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Application of Multivariate Singular Spectrum Analysis for Forecasting the Production of Plantation Commodities

Sintia Agustina Siregar [1*], Rina Filia Sari[2], Rina Widyasari[3]

[1,2,3]Mathematics Study Program, Faculty of Sains and Technology,
State Islamic University of North Sumatera
[1,2,3] Golf Course Road No.120, Kampung Tengah, Pancur Batu District,
Deli Serdang Regency, 20353, North Sumatera, Indonesia.

E-mail Correspondence Author: *sintia0703212037@uinsu.ac.id*

Abstract

Forecasting plantation commodity production is important to support agricultural planning and policy making in North Sumatra Province. High global and domestic demand for raw materials derived from plantation commodities such as palm oil, rubber, coffee, cocoa, and tobacco, driven by population growth, has led to a continued influx of imported plantation commodities into the domestic market, with a 8.2% increase in value. However, production data of plantation commodities such as palm oil, rubber, coffee, cocoa, and tobacco generally exhibit fluctuating patterns and interrelationships among variables, making forecasting more complex. Previous studies mostly applied univariate forecasting approaches that analyze each commodity separately, so the relationships among commodities have not been optimally considered. This study aims to determine the production forecast of plantation commodities using data from the North Sumatra Provincial Plantation Service, including palm oil, rubber, coffee, cocoa, and tobacco. Therefore, a forecasting method that can capture patterns and interrelationships between variables simultaneously is needed. This study applies the Multivariate Singular Spectrum Analysis (MSSA) method in forecasting the production of several major plantation commodities in North Sumatra Province. The results obtained from the MSSA analysis stage are a window length (L) of 2 and r-grouping of 2 with a forecasting period length of 2 periods in chronological order. The forecasting results based on the forecasting accuracy level using MAPE for the production of palm oil, rubber, coffee, cocoa, and tobacco in North Sumatra Province using the Multivariate Singular Spectrum Analysis method are 3.57223%, 3.95038%, 6.92317%, 3.03589%, and 2,17216 %Based on the MAPE accuracy category for each variable, the MAPE values are < 10% and MSSA method showed good forecasting performance for the available data. This study is expected to provide benefits through the application of MSSA in the field of multivariate agricultural forecasting and as a reference source for production planning policies and their derivatives for plantation commodities in North Sumatra.
forecasting.

Keywords: *Forecasting, Multivariate Singular Spectrum Analysis, Plantation Commodity Production*

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1. INTRODUCTION

Indonesia, endowed with abundant natural resources, derives a significant portion of its economic income from various primary sectors. Among these, agriculture constitutes the core of the nation's industrial base. Consequently, a large share of Indonesia's population relies on agricultural activities for their livelihood[1], whether as farmers or as laborers in related agribusiness industries. This heavy reliance on agriculture underpins Indonesia's characterization as an agrarian country[2]. By boosting the GDP, producing foreign exchange through the export of goods, supplying food and raw materials for industrial processes, generating jobs, and aiding in the fight against poverty, the agricultural sector is essential to the growth of the country's economy[3].

North Sumatera is one of Indonesia's leading plantation-based provinces. The plantation sub-sectors that exert a substantial influence on the province's economy include palm oil, rubber, coffee, cocoa, and tobacco [4]. These sub-sectors collectively serve as the largest contributors to the agricultural component of the GRDP [5]. According to data from the Ministry of Agriculture of the Republic of Indonesia[6], North Sumatra has 2,018,727 hectares of oil palm plantations, producing 5,264,734 tons of palm oil in 2021. Rubber plantations cover approximately 369.39 thousand hectares, generating 310.02 thousand tons of rubber in 2020. Coffee production in 2020 reached around 75 thousand tons, cultivated across 95.47 thousand hectares. Meanwhile, cocoa plantations encompass 54,467 hectares with a production volume of 36,310 tons. Furthermore, tobacco remains an important regional commodity, cultivated on 1,896 hectares and yielding up to 1,896 tons annually.

