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Article

Clustering Provinces in Indonesia Based on The Main Food Crop Production Using The Spatial Fuzzy C-Means

Hazmira Yozza[1*], Aldi Mukhlis[1], Maiyastri[1]

[1]Department of Mathematics and Data Science, Faculty of Mathematics and Natural Sciences, Andalas University, Padang, Indonesia

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Abstract. Agriculture plays a strategic role in achieving food security in Indonesia. However, the production of major food crops in Indonesia shows uneven distribution, which may affect efforts to achieve food self-sufficiency. This study aims to cluster 34 provinces in Indonesia based on the total production of seven major food crops (rice, corn, soybean, mung bean, peanut, cassava, and sweet potato) using the Spatial Fuzzy C-Means (sFCM) method. Food crop production data was obtained from the Ministry of Agriculture in 2020. The results showed two optimal clusters. The first cluster includes three provinces in Java (West Java, Central Java, and East Java), with much higher production levels than the second cluster consisting of 31 other provinces. Cluster validation using Modified Partition Coefficient (MPC) and Partition Entropy (PE) shows that the clustering results have high membership clarity and low entropy, making them relevant for spatial data analysis. The findings highlight the unequal distribution of food crop production and provide policy recommendations, where the first cluster can be optimized as a national food production hub, while the second cluster requires interventions based on infrastructure, technology, and redistribution policies. This research makes an important contribution in providing a data-driven scientific basis for food production equity planning. The sFCM method used demonstrates effective capabilities in analyzing data with spatial elements, supporting more inclusive policies for the improvement of national food security and the achievement of sustainable development goals in Indonesia.

Corresponding Author :
Hazmira Yozza
Department of Mathematics and Data Science, Faculty of Mathematics and Natural Science, Andalas University, Padang, Indonesia
Email : hazmirayozza@sci.unand.ac.id

1. Introduction
Agriculture is a cornerstone of Indonesia's economic development, holding a strategic role not only in ensuring food sufficiency but also in enhancing national welfare. This sector contributes significantly to the Gross Domestic Product (GDP) and serves as the primary source of livelihood for many rural households. Additionally, agriculture supplies essential raw materials for industries, provides employment opportunities, and supports bioenergy production and environmental sustainability by helping to reduce greenhouse gas emissions [1-2]. Given its pivotal role, any disruption to agriculture invariably impacts other economic sectors.

Food security is one of the critical objectives embedded in the Sustainable Development Goals (SDGs), and Indonesia has shown progress in this regard. The Global Food Security Index (GFSI) in 2022 placed Indonesia at a moderate level, with a 1.7% improvement from the previous year [3]. However, to achieve its ambitious vision of becoming a global food barn by 2045, the Indonesian government must overcome various challenges, particularly concerning the uneven distribution of food crop production across provinces [4].

Indonesia's main food crops rice, corn, soybean, mung bean, peanuts, cassava, and sweet potato play a vital role in sustaining its population. While some provinces produce these crops in abundance and act as "food barns," others lag, creating disparities in food availability. For instance, East Java consistently demonstrates high production levels for several crops, whereas regions like Riau Islands face significant shortfalls. These inequalities necessitate targeted policies to boost productivity in low-yield provinces and maintain stability in high-producing regions [5-6].

A critical first step in addressing this issue is to identify provinces with similar agricultural characteristics and production levels. This can be achieved through cluster analysis, which statistically segments regions based on specific variables [7-8]. Among various clustering techniques, the Spatial Fuzzy C-Means (sFCM) approach incorporates spatial information, making it particularly suitable for analyzing geographically sensitive data. By identifying clusters of provinces based on food crop production, policymakers can tailor interventions to regional needs, thereby fostering equitable agricultural development [9].

This study aims to classify Indonesia’s 34 provinces based on the total production of its seven main food crops using the sFCM method. By integrating spatial data, this approach provides a comprehensive view of production disparities, enabling the development of well-informed policies. The findings will serve as a data-driven foundation to support equitable food distribution and enhance overall food security in Indonesia.

