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CLUSTERING ANALYSIS OF PATCHOULI PLANTATIONS FOR SUSTAINABLE PATCHOULI OIL SUPPLY CHAIN USING K-MEANS ALGORITHM

Hazful Maizi[1*], Prima Denny Sentia[2], Geta Ambartiasari[3], Friesca Erwan[4]
Mechanical and Industrial Engineering Department, Universitas Syiah Kuala, Indonesia[124]
Economic Education, Serambi Mekkah University, Indonesia[3]
Doctoral School of Regional and Business Administration Sciences, Széchenyi István University, Hungary[4]
hazful@usk.ac.id

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**Corresponding Author*

ABSTRACT
Growing demand for patchouli oil has undoubtedly become an opportunity for the patchouli industry, particularly in Aceh, which supplies about 80% of Indonesia's patchouli oil in the global supply chain system. However, the opportunity is often misguided by farmers and even the government, which implements various programs related to patchouli cultivation without identifying the potential land that is suitable to be used for it. The condition indicated that not every land is suitable for patchouli cultivation. Thus, it is necessary to cluster the distribution of existing patchouli plantations. The clustering aims to identify the existing patchouli plantations that have the potential for replication. This study uses the K-Means method that combines variables (the planting land, the harvesting land, and total production) to provide information on the plantation's potential scale in each region. The clustering measurement pointed out that the plantation in South Aceh Regency has the most potential land for sustainable cultivation, followed by several other areas included in Cluster 2 and Cluster 3. The study's result is essential in contributing significantly to optimizing patchouli cultivation management sustainability to fulfill Aceh Province's role as the best quality patchouli oil supplier.
Keywords: *Patchouli, Clustering, Sustainability, Supply Chain, K-Means.*

1. Introduction

Patchouli oil has a good prospect as a raw material that is needed for several industries around the world, where the most significant supply for patchouli oil is from Indonesia (Daud et al., 2024; Swamy & Sinniah, 2016; Zulfadli et al., 2023). Patchouli oil is one of the leading commodities that makes Aceh Province a key role in the global patchouli oil supply chain system, not only just as a supplier but also as an industry that produces high-quality patchouli oil (Adhayani et al., 2023; Ernawati et al., 2021). Many factors determine the scale of patchouli oil quality. In the patchouli oil supply chain, four main activities, which are pre-source, source, make, and deliver, need careful consideration (Maizi et al., 2020; Meilizar et al., 2024; Zuhri et al., 2019). Each aspect represents specific activities directly contributing to patchouli oil's productivity and quality (Zikri et al., 2021). Every process involves at least one actor who performs various activities.

Generally, in the patchouli oil industry in Aceh, farmers carry out most of the activities in each process. About 40% of the activities were conducted in the pre-source section (Maizi et al., 2020). That means most risks associated with patchouli productivity and quality occur in the pre-source section (Sentia et al., 2022). Two activities included in the pre-source are land and environment suitability identification. Both activities are the first step that must be done correctly to support the supply chain sustainability with quality patchouli cultivation (Paillin et al., 2024). Quality patchouli cultivation efforts will impact the optimum terna productivity and oil yield in the Terna to produce quality patchouli oil (P. L. B. Jain et al., 2022; Swamy & Sinniah, 2016).

The main challenge in patchouli cultivation lies in how farmers respond to fluctuating patchouli oil prices. When prices rise, they rapidly increase cultivation by intercropping and converting other land—even when land suitability is not assessed (Prakhyath et al., 2024). This opportunistic expansion aims for short-term profit but often leads to poor productivity and oil quality, weakening farmers' bargaining position. Consistent supply of the right quantity and quality, achievable through careful land selection, is essential for stable bargaining power and sustainable cultivation (Swain et al., 2024; Yusnidar et al., 2021).

Environmental factors are difficult to control and significantly affect agriculture commodity’s growth and productivity (Cong, 2021; Lallo et al., 2020). It requires many resources to create a suitable environment. Instead of enhancing productivity, these efforts resulted in a decline in the effectiveness and efficiency of the cultivation. This effectiveness and efficiency can be achieved by harmonizing and utilizing the suitability of the plantation land and the environment for patchouli plants (Gavioli et al., 2019; Rusdi, 2023). Therefore, it is essential to have data and understand the criteria of a plant’s needs for the land and environment that will be utilized. Of course, efforts to realize the suitability can be done by clustering all existing plantation land. The clustering method is a process of grouping data objects that have similarities to each other into the same cluster and different from data objects in other clusters (Javadi et al., 2022; Oyelade et al., 2019).

Although several studies have assessed land suitability for patchouli crops, most continue to use expert-driven evaluations, GIS-MCDA techniques, and localized agronomic trials (Salsabila, 2025; Setiawan, 2021; Vital et al., 2024). The current gap is the lack of research on land potential clustering at the district/city level in Aceh, using operational indicators (planting area, harvest area, and terna production) in a quantitative, reproducible, and rigorous manner. Furthermore, the links between land suitability assessments, pre-source risks, and cultivation program intervention priorities at the regional scale remain unmapped. This study addresses these gaps by clustering district/city-level patchouli centers with a K-Means algorithm that enables robust and repeatable classification.

In this study, clustering was carried out using the K-Means method to group the existing patchouli plantation land distributed in Aceh into three clusters. Cluster 1 is a cluster that covers less potential patchouli plantation land, Cluster 2 is a cluster that covers potential patchouli plantation land, and Cluster 3 is a cluster that covers the most potential patchouli plantation land. Data related to the planting land area, the harvesting land area, and total production can be a reference for plantation clustering. The clustering aims to analyze the potential of existing plantation land based on planting land area (hectares), harvesting land area (hectares), and terna production (tons), thus providing actual and accurate information to stakeholders on the potential of patchouli plantation land distributed across regencies and cities in Aceh.

Patchouli cultivation programs initiated by farmers or local governments should be implemented effectively and efficiently on suitable plantation lands. Thus, efforts to enhance the productivity and quality of patchouli oil can be carried out properly. Thus, the clustering method can support optimizing the sustainability of the patchouli oil supply chain by ensuring the suitability of the plant’s need to enhance the productivity and quality of patchouli oil produced.

2. Literature Review

2.1 Patchouli Plantation Zoning

The success of patchouli cultivation is strongly influenced by the suitability of abiotic factors, including soil, topography, and climate. Several previous studies have also confirmed that the majority of patchouli cultivation development is still constrained by the absence of a systematic land suitability evaluation, which has the potential to reduce the productivity and quality of patchouli oil produced. Inappropriate land utilization will result in low productivity and increase the risk of land degradation (Salsabila, 2025). In addition, most research is conducted within a fairly limited area. Potential sites are often evaluated without considering growth and productivity indicators.

