

Article

Do Rural Roads Reduce Poverty? A Spatial and Panel Analysis of Village Fund Investments in Kebumen, Indonesia

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Abstract

This study examines whether Village Fund investments in rural road connectivity effectively reduce poverty in Kebumen Regency, the poorest region in Central Java. Using village-level data from 2022 to 2024, the analysis combines spatial clustering methods (Moran's I and LISA) with panel data models to assess both geographic patterns and causal relationships. Spatial results reveal persistent and intensifying poverty clusters in the northern hilly areas, while low-poverty clusters remain concentrated in the southern coastal zone. Village Fund Road investments also show uneven spatial concentration, with increasing clustering over time but limited alignment with poverty hotspots. Panel data analysis finds that although road budget allocations are statistically associated with reductions in village poverty rates, the effect size is very small and becomes insignificant once year effects are included, suggesting that broader macroeconomic conditions outweigh local infrastructure spending. Geographic constraints—particularly slope and elevation—significantly moderate road investment effectiveness, indicating weaker impacts in more difficult terrains. Overall, the findings show that rural road investments under the Village Fund have had only marginal short-term effects on poverty reduction. The study argues that future Village Fund allocations should shift toward human capital and livelihood-based programs rather than prioritizing physical infrastructure in already connected regions.

Keywords: Village Fund; Rural Road Connectivity; Poverty Reduction; Spatial Analysis; Panel Data Regression.

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I. Introduction

Poverty remains a major global development challenge, often characterized by deprivation, vulnerability, and isolation, with the latter closely tied to regional connectivity (Chambers, 1995, as cited in Listyaningsih et al., 2021). In Indonesia, poverty alleviation programs generally aim to reduce expenses and increase income, while the spatial dimension of poverty, particularly the role of rural connectivity, has received comparatively less empirical attention. Limited connectivity constrains access to markets, public services, and employment opportunities, reinforcing poverty in rural areas.

Rural road infrastructure plays a critical role in reducing spatial isolation by lowering transport costs, improving mobility, and facilitating access to education, healthcare, and economic activities. In Indonesia, programs to encourage rural connectivity investment include the Village Fund program (*Dana Desa*). The program, first introduced in 2014 by Law No. 6 of 2014 on village governance, is a national-scale village governance management program initiated by the central government. The program provides fiscal transfers to village governments and grants them autonomy to determine local development priorities, including infrastructure development (Rammohan & Tohari, 2023). The Village Fund Program enabled the village leadership and community to make decisions about their development priorities and make corresponding investments. Although rural road construction absorbs a substantial share of Village Fund expenditures, empirical evidence on its effectiveness in reducing poverty, and particularly using spatially explicit approaches, remains limited. This study addresses this gap by examining the relationship between Village Fund-financed rural road connectivity and poverty reduction in Kebumen Regency, Central Java.

1.1. Background of Problems

As one of the 35 regions in the *Jawa Tengah* or Central Java Province, Kebumen has recorded the highest poverty rate in the province over the past five years. According to the Agency for Statistics of Kebumen Regency, the region encompasses a total area of 1,281.12 km², comprising 449 villages and 11 urban villages distributed across 26 subdistricts. On average, each village has an area of 2 km². Its geographical conditions are diverse, ranging from hilly terrain in the north, relatively flat central areas, to coastal zones along the Indian Ocean in the south. These physical variations influence settlement patterns, accessibility, and infrastructure development.

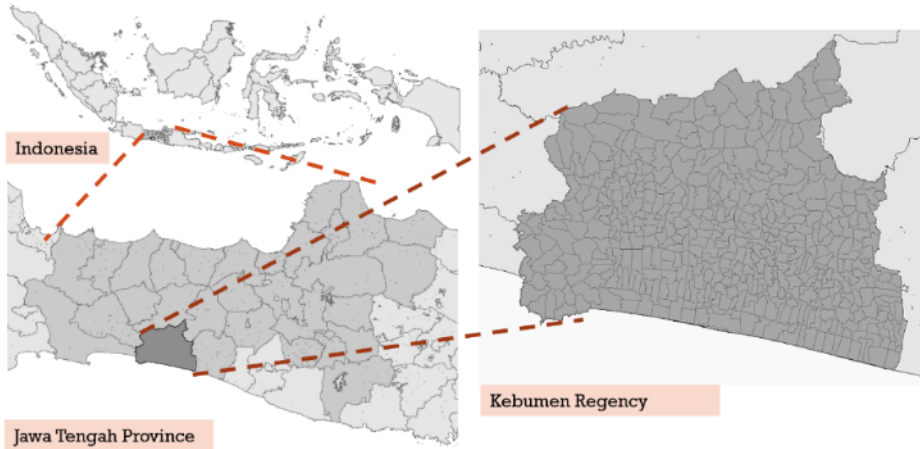


Figure 1. Location of Kebumen Regency in Jawa Tengah Province, Indonesia

Source: Department of Public Works and Spatial Planning of Kebumen Regency

The population of Kebumen Regency was estimated at 1,434,023 in 2023, with an average village population of approximately 3,118 people. Before the COVID-19 pandemic, the poverty rate increased from 16.82% in 2019 to 17.59% in 2020. Followed by a further rise in 2021. Although poverty levels declined between 2021 and 2023, they remain significantly higher than provincial and national averages. This persistent disparity highlights structural challenges in poverty reduction and raises questions about the effectiveness of existing development interventions.

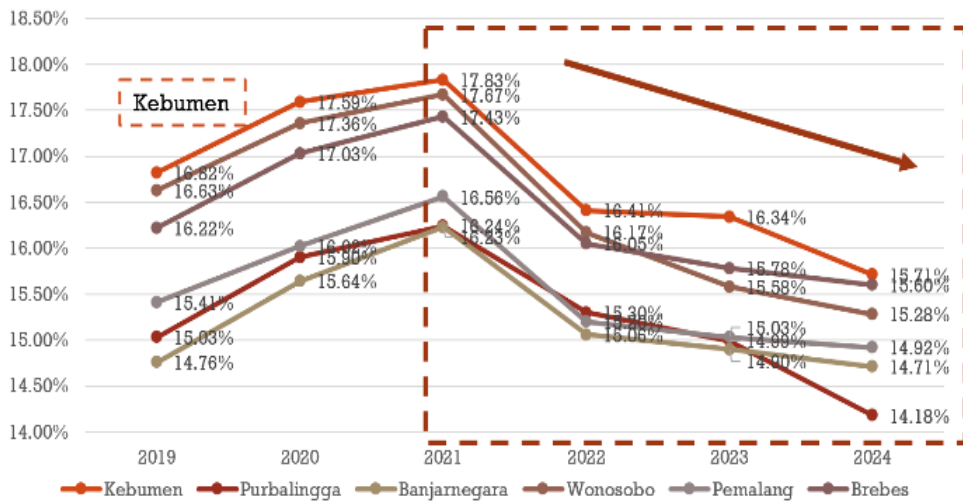


Figure 2. The Comparison between Poverty Rate in Kebumen Regency and other Regencies with a high percentage of poverty in Jawa Tengah Province in 2019–2023

