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Grouping Districts / Cities in Central Sulawesi Province Based on Poverty Indicators Using the Fuzzy Geographically Weighted Clustering -Artificial Bee Colony Method

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ABSTRACT

Introduction: Poverty is the main problem that is the focus of attention of the government in Indonesia. In general, poverty is a person's inability to meet basic basic needs in every aspect of life. Cluster analysis is a solution to map this problem. **Method:** Fuzzy Geographically Weighted Clustering-Artificial Bee Colony (FGWC-ABC) is one clustering method that is an integration of classical fuzzy clustering methods and geodemographic elements. Artificial Bee Colony is a metaheuristic algorithm that is used as a global optimization to increase cluster accuracy. Artificial Bee Colony can efficiently and effectively solve various function optimization problems in various cases. **Result and Discussion:** The research results obtained 3 optimum clusters with each cluster characteristic relatively different based on poverty indicators. Cluster 1 with low poverty, cluster 2 with high poverty, and cluster 3 with moderate poverty. **Conclusion:** By using the IFV validity index, 3 optimum clusters were obtained with different characteristics of each cluster based on its indicators. Cluster 1 consists of three regencies/cities with low poverty status, cluster 2 consists of seven regencies/cities with high poverty status, and cluster 3 consists of six regencies/cities with moderate poverty status.

1. Introduction

Poverty is a situation where there is a lack of resources such as food, clothing, shelter, natural resources, human resources, and things that are closely related to quality of life. Poverty is a major problem that is the focus of government attention in Indonesia. In general, poverty is the inability of a person to meet the basic needs of standards for every aspect of life [1].

Based on 2022 data from the Central Statistics Agency (BPS), the number of poor people in Central Sulawesi is 389.71 thousand people. In percentage terms, the poverty rate in Central Sulawesi Province is 12.30%. This is because Central Sulawesi Province consists of 13 regencies/cities with highly variable poverty rates. In 2022, Palu City had the lowest poverty rate at 6.63%, followed by Banggai Regency at 7.33%, while the other 11 districts averaged above 10% and Tojo Una-una Regency had the highest percentage at 16.12%. Although there has been a decrease in poverty from 2013 to 2021, this poverty condition needs to be watched out for, because most of the population is below the poverty line and some are around the poverty line.

The poverty data is known for each Regency / City of Central Sulawesi Province which is different. So the handling in overcoming the problem of poverty in each region is different [2]. Therefore, there is a need for government efforts to overcome this problem, so the government needs accurate information in seeing the distribution of areas with poverty indicators. One way to get accurate information is by clustering based on poverty indicators, the results of the clustering can provide an overview in the form of areas with poverty levels in each Regency / City in Central Sulawesi. This can help the government in determining priority areas. This indicator clustering can be done by considering *geographical* effects using the *Fuzzy Geographically Weighted Clustering* (FGWC) method integrated with the *Artificial Bee Colony (*ABC) algorithm.

The clustering process using FGWC - ABC is carried out with the following steps:

a) Data normalization using the Min-Max normalization method. This method uses the following equation:

$$ndata = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

with:
$ndata$: Normalized data
x : Data to be normalized
$min(x)$: Minimum value of x
$max(x)$: Maximum value of x

b) Determine the initial parameters, namely the number of clusters formed (k ≥2), fuzziness (m>1), maximum iteration (t_max), and smallest error (ε).
c) Initialize the cluster centers using the ABC algorithm.
d) Determine the initial membership degree using the following formula:

$$\mathbf{U}= \begin{bmatrix} \mu_{11}(x_1) & \mu_{12}(x_1) & \cdots & \mu_{1k}(x_1) \\ \mu_{21}(x_2) & \mu_{22}(x_2) & & \mu_{2k}(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{n1}(x_n) & \mu_{n2}(x_2) & \cdots & \mu_{nk}(x_n) \end{bmatrix} \quad (2)$$

e) Modify the geographic cluster as follows:

$$w_{ij} = \begin{cases} \frac{(m_i m_j)^b}{d_{ij}^a}, i \neq j \\ 0, i = j \end{cases} \quad (3)$$

with :
m_i : Total population of the i-th region
m_j : Total population of the jth region
d_{ij} : Distance between i-th region and j-th region
a : Distance effect weighting
b : Population effect weighting

f) Refine the final membership matrix

$$\mu_i' = \alpha\mu_i + \beta\frac{1}{A}\sum_j^n w_{ij}\mu_j \quad (4)$$

with :
μ_i' : new membership value of object to i
μ_i : old urbanization value of an object to i
w_{ij} : a measure weighing a number of interactions between regions
α, β : Multiplier for the old membership value and the weighted value of the average membership of other observation units.
A : Value to ensure the weight value is not more than 1

g) If $V^{(t+1)} - V^{(t)} \leq \varepsilon$ or $(t \geq t_{max})$ then stop, otherwise go back to step (c) $V^{(t)} = V^{(t+1)}$.

2. Research Methods

The data research location is located at the Central Bureau of Statistics (BPS). The research site was at the Applied Statistics Laboratory of the Statistics Study Program, Department of Mathematics, Faculty of Mathematics and Natural Sciences, Tadulako University. The population and samples used in this study were 13 districts/cities in Central Sulawesi in 2022.

The data used in this research is secondary data obtained from the Central Sulawesi Statistics Agency (BPS) based on district/city. The variables that will be used in this study are 10 poverty variables. Data analysis in this study used the help of R *Studio software*. The stages of analysis used are as follows: :

1. Collecting secondary data from the official website of BPS Central Sulawesi province
2. Construct an n x m matrix, where n is the number of observations (13 districts/cities in Central Sulawesi Province) and m is the number of indicators (10 indicators).
3. Conduct descriptive statistical analysis for each variable of poverty indicators in districts/municipalities in Central Sulawesi Province.
4. Normalizing district/city poverty indicator data in Central Sulawesi Province
5. Determining the optimal number of *clusters* in FGWC-ABC analysis using the IFV validity index
6. Perform the steps of the FGWC-ABC algorithm as follows:
   a) Determine the initial parameters of FGWC, namely the number of *clusters (c)*, *fuzziness* value, maximum iteration, and *threshold* value.
   b) Initialize the *cluster* center
   c) Determine the initial membership degree
   d) Modify geographic *clusters*
   e) Refine the final membership matrix
   f) If $V^{(t+1)} - V^{(t)} \leq \varepsilon$ or $(t \geq t_{max})$ then stop, otherwise go back to step (c) $V^{(t)} = V^{(t+1)}$.
7. Data visualization of *clustering* results in the form of a map of the Central Sulawesi Province area
8. Draw conclusions
9. Finish.

3. Results and Discussion

3.1 Data Normalization

The data in this study has different of measurement between variables, so the original data be normalized first before using *Fuzzy Geographically Weighted Clustering - Artificial Bee Colony* analysis. The following is the normalized data obtained using equation (1)

Table1. Normalization Result Data

District/City	X_1	X_2	X_3	....	X_8
Banggai islands	1	0	0.70423	....	0.31355
Banggai	0.92927	0.34475	0.07238	....	0.55447
Morowali	0.14575	0.3683	0.6153	....	0.43401
Poso	0.86346	0.04282	0.88417	....	0.2604
Donggala	0.84009	0.29122	1	....	0.84588
Toli-Toli	0.38929	0.39186	0.63185	....	0.72542
Buol	0.66482	0.34047	0.64322	....	0.71036
Parigi Moutong	0.96432	0.04925	0.82730	....	1
Tojo Una-una	0.62115	0.33618	0.98138	....	0.62710
Sigi	0.88068	0.32976	0.58634	....	0.39946
Banggai Laut	0	0.45396	0.67631	....	0.63596
North Morowali	0.71094	0.16488	0.65563	....	0.55535
Hammer	0.40344	1	0	....	0

3.2 Determining the Optimum Number of *Clusters*

The optimum number of *clusters is* obtained by simulating *clusters of* 2 to 5 using the *Fuzzy Geographically Weighted Clustering* method. *Cluster* simulation is carried out only up to 5 *clusters* by considering the amount of data used in this study is 13 data. The number of *clusters* to be used is determined based on the optimum *cluster* criteria given by the IFV validity index value. Simulation of the optimum number of *clusters* obtained the following results.

