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Spatial Analysis in Formulating Poverty Alleviation Policies in Bogor Regency

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ABSTRACT

Bogor Regency faces a persistent poverty paradox where robust aggregate peri-urban economic growth coexists with the highest absolute number of poor residents at the regency level in Indonesia. Relying on macro-level regional indicators in development planning risks committing an ecological fallacy, which masks severe welfare disparities at the grassroots village level. This study spatially and temporally analyzes the dynamics of the Percentage of Poor Population (PPP) at the village level in Bogor Regency between 2020 and 2024 to identify spatial poverty traps (SPTs). Utilizing micro-level data from 416 villages, integrating Integrated Social Welfare Data (DTKS) and official BPS population projections, this study applies a paired samples t-test, a tertile interval classification with a fixed 2020 baseline, and spatial autocorrelation using Global Moran's I and local indicators of spatial association (LISA) under a first-order queen contiguity weights matrix with 999 random permutations. The t-test results reveal that average village poverty experienced statistical stagnation, increasing insignificantly from 22.96% to 23.20% ($p = 0.819$; Cohen's $d = –0.0112$). However, a highly significant paired Pearson correlation of 0.452 ($p = 0.000$) indicates strong structural poverty persistence. At the village level, dynamic welfare fluctuations occurred: 94 villages improved, while 96 deteriorated (including 21 experiencing extreme decline). LISA analysis confirms that poverty is highly clustered geographically (Global Moran's I = 0.127132; z = 6.111465; p = 0.000000), showing a stark geographic polarization. High-High (HH) (hotspot) clusters are persistently concentrated in the physically isolated and ecologically vulnerable Western periphery, whereas Low-Low (LL) (coldspot) clusters are consolidated in the urban-linked Northern and Central corridors within metropolitan Jabodetabek. Ultimately, stagnant regional averages obscure sharp micro-level disparities. Local governments must shift to micro-level geographic targeting by investing in physical connectivity in the West and preventing urban-biased spatial capture of public resources.

1. INTRODUCTION

The Jabodetabek metropolitan area (Jakarta, Bogor, Depok, Tangerang, and Bekasi) is the primary economic engine of Indonesia and the second-most populous urban agglomeration in the world, housing more than 32 million people [1]. Strengthening metropolitan agglomeration as a strategic area demands spatial planning instruments capable of integrating metropolitan economic functions with the carrying capacity of surrounding regions. An accurate typology and spatial delimitation between urban and peri-urban zones serve as the primary foundation for formulating affirmative policies to prevent development disparities between regions in mega-urban areas [2]. In long-term national planning, Jabodetabek is projected to merge with the Bandung metropolitan corridor by 2045, forming a massive urban megacity [3]. Within this regional urban network, Bogor Regency holds a highly critical strategic role. Serving as the primary buffer zone south of Jakarta, it provides vital ecological services, residential space, agricultural commodities, and daily labor mobility, while simultaneously undergoing rapid peri-urban transformation [4, 5]. However, a serious issue persists: Bogor Regency records a sharp contradiction: amid average economic growth above 5%, it registered the highest absolute number of poor residents at the regency level in Indonesia in 2024 (446,790 people) and the highest poverty rate in the Bodetabek region (>7.0%) [6, 7].

This persistent poverty paradox indicates that rapid urbanization and infrastructure investments have generated uneven spatial development. Rapid conversion of agricultural land into housing complexes and industries in peri-urban areas has increased environmental degradation, reduced traditional agrarian livelihoods, and worsened urban-rural disparities [8, 9]. While sub-districts adjacent to core urban nodes (such as

Depok and South Tangerang) benefit from economic spillovers and infrastructure integration, rural villages on the periphery remain geographically and socio-economically isolated [10]. The friction between rapid urban expansion and local isolation creates persistent pockets of poverty that are resistant to aggregate economic growth.

Existing literature on regional poverty in Indonesia frequently relies on aggregate macro indicators at the national, provincial, or regency/city levels [11, 12]. However, macro-level evaluations risk committing an ecological fallacy-a logical flaw where localized poverty is masked by aggregated regional averages [13]. For instance, a sub-district classified as prosperous due to an industrial estate may contain deeply impoverished rural villages that are entirely overlooked by broad policy interventions [14]. To eliminate these policy blind spots, spatial poverty analysis must be conducted at a highly granular micro-scale.

Therefore, the primary objective of this study is to analyze the temporal dynamics and spatial distribution patterns of the Percentage of Poor Population (PPP) across 416 villages in Bogor Regency between 2020 and 2024. Specifically, this study aims to: (1) evaluate whether aggregate village-level poverty experienced statistically significant changes over the four-year period using a paired samples t-test; (2) examine spatial autocorrelation and poverty clustering using Global Moran's I and Anselin's local indicators of spatial association (LISA); and (3) detect the presence and location of spatial poverty traps (SPTs) in peripheral border areas. By utilizing highly granular micro-data from the Ministry of Social Affairs' Integrated Social Welfare Data (DTKS), this research provides actionable geospatial evidence to guide precisely targeted, place-based poverty alleviation interventions.

