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Spatial Clustering and Socioeconomic Correlates of Poverty Across Indonesian Provinces: Evidence from 2024

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Abstract
This study examines the spatial distribution of poverty and its socioeconomic correlates across 38 provinces in Indonesia in 2024. Using a cross-sectional dataset compiled from provincial secondary statistics attributed to Statistics Indonesia (BPS), the analysis considers the provincial poverty rate as the dependent variable and internet access, adjusted expenditure per capita (Pengeluaran per Kapita Disesuaikan; PKP), the Gini ratio, the open unemployment rate, and the Human Development Index (HDI) as explanatory variables. Spatial weights are constructed using four-nearest neighbours (KNN-4) from the supplied provincial coordinates and row-standardized. Exploratory analysis, Global Moran's I, Local Indicators of Spatial Association (LISA), OLS diagnostics, and competing OLS, SAR, SEM, and SDM specifications are employed. Global Moran's I is 0.5963, with a Monte Carlo permutation p-value of 0.001 (999 permutations), indicating positive spatial autocorrelation in provincial poverty. LISA identifies four High to High provinces Papua, Papua Selatan, Papua Tengah, and Papua Pegunungan while the remaining provinces are classified as not significant in the adjusted local analysis. Under KNN-4, SAR has the lowest AIC among the OLS, SAR, SEM, and SDM models (198.72), a significant positive spatial autoregressive parameter ($\rho = 0.3139$; Wald $p = 0.0090$), and no significant residual spatial autocorrelation ($p = 0.2529$). Sensitivity estimates using SAR with KNN-3 and KNN-5 retain positive spatial parameters and non-significant residual Moran tests; KNN-3 has the lowest AIC among the three SAR weight specifications. The Gini ratio is positively associated with poverty, whereas HDI is negatively associated; internet access, PKP, and unemployment are not statistically significant at the 5% level in the KNN-4 SAR model. The findings describe cross-sectional associations and spatial clustering; they do not establish causality.
Keywords: poverty; spatial autocorrelation; Moran's I; LISA; spatial autoregressive model; Indonesia

1. Introduction

Poverty is a multidimensional development challenge that reflects constraints in income, employment, education, health, and access to productive resources. Its geographical distribution is important because economic opportunities and public services are unevenly distributed across regions. Poverty in one area may be associated with conditions in nearby areas through shared labour markets, transport links, economic networks, public-service systems, and historical development conditions. Consequently, treating provincial observations as fully independent may overlook spatial similarities and interregional dependence. Evidence from Indonesia has documented spatial clustering of poverty at subdistrict, district, and provincial scales, supporting the relevance of geographically informed poverty analysis (Cahyadi et al., 2020; Santi et al., 2020; Anwar, 2022; 'Iffah et al., 2023). Indonesia provides a relevant setting for spatial analysis because its provinces differ in geography, population structure, economic scale, digital connectivity, inequality, and human development. The administrative division of Papua into additional provinces also makes it important to use a clearly defined territorial configuration. This study therefore uses a single cross-section of 38 provinces for 2024, rather than combining observations from different provincial configurations or interpreting the data as a time series or panel. The poverty indicator and other socioeconomic measures are taken from secondary provincial statistics, with the poverty observations referring to September 2024. Spatial exploratory analysis provides a way to assess whether similar poverty values are geographically clustered. Moran's I is a global measure of spatial autocorrelation that summarizes the degree of spatial association across the study area (Moran, 1950). However, a global statistic does not identify the specific locations that contribute to the overall pattern. Local Indicators of Spatial Association (LISA) address this limitation by decomposing global spatial association into location-specific measures and identifying local clusters or spatial outliers (Anselin, 1995). Indonesian applications have combined Global Moran's I and LISA to identify poverty concentrations and local spatial patterns, including studies at the national, provincial, and subnational levels (Cahyadi et al., 2020; Santi et al., 2020; Anwar, 2022; Baharuddin et al., 2025). When spatial dependence is present, conventional regression may provide an incomplete representation of spatial data because observations are not necessarily independent. Spatial econometric models distinguish dependence in the outcome, dependence in the disturbance process, and spatially lagged explanatory variables. The spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) represent alternative forms of spatial dependence and require careful specification and interpretation (LeSage & Pace, 2009; Elhorst, 2014). Applications to Indonesian poverty data have compared classical regression with spatial lag and spatial error specifications, with the preferred model varying according to the study area, variables, and spatial weights (Anwar, 2022; 'Iffah et al., 2023; Baharuddin et al., 2025). A significant spatial autoregressive parameter