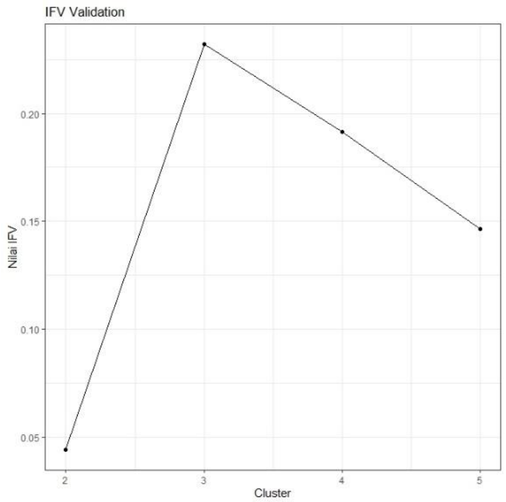

Figure 1. Plot of IFV Validity Index Values

The figure 1 above shows the value of the IFV validity index at *cluster* numbers 2 to 5. Determination of the optimum number of clusters on the IFV validity index can be known from the maximum IFV validity index value. Based on the plot above, the IFV validity index gives the maximum value at the number of *clusters* 3, so the grouping of districts/cities in Central Sulawesi Province based on 10 poverty variables uses 3 *clusters*.

3.3 Fuzzy Geographically Weighted Clustering Analysis - Artificial Bee Colony

1) Determining Initial Parameters

The FGWC ABC method first determines the initialization of the parameters to be used, namely determining the number of *clusters* (c), *fuzziness* (m), maximum iteration (t_{max}), smallest *error* (a), and population effect (b). (ε), distance effect weighting (a), and population effect weighting (b). The number of *clusters* used is 3 *clusters* based on the test results using the IFV validity index. *Fuzziness* (m) used is m = 2, and the maximum iteration is 100, in terms of determining the number of limits of the maximum iteration there are no rules governing the limits of the maximum number of iterations. The *threshold* value used is 1×10^{-5} or 0.00001. Then, to determine the distance effect weight (a) and population effect weight (b) if it is assumed that spatial interactions have the same impact as demographic features of community behavior, then: $a = b = 1$, then the researcher uses the value of $a = 1$ and $b = 1$. The value of the number of *clusters*, *fuzziness*, maximum iteration, smallest *error*, distance effect weight, and population effect weight can be seen in the following table.

Table 2. Initial Parameters

Cluster	***Fuzziness (m)***	**Maximum Iterations (t_{max})**	**Smallest *Error* (ε)**	**Distance Effect Weighting (a)**	**Population Effect Weights (b)**
3	2	100	1×10^{-5}	1	1

2) Calculating P Cluster

Determining the *cluster* center aims to determine the distance of data to the *cluster* center. A data object is included in a *cluster* if it has the shortest distance to the *cluster* center. The *cluster* center values obtained are as follows

Table 3. Cluster Center Value

Variables	**Cluster 1**	**Cluster 2**	**Cluster 3**
X_1	0.6452115	0.6706945	0.6154751
X_2	0.3223577	0.3141361	0.3095062
X_3	0.621612	0.6550858	0.6344961
X_4	0.230008	0.2050119	0.2640375
X_5	0.3281373	0.2775497	0.4284244
X_6	0.3202723	0.2766937	0.3925414
X_7	0.3743772	0.3894433	0.3608865
X_8	0.2208626	0.2151512	0.2234787
X_9	0.4384981	0.4220727	0.3915478
X_{10}	0.5344167	0.5826636	0.5055537

