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Basic infrastructure and income inequality in Indonesia: a spatial econometrics approach

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Abstract

This study investigates the association between basic infrastructure and income inequality in Indonesia using a spatial panel econometric framework. Based on provincial panel data for 34 provinces from 2015 to 2024, the analysis first documents significant positive spatial dependence in the Gini ratio and then estimates a Spatial Autoregressive Random Effects (SAR-RE) model. The results show a positive, statistically significant spatial autoregressive coefficient ($\rho = 0.1926$), indicating that provincial inequality is linked to that of neighboring provinces. Better access to clean water and sanitation is associated with lower inequality, with sanitation showing the strongest equalizing effect. By contrast, GRDP continues to have a positive effect, suggesting that regional output expansion alone does not automatically yield inclusive distributional outcomes. This study contributes to the literature by applying spatial panel analysis to Indonesian provinces and by positioning basic infrastructure as an indirect human-capital channel in an archipelagic setting. Although the findings should be interpreted as associative rather than strictly causal, they highlight the importance of cross-provincial coordination in water and sanitation policy to reduce persistent regional inequality.

Keywords: *Basic infrastructure; Income inequality; Place-based policies; Spatial autoregressive; Spillover effects.*

JEL Classification: D63, H54, R12

INTRODUCTION

Over the past decade, Indonesia’s national development has exhibited relatively stable macroeconomic performance; however, this achievement has been accompanied by persistent income inequality. The issue is no longer merely distributive but increasingly structural and spatial. Data from BPS–Statistics Indonesia show that the provincial Gini ratio remains within a relatively wide range, indicating that aggregate national growth has not eliminated interregional disparities (Badan Pusat Statistik RI, 2025). Beneath national averages lies a markedly uneven geography of welfare, in which growth poles remain concentrated in certain areas while peripheral regions continue to experience weaker distributive outcomes (Wolf, 2025).

This inequality also displays a pronounced geographical pattern. Provinces in Java and Bali remain dominant growth centers; yet highly urbanized regions such as D.I. Yogyakarta frequently report among the highest Gini levels in the country. This suggests that urban agglomeration does not automatically generate broad-based distributional gains; rather, it may intensify the concentration of benefits in already advantaged locations (Renninger et al., 2025). Such a spatial pattern reinforces the theoretical view that the trajectory of inequality within any given region (Khan & Siddique, 2021) is intricately linked to the economic conditions and developmental dynamics of surrounding regions (Cartone et al., 2022), rather than operating as a purely localized phenomenon isolated from its geographic neighbors (Quito et al., 2024).

The spatial character of inequality is consistent with Tobler's First Law of Geography, which posits that nearby places are more strongly related than distant ones (Tobler, 1970). In the Indonesian context, labor mobility, trade, and infrastructure connectivity increasingly link provinces across administrative borders, rendering the assumption of cross-provincial independence less tenable (M. Li et al., 2025). This reasoning is further supported by the New Economic Geography perspective (Fujita & Krugman, 2003), which suggests that agglomeration forces may reinforce growth concentration and generate backwash effects when the benefits of development do not diffuse evenly across space (Gómez-Tello et al., 2025). Within this framework, infrastructure emerges as a central yet still contested determinant in the inequality literature. One strand of research argues that infrastructure can promote inclusive growth by reducing costs and improving access. At the same time, another suggests that its benefits may remain unevenly distributed, disproportionately captured by urban cores, formal firms, or capital-intensive sectors. This unresolved debate is particularly salient in Indonesia, where large-scale connectivity projects coexist with persistent disparities in basic public services. The empirical gap, therefore, lies not only in the need for a spatial approach but also in the limited evidence on whether basic infrastructure—rather than infrastructure in general—is more closely associated with lower inequality once interprovincial spillovers are taken into account (Acheampong et al., 2024).