indicates conditional spatial dependence under the selected spatial weights matrix; it does not, by itself, establish a causal transmission mechanism between provinces. Against this background, this study examines poverty clustering and the association of internet access, adjusted expenditure per capita (PKP), the Gini ratio, open unemployment, and the Human Development Index with provincial poverty in Indonesia in 2024.

2.1. Poverty and socioeconomic conditions

Provincial poverty can be associated with the distribution of income, employment opportunities, economic activity, and human capabilities. The Gini ratio summarizes inequality in the distribution of expenditure or income, depending on the underlying statistical definition. A higher ratio may coexist with higher poverty when gains from economic activity are distributed unevenly. Evidence from Indonesia emphasizes the role of inequality in poverty reduction and poverty persistence (Purwono et al., 2021; Agussalim et al., 2024). Unemployment may reduce household labour income, while regional economic conditions can shape the availability and quality of work. These relationships are empirical rather than mechanical and may differ across regions. Human development captures achievements in health, education, and standard of living. Better human development may be associated with greater capabilities to participate in economic activity and withstand economic shocks. Studies of Indonesian regional poverty have identified education, life expectancy, and adjusted expenditure per capita as relevant correlates, although the estimated effects vary with geographic coverage and model specification (’Iffah et al., 2023; Baharuddin et al., 2025). Internet access may support information acquisition, education, market participation, and access to services, but connectivity alone does not guarantee digital skills or equal benefits from technology. Recent evidence for Indonesia suggests that the relationship between internet use and poverty reduction may differ between urban and rural areas (Yokota et al., 2025).

2.2. Spatial autocorrelation and local clustering

Spatial autocorrelation describes the extent to which values observed in geographically related locations are similar or dissimilar. Moran’s I provides a global measure of spatial association (Moran, 1950). A positive value indicates that similar values tend to be located near one another under the specified spatial weights. Global statistics do not identify the specific locations responsible for the pattern. Local Indicators of Spatial Association (LISA) decompose global spatial association into location-specific statistics and can identify local clusters and spatial outliers (Anselin, 1995). The conventional cluster categories are High to High, Low to Low, High to Low, and Low to High. Local results depend on the weights matrix, the inference procedure, and the treatment of multiple testing; therefore, a local cluster should be interpreted only when the adjusted significance criterion is met.

2.3. Spatial regression models

Spatial regression distinguishes dependence in the outcome from dependence in the disturbances and from spatially lagged explanatory variables. The spatial autoregressive model (SAR) includes a spatial lag of the dependent variable. The spatial error model (SEM) models spatial dependence in the disturbance process. The spatial Durbin model (SDM) includes spatial lags of both the dependent variable and explanatory variables. These models represent different dependence structures and should be selected using substantive reasoning, diagnostic tests, residual checks, and model-comparison criteria rather than by choosing the most complex specification automatically (LeSage & Pace, 2009; Elhorst, 2014).

3. Conceptual Framework

The empirical framework treats the provincial poverty rate (POV) as the outcome and internet access (INTERNET), adjusted expenditure per capita (PKP), the Gini ratio (GINI), the open unemployment rate (TPT), and the Human Development Index (IPM) as explanatory variables. The non-spatial benchmark is:

$$POV_i = \beta_0 + \beta_1 INTERNET_i + \beta_2 PKP_i + \beta_3 GINI_i + \beta_4 TPT_i + \beta_5 IPM_i + \varepsilon_i$$

The SAR specification adds the spatially lagged dependent variable, ρWPOV, to the right-hand side. Here, i denotes a province, W is the row-standardized spatial weights matrix, ρ is the spatial autoregressive parameter, and ε is the disturbance. The expected signs are not imposed as empirical facts: internet access and IPM may be negatively associated with poverty; unemployment and inequality may be positively associated; and the association of PKP reflects adjusted household expenditure per capita rather than aggregate regional output.

