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Fuzzy Geographically Weighted Clustering Analysis of Poverty Indicators in South Sulawesi, Indonesia

Nurawalia Annisa, Muhammad Kasim Aidid, Sitti Masyitah Meliyana*

Universitas Negeri Makassar, Makassar, 90224, Indonesia

Abstract

Cluster analysis is a method used to group data into several clusters, where the data within a single cluster exhibit high similarity, while the data between clusters show low similarity. This study aims to classify the regencies and cities in South Sulawesi based on poverty indicators using the Fuzzy Geographically Weighted Clustering (FGWC) method. FGWC is an integration of the classical fuzzy clustering approach with geo-demographic components, incorporating geographical aspects into the analysis. As a result, the clusters formed are sensitive to environmental effects, which influence the values of cluster centers. In this study, the optimal number of clusters was determined using the IFV (Index of Fuzzy Validity) validity index, which indicated an optimal solution of three clusters. Cluster 1 consists of 9 regencies/cities characterized by a high level of poverty. Cluster 2 comprises 7 regencies/cities with a moderate level of poverty. Cluster 3 includes 8 regencies/cities with a low level of poverty.

Keywords: Cluster Analysis, Fuzzy Geographically Weighted Clustering, Poverty Indicators

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1. Introduction

Cluster analysis is a statistical method used to group objects or variables into clusters such that the objects within a cluster are more similar to each other than to those in other clusters (Johnson & Wichern, 2007). It groups a set of n objects based on p variables that share relatively similar characteristics, resulting in lower intra-cluster variance compared to inter-cluster variance. The objects being clustered may include goods, services, plants, animals, or individuals (such as respondents, consumers, or others). These objects are classified into one or more clusters based on shared attributes or characteristics (Paramadina et al., 2019).

Poverty is not a uniform phenomenon. Poverty levels, contributing factors, and the strategies for addressing them vary significantly across different regions, even within relatively small geographical areas. One method capable of analyzing poverty levels in a region is Fuzzy Geographically Weighted Clustering (FGWC), which provides a more accurate and detailed picture of poverty conditions across regions. FGWC is an enhancement of the Fuzzy C-Means (FCM) algorithm, integrating geographic elements into the clustering process. The spatial effects are considered in the calculation of membership values in the FGWC algorithm (Mason & Jacobson, 2006). According to Son, Cuong, Lanzi, and Thong (2012), FGWC is a suitable algorithm for handling regional effects (Mashfufah et al., 2021). To address spatial interaction errors, this method applies fuzzy clustering, in which each region is assigned a degree of membership to multiple clusters rather than being assigned exclusively to one. The movement or interaction among different regions is referred to as spatial interaction (Syifa Nabilah Wandira et al., 2023).

South Sulawesi Province is one of the regions in Indonesia still facing persistent poverty issues. Although it is considered one of the more economically advanced provinces, the poverty rate remains relatively high. Among the provinces on Sulawesi Island, South Sulawesi has the largest number of people living in poverty, with an average of 915.11 thousand individuals between 2005 and 2019. As of September 2019, the number stood at 759.58 thousand people. The well-being of impoverished communities in South Sulawesi remains stagnant due to a lack of resources and

* Corresponding author.
E-mail address: sittimasyitahmr@unm.ac.id

capital, as well as limited knowledge and education, which hinder their employment opportunities unless they engage in self-employment.

Government intervention is crucial in tackling poverty in South Sulawesi. To effectively address this issue, policymakers require accurate information regarding the spatial distribution of poverty indicators (Maliku et al., 2022). One approach to obtaining such information is through clustering based on economic development indicators across all regencies and cities in South Sulawesi. The resulting clusters can reveal areas with varying levels of development, thereby aiding the government in prioritizing regions with lower economic development. Clustering based on economic indicators should incorporate geographical effects, which can be achieved using the FGWC method.

Several studies have explored the application of FGWC. For instance, Nugroho (2019) conducted a study on clustering Human Development Index (HDI) indicators using FGWC and identified five optimal clusters. Another study by Sumayya (2016) used FGWC to cluster public welfare indicators and obtained three optimal clusters. Additionally, Hadi et al. (2017) employed FGWC to cluster stunting factors among children under five in East Java Province, resulting in three optimal clusters using the IFV validity index. This study aims to cluster the regencies and cities in South Sulawesi Province based on poverty indicators, with the goal of producing geographically sensitive groupings that account for both population effects and spatial distances in the calculation of membership weights. The resulting clusters are expected to support strategic planning by the government in addressing interregional poverty disparities in South Sulawesi.

