

The Role of Machine Learning Techniques in Improving Supply Chain Management: A Comparative Analysis of Predictive Models with an Application to Wheat Consumption in Algeria

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ABSTRACT

With the rapid advancement of information technology, global competition has intensified, prompting many organizations to anticipate a fundamental transformation in the future of operations and supply chain management. This shift particularly affects areas such as planning, scheduling, optimization, and transportation, driven by the increasing adoption of artificial intelligence (AI) and machine learning (ML) technologies. In this context, the integration of intelligent systems into supply chain management has become a key area of interest to enhance performance and resilience.

This study investigates the role of machine learning techniques in improving forecasting accuracy for domestic wheat consumption in Algeria, aiming to support supply chain optimization and reduce risks associated with inventory imbalances. A comparative analysis was conducted using three models: the traditional ARIMA model, the Multilayer Perceptron Neural Network (MLPNN), and the Support Vector Machine (SVM) model. Annual data spanning from 1960 to 2024 were used to build and validate the models.

The results reveal that machine learning models, particularly SVM, outperform traditional methods in terms of accuracy and error minimization, especially in the context of nonlinear and volatile data. MLPNN also showed better performance than ARIMA, confirming its ability to detect complex patterns. These findings highlight the potential of machine learning to enhance supply chain forecasting, improve responsiveness to demand changes, and contribute to long-term business sustainability and food security.

1. Introduction

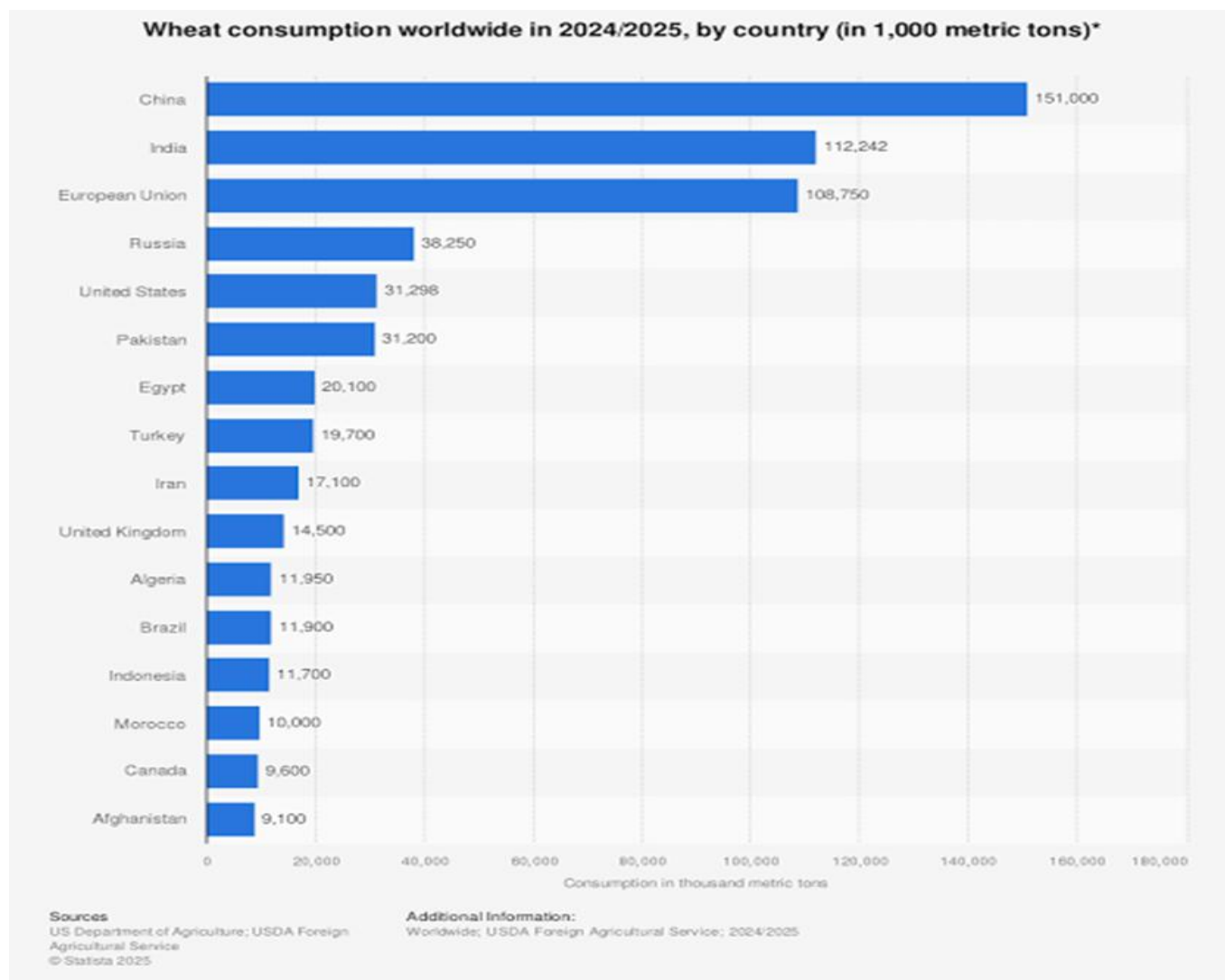
Supply chain management (SCM) is one of the most challenging fields, focusing on the interactions between various sectors, particularly marketing, logistics, and production. Therefore, the success of supply chain management depends on the overall success of any company (Dash, 2019, p. 45). Improving supply chain management has become critical in today's highly competitive and increasingly globalized markets (Jampani, 2023, p. 217), for companies seeking to efficiently meet customer demands while minimizing costs. Customer demand patterns are currently characterized by volatility, diversity, and nonlinearity (Kantasa-Ard, 2021, p. 2). Machine learning (ML) algorithms are radically transforming supply chain management by enabling smarter, faster decision-making based on data-driven insights. Traditional supply chain models often struggle to handle complex and dynamic environments, while machine learning algorithms provide adaptive solutions capable of learning from massive datasets and adapting to changing trends (Thakur, 2023, p. 2839).

