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Performance evaluation of single moving average and exponential smoothing in shallot production prediction

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ABSTRACT

Shallots are a strategic commodity that has significant health benefits, including its ability to prevent cancer. The commodity also plays an important role in the agricultural economy, especially in Indonesia, where high demand in domestic and international markets contributes greatly to farmer's income. However, fluctuations in shallot production often lead to price instability, which has a negative impact not only on consumers but also on the sustainability of farmers' income. This research aims to develop a forecasting model that can assist in more effective planning of shallot production. To achieve this goal, the study tested and compared two forecasting methods: Single Moving Average (SMA) and Single Exponential Smoothing (SES), which are known for their ease of implementation and accuracy in predicting time series data. Using a dataset of shallot production from Brebes Regency over the period 2020-2023, the study found that Single Exponential Smoothing consistently provided more accurate results than Single Moving Average. SES performance is more responsive to recent changes in production data, which is particularly important given the rapid fluctuations that often occur in the agricultural sector. The findings suggest that the application of the SES method in shallot production forecasting can facilitate more informed decision-making in production management and distribution planning, potentially stabilizing market prices and improving farmers' economic conditions.

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1. INTRODUCTION

Shallot (Allium ascalonicum L.) is one of the strategic vegetable commodities that is widely cultivated by farmers in the almost fertile highlands of Indonesia due to its high economic value and attractive market prospects (Rahman et al., 2022). This commodity is one of the food ingredients that cannot be separated from Indonesian cuisine, both as a seasoning and as a complement to dishes. The high demand for shallots in both domestic and export markets makes this commodity of significant economic value to farmers (Sampebua & Suyono, 2022). In addition, shallots also have health benefits, such as preventing cardiovascular disease, and cancer, and boosting the immune system (Nasus & Mutmainah, 2023).

Due to its universal distribution and easy-to-apply planting medium, shallots are also very popular around the world (Fahrizal et al., 2021). In this study, the analysis focused on shallot production data in Brebes Regency, one of the largest shallot-producing regions in Indonesia with a contribution of 18.5% of the total national production (Astuti et al., 2019), (Immanuella & Tinaprilla, 2023). The historical data used covers shallot production in 17 sub-districts in Brebes District over the period 2020 to 2023, which is expected to capture significant fluctuations due to factors such as weather conditions, planting season, and the impact of the COVID-19 pandemic. Brebes Regency is located on the north coast of Central Java and has a tropical climate with distinct rainy and dry seasons. One of the main challenges faced by shallot farmers in this area is extreme rainfall and weather which can affect crop yields. Apart from that, pest attacks and plant diseases are also threats that must be watched out for. By using concrete data from the Brebes District, this study can provide more relevant and specific insights in analyzing the performance of SMA and SES forecasting methods to predict shallot production in an area that has a significant contribution to national production.

However, shallot production in Indonesia often experiences fluctuations caused by various factors, such as weather conditions, pest and disease attacks, and changes in the growing season. These production fluctuations can affect the availability of shallots in the market and have an impact on selling prices that fluctuate. The instability of shallot prices not only makes it difficult for consumers to meet their daily food needs, but can also significantly reduce farmers' income and welfare. High shallot prices can make it difficult for consumers to meet food needs, while low prices can harm farmers (Agustia & Aulia, 2022; Chanifah & Suwandi, n.d.). Therefore, good production planning is needed to ensure the availability of shallots is stable and prices are affordable for consumers.

One of the ways that can be used to plan shallot production is by predicting production. Onion production prediction can be done using various methods, other prediction methods such as Linear Regression and Time Series Decomposition have been used in similar studies. Linear Regression models the relationship between independent and dependent variables, while Time Series Decomposition separates historical data into components such as trends, seasonality, and residuals (Shi et al., 2019). Linear Regression has ease of interpretation and application but is less effective in handling data with non-linear or seasonal patterns. Time Series Decomposition, on the other hand, can identify and separate the different components of a time series, but requires quite long historical data and is often complex in its application (Parmezan et al., 2019; Zhao et al., 2019).

In this research, the application is done using the Single Moving Average (SMA) and Single Exponential Smoothing (SES) methods. The SMA method is a smoothing method that uses the average of historical data with a fixed amount of data, while the SES method is a smoothing method that gives greater weight to recent data than older data (Aziza, 2022; Romadhon et al., 2024). These two methods were chosen due to their ease of implementation and good performance in predicting time series data. However, both methods also have limitations. With accurate forecasting capabilities, the results of this research can help stakeholders such as farmers, cooperatives, and local governments to plan shallot production more effectively, maintain market price stability, and improve farmers' economic welfare. However, both methods also have limitations. They tend to be more effective for short- and medium-term predictions, but may be less optimal in dealing with long-term fluctuations or more complex trend changes.

