SOSMANIORA (Jurnal Ilmu Sosial dan Humaniora)
https://journal.literasisains.id/index.php/sosmaniora
DOI: 10.55123/sosmaniora.v5i2.7525
e-ISSN 2829-2340 | p-ISSN 2829-2359
Vol. 5 No. 2 (Juni 2026) 686-695
Submitted: January 12, 2026 | Accepted: February 26, 2026 | Published: June 15, 2026

# Evaluation of Indonesian Marine and Fishery Product Exports by Commodity and Destination Country

**Ekka Pujo Ariesanto Akhmad[1*], Budi Priyono[2]**
[1*,2]Fakultas Vokasi Pelayaran, Universitas Hang Tuah, Indonesia
Email: [1*]eka.pujo@hangtuah.ac.id

***Abstract***

This study aims to evaluate the performance of Indonesia's marine and fisheries export sector based on product commodities and destination countries during the period of 2019–2023. Utilizing an unsupervised learning approach through the K-Means Clustering algorithm, export data were classified into three main groups according to export volume and value: high, medium, and low. The dataset was obtained from the official portal of the Indonesian Ministry of Marine Affairs and Fisheries (KKP), covering export statistics for key commodities such as shrimp, tuna, seaweed, and other captured fishery products exported to major destinations including the United States, China, Japan, and other countries. Preprocessing included data cleaning and normalization using StandardScaler to ensure data quality and consistency. Cluster validation was conducted using the Davies-Bouldin Index (DBI), where lower DBI values indicate better clustering performance. The results revealed consistent export trends for Indonesia’s flagship commodities while identifying new opportunities for market expansion. This study provides strategic insights for policymakers and industry stakeholders in designing export development strategies and diversifying international markets. Furthermore, it contributes a methodological framework for data-driven export mapping of fisheries products that is both comprehensive and sustainable.

***Keywords:*** *Clustering, Commodities, DBI, Destination Countries, Fisheries Export, K-Means.*

## INTRODUCTION

Indonesia, as the world’s largest archipelagic state with more than 17,000 islands, possesses significant marine and fisheries resource potential that plays a strategic role in national economic development. The capture fisheries sector, in particular, contributes substantially to export earnings and supports the livelihoods of coastal communities. Indonesian fishery commodities such as shrimp, tuna, squid, seaweed, and pearls have strong competitiveness in global markets and consistently contribute to foreign exchange revenues (Perikanan, 2023). Indonesian fishery products are widely recognized in the international market, such as shrimp, tuna, tuna, squid, seaweed, and pearls (Indri et al., 2022; Statistik, 2021). However, challenges in fisheries export management are still considerable, especially in terms of market diversification and increasing product added value. Information on export distribution by commodity type and destination country is still scattered and not systematically presented. Therefore, an analytical approach is needed to categorize export performance so that it can be used in formulating strategic policies (Cebeci et al., 2012; Godwin & Oshodi, 2021).

Despite its strong export potential, the Indonesian fisheries sector faces considerable socio-economic challenges, particularly related to export market volatility and limited diversification of destination countries. Export performance fluctuations recorded in 2023 indicate a structural vulnerability in Indonesia’s fisheries trade, which remains highly dependent on several major importing countries. Such dependency increases exposure to global economic instability, trade policy changes, and shifts in consumer demand patterns, which can directly influence domestic production stability and fishermen’s income sustainability. Several studies emphasize that excessive reliance on limited export markets can weaken national economic resilience and increase the risk of income inequality among coastal communities (Development & Lord, 2022; Salsabila et al., 2024). In the Indonesian context, unstable export performance may also affect food security and social welfare, as fisheries not only function as an export commodity but also as a primary protein source and livelihood foundation for millions of small-scale fishermen.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

Market diversification therefore emerges as a critical socio-economic issue that requires systematic policy attention. Diversification of export destinations can reduce trade risk, stabilize foreign exchange earnings, and enhance the bargaining position of Indonesian fisheries products in global markets (Perikanan, 2023; Pusat Data, 2024). Furthermore, diversified markets enable more balanced distribution of economic benefits across regions and support sustainable fisheries development. However, empirical information regarding the distribution pattern of fisheries export commodities based on export performance intensity remains fragmented and insufficiently analyzed. Previous studies have largely focused on specific commodities or limited geographical scopes, resulting in a lack of comprehensive analytical mapping that integrates multiple major marine capture commodities at the national level.

To address this gap, a data-driven analytical approach is required to classify export performance patterns systematically. Clustering techniques provide an effective framework to identify natural groupings within large datasets, allowing policymakers to recognize dominant export commodities and prioritize strategic interventions. The K-Means Clustering method has been widely utilized in economic and trade data analysis due to its efficiency in handling multidimensional data and its interpretability in identifying performance segmentation (Kitta et al., 2022; Rivaldo et al., 2024; Yaman et al., 2020). In addition, clustering quality evaluation using the Davies-Bouldin Index (DBI) provides quantitative validation to ensure reliability and accuracy of classification results (Kusnawi, 2021a).