Forecasting, a key application of machine learning, which studies computer algorithms that self-improve through experience and is considered a branch of artificial intelligence (Tarmanini, 2023, p. 551), is a key application of supply chain optimization. By analyzing historical data and the external factors that influence it (Eichenseer, 2025, p. 1), predictive models can accurately forecast future consumption, helping organizations avoid stockouts or surpluses. Additionally, machine learning-powered algorithms enable companies to improve inventory management and coordinate warehouse operations by identifying optimal inventory levels and reorder points in real time (Bhalodiya, 2023, p. 1156). These systems can also improve logistics efficiency by selecting faster and less expensive distribution routes, which contributes to reducing transportation costs and delivery times. Companies also benefit from the use of machine learning in supplier evaluation by analyzing historical performance data to identify the most reliable and efficient suppliers (Gidiagba, 2025, p. 2).

There are many methods that can be used for forecasting, and choosing a reliable method with a high degree of accuracy is crucial to improving supply chain performance. Based on the above, it is essential to use machine learning-based forecasting. The multilayer permutation neural network (MLPNN) and support vector machine (SVM) models are a type of machine learning, which is a branch of artificial intelligence. These methods have been widely used by researchers in many fields in their work related to forecasting, due to their effectiveness in producing good results (Mellit, 2013), (Liu, 2022), (Frimpong, 2018). To demonstrate the effectiveness of these models, a comparison was made with the ARIMA model, which is a widely used statistical (econometric) model. By adopting a mathematical approach based on historical data, this method does not require time-consuming calculations, making it a good option with a high degree of accuracy (Ozturk, 2018), (Dritsaki, 2021) (Dey, 2023).

Based on the above, Figure (1) presents the world's leading wheat-consuming countries during the 2024/25 season. China, India, and the European Union top the list, with significant differences attributable to their large populations. Algeria ranks twelfth globally in wheat consumption, with an annual average estimated at approximately 11.95 million metric tons, according to data from the United States Department of Agriculture (USDA). This figure highlights Algeria's position among the top consumers of this staple commodity, despite being a developing country with a moderate population density compared to the top-ranked nations. This ranking underscores the strategic importance of wheat in Algeria and emphasizes the need to strengthen domestic production and reduce reliance on imports, along with the urgent necessity of utilizing accurate forecasting tools. It also points to the critical role of enhancing supply chain efficiency to ensure national food security, particularly given the high consumption levels relative to limited domestic production capacity. This situation provides a strong rationale for the present study, which aims to develop accurate predictive models based on artificial intelligence techniques to support agricultural policy and promote supply chain sustainability.

