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Forecasting Model of Corn Commodity Production in Indonesia: Production and Operation Management-Quantitative Method (POM-QM) Software

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Abstract: Food is essential for humans. In addition to being consumed, it can also be a valuable commodity for economic purposes through the production of food crops. Therefore, this study aims to model the forecasting of maize production in Indonesia using Production and Operations Management-Quantitative Method (POM-QM) software. The uniqueness of this research lies in its innovative approach to predicting corn production, which contributes a valuable addition to the existing body of knowledge in the field of production and operations management. This model not only enhances forecasting accuracy but also offers a novel perspective on optimizing corn production processes in the Indonesian context. The data collected on the production of corn commodities in Indonesia between 1980 and 2019 shows fluctuations, with both deficit and surplus periods. Secondary data in the form of time series sourced from the data and information center (Pusdatin) under the Ministry of Agriculture and the Central Bureau of Statistics (BPS) were used in this study. Our research employs advanced quantitative methods to analyze this historical data, aiming to develop a robust forecasting model that enhances the accuracy of predicting corn commodity production in Indonesia. This study uses a time series data-based forecasting model consisting of three methods: Double Moving Average (DMA) of 29.5 million tons, Weighted Moving Average (WMA) of 28.9 million tons, and Single Exponential Smoothing (SES) of 27.7 million tons. The selection of the best model was conducted based on the Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percent Error (MAPE). DMA emerged as the most preferred, with a lower MAPE value of 10.703%. The predicted production of corn in Indonesia is estimated at 29,5 million tons, sufficient to meet consumers' demand. The fusion of advanced quantitative methods and real-world data positions our forecasting model as a valuable asset in the pursuit of a more sustainable and resilient corn production sector in Indonesia.

Keywords: Forecasting Model, Production, Corn Commodity, POM-QM

Introduction

Food can refer to either a daily necessity or a fundamental human need. In Indonesia, food security is a critical concern. Moreover, to prevent protracted political and social unrest, there must be enough food available to suit the demands of the populace. Another

measure of a nation's economic expansion is its level of food security. Particularly when it comes to people's output and consumption, it can serve as a barometer of prosperity and welfare (Asriani and Herdhiansyah, 2019). Consequently, to maximize the use of natural resources in every region, management strategies that are specific to those regions' characteristics must be put into

place (Herdhiansyah *et al.*, 2012a-b; 2021; 2022; Herdhiansyah and Ode Midi, 2022).

Law Number 18 of 2012, which recognizes food as a human right for Indonesian individuals, is proof of the government's commitment to ensuring food security. This is in line with the first and second Sustainable Development Goals (SDGs), which seek to eradicate global poverty, increase food security and nutrition, and advance sustainable agriculture. *Zea mays* L., sometimes known as commodity corn, is a grain plant belonging to the Gramineae family and a substitute staple food. The principal producing regions of maize in Indonesia are Maluku, North Sulawesi, South Sulawesi, Madura, Special Region of Yogyakarta, East Nusa Tenggara, Central Java, West Java, and East Java. Corn plants are heavily farmed, particularly in Madura and East Java, because of the ideal soil and environment for their growth (Ministry of Agriculture, 2022b).

According to the Director General of Food Crops (2016), corn is a food product that is crucial and strategically important to the growth of a country. Its annual GDP contribution also rises, especially in times of economic crisis (Zubachtirodin and Pabbage, 2016). It is among Indonesia's most significant staple foods. Furthermore, the Ministry of Agriculture's primary goal in achieving food self-sufficiency is this crop, along with two other commodities: Rice and soybeans.

Corn is also extensively utilized for a variety of uses, such as an ingredient in food and feed. It is becoming more and more popular both domestically and globally as a substitute fuel source (Director General of Food Crops, 2016). Due to its use as a component in animal feed and other food processing sectors, this crop is still in great demand (Panikkai *et al.*, 2017). The primary food items, according to the Ministry of Agriculture, are five commodities: Corn, rice, soybeans, sugar, and beef (Ministry of Agriculture, 2022a).

Corn is the food that is produced the second most after rice, and its high demand for animal feed and industrial uses presents problems including resource depletion and the effects of climate change. To assist the development of sustainable corn commodities, cooperation, and collaboration are needed (Nurliza *et al.*, 2020). However, Indonesian agriculture is limited by the issue of land-carrying capacity. The country's corn yield is impacted by the conversion of agricultural land due to the necessity for more space to accommodate the growing population.

Between 1980 and 2019, Indonesian production increased somewhat, although altogether, the increase was just 3.98 tons/ha/year, or 0.102% annually (Ministry of Agriculture, 2022b). The production of commodities made by corn varies greatly. Both internal and external variables, including the environment, the weather, and governmental regulations, are blamed for this variation.

Maize was mostly used as food thirty years ago. However, corn started to be employed as an energy source for contemporary poultry feed when the poultry business grew in the early 1970s (Tangendjaja and Wina, 2016). It was demonstrated that, before 1990, 86% of this crop in Indonesia was consumed directly, with only 6% going toward the feed sector. Despite this, the food industry still uses a small amount of maize (7.5%). Compared to the dry season, the rainy season offers greater availability of this product (Purwanto, 2016). During the wet season, this crop is usually grown on dry land. There is not enough corn available to meet the needs of the domestic industry because of the restricted harvest area during the dry season (Director General of Food Crops, 2016).

Purwanto (2016) reports that there was a change in the way maize was used between 1989 and 2002, but direct consumption remained the main usage. A larger percentage was used after 2002 to satisfy the feed industry's needs. This commodity has also been used more frequently in the culinary business. Due to this modification, maize is now an industrial raw material rather than a staple food (Kasryno *et al.*, 2016). Because of the growing industry and population, the commodity's demand is rising yearly (Purwanto, 2016).