Source: Planning Agency of Kebumen Regency

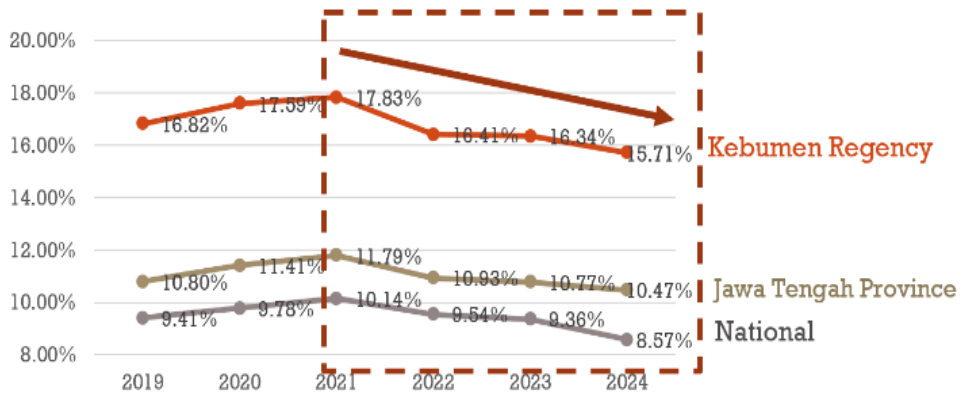


Figure 3. Percentage of Poverty Rate in Kebumen (compared to national and provincial levels) in 2019–2023

Source: Planning Agency of Kebumen Regency

1.2. The Problems

Previous studies have shown that the Village Fund Program has effectively contributed to poverty reduction and rural development in Indonesia. Sigit and Kosasih (2020), found that the program reduces poverty, while Arifin et al. (2020) noted that it increases the number of village-owned enterprises and job opportunities across both Java and non-Java regions. Similarly, Rammohan and Tohari (2023) observed that the program improved rural household consumption and labor participation, contributing to poverty alleviation, and Sijabat (2024) reported that it significantly enhanced the Human Development Index (HDI) through better health, education, and living standards. However, existing research treats the Village Fund as a homogeneous intervention without distinguishing between different types of its expenditures.

In practice, a large share of Village Fund resources is allocated to rural road construction and improvement. Despite this emphasis, few studies explicitly assess whether road connectivity investments generate meaningful poverty reduction effects at the village level. Moreover, existing research rarely incorporates spatial dependence or spillover effects, even though poverty and infrastructure outcomes tend to be geographically clustered. As a result, the contribution of Village Fund allocation for rural road improvements to poverty alleviation remains insufficiently understood, especially in regions that are not classified as underdeveloped but continue to exhibit persistently high poverty rates, such as Kebumen Regency. This study addresses these gaps by focusing specifically on rural road connectivity as a key expenditure component of the Village Fund Program and by applying a spatial analytical approach to evaluate its relationship with poverty. It aims to determine how the Village Fund Program’s investment in rural road connectivity has contributed to reducing poverty in Kebumen Regency by investigating the relationship between rural road connectivity and poverty.

1.3. Research Framework

To explain the link between government investment, rural road connectivity, and poverty alleviation, this study’s theoretical framework integrates four complementary theoretical perspectives: Growth Poles Theory, Basic Needs Theory, the First Law of

Geography, and Spatial Accessibility. Growth Poles Theory (Perroux, 1955) suggests that development concentrates around specific “poles” of activity, where infrastructure such as roads stimulates local economies by improving accessibility, reducing costs, and attracting investment (Muturi, 2023; Ng et al., 2019; Ojile, 2021). Villages allocating substantial Village Fund resources to road improvement can thus act as localized growth poles that generate wider socioeconomic benefits. Basic Needs Theory (Streeten et al., 1981) emphasizes that infrastructure enables access to essential services like health, education, and clean water, directly improving welfare and reducing poverty—particularly in developing regions where road connectivity supports sustainable growth (Oliva, 2017). Tobler’s First Law of Geography (Tobler, 1970) explains spatial dependence, where poverty in one area tends to resemble that in nearby areas, as seen in studies across China, Colombia, and Indonesia (Builes-Jaramillo & Lotero, 2020; Harmes et al., 2017; Shi et al., 2020). This highlights the importance of spatial analysis in understanding poverty distribution. Lastly, Spatial Accessibility Theory holds that improved rural roads enhance social welfare by reducing travel barriers, expanding access to markets and services, and fostering economic participation (Imi et al., 2016; Liu et al., 2018; Singh, 2010).

Together, these perspectives provide a conceptual basis for analyzing how Village Fund investments in rural road connectivity influence poverty both directly and through spatial spillover effects. Accordingly, this study examines the spatial patterns of Village Fund disbursement, road connectivity, and poverty rates, and estimates the relationship between connectivity improvements and poverty reduction while accounting for geographical characteristics and inter-village interactions.

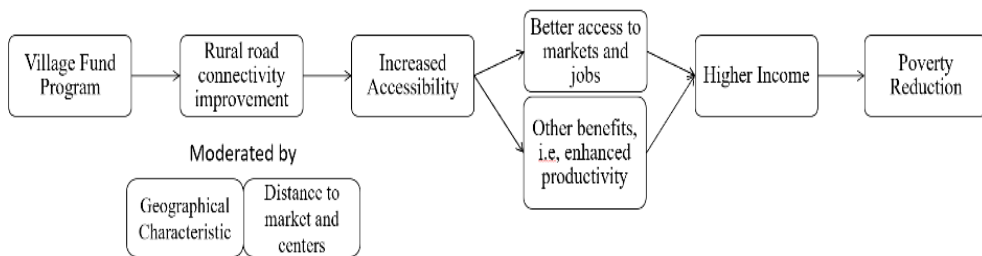


Figure 4. Theoretical Framework

Source: Author, 2025

II. Method

This study adopts a deductive, quantitative approach to assess the relationship between Village Fund-financed rural road connectivity and poverty reduction at the village level. The analysis combines spatial data analysis and panel data analysis to capture both geographic patterns and temporal dynamics. The study area comprises all 449 villages in Kebumen Regency, observed over the period 2022-2024.

Secondary data were obtained from government agencies in Kebumen Regency and include village-level poverty rates, Village Fund allocations, and spatial data on road networks, topography, and settlement locations. Spatial processing and mapping were conducted using Geographic Information System (GIS), while panel data analysis was

employed to identify the correlations and/or the cause-and-effect relationships between the variables in a changing period of time.

2.1. Variables

The dependent variable in this study is the change in village-level poverty rates, which serves as an indicator of socioeconomic improvement. The main explanatory independent variable is the proportion of Village Fund expenditure allocated to rural road connectivity, calculated as the share of total Village Fund spending devoted to the improvement or development of village roads. Additional independent or control variables include the road density from the existing road network, geographical characteristics (slope and elevation), and distance to city or subdistrict centers. Road density is derived from GIS line-density calculations using the existing road network. Slope and elevation capture terrain constraints that may affect accessibility and infrastructure effectiveness. Distance to centers is measured as the straight-line (Euclidean) distance from village centroids to the nearest administrative and city centers. Euclidean distance is used because it provides a consistent and transparent proxy for relative accessibility across villages, particularly where detailed travel time or origin-destination data are unavailable.

Table 1. Research Variables

Type	Variable
Dependent	Poverty rate at the village level
Independent	Share of the Village Fund Program allocated to rural road connectivity
Control	Road density
Control	Geographical characteristics: slope and elevation rate
Control	Village distance to city/subdistrict centers

Source: Author, 2025

2.2. Limitation

Several limitations may influence the interpretation of the results of this study. First, the period available for estimating the impact of road infrastructure investments on poverty rates is limited because the panel dataset used only spans three years (2022-2024). Since reducing poverty often involves long-term processes, the later or cumulative effects of improved road connectivity may not be adequately captured by a brief observation period. Therefore, rather than representing long-term causal effects, the estimated relationships should be interpreted as reflecting short-term relationships. Second, accessibility is approximated using Euclidean distance rather than network-based travel time, which may oversimplify actual movement patterns. Third, road density includes all road types (national, provincial, regional, and rural roads) due to data constraints, potentially diluting the specific effect of rural roads. These limitations are acknowledged when interpreting the results and suggest directions for future research using longer time periods and more detailed transport data.

