Research Article

Comparative Evaluation of Quantitative Forecasting Models for Soybean Harvest Area Prediction in Indonesia Using POM-QM Software

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Abstract | Soybean is a strategic agricultural commodity in Indonesia, contributing to both national food security and rural economic stability. However, fluctuations in harvested area have constrained domestic supply, leading to persistent dependence on imports. Accurate forecasting of soybean harvested area is therefore crucial for evidence-based policy formulation and agricultural planning. This study applies three quantitative time-series models Double Moving Average (DMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES) using POM-QM software to forecast soybean harvested area in Indonesia during 2000-2024. Model performance was evaluated using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The DMA model demonstrated the highest predictive accuracy, yielding a MAPE of 15.394%. The forecast projects the soybean harvested area to reach approximately 318.355 thousand hectares, indicating moderate potential to meet domestic demand. The results highlight the importance of adopting quantitative forecasting tools in national agricultural systems to improve policy design, optimize land allocation, and enhance resilience against global market volatility. This study provides a replicable methodological framework that supports Indonesia's long-term strategy for achieving soybean self-sufficiency and sustainable food security.

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Introduction

Food security remains one of the most pressing global challenges, particularly for developing nations where agriculture functions as both an economic foundation and a source of livelihood. Ensuring access to sufficient, safe, and nutritious food is vital for maintaining human welfare and political stability. In the context of Indonesia, food security has long been regarded as a cornerstone of national resilience and economic sovereignty. It reflects a multidimensional concept encompassing not only food availability and accessibility but also nutritional quality and sustainability (Asriani and Herdhiansyah, 2019, Herdhiansyah *et al*., 2022). Consequently, any disruption in food systems whether due to climate shocks, market volatility, or policy misalignment can have profound implications for social stability and economic growth.

Soybean (*Glycine max* L.) plays a strategic role in global and national food systems. As one of the most important legume crops worldwide and among the top five major food commodities, soybean serves as a primary source of plant-based protein, essential minerals, and vegetable oil (Jan *et al*., 2025; Altaf *et al*., 2023). In Indonesia, soybean is a key raw material for staple foods, animal feed, and increasingly for biofuel production, making its availability and productivity critically important for food security and agro-industrial development.

Despite its significance, soybean productivity is frequently constrained by a range of abiotic and biotic stresses. Drought, salinity, pest infestations, and other environmental pressures remain major limiting factors that adversely affect soybean growth, physiology, and yield stability (Altaf *et al*., 2023; Altaf *et al*., 2024). These challenges are further exacerbated by climate change, which increases the frequency and intensity of extreme weather events, thereby amplifying production risks. Addressing these constraints is therefore essential to enhance soybean resilience, secure sustainable yields, and support long-term food security strategies, particularly in developing agricultural economies such as Indonesia.

The Indonesian government explicitly recognizes food as a basic human right, as mandated by Law No. 18 of 2012 on Food. This legal framework aligns with the Sustainable Development Goals (SDGs), particularly Goal 2: *Zero Hunger*, which emphasizes eradicating hunger, achieving food security, improving nutrition, and promoting sustainable agriculture. The government's commitment extends to strengthening national agricultural productivity through policies aimed at self-sufficiency and rural development. However, the effectiveness of these programs largely depends on the optimal utilization of natural resources and the adoption of adaptive management strategies that account for the ecological and socioeconomic diversity across Indonesia's regions (Herdhiansyah *et al*., 2012; Herdhiansyah and Asriani, 2018; Herdhiansyah *et al*., 2021; Herdhiansyah *et al*., 2022).

Among Indonesia's strategic food commodities, soybean (*Glycine max*) holds a unique position due to its nutritional, economic, and industrial significance. It serves as a primary source of plant-based protein and an essential raw material for food industries producing tofu, tempeh, soy sauce, and *tauco*, which are integral to the Indonesian diet (Panikkai *et al*., 2017). Additionally, soybeans are a critical component in livestock feed production and have been increasingly explored as a potential raw material for biofuel (Director General of Food Crops, 2022). These multiple functions position soybean as a vital commodity that underpins both household food consumption and broader agro-industrial development.

Despite its importance, domestic soybean production in Indonesia has consistently lagged behind national demand. The harvested area for soybean has exhibited a long-term decline, driven by factors such as limited arable land, land-use competition with rice and maize, and declining soil fertility. Fragmented land tenure, low adoption of high-yield varieties, and inadequate mechanization further constrain productivity. As a result, Indonesia's dependence on imported soybeans has intensified exceeding 70% in recent years (Ministry of Agriculture, 2024). This reliance exposes the nation to global price volatility, currency fluctuations, and supply chain disruptions, thereby undermining food sovereignty and economic resilience (Zubachtirodin, 2022).

Government efforts to revitalize soybean production through programs such as the Gerakan Nasional Penanaman Kedelai (Gernas Kedelai) and agricultural intensification between 2010 and 2015 yielded only modest results (Nurliza *et al*., 2020). While these initiatives aimed to expand land area and improve yields through better seed distribution and fertilizer access, persistent structural challenges such as limited infrastructure, weak extension services, and insufficient private sector participation continued to hinder large scale progress. Addressing these issues requires not only technical interventions but also data-driven planning to better understand production dynamics and anticipate future trends.

Forecasting serves as a fundamental decision-support tool in agricultural management, providing a quantitative foundation for planning and policy formulation. It allows policymakers to anticipate production levels, allocate resources efficiently, and design adaptive strategies in response to changing climatic, market, and policy conditions (Sinaga and Irawati, 2018; Montgomery *et al*., 2008; Yuniastari and Wirawan, 2017; Asriani *et al*, 2025). In agricultural forecasting, time-series methods such as moving averages, exponential smoothing, and regression-based techniques are among the most widely applied due to their balance between simplicity and interpretability (Makridakis *et al*., 1998; Makridakis *et al*., 2000; Hyndman and Athanasopoulos, 2021).

Recent advancements in forecasting have emphasized the importance of accuracy metrics such as Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) in evaluating model reliability (Sukarti, 2015; Hanke and Dean, 2014; Asriani *et al*., 2023). Statistical tools such as Production and Operations Management Quantitative Methods (POM-QM) software have made it easier for researchers to implement these models efficiently (Kristiyanti & Sumarno, 2020; Prakoso *et al*., 2021; Herdhiansyah *et al*, 2025). POM-QM provides a user-friendly interface for comparing forecasting approaches, simplifying the computation process, and generating reliable results even in data-limited environments making it particularly suitable for developing-country applications.

