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*Corresponding author(s)
email: ardiyanto_maksimilianus@lecturer.itn.ac.id

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Sustainable Livelihood Approach (SLA) using Spatial Model: A Case from Labuan Bajo, Indonesia

Ardiyanto Maksimilianus Gai[1,2*], Ernan Rustiadi[3,6], Baba Barus[4,6], Akhmad Fauzi[5]

1. *Regional and Rural Development Planning Science, Faculty of Economic and Management, IPB University, Indonesia*
2. *Urban and Regional Planning, Faculty of Civil Engineering and Planning, Institut Teknologi Nasional Malang, Indonesia*
3. *Division of Regional Development Planning, Department of Soil and Land Resource, Faculty of Agriculture, IPB University, Indonesia*
4. *Division of Remote Sensing and Spatial Information, Department of Soil and Land Resource, Faculty of Agriculture, IPB University, Indonesia*
5. *Department of Resource and Environmental Economics and Management, IPB University, Indonesia*
6. *Center for Regional Systems Analysis, Planning and Development (CrestPent), IPB University, Indonesia*

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Abstract

Despite its economic potential, Indonesia's rapidly developing tourism hub faces socio-economic disparities. While tourism contributes significantly to local incomes, many communities still struggle with poverty, unequal access to resources, and environmental degradation. Labuan Bajo, located in West Manggarai Regency, depends heavily on tourism, fishing, and small-scale agriculture, yet faces challenges such as seasonal water scarcity, limited infrastructure, and land-use conflicts that threaten sustainable development. While some areas benefit from tourism-driven economic growth, others remain marginalized due to inadequate access to capital assets. The Sustainable Livelihood Approach (SLA) provides a framework for understanding how local assets—human, social, natural, financial, and physical—shape livelihood outcomes. However, livelihoods are spatially heterogeneous and require localized analysis to inform targeted interventions. By integrating Geographically Weighted Regression (GWR), this study aims to identify spatial disparities in livelihood sustainability and the key drivers of economic resilience in different areas of Labuan Bajo. The results provide spatially explicit evidence on livelihood assets and poverty clusters, supporting local governments and communities in designing targeted interventions for employment access, infrastructure provision, financial inclusion, and essential services.

1. Introduction

Tourism-driven economies often present a paradox of rapid economic growth alongside persistent socio-economic disparities. Labuan Bajo, located in West Manggarai Regency, is an example of this duality. As the renowned gateway to Komodo National Park, the area has seen significant investment in hospitality, infrastructure and related service industries (Dwyer et al., 2020; Fatina et al., 2023a). Despite these developments, local communities continue to face challenges such as poverty, unequal access to resources and environmental degradation, which limit their prospects for sustainable livelihoods (Hill, 2021; Rahman et al., 2025).

The economic structure of Labuan Bajo is primarily based on tourism, fishing and small-scale agriculture. However, the region's diverse topography, ranging from coastal areas to upland settlements, contributes to spatial inequalities in livelihood opportunities. Seasonal water scarcity, inadequate infrastructure and land-use conflicts exacerbate these inequalities and limit access to essential resources (Fatina et al., 2023b; Hudalah et al., 2007) While some areas benefit from tourism-driven economic growth, others remain marginalized due to limited financial capital, insecure land tenure and limited access to markets (Singgalen et al., 2020).

The Sustainable Livelihoods Approach (SLA) provides a comprehensive framework for assessing how communities sustain their livelihoods by using different forms of capital - human, social, natural, financial and physical - to address socio-economic and environmental challenges (Department for International Development (DFID), 1999). This approach focuses on building resilience and adaptive capacity by identifying key livelihood strategies and the external forces that shape them. SLA has been widely used in rural and developing regions to assess vulnerability, inform policy interventions and promote sustainable development (Scoones, 2015).

Traditional livelihood assessments rely primarily on household surveys and general statistical methods, which may not capture geographic variations in resource availability and socio-economic conditions. Spatial analysis, on the other hand, allows livelihood determinants to be mapped, enabling a more detailed examination of how different areas experience development disparities. By incorporating Geographical Information Systems (GIS), Geographically Weighted Regression (GWR) and spatial autocorrelation analysis, researchers can uncover spatial patterns and relationships that influence local economies (Comber et al., 2023; Hanin et al., 2024; Lu et al., 2014).

Among these techniques, GWR is particularly valuable for analyzing the spatial variability of factors affecting livelihoods. Unlike traditional regression models, which assume uniform relationships across a study area, GWR accounts for site-specific differences, providing a more nuanced insight into the factors that drive livelihood sustainability in different sub-regions (Brunsdon et al., 1998; Comber et al., 2023). This approach has been used to assess poverty and spatial inequality in Indonesian contexts, including Kalimantan and Central Java, demonstrating its usefulness for policy-oriented regional analysis (Alya et al., 2024; Hanin et al., 2024). In Labuan Bajo, the use of GWR can help policymakers understand why some communities benefit more from tourism than others, and what interventions can address spatial inequalities.

Tourism is a key driver of economic growth in Labuan Bajo, with the region attracting international visitors due to its status as the gateway to Komodo National Park. While the tourism sector has created employment opportunities and stimulated investment in infrastructure, the benefits are not evenly distributed. Studies of tourism-led economies have shown that regions closer to tourism hotspots tend to experience higher income levels and improved public services, while remote areas continue to face economic marginalization (Ashley & Haysom, 2006).

Land conflicts and environmental degradation are also emerging issues in Labuan Bajo. Unregulated development and rising land values have displaced local communities and reduced access to traditional livelihoods such as fishing and agriculture. Using spatial modelling, this study aims to assess how tourism has reshaped livelihoods and land use patterns to inform policies that ensure more equitable development while minimizing environmental impacts. Understanding these dynamics is crucial for sustainable urban and rural planning in tourism-driven regions.

The integration of SLA with spatial modelling provides a powerful tool for localized policy making. While SLA identifies the strengths and vulnerabilities of local livelihoods, spatial modelling helps to identify the area's most in need of intervention. This combination allows for the design of targeted policies that address specific geographic challenges, rather than applying one-size-fits-all development strategies.

For example, previous studies have shown that GIS-based multi-criteria analysis can improve decision-making in land-use planning by assessing factors such as proximity to economic centers, infrastructure availability and environmental risks (Jenkins et al., 2014). Similarly, integrating GWR with SLA assessments

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can reveal which factors such as access to capital, education or land tenure security have the greatest impact on livelihoods in different parts of Labuan Bajo. This localized approach is essential for achieving sustainable and inclusive development in rapidly changing regions.

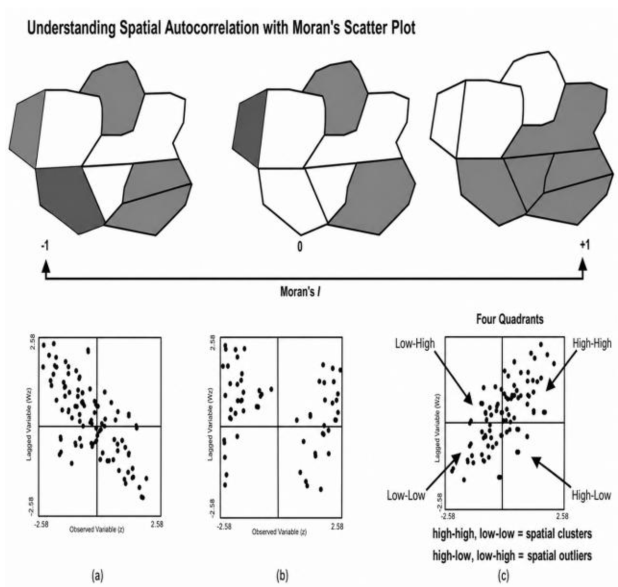
The Sustainable Livelihoods Approach (SLA) provides a comprehensive framework for examining how different forms of capital - human, social, natural, financial and physical - interact to shape livelihood outcomes (Scoones, 2015). This approach facilitates a holistic assessment of community resilience and socio-economic adaptability. However, as the sustainability of livelihoods varies across spatial contexts, targeted interventions require geographically explicit analyses (Anselin, 1995; Pramono, 2018). Recognizing this need, spatial modelling techniques can provide deeper insights into the underlying disparities that affect economic resilience.

To address this knowledge gap, this study uses local indicators of spatial autocorrelation LISA and geographically weighted regression (GWR) to analyze spatial variation in livelihood sustainability across Labuan Bajo. GWR provides a localized perspective on economic resilience by identifying key factors influencing livelihood outcomes at different spatial scales (Brunsdon et al., 1998; Comber et al., 2023). The results of the study will contribute to the development of a spatial map of livelihood assets, highlighting resource distribution and gaps in Labuan Bajo. These findings will inform policy decisions, enabling local government and community stakeholders to improve access to employment, infrastructure and essential services, while prioritizing support for vulnerable areas (Gai et al., 2025; Waris et al., 2022). Ultimately, this research aims to promote equitable and sustainable livelihood strategies that balance economic growth with social and environmental sustainability in the region.