2. LITERATURE REVIEW

The rapid urbanization process and massive land conversion in peri-urban areas like Bogor Regency induce significant environmental degradation, ranging from pollution and hydrological disturbances causing flash floods to the drastic shrinkage of productive agricultural land [8, 9, 15, 16]. This urban expansion phenomenon not only damages ecosystems but also widens socio-economic disparities between rural and urban areas in terms of economic productivity, infrastructure adequacy, and accessibility to basic public services such as education and health [17, 18]. According to Sen [19, 20], poverty is inherently not merely a lack of income but rather a deprivation of capabilities and opportunities. In rural areas, these limitations are rooted in geographical isolation and poor physical connectivity [18], which erode rural capital assets-both economic and social [21-23]-thereby making rural poverty more persistent than urban poverty [24-26]. This disparity is exacerbated by development policies that tend to exhibit an urban bias, as identified by Lipton [27], where public investment, capital, and service facilities are concentrated heavily in urban areas rather than rural ones. This pattern aligns with David Harvey's Spatial Fix Theory [28, 29], which explains that capital accumulation geographically tends to produce structured economic fragmentation and spatial inequality.

Although regional inequalities are evident, most prior studies on regional poverty have been criticized for over-relying on macro-aggregated data at the regency or sub-district levels, which risk obscuring local variations due to high spatial autocorrelation [11, 12]. The use of macro-aggregate indicators is prone to triggering an Ecological Fallacy, as explained by Robinson [13], a logical bias where conclusions about micro units are incorrectly inferred based on aggregate statistics of larger groups. This phenomenon gives rise to the 'aggregation illusion' [14], where a sub-district classified on average as a low-poverty (prosperous) area can conceal remote villages trapped in chronic poverty with poverty rates reaching 40% [14]. The lack of micro-scale geographic accuracy also triggers the risk of spatial capture of development budgets, as local resource allocation in decentralized Indonesia is often dictated by political compromise and lobbying rather than objective spatial targeting metrics [30], where public investment and social assistance tend to be absorbed in already-developed sub-district growth centers instead of reaching peripheral village areas that desperately need help. This underscores the urgency of spatial analysis at a granular village scale to capture the unique sociological characteristics and diversity of local capital in each village, modeled under the Community Capitals Framework [22, 23].

When socio-economic deprivation clusters non-randomly within a geographic area and persists chronically over time, the area is indicated to be experiencing a SPT [31-33]. The formation of these traps is dynamically constructed by the interaction between biophysical vulnerabilities-such as complex topography, steep slopes, high elevation ecosystems, and natural disaster risks-and physical isolation due to poor micro-connectivity and the absence of basic local facilities [31, 34-36]. The combination of these factors leads to low 'geographic capital' for the region, where extremely high transaction costs, cut-off market access, and minimal economic returns on development investments cause marginalized communities in peripheral areas to remain trapped in a structured cycle of regional decline and intergenerational poverty that is difficult to break [31].

3. METHODOLOGY

3.1 Methodology framework

The methodology of this study is designed to empirically analyze the spatial distribution and detect the existence of SPTs in Bogor Regency. The research approach integrates temporal descriptive-inferential statistics with spatial autocorrelation analysis using micro-level village data from 2020 and 2024. The research workflow begins with data collection and alignment, testing for temporal mean differences, classifying village welfare status through cross-tabulation analysis, and mapping local spatial dependency patterns to identify poverty pockets validly and systematically.

3.2 Data sources and operational definition of variables

The spatial analysis in this study uses a micro-level unit of analysis at the village scale, covering all N = 416 administrative villages/wards in Bogor Regency for two temporal observation periods, namely 2020 and 2024. The primary empirical data on the number of poor individuals were extracted from the DTKS of the Ministry of Social Affairs of the Republic of Indonesia, which was then combined with official village-level total population projections based on census results from the Central Bureau of Statistics (BPS). Spatial boundaries were sourced from the official digital

shapefiles (GIS shapefiles) provided by the Regional Development Planning, Research, and Development Agency (Bappedalitbang) of Bogor Regency.

To maintain consistency, the primary variable is standardized as the PPP, an administrative poverty proxy defined as the proportion of DTKS-registered individuals relative to each village's projected population.

3.3 Paired samples t-test and effect size evaluation

To evaluate the temporal shift, the mean difference ($\bar{D}$) in the paired samples t-test was computed as the baseline year minus the endline year ($\bar{D} = \mu_{2020} - \mu_{2024}$). Practical significance was evaluated using Cohen's d effect size for paired observations, formulated as: $d = \frac{\bar{D}}{s_D} = \frac{\overline{X_{2020}} - \overline{X_{2024}}}{s_D}$, where, $\bar{D}$ represents the mean paired difference and s_D is the standard deviation of the difference scores. Under this formulation, a negative sign indicates an upward trajectory in poverty from 2020 to 2024. Following Cohen's convention, effect sizes are categorized as small ($|d| = 0.20$), medium ($|d| = 0.50$), and large ($|d| = 0.80$), whereas values with $|d| < 0.20$ are considered trivial or practically negligible [37].