The high level of demand for raw materials derived from plantation commodities in the global and national business world is due to population explosion and urbanization[7]. This is the reason why imports of plantation commodities continue to flood the domestic market, with an 8.2% increase in value. This confirms that domestic producers are still unable to meet the demand and participation of domestic processed plantation products in terms of volume, price competitiveness, and quality.

The above issues require optimal commodity production planning in order to meet global and national market demand. Planning in plantation production requires forecasting to look into the future using past production data[8]. Historical production observation data for plantation commodities over a certain period of time constitutes time series data. Time series analysis involving such production data requires multivariate time series forecasting because production data moves simultaneously and is interrelated. The forecasting method involving multivariate time series analysis is Multivariate Singular Spectrum Analysis (MSSA)[9].

MSSA is an extension of the Univariate Singular Spectrum Analysis (SSA) method[10]. MSSA serves as a forecasting technique applied to multivariate time series data, consisting of two or more variables observed simultaneously. This method is capable of capturing seasonal, trend, and cyclical components within the data[11]. The analytical procedure in MSSA largely mirrors that of SSA, encompassing the decomposition and reconstruction stages. The distinction lies in the initial phase, where the embedding process in MSSA employs *Hankel block matrices* [12]. This approach was chosen because it is very flexible and more accurate than a number of other time series forecasting methods.This advantage arises from its non-parametric statistical nature, which allows MSSA to operate independently of classical assumptions such as normality, stationarity, and linearity.

Research on MSSA has been carried out in several previous studies. For example, [12]examined the forecasting of global precious metal commodity prices sourced from the website *https://investing.com* using the MSSA method. With an optimal window length (L) of 10 and a grouping component (K) of 149, the 32-period-ahead forecasts obtained were 1800.401 USD, 966.5725 USD, and 1909.453 USD, with corresponding MAPE values of 10.69%, 11.75%, and 13.78.

Based on the background described above, this study aims to estimate the production of major plantation commodities in North Sumatra using the Multivariate Singular Spectrum Analysis (MSSA) method. This study employs a multivariate forecasting approach to analyze five major plantation commodities simultaneously namely palm oil, rubber, coffee, cocoa, and tobacco whereas previous research on plantation commodity forecasting has largely focused on single commodities or univariate forecasting principles. This study applies MSSA to plantation production data from North Sumatra, thereby enabling the capture of interrelationships among the production of various commodities simultaneously. This study provides empirical evidence regarding the forecasting accuracy of MSSA for the plantation sector by utilizing regional production data from North Sumatra Province. Thus, the results of this study are expected to provide benefits through the application of MSSA in the field of multivariate agricultural forecasting and as a reference source for production planning policies and their derivatives for plantation commodities in North Sumatra.

2. RESEARCH METHOD

2.1 Type Of Research

This studies uses a quantitative approach with a descriptive method, focusing on time series data analysis to forecast production of plantation commodities in North Sumatra Province. The research was conducted at the North Sumatra Provincial Plantation and Livestock Service Office at Jl. Jenderal Besar A.H. Nasution No.24, Pangkalan Masyhur, Kec. Medan Johor, Medan City. The research period was from September 2024 to July 2025. The production statistics for agricultural commodities in North Sumatra Province from 2014 to 2023, encompassing palm oil, rubber, coffee, cocoa, and tobacco, constituted the variables of the investigation. The 50 data entries were divided into two classifications: training data and testing data. The training data is utilized to ascertain the model derived from 80% of the data, comprising 40 data entries, whereas the testing data is employed for prediction, sourced from 20% of the data, totaling 10 data entries.

2.2 Multivariate Singular Spectrum Analysis

MSSA is a non-parametric forecasting method that extends SSA. While SSA is applied to a single (univariate) time series, MSSA is designed to handle multivariate time series, consisting of two or more time series observed simultaneously. Forecasting using MSSA can achieve high accuracy because it relies on a non-parametric statistical approach, making it independent of assumptions such as normality, stationarity, and linearity[13]. Another pivotal differentiation between SSA and MSSA resides in the formulation of the trajectory matrix. The MSSA methodology has the capacity to decompose temporal series data into temporal series constituents such as trend, seasonality, and noise [14]. Similar to SSA, the MSSA methodology encompasses two principal phases: decomposition and reconstruction.

