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SPATIAL K-MEANS CLUSTERING FOR IDENTIFYING OPTIMAL SUSTAINABLE AVIATION FUEL PRODUCTION LOCATIONS IN INDONESIA

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Abstrak

Indonesia memiliki bahan baku potensial yang besar untuk produksi *Sustainable Aviation Fuel* (SAF), khususnya dari minyak jelantah dan limbah cair kelapa sawit (POME). Namun hingga saat ini baru terdapat satu fasilitas produksi SAF yang beroperasi di Indonesia. Ketimpangan geografis antara sumber bahan baku yang tersebar luas dengan infrastruktur produksi yang masih terpusat menjadi hambatan utama dalam pengembangan SAF nasional. Penelitian ini menerapkan pendekatan *K-Means Clustering* pada koordinat 15 provinsi penghasil bahan baku dan 36 bandara internasional di Indonesia untuk mengidentifikasi lokasi optimal fasilitas produksi SAF. Tiga skenario dianalisis secara komparatif menggunakan metrik *Within-Cluster Sum of Squares* (WCSS), mencakup konfigurasi 2, 3, dan 4 fasilitas produksi dengan fasilitas *existing* di Cilacap ditetapkan sebagai *centroid* tetap. Hasil analisis menunjukkan bahwa skenario 3 fasilitas merupakan konfigurasi paling optimal, merekomendasikan dua fasilitas baru di Riau dan Kalimantan Tengah sebagai pelengkap fasilitas Cilacap yang sudah ada, dengan penurunan WCSS sebesar 55% dibandingkan skenario 2 fasilitas. Penelitian ini juga mengidentifikasi kesenjangan infrastruktur di Indonesia Timur yang memerlukan pendekatan kebijakan tersendiri, mengingat keterbatasan ketersediaan *feedstock* UCO dan POME di wilayah tersebut.

Kata Kunci: Fasilitas Produksi, Indonesia, K-Means Clustering, Limbah Cair Kelapa Sawit, Minyak Jelantah, Sustainable Aviation Fuel

Abstract

Indonesia holds substantial feedstock potential for Sustainable Aviation Fuel (SAF) production, particularly from Used Cooking Oil (UCO) and Palm Oil Mill Effluent (POME), yet only one SAF production facility is currently in operation. The geographical mismatch between widely dispersed feedstock sources and centralized production infrastructure remains a key bottleneck for national SAF development. This study applies a Spatial K-Means Clustering approach to the coordinates of 15 feedstock-producing provinces and 36 international airports across Indonesia to identify optimal locations for SAF production facilities. Three scenarios were comparatively analyzed using the Within-Cluster Sum of Squares (WCSS) metric, which covers configurations of 2, 3, and 4 production facilities with the existing facility in Cilacap incorporated as a fixed centroid. The results show that the 3-facility scenario is the most optimal configuration, recommending two new facilities in Riau and Central Kalimantan to complement the existing Cilacap facility, achieving a 55% reduction in WCSS compared to the 2-facility scenario. This study also identifies an infrastructure gap in Eastern Indonesia that warrants a dedicated policy approach, given the limited availability of UCO and POME feedstock in that region.

Keywords*: *Facility Location, Indonesia, K-Means Clustering, Palm Oil Mill Effluent, Sustainable Aviation Fuel, Used Cooking Oil

1.0 INTRODUCTION

Decarbonization pressure on the aviation sector continues to grow as the industry currently accounts for approximately 2.5% of global carbon emissions, with projections suggesting this figure could rise into 22% driven by increasing air travel demand across the Asia-Pacific region [1]. In response, the International Air Transport Association (IATA) established the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), targeting a 5% emissions reduction by 2030 through the adoption of Low Carbon Aviation Fuel (LCAF) [2]. Sustainable Aviation Fuel (SAF) has been identified as the most feasible near-to-medium-term solution, capable of reducing lifecycle emissions by up to 80% compared to conventional jet fuel while functioning as a drop-in fuel that requires no modifications to existing aircraft engines [3]. These developments have prompted countries worldwide to accelerate the buildout of domestic SAF production infrastructure.