However, within the context of Indonesia's agricultural system, research focusing on quantitative forecasting of soybean harvested area remains limited. Previous studies have primarily relied on classical regression and ARIMA-based models (Prakoso *et al*., 2021), which, while statistically robust, often require extensive data preprocessing and parameter optimization. Simpler methods such as Double Moving Average (DMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES) offer more practical and transparent alternatives that remain underexplored for key commodities like soybean. Hence, there is a clear need to evaluate these methods' performance in modeling Indonesia's soybean production dynamics and to integrate forecasting outcomes into agricultural policy design.

To address this research gap, the present study applies three time-series forecasting methods DMA, WMA, and SES to estimate Indonesia's soybean harvested area for the 2000–2024 period using POM-QM software. The accuracy of each model is evaluated using MAD, MSE, and MAPE as comparative performance indicators. The objectives of this research are threefold: (1) to conduct a comparative evaluation of simple yet effective forecasting models within a decision-support framework; (2) to generate empirical insights into long-term trends in soybean harvested area; and (3) to provide policy relevant recommendations for enhancing national food security through sustainable, data-driven agricultural planning.

Materials and Methods

Study context and data sources

This study focuses on soybean (*Glycine max*) production systems in Indonesia, where the commodity is classified as one of the nation's five priority food crops alongside rice, maize, sugar, and beef. The analysis covers the period from 2000 to 2024, representing more than two decades of national agricultural transformation. The research utilizes secondary data derived from two authoritative institutions: (1) the Central Statistics Agency (Badan Pusat Statistik – BPS), and (2) the Data and Information Center (Pusdatin) of the Ministry of Agriculture of Indonesia.

Both data sources provide consistent and validated records of national harvested area, ensuring high temporal comparability. The variable under study is soybean harvested area (thousand hectares) on an annual basis, which serves as a key indicator of production capacity and agricultural resource allocation. The dataset was compiled into a chronological series and treated as a single population. Therefore, a saturated sampling technique was applied, using all available observations (2000–2024) to construct the forecasting models. This approach minimizes selection bias and ensures the representativeness of the national-scale trends.

Forecasting framework

Forecasting was conducted using the Production and Operations Management – Quantitative Methods (POM-QM) software. POM-QM provides an integrated environment for implementing quantitative forecasting methods, error evaluation, and visualization. It was selected for its computational efficiency, intuitive interface, and applicability in developing-country research contexts where access to advanced modeling tools may be limited.

Three forecasting techniques were employed to model and project the soybean harvested area: (a) Double

Moving Average (DMA); (b) Weighted Moving Average (WMA); and (c) Single Exponential Smoothing (SES) These models were selected for their simplicity, interpretability, and suitability for time-series data characterized by moderate linear trends and limited seasonality.

Forecasting models

Double moving average (DMA)

The Double Moving Average (DMA) method is a quantitative forecasting technique designed for time-series data that exhibit a linear trend (Hanke and Dean, 2014). Often referred to as the *multiple* or *linear moving average* approach, this method extends the fundamental principles of the single moving average by incorporating an additional layer of smoothing. The process involves calculating successive moving averages to eliminate short-term fluctuations and better capture the underlying linear trajectory of the data. As such, the DMA method is particularly effective in identifying and projecting patterns where gradual, trend-consistent changes occur over time (Hudiyanti *et al*., 2019).

In practical application, the Direct Moving Average (DMA) operates by systematically computing both the first and second moving averages within a given dataset. The method is symbolically represented as *(k × k)*, indicating that the moving average is computed over *k* consecutive periods (Makridakis *et al*., 2000). However, one inherent limitation of the moving average technique lies in the absence of a universal empirical rule for determining the optimal number of periods or moving average orders to be applied (Hatimah *et al*., 2013). This necessitates careful model calibration and sensitivity analysis to ensure forecasting accuracy and reliability.

The DMA approach has been widely adopted in forecasting studies where data exhibit moderate linear characteristics but lack significant trend or seasonal components. It is particularly suitable for datasets that maintain a consistent average pattern across multiple time periods (Oktarini *et al*., 2017). By employing historical observations across two sequential averaging stages, the DMA effectively smooths random variations and enhances predictive stability, making it especially relevant for longitudinal agricultural datasets (Astuti *et al*., 2019). The mathematical representation of the DMA model is formally expressed in Equation (1).

$$F_{t+1} = \frac{X_1 + X_2 + .. X_T}{T}$$

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 interpreting data within the soybean yield forecasting model based on the Double Moving Average (DMA) methodology involves a structured, multi-stage approach. The process begins with the identification of temporal patterns within the time-series data to determine underlying trends and eliminate irregular fluctuations. Subsequently, the first moving average (M_1) is computed to smooth the raw dataset, followed by the second moving average (M_2) to further refine the representation of the trend component.

Once both moving averages are established, the intercept constant (a_t) and the trend coefficient (b_t) are derived to quantify the linear relationship embedded within the data. These parameters form the foundation for constructing the DMA forecasting equation, which projects future observations based on the identified trend structure. The most suitable forecasting model is then selected according to predefined accuracy criteria, such as Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), ensuring model validity and precision.

Finally, the validated model is utilized to generate forecasts for subsequent periods, providing a quantitative basis for decision-making in soybean production planning. All computational processes and statistical analyses were performed using POM-QM for Windows software, which enhances computational efficiency, facilitates model comparison, and minimizes potential calculation errors inherent in manual operations.

Weighted moving average (WMA)

The Weighted Moving Average (WMA) method represents an advancement over the traditional moving average technique by introducing a system of differential weighting within the computational process. Unlike the simple moving average, which assumes that all observations contribute equally to the forecast, the WMA approach assigns varying levels of importance to each data point according to its relative significance or temporal relevance. In this framework, more recent observations are typically given greater weight, reflecting their stronger influence on current and future trends. Conceptually, the WMA is a refined form of the moving average model in which each element in the time series is multiplied by a specific weight before averaging (Handoko, 1999; Aritonang, 2002).

The determination of appropriate weights within the WMA model is often subjective and depends on the analyst's judgment, domain knowledge, and the objectives of the forecasting task. Analysts may choose to emphasize more recent data points if these are considered more reflective of present conditions, or assign greater weight to earlier observations when historical stability is prioritized. In practice, the magnitude of the weighting factor tends to increase toward the most recent period, allowing the model to respond more sensitively to short-term variations and emerging patterns. As the length of the forecasting horizon expands, this weighting mechanism ensures that contemporary data exert a proportionally greater impact on the predicted values (Eris *et al*., 2014).

Through this dynamic weighting structure, the WMA method enhances the responsiveness and adaptability of the forecasting model, making it particularly effective in contexts characterized by gradual or short-term fluctuations, such as agricultural production systems. Accordingly, the Weighted Moving Average (WMA) forecasting equation applied in this study for estimating soybean harvested area is expressed in Equation (2).