Specific research examining the feasibility of variations of K-Means for clustering patchouli plantations is limited, providing little information on clustering patchouli plantations into implementable supply chain zones that together reflect production intensity and agronomic constraints(Keumalasari et al., 2025). By applying K-Means with robust initialization and objective K-selection to multi-year planted area, harvested area, and terna production variables, the study progressed from suitability determination to operational zoning, resulting in transparent, reproducible clusters that can be used to target expansion, prioritize processing infrastructure, and dampen supply volatility.

Thus, mapping land potential across a wider area at the district/city scale in Aceh and utilizing patchouli growth and productivity data as parameters in clustering using the K-Means Algorithm can help fill the existing gaps. This directly addresses a previously identified gap in patchouli research, where it has not linked spatial production clusters to supply chain resilience (E. D. Chaves et al., 2020; Ikotun et al., 2023; Rivera et al., 2022).

2.2 Distribution of Patchouli Plantation

Patchouli cultivation is distributed in several regencies and cities in Aceh Province. In 2005, the decree issued by the Minister of Agriculture of the Republic of Indonesia No. 320/Kpts/SR.120/8/2005 and 321/Kpts/SR.120/8/2005 stipulates that the Lhokseumawe and Tapak Tuan Variety are the patchouli superior variety from Aceh Province. International trade requires high-quality patchouli oil. Thus, Indonesia's patchouli oil industry, especially Aceh's, strives to produce high-quality patchouli oil with specifications referred to standards issued by the National Standardization Institution in 2006 with document number SNI 06-2385-2006.

Many factors determine the quality of patchouli oil, starting with all activities conducted from upstream to downstream. The factor that becomes the preliminary capital for the success of patchouli cultivation is the suitability of plantation land and the environment. The suitability includes plantation altitude, rainfall intensity, sunlight intensity, climate, temperature, humidity, soil acidity, and soil type to optimize patchouli plant growth (Nisa et al., 2024; Vital et al., 2024; Yusnidar et al., 2021).

Figure 1 visualizes the patchouli plantation distribution in Aceh Province from 2019 until 2023 based on data collected from the Agriculture and Plantation Service of Aceh Province.

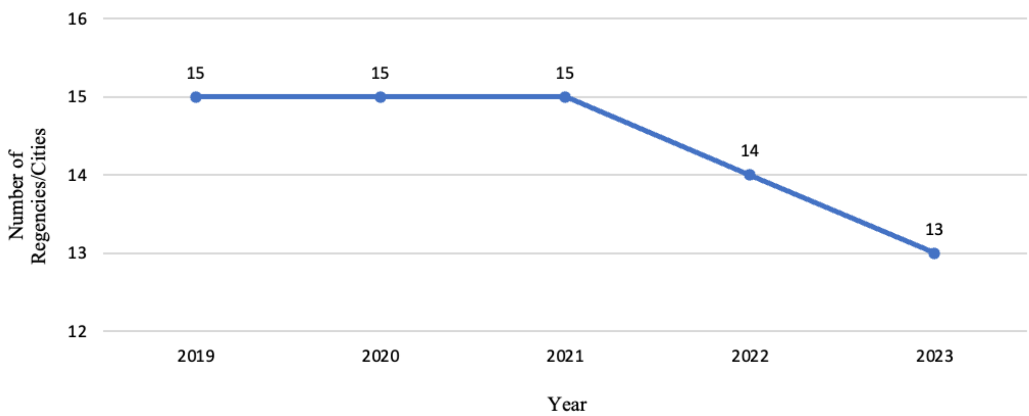


Fig. 1. Graph of patchouli plantation distribution 2019-2023

Figure 1 shows a reduction in patchouli plantation distribution around the Aceh Province. In 2023, as many as 13 regions, which include 12 regencies and a city, have various total allocation areas of patchouli plantation. The distribution of patchouli plantation area in hectares is represented in Figure 2. In this study, three variables were used as parameters in clustering analysis to delimit the scope of the analysis conducted. The first variable is the planting land area with a unit value of hectares, which became the initial reference in visualizing the distribution of plantation land. The second is the harvesting land area with a unit value of hectares, which is one of the effective indicators of environmental suitability. The last is Terna production volume with a unit of tons, which became a reference value for analyzing the productivity of each existing patchouli plantation.

Fig. 2. Patchouli plantation distribution in 2023

2.3 Clustering Method

The clustering method is used in data processing, which aims to classify data based on the similarity of unique characteristics in a data set (Borlea et al., 2021; Hertina et al., 2021). Generally, the clustering process involves at least the following steps: determination of data variables that will be used as the basis for data grouping, selection of a clustering algorithm that meets the characteristics of the data and the purpose of data analysis, determination of the appropriate number of clusters to produce an analysis that can represent the data, calculation of the clustering algorithm systematically based on the similarity of data characteristics to predetermined variables, and evaluation the result of clustering method uses a specific matrix (Wahyudi & Silfia, 2022).

3. Research Methods

3.1 Data and Samples

This study uses quantitative data on a ratio scale, which is appropriate for K-Means because all variables are continuous. The unit of analysis is 23 districts/cities in Aceh Province. The main analysis uses cross-sectional data for 2023 (n = 23), while panel data for 2019-2023 (n = 23 × 5) is used for sensitivity testing. The three variables grouped are planted area (hectares), harvested area (hectares), and patchouli production (tons). Data is sourced from routine publications of the Aceh Provincial Statistics Agency and the Aceh Provincial Plantation Office, which we have harmonized to the most recent administrative boundaries.

3.2 K-Means Algorithm

Compared with hierarchical or DBSCAN approaches, K-Means is generally more computationally efficient and produces results that are easier to interpret for centroid-based partitions (Belhadi et al., 2020; Ikotun et al., 2023). Applicatively, K-Means is also commonly used for policy categorization at the city scale to map development disparities between regions, group local authorities as policy “control groups”, and infrastructure planning/clustering, so that cluster results are easily mapped into “low-medium-high” categories (Alguliyev et al., 2021; Gao et al., 2024; Majumder et al., 2023; Rodrigues et al., 2025). K-Means was chosen to cluster districts in Aceh based on planted area, harvested area, and terna productivity due to its simplicity, efficiency, and track record of success across domains, making it a strong choice for medium-sized numerical data partitioning (A. K. Jain, 2010; X.-D. Wang et al., 2019). This algorithm minimizes the within-cluster sum of squares and represents each cluster with a centroid, making the resulting cluster profiles easily interpretable for continuous agricultural production indicators such as the three variables above. Computationally, K-Means is scalable and practical for tracking multiple values of k at the district/city unit of analysis, supporting model exploration without excessive computational burden (Ahmed et al., 2020). This description emphasizes the practical novelty of a procedure that is objective, replicable, and readily reusable in annual data updates.