Figure 1: Global Ranking of Wheat Consumption by Country (2024/2025)



Source : <https://www.statista.com/statistics/1094065/total-global-wheat-consumption-by-country/>

- Research problem:

Wheat consumption in Algeria is a strategic issue that directly impacts food security and the national economy. The country faces significant challenges in meeting the growing demand for this vital resource due to its heavy reliance on imports. In this context, enhancing domestic wheat production becomes a key objective to reduce dependency and ensure supply sustainability. Achieving this goal requires a thorough analysis of data related to production, consumption, and import volumes to enable sound planning and effective decision-making.

Supply chain management plays a crucial role in this regard, necessitating coordination among various stakeholders such as producers, suppliers, and distributors to ensure the timely and efficient delivery of wheat. Moreover, artificial intelligence technologies—particularly machine learning and deep learning—have become increasingly important in analyzing wheat consumption patterns and forecasting future demand. These technologies help improve production and import strategies by offering accurate and innovative solutions. They also contribute to enhancing supply chain efficiency through data-driven decisions that support agricultural policies, market stability, and optimized wheat consumption in Algeria.

Based on the above, the following research question is proposed:

To what extent can machine learning models improve the accuracy of forecasting domestic wheat consumption compared to the ARIMA model, and how can these forecasts be utilized to enhance the efficiency and sustainability of supply chains in Algeria?

- **Sub-questions:**

Based on the presented problem and the adopted theoretical framework (MLPNN, SVM, and ARIMA models), the sub-questions can be formulated as follows:

- ✓ How accurate is the machine learning model (MLPNN) compared to the ARIMA model in predicting domestic wheat consumption in Algeria?
- ✓ How does the performance of the SVM model compare to the ARIMA model in the context of wheat consumption forecasting?
- ✓ How can the results of more accurate models be leveraged to improve supply chain management and ensure its sustainability in Algeria?

- **Study Hypothesis:**

Machine learning models contribute to improving the accuracy of domestic wheat consumption forecasting compared to the ARIMA model, leading to enhanced efficiency and sustainability of supply chains in Algeria.

- **Study Objectives:**

This study seeks to achieve the following objectives:

- ✓ Evaluate the accuracy of different models in forecasting domestic wheat consumption.
- ✓ Analyze the effectiveness of machine learning models in handling non-linear data on wheat consumption compared to traditional statistical models (ARIMA).
- ✓ Improve supply chain management through accurate forecasting to support informed decision-making and ensure supply chain sustainability.

- **Methodology:**

To address the research problem and test the validity of the proposed hypotheses, this study adopts both a descriptive and an applied approach. We present forecasting models, starting with the ARIMA model, followed by the multilayer perceptron neural network (MLPNN) and the support vector machine (SVM) model, all of which are based on mathematical logic for data analysis and processing. Quantitative analysis is conducted by applying these models to predict domestic wheat consumption using annual data from 1960 to 2030, in order to demonstrate the effectiveness of deep learning models in the context of supply chain optimization.

2. Literature Review :

Before delving into the details of this study, it is essential to review some previous studies that have addressed forecasting using machine learning models and traditional statistical models. This review aims to highlight the scientific foundations upon which this research is based and to identify the research gaps it seeks to address. Some of these studies include:

Cao (2005) aimed to predict the exchange rate using the Support Vector Machine (SVM) model. Daily USD/GBP exchange rate data were collected to train the model and assess its predictive performance. The results demonstrated that the SVM model possesses strong forecasting capabilities and can be effectively used to predict financial time series.

Di Pillo (2016) aimed to forecast sales in large retail stores. While statistical methods such as ARIMA and exponential smoothing are commonly used, they may fail in the presence of high sales volatility, such as during promotional events.

In recent years, machine learning specifically Support Vector Machines (SVMs) has emerged as a promising alternative. This study evaluated the application of SVMs for sales forecasting under promotional influences.