2. Experimental Section
This study uses secondary data taken from the official website of the Ministry of Agriculture of the Republic of Indonesia. The data includes the total production of seven main food crops, namely rice, corn, soybean, mung bean, peanut, cassava, and sweet potato, from all 34 provinces in Indonesia in 2020. These variables are measured in tons and used as the basis for grouping provinces based on food crop production characteristics.

The method applied is Spatial Fuzzy C-Means (sFCM), a development of the Fuzzy C-Means (FCM) method that considers spatial information in the clustering process [10-11]. This method takes into account the geographical proximity between provinces to ensure that geographically close provinces tend to be grouped in the same cluster. The clustering process is performed iteratively to minimize the objective function until convergence criteria are achieved. The analysis stages include initialization of membership values, calculation of cluster centers based on production data, and modification of membership functions by incorporating spatial information from surrounding provinces.

The research process begins by describing the data, which includes the total production of seven main food crops for 34 provinces in Indonesia, measured in tons. The analysis uses the Spatial Fuzzy

C-Means (sFCM) method, which incorporates spatial information into fuzzy clustering to enhance the clustering process by grouping provinces based on both production characteristics and geographic location. The following notations are employed in the sFCM algorithm:

- X_{kj} as the value of the *j*-th variable for the *i*-th province
- μ_{ik} as the membership of *i*-th province in *k*-cluster
- V_{kj} as the center of k-th cluster for *j*-th variable
- d_{ik} is the distance between *the* province and the center of the *k*-th cluster.
- h_{ik} is the value of the spatial function of the *i*-th province in the k-th cluster

The algorithm of sFCM for a given number of clusters is as follows [12]:

1. **Initialization:** The number of clusters (c), the weight rank (w=2), the smallest expected error (ε), the initial objective function ($P_0 = 0$), spatial control parameter (p), and non-spatial control parameter (q). In this study, we used w=2; c=2,3,4,5,6; ε =0.5; p=q=1
2. **Generate Membership:** generate random numbers μ_{ik} as the initial degree of membership
$$\mu_{ik} \epsilon [0,1]$$
subject to $\sum_{k=1}^{c} \mu_{ik} = 1$. In this study, random numbers are generated using Excel.
3. **Calculate cluster Center:** Calculate the clusters center, for *j*-th variable (*j*=1, 2, …, *p*) and *k*-th cluster (*k*=1, 2, …, *c*), it is formulated as
$$V_{kj} = \frac{\sum_{i=1}^{n} (\mu_{ik})^{w} (X_{ij})}{\sum_{i=1}^{n} (\mu_{ik})^{w}}$$
4. **Update Membership Value:** Calculate the modified of $\boldsymbol{\mu_{ik}}$, denoted by $\boldsymbol{\mu_{ik}}^*$
$${\mu_{ik}}^* = \frac{\left(\left[\sum_{j=1}^{m} (X_{ij} - V_{kj})^2\right]\right)^{\frac{-1}{w-1}}}{\sum_{k=1}^{c} \left(\left[\sum_{j=1}^{m} (X_{ij} - V_{kj})^2\right]\right)^{\frac{-1}{w-1}}}$$
5. **Calculate Spatial Function**
$$h_{ik} = \sum_{i' \epsilon NB(i)} {\mu^*}_{ik}$$
where $NB(i)$ is the neighbors of *i*-th province. In this study, the neighbors of every province are determined using Geoda v.1.2.
6. **Recalculate Membership**: Calculate the second modified of $\boldsymbol{\mu_{ik}}$, denoted by $\boldsymbol{\mu'_{ik}}$
$$\boldsymbol{\mu'_{ik}} = \frac{\boldsymbol{{\mu_{ik}}^p {h_{ik}}^q}}{\boldsymbol{\sum_{k=1}^{c} ({\mu_{ik}}^p {h_{ik}}^q)}}$$
7. **Objective Function:** Calculate the objective function, for *t*-th iteration, the objective function is formulated as
$$P_t = \sum_{i=1}^{n} \sum_{k=1}^{c} ({\mu'}_{ik})^2 (d_{ik})^2$$
The iteration is stopped if $|P_t - P_{t-1}| < \varepsilon$. Otherwise, repeat steps c-g.