The K-Means algorithm is included in the exclusive clustering classification, which groups data with an exclusive method so that other clusters cannot use the distinctive facts of a cluster. The algorithm is an unsupervised classification method used to group the data based on the uniqueness of the data, which aims to minimize the distance between the data and the cluster centroid (Ikotun et al., 2023). The K-Means clustering method is a non-hierarchical data clustering method that groups data in one or more clusters . The scheme of the K-Means algorithm can be seen in Figure 3.

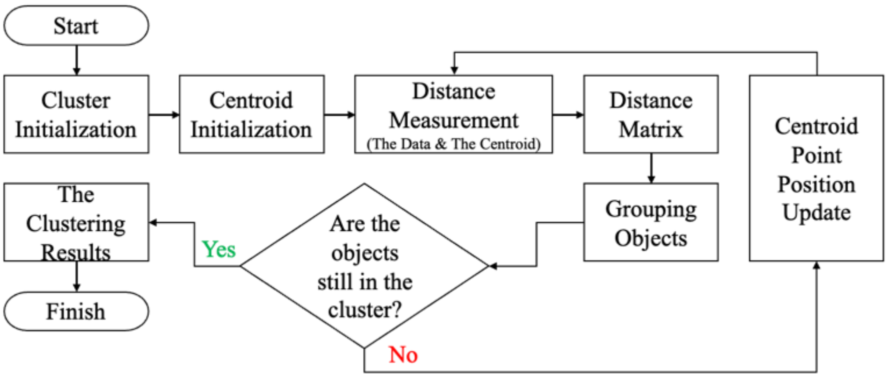


Fig. 3. Flowchart of the methodological steps

Prior to the clustering process, all data were standardized to ensure that the Euclidean metric in K-Means would not be biased by scale/unit differences between variables, as recommended in cluster validation studies(Henderi et al., 2021; Milligan & Cooper, 1988; Wongoutong, 2024). The number of clusters (k) was determined by referring to the general policy as a target for interpreting the land's potential cluster (low, medium, and high). Low cluster (C1) represents districts/cities with negative z values on ≥2 of the 3 variables (planted area, harvested area, and terna production), thus characterized by small cultivation scale and below-median terna performance. The medium cluster (C2) represents the “baseline” condition with variable values around the mean (middle quartile range). The high cluster (C3) characterizes areas with large cropping areas and productivity above the median (positive z-values on ≥2 variables), making it useful as a benchmark.

The number of clusters has been evaluated using the Silhouette Score Analysis, a standard criterion compatible with the K-Means output and proven to help select the most reasonable cluster structure(Rousseeuw, 1987). To process data for Silhouette Score and K-Means Analysis, Python is used to support data processing and optimal analysis.

There are several steps to apply the algorithm. First, the cluster initialization stage is to determine the desired number of clusters or consider the distribution of existing data by utilizing a scatter diagram to visualize the distribution of data, so that the tendency of data gathering in a particular area can be identified. The second stage is centroid initialization, which determines the centroid value by randomly selecting one point as the initial centroid of each cluster. The next step is calculating the distance between the data and the centroid point. This calculation applies to all data against each centroid using the following formulation (Faisal & Zamzami, 2020; Singh et al., 2013).

$$D_e = \sqrt{(x_i - s_i)^2 + (y_i - t_i)^2}$$

Remarks:

D_e	=	Euclidean Distance
i	=	Number of objects
x, y	=	Coordinates of the object
s, t	=	Coordinates of centroid

From the formulation, the distance matrix is obtained as follows:

$$D^0 = \begin{pmatrix} D_e(x_1,y_1),(s_1,t_1) & D_e(x_2,y_2),(s_1,t_1) & \dots & D_e(x_i,y_i),(s_1,t_1) \\ D_e(x_1,y_1),(s_2,t_2) & D_e(x_2,y_2),(s_2,t_2) & \dots & D_e(x_i,y_i),(s_2,t_2) \\ \vdots & \vdots & \vdots & \vdots \\ D_e(x_1,y_1),(s_i,t_i) & D_e(x_2,y_2),(s_i,t_i) & \dots & D_e(x_i,y_i),(s_i,t_i) \end{pmatrix} \begin{matrix} \rightarrow & \text{cluster 1} \\ \rightarrow & \text{cluster 2} \\ & \vdots \\ \rightarrow & \text{cluster i} \end{matrix}$$

The next stage is object grouping, which determines cluster members based on the minimum distance value from the centroid by referring to the distance matrix. The minimum distance value is initialized with "1", while other values are initialized with "0".

$$D^0 = \begin{pmatrix} D_e(x_1,y_1),(s_1,t_1) & D_e(x_2,y_2),(s_1,t_1) & D_e(x_3,y_3),(s_1,t_1) \\ D_e(x_1,y_1),(s_2,t_2) & D_e(x_2,y_2),(s_2,t_2) & D_e(x_3,y_3),(s_2,t_2) \\ D_e(x_1,y_1),(s_3,t_3) & D_e(x_1,y_1),(s_3,t_3) & D_e(x_3,y_3),(s_3,t_3) \end{pmatrix}$$

If,

$D_e(x_1,y_1),(s_1,t_1) < D_e(x_1,y_1),(s_2,t_2) < D_e(x_1,y_1),(s_3,t_3)$

$D_e(x_2,y_2),(s_1,t_1) > D_e(x_2,y_2),(s_2,t_2) > D_e(x_2,y_2),(s_3,t_3)$

$D_e(x_3,y_3),(s_1,t_1) > D_e(x_3,y_3),(s_2,t_2) < D_e(x_3,y_3),(s_3,t_3)$

Then,

$$G^0 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \begin{matrix} \rightarrow & \text{cluster 1} \\ \rightarrow & \text{cluster 2} \\ \rightarrow & \text{cluster 3} \end{matrix}$$

The last stage calculates the value of updating the centroid position from the iteration with the following formulation.

$$\bar{v}_{ij} = \frac{1}{N_i} \sum_{k=0}^{N_i} x_{kj}$$

Remarks:

v_{ij}	=	Centroid/cluster mean-i for j variable
N_i	=	The number of data which is a member of cluster-i
i, k	=	Cluster index
j	=	Variable index
x_{kj}	=	The value of data-k in the cluster for j variable

Continue iterating to update the centroid position until there is no significant change in the centroid position or reach the specified number of iterations.

