Mapping poverty traps in Indonesia: a spatial perspective

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Spatial poverty traps may arise in regions characterized by low geographical capital – encompassing ecological, economic, and social resilience – where there is a high percentage of impoverished citizens. Recent reports on poverty in Indonesia have primarily focused on distribution, lacking comprehensive geographical context. This study aims to delineate the poverty traps across Indonesia by examining both geographical settings and poverty levels. To achieve this objective, the study employs a spatial poverty trap framework that integrates economic parameters with geographic considerations. Secondary data sourced from third parties were utilized; specifically, data on geographical capital were derived from the village development index (VDI), while poverty level data were obtained from Statistics Indonesia. Data analysis involved the application of various statistical methods, including crosstab contingency analysis, geographically weighted regression (GWR), and geographic information systems (GIS). The crosstab method was employed to identify clusters of poverty levels in relation to the VDI. Regression analysis was conducted to assess the local influence of geographical settings on poverty levels within the regions. Subsequently, GIS analysis was performed to illustrate the distribution of poverty traps across Indonesia's topography. The findings indicate that 26 regions are identified as spatial poverty traps. Specifically, the topographical analysis reveals that these regions consist of 10 areas situated in mountainous regions and 16 areas located along coastal zones. Overall, this study concludes that poverty traps in Indonesia are predominantly found in mountainous and coastal areas.

Keywords:
geographic capital,
remote region,
mountainous and coastal poverty,
spatial poverty traps

Introduction

Although Indonesia has achieved middle-income status with an average economic growth rate of 5% and a GDP exceeding USD 1.000 trillion (BPS 2020), poverty remains a persistent issue within the country's development dynamics. The economic decentralization implemented in 1999, intended as a solution to the disparities considered the root causes of poverty, has not been entirely successful. Poverty pockets still persist, giving rise to urban and rural poverty incidents in various regions of Indonesia (Arif et al. 2019). Data from the Bureau of Statistics Indonesia indicates that in the year 2000, the per capita income in Papua Province, which had the highest poverty rate in Indonesia, was recorded at USD 735. In the same year, Jakarta, as the economic hub, had a per capita income of USD 2,312. This disparity in income and development highlights the extent of inequality that prevails in Indonesia. Twenty years later, in 2020, it was observed that the per capita income in Papua Province had reached USD 1,956, while Jakarta's per capita income had risen to USD 6,394. These figures depict a lack of substantial progress in the equitable distribution of development in Indonesia over the course of two decades (see in Appendix, Figure A1).

The stagnation of development, as evidenced by per capita income data (Kraay–McKenzie 2014), is believed to be a consequence of the poverty trap. This mechanism implies that impoverished regions tend to remain entrenched in poverty, wherein current poverty perpetuates future poverty (Azariadis–Stachurski 2005). The phenomenon of extreme poverty in Indonesia, particularly in Papua Province, is significantly influenced by non-economic factors, which include a lack of services and difficulties in accessing these regions (Daimon 2001). This situation is further exacerbated by weak connectivity between rural and urban areas, which are integral to economic activities (Rijanta 2001). As a result, the impoverished population in these areas confronts not only the challenges posed by the poverty trap but also a deficiency in physical infrastructure, institutional support, and access to networks that are conducive to economic advancement. This condition can be specifically described as being spatially trapped in poverty (spatial poverty traps) (Bird 2019).

To date, research on poverty in Indonesia has predominantly focused on economic factors, often neglecting geographical elements (Rahim et al. 2023). Therefore, this study introduces a novel perspective on poverty in Indonesia, emphasizing a more holistic approach that considers the critical role of geographical capital as a determinant in the context of poverty.

The discourse surrounding spatial poverty traps, as noted by Sachs et al. (2004), Burke–Jayne (2008), and Cuong et al. (2010), is linked to the limited access of certain regions to other areas, resulting in isolation and the entrapment of their populations in impoverished conditions. Moreover, a study encompassing 89 developing countries globally revealed that poverty traps frequently occur in rural areas (Castañeda et al. 2018). In this context, accessibility plays a significant role in the emergence of poverty-related issues. According to Bird et al. (2010), spatial poverty traps arise in regions where "geographical capital", which encompasses physical, environmental, social, political, and human factors, is rated low and where high poverty rates prevail. This definition provides a clear framework for identifying areas spatially trapped in poverty, where low geographical capital and high poverty rates coexist.

Referring to the concept articulated by Jalan and Ravallion, geographical capital encompasses the interaction between humans and the physical environment in the dimensions of time and space. This concept includes factors such as location, climate, topography, land, natural resources, technology, culture, economy, and social systems (Jalan–Ravallion 1997). These physical characteristics significantly influence land use dynamics, population distribution, and human economic activities within a region, making geographical capital a crucial determinant of economic development. Low geographical capital has far-reaching consequences for a region. Firstly, it imposes limitations on land use for agriculture, settlement, and other economic activities, thereby hindering the region's economic and social development. Secondly, such areas often become overly reliant on limited natural resources, which restricts economic diversification and heightens the risk of economic instability. Additionally, limited accessibility and connectivity undermine the region's overall economic growth and development. Regions with low geographical capital are also more susceptible to natural disasters, which can adversely affect infrastructure, deplete natural resources, and disrupt the regional economy. Beyond these direct impacts, low geographical capital can lead to increased outmigration and induce significant social changes. If these challenges are not addressed promptly, they can jeopardize the sustainability and dynamics of the region as a whole (Wang et al. 2021).

This research aims to identify districts in Indonesia that exhibit spatial poverty traps, contributing to a comprehensive approach to poverty alleviation. By illuminating these regions, the study will provide the government with a more nuanced understanding, serving as a foundation for developing specific, effective, and accurate poverty alleviation policy strategies.

Overview of the study area

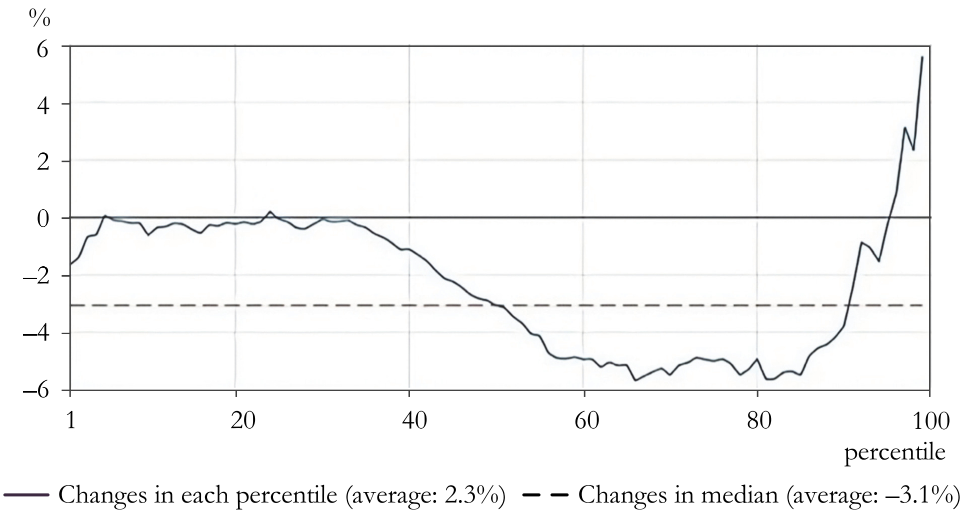
This research utilizes district-level data from across Indonesia to examine the influence of geographical capital on poverty. Indonesia presents an intriguing and critical case for the study of poverty, primarily due to its high level of heterogeneity. With a vast landmass of 3.25 million square kilometers spread across 17,499 islands and a coastline exceeding 99,083 kilometers, Indonesia holds the distinction of being the world's largest archipelagic nation (Passarella–Nurmaini 2022). The demographic composition, as revealed by the 2020 census, indicates a population of 270.20 million people, encompassing 1,340 ethnic groups throughout the country. These factors render Indonesia a complex and vulnerable region, confronted with a myriad of geographical challenges, including droughts, landslides, and earthquakes, alongside socio-economic issues such as poverty.