3) Determining the Initial Membership Degree

Determining the value of the initial degree of membership with size $n \times c$ where n is a lot of data, while c is a lot of *clusters*. The sample data used is 13 and the *clusters to* be formed are 3 *clusters*. What must be done is to generate *random* numbers partition matrix **U** with components μ_{ik}, with $i = 1, 2, 3, \cdots, 13$; $k = 1, 2, 3$; as the initial membership degree value. The value is determined randomly with the condition that the number of element values in each row is 1.

Table 4. Initial Membership Degree Values

District/City	μ_{i1}	μ_{i2}	μ_{i3}	$\sum \mu_{ik}$
1	0.4266	0.2064	0.367	1
2	0.3128	0.3416	0.3457	1
3	0.3521	0.3521	0.2958	1
4	0.1726	0.3214	0.506	1
5	0.1714	0.5619	0.2667	1
6	0.5562	0.426	0.0178	1
7	0.254	0.3669	0.379	1
8	0.3297	0.4066	0.2637	1

9	0.1768	0.4495	0.3737	1
10	0.2632	0.2456	0.4912	1
11	0.6311	0.2233	0.1456	1
12	0.5099	0.0662	0.4238	1
13	0.0826	0.1322	0.7851	1

4) Calculating Geographic Weighting

Determination of geographic weights using population data and distance data between regions from a sample of 13 data. The thing to do is to calculate the weights using equation (3) with components w_{ij}, with $i = 1, 2, 3, \cdots, 13$; $j = 1, 2, 3, \cdots, 13$; as a geographic weight, it produces a matrix 13×13. The following is a description of the manual calculation of the geographic weighting value obtained using the equation

- Calculation of the weight value of Banggai Islands Regency & Banggai Regency:

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

$$w_{i1\ j2} = \frac{(12358\ x\ 37097)}{0.6}$$

$$w_{i1\ j2} = \frac{458444726}{0.6}$$

$$w_{i1\ j2} = 763654391.6$$

Table 5. Geographic weighting values

$$\begin{bmatrix} 0 & 7.64\times10^8 & 1.21\times10^8 & 1.23\times10^8 & \cdots & 1.37\times10^8 \\ 7.64\times10^8 & 0 & 3.81\times10^8 & 4.52\times10^8 & \cdots & 4.88\times10^8 \\ 1.21\times10^8 & 3.81\times10^8 & 0 & 2.78\times10^8 & \cdots & 2.6\times10^8 \\ 1.23\times10^8 & 4.52\times10^8 & 2.78\times10^8 & 0 & \cdots & 9.68\times10^8 \\ 1.05\times10^8 & 3.72\times10^8 & 1.91\times10^8 & 6.27\times10^8 & \cdots & 4.47\times10^9 \\ 8.27\times10^7 & 3\times10^8 & 1.1\times10^8 & 2.39\times10^8 & \vdots & 4.11\times10^8 \\ 5.88\times10^7 & 2.14\times10^8 & 7.09\times10^7 & 1.42\times10^8 & \ddots & 2.2\times10^8 \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ 1.37\times10^8 & 4.88\times10^8 & 2.6\times10^8 & 9.68\times10^8 & \cdots & 0 \end{bmatrix}$$

5) Final Membership Degree Value

The final membership degree value is the membership degree value after *geographical* weighting for determining group membership in *Clustering - Artificial Bee Colony* so that the *clusters* formed have a geographical effect. The improved value of the membership degree obtained is as follows:

Table 6. Final Membership Degree Values

District/City	Cluster 1	Cluster 2	Cluster 3	Cluster
1	0.3562	0.3769	0.2668	2
2	0.365	0.3508	0.2843	1
3	0.3232	0.2951	0.3817	3
4	0.3214	0.3243	0.3542	3

