Geographic Barriers and Extreme Poverty: Micro-Spatial Evidence from the Riau Islands Province

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Submitted:
February 7, 2026

Revised:
February 24, 2026

Accepted:
April 28, 2026

Published Online:
April 30, 2026

ABSTRACT

Extreme poverty in archipelagic regions is strongly shaped by geographical constraints such as inter-island isolation, weak connectivity, and high logistics and basic service costs, with the Riau Islands Province showing pronounced and uneven poverty across sub-districts. This study aims to analyze the relationship between geographical constraints and extreme poverty, as well as to identify spatial clustering patterns that can inform more targeted policy interventions. The study employs a quantitative approach using microdata on extremely poor households. The analysis applies Spearman's rank correlation to examine the relationship between variables, along with Global Moran's I and Local Indicators of Spatial Association to detect spatial autocorrelation and clustering patterns. The findings indicate a significant positive relationship between geographical constraints and extreme poverty, showing that stronger spatial barriers are associated with deeper and more severe poverty conditions. Spatial analysis further reveals the presence of distinct high-poverty clusters across several sub-districts in multiple regencies and cities. These results highlight the importance of place-based policy approaches that are sensitive to local spatial conditions. Such policies are essential for addressing uneven development and improving the effectiveness of poverty reduction strategies at the sub-district level in archipelagic regions.

Keywords*: Archipelagic Regions, Extreme Poverty, Geographical Constraints, Place-Based Policy, Spatial Clusters.*

INTRODUCTION

Eliminating extreme poverty remains one of the most fundamental challenges in global and national development agendas. Within the framework of the Sustainable Development Goals (SDGs), extreme poverty is no longer understood solely as a matter of low income, but as a manifestation of structural inequality, limited access to basic services, and the exclusion of certain regions from broader development processes. According to the Central Bureau of Statistics (2024), extreme poverty is defined as the condition of individuals living below the extreme poverty line equivalent to Purchasing Power Parity (PPP) USD 2.15, or approximately IDR 11,924 per person per month. This multidimensional perspective reflects a growing consensus that poverty reduction strategies must extend beyond income-based measures to incorporate spatial, institutional, and infrastructural dimensions of deprivation (Martinez & Cooray, 2025). Empirical evidence in the Indonesian context shows that poverty reduction is strongly influenced by macroeconomic conditions and human capital development, reinforcing the structural nature of poverty (Majid et al., 2019; Kurniawan & Ramadhan, 2025).

Empirical evidence shows that extreme poverty is often geographically concentrated in remote and hard-to-access areas. World Bank (2022) notes that limited access to infrastructure, markets, and public services increases the risk of persistent poverty despite overall economic growth. High logistics costs and weak connectivity create a

JIAKES
Jurnal Ilmiah Akuntansi Kesatuan
Vol. 14 No. 2, 2026
pp. 599-614
IBI Kesatuan
ISSN 2337 – 7852
E-ISSN 2721 – 3048
DOI: 10.37641/jiakes.v14i2.5107

"geographical penalty," leading to higher living costs and lower economic opportunities (Kanbur & Venables, 2005). In addition, factors such as remoteness, terrain, and limited transportation are key determinants of regional poverty (Liu et al., 2023). As a result, extreme poverty is reflected not only in its incidence but also in its depth (P1) and severity (P2), indicating deeper and more chronic deprivation.

The spatial nature of poverty is reinforced by the interdependence of socio-economic conditions across neighboring regions. Anselin (2010) explains that these interactions often lead to the formation of geographic clusters. Empirical studies using Moran's I statistics consistently find significant positive spatial autocorrelation, indicating that poor regions tend to be surrounded by similarly poor areas (Liu et al., 2023). In the Indonesian context, Miranti (2021) documents persistent West–East disparities in poverty across districts and confirms stable spatial clustering patterns over time, even as overall poverty declines. Similarly, Martinez and Cooray (2025) show that conventional poverty targeting approaches often overlook spatial dependencies, leading to exclusion errors. Furthermore, Wang et al. (2021) identify a stronger "island effect" at finer spatial scales, where poverty clustering becomes more pronounced, highlighting the limitations of analyses conducted at more aggregated regional levels.

Despite this growing body of evidence, poverty alleviation policies in Indonesia remain largely dominated by aggregate approaches at the provincial or district/city level. Such approaches are relatively insensitive to identifying pockets of extreme poverty at the sub-district or small-island level, particularly in regions with high spatial fragmentation (Yudhistira & Sofiyandi, 2018). In practice, official poverty statistics are generally reliable only up to the district level, leaving sub-district and village-level dynamics insufficiently captured in policymaking. This limitation contributes to policy mistargeting, where interventions fail to reach the most vulnerable areas. In line with Barca et al. (2012), addressing this issue requires a place-based development approach that explicitly considers local characteristics and spatial interdependencies.

This challenge is particularly evident in the Riau Islands Province, a region characterized by extreme spatial fragmentation, with more than 96 percent of its territory consisting of water. The reliance on aggregate district-level analysis often obscures the presence of chronic extreme poverty in specific sub-districts, increasing the risk of ineffective policy targeting. Studies in similar archipelagic contexts confirm that geographic isolation, limited transport connectivity, and institutional constraints reinforce the persistence of poverty in fragmented regions (Adeoti et al., 2020). However, existing studies predominantly rely on aggregated data and rarely integrate microdata on extremely poor households with spatial indicators of geographic barriers at the sub-district level, particularly in island regions. This indicates a clear research gap in understanding how geographic barriers influence different dimensions of extreme poverty within a micro-spatial framework.