4. Research Questions

1. How are poverty and the selected socioeconomic indicators distributed across Indonesia’s 38 provinces in 2024?
2. Does provincial poverty exhibit significant global spatial autocorrelation, and which provinces form statistically significant local clusters?
3. Which of the OLS, SAR, SEM, and SDM specifications provides the most defensible representation of the 2024 cross-sectional data?

4. Which socioeconomic variables are significantly associated with provincial poverty in the selected spatial regression model?

5. Significance of Study

This study provides a provincial-level account of poverty clustering and its association with socioeconomic indicators using a reproducible spatial econometric workflow. The LISA results can help identify a geographically concentrated group of provinces that may warrant closer policy attention. The regression comparison distinguishes spatial clustering in the outcome from conditional spatial dependence in a regression model. In relation to Islamic development thought, the results can inform discussion of equitable welfare, social justice, and attention to disadvantaged regions; they do not test religious institutions or establish the causal impact of Islamic economic policy.

6. Research Methodology

6.1. Data and unit of analysis

The study uses secondary cross-sectional data for 38 Indonesian provinces in 2024 (N = 38). The dataset contains the provincial poverty rate (POV), internet access (INTERNET), adjusted expenditure per capita (PKP), Gini ratio (GINI), open unemployment rate (TPT), and Human Development Index (IPM). Provincial coordinates are also supplied and used to construct spatial weights. The analysis file reports no missing values for the nine fields used in the spatial dataset.

Table 1. Variable definitions and measurement used in the supplied dataset

Variable	Role	Measurement in analysis
POV	Dependent	Provincial poverty rate (%)
INTERNET	Explanatory	Internet access (%)
PKP	Explanatory	Adjusted expenditure per capita (thousand rupiah/person/year)
GINI	Explanatory	Gini ratio
TPT	Explanatory	Open unemployment rate (%)
IPM	Explanatory	Human Development Index

6.2. Spatial weights matrix

Provincial coordinate pairs were converted to spatial points and transformed to projected coordinate reference system EPSG:6933 before calculating nearest neighbours. A K-nearest-neighbour procedure with k = 4 was used to define the neighbouрod list. The resulting weights were row-standardized (style W). The reported matrix contains 38 regions and 152 directed links, with four neighbours assigned to each province. The neighbour structure is non-symmetric, which is a characteristic of the KNN construction used in the analysis. Because Indonesia is an archipelago, KNN based on projected straight-line distance is an operational approximation of spatial proximity. It does not necessarily represent actual transport, maritime, trade, or administrative connections. The main spatial specification uses KNN-4. As a sensitivity assessment, SAR was re-estimated using KNN-3 and KNN-5 with the same outcome and explanatory variables. The spatial parameter remained positive in all three specifications, and residual Moran tests were not significant. The AIC was lowest for KNN-3 (197.89), followed by KNN-4 (198.72) and KNN-5 (200.59). These results support stability in the direction of spatial dependence, while indicating some sensitivity of model fit to the choice of k. KNN-4 is retained as the primary specification to preserve consistency with the main model comparison; KNN-3 is noted as the best-fitting SAR among the three alternative k values by AIC.

6.3. Spatial exploratory analysis

Descriptive statistics and Pearson correlations were calculated for the six substantive variables. Global spatial autocorrelation in POV was tested using Moran's I. In addition to the analytical randomization test, a Monte Carlo permutation test with 999 permutations was performed. Local Moran statistics were calculated using 999 permutations, and the resulting local p-values were adjusted using the Benjamini–Hochberg procedure. Provinces were classified as High to High, Low to Low, High to Low, Low to High, or not significant using the signs of standardized poverty and its spatial lag. SAR sensitivity estimates were also obtained under KNN-3 and KNN-5, in addition to the primary KNN-4 specification.

