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Analysis of Trends and Seasonal Patterns of Indonesian Leading Agricultural Commodity Exports: January 2023 – February 2026

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ABSTRACT

Purpose – This study identifies monthly export trends of 13 leading Indonesia agricultural commodities (January 2023-February 2026), Analyze seasonal patterns via seasonal indices, compare export performance using CAGR and Coefficient of Variation (CV), and develop commodity segmentation for risk management and export planning.
Design/methodology/approach – A descriptive-quantitative approach combined time series decomposition (additive and multiplicative), 3- and 6 month moving-average, CAGR, CV, and K-Means clustering on secondary monthly export data (USD million) for 13 commodities over 38 months from Statistics Indonesia (BPS) and analyzed using Python on Google Colaboratory.
Finding/Results – Decomposition revealed seasonal patterns, with Coffee showing strongest amplitude, peaking in October and troughing in April. CAGR ranked Coffee (65,21%), Black Pepper, and Perennial Fruits as fastest-growing, while Maize, Seaweed, and Bird's Nest contracted most. Bird's Nest and Medicinal Plants were most stable, Maize and Black Pepper were most volatile. K-Means clustering (k=2) isolated Coffee as a distinct high-value Cluster (mean export USD 138,75 million). Informing a four-quadrant strategic Matrix combining CAGR, CV, and mean export value.
Originality/Value – This study addresses five research gaps through multi-commodity coverage, monthly temporal granularity, integrated growth-volatility metrics, an evidence-based typology via K-Means clustering, and an interactive Python dashboard for real-time monitoring. Offering an empirical basis for differentiated export risk management strategies.

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1. Introduction

Indonesia, as an agrarian economy, possesses a diverse portofolio of agricultural export commodities that contribute significantly to non-oil and gas exports. This study develops an integrated descriptive-screening framework that jointly maps export trends, seasonality, growth, and volatility across 13 leading agricultural commodities. Its primary scientific contribution is not methodological novelty per se, but the new knowledge that emerges from a comparative, multi-commodity lens: (1) growth and volatility behave as orthogonal dimensions, so high-growth commodities can be either stable or erratic, (2) seasonal amplitude differs by an order of magnitude across commodities, with Coffee's seasonal swing dwarfing that of White Pepper by a factor of 25, and (3) classical and STL decomposition yield divergent peak estimates for several commodities, underscoring the need for robustness checks in short-span or annual-data analyses. The framework also generates a four-quadrant strategic matrix as a replicable decision-support tool. This study distinguishes three layers of contribution: descriptive-analytical layer (characterizing patterns), conceptual layer (portofolio screening heuristic), and policy-support layer (matrix as a triage instrument) (Putri, 2023).

In this study, agricultural commodities are classified as "leading" based on three empirical criteria: (1) consistent export revenue contribution over at least past three years as recorded by Central Bureau of Statistics (BPS), (2) annual export value exceeding USD 50 million per commodity, and (3) Indonesia's position as a major global producer or exporter for commodity in question. Based on these criteria, 13 leading commodities were identified: (1) Coffee, (2) Bird's Nest, (3) Medicinal Plants, Aromatics, and Spices, (4) Perennial Fruits, (5) Seaweed and other Algae, (6) Vegetables, (7) Fresh/Chilled Fish, (8) Tobacco, (9) White Pepper, (10) Cocoa Beans, (11) Black Pepper, (12) Maize, and (13) Other Non-Timber Forest Products (*Badan Pusat Statistik Indonesia*, 2026).

Contribution of these commodities to national non-oil and gas exports shows dynamics that merit closer investigation. BPS data indicate that their combined export value reached USD 4,29 billion in 2023 and rose to USD 4,79 billion in 2024, while January-February 2026 alone recorded USD 822,8 million, led by coffee at USD 229,6 million (27,9%), Perennial Fruits at USD 83,9 million (10,2%), and Bird's Nest at USD 83,1 million (10,1%). This upward trajectory confirms strategic weight of agricultural sector, even as it reveals month to month fluctuations in export value that call for closer characterization(Khairad & Khairad, 2026).

The 38-month window from January 2023 to February 2026 was chosen based on four empirical considerations. It captures post-COVID-19 recovery phase, coincides with global food-price volatility triggered by geopolitical conflict, reflects intensified El Nino-La Nina climate phenomena, and covers ongoing trade-policy shifts in major destination markets (Min et al., 2025) (Khairad & Khairad, 2026). Methodologically, 38 months exceed the 36-month minimum for seasonal time series analysis (three complete cycles). However, three cycles represent a lower bound for stable seasonal index estimation. To assess reliability, this study supplements classical decomposition with STL (Seasonal Trend decomposition using loess) and rolling 12 month seasonal indices. All seasonal results are framed as exploratory profiles rather than definitive norms. The short span also means that trend estimates are sensitive to endpoint choice, CAGR robustness checks using regression based and theil sen trend estimators are therefore reported alongside standard CAGR (R. J. . Hyndman & Athanasopoulos, 2021).

Despite their contribution to the trade balance, agricultural export values remain highly volatile. This volatility arises from interacting forces: seasonal harvest cycles, global climate conditions, international commodity price swings, and destination country trade policy. Without a means of separating seasonal fluctuation from structural change, trends risk being misread and policy responses may lag. The present analysis is descriptive, it characterizes observed patterns without establishing causal relationships. This distinction is carried through to the policy implications, which are presented as indicative screening inputs, not definitive prescriptions (Khairad & Khairad, 2026) (Min et al., 2025).