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

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

Single exponential smoothing

The Single Exponential Smoothing (SES) method is one of the most fundamental and widely applied techniques in quantitative forecasting. It requires the estimation of a single smoothing parameter and utilizes exponentially weighted averages across all historical observations. By assigning exponentially decreasing weights to older data points, the method prioritizes recent information while gradually diminishing the influence of earlier values. This weighting mechanism produces a smoothing effect that stabilizes fluctuations and enhances the precision of forecasts over successive iterations (Indrajit and Djokopranoto, 2003; Siregar *et al*., 2017; Tularam and Saeed, 2016).

The SES approach is particularly suitable for time-series datasets that do not exhibit significant trends or seasonal patterns. It is predominantly employed to predict values for a single future period by extrapolating the most recent level of the series. The simplicity of the model, combined with its responsiveness to short-term variations, makes SES highly applicable in agricultural forecasting contexts where data continuity and trend constancy are maintained. Within this framework, the forecasting of soybean harvested area in this study is formulated using the Single Exponential Smoothing (SES) model, mathematically represented in Equation (3) (Makridakis *et al*., 2003).

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

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:

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

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:

$$Ft+1 = Ft + \alpha(X1 - Ft)$$

Exponential smoothing refines each preceding forecast (Ft) by incorporating an adjustment term that reflects the magnitude and direction of the previous forecasting error. The smoothing constant, denoted by α, is restricted to the interval (0,1), ensuring that both historical and recent observations contribute proportionally to the updated forecast. For a forecast to remain stable and exhibit random smoothing behavior, the choice of α plays a critical role in balancing responsiveness and stability.

A smaller value of α is generally recommended when the dataset exhibits minimal variability, as it produces smoother forecasts with reduced sensitivity to short-term fluctuations. Conversely, a larger α is more appropriate for volatile or rapidly changing datasets, allowing the model to adjust more quickly to recent shifts in the data pattern. To determine the most effective smoothing coefficient, a trial and error procedure is typically appliedtesting a range of α values (e.g., 0.1, 0.2, 0.3, …, 0.9) and selecting the one that yields the lowest Mean Squared Error (MSE), thereby ensuring optimal predictive performance for subsequent forecasts.

Model evaluation and forecast accuracy

The accuracy of forecasting computations often fluctuates in response to variations in data behavior and underlying patterns. Consequently, the selection of an appropriate forecasting technique is critical to minimizing prediction errors and ensuring reliable results (Prabowo and Aditia, 2020). Each forecasting method exhibits a distinct level of accuracy depending on its structural assumptions and sensitivity to data variability. Therefore, careful evaluation is necessary to identify the model that most effectively reduces forecasting discrepancies and improves predictive reliability. As emphasized by Chopra and Meindl (2016) and Athanasopoulos *et al*. (2017), an effective forecasting model is characterized by minimal error values, with the magnitude of error inversely related to the precision of its predictions.

The determination of the most suitable forecasting model depends primarily on the quantitative assessment of its associated error metrics. In time-series analysis, three standard criteria are widely applied to evaluate model accuracy: (a) Mean Absolute Deviation (MAD), (b) Mean Squared Error (MSE), and (c) Mean Absolute Percentage Error (MAPE). These measures respectively quantify the average absolute deviation, squared deviation, and relative percentage deviation between actual and predicted values. A lower value for each of these indicators signifies greater forecasting precision and model reliability (Render and Heizer, 2009; Hudaningsih *et al*., 2020; Kima and Kimb, 2016). Accordingly, the model yielding the smallest error metrics is selected as the optimal forecasting approach for subsequent estimation and policy interpretation.

Mean absolute deviation (MAD)

The Mean Absolute Deviation (MAD) is a statistical measure used to quantify the average magnitude of forecast errors in a given dataset. It represents the mean of the absolute differences between the actual and predicted values, thereby providing a direct indication of overall forecast accuracy. The MAD metric is computed by dividing the sum of the absolute values of individual forecast errors by the total number of observations or forecast intervals considered in the analysis (Render and Heizer, 2009; Hudaningsih *et al*., 2020). A lower MAD value signifies a closer correspondence between forecasted and actual outcomes, indicating higher predictive precision. The mathematical formulation of MAD is expressed in Equation (6) as follows:

$$MAD = \frac{\sum_{t}^{n} (At - Ft)}{n}$$

information:

A_t = Actual demand in period t

F_t = Forecasting demand in period t

n = Number of forecasting periods involved

Mean squared error (MSE)

The Mean Squared Error (MSE) serves as a widely recognized statistical indicator for evaluating forecasting accuracy by emphasizing larger deviations through the process of squaring error terms. This metric is obtained by summing the squared differences between actual observations and their corresponding forecasts across all time intervals, followed by dividing the total by the number of forecasting periods under consideration (Render and Heizer, 2009; Hudaningsih *et al*., 2020). Because squaring amplifies the impact of larger errors, the MSE provides a more sensitive measure of forecast dispersion than absolute error metrics. A lower MSE value reflects greater predictive reliability and improved model performance. The mathematical formulation of MSE is expressed in Equation (7) as follows:

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

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

Mean absolute percentage error (MAPE)
The Mean Absolute Percentage Error (MAPE) is a widely adopted statistical measure used to evaluate the accuracy of forecasting models (Kima and Kimb, 2016; Thitima and Apidet, 2018; Farizal *et al*., 2021). This metric was selected in the present study due to its ability to provide a consistent and interpretable evaluation of diverse forecasting methodologies (Tratar and Srmcnik, 2016; Booranawong and Booranawong, 2017). A key advantage of MAPE lies in its scale independence, meaning that it can effectively compare forecasting performance across datasets with varying magnitudes (Gentry *et al*., 1995; Alon *et al*., 2001).

MAPE has gained substantial popularity in both academic and practical forecasting applications owing to its straightforward interpretation and intuitive percentage-based framework (Chatfield, 2001; Byrne, 2012). It quantifies the average magnitude of forecast errors relative to actual observations, expressed as a percentage, thereby enabling direct comparisons between models or datasets regardless of scale differences (Ravindran and Warsing, 2013). The lower the MAPE value, the higher the model's predictive accuracy and stability. The mathematical expression of MAPE is presented in Equation (8) as follows:

$$MAPE = \frac{(100)}{n} \sum_t^n \frac{(At - Ft)}{[n]}$$

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) measures the average absolute deviation as a percentage of the total error relative to actual observations across the analyzed time period. This metric provides an intuitive representation of forecast precision, as it expresses the average forecasting error in percentage terms rather than absolute units. According to established evaluation standards, a lower MAPE value indicates greater forecasting accuracy and improved model reliability. The classification criteria for interpreting MAPE performance levels are summarized in Table 1 (Chang *et al*., 2007).