Previous studies have demonstrated the usefulness of clustering approaches in fisheries sector analysis. N. Fadhilah et al. (2024) applied X-Means Clustering to analyze shrimp export distribution patterns and revealed significant geographic segmentation. Similarly, Rivaldo et al. (2024) employed K-Means Clustering to classify fish catch production patterns in Karimunjawa, while Salsabila et al. (2024) highlighted the effectiveness of clustering techniques in identifying export destination patterns of fisheries commodities. Nevertheless, these studies generally examine limited commodity coverage and rarely integrate export volume and export value simultaneously as key indicators of trade performance.

This research contributes to the existing literature by providing a comprehensive clustering analysis of Indonesia’s major marine capture fisheries export commodities using export volume and export value as dual analytical dimensions. By incorporating export data from 2019 to 2023 (R. Fadhilah et al., 2024), this study aims to identify structural patterns of export performance and evaluate cluster quality to support evidence-based policy formulation. The findings are expected to provide strategic insights for strengthening export market diversification, enhancing economic resilience, and improving the welfare sustainability of fisheries-dependent communities in Indonesia

## METHOD

This research applies a descriptive-quantitative approach to analyze fisheries export performance patterns. Fisheries export data were obtained from the official portal of the Indonesian Ministry of Maritime Affairs and Fisheries for the 2019–2023 period. The dataset includes export volume and export value categorized by destination country and commodity type. The research stages (Fig. 1) consisted of the following procedures:

### Data Collection

Four datasets were utilized in this research, namely export volume by destination country, export value by destination country, export volume by commodity type, and export value by commodity type. The selection of these variables was based on their capacity to represent the multidimensional characteristics of export performance. Export volume reflects the physical quantity of traded fisheries products, while export value indicates the economic contribution and market competitiveness. Combining both indicators allows the clustering process to capture not only trade scale but also the relative economic significance of each export destination and commodity group.

### Data Pre-processing

a. Data Cleaning

The dataset was examined to remove incomplete records, duplicated entries, and inconsistent data formatting to ensure reliability and accuracy in further analysis.

b. Data Integration and Feature Selection

Data integration was conducted by combining datasets based on common identifiers such as year, commodity category, and export destination country. Feature selection focused on two primary

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

indicators, namely export volume and export value, as these variables are widely recognized as fundamental economic indicators in international trade analysis. The selection was also intended to reduce data dimensionality while maintaining meaningful economic representation of export patterns.

c. Data Normalization Using StandardScaler

Normalization was performed using the *StandardScaler* method to standardize the range of each feature by transforming data into a distribution with a mean of zero and a standard deviation of one. This method was selected because fisheries export data typically exhibit substantial variations in magnitude between commodities and export destinations, often resulting in extreme values or outliers. In economic datasets, export value can be disproportionately higher than export volume, causing clustering algorithms to be biased toward variables with larger numeric scales. The application of *StandardScaler* ensures that each feature contributes proportionally to the clustering process, improves numerical stability, and enhances the interpretability of cluster formation. Additionally, this normalization technique is particularly suitable for K-Means clustering, which relies on Euclidean distance calculations that are sensitive to scale differences among variables.

**Data Clustering**

The K-Means clustering algorithm was employed to identify groups of export performance patterns based on similarities in export volume and export value. K-Means partitions data into several clusters by minimizing the distance between data points and their respective cluster centroids. The determination of the optimal number of clusters was conducted using the *Elbow Method* and validated using the *Silhouette Score*. The Elbow Method evaluates cluster compactness by measuring the Within-Cluster Sum of Squares (WCSS) across multiple cluster numbers. The optimal cluster number is identified at the point where additional clusters no longer significantly reduce WCSS. The visualization of the Elbow Method is presented in Fig. 2, which demonstrates that k=3 provides the most balanced clustering structure.

**Evaluation of Clustering Results**

The quality of clustering results was evaluated using the Davies-Bouldin Index (DBI). DBI measures cluster separation and compactness by comparing intra-cluster similarity and inter-cluster distance. A lower DBI value indicates better clustering quality, reflecting well-separated and internally cohesive clusters. This evaluation ensures that the formed clusters represent meaningful and statistically valid export performance groupings.

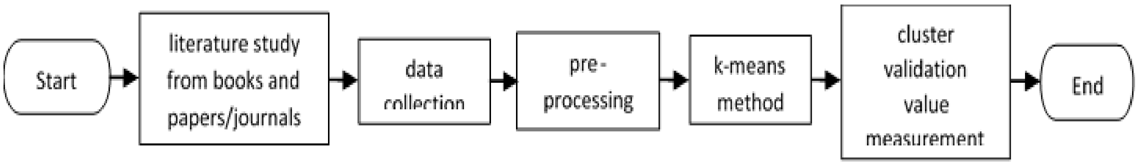


**Figure 1.** Research flow diagram

## RESULT AND DISCUSSION

**Result**

**Export Data Clustering**

Determination of the number of clusters was done using the elbow method. The results of the elbow graph show that the optimal number of clusters is 3. This is based on the bending point (elbow) of the inertia graph which indicates a decreasing marginal gain after the third cluster.

