Relative Spatial Poverty Analysis using Remote Sensing and Points of Interest

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Abstract

Poverty mapping is a crucial aspect in designing targeted policy interventions. However, conventional approaches based on household surveys are often constrained by high costs. This study proposes the development of a Relative Spatial Poverty Index (RSPI) derived from multisource geospatial data, including nighttime light intensity (NTL), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and accessibility to Points of Interest (POI). Variable weighting was performed objectively using Principal Component Analysis (PCA) on a 1.5 × 1.5 km spatial grid to estimate poverty levels on Timor Island, East Nusa Tenggara. Furthermore, hotspot analysis using the Getis-Ord Gi method was used to identify poverty clusters, while model validation was performed using simple linear regression. The results showed that the RSPI performed strongly, with a high correlation to official poverty data from the Central Statistics Agency (BPS) (Pearson's Correlation Coefficient = 0.84; R^2 = 0.70) with an RMSE of 19.65. Moran's I analysis confirmed the presence of significant positive spatial autocorrelation (Moran's I Index = 0.924). The spatial pattern revealed shows a concentration of poverty in rural and urban areas. Overall, this study offers an effective methodological framework for more granular spatial poverty mapping, which can be the basis for formulating more targeted intervention policies.

Keywords: relative poverty, remote sensing, PCA, hotspot mapping

Introduction

Poverty continues to be a global challenge with various impacts that can hinder sustainable development, making it a top priority for many countries, including Indonesia (Aklilu Zewdie, 2015). This is reflected in 2020 data from Statistics Indonesia (BPS) showing that 26.42 million people live below the national poverty line, which is set at Rp 454,652 per capita per month. This data was obtained through socio-economic household surveys, such as Susenas, which is conducted every six months. The BPS conventional approach defines poverty in absolute terms, based on insufficient income below a certain (Braithwaite & Mont, 2009; Brandolini et al., 2009). Although this method is simple and relevant to economic policy, conventional surveys still have limitations due to high costs, long implementation times, and delays in publication (Dang, 2021; Ziulu et al., 2022).

This technology enables more efficient and granular poverty mapping. Various studies have shown that variables such as night light (Niu et al., 2020a), vegetation index (NDVI) and water index (NDWI) (Pan et al., 2020; Putri et al., 2022), as well as infrastructure accessibility, correlate with welfare levels (Yin et al., 2021). However, most studies still focus on mapping poverty indices, while estimates of the number of poor people (people) are still relatively rare, especially in Indonesia. Based on this research background, this study aims to estimate the number of poor people from the Relative Spatial Poverty Index (RSPI) and identify poverty hotspots at a grid resolution of 1.5 × 1.5 km on Timor Island, East Nusa Tenggara. By estimating the number of poor people, it is hoped that this will contribute to more accurate, granular, and applicable poverty mapping as a recommendation for policy formulation so that rapid intervention can be provided to areas in need of assistance.

Literature Review

Remote sensing and geospatial data-based approaches are increasingly being developed in poverty mapping. Satellite image variables are widely used for poverty models. For example, Niu et al. (2020b) used vegetation indices (NDVI) and water indices (NDWI) to represent environmental conditions related to economic vulnerability. NDVI and NDWI are related to agricultural livelihoods and food security. In rural contexts, these variables often correlate with poverty because they affect agricultural productivity and access to natural (Yin et al., 2020a). In addition, nighttime light (NTL) has been shown to be a relevant indicator of economic activity in poverty mapping due to its empirical relationship with income, electrification, and infrastructure development (Elvidge et al., 2009; Henderson et al., 2012; Lin et al., 2022; van der Weide et al., 2024; Zheng et al., 2023). Beyond environmental indicators, other economic spatial factors are also gaining attention. Okwi et al. (2007) and Putri et al. (2023) emphasize that accessibility to public facilities such as education, health, economic centers, and tourism can influence welfare distribution. Classical statistical approaches such as Small Area Estimation (SAE) have long been used to model poverty by combining census household surveys to create more detailed poverty maps. Permatasari et al. (2025) developed image-based SAE to estimate poverty in West Java. However, its limitation lies in its dependence on census data. With advances in computing, machine learning-based approaches are becoming increasingly popular for poverty mapping. These methods are non-parametric and have the advantage of processing and integrating various data sources (Sholihah & Hermawan, 2023; Zhao et al., 2019).