The channel through which basic infrastructure may reduce inequality is plausibly linked to human-capital formation. Improved access to clean water and sanitation reduces exposure to disease, lowers coping costs for poorer households, and enhances time allocation, productivity, and labor-market participation. Because health externalities, labor mobility, and service networks extend across administrative boundaries, these benefits may also spill over to neighboring provinces. For this reason, access to clean water and sanitation is treated here as indirect proxies for human capital formation rather than as direct measures of human capital itself (Gao et al., 2024). Beyond infrastructure, macroeconomic conditions also shape regional inequality. GRDP growth does not necessarily become inclusive when expansion is concentrated in sectors with limited labor absorption, while unemployment may signal unequal access to development gains and labor-market failures. These asymmetries can reinforce spatial dependence across provinces, particularly when economic shocks or labor-market pressures extend beyond provincial borders (Prastiwi & Khoirunurrofik, 2025).

Given the structural reality of these interregional linkages, traditional non-spatial econometric models may be analytically inadequate (Annisa, 2025), primarily because they systematically ignore spatial autocorrelation and may therefore produce biased or statistically inefficient inferences (Pronti & Zoboli, 2024). This study addresses this issue by estimating a Spatial Autoregressive (SAR) model. Conceptually, the SAR specification is highly appropriate when the dynamics of inequality in one province are influenced not only by its own localized characteristics (Bulty et al., 2023) but also by inequality outcomes in neighboring provinces through structural transmission channels such as demonstration effects, market integration, labor mobility, and policy diffusion (Liu & Lian, 2025). This differs from a Spatial Error Model (SEM), which implies that spatial dependence arises mainly from omitted shocks or measurement error. Although more general models such as the Spatial Durbin Model (SDM) can also be informative, the present study prioritizes SAR because its central theoretical claim concerns outcome interdependence in inequality itself (Kopczewska & Elhorst, 2024). The absence of an SDM comparison is therefore acknowledged as a limitation rather than treated as evidence of SAR's universal superiority (Abban et al., 2025).

This study contributes in three delimited ways. First, it applies spatial panel analysis to Indonesian provinces, where archipelagic geography makes spatial interaction especially consequential. Second, it focuses on access to clean water and sanitation as indirect human-capital channels associated with inequality, rather than relying solely on aggregate growth indicators. Third, it decomposes SAR effects into direct and indirect components to show how infrastructure improvements may generate cross-provincial spillovers. Accordingly, this study aims to analyze the association between basic infrastructure and income inequality in Indonesia within a spatial panel framework and to determine whether access to clean water and sanitation is associated with equalizing effects at the local and provincial levels.

METHODS

This study employs a spatial panel econometric framework to accommodate both cross-sectional heterogeneity and temporal dynamics. Two baseline spatial specifications are considered: the Spatial Autoregressive (SAR) model and the Spatial Error Model (SEM). This comparison is intended to identify whether the dominant spatial process operates through the dependent variable itself or through unobserved spatially correlated disturbances. Because the substantive argument emphasizes contagion, interprovincial demonstration effects, and the diffusion of distributive outcomes across connected regions, SAR is treated as the conceptually central specification. At the same time, SEM serves as a relevant alternative benchmark (Yang & Lv, 2025). The SAR model is specified as:

$$Y_{it} = \rho W Y_{it} + \alpha_i + \beta X_{it} + \epsilon_{it} \quad (1)$$

The SEM model is specified as:

$$Y_{it} = \alpha_i + \beta X_{it} + u_{it}, \quad u_{it} = \lambda W u_{it} + \epsilon_{it} \quad (2)$$

The spatial weight matrix combines Queen contiguity with a k-nearest-neighbor correction using k = 3. The Queen criterion preserves first-order territorial adjacency; however, in an archipelagic country such as Indonesia, it is insufficient on its own because several island provinces would otherwise become mathematical “islands” in the spatial system—that is, observational units with no contiguous neighbors in the weight matrix. This would weaken national connectivity and distort the representation of interprovincial dependence. For this reason, the KNN correction is introduced as a technical necessity rather than merely an optional specification choice, ensuring that geographically separated island provinces remain connected within the national spatial structure

(Notonegoro et al., 2024). Row standardization is then applied so that each province's influence is interpreted relative to its total set of neighbors (Zhao et al., 2020).