3.4 Poverty classification based on the Tertile Method

Village-level poverty mobility analysis was conducted by grouping the 416 villages into three ordinal welfare classes, namely Low, Medium, and High. This classification was calculated using the Tertile Method (Tertiles or 3-quantile) based on ordered empirical data rankings. This non-parametric approach divides the data distribution into three equal-sized groups (each covering 33.33% of the total observations), making it free from normal population distribution assumptions.

To maintain the validity of temporal comparisons and avoid bias due to shifting class boundaries, the cutoff values were calculated exclusively using the baseline year data (Year 2020) as a fixed baseline. The resulting constant interval boundaries were then applied directly to classify the 2024 PPP data, ensuring that shifts in welfare classes between periods can be compared consistently.

3.5 Spatial autocorrelation analysis: Global Moran's I and local indicators of spatial association

The modeling of spatial contiguity structures among villages was constructed using the first-order queen contiguity boundary intersection criterion [38, 39]. Based on this criterion, two villages are defined as neighbors if they share a physical border in the form of either a common edge or a common vertex. This binary spatial weight matrix was then row-standardized to neutralize the influence of varying numbers of neighbors across locations and align the spatial interpretation as a weighted average.

The degree of aggregate (global) spatial autocorrelation across the region was calculated using the standard Global Moran's I index to detect whether the spatial distribution pattern of village poverty tends to be clustered (positive), dispersed (negative), or random. The index values range from –1 to 1, and its significance is tested using theoretical z-scores and p-values [39, 40].

Furthermore, to detect spatial heterogeneities, identify specific locations of poverty clusters, and discover local spatial outliers, LISA analysis was applied. The LISA formula (Local Moran's I) is defined [41] as the multiplication of the z-score of the standardized variable by its spatial lag:

$$I_i = z_i \sum_{j=1}^{N} w_{ij} z_j \quad (1)$$

where, z_i and z_j represent the standardized PPP variable deviation values (z-score) for villages i and j, and w_{ij} is the row-standardized spatial weight matrix element. Local significance testing was strictly conducted using the 999 random permutations method at a significance threshold of $p < 0.05$.

The combination of local significance values and the sign of statistical quadrants maps local spatial associations into four LISA spatial cluster typologies: HH (Hotspot), a high poverty area surrounded by high poverty areas; Low-Low (LL) (Coldspot), a low poverty area surrounded by low poverty areas; High-Low (HL) (Spatial Outlier), a high poverty area surrounded by low poverty areas; and Low-High (LH) (Spatial Outlier), a low poverty area surrounded by high poverty areas.

4. RESULTS

4.1 Paired samples t-test results and poverty classes

To evaluate whether there was a statistically significant change in poverty levels across the 416 villages during the four-year period, a paired samples t-test was conducted comparing the average percentage of poor residents between 2020 and 2024. The results show a very slight increase from 22.96% in 2020 to 23.20% in 2024. However, this difference is not statistically significant, as indicated by a p-value of 0.819 ($p > 0.05$), suggesting a trend of stagnation (Table 1). The effect size value of -0.0112 is classified as very small (near zero), confirming that the inter-year shift has almost no practical impact.

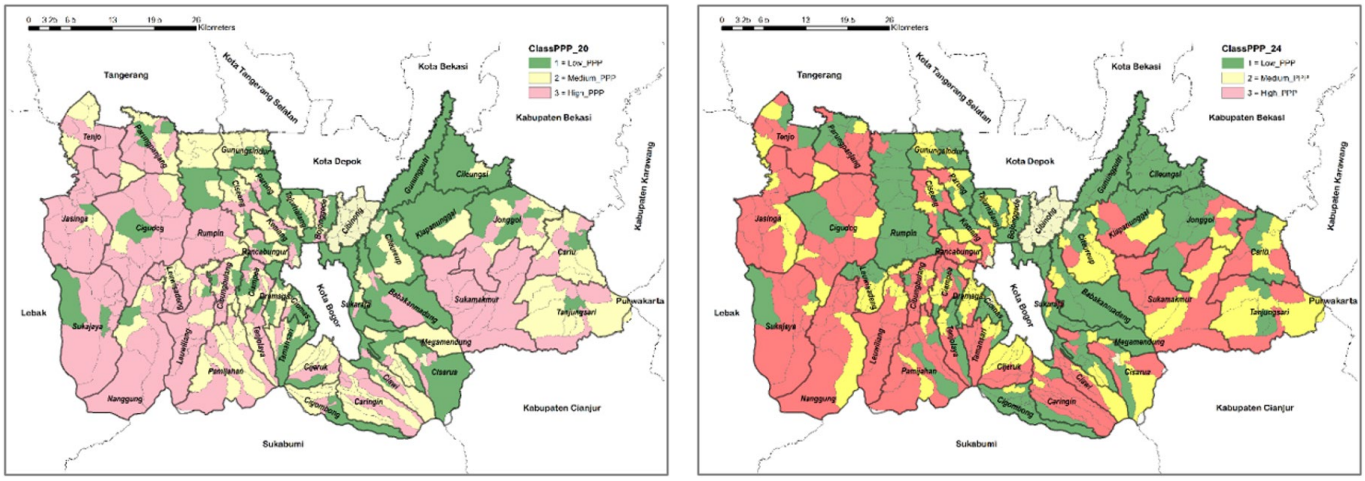
Although the paired samples t-test results indicate that there is no significant difference at the aggregate level, further analysis is required to examine movements at the observation unit level. A stagnant statistical average does not necessarily mean there is no change on the ground. To analyze the spatial mobility of poverty percentages between areas, the distribution of PPP was divided into three interval classes (Low, Medium, High) using the Tertile Method (33rd and 66th percentiles) based on 2020 baseline data. The resulting interval boundaries are as follows (Table 2).