Table 1: *Mape value criteria*

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

The soybean harvested area data were processed and analyzed using the Production and Operations Management – Quantitative Methods (POM-QM) software package. This analytical phase involved a systematic examination and computational processing of soybean production data spanning the period 2000 to 2024. The POM-QM software was employed to facilitate model implementation, automate calculations, and generate predictive outputs across multiple forecasting techniques available within the program. This approach ensured consistency, computational efficiency, and enhanced reliability of the results.

To conduct forecasting analysis within POM-QM, several procedural steps were followed. First, the QM for Windows application was launched, and the Forecasting module was selected from the main interface. Next, users navigated to the *File → New → Time Series Analysis* option, which prompted the appearance of a dialogue box titled *"Create Data Set for Forecasting/Time-Series Analysis."* Within this configuration window, the dataset was initialized by assigning the title "Harvest Area of Soybean Commodities" and specifying the total number of time-series periods corresponding to the years 2000 through 2024, which served as the training data for the forecasting process.

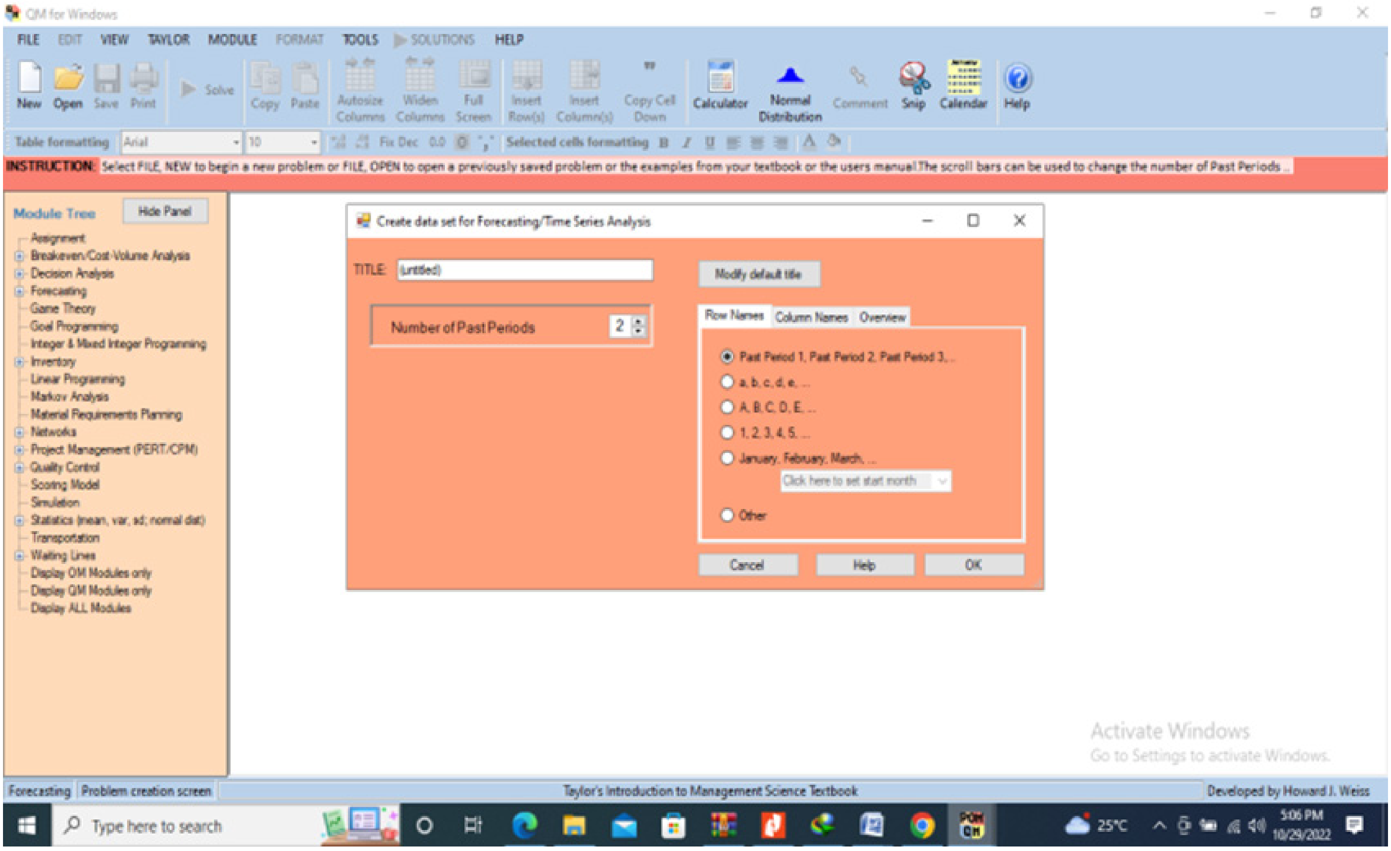

Figure 1: *Data settings in QM for windows*

Additionally, each time period (row entry) was assigned a label representing either numerical identifiers, alphabetical symbols, or corresponding months, depending on the temporal granularity of the dataset. Upon completion of the data configuration, the *OK* command was executed to finalize dataset initialization. The data configuration interface and parameter setup within the POM-QM environment are illustrated in Figure 1, which depicts the structural layout used for forecasting computations in this study.

Forecasting plays a critical role in organizational and agricultural decision-making, as it enables effective management of production processes, harvested area allocation, inventory control, and long-term strategic planning (Pennings and Van Dalen, 2017). Accurate forecasting supports evidence-based policy formulation, resource optimization, and the anticipation of future demand fluctuations, all of which are essential for maintaining production stability and food security.

As emphasized by Fong *et al*. (2020), reliance on a single forecasting model may lead to biased or incomplete results. Therefore, it is imperative to evaluate a diverse set of forecasting methodologies to identify the most accurate and context-appropriate approach. Comparative analysis across multiple models allows researchers to assess predictive reliability and minimize methodological bias.

In this study, the forecasting outcomes for soybean harvested area obtained from different quantitative models were systematically aggregated and assessed for accuracy using established statistical criteria. The selection of the most suitable model is thus crucial, as employing a suboptimal forecasting technique can significantly compromise prediction precision and reduce the reliability of subsequent policy recommendations.

Analytical procedure

The analytical process involved the following stages (Figure 2):

- **Data preparation:** Organizing annual soybean harvested area data (2000–2024).
- **Model construction:** Applying DMA, WMA, and SES models in POM-QM software.
- **Error evaluation:** Comparing MAD, MSE, and MAPE values for each model.
- **Model selection:** Identifying the most accurate model based on the lowest MAPE.