Several previous studies have explored the application of forecasting methods in predicting agricultural production. (Archontoulis et al., 2020) used the Single Exponential Smoothing method to forecast corn production in the United States, but the study did not specifically address significant fluctuations in production data. (Liu et al., 2021) applied the Single Moving Average method to forecast rice yields, but placed less emphasis on the comparison between forecasting methods and their impact on accuracy. Meanwhile, (Miguéis et al., 2022) focused on predicting fresh fish demand using linear regression and machine learning, but did not touch on the production aspect which is the focus in this context. Although there are not many studies that specifically apply SMA and SES in the context of shallot production, these two methods have been used in forecasting the production of other agricultural commodities such as corn (Archontoulis et al., 2020) and rice (Liu et al., 2021) in various countries.

In terms of agricultural supply chain coordination, (Anggraeni et al., 2022) show the application of hybrid methods in crop production prediction, although it is still limited to a commodity and geographical context that does not match the condition of shallots in Indonesia. Finally, (Kumar et al., 2024) provide an in-depth analysis of forecasting techniques for agricultural products in general, but does not provide a direct comparison between Single Moving Average (SMA) and Single Exponential Smoothing (SES), which is essential in this study.

Over time, several researchers have focused on understanding and developing prediction methods in various fields. However, the number of studies that are specifically related to a particular topic or method is still limited. Although some studies have applied forecasting methods in the context of agricultural production, it is still rare to specifically compare the performance of the Single Moving Average (SMA) and Single Exponential Smoothing (SES) methods in predicting production fluctuations of commodities such as shallots in Indonesia. With accurate forecasting capabilities, the results of this study can help stakeholders such as farmers, cooperatives, and local governments to plan shallot production more effectively, maintain market price stability, and improve farmers' economic welfare. Therefore, this study aims to fill the existing literature gap by directly comparing the performance of the SMA and SES methods in predicting shallot production which is known to have significant fluctuations. This evaluation is important to determine the most suitable and accurate forecasting method so that it can provide appropriate recommendations for stakeholders in planning optimal shallot production and ensuring stable availability in the market.

2. RESEARCH METHOD

This research starts by collecting historical shallot production data and then proceeds with data pre-processing or processing that will be used. Then proceed with the application of the Single Moving Average (SMA) and Single Exponential Smoothing (SES) methods for production prediction, to validation and evaluation of the prediction model developed. In this study, the data used is the production of shallots in Brebes Regency in 2020-2023. The research stages can be seen in Figure 1.

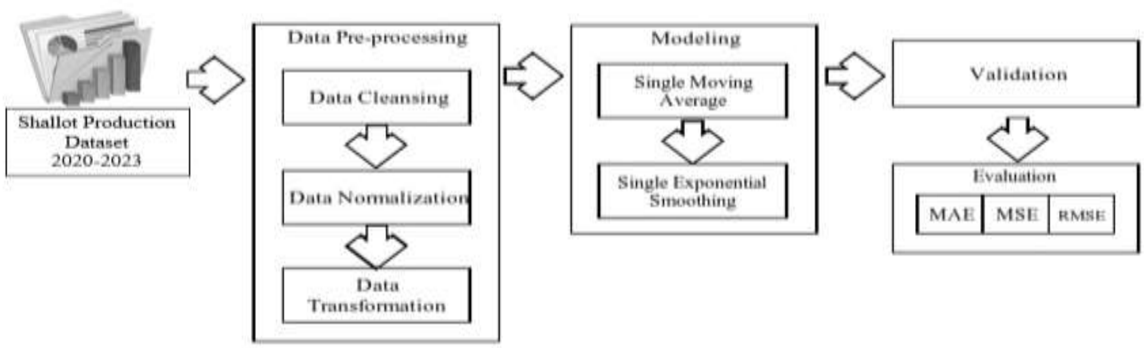

Figure 1. Research flow

The stage begins with the collection of datasets using data collection techniques through the website https://dpkp.brebeskab.go.id, which can be seen from the historical shallot production from the Agriculture and Resilience Office consisting of 17 sub-districts in Brebes Regency. The data collected includes the volume of shallot production in 2020-2023, which may be affected by fluctuations in production due to various factors such as seasonality, weather conditions, and post-COVID-19. The data used from shallot production is shown in Table 1.