Table 1. Paired samples t-test results

Year	Mean (%)	N	Std. Dev. (%)	Pearson Corr. (Sig.)	t-Statistic (df)	p-Value	Effect Size (|d|)	Conclusion
2020	22.96%	416	19.76%	0.452 (0.000)	–0.228 (415)	0.819	0.0112	No Significant Difference (Stagnant)

Table 2. Poverty classes based on Percentage of Poor Population (PPP)

Class Code	Class Category	Decimal Range	Percentage Range (%)
1	Low	0.00000 to 0.12145	0.00% to 12.15%
2	Medium	0.12146 to 0.25439	12.16% to 25.44%
3	High	0.25440 to Maximum	25.45% to Maximum



(a) 2020 (b) 2024

Figure 1. Percentage of Poor Population (PPP)

Table 3. Dynamics of poverty status transitions (2020 vs. 2024)

Transition Code	Change Pattern Category	Number of Villages	Percentage (%)
1 → 1	Persistently Low	90	21.6%
2 → 2	Persistently Medium	50	12.0%
3 → 3	Persistently High (Poverty Trap)	86	20.7%
2 → 1	Improving (Medium to Low)	41	9.9%
3 → 2	Improving (High to Medium)	24	5.8%
3 → 1	Significantly Improving (High to Low)	29	7.0%
1 → 2	Deteriorating (Low to Medium)	27	6.5%
2 → 3	Deteriorating (Medium to High)	48	11.5%
1 → 3	Significantly Deteriorating (Low to High)	21	5.0%
Total	Bogor Regency	416	100.0%

Distribution of poverty classes based on the PPP, with classifications as illustrated in Figure 1 and Table 3.

As shown in Table 3, there are 182 villages (86 + 96 villages, 43.75% of the total villages in Bogor Regency) currently in a non-ideal condition, namely: (1) Persistent/Poverty Trap Group (3 → 3 = Persistently High) of 86 villages (20.7%), which were consistently in the high poverty category in both 2020 and 2024; and (2) Deteriorating Group of 96 villages experiencing a decline in welfare status (moving up the poverty class). This deteriorating group is comprised of: (2a) Deteriorating-Low to Medium (1 → 2) with 27 villages (6.5%) that previously had a low poverty level shifting to the medium category; (2b) Deteriorating-Medium to High (2 → 3), which is the largest group in this category, namely 48 villages (11.5%) falling to a high poverty level from their previous medium level; and (2c) Significant Deterioration-Low to High (1 → 3), which is the most critical condition, where 21 villages (5.0%) experienced a drastic increase in poverty, jumping directly from the low to the high category within four years.

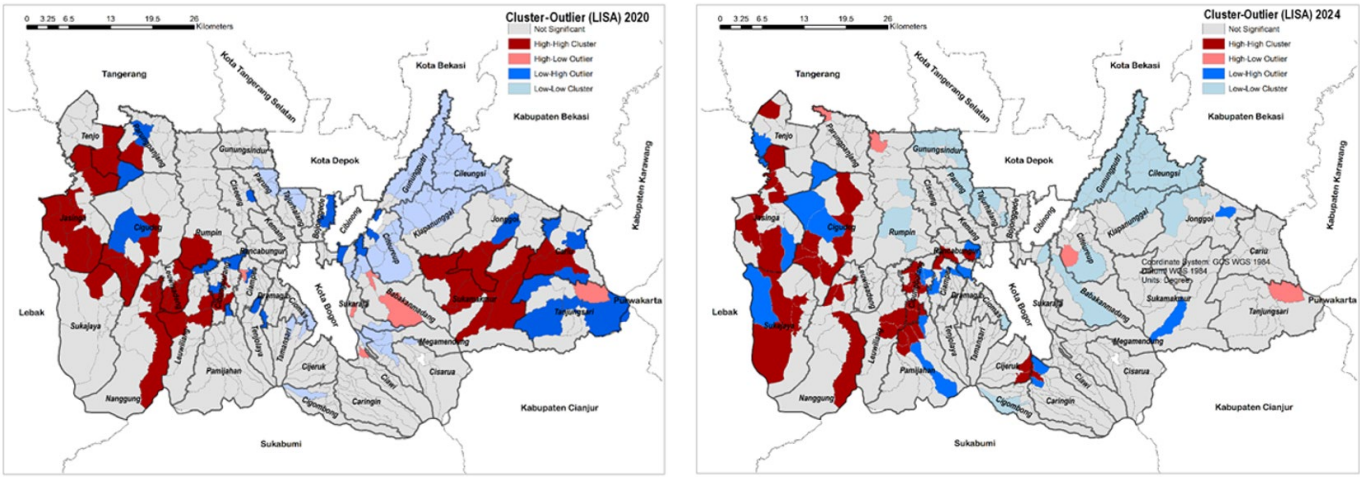
4.2 Spatial autocorrelation analysis (Global Moran's I and local indicators of spatial association)