Time series analysis offers a well-established route to understanding these temporal patterns, decomposing observed export data into trend, seasonal, and residual components and thereby producing a structured account of how data behaves over time(R. Hyndman & Athanasopoulos, 2018) (Setyoko et al., 2025). Although this method is widely used in export studies elsewhere, its application to Indonesian agricultural exports across a full set of 13 leading commodities, paired with integrated volatility metrics such as CV and CAGR, K-Means based segmentation, and current data through 2023-2026, remains scarce in existing literature(Shanavas et al., 2026) (Khairad & Khairad, 2026).

This study poses four research questions: (1) what monthly trend patterns characterize Indonesia's 13 leading agricultural commodities via Moving Average Smoothing, (2) what seasonal patterns emerge, and which months mark peaks and troughs, (3) which commodities can be classified as high-growth, high-stability, or high-volatility on the basis of CAGR and CV, and (4) how might a commodity segmentation built on CAGR, CV, and mean export value inform export-risk screening. The study adopts a descriptive-quantitative approach combining time series decomposition, Moving Average smoothing, CAGR, CV, K-Means clustering, and a four quadrant strategic matrix. The emphasis throughout is on synthesis and screening utility, not causal inference (Setyoko et al., 2025) (Billah et al., 2024) (Jason Fernando, 2026) (Adam Hayes, 2025) (Ikotun et al., 2023).

This design responds to five gaps in existing literature. First, prior research is fragmented by commodity, examining single commodity in isolation (Wardah & Sundari, n.d.) (Surojudin & Danny, 2025). Second, multi-commodity studies rely on annual data, missing intra year patterns (Putri, 2023). Third, literature lacks integrated volatility metrics that pair CV and CAGR as complementary dimensions (Adam Hayes, 2025) (Jason Fernando, 2026). Fourth, no existing study produces a performance based commodity typology jointly considering trend and volatility (Wooldridge, 2016). Fifth, the field lacks interactive analytical visualization tools for policy exploration (Min et al., 2025) (Ikotun et al., 2023). This study addresses all five gaps simultaneously. Its contribution is not merely methodological integration it demonstrates that portfolio level patterns emerge from integration that are not discernible in single commodity or single dimension analyses. The framework provides a replicable screening heuristic for classifying commodity export profiles, enabling policymakers to triage which commodities warrant deeper investigation (*Badan Pusat Statistik Indonesia*, 2026).

2. Literature Review & Hypothesis Development

Comparative Advantage and International Trade

This study is anchored in classical trade theory as contextual motivation rather than as a testable hypothesis. Ricardo's principle of comparative advantage and Heckscher-Ohlin model hold that nations export goods intensive in their abundant factors. Indonesia's tropicals climate, arable land, and agrarian workforce endow it with a natural comparative advantage in tropical agricultural commodities. However, converting this endowment into consistent export earnings requires understanding seasonal cycles, trend trajectories, and volatility patterns focus of this study. It is important to clarify that this study does not directly measure Revealed Comparative Advantage (RCA), factor endowments, trade specialization indices, or export competitiveness metrics (Soumya & Yeledhalli, 2021). Classical trade theory provides the conceptual motivation for why agricultural export dynamics matter, but the empirical analysis is descriptive rather than hypothesis testing. Commodities with strong growth and low volatility may reflect realised comparative advantage, while persistent volatility may signal structural constraints, but these interpretaions are indicative, not inferential. Future research incorporating RCA indices or gravity model frameworks would complement the present screening approach (Soumya & Yeledhalli, 2021).

Time Series Decomposition

Time series decomposition was chosen because it was able to separate observational data into three independent components: trend (T), seasonal (S), and residual/irregular (R). additive models are used when amplitude of seasonal fluctuations is relatively constant to trend level, whereas multiplicative model is applied when amplitude fluctuates proportionally to trend level. Selection of right model will be based on visual analysis of $(Y = T + S + R)$ $(Y = T\ x\ S\ x\ R)$ tim series plot and stationarity test(Setyoko et al., 2025).

Moving Average Smoothing

Moving Average (MA) smoothing strips out short-term noise to reveal a cleaner trend underneath. Two windows are used here, each doing a different job. MA-3 tracks short-term shifts and reacts quickly to new movements in data, while MA-6 captures a semi-annual trend that holds up better against outliers and month-to-month seasonal noise. Read together, two give a multi-temporal view of export dynamics: MA-3 flags emerging changes early, and MA-6 shows whether those changes are part of something more lasting(Billah et al., 2024).

Growth and Volatility Measurement in Export Performance

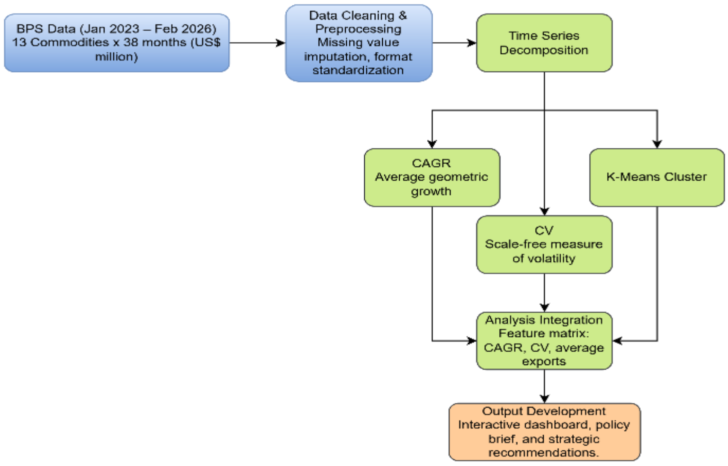
CAGR was chosen because it provides a normalized and comparable measure of average growth between commodities with different export value baselines. In contrast to a simple average growth rate that is biased towards high volatility, CAGR measures geometric growth that is more representative of medium-term performance comparisons (Sunandar & Dwi Fitrizal Salim, 2023).