2.3. Analysis Method

2.3.1. Poverty Rate and Village Fund Data Analysis

To illustrate baseline spatial patterns and temporal changes, the poverty rate and village fund for rural road connectivity investment data are mapped with pattern information of the percentage change over the period of 2022-2024. Changes in poverty rates are measured using percentage changes when baseline values are greater than zero, allowing relative increases or decreases over time to be clearly identified. For the village fund allocations, absolute changes in percentage points are used, as several villages recorded zero values in the base year. This approach avoids the problem of division by zero and provides a more stable and interpretable measure of change for proportional budget indicators in a spatial context (OECD, 2008).

$$\text{Percentage Change} = \frac{(V2-V1)}{|V1|} \times 100 \quad (1)$$

2.3.2. Spatial Data Analysis

This research will utilize Global Spatial Autocorrelation, also known as Moran's I, and the Local Indicators of Spatial Association (LISA), as the spatial data analysis methods. Spatial data analysis can detect spatial patterns that help determine whether poverty rates are concentrated in specific areas or road improvements are concentrated in particular regions. These insights are critical when the research aims not only to understand what is happening, but also where it is happening (Das Majumdar & Biswas, 2016). Spatial data analysis also reveals hidden relationships between variables that may not be evident in standard statistical analysis. The results from spatial data analysis can be used to support evidence-based policy informed by the identified spatial clusters.

To analyze spatial autocorrelation within the dataset, this study employs Moran's I statistic, a global indicator that measures the degree to which a variable is spatially clustered across geographic units (Gao et al., 2019). It determines whether patterns are random, scattered, or clustered. The values of Moran's I range from -1 to $+1$. A positive value indicates spatial clustering of similar values (high-high or low-low), while a negative value suggests spatial dispersion (high-low or low-high). A value close to zero indicates a random spatial pattern. Moran's I is used to determine whether poverty rates or the amount of investment in rural infrastructure show spatial dependence across villages. Moran's I index is defined as:

$$I = \frac{N \sum_{i=1}^N \sum_{j=1}^{N, j \neq i} w_{ij} Z_i Z_j}{S_0 \sum_{i=1}^N Z_i^2} \quad (2)$$

where N equals the number of regions; w_{ij} is a weight denoting the strength of the connection between areas i and j ; z_i is the rate in region i centered about the mean rate (using $z_i = x_i - \text{ave}(x)$); x_i is the rate in region i ; and S_0 is the sum of the weights. The weights, which usually indicate geographic proximity, show how "connected" two areas are perceived to be. Moran's I is used to determine whether "connected" areas are more similar than would be predicted under spatial randomness. This raises the question of whether rates vary in connected areas. When nearby areas have similar exposures and populations, their rates tend

to be similar. Moran's I values will be large and positive when rates in nearby, connected areas are comparable, whereas they will be negative when rates in related areas differ.

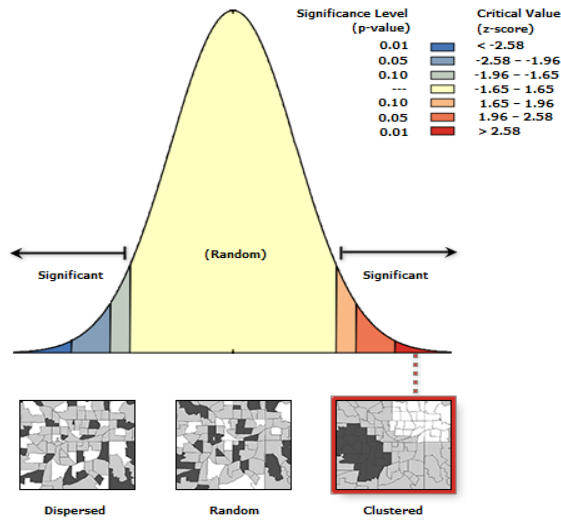


Figure 5. Moran's I spatial autocorrelation result example

Source: ArcGIS processing

This study uses LISA (Anselin, 1995) in addition to Moran's I to identify local spatial clustering patterns within the study area. Although Moran's I provides a global measure of spatial autocorrelation, LISA breaks this statistic down to the local level, allowing for the identification of particular places where notable spatial clusters or outliers are present. LISA detects spatial outliers, such as high values surrounded by low values (high–low) or vice versa (low–high), as well as areas with high values surrounded by high values (high–high) and low values surrounded by low values (low–low). This technique is beneficial for identifying regional spatial patterns that global statistics might hide. To investigate spatial heterogeneity and identify priority areas for targeted policy interventions, LISA is applied to variables such as poverty rates and village infrastructure investments.

2.3.3. Panel Data Analysis

This study analyzes the connection between investments in rural road connectivity improvement and the reduction of poverty by employing panel data analysis. Panel data analysis, also known as longitudinal data analysis, is a statistical method for examining datasets that follow several entities, such as populations of people, businesses, regions, or nations, over multiple periods. Complex phenomena can be modeled more comprehensively and accurately with the help of a richer dataset that combines cross-sectional and time-series data. Dynamic changes within villages over time can be analyzed using panel data, which combines cross-sectional and time-series dimensions and accounts for unobserved heterogeneity among them (Baltagi, 2005). The dataset includes time-invariant variables, such as road density, geographical characteristics, and village distance to urban centers, as well as annual observations of poverty rates and village road budget allocations from the Village Fund program over three years across the villages.

The general panel data regression model used in this study can be expressed as follows:

$$Y_{it} = \alpha + \beta X_{it} + \gamma Z_i + u_i + \epsilon_{it} \tag{3}$$

where Y is the dependent variable, representing the poverty rate for village i in year t; X_{it} represents time-varying explanatory variables which is the Village Fund budget for rural roads improvement; Z_i is a vector of time-invariant explanatory variables that are the road density, geographical characteristics, and distance to centers; α is a constant; u_i represents unobserved time-invariant village-specific effects; and ϵ_{it} is the error term that allows any differences across groups to enter the model.

Both fixed effect (FE) and random effect (RE) models are estimated. By allowing each village to have its own intercept, the FE model eliminates the impact of time-invariant factors and accounts for unobserved heterogeneity across villages (Torres-reyna, 2007). However, doing so means removing the key explanatory points of this study that do not vary over time, such as road density, geographical characteristics, and distance to centers. To address this, the RE model, which assumes that unobserved effects have no relationship with the regressors, is also estimated (Verbeek, 2017). A Hausman specification test is conducted to assess the consistency of the RE estimator and guide model selection.