2. Literature Review

2.1. Cluster Analysis

Cluster analysis is a method used to group data into several clusters in such a way that the data within a single cluster exhibit high similarity, while data across different clusters have low similarity. It is a classification technique employed to categorize objects or cases (respondents) into relatively homogeneous groups known as clusters (Windasari, 2020). Cluster analysis emphasizes comparing objects based on their variables. Most clustering methods are algorithm-driven rather than based on extensive theoretical reasoning (Manfaati Nur et al., 2023).

2.2. Fuzzy Geographically Weighted Clustering (FGWC)

Fuzzy Geographically Weighted Clustering (FGWC) is a clustering method developed to overcome the limitations of traditional clustering techniques such as Fuzzy C-Means (FCM). According to Wijayanto and Purwarianti (2014), in FGWC, the spatial interaction between regions is interpreted through the population of each area. The updated membership degree of each object is recalculated in every iteration using the following equation (Nugroho, 2019):

$$\mu'_{\text{i}} = \alpha\mu_i + \beta \frac{1}{A} \sum_j^n w_{ij}\, \mu_j \tag{1}$$

where: μ'_{i} is updated membership value of object I; μ_i is previous membership value of object i; w_{ij} is weight representing spatial interaction between areas i and j; A is normalization constant to ensure weights do not exceed 1

The membership weight w_{ij} is defined as follows (Nugroho, 2019):

$$w_{ij} = \frac{(m_i m_j)^2}{d_{ij}^a} \tag{2}$$

where: m_i is population of area I; m_j is population of area j; d_{ij} = distance between area i and area j

In this study, Euclidean distance is used to measure spatial distance. Euclidean distance is defined as the straight-line distance between two locations, calculated using the coordinates of the centroid (latitude and longitude). The equation is as follows (Hidayah, 2024):

$$\boldsymbol{d_{ij}} = \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} \tag{3}$$

where:

d_{ij} is distance between region i and region j; x_i, x_j is latitude coordinates of regions i and j, respectively; y_i, y_j is longitude coordinates of regions i and j, respectively

The parameters a and b are determined based on the relative importance of population and distance. If both factors are considered equally important, then both a and b are set to 1 (Wijayanto, Purwarianti, & Son, 2016).

2.3. Objective Function of FGWC

FGWC addresses the initialization weaknesses of Fuzzy C-Means by incorporating geographic influence into clustering. The objective function of FGWC is expressed as follows (Nugroho, 2019):

$$\boldsymbol{J_{FGWC}(U,V;X)} = \sum_{i=k}^{C}\sum_{k=1}^{n} \boldsymbol{u_{ik}^{m}} \ \|\boldsymbol{v_i} - \boldsymbol{x_k}\|^2 \tag{4}$$

where: U is membership matrix; V is cluster center matrix; X is data matrix; $\boldsymbol{v_i}$ is cluster center for object i; $\boldsymbol{u_{ik}}$ is element of the membership matrix; $\boldsymbol{x_k}$ is data point k; m is fuzziness coefficient (m > 1) indicating the degree of fuzziness

The cluster center $\boldsymbol{v_i}$ is defined as (Nugroho, 2019):

$$\boldsymbol{v_i} = \frac{\sum_{k=1}^{n} \boldsymbol{u_{ik}^{m}} x_k}{\sum_{k=1}^{n} \boldsymbol{u_{ik}^{m}}} \tag{5}$$

where:

n is number of data points; $\boldsymbol{v_i}$ is cluster center for region i; $\boldsymbol{u_{ik}}$ is membership degree of region i in cluster k; $\boldsymbol{x_k}$ is data point; m is fuzziness coefficient

2.4. Elbow Method

The Elbow Method is commonly used to determine the optimal number of clusters by identifying the "elbow point" on a graph, which represents the point where the within-cluster variance (SSE) starts to decrease more slowly (Madhulatha, 2012). A sharp decline at a specific point suggests the ideal number of clusters. SSE is calculated as follows (Dewi & Pramita, 2019; Hidayah, 2024):

$$\boldsymbol{SSE} = \sum_{K=1}^{K}\sum_{X_i \in S_k} \|\boldsymbol{X_i} - \boldsymbol{C_k}\|_2^2 \tag{6}$$

where:

K is number of clusters; $\boldsymbol{X_k}$ is data point in cluster k; $\boldsymbol{C_k}$ is center of cluster k

2.5. Validity Index

In fuzzy clustering, each data point may belong to multiple clusters with varying degrees of membership. To identify the optimal number of clusters, a validity index is employed. One widely used validity index for fuzzy clustering is the IFV index, which has demonstrated stability and reliability in spatial data clustering (Chunchun et al., 2008). The higher the IFV value, the better the clustering quality. The IFV index is calculated as follows (Nugroho, 2019):

$$IFV = \frac{1}{c}\sum_{j}^{c}\left\{\frac{1}{N}\sum_{k=1}^{N}\mu_{kj}^2 \ \left[log_2 c - \frac{1}{N}\sum_{k}^{N} log_2\, \mu_{kj}^2\right]^2 \frac{SD\ max}{\sigma\ D}\right\} \tag{7}$$

where: μ_{kj} is membership value of data point j in cluster I; N is total number of data points; c is number of clusters

2.6. Data Standardization

Data standardization is essential when the variables in a dataset have different units of measurement. This study applies min-max normalization using the following formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{8}$$

where:

X' is standardized value; X is original value; X_{min} is minimum value in the dataset; X_{max} is maximum value in the dataset.

2.7. Poverty

According to Statistics Indonesia (Badan Pusat Statistik, 2022), poverty is a condition in which individuals or households lack sufficient access to basic needs such as food, clothing, and adequate shelter. Poverty is measured through indicators such as income level, asset ownership, or consumption. BPS defines poverty through a multidimensional approach that includes food, clothing, and housing. Poverty is a complex issue influenced by socioeconomic, cultural, and structural factors. Chronically poor households often remain in poverty due to deep-rooted structural barriers (Nurohmah et al., 2023).

2.8. Poverty Indicators

Yacoub (2012) highlights that poverty is a fundamental issue because it relates to the fulfillment of essential human needs. Poverty is also a global problem affecting many countries. The World Bank (2004) attributes poverty to a lack of income and assets, which hampers the ability to meet basic needs such as food, clothing, housing, health, and education. Furthermore, poverty is associated with limited employment opportunities, high unemployment rates, and generally low levels of education and health among the poor (Ferezegia, 2018).

3. Methods

This study employs a quantitative research design. Quantitative research involves collecting the required data and analyzing it using the Fuzzy Geographically Weighted Clustering (FGWC) method. The data used in this research are secondary data obtained from the official website of Statistics Indonesia (Badan Pusat Statistik/BPS) for South Sulawesi Province (https://sulsel.bps.go.id/). The variables used in this study are defined as follows:

1) Poverty Rate (%).

   Poverty is typically defined as the extent to which an individual falls below the minimum acceptable standard of living as determined by society or community (Padambo et al., 2021). The poverty rate refers to the percentage of the population living below the poverty line. A high poverty rate indicates a higher level of poverty in a given region (Badan Pusat Statistik, 2018; Ferezegia, 2018). Niemietz defines poverty as the inability to afford basic necessities such as food, clothing, housing, and medicine (Maipita, 2013).

2) Poverty Severity Index

   The Poverty Severity Index provides an overview of expenditure inequality among the poor population. It offers complementary information to the poverty incidence index.

3) Poverty Depth Index

   The Poverty Depth Index measures the average shortfall of poor individuals' expenditures compared to the poverty line. It reflects the depth or intensity of poverty within a population.

4) Expected Years of Schooling

   Expected years of schooling is the number of years a child of a certain age is expected to attend school in the future, assuming age-specific enrollment ratios remain the same (Badan Pusat Statistik, 2021).

5) Per Capita Expenditure

   Per capita expenditure is used as a measure of an individual's standard of living. It is influenced by knowledge and the opportunities available to utilize that knowledge in productive activities, leading to the production of goods and services as sources of income.

Data analysis was conducted to process and interpret the data in the context of the research objectives. The steps taken in this study are as follows:

1) Collecting secondary data from the Statistics Indonesia (BPS) website for South Sulawesi Province.
2) Performing descriptive analysis for each poverty indicator in the districts and municipalities of South Sulawesi Province.
3) Standardizing the data using appropriate normalization techniques.
4) Determining the optimal number of clusters using the Elbow Method in the context of FGWC.
5) Performing clustering using the Fuzzy Geographically Weighted Clustering (FGWC) algorithm, which involves:
   a. Setting initial parameters
   b. Defining geographic weights
   c. Constructing the initial membership matrix
   d. Calculating the cluster centers
   e. Updating the membership values by incorporating geographic effects
   f. Obtaining the final clustering results
6) Analyzing the characteristics of each resulting cluster.
7) Drawing conclusions based on the findings.