Cluster Analysis for Commodity Segmentation

K-Means clustering partitions a set of observations into k clusters by minimizing within-cluster variance. Applied to commodity performance indicators (CAGR, CV, and export scale), It yields archetypal groupings that can support differentiated, rather than uniform, policy responses. Appropriate number of clusters is typically determined using Elbow together with Silhouette Score(Ikotun et al., 2023).

3. Methodology

Figure 1. Research Flow



This study uses a descriptive-explanatory quantitative approach based on time series analysis with Data-Driven Policy Analytics framework. This design was chosen to extract systematic patterns from historical export data and translate them into policy recommendations based on empirical evidence.

Data Sources, Population, and Commodity Specifications

Data used are secondary data on monthly export value in units (Million US$) from 13 agricultural commodities for period January 2023 – February 2026 (38 months of observation) sourced from Central Statistics Agency (BPS). Data were extracted from BPS statistics table download feature in Excel/CSV format, covering 13 leading agricultural commodities determined based on following criteria: Consistency of BPS data recording during observation periode, significant contribution to total non-oil and gas agricultural exports, and data availability at 4-digits HS code level.

Tabel 1. List of 13 Commodities and HS Codes

Commodities	**HS Code**
Coffee	0901
Swallow's Nest	0410
Medicial Plants, Aromatics, Spices	0910
Annual Fruits	0804
Seaweed and Algae	1212
Vegetables	0701
Fresh/Cold Fish Caught	0302
Tobacco	2401
White Pepper	0904
Cocoa Beans	1801
Black Pepper	0904
Corn	1005
Other Non-Timer Forest Products	1302

Stages of Analysis

Dataset spans 38 months, from January 2023 through February 2026. That window was deliberately chosen: seasonal analysis typically benefits from at least three complete annual cycles before a seasonal index becomes reasonably stable. Nevertheless, three cycles is the minimum recommended threshold, seasonal indices reported here should be interpreted as exploratory estimates rather than robust long-term norms. All data within study period are complete no monthly observations are missing for any of the 13 commodities between January 2023 and February 2026. A small number of zero-exports months were recorded (three for Maize, one for Cocoa Beans) and retained as valid observations. The 2026 CSV file naturally ends at February, months March through December 2026 are outside the study period and were excluded rather than imputed (Sarstedt et al., 2021).

a. Data collection and preprocessing

Data preprocessing followed two step. First, annual CSV files from BPS were loaded and reshaped from wide to long (tidy) format. Second, commodity labels were standardized and numeric types validated. No missing-value interpolation was applied, all reported values original BPS figures. We pulled monthly export values from BPS portal (bps.go.id) as CSV files covering agricultural commodity exports, then loaded them into a Python dataframe using pandas library. Cleaning data involved three steps, done in order:

- Handling data structure across annual files. Each year's CSV was loaded, and the monthly columns were reshaped into a long-format (tidy) dataframe. 2026 file covered only January and February, consistent with the study period end date. After reshaping, rows corresponding to months beyond study period (March-December 2026) were excluded. Within January 2023 – February 2026 window, no missing monthly values were found. Four zero-value observations three for Maize (January 2023, November 2024, December 2024) and one for Cocoa Beans (January 2024) were verified against original BPS records and retained as genuine zero-export months. No interpolation was applied, so the seasonal decomposition operates on actual reported values only.
- Finding and handling outliers. For outliers, we used interquartile range (IQR) method: any value below $Q1 - 1{,}5\ x\ IQR$ or above $Q3 + 1{,}5\ x\ IQR$ was flagges, then checked by hand against original BPS records. If a spike or dip matched a real event, we kept value and marked it as an annotated outlier. If nothing explained it, we replaced value with average of three nearest months.
- Standardizing and validating format. We reshaped all data into a long-format Python dataframe and checked it for consistent data types and commodity labels before moving on to analysis.

b. Trend analysis and seasonal decomposition

We decomposed each commodity's time series using additive and multiplicative models. An additive model fits when seasonal swings stay roughly same amplitude regardless of trend level, multiplicative model fits when seasonal amplitude scales with trend. Model selection was guided by Seasonal Strength Index (Fs), $Fs = Max(0{,}1 - \frac{Var(R_t)}{Var(S_t + R_t)}$ (Wang et al., 2006).

An Fs above 0,64 indicates strong seasonality, below this threshold, seasonal patterns are weaker relative to residual noise. Additive model was used as defaults, with multiplicative model applied as a sensitivity check. For commodities with zero-export months, additive model was preferred since multiplicative model requires strictly positive values.

$Y = Tt + St + Rt$ a multiplicative model fits better when seasonal swings scale up or down with trend. $Y = Tt \times St \times Rt$ we chose between two first inspecting time series and residual plots by eye, then calculating Seasonal Strength Index $Fs = Max(0{,}1 -$

$\frac{Var(R_t)}{Var(S_t+R_t)}$ An f, above 0,64 points to a strong seasonal pattern, and multiplicative model tends to fit better once residual variance starts growing along with trend. MA-3 and MA-6 moving averages smoothed out short-term noise so underlying trend stood out more clearly. Peak months and export troughs came from each commodity's highest and lowest seasonal indices, averaged across years in sample(Fredianto & Putri, 2023).