Table 1. Data on shallot productivity result in Brebes Regency 2020-2023

No	SUBDISTRICT	SHALLOT PRODUCTION (TONS)			
		2020	2021	2022	2023
1	Salem	0	0	0	0
2	Bantarkawung	1298	1332	1350	375
3	Bumiayu	0	0	0	0
4	Paguyangan	0	0	0	0
5	Sirampog	16	5	67	0
6	Tonjong	9	0	0	13
...	...	...	...	...	...
17	Brebes	44388	40878	72210	45719

The collected data then underwent a pre-processing process to ensure good data quality. This process includes data cleaning where outliers and missing data will be eliminated, data normalization to reduce bias and ensure that different production scales in each sub-district do not affect the analysis results, and data transformation if needed, to ensure the data is ready to be used in the prediction model.

Then the data results from pre-processing are used to be applied with two-time series prediction methods, namely Single Moving Average (SMA) and Single Exponential Smoothing (SES). SMA is applied to average production data in a certain period, while SES is used to predict shallot production. The process of applying the method can be seen in Figure 2.

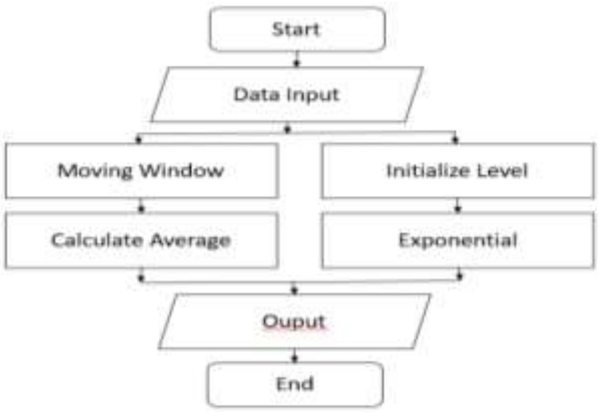

Figure 2. Method flow schematic diagram

Single Moving Average (SMA) is a smoothing method that calculates the average of historical data with a fixed amount of data (Su et al., 2022). The SMA calculation formula is shown in Equation 1.

$$SMA_t = \frac{\sum_{i+1}^{n} X_{t-i+1}}{n} \quad (1)$$

With n being the number of periods used. Determining the value of n optimized for the data used is very important in this method. The larger the value of n, the smoother the resulting forecasting line, but the slower the forecasting will follow changes in actual data.

Single Exponential Smoothing (SES) is a smoothing method that gives greater weight to the latest data than the old data (Svetunkov et al., 2022). The SES calculation formula is shown in Equation 2.

$$S_t = \alpha . X_t + (1 - \alpha). S_{t-1} \tag{2}$$

With S_t is the smoothing value in period t, X_t is the actual data in period t, and α is the smoothing constant (0< α < 1). Determining the optimal α value for the data used is also very important in this method. A small α value will result in smoother forecasting, but less responsive to changes in actual data. Conversely, a large α value will make the forecasting more responsive, but also more volatile.

After forecasting with the SMA and SES methods, the next step is to validate the model to test the performance and accuracy of forecasting on data that has never been seen before (Wainer & Cawley, 2021). In this research, a cross-validation technique will be used to ensure that the validation results do not depend on a specific division of the data. The cross-validation technique involves dividing the data into several parts (folds), where each fold will be used as test data in turn, while the rest becomes training data (De Bruin et al., 2022). The calculation formula can be seen in Equation 3.

$$Performa\ Model = \frac{1}{k}\sum_{i=1}^{k} Metrik\ Performa_i \tag{3}$$

k is the number of folds (subsets) selected, and $Metrik\ Performa_i$ is the performance metric value at the i-th literacy.

In this research, the evaluation process uses the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics to measure the performance and accuracy of forecasting. MAE measures the average absolute error between the prediction and the actual. MSE calculates the average squared error between the actual value and the forecasting value. Meanwhile, RMSE is the root of MSE, which gives the error value in the same units as the original data (Chicco et al., 2021). The evaluation matrix equation formula can be seen in equations 4, 5, and 6.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{4}$$

Where n is the amount of data, i is the order of data in the database, y_i is the actual and $\hat{y}_i$ is the predicted value.

$$MSE = \sum \frac{(\hat{y} - y)^2}{n} \tag{5}$$

Where n is the amount of data, $\hat{y}$ is the predicted value y is the actual.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{6}$$

Where n is the amount of data, i is the order of data in the database, y_i is the actual and $\hat{y}_i$ is the predicted value.