Aisyah (2022) aimed to forecast electricity load on the island of Bali, Indonesia, using weather parameters such as temperature, solar radiation, and wind speed. The study employed two machine learning models: the Generalized Regression Neural Network (GRNN) and the Support Vector Machine (SVM). The results indicated that temperature had the strongest correlation with electricity load. The highest prediction accuracy was achieved using SVM and GRNN, with correlation coefficients of 0.965 and 0.95, respectively.

Nurunnahar (2017) aimed to forecast wind speed in Bangladesh using machine learning techniques such as Support Vector Regression (SVR) and Artificial Neural Networks (ANN) with backpropagation (MLP). The results showed that both the SVR and ANN models were able to predict wind speed with over 99% accuracy in short-term forecasts. ANN outperformed in some cases with an accuracy of up to 99.80%, while SVR proved to be more suitable for general wind speed forecasting across different time horizons, achieving 99.60% accuracy. These results outperformed those of previous studies in the field.

Hamidi O. (2015) aimed to compare the Support Vector Machine (SVM) and Artificial Neural Network (ANN) models in modeling monthly rainfall variability. The findings indicated that the SVM model outperformed the ANN, with SVM predictions being closer to the observed values, thus confirming its effectiveness in forecasting monthly rainfall fluctuations.

Szostek (2024) aimed to forecast monthly electricity production from wind farms using three models: ARIMA, SARIMA, and SVR. Data from two wind farms in Poland were analyzed. The results showed that ARIMA performed best at the Jezalki farm, while SARIMA was more accurate at the Lenki Dukielski farm. The SVR model was the least effective. The findings suggest that ARIMA and SARIMA are reliable for energy production forecasting, although their performance is influenced by seasonal patterns.

Ayesha (2024) investigated the impact of air pollution on public health in Middle Eastern countries using analytical tools such as SVM, ARIMA, and ANN. The SVM model demonstrated the highest accuracy, with a mean relative error of approximately 1%. Air pollution-related deaths in Qatar were estimated at 959. The results emphasize the importance of context-specific modeling strategies and support the use of machine learning models in public health planning.

Singh (2024) aimed to improve the accuracy of rainfall forecasting using SVM and SARIMA models to support crop cycle planning and disaster prevention. Given the significant variability in rainfall patterns, the SARIMA model provided accurate estimates of future rainfall values, contributing to a deeper understanding of rainfall dynamics. Accurate rainfall prediction is essential for ensuring freshwater sustainability and plays a critical role in environmental management and resource planning. The models performed well, achieving a Root Mean Square Error (RMSE) of 232.41 and a Mean Absolute Error (MAE) of 23.63.

Du (2025) aimed to apply machine learning models particularly Artificial Neural Networks (ANN) and compare them to traditional models such as ARIMA in forecasting economic resilience. The results showed that ANN outperformed other models, effectively capturing the complex and nonlinear interactions that ARIMA failed to model. The weak correlations observed in the initial analysis suggest that the relationships influencing economic resilience are nonlinear in an area where machine learning models like ANN and SVR show significant strength in handling complexity.

Although numerous previous studies have demonstrated the effectiveness of machine learning techniques particularly SVM and ANN models in forecasting across various domains such as energy demand, climate phenomena, and financial markets, few have explored their application in forecasting agricultural consumption within the context of supply chain management. Most of the existing literature focuses on short-term forecasting or technical comparisons of model performance, often neglecting the practical implications of these models for enhancing supply chain sustainability and efficiency.

In the Algerian context specifically regarding wheat consumption, which is a strategic commodity and one for which the country relies heavily on imports there is a noticeable lack of applied research employing modern artificial intelligence techniques, such as machine learning, to forecast consumption and integrate it with supply chain

performance improvement. Existing studies frequently rely on traditional econometric models such as ARIMA or limit their analysis to general production trends without linking them to accurate, data-driven forecasting strategies supported by advanced tools.

Accordingly, this study aims to fill this gap by applying ARIMA, MLPNN, and SVM models to forecast wheat consumption in Algeria. It seeks to evaluate the predictive accuracy of these models and explore how more precise forecasts can enhance the efficiency and sustainability of supply chain management in the agricultural sector.