Therefore, this study aims to analyze the relationship between geographic barriers and extreme poverty at the sub-district level in the Riau Islands Province by examining their differential effects on poverty depth and severity, as well as identifying significant spatial clustering patterns. By integrating microdata on extremely poor households with spatial analysis, this research seeks to capture the spatial dynamics of extreme poverty and provide an empirical basis for identifying priority areas for more targeted and geographically sensitive poverty alleviation policies.

LITERATURE REVIEW

Extreme Poverty in Spatial Perspective

Extreme poverty, from a structural perspective, is understood as a condition resulting from systemic inequality of opportunity, not simply the failure of individuals or households. This inequality includes limited access to productive assets, labor markets, basic services, and public institutions that determine a household's ability to sustainably escape poverty (Gweshengwe & Hassan, 2020; Zhang, 2025). Within this framework, extreme poverty is persistent because poor households face barriers that are difficult to overcome through short-term interventions alone. A spatial approach expands the structural perspective by emphasizing that inequality of opportunity is inherent in geographic location. Kanbur and Venables (2005) demonstrated that spatial inequality is a significant phenomenon and is often greater than inequality between social groups within an administrative area. Residential location plays a crucial role in determining economic and social opportunities, so poverty is not distributed randomly across geographic space (Zhou & Li, 2022; van Ham et al., 2024).

Similarly, Anselin (2010) emphasized that the socioeconomic conditions of a region are influenced by the conditions of its surrounding areas, so poverty tends to form spatially linked patterns. In the Indonesian context, various empirical studies have shown that poverty forms strong regional clustering patterns (Purwono et al., 2021). Cahyadi et al. (2020) show that using aggregate indicators risks overlooking pockets of extreme poverty at the micro-scale. This finding emphasizes the need to understand extreme poverty as a structural-spatial phenomenon, particularly in areas with high geographic fragmentation.

Recent spatial econometric studies in Indonesia confirm that extreme poverty is strongly associated with geographically clustered deprivation, particularly in remote and archipelagic regions where infrastructure gaps persist (Belantika et al., 2023; Arif et al., 2025; Hidayati et al., 2025). Furthermore, micro-level spatial analysis shows that poverty heterogeneity within districts can be substantial, indicating that aggregated regional indicators often conceal localized poverty traps (Martinez & Cooray, 2025).

Geographical Barriers and Exclusion of Archipelagic Regions

Archipelagic regions have geographic characteristics that inherently present greater transportation and logistical barriers than mainland regions. Island fragmentation, dependence on maritime transportation, and limited connectivity create a high and unstable cost of living structure. In regional literature, this condition is the geographical penalty, supported by recent evidence of persistent transport cost inflation and spatial price dispersion in island economies (Kanbur & Venables, 2005; Barca et al., 2012; Hill, 2020; Winterford et al., 2020; Ramesh, 2025). The World Bank (2023) notes higher prices of basic necessities in archipelagic regions due to distribution costs and thin markets. This increases poverty risk as rising living costs are not offset by income growth.

In addition to the cost of living, geographical barriers also significantly limit access to education, health care, and labor markets, thereby constraining human capital accumulation and reinforcing conditions of chronic and intergenerational poverty (Francisco & Librero, 2025; Nafiah et al., 2025; Permana, 2025). These constraints are often more severe in remote and island-based regions, where limited transportation infrastructure, high mobility costs, and weak service connectivity reduce households' ability to access essential public services and economic opportunities. Empirical studies in Indonesia further show that regions with low accessibility tend to experience higher poverty incidence and deeper poverty severity, consistent with broader patterns of spatial inequality in archipelagic development contexts (Rukmana & Roitman, 2023). These findings align with earlier evidence on Indonesia's persistent connectivity constraints, particularly the uneven distribution of infrastructure and services across regions (Halimatussadiah, 2020). This literature indicates that addressing geographical disparities requires sustained infrastructure development, improved inter-island connectivity, and integrated service delivery policies to effectively reduce regional poverty gaps.

Place-Based Policy in Poverty Alleviation

Place-based policy is a policy approach that emphasizes the importance of local context in formulating development interventions. This approach differs from place-neutral policies, which assume that economic growth will flow evenly across regions. Barca et al. (2012) assert that uniform policies tend to be less effective in addressing regional disparities, especially in areas with strong geographic and structural barriers. The OECD (2020) emphasizes that effective place-based policy must be multisectoral, coordinated across levels of government, and based on empirical evidence. Recent empirical studies show that regional development outcomes are strongly shaped by spatial heterogeneity, where "one-size-fits-all" policies often fail to reduce inequality across territories (Rodríguez-Pose, 2018; Crescenzi & Giua, 2020). These findings strengthen the argument that place-based strategies are essential for addressing persistent regional gaps.

In the context of tackling extreme poverty, this approach allows for sharper regional targeting and better integration of policy instruments across sectors (Mariotti & Shepherd, 2015). Rather than relying on aggregate administrative units, sub-district level targeting enables policymakers to identify micro-regional disparities that are often hidden in district-level statistics. This is particularly relevant for archipelagic countries like Indonesia, where geographic fragmentation creates unequal access to markets, services, and infrastructure. Recent literature highlights that effective regional policy must combine localized knowledge with multi-level governance coordination to address spatial inequality more effectively (Garretsen et al., 2013). In addition, place-based development is increasingly recognized as a critical tool for reducing territorial disparities through tailored interventions in infrastructure, human capital, and institutional capacity (Iammarino et al., 2019; Weck et al., 2022). Therefore, adopting a place-based approach enhances policy precision and effectiveness in reducing extreme poverty across geographically diverse regions.