$$G^{iterations\ i-1} = G^{iterations\ i}$$

4. Results and Discussions

4.1 Clustering Analysis

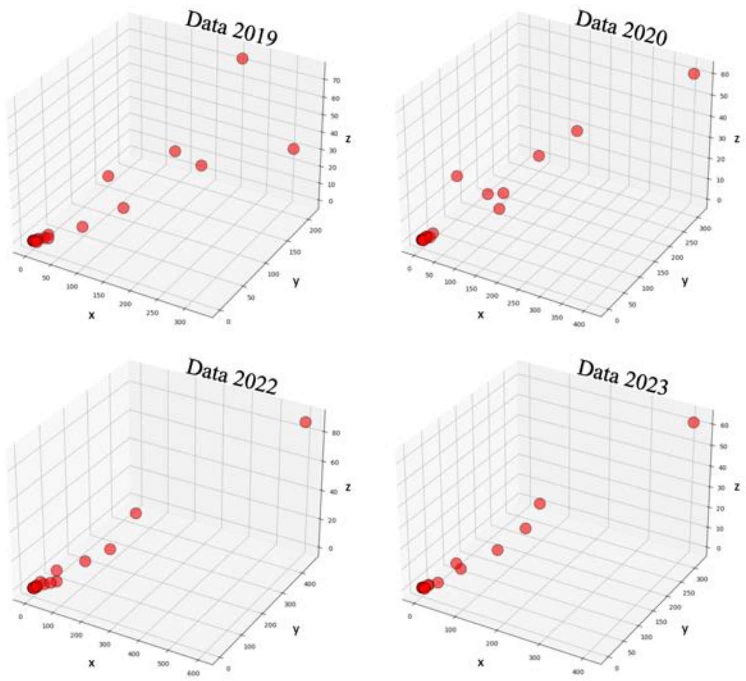
Utilizing plantation land for patchouli cultivation has long been carried out to increase productivity and produce quality patchouli oil. The Patchouli plantation profile in Aceh shows fairly dynamic growth in the development and utilization of the plantation. The data includes the expansion of planting land area (hectares), harvesting land area (hectares), and terna production (tons). Patchouli plantation land profile data from 2019 to 2023 is presented in Table 1.

Table 1 - Patchouli plantation data profile 2019-2023

Year	Number of Regencies/ Cities	Total Planting Land Area *(hectares)*	Total Harvesting Land Area *(hectares)*	Percentage of Harvesting Land Area *(%)*	Terna Production *(tons)*
2019	15	1,220	865	70.90%	226
2020	15	1,229	1,023	83.24%	178
2021	15	1,213	871	71.81%	159
2022	14	1,322	1,016	76.85%	181
2023	13	1,019	810	79.49%	147

Data in Table 1 interprets some conditions related to patchouli plantation land from 2019 to 2023. Based on the data 2023 on the distribution of patchouli plantation areas, including planting land area, harvesting land area, and terna production, these parameters tend to decrease. However, the percentage of harvesting land area to planting land area in 2023 tends to increase, equivalent to 80%. Furthermore, when referring to the rate of terna production calculated from the ratio between terna production and planting land area, the ratio of terna production in 2023 almost reached 15%, indicating that Terna production is 150 kilograms per hectare. Although not as good as in 2019, the terna production has been quite good in the past five years. This condition indicates the increasing effectiveness of patchouli plantation utilization.

The effectiveness is highly related to the implementation of each activity process carried out in quality and accordance with predetermined standards from upstream to downstream, hence allowing patchouli plants to grow optimally. All of the resources contributed significantly to the quality-patchouli oil produced. Figure 4 shows the distribution of patchouli plantations based on planting land area, harvesting land area, and terna production in 2019-2023.



Remarks:

x = Planting Land Area (hectares)
y = Harvesting Land Area (hectares)
Z = Terna Production (tons)

Fig. 4. The distribution of patchouli plantations 2019-2023

The plantation distribution diagram in Figure 4 shows the regencies and the cities with patchouli plantations, mainly distributed or centered on x, y, and z coordinate axes, which are close or equivalent to zero. It is interpreted that most areas have minimal patchouli plantation area and productivity. Only a few have significant patchouli plantation areas and productivity. Figure 4 illustrates heterogeneity across regions, validating the structural variation that underpins the need for clustering. Mapping the distribution of patchouli plantations is the first step to clustering potential land. Therefore, it can be a reference for land development and replication to enhance quality patchouli production in certain areas.

Calculation of the K-Means Algorithm for clustering patchouli plantation is carried out based on three variables such as planting land area (v1), harvesting land area (v2), and terna production (v3). The variables provide important information regarding the potential of the resources. The planting land area indicates how much plantation area in a particular region has been utilized and expanded for patchouli plantations; the harvesting land area indicates the area that can be harvested, and terna production variables provide information related to the amount of terna that has been produced on each unit area (hectares) as raw material for patchouli oil production.

The model created three cluster labels (low, medium, and high) based on the three variables, and the number of clusters (k=3) was validated using silhouette score analysis to ensure separation between clusters. The silhouette approach was used to assess cohesion-separation and assist in selecting the optimal number of clusters. The average silhouette score for each year (2019-2023) is presented in Figure 5.

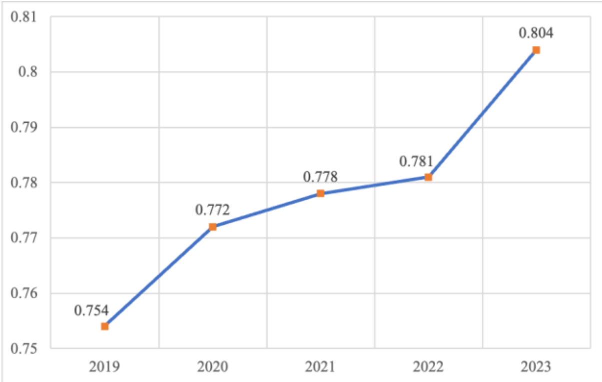


Fig. 5. Average of silhouette value 2019-2023

A recapitulation of the average silhouette value (k=3) shows consistently good cluster separation throughout 2019-2023, with a range of 0.754 to 0.804. Given that this index ranges from -1 to 1, values above 0.75 indicate a cohesive cluster within members and a clearly separated distance between clusters. The pattern of gradual increase from 0.754 (2019) to 0.772 (2020), 0.778 (2021), 0.781 (2022), and reaching 0.804 (2023) indicates improved inter-cluster separability as well as reduced intra-cluster dispersion, so that the validity of selecting three clusters (low, medium, and high) is stronger in recent years. This trend also implies consistency in data preprocessing and a possible decrease in the influence of extreme values or zeros that can pull clusters to one side. Such stability and gradual increase provide strong justification for using three clusters for trend analysis and policy mapping based on planted area, harvested area, and terna production.

