JESICA: Journal of Enhanced Studies in Informatics and Computer Applications
Journal homepage: jesica.itsk-soepraoen.ac.id
ISSN: e-ISSN: 3046-6938 p-ISSN: 3046-6997
Vol. 3, No. 1, February 2026, Pp. 28-33

Hierarchical Clustering Analysis of Biopharmaceuticals Crop Production Across Indonesian Provinces

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Keywords:
Biopharmaceuticals crop, hierarchical clustering, medicinal plants, regional analysis

Abstract
This study analyzes biopharmaceuticals (medicinal crop) production across Indonesian provinces using 2023 data from eight major commodities: ginger, galangal, kencur, turmeric, lempuyang, temulawak, temu ireng, and keji beling. Data from 38 provinces were normalized and analyzed using agglomerative hierarchical clustering with Ward's linkage and Euclidean distance. The results identify three distinct clusters representing high, medium, and low production levels, with Java provinces dominating the high-production cluster, while provinces outside Java fall into moderate and low clusters. These findings highlight regional disparities and potential specialization in biopharmaceuticals cultivation. This study contributes a comprehensive national-scale multivariate clustering framework for medicinal crop production and demonstrates the applicability of hierarchical clustering for spatial agricultural analysis. The findings provide practical implications for policymakers in designing targeted agricultural development strategies, regional specialization planning, and supply chain optimization in Indonesia's biopharmaceuticals sector.

1. Introduction

Biopharmaceuticals (medicinal crops) are an important component of Indonesia's agricultural and bioeconomic sectors, as they support traditional medicine, pharmaceutical industries, and the development of herbal-based products. Commodities such as ginger, turmeric, galangal, kencur, and other medicinal plants are widely used both for domestic consumption and commercial purposes, contributing to rural livelihoods and regional economic growth. With increasing global demand for natural and herbal products, the strategic role of biopharmaceutical cultivation in Indonesia continues to expand.

Indonesia's geographical diversity, climate variability, and differences in agricultural practices across provinces result in substantial disparities in biopharmaceutical production levels. Some regions benefit from favorable agroecological conditions, infrastructure, and market access, enabling higher production volumes, while others face limitations related to land suitability, technology adoption, and resource availability. These regional differences highlight the need for systematic analysis to better understand spatial production patterns and regional strengths in biopharmaceutical cultivation.

Despite the importance of biopharmaceuticals, studies that comprehensively analyze provincial-level production patterns using multiple commodities remain limited. Existing research often focuses on single commodities or localized areas, which may not fully capture national-level production dynamics. A multivariate approach that considers several biopharmaceutical commodities simultaneously is therefore essential to identify similarities and differences among provinces and to support strategic planning at both regional and national levels.

Recent studies show that data-driven and intelligent analytical methods have been widely applied to agricultural and biopharmaceutical-related problems in Indonesia, including production forecasting, decision support, and clustering analysis. Machine learning and time-series approaches have been used to predict rainfall, crop yields, and planting schedules, supporting more accurate agricultural planning [1],[2],[3],[4]. In biopharmaceutical studies, clustering techniques such as K-Means and K-Medoids have been employed to identify regional similarities and disparities in medicinal crop production, while information and decision support systems have supported structured decision-making and policy formulation [5],[6],[7],[8]. From an economic and policy perspective, research highlights the strategic role of biopharmaceuticals within the agro-pharmaceutical value chain and the usefulness of clustering methods for regional and environmental analysis [9], [10],[11]. However, comprehensive multivariate clustering at the provincial level that integrates multiple biopharmaceutical commodities remains limited, motivating this study to apply

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hierarchical clustering to reveal national-scale production patterns. Unlike previous studies that focus on single commodities or limited regions, this study provides a national-scale multivariate clustering analysis integrating eight major biopharmaceutical commodities. This research fills the gap by identifying provincial production patterns and offering a data-driven basis for regional specialization and policy planning.

Hierarchical clustering analysis offers a robust data-driven method for grouping regions based on production characteristics, allowing policymakers to identify clusters of provinces with similar production capacities. By classifying provinces into high, medium, and low production groups, this approach can reveal spatial disparities and potential regional specialization. Such insights are valuable for formulating targeted agricultural policies, optimizing resource allocation, and promoting balanced development in Indonesia's medicinal plant sector.

Overall, understanding regional biopharmaceuticalproduction patterns is crucial for strengthening Indonesia's position in the medicinal plant industry. A comprehensive clustering-based analysis can serve as an analytical foundation for policy formulation, regional development planning, and strategic decision-making aimed at enhancing productivity, sustainability, and competitiveness in the biopharmaceutical sector.