c. Growth, volatility, and clustering

CAGR (Compound Annual Growth Rate) gives a geometric average growth rate that is comparable across commodities. CV (Coefficient of Variation) is a scale-free measure of relative volatility. A CV above 30% marks a commodity as highly volatile, 15-30% as moderately volatile, and below 15% as stable. We then ran K-Means clustering on two alternative feature sets: (a) a five-feature matrix (mean export, CV, CAGR, seasonal amplitude, linear trend slope) and (b) a three-feature matrix with log-transformed mean export value to reduce scale dominance. Elbow method and silhouette scores determined number of clusters. Because dataset includes only 13 commodities, a small sample for cluster analysis. Results were cross-checked against hierarchical clustering (Ward linkage, Euclidean distance) and a four-quadrant strategic matrix (CAGR versus CV with median-based thresholds, supplemented by bootstrap confidence intervals for thethreshold lines). For-quadrant matrix serves as the primary segmentation tool ,with K-Means providing a complementary perspective. $CAGR = \left(\left(\frac{EV^{\frac{1}{n}}}{BV}\right) - 1\right) x\ 100\ \ CV = \frac{Standar\ deviation}{mean} x\ 100\%$. (Chen et al., 2021) (Jalilibal et al., 2021) (Hayati, 2023)

d. Dashboard and recommendations

An interactive Python dashboard visualizes trends, seasonal patterns, and clustering results, built with user-centered design principles to make data easy for stakeholders to explore. Policy recommendation draw on trend findings, seasonal patterns, and volatility profile for each commodity, and come packaged as a policy brief: an executive summary, findings for each commodity, strategic implications, and concrete next steps.

4. Result and Discussion

BPS Data and Dataset Integration

Monthly export figures for 13 commodities were pulled from BPS for full January 2023 to February 2026. Raw material came in as four separate annual CSV files, which were then cleaned and merged into a single, consistent analytical dataset. This stage covered:

a. Standardizing data formats across files
b. Converting data from wide to long (tidy) format
c. Isolating core commodity records from broader aggregate data
d. Validating monthly entries for each commodity

Processing produced 494 core observations, 13 commodities tracked across 38 months of valid data.

Table 2. Research Dataset Summary

Component	Value
Number of CSV files	4
Period	January 2023 – February 2026
Number of commodities	13

Number of core observations	494

13 commodities analyzed are: Coffee, Edible Bird's Nest, Medicinal, Aromatic, and Spice Plants, Perennial Fruits, Seaweed and Algae, Vegetables, Fresh/Chilled wild-caught fish, Tobacco, White Pepper, Cocoa Beans, Black Pepper, Corn, and Other Non-Timber Forest Products

Figure 2. List of 13 Commodities Analyzed

```
============================================================
No.    | Leading Indonesian Agricultural Commodities
============================================================
1      | Coffee
2      | Bird's Nest
3      | Medicinal Plants, Aromatics, Spices
4      | Perennial Fruits
5      | Seaweed and Other Algae
6      | Vegetables
7      | Fresh/Chilled Capture Fish
8      | Tobacco
9      | White Pepper
10     | Cocoa Beans
11     | Black Pepper
12     | Maize
13     | Other Non-Timber Forest Products
============================================================
Total: 13 commodities
```

This stage lines up with first phase of research plan: data collection and preprocessing, Using BPS data as primary source also follows standard practice in Indonesian commodity trade research, where official export figures from basis for assessing agricultural sector performance.

Data Cleaning, Preprocessing, and Format Adjustment

once BPS data had been collected, next step was cleaning and preprocessing to get it ready for time-series analysis. This meant adjusting variable formats, standardizing commodity names, and handling incomplete 2026 records, since observations for that year run only through February.

Getting this right mattered for keeping data structure consistend, avoiding duplicate file reads, and giving every commodity same time dimension. What came out of it is tidy dataset ready for further analysis, whether that's descriptive statistics or interactive visualization.

Time Series Decomposition and Trend Analysis

Trend analysis used MA-3 and MA-6 moving averages to smooth out short-term swings in export value. Time series decomposition then split data into trend, seasonal, and residual componens, which made it easier to see how each commodity actually behaves over time. Results point to fairly sharp performance differences from one commodity to next.

Figure 3. Monthly Export Value Trends

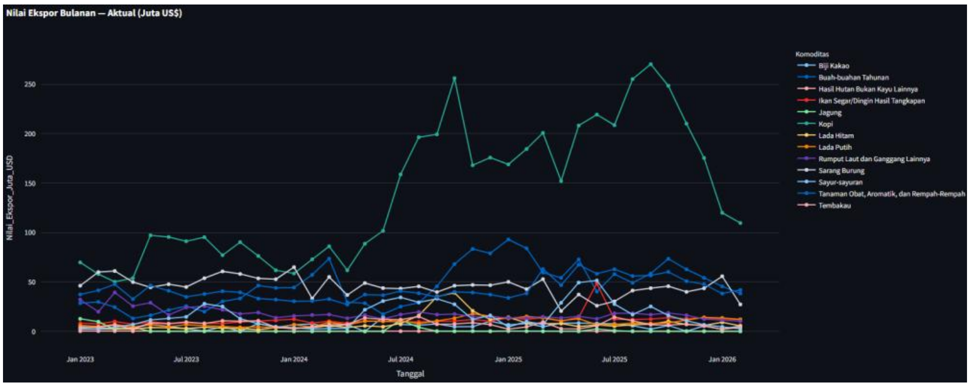
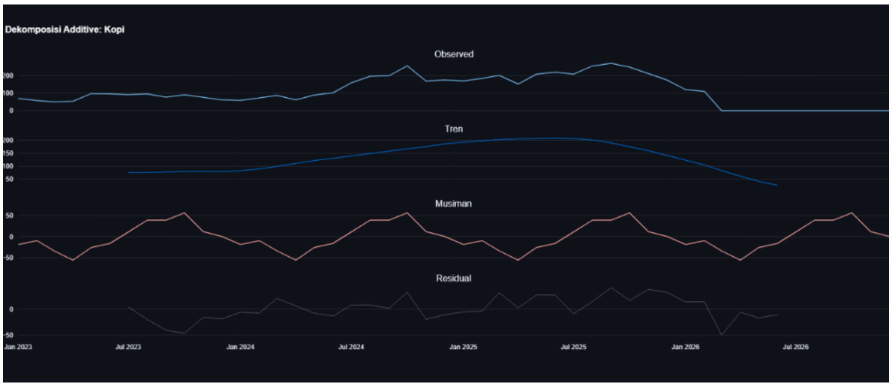


Figure 3 plots monthly export value of all 13 commodities from January 2023 through February 2026, in millions of USD. It shows how each one moves over time, including its long-run trend direction and seasonal fluctuations that recur year after year. How differently these commodities move comes down to how varied their production characteristics and market demand dynamics.