Rising oil costs also affect its dynamic demand. It is anticipated that maize will continue to be used more frequently as a raw ingredient for food and feed and as an alternate energy source. Moreover, Zubachtirodin and Pabbage (2016) found that an increase in per capita income leads to a rise in demand for products derived from corn commodities.

Forecasting entails projecting future needs, such as the kind of commodities, the amount of time, and the location required to satisfy demand (Sinaga and Irawati, 2018). It is both an art and a science to forecast future events by consistently utilizing historical data (Montgomery *et al.*, 2009; Yuniastari and Wirawan, 2017).

Zea mays, or corn, is a vital staple crop for Indonesia's expanding population and a pillar of the country's agricultural environment. The effectiveness of forecasting techniques becomes critical to guaranteeing sustainable production and satisfying the country's nutritional needs as the demand for corn rises.

While corn plays a pivotal role in Indonesian agriculture, the existing forecasting methods that guide production decisions are faced with challenges that warrant further investigation. This study is dedicated to scrutinizing the efficiency of current forecasting mechanisms utilized in the corn production landscape. By delving into the intricacies of these methods, we aim to identify gaps, limitations, and potential areas for improvement.

The importance of this research is underscored by the critical role accurate forecasting plays in shaping agricultural policies, informing farmers' decisions, and

ultimately influencing the overall productivity and stability of the corn industry. Inaccurate forecasts can lead to suboptimal resource allocation, affecting both farmers' livelihoods and the broader economic landscape.

Through a careful examination of the existing forecasting techniques, this study seeks not only to pinpoint shortcomings but also to propose improvements that could revolutionize the accuracy and reliability of corn production forecasts. By doing so, we aspire to contribute valuable insights that can inform policymakers, empower farmers with more precise information, and bolster the resilience of the corn industry in the face of evolving agricultural challenges.

In the subsequent sections, we will delve into the methodologies employed, the data sources utilized, and the specific metrics by which we assess the efficiency of current forecasting methods. Through these investigations, we aim to pave the way for advances in corn production forecasting that align with the demands of a growing population and a changing agricultural landscape. Evans (2003); Heizer and Render (2011) state that forecasting is an essential part of decision-making that necessitates the prediction of future occurrences to guide effective judgments. A recurring problem is inaccurate predicting outcomes (Sinaga and Irawati, 2018).

Forecasting and time series analysis are current research topics (Zheng and Zhong, 2011). When making decisions, time series forecasting accuracy is very important. The time series method, which is divided into averages Single Moving Average (SMA) and Double Moving Average (DMA), smoothing Single Exponential Smoothing (SES), double exponential smoothing from Brown and Holt, and regression (time series regression) are among the various methods used in prediction (Makridakis *et al.*, 1998; 2008; Hyndman and Athanasopoulos, 2018).

Although significantly varied, forecasting techniques are tailored to the data pattern. To ascertain the error level, there are typically three different approaches. These include the average absolute difference, average difference in rank, and average absolute difference percentage, which are calculated by the methods MAD, MSE, and MAPE, respectively (Sukarti, 2015). The data pattern type, cyclical, seasonal, and horizontal must be determined before applying the time series method (Hanke and Dean, 2008).

The selection of forecasting methodologies is supported by the availability of multiple statistical software packages. A range of research analysts have employed software to aid in the computation of forecasting models (Prakoso *et al.*, 2021). For product sales forecasting, for example, POM-QM software has been researched (Kristiyanti and Sumarno, 2020; Rianse *et al.*, 2023). A computer program called the POM program is used to resolve quantitative management issues in

operations and production. POM for Windows is a different application that can help with decision-making because of its ease of use

This research is unusual because it takes a fresh method to forecasting corn yield, making a significant contribution to the corpus of information already available in the field of production and operations management. This model provides a fresh viewpoint on maize production process optimization within the Indonesian setting in addition to improving forecasting accuracy.

Furthermore, this method provides module options for mathematical calculations. Its forecasting model has several methods, including Naive, Moving Average, Weighted Moving Average (WMA), Exponential Smoothing, Trend Analysis (regression over time), linear regression/least square, multiplicative decomposition (seasonal), and Additive Decomposition (seasonal). Given these considerations, it is necessary to have a model to predict the productivity of corn commodities. Therefore, this study aims to establish a forecasting model for corn commodity production in Indonesia using Production and Operation Management-Quantitative Method (POM-QM) software.

Materials and Methods

The variable used was the production of corn per year from 1980-2019. Secondary data in the form of time series sourced from the data and information center (Pusdatin) under the ministry of agriculture and the central Bureau of Statistics (BPS) were used in this study. The population consists of information on the production of corn commodities from 1980-2019. A saturated sampling method was employed, where all population members were used as samples. Our research employs advanced quantitative methods to analyze this historical data, aiming to develop a robust forecasting model that enhances the accuracy of predicting corn commodity production in Indonesia. The fluctuations observed over the decades pose challenges and opportunities for stakeholders in the agricultural sector. Understanding and predicting these trends is essential for effective decision-making and resource allocation.

The ministry of agriculture and the central statistics agency apply strict methodologies in collecting and compiling agricultural data. Primary data sources include surveys, field observations, and records obtained from agricultural institutions across the country. This data set undergoes comprehensive quality control measures to ensure accuracy and predictability.

Although datasets serve as valuable resources, it is important to recognize certain limitations inherent in secondary data. Variations in data collection methodologies over the study period, potential

differences in reporting practices, and slow availability of data are aspects that may give rise to interactions.

In addition, it includes data sets limited to parameters covered by official agricultural and statistical institutions. Unaccounted-for variables or new factors not adequately captured in the data set may pose challenges to a holistic understanding of the intricacies of corn production dynamics.