Several countries in the region have made concrete progress in this direction. Singapore operates two facilities with a combined capacity exceeding 1.55 million tonnes per year, including Neste’s refinery, which is the world’s largest SAF facility, and Shell’s Energy and Chemicals Park [4]. Malaysia is completing its second facility in Pengerang, Johor, targeted for full operation by 2028, while Thailand has been operating two facilities since 2024 with a combined target capacity of 6 million litres per day [5, 6]. Japan operationalized its first domestic SAF facility through Cosmo Energy’s Saffaire Sky Energy joint venture at its Sakai refinery in Osaka in April 2025, with a production capacity of 30,000 kL per year, and has four additional projects in its development pipeline targeting a combined capacity of over 950,000 kL per year [7]. The pace of regional infrastructure development underscores that SAF production is transitioning from pilot-scale initiatives to strategic national energy assets across Asia.

Against this regional backdrop, Indonesia’s SAF infrastructure position is disproportionately limited relative to its resource endowment. As the world’s largest palm oil producer, Indonesia generates over 120 million tons of Palm Oil Mill Effluent (POME) annually as a byproduct of crude palm oil processing, alongside substantial volumes of Used Cooking Oil (UCO) from its large urban population, both of which are established feedstocks for SAF production via the Hydroprocessed Esters and Fatty Acids (HEFA) pathway [8-10]. Yet the country operates only a single SAF production facility with a target capacity of 9,000 barrels per day. This gap between feedstock abundance and production capacity is compounded by a spatial mismatch, as feedstock sources are dispersed across 38 provinces while production infrastructure remains centralized at a single location in Cilacap, Central Java, creating systematic inefficiencies in both inbound feedstock collection and outbound SAF distribution to aviation demand centers nationwide [11].

Addressing this spatial mismatch requires an analytical capable of simultaneously optimizing facility placement relative to distributed supply and demand points. The facility location problem is well-established class of optimization in operations research, and K-Means Clustering has been increasingly adopted as a computationally accessible approach to its solution, particularly in the context of renewable energy infrastructure planning where precise cost data may be unavailable at the planning stage [12]. In this formulation, each cluster centroid represents a candidate facility location that minimizes aggregate distance to all assigned supply and demand nodes, functioning as a data-driven analogue to the classical p-median location model [13].

Empirical applications of this approach in the regional energy context support its validity for present study. Tanoto et al. (2024) applied K-means and DBSCAN clustering to identify potential solar PV sites in Indonesia's Java-Bali region, demonstrating that spatially-driven clustering produces more representative location candidates than conventional methods [14]. Christou et al. (2024) further extended this line of work by developing a weighted K-means algorithm for biomass supply chains that simultaneously accounts for both field coordinates and field size, yielding cluster centroids that more accurately reflect actual transportation costs [12].

On the supply chain optimization front, several global studies have laid important groundwork for this research. Doliente et al. (2020) provided a comprehensive mapping of bio-aviation fuel supply chain components from feedstock sourcing through to end use [15]. Jorje et al. (2025) developed a Mixed-Integer Linear Programming (MILP) model to optimize SAF supply chain configurations in Brazil using microalgae cultivated in sugarcane vinasse, with total system cost minimization as the objective function [16]. Li et al. (2026) represent perhaps the most comprehensive study to date, explicitly addressing facility siting within SAF supply chain optimization. However, it was developed in the context of the United States using forest residues as feedstock via fast pyrolysis, making it difficult to directly implement in Indonesia's fundamentally different conditions in an archipelagic geography and a distinct feedstock landscape [17].