6.4. Regression specifications and model selection

OLS was estimated as the non-spatial benchmark. SAR, SEM, and SDM were estimated by maximum likelihood using the same KNN-4 weights matrix. Model selection considered the AIC, spatial Lagrange Multiplier diagnostics from the OLS model, the significance of the spatial parameter, and the residual spatial autocorrelation test. The choice was not based on AIC alone. Statistical significance is evaluated at the 5% level. The OLS diagnostics included variance inflation factors (VIF), the Breusch–Pagan test for heteroskedasticity, and the Shapiro–Wilk test for normality of residuals. Because the design is cross-sectional and observational, coefficient estimates are interpreted as conditional associations,

not causal effects. The SDM impacts reported in the R output are not used as the main substantive effects because the SDM was not selected as the preferred specification and its residual spatial autocorrelation test remained significant.

7. Findings

7.1. Descriptive statistics

Table 2 shows substantial cross-provincial variation in poverty and the explanatory indicators. The mean poverty rate is 10.66%, with a standard deviation of 6.37 percentage points and a range from 3.80% to 29.66%. Internet access averages 86.27%, although the standard deviation is 15.99 percentage points and the observed minimum is 12.15%. The mean Gini ratio is 0.341, while mean IPM is 72.39. Adjusted expenditure per capita (PKP) has a mean of 84,377.34 thousand rupiah per person per year in the supplied dataset, with substantial variation across provinces.

Table 2. Descriptive statistics of provincial indicators, 2024 (N = 38)

Variable	Mean	Std. deviation	Minimum	Maximum
POV (%)	10.6647	6.3668	3.80	29.66
INTERNET (%)	86.2745	15.9913	12.15	98.18
PKP (thousand rupiah/person/year)	84,377.3421	62,202.9262	18,105	344,383
GINI	0.3406	0.0478	0.235	0.431
TPT (%)	4.3797	1.4142	1.32	6.75
IPM	72.3884	5.1502	53.42	83.08

7.2. Correlation analysis

The correlation matrix indicates a strong negative bivariate correlation between poverty and internet access ($r = -0.806$) and between poverty and IPM ($r = -0.804$). Poverty is positively correlated with the Gini ratio ($r = 0.273$), and negatively correlated with adjusted expenditure per capita (PKP; $r = -0.299$) and TPT ($r = -0.334$). Internet access and IPM are strongly positively correlated ($r = 0.832$), suggesting overlapping information in these indicators. These are descriptive pairwise correlations and should not be interpreted as adjusted effects.

Table 3. Pearson correlations among provincial indicators

Variable	POV	INTERNET	PKP	GINI	TPT	IPM
POV	1.000	−0.806	−0.299	0.273	−0.334	−0.804
INTERNET	−0.806	1.000	0.229	−0.136	0.434	0.832
PKP	−0.299	0.229	1.000	0.083	0.230	0.418
GINI	0.273	−0.136	0.083	1.000	0.058	0.101
TPT	−0.334	0.434	0.230	0.058	1.000	0.451
IPM	−0.804	0.832	0.418	0.101	0.451	1.000

7.3. Global Moran's I and LISA

Global Moran's I for the provincial poverty rate is 0.5963. The analytical randomization test reports a p-value of 1.0875×10^{-10}, while the Monte Carlo test based on 999 permutations reports $p = 0.001$ (observed rank = 1,000 of 1,000). Both results indicate statistically significant positive spatial autocorrelation under the KNN-4 weights matrix. Provinces with relatively high poverty therefore tend to be located near other provinces with relatively high poverty, and/or low-poverty provinces tend to be near low-poverty provinces.

Table 4. Global spatial autocorrelation in provincial poverty

Statistic	Estimate / value	Inference
Global Moran's I	0.596317	Positive spatial autocorrelation
Expected Moran's I	−0.027027	Under spatial randomness
Analytical p-value	1.0875×10^{-10}	Significant
Monte Carlo p-value	0.001 (999 permutations)	Significant