a. Embedding

Embedding is the procedure of transforming a unidimensional temporal series into a trajectory matrix $(\mathbf{X})$ with size $L \times K$ [15], where l represents the window length, subject to the condition $L\ (2 \le L \le n)$. Then, to determine the window length (L) for each time series, use the following equation:

$$L = \frac{p(n+1)}{p+1} \tag{1}$$

Where:

L = window length
p = number of variables
n = amount of test data for each variable

Next, utilizing the subsequent equation to ascertain the value of k [16]:

$$K = n - L + 1 \tag{2}$$

Where :

K = denotes the number of columns in the trajectory matrix
L = window length
n = amount of test data for each variable

This embedding process will produce a Hankel trajectory, with the following matrix structure:

$$\mathbf{X}^{(p)} = \begin{bmatrix} X_1^{(p)} & X_2^{(p)} & X_3^{(p)} & \dots & X_K^{(p)} \\ X_2^{(p)} & X_3^{(p)} & X_4^{(p)} & \dots & X_{K+1}^{(p)} \\ X_3^{(p)} & X_4^{(p)} & X_5^{(p)} & \dots & X_{K+2}^{(p)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_L^{(p)} & X_{L+1}^{(p)} & X_{L+2}^{(p)} & \cdots & X_n^{(p)} \end{bmatrix} \tag{3}$$

Where:

$\mathbf{X}^{(p)}$ = Hankel (trajectory) matrix of the p - th variable
p = Index of the variable in the multivariate time series, $p = 1, 2, \dots, p$
$X_i^{(p)}$ = Observed value of variable p at time index i
n = Total number of data points in the time series

b. Singular Value Decomposition

Performed in the step to find the eigentriple of the matrix[17]:

$$\mathbf{S} = \mathbf{X}\mathbf{X}^{\mathrm{T}} \tag{4}$$

Where :
$\mathbf{S}$ = covariance matrix
$\mathbf{X}$ = trajetory matrix
$\mathbf{X}^{\mathrm{T}}$ = transpose of the trajectory matrix

The eigentriple consists of singular values $(\sqrt{\lambda_i})$, eigenvectors $(\mathbf{U}_i)$ and principal components $(\mathbf{V}_i^{\mathrm{T}})$. These three components are referred to as the eigentriple, so the SVD of the trajectory matrix $(\mathbf{X})$ is as follows[18]:

$$\mathbf{X}_i = \sqrt{\lambda_i}\mathbf{U}_i\mathbf{V}_i^{\mathrm{T}} \quad (5)$$

Where :
$\mathbf{X}_i$ = the i-th elementary matrix
λ_i = the i-th eigenvalue
$\mathbf{U}_i$ = the i-th eigenvector
$\mathbf{V}_i^{\mathrm{T}}$ = the i-th transpose of principal component

c. Grouping

The graphing procedure is the categorization of each eigentriple predicated upon specific attributes inherent to each element. This categorization is executed by organizing the index collection $i = \{1, 2, \ldots, d\}$ into m, which is a disjoint $\mathbf{I}_1, \mathbf{I}_2, \ldots, \mathbf{I}_m$ subset of with $m = d$. Next, the eigentriple matrix $\mathbf{X}_i$ is adjusted to group $\mathbf{I}$. Thus, the expansion of matrix $\mathbf{X}_i$ is obtained as follows[19]:

$$\mathbf{X} = \mathbf{XI}_1 + \mathbf{XI}_2 \ldots + \mathbf{XI}_m \quad (6)$$

Where:
$\mathbf{X}$ = trajectory matrix obtained from the decomposition process
$\mathbf{XI}_1 + \mathbf{XI}_2 \ldots + \mathbf{XI}_m$ = grouped matrices based on the eigentriple index subsets
$\mathbf{I}_1 + \mathbf{I}_2 \ldots + \mathbf{I}_m$ = disjoint index subsets used in the grouping process
m = number of grouped components