However, machine learning models are susceptible to biases inherent in the training data (Mohale & Obagbuwa, 2024). If the field survey data used to train the model has demographic or spatial biases, the model will replicate these biases in its predictions. On the other hand, Shi et al. (2020) have proven the great potential of using multi-source data to create a spatial poverty index. However, this research has not yet estimated the population from the poverty index. Although there are various approaches, efforts to develop poverty models to estimate poverty spatially have not been widely carried out in Indonesia.

Materials and Methods

a. Study Area:

BPS data (2020b) recorded the poverty rate in East Nusa Tenggara Province (NTT) in March 2020 at 20.90%, almost twice as high as the national average. The capital of NTT province is the city of Kupang, which is also located on Timor Island, making it the reason why this research was conducted on Timor Island. It is important to understand the contrasting conditions of poverty in the administrative regions of Timor Island. Timor Island is an island that shares a land border with the country of Timor Leste, making it one of the international trade corridors.

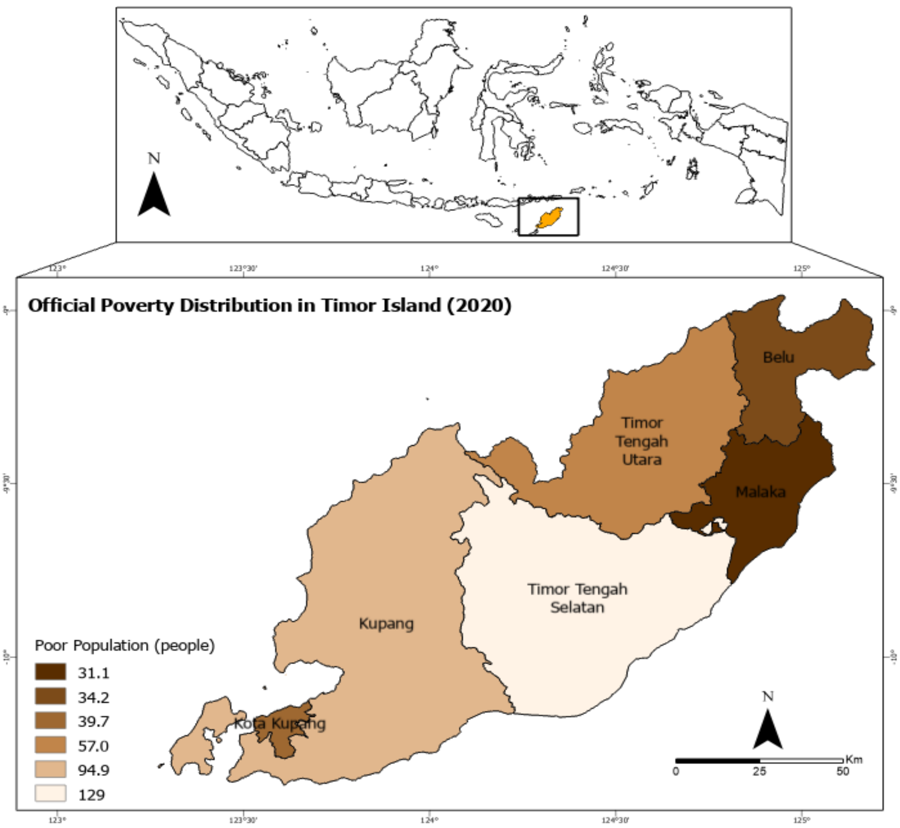

Figure 1: Study area

b. Field data collection:

This study uses a multi-source dataset to estimate poverty levels on Timor Island, NTT, based on economic activity, basic environmental conditions, and social access. Before use, the image data underwent preprocessing through geometric correction and atmospheric correction to ensure that the data used accurately represented conditions on the earth's surface. Details of the data used in this study are provided in Table 1.