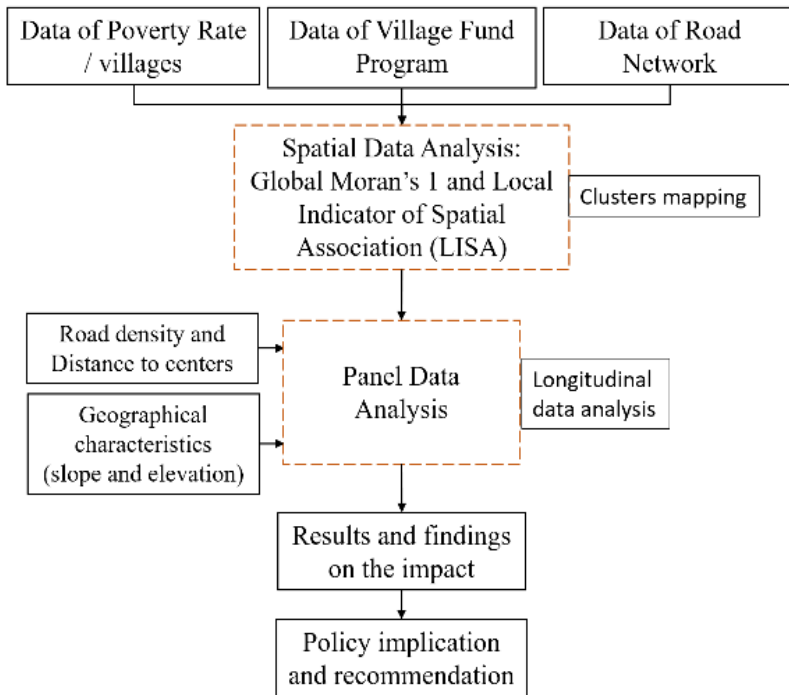


Figure 6. Research Workflow

Source: Author, 2025

III. Results, Analysis, and Discussions

3.1. Location Mapping Analysis

Kebumen Regency has a diverse range of geographical conditions within its region that affect accessibility and development. As shown in Figure 7, the southern and central parts are mostly low elevation with gentle slopes, while the northern and southwestern areas have higher elevation and steeper terrain. These physical conditions influence infrastructure development.

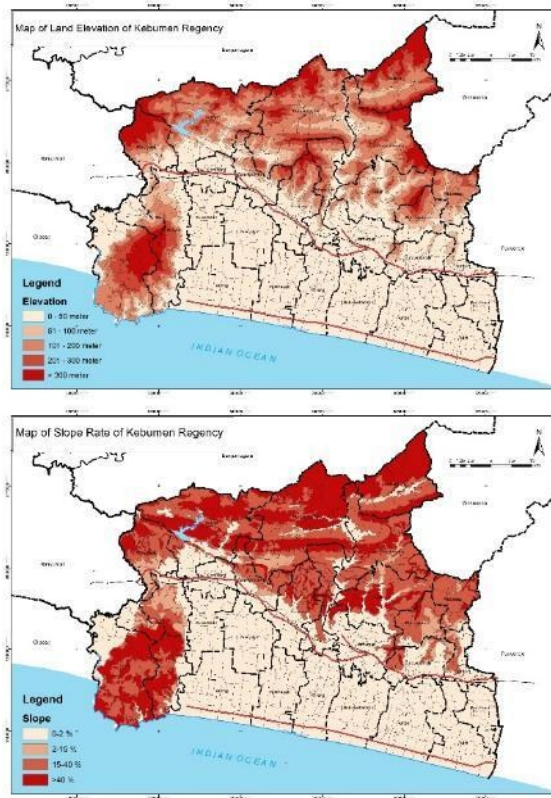


Figure 7. Map of Land Elevation (left) and Slope Rate (right) of Kebumen Regency

Source: DPUPR Kebumen (2019)

Figure 8 shows that road networks are more concentrated in the southern and central areas, where the land is flatter. These areas are also connected to national roads and railway lines. In contrast, the northern and western parts have fewer roads, especially higher-level roads. Kebumen has its main urban center in the central part while also having activity centers in each subdistrict that serve the villages with basic infrastructure needs. The proximity of each subdistrict center varies, as its location may be determined by the road network, geographical conditions, and the preexisting conditions of the settlement. This indicates that accessibility to markets and public services is not evenly distributed across the regency.

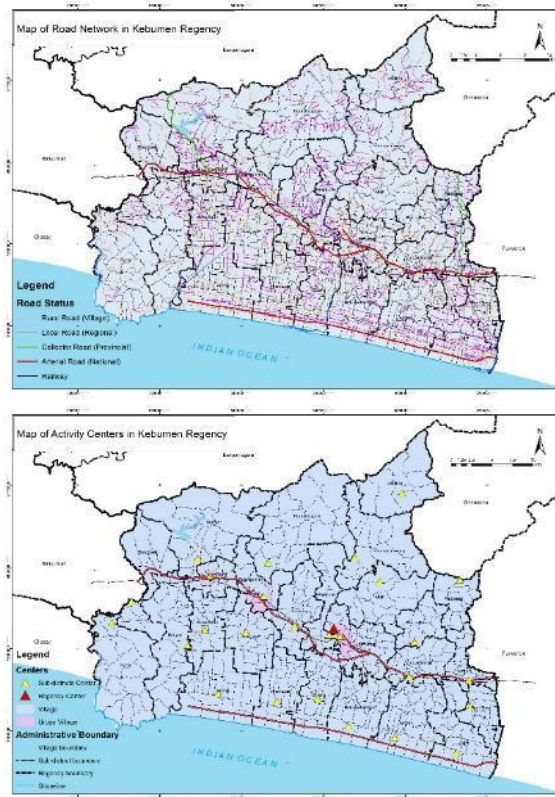


Figure 8. Map of Road Network (left) and Activity Centers (right) of Kebumen Regency

Source: DPUPR Kebumen (2019)

3.2. Poverty Rate Data Analysis

The poverty rate of every village in the Kebumen Regency is measured based on decile rankings, with the first to third deciles representing the poorest condition, relative to the total village population. The calculation differs from the regional poverty rate stated by the Statistics Agency, as they employ a more macroeconomic approach for a larger region.

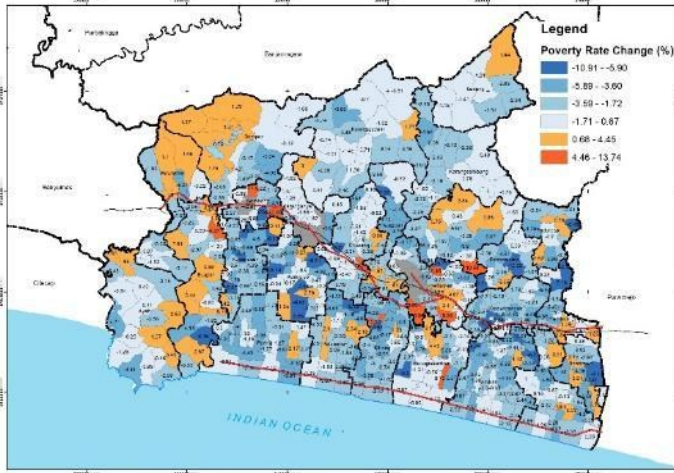


Figure 9. Map of poverty rate change (%) in every village in Kebumen from 2022 to 2024

Source: Analysis, 2025

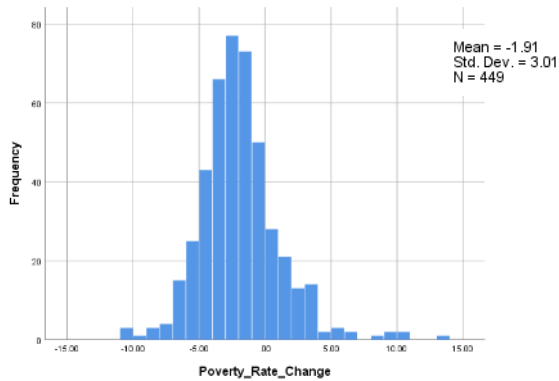


Figure 10. Graph of data distribution of poverty rate change in Kebumen Regency from 2022 to 2024

Source: Analysis, 2025

The spatial map in Figure 9 illustrates varying levels of change in poverty rates across villages in Kebumen Regency from 2022 to 2024. Most of the villages experienced a decrease in the poverty rate, as represented by the dominant blue shades. Some pockets of poverty increased (orange-colored areas), which are visible in the western part of the region and scattered to the east and north, suggesting localized disparities in development impact. Additionally, the histogram in Figure 10 indicates that the data distribution is left-skewed, with the majority of villages clustered around moderate reductions (-5.0% to 0.0%), which supports the spatial pattern. The mean change in poverty rate is -1.91%, indicating an average decline in poverty.