2. Data and Methods

2.1 Spatial Livelihood Asset Mapping using Local Indicators Spatial Autocorrelation (LISA)

Spatial livelihood asset mapping is conducted using Local Indicators of Spatial Autocorrelation (LISA) to examine spatial clustering and disparities in livelihood assets across Labuan Bajo. LISA identifies statistically significant hot spots (areas of high asset concentration) and cold spots (areas of low asset concentration) to highlight localized disparities (see Figure 1). The mapping approach integrates multiple geospatial datasets, including land use, infrastructure, population density, and access to financial and social services, to provide a detailed assessment of livelihood conditions (Gai et al., 2025; Waris et al., 2022).



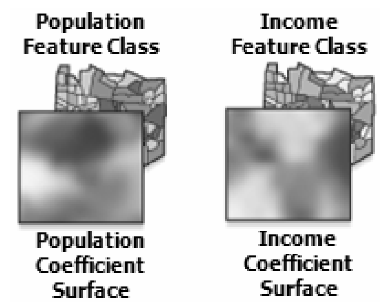
Source: Anselin, 1995

Figure 1. Local Indicators Spatial Autocorrelation (LISA)

The implementation of LISA includes the use of Moran's I statistic to measure spatial autocorrelation, which determines whether the distribution of livelihood assets exhibits clustering or dispersion. High positive spatial autocorrelation indicates the presence of asset-rich clusters, while negative autocorrelation signals inequalities in resource allocation. The results of LISA guide policy makers in identifying regions in need of targeted interventions to ensure that investments in infrastructure, education and financial resources are aligned with community needs.

2.2 Geographic Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is used to examine the spatial heterogeneity of key livelihood determinants (Brunsdon et al., 1996). Unlike traditional regression models that assume uniform relationships across a study area, GWR captures localized variations in the influence of socio-economic and environmental factors (see Figure 2) (Brunsdon et al., 2000). This approach allows the identification of spatial clusters where specific livelihood constraints or assets are more pronounced. The results of the GWR inform localized policy recommendations by identifying key drivers of economic resilience and vulnerability.



Source: https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/geographicallyweightedregression.htm

Figure 2. Geographic Weighted Regression (GWR) Method

Implementing the GWR involves defining independent and dependent variables that represent socio-economic resilience indicators. Independent variables include access to financial institutions, education levels, employment rates and land ownership status, while dependent variables reflect livelihood sustainability. GWR produces spatially varying coefficients that highlight the extent to which different factors contribute to livelihood success in different locations, allowing for more targeted interventions in underdeveloped areas.

In this research, LISA and GWR are valuable spatial analysis tools for studying sustainable livelihoods in Labuan Bajo, particularly for understanding spatial heterogeneity in livelihood determinants. LISA is effective in identifying clusters and spatial dependencies, helping to identify areas with high or low concentrations of key livelihood indicators such as income levels, employment opportunities and access to tourism related economic benefits. By using LISA, this study can identify regions where livelihood disparities are statistically significant and show whether economic benefits are unevenly distributed across different sub-districts. This approach is consistent with research in spatial economics and spatial planning, which emphasizes the importance of identifying localized patterns in socio-economic data for more targeted interventions (Anselin, 1995; Ord & Getis, 1995).

Meanwhile, GWR extends this analysis by assessing the spatial variability in the relationships between livelihood factors and key socio-economic drivers. Unlike traditional regression models, which assume relationships are constant across space, GWR allows for local variation, meaning that factors influencing sustainable livelihoods such as proximity to tourism centers, access to infrastructure and environmental conditions - may have different effects in different locations (Brunsdon et al., 1996). This is particularly useful for Labuan Bajo, where tourism-led economic growth has led to unequal access to livelihood resources. By using GWR, the study can identify which factors are most influential in specific areas, guiding the development of

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spatially adaptive policies to support sustainable and inclusive economic development. Previous studies have demonstrated the effectiveness of GWR in assessing spatial inequalities in urban and rural economies, highlighting its usefulness in policy-making for regional development (Brunsdon et al., 2000; Lu et al., 2014).

The research integrates Geographically Weighted Regression (GWR) and Local Indicators of Spatial Association (LISA) to analyze spatial disparities in livelihood sustainability in Labuan Bajo, Indonesia. GWR provides a localized regression approach that allows the study to capture variations in the influence of socio-economic and environmental factors on poverty levels across different regions, providing more precise insights compared to global regression models. Meanwhile, LISA identifies statistically significant spatial clusters of high and low livelihood assets, helping to identify areas of persistent poverty or economic resilience. Integrating these spatial techniques enables policymakers to design targeted interventions that improve access to resources and infrastructure in disadvantaged communities. However, there are limitations to these methods: GWR requires large datasets with spatially dense observations, which can lead to model instability if data points are unevenly distributed, and it assumes that spatial relationships are smooth, potentially oversimplifying abrupt socio-economic changes. While LISA is effective at identifying clusters, it does not explain causality, meaning that additional qualitative or economic modelling is needed to fully understand the underlying drivers of poverty and livelihood inequalities. The research flowchart for this study is shown in Figure 3,

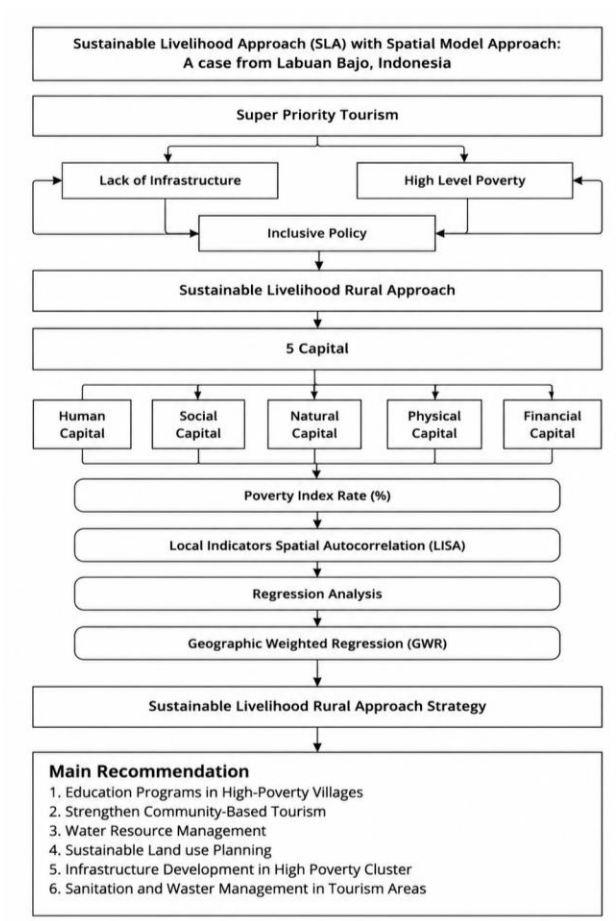
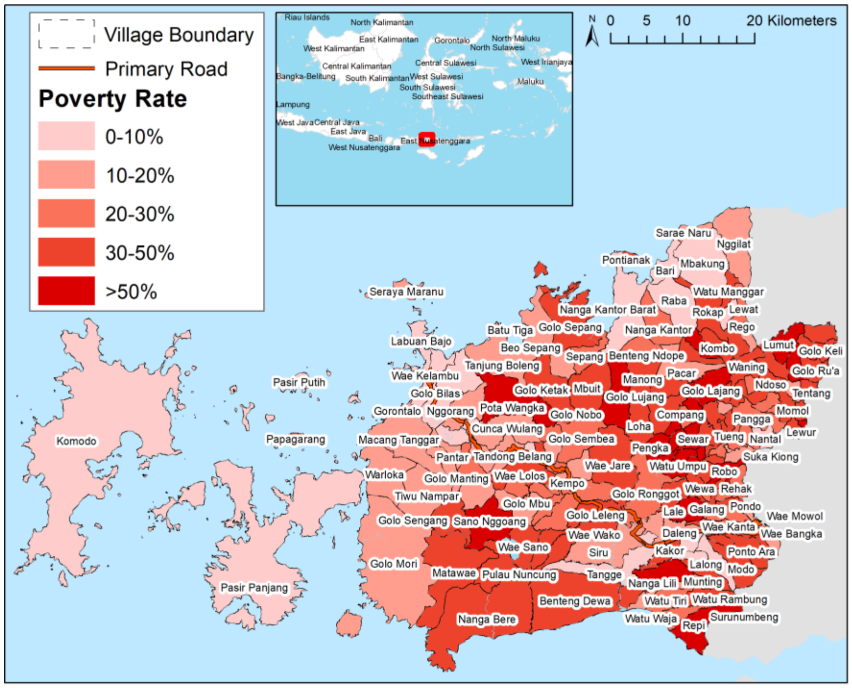