Existing research has largely focused on feedstock availability assessments and lifecycle analyses without extending to the engineering question of how many facilities are needed and where they should be located to minimize total logistics distance across an archipelagic geography. This study addresses that gap by applying Spatial K-Means Clustering to the coordinates of 15 feedstock-producing provinces and 36 international airports to identify optimal SAF production facility locations under three configuration scenarios (k=2, k=3, k=4). The Within-Cluster Sum of Squares (WCSS) metric is used as a proxy for aggregate logistics cost, and the existing Pertamina facility in Cilacap is incorporated as a fixed centroid to ensure that recommended configurations are complementary to existing infrastructure rather than developed in isolation.

2.0 RESEARCH METHOD

This study draws on two primary datasets. The first consists of geographic coordinates of feedstock sources from the 15 provinces in Indonesia with the highest UCO and POME production, based on data from *the Badan Pusat Statistik* (BPS) for the year 2024. These provinces were selected because they collectively represent the country's main feedstock production centers, with volumes considered sufficient and sustainable to support commercial-scale SAF facility operations, while also ensuring that feedstock availability remains within safe limits as SAF demand gradually increases. The second dataset comprises the geographic coordinates of 36 international airports across Indonesia, serving as demand points in the analysis.

2.1. Potential SAF Values Estimation

SAF potential for each province was estimated by first converting feedstock mass (kg) into volume using the respective density values, then converting that volume into tonnes, and finally multiplying by the SAF conversion factor. The estimation equation is as follows:

$$P_{SAF} = \frac{M_i \ x \ CF_i}{p^1 \ x \ 10^6} \quad (1)$$

where P_{SAF} is the SAF potential in kL, M_i is the feedstock mass in kg, ρ_i is the feedstock density in kg/L used to convert units, and CF_i is the conversion factor in L SAF per tonne of feedstock. Density values used are 0.93 kg/L for UCO and 0.907 kg/L for POME [18, 19]with conversion factors of 550 L SAF/tonne for UCO and 537 L SAF/tonne for POME [11, 20]. The estimated SAF potential per province is presented in Table 1.

Table 1: SAF Potential Estimation for Each Province

Province	Latitude	Longitude	Wastes (kg)		Potential SAF (kL)		Total SAF (kL)
			UCO	POME	UCO	POME	
West Java	-7.0909	107.6689	166,598,896	14,508	98,517,649	8,590	98,526,238
East Java	-7.5361	112.2384	142,049,996	-	84,008,062	-	84,008,062
Central Java	-7.1510	110.1403	125,356,859	-	74,135,777	-	74,135,777
Riau Island	0.9187	104.4589	67,346,240	7,912	39,828,421	4,684	39,833,106
North Sumatra	2.1154	99.5451	56,297,264	2,632,367	33,294,081	1,558,524	34,852,604
Banten	-6.4058	106.0572	47,781,133	15,215	28,257,660	9,008	28,266,667
DKI Jakarta	-6.2115	106.8452	42,452,043	-	25,106,047	-	25,106,047
Lampung	-4.5586	105.4068	35,468,779	225,000	20,976,160	133,214	21,109,373
Riau	0.2933	101.7068	30,554,417	4,480,970	18,069,816	2,653,011	20,722,827
South Sumatra	-3.3194	103.9144	32,728,030	1,845,851	19,355,286	1,092,857	20,448,144
South Sulawesi	-3.6688	119.9741	26,596,425	56,800	15,729,069	33,629	15,762,697
West Sumatra	-0.7399	100.8000	23,073,901	698,406	13,645,855	413,499	14,059,355
West Kalimantan	-0.2787	111.4753	17,581,482	2,666,169	10,379,651	1,578,537	11,976,187
Aceh	4.6871	96.6324	19,523,824	483,022	11,546,347	285,979	11,832,326
Jambi	-1.6275	103.7186	16,805,226	1,215,822	9,938,575	719,841	10,658,416