The analysis uses a balanced panel dataset of 34 Indonesian provinces from 2015 to 2024, obtained from BPS–Statistics Indonesia (Badan Pusat Statistik RI, 2025). The dependent variable is the Gini ratio. The explanatory variables are GRDP, the unemployment rate, access to improved clean water, and access to sanitation. In line with the theoretical discussion, the last two variables are interpreted as indirect proxies for human-capital formation (Asamoah et al., 2021) because they affect health, productivity, and household vulnerability. However, they are not direct indicators of education or skills (Wang et al., 2024). The empirical procedure follows five stages. First, pooled, fixed-effects, and random-effects panel models are estimated. Second, the Chow, LM, and Hausman tests are used to identify the preferred non-spatial baseline estimator. Third, spatial dependence is assessed using Moran's I and related diagnostics. Fourth, SAR and SEM specifications are estimated and compared based on the significance of the spatial parameters, model fit, and consistency with the theoretical mechanism under study. Fifth, the coefficients of the selected SAR model are decomposed into direct, indirect, and total effects.

Because the study relies on observational provincial panel data, the estimates should be interpreted as associative rather than strictly causal. Reverse causality cannot be fully eliminated; for example, inequality may also influence the allocation of infrastructure (Ratnasari et al., 2023). In addition, although the Hausman test statistically supports the Random Effects specification, the assumption that province-specific effects are uncorrelated with the regressors remains substantively strong in regional inequality research. Accordingly, the RE-based spatial estimates are interpreted with caution (Abban et al., 2025).

RESULTS AND DISCUSSION

Results

The panel data analysis of 34 Indonesian provinces from 2015 to 2024 reveals highly heterogeneous dynamics in income inequality and the provision of basic infrastructure. According to the descriptive statistics presented in Table 1, the national average Gini ratio was 0.3502, with substantial variation ranging from 0.2350 to 0.4590 (Badan Pusat Statistik RI, 2025). This inequality is positively associated with disparities in access to basic infrastructure. Specifically, access to improved clean water (Wan et al., 2024) had an average achievement rate of 80.24%, yet still exhibited a critical minimum of 37.35%.

Table 1. Descriptive statistics of research variables (2015-2024)

Variable	Min.	Max	Mean	Median
Gini Ratio Index (Y)	0.2350	0.4590	0.3502	0.3470
GRDP (X_1) (Rp billion)	20,380	2,151,041	321,725	135,349
Unemployment Rate (X_2) (%)	1.40	10.95	5.12	4.74
Access To Clean Water (X_3) (%)	37.35	99.96	80.24	81.58
Access To Sanitation (X_4) (%)	16.12	97.12	72.06	74.64

As shown in Figure 1, there is a discernible trend toward improved basic infrastructure quality and aggregate income equalization. Although the average Gini ratio exhibits a downward trajectory, converging toward 0.340, the wide disparities highlighted in Table 1 underscore the persistence of regional inequality. This suggests that although economic growth, as reflected in GRDP, continues to expand, it has not yet fully mitigated the geographical polarization embedded in infrastructure accessibility and income distribution. Figure 1 likewise indicates that, despite improvements in average infrastructure access over time, provincial inequality remains uneven.

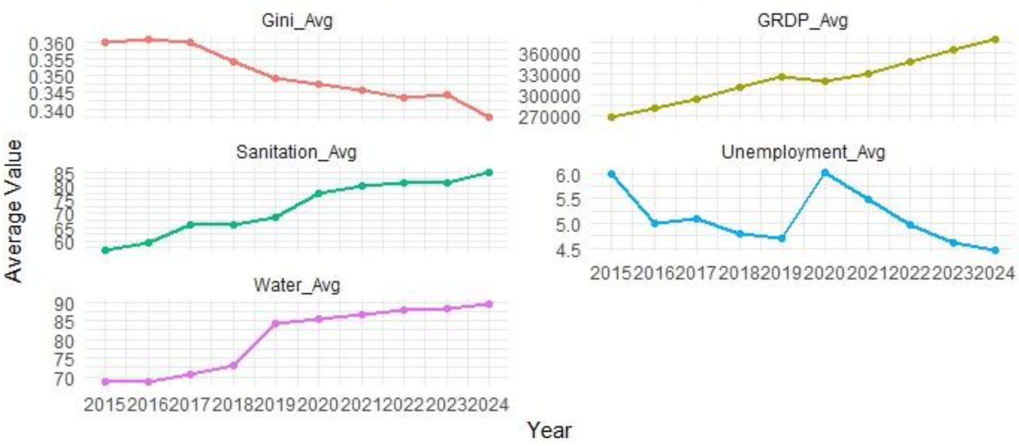


Figure 1. Trends in socioeconomic indicators and basic infrastructure access (2015-2024)