Figure 3. Research Flowchart

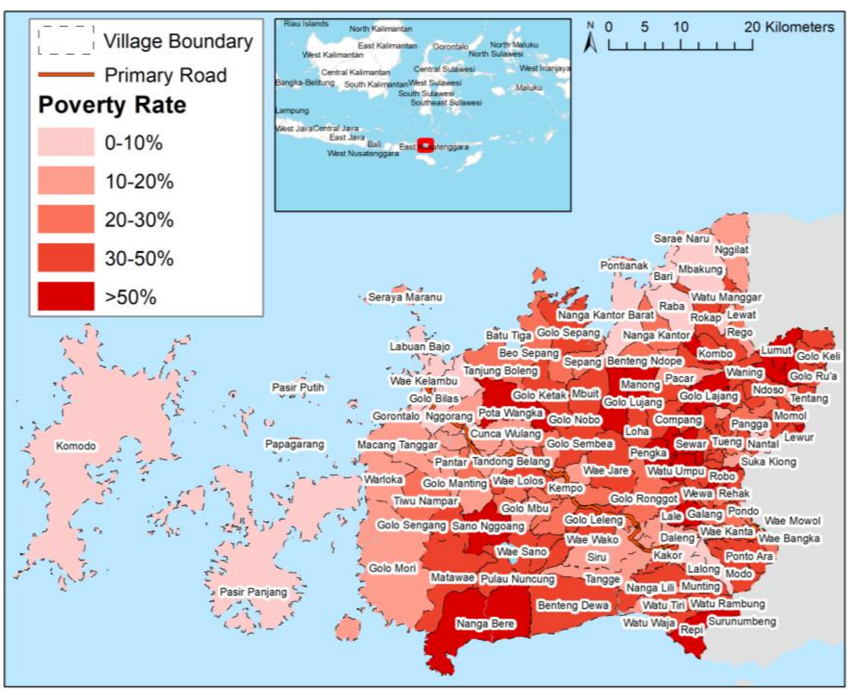
3. Result and Discussion

3.1. Poverty Rate Classification

The spatial analysis of poverty classification in 2022 and 2024 reveals significant disparities in poverty levels between different villages and districts (see Figure 4). Poverty classification maps show that in 2022, high poverty rates were concentrated in southern districts, particularly in Rego, Raba, Wae Mowol, Ngilat, and Ponto Ara, where poverty rates exceeded 50%. These areas faced challenges such as limited access to economic opportunities, underdeveloped infrastructure, and reliance on agriculture and informal labor. By 2024, improvements are visible in villages like Lalong, Modo, and Watu Waja, indicating the potential impact of targeted poverty reduction programs, improved service access, and local economic initiatives.



(a) 2022



(b) 2024

Figure 4. Poverty Classification (%) Maps

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The bar chart further illustrates the variation in poverty rates between villages within each district (see Figure 5). In 2022, the highest poverty rates were found in Rego (Rego District), Wae Mowol, and Ponto Ara (Raba District), with values exceeding 65%. In contrast, villages such as Seraya Maranu and Mbui (Komodo District) recorded significantly lower poverty levels. By 2024, improvements in several villages including Lalong, Modo, and Watu Waja reflect the positive impact of poverty reduction programs, increased access to financial services, and local economic diversification. However, areas like Ponto Ara and Ngilat continue to face high poverty levels, highlighting uneven development progress and the ongoing need for more inclusive and targeted economic policies.

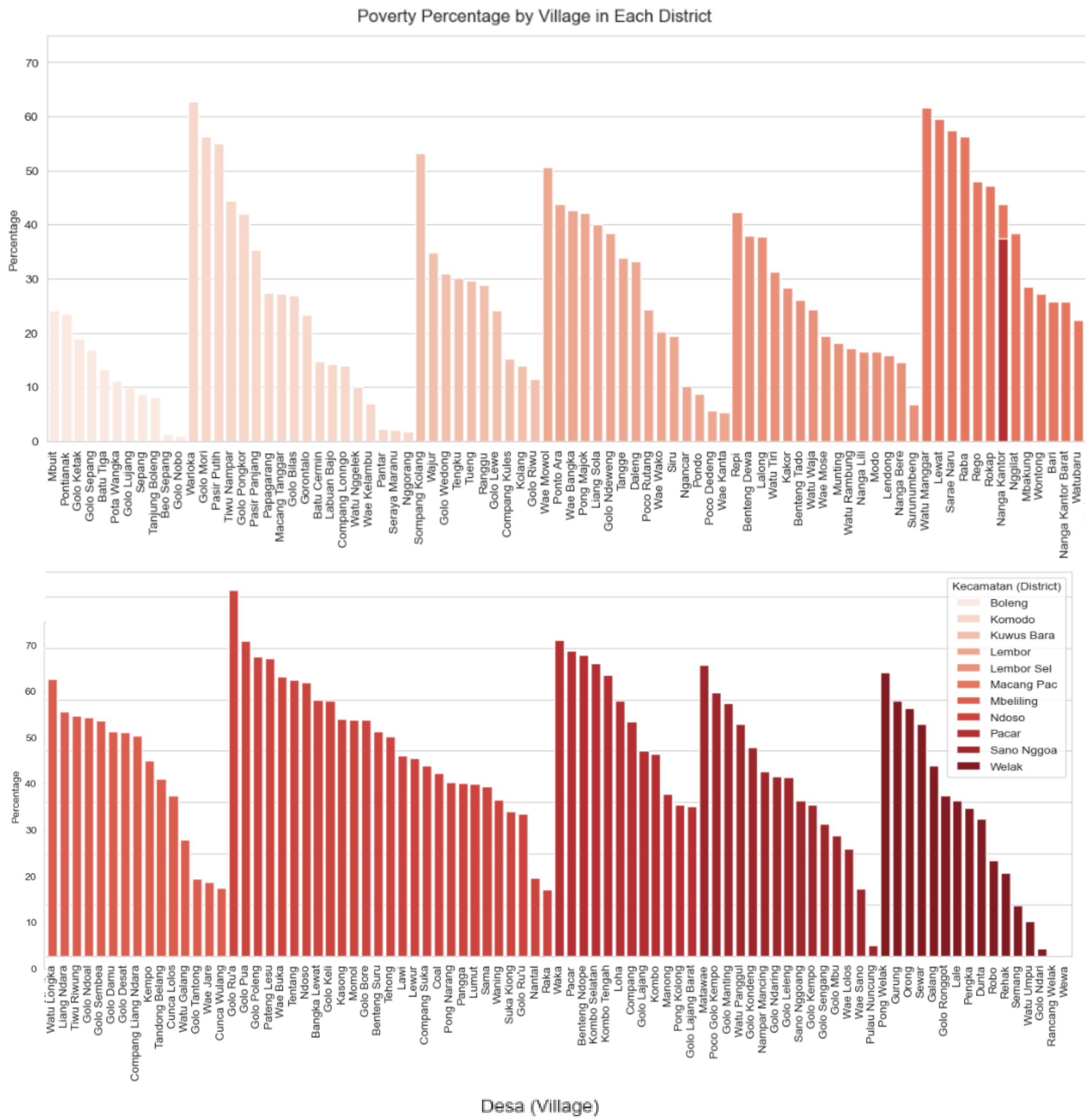

Figure 5. Poverty Classification

3.2. Local Indicators of Spatial Autocorrelation (LISA)

3.2.1. Poverty Index

The Poverty Index maps for 2022 and 2024 highlight distinct clusters of high-poverty (hot spots) and low-poverty (cold spots) areas (see Figure 6).

