contracts, and limited access to technology or capital. Similarly, the informal service sector often provides work with no formal benefits or legal protections, perpetuating the cycle of poverty.

According to the Indonesia Economic Prospects (IEP) report published by the World Bank in December 2025, real wages for the working class in Indonesia declined by around 1.1% annually from 2018 to 2024. This highlights a broader issue where the working population, particularly in low-wage sectors, faces stagnant or declining wages despite stable employment figures. [Brummund et al., \(2018\)](#) highlight that securing a job is not sufficient to escape poverty if the job does not offer wages above the poverty line, lacks social security, and does not provide job stability. Similarly, [Sehnbruch et al. \(2024\)](#) emphasize that improvements in labor market indicators, such as the unemployment rate, do not necessarily translate into improvements in welfare when job creation is dominated by informal, low-productivity sectors.

Conversely, population density has a positive and significant effect on poverty. The coefficient for population density is 0.002, which suggests that for each 1 person per km² increase in population density, the poverty rate increases by 0.002%, holding other factors constant. High population concentration leads to pressure on employment opportunities, housing, and public services. When population growth is not matched by proportional economic expansion, competition for resources intensifies, worsening poverty levels. Additionally, high population density often limits access to employment, public services, and natural resources, exacerbating inequality and poverty. These results align with the phenomenon of urbanization of poverty, where large numbers of low-skilled migrants move to urban areas, contributing to the expansion of slum areas. These areas often lack access to basic services, such as clean water and sanitation. According to [Novianti and Utomo \(2025\)](#), densely populated areas face significant pressure on resources and employment opportunities, which increases the likelihood of higher poverty levels. Furthermore, the rapid growth of cities creates slum areas with inadequate infrastructure, leading to urban poverty traps.

The decline in job availability and rising unemployment rates further widen income inequality. These conditions foster social problems, including the growth of informal settlements and increased criminal activity ([Edwart & Azhar, 2019](#)). The paradox of agglomeration emerges when the economic efficiency of urban areas is overshadowed by social and spatial inequalities arising from unmanaged population growth. However, previous studies also highlight the potential economic benefits of

population concentration. [Duranton and Puga \(2020\)](#) show that higher density can increase economic productivity and efficiency through agglomeration effects, including broader market access, more efficient infrastructure and public services, and deeper labor markets. These conditions may improve income opportunities and support economic growth in densely populated regions. Similarly, [Henderson et al., \(2021\)](#) argue that economic density reflects the concentration of productive activities associated with higher income levels and stronger regional economic performance.

The role of human development is clearly evident through the Human Development Index (HDI), which has a coefficient of -0.148 and a negative and highly significant impact on poverty. This suggests that for each 1 point increase in the HDI, the poverty rate decreases by 0.148%. Improvements in education, healthcare, and living standards enhance human capital, thereby increasing productivity and income opportunities. As a result, individuals in regions with higher HDI scores are better equipped to access higher-paying jobs, which directly reduces poverty by increasing their purchasing power and access to essential goods and services. Unlike GRDP, which is aggregate in nature, the HDI directly reflects individual quality, making its impact on poverty more consistent and substantial. These results confirm that investment in people is a key strategy in poverty alleviation. [Omoniyi \(2013\)](#) asserts that education increases individual productivity and ability to participate in economic activities, as well as contributing to improved income distribution, thereby reducing poverty. This finding is reinforced by [Onsomu and Munga \(2010\)](#), who show that secondary education, higher education, and technical training significantly reduce the risk of individuals and households falling into poverty through increased income and access to better employment opportunities.

This relationship is further strengthened by the variables of access to drinking water and sanitation, both of which have a significant negative impact on poverty. The coefficient for access to drinking water is -0.037, indicating that for each unit increase in access to drinking water, the poverty rate decreases by 0.037%, holding other factors constant. Similarly, the coefficient for proper sanitation is -0.022, meaning that for each unit increase in access to proper sanitation, the poverty rate decreases by 0.022%. Access to these basic services not only has implications for health, but also for household expenditure efficiency and labor productivity. With reduced risk of disease and healthcare costs, households have a greater chance of escaping poverty. These findings place basic infrastructure as an important factor in the poverty reduction framework. Basic infrastructure development contributes significantly to poverty reduction through improved welfare and household consumption expenditure, as evidenced by empirical evidence in BRICS countries ([Chotia & Rao, 2017](#)).

On the other hand, the Gini ratio does not show a significant effect on poverty. This indicates that income inequality among residents at the provincial level does not necessarily directly determine the poverty rate. Income inequality among residents at the provincial level is not always a direct determinant of the poverty rate. [Fosu \(2017\)](#) shows that income inequality primarily affects the ability of economic growth to reduce poverty, rather than acting as a major determining factor. In line with this, [Dollar et al., \(2016\)](#) found that changes in poverty levels are more influenced by average income growth than by changes in income distribution. Poverty appears to be more sensitive to access to basic services and human capacity than to aggregate income distribution. In other words, inequality and poverty are two interrelated phenomena but do not always move in the same direction at the regional level.