K-Means Clustering was then applied to the combined coordinates of all feedstock source points and demand points. K-Means was selected for this analysis based on three engineering criteria. First, it directly solves a variant of the p-median facility location problem by minimizing the sum of squared distances between supply or demand points and their assigned facility centroids, an objective that serves as a computational proxy for minimizing total logistics cost [13]. Second, K-Means scales efficiently to the dataset size used in this study, producing deterministic and reproducible results under a fixed random seed. Third, its centroid output is directly interpretable as a candidate facility location, unlike density-based methods such as DBSCAN which produce cluster representatives that may not correspond to geographically actionable coordinates [14].The algorithm works by minimizing the Within-Cluster Sum of Squares (WCSS) objective function:

$$\boldsymbol{WCSS} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{k}} \sum_{\boldsymbol{x_i \in C_j}} ||\boldsymbol{x_i} - \boldsymbol{y_i}||^{\boldsymbol{2}} \quad (2)$$

where k is the number of clusters, C_j is the set of points in the cluster j, x_i is the coordinate of the data point i, and $y_i$is the centroid of the cluster j. The distance between points is calculated using Euclidean Distance:

$$d(x_i, y_i) = \sqrt{(a_i - a_j)^2 + (b_i - b_j)^2} \quad (3)$$

where a and b represent latitude and longitude coordinates respectively. The use of Euclidean Distance was chosen for its computational simplicity and direct interpretability as a geographic approximation at the provincial scale. However, a key limitation must be acknowledged: in an archipelagic context such as Indonesia, Euclidean distance does not account for sea barriers, inter-island shipping routes, or actual road network distances, which means it systematically underestimates true logistics costs for cross-island distribution [21].

The existing SAF production facility in Cilacap, Central Java (−7.7460° S, 109.0156° E) was incorporated into the clustering algorithm as a fixed centroid, meaning its position remained locked throughout the iterative process while all other centroids were updated freely.

This ensures that the recommended new facilities are complementary to existing infrastructure rather than redundant. All analyses were conducted in R with a fixed random seed to guarantee reproducibility across runs.

Three scenarios were comparatively analyzed 2, 3, and 4 production facility configurations. This range was chosen based on the reasoning that 2 centroids represent the minimum addition to existing infrastructure, while 4 centroids represent a realistic upper bound from a national infrastructure investment perspective. It is worth noting that the recommendations produced are indicative in nature from a geographic and feedstock distribution standpoint, and the final decision on specific facility locations should ultimately rest with policymakers, taking into account a broader set of operational and strategic considerations.

3.0 RESULT AND DISCUSSION

A K-Means Clustering analysis was applied to 15 feedstock source coordinates and 36 international airport demand points across Indonesia to identify optimal SAF production facility locations. Three scenarios were comparatively analyzed — 2, 3, and 4 production facilities — with the existing facility incorporated as a fixed centroid in each scenario to reflect current infrastructure conditions. The resulting centroid coordinates for all three scenarios are presented in Table 2.

Table 2: K-Means Clustering Centroid Coordinates

Scenario	Plant	Latitude	Longitude	Province	Island	Status
k = 2	1	-7.7491	109.0151	Central Java	Java	Existing
	2	-2.7055	106.0388	South Sumatra	Sumatra	Hypothetical
k = 3	1	-7.7491	109.0151	Central Java	Java	Existing
	2	-0.3311	101.5395	Riau	Sumatra	Hypothetical
	3	-2.9703	111.1513	Central Kalimantan	Kalimantan	Hypothetical
k = 4	1	-7.7491	109.0151	Central Java	Java	Existing
	2	-1.2670	116.8290	East Kalimantan	Kalimantan	Hypothetical
	3	-2.9703	111.1513	Central Kalimantan	Kalimantan	Hypothetical
	4	-0.3311	101.5395	Riau	Sumatra	Hypothetical

