

FUZZY CLUSTERING ALGORITHM TO CATCHING PATTERN OF CHANGE IN DISTRICT/CITY POVERTY VARIABLES BEFORE AND THE BEGINNING OF THE COVID-19 PANDEMIC IN SULAWESI ISLAND

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ABSTRACT

The first goal of the SDGs is to end poverty in any form. The COVID-19 pandemic has greatly affected several economic indicators, especially absolute poverty, especially in Sulawesi Island, which has increased poverty indicators, leading to the movement of values between districts/cities. The grouping will show similar characteristics of absolute variable poverty. By the Fuzzy method clustering, each observation has a degree of membership so that from the degree of membership can be identified which areas have vulnerable to move from one cluster to another. Grouping using fuzzy algorithms will get an overview of districts of concern to the government during the pandemic so that the variable indicators of absolute poverty do not worsen due to the pandemic. Comparison with the absolute variables of poverty in 2019 and 2020 in the headcount index (P0), Poverty Gap Index (P1), and Poverty Severity Index (P2) in districts/cities on the island of Sulawesi based on silhouette coefficients shows that optimum clusters formed as many as 2 clusters, with a coefficient of 0.57 and 0.60 respectively. Cluster 1 has characteristics including areas with absolute poverty rates that tend to be more prosperous than cluster 2 in the 2019 and 2020 data groups on the island of Sulawesi. The fuzzy algorithm detects areas prone to displacement from cluster 1 to cluster 2, namely Bombana, Bone, Sangihe Islands, South Konawe, and Siau Tagulandang Biaro in 2019 and Bombana, Bone, Sangihe, and Maros Islands in 2020. The COVID-19 pandemic in March 2020 has not had much impact on the macro indicators of poverty seen in the transfer of membership from 2019 to 2020, which only occurred to 3 districts that changed, namely bolaang mongondouw and konawe selatan from cluster 1 to cluster 2 and Maros from cluster 2 to cluster 1.

Keywords: Absolute Poverty, COVID-19, Fuzzy Clustering, Silhouette Coefficient, Sulawesi.

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INTRODUCTION

Poverty begins with a person's inability to meet basic needs. Poverty has a broad meaning. Meanwhile, Indonesian poverty is measured from the level of income of a household against the poverty line. However, poverty has a deeper meaning because it relates to the inability to achieve aspects outside of income (non-income factors) (Nurwati, 2008). During the last 25 years, extreme poverty in this part of the world has continued to decline, which is the first sustainable development goal (World Bank, 2020).

In its calculations, several instruments are used to measure poverty in various countries by using the information on the necessities of life (Romero et al., 2018). From 1981 to 2004, reported in a study on the calculation of poverty using the absolute probability method for developing countries (Ravallion & Chen, 2007). In addition to absolute poverty, poverty can also be calculated using relative poverty by ranking the lowest 20 percent to 40 percent based on income. The maximum result is by combining relative poverty and absolute poverty to form a poverty line based on relative poverty and cut off by using absolute poverty (Foster, 1998).

Statistics Indonesia (BPS) calculates poverty using the basic needs approach to be classified as poor if he cannot fulfill his basic needs (Maipita, 2013). Basic needs are calculated from the minimum basic needs. Minimum basic needs are defined in units of money in rupiah, which shows that poverty is absolute when a person's basic needs are below the poverty line (Badan Pusat Statistik, 2020a). Furthermore, absolute poverty is reflected in the three indicators, namely Head Count Index (P0), Poverty Gap Index (P1), and Poverty Severity Index (P2).

Corona Virus Disease (COVID-19) in December 2019 in the city of Wuhan, which is in Hubei province, China, spreads around the world. This pandemic condition caused macroeconomic conditions to slow down. Limited transportation between regions has further slowed global economic activity (McKibbin & Fernando, 2020). Economic conditions certainly have an impact on worsening the welfare of the people. BPS 2020 states the poverty picture in Indonesia, namely P0 in March 2020 of 9,78 percent, an increase of 0,56 percentage points against September 2019, and an increase of 0,37 percentage points against March 2019 (Badan Pusat Statistik, 2020b). This figure still has no impact if measured in March 2020, but it has started to take effect globally, for example, in Indonesia. From 2019 to 2020, there are 514 districts/cities in Indonesia, around 41,63 percent of districts/cities experiencing an increase in the percentage of the poverty rate or commonly known as P0. This increase occurred on the island of Sulawesi, where 6,5 percent of districts/cities experienced an increase in Sulawesi Island's poverty rate. The increase in the poverty rate (P0) on the island of Sulawesi is relatively high, namely around 0,21 percent compared to the increase in the poverty rate on the island of Kalimantan average increase of 0,16 percent.

The Poverty Line in March 2020 recorded an increase of IDR 454.652 / capita/month with the composition of the Food Poverty Line of IDR 335.793 (73,86 percent) and the Non-Food Poverty Line of IDR 118.859 (26,14 percent). Besides P1 or the depth of poverty, there is 51,36 percent of districts/cities in Indonesia have increased with an average increase of 0,34, while districts/cities on the island of Sulawesi have an average increase 0,33. The poverty severity index also records districts/cities that have increased by 49 percent with an average increase of 0,17 in Indonesia and Sulawesi, an average increase of 0,14.