The validity of clustering results was evaluated using Modified Partition Coefficient (MPC) and Partition Entropy (PE). The optimal indicator is obtained with the highest MPC and lowest PE, which shows the best performance in clustering. The clustering results divide 34 provinces in Indonesia into two clusters, each reflecting significant differences in total food crop production. This clustering provides an in-depth view of productivity disparities among provinces and can be used as a basis for policy making on production equity. The MPC is calculated using the following equation [13]
$$MPC = 1 - \frac{c}{c-1} (1 - PC)$$
where:

$$PC = \frac{1}{n}\sum_{k=1}^{c}\sum_{i=1}^{n}(\mu_{ik})^2$$

while the partition entropy is calculated by

$$PE = -\frac{1}{n}\sum_{k=1}^{c}\sum_{i=1}^{n}\mu_{ik} log \mu_{ik}.$$

Noted that the membership function value used in these formulas is the one obtained in the last stage of algorithm. Choose the best clustering, namely the one that gives the largest MPC and the lowest PE.

3. Results and Discussion

Table 1 shows the descriptive statistics of the production of seven major food crops in Indonesia in 2020, namely rice, corn, soybean, mung bean, peanut, cassava, and sweet potato. Rice production was recorded as the highest with a total production of 83.037.170 tons, while the lowest production was groundnuts at 512.199 tons. The high production of rice reflects the dominance of rice as the main source of carbohydrates for Indonesians. This is in line with the Central Bureau of Statistics (BPS) statement that rice is the staple food of the majority of the Indonesian population, while other crops are more segmented in their use [14-15].

Table 1. Descriptive statistics of the main food crops in Indonesia

No	Food crop	Total	Minimum	Maximum	Standard deviation
1	Rice	83.037.170	651	13.000.475	3.525.458
2	Corn	30.055.644	0	6.543.359	1.355.526
3	Soya bean	982.600	0	244.442	20.944
4	Mung bean	982.600	0	112.162	20.944
5	Peanut	512.199	0	150.180	34.216
6	Cassava	19.841.234	0	6.683.758	1.305.519
7	Sweet potato	1.914.427	0	547.879	107.383

From the table, we can see that the distribution of production varies greatly between provinces. For example, rice production reached a maximum of 13.000.475 tons in East Java, while Riau Islands only produced 651 tons. This variation is not only influenced by differences in land area, but also by agricultural practices, regional policies, and infrastructure support. Differences in production capacity often reflect technology and policy gaps between regions [16-17]. A localized approach is needed to improve food security in low-production areas [18].

Maize and cassava production also show quite high figures, reaching 30.055.644 tons and 19.841.234 tons respectively. These crops have a major contribution in meeting the needs of raw materials for animal feed and the food industry. In contrast, legumes (mung beans, soybeans and peanuts) show much lower production levels, signaling challenges in meeting domestic demand for vegetable protein. This indicates a less than optimal policy for the development of legumes in Indonesia [19].

Furthermore, the large standard deviations for rice (3.525.458) and maize (1.355.526) reflect the uneven distribution of production between provinces, while the low standard deviations for soybean (20.944) and mung bean (20.944) indicate relatively uniform production levels, but at a very low scale. These inequalities support the argument that uneven food production requires policy interventions for redistribution through improved logistics and subsidies between less productive regions. A study by the World Bank (2018) also confirms that adequate transportation infrastructure is a key factor in addressing inequality in the distribution of food products [20].

The results in Table 1 support the objective of this study, which is to understand the production patterns of major food crops to support food equity policy formulation. The analysis shows that spatial-based clustering is crucial in determining policy strategies, as the large variations in production require a more targeted data-driven approach to address productivity gaps. As an implication, the results confirm the need for cluster-based interventions, the use of fuzzy algorithms as optimization tools in regional planning.