4. Result and Discussion

4.1. Descriptive Analysis

Descriptive analysis was conducted to provide an overview of the poverty indicator data in South Sulawesi Province for the year 2023. The data were obtained from the official website of the Central Statistics Agency (BPS) of South Sulawesi. Table 1 presents the descriptive statistics of these indicators.

Table 1. An example of a table.

Indicator	Minimum	Maximum	Mean
Poverty Rate (%)	5,07	13,40	9,33
Poverty Severity Index	0,10	0,70	0,36
Poverty Depth Index	0,54	2,47	1,46
Expected Years of Schooling (Years)	12,12	15,61	13,39
Expenditure per Capita (Thousands IDR)	8017	17889	11685

The average poverty rate across South Sulawesi in 2023 was 9.33%, with the lowest rate recorded in Makassar City (5.07%) and the highest in Jeneponto District (13.40%). The average Poverty Severity Index stood at 0.36, ranging from 0.10 in Sidenreng Rappang (Sidrap) to 0.70 in North Toraja. Meanwhile, the Poverty Depth Index had an average of 1.46, with Sidrap recording the lowest (0.54) and North Toraja the highest (2.47). The average expected years of schooling was 13.39 years, with Jeneponto having the lowest (12.12 years) and Makassar City the highest (15.61 years).

4.2. Data Normalization

To ensure comparability across indicators with different units, min-max normalization was applied. This method linearly transforms the original data into a 0–1 scale using the formula (8). For example, for the poverty rate (X1) in Bantaeng, where the raw value is 9.18, the maximum is 13.40, and the minimum is 5.07, the normalized value is:

$$X' = \frac{9{,}18 - 5{,}07}{13{,}40 - 5{,}07} = \frac{4{,}11}{8{,}33} = 0{,}4933$$

Thus, the normalized value for Bantaeng on variable X1 is 0.4933.

4.3. Determining Parameters for Fuzzy Clustering

Initial parameters in fuzzy clustering include the number of clusters ccc, fuzziness mmm, maximum iterations t_{max} and convergence threshold ε. Fuzziness was evaluated at $m = 1.5$, $m = 2.0$, and $m = 2.5$ using the Improved Fuzzy Validity (IFV) index. The results are summarized in Table 2.

Table 2. IFV Scores for Different Fuzziness Levels and Cluster Counts

Fuzziness (m)	*Cluster* Count(c)	IFV Score
$\boldsymbol{m = 1,5}$	2	30,641
	3	**43,2865**
	4	37,5678
	5	41,8782
	6	40,9213
$m = 2$	2	25,5614
	3	29,3612
	4	27,2201
	5	17,8190
	6	20,7030
$m = 2,5$	2	24
	3	26,7958
	4	24
	5	17,8190
	6	20,7030

The highest IFV score was obtained at $m = 1.5$ and $c = 3$ indicating this as the optimal parameter combination for the fuzzy clustering model.

Table 3. Selected Initial Parameters for FGWC

Cluster Count (c)	*Fuzziness*	Max. Iteration	*Threshold*
$\mathbf{2-6}$	$\boldsymbol{m = 1,5}$	$\boldsymbol{t_{max} = 1000}$	$\boldsymbol{\varepsilon = 10^{-5}}$

4.4. Fuzzy Geographically Weighted Clustering (FGWC)

4.4.1. Determining Optimal Cluster Count

1) Elbow Method

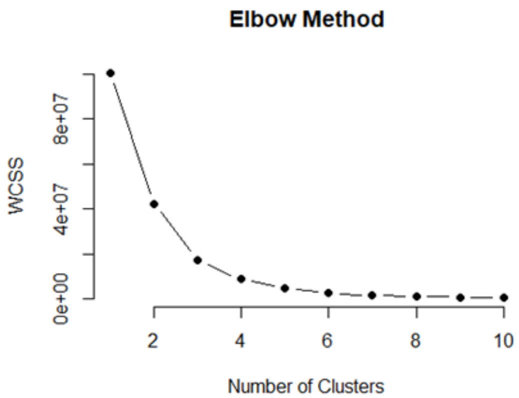

Figure 1. Graph of *Elbow* Method

The Elbow Method was used to determine the appropriate number of clusters based on Within-Cluster Sum of Squares (WCSS). A sharp decline or "elbow" in the WCSS plot indicates the optimal number of clusters. As shown in Figure 1, the most significant decrease occurs between cluster 2 to 3 and 3 to 4, suggesting that the optimal number of clusters lies between 3 and 4.