RESEARCH METHODS

This study's conceptual framework assumes geographic barriers as the main structural driver of extreme poverty in island regions. These barriers, such as remoteness, weak connectivity, high logistics costs, and limited access to services and labor markets, are expected to differentially affect poverty dimensions. Specifically, they are hypothesized to have a stronger impact on poverty depth (P1) through higher living costs and constrained access, while their effect on poverty severity (P2) is weaker due to household asset heterogeneity and socioeconomic conditions. Extreme poverty is also assumed to be spatially dependent across sub-districts, forming statistically significant clusters. This framework supports the use of spatial autocorrelation analysis to identify inter-regional linkages and extreme poverty hotspots for targeted policy intervention (Ravallion, 2016; Rodríguez-Pose, 2018).

This study employs a descriptive-quantitative design with a micro-spatial approach to examine the relationship between geographic barriers and extreme poverty at the sub-district level. The analysis covers 80 sub-districts across seven districts/cities in Riau Islands Province, which are selected due to the localized concentration of extreme poverty as identified by the Coordinating Ministry for Human Development and Culture (2023), as well as the strategic role of sub-districts as operational units in place-based poverty alleviation policies. This approach enables both statistical testing of relationships and the identification of spatial poverty patterns that are not captured by aggregate district-level analysis.

The research population covers all sub-districts (80) in the Riau Islands Province. This research uses total sampling (regional census), so that all sub-districts are used as research samples. The census approach was used because the number of analysis units is relatively limited, and spatial analysis requires coverage of the entire region to avoid spatial bias. The study area includes the Anambas, Natuna, Lingga, Karimun, and Bintan Islands regencies, as well as Batam and Tanjungpinang cities. Riau Islands Province was chosen due to its archipelagic characteristics, high spatial fragmentation, dependence on sea transportation, and significant variation in extreme poverty between sub-districts.

This study utilizes quantitative and spatial secondary data at the sub-district level. The data include microdata on extremely poor households that have undergone verification and validation processes and are subsequently aggregated to generate key poverty indicators, namely P0 (the proportion of extremely poor people), P1 (poverty depth), and P2 (poverty severity). In addition, the study incorporates geographical barriers data, which capture the extent of regional remoteness, limited transportation connectivity, and restricted access to basic services and labor markets; these variables are further processed into a composite geographic barriers index at the sub-district level. Furthermore, spatial data on sub-district administrative boundaries in vector (polygon) format are employed to support mapping and the construction of the spatial weight matrix.

The relationship between geographic barriers and the dimensions of extreme poverty (P1 and P2) was tested using the Spearman Rank correlation (ρ). This test was chosen because it does not assume a normal distribution and is suitable for monotonic relationships. The Spearman Rank correlation formula is:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}$$

where:
ρ = Spearman's correlation coefficient,
di = difference in ranking between geographic barriers and extreme poverty indicators in the ith sub-district,
n = number of sub-districts.
The ρ value ranges from -1 to +1. Statistical significance was tested at the 95 percent confidence level.

To test the spatial relationship between extreme poverty and sub-districts, Global Moran's I was used. This index examines whether the distribution of extreme poverty is clustered, dispersed, or random. The formula for Global Moran's I is:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where:
I = Moran's index,
xi = extreme poverty indicator value in the ith sub-district,
x = average extreme poverty indicator value,
wij = element of the spatial weight matrix between sub-districts i and j,
n = number of sub-districts.
A value of I > 0 indicates positive spatial autocorrelation (clustering), I < 0 indicates a scattered pattern, and a value close to zero indicates a random pattern.

Identification of extreme poverty clusters at the sub-district level was conducted using Local Indicators of Spatial Association (LISA). The Local Moran's I statistic is formulated as:

$$\boldsymbol{I_i = \frac{(x_i - \bar{x})}{S^2} \sum_j w_{ij}\,(x_j - \bar{x})}$$

with:

$$\boldsymbol{S^2 = \frac{\sum_i (x_i - \bar{x})^2}{n}}$$

where Ii indicates the level of local spatial connectivity in the ith sub-district. LISA analysis groups sub-districts into high–high, high–low, low–high, and low–low clusters.

The final stage involves integrating the results of the Spearman Rank Correlation and spatial analyses, namely Global Moran's I and Local Indicators of Spatial Association (LISA). Subdistricts are identified as priority areas for addressing extreme poverty when they exhibit high levels of extreme poverty, particularly in the P1 (poverty depth) dimension, and show a significant correlation with geographic barriers. In addition, these areas must be part of a statistically significant spatial cluster, specifically within the high-

high category, indicating that they are surrounded by neighboring areas with similarly high values. This integrated approach provides an empirical foundation for formulating targeted, region-based policy recommendations aimed at alleviating extreme poverty. With this design and stages, this research is explanatory-spatial in nature, as it not only describes conditions of extreme poverty but also explains the structural relationship between geographic barriers and extreme poverty and identifies cluster patterns of priority areas. This approach ensures both academic relevance and policy utility, particularly for island regions with high spatial fragmentation.