The results in Table 2 provide evidence that the sFCM approach is effective for integrating spatial elements in the clustering process. Consistent iterations with improved objective function values suggest that spatial data characteristics, such as the geographical distribution of provinces, play an important role in the formation of more meaningful clusters. In the context of this study, the sFCM method has helped to separate provinces with very high levels of food crop production (e.g. East Java, Central Java and West Java) from other provinces.

Table 2. The objective function and error for 2 cluster

t	Objective Function (P_t)	$\lvert P_t - P_{t-1}\rvert$
1	26.512,157	26.512,157
2	26.046,566	465,591
3	17.201,535	8.845,031
4	14.448,277	8.845,031
5	14.448,277	139,648
6	14.654,807	346,178
7	14.654,807	89,738
8	14.754,371	9,825
9	14.754,371	0,000

Fuzzy C-Means (FCM) results as a flexible method to group objects with partial membership in clusters. The development carried out through sFCM further strengthens this advantage by adding a spatial dimension, so that clustering is not only based on data characteristics but also the relationship between regions [21-22].

The consistent and measurable derivation of the objective function shows that this method has successfully clustered provinces based on total production of major food crops. This is relevant to the research objective, which is to provide a scientific basis for the formation of food production equity policies. For example, the first cluster consisting of provinces with high production can be prioritized as food surplus centers, while the second cluster with low production requires special attention in terms of infrastructure development, technology and distribution. In addition, the use of objective values in determining the termination of iteration provides mathematical validation of the quality of the resulting clusters. The method also has a positive impact on the accuracy of the results, integrating the spatial dimension improves the stability and quality of the clusters.

The sFCM procedure is repeated for c = 2,3,4,5,6 (c = number oclusterser). The number of iteration and the difference of the objective function at the last two consecutive iterations, $\lvert P_t - P_{t-1}\rvert$ are shown in Table 3.

Table 3. The number oiterationson aerrorsror for 2-6 clusters

c	Iteration	$\lvert P_t - P_{t-1}\rvert$
2	9	0.0002
3	19	0.3256
4	12	0.1338
5	9	0.1865
6	21	0.4799

Table 4 presents the results of the cluster validation functions, namely Modified Partition Coefficient (MPC) and Partition Entropy (PE), for each number of clusters ($c = 2, 3, 4, 5, 6$). The highest MPC value is 0.9623, while the lowest PE is 0.01696, which are both found at ($c = 2$). This indicates that the best clustering is achieved with two clusters, as it provides high membership clarity and minimum entropy.

Table 4. The statistical result of validity functions

Number of clusters	MPC	PE
2	0.9623393	0.0169609
3	0.8949079	0.0548128
4	0.8450239	0.0548128
5	0.8275701	0.1192690
6	0.8137036	0.1389157

From a theoretical perspective, a high MPC value indicates that each province has a clear level of membership in one of the clusters. On the other hand, a low PE value indicates that the distribution of membership in the cluster has minimal uncertainty. By choosing ($c = 2$), this study produces a more stable and informative cluster in grouping 34 provinces based on food production.

The findings have several important implications. First, the division into two clusters shows that food crop production in Indonesia has a significant degree of disparity, with a small number of provinces being the main centers of production, while the majority have relatively lower contributions. This is consistent with the pattern of economic concentration often found in the agrarian sector.

Second, the cluster validation results show that increasing the number of clusters ($c > 2$) does not provide significant additional benefits, as both MPC and PE show declining performance. This suggests that too many clusters can reduce the stability of the analysis and obscure the clarity of the main patterns in the data [23-24]. In this context, two clusters offer an optimal balance between analysis complexity and data pattern representation.

The results in Table 4 confirm that the division of provinces into two clusters is the most effective approach to illustrate the disparity of food crop production in Indonesia. The sFCM method has proven its ability to produce clusters with high validity, relevant to theory and previous research [25-26]. This finding not only supports the research objectives, but also provides a solid scientific basis for the formulation of policies to equalize food production and improve national food security.