2. Research Method

This study employed a quantitative approach using secondary data on biopharmaceutical production collected from official statistical sources. The dataset consists of 2023 production data for eight major biopharmaceutical commodities: ginger, turmeric, galangal, kencur, lempuyang, temu ireng, and keji beling across 38 provinces in Indonesia. Before analysis, the data were preprocessed through normalization to minimize scale differences among commodities with varying production volumes, ensuring that each variable contributed proportionally to the clustering process.

Hierarchical clustering analysis was applied using an agglomerative approach with Ward's merging method and Euclidean distance to identify similarities in provincial biopharmaceutical production patterns. This method was chosen due to its effectiveness in minimizing within-cluster variance and producing well-defined clusters. The clustering results were then interpreted to classify provinces representing high, medium, and low levels of biopharmaceutical production, providing insights into regional disparities and potential specialization in medicinal plant cultivation across Indonesia.

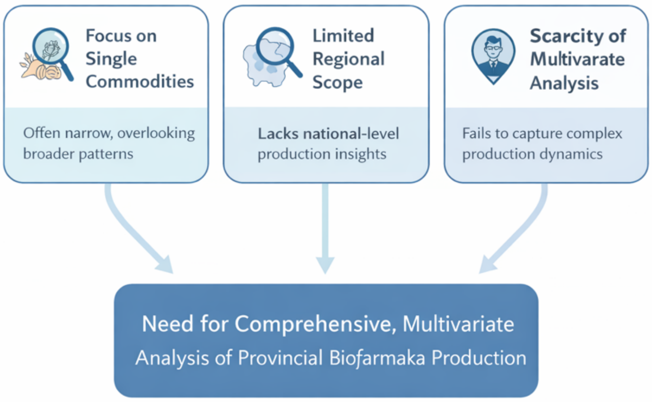

Figure 1. Illustration of the limitations of previous studies on biopharmaceutical crop production

Figure 1 illustrates the key limitations identified in previous studies on biopharmaceutical crop production. Many studies tend to focus on a single commodity, resulting in a narrow perspective and overlooking broader production patterns. Furthermore, some analyses are limited to specific regions, making it difficult to capture national-level production dynamics. The scarcity of multivariate analytical approaches further limits the ability to understand the complex interactions between different biopharmaceutical crops. This gap highlights the need for comprehensive multivariate analyses at the provincial level to better represent biopharmaceutical production patterns across Indonesia.

2.1. Biopharmaceutical Plants and Their Importance in Indonesia

In Indonesia, biopharmaceutical crops, which include medicinal and herbal plants, play a significant role in the agricultural sector. These crops are closely linked to the long-standing tradition of herbal medicine (*jamu*) and are increasingly utilized in the pharmaceutical industry and health supplement production. Indonesia's diverse agro-climatic conditions, including variations in climate, soil type, and topography across provinces, lead to substantial differences in biopharmaceutical crop production. Previous studies indicate that disparities in land suitability,

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cultivation practices, technological adoption, and farmers' capacity contribute to unequal production levels among regions. Therefore, analyzing provincial biopharmaceutical production patterns is essential to support sustainable agricultural development, improve regional competitiveness, and inform evidence-based policy planning in Indonesia.

Table 1 presents a dataset of biopharmaceutical (medicinal plant) production in 38 Indonesian provinces in 2023 [12], which includes eight key commodities: ginger, galangal, kencur, turmeric, lempuyang, curcuma, temuireng, and kejibeling. Data are reported in kilograms and represent provincial-level production, which was used as the primary input for cluster analysis to identify regional patterns and similarities in biopharmaceutical production across Indonesia.

Table 1. Biopharmaceutical dataset (medicinal plants) [12]