3. Research Methodology :

3.1. Autoregressive Integrated Moving Average (ARIMA) Model:

For forecasting purposes, the ARIMA model utilizes past values of the time series. It was developed by Box and Jenkins in 1974 (Hardiyanti, 2020, p. 159) and is considered a widely used predictive model. ARIMA combines two components (Michalková, 2023, p. 37): the Autoregressive (AR) model and the Moving Average (MA) model, using a lag operator denoted as L . The AR component represents the lagged values of the dependent variable, with the lag order denoted as p , indicating the number of time lags. The AR(p) model without seasonality can be expressed as follows (Mahia, 2019, p. 2):

$$AR(p) = \varphi_1 y_{t-1} + \dots + \varphi_p y_{t-p} \dots \dots \dots 1$$

The MA component represents the lagged forecast errors, which are the differences between previous actual and predicted values. These are known as the moving average order q , and the MA(q) model without seasonality is expressed as (Alfaki, 2015, p. 915):

$$MA(q) = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \dots \dots \dots 2$$

As mentioned earlier, the general ARIMA model (Ahmar, 2023, p. 141) is given by:

$$y_t = \theta_0 + \varphi_1 y_{t-1} + \dots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \dots \dots \dots 3$$

Where y_t is the actual value at time t , θ and φ are model parameters, and p and q are non-negative integers representing the autoregressive and moving average orders, respectively. ε_t represents the error term. The parameter d refers to the number of differencing steps applied to the original time series to achieve stationarity. Differencing represents the changes in successive observations. If the original series is non-stationary, first-order or second-order differencing can be applied accordingly. When d equals 0, the model becomes ARMA(p, q), and ARIMA is thus an extension of ARMA to handle non-stationary data.

To determine the appropriate values for p and q , Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) are commonly used (Yakubu, 2022, p. 83). These functions help identify the lag structure of a stationary series by observing the patterns in their plots. Autocorrelation refers to the correlation between a time series and its own past values, while partial autocorrelation refers to the correlation between the time series and its lagged values, excluding the effect of intermediate observations.

3.2. Multilayer Perceptron Neural Network (MLPNN):

The Multilayer Perceptron Neural Network (MLPNN) is a type of artificial neural network that has attracted significant attention from researchers due to its simplicity and successful applications in various fields (Aras, 2017, p. 179). It is one of the most widely used models for time series forecasting. The MLPNN consists of an input layer (which performs no processing), at least one hidden layer, and an output layer. The number of nodes in the input and output layers depends on the number of independent variables and the dependent variable, respectively. The layers are connected through signal propagation from one layer to another.

Learning in MLP networks generally occurs through the **backpropagation algorithm**, which is considered the most widely used method (Ramos, 2013, p. 9). The MLPNN is a **feedforward network** that employs **supervised learning**. The process begins by sending input values x_{ix} from the input layer to the hidden layer, where no processing is performed initially. The hidden layer receives signals from the input layer through nodes, transforms them, and forwards

them to all output units. The output layer then processes these signals into results. Weight adjustments are conducted using specific learning algorithms designed to solve nonlinear problems (Rasouli, 2016, p. 5).

- Time Series Forecasting Using MLP Neural Networks:

The forecasting process using an MLP involves the following steps (Khashei, 2019, p. 2631):

- **Step 1:** In this step, the data is introduced through the input layer. Since time series often face lag-related issues, the MLP is supplied with previous lagged values of actual data ($y_{t-1}, \dots, y_{t-p}$) as input vectors. Accordingly, the input layer consists of p nodes connected to the hidden layer.
- **Step 2:** The hidden layer, located between the input and output layers, is configured. The number of hidden layers is determined based on the specific study. Choosing the type and activation function is crucial at this stage, as it defines the relationship between the input and output layers. Common activation functions include the **sigmoid function**, **hyperbolic tangent function**, and **linear function** (Hamidi, 2012, p. 243). The hyperbolic tangent function takes the following form (Badyalina, 2020, p. 130):

$$\lambda(f) = \frac{2}{(1+e^{2n})} - 1 \dots \dots \dots 4$$

- **Step 3:** This step represents the output layer. After determining the activation function and the appropriate number of nodes, the output of the neural network is used to predict future values of the time series.