d. Diagonal Averaging

Diagonal Averaging, in this phase each elementary matrix is transmuted into a novel temporal series with an extent of n[20]. Diagonal averaging is performed by transforming each matrix $\mathbf{X}_{ij}$ in the clustering stage into a new sequence with length n. Given a matrix $\mathbf{Y}$ of size with $L \times K$ elements y_{ij}, where $1 \le i \le L$ and $1 \le j \le K$. Diagonal averaging will transform the matrix $\mathbf{Y}$ back into a sequence using the following formula[21]:

$$g_i = \begin{cases} \frac{1}{K}\sum_{m=1}^{K} y^*_{m,j-m+1} & \text{for } 1 \le K \le L \\ \frac{1}{L^*}\sum_{m=1}^{L*} y^*_{m,j-m+1} & \text{for } L^* \le K \le K^* \\ \frac{1}{n-K+1}\sum_{m=K-K^*+1}^{n-K^*+1} y^*_{m,k-m+1} & \text{for } K^* < K \le n \end{cases} \quad (7)$$

Where :

g_i = reconstructed time series value at the i

K = number of columns in the trajectory matrix

m = row index of the reconstructed matrix

$K^* = \max(L, K)$

L = window lenght

$L^* = \min(L, K)$

$y^*_{m,j-m+1}$ = Element at row m, colomn $(j-m+1)$ of the reconstructed matrix

2.3 Mean Absolute Persentage Error (MAPE)

MAPE is the average of the absolute percentage of forecasting error for each period. This approach is useful when the scale of the variable significantly affects the evaluation of forecast accuracy. MAPE will show the percentage error in the forecast compared to the actual value. The smaller the MAPE percentage value, the more accurate the forecast using that forecasting method. To determine the accuracy level of a forecast, you can refer to the MAPE percentage categories in the following table[22]:

Table 1. MAPE accuracy value

MAPE	Rating
< 10%	Excellent
10-20%	Good
20-50%	Acceptable
>50%	Poor

2.4 Research Method

The research procedure performed in completing this study is as follows:

1. Collect production data on plantation commodities in North Sumatra and plot the data to determine the time series components.
2. Distribute all research data into 80% training data and 20% testing data.
3. Embedding, In this step, time series embedding is performed to form a Hankel matrix $(\mathbf{X})$ with size $L \times K$.
4. Singular Value Decomposition (SVD), performed in the step to find the eigentriple of the matrix.
5. Grouping, in this step, eigenvector triplets will be classified in accordance with the attributes of each constituent.
6. Diagonal Averaging, in this phase, each elementary matrix is transmuted into a novel temporal series with a magnitude of n.
7. Forecasting the production of plantation commodities in North Sumatra Province from time series data using diagonal averaging with R-Forecasting.

8. Calculate the accuracy value of production forecasts for plantations in North Sumatra Province using MAPE values to evaluate the model using testing data.

3. RESULTS AND DISCUSSION

3.1 Data Collection and Plot Data

The data to be processed in this study is the production data of smallholder plantations in North Sumatra Province which 10 annual observations (2014–2023) with five plantation commodity variables observed simultaneously includes palm oil, rubber, coffee, cocoa, and tobacco, obtained from the North Sumatra Provincial Plantation Service. The data obtained is as follows:

Table 2. Data of Plantation Commodity Production in North Sumatera

Year	Palm Oil	Rubber	Coffee	Cocoa	Tobacco
2014	1.186.866	209.591	58.175	15.846	584
2015	1.192.731	204.483	60.179	13.707	635
2016	1.198.596	207.197	60.310	15.767	649
2017	2.018.126	246.196	66.640	20.114	1.185
2018	2.072.586	246.316	67.179	20.612	1.071
2019	1.541.537	309.973	66.831	34.792	1.405
2020	1.583.945	310.016	67.469	35.696	1.737
2021	1.639.416	310.018	71.588	36.310	1.751
2022	1.713.582	310.020	76.528	35.299	1.832
2023	1.766.698	310.700	79.057	37.912	1.879

Source : North Sumatra Provincial Plantation Service

Shown in the following Table 2 the lowest plantation production was tobacco, with 584 tons in 2014, and the highest was palm oil, with 2,072,586 tons in 2018. The table above shows that plantation production data includes palm oil, rubber, coffee, cocoa, and tobacco in tons (t) and there is no missing data.