38 Provinces	Ginger (Kg)	Galangal (Kg)	Kencur (Kg)	Turmeric (Kg)	Lempuyang (Kg)	Curcuma (Kg)	Temu ireng (Kg)	Keji beling (Kg)
	2023	2023	2023	2023	2023	2023	2023	2023
ACEH	4345136	776506	91805	2384875	6	13339	90	-
SUMATERA UTARA	16637643	931247	1500313	3594877	27752	27180	1847	-
SUMATERA BARAT	5473718	1240713	190612	2260163	11997	8804	204	-
RIAU	1070335	1189048	722104	1414919	161093	610079	12297	-
JAMBI	2508430	694404	128105	623398	14779	29472	12834	-
SUMATERA SELATAN	2241128	2644358	1463757	1472517	11655	225682	100510	-
BENGKULU	16879563	1533213	669497	5458374	6028	17838	8196	-
LAMPUNG	2825270	1183187	6042319	1479313	106751	196860	76444	-
KEP. BANGKA BELITUNG	762841	1023903	491764	660763	-	36090	-	-
KEP. RIAU	39340	63575	8599	29401	176	1542	-	-
DKI JAKARTA	1937	1725	443	939	33	114	28	-
JAWA BARAT	39976740	15967432	15248833	22447402	152777	195067	34641	-
JAWA TENGAH	33302216	9349170	9895354	20568314	583636	3022592	745644	-
DI YOGYAKARTA	4821591	1161345	2697539	3539394	561783	1569671	573138	-
JAWA TIMUR	29162669	9732999	3190427	113283709	1760233	17320203	2194243	-
BANTEN	793604	772868	217419	310674	94883	3228	330	-
BALI	8340720	671614	499233	2221772	-	6299	-	-
NUSA TENGGARA BARAT	2383397	395903	153614	530302	14594	104189	3340	-
NUSA TENGGARA TIMUR	1384763	692058	106600	1243534	289	210264	1975	-
KALIMANTAN BARAT	5162851	507741	410186	1269217	16283	101719	38901	-
KALIMANTAN TENGAH	452657	306180	118032	264465	13686	23353	10177	-
KALIMANTAN SELATAN	3153927	618517	2463810	1525833	225	237771	-	-
KALIMANTAN TIMUR	539284	197238	44118	125183	3294	27154	34480	-
KALIMANTAN UTARA	762686	1197173	142095	267431	57257	43952	50727	-
SULAWESI UTARA	1432905	70394	3745	450603	-	16191	-	-
SULAWESI TENGAH	1080228	301419	461321	745370	6597	114087	7391	-
SULAWESI SELATAN	8311368	3099114	225758	14546000	28165	61859	333	-
SULAWESI TENGGARA	1014742	341764	210670	279362	3590	37917	5539	-
GORONTALO	25556	20	548	16723	-	432	225	-
SULAWESI BARAT	84507	83380	32756	94810	16292	295	10	-
MALUKU	890873	294478	306397	790069	7700	1524	6000	-
MALUKU UTARA	2719584	1021490	87132	1499445	-	32375	7	-
PAPUA BARAT	72573	52276	31349	183066	1986	17316	592	-
PAPUA BARAT DAYA	-	-	-	-	-	-	-	-
PAPUA	218555	72676	34136	73866	5470	12469	6106	-
PAPUA SELATAN	-	-	-	-	-	-	-	-
PAPUA TENGAH	-	-	-	-	-	-	-	-
PAPUA PEGUNUNGAN	-	-	-	-	-	-	-	-
INDONESIA	198873337	58189128	47890390	205656083	3669010	24326927	3926249	-

2.2. Hierarchical Clustering

Recent advances in data-driven and intelligent analytical methods have been widely applied in various fields of socioeconomics [13], environment, image reconstruction [14][15][16], and education [17][18], demonstrating their effectiveness in extracting patterns from complex and incomplete datasets and supporting distance learning innovations [19]. Based on these developments, clustering-based methods are highly relevant for exploring data structures and grouping objects based on inherent similarities. Hierarchical clustering was chosen given the dataset's characteristics and the research objectives. The dataset comprises a relatively small number of observations (38 provinces) and continuous numeric variables representing the production volumes of various biopharmaceutical commodities. Unlike K-Means, hierarchical clustering does not require a predetermined number of clusters and provides a dendrogram that allows for intuitive interpretation of regional production structures. In addition, hierarchical clustering is suitable for revealing interconnected regional similarities, which is important for policy-oriented spatial analysis.

Hierarchical clustering is an unsupervised learning method used to group objects based on similarity, without requiring a predetermined number of clusters. This method organizes data into a hierarchical structure that can be visualized using a dendrogram. In agglomerative hierarchical clustering, each object initially forms a single cluster, and clusters are merged step by step based on a chosen distance metric. One of the most used distance measures is the Euclidean distance, defined as Equation 1 below.