Forecasting Model for Corn Commodity Production in Indonesia

Forecasting Model of Corn Commodity Production with DMA

Time series data with a linear trend can be predicted using a double-moving average (Hanke and Dean, 2008). When it comes to time series data with patterns that frequently follow a linear trend, multiple moving averages, also known as linear moving averages, are utilized. In addition, single-moving average data with trend and first and second-moving average adjustments is used in the double-moving average approach (Hudiyanti *et al.*, 2019). The first and second moving average groups are computed using the DMA method. The sign ($k \times k$) indicates that the k periods are used to calculate the moving average (Makridakis *et al.*, 1998). The number of moving average orders in the moving average approach is not objectively determined (Hatimah *et al.*, 2013).

Many methods can be used in forecasting, including DMA. The data used for calculations does not have elements of trend or seasonality. DMA is a forecasting method performed on past data for two periods with an average pattern (Oktarini *et al.*, 2017), which is suitable for long-term data (Astuti *et al.*, 2019). The mathematical equation of DMA is presented in Eq. 1:

$$F_{t+1} = X_1 + X_2 + \dots + X_T \quad (1)$$

Information:

- F_{t+1} = Forecast for period $t + 1$
- X_T = True value of t period
- T = Timeframe of moving average

Identifying time-series data patterns, determining the values of the first and second moving averages, determining the value of the constant (a), determining the value of the trend coefficient (bt), choosing the best model based on forecasting accuracy criteria, and determining forecast results for future periods are all steps in the process data analysis of the corn commodity productivity forecasting model using DMA. POM-QM software was utilized to streamline the computing procedure throughout the data analysis.

Forecasting Model of Corn Commodity Production with WMA

By adding more weights to the computation, the moving average method is developed in the WMA forecasting method. It is computed by giving particular values in a data set more weight according to their characteristics. On the other hand, weight determines the average. The moving average approach is enhanced by the WMA forecasting method, which assigns a distinct weight to each time series (Handoko, 1999). According to Aritonang (2002), a WMA is essentially a moving average based on the weight of each item of data.

When determining weights for WMA, it's important to consider the characteristics of the data, the forecasting objectives, and the desired balance between responsiveness to recent changes and stability over time. Additionally, the choice of weights may involve some trial and error or statistical optimization to find the most effective set of weights for a specific forecasting problem

The data analyst's judgment and experience play a role in determining the weight. For example, the analyst might prioritize the most recent observation or the other way around. Compared to the early period, when the weighting opportunity was higher in the preceding observation, the weighted factor will be larger in the final era. The most recent data is given a higher weighting the longer the period is provided, and the number of weighted opportunities equals one (Eris *et al.*, 2014). Equation 2 presents the formula utilized in the corn commodity production forecasting model with WMA:

$$WMA_{t+1} = kX_1 + (k-1)X_{t-1} + \dots + X_{t-(n-1)} / k + (k-1) + \dots + 1 \quad (2)$$

Information:

- K = Number of periods or ranges of forecasting numbers
- X_t = The time series data value at point t

Forecasting Model for Corn Commodity Production with SES

SES is a straightforward technique that necessitates one parameter estimation. It gives all historical data weights based on the Exponential Moving Average (EMA). According to Indrajit and Djokopranoto (2003); Siregar *et al.* (2017); Tularam and Saeed (2016), the exponential smoothing forecasting method is an iterative process of repeating calculations that improves the forecast (smoothing) by exponentially calculating the average of past values in a time series. SES is appropriate for data without extreme trends and is typically used for forecasting one period in the future.

The objective is to forecast previous values by estimating the current level. Equation 3 is used in the corn production forecasting model with SES (Makridakis *et al.*, 2003):

$$F_{t+1} = \alpha \cdot X_t + (1 - \alpha) F_t \quad (3)$$

Information:

F_{t+1} is the forecast for the next period, α is the smoothing constant, X_t is the t^{th} data or observation, and F_t is the t^{th} period data. The F_{t+1} forecast is based on the weighting of the latest X_t data with a weight of α and the newest forecasting weighting of F_t with a weight of $1 - \alpha$. By repeating this process and replacing F_{t+1} and F_{t+2} with their components, the result in Eq. 4 is obtained:

$$\begin{aligned} F_{t+1} &= \alpha \cdot X_t + (1 - \alpha) F_t = \alpha \cdot X_t + (1 - \alpha) \\ &[\alpha \cdot X_{t+1} + (1 - \alpha) F_{t+1}] = \alpha \cdot X_t + \alpha(1 - \alpha) \\ X_{t+1} + (1 - \alpha)^2 F_{t+1} &= \alpha \cdot X_t + \alpha(1 - \alpha) \\ X_{t+1} + \alpha(1 - \alpha)^2 F_{t+1} \end{aligned} \quad (4)$$

Therefore, F_{t+1} is the WMA of all historical data. As t increases, the value of $(1 - \alpha)^2$ decreases, leading to a smaller contribution from F_1 . Since F_1 is not known, the initial value can be estimated. For volatile initial data, one method is to set the first forecast equal to the first observation, $F_1 = y_1$. Furthermore, for initial data that is quite constant, the average of the first five or six data points can be used as the first forecast: $F_1 = MA$ (5) or $F_1 = MA$ (6). The exponential smoothing equation can be rewritten in a form that describes the role of the weighting factor α , as shown in Eq. 5:

$$F_{t+1} = F_t + \alpha(X_t - F_t) \quad (5)$$

Exponential smoothing is used to adjust a previous forecast (F_t) by incorporating adjustments for errors. The value of α , which ranges between 0 and 1, cannot be equal to 0 or 1. To obtain a stable forecast with random smoothing, a small α value should be used for data that does not fluctuate too much. In contrast, a large α value is more appropriate for data that fluctuates significantly and requires a fast response to changes. To determine the optimal α value, one can estimate it using trial and error, testing values of 0.1, 0.2, 0.3, ..., 0.9, and selecting the value with the smallest MSE for the next forecast.