Interestingly, impoverished communities in Indonesia have demonstrated a remarkable capacity for managing their economic resources during crises (Saputra et al. 2022). This is exemplified by the relatively stable consumption patterns observed among these communities during the Covid-19 pandemic. Such resilience suggests that impoverished populations are often more adaptable in times of crisis compared to the middle class. In essence, these communities have become accustomed to navigating limitations, which presents a significant challenge to ongoing poverty alleviation efforts in the country.

In this context, the deeply entrenched problem of poverty in remote regions of Indonesia, compounded by limited government resources for poverty alleviation, necessitates a multidisciplinary approach to formulate more effective policies for these areas (Rahim et al. 2023). As suggested by Daimon (2001), geographical factors are essential tools for designing poverty alleviation programs in Indonesia. Over nearly two decades, governmental innovations and holistic approaches have led to the emergence of geographical capital as a key indicator of development, now incorporated into the village development index (VDI) data. The VDI serves as a foundational dataset for the allocation of development funds in Indonesia, as outlined in the Ministry of Village Development of Disadvantaged Regions and Transmigration Number 2 of 2016. Essentially, Indonesia's development efforts are increasingly focused on rural areas, emphasizing indicators of social, economic, and environmental resilience (Yudha et al. 2020). The VDI represents the geographical capital in Indonesia, as villages typically possess less geographical capital than urban areas, making spatial poverty traps more likely to occur in these rural contexts.

The regionalization of development status, as indicated by VDI data at the village level, categorizes Indonesia into five clusters: self-reliant, advanced, developing, underdeveloped, and severely underdeveloped regions. However, at the provincial level, as illustrated in Appendix Figure A2, Indonesia's regional development is consolidated into only four categories, omitting the self-reliant cluster from this classification. According to calculations for the year 2020, three regions are categorized as advanced: DKI Jakarta, the Special Region of Yogyakarta, and Bali Province. Conversely, underdeveloped and severely underdeveloped regions are predominantly concentrated in the eastern part of Indonesia, specifically in Maluku, East Nusa Tenggara, West Papua, and Papua, as well as in Sumatra, particularly North Sumatra. Meanwhile, a significant portion of other regions is classified as medium-level development.

Figure 1
Changes in household per capita expenditure from September 2019 (pre-pandemic) to September 2020 (during the pandemic) (Anonymous growth incidence curve)



Source: Smeru (2021).

Research method

Scope of the analysis

The geographical scope of this study encompasses all regencies in Indonesia for the year 2020, totaling 416 regions. These regions are categorized into two primary divisions: western Indonesia and eastern Indonesia. This division reflects the disparities in economic performance and the chronic polarization of poverty that characterize the prevailing inequalities in the country (BPS 2021). The primary objective of this study is to identify areas with spatial poverty traps in Indonesia by employing indicators of geographical capital, which include physical, social, and economic elements, alongside the incidence of poverty at the regency level. Furthermore, utilizing the same dataset, we aim to create a typology of regions based on the locations of these spatial poverty traps. The findings of this research will result in the identification of a typology of regions affected by spatial poverty traps in Indonesia, which can inform the government in formulating targeted poverty alleviation policies tailored to specific regional characteristics. Consequently, the developed programs can be more effective and focused.

Data

This study employs secondary data sourced from various publications. The primary data utilized includes the percentage of poverty at the regency level for the year 2020, obtained from the publications of Statistics Indonesia, encompassing a total of 416 districts. The data on geographical capital is represented through the village development index (VDI) variable, which encompasses ecological (environmental), social, and economic components at the regency level, sourced from the Ministry of Villages, Development of Disadvantaged Regions and Transmigration. Spatial data, including administrative boundaries, elevation, and geographical coordinates, were acquired from the National Geospatial Information Agency through the Ina Geoportal website. All data utilized in this research are summarized in Table 1.

Table 1

Data used in the study

No	Data	Source	Utilization
1	Percentage of poverty rate in district level	BPS (1999–2020)	Percentage of the population below the poverty line
2	District in figures	BPS (2020)	Extraction of demographic data, gross regional domestic product (GRDP) per capita, and regional potential
3	Village development index in district level	Ministry of Villages, Development of Disadvantaged Region and Transmigration (2020)	Representation of the geographical capital of regions
4	Geographic coordinates, administrative boundaries, elevation data (RBI)	National Geospatial Information Agency (Scale 1:25,000)	Base maps for spatial poverty trap analysis and spatial weighting

Drawing on the theory advanced by Bird, spatial poverty traps manifest in areas characterized by both elevated poverty rates and diminished geographical capital. In accordance with these parameters, poverty conditions at the district level are represented by the poverty rate (P_0), which is calculated using the Foster-Greer-Thorbecke (FGT) headcount poverty formula:

$$P_0 = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^0 \quad (1)$$

where P_0 = percentage of the population in poverty (headcount index), Z = poverty line, y_i = average monthly per capita expenditure of the population below the poverty line (i = 1,2, 3,…, q), yi < z, q = number of people below the poverty line, n = total population.

The value of P_0 ranges from 0 to 100, with higher values signifying greater levels of poverty within a given region. As per the classification system (established by Statistics Indonesia), poverty levels in a region are categorized into four degrees of severity (Table 2).

Table 2

Classification of regional poverty levels

No	Poverty status	Threshold value
1	Low poverty level	< 10
2	Middle low poverty level	10–25
3	Middle high poverty level	26–40
4	High poverty level	> 40

Source: BPS (2021).

The geographical capital parameter is calculated using a formula derived from the Ministry of Villages, which is based on the VDI. The formula is as follows:

$$VDI = \frac{1}{3}[IKS + IKE + IKL], \tag{2}$$

The database and calculation methodologies used in developing this index align with the theoretical frameworks established by Bird and Jalan, which assert that regional development must consider the complexity of interrelated regional elements (Bird 2019, Jalan–Ravallion 1997). Furthermore, the VDI is grounded in the concept that advancing self-sustaining regions necessitates a sustainable development framework, where social, economic, and ecological dimensions interact to enhance a region's potential and capacity to improve the well-being of its inhabitants.

Table 3

Indicators, dimensions, and composite variables of the village development index

Indicators	Variables
Social resilience index (IKS)	1. Social solidarity 2. Existence of tolerance 3. Population's sense of security 4. Social well-being
	1. Healthcare services 2. Community empowerment 3. Health insurance
	1. Access to primary and secondary education 2. Access to non-formal education and knowledge
	1. Access to clean water 2. Access to sanitation 3. Access to electricity 4. Access to information and communication
Economic resilience index (IKE)	1. Diversity of village community production 2. Availability of trade service centres 3. Access to distribution/logistics 4. Access to financial and credit institutions 5. Access to economic institutions 6. Regional openness
Environmental/ecological resilience index (IKL)	1. Environmental quality 2. Disaster prone potential 3. Disaster response

Source: Ministry of Village, Development of Disadvantaged Regions and Transmigration (2020).

A detailed overview of the composite indicators used in the VDI is presented in Table 3. The data utilized in the VDI calculations are sourced from the Village Potential Statistics of Indonesia (PODES) (BPS 2021).

The VDI, as formulated in equation 2, is a composite index derived from three key indicators: the social resilience index (IKS), the economic resilience index (IKE), and the environmental resilience index (IKL). Each indicator encompasses a set of variables, aggregated into an index scored on a scale from 0 to 5. Higher scores reflect greater importance of the variables. The individual variable scores are summed, divided by the maximum possible score, and then multiplied by the total number of variables, producing an index value ranging from 0 to 1. The classification of these index values is outlined in Table 4.

