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Quantitative Forecasting of Soybean Commodity Production in Indonesia using POM-QM Software

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Food serves not only as a fundamental requirement for human existence but also embodies a significant economic asset, particularly through the agricultural production of food crops. The objective of this research is to project soybean output in Indonesia utilizing Production and Operations Management-Quantitative Method (POM-QM) software. The dataset concerning soybean production spanning from 2000 to 2024 reveals notable variability, characterized by intervals of both scarcity and abundance. Three distinct time-series forecasting methodologies were implemented: Double Moving Average (DMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES). The optimal model was determined based on critical precision indicators, which include Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE). Among the employed methodologies, WMA emerged as the most precise, demonstrating a MAPE value of 17.89%. The projected soybean production is approximated at 558.3 tons, suggesting an adequate supply to satisfy consumer requirements. It is advisable for the government to leverage these projections to proficiently forecast and strategize for forthcoming national soybean demand.
Keywords: Quantitative forecasting, production, soybean commodity, POM-QM.

INTRODUCTION

Food constitutes an essential requirement for human sustenance on a daily basis, and the issue of food security has emerged as a paramount concern within the context of Indonesia. The assurance of an adequate food supplies to satisfy the demands of the populace is vital in order to avert extended periods of political and social instability. Furthermore, food security functions as a significant gauge of a nation's economic advancement, encapsulating overall societal welfare and acting as a metric of affluence, particularly concerning the levels of production and consumption (Asriani and Herdhiansyah, 2019). Consequently, the optimization of natural resource utilization across diverse regions necessitates the execution of management strategies that are specifically adapted to the distinctive characteristics inherent to each region (Herdhiansyah *et al.*, 2012; Herdhiansyah and Asriani, 2018; Herdhiansyah *et al.*, 2021).

The commitment of the Indonesian government to food security is evidenced by its acknowledgment of food as an inherent human right, as articulated in Law No. 18 of 2012. This recognition is congruent with the first and second objectives of the Sustainable Development Goals (SDGs), specifically the eradication of global poverty and the attainment of food security, enhancement of nutrition, and the encouragement of sustainable agricultural practices. The soybean, recognized as a strategic commodity in Indonesia, serves a critical function both as a primary food source and as a raw material for various industrial applications. Nonetheless, domestic production of soybeans continues to encounter a multitude of challenges, leading to a significant reliance on imports.

Soybeans (Glycine max) represent a critical food commodity within the Indonesian agricultural landscape, contributing to several significant domains: (a) soybeans constitute the foundational ingredient in widely consumed food products such as tempeh, tofu, soy sauce, and tauco, which are essential components of the Indonesian dietary regimen; (b) soybeans act as a vital source of plant-derived protein, particularly for individuals who restrict their consumption of animal-based proteins; and (c) soybeans are also utilized within the animal

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husbandry sector, especially for the formulation of poultry feed.

Despite the characterization of soybeans as a strategic commodity, the domestic production levels remain inadequate to satisfy the national demand. The principal regions engaged in soybean cultivation within Indonesia encompass: (a) Central Java, East Java, and West Java: These areas make substantial contributions to the national soybean output owing to their advantageous soil and climatic conditions; and (b) Sumatra and Sulawesi: While these regions possess considerable potential for soybean cultivation, the actual production remains limited, frequently yielding to more economically lucrative crops such as rice and maize.

Soybeans hold a significant position in the context of national development (Director General of Food Crops, 2022), with their contribution to the Gross Domestic Product (GDP) exhibiting a consistent increase on an annual basis, even amidst periods of economic downturn (Zubachtirodin, 2022). As a critical staple crop within Indonesia, soybeans, in conjunction with rice and maize, have been prioritized by the Ministry of Agriculture in its initiatives aimed at attaining food self-sufficiency.

Soybeans are extensively utilized for a myriad of applications, encompassing both human consumption and the production of livestock feed. Furthermore, soybeans have been embraced as a viable alternative fuel source on both a national and global scale (Director General of Food Crops, 2022). The sustained demand for soybeans can be attributed to their function as essential raw materials within the food processing and animal feed sectors (Panikkai *et al.*, 2017). The Ministry of Agriculture identifies five key commodities—soybeans, rice, sugar, and beef—as fundamental dietary staples for the nation (Ministry of Agriculture, 2022).