- **Projection:** Estimating the harvested area for the next period (2025) and interpreting policy implications.

Results and Discussion

Quantitative Forecasting of Soybean Harvested Area Using the Double Moving Average (DMA) Method

The Double Moving Average (DMA) method is a time-series forecasting approach that estimates future values by applying a two-stage smoothing process to historical observations. This technique operates by averaging the data from two consecutive periods, thereby producing a forecast that reflects the general direction of the trend rather than short-term fluctuations. In the context of this study, the DMA model aggregates the soybean harvested area data from the two most recent years and divides the total by two, effectively capturing the underlying trend while minimizing random variation.

By emphasizing medium-term movements and filtering out transient irregularities, the DMA method provides a reliable means of detecting and projecting linear patterns within the dataset. This makes it particularly suitable for agricultural forecasting applications, where production data often exhibit gradual yet consistent directional changes. The forecasting results derived from the DMA model are presented in Table 2, offering a comparative summary of the projected and actual soybean harvested area values throughout the study period.

Table 2: *Calculation of the double moving average forecast at soybean commodity harvest area*

Measure	Value
Error Measures	
MAPE (Mean Absolute Percent Error)	15.394%
Forecast	
next period	318.355

Application of the Double Moving Average (DMA) method for forecasting the harvested area of soybean commodities yielded a Mean Absolute Percentage Error (MAPE) of 15.394%, as shown in Table 2. This error rate indicates a *moderate level of forecasting accuracy*, demonstrating that the DMA model is capable of effectively capturing the general trend of soybean harvested area fluctuations while exhibiting minor discrepancies between actual and predicted values. Although the model successfully smooths short-term variability, its capacity to precisely approximate observed data remains limited.

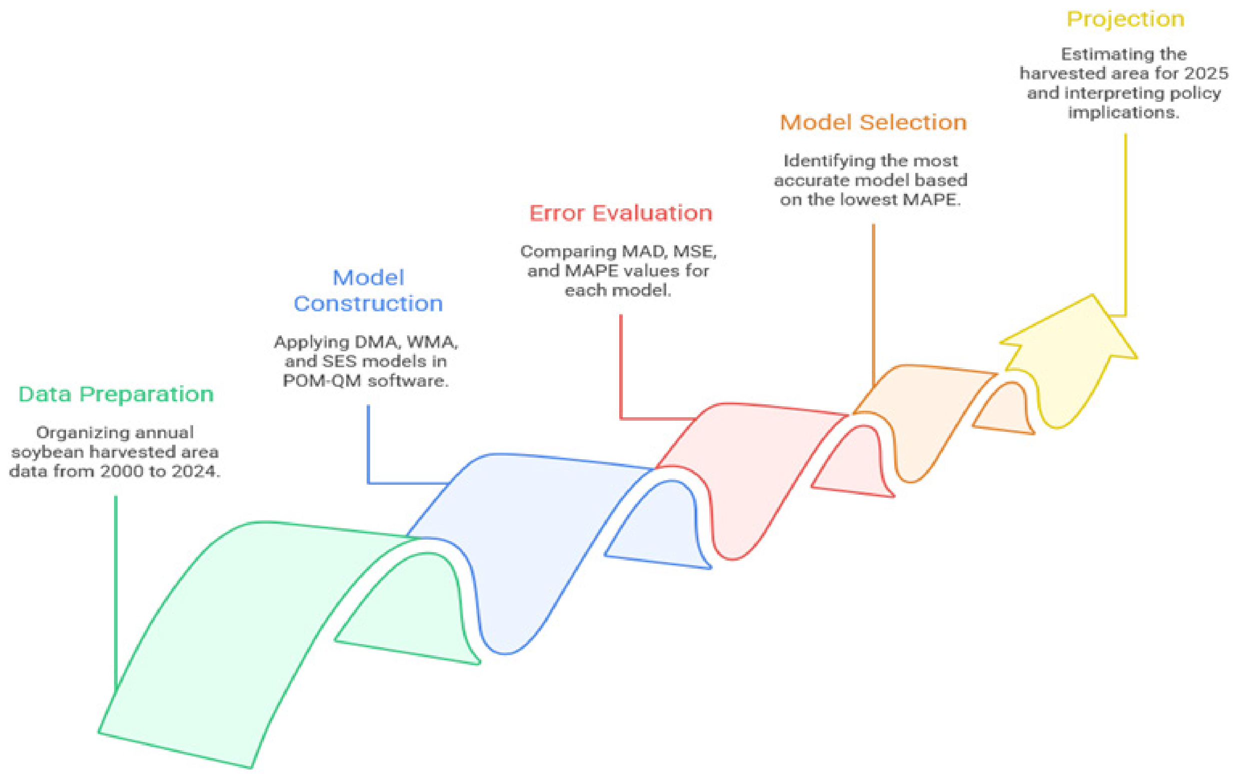

Figure 2: *Analytical procedure*

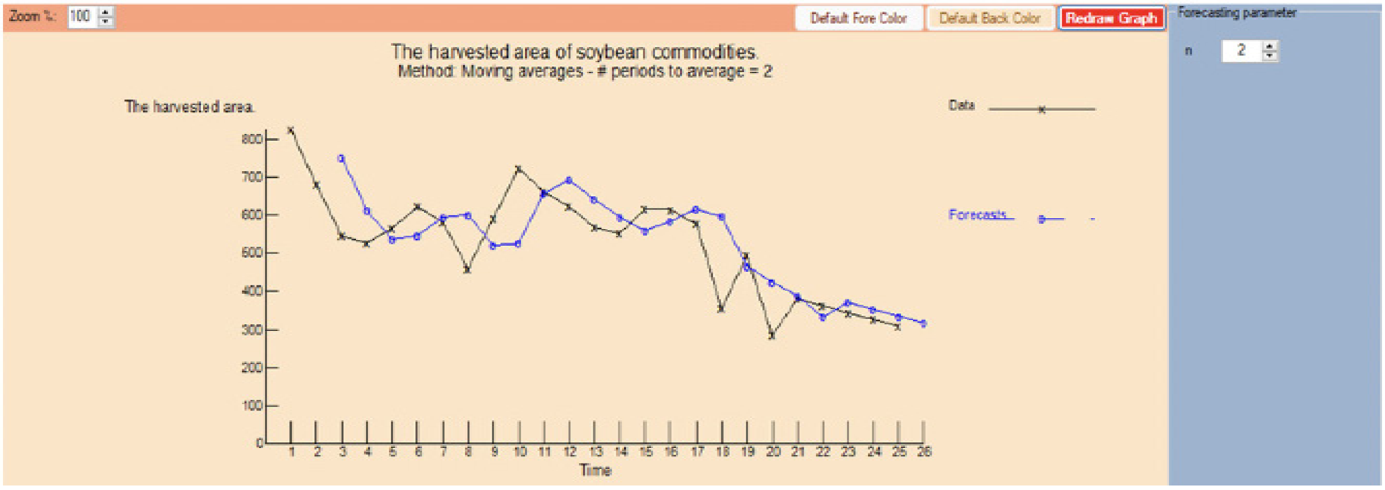

Figure 3: *Forecasting graph with the double moving average method on harvest area commodity soybean*