The model selection and diagnostic tests reported in Table 2 justify the use of a spatial panel specification. The Chow test rejects the pooled OLS model, the LM test supports the presence of random effects, and the Hausman test does not reject the Random Effects model (Kapetanios et al., 2023). More importantly, Moran's I values are positive and significant in multiple years, indicating that inequality is spatially clustered rather than randomly distributed. Provinces with relatively high inequality tend to be located near provinces with similarly high inequality, and the same pattern applies to lower-inequality clusters (Mendez & Santos-Marquez, 2021).

Table 2. Summary of model specification and diagnostic tests

Testing phase	Test method	Test statistic	P-value	Decision/Interpretation
I. Panel model selection				
Individual Effects	Chow Test (F-test)	F = 86.269	< 0.0001***	Pooling rejected; Fixed Effect preferred
Random Effects	LM Test (Breusch-Pagan)	χ^2 = 1061.8	< 0.0001***	Random effects present; RE preferred over Pooling
Parameter Consistency	Hausman Test	χ^2 = 3.0146	0.5554	Random Effect (RE) selected as a consistent estimator
II. Spatial dependence diagnostics				
Spatial Autocorrelation (Residuals)	Global Moran's I (2018)	I = 0.2078	0.0231**	Significant positive spatial dependence
Spatial Autocorrelation (Residuals)	Global Moran's I (2019)	I = 0.3627	0.0005***	Strong spatial clustering
Spatial Autocorrelation (Residuals)	Global Moran's I (2020)	I = 0.1939	0.0305**	Significant spatial dependence

Testing phase	Test method	Test statistic	P-value	Decision/Interpretation
Spatial Autocorrelation (Residuals)	Global Moran's I (2023)	I = 0.2081	0.0231**	Persistent spatial dependence
Spatial Dependence (Panel-based)	LM Test (Breusch-Pagan) + Moran's I	-	-	Panel RE model potentially inefficient due to spatial interdependence
III. Spatial model specification				
Spatial Specification	Wald Test (SAR)	$\chi^2 = 9.154$	0.0025***	SAR model appropriate (H_0 rejected)
Spatial Coefficient	Spatial Autoregressive Coefficient (λ)	λ = 0.1926	0.0025***	Positive and significant spatial spillover effects

Figure 2 provides a visual illustration of this clustering pattern through a Moran's I scatter plot for the selected year.

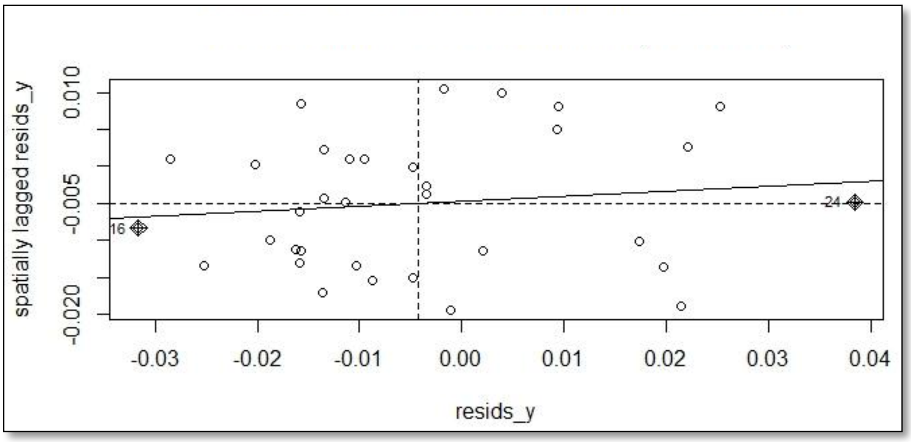


Figure 2. Moran's I scatter plot of residuals for income inequality model (Year 2024)

Table 3 shows that the SAR-RE model provides the most convincing spatial specification in this study. The spatial autoregressive coefficient is positive and statistically significant (ρ = 0.1926; p = 0.0025), whereas the SEM spatial error parameter is not significant at conventional levels. This finding suggests that the dominant spatial process is better explained by interdependence in inequality outcomes than by purely spatially correlated residual shocks.