RESULTS

Relationship Geographical Barriers and Extreme Poverty at the Sub-district Level

The Spearman Rank correlation results demonstrate that geographic barriers have a positive and statistically significant relationship with extreme poverty, particularly in the poverty depth dimension (P1). With a correlation coefficient of $\rho = 0.531$ ($p < 0.01$), the relationship can be categorized as moderate to strong, indicating that geographic constraints are not merely peripheral factors but play a meaningful role in shaping poverty conditions. This finding implies that as geographic barriers increase, reflected in remoteness between islands, limited transportation connectivity, and higher logistics costs, the depth of extreme poverty also intensifies. In other words, households located in more isolated areas tend to experience a greater shortfall between their actual expenditure and the established extreme poverty line.

This pattern becomes more evident when examining specific sub-districts in the outermost and most remote island regions. Sub-districts such as Palmatak (P1 = 0.73) and Siantan Selatan (P1 = 0.68) in Anambas Islands Regency, along with Midai (P1 = 0.66) and Suak Midai (P1 = 0.64) in Natuna Regency, exhibit poverty depth levels that are substantially higher than the provincial average (P1 = 0.43). These elevated values suggest that extremely poor households in these areas face more severe economic deprivation, as their average expenditure lies far below the extreme poverty threshold. The geographical isolation of these regions likely limits access to markets, employment opportunities, education, and basic services, thereby exacerbating the depth of poverty experienced by households.

In contrast, sub-districts with relatively better accessibility, such as Batam City (P1 = 0.24) and North Bintan (P1 = 0.34), show significantly lower levels of poverty depth. Improved infrastructure, stronger connectivity, and more developed economic activities in these areas contribute to reducing the gap between household expenditure and the poverty line. This disparity between remote and accessible regions reinforces the conclusion that geographic barriers serve as a critical structural determinant of extreme poverty in the Riau Islands. Therefore, addressing infrastructure gaps, improving inter-island connectivity, and reducing logistics costs are essential policy priorities to alleviate the depth of poverty in geographically disadvantaged areas.

Differences in the Influence of Geographical Barriers on P1 and P2

The results of the study indicate that the influence of geographic barriers on P1 is consistently stronger than on P2. The correlation coefficient between geographic barriers and P2 is $\rho = 0.398$ ($p < 0.05$), which is still significant but weaker than P1. This finding indicates that geographic barriers not only influence the number of extremely poor households but also primarily deepen the conditions of poverty experienced collectively within a sub-district.

Table 1 shows that across all sub-districts with high geographic barriers, P1 values are consistently significantly higher than P2, with P1:P2 ratios ranging from 3.7 to nearly 5.0. This pattern provides strong empirical evidence that geographic barriers play a greater role in collectively deepening extreme poverty than in exacerbating internal inequality among extreme poor households. Outlying island sub-districts such as Palmatak, Midai, and Senayang recorded P1 values above 0.65, indicating that the average expenditure of extreme poor households is significantly below the poverty line. However, P2 values in these sub-districts are relatively moderate (0.13–0.16), indicating that poverty pressure is experienced relatively evenly by extremely poor households within the sub-district. Conversely, in urban island sub-districts such as Galang, Bulang, and Bukit Bestari, P1 values remain higher than the provincial average, although P2 values do not increase proportionally. These findings confirm that pockets of extreme micro-poverty can persist in urban areas if geographic barriers (access to small islands, sea transportation, and mobility costs) remain.

Table 1. Comparison of the Depth & Severity of Extreme Poverty

Regency/City	Subdistrict	Geographic Character	P1 (Depth)	P2 (Severity)	Ratio P1:P2	Main Interpretation
Kep. Anambas	Palmatak	Outermost islands	0.73	0.16	4.56	Deep poverty. collective pressure
Kep. Anambas	Siantan Selatan	Outermost islands	0.68	0.15	4.53	High and uniform cost of living
Natuna	Midai	Outermost islands	0.66	0.14	4.71	Extreme remoteness
Natuna	Suak Midai	Outermost islands	0.64	0.13	4.92	Logistics cost pressures
Natuna	Pulau Laut	Outermost islands	0.62	0.13	4.77	Very limited access to services
Lingga	Senayang	Remote islands	0.69	0.15	4.60	Institutional barriers
Lingga	Bakung Serumpun	Remote islands	0.67	0.15	4.47	Low access to education and healthcare
Lingga	Temiang Pesisir	Remote islands	0.63	0.14	4.50	Cost and access pressures
Karimun	Belat	Middle-area islands	0.58	0.12	4.83	Inefficient access
Karimun	Durai	Middle-area islands	0.55	0.12	4.58	Single node dependency
Bintan	Mantang	Middle-area islands	0.52	0.11	4.73	Limited market access
Batam	Galang	Urban islands	0.44	0.12	3.67	Pockets of micro-poverty
Batam	Bulang	Urban islands	0.42	0.11	3.82	Low job mobility
Tanjungpinang	Bukit Bestari	Urban islands	0.41	0.11	3.73	Inner-city island pockets

Source: Processed microdata of extremely poor households at the sub-district level (2024)

This pattern indicates that the primary geographic constraints are rising minimum living costs and limited access to services, which are experienced almost equally by extremely poor households within a sub-district. As a result, the gap between average expenditure and the poverty line increases sharply, while internal inequality among extremely poor households does not increase proportionally. Thus, extreme poverty in the Riau Islands is characterized more by deep poverty than severe poverty.

Spatial Clusters of Extreme Poverty and District-Based Policy Synthesis

Spatial autocorrelation analysis confirmed that extreme poverty is not randomly distributed but rather forms significant spatial clusters at the sub-district level. The Global Moran's I value for P1 of 0.412 ($z = 3.87$; $p < 0.01$) indicates strong positive spatial autocorrelation. This means that sub-districts with high extreme poverty depth tend to be adjacent to other sub-districts with high P1. The LISA analysis further identified a High-High (HH) cluster, predominantly located in island regions and sub-districts with high geographic barriers. Sub-districts within this cluster had average P1 values above 0.60, far exceeding the provincial average.