The mathematical forecasting function used in MLPNNs is represented as follows (Azadeh, 2008, p. 2274):

$$Y_t = \alpha_0 + \sum_{j=1}^n \alpha_j f\left(\sum_{i=1}^m B_{ij} y_{t-1} + B_{0j}\right) + \varepsilon_t \dots \dots \dots 5$$

Where: m is Number of input nodes, and n is the Number of hidden layer nodes, $f(x)$ and $\{\alpha_j, j = 0, 1, \dots, n\}$ and $\{B_{ij}, i = 1, 2, \dots, m, j = 0, 1, \dots, n\}$, ε_t are respectively Activation function

, Weights from the hidden layer to the output nodes, Weights from the input layer to the hidden layer, Error term .

3. -3- Support Vector Machine (SVM):

Support Vector Machine (SVM) is currently considered one of the modern statistical learning techniques that has gained wide attention in the fields of classification and forecasting. Its application has later expanded to include other areas such as function approximation, regression estimation, and time series forecasting (Siraj-Ud-Doula, 2019, p. 26). This technique was first introduced by Vapnik in the early 1990s (Adhikari, 2013, p. 31), and it is categorized under supervised learning methods (Puspita, 2019, p. 4).

SVM has proven to be more effective than many computational intelligence models, particularly artificial neural networks, as it involves a limited number of tunable parameters, which reduces the complexity of the training process (Sun, 2006, p. 2374). Furthermore, its results are more stable since it does not rely on random weight initialization. Instead, it is built upon solving a quadratic optimization problem that guarantees a unique solution, enhancing result reproducibility and model reliability.

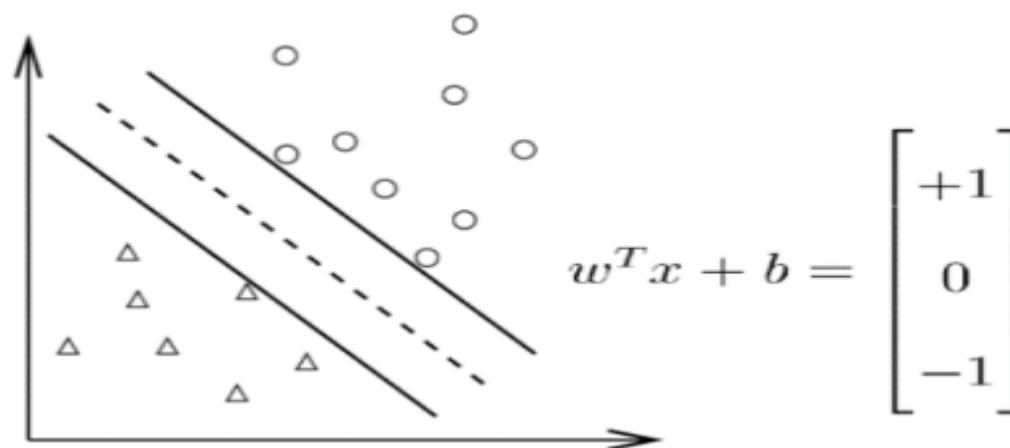
SVM is used in two main cases: classification, where it is referred to as Support Vector Classification (SVC), and regression, where it is known as Support Vector Regression (SVR) (Yaslan, 2017, p. 5). SVR has attracted increasing interest in forecasting nonlinear and non-stationary time series, such as economic and financial data, due to its ability to efficiently model complex relationships.

The core mechanism of SVM is based on mapping the input data into a high-dimensional feature space using kernel functions, and then determining the hyperplane that separates the data with the maximum possible margin. This makes

it particularly suitable for data that is not linearly separable in its original space, as the kernel function implicitly embeds the data in a feature space that enables optimal separation or estimation.

and figure2shows the separating hyperplane, which represents the optimal boundary that maximizes the margin between data classes in a Support Vector Machine (SVM).

Figure 2: The Separating Hyperplane in Support Vector Machine (SVM)



SOURCE : Fawzy, H., Rady, E. H. A., & Abdel Fattah, A. M. (2020). Comparison between support vector machines and k-nearest neighbor for time series forecasting. *J. Math. Comput. Sci.*, 10(6), 2342-2359.p 2348

We notice from the figure above that the equation of the hyperplane is written as follows :

$$y(x) = w^T \varphi(x) + b \dots \dots \dots 6$$

here w is the weight vector, b is the bias (also referred to as the threshold), and x represents the high-dimensional feature space to which the input data x is non-linearly transformed.