Table 1: Data used

Data	Source	Spatial Resolution	Equation	
NTL	(NOAA-VIIRS)	463.83m		
NDVI	Sentinel-2	10m	$\frac{NIR_{band\ 8} - Red_{band\ 4}}{NIR_{band\ 8} + Red_{band\ 4}}$	(1)
NDWI	Sentinel-2	10m	$\frac{Green_{band\ 3} - NIR_{band\ 8}}{Green_{band\ 3} + NIR_{band\ 8}}$	(2)
POI distance	Open Street Map	-		

Methodology

The overall methodology applied in this study is schematically illustrated in Figure 2.

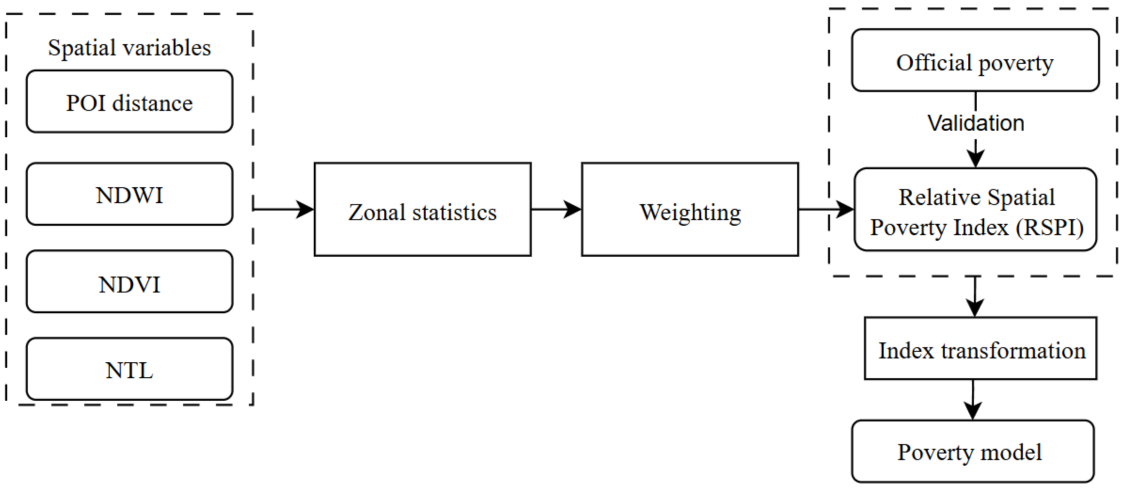

Figure 2: Research methodology

- **Normalization**

  Spatial variables in the dataset have different units, so they must be normalized to the same interval in order to be compared and maintain the monotonicity of the aggregation function (Carrino, 2016). Normalization in this study uses the equation mentioned in (Cohen & Sullivan, 2010):

$$Normalized = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (3)$$

A scale of 0–1 is used, where 1 represents a high or positive value, and 0 represents the minimum value. Min-max normalization adjusts the indicators to the same range.

- **Agregation and Relative Spatial Poverty Index**

All spatial variables were aggregated using zonal statistics on a 1.5 km grid. Principal Component Analysis (PCA) was applied to calculate indicator weights objectively for the formation of the poverty index. This method has been proven effective in similar studies, such as that applied by Li et al. (2023), who used PCA to reduce the dimensions of multiple indicators and determine automatic weights based on the variance contribution of each principal component. Furthermore, Putri et al. (2022) reinforced the validity of this approach by developing the Relative Spatial Poverty Index (RSPI) through the integration of remote sensing data and geospatial big data, in which PCA played a role in the integration and weighting of poverty indicators. PCA does not take into account the spatial correlation between pixels, but rather highlights the largest variance structure in the data set (Avena et al., 1999; Demšar et al., 2013). This method extracts a linear combination of the original variables (principal components) so that the first component (PC1) explains the largest proportion of variance and is often assumed to represent the dimension. The Relative Spatial Poverty Index (RSPI) is then constructed using the equation:

$$RSPI = \sum_{i=1}^{p} w_i x_i \quad (4)$$

where wi is the weight of the i-th variable in PCA and xi is the value of the spatial variable.