The results from the VDI range from 0 to 1. Based on these values, villages are categorized into five performance classifications, as shown in Table 4:

Table 4

Village classification based on the village development index

No	Village status	Threshold value
1	Severely disadvantaged	≤ 0.491
2	Underdeveloped	> 0.491 and ≤ 0.599
3	Developing	> 0.599 and ≤ 0.707
4	Advanced	> 0.707 and ≤ 0.815
5	Self-reliant	> 0.800

Source: Ministry of Village, Development of Disadvantaged Regions and Transmigration (2020).

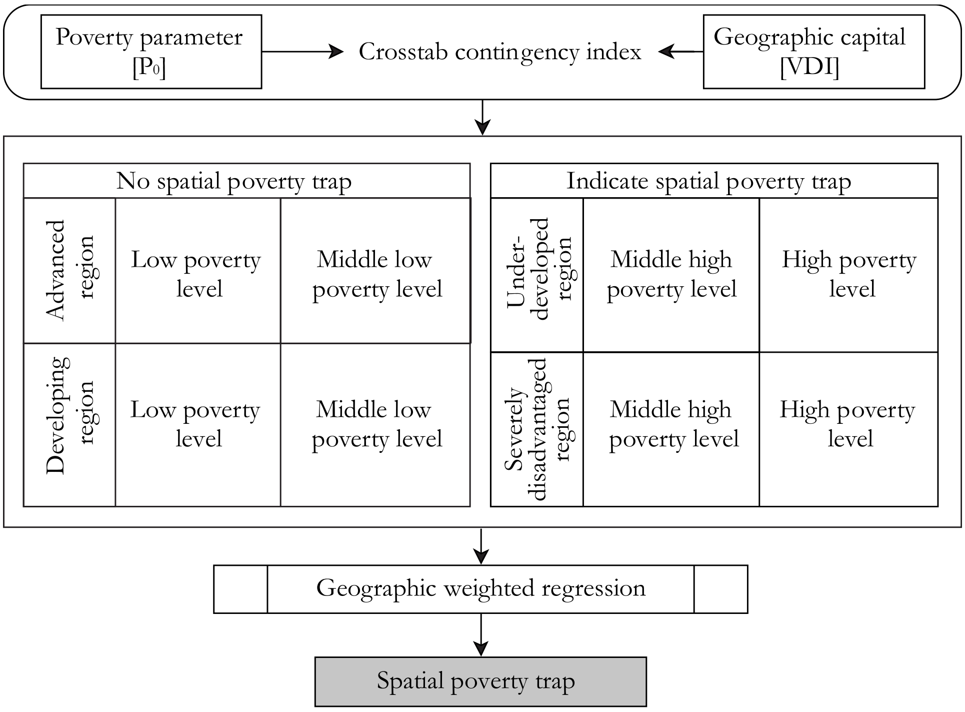
Both parameters are subsequently analyzed using contingency methods (classification via cross tabulation) to develop a matrix that reveals regional types with spatial poverty traps (see in Appendix Figure A2). The analysis then proceeds to statistically validate the existence of these traps through the geographically weighted regression (GWR) method, which produces coefficients and assesses the significance of geographical capital variables on poverty across all examined regions.

Classification of regional types and spatial poverty traps

Through the application of the contingency matrix method, a cross tabulation of poverty levels and regional development indices generates a quadrant-based typology, as illustrated in Figure 2. This approach identifies regions characterized by spatial poverty traps. Such regions, typically classified as "underdeveloped" or "severely disadvantaged", exhibit middle high to high levels of poverty.

Figure 2

Regional typology based on poverty levels and regional development



Delineation of spatial traps using geographically weighted regression

Geographically weighted regression (GWR) is an extension of global linear regression that applies local weighting to each location (Fotheringham et al. 2002). Unlike global regression, GWR allows for variation in the parameter coefficients of each explanatory variable across locations, depending on geographic distance. This localized approach emphasizes the relationship between dependent and independent variables within specific areas (Fábián 2014). GWR is estimated using weighted least squares (WLS) and is particularly useful in cases of spatial heterogeneity, where heteroscedasticity is present in global regression models. The general form of the GWR model is expressed by the following equation:

$$Pov_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)VDI_{ik} + \varepsilon_i \quad (3)$$

In this equation, Pov_i represents the value of the dependent variable at location *i*, while VDI_{ik} is the *k*-th independent variable at location *i*. The coordinates of location *i* are represented by (u_i, v_i), where $\beta_0(u_i, v_i)$ is the intercept at that location, and β_k (u_i, v_i) is the parameter of the *k*-th explanatory variable at location *j*. The term

ε_i represents the error at location *j*. In the GWR model, neighbourhood criteria are determined by distance, and the weighting is applied through a kernel function (Oshan et al. 2019). This kernel function is used to assign weights to each location. The Gaussian and bi-square kernel functions used in this study are defined as follows:

$$w_{ij} = exp\left(-\frac{d_{ij}^2}{2h^2}\right) \quad (4)$$

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2 & if\ d_{ij} < h \\ 0 & if\ d_{ij} \geq h \end{cases} \quad (5)$$

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2} \quad (6)$$

Equation (6) represents the Euclidean distance between locations *i* and *j*, where *h* is the bandwidth or smoothing parameter. This parameter must have a positive value, and the function can either be fixed (with a constant bandwidth across all locations) or adaptive (with varying bandwidth across locations) (Putra et al. 2022).

The best model is chosen based on several criteria, including the Akaike information criterion (AIC), corrected AIC (AICc), Bayesian information criterion (BIC), R^2, and adjusted R^2. A superior model will have lower AIC, AICc, and BIC values, while exhibiting higher R^2 and adjusted R^2 values.

The process of GWR analysis involves several stages. Initially, the model is developed using linear regression. This is followed by classical assumption tests and an examination of spatial variability. Afterward, GWR modelling is conducted, and the best model is selected based on the aforementioned criteria. Finally, the results of the selected GWR model are interpreted.

Results and discussions

Identification of geographical traps in Indonesia

The primary objective of this research is to identify the presence of spatial poverty traps at the district level in Indonesia. The data utilized in this study comprise poverty percentage figures from Statistics Indonesia and the village development index (VDI) provided by the Ministry of Villages and Disadvantaged Regions for the year 2020. Through this data, a discernible pattern emerges, illustrating the relationship between poverty and geographical capital across Indonesia.

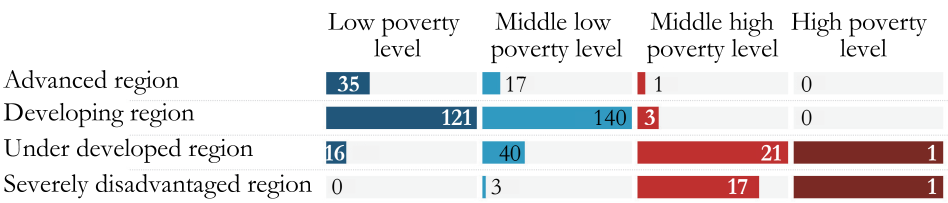
As shown in Appendix Figure A1, although there has been a considerable reduction in poverty rates over the past 30 years, poverty remains highly polarized in the eastern regions of Indonesia, particularly in Papua, West Papua, Maluku, and East Nusa Tenggara. These regions report average poverty rates exceeding 25%, meaning that 25 out of every 100 residents are living in poverty.

Conversely, the development performance, illustrated in Appendix Figure A2, reveals that most regions in Indonesia fall within the "developing" classification. Only three regions – Special Capital Region of Jakarta, Special Region of Yogyakarta, and Bali – are classified as "advanced". In contrast, the eastern regions, which are also marked by high poverty rates, are categorized as lagging or severely disadvantaged in terms of development. This disparity highlights a significant imbalance in development across the country, where underdevelopment in certain regions exacerbates poverty, thereby indicating the existence of spatial poverty traps.

The identification of these traps is achieved through a contingency analysis of poverty and regional development (VDI), which serves as a representation of geographical capital. This analysis leads to the classification of regional types, as depicted in Figure 2.