Figure 4. Coffee Time Series Decomposition Results (additive model)



This figure splits Coffee's export data into three parts: trend, seasonal pattern, and residual. Separating them out gives a clearer, more structural read on how Coffee exports actually behave. Seasonal component turns out to be strikingly consistent: exports peak in October and bottom out in April, year after year.

Figure 5. Coffee Seasonal Patterns

This chart plots Coffee's seasonal pattern using an average seasonal index built from several years of data. Exports peak in October, with a sesasonal index of 147,7, and his their low point in April, at an index of 46.9. Pattern tracks closely with Indonesia's main coffee harvest cycle and rhythm of global deman, which is useful for planning shipment schedules and export contracts further ahead.

Over observation period, strongest growth came from:

- Coffee, CAGR 65,21%
- Black Pepper, CAGR, 60,47%
- Perennial Fruits, CAGR 50,96%

Sharpest contractions hit:

- Corn, CAGR -58,28%
- Seaweed and Algae, CAGR -19,51%
- Edible Bird's Nest, CAGR -13,46%

Table 3. CAGR Summary 2023 - 2025

Commodities	Total 2023	Total 2025	CAGR
Coffee	916,6	2.501,9	65,21
Black Pepper	36	92,7	60,47
Annual Fruits	333,4	759,8	50,96
White Pepper	63,9	129,6	42,41
Vegetables	134	254,9	37,92
Fresh/Cold Fish Caught	106,7	189,9	33,41
Cocoa Beans	46,9	71,1	23,13
Medicinal Plants, Aromatics, and Spices	465,2	642,3	17,50
Other Non-Timber Forest Products	3,1	3,3	3,18
Tobacco	86,8	78,8	-4,72
Swallow's Nest	633,4	474,4	-13,46
Seaweed and Algae	284,8	184,5	-19,51
Corn	29,3	5,1	-58,28

These numbers suggest Indonesia's agricultural commodity exports don't move as one block. Each commodity is shaped by its own production characteristics, international market dynamics, and demand patterns. That matches dynamics, and demand patterns. That matches BPS publications documenting real disparities in export performance across sectors and commodities over same period.

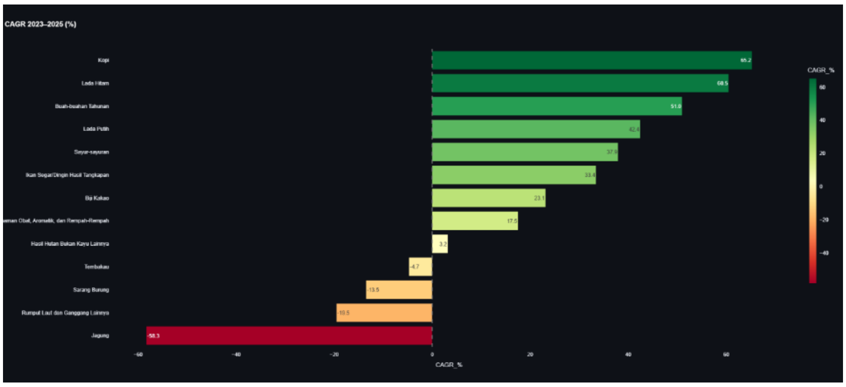
CAGR, CV, and K-Means Clustering Analysis

With trend and seasonal patterns in hand, research branched into three further analyses: CAGR, CV, and K-Means clustering. Together, these three results form feature matrix behind commodity segmentation.

a. CAGR as a measure of average geometric growth

CAGR measures relative growth across commodities over 2023-2025, and it's a solid indicator for spotting which commodities have grown consistently fast. By this measure, strongest performers are Coffee (65,21%), Black Pepper (60,47%), and Perennial Fruits (50,96%).

Figure 6. Yield CAGR Commodity



This bar chart compares Compound Annual Growth Rate of all 13 commodities from 2023 to 2025. Coffee posts highest growth, at 65,21%, followed by Black Pepper at 60,47% and Perennial Fruits at 50,96%. At other end, Corn shows deepest contraction at -58,28%, a decline steep enough to call for closer policy attention.

b. CV as a scale-independent measure of relative volatility

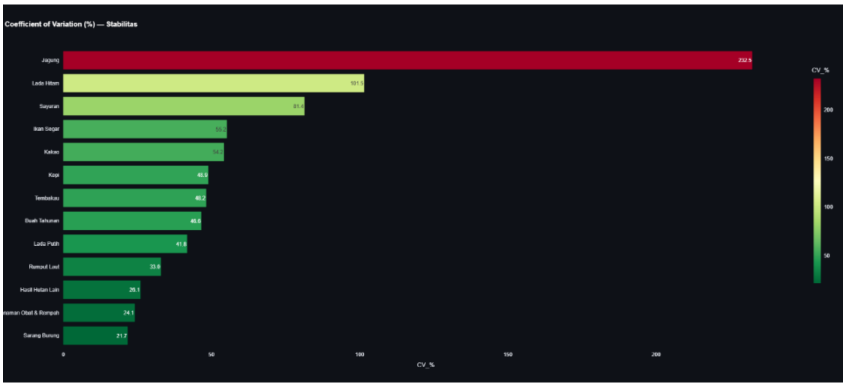
CV captureshow volatile a commodity’s exports are without being skewed by how large or small its export volume is A low CV points to greater stability a high CV signals sharp swings.