As the second most vital agricultural commodity subsequent to rice, the elevated demand for soybeans for both livestock feed and industrial applications engenders numerous challenges, including the depletion of natural resources and the ramifications of climate change. Collaborative efforts and cooperative initiatives are paramount to facilitate the sustainable advancement of soybean commodities (Nurliza *et al.*, 2020). Nevertheless, the restricted availability of arable land constitutes a considerable obstacle for soybean cultivation in Indonesia.

In the early 2000s, Indonesia's soybean production encountered a multitude of obstacles. The output progressively diminished throughout the decade as a result of various determinants: (a) Land conversion: A significant portion of agricultural land was reallocated for the establishment of plantations and residential developments; (b) Low productivity: The inadequate utilization of superior seed varieties and suboptimal agricultural practices contributed to a reduction in yield; and (c) Dependence on imports: With domestic demand exceeding local production capabilities, Indonesia commenced the importation of substantial quantities of soybeans, thereby diminishing the incentives for local agricultural producers.

From 2010 to 2015, the Indonesian government implemented a series of policies aimed at enhancing soybean production, which included: (a) Agricultural intensification programs: In order to elevate per-hectare productivity, the government facilitated access to superior seeds and fertilizers; and (b) Land expansion initiatives: Concerted efforts were undertaken to augment the land area allocated for soybean cultivation. Nonetheless, despite these initiatives, soybean production did not exhibit substantial enhancement owing to deficiencies in agricultural infrastructure and a scarcity of investment within the soybean sector.

Forecasting encompasses the systematic estimation of prospective requirements, which includes the quality, timing, and geographical distribution of goods necessary to satisfy demand (Sinaga and Irawati, 2018). It constitutes both an art and a science aimed at anticipating occurrences that have yet to transpire, utilizing historical data as a foundational resource (Montgomery *et al.*, 2008; Yuniastari and Wirawan, 2017). As an integral element of the decision-making process, forecasting plays a pivotal role in the anticipation of future occurrences to facilitate effective decision-making methodologies (Evans, 2003; Heizer and Render, 2011). The challenge posed by inaccuracies in forecasting results remains a persistent issue (Sinaga and Irawati, 2018).

The domains of time series analysis and forecasting have emerged as prominent fields of academic inquiry (Zheng and Zhong, 2011). The precision of time series forecasting is integral to the processes involved in decision-making. A multitude of methodologies is utilized in forecasting, encompassing time series techniques that are classified into moving averages (Single Moving Average (SMA) and Double Moving Average (DMA)), smoothing methodologies (Single Exponential Smoothing (SES), as well as Brown and Holt's double exponential smoothing), and regression approaches, including time series regression (Makridakis *et al.*, 1998; Makridakis *et al.*, 2000; Hyndman and Athanasopoulos, 2019).

Forecasting methodologies exhibit variability; however, their selection is predicated on the underlying patterns within the data. Generally, three predominant methodologies are employed to ascertain error rates. These methodologies encompass Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), which serve to compute mean absolute deviations, mean square errors, and mean absolute percentage errors, respectively (Sukarti, 2015). In the application of time series methodologies, it is imperative to discern data patterns, which may encompass trends, cycles, seasonality, and horizontal fluctuations (Hanke and Dean, 2014).

Numerous statistical software applications facilitate the selection of forecasting methodologies. A multitude of analysts have employed forecasting models utilizing software to streamline computational processes (Prakoso *et al.*, 2021). For instance, the POM-QM software has been utilized to project product sales (Kristiyanti and Sumarno, 2020). The POM (Production and Operations Management) software is specifically engineered to address quantitative management challenges associated with production and operations. Its user-friendly interface renders POM for Windows an indispensable instrument within decision-making frameworks.