The LISA classification identifies four statistically significant High to High provinces: Papua, Papua Selatan, Papua Tengah, and Papua Pegunungan. The other 34 provinces are classified as not significant in the adjusted output. No Low to Low, High to Low, or Low to High locations are reported. The High to High group is concentrated in the Papua region and indicates a local concentration of high poverty values under the selected KNN-4 weights and Benjamini–Hochberg adjusted inference. The LISA results identify four statistically significant High to High provinces: Papua (18.1%), Papua Selatan (19.4%), Papua Tengah (27.6%), and Papua Pegunungan (29.7%). These provinces have above-average poverty values and are surrounded, under the KNN-4 weights structure, by provinces with relatively high poverty values. The other 34 provinces are classified as not significant after Benjamini Hochberg adjustment. No statistically

significant Low to Low, High to Low, or Low to High clusters are detected. The result indicates a localized concentration of high poverty in the Papua region; it does not imply that all provinces in eastern Indonesia belong to the same cluster.

Table 5A. Summary of local LISA classifications, 2024

LISA category	Provinces	Number
High to High	Papua; Papua Selatan; Papua Tengah; Papua Pegunungan	4
Low to Low	None	0
High to Low	None	0
Low to High	None	0
Not significant	34 other provinces	34
Total	38 provinces	38

7.4. OLS estimation and diagnostics

The OLS model is jointly significant ($F = 23.90$, $p = 6.059 \times 10^{-10}$) and has $R^2 = 0.7888$ and adjusted $R^2 = 0.7558$. In the OLS estimates, the Gini ratio is positively associated with poverty ($\beta = 40.51$, $p = 0.00183$), while IPM is negatively associated with poverty ($\beta = -0.809$, $p = 0.00073$). Internet access, adjusted expenditure per capita (PKP), and TPT are not statistically significant at the 5% level. These OLS estimates are presented as a benchmark because spatial diagnostics indicate dependence that should be considered in the regression specification.

Table 5. OLS coefficient estimates

Variable	Estimate	Std. error	t value	p-value
Intercept	62.7501	10.2545	6.1193	<0.001
INTERNET	−0.0959	0.0662	−1.4480	0.1573
PKP	-7.78×10^{-7}	9.467×10^{-6}	−0.0822	0.9350
GINI	40.5123	11.9192	3.3989	0.0018
TPT	0.2254	0.4152	0.5428	0.5910
IPM	−0.8086	0.2164	−3.7364	0.0007

OLS diagnostics do not indicate severe multicollinearity under the conventional VIF threshold of 5: VIF values range from 1.21 to 4.64, with the highest value for IPM (4.64) and INTERNET (4.19). The Breusch–Pagan test yields $p = 0.0756$, so heteroskedasticity is not detected at the 5% level, although the result is relatively close to the 10% threshold. The Shapiro–Wilk test yields $p = 0.4675$ and does not reject residual normality.

7.5. Spatial diagnostics and model comparison

The OLS spatial diagnostics indicate a significant spatial lag component. The standard LM lag test is significant ($p = 0.0168$), and the robust LM lag test remains significant ($p = 0.00549$). By contrast, the standard LM error test ($p = 0.8100$) and robust LM error test ($p = 0.1519$) are not significant. This pattern supports considering a spatial-lag specification rather than an error-only specification.

Table 6. Model comparison and spatial diagnostics

Model	AIC	Spatial parameter / test	Residual spatial autocorrelation
OLS	202.42	-	OLS spatial LM diagnostics below
SAR	198.72	$\rho = 0.3139$; $p = 0.0090$	$p = 0.2529$
SEM	204.24	$\lambda = 0.1760$; $p = 0.4215$	-
SDM	200.85	$\rho = -0.4688$; $p = 0.0816$	$p = 0.0162$

Under the common KNN-4 weights matrix, SAR has the lowest AIC (198.72), followed by SDM (200.85), OLS (202.42), and SEM (204.24). The SAR spatial parameter is positive and statistically significant ($\rho = 0.31387$; $z = 2.6139$; Wald $p = 0.00895$). The residual spatial autocorrelation test for SAR is not significant ($p = 0.25294$), suggesting that the SAR specification captures the spatial dependence detected in the OLS diagnostics under KNN-4. The SEM spatial error parameter is not significant ($\lambda = 0.17603$; $p = 0.42148$). In the SDM, the spatial parameter is not significant at 5% ($p = 0.08162$), and residual spatial autocorrelation remains significant ($p = 0.01622$). On the combined evidence of AIC, robust LM diagnostics, the spatial parameter, and residual diagnostics, SAR is selected as the preferred specification within the KNN-4 model set.