Once the number of clusters was determined, the K-Means algorithm was used to cluster the destination countries and commodities. The first cluster contains countries with high export volumes such as the United States and China. The second cluster contains countries with medium export volumes, while the third cluster is countries with small volumes but positive growth trends (Table 1).

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

**Table 1.** Destination countries clustering using k-means

| COUNTRIES | Cluster |
|---|---|
| ALBANIA | 0 |
| ALGERIA | 0 |
| AMERICAN SAMOA | 0 |
| ANDORRA | |
| ANGOLA | 0 |
| ANTIGUA AND BARBUDA | |
| ARGENTINA | 0 |
| ARMENIA | 0 |
| ARUBA | 0 |
| AUSTRALIA | 0 |
| AUSTRIA | 0 |
| AZERBAIJAN | |
| BAHAMAS | |
| BAHRAIN | 0 |
| BANGLADESH | 0 |
| BARBADOS | |
| BELARUS | |
| BELGIUM | 0 |
| BELIZE | |
| BENIN | 0 |
| BERMUDA | |
| BOSNIA AND HERZEGOVINA | |
| BOTSWANA | |
| BRAZIL | 0 |
| BRUNEI DARUSSALAM | 0 |
| BULGARIA | 0 |
| BURKINA FASO | |
| CAMBODIA | 0 |
| CAMEROON | 0 |
| CANADA | 0 |
| CAPE VERDE | |
| CAYMAN ISLANDS | |
| CENTRAL AFRICAN REPUBLIC | |
| CHILE | 0 |
| CHINA | 2 |
| COLOMBIA | 0 |
| COMOROS | |
| CONGO | |
| COOK ISLANDS | |
| COSTA RICA | |
| COTE D IVOIRE | |
| COTE DIVOIRE | |
| CROATIA | 0 |
| CUBA | |
| CYPRUS | 0 |
| CZECH REPUBLIC | 0 |
| DEMOCRATIC REP. OF THE CONGO | 0 |
| DENMARK | 0 |
| DJIBOUTI | |
| DOMINICA | 0 |
| DOMINICAN REPUBLIC | 0 |
| EAST TIMOR | 0 |
| ECUADOR | 0 |
| EGYPT | 0 |
| EL SALVADOR | |
| EQUATORIAL GUINEA | 0 |
| ESTONIA | 0 |
| ETHIOPIA | |
| FIJI | 0 |
| FINLAND | 0 |
| FRANCE | 0 |
| FRENCH POLYNESIA | 0 |
| GABON | 0 |
| GAMBIA | 0 |
| GEORGIA | 0 |
| GERMANY, FED. REP. OF | 0 |
| GHANA | 0 |
| GREECE | 0 |
| GRENADA | |
| GUADELOUPE | 0 |
| GUAM | 0 |
| GUATEMALA | 0 |
| GUINEA | |
| GUINEA BISSAU | |
| HAITI | |
| HONDURAS | |
| HONG KONG | 0 |
| HUNGARY | 0 |
| ICELAND | 0 |
| INDIA | 0 |
| IRAN (ISLAMIC REPUBLIC OF) | 0 |
| IRAQ | 0 |
| IRELAND | 0 |
| ISRAEL | 0 |
| ITALY | 0 |
| JAMAICA | 0 |
| JAPAN | 0 |
| JORDAN | 0 |
| KAZAKHSTAN | 0 |
| KENYA | 0 |
| KIRIBATI | |
| KOREA, DEM. PEOPLES REP. | |
| KOREA, REPUBLIC OF | 0 |
| KUWAIT | 0 |
| KYRGYZSTAN | |
| LAO PEOPLE S DEM. REP. | |
| LAO PEOPLES DEM. REP. | |
| LATVIA | |
| LEBANON | 0 |
| LIBERIA | 0 |
| LIBYAN ARAB JAMAHIRIYA | 0 |
| LITHUANIA | 0 |
| LUXEMBOURG | |
| MACAU | 0 |
| MADAGASCAR | |
| MALAYSIA | 0 |
| MALDIVES | 0 |
| MALI | |
| MALTA | 0 |
| MARSHALL ISLANDS | |
| MARTINIQUE | 0 |
| MAURITIUS | 0 |
| MAYOTTE | 0 |
| MEXICO | 0 |
| MICRONESIA, FED. STATES OF | |
| MOLDOVA, REPUBLIC OF | |
| MONACO | |
| MONGOLIA | |
| MONTENEGRO | 0 |
| MOROCCO | 0 |
| MOZAMBIQUE | 0 |
| MYANMAR | 0 |
| NAMIBIA | 0 |
| NAURU | |
| NEPAL | |
| NETHERLANDS | 0 |
| NETHERLANDS ANTILLES | 0 |
| NEW CALEDONIA | |
| NEW ZEALAND | 0 |
| NIGER | |
| NIGERIA | 0 |
| NORWAY | 0 |
| OMAN | 0 |
| PAKISTAN | 0 |
| PANAMA | 0 |
| PAPUA NEW GUINEA | 0 |
| PARAGUAY | |
| PERU | 0 |
| PHILIPPINES | 0 |
| POLAND | 0 |
| PORTUGAL | 0 |
| PUERTO RICO | 0 |
| QATAR | 0 |
| REP. OF MACEDONIA | |
| REUNION | 0 |
| ROMANIA | 0 |
| RUSSIA FEDERATION | 0 |
| RWANDA | |
| SAINT HELENA | |
| SAMOA | 0 |
| SAUDI ARABIA | 0 |
| SENEGAL | 0 |
| SERBIA | 0 |
| SEYCHELLES | 0 |
| SIERRA LEONE | 0 |
| SINGAPORE | 0 |
| SLOVAKIA | |
| SLOVENIA | 0 |
| SOLOMON ISLANDS | |
| SOMALIA | 0 |
| SOUTH AFRICA | 0 |
| SPAIN | 0 |
| SRI LANKA | 0 |
| SUDAN | 0 |
| SURINAME | 0 |
| SWEDEN | 0 |
| SWITZERLAND | 0 |
| SYRIA ARAB REPUBLIC | |
| TAIWAN | 0 |
| TANZANIA, UNITED REP. OF | 0 |
| THAILAND | 0 |
| TOGO | 0 |
| TOKELAU | |
| TRINIDAD AND TOBAGO | 0 |
| TUNISIA | 0 |
| TURKEY | 0 |
| TURKS AND CAICOS ISLANDS | |
| U.S. VIRGIN ISLANDS | |
| UKRAINE | 0 |
| UNITED ARAB EMIRATES | 0 |
| UNITED KINGDOM | 0 |
| UNITED STATES | 1 |
| URUGUAY | 0 |
| UZBEKISTAN | 0 |
| VIET NAM | 0 |
| VIRGIN ISLANDS (BRITISH) | |
| WALLIS AND FUTUNA ISLANDS | |
| YEMEN | 0 |