This research endeavors to formulate a predictive model for soybean commodity productivity within the Indonesian context, employing the Production and Operation Management-Quantitative Method (POM-QM) software, with the objective of delivering precise forecasts that can facilitate strategic decision-making processes pertinent to soybean cultivation and food security strategy formulation.

MATERIALS AND METHODS

The research employed annual data pertaining to soybean production spanning the years 2000 to 2024. This data, depicted in a time series format, was sourced from secondary references, specifically the Data and Information Center (Pusdatin) affiliated with the Ministry of Agriculture and the Central Statistics Agency (BPS). The demographic for this investigation included soybean production statistics for the complete duration from 2000 to 2024. A saturated sampling technique was implemented, indicating that all accessible data from the population was incorporated as samples.

Quantitative forecasting of soybean commodity production in Indonesia

***A. Quantitative forecasting of soybean commodity production with DMA*:** The double-moving average methodology forecasts time series data that demonstrates a linear trend (Hanke and Dean, 2014). This technique, which is also referred to as multiple or linear moving averages, is appropriate for time series data that adheres to a linear trajectory. Furthermore, the double-moving average methodology extends the concepts of single-moving average data, incorporating modifications between the initial and subsequent moving averages alongside adjustments in trend (Hudiyanti *et al.*, 2019).

The Direct Moving Average (DMA) represents a systematic approach through which the initial and subsequent moving average cohorts are computed. This concept is denoted by the notation ($k \times k$), signifying that the computation of the moving average is performed over the span of k periods (Makridakis *et al.*, 2000). Furthermore, the moving average technique lacks a definitive empirical foundation for establishing the quantity of moving average orders (Hatimah *et al.*, 2013).

Numerous methodologies can be employed in the realm of forecasting, including the method known as DMA. The dataset utilized for the computations is devoid of constituent's indicative of trend or seasonality. DMA constitutes a forecasting technique that is executed on historical data spanning two periods exhibiting an average pattern (Oktarini *et al.*, 2017), which is deemed appropriate for longitudinal datasets (Astuti *et al.*, 2019). The mathematical formulation of DMA is delineated in Equation 1:

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

Information:

F_{t+1} = Forecast for period t+1

X_T = True value of t period

T = Timeframe of moving average

The analytical procedure for data interpretation within the forecasting model pertaining to soybean commodity yield utilizing the DMA methodology comprises several stages, which include:

Identifying patterns within time-series data. Calculating the value of the initial moving average. Calculating the value of the subsequent moving average. Calculating the value of the constant. Calculating the value of the trend coefficient (bt). Selecting the optimal model based on established criteria for forecasting precision. Estimating forecast outcomes for forthcoming periods. The data analysis was executed utilizing POM-QM software to enhance the computational efficiency of the process.

***B. Quantitative forecasting of soybean commodity production with WMA*:** The Weighted Moving Average (WMA) forecasting methodology enhances the traditional moving average technique by integrating weights into the computational framework. This methodology allocates increased significance to particular values within a dataset based on their inherent characteristics. In contrast to a simple average, wherein all values are regarded with equal importance, WMA computes the average by applying diverse weights to each individual data point. Fundamentally, WMA represents a sophisticated variant of the moving average approach, whereby each element within the time series is assigned a unique weight (Handoko, 1999). To put it more plainly, WMA modifies the moving average by applying weights to each data point (Aritonang, 2002).

The determination of weight is inherently subjective, hinging upon the expertise and perspectives of the data analyst. For example, the analyst might ascribe greater significance to the most recent observation or, conversely, to earlier data points. The weighted factor will exhibit an increased magnitude in the concluding period relative to the initial period, particularly when the opportunity for weighting was more pronounced in the prior observation. As the duration under consideration extends, the emphasis placed on the most contemporary data intensifies, with the number of weighted opportunities equating to one (Eris *et al.*, 2014). Ultimately, the equation employed in the forecasting model for soybean commodity production utilizing Weighted Moving Average (WMA) is delineated in Equation 2.

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

Information:
k number of periods or ranges of forecasting numbers,
X_t is the time series data value at point t.