Selection of the Best Model for Forecasting Production of Corn Commodities

Variations in data patterns frequently affect the forecasting method's calculating accuracy. To reduce

errors in forecasting outcomes, it is crucial to choose the appropriate method (Prabowo and Aditia, 2020). It is necessary to take into account the accuracy degree of each procedure. Consequently, picking a strategy that may reduce predicting errors is crucial. Athanasopoulos *et al.* (2017); Chopra and Meindl (2016) state that forecast facts should have small values and mistakes. The forecast result's accuracy is negatively correlated with the error value.

The resulting inaccuracy determines which forecasting model is optimal. Metrics like (a) Mean Absolute Deviation (MAD), (b) Mean Square Error (MSE), and (c) Mean Absolute Percent Error (MAPE) are frequently used to determine how accurate the model predictive time series is. The better the prediction outcomes, the smaller the criterion value (Hudaningsih *et al.*, 2020; Kim and Kim, 2016; Heizer and Render, 2008).

MAD

According to Heizer and Render (2008); Hudaningsih *et al.* (2020), the sample size (the number of prediction periods) is divided by the total of the absolute values of each error to determine the overall forecast error or *MAD*. At last, the *MAD* mathematical formula is shown in Eq. 6:

$$MAD = \frac{\sum_{t=1}^n (A_t - F_t)}{n} \quad (6)$$

Information:

A_t = Actual demand in period t
 F_t = Forecasting demand in period t
 n = Number of forecasting periods involved

MSE

According to Heizer and Render (2008); Hudaningsih *et al.* (2020), *MSE* is computed by squaring the sum of all mistakes for each period and dividing the result by the number of forecasted periods. Equation 7 presents the *MSE* mathematical expression:

$$MSE = \sum_{t=1}^n |A_t - F_t|^2 \quad (7)$$

Information:

A_t = Actual demand in period t
 F_t = Forecasting demand in period t
 n = Number of forecasting periods involved

MAPE

The MAPE computation is a tool utilized in evaluation to assess the precision of forecasts (Farizal *et al.*, 2021; Kim and Kim, 2016; Booranawong and Booranawong, 2018).

In order to properly evaluate the forecasting method, it was selected as the performance parameter (Tratar and Srncnik, 2016; Booranawong and Booranawong, 2017).

Moreover, the expected time series magnitude has no bearing on MAPE (Gentry *et al.*, 1995; Alon *et al.*, 2001). Industry practitioners also find it attractive since it is straightforward to understand, regardless of scale, and widely applied in practice (Ravindran *et al.*, 2023). (Chatfield, 2000; Byrne, 2012). As a proportion of the average absolute error rate for the real data period, MAPE calculates the average absolute error. Equation 8 displays the mathematical expression:

$$MAPE = \frac{(100)}{n} \sum_t^n \frac{(A_t - F_t)}{[n]} \quad (8)$$

Information:

A_t = Actual demand in period t

F_t = Forecasting demand in period t

n = Number of forecasting periods involved

As a proportion of the average overall error rate for the real data period, MAPE calculates the average absolute errors. Its standards clarify that greater accuracy corresponds with a reduced MAPE score. The scoring criteria are displayed in Table 1 (Chang *et al.*, 2007).

Production Data Processing of Corn Commodities is Carried Out Using POM-QM Software

The next step is to describe and process data related to corn commodity production. The POM-QM software program was used to analyze data on the commodity output of corn from 1980 to 2019. In the POM-QM application, a number of forecasting techniques were applied, leading to the production of expected forecast results.

To apply the POM-QM software in forecasting productivity of corn commodities, the steps to be followed include: (a) Running the QM program and selecting the module-forecasting; (b) Selecting the menu File-New-Time series Analysis and a dialogue box titled "Create data set for Forecasting/Time-series Analysis" will appear (c) In the dialog box, provide the title of the forecast, "Production of corn commodities," along with the number of time series data periods to be used as training data, starting from 1980-2019. Specify the name for each row's period name using numbers, letters, or months. After completing the above steps, press the OK button. The data settings in QM for Windows are shown in Fig. 1.

Table 1: Mape value criteria

MAPE value	Criteria
< 10	Very good
10–20	Well
20–50	Enough
>50	Bad

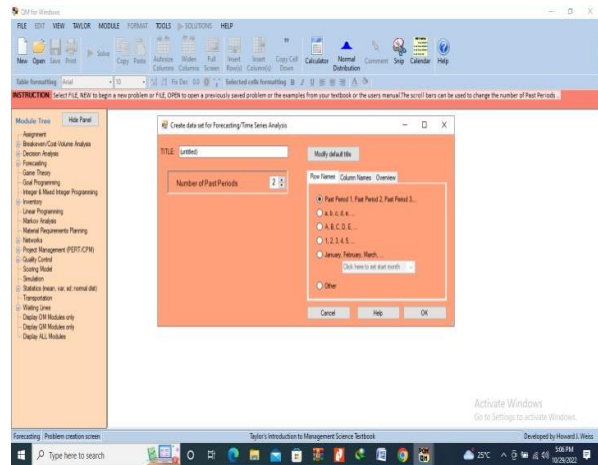


Fig. 1: Data settings in QM for windows

For businesses, forecasting is essential since it helps with inventory, production, and planning decisions (Pennings and Van Dalen, 2017). Fong *et al.* (2020) say that using many forecasting models is necessary. To get the most accurate prediction, a number of forecasting model options should be taken into consideration. Next, each method's corn production predicting figures are gathered and examined for accuracy. As a result, picking the right forecasting technique is crucial as utilizing the wrong one could make the forecast less accurate.

Results and Discussion

Forecasting Model of Corn Commodity Production with DMA

Adding the production data of corn commodities from the two preceding periods and dividing the total by two is the DMA forecasting method. An alternative method is to compute the mean of the corn commodity production figures from the two preceding timeframes. Table 2 displays the moving average predicting results.

Based on DMA applied to forecast corn commodity production, Table 2 presents the mean absolute percent error results, which is 10.703%. Figure 2 shows the forecasting graph of the production of corn commodities using this method.