7.6. SAR coefficient estimates

In the primary KNN-4 SAR model, the Gini ratio has a positive and statistically significant coefficient ($\beta = 31.142$; $p = 0.00349$), while IPM has a negative and statistically significant coefficient ($\beta = -0.6762$; $p = 0.00033$). The coefficients for internet access ($p = 0.2866$), adjusted expenditure per capita (PKP; $p = 0.8396$), and TPT ($p = 0.9632$) are not statistically significant at 5%. The positive spatial autoregressive parameter indicates positive conditional dependence

in provincial poverty under the specified KNN-4 matrix. Because SAR coefficients in a spatial-lag model are not generally equal to marginal impacts, the covariate coefficients should not be described as complete direct or spillover effects.

Table 7. SAR coefficient estimates

Variable	Estimate	Std. error	z value	p-value
Intercept	51.0847	9.5877	5.3281	<0.001
INTERNET	−0.0610	0.0572	−1.0656	0.2866
PKP	-1.624×10^{-6}	8.025×10^{-6}	−0.2023	0.8396
GINI	31.1420	10.6604	2.9213	0.0035
TPT	0.0165	0.35697	0.0461	0.9632
IPM	−0.6762	0.18824	−3.5923	0.0003
Spatial ρ	0.31387	0.12008	2.6139	0.0090

7.7. Robustness test: SAR under alternative KNN weights

To assess sensitivity to the spatial weights specification, the SAR model was re-estimated using KNN-3 and KNN-5 in addition to the primary KNN-4 model. All three estimates produce a positive spatial autoregressive parameter: ρ = 0.3141 for KNN-3, ρ = 0.3139 for KNN-4, and ρ = 0.2763 for KNN-5. The Wald tests indicate statistically significant ρ estimates at the 5% level in all three models (p = 0.0031, 0.0090, and 0.0452, respectively). For KNN-5, however, the likelihood-ratio test is marginally above the 5% threshold (p = 0.0504), so the inference should be described as borderline rather than unequivocally significant. Moran tests of the SAR residuals are non-significant for KNN-3 (I = −0.0209; p = 0.8331), KNN-4 (I = −0.0975; p = 0.7587), and KNN-5 (I = −0.1099; p = 0.8235). Thus, no residual spatial autocorrelation is detected at the 5% level in these three specifications. The AIC is lowest for KNN-3 (197.89), followed by KNN-4 (198.72) and KNN-5 (200.59). The results indicate that the positive direction of spatial dependence and the residual diagnostic conclusion are stable across the three KNN choices, although model fit varies with k. Since the primary OLS/SAR/SEM/SDM comparison was conducted under KNN-4, KNN-4 remains the reference specification for that comparison; the lower KNN-3 AIC is reported as a sensitivity finding and should not be interpreted as a full cross-model selection result.

Table 8. SAR sensitivity estimates under alternative KNN weights

SAR weights	AIC	P	SE (ρ)	Wald p-value	LR p-value	Residual Moran I (p-value)
KNN-3	197.8922	0.31411	0.10605	0.00306	0.01061	−0.02086 (0.83309)
KNN-4	198.7223	0.31387	0.12008	0.00895	0.01697	−0.09751 (0.75867)
KNN-5	200.5928	0.27633	0.13798	0.04522	0.05037	−0.10992 (0.82354)