***C. Quantitative forecasting for soybean commodity production with SES*:** Single Exponential Smoothing (SES) represents a fundamental methodology that necessitates the estimation of a singular parameter. It employs Exponential Moving Average (EMA) weights across all historical data points. This forecasting methodology systematically refines the prognostic outcome by exponentially averaging antecedent values within a time series framework, thereby achieving a smoothing effect on the results and enhancing accuracy over successive iterations (Indrajit and Djokopranoto, 2003; Siregar *et al.*, 2017; Tularam and Saeed, 2016).

Simple Exponential Smoothing (SES) is suitable for datasets that do not exhibit significant trends and is predominantly utilized for predicting values for a single future period. The primary objective is to assess the existing level and apply it to forecast prior values. The forecasting model utilized for soybean production through SES incorporates the mathematical expression delineated in equation 3 (Makridakis *et al.*, 2003).

$$F_{t+1} = \alpha.X_t + (1-\alpha)\,F_t \tag{3}$$

Information:
Ft+1 represents the prognostication for the subsequent period, α denotes the smoothing coefficient, Xt signifies the t-th data point or observation, and Ft corresponds to the t-th period's data. The forecast Ft+1 is derived from the amalgamation of the most recent Xt observation, weighted by α, and the latest forecasting value Ft, weighted by 1-α. By iteratively applying this methodology and substituting Ft+1 and Ft+2 with their respective constituents, the resultant expression in Equation 4 is achieved:

$$\begin{aligned} F_{t+1} &= \alpha.X_t + (1-\alpha)\,F_t \\ &= \alpha.X_t + (1-\alpha)(\alpha.X_{t+1} + (1-\alpha)\,F_{t+1}) \\ &= \alpha.X_t + \alpha(1-\alpha)X_{t+1} + (1-\alpha)^2\,F_{t+1} \\ &= \alpha.X_t + \alpha(1-\alpha)X_{t+1} + \alpha(1-\alpha)^2\,F_{t+1} \end{aligned} \tag{4}$$

Therefore, Ft+1 represents the Weighted Moving Average (WMA) derived from the entirety of historical data. As the value of t increases, the magnitude of $(1–\alpha)^2$ diminishes, resulting in a reduced contribution from F(1). Given that F1 remains unknown, an initial approximation can be formulated. In scenarios characterized by volatile initial data, one effective approach entails setting the inaugural forecast equal to the first observation, denoted as F1=y1. Moreover, for initial data exhibiting considerable constancy, the mean of the initial five or six data points may be employed as the first forecast: F1=MA(5) or F1=MA(6). The exponential smoothing formula can be restructured to elucidate the function of the weighting factor α, as illustrated in Equation 5:

$$Ft+1 = Ft + \alpha(X1 - Ft) \tag{5}$$

Exponential smoothing serves the purpose of modifying a preceding forecast (Ft) through the incorporation of adjustments that account for forecasting errors. The parameter α, which is constrained within the interval (0, 1), must not take on the values of 0 or 1. In order to achieve a stable forecast characterized by random smoothing, it is advisable to employ a diminutive α value for datasets that exhibit minimal fluctuation. Conversely, a larger α value is deemed more suitable for datasets that display considerable variability and necessitate a rapid adaptation to alterations. To identify the most effective α value, one may employ a trial-and-error method, evaluating values of 0.1, 0.2, 0.3, ..., 0.9, and subsequently selecting the value that yields the lowest Mean Squared Error (MSE) for the subsequent forecast.

***Selection of the best model for forecasting production of soybean commodities*:** The precision of computations within the forecasting methodology frequently experiences fluctuations due to variations in data patterns. Consequently, the selection of an appropriate method is crucial in order to reduce inaccuracies in the forecasting outcomes (Prabowo and Aditia, 2020). Each methodology possesses a specific level of accuracy that warrants careful consideration. Thus, it is vital to select a method that effectively mitigates forecasting inaccuracies. As posited by Chopra and Meindl (2016); Athanasopoulos *et al*. (2017), forecast metrics are anticipated to exhibit minimal values and associated errors. The magnitude of the error is inversely correlated with the precision of the predictive outcomes.