5	0.3114	0.439	0.2495	2
6	0.3505	0.4346	0.2149	2
7	0.3357	0.4435	0.2208	2
8	0.3149	0.4316	0.2535	2
9	0.3448	0.3721	0.2831	2
10	0.3756	0.3743	0.2502	1
11	0.3608	0.3392	0.3	1
12	0.3417	0.2905	0.3678	3
13	0.3438	0.3619	0.2943	2

6) Termination of Iteration

The iteration process stops at the 17th iteration, the process is declared stopped when $V^{(t+1)} - V^{(t)} \leq \varepsilon$ Where *fitness is* the convergence value of the objective function value, which function is fulfilled at the 17th iteration with a value of 3.212546.

7) *Cluster* Result

The results of the *Fuzzy Geographically Weighted Clustering* - *Artificial Bee Colony* analysis form 3 optimal *clusters* with the number of members in each *cluster* as follows.

Table 7. *Cluster* Members

District/City	Membership Degree	Cluster
Banggai Islands	0.3769	2
Banggai	0.3508	1
Morowali	0.3232	3
Poso	0.3542	3
Donggala	0.2495	2
Tolitoli	0.4346	2
Buol	0.4435	2
Parigi Mautong	0.4316	2
Tojo Una-Una	0.3721	2
Sigi	0.3743	1
Banggai Laut	0.3608	1
North Morowali	0.3417	3
Hammer	0.2943	2

Based on the table above, here is the distribution of members of each *cluster*:

1. *Cluster* 1 has 3 districts/cities, namely Banggai, Sigi, and Banggai Laut.
2. *Cluster* 2 has 7 districts/cities including Banggai Islands, Donggala, Toli-toli, Buol, Parigi Mautong, Tojo Una-una, and Palu.

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8) Interpretation of *Cluster* Criteria

Each *cluster* has its own specific characteristics that are indicators of the socio-economic welfare of households to describe the contents of the *cluster*, therefore it is necessary to identify each *cluster* formed. The *cluster* results used are the average of each variable in each *cluster*, *which is* as follows:

Table 8. *Cluster* averages

Variables	Cluster 1	Cluster 2	Cluster 3
X_1	63.013	71.029	69.79
X_2	3.017	2.676	3.557
X_3	12.907	12.773	12.703
X_4	69.247	67.641	73.4
X_5	663649	517037.7	581763.7
X_6	572746	435491.714	598848.667
X_7	46.403	56.034	45.957
X_8	3.147	4.31	8.41
X_9	265693.3	244658.6	160570
X_{10}	10.467	11.334	8.513

From the table above, the highest average value of a *cluster is* marked in green. Based on this, the characteristics of the three *clusters* formed are known, so the following interpretation is obtained.

1. *Cluster* 1 consists of three districts/cities, namely Banggai, Sigi, and Banggai Laut. The districts/cities in this *cluster* have the highest poverty status based on the indicators of the Percentage of Poor People (X_3), Food Per Capita Income (X_5), and Rice Aid Recipients (X_9). However, this cluster also has the lowest poverty status based on the indicators Labor Force Participation Rate and Percentage of Households Having Defecation Facilities. (X_1) and Percentage of Households with Shared Defecation Facilities (X_8). This means that the districts/cities in cluster 1 have low poverty status based on the indicators.
2. *Cluster* 2 consists of seven districts/cities including Banggai Islands, Donggala, Toli-toli, Buol, Parigi Mautong, Tojo Una-una, and Palu, with indicators of Labor Force Participation Rate (X_1), BPJS Beneficiaries (X_7)and Percentage of Population 15 Years and Over Who Have Not Graduated from Elementary School (X_{10}) has the highest average, then this *cluster* has the lowest average with indicators of Open Unemployment Rate (X_2), Human Development Index (X_4), Food Per Capita Income (X_5), Non-Food Per Capita Income (X_6)This means that the districts/cities in *cluster* 2 have a high poverty status based on the indicators.
3. *Cluster* 3 consists of three districts/cities including Morowali, Poso and North Morowali districts, with indicators of Open Unemployment Rate (X_2), Human