The RSPI that has been formed is then validated using linear regression. Regression can be used to determine the systematic relationship between the predictor/independent variable (X) and official poverty data from BPS as the dependent variable (Y). Linear regression will produce an R^2 value and Root Mean Square Error (RMSE) as a model error residual value. If the resulting RMSE is closer to zero, the model is very good at representing the official data. A negative R^2 value indicates that the model is worse than the baseline, $R^2 = 0$ means that the model does not explain the variability of the data, while a value close to 1 indicates that the model is better at explaining the variation in the data (Chicco et al., 2021).

- **Poverty Analysis**

The analysis of spatial poverty patterns in this study uses a combination of Global Moran's I and Getis-Ord Gi* hotspot analysis. Global Moran's I is used to identify overall spatial autocorrelation and determine whether the distribution of poverty levels tends to form clusters or is randomly scattered (Asrirawan et al., 2021). Moran's I values range from -1 to +1, where values close to +1 indicate strong positive spatial autocorrelation or an indication that poverty is concentrated in a cluster, while values close to -1 indicate a dispersed distribution pattern (Nawawi et al., 2020; Su et al., 2017, 2019). Furthermore, to determine the specific locations with the highest and lowest poverty rates, Getis-Ord Gi* hotspot analysis was used. This method is capable of detecting significant spatial concentrations by identifying hotspots (areas with high poverty concentrations) and coldspots (areas with low poverty concentrations), so that the results can provide a clearer picture of priority areas for intervention (Songchitruksa & Zeng, 2010; Yin et al., 2020b).

d. Results and discussion

- **Relative Spatial Poverty Index Calculation**

The PCA analysis produced PC1 weights, which are shown in Table 2. PC1 weighs 69.86% of the total data variation, with the highest weights in the NTL (0.554) and NDVI (0.542) variables. The dominance of these two variables indicates that the intensity of human activity represented by nighttime light and vegetation conditions (NDVI) are the main factors driving the spatial variation of poverty, which has a gradient of land use intensity. Areas with high nighttime light and low vegetation tend to be more developed, while areas with low nighttime light and high vegetation are potentially more vulnerable. PC1 loading (variable weight) is obtained from the eigenvector resulting from the decomposition of the data matrix.

Table 2: Weight calculation results

Parameter	W-PCA
NTL	0.554
NDWI	0.421
NDVI	0.542
POI distance	0.469

Finally, the RSPI was calculated on a 1.5 km × 1.5 km grid using the weights in Table 2. The calculation results are shown in Figure 3, which presents the poverty index results visually to illustrate areas with high to low poverty levels.