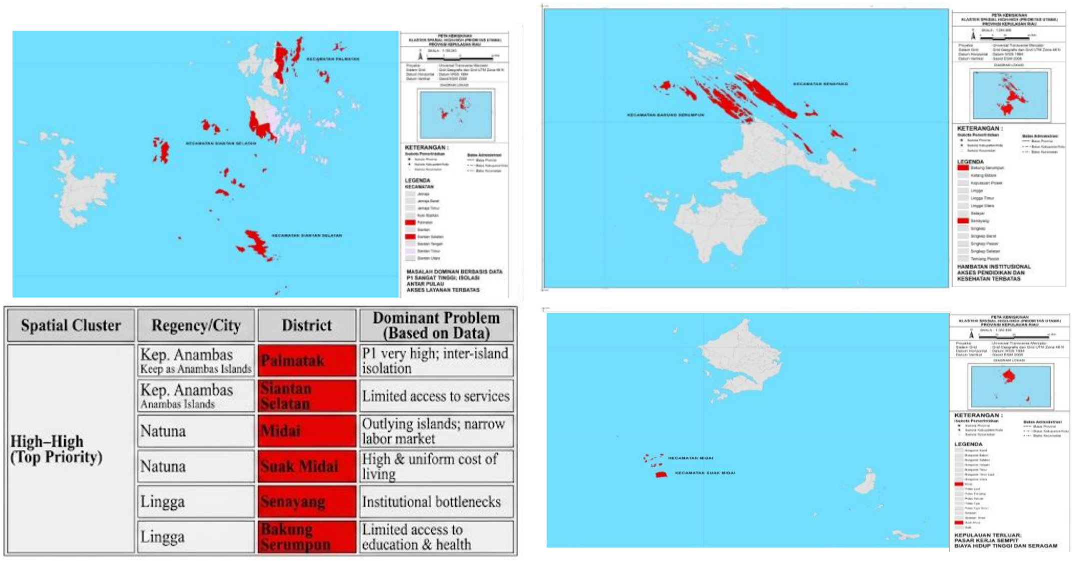
To operationally address the third research objective, the spatial cluster results were synthesized with data-based dominant problems and relevant policy directions. This synthesis is presented in Table 2, which shows that each cluster has distinct problem characteristics, despite all being in the high-high category.

Table 2. Spatial Clusters of Extreme Poverty Based on Districts

Spatial Cluster	Regency /City	Subdistrict	Dominant Issues (Data-Driven)	Policy Direction	Operational Instruments	Performance Indicators
High–High (Top Priority)	Anambas Islands	Palmatak	P1 very high, inter-island isolation	Lowering the cost of living	Food logistics subsidies, regular sea routes	P1 sub-district ↓
	Anambas Islands	Siantan Selatan	Limited access to services	Access to basic services	Mobile health and civil administration services	P1 ↓, coverage ↑
	Natuna	Midai	Outermost islands, narrow job market	Income stability	Labor-intensive fisheries and local transport	RT income ↑
	Natuna	Suak Midai	High & uniform cost of living	Basic connectivity	Cluster transportation and logistics subsidies	P1 ↓
	Lingga	Senayang	Institutional barriers	Cluster service nodes	Sub-districts as service hubs	Access costs ↓
	Lingga	Bakung Serumpun	Limited access to education & healthcare	Intermediate service access	Scheduled referral services	P1 ↓
High–High (Medium)	Karimun	Belat	Inefficient access	Service efficiency	Social assistance and empowerment integration	RT graduation
	Karimun	Durai	Single node dependency	Intermediate connectivity	Scheduled transportation	P1 ↓
	Bintan	Mantang	Middle islands	Market and service access	Strengthening sub-district nodes	P1 ↓
High–High (Micro Urban)	Batam	Galang	Urban island enclaves	Micro-spatial interventions	Adaptive labor-intensive services	P1 RT ↓
	Batam	Bulang	Low job mobility	Labor market access	Worker transportation subsidies	Income ↑
	Tanjungpinang	Bukit Bestari	Urban island enclaves	Precision targeting	By-name, by-address sub-districts	P1 ↓
Non-High–High	Batam	Batam Kota	High access, low P1	Prevention	Regular social protection	Stability
	Bintan	Bintan Utara	Transition area	Early warning	Routine monitoring	Not In HH

Table 2 shows that the high-high cluster is not only found in outermost island regions such as Anambas, Natuna, and Lingga, but also appears as pockets of urban micro-poverty in Galang and Bulang (Batam) and Bukit Bestari (Tanjungpinang), with P1 values of 0.44–0.42–0.41, respectively. This finding suggests that extreme poverty based on geographic barriers can persist even in regions with relatively good aggregate economic performance.