The main objective of SVM is to determine the optimal values of w and b such that the hyperplane is positioned as far as possible from the nearest data points (support vectors). These parameters are estimated by minimizing the following objective function (Ismail, 2014, p. 12)

$$\min \left(\frac{1}{2} w^T w \right) \dots \dots \dots 7$$

This objective function is subject to the following constraints:

$$\begin{cases} y_t - w^T \varphi x_i - b \leq \varepsilon \\ w^T \varphi(x_i) + b - y_i \leq \varepsilon \end{cases} \dots \dots \dots 8$$

which can be rewritten as:

$$y_t (w^T \varphi(x_i) + b) - 1 \leq 0 \dots \dots \dots 9$$

In machine learning, particularly in Support Vector Machines (SVM), **kernel functions** are fundamental tools that extend the class of decision functions to nonlinear cases. Thanks to these kernels, data can be mapped into higher-dimensional spaces, allowing for linear separation even when the data is not linearly separable in its original form.

Among the most commonly used **kernel tricks** (Rüping, 2001, p. 4), (Al-Mejibli, 2018) we find:

- ✓ **Gaussian (RBF) Kernel:** $k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$
- ✓ **Linear Kernel:** $k(x_i, x_j) = x_i^t x_j$
- ✓ **Polynomial kernel:** $K(X_i, X_j) = (\gamma X_i * X_j + C)^d$
- ✓ **Sigmoid Kernel:** $K(X_i, X_j) = \tanh(\gamma X_i * X_j + C)$

4. Analysis of the Results:

This study utilizes data on domestic wheat consumption in Algeria from 1960 to 2024 to conduct a forecasting analysis using ARIMA models, the Multi-Layer Perceptron Neural Network (MLPNN), and the Support Vector Machine (SVM) model. The data was obtained from the following source: [Algeria Wheat Domestic Consumption by Year \(1000 MT\) \(indexmundi.com\)](https://indexmundi.com) The analysis was performed using the Python programming language, which enabled efficient implementation of the statistical and machine learning models.

4.1. ARIMA Model:

Before applying the ARIMA model commonly referred to as the Box-Jenkins methodology it is essential to examine the stationarity of the time series, . To formally confirm the stationarity of the series, the Dickey-Fuller test was employed. The following table presents the test results

Table1: Unit Root Test Results (ADF Test)

Null Hypothesis: The variable has a unit root (i.e., it is non-stationary)

Statistic	Value	Interpretation
ADF Statistic	2.2017	Indicates failure to reject the null hypothesis
p-value	0.9989	Greater than 0.05, suggesting non-stationarity
Conclusion	Non-stationary at level	

Source: Prepared by the researchers

We note from the results of the table above that the domestic wheat consumption series is non-stationary according to the ADF test. To achieve stationarity, we apply the first difference transformation and re-evaluate the series using the same test. The results are presented in the following table, where it becomes evident that the domestic wheat consumption series achieves stationarity after the first differencing.

Table 2: ADF Test on First Difference

Statistic	Value	Interpretation
ADF Statistic	-10.6408	Indicates strong evidence against the null hypothesis
p-value	≈ 0	Less than 0.05, suggesting stationarity after differencing
Conclusion	Stationary at first difference	

Source: Prepared by the researchers

After confirming the stationarity of the time series using the Augmented Dickey-Fuller (ADF) test, the next step was to identify and estimate the appropriate ARIMA model. Upon evaluating several candidate models, the ARIMA(1,1,1) model was found to yield the lowest values for both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), indicating that it is the most suitable for forecasting domestic wheat consumption. The model was trained using 65 time points, covering the period from January 1960 to January 2024.

One of the key metrics used in evaluating the model is the log-likelihood, which reached a value of -442.931. This measure is instrumental in calculating other information criteria. The AIC was recorded at 891.863, the BIC at 898.339, and the Hannan-Quinn Information Criterion (HQIC) at 894.414. These relatively low values suggest that the model provides a good fit to the data.

Regarding model parameters, the estimation results showed that the first-order autoregressive coefficient AR(1) was 0.9970, indicating a strong temporal correlation between past and current values. This coefficient was statistically significant ($p < 0.05$). Similarly, the first-order moving average coefficient MA(1) was -0.9503, suggesting a negative correlation between successive residuals, and it was also statistically significant.