3.1. 2-Facility Scenario

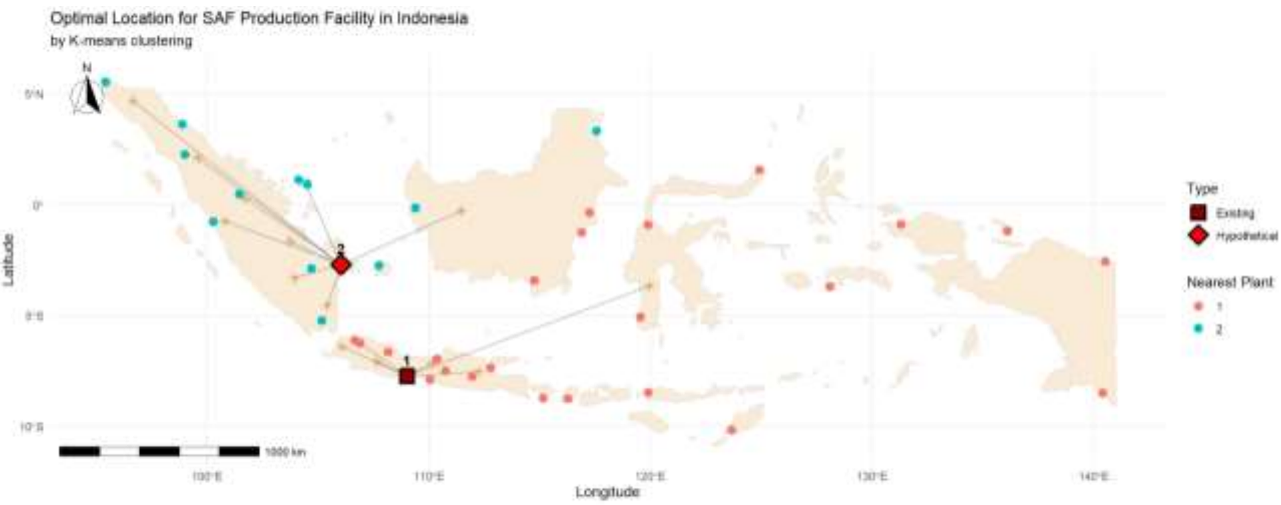

Figure 1. Map of the 2-Facility Scenario

In the 2-facility scenario, the algorithm places a new production facility at coordinates −2.7055° S, 106.0388° E, located in the Sumatra region, as illustrated in Figure 1. Based on Euclidean distance calculations, this new facility would serve all airports in Sumatra along with 2 airports in Kalimantan, with an estimated total demand of 1,559,209 kL per year. Meanwhile, the existing facility in Cilacap would be responsible for serving all airports in Java, Bali, most of Kalimantan, and all airports across Eastern Indonesia, carrying an estimated demand of 4,748,345 kL per year.

The stark imbalance in demand between the two facilities is largely driven by the concentration of major airports like Soekarno-Hatta, I Gusti Ngurah Rai, Juanda, and Hasanuddin, all falling within Cilacap's service radius. This is consistent with findings from Tanoto et al. (2024), who noted that in archipelagic contexts like Indonesia, single-facility configurations tend to produce uneven load distributions due to the geographically non-homogeneous concentration of demand [14].

While this scenario offers the lowest infrastructure complexity by focusing investment on large-scale facilities, it comes with notable trade-offs. Logistics costs for both feedstock collection and SAF distribution to each demand center are likely to be high, and the configuration carries significant supply chain vulnerability that makes a disruption at either facility could simultaneously affect a large portion of national demand [22].

Quantitatively, the 2-facility scenario produces a total WCSS of 675.929, the highest among the three scenarios analyzed. This reflects a large spatial dispersion between data points and their respective cluster centroids, suggesting that two facilities are insufficient to meaningfully minimize logistics distances across Indonesia's vast and dispersed geography.