In agricultural forecasting contexts, a MAPE value below 10% is typically classified as highly accurate, while values between 10% and 20% denote good predictive reliability. Conversely, a MAPE exceeding 20% is generally considered less suitable for precise decision-making (Chang *et al*., 2007). Based on these criteria, the DMA model provides a reasonable yet improvable level of accuracy for national soybean forecasting applications. Consequently, the findings highlight the importance of comparing DMA performance with alternative methods such as the Weighted Moving Average (WMA) and Single Exponential Smoothing (SES) models to identify the most robust and statistically reliable forecasting approach for supporting soybean production strategies and agricultural policy planning in Indonesia.

Figure 3 shows that the forecasting results for soybean commodity Harvest Area from DMA appear different from the actual data.

Table 3: *Forecasting the weighted moving average on harvest area commodity soybean*

Measure	Value
Error measures	
MAPE (Mean absolute percent error)	16.218%
Forecast	
next period	309.849

Quantitative forecasting of soybean harvested area using the weighted moving average (WMA-2) method

The Weighted Moving Average (WMA-2) method was implemented by assigning distinct weights to the harvested area data of soybean commodities from the two preceding time periods. This approach prioritizes more recent observations, acknowledging their greater relevance in reflecting short-term agricultural dynamics. In contrast to the simple moving average, which treats all historical data equally, the WMA technique integrates the principle that recent information typically holds stronger predictive value for forecasting changes in production and land use.

The forecasting analysis employed annual soybean harvested area data covering the period from 2000 to 2024, as summarized in Table 3. By incorporating a differential weighting scheme, the WMA-2 model enhances the responsiveness of forecasts to temporal fluctuations in land allocation and climate variability two critical factors influencing Indonesia's soybean production trends. Consequently, this methodological refinement enables a more adaptive and context-sensitive projection framework, improving the model's applicability for agricultural policy and planning.

Application of the Weighted Moving Average (WMA) method to forecast the harvested area of soybean commodities produced a Mean Absolute Percentage Error (MAPE) of 16.218%, as shown in Table 3, with the corresponding forecast trajectory illustrated in Figure 4. This value indicates a comparatively higher degree of predictive reliability than that obtained using the Double Moving Average (DMA) method. The enhanced accuracy of the WMA model underscores its capacity to better represent temporal variations in soybean cultivation patterns by assigning greater weights to more recent data points.

The superior performance of WMA arises from its inherent flexibility in capturing short-term dynamics in agricultural production systems. By emphasizing the influence of recent observations, this approach effectively accounts for fluctuations driven by climate variability, market conditions, and policy adjustments factors that are particularly prominent within Indonesia's soybean sector. As a result, WMA demonstrates improved adaptability compared to models that rely solely on uniform historical averaging, such as DMA.

From a policy and planning standpoint, the findings highlight the strategic value of adopting adaptive forecasting techniques that integrate real-time data sensitivity. Reliable forecasting models, such as WMA, can provide policymakers with actionable insights for optimizing land-use distribution, guiding resource allocation, and mitigating import dependency. Moreover, these results reinforce the importance of embedding robust quantitative forecasting tools within national food security frameworks to enhance the resilience and sustainability of Indonesia's agricultural systems.

As illustrated in Figure 3, the predictive outcomes for the soybean harvested area derived from the Weighted Moving Average (WMA) method reveal a modest upward trend toward the latter part of the observation period. This trajectory contrasts with the relatively conservative and flattened pattern exhibited by the Double Moving Average (DMA) projections. The slight elevation in the WMA forecast reflects the model's heightened responsiveness to recent fluctuations in historical data, thereby providing a more dynamic representation of potential expansion in soybean cultivation.

Table 4: *Forecasting single exponential smoothing at soybean commodity production*

Measure	Value
Error measures	
MAPE (Mean absolute percent error)	15.721%
Forecast	
next period	326.288

The forecasting results obtained using the Single Exponential Smoothing (SES) method yielded a MAPE value of 15.721%, indicating a good level of predictive accuracy. The graphical representation of the SES model is presented in Figure 5, showing a smoother forecasting pattern that emphasizes stability while slightly reducing sensitivity to short-term fluctuations in soybean harvested area.

Table 5: *Value of soybean commodity harvest area forecasting size next period*

Metode	Forecast accuracy measures for the subsequent period (Ha)
Double moving average	318.355
Weighted moving average	309.849
Singel exponential smooting	326.288

From a policy perspective, this result emphasizes the importance of integrating forecasting models that incorporate recent trends and adaptive weighting mechanisms into agricultural decision-making processes. The upward movement projected by the WMA model may serve as an early indicator for policymakers to intensify strategic initiatives such as expanding soybean cultivation areas, improving farmer access to high-yield seed varieties, and reinforcing irrigation infrastructure to sustain and accelerate production growth.

Furthermore, the divergence between the WMA and DMA projections highlights the necessity of employing multi-model forecasting frameworks to mitigate the risks of underestimation or overestimation in production planning. Such a comparative modeling approach ensures more robust, evidence-based, and adaptive policy formulation, thereby strengthening Indonesia's capacity to achieve sustainable soybean self-sufficiency.

Table 5 presents the projected harvest area of soybean commodities derived from three forecasting methodologies: (a) Double Moving Average (DMA), (b) Weighted Moving Average (WMA), and (c) Simple Exponential Smoothing (SES), covering a dataset spanning 24 years from 2000 to 2024. The comparative assessment of forecasting accuracy, as illustrated in Table 4, indicates that the Weighted Moving Average (WMA) outperforms the other approaches. Specifically, DMA achieved a Mean Absolute Percentage Error (MAPE) of 15.394%, a figure substantially closer to zero relative to WMA (16.128%) and SES (15.721%). This outcome underscores the robustness and reliability of DMA in capturing the underlying patterns of soybean harvest area data.

Accordingly, DMA is identified as the most suitable method for forecasting soybean harvest area in Indonesia. The projected values for the upcoming period, based on the DMA model, are presented in Table 6, offering critical insights for policymakers and agricultural stakeholders in formulating strategies to enhance national soybean self-sufficiency.