8. Discussion

The positive Global Moran's I and the four High–High LISA classifications indicate that poverty in 2024 is not randomly distributed across the 38 provinces under the selected KNN-4 spatial structure. The concentration of High–High provinces in Papua is consistent with the descriptive pattern of comparatively high poverty rates in Papua, Papua Selatan, Papua Tengah, and Papua Pegunungan. This local pattern supports the value of geographically targeted poverty analysis. However, it should not be generalized to all eastern Indonesian provinces, because the supplied LISA results classify the remaining 34 provinces as not significant. The model comparison points to SAR rather than SDM as the preferred model within the KNN-4 candidate set. The robust LM lag statistic is significant while the robust LM error statistic is not, and SAR has the lowest AIC among OLS, SAR, SEM, and SDM estimated with KNN-4. The significant positive ρ suggests that poverty outcomes are spatially interdependent conditional on the included covariates and the chosen weights. The non-significant residual autocorrelation test provides additional support that the KNN-4 SAR specification accounts for the remaining spatial pattern. The significant positive Gini coefficient suggests that provinces with greater measured inequality tend to have higher poverty rates after controlling for the other included variables and the spatial lag of poverty. The negative IPM coefficient is consistent with the interpretation that stronger human development is associated with lower poverty. These relationships remain observational. In particular, IPM and internet access are strongly correlated (r = 0.832), and poverty is strongly negatively correlated with both. The VIF values remain below 5 in the OLS diagnostic, but the overlap in information should still be considered when interpreting individual coefficients. Internet access, adjusted expenditure per capita (PKP), and TPT are not statistically significant in the KNN-4 SAR specification. This does not establish that digital connectivity, household expenditure, or labour-market conditions are irrelevant to poverty. Their estimates may depend on the operational definition of the internet indicator, the reference periods of the BPS indicators, the limited cross-sectional sample size, and correlation with other regressors. PKP should be interpreted as adjusted expenditure per person per year, not as aggregate regional output. The results have policy relevance for regional planning. The Papua High–High cluster suggests that anti-poverty programmes in these provinces may benefit from coordinated attention to basic services, education, health, employment opportunities, connectivity, and

the distribution of economic benefits. The positive spatial dependence also supports considering interregional coordination rather than treating provincial poverty as a purely isolated outcome. These implications are consistent with concern for social justice and equitable welfare, but the analysis does not identify the causal effect of any particular intervention. Several limitations qualify the findings. First, the analysis uses a single year and 38 cross-sectional observations; it cannot describe changes over time or establish temporal precedence. Second, the spatial weights are based on KNN coordinates and may not represent the actual economic or transport connections of an archipelagic country. Third, the operational definition of INTERNET and the reference periods of GINI and TPT should be verified against their original BPS metadata. Fourth, although SAR sensitivity estimates under KNN-3 and KNN-5 retain positive ρ estimates and non-significant residual Moran tests, KNN-3 has a lower AIC than KNN-4 and KNN-5, indicating that model fit is somewhat sensitive to the choice of k. Finally, the analysis remains cross-sectional and observational.

9. Conclusion

This study examined the spatial distribution and socioeconomic correlates of poverty across 38 Indonesian provinces in 2024. The descriptive results show a mean provincial poverty rate of 10.66%, with substantial variation across provinces. Global Moran's I (0.5963; Monte Carlo p = 0.001) indicates positive spatial autocorrelation under KNN-4. LISA identifies four High to High provinces Papua, Papua Selatan, Papua Tengah, and Papua Pegunungan while the other 34 provinces are not significant in the adjusted local analysis. Among OLS, SAR, SEM, and SDM estimated under KNN-4, SAR is the preferred specification based on its lowest AIC within that model set, significant positive spatial autoregressive parameter, support from robust LM lag diagnostics, and non-significant residual spatial autocorrelation. Sensitivity SAR estimates under KNN-3 and KNN-5 also yield positive spatial parameters and non-significant residual Moran tests. KNN-3 has the lowest AIC among the three SAR weight specifications, while the KNN-5 ρ inference is borderline (Wald p = 0.0452; LR p = 0.0504). In the primary KNN-4 SAR model, the Gini ratio is positively associated with poverty and IPM is negatively associated with poverty; internet access, PKP, and TPT are not statistically significant at the 5% level. These findings are cross-sectional associations rather than causal effects. Future work should verify the operational definitions and reference periods of all BPS indicators and consider alternative spatial structures such as contiguity, distance-based, or maritime/economic connectivity weights where substantively defensible. A multi-year analysis with harmonized provincial boundaries would be needed to investigate whether the spatial pattern persists and how it changes over time.

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