Next, data will be plotted to identify patterns in the data, which will be displayed in the following figure:

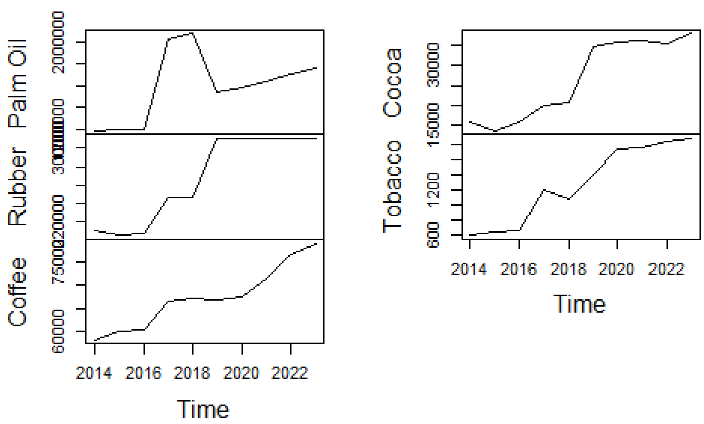

Figure 1. Plot Time Series of Plantation Commodity Production

Figure 1 shows that the production patterns of plantation commodities in North Sumatra Province from 2014 to 2023 have trend components. Palm oil production shows an upward trend until around 2018, followed by a sharp decline and then a gradual increase thereafter. Similar trend patterns can be seen in the production data for rubber, coffee, cocoa, and tobacco, although the rates of change differ. There is no clear seasonal component in this graph, possibly because the data used is annual.

Before starting data analysis, the first step is to divide the data into two parts consisting of 80% training data from the 2014 to 2021 period, amounting to 8 data points from each variable, and 20% testing data from the 2022 to 2023 period, amounting to 2 data points from each variable. The training data will be used to apply the Multivariate Singular Spectrum Analysis method by creating an trajectory matrix $(\mathbf{X})$. Meanwhile, the testing data will be used to measure the forecasting accuracy of the model that has been formed from the training data.

3.2 Decomposition

a. Embedding

In the data decomposition stage, two steps will be carried out, namely Embedding and Singular Value Decomposition (SVD). Initially, the insertion phase will transmute the temporal series data into a trajectory matrix $(\mathbf{X})$ with size $L \times K$. To determine the value of L, the following applies:

$$L = \frac{p(n+1)}{p+1} = \frac{5(8+1)}{5+1} = \frac{5(9)}{6} = \frac{45}{6} = 7{,}5 \approx 7$$

From the **Equation (1)**, it is known that n represents the number of time series observations in the training data for each variable, which is 8 data points, and p denotes the number of variables, which is 5. Thus, the range of L values, which is the window length, is between 2 and 7. To determine the optimum L value, trial and error is performed by looking at the minimum MAPE value. Based on trial and error between 2 and 7, it can be seen that the value $L = 2$ has the minimum MAPE value for each variable, so the optimum L value is determined to be 2. Next, the K value is determined from **Equation (2)** as follows:

$$K = n - L + 1 = 8 - 2 + 1 = 7$$

The obtained values of L and K will be used in the formation of the trajectory matrix. The trajectory matrix $(\mathbf{X}_i)_{2\times 7}$ for each variable is arranged vertically or VMSSA, which has the following structure. Thus, $\mathbf{X}_{\text{VMSSA}}$ the matrix is as follows:

$$\mathbf{X}_{\text{VMSSA}} = \begin{bmatrix} 1186866 & \cdots & 1583945 \\ 1192731 & \cdots & 1639416 \\ \hline 209591 & \cdots & 310016 \\ 204483 & \cdots & 310018 \\ \hline 58175 & \cdots & 67469 \\ 60179 & \cdots & 71588 \\ \hline 15846 & \cdots & 35696 \\ 13707 & \cdots & 36310 \\ \hline 584 & \cdots & 1737 \\ 635 & \cdots & 1751 \end{bmatrix} \begin{matrix} \rightarrow \text{ Palm Oil} \\ \\ \rightarrow \text{ Rubber} \\ \\ \rightarrow \text{ Coffee} \\ \\ \rightarrow \text{ Cocoa} \\ \\ \rightarrow \text{ Tobacco} \\ \\ \end{matrix}$$