2) *Improved* Fuzzy Validity Index (IFV)

To confirm the optimal cluster count, the IFV index was again evaluated for $c = 2$ throught $c = 6$, as presented in Table 4.

Table 4. IFV Scores for Cluster Counts

Jumlah *Cluster*	Indeks Validitas IFV
2	30,641
3	43,2865
4	37,5678
5	41,8782
6	40,9213

Cluster **3** yielded the highest IFV score, thus it was selected as the optimal clustering solution for classifying the 24 districts/cities based on poverty indicators.

4.4.2. Geographical Weighting Matrix

Geographical weighting was computed using population data and inter-regional distances to form a 24×24 matrix. For instance, the geographic weight between Bantaeng (region 1) and Barru (region 2) was calculated as follows:

Coordinates:

- Bantaeng: $x_1 = -4.6954\,, y_1 = 120.1293$
- Barru: $x_2 = -5.43158\,, y_2 = 120.2352$

$$\boldsymbol{d_{1,2}} = \sqrt{(\boldsymbol{x_1} - \boldsymbol{x_2})^2 + (\boldsymbol{y_1} - \boldsymbol{y_2})^2} == \sqrt{\boldsymbol{0,5419609924 + 0,01121481}} = \boldsymbol{0,7438}$$

With population $m_1 = 203140, m_2 = 187950$ and parameter $a = b = 1$;

$$\boldsymbol{w_{1,2}} = \boldsymbol{w_{2,1}} = \frac{(\boldsymbol{m_1 m_2})^{\boldsymbol{b}}}{\boldsymbol{d_{1,2}^{a}}} == \frac{\boldsymbol{38180163000}}{\boldsymbol{0,7437}} = \boldsymbol{51443361158,1}$$

Geographic weights for all regions were calculated similarly, and a matrix was constructed (Appendix 4). Diagonal entries are zero since no region influences itself.

4.4.3. Initialization of Membership Matrix

The initial fuzzy membership matrix U was generated with dimensions $n\ x\ c$, where $n = 24$ and $c = 3$. Each row of U represents the degree of membership of a region to each cluster and must sum to 1. These values were randomly initialized using RStudio. An example is shown in Table 5.

Table 5. Initial Membership Degrees (Partial View)

Kabupaten/Kota	$\boldsymbol{u_{i1}}$	$\boldsymbol{u_{i2}}$	$\boldsymbol{u_{i3}}$	$\sum \boldsymbol{u_{ik}}$
Bantaeng	0.2029933	0.4904542	0.3065525	1
Barru	0.2274464	0.6087126	0.1638410	1
Bone	0.2426073	0.4641138	0.2932789	1
…	…	…	…	…
Toraja Utara	0.5871420	0.2409966	0.1718614	1
Wajo	0.1940662	0.5410991	0.2648347	1

4.4.4. Cluster Centroid Calculation

The determination of cluster centroids aims to measure the proximity or distance of a data point to the center of each cluster. In the FGWC (Fuzzy Geographically Weighted Clustering) algorithm, each object is assigned to the cluster with the shortest distance to its corresponding centroid. The centroid values represent the weighted average of each indicator variable within the formed clusters. The results of the centroid calculations are presented in Table 6.

Table 6. Cluster Centroid Values

4.4.5. Membership Degree Matrix

Following the determination of cluster centroids and the application of geographical weighting in the membership matrix, the degree of membership for each object in the FGWC model is obtained. The membership degree matrix illustrates the extent to which each district/city belongs to the respective clusters. Each observation is assigned to the cluster with the highest membership degree value. Table 7 presents the membership degrees and the resulting cluster classification for each district/city in South Sulawesi Province.