3.2. 3-Facility Scenario

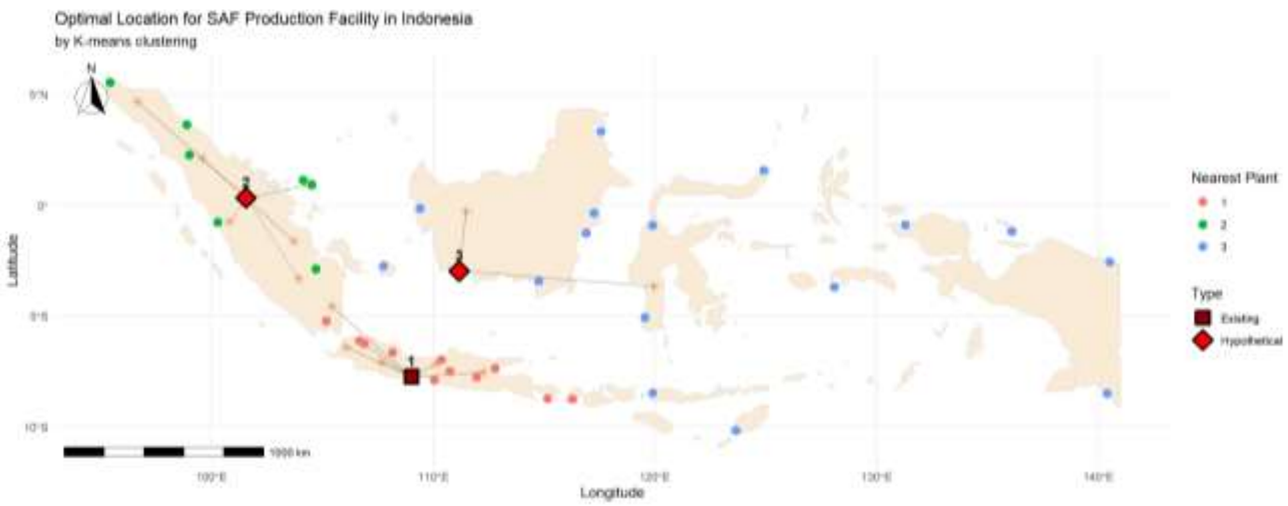

Figure 2. Map of the 3-Facility Scenario

As shown in Figure 2, the 3-facility scenario is arguably the most geographically representative configuration for Indonesia’s diverse regional landscape. Two new facilities are placed in (-0.3311° S, 101.5395° E) and Central Kalimantan (−2.9703° S, 111.1513° E), resulting in each of the three facilities being located on one of Indonesia's three largest islands, all of which also happen to be the primary hubs for UCO and POME feedstock availability.

Demand distribution in this scenario is considerably more balanced than the 2-facility configuration. The Cilacap facility serves 12 airports with an estimated annual demand of 3,097,039 kL. The Riau facility serves 8 airports and has an estimated demand of 1,074,867 kL per year. The Central Kalimantan facility, which primarily serves airports across Eastern Indonesia, is projected to receive demand of 2,135,634 kL per year.

Quantitatively, this scenario has a total WCSS of 289.19, representing a 55% reduction compared to the 2-facility scenario. This decrease reflects a meaningful improvement in spatial efficiency, indicating that adding a third facility significantly reduces the average distance between demand points and their nearest production facility.

The placement of facilities across three major islands also delivers a dual logistical advantage. First, the average distance between each airport and its nearest facility drops considerably compared to the 2-facility scenario, which directly impacts lower SAF distribution costs. Second, the geographic proximity between each facility and its surrounding feedstock sources helps minimize collection and inbound transportation costs, a principle well-established in biofuel supply chain planning literature, which consistently emphasizes the importance of co-locating production facilities with feedstock centers to achieve overall logistical efficiency.

From a network lifecycle and scalability standpoint, the 3-facility scenario provides the necessary structural architecture to accommodate future demand surges without triggering localized supply failures [23]. Transitioning from a highly centralized framework to this decentralized, three-node model mitigates systemic risks associated with single-point operational disruptions at the primary Java facility [24]. By establishing independent processing nodes that operate within separate feedstock and demand catchments, the network achieves greater infrastructural resilience, ensuring that long-term capacity expansion can be sustained through localized scaling rather than costly overhauls of the entire supply chain web.