The resulting matrix $\mathbf{X}_{VMSSA}$ is a Hankel matrix, which is a combination of the univariate trajectory matrices of each variable of size $\mathbf{X}_{10\times7}$.

b. Singular Value Decompotion (SVD)

To obtain the eigentriple, the initial phase is to construct a matrix $\mathbf{S} = \mathbf{XX}^{T}$ based on the trajectorytr matrix $\mathbf{X}_{VMSSA}$.

$$\mathbf{S} = \mathbf{X}_{(10\times7)} \times \mathbf{X}^{T}_{(7\times10)}$$

$$\mathbf{S} = \begin{bmatrix} 1186866 & \cdots & 1583945 \\ 1192731 & \cdots & 1639416 \\ \vdots & \cdots & \vdots \\ 635 & \cdots & 1751 \end{bmatrix} \times \begin{bmatrix} 1186866 & 1192731 & \cdots & 1737 \\ 1192731 & 1198596 & \cdots & 1751 \end{bmatrix}$$

$$\mathbf{S}_{10\times10} = \begin{bmatrix} 1.880059\times10^{13} & \cdots & 11947535992 \\ 1.768029\times10^{13} & \cdots & 11756793599 \\ \vdots & \ddots & \vdots \\ 1.94754\times10^{10} & \cdots & 8707942 \end{bmatrix}$$

The eigentriple values are then computed from the above matrix. The following are the eigenvalues and eigenvectors presented in the scree plot below:

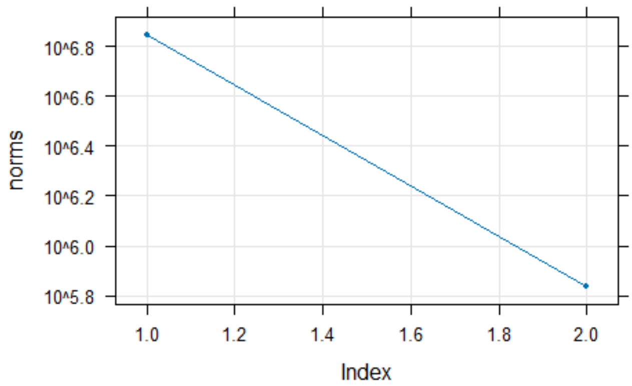

Figure 3. Scree Plot

The scree plot of the component norms shows that the first eigentriple contributes the most compared to the second eigentriple. This indicates that the first eigentriple captures the dominant structure of the series and is associated with the long-term trend component. Although the second eigentriple accounts for a smaller proportion of the variance, it is retained to support the reconstruction of the trend component in the MSSA decomposition.

3.3 Reconstruction

a. Grouping

First, the grouping stage involves grouping using the values of the main components (eigentriple) of SVD predicated on the attributes of each element, with the aim of breaking down the matrix into separate groups. The eigentriple plot with values $i = 1,2$ is as follows:

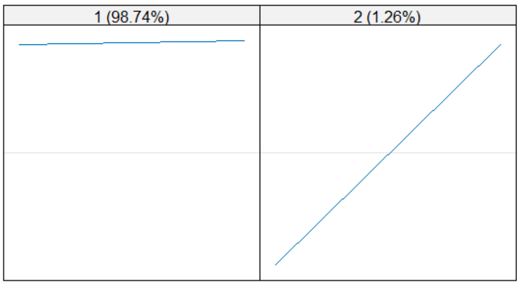

Figure 3. Eigentriple Plot

Figure 3 It can be seen that the first component explains nearly all of the variance (98.74%); almost all of the data's information is contained in the first two components. The pattern is very flat, so this is most likely the trend component. Furthermore, the second component contributes a relatively small amount of variance (1.26%); this component is grouped with the first because together they reconstruct the long-term movement of the data series. To determine the strength of the correlation between each group, it can be clearly seen from the W-correlation plot below:

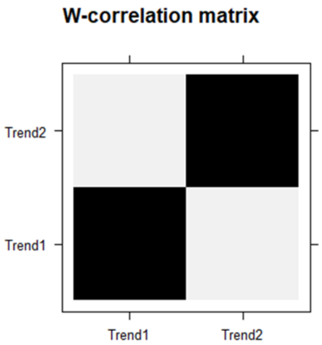

Figure 4. W-correlation plot

The W-correlation plot shows low correlations among the clustered components outside the diagonal elements, indicating good separation among the reconstructed components. Therefore, the first two clustered components can be accurately classified as trend components because they represent the dominant structure of the series without significant mixing with the other components. Each component can produce two groups as follows:

Table 3. Grouping Result

Component	Group
1	Trend1
2	Trend2

The **Table 3** shows the two components of the result group from the eigenvector plot determined in the trend component.

b. Diagonal Averaging

The final stage of Multivariate Singular Spectrum Analysis is diagonal averaging. This phase involves rearranging the components of the groups to produce a new time series. The total of each grouping result's reconstruction results yields the diagonal averaging. The following plot displays the reconstruction findings:

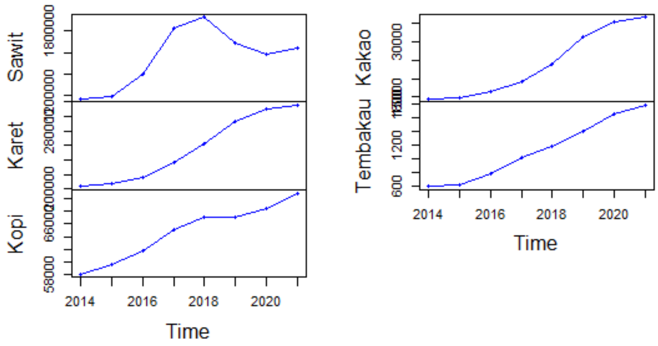

Figure 5. **Reconstruction Trend1 Plot**

Figure 5 shows a plot formed from the results of Trend1 reconstruction with the first eigentriple, producing 40 new time series data from each variable. The plot shows the trend component and does not show other components such as seasonal and cyclical components.

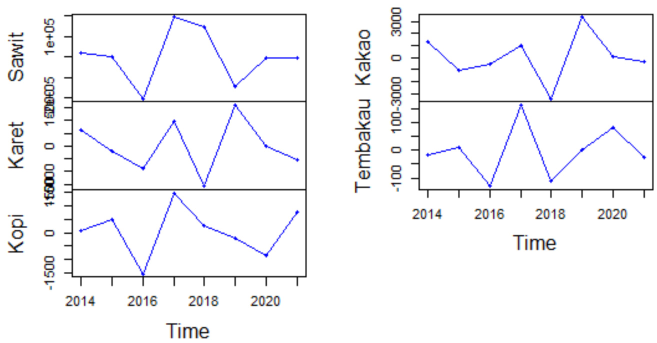

Figure 6. **Reconstruction Trend2 plot**

Figure 6 show a plot formed from the Trend2 reconstruction results with the second eigentriple and producing 40 new time series data from each variable. The resulting plot shows the trend component and does not show other components such as seasonal and cyclical components.

3.4 Forecasting with R-Forecasting

Before performing MSSA forecasting on the commodity plantation production of North Sumatra Province for the next two periods, forecasting was performed on testing data to test the MSSA forecasting model. Forecasting was performed using R-Forecasting using the results of Trend1 reconstructionand the results of forecasting with training data are as follows:

Table 4. **Data Training Forecasting Results**

Variable	Forecasting Result	
	2022	**2023**
Palm Oil	1667551	1687929
Rubber	320663	324582
Coffee	71955	72834
Cocoa	37245	37700
Tobacco	1804	1826

Based on **Table 4** above, it shows that the results of forecasting training data against testing data have a relatively minor disparity between empirical data and projected data.