Figure 3

Regionalization of poverty and spatial capital in Indonesia



The classification of regions using a contingency technique that examines the relationship between poverty percentages and geographical capital (see in Appendix Figure A2) results in the detailed delineation of 16 regional clusters across Indonesia, as shown in Figure 3. Administratively, Indonesia is divided into 416 districts, with the majority of these regions categorized as developing areas characterized by low to moderately low poverty rates. These regions share several common traits prevalent throughout the country. A key distinguishing feature is their high levels of social resilience and environmental sustainability, indicating that these areas generally possess sufficient economic potential to meet the needs of their populations, coupled with low incidences of natural disasters and social conflicts. These regions are predominantly located in Java, Sumatra, Kalimantan, and Sulawesi (see in Appendix Figure A3), and are typically characterized by low to medium elevation terrain, with the majority of the population engaged in agricultural activities (BPS 2021).

In contrast, regions classified as advanced with low poverty rates are found in the provinces of Bali, Yogyakarta, Central Java, West Java, West Sumatra, West Kalimantan, Central Kalimantan, East Kalimantan, Bangka Belitung Islands, Riau, Maluku, and South Sulawesi. These regions are distinguished by good access to education, adequate infrastructure, growing economies, active community participation, and efforts towards achieving social equity and justice. As centers of economic activity, these advanced regions serve as hubs capable of supporting surrounding areas, and thus represent ideal conditions for sustained development.

According to the analysis results presented in Figure 3, regions identified as spatial poverty traps are found in 40 districts, with the vast majority concentrated in Eastern Indonesia, with the exception of North Nias and West Nias. Within this category, two distinct types of regions emerge: highland regions and coastal regions. Both geographic features exhibit characteristics that contribute to spatial poverty traps. In highland areas, challenging topography severely limits infrastructure access, creating significant obstacles for residents to participate in economic activities. Additionally, a heavy reliance on traditional agricultural sectors constrains economic growth potential, leading to developmental stagnation (Pan–Feng 2020).

Coastal and island regions, on the other hand, face challenges related to isolation and limited connectivity due to their geographical separation by the sea. Moreover, a high dependency on limited natural resources hampers economic diversification, rendering these communities particularly vulnerable in their efforts to meet basic needs (Muta'ali 2014).

Geographically weighted regression model for identifying regions with spatial poverty traps

Geographically weighted regression (GWR) is a spatial analytical technique used to model and understand the relationship between dependent and independent variables that exhibit spatial variation (Fotheringham et al. 2002). The primary objective of GWR is to uncover and account for spatial variations in these relationships by applying distinct spatial weights for each location in the analysis. This method enables GWR to capture local patterns, spatial heterogeneity, and the region-specific impacts of independent variables (Murakami et al. 2020). As a result, GWR provides a robust statistical framework for examining how geographical capital influences poverty in Indonesia, facilitating the identification of regions characterized by spatial poverty traps through both theoretical foundations and empirical testing.

Table 5

Global regression model

Pov_i = 13.061447 – 5.012748 VDI_{ik} (0.0000) * (0.0000) *
R^2 = 0.433109; adjusted R-squared = 0.430409 DW-stat = 1.066554; F-stat = 320.4816; Sig. F-stat = 0.00000; SE = 0.279503; t-statistic value = 17.934507

Note: * significant at α = 0.01. Numbers in parentheses are the probability of the t-statistic value.

The results of the global regression analysis, conducted using the Ordinary Least Squares (OLS) method (see Table 5), indicate that the geographical capital variable (VDI) has a probability value smaller than α, with a negative coefficient. This suggests that the VDI variable has a significant and inverse effect on the percentage of poverty in Indonesia.

Table 6

Classic assumption in global regression model test results

1. Ramsey RESET linearity test*

	Value	df	Probability
F-statistic	0.002438	(1.413)	0.9606

2. Heteroscedasticity test: Breusch-Pagan-Godfrey
Obs* R-square = 25.1460
Prob chi-squared = 0.0000

Note: * parameter test is performed in a logarithmic equation model.

The validity of the global regression model is evaluated through classic assumption tests for linearity and heteroscedasticity. Tests for multicollinearity and data normality are omitted since the model includes only one independent variable and the dataset comprises over 100 observations. The results of the linearity test, using the Ramsey RESET method, indicate that the F-statistic probability value exceeds the significance level (α), confirming that the regression model employed in the analysis is linear.

However, the heteroscedasticity test reveals that the chi-squared probability in the model is less than the α value, indicating a violation of the homoscedasticity assumption and suggesting the presence of spatial heterogeneity. Consequently, the global regression model using the OLS method is deemed inappropriate for analysing the relationship between geographical capital and poverty in Indonesia.

Table 7

Geographical variability tests of local coefficients

Variable	F	DIFF of criterion	Result
Intercept	7.831782	–6.912528	
VDI	17.079808	–17.410365	local variable

The spatial variability test determines whether an independent variable exhibits local or global distribution. The results demonstrate that the geographical capital variable (VDI) is classified as a local variable, given that its DIFF of criterion is less than 2 (Nakaya et al. 2012).

Table 8

Selection of the best kernel

Kernel	AIC	AICc	BIC	R^2	Adj-R^2
Fixed Gaussian	2375.92*	2402.38*	2650.93	0.7988*	0.7453*
Fixed bi-square	2388.60	2410.48	2640.53*	0.7870	0.7394
Adaptive Gaussian	2446.01	2459.50	2646.86	0.7410	0.6929
Adaptive bi-square	2421.18	2445.35	2684.95	0.7731	0.7172

Note: * optimal kernel.

Based on the results of the analysis using GWR4, the optimal kernel for the spatial regression model between the village development index (VDI) and poverty percentage is the fixed Gaussian kernel. This conclusion is drawn from the minimum values of AIC and AICc, alongside the highest values of R^2 and adjusted R^2. Therefore, the spatial regression model in this study is best fitted using the fixed Gaussian kernel.

The results of the spatially weighted regression analysis (see in Appendix Figure A4) indicate that the geographical capital variable (VDI) exhibits a significant negative relationship with poverty levels in Indonesia, with a t-statistic of –7.9345. Given that the analysis encompasses 416 regions, the critical t-value is –1.9656. Therefore, it can be statistically concluded that geographical capital, represented by the VDI, has a significant influence on poverty levels in Indonesia. The VDI coefficient is –5.0127, which implies that for every one-unit increase in geographical capital, the poverty rate decreases by 5.01%.

Geographically weighted regression (GWR) enables the exploration of spatial effects within the regression model (Isazade et al. 2023). As shown in Figure 3, 40 regions in Indonesia are suspected of having spatial poverty traps. However, the GWR analysis confirms that only 26 of these regions are statistically identified as areas with spatial poverty traps. These regions are distributed across four provinces: two in North Sumatra, seven in East Nusa Tenggara, eleven in Papua, and six in West Papua. Furthermore, Figure A4 (see in Appendix) reveals that these regions are predominantly concentrated in Eastern Indonesia, including Papua, West Papua, East Nusa Tenggara, and parts of Nias Island (North Sumatra).

Upon further investigation, these regions are characterized by two distinct geographical features. The first group includes highland areas, with elevations ranging from 2,303.59 meters above sea level (masl) in Puncak Jaya to 1,452.60 masl in the Bintang Mountains region of Papua Province. The second group consists of coastal regions, such as those in East Nusa Tenggara and Nias Island.

Spatial poverty traps in highland regions of Indonesia

Poverty in highland regions, as explained by Mauna et al. (2018), arises from challenging topographical conditions and limited accessibility. These factors lead to social and economic isolation for the residents of these areas, resulting in chronic poverty. The findings of this study align with this explanation, underscoring the prevalence of geographically trapped poverty. Specifically, analysis using the digital elevation model (DEM) in geographic information systems (GIS) reveals that such conditions are particularly prevalent in areas situated at elevations exceeding 1,000 meters above sea level, compounded by limited access networks and inadequate infrastructure, as illustrated in Figure A6 (see in Appendix) and Table 9.