3.3. Village Fund for Rural Road Connectivity Investment Data Analysis

The spatial distribution of Village Fund utilization for rural road connectivity investments in Kebumen Regency from 2022 to 2024 reflects dynamic changes in policy priorities and regulatory frameworks. Each year displays a distinct pattern in investment

allocation, indicating the shifting emphasis of national and local governance in response to socioeconomic challenges.

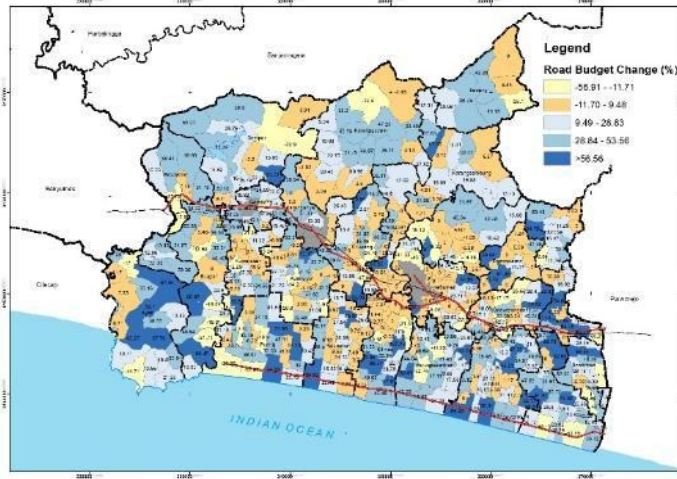


Figure 11. Map of road investment change (%) from the Village Fund in every village in Kebumen from 2022 to 2024

Source: Analysis, 2025

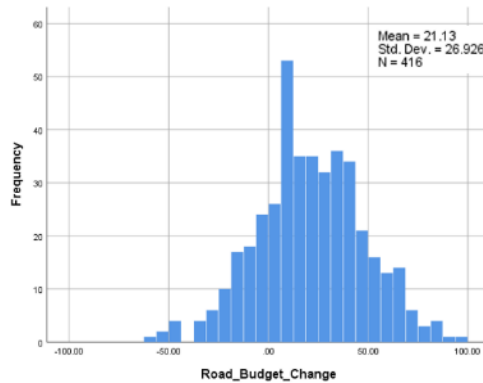


Figure 12. Graph of data distribution of road investment change (%) from the Village Fund in Kebumen Regency from 2022 to 2024

Source: Analysis, 2025

The spatial map in Figure 11 illustrates the percentage change in village road investment from the Village Fund program. The various colors indicate a range from significant decreases (orange shades) to substantial increases (blue shades). Several villages, especially in the southern and central-southern areas, show increases in road budget allocation, while villages with decreasing budgets are scattered throughout the region. Additionally, from the histogram in Figure 12, the mean change is +21.13%, indicating that, on average, villages increased their road investment significantly over the three years. The distribution is also positively skewed, with the tail extending toward higher investment increases. However, many villages still have reduced or stagnant budget shares (left tail of the graph), with some even declining by more than 50%.

3.4. Spatial Data Analysis of the Poverty Rate

Over the course of three years, Kebumen Regency’s poverty levels, as indicated by the proportion of the population in the lowest welfare deciles (1–3), exhibited a stable and consistent spatial clustering pattern. As shown in Table 2, a consistent rise in spatial autocorrelation is indicated by the Moran’s I values, 0.342913 in 2022, 0.350570 in 2023, and 0.358461 in 2024, which are statistically significant at $p < 0.01$. These numbers indicate a persistent and growing spatial dependency in poverty conditions, in which similarly impoverished villages surround low-poverty areas, and vice versa.

Table 2. Result of Moran’s I Analysis of Poverty Rate in Kebumen Regency, 2022–2024

	2022	2023	2024
Moran’s Index	0.342913	0.350570	0.358461
z-score	17.138787	17.516284	17.728627
p-value	0.000000	0.000000	0.000000

Source: GIS calculation analysis, 2025

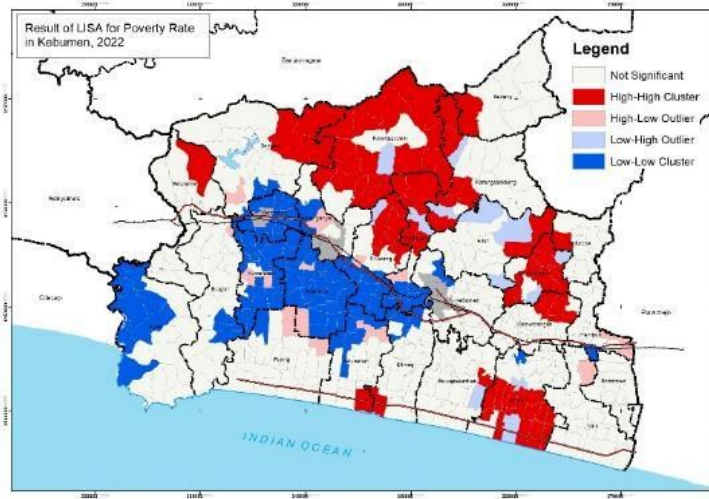


Figure 13. Map of the Result of LISA for Poverty Rate in Kebumen, 2022

Source: Analysis, 2025

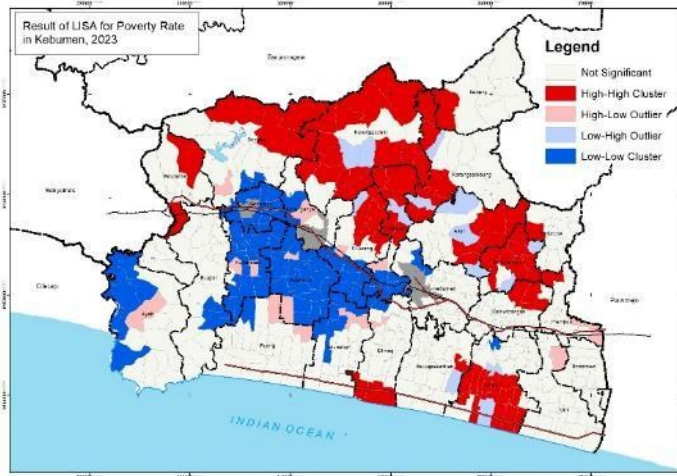


Figure 14. Map of the Result of LISA for Poverty Rate in Kebumen, 2023

Source: Analysis, 2025

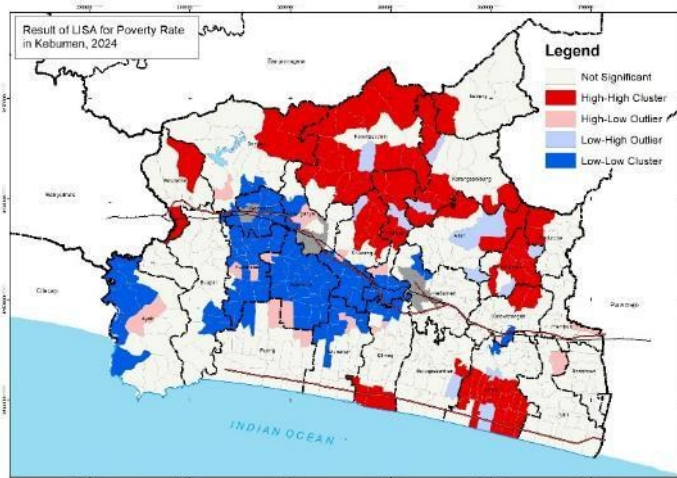


Figure 15. Map of the Result of LISA for Poverty Rate in Kebumen, 2024

Source: Analysis, 2025

Overall, the three-year spatial analysis reveals that spatial poverty inequality in Kebumen Regency remains prevalent and is worsening. The LISA results (Figure 13-15) reveal persistent high-high poverty clusters concentrated in the northern inland areas and stable low-low clusters along the southern coastal belt. Over time, high poverty clusters expanded eastward, suggesting that spatial inequality is not diminishing but becoming more established. These patterns imply that poverty reduction efforts have had limited spillover effects in structurally disadvantaged areas, where geographic constraints and limited connectivity continue to reinforce deprivation.