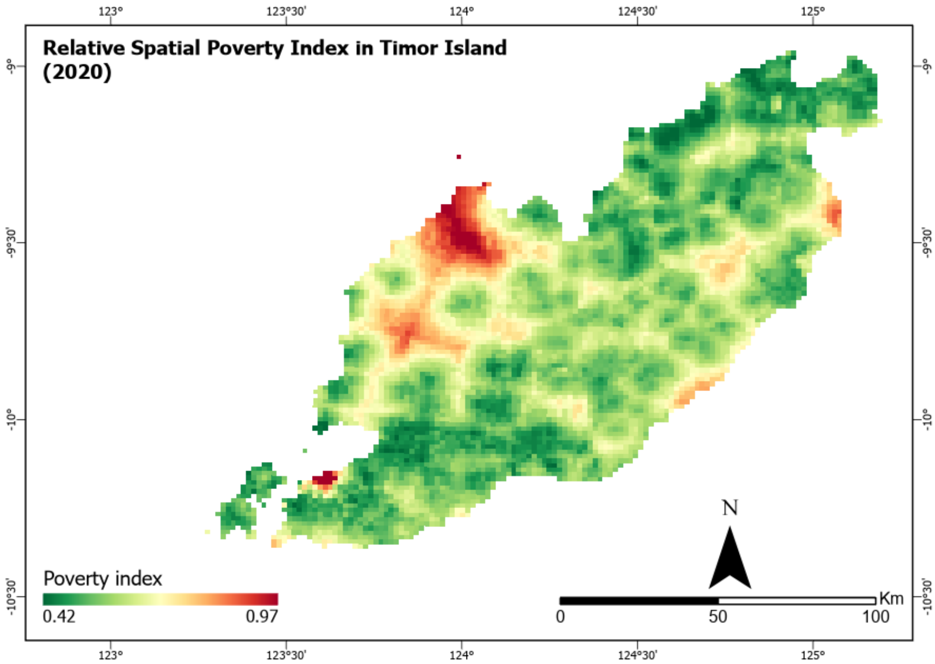

Figure 3: Poverty index

The RSPI Index calculation results in Figure 3 show the distribution of poverty visually, with red areas representing relatively high poverty levels and green areas representing relatively lower poverty levels. The resulting index was then validated against official poverty data using simple linear regression and measured for suitability using the Pearson correlation coefficient. The RSPI validation results presented in Table 3 show a strong relationship between the poverty index and BPS poverty data, with a Pearson correlation coefficient of 0.84, R^2 of 0.70, and RMSE of 19.65 thousand people. These values explain that around 70% of the variation in poverty data can be explained by the RSPI. Meanwhile, the remaining 30% is influenced by other factors that have not been accommodated, such as socio-economic variables that are not detected in images of access to health services, education, and infrastructure. The RMSE of 19.65 thousand people is relatively small when compared to the total poor population of 385.9 thousand people in the study area, so this index has the potential to represent spatial poverty patterns well.

Table 3: RSPI Validation results

RSPI	Linear Regression			Pearson Correlation	
	Y	**RMSE (thousands of people)**	**R^2**	**Correlation coefficient**	**P-value**
w-PCA	-38.7939 + 157.1085 * X	19.65	0.70	0.84	0.036

Figure 4 shows a linear regression validation graph that illustrates the contrasting differences between regions. South Central Timor Regency is far above the regression line, with a significantly larger number of poor people than predicted based on the RSPI, making it appear as an outlier. This condition indicates the existence of socioeconomic factors that are not fully captured by the spatial proxies used in the model. Kupang Regency also has a high RSPI value, but the estimated number of poor people in this region is still around the regression line. Meanwhile, Belu Regency, Malaka Regency, and Kupang City tend to be closer to the regression line, because the number of poor people based on RSPI is relatively comparable to BPS data. In general, these results show that RSPI is quite accurate in predicting the number of poor people in regions with relatively homogeneous populations. However, the model becomes less stable when applied to districts with a suddenly much higher number of poor people. BPS data records the number of poor people in South Central Timor District at 129 thousand, far exceeding the range of other districts, which only ranges from 31.1 to 94.9 thousand.

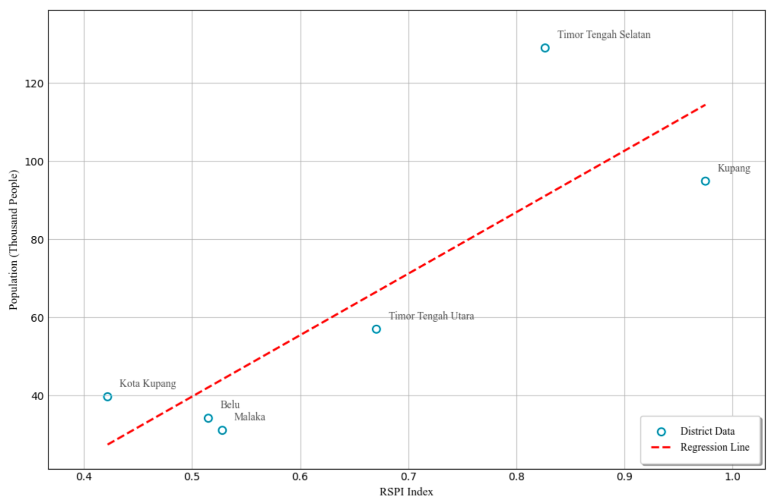

Figure 4: Linear regression graph of the RSPI index and the number of officially registered poor people

Calibration to estimate the number of poor people was developed through a linear regression equation shown in Table 3. Figure 5 shows the results of converting RSPI values into estimates of the number of poor people, so that poverty patterns can be mapped spatially and compared with BPS data. The calibration results show that the estimated number of poor people based on RSPI is in the range of 27.210–114.320 people, which is generally lower than the existing data in Figure 1, which is 31.100–129.000 people.