The initialization of the number of clusters and centroid coordinates used in the K-Means Algorithm for clustering formulation are shown in Table 2.

Table 2 - The initialization of clusters and centroid coordinates

Cluster	Potential	The Initialization of The Centroid Coordinates (x, y, z)				
		2019	2020	2021	2022	2023
C1	Low	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
C2	Medium	(6, 2, 0.4)	(5, 5, 0.49)	(6, 2, 0.2)	(6, 5, 0)	(3, 1, 0.05)
C3	High	(65.5, 50.5, 9)	(72.5, 56, 8)	(40.5, 22.5, 3)	(47.5, 31, 3.5)	(37.5, 30, 4)

The initial centroid coordinates are calculated based on the data's quantile values (Q1, Q2, and Q3) for each variable per year. The first quantile (Q1) values become "centroid 1" coordinates (C1), the second quantile (Q2) values become "centroid 2" coordinates (C2), and the third quantile (Q3) values become "centroid 3" coordinates (C3). These coordinates become the initial reference for calculating the distance between each data to the centroid points (C1, C2, and C3), and then the distance matrix can be obtained for the overall data. After that, data grouping is carried out to determine cluster members based on the minimum distance value of the data to the centroid point. This calculation continues to be iterated until the number of members in each centroid (C1, C2, and C3) is fixed. If the condition has been reached, then the iteration can be stopped. Therefore, the centroid coordinate value at the end of the iteration becomes the final centroid coordinate. Table 3 shows the data of the calculation results of the K-Means algorithm in determining the final coordinate point of the centroid as a reference for clustering grouping.

Table 3 - The centroid coordinate of clustering

Year	Σ Iteration	Centroid	Centroid Coordinate	
			Initial	Final
2019	3	C1	(0, 0, 0)	(4.7, 2.3, 0.3)
		C2	(6, 2, 0.4)	(83, 58.7, 14.7)
		C3	(65.5, 50.5, 9)	(224, 163.3, 44.3)
2020	6	C1	(0, 0, 0)	(6.7, 5.1, 0.5)

Year	∑ Iteration	Centroid	Centroid Coordinate	
			Initial	Final
		C2	(5, 5, 0.49)	(124.3, 104, 18)
		C3	(72.5, 56, 8)	(309.5, 260.5, 48.5)
2021	7	C1	(0, 0, 0)	(8.6, 3.8, 0.5)
		C2	(6, 2, 0.2)	(140.5, 120.5, 21.8)
		C3	(40.5, 22.5, 3)	(496, 321, 62)
2022	6	C1	(0, 0, 0)	(11.2, 8.3, 1.1)
		C2	(6, 5, 0)	(168.3, 134.7, 24)
		C3	(47.5, 31, 3.5)	(604, 454, 88)
2023	8	C1	(0, 0, 0)	(8.7, 6.6, 1)
		C2	(3, 1, 0.05)	(147.3, 121.3, 22)
		C3	(37.5, 30, 4)	(411, 321, 62)

Figure 6 shows the results of calculating the final centroid coordinates, which serve as the clustering reference for each data point set.

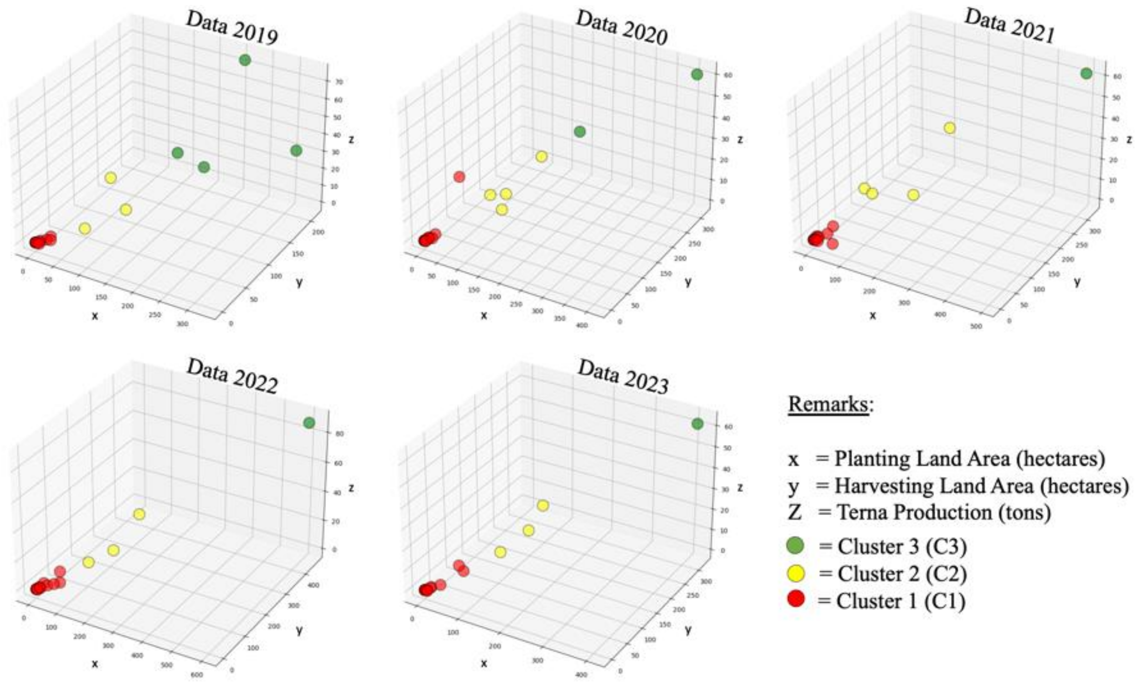


Fig. 6. The clustering of patchouli plantation

Figure 6 interprets the decline in the number of patchouli plantations managed by the government and communities (groups/individuals) in the last five years. Some areas that were initially in Cluster 3 (Southeast Aceh, West Aceh, and Aceh Jaya) dropped to members of Cluster 2 in 2023. Of course, this needs to be further observed instead of immediately concluding that the existing plantation land in the areas has no potential for patchouli cultivation. It is concerned that this condition is caused by the behavior of farmers who decide to stop cultivating patchouli when the price of patchouli oil is low. It could be that the decline in the amount of land utilized for patchouli cultivation is not due to land and environmental unsuitability. Meanwhile, based on the clustering, South Aceh consistently conducts and develops patchouli cultivation.