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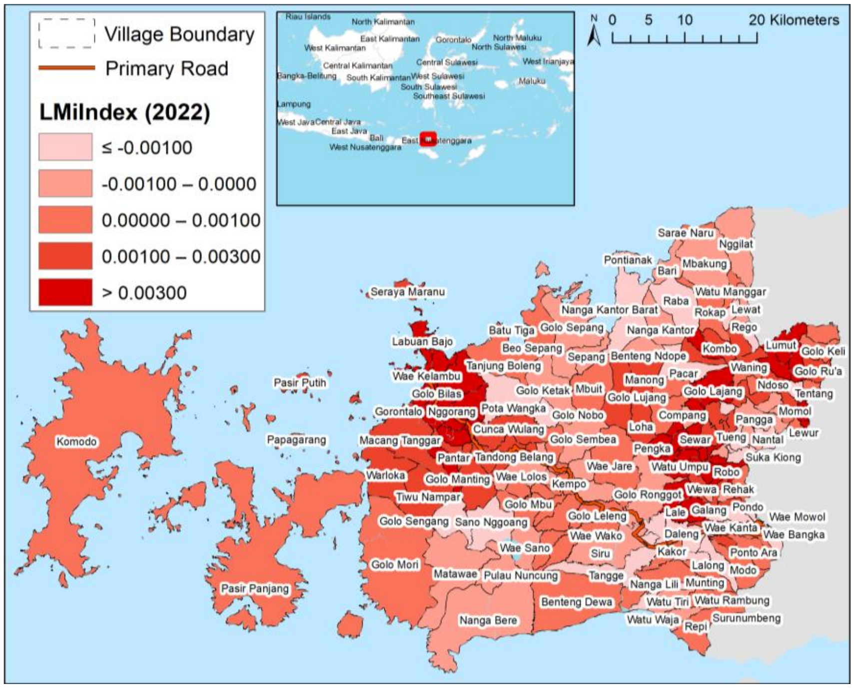
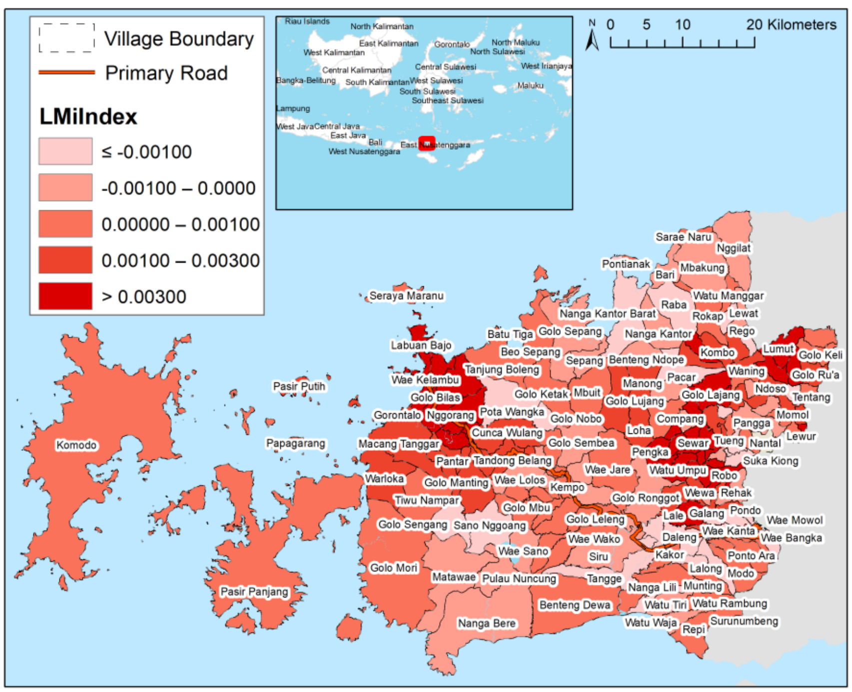


(a) 2022



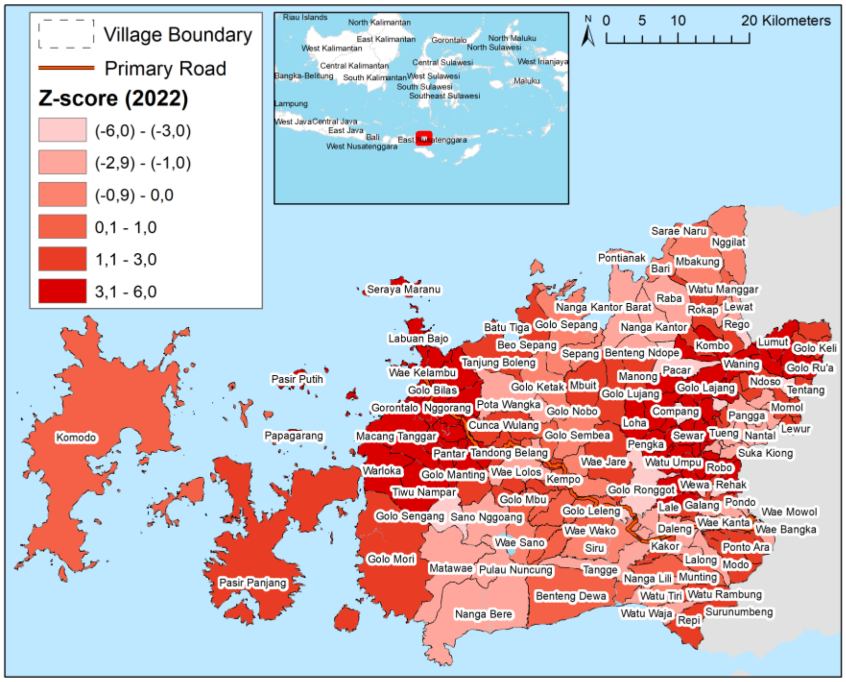
(b) 2024

Figure 6. Poverty Index Maps

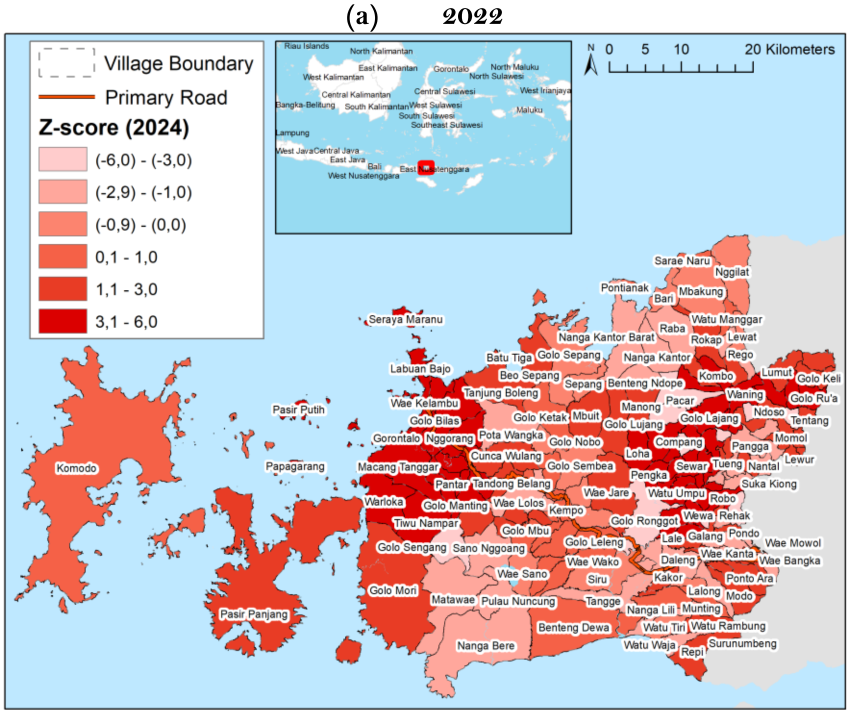
In 2022, high-poverty clusters were prominent in Pasir Putih, Warloka, Rego, Raba, Wae Mowol, and Ponto Ara, where the poverty index exceeded 0.00275. These regions experienced high poverty due to limited economic diversification, poor infrastructure, and dependency on agriculture and informal labor markets. By 2024, the intensity of poverty clustering decreased in Lalong, Watu Waja, and Modo, suggesting that poverty alleviation programs and improved socio-economic opportunities contributed to positive change. However, Rego, Raba, and Wae Mowol continue to exhibit persistently high poverty rates, underscoring the need for more targeted interventions and inclusive policies.

3.2.2. Score

The Z-score maps provide insights into the statistical significance of observed poverty clusters (Figure 7). High positive Z-scores indicate significant high-poverty clusters, while negative Z-scores indicate low-poverty clusters. In 2022, villages such as Wae Mowol, Ponto Ara, and Warloka exhibited high Z-scores (above 3.7), indicating strong spatial clustering of poverty. By 2024, some areas, such as Lalong and Modo, showed decreases in Z-scores, indicating that poverty became less spatially concentrated. However, Pong Welak, Ngilat, and Pandak experienced increasing Z-scores, suggesting worsening poverty and the need for targeted intervention.