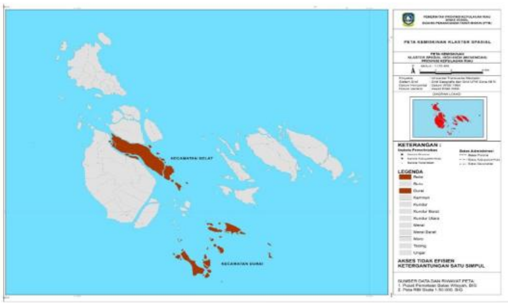
This research finding confirms that extreme poverty in island regions is a spatial phenomenon that cannot be explained solely by household characteristics but must be understood within the framework of inherent geographic barriers. These findings align with global literature developed by the World Bank, the OECD, and regional development economists such as Ravi Kanbur and Anthony Venables. The World Bank (2022) introduced the concept of spatial poverty traps, a condition where poor households living in remote and isolated areas face limited access to markets, basic services, and public infrastructure, resulting in persistent poverty despite aggregate economic growth. The findings of this study provide empirical evidence at the micro level that spatial poverty traps in the archipelago operate primarily through deepening extreme poverty, rather than through increasing internal inequality among extremely poor households. This is reflected in the stronger correlation coefficient between geographic barriers and poverty depth (P1) compared to poverty severity (P2). Spatial Cluster Maps of High-High Sub-districts (Main Priority, Medium, Micro-Urban, and Non-High-High Sub-districts in Figures 1, 2, and 3 below.

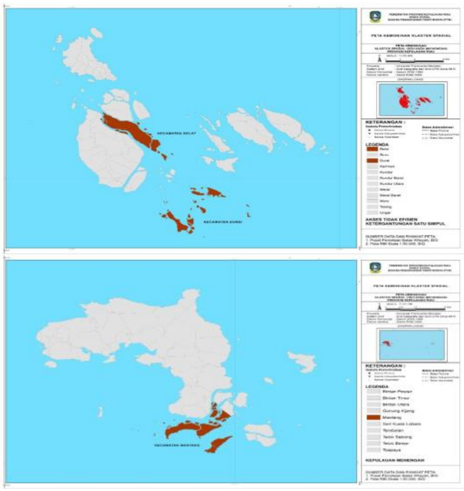


Spatial Cluster	Regency/City	District	Dominant Problem (Based on Data)
High–High (Top Priority)	Kep. Anambas Keep as Anambas Islands	Palmatak	P1 very high; inter-island isolation
	Kep. Anambas Anambas Islands	Siantan Selatan	Limited access to services
	Natuna	Midai	Outlying islands; narrow labor market
	Natuna	Suak Midai	High & uniform cost of living
	Lingga	Senayang	Institutional bottlenecks
	Lingga	Bakung Serumpun	Limited access to education & health

Figure 1. Spatial Cluster Map of High-High District (Top Priority)

The micro-spatial analysis results in Figure 1 show that the High-High (top priority) cluster of extreme poverty in the Riau Islands Province is concentrated in the outermost and remote island regions, particularly in the Anambas Islands Regency (Palmatak, South Siantan), Natuna Regency (Midai, Suak Midai), and Lingga Regency (Senayang, Bakung Serumpun). These regions are characterized by inter-island isolation, limited access to basic services, high living costs, and institutional barriers, which simultaneously reinforce the depth of poverty (P1). The clustered spatial pattern confirms that extreme poverty in the Riau Islands is structural and geographical in nature, so policy interventions need to be targeted, area-based, and improve connectivity and basic services.





Spatial Cluster	Regency/City	District	Dominant Problem (Based on Data)
High–High	Karimun	Belat	Inefficient access
	Karimun	Durai	Single-node dependency
	Bintan	Mantang	Intermediate islands

Figure 2. Spatial Cluster Map of High-high (Middle) District

Figure 2 is a spatial cluster category that indicates that a region has a relatively high indicator value and is surrounded by other regions with similarly high values, but the intensity is at a medium level, not yet extreme. The value of the main indicator (poverty, vulnerability, or access barriers) is above the regional average, high (neighbors). The surrounding regions also have high indicator values, medium, the severity level is not yet in the extreme category, but is quite significant and has the potential to increase if not intervened. The high–high (medium) cluster reflects collective structural vulnerability. The problems faced do not stand alone, but are amplified by conditions in the surrounding region, such as limited inter-island connectivity, dependence on certain service nodes, and a small economic scale. High–high (medium) is not the most severe region, but is a vulnerable point for strengthening spatial problems that must be a medium–high priority in regional-based development planning.

Spatial Cluster	Regency/City	District	Dominant Problem (Based on Data)
High–High (Micro Urban)	Batam	Galang	Urban island pocket
	Batam	Bulang	Low labor mobility
	Tanjungpinang	Bukit Bestari	City island pocket

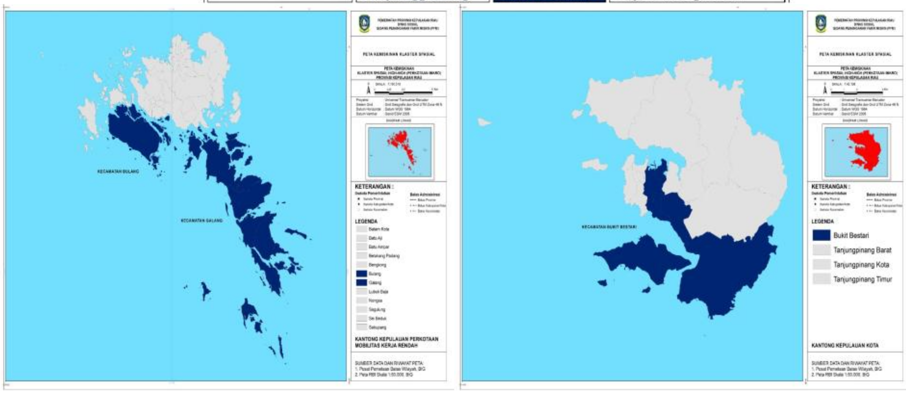


Figure 3. Spatial Cluster Map of High-High District (Micro Urban)

The micro-spatial analysis of Figure 3 shows that the High-High urban poverty cluster is concentrated in Galang and Bulang Districts (Batam City) and Bukit Bestari District (Tanjungpinang City). These areas are island-based poverty pockets characterized by spatial isolation, limited connectivity, and low labor mobility, thus reinforcing poverty structurally. This clustering pattern confirms that urban poverty in the Riau Islands Province is heavily influenced by island geography, thus requiring region-specific and targeted policy interventions, rather than a generalized mitigation approach.