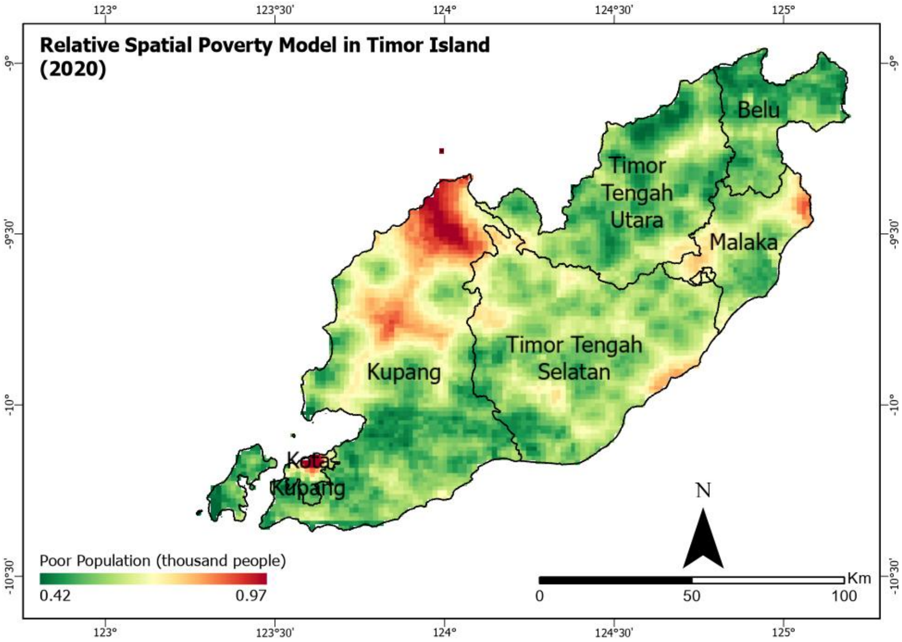

Figure 5: Relative spatial poverty model in Timor Island

The graph in Figure 6 shows the variation in the accuracy of poverty estimates based on RSPI compared to BPS data in six districts/cities on Timor Island. The results show that the RSPI estimates are relatively close to the BPS data in North Central Timor Regency and Malaka Regency, with estimated values of 88,500 and 26,570 people, respectively. This similarity is further clarified by the relatively low error percentages of 6.9% and 14.6%. However, a significant difference occurred in Kupang City, where the RSPI estimated the number of poor people to be 122.61 thousand, much higher than the BPS data of 94.9 thousand. This estimate resulted in a very high error rate of 90.1%, indicating that the RSPI model is not yet able to represent the complexity of poverty in urban areas. This may be due to the limitations of the proxy variables used, which do not fully reflect the socio-economic dynamics characteristic of urban areas. Meanwhile, in South Central Timor Regency, the RSPI estimate tends to be lower than the BPS data (error 31.3%) and higher than in Kupang Regency (error 29.2%). Based on these variations in error, it can be concluded that the environment- and economy-based indicators (such as NTL) used in the preparation of the RSPI are relatively capable of representing the characteristics of poverty in rural areas, but are not yet fully suitable for measuring poverty in urban areas due to differences in geographical conditions.