Table 3. Estimation results of Spatial Autoregressive (SAR) and Spatial Error Model (SEM)

Independent variables	SAR Model (Spatial Lag)	SEM Model (Spatial Error)
Constant	0.32104*** (0.0098)	0.39730*** (0.0106)
GRDP (X_1)	1.937e-08* (9.073e-09)	1.968e-08* (9.568e-09)
Unemployment Rate (X_2)	0.00094 (0.0007)	0.00104 (0.0008)
Access To Clean Water (X_3)	-0.00028* (0.0001)	-0.00035* (0.0001)
Access To Sanitation (X_4)	-0.00036*** (0.0001)	-0.00041*** (0.0001)
Spatial parameters		
Spatial Coefficient (ρ/λ)	0.19263*** (0.0636)	0.12188 (0.0744)
Variance Parameter (σ^2)	8.5448*** (2.2470)	9.5454*** (2.5076)
Diagnostic Statistics		
Wald Test (*p*-value)	0.00248***	0.10172
Log-Likelihood	785.12	772.45
Number of Observations (*N*)	340	340

Table 4 decomposes the SAR estimates into direct, indirect, and total effects. Improved access to clean water and sanitation both exhibit negative direct effects on inequality, with sanitation producing the strongest equalizing effect. Specifically, sanitation has a direct effect of $-3.67 \times 10^{-4}$and a total effect of -4.55×10^{-4}, while Access to Clean Water shows a direct effect of $-2.87 \times 10^{-4}$and a total effect of -3.56×10^{-4}. By contrast, GRDP has a positive total effect of 2.39×10^{-8}.

Table 4. Decomposition of spatial impacts: direct, indirect (spillover), and total effects

Variable	Direct effect	Indirect effect (Spillover)	Total effect
GRDP (X_1)	1.93×10^{-8}	4.62×10^{-9}	2.39×10^{-8}
Unemployment Rate (X_2)	9.44×10^{-4}	2.25×10^{-4}	1.16×10^{-3}
Access to Clean Water (X_3)	-2.87×10^{-4}	-6.86×10^{-5}	-3.56×10^{-4}
Access to Sanitation (X_4)	-3.67×10^{-4}	-8.77×10^{-5}	-4.55×10^{-4}

The indirect effects further indicate that the association between infrastructure and inequality is not purely local. Sanitation produces the largest negative spillover effect -8.77×10^{-5}, followed by Access to Clean Water -6.86×10^{-5}. Figure 3 reinforces this result, showing that the total effects of Access to Clean Water and sanitation remain negative across most provinces (S. Li et al., 2024), while the positive total effect of GRDP suggests that regional growth can remain spatially uneven and concentrated rather than broadly diffused (Wen et al., 2023).

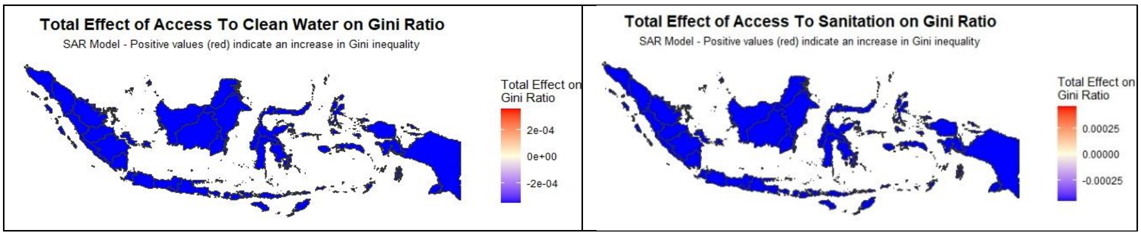


Figure 3. Thematic Maps of total spatial effects on gini ratio across Indonesian provinces