(a) 2022



(b) 2024

Figure 7. Z-Score Maps

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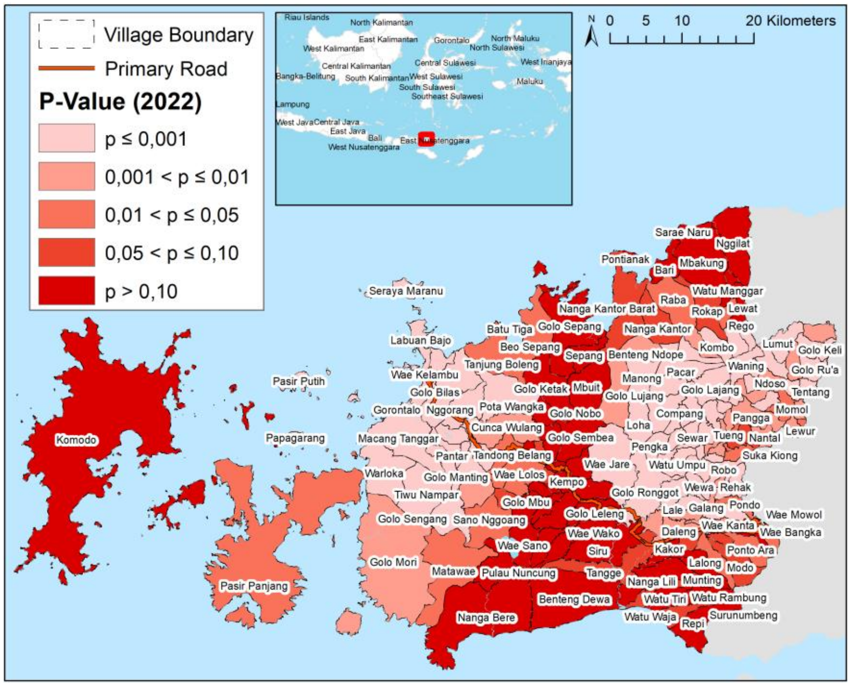
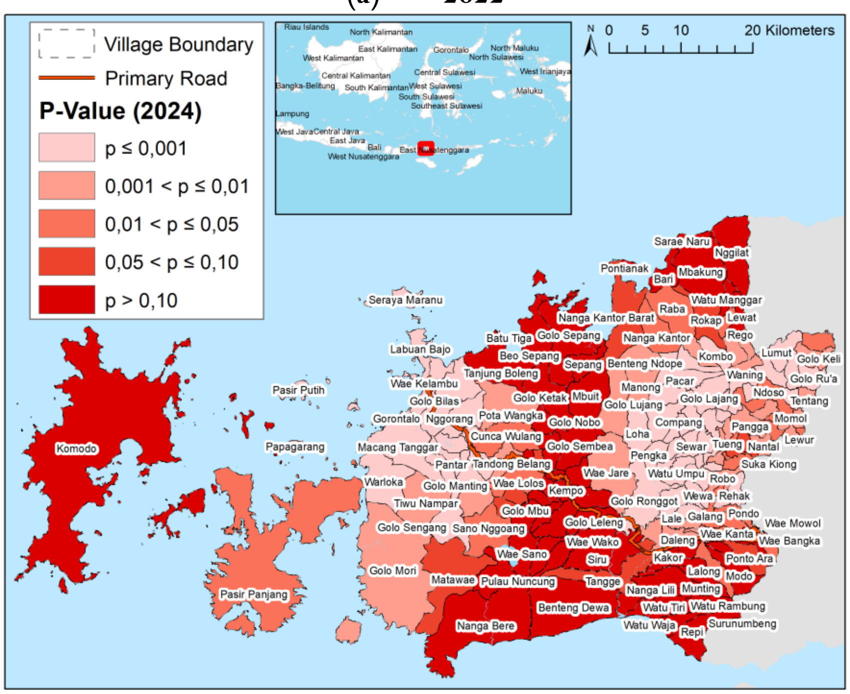
3.2.3. P-Value

The P-value maps confirm the statistical reliability of poverty clustering patterns (see Figure 8). In 2022, high-poverty clusters with strong statistical significance ($p < 0.05$) were concentrated in Wae Mowol, Ponto Ara, and Seraya Maranu, reinforcing the need for targeted socio-economic programs in these villages. These areas, highlighted in dark red, reflect strong confidence in the spatial concentration of poverty. By 2024, some areas, such as Lalong and Modo, show a decline in statistical significance, supporting the observation that interventions in these locations may have contributed to poverty alleviation and reduced cluster intensity.



(a) 2022



(b) 2024

Figure 8. P-Value Maps

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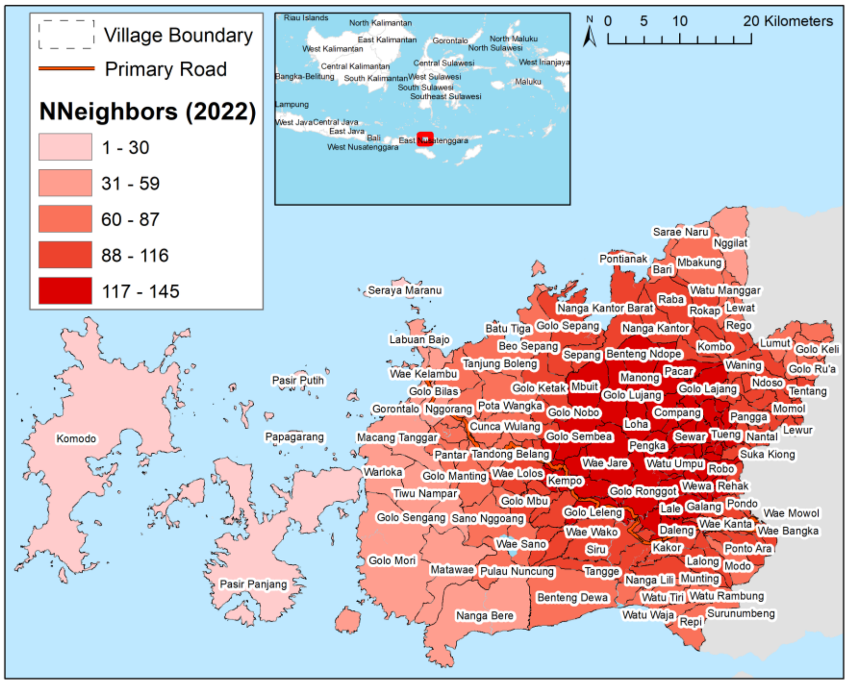
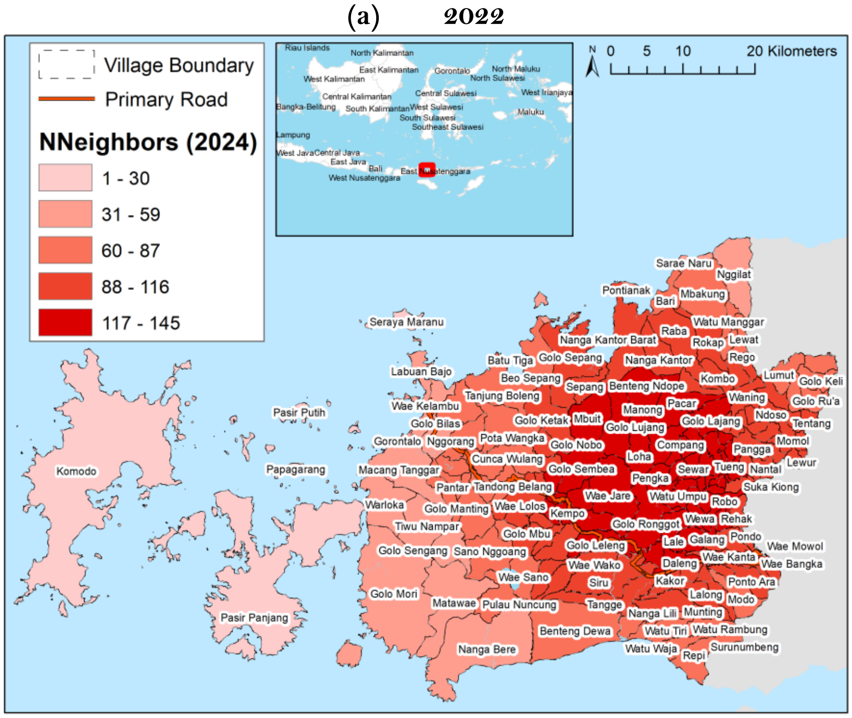
3.2.4. Neighborhood

The Neighborhood Clustering analysis further confirms the spatial dependence of poverty rates (see Figure 9). In 2022, the strongest poverty clusters were located in the central and southern villages, such as Pong Welak, Ponto Ara, and Ngilat, where the number of neighboring high-poverty areas was the highest. In 2024, the pattern slightly shifted but remained centered, with a more dispersed yet persistent cluster in the same core region.



(a) **2022**



(b) **2022**

Figure 9. Neighborhood Maps

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The LISA analysis highlights persistent clusters of poverty in villages such as Wae Mowol, Ponto Ara, and Warloka, where poverty remains spatially concentrated across neighborhoods. Despite improvements in Lalong and Watu Waja, newly emerging clusters in Pandak and Ngilat suggest that poverty is shifting rather than being eradicated. To address these inequalities, policymakers should prioritize localized interventions, such as improving infrastructure, expanding access to financial services, and supporting economic diversification in high-poverty and high-clustering districts.