Additionally, research by Passarella–Nurmaini (2022) highlights that Papua Province is one of the most perilous regions for air transportation, corroborating the findings of this study. Furthermore, a 2017 report by the International Labour Organization (ILO) found that 80% of the highland regions in Papua are entrenched in severe poverty (Jansen et al. 2006). The challenging topography of Papua, combined with limited access due to ongoing armed conflicts, significantly hinders community activities, further exacerbating the region's poverty.

Table 9

Regions with spatial poverty traps in highland terrain

Province	Regions	Height [masl]	GWR coefficient	
			β_0	β_1VDI
Papua	Jayawijaya	1,659.40	21.932654	–3.974562
Papua	Central Mamberamo	989.91	18.843587	–5.009973
Papua	Bintang Mountains	1,452.60	9.585429	–7.890066
Papua	Puncak Jaya	2,303.59	26.142200	–2.560639
Papua	Tolikara	1,117.87	22.347202	–3.848059
Papua	Yahukimo	1,066.56	17.618953	–5.337294
Papua	Yalimo	1,550	16.012280	–5.894383
Papua	Lanny Jaya	2,117.42	25.081827	–2.908754
West Papua	Manokwari Selatan	2,411.67	15.007385	–6.312424
West Papua	Maybrat	1,012	13.404734	–6.675163

Table 9 illustrates the identification of spatial poverty traps in the highland regions of Indonesia. This research highlights 10 regions, located in the provinces of Papua and West Papua, as falling within this type of poverty trap. The findings from the GWR analysis suggest a tendency for the constant term to increase in areas situated at elevations exceeding 1,000 meters above sea level. This indicates that higher altitudes are associated with a higher likelihood of elevated poverty rates. These findings underscore the significant challenges related to infrastructure and accessibility, particularly in the mountainous terrain of Papua Island, which hinders the population's ability to meet basic needs.

Despite these limitations, the regions of Papua and West Papua are rich in natural resources, positioning them as resource enclaves (Muta'ali 2014). Therefore, there is a critical need for infrastructure development and improved connectivity to facilitate access to the outside world, thereby improving the well-being of the local population.

Distribution of coastal spatial poverty traps in Indonesia

The second type of geographical poverty trap is observed in coastal regions, particularly in North Sumatra, East Nusa Tenggara, Papua, and West Papua (see in Appendix Figure A7 and Table 10). The results of the GIS analysis reveal that coastal spatial poverty traps are frequently found in island clusters. The GWR analysis further supports this, showing that regions with a higher concentration of islands tend to have elevated coefficients, indicating a greater susceptibility to poverty traps in these coastal areas. These findings emphasize the need for targeted interventions in island districts, which are more prone to poverty due to geographic isolation and frequent climate-related disruptions, as noted by Olivia et al. (2011).

The findings of this study align with the comprehensive research by Widayatun (2016), which examined human resource development in coastal areas. Poverty in Indonesia's coastal and island regions is driven by a combination of internal and external factors. Internally, coastal and fishing communities face challenges such as (1) limited technological skills and business management, (2) reliance on traditional and subsistence livelihoods that provide only short-term survival, (3) insufficient financial resources for business development, and (4) widespread poverty among coastal communities and fishermen.

Externally, government policies on coastal and marine development primarily focus on productivity, favouring economic growth in non-traditional sectors, while often neglecting the needs of traditional fishermen. These policies tend to have a partial economic impact. Furthermore, environmental degradation from illegal fishing practices – such as the use of explosives and potassium – and the destruction of coral reefs through mining have further compounded the challenges in these regions.

A lack of awareness about the strategic importance of integrated coastal and marine resource management has hindered the optimal use of natural resources in coastal and island regions. Consequently, the complexity of issues in these regions suggests that escaping poverty is often more challenging compared to highland areas.

Table 10

Regions with coastal spatial poverty traps

Province	Regions	Number of islands	Local regression model	
			β_0	β_1VDI
North Sumatera	North Nias	1	10.603765	–5.116115
North Sumatera	West Nias	1	10.420282	–5.085453
East Nusa Tenggara	Lembata	69	13.453490	–9.148367
East Nusa Tenggara	East Manggarai	1	14.423962	–9.868490
East Nusa Tenggara	Sabu Raijua	5	14.061445	–12.385456
East Nusa Tenggara	Sumba Barat	29	18.328763	–8.743702
East Nusa Tenggara	Southwest Sumba	1	18.715043	–8.241433
East Nusa Tenggara	Central Sumba	16	17.507802	–9.118270
East Nusa Tenggara	East Sumba	78	15.869903	–11.178086
Papua	Asmat	4	25.027800	–2.756982
Papua	Mappi	3	–1.577607	–11.703268
Papua	Memberamo Raya	10	23.217952	–3.568513
West Papua	Teluk Wondama	249	20.527346	–3.735430
West Papua	Sorong	110	12.887698	–6.548539
West Papua	Tambrauw	2	11.874387	–7.573825
West Papua	Teluk Bintuni	29	17.047497	–5.228690

To effectively address these spatial poverty traps, a holistic approach is essential. This approach should include infrastructure development, economic diversification, equitable access to education and healthcare, and the empowerment of local communities. A comprehensive strategy of this nature will enhance accessibility, create economic opportunities, and reduce disparities among highland, island, and other marginalized regions in Indonesia.

Conclusion

The identification of spatial poverty traps in Indonesia, based on geographical capital parameters and poverty percentages, was conducted through a crosstab contingency index and spatial regression analysis. The results reveal that 26 regions in Indonesia are trapped in spatial poverty. Of these, 16 regions exhibit island topography and are distributed across West and North Nias in North Sumatra Province, seven in East Nusa Tenggara, four in West Papua, and two in Papua Province. Additionally, spatial poverty traps are identified in 10 highland regions, with seven located in Papua Province and three in West Papua Province. Statistical analysis demonstrates that these two geographic features – highland and island topography – play a significant role in the formation of spatial poverty traps in Indonesia. This study provides new insights into the existence of poverty traps in mountainous and coastal areas of the country. Future research will further explore the key factors contributing to these spatial poverty traps and offer deeper analysis into the underlying causes in these regions.

Appendix

Figure A1

Distribution of percentage of poor population among provinces over time in Indonesia