Development Index (X_4), Non-Food Per Capita Income (X_6)Percentage of Households Having Shared Defecation Facilities (X_8) has the highest average, then this *cluster* has the lowest average with indicators of the Percentage of Poor People (X_3), BPJS Assistance Recipients (X_7), Rice Aid Recipients (X_9), Percentage of Population 15 Years of Age and Over Has Not Graduated from Elementary School. (X_{10}). This means that the districts/cities in *cluster* 3 have moderate poverty status based on the indicators.

Based on the interpretation of the characteristics above, the results show that districts/cities included in *Cluster* 1 have low poverty status, districts/cities included in *Cluster* 2 have high poverty status, and districts/cities included in *Cluster* 3 have moderate poverty status. The results of the clustering of districts/cities based on poverty indicators using the *Fuzzy Geographically Weighted Clustering-Artificial Bee Colony* method are able to provide an overview of the characteristics of each *cluster* obtained and these results can be used as a reference by the government in taking an appropriate policy for poverty issues.

3.4 *Cluster* Visualization Using Maps

The Fuzzy Geographically Weighted Clustering- Artificial Bee Colony (FGWC-ABC) method is used to visualize the *clustering* results with a map of Central Sulawesi Province to make it easier to know the *clustering* results that have been obtained. The mapping results are as follows:

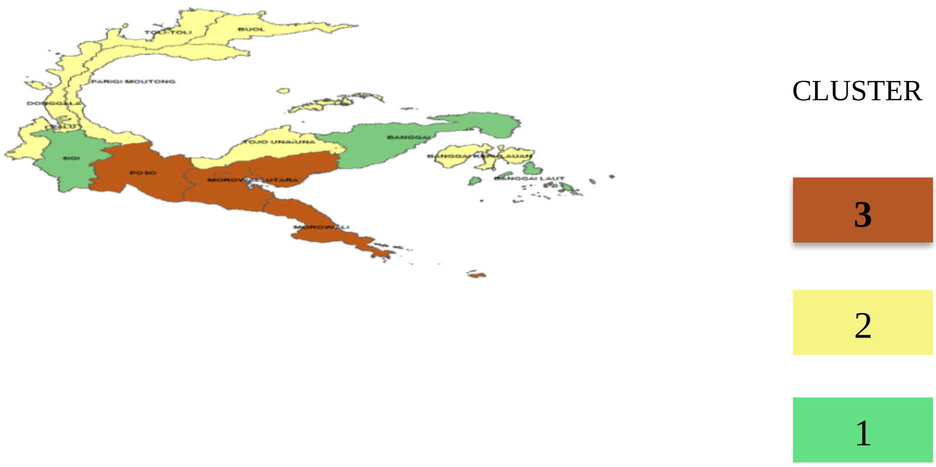

Figure 2. Mapping Image of *Clustering* Results

In Figure 2, you can see the map of Central Sulawesi from the *clustering* results of FGWC-ABC analysis where on the map *cluster* 1 members are colored green, *cluster* 2 members are colored yellow, and *cluster* 3 members are colored brown. This can make it easier for readers to find out which areas are in the *cluster* according to the results obtained from cluster*ing* using the FGWC-ABC method.

4. Conclusions

Based on the discussion in the previous chapter, the *Fuzzy Geographically Weighted Clustering - Artificial Bee Colony* method used to group districts/cities based on poverty indicators has been conducted. By using the IFV validity index, 3 optimum *clusters* were obtained with the characteristics of each *cluster* varying based on the indicators. *Cluster* 1 consists of three districts/cities with low poverty status, *cluster* 2 consists of seven districts/cities with high poverty status, and *cluster* 3 consists of six districts/cities with medium poverty status.

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