Spatial statistical processing using ArcMap 10 software produced highly significant global and local spatial autocorrelation index values. Spatial autocorrelation analysis confirmed strong positive clustering (Global Moran's I = 0.127132, z = 6.111, $p < 0.001$). This Global Moran's I result mathematically confirms a pronounced spatial clustering pattern of poverty. Furthermore, LISA analysis was used to map the precise locations of these clusters and spatial outliers. The distribution of clusters and outliers in 2020 and 2024 is shown in Figure 2 and Table 4.

Table 4 presents the dynamics of changing spatial cluster-outlier typology (COT) composition based on LISA analysis across 416 villages with a total area of 2,933.2 km^2 area units between 2020 and 2024. In general, the spatial distribution of the area is divided into five categories:

1. HH/Hotspot Cluster: In 2020, 45 villages (10.82%) with a total area of 491.2 km^2 were recorded in the HH cluster. In 2024, this number decreased to 40 villages (9.62%) with a total area of 317.4 km^2. There was a decrease in proportion of –1.20% (reduction of 5 villages) and a spatial contraction of –173.77 km^2 area units.

2. HL Outlier: In 2020, the HL typology included 6 villages (1.44%) with an area of 42.6. In 2024, this typology fell to 4 villages (0.96%) with an area of 30.6 km^2. A decrease of –0.48% (reduction of 2 villages) with an area deficit of –11.94 km^2 was recorded.



(a) 2020 (b) 2024

Figure 2. Distribution of clusters and outliers (local indicators of spatial association (LISA)) in 2020 and 2024

Table 4. Comparison of local indicators of spatial association (LISA) cluster-outlier composition (2020 vs. 2024)

LISA Type	2020-Villages	2020-Share (%)	2020-Area	2024-Villages	2024-Share (%)	2024-Area (km^2)	Change Share (%)	Change Area
High-High (HH / Hotspot)	45	10.82%	491.2	40	9.62%	317.4	–1.20%	–173.77
High-Low (HL / Outlier)	6	1.44%	42.6	4	0.96%	30.6	–0.48%	–11.94
Low-High (LH / Outlier)	27	6.49%	200.7	19	4.57%	158.5	–1.92%	–42.16
Low-Low (LL / Coldspot)	55	13.22%	298.2	56	13.46%	361.4	0.24%	63.17
Not Significant	283	68.03%	1,900.6	297	71.39%	2,065.3	3.37%	164.71
Grand Total	416	100.00%	2,933.2	416	100.00%	2,933.2	-	-

3. LH Outlier: In 2020, there were 27 villages (6.49%) with an area of 200.7. In 2024, the number decreased to 19 villages (4.57%) with an area of 158.5 km^2. This category experienced a decrease in proportion of –1.92% (reduction of 8 villages) and a decrease in area of –42.16 km^2.

4. LL / Coldspot Cluster: In 2020, there were 55 villages (13.22%) covering an area of 298.2 km^2. In 2024, the number slightly increased to 56 villages (13.46%) with an area of 361.4 km^2. There was an increase in proportion of +0.24% (addition of 1 village) and an area expansion of +63.17 km^2.

5. Not Significant Category (blank): This non-cluster/random group dominated the entire study area, with 283 villages (68.03%) with an area of 1,900.6 km^2 in 2020. In 2024, this category increased to 297 villages (71.39%) with an area of 2,065.3 km^2. There was an increase in proportion of +3.37% (addition of 14 villages) and an expansion of the area by +164.71 km^2.

5. DISCUSSION

5.1 Temporal analysis of paired samples t-test and correlation parameters

The evaluation of temporal poverty dynamics was conducted to test whether there is an aggregate shift in village-level poverty across Bogor Regency between 2020 and 2024. This test utilized a paired samples t-test on N = 416 villages/wards. The tested variable was the PPP at the village level, which measures the proportion of registered poor residents in the Ministry of Social Affairs' DTKS relative to the official census-projected village total population from the BPS. This statistical test is crucial to prove whether the economic development dynamics of Bogor Regency, which recorded robust annual growth averaging above 5% in the 2021–2024 period, significantly correlate with a reduction in the incidence of poverty at the grassroots (village) level.