For commodities, the high cluster includes shrimp and tuna, the medium cluster consists of seaweed and squid, while the low cluster contains new commodities with small export volumes (Table 2)

**Table 2.** Commodities clustering using k-means

| Commodities | Cluster |
|---|---|
| Bawal | 0 |
| Catfish | 0 |
| Cumi-Sotong-Gurita | 2 |
| Kekerangan | 0 |
| Kerapu | 0 |
| Komoditas Lainnya | 2 |
| Layur-Gulama-Reeve S Croakers-Bigeye Croakers | 0 |
| Lobster | 0 |
| Makarel | 0 |
| Mutiara | 0 |
| Rajungan-Kepiting | 0 |
| Rumput Laut | 2 |
| Sarden-Sardinella | 0 |
| Sidat | 0 |
| Tepung Ikan-Pellet-Makanan Ikan | 0 |
| Tilapia | 0 |
| Tuna-Tongkol-Cakalang | 2 |
| Ubur-Ubur | 0 |
| Udang | 1 |

### Clustering Visualization

To improve the interpretation of the clustering results, two visualization methods were used: Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE). The visualization images (Fig. 2 and Fig. 3) show a fairly clear and non-overlapping cluster separation, indicating that the data in each cluster has similar characteristics.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

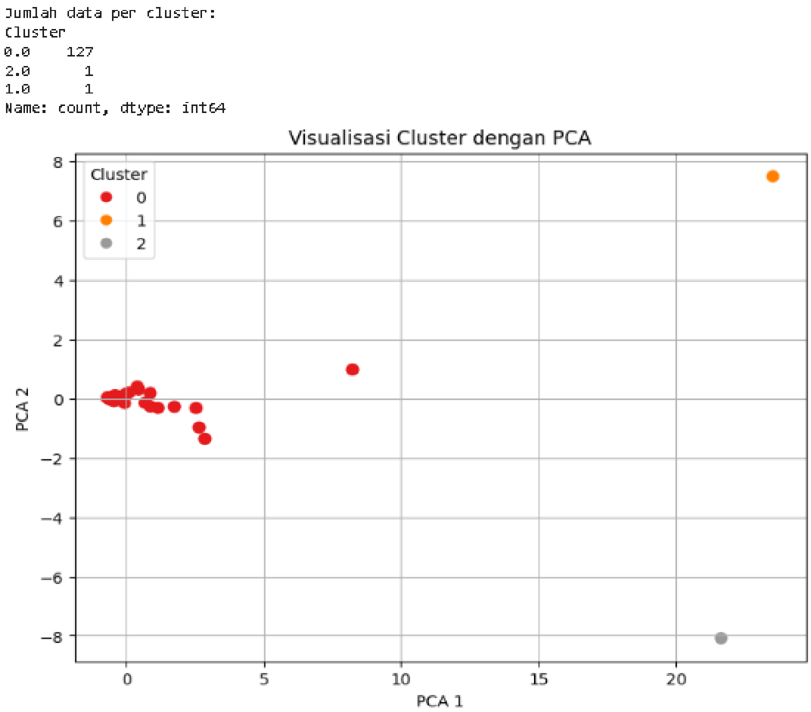


**Figure 2.** Cluster visualization with PCA for fisheries exports by destination country in 2019-2023

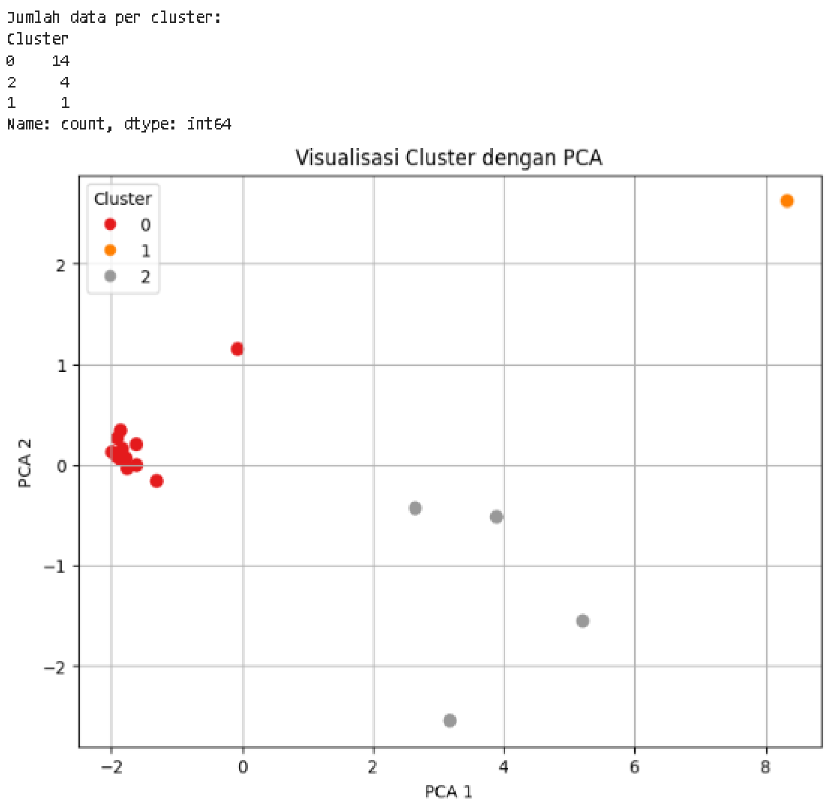


**Figure 3.** Cluster visualization with PCA for fisheries exports by commodities in 2019-2023

### Cluster Validation with Davies-Bouldin Index

Validation of clustering results is done using the Davies-Bouldin Index (DBI). The highest DBI value close to 2 indicates poor clustering results, while a value close to 0 indicates good clustering. In this study, the DBI value for the clustering of destination country and commodity data shows a number below 0.9, which indicates good cluster quality.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