Spatial Cluster	Regency/City	District	Dominant Problem (Based on Data)
Non-High–High	Batam	Batam City	High Access; Low P1
	Bintan	North Bintan	Transition Area

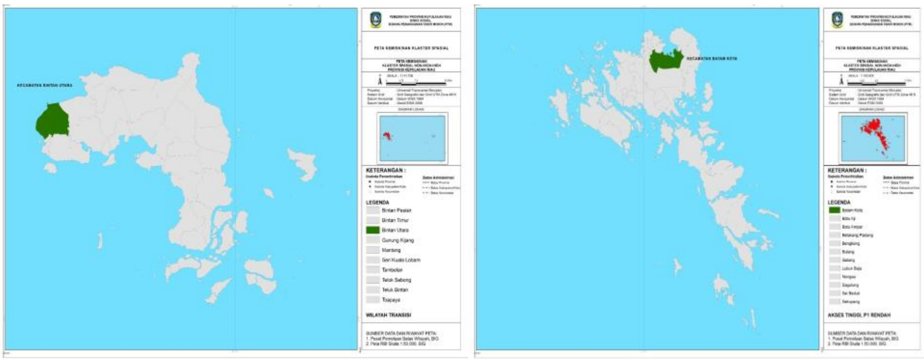


Figure 4. Spatial Cluster Map of Non-High-High Districts

The Non-High–High cluster in Figure 4 indicates that the indicator value for the region is not high, but it is surrounded by high-value areas. Batam Kota (Batam City) and Bintan Utara (Bintan Regency) districts function as buffer/transition zones, not the main problem centers, but are vulnerable to the impacts of the dynamics of the surrounding area. High access indicates the availability of infrastructure, services, or relatively good connectivity. Low P1 indicates that the benefits of access have not been optimally converted into development outcomes (welfare, service quality, or specific socio-economic outputs). This indicates structural inefficiency: barriers can be service quality, human resource capacity, governance, or mismatches between needs and services. Because they are surrounded by high-value areas, there is potential for positive spillover (spillover effects, the impact of one area, policy, or activity that is felt by other surrounding areas), even though these areas are not the primary targets.

Table 3. Recommendations for District-Based Extreme Poverty Alleviation Policies

Sub-district Clusters	Regency, Sub District	(P1–P2 & Spatial)	Measurable Issues	Policy Recommendations	Operational Policy Instruments
Outermost Islands – Extreme Deep Poverty	Anambas Islands, South Palmata, Siantan	P1 very high (0.68–0.73), P2 moderate, HH cluster	High minimum cost of living, low connectivity	Reducing collective living costs at the sub-district level	Food and fuel logistics subsidies, regular pioneering sea routes, and basic mobile services
	Natuna, Midai, Suak Midai, Pulau Laut	P1 high (0.62–0.66), HH cluster	Extreme remoteness and price volatility	Affirming connectivity and distribution of basic needs	Subsidized sea transportation,sub-district logistics warehouses, schedule-based aid distribution
Remote Islands – Institutional Barriers	Lingga, Senayan, Bakung Serumpun, Temiang Pesisir	P1 high (0.63–0.69), P2 relatively stable, HH cluster	Limited access to education, health, and the job market	Strengthening sub-district-based institutional services	Cross-island education and health services, sub-district service centers, and strengthening coastal economies
Middle-East Islands – Inefficient Access	Karimun, Belat, Durai	P1 medium-high (0.55–0.58), HH cluster	Access exists but is expensive and inefficient	Efficient connectivity and market access	Adjustment of transport fares and schedules, support for local value chains
	Bintan, Mantang,	P1 medium (0.49–0.52), HH cluster	Distribution and	Sharpening sub-district-based	Micro-enterprise assistance, strengthening

Sub-district Clusters	Regency, Sub District	(P1–P2 & Spatial)	Measurable Issues	Policy Recommendations	Operational Policy Instruments
	Gunung Kijang		market access costs	productive assistance	district market access
Urban Micro-Islands – Hidden Pockets of Poverty	Batam, Galang, Bulang	P1 above provincial average (0.42–0.44), HH cluster	Small island access within urban areas	Sharpening micro-urban poverty policies	Island-city transportation, protection of informal workers, mobility subsidies
	Tanjungpinang, Bukit Bestari	P1 = 0.41, HH cluster	Island pockets within urban areas	Integrating social and urban planning policies	Adaptive social assistance for living costs, basic island services
Cross-District HH Cluster	All, All HH clusters	P1 average > 0.60, positive spatial autocorrelation	Extreme poverty across regions	Sub-district cluster-based governance	Determination of priority districts across districts/cities, micro-spatial monitoring

Source: Results of micro-spatial analysis of extreme poverty at the sub-district level, 2024–2025

Table 3 presents a spatially differentiated policy framework for extreme poverty alleviation across sub-district clusters in the Riau Islands Province. The findings indicate that extreme poverty is not spatially uniform, but instead forms distinct clusters with varying structural characteristics and intensity of poverty (P1–P2). Outermost and remote island clusters are primarily constrained by high living costs and severe connectivity limitations, while middle-island areas experience inefficiencies in access and market integration. In contrast, urban micro-islands exhibit "hidden poverty" pockets despite relatively strong regional economic performance, highlighting intra-urban spatial inequality. These differentiated conditions reinforce the need for place-based policy interventions tailored to local geographic and institutional constraints rather than uniform approaches.