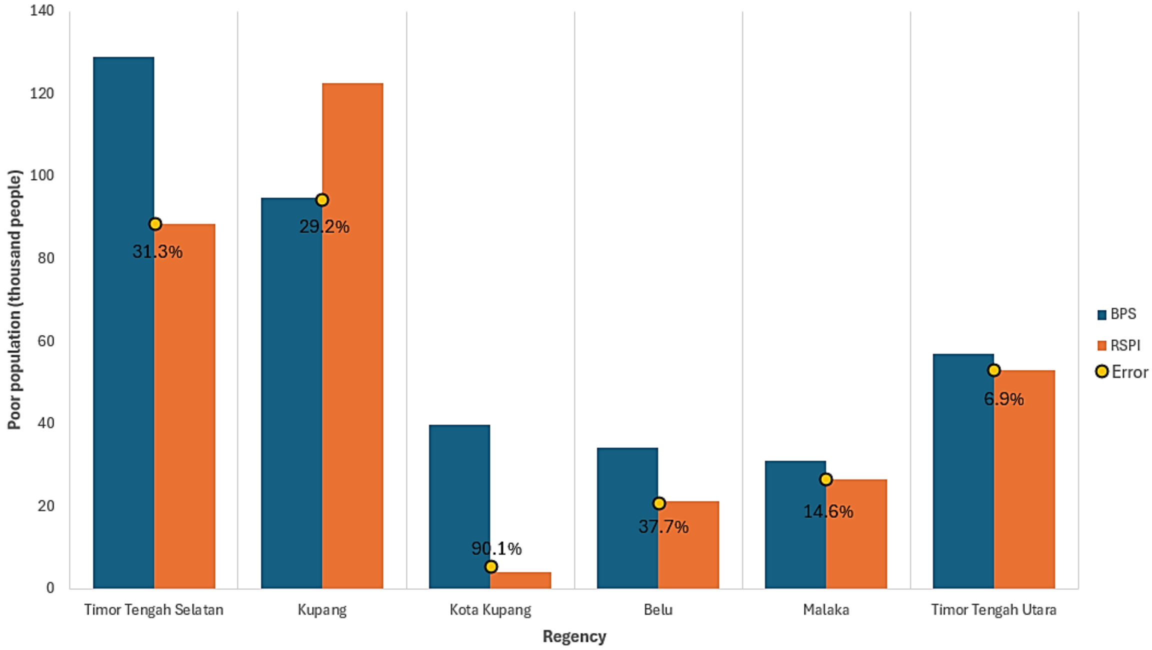

Figure 6: Comparison of the number of poor people according to BPS and the RSPI model

- **Poverty Analysis**

The poverty cluster pattern based on Global Moran's I analysis in Table 4 shows a value close to 1. This value indicates a very strong positive spatial autocorrelation, where areas with similar poverty levels tend to be geographically close and form clusters. The very small p-value ($p < 0.01$) further confirms that this clustering pattern is statistically significant.

Table 4: Moran's I analysis

Moran's Index	**p-value**
0.924	0.000

To identify poverty clusters on the island of Timor, a Hotspot analysis (Getis-Ord Gi*) was conducted. This method maps areas with high concentrations of poverty (hotspots, marked in red) and low concentrations (coldspots) that are statistically significant. The results shown in Figure 6 reveal a number of significant hotspots marked in red, representing areas with the most acute poverty crisis and highly concentrated burdens.

Visually, several districts have critical high poverty points identified from the RSPI model, including in Kupang District covering Kefu, Afoan, Binatun, Fatumetan, Bioba Baru, Benu, and Kalali subdistricts. In the western part, around Kupang City, hotspots are visible in the subdistricts of Airmata, Fatululi, Kelapa Lima, Airnona, and Belo, which show a high concentration of poverty in urban areas and their surroundings. In the east-central part of the island, especially on the border of Malaka Regency (Alas Subdistrict) and part of North Central Timor, dense red zones are also visible. In addition, several small areas of poverty on the east and southwest coasts were detected as local-scale hotspots. This pattern confirms that poverty on Timor Island is not evenly distributed, but rather concentrated in certain locations that require more targeted policy interventions.