**Trends in Export Volume and Value 2019-2023**

**Table 3.** Commodity Export Volume (Tons)

| Details | Year | | | | | Average Increase (%) | |
|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2023 | 2019 - 2023 | 2022 - 2023 |
| Rumput Laut | 209.241,30 | 195.573,60 | 225.612,16 | 253.680,06 | 265.843,76 | 6,52 | 4,79 |
| Komoditas Lainnya | 294.492,12 | 288.393,18 | 238.262,65 | 243.897,60 | 236.214,81 | -2,30 | -0,61 |
| Udang | 207.702,65 | 239.282,01 | 250.715,43 | 241.200,64 | 220.889,26 | 1,94 | -8,42 |
| Tuna-Tongkol-Cakalang | 184.130,23 | 195.759,30 | 174.764,04 | 194.723,53 | 203.202,59 | 2,84 | 4,35 |
| Cumi-Sotong-Gurita | 143.847,34 | 140.036,31 | 168.225,55 | 157.722,81 | 152.909,97 | 2,05 | -3,05 |
| Rajungan-Kepiting | 25.942,91 | 27.616,33 | 32.183,31 | 29.177,61 | 29.371,29 | 3,58 | 0,66 |
| Lobster | 1.633,22 | 2.150,42 | 1.959,91 | 1.469,56 | 1.144,86 | -6,08 | -22,09 |
| Mutiara | 8,03 | 6,29 | 9,57 | 13,49 | 10,78 | 12,85 | -20,13 |
| **Total** | 1.184.171,69 | 1.262.829,69 | 1.221.904,59 | 1.224.059,70 | 1.221.196,35 | 0,84 | -0,23 |

The data shows that in 2023 (Table 3 and Table 4), Indonesia's fishery product exports experienced a slight decline compared to the previous year. However, over the past five years, there has been an overall upward trend in export volume and value. Key commodities such as shrimp and tuna experienced significant increases in export volume and value, although there were fluctuations in 2023.