The determination of the most appropriate forecasting model is contingent upon the resultant error. Several criteria that are frequently employed to assess the precision of the model's forecasting of time series data encompass: (a) Mean Absolute Deviation (MAD), (b) Mean Square Error (MSE), and (c) Mean Absolute Percent Error (MAPE). A diminished criterion value correlates with enhanced predictive outcomes (Render and Heizer, 2009; Kima and Kimb, 2016).

A. MAD: The methodology for ascertaining the total forecast deviation is represented by the Mean Absolute Deviation (MAD), which is derived by calculating the quotient of the aggregate of the absolute values of each individual error and the sample size (defined as the number of forecast intervals) (Render and Heizer, 2009; Hudaningsih *et al.*, 2020). Ultimately, the mathematical representation of MAD is delineated in Equation 6:

$$MAD = \frac{\sum_t^n \ (At-Ft)}{n} \tag{6}$$

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

B. MSE: The Mean Squared Error (MSE) is determined by summing the squares of all discrepancies observed in each time interval and subsequently dividing this total by the quantity of forecasting intervals (Render and Heizer, 2009; Hudaningsih *et al.*, 2020). The mathematical representation of MSE is delineated in Equation 7:

$$\text{MSE} = \sum_t^n |At - Ft|^2 \tag{7}$$

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

C. MAPE: Mean Absolute Percentage Error (MAPE) serves as a quantitative metric utilized for the assessment of forecasting accuracy (Kima and Kimb, 2016; Thitima and Apidet, 2018; Farizal *et al.*, 2021). This particular metric was chosen as the evaluative criterion for the present study owing to its capability to precisely appraise various forecasting methodologies (Tratar and Srmcnik, 2016; Booranawong and Booranawong, 2017). The utility of MAPE is particularly noteworthy as it remains unaffected by the scale of the projected time series data (Gentry *et al.*, 1995; Alon *et al.*, 2001).

Furthermore, it is frequently employed in practical applications (Ravindran and Warsing, 2013), maintains independence from scale, and possesses an uncomplicated interpretative framework, which enhances its appeal among professionals in the industry (Chatfield, 2001; Byrne, 2012). The Mean Absolute Percentage Error (MAPE) quantifies the mean of absolute discrepancies expressed as a percentage of the mean absolute error rate corresponding to the actual data interval. The formal mathematical representation is delineated in Equation 8:

$$MAPE = \frac{(100)}{n} \sum_{t}^{n} \frac{(At-Ft)}{[n]} \qquad (8)$$

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

The Mean Absolute Percentage Error (MAPE) quantifies the mean absolute deviations expressed as a proportion of the mean total error rate associated with the actual data period. The established criteria indicate that a lower MAPE value corresponds to enhanced accuracy. Table 1 presents the evaluative criteria (Chang *et al.*, 2007).

Table 1. Mape value criteria.

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

***Production data processing of soybean commodities is carried out using POM-QM software*:** The subsequent phase entails a comprehensive examination and systematic processing of the data pertinent to soybean commodity production. The POM-QM software was employed to manage the production data for soybeans spanning the years 2004 to 2024. A variety of forecasting methodologies accessible within the POM-QM application were implemented on this dataset, yielding the expected predictive outcomes.

To utilize the POM-QM software to forecast the productivity of soybean commodities, the procedural steps that must be adhered to are: (a) initiating the QM program and electing the module designated for forecasting; (b) navigating to the menu option File-New-Time Series Analysis, which will trigger the appearance of a dialogue box labeled "Create Data Set for Forecasting/Time-Series Analysis"; (c) within the aforementioned dialogue box, it is imperative to input the title of the forecast, "Production of Soybean Commodities," in conjunction with specifying the total number of time series data periods to be utilized as training data, commencing from the year 2000 and concluding in 2024.

Furthermore, it is essential to designate a name for each row's period, which may consist of numerical values, alphabetical characters, or designated months. Upon the completion of these outlined steps, it is necessary to select the OK button. The data configuration settings within QM for Windows are illustrated in Figure 1.