3.5. Spatial Data Analysis of the Village Fund Investment on Rural Road Connectivity

A nonlinear trend in spatial autocorrelation of village fund allocation for rural road connectivity in Kebumen Regency is indicated by Moran's I values, as shown in Table 4.2,

which begin at 0.080069 in 2022, decrease slightly to 0.061140 in 2023, and then increase to 0.093919 in 2024. At $p < 0.01$, all values are statistically significant, indicating that spatial clustering is consistently present despite variations in intensity. While the increase in 2024 suggests a renewed spatial structuring of investment—possibly driven by coordinated planning efforts or shared development priorities across adjacent villages—the decline in 2023 could be the result of a brief period of decentralization or local discretion in funding decisions.

Table 3. Result of Moran’s I Analysis of the Village Fund Investment on Rural Road Connectivity in Kebumen Regency, 2022–2024

	2022	2023	2024
Moran’s Index	0.080069	0.061140	0.093919
z-score	4.093795	3.145552	4.779532
p-value	0.000042	0.001658	0.000002

Source: GIS calculation analysis, 2025

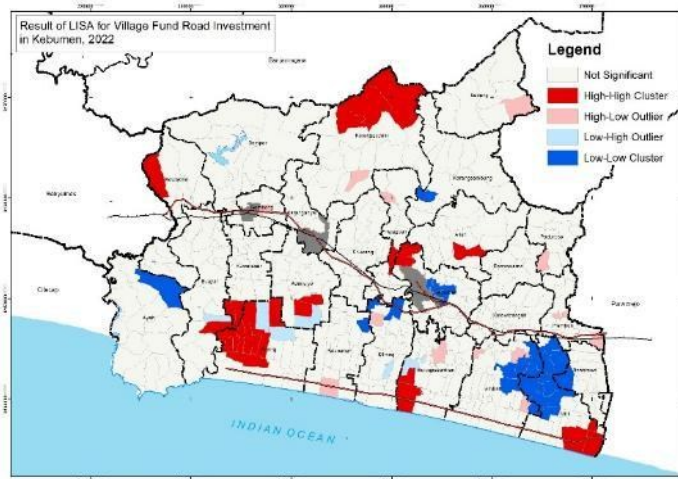


Figure 16. Map of the Result of LISA for Village Fund Investment on Rural Road Connectivity in Kebumen, 2022

Source: Analysis, 2025

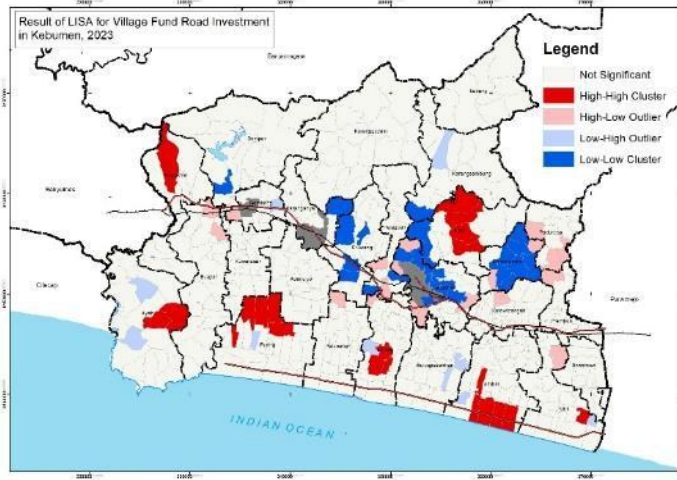


Figure 17. Map of the Result of LISA for Village Fund Investment on Rural Road Connectivity in Kebumen, 2023

Source: Analysis, 2025

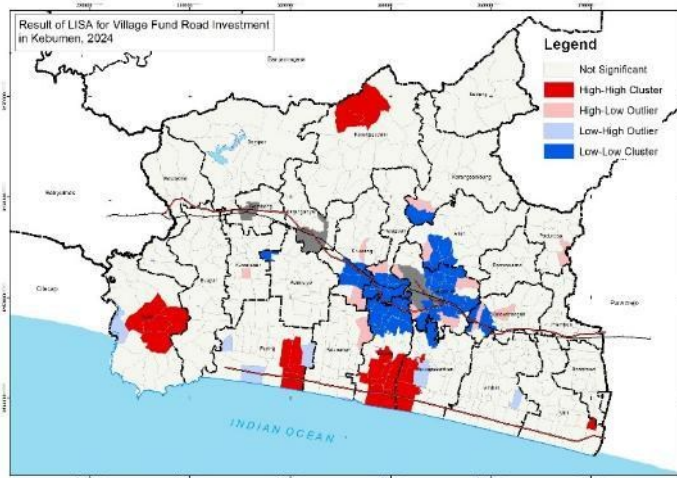


Figure 18. Map of the Result of LISA for Village Fund Investment on Rural Road Connectivity in Kebumen, 2024

Source: Analysis, 2025

Overall, the LISA maps (Figure 16-18) show that investment patterns became more spatially consolidated by 2024. High-high investment clusters emerged in northern and southern peripheral areas, while low-low clusters expanded in the central-eastern region, suggesting persistent underinvestment. The presence of spatial outliers indicates inconsistent coordination across neighboring villages, potentially reflecting differences in administrative capacity, geographic constraints, or local priorities.

3.6. Panel Data Analysis

3.6.1. Panel Dataset

The panel data analysis requires that the data be prepared and structured as a panel dataset. The entities in this research dataset are the villages with three years of observation for every village. The dependent variable is the poverty rate, while the independent time-changing variable is the percentage of the road budget allocated from the Village Fund. The time-invariant variables are road density, distance to the center, slope, and elevation.