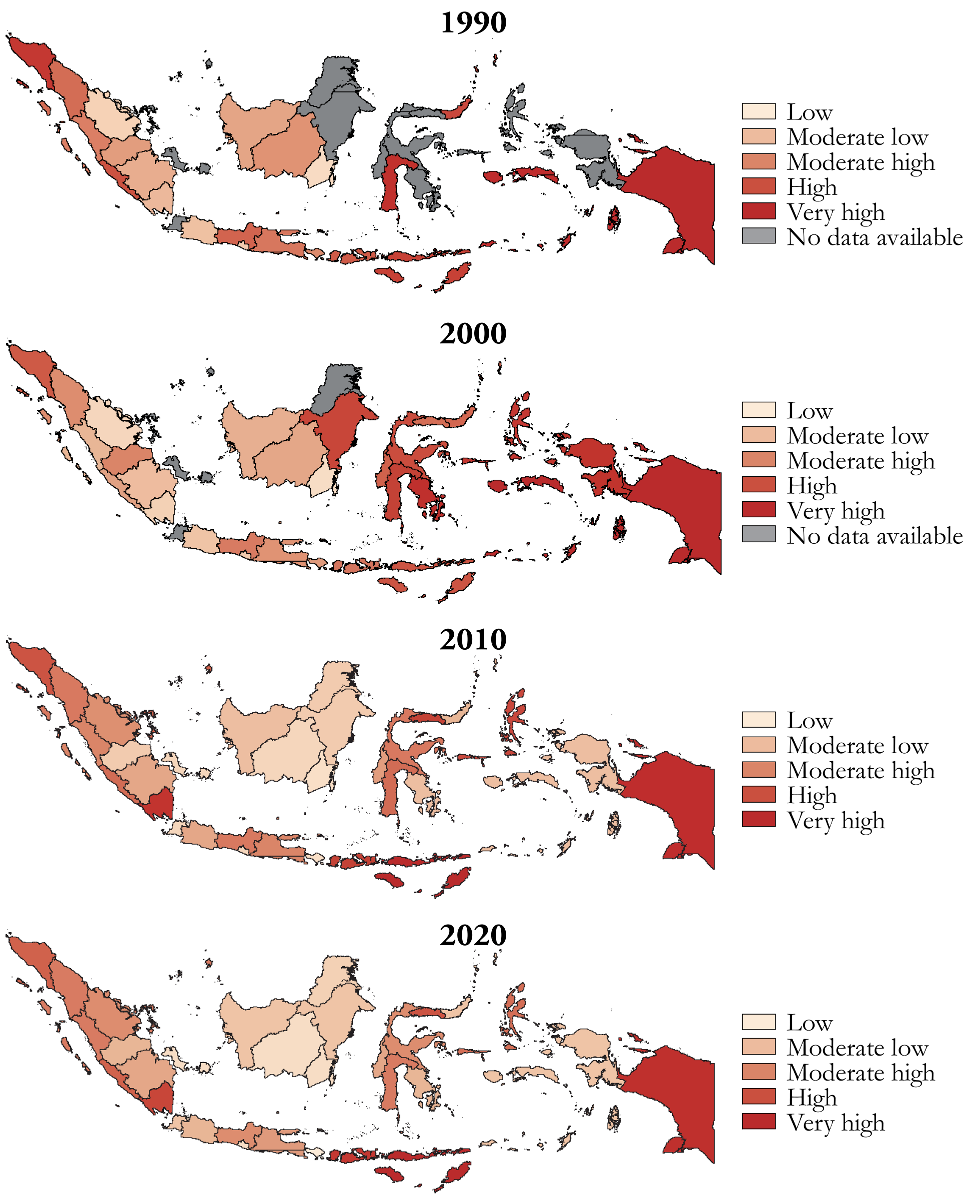


Figure A2
Regional development distribution in Indonesia, 2020

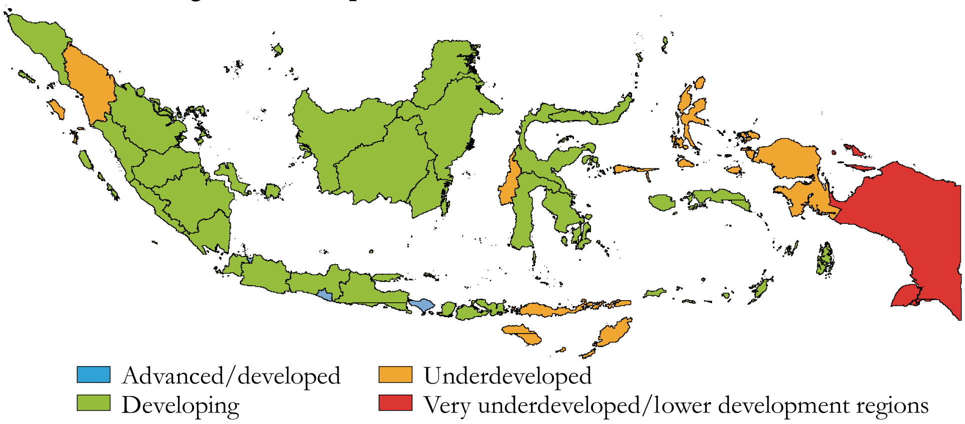


Figure A3
Poverty and regional development levels of districts in Indonesia

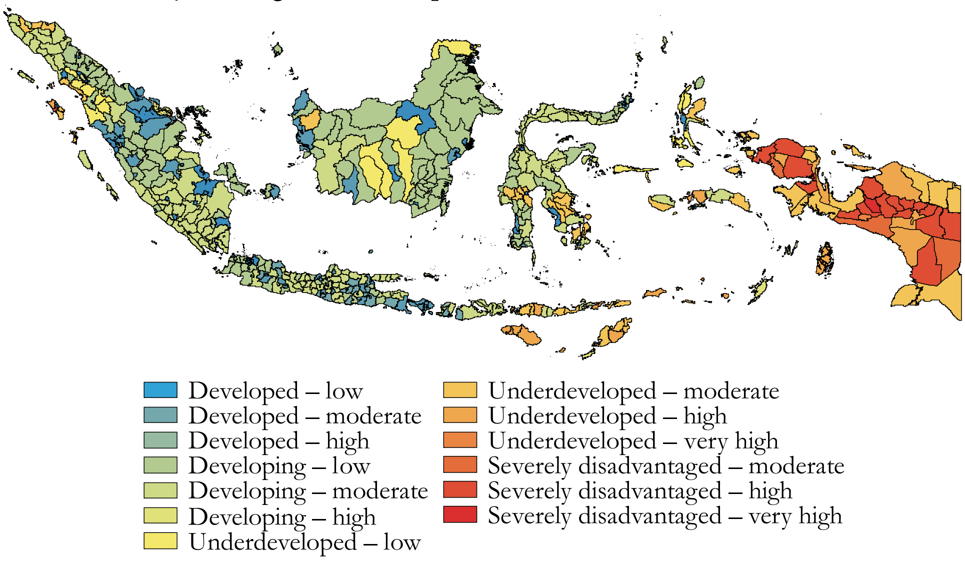


Figure A4

Results of the geographically weighted regression analysis

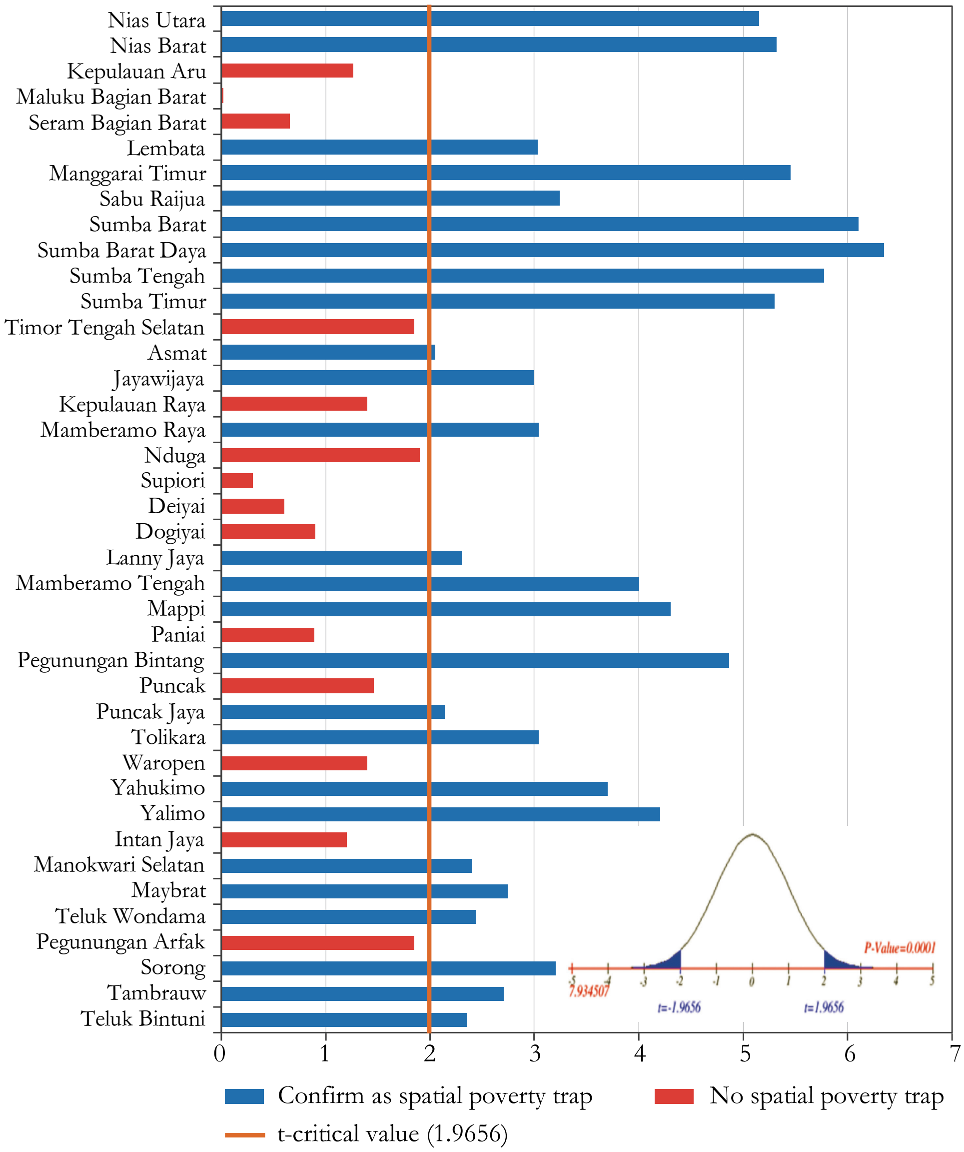


Figure A5

Regions with spatial poverty traps in Indonesia

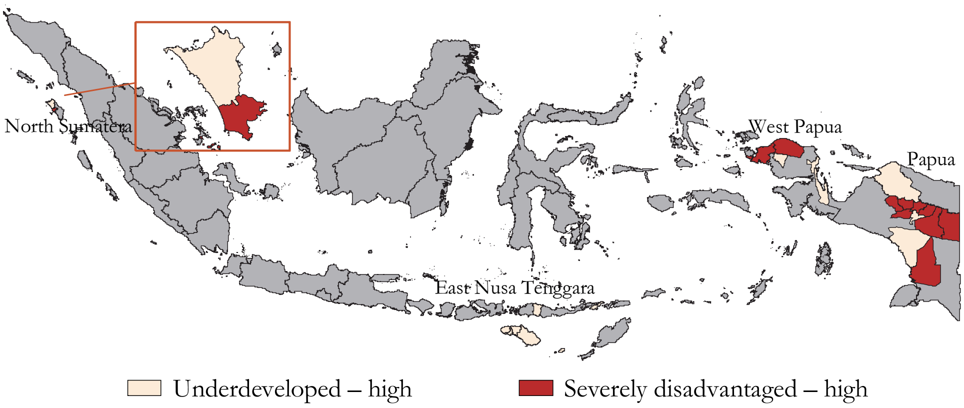


Figure A6

Indonesia mountainous poverty trap

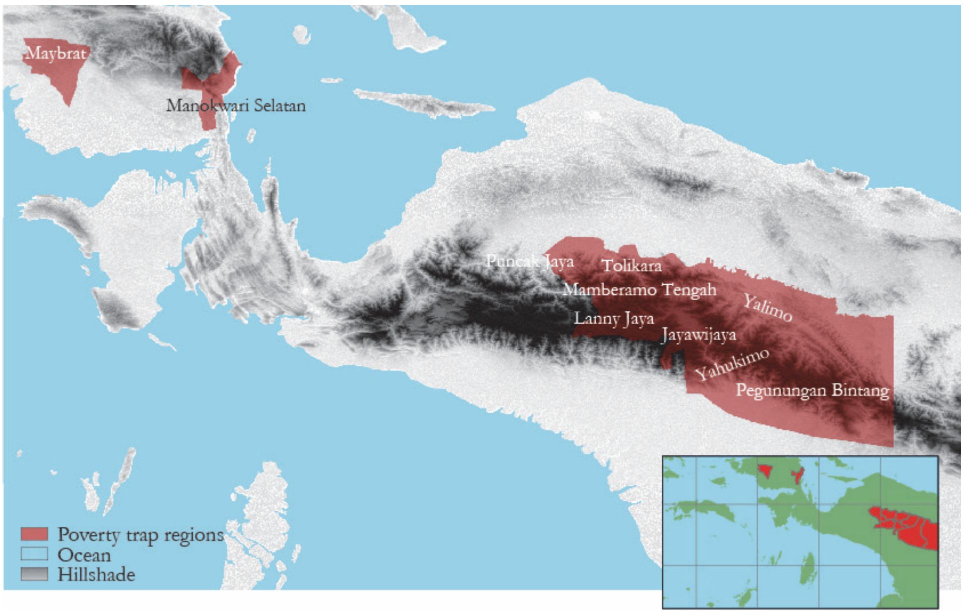
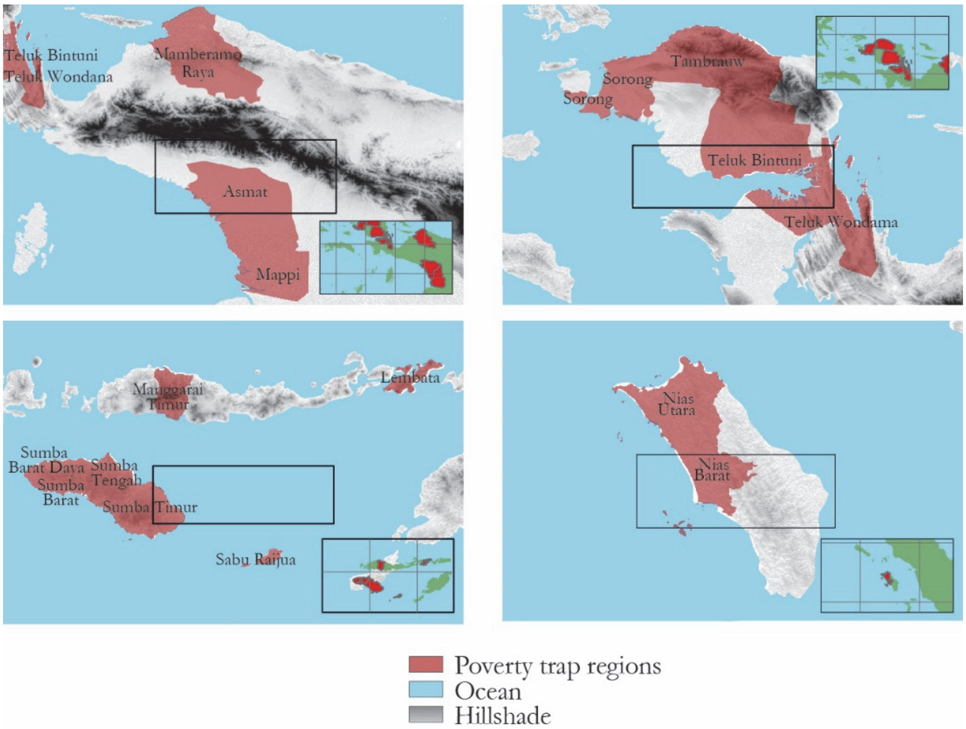


Figure A7

Indonesia coastal poverty trap



REFERENCES

ARIF, M.–SIDIQ, P. N.–WAWAN, K.–WAHYUDI, W.–AGUS, U.–ENY, P. (2019): Distribusi spasial masyarakat terkategori miskin dalam basis data terpadu kabupaten Sragen *Jurnal Litbang Sukowati : Media Penelitian dan Pengembangan* 2 (2): 16. https://doi.org/10.32630/sukowati.v2i2.76

BADAN PUSAT STATISTIK INDONESIA [BPS] (2021): *Data dan informasi kemiskinan kabupaten/kota* Jakarta.

BIRD, K. (2019): Addressing spatial poverty traps *Eradicating Rural Poverty to Implement the 2030 Agenda for Sustainable Development.* United Nations, London.

BURKE, W. J.–JAYNE, T. S. (2008): Spatial disadvantages or spatial poverty traps: household evidence from rural Kenya. *ODI Working Paper* 327, London.