Per capita expenditure variables provide a clearer picture of the welfare conditions of the community. The coefficient for per capita expenditure is -0.001, which indicates that for each unit increase in per capita expenditure, the poverty rate decreases by 0.001%, holding other factors constant. This negative and highly significant effect shows that an increase in the purchasing power of the community is directly related to a decrease in poverty. Unlike GRDP, per capita expenditure reflects the real conditions of households in meeting their basic needs. According to [Prianto et al. \(2023\)](#), per capita expenditure reflects the real welfare conditions of households because wage-based indicators are not yet able to adequately describe the ability to meet basic needs.

Positive and significant spatial error coefficients confirm the existence of spatial dependence in interregional poverty. Poverty conditions in a province are influenced by conditions in surrounding provinces through economic linkages, population mobility, and similarities in regional characteristics. This finding reinforces the relevance of a spatial approach in analyzing poverty dynamics, as poverty is not an isolated administrative phenomenon but rather a regional process influenced by spatial interactions. Spatial dependence in poverty also reflects differences in regional geography between mainland regions such as Java and Sumatra and archipelagic regions such as Papua and Maluku. In mainland regions, economic interactions between provinces tend to be stronger because of better

transportation networks, higher population mobility, and more integrated production systems. Provinces in Java and Sumatra are connected by relatively dense road infrastructure and shorter travel distances, which facilitate labor mobility, trade flows, and interregional economic spillovers. Previous studies show that poverty in Indonesia exhibits spatial clustering patterns, where lower poverty rates tend to concentrate in western regions while higher poverty rates are more prevalent in eastern regions (Pramono & Marsisno, 2018). In addition, economic development in Indonesia remains highly concentrated in Java, while regions outside Java, particularly in eastern Indonesia, experience slower development and more limited access to public services (Ananda et al., 2023). Better infrastructure connectivity in western Indonesia also supports stronger regional economic integration and interregional spillover effects (Wahyuni et al., 2022).

In contrast, archipelagic regions such as Papua and Maluku tend to experience weaker spatial transmission effects due to geographical fragmentation and limited connectivity. The separation of provinces by sea, higher transportation costs, and limited infrastructure development reduce the intensity of economic interaction between neighboring regions. These structural constraints contribute to more localized poverty patterns where economic improvements in one province do not easily spill over to surrounding provinces. Infrastructure gaps and regional development disparities between western and eastern Indonesia remain persistent despite decentralization policies (Ananda et al., 2023). Aji (2020) shows that the dynamics of economic growth, redistribution, and poverty reduction in Indonesia form different spatial patterns across provinces, indicating that poverty alleviation performance cannot be separated from the regional context. This result is also consistent with Joshi (2012) and Gebremedhin (2012), who demonstrate that poverty levels in a region are significantly influenced by conditions in neighboring regions through economic and social spillovers. Furthermore, Syafiudin et al. (2025) show that poverty and income inequality in Indonesia tend to be geographically concentrated.

The robustness test was conducted to ensure that the estimation results are not sensitive to a particular model specification. In this study, robustness was examined by comparing the estimation results of several spatial econometric models, namely the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM), alongside the OLS Fixed Effects model as the baseline specification.

Conclusion and Recommendations

Conclusions

Poverty in Indonesia has a strong spatial dependency, where the poverty conditions of one province are interrelated with those of neighboring provinces, as confirmed by the significance of the lambda parameter in the Spatial Error Model (SEM). Factors that have been proven to have a significant effect in reducing poverty levels are improvements in human resource quality through the Human Development Index (HDI), the provision of basic infrastructure in the form of access to drinking water and proper sanitation, per capita expenditure that reflects real purchasing power, and population density that provides a positive agglomeration effect. Conversely, macroeconomic indicators such as GRDP growth rate, unemployment rate, and Gini ratio did not show a significant effect on poverty reduction, indicating that aggregate economic growth is not yet inclusive and that poverty is more influenced by structural factors and quality of life than simply the size of a region's economic output.

Recommendations

The government should shift from a sectoral approach to an integrated regional approach to poverty alleviation, as spatial dependence shows that poverty in one region affects neighboring areas. Therefore, the focus of budget policy should prioritize human capital investment, particularly in education and healthcare, which have been proven to have a greater impact on poverty reduction than focusing solely on GRDP growth targets. Expanding access to education and improving healthcare will enhance labor productivity and increase income opportunities for the poor. Additionally, there should be a stronger emphasis on developing basic infrastructure, particularly clean water and sanitation, in high-poverty areas, as this will improve the quality of life and public health, which directly contributes to poverty reduction. The government must also maintain price stability to protect the purchasing power of the poor, ensuring that basic goods remain affordable. Finally, a more equitable economic growth strategy

is necessary, one that promotes small-medium enterprises (SMEs) and job creation in labor-intensive sectors, especially in poverty-stricken regions. Given the spatial linkages identified in this study, these policies must be implemented regionally, recognizing the spillover effects of poverty across provinces. This integrated approach ensures that the benefits of growth are shared equitably, addressing the interconnected nature of poverty and promoting regional collaboration to effectively tackle poverty and inequality.

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