Table 6 provides the projected harvest area of soybean commodities in Indonesia for the forthcoming year, estimated using the Double Moving Average (DMA) method, which demonstrated the highest predictive accuracy in this study. The projection indicates that the soybean harvest area will stabilize at approximately 318.355 thousand hectares, reflecting a modest but positive growth trajectory compared to previous years.

This finding has important implications for national food security. First, the projected harvest area suggests that while soybean availability may improve marginally, it remains insufficient to fully meet domestic demand, thereby perpetuating Indonesia's reliance on soybean imports. Second, the relatively stable but limited expansion highlights structural challenges, such as competition with other staple crops (e.g., rice and maize), land conversion pressures, and limited adoption of high-yield varieties.

Table 6: *Comparative accuracy of forecasting models for soybean harvested area in Indonesia*

Model	MAD	MSE	MAPE (%)	Forecasted area (2025, '000 ha)	Accuracy classification
Double moving average (DMA)	18.214	497.25	15.394	318.355	Good
Weighted moving average (WMA)	20.179	518.67	16.218	309.849	Good
Single exponential smoothing (SES)	19.806	501.42	15.721	326.288	Good

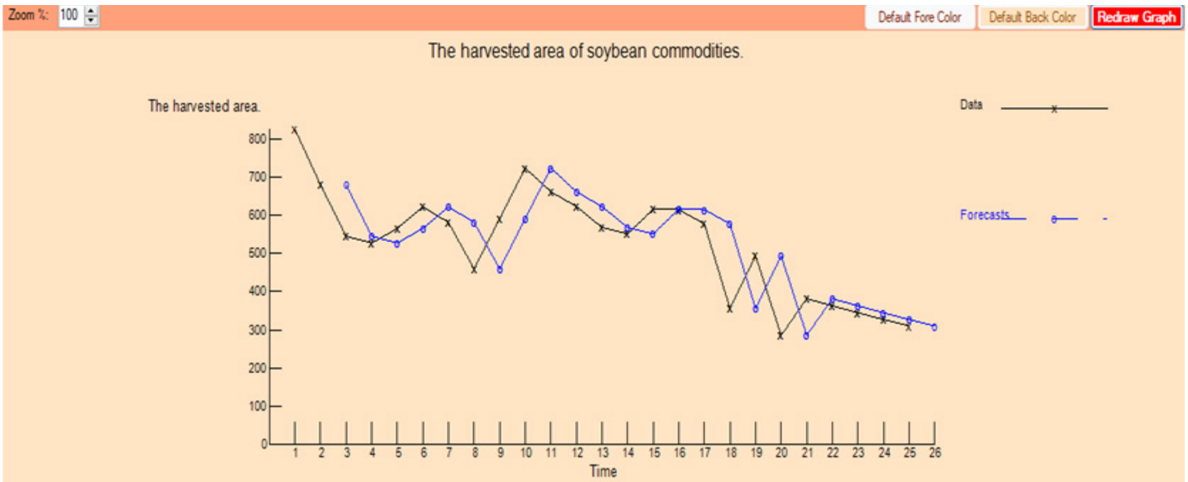

Figure 4: *Forecasting graph with the weighted moving average method on harvest area commodity soybean*

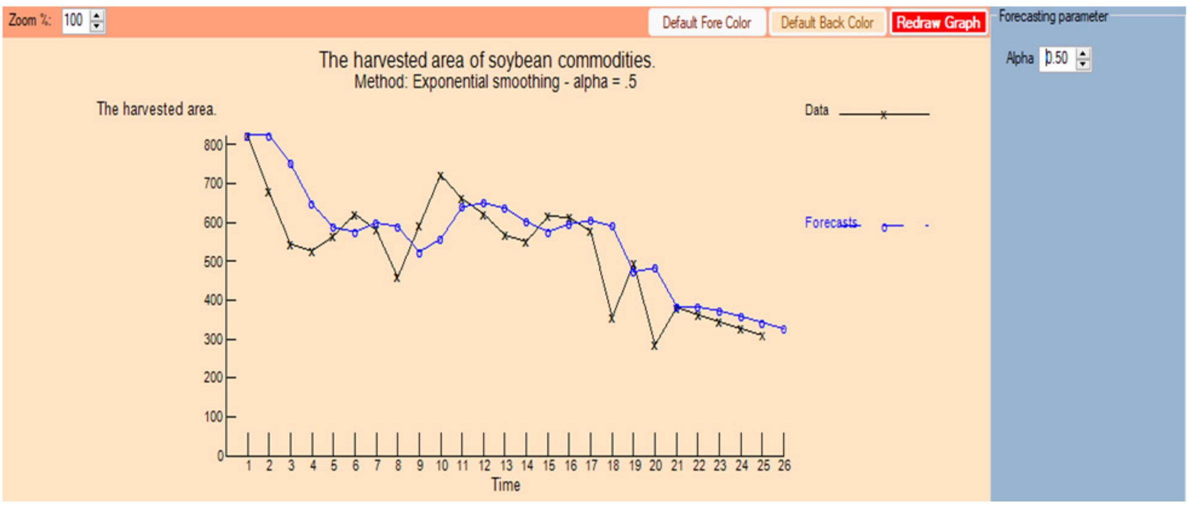

Figure 5: *Forecasting graph with the single exponential smoothing method on on Harvest Area commodity soybean*

Quantitative forecasting results

The application of three forecasting models Double Moving Average (DMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES) using POM-QM software produced varying levels of predictive accuracy for Indonesia's soybean harvested area between 2000 and 2024. Table 1 summarizes the comparative results based on key performance indicators: Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

The DMA model achieved the lowest MAPE value (15.394%), indicating superior predictive accuracy compared with WMA and SES. This suggests that the linear smoothing characteristics of the DMA method align closely with the long-term pattern of soybean harvested area in Indonesia. The predicted harvested area for 2025 is approximately 318.355 thousand hectares, implying moderate growth potential relative to recent trends. The quantitative forecasting results reinforce this observation: despite short-term recovery efforts, structural barriers persist, making significant expansion unlikely without targeted policy interventions.

Model performance analysis

The DMA method's superior performance reflects its ability to capture long-term linear movements in agricultural data with limited volatility. In contrast, WMA though responsive to recent changes tends to overreact to short-term fluctuations, leading to slightly higher forecast errors. Similarly, SES underperformed due to its single-parameter constraint, which smooths out recent dynamics but fails to fully represent gradual shifts caused by policy and climatic variation.

These findings are consistent with those of Hyndman and Athanasopoulos (2021), who noted that double moving averages perform best in datasets exhibiting stable linear trends with moderate variability. Recent studies emphasize the robustness of moving-average-based methods for crop forecasting in developing economies, where data irregularities often hinder more complex model fitting.