CASTAÑEDA, A.–DOAN, D.–NEWHOUSE, D.–NGUYEN, M. C.–UEMATSU, H.–AZEVEDO, J. P.(2018): A new profile of the global poor. *World Development* (101): 250–267. https://doi.org/10.1016/j.worlddev.2017.08.002

CUONG, N. V.–TRUONG, T. N.–VAN DER WEIDE, R. (2010): Poverty and inequality maps in rural Vietnam: an application of small area estimation. *Asian Economic Journal* 24 (4): 355–390. https://doi.org/10.1111/j.1467-8381.2010.02043.x

DAIMON, T. (2001): The spatial dimension of welfare and poverty: lessons from a regional targeting programme in Indonesia. *Asian Economic Journal* 15 (4): 345–367. https://doi.org/10.1111/1467-8381.00149

FÁBIÁN, ZS. (2014): Method of the geographically weighted regression and an example for its application *Regional Statistics* 4 (1): 61–75. https://doi.org/10.15196/rs04105

FOTHERINGHAM, A.–BRUNSDON, S. C.–CHARLTON, M. (2002): *Geographically weighted regression: the analysis of spatially varying relationships* Wiley.

ISAZADE, V.–QASIMI, A. B.–DONG, P.–KAPLAN, G.–ISAZADE, E. (2023): Integration of Moran's I, geographically weighted regression (GWR), and ordinary least square (OLS) models in spatiotemporal modeling of Covid-19 outbreak in Qom and Mazandaran provinces, Iran. *Modeling Earth Systems and Environment* 9 (4): 3923–3937. https://doi.org/10.1007/s40808-023-01729-y

JANSEN, H. G. P.–PENDER, J.–DAMON, A.–SCHIPPER, R. (2006): Rural development policies and sustainable land use in the hillside areas of Honduras: a quantitative livelihoods approach. *Research Report of the International Food Policy Research Institute* no.147. Washington. https://doi.org/10.2499/0896291561

KRAAY, A.–MCKENZIE, D. (2014): Do poverty traps exist? Assessing the evidence. *Journal of Economic Perspectives* 28 (3): 127–148. https://doi.org/10.1257/jep.28.3.127

MAUNA, N.–FITRINIKA, E.–RAHAYUNINGSIH, H. W. D.–DINAYANTI, E.–AULIA, F. M.–WAHYU, M. R. M. H. R. R.–PUTRA, R.–WIDARYATMO, V. K.–KEDEPUTIAN (2018): Analisis Wilayah dengan kemiskinan tinggi. *Kedeputian Bidang Kependudukan dan Ketenagakerjaan*. Jakarta.

MINISTRY OF VILLAGE, DEVELOPMENT OF DISADVANTAGED REGIONS AND TRANSMIGRATION (2020*): Standar operasional prosedur pengukuran indeks Desa membangun tahun, 2020* Kementerian Desa, Pembangunan Daerah Tertinggal, dan Transmigrasi Jakarta.

MURAKAMI, D.–TSUTSUMIDA, N.–YOSHIDA, T.–NAKAYA, T.–LU, B. (2020): Scalable GWR: a linear-time algorithm for large-scale geographically weighted regression with polynomial Kernels. *Annals of the American Association of Geographers* 111 (2): 459–480. https://doi.org/10.1080/24694452.2020.1774350

MUTA'ALI, L. (2014): *Pengembangan wilayah tertinggal.* Badan Penerbit Fakultas Geografi, Universitas Gadjah Mada, Yogyakarta.

OLIVIA, S.–GIBSON, J.–ROZELLE, S.–HUANG, J.–DENG, X. (2011): Mapping poverty in rural China: how much does the environment matter? *Environment and Development Economics* 16 (2): 129–153. https://doi.org/10.1017/S1355770X10000513

PAN, J.–FENG, Y. (2020) Spatial distribution of extreme poverty and mechanism of poverty differentiation in rural China based on spatial scan statistics and geographical detector. *Dili Xuebao/Acta Geographica Sinica* 75 (4): 769–788. https://doi.org/10.11821/dlxb202004008

PASSARELLA, R.–NURMAINI, S. (2022): Data analysis investigation: Papua is the most unsafe province in Indonesia for aviation: an exploratory data analysis study from KNKT-database accidents and incidents (1988–2021). *Journal of Engineering Science and Technology Review* 15 (3): 158–164. https://doi.org/10.25103/jestr.153.17

PUTRA, R.–TYAS, S. W.–FADHLURRAHMAN, M. G. (2022): Geographically weighted regression with the best Kernel function on open unemployment rate data in East Java province. *Enthusiastic : International Journal of Applied Statistics and Data Science* 2 (1): 26–36. https://doi.org/10.20885/enthusiastic.vol2.iss1.art4

RAHIM, D.–PRIYARSONO, A. D. S.–RUSTIADI, E.–SYAUKAT, Y. (2023): Sustainable development of Indonesia's land border areas; overview from an economic perspective. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi dan Pembangunan* 24 (1): 172–198. https://doi.org/10.23917/jep.v24i1.20387

RIJANTA, R. (2001): Rural-urban linkages in a resource frontier region: the case of Sorong, Irian Jaya, Indonesia *Indonesian Journal of Geography* 33 (2): 59–81.

SACHS, J. D.–MCARTHUR, J. W.–SCHMIDT-TRAUB, G.–KRUK, M.–BAHADUR, C.–FAYE, M.–MCCORD, G.–KREMER, M.–O'CONNELL, S. A. (2004): Ending Africa's poverty trap *Brookings Papers on Economic Activity* (1): 117–240. https://doi.org/10.1353/eca.2004.0018

SAPUTRA, A.–SETIAWAN, W.–ARIF, M.–NURMALASARI, S. I. R.–DIJAYA, R.–ULINUHA, A.–HERMAWAN, S. (2022): Non-medical risk assessment of Covid-19 in parts of Central and East Java, Indonesia. *Quaestiones Geographicae* 41 (1): 147–169. https://doi.org/10.2478/quageo-2022-0010

WANG, B.–TIAN, J.–YANG, P.–HE, B. (2021): Multi-scale features of regional poverty and the impact of geographic capital: a case study of Yanbian Korean autonomous prefecture in Jilin province, China. *Land* 10 (12): 1406. https://doi.org/10.3390/land10121406

WIDAYATUN (2016): Satu dekade pembangunan sumber daya manusia (Kasus Pulau Mapur, Kabupaten Bintan). *Jurnal Kependudukan* 11 (2): 119–132.

YUDHA, E. P.–JUANDA, B.–KOLOPAKING, L. M.–KINSENG, R. A. (2020): Rural development policy and strategy in the rural autonomy era. Case study of Pandeglang Regency – Indonesia *Human Geographies* 14 (1): 125–47. https://doi.org/10.5719/hgeo.2020.141.8

INTERNET SOURCES

BIRD, K.–HIGGINS, K.–DAN, H. (2010): *Spatial poverty traps.* London. https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/5514.pdf (downloaded: June 2024)

BADAN PUSAT STATISTIK INDONESIA [BPS] (2020): *Statistik Indonesia.* Vol. 1101001. Jakarta. https://www.bps.go.id/publication/2020/04/29/e9011b3155d45d70823c141f/statistik-indonesia-2020.html (downloaded June 2024)

JALAN, J.–RAVALLION, M. (1997): *Spatial poverty traps?* World Bank, Washington. https://documents1.worldbank.org/curated/es/207861468743989544/pdf/multi0page.pdf (downloaded June 3024)

NAKAYA, T.–CHARLTON, M.–LEWIS, P.–BRUNSDON, C.–YAO, J.–FOTHERINGHAM, S. (2012): *GWR4 User manual. Windows application for geographically weighted regression modelling.* http://geoinformatics.wp.st-andrews.ac.uk/download/software/GWR4manual.pdf (downloaded: June 2024)

SMERU RESEARCH INSTITUTE [SMERU] (2021): *Situasi kemiskinan selama pandemi.* https://smeru.or.id/id/article-id/situasi-kemiskinan-selama-pandemi (downloaded: June 2024)