No	village_ID	subdistrict	village_name	year	poverty_rate	road_budget_percent	road_density	distance_to_center	slope	elevation
1	1	AYAH	Argopeni	2024	32.25	45.37	1.00	9.33	4.00	3.00
2	1	AYAH	Argopeni	2023	32.41	42.78	1.00	9.33	4.00	3.00
3	1	AYAH	Argopeni	2022	32.67	34.66	1.00	9.33	4.00	3.00
4	2	AYAH	Karangduwur	2024	20.47	37.74	0.00	11.00	3.00	3.00
5	2	AYAH	Karangduwur	2023	21.30	59.81	0.00	11.00	3.00	3.00
6	2	AYAH	Karangduwur	2022	21.41	49.45	0.00	11.00	3.00	3.00
7	3	AYAH	Srati	2024	35.75	20.83	1.00	10.81	4.00	3.00
8	3	AYAH	Srati	2023	35.89	44.52	1.00	10.81	4.00	3.00
9	3	AYAH	Srati	2022	36.06	10.28	1.00	10.81	4.00	3.00
10	4	AYAH	Pasir	2024	37.29	33.23	1.00	9.68	4.00	1.00
11	4	AYAH	Pasir	2023	37.89	34.37	1.00	9.68	4.00	1.00
12	4	AYAH	Pasir	2022	38.31	11.98	1.00	9.68	4.00	1.00
13	5	AYAH	Jintung	2024	39.10	43.91	0.00	9.43	4.00	3.00
14	5	AYAH	Jintung	2023	39.47	0.00	0.00	9.43	4.00	3.00
15	5	AYAH	Jintung	2022	39.28	24.11	0.00	9.43	4.00	3.00

Figure 19. Illustration of the panel dataset used in the research

Source: Analysis, 2025

The data on road density in every village was gained from GIS data processing, where raster data was produced. As a time-invariant variable, the data on road density was sourced from 2019. To use the produced data, the data must be simplified to be in a range of 0 to 4, where each digit represents data. The data on the distance to the center represent the length of linear distance from each center point of the village to the nearest subdistrict or region center, presented in kilometers. For geographical characteristic data, slope and elevation rate are the variables chosen for processing. The source data for slope rate are presented as a percentage, with four ranges of slope data, while the elevation data are presented in five different ranges, with the unit of meters above sea level. The data value representation can be seen in Appendix 1.

The statistical significance of the result is interpreted at a 95% confidence level. Thus, a variable is significant when the z-value and/or t-value is <-1.96 or $>+1.96$ and with a p-value of <0.05 . Meanwhile, the coefficient result provides the value that multiplies the variable in the mathematical expression.

3.6.2. Fixed Effects Model

The FE model is tested for the relationship between the independent variable and the time-varying dependent variable. The FE regression reveals a statistically significant negative association between road budget allocation and village-level poverty.

Table 1 in Appendix 2 presents the result with a coefficient for the road budget percentage is -0.00745 with a standard error of 0.00209 . This coefficient is significant at the 1% level with $p = 0.000$ ($p < 0.05$). The t-value of -3.57 also implies a statistically significant variable, as it is far from 0, and the absolute value of 3.57 is greater than 1.96 (the standard), for a significance level of 5%. This implies that a 1 percentage point increase in the proportion

of the budget allocated to roads is associated with a 0.00745 percentage point decrease in the poverty rate. Despite its statistical significance, the coefficient appears low, indicating a relatively minor impact on the dependent variable. Although the R-squared is also relatively low (0.0017), the strength of the statistical evidence suggests a meaningful relationship when controlling for time-invariant village characteristics.

3.6.3. Random Effects Model

The RE model analysis includes additional controls such as road density, distance to the center, slope, and elevation, which are time-invariant variables. The result (see Appendix 2, Table 2) estimates the coefficient for road budget percentage at -0.00725 with $p = 0.001$ ($p < 0.05$) and a z-value of -3.48 ($z < -1.96$), confirming a significant inverse relationship with poverty. Slope and elevation also show positive and significant coefficients, suggesting that villages in steeper and/or more elevated areas tend to have higher poverty rates. The slope coefficient is 1.833 , with a z-value of 2.76 ($z > 1.96$), and a p-value of 0.006 ($p < 0.05$), and the elevation coefficient is 2.164 , with a z-value of 3.04 ($z > 1.96$), and a p-value of 0.002 ($p < 0.05$). In contrast, road density and distance to the center are not significant in this model, despite road density having a negative relationship, while distance to the center has a positive relationship with the poverty rate. These results highlight both the direct role of budget allocation and the indirect effects of geographic constraints.

3.6.4. Hausman Test (FE vs RE)

The Hausman test is conducted to determine the most appropriate model between the FE and RE models. The Hausman test as shown in Table 3 in Appendix 2 comparing FE and RE models yields a chi-square of 1.82 with a p-value of 0.1779 , indicating that the null hypothesis (that RE is consistent) cannot be rejected. Although this statistical result technically favors the RE model, the consistent sign and magnitude across specifications, as well as the policy logic for controlling unobserved village factors, still make the FE estimates more interpretable for causal inference. In practical terms, this means that while both models produce similar point estimates, the FE approach is preferable for making conservative inferences.

3.6.5. Year Fixed Effects

The year FE model is used to control for unobserved shocks or policy changes that occur uniformly across all villages in any given year but vary across years. This model ensures the separation of local effects and gives year-specific influences that affect all villages simultaneously. Including year dummies into the FE model results (see Appendix 2, Table 4) in a reduction in the magnitude and loss of significance for the road budget variable (coefficient = -0.00084 , SE = 0.00223 , $p = 0.707$). This suggests that much of the variation in poverty might be captured by year-level shocks, such as macroeconomic or policy changes. The dummy for 2024 shows a significantly negative effect (coefficient = -0.894 , $p = 0.000$), indicating a widespread decline in poverty, possibly due to external interventions. These results underscore the importance of accounting for temporal effects when evaluating the localized spending impacts.

3.6.6. Interaction with Geographical Characteristics

To examine whether geographical conditions affect the impact of road investment, interaction terms between road budget percentage and geographical variables are included.

The interactions with slope and elevation are estimated using the RE model. The results are presented in Table 5 in Appendix 2.

The interaction model with slope shows that the base effect of road budget percentage remains negative and statistically significant (-0.00717 , $p = 0.002$). The interaction with slope category 2 (2–15%) is also negative and significant (-0.028 , $p = 0.004$). This indicates that the poverty-reducing effect of road investment is weaker in moderately sloped areas. The interaction terms for steeper slope categories are not statistically significant.

The elevation interaction model also shows variation across altitude levels. The base coefficient for road budget percentage is negative and significant (-0.00690 , $p = 0.002$). The interaction with the highest elevation category is positive and statistically significant (0.01391 , $p = 0.005$), indicating that the effectiveness of road investment declines in high-elevation areas. Other elevation categories do not show significant interaction effects.

3.6.7. Summary of Panel Data Results

In summary, the panel data analysis using village-level data from 2022 to 2024 shows a consistent negative relationship between road budget allocation and poverty rates. Both FE and RE models indicate that higher road budget shares are associated with lower poverty, but the magnitude of the effect is very small.

Geographical variables, especially slope and elevation, are significantly associated with higher poverty levels. Interaction models further show that the poverty-reducing effect of road investment is weaker in villages with steeper slopes and higher elevations. When year fixed effects are included, the road budget variable becomes insignificant, suggesting that poverty changes may be strongly influenced by broader temporal factors. Overall, the results indicate that while rural road investment has a statistically significant relationship with poverty reduction, its practical impact is limited and highly dependent on geographical and temporal conditions.

3.7. Theoretical Discussion

This study challenges the conventional assumption that rural development can be effectively accelerated through infrastructure investment, particularly rural road connectivity. The findings reveal that road development has no significant direct effect on poverty alleviation at the village level, suggesting that infrastructure alone cannot address the multidimensional nature of rural poverty. While improved road connectivity may enhance mobility and stimulate local economic activities, its benefits are often indirect, long-term, and unevenly distributed, accommodating more of the villages with pre-existing economic advantages. In this regard, the role of village governments, especially through the budgeting of the Village Fund, should not be focused more on the physical infrastructure provision, but rather toward social and human development programs that directly enhance local welfare. The investment in rural roads and other rural infrastructures should be left to the higher level of government, i.e., national, provincial, and regional government. Investments in education, skills training, healthcare, empowerment of vulnerable groups, and entrepreneurship development can yield more inclusive and sustainable poverty reduction outcomes by strengthening human and social capital rather than merely physical assets (Chambers, 1983; Rauniyar & Kanbur, 2010).