This data shows that there are vulnerable areas to changing conditions due to COVID-19, so it is necessary to group districts/cities to see the characteristics of absolute poverty variables, namely P0, P1 and P2. This grouping will show the similarity in the characteristics of the absolute variable of poverty and with the Fuzzy clustering method, each observation has a degree of membership so that the degree of membership can be identified which areas are prone to moving from one cluster to another. Fuzzy grouping will get a picture of the districts that are the government's attention during the pandemic so that the absolute poverty variable indicators do not get worse due to the pandemic.

MATERIALS AND METHODS

1. Cluster Analysis

The cluster method is a method of grouping a set of observations based on the level of similarity or closeness (Nejatian et al., 2018). Objects grouped in one cluster have a high level of similarity and objects between clusters have a low similarity level (Mattjik et al., 2011). The results of the formation

of clusters are clusters, which are a set of observations that are similar in a cluster and have similarities with objects that are in different clusters. The cluster method has two parts. The first is hard-clustering, objects will be partitioned into clusters where an object will be a member of precisely one hard-partition cluster and the next is a soft cluster (Döring et al., 2006). Before grouping, the optimum number of clusters was determined using the silhouette coefficient.

2. Silhouette Coefficient

The silhouette coefficient is a method often used in cluster analysis to determine the correct number of k (number of clusters) in the clustering process (Rao & Govardhan, 2015). The silhouette coefficient can also be used to measure the quality of the clusters that have been formed (Ansari et al., 2015). The silhouette coefficient measurement is formulated as follows (Rousseeuw, 1987).

$$S_i = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{1}$$

Where,

a_i : The average distance between object i and all objects in the same cluster

b_i : The average distance between object i and all objects in the closest cluster

3. Fuzzy Clustering

After getting the optimal number of clusters, each observation's membership degree is carried out using the fuzzy clustering algorithm (Nejatian et al., 2018). A fuzzy clustering algorithm is a form of soft-clustering where each member has a member's degree in each of its clusters (Rashidi et al., 2019). Each object is partitioned into clusters with a certain degree of membership (soft partition), which is defined as follows (Abbasi et al., 2019).

X is a set of data, and $x_i \in X$

A partition $P = \{C_1, C_2, \dots, C_L\}$ of X is a soft partition if it meets

(1) $\forall x_i \in X, \exists C_j \in P \ni 0 \leq \mu_{C_j}(x_i) \leq 1$

(2) $\forall x_i \in X, C_j \in P \ni \mu_{C_j}(x_i) > 0$, where $\mu_{C_j}(x_i)$ is the degree of membership x_i in the cluster C_j

In fuzzy membership, the opportunities from observations to enter a specific cluster can be illustrated as follows (Abdy, 2018).

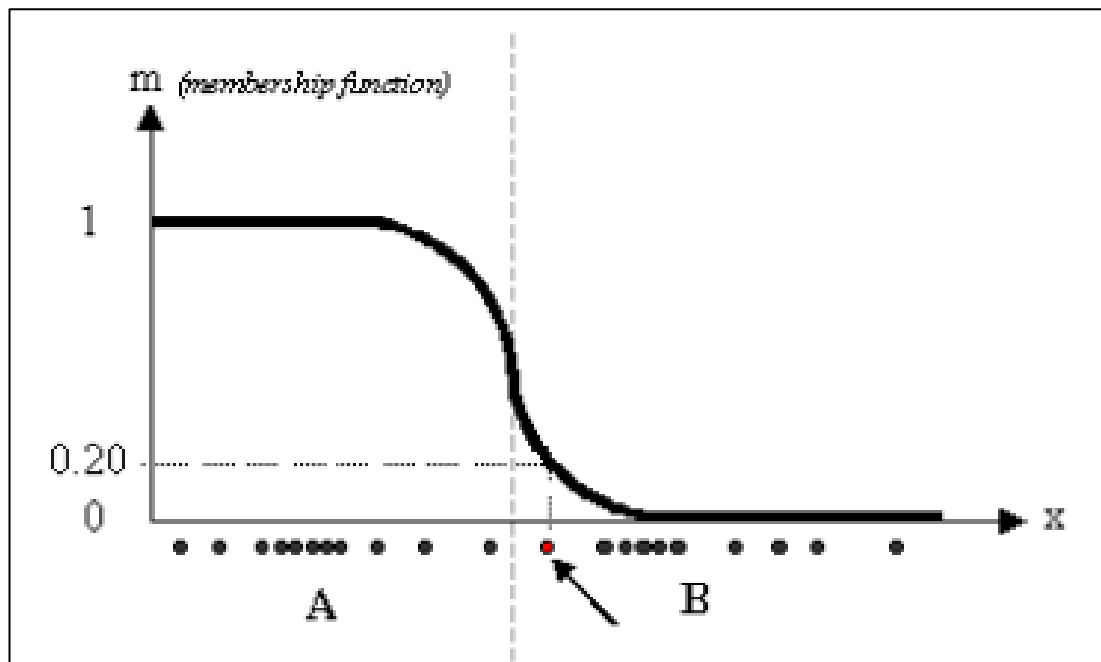


Figure 1. Soft-clustering Membership Functions

A fuzzy that fulfills additional conditions $\sum_j \pi_{C_j}(x_i) = 1$ called soft certainly constrained. Suppose $X = \{X_k\}_{k \in [1, n]}$ is a finite set. $M_{c \times n}$ is a matrix whose members exist in intervals $[0, 1]$ and $c(2 < c < n)$ is