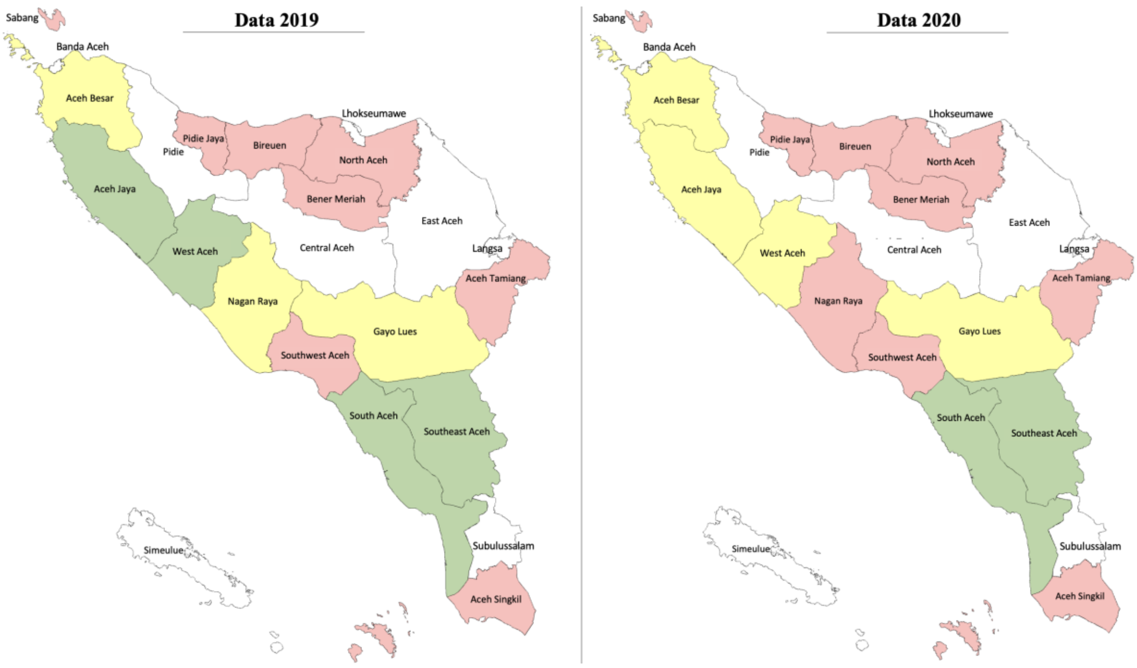
Clustering based on variables of the planting land area, the harvesting land area, and terna production aims to gather the areas that have successfully empowered their plantation land for patchouli cultivation. In addition, it provides information on productivity levels, which can serve as a benchmark for identifying potential land to replicate plantations effectively and efficiently. Every cluster has characteristics based on the potential level of patchouli plantation affected by the variables. The clustering characteristics are shown in Table 4.

Table 4 - The clustering characteristics of patchouli plantations

Clusters	Variables			Potential
	Planting Land Area (*hectares*)	Harvesting Land Area (*hectares*)	Terna Production (*tons*)	
	x	y	z	
C1	0 - 56	0 - 49	0 - 9	Low
C2	56 - 207	41 - 207	3 - 37	Medium
C3	158 - 604	124 - 454	30 - 88	High

The limit value for each variable is set to the minimum and maximum values of the members of each cluster, ensuring the range encompasses all members of the cluster. Cluster C1 (Low) consists of areas with the lowest values for the variables, with an average planting land area of 22 hectares, an average harvesting land area of 19.07 hectares, and an average terna production of 1.82 hectares. Cluster C2 (Medium) consists of areas with medium values for the variables, with an average planting land area of 136 hectares, an average harvesting land area of 111.2 hectares, and an average terna production of 21.62 hectares. Meanwhile, Cluster C3 (High) consists of areas with the highest values for the variables, with an average planting land area of 352 hectares, an average harvesting land area of 248.43 hectares, and an average total production of 55.43 hectares. The value of each variable indicates the potential of patchouli plantations. When the value for each variable approaches its maximum, it indicates that the patchouli plantation's potential is relatively high.

Visualization of clustering results using the K-Means Algorithm is presented in Figure 7.