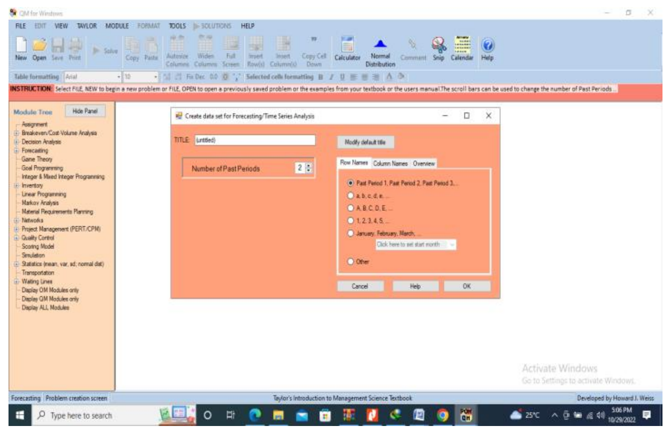

Figure 1. Data settings in QM for windows.

Forecasting is of paramount importance for organizations as it facilitates the management of production processes, inventory levels, and strategic planning decisions (Pennings and Van Dalen, 2017). As articulated by Fong *et al*. (2019), it is imperative to transcend reliance on a singular forecasting model. A diverse array of forecasting models ought to be evaluated to achieve the most precise predictions. The forecasting outcomes for soybean production derived from each methodology are subsequently aggregated and scrutinized for their accuracy. Hence, the selection of an appropriate forecasting methodology is critical, given that the utilization of a suboptimal model may compromise the accuracy of the forecast.

RESULTS AND DISCUSSION

***A. Quantitative forecasting of soybean commodity production with DMA*:** The Direct Moving Average (DMA) represents a predictive analytic technique that involves aggregating soybean commodity production data from the two preceding time periods and subsequently dividing the resultant sum by two. Alternatively, this method can be executed by computing the arithmetic mean of soybean commodity production data from the two prior periods (Hanke and Dean, 2014). The outcomes derived from the moving average forecasting are illustrated in Table 2.

Table 2. Calculation of the double moving average forecast at soybean commodity production.

Measure	Value
Error Measures	
MAPE (Mean Absolute Percent Error)	21.24%
Forecast	
next period	567.3Tons

In accordance with the application of the Data Mining Algorithm (DMA) to predict the production of soybean commodities, Table 2 illustrates the outcomes of the mean absolute percent error, which is recorded at 21.24%. Figure 2 delineates the forecasting graph representing the production trajectory of soybean commodities utilizing this methodological approach.

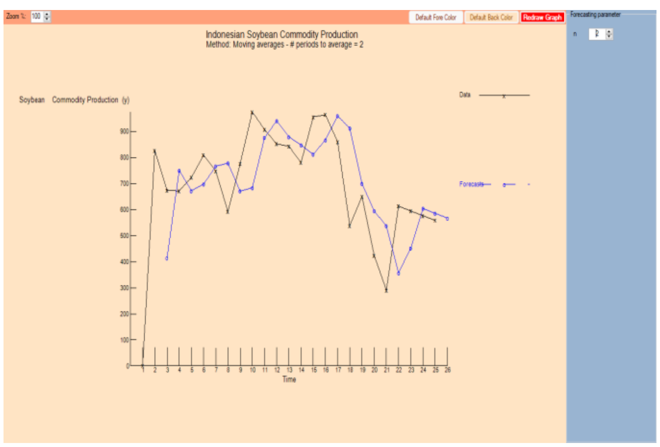

Figure 2. Forecasting graph with the double moving average method on production commodity soybean.

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

***B. Quantitative forecasting of soybean commodity production with WMA*: ** The Weighted Moving Average (WMA) 2 methodology is executed by allocating weights to soybean commodity production data accumulated over the preceding two years. The initiation of soybean commodity production forecasting commenced in the temporal span from 1980 to 2019 (Chang *et al.*, 2007). The procedural intricacies associated with the computation of this forecasting technique are delineated in Table 3.