Table 7. Membership Degrees and Final Cluster Assignment

Variable	*Cluster 1*	*Cluster 2*	*Cluster 3*
X_1	0.7177	0.4279	0.3500
X_2	0.6215	0.4194	0.2459
X_3	0.6792	0.4300	0.2918
X_4	0.3232	0.3557	0.4183
X_5	0.3152	0.3893	0.4149

District/City	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster*
Bantaeng	0,2029	**0,4904**	0,3065	2
Barru	0,2264	**0,6087**	0,1638	2
Bone	0,2426	**0,4641**	0,2932	2
Bulukumba	0,2392	0,1700	**0,5906**	3
Enrekang	**0,5797**	0,2676	0,1526	1
‘’	**‘’**	‘’	‘’	‘’
Toraja Utara	**0,5871**	0,2409	0,1718	1
Wajo	0,1940	**0,5410**	0,2648	2

As shown in Table 7, each district or city is assigned to a specific cluster based on the highest membership degree. This classification reflects the degree of association of each district/city with a particular cluster, indicating its tendency to share similar characteristics with other members of the same cluster.

4.4.6. Cluster Results

Based on Table 4, the results of the FGWC analysis formed three optimal clusters. The number of members in each cluster and the corresponding districts/cities are presented in Table 8.

Table 8. Cluster Results

Cluster	District/City
1	Enrekang, Jeneponto, Kepulauan Selayar, Luwu, Luwu Utara, Maros, Pangkep, Tana Toraja, Toraja Utara
2	Bantaeng, Barru, Bone, Luwu Timur, Pinrang, Soppeng, Wajo
3	Bulukumba, Gowa, Makassar, Palopo, Pare-pare, Sidrap, Sinjai, Takalar

4.4.7. Cluster Characteristic Analysis

Each resulting cluster exhibits distinct characteristics based on the poverty indicator variables in South Sulawesi Province. The classification of each cluster is determined by comparing the average values of each indicator derived from the cluster centroids (Table 6) to the global mean of each indicator variable.

Table 9. Average Indicator Values for Each Cluster

Variable	*Cluster 1*	*Cluster 2*	*Cluster 3*
X_1	0,7177	0,4279	0,3500
X_2	0,6215	0,4194	0,2459
X_3	0,6792	0,4300	0,2918
X_4	0,3232	0,3557	0,4183
X_5	0,3152	0,3893	0,4149

Table 10. Global Average of Each Indicator

Variabel	Rata-rata Global
X_1	0,5116
X_2	0,4395
X_3	0,4788
X_4	0,3643
X_5	0,3715

The following criteria were used to categorize each cluster based on the indicator averages:

- High: Indicator average > Global mean
- Medium: Indicator average ≈ Global mean
- Low: Indicator average < Global mean

Based on the values shown in Tables 9 and 10, the characteristics of the three clusters can be interpreted as follows:

1) Cluster 1 is categorized as high on three poverty indicators: Percentage of Poor Population (X_1), Poverty Severity Index (X_2), and Poverty Depth Index (X_3). The remaining two indicators fall into the low category. This implies that districts/cities in Cluster 1 exhibit high poverty status based on the poverty indicators.
2) Cluster 2 falls into the medium category across all indicators. This suggests that the poverty status of the districts/cities in Cluster 2 is at a moderate level.

Cluster 3 is characterized by low values in three indicators—Percentage of Poor Population (X_1), Poverty Severity Index (X_2), and Poverty Depth Index (X_3)—and high values in the remaining two indicators. This indicates that districts/cities in Cluster 3 generally experience lower levels of poverty according to the poverty indicators.

5. Conclusion

5.1. Conclusion

Based on the research findings and discussions conducted, the following conclusions can be drawn:

1) The lowest percentage of poor population was recorded in Makassar City at 5.07%, while the highest was observed in Jeneponto Regency at 13.40%. The average percentage of the poor population relative to the total population in South Sulawesi Province in 2023 was 9.33%.
2) The clustering of districts/cities in South Sulawesi Province using the Fuzzy Geographically Weighted Clustering (FGWC) method resulted in three optimal clusters. Cluster 1 consists of 9 districts/cities representing areas with high poverty status. Cluster 2 includes 7 districts/cities representing areas with moderate poverty status. Cluster 3 comprises 8 districts/cities representing areas with low poverty status.

5.2. Recommendations

1) Future research is encouraged to incorporate more diverse datasets and include additional relevant variables to enhance clustering accuracy.
2) Communities are encouraged to increase participation in government programs or initiatives aimed at improving the economic conditions of households or communities collectively.

3) The government should prioritize areas identified with high poverty status by strengthening infrastructure and developing programs tailored to the specific needs of the local population.

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