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$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2} \qquad (1)$$

Where x_i and x_j represent two objects and n denotes the number of variables. This distance calculation determines the level of similarity between regions or objects in the clustering process. The merging of clusters in hierarchical clustering depends on the linkage method used to measure the distance between clusters. Ward's linkage is widely applied in agricultural and regional studies because it minimizes the total variance within the clusters. The objective function of Ward's method can be expressed as Equation 2 below.

$$\Delta ESS = \sum_{k=1}^{K} \sum_{i \in C_k} (x_i - \mu_k)^2 \qquad (2)$$

Where C_k is the k-th cluster and μ_k is the centroid of that cluster. By minimizing the increase in Error Sum of Squares (ESS) at each merging step, Ward's method produces compact and homogeneous clusters. This approach is particularly suitable for analyzing regional agricultural production data, such as biofarmaka crop production across Indonesian provinces, as it provides clear and interpretable cluster structures.

3. Results and Discussion

The results of a hierarchical clustering analysis of biopharmaceutical crop production data from 38 provinces in Indonesia in 2023 revealed the formation of three main clusters based on similarities in the production of eight biopharmaceutical commodities. The clustering process was performed using Euclidean distance and Ward's linkage method to minimize variance within clusters, and the results were visualized using a dendrogram. Cluster 1 encompasses most provinces, characterized by low to moderate production levels and relatively homogeneous production patterns. Cluster 2 consists of West Java and Central Java, which exhibit high and balanced production across most key biopharmaceutical crops. Meanwhile, East Java forms Cluster 3 as a separate cluster due to its very high production volume, particularly of turmeric and Javanese ginger, significantly different from other provinces. These findings indicate significant regional disparities in biopharmaceutical production in Indonesia and highlight the dominant role of Java Island, particularly East Java, as the national biopharmaceutical crop production center.

Table 3 presents the results of a hierarchical clustering analysis, which groups Indonesian provinces based on similarities in biopharmaceutical crop production in 2023. This analysis yields three distinct clusters. Cluster 1 contains most provinces, encompassing most of the area outside Java, with relatively similar production patterns and a smaller scale. Cluster 2 consists of West Java and Central Java, demonstrating closer similarities in production structure and volume between these two provinces. Cluster 3 contains only East Java, reflecting its unique production profile, and is significantly different from all other provinces.

Table 3. Provincial grouping based on hierarchical clustering

Cluster	Provinces
Cluster 1	Aceh, North Maluku, Maluku, West Sulawesi, Gorontalo, Southeast Sulawesi, South Sulawesi, Central Sulawesi, North Sulawesi, North Kalimantan, East Kalimantan, South Kalimantan, Central Kalimantan, West Kalimantan, East Nusa Tenggara, West Nusa Tenggara, Bali, Banten, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, West Papua, Lampung, Riau Islands, DKI Jakarta, DI Yogyakarta, Bangka Belitung Islands, Papua
Cluster 2	West Java, Central Java
Cluster 3	East Java

Table 4. Interpretation of biofarmaka production clusters

Cluster	Characteristics	Interpretation
Cluster 1	Low to moderate biofarmaka production levels across most crop types	Provinces in this cluster have relatively limited production capacity, influenced by land suitability, cultivation scale, and technological adoption.
Cluster 2	High and balanced production of major biofarmaka crops	This cluster represents provinces with strong agricultural infrastructure and consistent biofarmaka cultivation.
Cluster 3	Very high biofarmaka production with dominant output	East Java stands alone due to its significantly higher production volume compared to other provinces.

As shown in Table 4, each cluster represents a different level of biopharmaceutical production capacity. Cluster 1 is characterized by low to moderate production across most biopharmaceutical crops, indicating limitations related to

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land suitability, cultivation scale, and technology adoption. Cluster 2 reflects provinces with high and relatively balanced production of key biopharmaceutical crops, supported by stronger agricultural infrastructure and more intensive cultivation practices. Cluster 3, represented solely by East Java, exhibits very high biopharmaceutical production with dominant output levels, highlighting its role as a major production center for medicinal plants and herbs in Indonesia.

The hierarchical clustering dendrogram visually confirms the clustering results by showing clear separation among the three clusters. Most provinces merge at lower linkage distances, forming Cluster 1, which exhibits relatively similar production characteristics. West Java and Central Java form distinct branches at higher linkage distances, reflecting their higher and more consistent production levels. East Java separates at the highest linkage distance, indicating its extreme dominance in biopharmaceutical production compared to other provinces. This structure validates the robustness of the clustering results and emphasizes the strong regional disparities in biopharmaceutical crop production across Indonesia.