Table 3. Forecasting the weighted moving average on production commodity soybean.

Measure	Value
Error Measures	
MAPE (Mean Absolute Percent Error)	17.89%
Forecast	
next period	558,3 Tons

According to the Weighted Moving Average (WMA) employed for predicting soybean commodity production, Table 3 delineates the findings of the mean absolute percent error, which is calculated at 17.89%. Figure 3 illustrates the forecasting graph utilizing WMA for the production of soybean commodities.

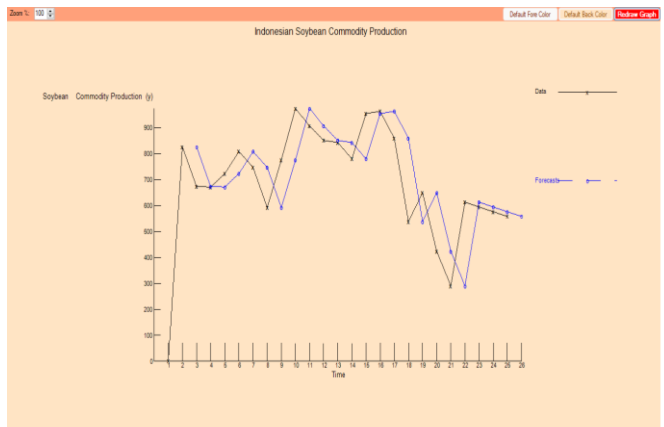

Figure 3. Forecasting graph with the weighted moving average method at soybean commodity production.

According to Figure 3, the predictive outcomes for soybean commodity production employing Weighted Moving Average (WMA) exhibit a marginal elevation as the period concludes in contrast to the results derived from the Double Moving Average (DMA).

***C. Quantitative forecasting of soybean commodity production with SES*: ** To ascertain the projections of soybean commodity production utilizing Simple Exponential Smoothing (SES), the α coefficient is initially established. This is accomplished by multiplying α with the actual demand figures. Subsequently, the resultant value is augmented by the product of (1 minus α) and the soybean commodity production forecast from the preceding period. For the purposes of this model, the value of α is postulated to be 0.5. The methodology of forecasting via SES is elucidated in Table 4.

Table 4. Forecasting single exponential smoothing at soybean commodity production.

Measure	Value
Error Measures	
MAPE (Mean Absolute Percent Error)	24.39%
Forecast	
next period	262, 26 Tons

Table 4 illustrates that the outcomes derived from the forecasting of soybean commodity production utilizing Simple Exponential Smoothing (SES) yield a mean absolute percentage error of 24.39%. Figure 4 presents the graphical representation of the SES forecasting.

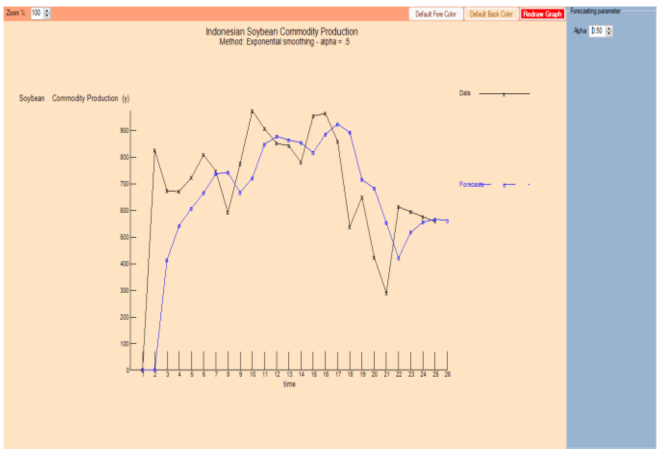

Figure 4. Forecasting graph with the single exponential smoothing method on soybean commodity production.

Figure 4 illustrates that the predictive outcomes concerning soybean commodity production derived from the Weighted Moving Average (WMA) methodology demonstrate a greater degree of stability in comparison to the Simple Exponential Smoothing (SES) technique (Pennings and Van Dalen, 2017).