The statistical analysis from the paired samples t-test shows a very minor increase in the average PPP at the village level, from 22.96% in 2020 to 23.20% in 2024. This temporal increase of 0.24% was proven to be statistically insignificant. This is demonstrated by the p-value (Sig. 2-tailed) of 0.819, which is far greater than the established alpha significance threshold ($p > 0.05$). This statistical finding is reinforced by the Cohen's d effect size of –0.0112, which is extremely small and close to zero. Practically, this near-zero effect size confirms that there is no meaningful temporal shift in aggregate village poverty. Visually, the summary of the t-test results is presented in Table 1. Three crucial quantitative findings emerge from this test:

1. Paired Correlation Coefficient (Pearson Correlation) of 0.452 with extremely high significance ($p = 0.000$). This highly significant positive correlation coefficient proves a strong structural persistence in village poverty patterns. It empirically indicates that villages with high poverty levels in 2020 had a very strong tendency to remain in high poverty conditions in 2024. Conversely, low-poverty villages remained at low levels. This correlation coefficient serves as

strong initial evidence of structural poverty traps at the micro-regional level.

2. Standard Deviation Increase from 19.76% (2020) to 20.53% (2024). Although the average village poverty (mean) tended to be stagnant, this increase in standard deviation shows that the distribution of village poverty data became more varied or widened. This indicates that poverty disparities among villages in Bogor Regency, rather than shrinking, underwent a sharper polarization. Some villages experienced extremely rapid welfare improvements, while other peripheral villages suffered deep welfare declines, widening the horizontal inequality gap.

3. Very Small t-value ($t = –0.228$, $df = 415$) with Negligible Effect Size ($d = –0.0112$). Statistically, the t-value lying far within the acceptance region of the null hypothesis (between -1.96 and 1.96) confirms that the poverty fluctuation from 22.96% to 23.20% is merely random sample variation without substantive meaning. According to Cohen's criteria, an effect size of $d < 0.10$ is classified as trivially small or practically negligible.

5.2 Dynamics of changing poor population classes at the micro level

A stagnant and insignificant aggregate statistical average on the paired t-test must not be misinterpreted as an absence of welfare dynamic shifts at the grassroots (local) level. Average values have an inherent limitation that can mask dynamic internal fluctuations (ecological fallacy). To dissect village poverty mobility at a more granular level, PPP data from 416 villages were divided into three ordinal classes (Low, Medium, High) using the non-parametric Tertile Method with baseline 2020 data as a fixed baseline. The baseline tertile cutoffs yielded consistent boundaries: Tertile 1 (T1) at 12.15% and Tertile 2 (T2) at 25.44%. Based on these constant interval boundaries (Table 2), the transition dynamics matrix of village welfare status (2020 vs. 2024) is comprehensively mapped in Table 3.

The analysis in Table 3 uncovers highly dynamic facts that contradict the assumption of aggregate stagnation from the t-test. Behind the stability of the regency-level average, a highly active and symmetrical welfare turbulence occurred at the micro level. A total of 94 villages (22.60% of the total villages) experienced an improvement in welfare quality (moving to a lower poverty class), dominated by the group showing significant improvement from the High directly jumping to the Low class (3 → 1) with 29 villages (7.0%). However, this positive trend was symmetrically offset by welfare deterioration in 96 villages (23.08% of the total villages) falling into worse poverty classes (moving up the poverty class). It is this canceling-out effect between the number of improving and deteriorating villages that mathematically produces aggregate stagnation in the t-test, while simultaneously proving the danger of the Ecological Fallacy if development evaluation relies solely on regency-level spatial averages.

This transition status analysis also identifies a very large vulnerable group in Bogor Regency. There are 182 villages (43.75% of the entire region) in less-than-ideal spatial conditions. This group is divided into two primary sub-categories that require urgent affirmative policy attention:

•Trapped Group (Poverty Trap Group): A total of 86 villages (20.7%) were persistently in the High poverty class (3 -> 3) throughout the 2020–2024 period. These villages showed no welfare improvement despite rapid peri-urban economic growth. This group provides a strong indication of SPTs locking the area structurally.

•Welfare Deterioration Group (Deteriorating Group): A total of 96 villages experienced a decline in welfare class, with the largest group being villages falling from Medium to High (2 -> 3) at 48 villages (11.5%), followed by shifts from Low to Medium (1 -> 2) at 27 villages (6.5%). The most critical condition was experienced by 21 villages (5.0%) that suffered extreme deterioration, falling free from the Low directly into the High class (1 -> 3) within four years.