**Table 4.** Commodity Export Value (US$ 1000)

| Details | Year | | | | | Average Increase (%) | |
|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2023 | 2019-2023 | 2022-2023 |
| Udang | 1719172,13 | 2040184,25 | 2228947,83 | 2157134,39 | 1729521,19 | 1,22 | -19,82 |
| Tuna-Tongkol-Cakalang | 747538,12 | 724095,09 | 732944,41 | 960265,83 | 927131,10 | 6,41 | -3,45 |
| Cumi-Sotong-Gurita | 556290,65 | 509223,24 | 618934,66 | 737127,12 | 762586,99 | 8,91 | 3,45 |
| Rajungan-Kepiting | 393497,77 | 367519,71 | 613245,48 | 484227,86 | 447651,20 | 7,92 | -7,55 |
| Rumput Laut | 324849,98 | 279582,59 | 345114,33 | 600356,45 | 433715,44 | 13,93 | -27,76 |
| Komoditas lainnya | 837545,99 | 795597,68 | 799364,63 | 946330,10 | 881979,49 | 4,17 | -0,19 |
| Mutiara | 47540,83 | 40325,35 | 44499,08 | 54658,17 | 112896,71 | 31,14 | 106,55 |
| Lobster | 33189,39 | 76106,25 | 28616,96 | 25700,74 | 23929,43 | 12,46 | -6,89 |
| **Total** | 4935960 | 5205192,52 | 5718827,83 | 6242084,72 | 5630946,74 | 3,67 | -9,79 |

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

**Analysis Based on Destination Countries**

**Table 5.** Export Volume of Destination Countries (Tons)

| Details | Year | | | | | Average Increase (%) | |
|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2023 | 2019-2023 | 2022-2023 |
| China | 405.955 | 422.565 | 428.056 | 403.744 | 438.653 | 2,09 | 8,65 |
| US | 210.990 | 238.390 | 263.245 | 239.634 | 217.725 | 1,33 | -9,14 |
| Japan | 120.236 | 99.767 | 95.576 | 112.103 | 113.922 | -0,58 | 1,62 |
| Malaysia | 65.356 | 71.412 | 66.607 | 69.527 | 66.802 | 0,75 | -3,92 |
| Vietnam | 44.705 | 41.510 | 43.431 | 60.523 | 52.332 | 5,83 | -13,53 |
| Thailand | 54.403 | 98.332 | 54.279 | 48.905 | 45.201 | 4,62 | -7,57 |
| Negara Lainnya | 282.527 | 290.854 | 270.711 | 289.597 | 286.561 | 0,49 | -1,05 |
| **Total** | 1.184.172 | 1.262.830 | 1.221.905 | 1.224.060 | 1.221.196 | 0,84 | -0,23 |

**Table 6.** Export Value of Destination Countries (US$ 1000)

| Details | Year | | | | | Average Increase (%) | |
|---|---|---|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 | 2023 | 2019-2023 | 2022-2023 |
| US | 1.828.979 | 2.096.627 | 2.532.864 | 2.316.295 | 1.907.305 | 2,31 | -17,66 |
| China | 828.364 | 817.367 | 890.144 | 1.124.187 | 1.138.513 | 8,79 | 1,27 |
| Japan | 665.191 | 608.939 | 621.013 | 742.926 | 690.704 | 1,53 | -7,03 |
| Vietnam | 157.541 | 171.596 | 150.596 | 283.832 | 213.265 | 15,07 | -24,86 |
| Malaysia | 137.202 | 133.687 | 131.293 | 160.053 | 149.951 | 2,81 | -6,31 |
| Thailand | 133.967 | 199.004 | 138.190 | 152.133 | 140.621 | 5,13 | -7,57 |
| Negara Lainnya | 1.184.716 | 1.177.973 | 1.254.728 | 1.462.573 | 1.390.588 | 4,39 | -4,92 |
| **Total** | 4.935.960 | 5.205.193 | 5.718.828 | 6.242.085 | 5.630.947 | **3,67** | **-9,79** |

China and the United States are the two main destination countries for Indonesian fishery product exports. Exports to China increased by 8.65% in 2023, while those to the United States decreased by 9.14% (Table 5). Japan and Malaysia showed relatively high stability. Positive growth trends were also observed in other developing countries (Table 6) that began to actively import Indonesian fishery commodities.

**Discussion**

The results of this study reveal that Indonesia's marine and fisheries export performance during 2019–2023 exhibits a structured and distinguishable pattern when examined through commodity-based and destination-country clustering. By applying the K-Means algorithm and validating the results using the Davies-Bouldin Index (DBI), this research confirms that Indonesian fisheries exports can be meaningfully classified into high-, medium-, and low-performance clusters. This finding reinforces the relevance of unsupervised learning methods for export performance evaluation, as also demonstrated in prior international studies.