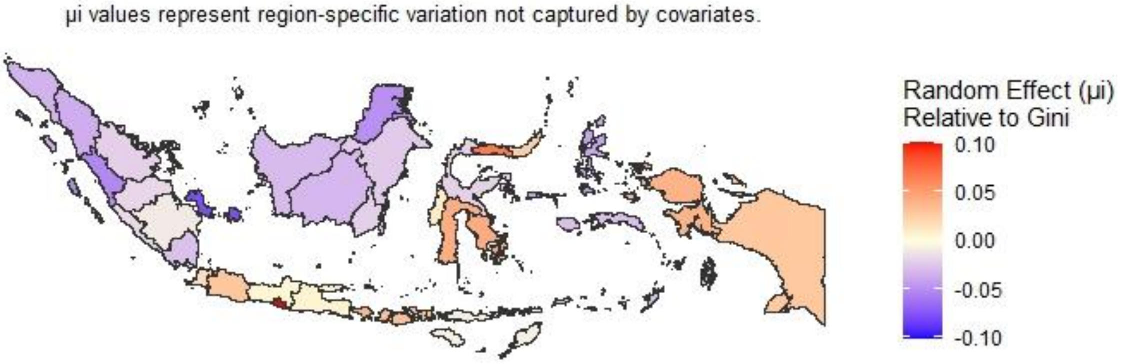
Robustness checks were conducted using alternative spatial weight matrices, namely KNN with k = 4, KNN with k = 5, and an inverse-distance matrix. The substantive conclusions remain stable, which is important given the sensitivity of spatial panel estimates to alternative weighting schemes and specification choices (Ren et al., 2024). The spatial autoregressive coefficient remains positive across all specifications, ranging from 0.1926 in the baseline Queen + KNN3 matrix to 0.3533 in the inverse-distance matrix. Likewise, access to clean water and sanitation remains negative, while GRDP and unemployment remain positive. Although the coefficient magnitudes vary moderately, the direction and substantive interpretation of the main findings remain unchanged, indicating that the baseline results are not unduly sensitive to the choice of spatial weights.

Table 5. Robustness check of SAR estimates under alternative spatial weight matrices

Spatial weight matrix	ρ	Log-likelihood	GRDP	Access to Clean Water	Access to Sanitation	Unemployment
Queen + KNN (k=3)	0.1926	937.51	1.94E-08	-0.000288	-0.000368	0.000944
KNN (k=4)	0.2394	939.02	1.80E-08	-0.000275	-0.000343	0.000844
KNN (k=5)	0.2274	937.42	1.97E-08	-0.000279	-0.000347	0.000892
Inverse distance	0.3533	938.47	2.19E-08	-0.000222	-0.000334	0.000814

Note: The table reports coefficient estimates from SAR models re-estimated using alternative spatial weight matrices. The signs of the main coefficients remain unchanged across specifications, suggesting that the substantive conclusions are robust to different definitions of spatial connectivity.

Figure 4 presents the province-specific random effects, indicating that substantial heterogeneity remains even after accounting for observed covariates and spatial dependence (Marbler, 2024). Provinces such as D.I. Yogyakarta, along with several provinces in Sulawesi and Papua, exhibit positive random effects, whereas North Kalimantan, parts of Sumatra, and the Riau Islands show negative random effects (Yin et al., 2024). Several provinces in Kalimantan and Java remain close to zero, suggesting that their inequality dynamics are comparatively well explained by the observed regressors and the estimated spatial structure (Zanfack, 2025).



μi values represent region-specific variation not captured by covariates.

Figure 4. Map of province specific inequality (μ_i) random effect model

Discussion

The findings imply that the quality of development in Indonesia depends not only on how much provinces grow but also on the type of public capital stock that supports such growth and on how its gains spread across space. The positive GRDP coefficient is strongly consistent with a structural pro-rich growth pattern (Steenbrink & Skali, 2026), in which aggregate economic gains are captured disproportionately by formal urban sectors, resource-based enclaves, or specific socioeconomic groups already well positioned to benefit from expanding markets (Szymczak, 2024). This interpretation should remain cautious because endogeneity may still be present; however, it is consistent with broader evidence showing that growth can coexist with unequal distributive outcomes when labor absorption, service access, and redistribution remain weak (Hope & Limberg, 2022).