Figure 1 shows the clustering map of provinces in Indonesia as the optimal result of sFCM. It can be seen see that the first cluster consists of 3 provinces located on Java Island, namely West Java, Central Java, and East Java. Since the total production of main food crops differs greatly from that of the three provinces in Cluster 1, the remaining three provinces on Java Island (Banten, DKI Jakarta, and DI Yogyakarta) are put the different cluster. These provinces are included in the same cluster as the other province in Indonesia.

Figure 1. The clustering map of provinces in Indonesia

Table 5 presents the average production of major food crops for each cluster based on the results of Spatial Fuzzy C-Means (sFCM) clustering in 34 provinces in Indonesia. The first cluster, consisting of West Java, Central Java and East Java, shows much higher average production than the national average for all major food crops. In contrast, provinces in the second cluster have lower average production than the national average in every crop category.

Table 5. Overall and clusters mean of the main food crops production

No	Food crop	Overall mean	Cluster-1 mean	Cluster-2 mean
1	Rice	2.442.270	12.299.071,7 (+)	1.488.386,0 (-)
2	Corn	883.990	3.927.600,7 (+)	589.446,5 (-)
3	Soya bean	28.900	169.022,0 (+)	15.339,7 (-)
4	Mung bean	6.903	56.031,0 (+)	2.149,2 (-)
5	Peanut	15.065	94.690,7 (+)	7.358,9 (-)
6	Cassava	583.566	2.484.762,7 (+)	399.578,9 (-)
7	Sweet potato	56.307	316.787,0 (+)	31.098,8 (-)

Note : + sign is added if cluster mean more than overall mean; otherwise, (-) sgn is added

These results reflect significant disparities between the clusters. The first cluster, referred to as the production center or food barn, shows a dominant contribution to national food production. For example, the average rice production in the first cluster is 12.299.071,7 tons, about five times the national average of 2.442.270 tons. This condition is consistent with the pattern of productivity distribution often found in Indonesia, where regions in Java tend to have better infrastructure, technology, and access to markets than provinces outside Java. This supports the core-periphery theory, which explains the economic concentration in the core with superior resources supporting the periphery [27-28].

The much lower standard of production in the second cluster indicates limited access to technology, skilled labor, and limitations in logistics and distribution systems. Disparities in access to resources and technology are a major constraint to economic growth and food security in less developed regions [29-30].

The results in Table 5 confirm the need for different interventions for each cluster. The first cluster can continue to be focused as a national production center by maintaining high efficiency, while the second cluster requires policies geared towards increasing production capacity and food security. This research makes an important contribution to the formulation of evidence-based policies to support a more equitable and sustainable development of the agricultural sector in Indonesia.

4. Conclusion

This study successfully clustered 34 provinces in Indonesia based on the total production of seven major food crops using the Spatial Fuzzy C-Means (sFCM) method. The clustering results showed that two optimal clusters were formed, with very different characteristics. The first cluster, which includes three provinces in Java (West Java, Central Java and East Java), shows a much higher level of food crop production compared to other provinces. This cluster can be considered as the main center or food barn that supports the national food demand. In contrast, the second cluster consists of 31 other provinces with production capacity lower than the national average for all types of food crops.

The results of this analysis successfully address the research objective, which is to provide data-driven insights to support the formulation of food production equity policies in Indonesia. The disparities found indicate the need for a cluster-based approach in agricultural development policy. The first cluster can be focused on providing food surplus, while the second cluster requires intervention through agricultural infrastructure development, access to technology, and inclusive redistribution policies.

The sFCM method proved effective in integrating spatial dimensions and production data, resulting in valid and meaningful clusters. This finding supports the *core-periphery* theory and previous research that emphasizes the importance of spatial data-based analysis to develop more efficient and equitable food sector development strategies.

This research makes an important contribution to policy makers in designing food management and distribution strategies in Indonesia. By addressing production inequality between regions, this research can contribute to improving national food security and achieving the food sector's Sustainable Development Goals (SDGs). However, further efforts are needed to apply similar approaches in other relevant sectors and to integrate these findings with development programs at the local level.

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