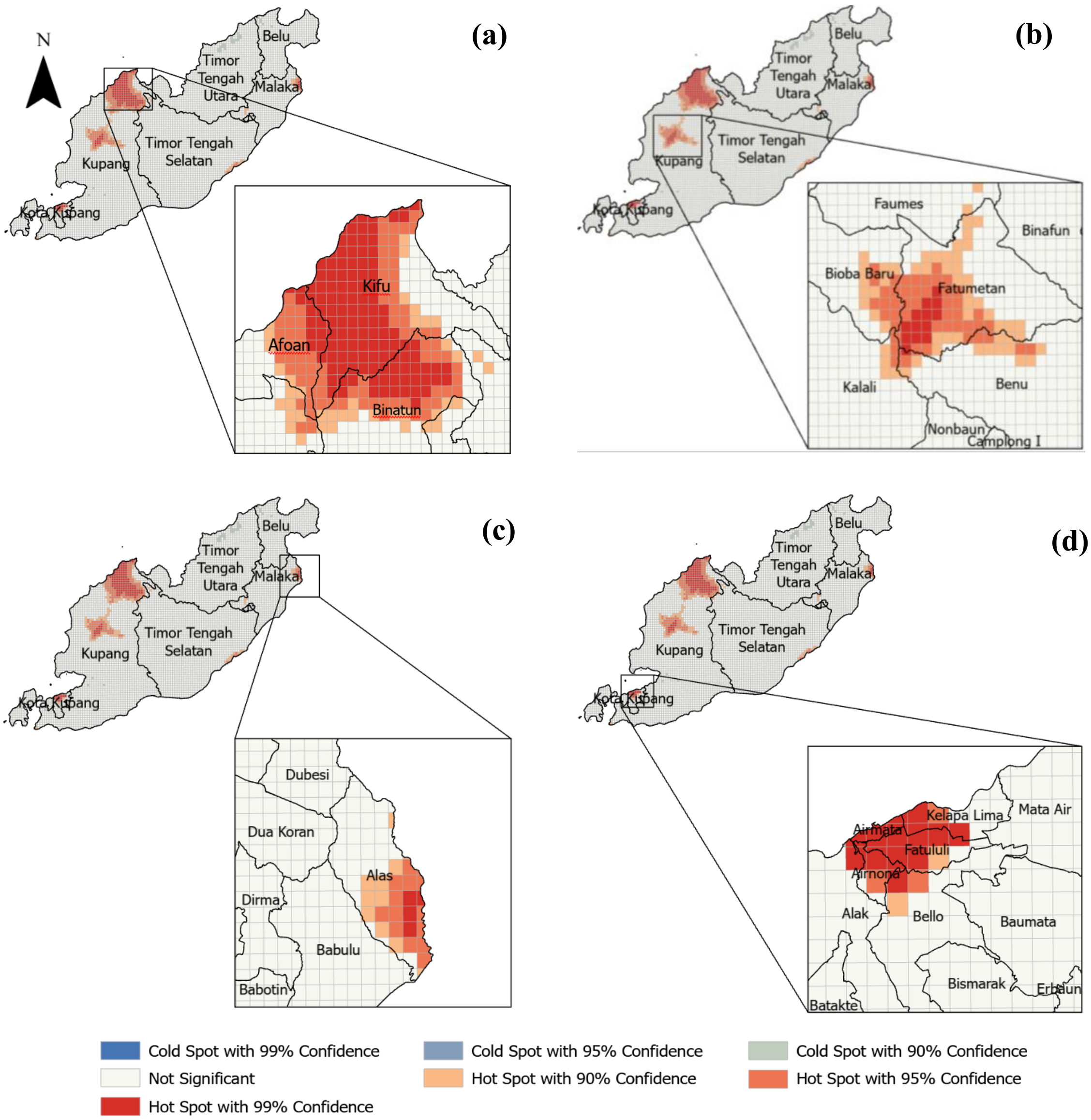

Figure 7. Hotspot analysis

f. Conclusion and Recommendation

The RSPI approach, which integrates remote sensing and geospatial data, has proven capable of estimating and mapping poverty patterns at a more granular resolution. The indicator weights calculated using PCA underscore the significance of NTL and NDVI as the main drivers of poverty variation, reflecting human activity and environmental conditions. Model validation shows a strong relationship between RSPI and official poverty data from BPS, as evidenced by a high Pearson correlation coefficient (0.84), an R^2 value of 0.7, and a relatively small RMSE error. This reinforces the potential of remote sensing data to complement conventional methods that have cost and time limitations. Global Moran's I analysis confirmed the existence of significant spatial clustering. Further hotspot analysis revealed critical locations in rural and urban areas that could be used as a reference for priority interventions. However, this study has several limitations, namely: 1) urban poverty estimates, particularly for Kupang City, tend to be lower due to the limitations of proxies in capturing the complexity of urban areas. 2) This study is limited to 2020 and therefore does not capture temporal dynamics. This limits its usefulness for monitoring poverty alleviation efforts over time. 3) It is necessary to explore the use of weights from other methods.

Conflict of Interes

Author(s) have no potential conflict of interest to disclose.

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