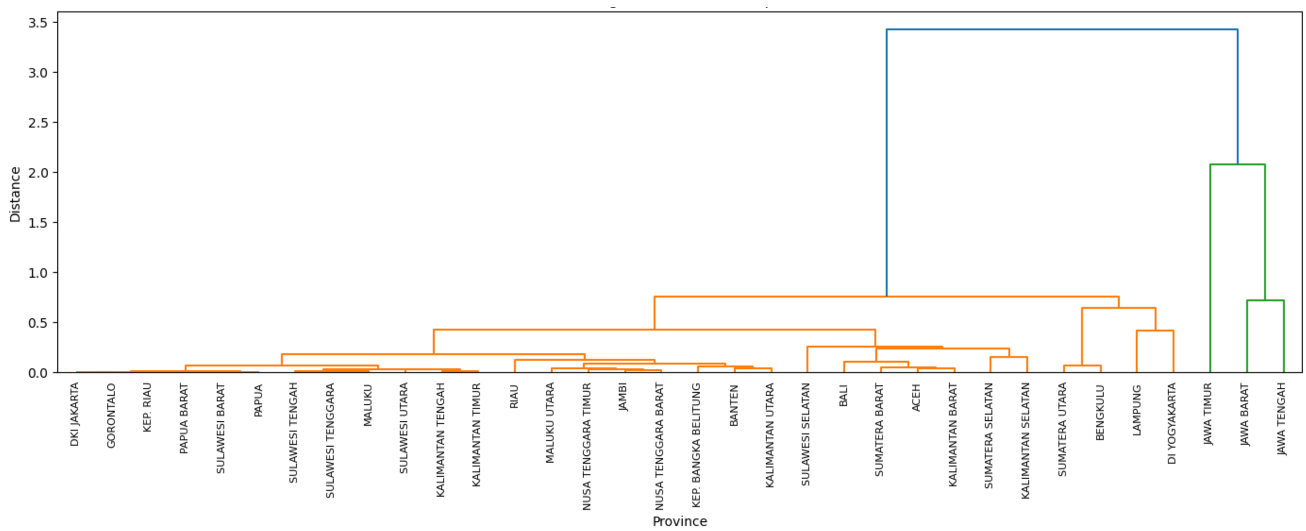

Figure 2. Hierarchical clustering biopharmaceutical crop production (2023)

Based on the hierarchical clustering results as shown in Table 2, Indonesian provinces can be clearly categorized into three distinct clusters according to their biopharmaceutical crop production characteristics. This classification provides a data-driven basis for policy decision-making and differentiated development strategies. Provinces in Cluster 1 require targeted interventions to increase production capacity through land optimization, farmer training, and technology adoption. Provinces in Cluster 2 should be strengthened as regional production hubs with a focus on supply chain efficiency and value-added processing. Meanwhile, East Java, as the sole member of Cluster 3, should be prioritized as a national hub for biopharmaceutical production and innovation, supporting downstream industries and acting as a benchmark for best practices. Overall, the clustering results offer a strategic framework for regional planning and the sustainable development of Indonesia's biopharmaceutical sector.

This classification provides a data-driven basis for differentiated policy decisions and development strategies. Provinces in Cluster 1 require targeted interventions to improve production capacity through land optimization, farmer training, and technology adoption. Cluster 2 provinces should be strengthened as regional production hubs with a focus on supply chain efficiency and value-added processing. Meanwhile, East Java, as the sole member of Cluster 3, should be prioritized as the national center for biopharmaceutical production and innovation, supporting downstream industries and acting as a benchmark for best practices. Overall, the clustering results offer a strategic framework for regional planning and sustainable development of Indonesia's biopharmaceutical sector.

The hierarchical clustering model achieved a Silhouette Score of 0.65 and a Davies–Bouldin Index of 0.47, indicating that the clusters are well separated and internally cohesive. A Silhouette Score close to 0.7 indicates a strong clustering structure, while a low Davies–Bouldin Index confirms high cluster cohesiveness and minimal overlap between clusters.

4. Conclusion

The main advantage of this study lies in its comprehensive provincial-level analysis of biopharmaceutical crop production using recent and official data from 38 Indonesian provinces. By applying hierarchical clustering with Ward's linkage, this research objectively identifies regional production patterns without requiring predefined cluster numbers, ensuring data-driven and interpretable results. The study integrates multiple major biopharmaceutical commodities

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simultaneously, providing a holistic view of production structures rather than focusing on a single crop. In addition, the clustering results offer practical insights for region-specific policy formulation and strategic planning, making the findings directly applicable to sustainable agricultural development and biopharmaceutical industry strengthening in Indonesia. Future research should incorporate multi-year time-series data and additional environmental and socio-economic variables to better explain regional production dynamics. Comparative studies using alternative clustering and machine learning methods are also recommended to improve model robustness and decision-support accuracy.

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