an integer. Matrix $U=(\mu_{ik})_{(i,k) \in [1,c] \times [1,n]} \in M_{c \times n}$ called the fuzzy C-Partition of X if it meets the following conditions (Bagherinia et al., 2020).

$$\mu_{ik} \in [0,1], 1 \leq i \leq c, 1 \leq k \leq n, \sum_{i=1}^c \mu_{ik} = 1, 1 \leq k \leq n, \quad (2)$$

$$0 \leq \sum_{k=1}^n \mu_{ik} \leq n, 1 \leq i \leq c \quad (3)$$

In a cluster represented by a central point ie $v_i = (v_{ij})_{j \in [1,p]} \in R^p$, concentrating around its objects. The criteria used are Euclidean distance $d_{ik}=d(x_k, v_i)$ where

$$d(x_k, v_i) = \|x_k - v_i\| = \left[\sum_{j=1}^p (x_{kj} - v_{ij})^2 \right]^{1/2} \quad (4)$$

The dissimilarity function (objective function), which is used in fuzzy separation of observations, so that differences between clusters appear, can be formulated as follows

$$J(U, v_1, v_2, \dots, v_c) = \sum_{i=1}^c J_i = \sum_{i=1}^c \sum_{j=1}^n \mu_{ij}^m d_{ij}^2 \quad (5)$$

With $\mu_{ij} \in [0,1]$, v_i is the center of the 1st cluster, d_{ij} is the Euclidean distance between the i -th cluster centers and the j -th data centers, $m \in [1, \infty]$ is a weight that determines the level of cluster fuzziness (*Fuzziness cluster*) (Bagherinia et al., 2019). By differentiating the objective function in equation 5 concerning v_i (U constant) and against μ_{ij} (v constant) with constraints, $\sum_{i=1}^c \mu_{ij} = 1$, then the objective function follows the formula (Mojarad et al., 2019).

$$c_i = \frac{\sum_{j=1}^n \mu_{ij}^m x_j}{\sum_{j=1}^n \mu_{ij}^m} \quad (6)$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \quad (7)$$

In detail, the fuzzy algorithm has the following stages (Abdy, 2018).

1. Determines the value for the fuzziness cluster m parameter, where $m > 1$
2. Specifies the value for the iteration termination criteria ε (that is $\varepsilon=0,0001$ provides a proper convergence)
3. Determines the measure of the distance of variable space (Euclidean distance)
4. Determine the number of clusters with $c=2,3, \dots, n-1$ (based on the silhouette coefficient)
5. Randomize initialization of membership matrix (U) with constraints $\sum_{i=1}^c \mu_{ij} = 1$, for each $j = 1, 2, \dots, n-1$
6. Calculate the center of the cluster (v_i) using the equation (6)
7. Calculate the dissimilarity between cluster centers and data points using equation 5, stop iteration if $\|U^{[k+1]} - U^{[k]}\| < \varepsilon$
8. Calculate a new U with equation 7. Continue to step 6.

RESULTS AND DISCUSSION

The data used in this study are data from the SUSENAS dissemination of poverty rates from 81 districts / cities on the island of Sulawesi in 2019 and 2020. The results of data processing for absolute poverty indicators, namely the HeadCount Index (P0), Poverty Gap Index (P1) and Poverty Severity Index (P2), get an overview of the general condition of absolute poverty in the years before the COVID-19 pandemic in 2019 and the beginning of the COVID-19 pandemic. 19 of 2020 on the island of Sulawesi. This picture can be seen in the following table.

Table 1. Comparison of Absolute Variable of District/City Poverty in Sulawesi Island

Descriptive	P0 - 2019	P0 - 2020	P1 - 2019	P1 - 2020	P2 - 2019	P2 - 2020
Number of regencies / cities	81	81	81	81	81	81
Minimum	4,28	4,34	0,46	0,36	0,09	0,04
Maximum	18,87	18,57	4,15	3,95	1,39	1,22
Mean	11,1695	10,9438	1,7562	1,7021	0,4359	0,4216
Std. Deviation	4,00970	3,81902	0,86034	0,79104	0,28515	0,25558

The data pattern shows a change in the average headcount index (P0) value from 2019 to 2020 from 81 districts/cities in Sulawesi, by 11,16 percent to 10,94 percent. The HeadCount Index (P0) shows a decrease, this also occurs in the poverty gap index (P1) and the poverty severity index (P2), which shows a decrease, but some districts/cities have an absolute poverty indicator rate that has increased by 17,3 percent in 2020. The average value of the P1 indicator in 2019 was 1,75 to 1,702 in 2020, while the average value of the P2 indicator in 2019 was 0,4359 to 0,2522 in 2020. The distribution of data, in general, can be seen in the standard deviation value, which, when compared, has decreased so that it can be seen that the distribution of poverty indicator data is also increasingly homogeneous. Then preprocessing is carried out to see the data pattern using the heatmap in Figure 2.