Figure 2 shows that the forecasting results for corn commodity production from DMA appear different from the actual data.

Table 2: Calculation of the double moving average forecast for corn commodity production

Measure	Value
Error measures	
Bias (mean error)	1032734.000
Mean Absolute Deviation (MAD)	1253492.000
Mean Squared Error (MSE)	3763437000000.000
Standard error (denom = n-2 = 35)	1994615.000
Mean Absolute Percent Error (MAPE)	10.703%
Forecast	
Next period	29588980.000

Table 3: Forecasting the weighted moving average on production commodity corn

Measure	Value
Error measures	
Bias (mean error)	1369668.000
MAD (Mean Absolute Deviation)	1564418.000
MSE (Mean Squared Error)	6239597000000.000
Standard Error (denom = n-2 = 35)	2568296.000
MAPE (Mean Absolute Percent Error)	12.553%
Forecast	
Next period	28924020.000



Fig. 2: Forecasting graph with the double moving average method on production commodity corn

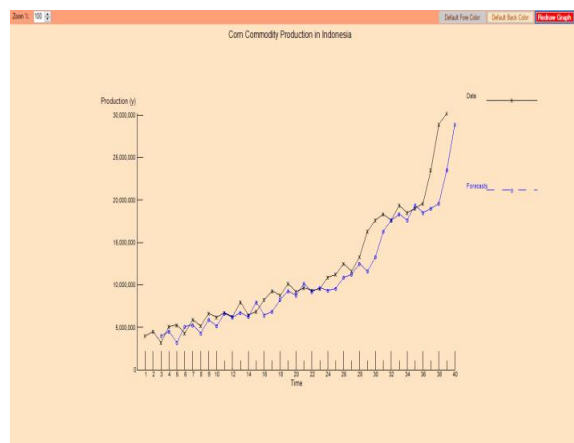


Fig. 3: Forecasting graph with the weighted moving average method at corn commodity production

Table 4: Forecasting single exponential smoothing at corn commodity production

Measure	Value
Error measures	
Bias (mean error)	1247938.000
Mean Absolute Deviation (MAD)	1395548.000
Mean Squared Error (MSE)	4406025000000.000
Standard error (denom = n - 2 = 36)	2156572.000
Mean Absolute Percent Error (MAPE)	11.688%
Forecast	
Next period	27701760.000

Forecasting Model for Production of Corn Commodity with WMA

WMA 2 is carried out by giving the last two years' worth of corn commodity output data weight. From 1980 to 2019, corn commodity output was forecasted. Table 3 displays the forecasting method's computation procedure.

Based on the WMA applied to forecast corn commodity production, Table 3 presents the results of the mean absolute percent error of 12.553%. Figure 3 shows the forecasting Graph with WMA for the production of corn commodities.

According to Fig. 3, the forecasting results for corn commodity production using WMA display a slight increase towards the end of the period compared to DMA.

Forecasting Model of Corn Commodity Production with SES

To calculate the forecasting of corn commodity production using SES, the α coefficient is first determined. It is performed by multiplying α by the actual demand. Afterward, the result is added with the outcome of $1 - \alpha$ multiplied by the corn commodity production forecast in the previous period. The value of α is assumed to be 0.5 in this model.

The selection of the α value is a pivotal decision in SES, influencing the model's responsiveness to recent changes in the data. The choice of 0.5 was made based on a balance between capturing short-term fluctuations and maintaining a degree of stability in the forecasting process. The forecasting process using SES is presented in Table 4.

Table 4 shows that from the results of forecasting production of corn commodities using SES, this forecast's mean absolute percent error is 11,688%. Figure 4 shows the forecasting Graph of SES.

Figure 4 shows that the forecasting results for corn commodity production from WMA appear to be more stable than SES.

Table 5 presents the forecasted corn commodity production using methods such as (a) DMA, (b) WMA, and (c) SES in the next (year). The data used in the analysis consist of 39 years of production, from 1980-2019.

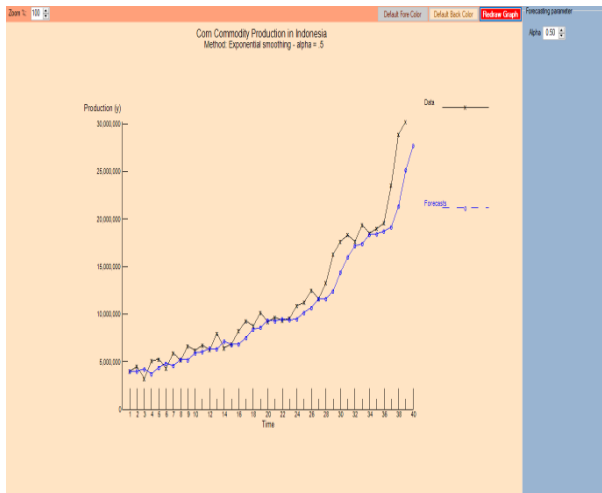


Fig. 4: Forecasting graph with the single exponential smoothing method on corn commodity production

Table 5: The value of the size of the error in the forecasting model for the production of corn commodities

Method	Error size value			
	MAD	MSE	SEE	MAPE (%)
Double moving average	1.564.418	6.239.597	2.568.296	10.703
Weighted moving average	1.564.418	6.239.597	2.568.296	12.553
Singel exponential smoothing	1.395.548	4.406.025	2.156.572	11.688

Table 6: Value of corn commodity production forecasting size next period

Method	The value of the next period forecasting measure (Tons)
Double moving average	29.588.980
Weighted moving average	28.924.020
Single exponential smoothing	27.701.760

The analysis in Table 4 compares the error rates of the three different methods for forecasting corn production. Based on the results, DMA outperforms the other method with a MAPE value of 10.703%, which is very close to zero. A lower MAPE indicates a closer alignment between predicted and observed values, suggesting higher forecasting accuracy. Conversely, a higher MAPE signifies a greater degree of deviation between predicted and actual outcomes. It is important to note that the practical significance of MAPE values depends on the context of corn production forecasting. Therefore, DMA is chosen for forecasting corn commodity production.