These findings differ from those of Wasudewa and Iskandar (2023), who reported a positive and significant effect of the Village Fund on regional economic growth and

development in Indonesia. Their Difference-in-Difference analysis covered a broader national scope at the regional level, including many regions in the category of underdeveloped regions outside Java, where Village Fund allocations for infrastructures likely had transformative effects by addressing severe deficits in basic connectivity and economic access. It may also stimulate macroeconomic improvement through infrastructure expansion and the establishment of village-owned enterprises (BUMDes).

However, the present study indicates that such growth does not necessarily translate into micro-level welfare improvements. This contrast between these findings underscores the contextual nature of infrastructure effectiveness: while the Village Fund may stimulate regional economic growth in less developed areas, its marginal impact diminishes in regions where infrastructure is already adequate. This highlights the persistent gap between macroeconomic expansion and micro-level welfare improvement, a phenomenon often described as growth without equity (Kakwani & Pernia, 2000). Economic growth driven by sectors like commodities may boost GDP and investment, but often fails to improve broader welfare indicators such as total consumption or unemployment rates, as seen in Colombia (Oviedo-Gomez & Viafara, 2022). On that account, the Village Fund program requires a reorientation toward people-centered development strategies that integrate physical investment with human capital formation and community empowerment, ensuring that rural economic progress leads to tangible and equitable welfare gains.

IV. Conclusion and Recommendation

4.1. Conclusion

This study reveals that spatial inequality in poverty remains persistent across Kebumen Regency, with high-poverty clusters concentrated in the northern areas and low-poverty clusters in the south. Meanwhile, Village Fund allocations for rural road development show an uneven spatial distribution, with high-investment areas located in the north and southern periphery, while low-investment clusters are concentrated in the central-east region. These patterns indicate unequal policy implementation and reinforce the importance of spatially responsive and equitable infrastructure planning. Addressing regional disparities requires geographically targeted interventions that prioritize high-poverty areas and draw lessons from more successful, low-poverty regions.

Although road budget allocations from the Village Fund are associated with a modest poverty reduction, the effect is statistically insignificant once temporal factors are considered, indicating that poverty outcomes are influenced more by macroeconomic and broader policy dynamics than by local infrastructure spending alone. Geographic characteristics, such as elevation and terrain, also moderate the effectiveness of road investments, reducing their impact in higher or steeper areas. Overall, the findings indicate that infrastructure alone cannot substantially reduce poverty, despite its high spending.

4.2. Recommendation

The findings suggest that the impact of infrastructure investment on poverty reduction is highly contextual, varying according to geography, development level, and local capacity. Therefore, policies should adopt spatially responsive and differentiated approaches that align with regional characteristics and socioeconomic conditions. In Kebumen Regency, where road networks are already well developed, further infrastructure investment yields limited welfare benefits, underscoring the need to redirect resources toward people-centered

programs that enhance human capital and economic resilience, such as education, vocational training, entrepreneurship, and social empowerment.

As short-term recommendations, first, village and district governments should improve the evaluation of road development outcomes, not only focusing on budget size but also on road quality, functionality, and maintenance conditions. Poor-quality roads in difficult terrain may reduce the effectiveness of infrastructure spending and limit access to markets and services. Second, poverty reduction programs should apply spatial targeting based on cluster analysis. High-poverty clusters in northern inland Kebumen should receive prioritized support, while lower-poverty southern areas can be used as reference models. This targeting should be supported by integrated planning between infrastructure, social assistance, and economic programs. Third, rural road investment should be better integrated with village economic activities, such as agriculture, local markets, tourism, and small enterprises. Roads should connect productive locations rather than being built as isolated projects, so that infrastructure directly supports income-generating activities.

In the long term, Village Fund allocation should gradually shift from infrastructure-dominated spending toward productive economic programs and human development. This includes vocational training, entrepreneurship support, cooperative development, and value-chain strengthening for local products. In addition, local government capacity needs to be strengthened to ensure effective decentralization. Continuous technical assistance, planning support, and monitoring mechanisms are required so village governments can design programs that are responsive to local geography and economic potential. Overall, the Village Fund should evolve from a mainly infrastructure-oriented instrument into a more integrated development tool that combines transport access, economic productivity, and human capital improvement. Such an approach is more likely to produce sustainable poverty reduction, especially in regions where physical infrastructure constraints are no longer the main development barrier.

Finally, future research should extend the analysis over longer periods and examine how Village Fund allocations for non-infrastructure components, particularly in human and social development, affect rural welfare outcomes. Understanding these dynamics will help refine the Village Fund's role from an infrastructure-focused initiative to a more inclusive and transformative instrument for sustainable poverty alleviation.

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Appendix 1

Panel Data Value Representation

Table of Road Density, Slope, and Elevation Data Value Representation

Data	Road Density Value	Slope Value	Elevation Value
0	0.00–1.00 km/km ²	-	-
1	1.01–2.00 km/km ²	0–2 %	0–50 meter
2	2.01–3.00 km/km ²	2–15 %	51–100 meter
3	3.01–4.00 km/km ²	15–40 %	101–200 meter
4	>4.00 km/km ²	>40 %	201–300 meter
5	-	-	>300 meters

Source: Analysis, 2025

Appendix 2

Panel Data Analysis Result

Table 1. Fixed Effects Model Result

Poverty rate	coefficient	Std. error	t-value	P > t
Road budget percentage	-0.0074532	0.0020892	-3.57	0.000
R-squared overall: 0.0017				

Source: Analysis, 2025

Table 2. Random Effects Model Result

Poverty rate	coefficient	Std. error	t-value	P > z
Road budget percentage	-0.0072517	0.0020838	-3.48	0.001
Road density	-0.5473571	0.5971898	-0.92	0.359
Distance to center	0.4899032	0.3230815	1.52	0.129
Slope	1.832987	0.6635376	2.76	0.006
Elevation	2.164074	0.7107577	3.04	0.002
R-squared overall: 0.1832				

Source: Analysis, 2025

Table 3. Hausman Test Result

Poverty rate	Coefficient FE	Coefficient RE	χ^2	$P > \chi^2 $
Road budget percentage	- 0.0074532	- 0.0072517	1.82	0.1779

Source: Analysis, 2025

Table 4. Year Fixed Effects Result

Poverty rate	coefficient	Std. error	t-value	$P > z $
Road budget percentage	-0.0008361	0.0022262	-0.38	0.707
Year				
2023	0.0965884	0.0912938	1.06	0.290
2024	-0.8939983	0.0936232	-9.55	0.000

Source: Analysis, 2025

Table 5. Interaction with Geographical Characteristics Result

Poverty rate	coefficient	Std. error	t-value	$P > z $
Road budget percentage	-0.0071741	0.0023683	-3.03	0.002
Slope x road budget%				
Slope category 2	-0.0280134	0.0097601	-2.87	0.004
Slope category 3	0.0021865	0.0041931	0.52	0.602
Slope category 4	0.0025671	0.0043878	0.59	0.559
R-squared overall: 0.1674				
Road budget percentage	-0.0069003	0.0069003	-3.16	0.002
Elevation x road budget%				
Elevation category 2	-0.0168061	0.009873	-1.70	0.089
Elevation category 3	-0.0034072	0.0052543	-0.65	0.517
Elevation category 4	0.0014669	0.0066293	0.22	0.825
Elevation category 5	0.0139095	0.0049816	2.79	0.005
R-squared overall: 0.1937				

Source: Analysis, 2025