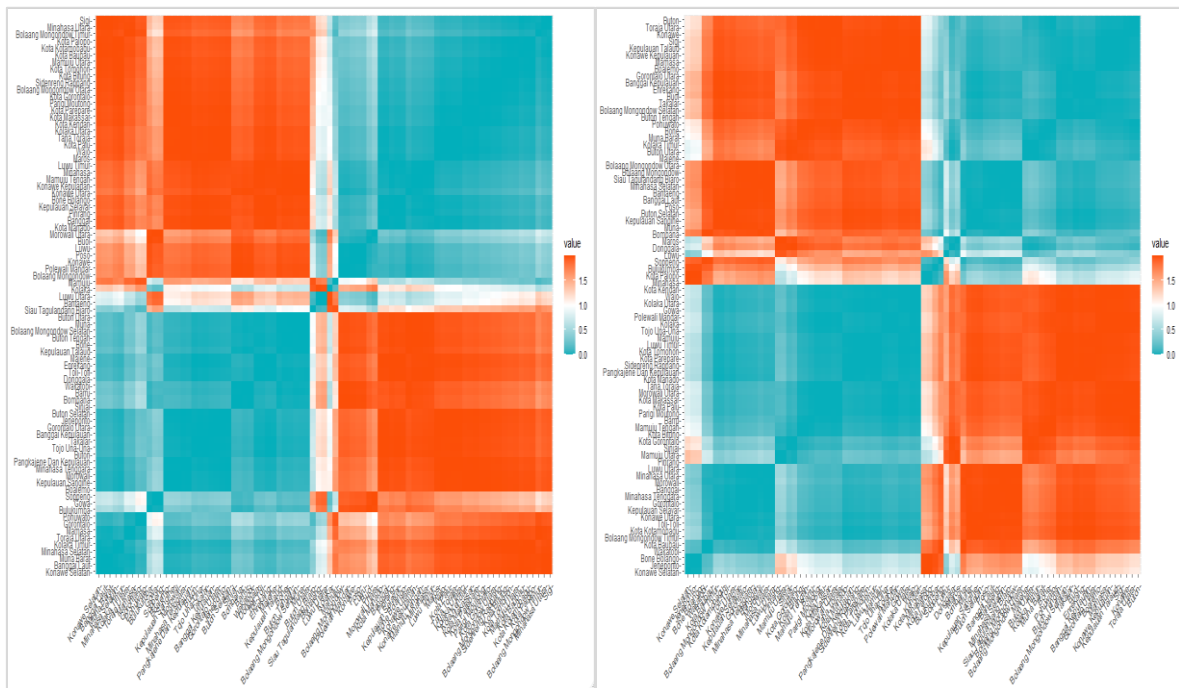


Figure 2. Heatmap of Absolute Poverty Variables in 2019 and 2020

Heatmaps are commonly used to see similarities based on signals given by observations based on absolute poverty indicators between districts/cities on the island of Sulawesi so that the level of similarity will cluster based on the signal strength of these observations. Figure 2 shows that the shift pattern between observations was not too extreme between 2019 and 2020. The data pattern on the heatmap shows a symmetrical pattern and tends to be clustered into gradations, which indicate the strength of grouped observations in specific colors, namely green and orange. So that in the formation

of clusters, an optimal number of clusters is needed so that the clusters formed tend to be homogeneous within the cluster and heterogeneous between clusters. Determination of the optimal cluster can be seen from the silhouette coefficient on both data is shown in Figure 3.