In summary, the selection of the Double Moving Average (DMA) model for corn production forecasting is grounded in its ability to address the unique challenges

posed by seasonal variations, its adaptability to time series data, its simplicity for effective communication, its historical success in agricultural forecasting, and its alignment with the distinctive characteristics of the corn production dataset in Indonesia. The forecasting values for the upcoming period are presented in Table 6.

Table 6 indicates that the forecasted corn commodity production for the next period is 29.588.980 tons. Implies that corn commodity production in Indonesia is expected to satisfy the entire consumer demand. The findings of this study hold significant implications for farmers, policymakers, and other stakeholders in the corn production sector. The identification of deficit and surplus periods provides valuable insights for strategic planning, risk management, and resource allocation. Moreover, our research contributes to the broader discourse on the application of quantitative methods in agricultural forecasting, paving the way for more informed decision-making in the field.

As we delve into the complexities of corn commodity production in Indonesia, this study not only enhances our understanding of historical patterns but also equips stakeholders with a powerful tool for navigating the uncertainties inherent in agricultural production. The fusion of advanced quantitative methods and real-world data positions our forecasting model as a valuable asset in the pursuit of a more sustainable and resilient corn production sector in Indonesia.

Policymakers can leverage the research findings to inform agricultural policies at regional and national levels. Accurate forecasts enable policymakers to design interventions that promote sustainable agricultural practices, allocate subsidies effectively, and address challenges related to food security. The research outcomes, therefore, provide a robust foundation for evidence-based policymaking.

The implications extend to the broader economic landscape. Accurate corn production forecasts contribute to overall economic planning by ensuring a stable and resilient agricultural sector. Policymakers can use this information to formulate strategies for economic diversification, rural development, and the sustainable growth of the agricultural industry, fostering economic stability.

Conclusion

Forecasting results of corn commodity production, using the following methods: (a) Double Moving Average, (b) Weighted Moving Average, and (c) Single Exponential Smoothing in the next (year), from 1980-2019: Forecasting model for corn commodity production The selected method, namely the Double Moving Average method, has a lower error rate than other forecasting

models, the MAPE value is 10.703%, The forecasting model for corn commodity production is 29.588.980 tons, meaning that corn commodity production in Indonesia is expected to meet all consumer demands for corn commodities. The results of this study are expected to assist the government in predicting the amount of corn commodity production in the next period by national corn needs. Policymakers can leverage the research findings to inform agricultural policies at regional and national levels. Accurate forecasts enable policymakers to design interventions that promote sustainable agricultural practices, allocate subsidies effectively, and address challenges related to food security. The research outcomes, therefore, provide a robust foundation for evidence-based policymaking.

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Author's Contributions

Asriani: Actively participated in all experimental procedures, skillfully coordinated data analysis, and made substantial contributions to the manuscript written process.

Dhian Herdhiansyah: Demonstrated effective coordination in planning and executing the research study.

Wa Embe: Made valuable contributions to result preparation and manuscript organization.

LM Fid Aksara: Significantly contributed to the preparation of results and overall manuscript structure.

Ethics

The paper reflects the author's own research and analysis in a truthful and complete manner. The paper properly credits the meaningful contributions of co-authors. The results are appropriately placed in the context of prior and existing research.

References

- Alon, I., Qi, M., & Sadowski, R. J. (2001). Forecasting aggregate retail sales: A comparison of artificial neural networks and traditional methods. *Journal of Retailing and Consumer Services*, 8(3), 147-156. [https://doi.org/10.1016/S0969-6989\(00\)00011-4](https://doi.org/10.1016/S0969-6989(00)00011-4)
- Aritonang. (2002). Customer satisfaction, Gramedia Pustaka Utama, Jakarta.
- Asriani, A., & Hedhiansyah, D. (2019). Factors Affecting the Economic Policy of Food in Indonesia. *Mega Aktiva: Jurnal Ekonomi dan Manajemen*, 8(1), 11-17. <http://dx.doi.org/10.32833/majem.v8i1.76>
- Astuti, Y., Novianti, B., Hidayat, T., & Maulina, D. (2019). Penerapan Metode Single Moving Average Untuk Peramalan Penjualan Mainan Anak. <https://ejurnal.diponegara.ac.id/index.php/sensitif/article/view/552/485>
- Athanasopoulos, G., Hyndman, R. J., Kourentzes, N., & Petropoulos, F. (2017). Forecasting with temporal hierarchies. *European Journal of Operational Research*, 262(1), 60-74. <https://doi.org/10.1016/j.ejor.2017.02.046>
- Booranawong, T., & Booranawong, A. (2017). Simple and double exponential smoothing methods with designed input data for forecasting a seasonal time series: In an application for lime prices in Thailand. *Suranaree Journal of Science & Technology*, 24(3). <https://www.thaiscience.info/Journals/Article/SJST/10988517.pdf>
- Booranawong, T., & Booranawong, A. (2018). Double exponential smoothing and Holt-Winters methods with optimal initial values and weighting factors for forecasting lime, Thai chili, and lemongrass prices in Thailand. *Engineering and Applied Science Research*, 45(1), 32-38. <https://ph01.tci-thaijo.org/index.php/easr/article/view/73088>
- Byrne, R. F. (2012). Beyond Traditional Time-Series: Using Demand Sensing to Improve Forecasts in Volatile Times. *Journal of Business Forecasting*, 31(2). ISSN-10: 1930-126X.
- Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications*, 32(1), 86-96. <https://doi.org/10.1016/j.eswa.2005.11.021>
- Chatfield, C. (2000). Time-Series Forecasting. 1st Ed. New York: Chapman & Hall. pp: 280. <https://doi.org/10.1201/9781420036206>
- Chopra, S., & Meindl, P. (2016). *Supply Chain Management: Strategy, Planning, and Operation*. (6th ed.) Pearson Education. pp: 528. ISBN-10: 97812920093567.