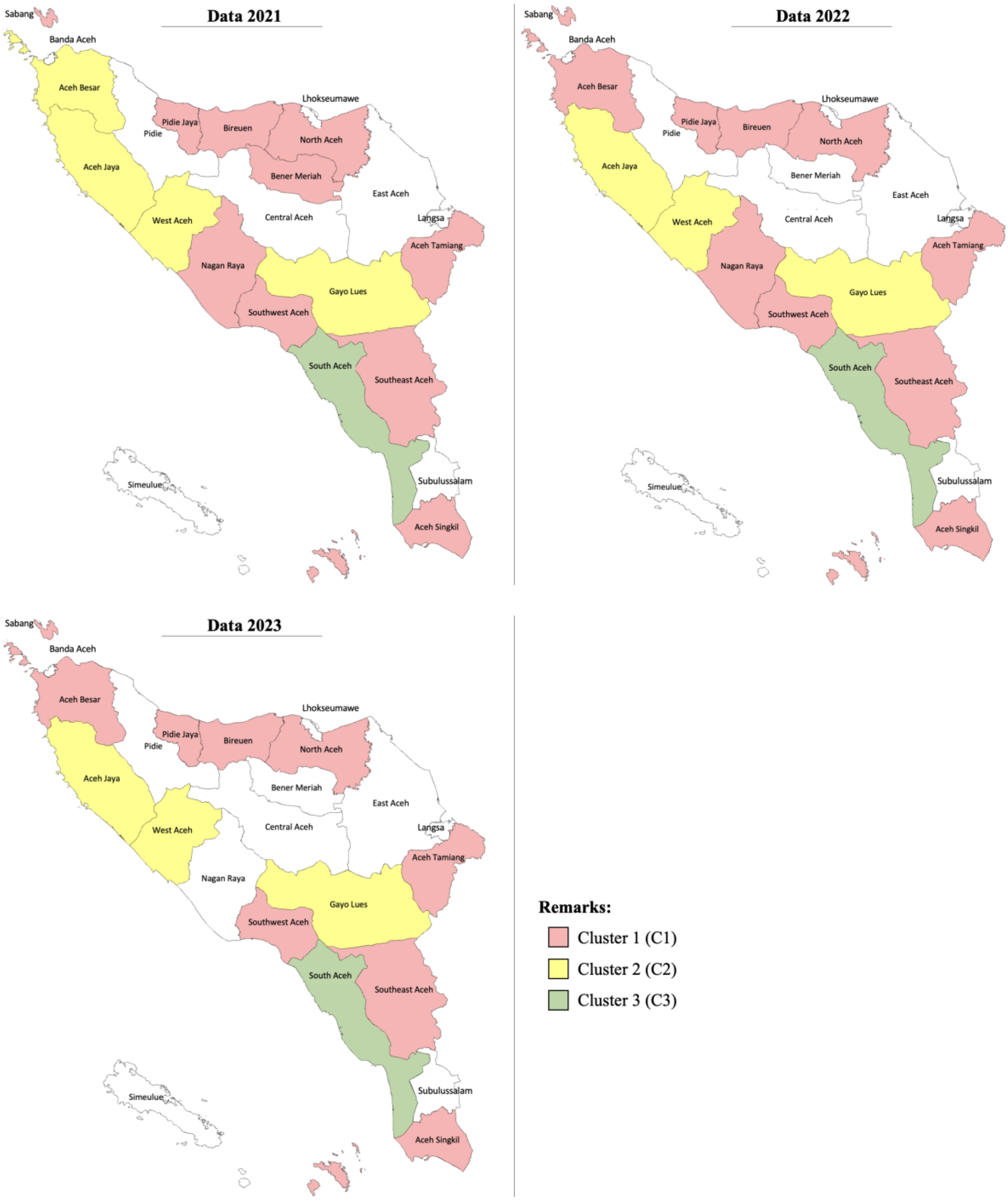


Fig. 7. Visualization of the clustering patchouli plantations 2019-2023

Based on the clustering results, it was found that South Aceh Regency was the only region that consistently belonged to cluster 3 (C3) from 2019 to 2023. It is understood that patchouli plantations in the area are used for sustainable patchouli cultivation. Hence, the clustering results indicate that patchouli plantations in South Aceh Regency have the potential to continue expanding and replicating. As well as Gayo Lues Regency, it also has similar conditions, where it remained a member of Cluster 2 (C2) until 2023. Meanwhile, as many as seven areas, including Aceh Singkil, Bireuen, North Aceh, Southwest Aceh, Aceh Tamiang, Pidie Jaya, and Sabang, remained in Cluster 1.

In contrast, patchouli plantations in Nagan Raya Regency, which have since 2020 continued to decline in clustering status from Cluster 2 (C2) to non-clustering, meaning no managed patchouli plantations in 2023, as well as in Bener Meriah Regency.

Table 5 - The clustering result of member detail 2019-2023

Regency/City	2019		2020		2021		2022		2023	
	D_e	Cls	D_e	Cls	D_e	Cls	D_e	Cls	D_e	Cls
Aceh Singkil	19.75	C1	1.24	C1	3.46	C1	5.70	C1	7.20	C1
South Aceh	105.21	C3	112.28	C3	0.00	C3	0.00	C3	0.00	C3
Southeast Aceh	57.15	C3	112.28	C3	21.30	C1	16.69	C1	19.69	C1
West Aceh	41.56	C3	34.05	C2	66.26	C2	24.61	C2	15.33	C2
Aceh Besar	35.03	C2	8.22	C2	82.56	C2	52.57	C1	55.54	C1
Bireuen	10.97	C1	7.62	C1	2.72	C1	3.53	C1	2.02	C1
North Aceh	1.34	C1	1.71	C1	5.76	C1	7.91	C1	8.04	C1
Southwest Aceh	16.41	C1	13.07	C1	33.25	C1	38.15	C1	63.70	C1
Gayo Lues	21.43	C2	38.43	C2	60.75	C2	71.42	C2	47.38	C2
Aceh Tamiang	2.77	C1	1.65	C1	4.04	C1	11.22	C1	5.97	C1
Nagan Raya	34.31	C2	61.10	C1	42.41	C1	51.25	C1	-	-
Aceh Jaya	77.23	C3	64.46	C2	110.17	C2	78.89	C2	43.79	C2
Bener Meriah	4.33	C1	6.89	C1	5.82	C1	-	-	-	-
Pidie Jaya	2.83	C1	6.26	C1	6.79	C1	11.74	C1	1.33	C1
Sabang	3.24	C1	1.97	C1	4.11	C1	4.55	C1	9.59	C1

Grouping objects based on the Euclidean Distance (De) value that has been calculated by comparing the minimum distance of each data with the centroid coordinates. The centroid coordinates used are the final coordinates of each cluster, as listed in Table 3. Therefore, the object is included in the closest cluster. Data in Table 5 shows that in 2019, the regencies of Southeast Aceh and West Aceh were classified in Cluster 3 (C3). However, in 2023, both experienced a decrease in clusters. A total of 6 regencies experienced a decrease in cluster, and 8 regencies/cities stayed in the same cluster from 2019 to 2023.

On the other hand, as many as 8 regions (distributed in 4 districts and 4 cities) have not utilized their plantation land for patchouli cultivation at all. Many factors certainly cause this condition. Thus, further assessment is needed to ensure the feasibility of land utilization for patchouli cultivation.

4.2 Analysis of Clustering Findings

Unlike many patchouli studies that emphasize FAO land suitability matching or agro-biophysical surveys, this study bases regional groupings on actual production performance (Setiawan, 2021; Sperandio et al., 2025). This complements patchouli studies focusing on its biophysical potential and soil suitability/fertility in Aceh. When compared to research on other objects, this study is consistent with cluster-based agricultural zoning research for spatial variability management, including management zone (MZ) delineation with K-Means/FCM, as well as recent field studies testing composite cluster models to find more stable management zones (Méndez-Vázquez et al., 2019; Y. Wang et al., 2025; Yuan et al., 2022).

The main novelty of this research is its focus on patchouli in Aceh at the district scale, using production indicators that directly reflect cultivation performance. By mapping performance zones, this research provides a complementary “yield-based” lens to cluster-based biophysical or soil texture suitability maps. The integration of environmental/climatic variables and remote sensing covariates has the potential to refine cluster boundaries and the relevance of interventions (Cong, 2021; Lallo et al., 2020; Reyes et al., 2023). Another contribution is to show that the performance cluster framework can serve as a stratum for prediction and recommendation models. The map of three performance clusters provides an operational basis for local governments: the high cluster (C3) for value-added intensification and value chain integration; the medium cluster (C2) for agronomic improvement packages and input efficiency; and the low cluster (C1) for evaluation of development or diversification feasibility. This zoning-based policy pattern aligns with the concept of site-specific management and the practice of delineating management zones across various agroecological contexts (Yuan et al., 2022). In the local context of Aceh, regional evidence on sub-regional productivity clustering confirms that district-level clustering can be directly translated into strategies to sharpen extension services and input allocation (Gavioli et al., 2019; Nurdin, 2025; Rusdi, 2023).