From a commodity perspective, shrimp and tuna consistently formed the high-performance cluster, indicating their dominant contribution to Indonesia's fisheries export value and volume. This result is consistent with the findings of Fadhilah et al., (2024), who applied X-Means clustering to shrimp exports in Indonesia and found strong geographical concentration and export stability in high-demand markets. Similarly, Salsabila et al. (2024) reported that shrimp and tuna remain Indonesia's most competitive fisheries commodities due to their established supply chains and compliance with international quality standards. However, unlike these studies, which focused on single commodities or specific regions, the present research extends the analysis by incorporating multiple major capture fisheries commodities simultaneously, thereby offering a more holistic export mapping framework.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

Medium-cluster commodities, such as seaweed and squid, demonstrate stable export growth but comparatively lower export value, indicating limited downstream processing and value addition. This finding aligns with Olasehinde-Williams & Oshodi (2021), who argued that developing countries often remain trapped in raw commodity exports unless deliberate value-chain upgrading strategies are implemented. The identification of this "value stagnation" cluster also reflects structural challenges in Indonesia's fisheries industrialization policy. Although the government has promoted downstream processing through industrial revitalization and marine-based processing zones, the clustering results suggest that seaweed and squid remain dominated by semi-processed or raw exports. This condition indicates that existing downstream policies may still face constraints related to processing technology adoption, investment capacity, and integration between upstream fishermen and processing industries. Furthermore, Vuong & Nguyen (2022) emphasized that export diversification must occur not only across markets but also across product sophistication levels, a proposition empirically supported by the clustering results of this research.

Low-cluster commodities, including lobster and emerging fishery products, exhibit relatively small export volumes and higher volatility. While this may initially suggest weak performance, the results are consistent with M. D. Rivaldo et al. (2024), who found that niche fisheries commodities often display limited volume but high unit value and regulatory sensitivity. Unlike previous studies that interpret low export volume as underperformance, this research supports a more nuanced interpretation, viewing low-cluster commodities as candidates for niche-market strategies rather than mass export expansion. This distinction is crucial for sustainable fisheries governance, especially for environmentally sensitive commodities, where overexploitation risks are closely linked to international conservation regulations and certification requirements.

In terms of destination countries, the clustering analysis confirms that China and the United States remain Indonesia's primary fisheries export markets, consistently occupying the high-volume and high-value clusters. This finding corroborates Oyewole & Thopil (2023), who demonstrated that export concentration in a small number of dominant markets is a common characteristic of resource-based exports in developing economies. However, this study advances the literature by revealing divergent trends between these two markets in 2023, where exports to China increased by 8.65% while exports to the United States declined by 9.14%. This divergence can be interpreted not only as market dynamics but also as a reflection of external non-technical factors, including geopolitical tensions, trade policy shifts, and regulatory requirements. The strengthening of China's seafood demand, supported by post-pandemic economic recovery and stable bilateral trade cooperation, likely contributed to increased Indonesian exports. Conversely, declining exports to the United States may be associated with tightening non-tariff measures, including stricter food safety regulations, sustainability certification requirements, and traceability standards in seafood imports. Similar regulatory intensification has been widely recognized as a trade barrier affecting developing-country exporters, as highlighted by Hoque & Zaidi (2020) in their analysis of export volatility influenced by external trade policies.

Notably, the identification of destination countries within the low-volume but positive-growth cluster offers new empirical evidence supporting export market diversification strategies. This result extends the findings of Fitria et al., (2023), who emphasized the importance of cluster validation in identifying emerging markets with growth potential. Unlike prior studies that rely solely on descriptive export statistics, this research employs DBI-validated clustering to systematically identify non-traditional markets that may contribute to long-term export resilience. Diversification into emerging markets also reduces dependency risks on dominant trading partners and enhances Indonesia's bargaining position in global seafood trade negotiations.

Methodologically, this study contributes to the existing literature by integrating export volume and value dimensions within a single clustering framework and validating the results using DBI. Compared to earlier studies that applied K-Means clustering without formal validation metrics (Kusnawi, 2021b; Yaman et al., 2020), the use of DBI in this research enhances analytical rigor and result reliability. The visualization using PCA further strengthens interpretability, consistent with best practices suggested by Utomo & Harjono (2021) for high-dimensional trade data analysis. Beyond methodological contributions, the integration of clustering results with policy and geopolitical analysis demonstrates the practical relevance of data-driven export mapping for strategic fisheries trade governance.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

## CONCLUSION

This study demonstrates that the application of the K-Means Clustering method is effective in classifying Indonesian marine and fisheries export data based on export volume and value across commodities and destination countries. The validation results using the Davies–Bouldin Index confirm that a three-cluster configuration provides optimal separation and cohesion, indicating a reliable and robust clustering structure. The findings reveal clear distinctions between high-, medium-, and low-performance export groups, offering valuable insights into the current structure and dynamics of Indonesia's fisheries export sector. By identifying key commodities and destination countries with strong and emerging export potential, this study provides an empirical basis for more targeted and data-driven export development strategies. Overall, the proposed clustering framework contributes to improved export mapping and supports strategic decision-making aimed at enhancing the competitiveness and sustainability of Indonesia's fisheries exports in the global market.

An interactive and integrated export performance dashboard is recommended to enable real-time monitoring and more responsive policy interventions. Future studies may expand the methodological approach by applying alternative clustering algorithms, such as DBSCAN or Fuzzy C-Means, to compare performance and enhance analytical robustness. In addition, policymakers can utilize the clustering results to strengthen export promotion programs and market penetration strategies, particularly in destination countries identified as having high growth potential.