- Director General of Food Crops. (2016). Technical instructions for hybrid corn development movement. *Directorate General of Food Crops*.
- Eris, P. N., Nohe, D. A., & Wahyuningsih, S. (2014). Forecasting with methods smoothing and verification methods forecasting with control charts moving range (mr) (case study: Clean water production in Herdhiansyah PDAM Tirta Kencana Samarinda). *Journal Exponential*, 5(1), 203-210. [https://fmipa.unmul.ac.id/files/docs/15.\[24\]%20jurnal%20PRISCA%20Edit.pdf](https://fmipa.unmul.ac.id/files/docs/15.[24]%20jurnal%20PRISCA%20Edit.pdf)
- Evans, M. K. (2003). *Practical business forecasting*. Blackwell (Malden). <https://doi.org/10.1002/9780470755624>
- Farizal, F., Dachyar, M., Taurina, Z., & Qaradhawi, Y. (2021). Disclosing fast-moving consumer goods demand forecasting predictor using multi linear regression. *Engineering and Applied Science Research*, 48(5), 627-636. <https://ph01.tci-thaijo.org/index.php/easr/article/view/242407>
- Fong, S. J., Li, G., Dey, N., Crespo, R. G., & Herrera-Viedma, E. (2020). Finding an accurate early forecasting model from small dataset: A case of 2019-ncov novel coronavirus outbreak. *International Journal of Interactive Multimedia and Artificial Intelligence*, 6(1), 132-140. <https://doi.org/10.9781/ijimai.2020.02.002>
- Gentry, T. W., Wiliamowski, B. M., & Weatherford, L. R. (1995). A comparison of traditional forecasting techniques and neural networks. In: Dagli CH, Akay M, Chen CLP, editors. *Intelligent engineering systems through artificial neural networks*, Vol. 5. New York: *American Society of Mechanical Engineers*; 765-770.
- Handoko, T. H. (1999). *Dasar Dasar Manajemen Produksi Dan Operasi Edisi 1 - Hani Handoko*. Tokopedia. ISBN-10: 9795032860.
- Hanke, J., & Dean, W. (2008). *Business Forecasting*, 9th Ed. *United States of America: Pearson*. ISBN-13: 978-0132301206.
- Hatimah, I. S., Wahyuningsih & Sifriyani. (2013). Comparison of the double moving average method and holt's double exponential smoothing in stock price forecasting. *Journal Exponential*, 4(1), 103-107.
- Heizer, J. H., & Render, B. (2008). *Operations Management*. United Kingdom: Pearson Prentice Hall. ISBN-10:9780138134549.
- Heizer, J., & Render, B. (2011). *Operations Management*, (10th Ed.). United States of America: Pearson. pp: 806. ISBN-10: 0136119417.
- Herdhiansyah, D., Sutiarto, L., Purwadi, D., & Taryono, T. (2012a). Strategi Pengembangan Potensi Wilayah Agroindustri Perkebunan Unggulan. *Jurnal Teknik Industri*, 13(2), 201-209. <https://doi.org/10.22219/JTIUMM.Vol13.No2.201-209>
- Herdhiansyah, D., Sutiarto, L., Purwadi, D., & Taryono. (2012b). Potential Areas Analysis for Development of Prime Commodities Plantation in the Kolaka District, Southeast Sulawesi. *Jurnal Teknologi Industri Pertanian*, 22(2). <https://journal.ipb.ac.id/index.php/jurnaltin/article/view/6723>
- Herdhiansyah, D., & Ode Midi, L. (2022). Analytical Hierarchy Process (AHP) in Expert Choice for determining superior plantation commodities: A case in East Kolaka Regency, Indonesia. *Songklanakar Journal of Science & Technology*, 44(4). 923. ISSN: 0125-3395.
- Herdhiansyah, D., Sudarmi, S., Sakir, S., & Asriani, A. (2021). Analisis faktor prioritas pengembangan komoditas perkebunan unggulan dengan metode AHP (Analytical Hierarchy Process). *Jurnal Teknik Pertanian Lampung (Journal of Agricultural Engineering)*, 10(2), 239-251. <https://doi.org/10.23960/jtep-l.v10i2.239-251>
- Herdhiansyah, D., Sudarmi, S., & Asriani. (2022). Techniques for Determining Leading Plantation Commodities, PT NEM.
- Hudaningsih, N., Utami, F. S., & Abdul Jabbar, W. A. (2020). Comparison of sales forecasting of PT. Sunthi Aknil Products. *Jinteks Journal*, 2(1), 15-22. <https://doi.org/10.51401/jinteks.v2i1.554>
- Hudiyanti, C. V, Bachtiar, F. A, & Setiawan B. D. (2019). Comparison of Double Moving Average and Double Exponential Smoothing for Forecasting the Number of Arrivals of International Tourists at Ngurah Rai Airport. *Journal of Information Technology Development and Computer Science*, 3(3), 2667-2672. <https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/4791>
- Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice*. OTexts.
- Indrajit, R. E, & Djokopranoto R. (2003). Inventory management of general goods and spare parts for repair maintenance and operations. *Jakarta: Grasindo*.
- Kasryno, F., Pasandaran, E., Suyanto, & Adnyana Made, O. (2016). Overview of the Indonesian corn economy. *Food Crops Research and Development Center*. <http://balitsereal.litbang.pertanian.go.id/wp-content/uploads/2016/11/satu.pdf>.
- Kim, S., & Kim, H. (2016). A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting*, 32(3), 669-679. <https://doi.org/10.1016/j.ijforecast.2015.12.003>
- Kristiyanti, D. A., & Sumarno, Y. (2020). Penerapan Metode Multiplicative Decomposition (Seasonal) Untuk Peramalan Persediaan Barang Pada PT. Agrinusa Jaya Santosa. *Jurnal SISKOM-KB (Sistem Komputer dan Kecerdasan Buatan)*, 3(2), 45-51. <https://doi.org/10.47970/siskom-kb.v3i2.145>