DISCUSSION

The findings of this study confirm that extreme poverty in the Riau Islands Province is fundamentally shaped by geographic constraints and spatial structure, consistent with the growing body of literature on spatial inequality and place-based development. Geographic barriers such as remoteness, weak inter-island connectivity, and high logistics costs operate as structural determinants that intensify poverty conditions, particularly in island settings where access to markets and services is inherently limited. This aligns with Kanbur and Venables (2005), who argue that spatial inequality emerges from persistent geographic disadvantages that systematically increase living and transaction costs, and with the broader concept of spatial poverty traps highlighted by the World Bank (2022).

The empirical pattern also supports OECD (2023) arguments that regional disparities are not only driven by differences in human capital or economic structure, but also by place-specific constraints embedded in geography. The clustering of extreme poverty observed across sub-districts demonstrates that regions with similar structural disadvantages tend to form spatially contiguous patterns, reinforcing the relevance of spatial dependence theory (Anselin, 2010; Liu et al., 2023). This spatial clustering is consistent with findings from Miranti (2021), who shows that poverty in Indonesia exhibits strong spatial persistence, and van Ham et al. (2024), who emphasize that socio-economic inequality is inherently geographic in nature.

A key contribution of this study is the differentiated impact of geographic barriers on poverty dimensions. The results indicate that geographic constraints are more strongly associated with poverty depth than poverty severity. This suggests that spatial isolation primarily deepens collective deprivation rather than increasing inequality among the poor. This finding extends Kanbur and Venables' (2005) geographical penalty framework by showing that in archipelagic contexts, the penalty is expressed through uniform deprivation pressures within localities rather than heterogeneous welfare dispersion. Similar dynamics are also observed in Wang et al. (2021), who find that geographic capital shapes poverty intensity in spatially constrained regions.

The identification of poverty clusters in both remote and urban island settings further expands the conventional understanding of spatial poverty. While rural and outer islands confirm classical accessibility constraints, the presence of poverty pockets in urban island areas challenges the assumption that urbanization automatically reduces poverty. This finding is consistent with Rodríguez-Pose (2018), who argues that "places that do not matter" can persist even within economically advanced regions, and with OECD (2023), which highlights the persistence of localized inequality within developed territories. Studies by Yudhistira and Sofiyandi (2018) further support the importance of connectivity infrastructure in shaping regional economic outcomes in archipelagic contexts.

From a policy perspective, the results strongly support place-based development approaches (Barca et al., 2012; Garretsen et al., 2013; OECD, 2020). The persistence of spatial clusters suggests that uniform policy interventions are insufficient in addressing structurally differentiated poverty conditions. Instead, targeted interventions that improve connectivity, reduce logistics costs, and strengthen local service delivery are necessary, in line with national strategies for poverty eradication (Bappenas, 2023; Coordinating Ministry for Human Development and Culture, 2023). Evidence from Cahyadi et al. (2020) also reinforces that targeted social protection combined with localized interventions yields stronger welfare impacts in Indonesia. This study contributes to the literature by integrating spatial econometric perspectives with archipelagic development constraints. It demonstrates that extreme poverty in island regions is not only a socioeconomic phenomenon but also a spatially structured condition shaped by geographic capital limitations. This reinforces the argument that reducing extreme poverty requires a territorial approach that accounts for spatial heterogeneity, connectivity constraints, and localized development traps.

CONCLUSION

This study examines the relationship between geographic barriers and extreme poverty, the differential effects on poverty depth and severity, and the spatial clustering of extreme poverty at the sub-district level in the Riau Islands Province. The findings show that geographic barriers such as remoteness, limited inter-island connectivity, and high logistics costs are a key structural driver of extreme poverty in island regions. These constraints intensify deprivation by deepening the gap between household expenditure and the poverty line. Spatial analysis further confirms that extreme poverty is not randomly distributed but forms significant clusters across remote islands and micro-poverty pockets in urban island areas, highlighting strong spatial dependence in poverty patterns.

The results also indicate that geographic barriers have a stronger effect on poverty depth than on poverty severity. This suggests that extreme poverty is characterized more by collective deprivation within sub-districts than by inequality among the extremely poor. In this context, geographic constraints generate relatively uniform poverty pressures within areas, reinforcing the need for place-based policies. Policy responses should prioritize improving connectivity, reducing logistics costs, and expanding access to basic services, while also addressing hidden poverty in urban island settings through spatially targeted interventions.

This study is limited by its cross-sectional design, which does not capture the temporal dynamics of poverty, and by constraints in measuring geographic barriers comprehensively. Future research should adopt longitudinal approaches to examine changes over time, incorporate more detailed accessibility and infrastructure indicators, and apply advanced spatial econometric or machine learning methods to strengthen causal inference. Extending the analysis to other archipelagic regions would also improve the generalizability of the findings.

FUNDING STATEMENT: This research did not receive any specific grant from funding agencies in the public, commercial, or not - for - profit sectors.

CONFLICTS OF INTEREST: The author declares no conflict of interest.

DECLARATION OF GENERATIVE AI STATEMENT: During the preparation of this work, the author(s) used ChatGPT, Grammarly, and Turnitin in order to assist with language refinement, grammar checking, and originality verification. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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