3.3. 4-Facility Scenario

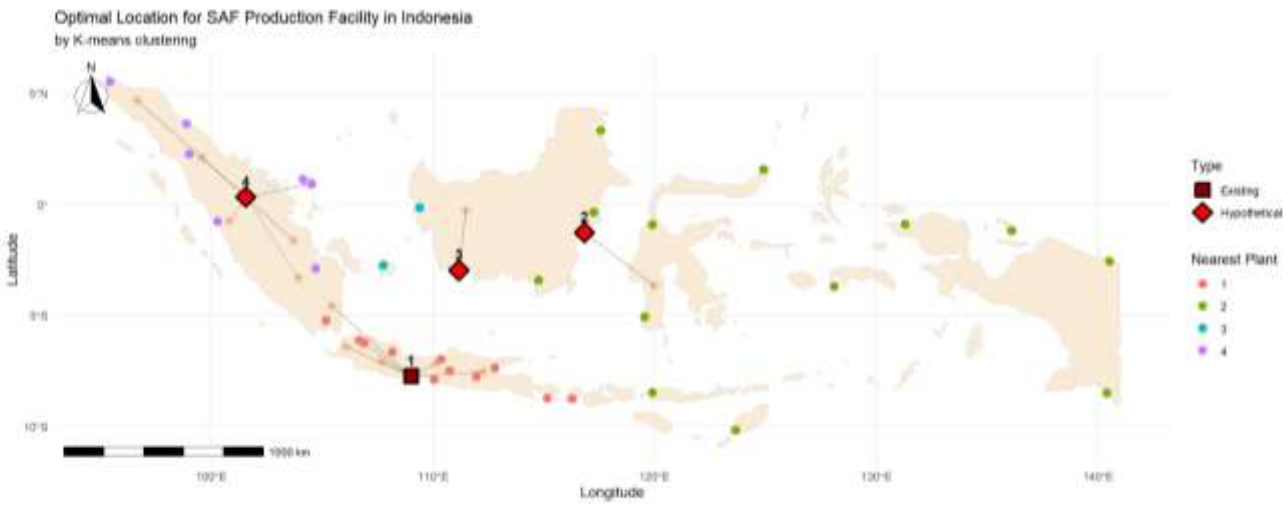

Figure 3. Map of the 4-Facility Scenario

The 4-facility scenario introduces three new facilities located in East Kalimantan (−1.2670° S, 116.8290° E), Central Kalimantan (−2.9703° S, 111.1513° E), and Riau (−0.3311° S, 101.5395° E). Demand distribution in this scenario is largely similar to the 3-facility configuration. The Cilacap facility continues to serve 12 airports across Java with an estimated annual demand of 3,097,039 kL. The East Kalimantan facility serves most airports in Eastern Indonesia with an estimated demand of 1,074,867 kL per year. The Central Kalimantan facility, however, serves only 2 airports with an estimated demand of just 242,164 kL per year. The Riau facility is projected to receive demand of 1,893,105 kL per year from 8 airports across Sumatra.

The most striking finding from this scenario is the presence of two centroids within Kalimantan. Mathematically, this does push the total WCSS down to 170.43, a 56% reduction compared to the 3-facility scenario. But when viewed through the lens of strategic infrastructure planning, having two facilities in relatively close proximity, with one of them serving only 2 airports, raises serious questions about investment proportionality. The marginal gain in spatial efficiency simply does not appear to justify the additional capital outlay.

This scenario also surfaces a consistent infrastructure gap that runs across all three configurations. There are no facilities recommended for Eastern Indonesia for covering Sulawesi, Nusa Tenggara, Maluku, and Papua. This is not because demand is absent in these regions, but rather it reflects the limited availability of UCO and POME feedstock in the dataset for that area. Addressing SAF development in Eastern Indonesia sustainably will likely require a separate line of inquiry, whether through developing local feedstock collection ecosystems or exploring alternative production pathways beyond HEFA that are better suited to the feedstock characteristics available in those regions.