Table 4. Volatility Ranking (CV)

Commodities	Mean	Hours	CV	Min	Max
Swallow's Nest	45,85	9,97	21,74	20,6	65
Medicinal Plants, Aromatics, and Spices	42,46	10,25	24,13	27,1	67,5
Other Non-Timber Forest Products	0,26	0,07	26,08	0,1	0,4
Seaweed and Other Algae	17,99	5,93	32,97	10,3	39,4
White Pepper	9,01	3,77	41,8	3,4	17,8
Annual Fruits	46,26	21,56	46,61	13,1	93
Tobacco	7,27	3,51	48,22	2,1	15
Coffee	138,75	67,89	48,93	50,2	270,3
Cocoa Beans	5,43	2,95	54,23	0	14,4
Fresh/Cold Fish Caught	11,67	6,45	55,24	7,2	48,5
Vegetables	16,14	13,13	81,36	2,2	51,5
Black Pepper	7,95	8,07	101,53	1,7	39,1
Corn	1,35	3,14	232,46	0	12,7

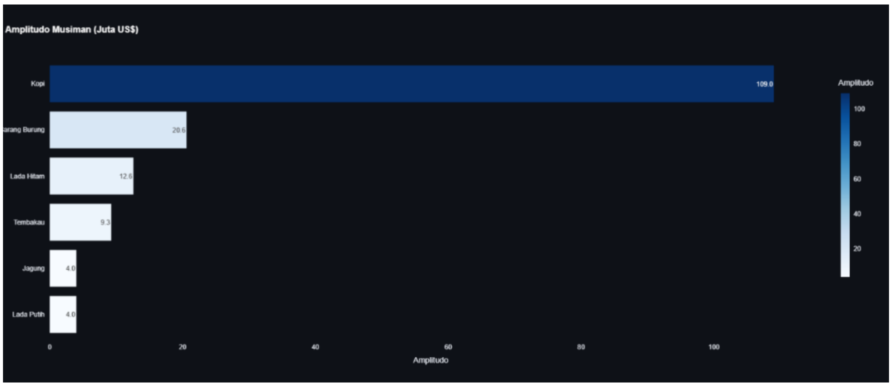
Most stable commodities are Edible Bird’s Nest (21,74%) and Medicinal, Aromatic, and Spice Plants (24,13%). Most volatile are Corn (232,46%) and Black Pepper (101,53%).

Figure 7. CV Results



This bar chart maps export volatility per commodity using Coefficient of Variation, which measures relative fluctuation regardless of how large or small a commodity's export scale. Edible Bird's Nest comes out most stable, with lowest CV at 21,74%, while Corn is most volatile by far, with a CV of 232,46%. Lower a commodity's CV, more it can be trusted as a basis for medium-term export planning.

Figure 8. Seasonal Amplitude Commodity

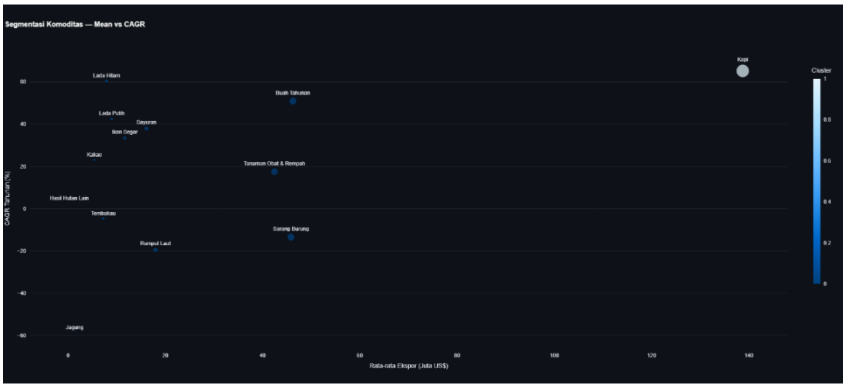


This bar chart shows seasonal amplitude of each commodity, calculated as gap between its peak and trough seasonal index. Coffee's amplitude of 109,03 is largest in dataset, a sign of how strongly its exports swing with seasons. Other Non-Timber Forest Products and White Pepper sit at other extreme, with amplitudes of just 0,17 and 4,03. Their exports stay fairly even across year, without meaningful seasonal spikes.

c. K-Means clustering for commodity segmentation

K-Means clustering grouped commodities by growth characteristics, volatility, export scale, seasonal amplitude, and trend slope. Silhouette score evaluation identified k=2 as best configuration. Under this setup, Coffee stands alone as cluster 1, its mean export value of USD 138,75 million per month is so far ahead of rest that it forms its own group, while other 12 commodities cluster together as Cluster 0. This result is primarily driven by scale differences rather than quanlitative structural heterogeneity, when same analysis was repeated with log-transformed mean export value to reduce scale dominance (three-feature matrix:log(Mean), CV, CAGR), silhouette score indicated a slightly different optimal configuration (k=3), demonstrating sensitivity to feature choice. Single commodity cluster reflects Coffee's outsized export value, not necessarily a distinct strategic profile. Hierarchical clustering dendrogram (Ward method) confirmed that Coffee branches off at highest distance threshold, with remaining commodities forming a large cluster with sub-structures. Due to small number of observations (n=13) and sensitivity to feature selection, K-Means results are interpreted as complementary to the four-quadrant strategic matrix, which provides more robust segmentation based on two most policy relevant dimensions: growth (CAGR) and risk (CV).