By contrast, the negative effects of access to clean water and sanitation suggest that basic infrastructure functions as an equalizing public input. More precisely, these variables should be understood as health-related public inputs that operate through an indirect human-capital channel: by reducing disease exposure, lowering coping costs, improving time allocation, and strengthening productivity, they improve the conditions under which human capital can accumulate and translate into more inclusive welfare outcomes. This interpretation is also consistent with Indonesian evidence linking human development (Dewi et al., 2021), ICT expansion (Kartika Sari, 2024), and regional development outcomes to more even welfare improvement (Dinda Rahmasari & Ramadhani, 2024).

Spatial spillovers enhance the policy relevance of the results. If improvements in water and sanitation in one province are associated with lower inequality in neighboring provinces, then fragmented infrastructure provision becomes suboptimal (Cameron et al., 2021). This point is particularly important in Indonesia's archipelagic and decentralized setting, where mobility, service access, and infrastructure disparities interact beyond administrative borders. In this sense, interprovincial coordination is not merely desirable but economically meaningful for reducing inequality (Hidayat & Yulianita, 2025).

These results support a place-based policy approach rather than a uniform national strategy. Transfers such as DAU and DAK should be understood not only as fiscal instruments but also as coordination mechanisms that generate spillovers. Provinces with weak sanitation and clean-water coverage may generate negative externalities that extend across borders, implying that infrastructure equalization has a national efficiency rationale in addition to an equity rationale (Wan et al., 2024). At the same time, the positive association between GRDP and inequality implies that growth-oriented policy packages require complementary redistributive supports, especially inclusive service provision, labor-market access, and targeted social investment (Y. Li et al., 2025).

Several limitations should be stated explicitly. First, the paper does not identify a fully causal effect of infrastructure on inequality; reverse causality and omitted time-varying confounders remain possible. Second, although sensitivity checks using alternative spatial weight matrices show stable substantive conclusions, the analysis does not yet include an SDM-based robustness exercise. Accordingly, the results should be interpreted as evidence of robust association within the tested SAR specifications, rather than as a complete causal-spatial identification strategy. Third, access to clean water and sanitation is treated here as indirect proxies for human-capital conditions, not as direct measures of human capital itself.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study shows that income inequality in Indonesia is spatially interconnected and that basic infrastructure is an important predictor within that system. Using a SAR-RE model for 34 provinces over 2015–2024, the analysis finds a positive and significant spatial autoregressive coefficient, indicating that provincial inequality is linked to inequality in neighboring provinces. The decomposition results show that Access to Sanitation has the strongest equalizing total effect, followed by Access to Clean Water, while GRDP retains a positive total effect. The robustness exercise using KNN and inverse-distance matrices also preserves the sign of ρ and the main coefficients, indicating that the baseline conclusions are not overly sensitive to the spatial-weight specification.

The broader conceptual implication is that, in the Indonesian archipelagic context, basic infrastructure should be viewed as an indirect human-capital channel embedded within a spatial system, rather than as a purely local public works variable. The study, therefore, makes a cautious but meaningful contribution by showing how Access to Clean Water and Access to Sanitation can serve as equalizing and spillover-generating inputs in a decentralized multi-island economy. At the same time, the findings remain associative rather than strictly causal, and substantial unobserved heterogeneity persists across provinces.

Recommendations

From a policy perspective, the central government should prioritize water and sanitation not only as service-delivery targets but also as instruments of inclusive regional development, supported by stronger interprovincial coordination and improved alignment of DAU, DAK, and other place-based financing mechanisms. Future research should extend this framework by estimating more comprehensive spatial specifications, such as the Spatial Durbin Model, testing alternative spatial-weight designs, and incorporating more direct channels, including digital infrastructure, education, health outcomes, and social capital.

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AUTHOR CONTRIBUTIONS

Conceptualization: Ardiansyah Abubakar, Arifin, Muhammad Fadillah
Methodology: Ardiansyah Abubakar
Software: Ardiansyah Abubakar
Validation: Arifin
Formal Analysis: Ardiansyah Abubakar
Investigation: Ardiansyah Abubakar, Muhammad Fadillah
Resources: Ardiansyah Abubakar
Data Curation: Muhammad Fadillah
Writing-Original Draft: Ardiansyah Abubakar
Writing-Review & Editing: Ardiansyah Abubakar, Muhammad Fadillah
Visualization: Ardiansyah Abubakar
Supervision: Arifin
Project Administration: Ardiansyah Abubakar
Funding Acquisition: Arifin

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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