3.3. Regression Analysis

3.3.1. Poverty Percentage (2022-2024)

The regression analysis of poverty percentages from 2022 to 2024 highlights the influence of human, social, physical, and financial capital on poverty levels across different villages (see Table 1). Among human capital factors, the number of high school graduates (SMA/MA/SMK) has a significant negative impact on poverty ($B = -5.839$, $p < 0.001$), suggesting that higher levels of education contribute to economic growth and poverty reduction. In addition, the prevalence of infectious diseases (KLB cases) is negatively associated with poverty ($B = -0.263$, $p = 0.001$).

Social capital also plays an important role in poverty reduction. The presence of community-initiated security systems ($B = -5.786$, $p = 0.011$) and the construction of security posts ($B = -7.467$, $p = 0.003$) significantly reduce poverty rates. This suggests that strong community engagement and organized social infrastructure can improve livelihood security. On the other hand, physical capital factors such as proper waste disposal ($B = 2.811$, $p < 0.001$) and lack of access to electricity ($B = 0.077$, $p = 0.029$) show a positive correlation with poverty, highlighting that inadequate infrastructure remains a key challenge to poverty reduction.

Table 1. Poverty Percentage Regression

Capital Variables	Indicator	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	10.278	7.627		1.348	0.180
Human Capital	Number of high school/MA/SMK Graduates	-5.839	1.505	-0.225	-3.88	<.001
Human Capital	Number of Epidemic Disease Patients	-0.263	0.081	-0.187	-3.258	0.001
Human Capital	Activation of Environmental Security Systems Initiated by Residents	-5.786	2.237	-0.174	-2.586	0.011
Social Capital	Development and Maintenance of Security Posts in Environmental	-7.467	2.507	-0.198	-2.979	0.003
Physical Capital	Final Disposal Site for Most Family Waste	2.811	0.593	0.275	4.743	<.001
Physical Capital	Percentage of families without electricity	0.077	0.035	0.133	2.208	0.029
Financing Capital	Credit Facilities for small businesses (KUK) received by village residents	9.730	3.793	0.146	2.565	0.011
Financing Capital	Number of Village-Owned Enterprises (BUMDes)	-3.385	1.075	-0.186	-3.15	0.002
Financing Capital	Distance to The Nearest Bank Agent	0.218	0.094	0.138	2.31	0.022

Note. Dependent variable: village poverty percentage. B = unstandardized coefficient; Beta = standardized coefficient; Sig. = p-value. Positive coefficients indicate association with higher poverty percentage; negative coefficients indicate association with lower poverty percentage. Interpret associations as non-causal unless supported by additional evidence.

In terms of financial capital, access to microcredit for small businesses ($B = 9.73$, $p = 0.011$) is positively associated with poverty reduction, reinforcing the role of financial inclusion in promoting economic stability. However, the presence of village-owned enterprises (BUMDes) ($B = -3.385$, $p = 0.002$) contributes to poverty reduction, suggesting that strong local business initiatives help to improve household income levels. Notably, longer distances to banking services ($B = 0.218$, $p = 0.022$) are associated with higher poverty levels, highlighting the need for better financial access to support economic growth.

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3.3.2. Poverty Change (2022-2024)

The analysis of poverty change between 2022 and 2024 provides insights into the dynamics of poverty reduction and the factors influencing socio-economic progress (see Table 2). One of the key findings is the ongoing impact of infrastructure access on poverty trends. The percentage of families without electricity (B = 0.016, p = 0.014) is positively associated with changes in poverty, suggesting that villages with poor electrification experience slower poverty reduction.

Education remains a key driver of poverty reduction, as evidenced by the negative association between secondary education (SMA/MA/SMK) and changes in poverty (B = -0.81, p = 0.008). This finding underscores the importance of human capital development in driving long-term socio-economic growth. Villages with higher levels of education are more likely to experience sustained poverty reduction.

Table 2. Poverty Change Regression

Capital Variable	Indicator	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	0.062	0.975		0.063	0.950
Physical Capital	Percentage of Families Without Electricity	0.016	0.007	0.185	2.494	0.014
Human Capital	Number of High Schools (SMA), Islamic High School (MA), and Vocational High School School (SMK) Graduates	-0.81	0.299	-0.201	-2.706	0.008
Natural Capital	Village/sub-district Location Relative to The Forest	0.88	0.359	0.181	2.454	0.015

Note. Dependent variable: poverty percentage change between 2022 and 2024. B = unstandardized coefficient; Beta = standardized coefficient; Sig. = p-value. Positive coefficients indicate slower poverty reduction or higher poverty change; negative coefficients indicate faster poverty reduction.

The proximity of a village to forests (B = 0.88, p = 0.015) is positively correlated with slower poverty reduction, suggesting that environmental constraints, resource dependency, or limited economic diversification hinder development in these areas.

3.3.3. Moran's Index of Poverty Percentage Change 2022-2024

The spatial autocorrelation analysis using Moran's index assesses the spatial clustering of the percentage change in poverty between 2022 and 2024 (see Figure 10). The results of the global Moran's I summary show that the Moran's index is 0.002478, with a z-score of 0.767538 and a p-value of 0.442762.

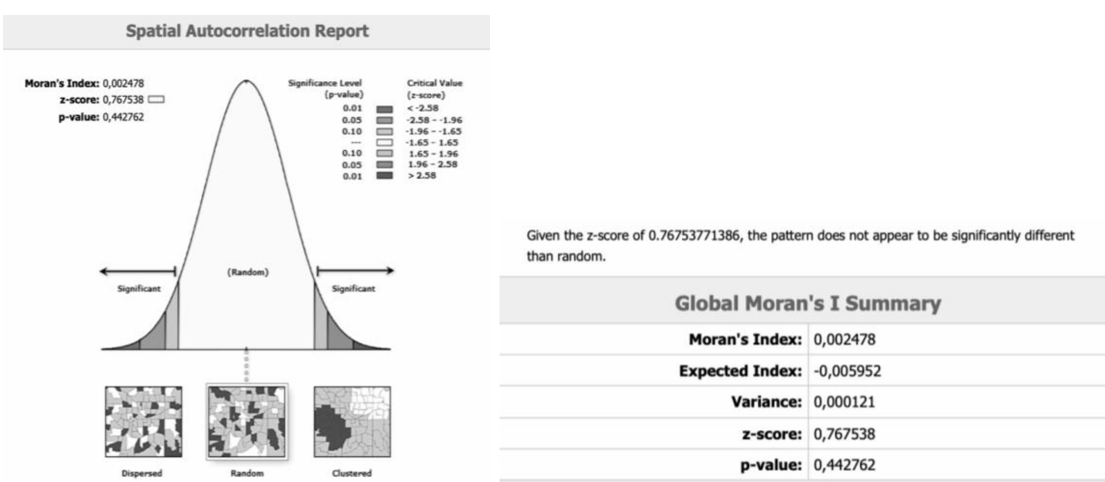

Figure 10. Moran's Index of Poverty Percentage Change 2022-2024

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The z-score (0.767538) falls within the random area of the normal distribution, indicating no statistically significant spatial autocorrelation in the percentage change in poverty. The p-value (0.442762) is greater than 0.05, confirming that the observed spatial pattern could have occurred by chance. If there were significant clustering, we would expect a higher Moran's index with a statistically significant z-score (greater than ±1.96) and a lower p-value (< 0.05).

These results suggest that changes in poverty between 2022 and 2024 do not follow a clear spatial pattern and may be driven more by village-level socio-economic conditions, policy interventions, and localized economic activities than by wider regional influences.

3.3.4. Moran's Index of Village Poverty Percentage in 2024

The Moran's index for the village poverty rate in 2024 assesses the spatial clustering of poverty across villages (see Figure 11). The results show a Moran's index of 0.113921, with a z-score of 10.631743 and a p-value of 0.000000. These results strongly suggest that poverty in 2024 is spatially clustered rather than randomly distributed, meaning that villages with high poverty rates tend to be located near other villages with high poverty rates, while villages with low poverty rates are also spatially clustered.

The z-score (10.631743) is well above the 2.58 critical value, confirming that the spatial clustering in the poverty distribution is statistically significant at the 99% confidence level. In addition, the p-value of 0.000000 (less than 0.01) further supports the conclusion that the pattern is not due to chance but reflects a real spatial structure of poverty concentration.