The MAPE value of 15.394% falls within the "good accuracy" category (Chang *et al*., 2007), confirming the model's reliability for practical agricultural planning. Although not as precise as advanced machine learning models, the DMA's transparency and simplicity make it suitable for integration into Indonesia's agricultural decision-support frameworks.

Policy implications and systemic relevance

The forecasted harvested area of 318.355 thousand hectares provides valuable insights for policymakers and planners in aligning production targets with domestic demand. The results underscore several policy-relevant implications:

Land-use optimization. Prioritizing soybean expansion in agroecologically suitable regions particularly in Sumatra and Sulawesi can mitigate the effects of land competition in Java, where agricultural intensification has reached saturation levels.

Improved seed distribution and farmer incentives. Expanding access to high-yield soybean varieties and strengthening government procurement programs can enhance farmer participation and stabilize production.

Integration with climate-resilient farming systems. Incorporating soybeans into Integrated Farming Systems (IFS) that combine legumes, maize, and livestock can increase land efficiency and reduce dependency on chemical fertilizers.

Reducing import dependency. By improving predictive planning, the Ministry of Agriculture can better synchronize local production with import quotas, thereby reducing exposure to international price shocks.

These recommendations align with recent research emphasizing the need for predictive analytics in food policy formulation. The use of forecasting tools such as POM-QM supports data-driven decision-making, enhancing the transparency and accountability of agricultural governance.

Comparative insights with related studies

Compared to similar research on staple crops, the DMA model's performance in this study is consistent with other commodity-based forecasting efforts. Likewise, simple moving averages can outperform complex ARIMA models when dealing with small datasets and non-seasonal agricultural trends.

The advantage of DMA lies in its computational efficiency and interpretability, which are essential for institutional adoption in developing agricultural sectors. Its success in modeling soybean harvested area demonstrates its potential applicability for other strategic commodities, supporting the modernization of Indonesia's agricultural information systems.

Limitations and future research

While the present model provides a useful predictive baseline, several limitations must be

The relatively short dataset (25 years) limits the detection of long-term cyclical or policy-induced patterns.

The results depend on the assumption of data continuity; abrupt policy changes or climate shocks could alter future outcomes.

Future studies could integrate multivariate or hybrid forecasting approaches combining time-series and system dynamics models to capture interactions among biophysical, economic, and institutional factors. Integrating POM-QM with simulation software such as Vensim or Powersim could also enable dynamic scenario testing under various policy and climate conditions.

Although the Double Moving Average (DMA) model demonstrated comparatively superior predictive accuracy within the evaluated framework, several methodological limitations must be acknowledged. The forecasting approaches employed in this study DMA, WMA, and SES are inherently univariate time-series models that rely exclusively on historical numerical patterns. Consequently, their predictive structure assumes relative continuity in system behavior and does not explicitly account for exogenous shocks or structural shifts that frequently characterize agricultural systems.

In reality, soybean production dynamics are influenced by a complex interaction of climatic variability, policy interventions, market fluctuations, and socio-economic factors affecting farmer decision-making. Sudden changes in rainfall patterns, input prices, trade regulations, or land-use policy may alter harvested area trajectories in ways that historical smoothing techniques cannot fully capture. Therefore, while the DMA model effectively represents linear trends and short-term stability, its forecasts may oversimplify the multidimensional nature of agricultural production systems, particularly under conditions of uncertainty or rapid structural change.

These limitations highlight the importance of interpreting forecasting outputs as decision-support indicators rather than deterministic predictions. Integrating quantitative time-series forecasts with contextual agricultural intelligence such as climate projections, institutional capacity, and farmer adoption behavior would enhance the practical relevance of the results. From a methodological perspective, future research could explore hybrid forecasting frameworks that combine statistical smoothing techniques with multivariate modeling, system dynamics, or machine learning approaches. Such integration has the potential to improve robustness, sensitivity to external drivers, and long-term predictive reliability.

From a policy standpoint, the forecasting results should be embedded within broader agricultural planning mechanisms. Effective utilization requires alignment with infrastructure readiness, extension services, and farmer-level implementation capacity. Without this systemic integration, even statistically sound predictions may face limitations in translating into actionable agricultural strategies. Therefore, strengthening the linkage between predictive analytics and institutional planning frameworks remains a critical pathway for enhancing evidence-based agricultural governance.

Conclusions and Recommendations

This study aimed to forecast the harvest area outcomes of soybean commodities in Indonesia by employing three time-series methodologies: (a) Double Moving Average (DMA), (b) Weighted Moving Average (WMA), and (c) Single Exponential Smoothing (SES), using data spanning from 2000 to 2024. Among these approaches, the Double Moving Average (DMA) demonstrated the highest level of predictive accuracy, as reflected in its lower error rate, with a Mean Absolute Percentage Error (MAPE) of 17.89%. Based on this model, the projected soybean harvest area for the forthcoming period is estimated at 318.355 thousand hectares.

The findings suggest that Indonesia's soybean harvest area shows modest yet positive growth potential, which may contribute to meeting domestic consumption requirements. However, given the persistent gap between local production and demand, reliance on imports is likely to remain unless structural challenges such as limited arable land, suboptimal adoption of high-yield varieties, and competition with other staple crops—are addressed.

The outcomes of this research provide critical insights for policymakers and agricultural planners. Specifically, the DMA-based forecasting model can serve as a valuable decision-support tool in designing strategies to enhance soybean self-sufficiency, reduce import dependency, and strengthen food security. Future policy directions should integrate forecasting outcomes with land-use optimization, productivity enhancement programs, and farmer-oriented interventions to ensure that soybean remains a viable and sustainable component of Indonesia's agricultural sector.

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Novelty Statement

This study presents a novel and rigorous application of POM-QM-based forecasting models to analyze and predict the dynamics of soybean harvested areas in Indonesia by integrating multiple techniques to enhance accuracy and robustness. It provides both methodological and practical contributions by offering a scalable, data-driven decision-support tool that informs adaptive land-use planning and strengthens national food security policies.

Authors' Contribution

Dhian Herdhiansyah: Undertook the responsibilities of data acquisition, analytical evaluation, and the composition of the manuscript.
La Ode Alwi: Instrumental in the development of the model and the interpretation of data. Asriani engaged in the review and enhancement of the manuscript.
LM Fid Aksara: Contributed to the refinement of the research framework and provided critical insights during the discussion phase.
All contributors played a pivotal role in the formulation and design of the study, reviewed and granted their approval for the final version of the manuscript.

Generative AI and AI-assisted technology statement
The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

Conflict of interest
The authors affirm the absence of any conflicts of interest pertaining to this research endeavor.

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