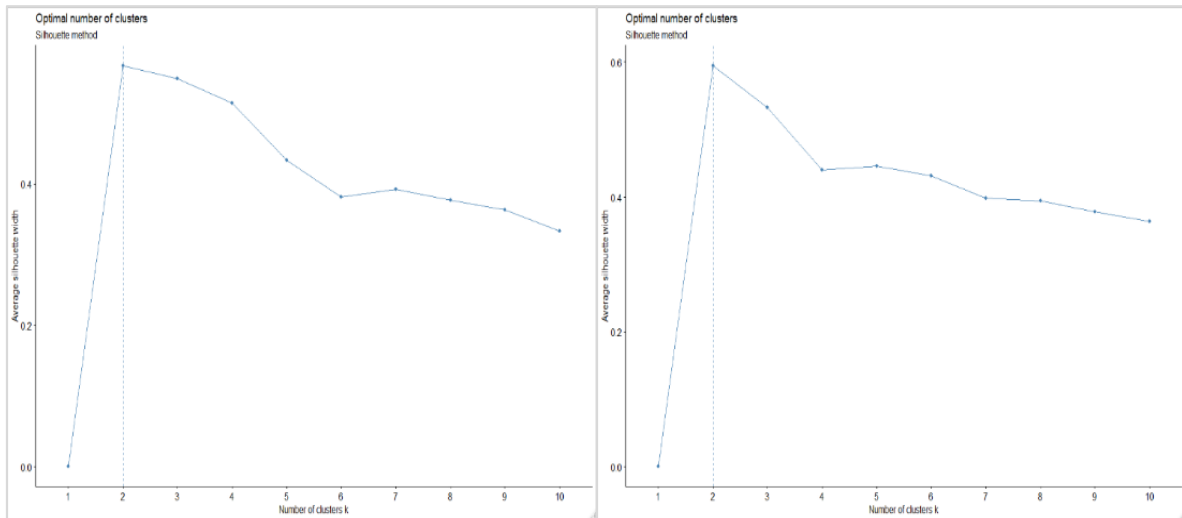


Figure 3. Silhouette Coefficient of Absolute Poverty Variable in 2019 and 2020

The silhouette coefficient shows the optimal value of the clusters formed from a grouping so that groups are formed as homogeneous as possible in clusters and as heterogeneous as possible between clusters. Figure 3 shows that the cluster formed between the data group and the absolute variable of poverty in 2019 and 2020 is optimal in the two groups. The fuzzy clustering algorithm produces an opportunity value wherein grouping each member has a different degree of membership, which has the sum of the probability value equal to 1 with a minimum of 2 clusters formed. Observations that have a high degree of membership will be classified into these clusters. The following is the membership degree value based on cluster 1 so that the cluster value under the classifier will be entered into cluster 2.

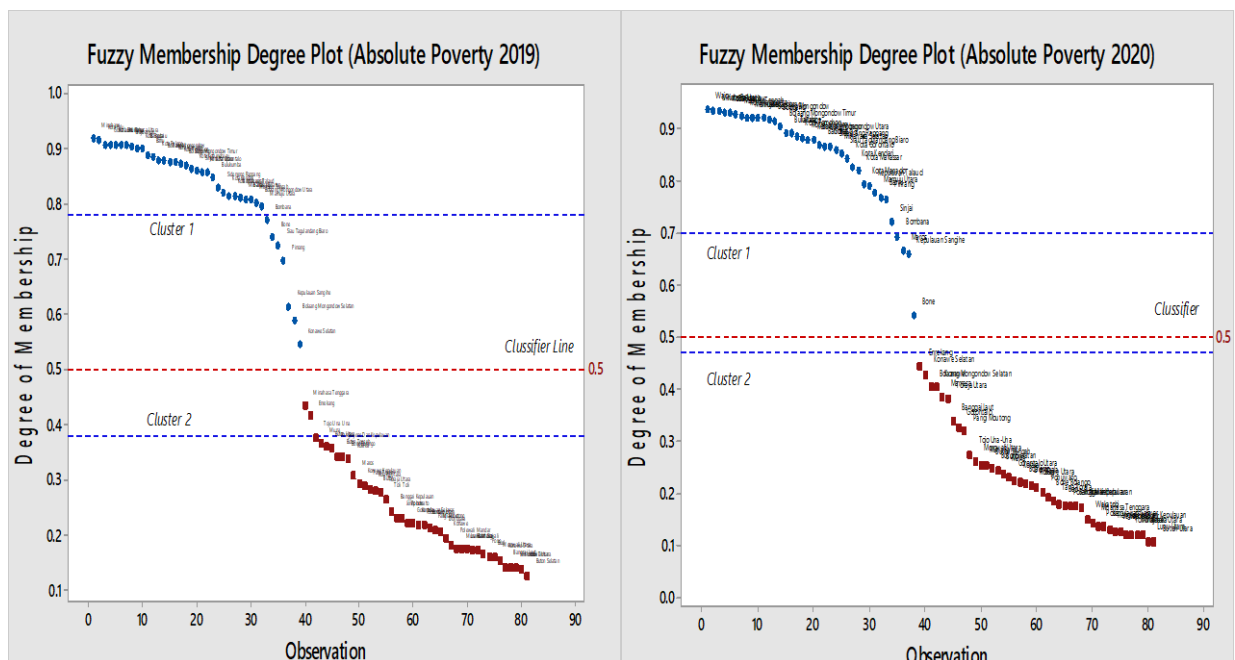


Figure 4. Comparison of the Degree of Membership in Fuzzy Cluster 1 in 2019 and 2020

The value of the degree of membership is an opportunity for an observation to be categorized into a cluster. Figure 4 shows that the degree of membership is seen from observation opportunities to enter cluster 1. The silhouette coefficient shows the optimum number of clusters divided into two so that the opportunity is divided into 0,5 to enter each

cluster. Observations that have a high degree of membership will enter the cluster. The classifier line in the fuzzy algorithm is not straight so that it can be depicted in a diagram in Figure 5.