5.3 Global Moran's I and local Moran's I spatial autocorrelation analysis

To prove that these pockets of poverty are not randomly distributed across Bogor Regency, spatial autocorrelation testing was conducted using the Global Moran's I statistic. The spatial relationship structure between villages was modeled using a Spatial Weight Matrix (W) based on first-order queen contiguity boundary intersections, which was row-standardized. The spatial statistical analysis indicates a highly statistically significant Global Moran's I index, with a positive index value of 0.127132, a z-score of 6.111465, and a p-value of 0.000000. The z-score far exceeding the statistical critical value ($Z > 2.58$ at alpha 1%) and a p-value near zero absolutely prove the existence of a strong positive spatial dependency. Villages with similar poverty levels have a pronounced tendency to cluster geographically.

To identify the specific locations of these poverty clusters, LISA analysis was applied to map four spatial cluster typologies: HH (poverty hotspot), LL (welfare coldspot), and spatial outliers HL and LH (Table 4). The visualization of spatial mapping and quantitative LISA data in Table 4 confirms a very sharp and persistent geographic polarization of poverty in Bogor Regency between the West and the North-Central regions:

1. HiH Cluster (poverty hotspot)

In 2020, 45 villages (10.82%) were in the HH cluster. In 2024, this decreased to 40 villages (9.62%). Although there was a reduction of 5 villages and a contraction of the cluster's geographic area by 173.77 km^2, this HH cluster persistently remained centered in Western Bogor Regency, especially in sub-districts bordering Lebak Regency, Banten Province. This dense geographic concentration indicates that poor villages in the West are surrounded by neighbors that also have high poverty levels, creating SPTs that are difficult to penetrate by mainstream economic spillovers.

Comparative LISA analysis reveals a stark spatial divergence between peripheral regions. In 2020, HH poverty clusters were not confined to the West; a distinct HH agglomeration also covered Eastern Bogor (notably Sukamakmur and Cariu). By 2024, however, this Eastern cluster dissolved into statistically non-significant zones, whereas Western Bogor remained persistently trapped in severe poverty clusters. This contrast stems from differing regional dynamics, driven primarily by enhanced Eastern connectivity and agrarian resilience, where gradual road improvements along the Sukamakmur-Puncak II corridor catalyzed local eco-tourism and off-farm income diversification. Concurrently, productive food-crop agriculture in Cariu provided economic stability that helped lift contiguous villages out of the poverty cluster threshold. In terms of Western biophysical isolation, by contrast, Western

Bogor (e.g., Sukajaya, Nanggung, Jasinga) remains locked in a classic SPT. Extreme terrain, steep slopes, high landslide risks, and poor micro-connectivity severely restrict market access and raise transportation costs. Bordering the economically lagging Lebak Regency, the West suffers chronic geographic isolation that public interventions have yet to dismantle. Thus, the decline in total HH villages from 45 to 40 is not a uniform regional gain, but rather the localized de-clustering of Eastern Bogor set against persistent spatial entrapment in the West.

2. LL Cluster (Welfare Coldspot)

Conversely, the LL cluster, depicting low-poverty villages surrounded by low-poverty neighbors, showed an increasing trend from 55 villages (13.22%) in 2020 to 56 villages (13.46%) in 2024, with an area expansion of 63.17 km^2. This LL coldspot cluster is consistently concentrated in Northern and Central Bogor Regency, which are peri-urban areas close to Depok City, South Tangerang City, and Bogor City. This region benefits from superior transportation infrastructure connectivity, access to metropolitan Jabodetabek labor markets, and a concentration of manufacturing industries and upper-middle residential estates.

3. Spatial outlier dynamics (HL & LH)

The spatial outlier groups experienced significant shrinkage. LH outliers-prosperous villages isolated amid a cluster of poor villages-shrank from 27 villages (6.49%) to 19 villages (4.57%). This pattern indicates a process of spatial absorption where these 'oasis' villages gradually lost their economic resilience and were absorbed into the negative influence of their poor surrounding environment, reinforcing the hypothesis of expanding SPTs in peripheral areas.

5.4 Spatial poverty traps and policy recommendations

The synthesis of the paired samples t-test (Table 1), transition status matrix (Table 3), and LISA cluster mapping (Table 4) explains the existence of SPT in Bogor Regency. The paired correlation coefficient of 0.452 ($p = 0.000$) shows a very strong temporal persistence of poverty. When this temporal pattern is spatially correlated with the persistent HH LISA clusters in the West, it becomes clear that poverty in Bogor Regency is no longer merely a matter of individual characteristics (such as low education or asset ownership) but is constructed by the geographic factors of the area they reside in. The SPT in Western Bogor Regency is triggered by the destructive interaction between two major structural dimensions: (1) Biophysical Vulnerability and Limited Geographical Capital: The Western region of Bogor is dominated by extreme topography consisting of steep slopes, high elevation, and high landslide susceptibility. This fragile environmental condition worsens the region's limited 'geographical capital.' Consequently, returns on any economic investment in this region-both physical and human capital-are very low due to high transaction costs. Extreme topography and high landslide vulnerability in Western Bogor directly multiply transportation costs through distance friction, wasted travel time, and risks of commodity damage in the supply chain [42, 43]. This physical isolation, according to Stiglitz [44] and Williamson [45], limits the penetration of telecommunication infrastructure, thereby triggering severe market information asymmetries, reinforcing the dominance of middlemen, and weakening the bargaining power of local producers in every economic transaction including their access to bank credit [46];(2) Physical Isolation and Poor Micro-Connectivity: Severely damaged road and bridge connectivity between villages in the Western region creates physical isolation from metropolitan economic growth centers. Local development policies historically tend to exhibit an urban bias, where public investment, modern transportation infrastructure, and basic service facilities like education [47] are heavily concentrated in the Northern and Central regions close to the Jabodetabek corridor.