The estimated variance (σ^2) was 58,960, indicating a moderate level of dispersion in the residuals. As for model diagnostics, the Ljung-Box test produced a test statistic of 7.38 with a p-value of 0.01, supporting the hypothesis that the residuals are independently distributed. Additionally, the Jarque-Bera test yielded a p-value of 0.24, indicating that the residuals follow a normal distribution, which enhances the credibility of the model. No signs of heteroskedasticity were observed, as the variance appeared stable over time ($p > 0.05$).

Overall, the ARIMA(1,1,1) model demonstrates strong performance in forecasting domestic wheat consumption, as evidenced by the statistical significance of most estimated parameters and the robustness of diagnostic tests.

The following table presents the forecasted values of wheat consumption for the period 2025 to 2030 using the ARIMA model

Table 3: Forecast Using the ARIMA Model

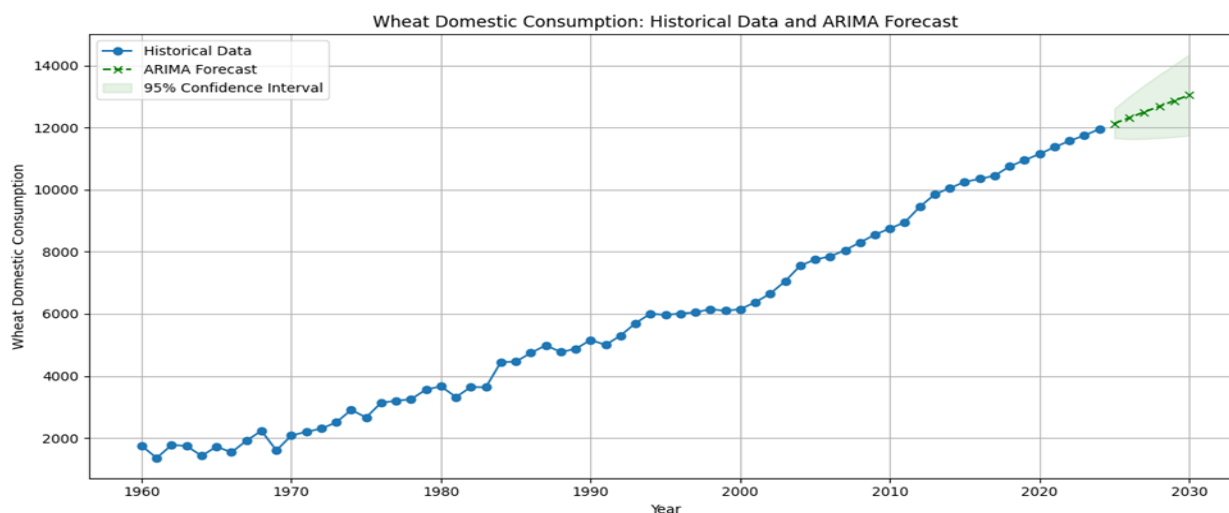
Year	2025	2026	2027	2028	2029	2030
Forecasted Values	12,134	12,318	12,501	12,683	12,865	13,046
Lower International Average	11,658	11,629	11,637	11,663	11,699	11,741
Upper International Average	12,610	13,007	13,364	13,703	14,031	14,351

Source: Prepared by the researchers

The results of forecasting domestic wheat consumption from 2025 to 2030 using the ARIMA(1,1,1) model indicate a gradual increase in consumption over this period. The projections show that consumption will steadily rise, reaching 12,134 thousand tons in 2025, with confidence intervals ranging from 11,658 to 12,610. By 2030, consumption is expected to reach 13,046 thousand tons, with confidence intervals between 11,741 and 14,351. These forecasts highlight an upward trend in wheat consumption, potentially reflecting an increase in domestic demand in the coming years.

The graph illustrates both the actual and predicted values of domestic wheat consumption using the Support Vector Regression (SVR) model for the period from 1960 to 2030

Figure 3: Graphical Representation of the Actual and Forecasted Values Using the ARIMA Model



Source: Prepared by the researchers

4.2.MLP Neural Network Model

- