
Regional Typology and Spatial Dependent Driving Factors of Poverty in Gowa Regency, Indonesia

Ahmad Syaifullah ¹, Andrea Emma Pravitasari ²,
Galuh Syahbana Indraprahasta ³

Abstract:

One notable societal challenge that urban and regional development has to deal with is poverty. In this paper, we focus on rural poverty by zooming in on Gowa Regency, Indonesia. We argue the importance of considering spatial aspect in analyzing poverty. By considering this aspect, it is expected that poverty reduction programs can be tailored to the specific needs of each location. As such, the purpose of this research is to better understand the spatial dimension of rural poverty in Gowa Regency by performing three spatial analyses. This was done at first by evaluating the characteristics of each region. The next step is identifying the distribution and spatial pattern of poverty to specifically map the pattern of poverty in rural areas of Gowa Regency. Next is identifying the diverse spatial factors that influence poverty in rural areas of Gowa Regency. The analyses were performed by using cluster analysis, Spatial Autocorrelation Analysis (Global Moran Index and Local Indicators of Spatial Autocorrelation), and Geographically Weighted Regression (GWR) accordingly. The results of the study show that rural areas in Gowa Regency can be divided into several typologies. Furthermore, there is an indication that the spatial distribution of rural poverty in Gowa Regency tends to cluster. Lastly, each significant variable has different effect on rural poverty in Gowa Regency. Therefore, this study provides refined insights into possible different poverty reduction interventions for each village.

Keywords: Poverty; Cluster Analysis; Spatial Autocorrelations

1. Introduction

One particular challenge of urban and regional development has been to address a variety of societal problems, including poverty (Mukwaya, Sengendo, & Lwasa, 2020). Poverty refers to an economic condition of life that falls below the minimum level of living standards (Baiyegunhi et al., 2014). In this paper, our focus is on rural poverty in Gowa Regency, Indonesia.

¹Regional and Rural Development Planning Science Program, Faculty of Economics and Management, Institut Pertanian Bogor, Indonesia. ahmad02syaifullah@gmail.com

²Division of Regional Development Planning, Department of Soil Science and Land Resource Faculty of Agriculture, Institut Pertanian Bogor, Indonesia. andreaemma@apps.ipb.ac.id

³Center for Regional, Systems, Analysis, Planning, and Development (CRESTPENT/P4W) LPPM, Institut Pertanian Bogor, Indonesia. galuh.syahbana@apps.ipb.ac.id

This paper's main attention is based upon what we see as some pivotal supporting figures. First, geographically, despite showing continuous urbanization trend, a large portion of Indonesian population still lives in rural areas. In particular, of 270.6 million Indonesian population, 151 million people (55.8%) live in urban areas, while 119.6 million people (44.2%) live in rural areas (Bukhari, 2021). Second, the country's urbanization processes itself entail urban-rural parasitism relations. By this we mean that due to the inequality between urban and rural areas in a wide variety of aspects, many rural residents have been forced to move to cities in search of more diverse income sources and better quality of life (Bukhari, 2021). Third, the percentage of poor people living in rural areas is higher than their urban counterparts. In 2021, rural poverty was 13.1%, while urban poverty was 7.89% (Central Bureau of Statistics, 2021). Fourth, the spatial pattern of poverty tends to form cluster(s). This happens because a region can influence its closest surrounding regions (Celemin & Velazquez, 2018).

In Gowa Regency, the issue of poverty has always been on the spotlight. The poverty gap index in Gowa Regency increased from 0.92 in 2019 to 1.38 in 2021, while the poverty severity index increased from 0.17 to 0.36 (Gowa Regency Central Bureau of Statistics, 2021). These figures indicate an increasing disparity in terms of expenditure of the poor. Some argue that in order to minimize program or policy failures, development programs aiming at reducing poverty should pay more attention to spatial elements (Harmes et al., 2017). Not only are traditional factors such as education, income, limited access to health, finance and public services important, but so is location (Susila, 2017). Similarly, poverty does not always require a focus on economic growth, but also a more in-depth understanding of the spatial factors (Barros & Gupta, 2017). Each region is distinct in terms of population, area, distance from the city center, education and health facilities, and village financial capacity (Nasution, 2018). Therefore, spatial analysis is required in poverty reduction policy making given the spatial distinctiveness of each region. Given this understanding, the purpose of this research is to better understand the spatial dimension of rural poverty in Gowa Regency. In doing so, three spatial analyses were performed. The details of these analyses are outlined in the following section.

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2. Methodology

Materials and Tools

The study's data was entered using Microsoft Office software (Word, Excel, and PowerPoint). Minitab, ArcGIS 10.8, and Geo Da softwares were then used for data processing, analysis, and mapping. Meanwhile, the materials used in this study include administrative maps of Gowa Regency, actual use of village funds, Village Potential (*Potensi Desa*) data, such as poverty percentage, population data, village area data, number of farmer groups, number of families using state electricity, distance data to the capital city, ratio data of education and health facilities, and data on the number of shops/grocery stalls.

Regional Typology Analysis Based on the Characteristics of Each Village in Gowa Regency

Regional typology analysis was done to identify types of regions. This was performed using cluster analysis (Kurnia et al., 2019). There are two approaches to cluster analysis:

Hierarchical Method

This method groups two or more objects that have the closest similarity. Then the process is forwarded to another object that has a second closeness. And so on, until the cluster resembles a tree with a clear hierarchy (level) of objects ranging from the most similar to the least similar. Dendograms are typically used to aid in the clarification of hierarchical processes.

Non-Hierarchical Method

This method is commonly called K-Means Cluster. This method groups regional characteristics by first determining the desired number of clusters (two clusters, three clusters or another) and then generating values that indicate the characteristics/typology of each cluster. The resulting value will classify each identifying variable into 3 categories: The findings of this analysis will also be mapped to make it easier to determine the distribution of village areas within each cluster. This analysis' identifying variables can be seen in Table 1.

Table 1. List of Identifier Variables

No.	Variable	Code	Explanation	Year	Unit
1	Headcount Index (Hci-Po)/ Poverty Percentage	PM	The Percentage of the Population below the poverty line	2021	Percent
2	Village Funds For The Development Sector	DD PEMDES	Total Realization of Village Funds in the Field of Village Development	2021	Billion Rupiah
3	Village Governance Sector	DD PPD	Total Realization of Village Funds in the Field of Village Government	2021	Billion Rupiah
4	Village Funds For The Field Of Village Community Development	DD PKD	Implementation Total Realization of Village Funds in the Field of Village Community Development	2021	Billion Rupiah
5	Village Funds For Village Community Empowerment	DD PMD	Total Realization of Village Funds in the Field of Community Empowerment	2021	Billion Rupiah
6	Village Funds for The Field of Disaster Management, Emergency and Urgent Conditions	DD DB	Total Realization of Village Funds in the Disaster, Emergency and Urgent Management Sector	2021	Billion Rupiah
7	Population	Pddk	Number of Population in Each Village	2021	Person
8	Rural Territorial Extend	LDes	Area of each village	2021	Km ²
9	Number Of Farmer Organizations	KTANI	Number of Farmer Organizations per Village	2018	Units
10	Number Of Households Using The Countrys Electricity	KPLN	Number of Households Using State Electricity Facilities.	2018	Head of Household

No.	Variable	Code	Explanation	Year	Unit
			the District Capital		
12	Educational Facilities Ratio	RFP	Total educational facilities divided by the number of residents	2018	
13	Health Facility Ratio	RFK	Total health facilities divided by population	2018	
14	Number Of Grocery Stores	Tkel	Number of Grocery Stores in each village	2018	Units

Source: Data Analysis (2022)

Analysis of the Distribution and Spatial Patterns of Poverty in Rural Areas of Gowa Regency

Global Moran Index

This technique was developed to describe and visualize spatial distribution, as well as to identify concentration points (clusters/hot spots) and outliers of certain socio-economic indicator (Pravitasari, et al., 2022). Here we used the percentage of poor people in all villages in Gowa Regency in 2021. The Moran test formula is formulated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})^2}$$

Where:

- I = Moran's Poverty Index
- n = The number of villages observed
- x_i = Observational value in village i
- x_j = Completion value in village j (neighboring i)
- \bar{x} = The average value of all observed variables
- w_{ij} = Matrix elements between villages i and j

At this stage the hypothesis used is:

- a. $H_0 I = 0$. There is no spatial autocorrelation of poverty between regions or locations in every village in Gowa Regency.
- b. $H_0 I \neq 0$. There is a spatial autocorrelation of poverty between regions or locations in every village in Gowa Regency.

To see the grouping and characteristics of each village, the Moran Scatterplot was used. The Moran Scatterplot is a visual representation in the form of a four-quadrant graph for each calculated unit of analysis (Santi, Pravitasari, & Lubis, 2020). The Moran Scatterplot consists of four quadrants which show the four classifications of poverty, namely:

- Quadrant I : Consists of areas with high poverty characteristics surrounded by areas with high poverty characteristics as well (HH, High-High clustering)
- Quadrant II : Consists of areas with low poverty characteristics surrounded by areas with high poverty characteristics (LH, Low-High clustering)
- Quadrant III: Consists of areas with low poverty characteristics surrounded by areas with low poverty characteristics as well (LL, Low-Low clustering)
- Quadrant IV : Consists of areas with high poverty characteristics surrounded by areas with low poverty characteristics (HL, High-Low clustering)

Local Indicator of Spatial Autocorrelation (LISA)

The Local Indicator of Spatial Autocorrelation (LISA) is used to partially identify spatial autocorrelation or detect each unit of observation. The higher the local value, the more adjacent locations have nearly identical values or form a clustered spread ([Lee and Wong, 2021](#)).

LISA formula:

$$I_i = Z_i \sum_{j=1}^n W_{ij} Z_j \quad [2]$$

Where:

- I_i = LISA coefficient
- Z_i and Z_j = Data that has undergone data standardization
- W_{ij} = Weighting between locations i and j , where j is the data villages located around i (other than i) a number of n .

Analysis of Spatial Diversity of Factors Affecting Poverty in Rural Areas of Gowa Regency

To see the factors that affect poverty in rural areas, Geographically Weighted Regression (GWR) analysis was used. GWR is the development of a simple regression model that is usually taken from non-parametric regression ([Artino et al., 2017](#)). In contrast to global regression which is generally applied at each observation location, GWR produces estimators of model parameters that are local for each observation location ([Risya, 2015](#)). Parameter values will be calculated at each geographic location point so that each geographic location point has different regression parameter values.

The GWR model formula is as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad [3]$$

Where ;

- Y_i = response variable at location- i ($i=1,2,...,n$)
- x_{ik} = the k predictor variable at the i location ($i=1,2,...,n$)
- u_i, v_i = longitude latitude coordinates of the i -point at a location geographical

$\beta_0(u_i, v_i)$ = k regression coefficient at each location or realization from the continuous function $\beta_0(u_i, v_i)$ at the-i point
 ε_i = errors assumed to be identical, independent, and distributed normal with zero mean and constant variance σ^2

For each variable used in the GWR, a significance test was carried out to see the effect of each of these variables on location-specific poverty in Gowa Regency. Significance tests were carried out for each variable in each village/kelurahan with a significant level of $\alpha = 5\% = 0.05$ and $\alpha = 10\% = 0.1$. Significance test can be done with test statistics:

$$t_{hit} = \frac{\beta_k^7(u_i, v_i) - \beta_k(u_i, v_i)}{Se(\beta_k(u_i, v_i))} \quad [4]$$

Where:

$\beta_k^7(u_i, v_i)$ = Observed value of the k predictor variable at the i observation location
 $Se(\beta_k^7(u_i, v_i))$ = Standard error of the k predictor variable at the i-observation location

By using a significant level of 0.05, the test criteria are:

The number of research units is 121 villages, then $t_{\alpha, db=n-k}$ value can be determined:

$$t_{\frac{0.05}{2}, 121-13-2} = t_{0.025, 106} = 1.98260$$

If value $t_{hit} > 1.98260$, then accept H_1 (significant)

If value $t_{hit} \leq 1.98260$, then accept H_0 (not significant)

By using a significant level of 0.1, the test criteria are:

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The next step is to categorize the number of villages belonging to each level of significance test for each variable. This was done to facilitate the mapping of the influence of each variable for each village. All variables used in the analysis is presented in Table 2:

Table 2. List of Data Variables

Variable	Data	Data Sources
Variable Y (Predicted variable)	Headcount Index (Hci-Po)/ Poverty Percentage	Social office in Gowa Regency
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3. Empirical Findings/Result

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2018	Head	o	h	406
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11	Distance to Regional Capital	JRK	The Distance of Each Village to the District Capital	2018	Km
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Source: Data Analysis (2022)

Judging from the results of the research conducted from the data that has been collected and tested on the problem, the following conclusion can be drawn as;

1. The Lagged Dividend (X1) variable has a significant effect on the Dividend Policy of Banking Sector Companies for the 2017-2021 period, which means that 1st hypothesis is accepted.
2. The Profit Growth Variable (X2) affects the Dividend Policy of Banking Sector Companies for the 2017-2021 period, which means that 2nd hypothesis is accepted.
3. The Company Growth Variable (X3) has a significant effect on the Banking Sector Company's Dividend Policy for the 2017-2021 period, which means that 3rd hypothesis is accepted
4. The Capital Structure moderates the relationship of Lagged Dividend to the Banking Sector Company's Dividend Policy for the period 2017-2021, which means that 4th hypothesis is accepted.
5. The Capital Structure does not moderate the relationship of Profit Growth to the Dividend Policy of Banking Sector Companies for the period 2017-2021, which means that 5th hypothesis is rejected.

The Capital Structure does not moderate the relationship of the Company's Growth to the Banking Sector's Corporate Dividend Policy for the 2017-2021 period, which means that 6th hypothesis is rejected.

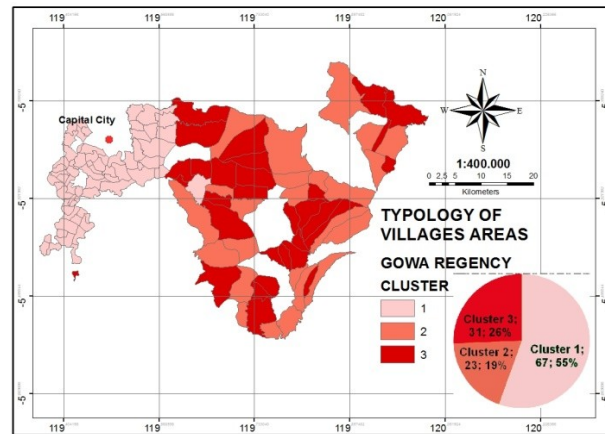


Figure 2. Map of Village Typology Distribution in Gowa Regency
Source: Data Analysis (2022)

Table 3. The Typology of Each Cluster Is Based on K-Means Clustering Analysis in Rural Areas of Gowa Regency

No.	Characteristic Variables	Typology Cluster 1	Typology Cluster 2	Typology Cluster 3
1.	Headcount Index (Hci-Po)/ Poverty Percentage	Low	Moderate	High
2.	Population	High	Moderate	Low
3.	Rural Territorial Extend	Low	Moderate	High
4.	Number of Households Using The Countries Electricity	High	Moderate	Low
5.	Distance to Regional Capital	Low	Moderate	High
6.	Educational Facilities Ratio	High	Moderate	Low
7.	Health Facility Ratio	High	Moderate	Low
8.	Number of Grocery Stores	High	Moderate	Low
9.	Number of Farmer Organizations	Moderate	High	Low
10.	Village Funds For Village Governance Sector	High	Low	Moderate
11.	Village Funds for The Development Sector	High	Low	Moderate
12.	Village Funds for The Field of Village Community Development	Moderate	High	Low
13.	Village Funds for Village Community Empowerment	Moderate	High	Low
14.	Village Funds for The Field of Disaster Management, Emergency and Urgent Conditions	High	Moderate	Low

Source : Analysis 2022

Analysis of the Distribution and Spatial Patterns of Poverty in All Villages in Gowa District

The results of the Moran Global Index analysis show that the Moran Index value is 0.412169 with z-scores of 7.128852. It can be concluded that there is a spatial autocorrelation of poverty in every village in Gowa Regency with a cluster distribution pattern. The pattern of poverty resulting from the Moran Index in Gowa Regency can be seen in Figure 3.

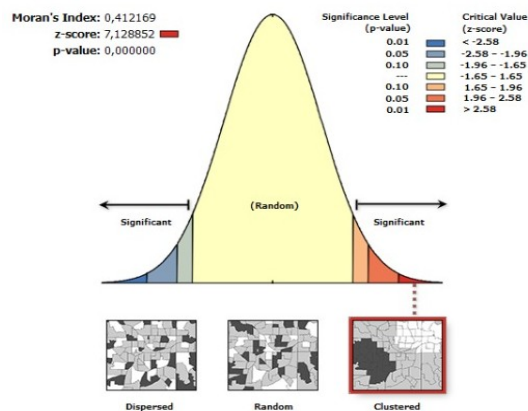


Figure 3. General Spatial Poverty Patterns in Gowa Regency Based on Moran's Index

Source: Data Analysis (2022)

The pattern of clustered poverty distribution explains that each village has a strong spatial influence on its poverty level. Villages that have a high poverty rate will affect other villages that are their neighbors. Every village with a low poverty rate has an impact on its surrounding villages.

The Local Indicators of Spatial Autocorrelation (LISA) investigation identified four quadrants: quadrant I (high-high), quadrant II (low-high), quadrant III (low-low), and quadrant IV (low-low).

- Quadrant I shows villages with high poverty rates that are near other villages with high poverty rates.
- Quadrant II illustrates villages with low poverty that are bordered by nearby villages with high poverty.
- Quadrant III describes villages near other villages with low levels of poverty.
- Quadrant IV indicates that high-poverty areas are bordered by low-poverty villages.

The table below illustrates the village classifications in Gowa Regency according to the findings of an analysis of the distribution and spatial patterns of poverty (Table 4):

Table 4. Categories of Villages in Gowa Regency Results of Analysis of Poverty Distribution and Spatial Patterns

<i>High-High</i>	Borisallo, Parigi, Lonjoboko, Tamalatea, Manuju, Manimbahoi, Bontotangnga, Bontoloe, Lassa-lassa, Ulujangang, Berutallasa, Julukanaya Biringbulu, Borimasunggu, Pencong, Datara, Rappoala, and Datara
<i>Low-high</i>	Erelembang and Desa Bilanrengi
<i>Low-Low</i>	Nirannuang, Sokkolia, Borongpa'la'la, Pattallasang, Tamanyeleng, Jenetallasa, Pallangga, Biringngala, Borimatangkasa, Toddotoa, Pakkatto, Paccellekang, Sunggumanai, and Pallangga.
<i>High-Low</i>	Lembangang, Romanglasa, Panyangkalang, and Bontoramba

Source: Data Analysis (2022)

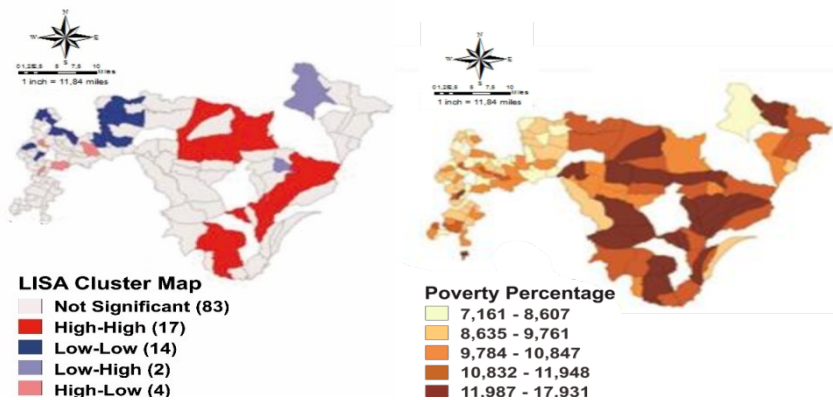


Figure 4. (a) Distribution Map of the Percentage of Poor Population (b) LISA Cluster Map

Source: Data Analysis (2022)

Figure 4 shows the frequency and spatial concentration of poverty in Gowa Regency. Recalling the regional typology analysis that is presented in table 3, the 17 villages in Gowa Regency that belong to the high-high category are located far away from the center of economic activities, thus limiting people residing in these village to engage in economic activities. On the contrary, the 14 villages that belong to the low-low category are located near the center of economic activities, thus making their residents easier to engage in economic activities. Two villages that belongs to the low-to-high category are not influenced by the nearby neighborhoods, i.e., villages with high poverty levels. Meanwhile, the 4 villages that fall into the high-low category are primarily agricultural land with a small number of farmer groups and are located near the center of economic activities.

Spatial Diversity Analysis of Factors Affecting Poverty in Rural Areas of Gowa Regency

The distribution value for each village is different according to the Geographically Weighted Regression (GWR) observation. Local values range (R^2) from 0.380716 –

0.717105 (Figure 5). This number shows that between 71-88% of the differences in poverty rates in Gowa Regency could be caused by the hypothesized independent variables.

The findings of the GWR analysis show the impact of the hypothesized variables on poverty in Gowa Regency. Table 5 demonstrates a variable effect on each village of the observation locations, as indicated by coefficient changes in the significance test at the levels of 0.05 and 0.1. A negative coefficient value suggests an influence of a variable in reducing poverty, while a positive coefficient value shows an influence of a variable in increasing poverty.

The minimum and maximum coefficient values as well as the level of significance allocation for each variable resulting from the GWR estimation are presented in Table 5

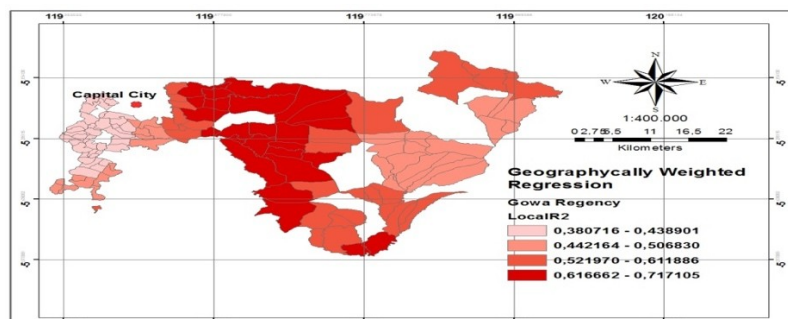


Figure 5. Distribution Map R^2 Local Estimates of the GWR Model and the Relationship Between Spatial Diversity (Independent Variable) Used for Poverty in Gowa Regency

Source: Data Analysis (2022)

Table 5. Variation of Coefficient Values and Distribution of Significance Levels of Variable GWR Estimation Results

Parameter	GWR Coefficient Parameter		Number of Significant Villages	
	Minimum	Maximum	Level Test 0,05	Level Test 0,10
Intersep	0,08344	0,15617	121	121
PDDK	-1,46957	-0,00694	97	101
LDES	0,00500	2,48904	93	101
KPLN	-1,94952	-0,00643	110	111
JRK	0,00206	0,68148	93	95
RFK	-5,16207	-0,00017	97	101
TKEL	-2,64784	-0,00052	76	79
KTANI	-1,44981	-0,00274	99	102
DD PEMDES	-5,00462	-0,00617	88	92

DD PPD	-3,09763	-0,00044	107	107
DD PKD	0,01437	4,11454	68	77
DD PMD	0,01678	13,52285	94	98
DD DB	-1,55604	-0,05150	104	107

Source: Data Analysis (2022)

Based on Table 5, there are nine variables that can reduce poverty, namely: 1) population (PDDK); 2) number of households using the country's electricity (KPLN); 3) educational facilities ratio (RFP); 4) health facilities ratio (RFK); 5) number of grocery stores (TKEL); 6) number of farmer groups (KTANI); 7) Village funds for village governance (DD PEMDES); 8) Village funds for development (DD PPD); and 9) Village funds for disaster management, emergencies, and urgent situations (DD DB). Meanwhile, the other 4 variables are indicated to increase poverty, namely: 1) rural territorial extension (LDES); 2) distance to regional capital (JRK); 3) village funds for the field of village community development (DD PKD); 4) village funds for village community empowerment (DD PMD)

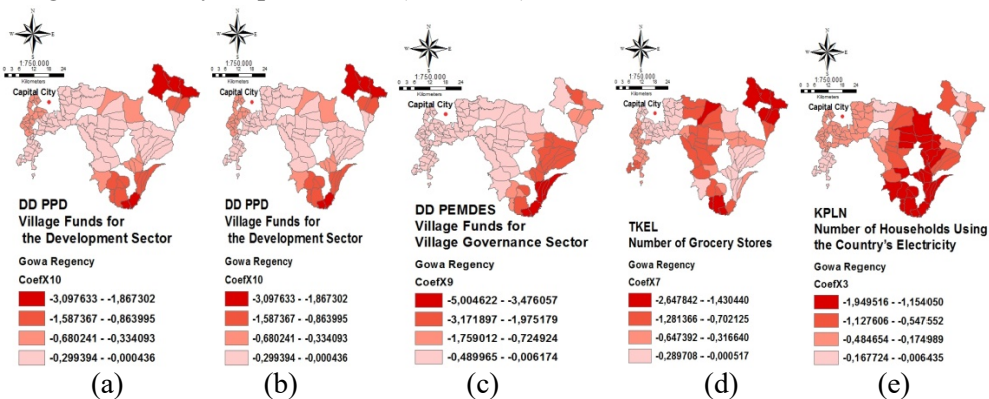


Figure 6. Distribution Map of the Most Influential Variable Coefficients for Reducing Poverty in Gowa Regency GWR Analysis (a) Number of households using the country's electricity (KPLN). (b) Health facility ratio (RFK). (c) Number of grocery stores (TKEL). (d) Village funds for village governance sector (DD PEMDES). (e) Village funds for the development sector (DD PPD)

Source: Data Analysis (2022)

4. Conclusion

The typology of villages resulted in our study indicate the different characteristics of villages in Gowa Regency. From our study, three typologies/clusters emerged: (1) Typology/cluster 1 comprises 67 villages, (2) Typology/cluster 2 comprises 23, and (3) Typology/cluster 3 comprises 31 villages. Each cluster has its distinct poverty profile. In particular, Cluster 1 consists of villages having low poverty rates, whereas clusters 2 and 3 consist of villages having relatively higher poverty rates. Furthermore, the spatial distribution and pattern of poverty in Gowa Regency's villages are

clustered, implying that poverty in one village is interconnected with poverty in other villages. Based on the spatial autocorrelation analysis, poverty profile of villages in Gowa Regency is mapped into four categories: 17 villages are in the high poverty category, surrounded by villages with high poverty rates (high-high); two villages are in the low poverty level category, surrounded by villages with high poverty rates (low-high); 14 villages are in the low poverty level category, surrounded by villages with low poverty levels (low-low); and four villages are in the high poverty category, surrounded by villages with low (high-low) poverty rates. The variables used have varying effects on each village/observed location, according to the GWR analysis results. Different policy recommendations for each village can be developed based on the various influences from each observation location. This strategy has the potential to improve policy efficacy and targeting.

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