This pattern also triggers the Spatial Capture phenomenon, where general development budget interventions at the regency level tend to be absorbed in already economically developed sub-district centers instead of reaching peripheral villages in desperate need. Therefore, poverty alleviation policies in Bogor Regency must shift from a generic sectoral approach to an affirmative, micro-geospatial approach (granular village-level targeting).

6. CONCLUSIONS

Based on the temporal and spatial analysis of the PPP at the village level in Bogor Regency for the 2020–2024 period, several main conclusions are formulated:

1. Aggregate Poverty Stagnation and Structural Persistence: The mean difference test shows a very minor increase in the average PPP at the village level, from 22.96% in 2020 to 23.20% in 2024. However, this 0.24% increase is statistically insignificant due to a p-value of 0.819 ($p > 0.05$), a very small t-value ($t = –0.228$, $df = 415$), and a negligible effect size (Cohen's $d = –0.0112$). On the other hand, the paired correlation analysis yields a Pearson correlation coefficient of 0.452, which is highly statistically significant ($p = 0.000$). This proves a strong structural persistence, where villages with high poverty rates in 2020 had a very strong tendency to remain trapped in the same poverty conditions in 2024. Additionally, the widening standard deviation from 19.76% to 20.53% confirms that the distribution of poverty data among villages is increasingly varied, driving a sharper polarization of horizontal inequality.

2. Welfare Dynamics Turbulence at the Micro Level: The stagnant regency-level average hides highly active and dynamic welfare fluctuations at the village level (ecological fallacy). Through class division using the Tertile Method, a canceling-out effect was found where 94 villages (22.60%) experienced poverty class improvements, but this was symmetrically offset by 96 villages (23.08%) experiencing welfare class deterioration. A critical phenomenon is shown by the 21 villages (5.0%) that suffered extreme deterioration, falling free directly from the Low to the High class. Overall, there are 182 villages (43.75%) in less-than-ideal conditions, including 86 villages (20.7%) chronically trapped in the high poverty class (poverty trap group) during 2020–2024, and 96 villages whose welfare deteriorated.

3. Geographic Polarization and SPTs: Spatial autocorrelation analysis proves that the distribution of poverty in Bogor Regency is highly clustered geographically. This is shown by a highly significant positive Global Moran's I index of 0.127132 with a z-score of 6.111465 ($p = 0.000000$). LISA analysis maps a highly contrasting regional polarization: (1) HH Cluster (Poverty Hotspot) persistently centers in Western Bogor Regency (especially sub-districts bordering Lebak Regency, Banten). The number of villages in this cluster experienced a slight shrinkage from 45 villages (10.82%) in 2020 to 40 villages (9.62%) in 2024. The concentration of this

HH cluster proves the existence of SPTs. (2) LL Cluster (Welfare Coldspot) consistently centers in Northern and Central Bogor Regency close to metropolitan Jabodetabek, increasing from 55 villages (13.22%) in 2020 to 56 villages (13.46%) in 2024. (3) LH Outlier shrank from 27 villages (6.49%) to 19 villages (4.57%), indicating a process of negative spatial absorption where prosperous 'oasis' villages in peripheral areas were gradually dragged into the surrounding poverty.

Based on the temporal and spatial analysis conclusions above, the recommended policy suggestions are:

1. Reorientation to Micro-Level Geographic Targeting: Local governments must abandon development policies that rely solely on sub-district or regency-level aggregate averages to avoid analytical errors (ecological fallacy). Poverty alleviation programs must use micro-spatial coordinates, directing interventions directly to the village level, specifically to villages in HH clusters and those identified as experiencing extreme welfare deterioration.

2. Mitigation of Budget Spatial Capture: The Bogor Regency Government must strictly monitor the distribution of development budgets to prevent spatial capture, where infrastructure investments and public funds tend to be absorbed only in already-developed sub-district centers. Budget allocations must be directed affirmatively and asymmetrically to isolated rural peripheral villages.

3. Improvement of Micro-Connectivity in the Western Region: To break the cycle of SPTs in the Western region, physical interventions must focus on increasing the density of village roads, constructing bridges, providing transportation facilities, and building basic public service facilities (education and health). This step is crucial to lower economic transaction costs and distance friction caused by extreme topography and biophysical vulnerability in the Western region.

4. Reduction of Urban Bias: Local governments need to balance development between the Northern-Central (peri-urban) and Western (peripheral) regions by creating new economic growth centers based on optimizing local rural capital to suppress the impact of urban-biased development.

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