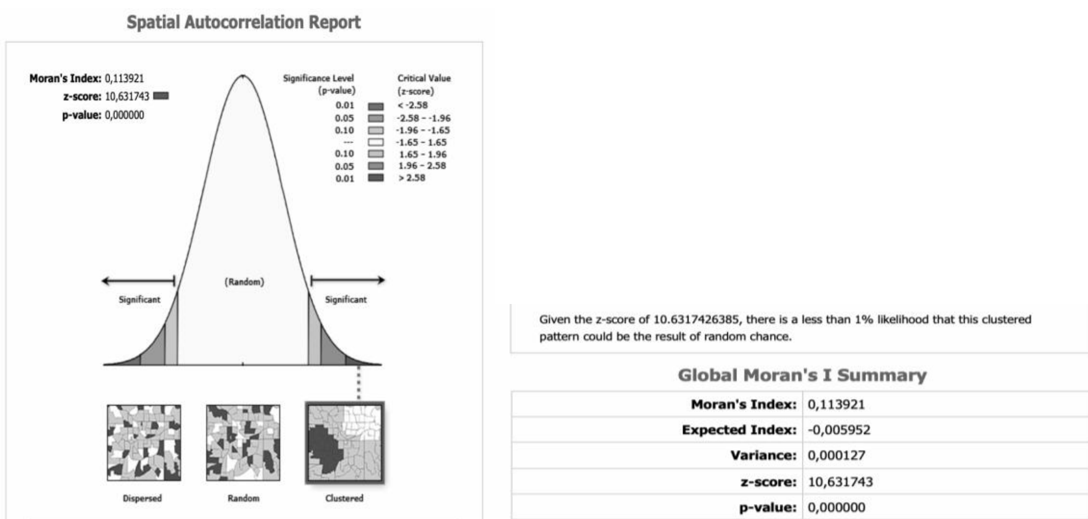
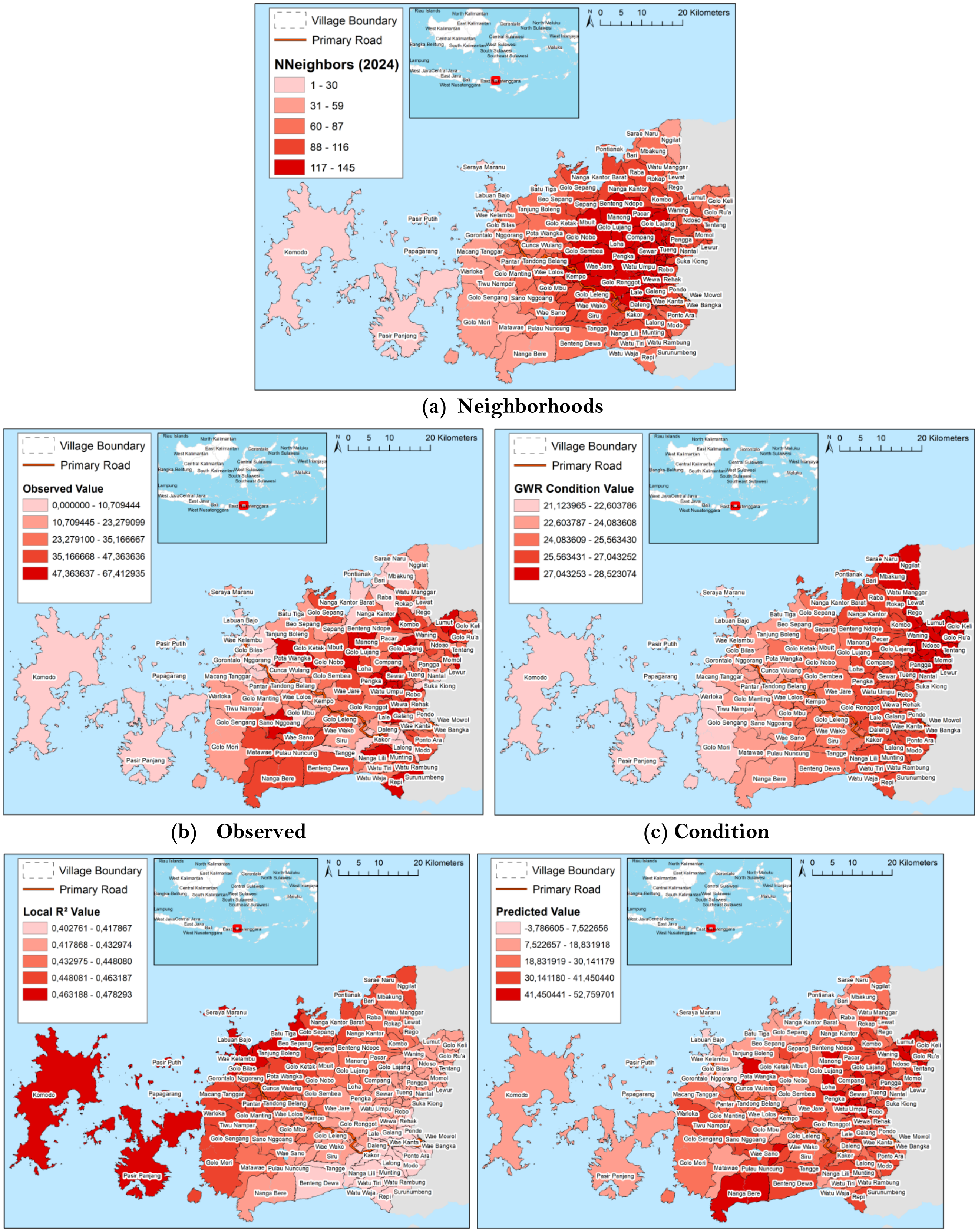


Figure 11. Moran's Index of Village Poverty Percentage Change 2024

The Observed and Condition maps reveal stark disparities in livelihood capital, with central and southern areas such as Ponto Ara, Wae Mowol, and Ngilat displaying low capital availability and high vulnerability. The Local R^2 map confirms these spatial patterns, indicating strong relationships between livelihood assets and sustainability, particularly in clustered poverty zones. For instance, in high-poverty areas, financial capital, such as access to microfinance and credit services, emerges as a key driver of economic resilience. Meanwhile, in other regions like Golo Kembo and Golo Leleng, human capital, including educational attainment and vocational training, is more influential in enhancing livelihood stability. The Predicted map then extrapolates these trends, identifying regions, especially Pong Welak, Golo Nggoang, and Ndoso Lawa, as areas likely to face persistent livelihood challenges without targeted interventions.



(a) Neighborhoods

(b) Observed

(c) Condition

(d) Local R²

(e) Predicted

Figure 12. GWR Outputs for the Five Livelihood Capitals

The GWR analysis (see Figure 12) shows that certain regions exhibit strong spatial clustering of poverty and livelihood vulnerability, reinforcing the importance of context-specific responses. For example, high-poverty districts such as Wae Mowol, Ponto Ara, and Ngilat (where poverty rates exceed 50%) show low levels of financial and physical capital, severely limiting economic opportunities (Gai et al., 2025). These findings emphasize that poverty is not random, but spatially clustered, calling for area-based interventions rather than generic solutions.

3.4. Discussion

3.4.1. Spatial Disparities in Poverty

Spatial disparities in poverty are clearly evident in the distribution of high-poverty clusters across Labuan Bajo and West Manggarai Regency, particularly in villages such as Ponto Ara, Wae Mowol, and Ngilat, where poverty rates exceeded 50% in 2022 (BPS, 2022). The LISA (Local Indicators of Spatial Association) results confirm that these villages form statistically significant high-poverty clusters due to a combination of limited access to economic infrastructure, poor connectivity, lack of financial services, and a high reliance on agriculture and informal employment (Suryahadi et al., 2012). By 2024, some areas, such as Lalong and Wae Mose, showed noticeable improvements, suggesting that targeted economic programs, including microfinance access and tourism-driven employment schemes, have positively contributed to poverty alleviation. (Gai et al., 2025).

Local development policies in Indonesia, including the National Medium-Term Development Plan (RPJMN), prioritize rural areas, yet often fall short of addressing the nuanced geographic and economic conditions of peripheral or remote villages. As highlighted by Indrawati et al (2023), overcoming spatial disparities in poverty requires tailored interventions that bridge spatial planning with equitable development strategies. Studies by Roitman & Rukmana (2022) further advocate for spatially sensitive planning mechanisms that enhance access to credit, support mobility, and diversify rural economies to ensure inclusive growth and a more equitable distribution of economic opportunities across West Manggarai.