Recent research on patchouli has largely focused on mapping ecological suitability or land characteristics, with the dominant methods being MaxEnt and ArcGIS. Such approaches can be applied to determine where the crop can thrive, but cannot show where production clusters actually form over a wide area to support sustainable cultivation (Rusdi, 2023; Setiawan, 2021; Zeng et al., 2021). Facts from crop mapping and regional agricultural zoning show that a compact and efficient clustering method, such as K-Means, can divide regions based on multi-year production variables and context at a large scale that is harmonized and verified with the silhouette index, as has been done in this study (Rivera et al., 2022; Zhang et al., 2025).

4.3 Cultivation Development

Over the past five years, local government support for patchouli commodities has shown consistent policy direction in two main areas, namely strengthening upstream and strengthening downstream. In the upstream aspect, the development of cultivated land in Aceh Jaya and South Aceh marked a simultaneous boost to traditional centers and replicated land. In the downstream sector, the local government is establishing a patchouli industry ecosystem through technology transfer, coaching, and product innovation, recognized as a national model of downstreaming. This was reinforced by a cross-ministerial initiative targeting five priority districts (Aceh Besar, Aceh Tamiang, Gayo Lues, South Aceh, and Nagan Raya) to strengthen the patchouli oil value chain, including mechanisms for sharing production facilities and developing centers. The overall policy direction remains grounded in the regional strategic framework, such as the Aceh Patchouli Industry Action Plan, so that the policies pursued not only expand cultivation capacity but also increase added value, enabling more farmers and local businesses to benefit.

From a clustering perspective, South Aceh's placement in the high-performing cluster, as reflected by the highest production achievement in 2023, indicates that the program's focus in the district is well-targeted. The expansion of land replication support in Aceh Jaya is a strategy to strengthen the production base in medium-status areas and help them transition to higher performance. Correspondingly, the cross-ministerial program targeting Aceh Besar, Aceh Tamiang, Gayo Lues, and Nagan Raya, in addition to South Aceh, shows a shift from a single-center orientation towards a more dispersed portfolio of potential areas. Methodologically, this policy direction is in line with the cluster map, which indicates that the target areas are in low and medium clusters with growth capacity through strengthening supporting factors such as land availability, extension intensity, and post-harvest and market access, so that institutional interventions and industrial strengthening act as levers to increase productivity and value chain stability.

Overall, local government policies consistently support patchouli cultivation through a combination of upstream and downstream interventions. The focus of program locations is relatively aligned with potential areas by maintaining high-performing centers (South Aceh) while expanding support to districts with indicative low-medium potential (Aceh Jaya, Nagan Raya, Aceh Besar, Gayo Lues, Aceh Tamiang) through targeted cultivation schemes and strengthening industrial ecosystems. Clustering adjustments based on the latest annual production data and cluster evaluation results will ensure that program allocations are more targeted.

5. Conclusion

This study developed a data-driven cluster model for patchouli plantations using the K-Means algorithm on three core indicators: planted land area, harvested land area, and terna production. The model produces an operational cluster map that distinguishes high, medium, and low priority areas for strengthening the patchouli oil supply chain. The cluster labels (low, medium, and high) align with agricultural clustering principles that emphasize spatial heterogeneity in productivity and access to inputs as the basis for differentiated intervention. Theoretically, this pattern supports the argument that upstream-downstream supply chain strategies need to be tailored to the region's typology. The validity of the number of clusters was evaluated using the silhouette approach, ensuring that the resulting clusters are not only descriptive but also scalable and can be replicated in subsequent periods or in other regions with similar data structures.

Clustering provides a basis for more precise policy targeting. In terms of sustainability, each cluster demands a different strategy. High cluster areas (C3) should focus on production consolidation, quality standardization, and downstream facilities. The medium cluster (C2) requires selective interventions, including agronomic assistance, improved access to inputs, and post-harvest improvements. Low clusters (C1) require basic support, such as infrastructure improvements, access to microfinance, and strengthening of farmer institutions, before encouraging expansion. For businesses, cluster maps facilitate planning for raw material procurement, harvest scheduling, and logistics network design to minimize supply and quality variations. Linking the findings to this framework bridges the gap between spatial diagnosis and policy design.

According to the study results, 12 regencies and a city have utilized their plantation land area for patchouli cultivation. Some plantation areas are utilized using intercropping and single-land methods. In 2023, only South Aceh Regency is included in Cluster 3, the highest potential plantation land for patchouli cultivation. According to historical data from 2019 to 2023, South Aceh Regency has been a member of Cluster 3 for five years. Therefore, based on the clustering, South Aceh Regency is the most suitable and potential plantation land for sustainable patchouli cultivation in Aceh.

Meanwhile, three regencies are included in Cluster 2, i.e., Aceh Jaya, West Aceh, and Gayo Lues, which means that regencies are categorized as regions with potential for patchouli cultivation. Moreover, based on the result of clustering, Aceh Jaya and West Aceh have been members of Cluster 3 in 2019. Therefore, it can be said that Cluster 2 and Cluster 3 almost have the same potential level. The members in both clusters should be suitable plantation land for sustainable patchouli cultivation in Aceh. In addition, the city or regency, which is included in Cluster 1, does not mean the land has no potential. However, further research should be conducted holistically and comprehensively to ensure the patchouli plantation’s potential in the region. Instead of conducting patchouli cultivation in various regions, it is better to focus and develop sustainable patchouli cultivation programs in the areas included in Clusters 2 and 3, as mentioned, and then make those areas the center of the patchouli oil industry.

This clustering approach is scalable enough to be applied to other commodities or regions. Its advantages include operational variables, fast, easy-to-interpret algorithm calculations for intervention planning, a quantitative feature structure that facilitates standardization across commodities or regions, and cluster results that can be directly mapped to support program prioritization. However, an important limitation is that variable relevance may differ across commodities and agroecologies. For example, productivity variables are strongly influenced by biophysical factors (soil, climate, altitude) and infrastructure that are not included, so patterns between regions can be biased. Thus, adding environmental variables improves clustering quality and its usefulness for planning. This description also emphasizes the limitations of this study, focusing on outcome indicators and expanding the variables so that clusters reflect development potential and readiness.

Future research directions could include extending the variables with biophysical and socioeconomic factors (soil type, rainfall, access to labor, distance to market) to refine cluster separation, as well as conducting structured field validation and piloting of cluster-based policies needed to assess impacts on oil quality, farmer prices, and supply continuity, which could then be translated into a decision-making matrix linking cluster maps, intervention recommendations, and simulated logistics and financing scenarios.

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