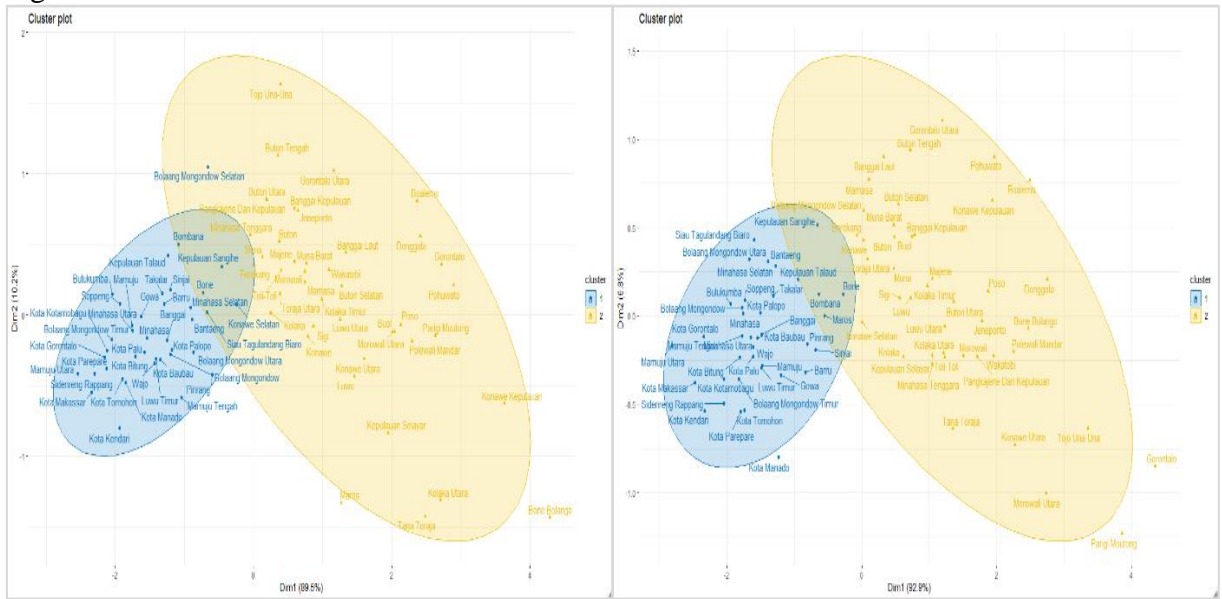


Figure 5. Cluster diagram $k = 2$ Absolute poverty in 2019 and 2020

The picture explains the clusters formed at $k = 2$ with the eigenvalue in the 2019 absolute poverty diagram of 99,2 percent and the eigenvalue in the 2020 absolute poverty diagram of 99,7 percent. This figure explains that the variability of the data can be explained by the clusters that have been established. The diagram explains that fuzzy is one of the soft clustering methods where there are observations that are members of several clusters according to membership degree. A slice between the line classifier explains that the value of the degree of membership has a minimal difference so that the observation is in the intersection area. This area is a vulnerable area with an error in the classifier that is relatively high and easy to move clusters.

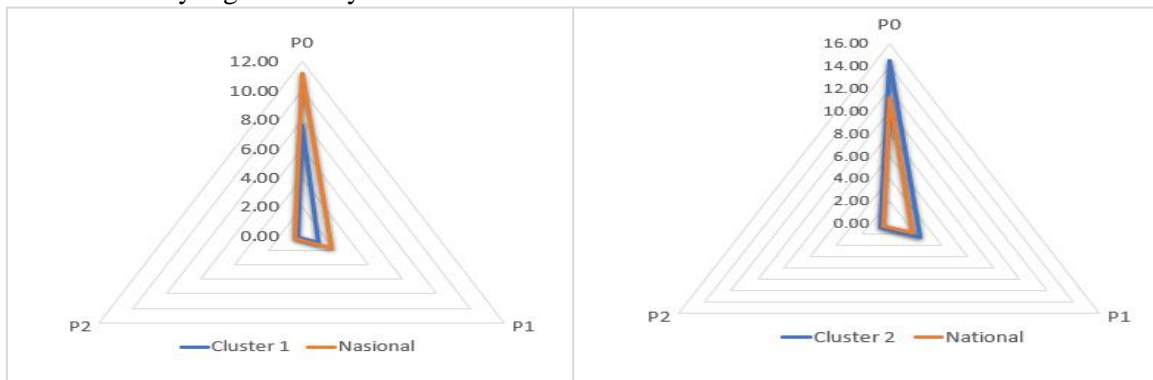


Figure 6. Comparison of Absolute Poverty Clusters with National and 2019

The clusters formed in the absolute poverty variable in 2019 are divided into two groups through fuzzy clustering. Figure 6 shows the comparison between the mean of the absolute poverty variables at district/city and national levels. Cluster 1 has an average of P0 of 7,59, P1 of 1,02 and P2 of 0,22, while cluster 2 has P0 of 14,49, P1 of 2,44 and P2 of 0,64. The comparison between the average value of cluster 1 is smaller than the cluster 2 and the national value, while the average absolute poverty value of cluster 2 is greater than the national. This comparison can be seen that cluster 1 is a group that has a high absolute poverty indicator value so that it can be said that the conditions of cluster 1 are more prosperous, while cluster 2 has a higher absolute poverty indicator value, so it can be said that the level of welfare is still low as for the areas that have cluster 1, vulnerable areas that intersect with cluster 2, namely Bombana, Sangihe Islands, Bone, Konawe Selatan and Siau Tagulandang Biaro. The districts which are included in cluster 2, which intersect with cluster 1, are Enrekang District.