- Makridakis, S., Wheelwright S., & McGee, V. E. (2008). Forecasting methods and applications, 2nd Ed. *John Wiley and Sons*.
- Makridakis, S. G., Wheelwright, S. C., Hyndman, R. J. (1998). Forecasting: Methods and Applications. Kiribati: *Wiley*. ISBN-10: 780471532330.
- Makridakis SC, Wheelwright S, & McGee, V. E. (2003). Methods and applications. *Forecasting, Jakarta: Binarupa Aksara*. ISBN-10: 26010108.
- Ministry of Agriculture. (2022a). Back consumption of corn as a food source of carbohydrates. *Agricultural Research and Development Agency*.
- Ministry of Agriculture. (2022b). Corn commodity harvested area in Indonesia.
- Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2009). Introduction to Time Series Analysis and Forecasting Solutions Set. United Kingdom: *Wiley*. pp: 547. ISBN-10: 9780470501474.
- Nurliza, N., Ruliyansyah, A., & Hazriani, R. (2020). Performance behavior of corn smallholders for sustainable cooperative change in West Kalimantan. *AGRARIS: Journal of Agribusiness and Rural Development Research*, 6(1), 1-11. <https://doi.org/10.18196/agr.6186>
- Oktarini, D., Irnanda, P., & Utami, O. P. (2017). Produktivty and inventory control planning in PT Melania Indonesia's Rubber Industry. *Integration Journal: Industrial Engineering Scientific Journal*, 2(2), 16-24.
- Panikkai, S., Nurmalina, R., Mulatsih, S., & Purwati, H. (2017). Analysis of national corn availability to become self-sufficiency throught dynamic model approachmen. *Informatika Pertanian*, 26(1), 41-48. <https://doi.org/10.21082/ip.v26n1.2017.p41-48>
- Pennings, C. L., & Van Dalen, J. (2017). Integrated hierarchical forecasting. *European Journal of Operational Research*, 263(2), 412-418. <https://doi.org/10.1016/j.ejor.2017.04.047>
- Prabowo, R., & Aditia, R. (2020). Analisis Produktivitas Menggunakan Metode POSPAC dan Performance Prism Sebagai Upaya Peningkatan Kinerja (Studi Kasus: Industri Baja Tulangan di PT. X Surabaya). *Jurnal Rekayasa Sistem Industri*, 9(1), pp. 11-22. <https://doi.org/10.26593/jrsi.v9i1.3362.11-22>
- Prakoso, I. A., Kusnadi, K., & Nugraha, B. (2021). Peramalan Penjualan Produk Dengan Metode Regresi Linear Dan Aplikasi POM-QM di PT XYZ. *Widya Teknik*, 20(1), 17-20. <https://doi.org/10.33508/wt.v20i1.3158>
- Purwanto, S. (2016). Development of produktivity and policy in increasing corn produktivity. *Food Crops Research and Development Center*. <http://balitsereal.litbang.pertanian.go.id/wp-content/uploads/2016/11/dua.pdf>.
- Ravindran, A. R., Warsing Jr, D. P., & Griffin, P. M. (2023). *Supply Chain Engineering: Models and Applications*. CRC Press.
- Rianse, U., Taufik, Y., & Herdhiansyah, D. (2023). Forecasting Model of Corn Commodity Productivity in Indonesia: Production and Operations Management, Quantitative Method (POM-QM) Software. *International Journal of Advanced Computer Science and Applications*, 14(5). <https://doi.org/10.14569/IJACSA.2023.0140565>
- Sinaga, H. D. E., & Irawati, N. (2018). Perbandingan Double Moving Average Dengan Double Exponential Smoothing Pada Peramalan Bahan Medis Habis Pakai. <https://doi.org/10.33330/jurteks.v4i2.60>
- Siregar, B., Butar-Butar, I. A., Rahmat, R. F., Andayani, U., & Fahmi, F. (2017). Comparison of exponential smoothing methods in forecasting palm oil real production. In *Journal of Physics: Conference Series* (Vol. 801, No. 1, p. 012004). IOP Publishing. <https://doi.org/10.1088/1742-6596/801/1/012004>
- Sukarti, N. K. (2015). Time Series Forecasting Using S-Curve and Quadratic Trend Model. *National Conference on Systems and Informatics 2015 STMIK STIKOM Bali, 9-10 October 2015*.
- Tangendjaja, B. & Wina, E. (2016). Plant waste and by-products of the corn industry for feed. *Food Crops Research and Development Center*.
- Tratar, L. F., & Strmčnik, E. (2016). The comparison of Holt-Winters method and Multiple regression method: A case study. *Energy*, 109, 266-276. <https://doi.org/10.1016/j.energy.2016.04.115>
- Tularam, G. A., & Saeed, T. (2016). The use of exponential smoothing (es), holts and winter (hw) and Arima models in oil price analysis. *International Journal of Mathematics, Game Theory, and Algebra*, 25(1), 13.
- Yuniastari, N. L., & Wirawan I. W. (2017). Forecasting demand for silver products using the simple moving average and exponential smoothing methods. *Journal of Systems and Informatics (JSI)*. 9(1), 97-106.
- Zheng, F., & Zhong, S. (2011). Time series forecasting using a hybrid RBF neural network and AR model based on binomial smoothing. *World Academy of Science, Engineering and Technology*, 75, 1471-1475. <https://doi.org/10.5281/zenodo.1072611>
- Zubachtirodin, M.S. Pabbage, Subandi. (2016). Produktivity area and corn development potential. *Food Crops Research and Development Center*.