Table 5. The value of the size of the error in the forecasting model for the production of soybean commodities.

Metode	error measurement values
	MAPE
Double Moving Average	21.24%
Weighted Moving Average	17.89%
Singel Exponential Smoothing	24.39%

Table 5 delineates the projected production of soybean commodities utilizing methodologies including (a) Double Moving Average (DMA), (b) Weighted Moving Average (WMA), and (c) Simple Exponential Smoothing (SES) for the forthcoming year. The dataset employed in this analysis encompasses a comprehensive span of 24 years of production data, specifically from the year 2000 to 2024 (Aritonang, 2002).

The examination illustrated in Table 4 evaluates the error rates associated with three distinct methodologies for predicting soybean output. According to the findings, the Weighted Moving Average (WMA) exhibits superior performance relative to the alternative methods, achieving a Mean Absolute Percentage Error (MAPE) of 17.89%, which is notably proximate to zero. Consequently, WMA is selected as the preferred approach for forecasting soybean commodity output (Chatfield, 2001; Byrne, 2012). The projected values for the subsequent period are delineated in Table 6.

Table 6. Value of soybean commodity production forecasting size next period.

Metode	Forecast accuracy measures for the subsequent period (Tons)
Double Moving Average	567.3
Weighted Moving Average	558,3
Singel Exponential Smoothing	562, 26

Table 6 elucidates that the projected output of soybean commodities for the forthcoming period totals 588.3 tons. This suggests that soybean commodity production in Indonesia is anticipated to meet the complete consumer demand.

The government is advised to utilize these projections to effectively anticipate and plan for future national soybean demand. Additionally, this study could strengthen policy recommendations with specific interventions such as providing subsidies, increasing investment in research and development, and promoting sustainable agricultural practices. These policy recommendations have the potential to enhance food security and encourage more sustainable soybean production in Indonesia (Ravindran and Warsing, 2013).

The limitations of this study include the availability of data spanning only from 2000 to 2024, which may not encompass all factors influencing soybean production, such as policy changes, climate trends, or soil condition variations across different regions. The complexity of the agricultural system also poses a challenge, as soybean production is affected by numerous external factors, including climate change, market price fluctuations, and the unpredictable dynamics of supply and demand (Handoko, 1999).

***Conclusion*:** The objective of this research is to forecast the production outcomes of soybean commodities employing the following methodologies: (a) Double Moving Average, (b)

Weighted Moving Average, and (c) Single Exponential Smoothing, for the forthcoming year, spanning the period from 2000 to 2024. The chosen methodology, specifically the Weighted Moving Average technique, exhibits a diminished error rate in comparison to alternative forecasting models, with a Mean Absolute Percentage Error (MAPE) value of 17.89%. The projected model for soybean commodity production indicates a total output of 558.3 tons, suggesting that soybean production in Indonesia is anticipated to adequately satisfy the entirety of consumer requirements for soybean commodities. The findings of this investigation are intended to provide valuable insights to governmental entities in estimating the forthcoming production levels of soybean commodities, in alignment with national soybean demand.

***Authors' contributions*:** All contributors played a pivotal role in the formulation and design of the study. Dhian Herdhiansyah undertook the responsibilities of data acquisition, analytical evaluation, and the composition of the manuscript. La Ode Alwi was instrumental in the development of the model and the interpretation of data. Asriani engaged in the review and enhancement of the manuscript. Each author reviewed and granted their approval for the final version of the manuscript.

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***Ethical statement*:** This manuscript does not encompass any investigations involving human participants or animals conducted by any of the authors.

***Availability of data and material*:** The data and materials utilized in this investigation can be obtained from the corresponding author upon a reasonable request.

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***Informed consent*:** Written informed consent was obtained from all participants regarding publishing their data and photographs

***Consent to participate*:** Not applicable, as there were no human subjects involved in this research.

***Consent for Publication*:** All authors have provided their consent for the publication of this manuscript.

***SDGs addressed*:** Zero Hunger, Responsible Consumption and Production.

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