3.4.2. The Role of Spatial Clustering in Poverty and Social Protection

Spatial clustering plays a critical role in understanding poverty dynamics and enhancing the effectiveness of social protection programs. Local Moran's I analysis confirms that poverty is not randomly distributed, but forms persistent high-poverty clusters in Ponto Ara, Wae Mowol, and Ngilat, which remain statistically significant in 2024 (BPS, 2024). However, these clusters have started to shift, with new pockets of poverty emerging in Golo Wontong and Wae Bangka, suggesting that poverty is evolving spatially rather than being eradicated (Thaariq et al., 2020). Social protection policies, such as Indonesia's Program Keluarga Harapan (PKH) and Bantuan Pangan Non-Tunai (BPNT), need to incorporate spatial analysis to prioritize high-poverty areas better. Research suggests that current social assistance programs do not always differentiate between persistent poverty clusters and transient poverty, leading to ineffective targeting and inefficiencies (Surtiari et al., 2024).

Integrating Geographically Weighted Regression (GWR) into social protection strategies would allow policymakers to identify spatially entrenched vulnerability, ensuring that cash transfers, food aid, and education subsidies reach the most affected communities. By aligning poverty alleviation efforts with spatial analysis, targeting accuracy and program impact can be significantly improved, ensuring that resources are allocated where they are most urgently needed (Gai et al., 2025; Lu et al., 2014).

3.4.3. Key Drivers of Poverty Reduction and Economic Resilience

Regression analysis shows that education, access to finance, and infrastructure development are the main drivers of poverty reduction (Rahmawati et al., 2024). Villages with more high school graduates (SMA/MA/SMK) have lower poverty rates ($B = -5.839$, $p < 0.001$), indicating the importance of human capital

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in reducing economic vulnerability (E. Rahmawati et al., 2024). Furthermore, financial capital, especially access to microcredit (B = 9.73, p = 0.011), contributes significantly to poverty reduction, while villages with longer distances to banking services (B = 0.218, p = 0.022) have higher poverty rates (Khandker, 2005). Access to infrastructure is crucial. Poor electrification is positively associated with slower poverty reduction (B = 0.077, p = 0.029), highlighting the need for rural electrification programs (Pramono, 2018).

3.4.4. Political and Social Barriers to Enhance Sustainable Livelihood

The promotion of sustainable livelihoods in Labuan Bajo has faced significant political and social barriers, particularly in areas where tourism benefits are unevenly distributed. A key policy barrier is the inadequate spatial targeting of development policies, which has resulted in persistent poverty clusters, especially in rural and interior areas. This study shows that while some parts of Labuan Bajo benefit from tourism-driven growth, others, such as Wae Mowol, Rego, and Ponto Ara, remain marginalized due to limited financial capital, insecure land tenure, and inadequate infrastructure (Gai et al., 2024). Integrating the Sustainable Livelihoods Approach (SLA) with spatial analysis using GWR and LISA indicates that poverty-reduction efforts are not spatially uniform, with high-poverty clusters persisting in Golo Mbu, Ndoso, and Watu Kantor (BPS, 2024). This highlights the need for spatially targeted infrastructure and financial resource interventions. However, weak governance and lack of data-driven planning continue to exacerbate these gaps, resulting in inefficient resource allocation and over-reliance on tourism as the key economic driver (Brunsdon et al., 1996).

At the social level, structural inequalities play a critical role in shaping livelihood outcomes, with education, financial access, and community resilience as key factors. Villages with higher education levels, such as Pacar, Wae Jare, and Wae Bangka, tend to show lower poverty rates, highlighting the role of human capital (Rahmawati et al., 2024). However, many remote villages still face challenges in accessing quality education and vocational training. Spatial clustering analysis shows new poverty hotspots emerging in Pong Welak and Galang, suggesting that current social protection mechanisms fail to reach the most vulnerable effectively (Gai et al., 2025; Scoones, 2015). Social capital also plays a role in villages with cooperatives or village-owned enterprises (BUMDes), like Kuwus and Ndoso, which have demonstrated stronger local economic stability (Nainggola et al., 2024). Nonetheless, disparities in land rights and access to finance, especially for women and indigenous communities, continue to hinder inclusive development. The study calls for spatially integrated policy interventions that address localized livelihood vulnerabilities (Surtiari et al., 2024).

3.4.5. Sustainable Livelihood Strategy for Poverty Reduction

A Sustainable Livelihood Approach (SLA) integrated with spatial analysis is essential to reduce poverty in high-risk districts of West Manggarai, such as Ndoso, Rego, and Wae Mowol (Gai et al., 2025; 2024). SLA identifies five key livelihood assets – human, social, natural, financial, and physical – that provide a holistic framework to understand poverty dynamics (Scoones, 2015).

An important policy implication is the need to create a rural development zone in tourism-dependent regions like Labuan Bajo's hinterland (Wiweka, 2023). Integrating SLA into spatial planning helps ensure that investments are more equitably distributed between urban centers and peripheral rural areas, preventing further marginalization of communities that remain excluded from tourism's economic benefits (Gai et al., 2025). The resulting spatially targeted livelihood strategies are summarized in Table 3.

Key policy recommendations include (1) Expand rural infrastructure: Prioritize road development, electrification, and digital connectivity in high-poverty villages, particularly in the inland and southern districts (Indrawati et al., 2023); (2) Improve spatial targeting: Modify PKH and BPNT to allocate more aid to persistent poverty clusters identified through LISA and GWR spatial analysis, such as in Golo Lijun, Golo Mbu, and Ponto Ara (Martinez & Cooray, 2025); and (3) Strengthen local economic initiatives: Encourage community-based and village-owned enterprises (BUMDes) in villages like Ndoso and Kuwus, which have shown higher financial resilience (Nainggola et al., 2023).

Table 3. Sustainable Livelihood Rural Approach Strategy

Sustainable Livelihood Approach (SLA)	Strategy
Human Capital	***Education Programs in High-Poverty Villages***
	Establish vocational training centers focused on skills in tourism, fishing, and agriculture.
	Health infrastructure in high-poverty areas
Social Capital	***Strengthen Community-Based Tourism (CBT)***
	Empower local tourism entrepreneurs to run eco-tourism services and community-managed homestays.
Natural Capital	***Water Resource Management***
	Reservoirs to combat seasonal droughts.
	Sustainable Land Use Planning
	Promote community-led conservation initiatives to reduce deforestation while introducing agroforestry techniques.
	Implement alternative livelihood programs to reduce over-reliance on forest resources.
Physical Capital	***Infrastructure Development in High-Poverty Clusters***
	Prioritize road and transportation improvements to connect rural producers with urban markets.
	Sanitation and Waste Management in Tourism Areas
	Establish community-led waste management programs to ensure environmentally friendly tourism conditions.

Note. Strategies are synthesized from the LISA and GWR findings and organized according to the five SLA capital assets. They are intended as spatially targeted policy directions for high-poverty villages rather than one-size-fits-all interventions.

By integrating spatial analysis with sustainable livelihood strategies, policymakers can develop adaptive, evidence-based poverty reduction programs that ensure long-term resilience and economic sustainability for vulnerable communities (Gai et al., 2025). The strategies below are derived from the findings for Human Capital, Social Capital, Natural Capital, Financial Capital, and Physical Capital. This strategy can be tailored to specific high-poverty districts, ensuring inclusive economic growth and long-term sustainability in Labuan Bajo and West Manggarai Regency.

4. Conclusion

This study integrates the Sustainable Livelihood Approach (SLA) with the spatial modeling technique, namely Local Indicators of Spatial Association (LISA) and Geographically Weighted Regression (GWR), to examine the spatial dynamics of poverty and resilience in Labuan Bajo, West Manggarai Regency. The findings confirm that poverty in the region is not randomly distributed but forms statistically significant clusters, particularly in villages such as Ponto Ara, Wae Mowol, and Ngilat, where poverty remains deeply entrenched due to limited infrastructure, lack of financial access, and dependence on informal livelihoods. The analysis also reveals a spatial shift in poverty, with improvements in areas such as Lalong, Modo, and Watu Waja, attributed to interventions including electrification, access to microfinance, and local economic initiatives. Conversely, new poverty hotspots have emerged in Pong Welak, Pandak, and Golo Wontong, highlighting the dynamic nature of vulnerability and the need for ongoing monitoring. Regression results underscore the importance of human capital, particularly education, as a key driver of poverty reduction, while financial access and physical infrastructure, especially electrification, also play significant roles. Social capital, including community-based institutions like BUMDes, contributes to economic stability, whereas environmental constraints near forest zones slow progress.

This study highlights that spatial inequalities require geographically targeted, asset-based interventions. National programs such as PKH and BPNT must be spatially realigned to prioritize persistent poverty clusters. Integrated policies that strengthen human capital, financial inclusion, and rural infrastructure tailored to local geographies are essential for achieving inclusive and sustainable livelihoods. The spatial maps generated in this study provide local governments with a valuable tool for planning evidence-based, equitable poverty-reduction strategies across West Manggarai. Future research should explore how climate change and land tenure disparities intersect with spatial poverty to inform adaptive planning.

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