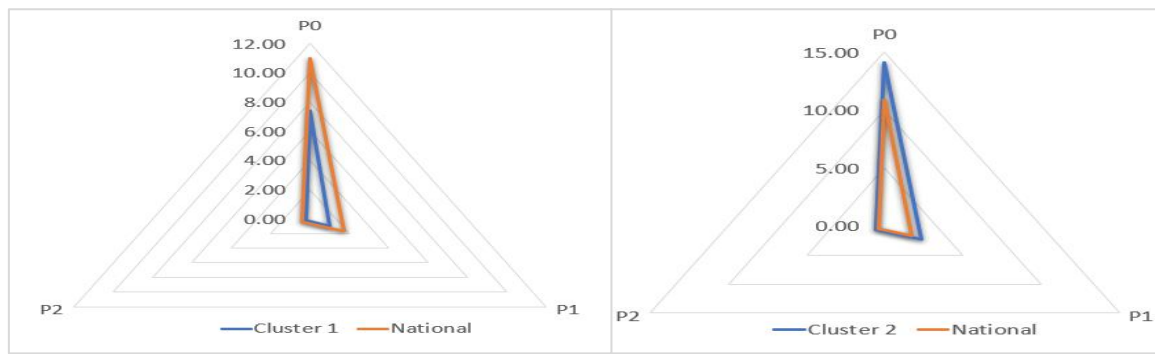


Figure 7. Comparison of Absolute Poverty Clusters with National and 2020

The figure shows the comparison of the absolute poverty indicators in 2020 according to the clusters that have been formed, namely two. Cluster 1 has an average value of P0 smaller than cluster 2, namely 7,37 and 14,10, while the national average value is 10.94. The P1 value owned by cluster 1 has an average value smaller than cluster 2 of 1 and 2,33 and the P2 value where cluster 1 has an average value smaller than cluster 2 of 0,4011 and 0,60. This data can conclude that cluster 1 is a cluster that has higher welfare than cluster 2. Regions that have vulnerable membership from cluster 1 to cluster 2 are the districts of Sangihe, Bombana, Bone and Maros Islands. The following is a clustering result using a fuzzy algorithm.

Table 2. Grouping Districts / Cities Using The Fuzzy Clustering Algorithm In 2019 And 2020

Years	Cluster 1	Cluster 2
2019	Banggai, Bantaeng, Barru, Bolaang Mongondow, Bolaang Mongondow Selatan, Bolaang Mongondow Timur, Bolaang Mongondow Utara, Bombana , Bone , Bulukumba, Gowa, Kepulauan Sangihe , Kepulauan Talaud, Konawe Selatan , Baubau City, Bitung City, Gorontalo City, Kendari City, Kotamobagu City, Makassar City, Manado City, Palopo City, Palu City, Parepare City, Tomohon City, Luwu Timur, Mamuju, Mamuju Tengah, Mamuju Utara, Minahasa, Minahasa Selatan, Minahasa Utara, Pinrang, Siau Tagulandang Biaro , Sidenreng Rappang, Sinjai, Soppeng, Takalar, Wajo	Banggai Kepulauan, Banggai Laut, Boalemo, Bone Bolango, Buol, Buton, Buton Selatan, Buton Tengah, Buton Utara, Donggala, Enrekang , Gorontalo, Gorontalo Utara, Jenepono, Kepulauan Selayar, Kolaka, Kolaka Timur, Kolaka Utara, Konawe, Konawe Kepulauan, Konawe Utara, Luwu, Luwu Utara, Majene, Mamasa, Maros, Minahasa Tenggara, Morowali, Morowali Utara, Muna, Muna Barat, Pangkajene Dan Kepulauan, Parigi Moutong, Pohuwato, Polewali Mandar, Poso, Sigi, Tana Toraja, Tojo Una-Una, Toli-Toli, Toraja Utara, Wakatobi
2020	Banggai, Bantaeng, Barru, Bolaang Mongondow, Bolaang Mongondow Timur, Bolaang Mongondow Utara, Bombana , Bone , Bulukumba, Gowa, Kepulauan Sangihe , Kepulauan Talaud, Baubau City, Bitung City, Gorontalo City, Kendari City, Kotamobagu City, Makassar City, Manado City, Palopo City, Palu City, Parepare City, Tomohon City, Luwu Timur, Mamuju, Mamuju Tengah, Mamuju Utara, Maros , Minahasa, Minahasa Selatan, Minahasa Utara, Pinrang, Siau Tagulandang Biaro, Sidenreng Rappang, Sinjai, Soppeng, Takalar, Wajo	Banggai Kepulauan, Banggai Laut, Boalemo, Bolaang Mongondow Selatan, Bone Bolango, Buol, Buton, Buton Selatan, Buton Tengah, Buton Utara, Donggala, Enrekang, Gorontalo, Gorontalo Utara, Jenepono, Kepulauan Selayar, Kolaka, Kolaka Timur, Kolaka Utara, Konawe, Konawe Kepulauan, Konawe Selatan, Konawe Utara, Luwu, Luwu Utara, Majene, Mamasa, Minahasa Tenggara, Morowali, Morowali Utara, Muna, Muna Barat, Pangkajene Dan Kepulauan, Parigi Moutong, Pohuwato, Polewali Mandar, Poso, Sigi, Tana Toraja, Tojo Una-Una, Toli-Toli, Toraja Utara, Wakatobi