Figure 9. K-Means Commodity Clustering Results



This scatter plot shows how 13 commodities group under K-Means clustering, using CAGR, CV, and average export value as analysis dimensions. Silhouette score evaluation settles on k=2 as optimal configuration, placing Coffee alone in Cluster 1 as dominant commodity while remaining 12 form Cluster 0. This split shows just how far Coffee's export scale outpaces everything else in dataset.

Table 5. K-Means Commodity Segmentation

Commodities	Cluster	Mean	CV	CAGR	Amplitudo
Vegetables	0	16,14	81,36	0,38	28,02
Tobacco	0	7,27	48,22	-0,05	9,28
Corn	0	1,35	232,46	-0,58	4,03
Coffee	1	138,75	48,93	0,65	109,03
Medicinal Plants, Aromatics, Spices	0	42,46	24,13	0,18	15,41
Black Pepper	0	7,95	101,53	0,6	12,6
White Pepper	0	9,01	41,8	0,42	4,03
Cocoa Beans	0	5,43	54,23	0,23	5,53
Annual Fruits	0	46,26	46,61	0,51	37,77
Swallow's Nest	0	45,85	21,74	-0,13	20,6
Other Non-Timber Forest Products	0	0,26	26,08	0,03	0,17
Fresh/Cold Fish Caught	0	11,67	55,24	0,33	13,6
Seaweed and Algae	0	17,99	32,97	-0,2	10,1

Integrating CAGR, CV, and Average Export Feature Matrix

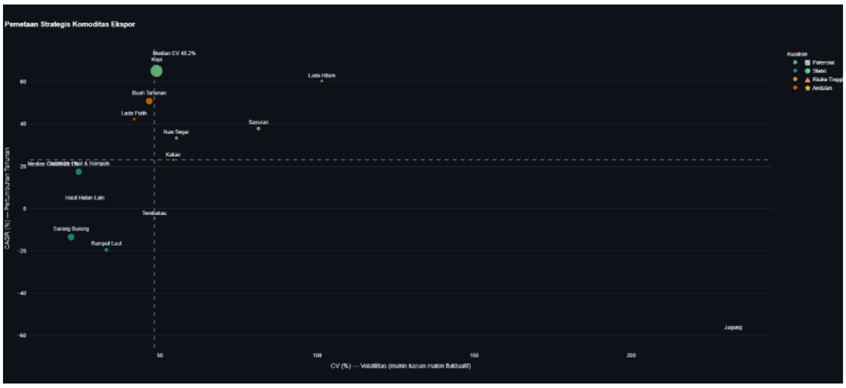
To support export risk management strategy, CAGR, CV, and average export value results were brought together into a strategic matrix that sorts commodities into four quadrants:

Table 6. K-Means Commodity Segmentation

Quadrant	Criteria	Commodities	Implications
Mainstay	High CAGR, low CV	White Pepper, Annual Fruit	Strong and relatively stable growth
Potensial	High CAGR, high CV	Coffee, Black Pepper, Vegetables, Cocoa, Fresh fish	Growing fast but needs risk mitigation
Stable	Low CAGR, low CV	Swallow's Nest, Medicinal Plants, Aromatics, Spices, Tobacco, Seaweed and Algae	Low risk, relatively stagnant/negative growth
High Risk	Low CAGR, high CV	Corn	Requires policy attention and stabilization

This segmentation gives export risk management recommendations a scientific footing, particularly in deciding which commodities deserve priority, which are already stable, and which need policy intervention.

Figure 10. Strategic Mapping of Export Commodities



This bubble chart places all 13 commodities across four strategic quadrans based on their combined CAGR and CV values, with bubble size representing each commodity's average export value. Quadrant boundaries are defined by median CAGR and median CV of the sample. Bootstrap resampling (10,000 iterations) yields 95% confidence intervals around these medians, indicating range within which thresholds could fall under sampling variation. Commodities located near threshold lines should be interpreted with caution, as small data updates could shift their quadrant assignment. White Pepper and Perennial Fruits sit in Mainstay quadrant (above-median growth, below-median risk). Coffee, Black Pepper, Vegetables, Cocoa Beans, and Fresh Fish fall under potential (above-median growth, above-median risk). Edible Bird's Nest, Medicinal and Aromatic Plants and Spices, Tobacco, Seaweed, and Non-Timber Forest Products land in Stable (below-median growth, below-median risk). Corn stands alone in high risk (below-median growth, above-median risk). this mapping is a decision-support tool:it flags relative positions across commodities for priority discussion, not a definitive policy prescription.

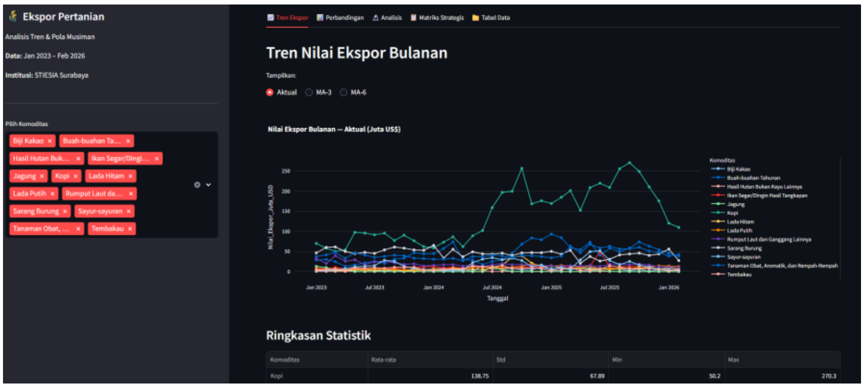
Output Development

Output development ran alongside data analysis itself, so findings could be put to use for dissemination and decision-making as soon as they were ready.

a. Interactive dashboard

A web-based interactive dashboard, built with streamlit and plotly, is now complete. It displays trend visualizations, seasonal patterns, segmentation, and strategic matrix, and lets users pick specific commodities, compare indicators side by side, and explore export patterns on their own.