3.4. Comparative Analysis of Three Scenarios

Each of the three scenarios presents a distinct set of trade-offs. The 2-facility scenario offers the lowest operational complexity, but produces a heavily skewed demand distribution with high dependency risk concentrated on a single facility serving the majority of the country. The 4-facility scenario achieves the lowest WCSS, but the appearance of two centroids in Kalimantan, with one of which serves only 2 airports, raises legitimate concerns about efficiency and investment rationale.

The 3-facility scenario stands out as the most balanced of the three. Distributing facilities across three different islands ensures proximity to feedstock centers while achieving a more even spread of demand coverage. This finding aligns with the broader literature, which consistently shows that in bioenergy supply chain planning for countries with complex geographical characteristics, spatially diversifying production facility locations contributes not only to lower transportation costs but also to overall supply chain resilience [12].

3.5. Discussion

The 3-facility scenario yields the lowest aggregate WCSS and most balanced cluster geometry. The two new facility centroids, which are located in Riau (-0.3311°S, 101.5395°E) and Central Kalimantan (-2.9703°S, 111.1513°E), partition Indonesia into three geographically coherent supply zones with mean intra-cluster distances of approximately 380 km, 520 km, and 610 km respectively. This represents a 55% reduction in WCSS relative to the 2-facility scenario, indicating a substantial improvement in aggregate logistics efficiency.

From a supply chain engineering perspective, this configuration resolves a critical structural vulnerability regarding demand concentration in Java. Modeling existing infrastructure as a single-node supply source reveals an operational bottleneck, as the centralized capacity cannot mathematically sustain the localized international aviation demand scaling. The introduction of the Riau and Central Kalimantan nodes successfully offloads the regional feedstock processing pressure. The Riau centroid optimally serves the dense feedstock belt of Sumatra while remaining proximate to Pekanbaru Sultan Syarif Kasim II Airport, reducing both inbound feedstock collection routes and outbound SAF distribution distances.

The Central Kalimantan centroid at 113.938°E sits near the geographic centroid of Borneo's palm oil production zone, minimizing average POME collection distance from the 8 provinces assigned to this cluster. The nearest major aviation hub, which is Sultan Aji Muhammad Sulaiman Sepinggan International Airport in Balikpapan, lies approximately 280 km to the northeast, a distribution distance that is logistically manageable via road infrastructure. This configuration also benefits from Kalimantan's existing industrial port infrastructure at Banjarmasin and Balikpapan, which reduces capital expenditure requirements for SAF export logistics.

Conversely, Eastern Indonesia, which comprises Papua, Maluku, and Nusa Tenggara, remains unserved by all three scenarios due to insufficient POME and UCO feedstock density to generate a natural cluster centroid in that region. This is not a limitation of the method but rather a structural supply-side constraint because the region would require alternative feedstock pathways such as coconut oil or sago biomass to support a viable production facility. Future engineering work should incorporate feedstock substitution modeling to assess whether an Eastern Indonesia facility becomes viable under alternative supply assumptions.

4.0 CONCLUSION

This study identifies optimal SAF production facility locations in Indonesia based on the spatial distribution of feedstock sources across 15 provinces and 36 international airport demand points. Of the three configurations analyzed, the 3-facility network architecture emerges as the mathematically optimal design, achieving the most significant reduction in aggregate transport work while establishing a decentralized, balanced allocation of demand across regional nodes.

Two critical technical and infrastructural gaps identified in this spatial optimization warrant further engineering attention. First, the extreme demand density on the Java node indicates that relying on localized, single-site production introduces severe capacity constraints, necessitating decentralized processing nodes to secure network fluidity. Second, the persistent exclusion of Eastern Indonesia from the optimized network reveals a severe geographical feedstock deficit, confirming that a standard POME and UCO supply chain model is non-viable for the region.

Future research is encouraged to build on these findings by incorporating multi-period logistics cost modeling, strict facility production capacity constraints, and stochastic optimization frameworks to further strengthen the empirical evidence base for SAF infrastructure development and network design in Indonesia.

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