The table above describes the membership of the cluster from 2019 to 2020. If the two datasets are grouped, it will produce the same characteristics, but some members experience changes. Members who experienced changes from cluster 1 to cluster 2 were 2 districts, namely Bolaang Mongondouw Selatan and Konawe Selatan Districts. However, the regency that moved from cluster 2 to cluster 1 was the Maros district. An evaluation is then carried out using the silhouette coefficient to determine that the optimal cluster formed is shown in Figure 8.

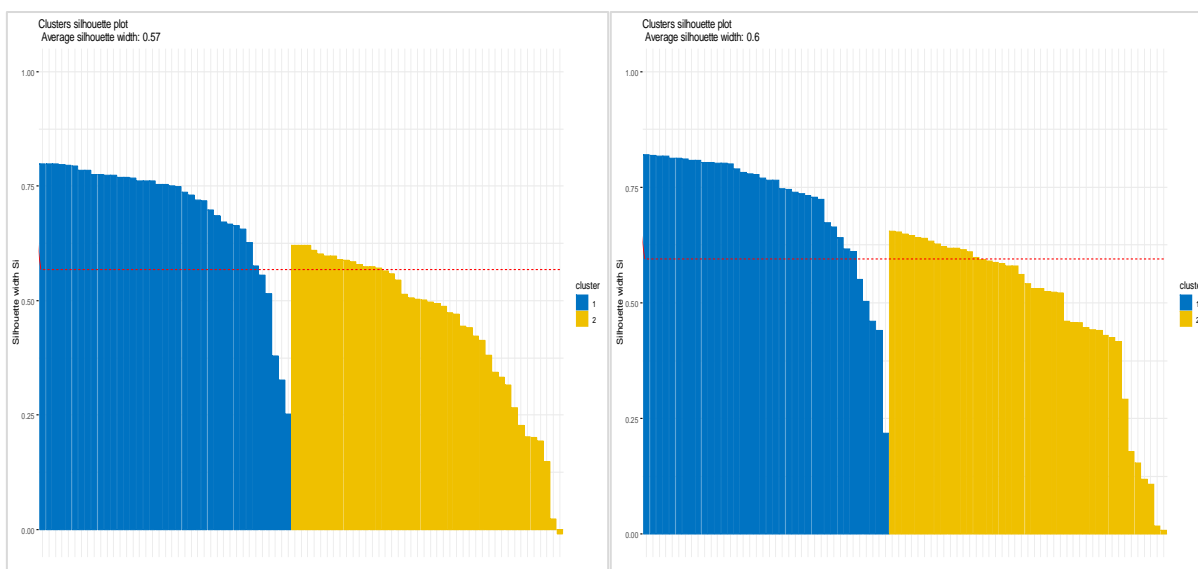


Figure 8. Comparison of Time Silhouette Coefficient Plots

Figure 8 describes the evaluation in cluster formation through the clustering coefficient of 0,57 in calculating the absolute poverty cluster in 2019 and the silhouette coefficient of 0,6 in calculating the absolute poverty cluster in 2020. The silhouette coefficient between 0,5 – 0,7 is a good value for cluster formation, and the silhouette coefficient value of 0,71 - 1 is a very good value to use in cluster formation (Kaufman & Rousseeuw, 2009). That shows that the cluster formed is homogeneous within the cluster and heterogeneous outside the cluster.

CONCLUSION

Comparison with the absolute poverty variable in 2019 and 2020 in the headcount index (P0), Poverty Gap Index (P1) and Poverty Severity Index (P2) in districts/cities on the island of Sulawesi based on the silhouette coefficient resulting in 2 optimum clusters with each coefficient amounting to 0,57 and 0,60. Cluster 1 has characteristics including areas with absolute poverty levels that tend to be more prosperous than cluster 2 in 2019 and 2020. The fuzzy algorithm can detect vulnerable areas from cluster 1 to cluster 2, namely Bombana, Bone, Sangihe Islands, Konawe Selatan and Siau Tagulandang Biaro in 2019 and Bombana, Bone, Sangihe and Maros Islands in 2020. The COVID-19 epidemic in March 2020 has not had a significant impact on the macro indicators of poverty, and it can be seen that only three districts have experienced changes, namely Bolaang Mongondouw and Konawe Selatan from cluster 1 to cluster 2 and Maros from cluster 2 to cluster 1.

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