3. RESULTS AND DISCUSSIONS

In this research, the implementation was done using python (Hill et al., 2024; Saharuddin & Prihatmono, 2022) on shallot production data in Brebes Regency 2020-2023. Before forecasting, several data pre-processing stages were carried out on the shallot production dataset. First, the data that was originally in text form was converted into a Pandas DataFrame to facilitate handling. Then, data cleaning is done by filling missing values (NaN) with 0, so that there is no missing data in the next processing process (Putra & Toba, 2020).

After that, data normalization is performed on the column containing shallot production values using MinMaxScaler from the Scikit-learn library (Raharja et al., 2024). This normalization aims to change the scale of the data into a range of 0 to 1 so that the data can be further processed better by the algorithm or model to be used. After normalization, the data also undergoes a log transformation using the np.log1p function to reduce the influence of extreme values and make the data distribution closer to a normal distribution. The normalization results can be shown in Table 2.

Table 2. Data normalization and information results

No	SUBDISTRICT	SHALLOT PRODUCTION (TONS)			
		2020	2021	2022	2023
1	Salem	0	0	0	0
2	Bantarkawung	0.0131752	0.0155908	0.0140859	0.00580277
3	Bumiayu	0	0	0	0
4	Paguyangan	0	0	0	0
...	...	...	...	...	...
17	Brebes	0.373999	0.393539	0.564616	0.53621

After the data is processed, two forecasting methods, namely Single Moving Average (SMA) and Single Exponential Smoothing (SES), are applied to shallot production data. For the SMA method, a window size of 3 is used, which means that each forecasting value is calculated from the average of the previous 3 values. Meanwhile, for the SES method, a smoothing constant (alpha) value of 0.3 is used. This alpha value determines how much weight is given to the latest data over the previous data in the forecasting calculation. This will provide a more comprehensive perspective on the performance of each method. In addition, you can conduct sensitivity analysis on parameters such as window length for SMA or alpha value for SES, as done in the study. (Chang et al., 2022). The forecasting results of the SMA and SES methods are shown in Table 3.

Table 3. Original results of Single Moving Average (SMA) and Single Exponential Smoothing (SES)

NO	SUBDISTRICT	*Single Moving Average* (SMA)	*Single Exponential Smoothing* (SES)
1	Salem	0	0
2	Bantarkawung	0.00704296	0.00658759
3	Bumiayu	0.00469531	0
4	Paguyangan	0.00469531	0
...	...	...	...
17	Brebes	0.260495	0.277954

To evaluate the performance of the two forecasting methods, calculate the RMSE (Root Mean Squared Error), MSE (Mean Squared Error), and MAE (Mean Absolute Error) values between the actual and predicted values of each method.

Table 4. Results of RMSE, MSE, and MAE data evaluation

Method	RMSE	MSE	MAE
Moving Averages	0.169337	0.0286749	0.110676
Exponential Smoothing	0.157542	0.0248196	0.0946672

In Table 4 the calculation results show that the Exponential Smoothing method has lower RMSE, MSE, and MAE values compared to the Moving Average method. The lower RMSE, MSE, and MAE values indicate that the Exponential Smoothing method has better performance in predicting shallot production compared to the Moving Average method. However, the matrix evaluation results show lower values in both methods that the MAE matrix has better performance (Davydenko & Fildes, 2013; Koutsandreas et al., 2022).

To get a clearer picture of the comparison between the actual data and the prediction results of the two methods, data visualization is done in the form of graphs (Purwayoga & Nurkholis, 2023). The script displays two types of graphs, namely a bar graph to compare the RMSE, MSE, and MAE values of the two methods, and a line graph to compare the actual data pattern with the prediction results using the SMA and SES methods.