3.5 Forecasting Accuracy

The Mean Absolute Percentage Error (MAPE) method of forecasting accuracy is used in this study. The table below displays the MAPE values of the forecasting results using testing data for each of the factors.

Table 5. MAPE Result

Variable	MAPE	Description
Palm Oil	3,57223 %	Accurate
Rubber	3,95038 %	Accurate
Coffee	6,92317 %	Accurate
Cocoa	3,03589 %	Accurate
Tobacco	2,17216 %	Accurate

Based on the MAPE accuracy category from **Table 1** , MAPE values obtained were 3.57% for palm oil, 3.95% for rubber, 692% for coffee, 3.03% for cocoa, and 2.17% for tobacco, indicating that each variable had a MAPE value < 10% and fell into the accurate category for forecasting.

3.6 Forecasting Result

After the model and its MAPE accuracy were deemed suitable for forecasting, the next step was to forecast plantation commodity production using testing data for the next two periods, namely 2024 and 2025. The forecasting results are as follows:

Table 6. Forcasting Result

Variable	Forecasting Result	
	2024	**2025**
Palm Oil	1675949	1652328
Rubber	322277	317735
Coffee	72317	71298
Cocoa	37432	36905
Tobacco	1813	1787

Table 6 shows that the forecast for palm oil production in the 2024 period is 1,675,949 tons, while the forecasts for the same period for rubber, coffee, cocoa, and tobacco are 322,277 tons, 73,317 tons, 37,432 tons, and 1,813 tons, respectively. For the 2025 period, the forecast for palm oil is 1,652,328 tons, while the forecasts for rubber, coffee, cocoa, and tobacco are 317,735 tons, 71,298 tons, 36,905 tons, and 1,787 tons, respectively. The forecast results indicate that palm oil and coffee production are expected to decline over the forecast period. This trend may be linked to fluctuations in production and market conditions. Meanwhile, rubber and tobacco production are projected to increase in 2024 before declining again in 2025. These results indicate that plantation commodity production in North Sumatra tends to fluctuate and may be influenced by economic and environmental factors. Therefore, forecasting can support plantation production planning and policy decision-making.

Based on the results of the study, the forecasting results with actual data did not show significant differences, indicating accurate results as evidenced by the MAPE value for each variable being below 10%. These results indicate that the MSSA method can be used for forecasting, which is consistent with previous studies [9]where the MAPE value for each variable below 10% indicates accurate forecasting results for weather predictions. The study [10]also reveals that the MSSA method has high forecasting accuracy and is used as an alternative reference for multivariate time series forecasting.

In this study, the forecasting results indicate that MSSA has potential for forecasting plantation commodity production. The purpose of production planning forecasting is to manage company needs and evaluate production control activities. It is hoped that this study can be used as a reference for production planning for other companies and for plantation agencies as a reference in the development of national plantation commodities.

4. CONCLUSION

It is clear from the findings and discussion in the preceding chapter that using the Multivariate Singular Spectrum Analysis (MSSA) method has proven successful in providing good forecasting results for plantation commodity production data in North Sumatra Province. The forecasting of plantation commodity production produced values of $L = 2$, $K = 7$, and r-grouping = 2, and a 2-period forecast for 2024 to 2025. The forecasting accuracy level using MAPE for plantation commodity production with the MSSA method for each variable is 3.57223%, 3.95038%, 6.92317%, 3.03589%, and 2,17216 %. Based on the accuracy category, the MAPE value for each variable has a MAPE value < 10% and is classified as accurate for forecasting.

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Author Contributions Statement

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Conflict of Interest Statement

The authors affirm that they had no conflicts of interest when they wrote this piece.

Informed Consent

Not applicable. This study used secondary data obtained from the North Sumatra Provincial Plantation Service and did not involve human participants or interviews.

Data Availability

The data processed in this study was obtained by the first author upon request in accordance with the regulations of the study program and the relevant agency. The data was collected from documents of the North Sumatra Provincial Plantation Agency and is publicly available at (http://disbunak.sumutprov.go.id/).

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