Figure 11. Interactive dashboard display



b. Policy brief and strategic recommendations

Strategic matrix results feed into a policy brief laying out export risk management recommendations for policymakers and industry players. Recommendations center on strengthening mainstay commodities, stabilizing potential commodities, improving efficiency for stable commodities, and revisiting policy for high-risk commodity.

5. Conclusion and Suggestion

Conclusion

This study examined trends, seasonality, growth, and volatility behind Indonesia's 13 leading agricultural export commodities from January 2023 through February 2026, using an integrated descriptive-screening framework. Four findings stand out. (1) Growth diverged sharply by commodity. Coffee, Black Pepper, and Perennial Fruits posted strongest gains over period, while Maize, Seaweed, and Bird's Nest contracted most. (2) Seasonality was present across commodities but uneven in magnitude: Coffee had widest seasonal amplitude (109.03 points), with exports consistently peaking in October (index 147,7) and troughing in April (index 46,9). Non-timber forest products and White Pepper, by contrast, showed minimal seasonal variation. (3) Growth and Volatility behaved almost independently commodities with high CAGR ranged from highly volatile to stable, underscoring that these two dimensions capture distinct aspects of performance. (4) four-quadrant strategic matrix sorted commodities into Mainstay (White Pepper, Perennial Fruits), Potential (Coffee, Black Pepper, Vegetables, Cocoa Beans, Fresh Fish), Stable (Bird's Nest, Medicinal Plants, Tobacco, Seaweed, Non-Timber Products), and High-Risk (Maize). K-Means clustering (k=2) set Coffee a part as a scale-dominated cluster, this result is sensitive to feature choice and should be interpreted together with quadrant analysis. These findings are descriptive they characterize observed patterns without establishing causal drivers. They provide an empirical baseline for prioritizing commodities for deeper investigation, but do not replace commodity-specific studies that incorporate price data, production costs, destination-market dynamics, and institutional constraints.

Suggestion

Quadrant positions suggest indicative priorities, each requiring commodity-specific validation before implementation. For White Pepper and Perennial Fruits (Mainstay quadrant), data show above-median growth with below-median risk. Maintaining quality standards and exploring market diversification appear consistent with their current trajectory, though a dedicated market-access study would be needed to confirm opportunities. For Coffee, Black Pepper, Vegetables, Cocoa Beans, and Fresh Fish (Potential quadrant), above-median growth coincides with above-median volatility. Risk management instruments futures contracts, forward agreements, buffer stocks, are worth investigating, but their feasibility depends on commodity-specific factors (exchange infrastructure, volume thresholds, storage costs) not analyzed here. For bird's Nest, Medicinal Plants, Tobacco, Seaweed, and Non-Timber Products (Stable quadrant), below-median growth and below median risk suggest that value-addition strategies (processing, certification, and branding) may offer more promise than volume expansion, but this should be assessed against destination market demand projections. For Maize (High-risk quadrant), steep growth contraction and high volatility point to structural rather than cyclical challenges. A comprehensive policy review covering import competition, domestic support, and export competitiveness, would be needed to determine whether export-oriented growth is a realistic objective. Three cross-cutting tools emerge from analysis:seasonal export calendars built from indices identified here could improve logistics planning, volatility-monitoring dashboards could serve as early-warning systems, and interactive dashboard developed for this research could be maintained as a standing policy tool. Each of these proposals requires implementation testing, the present study provides analytical foundation, not the implementation blueprint.

6. Limitations and Future Research

Several limitations qualify findings and suggest directions for future research. First, data window (38 months, three seasonal cycles) is sufficient for exploratory decomposition but constitutes a lower bond for stable seasonal index estimation. As additional monthly data accumulate, extending series to five or more cycles would validate whether seasonal peaks and troughs identified here persist. Second, assumption of stable seasonal patterns inherent in classical decomposition may not hold if climate patterns, harvest technologies, or trade policies shift over time. Time-varying seasonal models or STL decomposition could relax this assumption in future work. Third, clustering results are conditioned on a small sample (n=13) and are sensitive to feature selection, four quadrant matrix is more robust but still uses sample-median thresholds that may shift as new data are added. Fourth, analysis is entirely descriptive it identifies patterns that have already occurred rather than predicting future outcomes or establishing causal relationships. Trend and seasonal indices reported here are a starting point for forecasting, but they do not, by themselves, constitute a predictive model. Fifth, Findings depend on the quality of BPS data, revisions to published figures or changes in HS classification could alter results. Sixth, study examines export values (price x volume) in aggregate, decomposing this into price and volume components would provide deeper insight into whether volatility originates in quantity fluctuations or price shocks. Future research should address these limitations by. (a) extending time series as new data become available,

(b) incorporating external variables (exchange rates, global commodity prices, climate indices, trade policy dummies) into ARIMAX, VAR, or regression frameworks to move from description toward causal explanation, (c) applying machine learning methods (Random Forest, Gradient Boosting, LSTM) for forecasting, and (d) conducting commodity-specific deep dives for Coffee and maize that incorporate producer level data, global price benchmarks, and destination market dynamics. Descriptive screening framework presented here is designed to inform such targeted investivations, not to replace them.

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