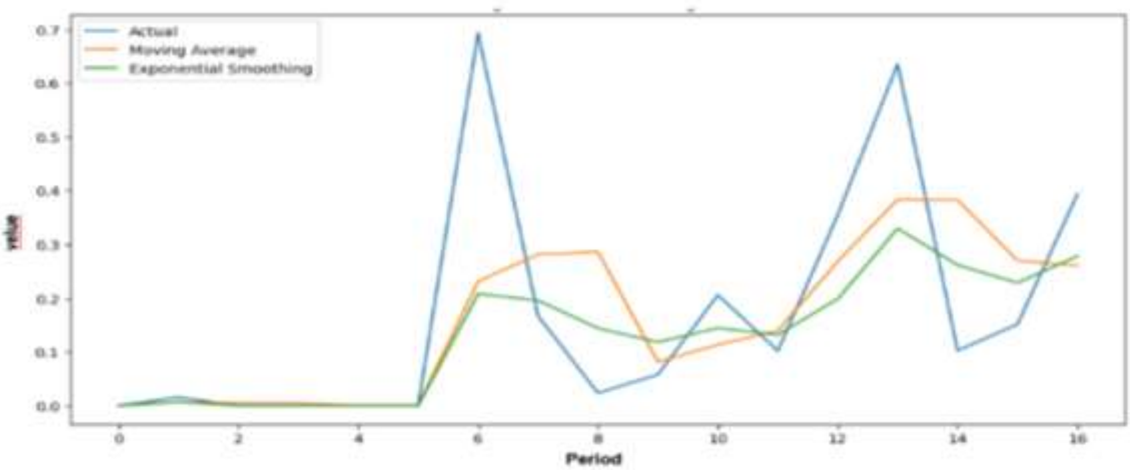

Figure 3. Comparison graph of actual and predicted data

On the line graph, it can be seen that the prediction results using the Exponential Smoothing method (blue line) follow the actual data pattern (green line) better than the Moving Average method (orange line). This is by the results of the calculation of RMSE, MSE, and MAE which show that the Exponential Smoothing method has better performance.

Based on the results obtained, the Exponential Smoothing method shows better performance than the Moving Average method in predicting shallot production on the given dataset. This can be caused by the characteristics of the Exponential Smoothing method which gives greater weight to the latest data than the old data, so that this method can be more responsive in capturing changes in data patterns that occur. (Dudek et al., 2021).

The results of this research are in line with the findings of (Archontoulis et al., 2020) who applied the Single Exponential Smoothing method to predict corn production in the United States. Although they did not specifically address significant production signals, their success using SES supports our finding that this method is effective in the context of agricultural forecasting. Meanwhile, (Liu et al., 2021) which uses the Single

Moving Average method to estimate rice harvest yields, places less emphasis on comparisons between forecasting methods. In contrast to their approach, we directly compare SMA with SES, providing deeper insight into the relative performance of the two methods. Our finding that SES is superior in dealing with the grip on onion production adds new nuance to the results (Liu et al., 2021), indicating that the choice of forecasting method can depend greatly on the specific characteristics of the commodity and its production patterns. Furthermore, our study strengthens the argument. (Chang et al., 2022) about the importance of sensitivity analysis on parameters such as window length for SMA or alpha value for SES, showing that optimization of these parameters is essential to improve forecasting accuracy in the agricultural context.

However, keep in mind that this study only uses two simple forecasting methods, namely SMA and SES, which have limitations in handling complex and unstable data patterns. In reality, shallot production data is often affected by external factors such as weather, pests, and price fluctuations, so the data pattern is not always stable.

To improve prediction accuracy, future research can explore more sophisticated forecasting methods that can handle more complex data patterns (Raup et al., 2022). In addition, future research can also consider other factors that can affect shallot production, such as planting area, fertilizer use, or soil conditions, to improve prediction accuracy.

4. CONCLUSION

This study aims to evaluate the performance of SMA and SES methods in predicting shallot production and determine the most suitable method to be used in shallot production planning. The Exponential Smoothing method with a smoothing constant (alpha) of 0.3 has higher accuracy than the Moving Average method. This is evidenced by the lower RMSE, MSE, and MAE values for the Exponential Smoothing method, as well as graph visualizations that show the prediction results using this method are more following the actual data pattern. This shows that the Exponential Smoothing method can be used as a tool in shallot production planning, especially in predicting future production needs based on historical data. However, keep in mind that the prediction accuracy is still limited because this study only uses two simple forecasting methods and has not considered other factors that can affect shallot production. This research makes an important contribution by highlighting the application and direct comparison between the Single Moving Average (SMA) and Single Exponential Smoothing (SES) methods in the case of shallot production which has significant fluctuations, expanding understanding of the suitability and limitations of each method in handling data patterns complex. Theoretically, this study enriches existing literature by providing new insights into the potential of using simple forecasting methods in production planning for agricultural commodities that are susceptible to fluctuations. In practice, the finding that the Exponential Smoothing method is superior can help stakeholders plan shallot production more effectively, potentially stabilizing market prices and improving farmers' economic conditions. Nevertheless, the authors also critically caution that the prediction accuracy is still limited because they only use two simple methods and have not considered other factors that may influence shallot production, demonstrating a balanced approach in presenting their contribution.

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