## REFERENCE

Cebeci, T., Fernandes, A. M., Freund, C. L., & Pierola, M. D. (2012). Exporter dynamics database. In World Bank Policy Research Working Paper (Vol. 6229). World Bank.

Development, O. for E. C. and, & Lord, S. (2022). Environmental Impacts Along Food Supply Chains: Methods, Findings, and Evidence Gaps. OECD Trade and Agriculture Directorate.

Fadhilah, R., Matdoan, M. Y., Safira, D. A., & Tahalea, S. P. (2024). Clustering Shrimp Distribution in Indonesia Using The X-Means Clustering Algorithm. Variance: Journal of Statistics and Its Applications, 6(1).

Fitria, M., Pandin, A. T., Shabrina, A., Gunawan, D. F., Prianka, W. T., & Gunadi, H. (2023). Penerapan Design Thinking dalam Perancangan Strategi Pemasaran UMKM Jahe Cap Maher. Journal of Research on Business and Tourism, 3(1), 1. https://doi.org/10.37535/104003120231

Godwin, J. U., & Oshodi, O. S. (2021). Export diversification and value addition in developing economies: Evidence from commodity-based trade. Journal of International Trade & Economic Development, 30(4), 567–586. https://doi.org/10.1080/09638199.2020.1860764

Hoque, M. E., & Zaidi, M. A. S. (2020). Global and country-specific geopolitical risk uncertainty and stock return of fragile emerging economies. Borsa Istanbul Review, 20(3), 197–213. https://doi.org/10.1016/j.bir.2020.05.001

Indri, A., Marpaung, N., & Nurwati. (2022). Analysis Of Supply Chain Management Methods In Raw Material Inventory And Distribution Of Crips In Ud. Bu Sri Web-Based. Jurnal Teknik Informatika (JUTIF), 3(2), 331–339. https://doi.org/10.20884/1.jutif.2022.3.2.225

Kitta, S. K., Tamar, M., & Radjab, M. (2022). Pengaruh Gender-Role Identity dan Gender-Role Attitudes terhadap stres akademik pada sistem pembelajaran dalam jaringan (daring) mahasiswa di Kabupaten Banggai. Yinyang: Jurnal Studi Islam Gender Dan Anak, 17(2), 137–162. https://doi.org/10.24090/yinyang.v17i2.6880

Kusnawi. (2021a). Cluster validation using Davies–Bouldin index in trade data analysis. Indonesian Journal of Computing and Cybernetics Systems, 15(3), 221–230. https://doi.org/10.22146/ijccs.58765

Kusnawi. (2021b). Evaluasi Cluster dengan Davies Bouldin Index (DBI). https://www.youtube.com/watch?v=3UTLjoWSlD4&t=5s

Olasehinde-Williams, G., & Oshodi, A. F. (2021). Can Africa raise export competitiveness through economic complexity? Evidence from (non)-parametric panel techniques. African Development Review, 33(3), 426–438.

Oyewole, O. A., & Thopil, G. A. (2023). Machine learning approaches for trade pattern analysis: Evidence from export clustering. Applied Artificial Intelligence, 37(1), 2170951. https://doi.org/10.1080/08839514.2023.2170951

Perikanan, K. K. dan. (2023). Statistik Ekspor Produk Perikanan. Kementerian Kelautan dan Perikanan.

Pusat Data, S. dan I. (2024). Analisis Indikator Kinerja Utama Sektor Kelautan dan Perikanan Kurun Waktu 2019–2023 (Vol. 2). Kementerian Kelautan dan Perikanan.

Rivaldo, Y., Saputra, D., & Nugroho, A. (2024). Classification of fish catch using K-means clustering: Evidence from Karimunjawa waters. Journal of Marine Science and Technology, 29(1), 55–66.

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)

Salsabila, N., Hidayat, R., & Prakoso, B. (2024). Clustering analysis of Indonesian fisheries exports based on destination countries. Jurnal Ilmu Kelautan, 29(2), 89–101.

Statistik, B. P. (2021). Buletin Statistik Perdagangan Luar Negeri Ekspor Menurut Kelompok Komoditi dan Negara, September 2021. Badan Pusat Statistik.

Utomo, S., & Harjono, A. N. (2021). Pentingnya Membangun Platform Kolaborasi Multi-Stakeholder sebagai Key Enabling Factor dalam Membangun Ekosistem Inovasi Industri 4.0 di Era New Normal. Jurnal Informatika Universitas Pamulang, 6(1), 67–76. https://doi.org/10.32493/informatika.v6i1.7261

Vuong, T. D. N., & Nguyen, L. T. (2022). The Key Strategies for Measuring Employee Performance in Companies: A Systematic Review. Sustainability, 14(21), 14017. https://doi.org/10.3390/su142114017

Yaman, A., Sartono, B., & Soleh, A. M. (2020). Identifikasi kecakapan inovasi lembaga riset di Indonesia berbasis dokumen 1 2 3. Berkala Ilmu Perpustakaan Dan Informasi, 16(2), 142–154. https://doi.org/10.22146/bip.v16i1.424

Lisensi: Creative Commons Attribution 4.0 International (CC BY 4.0)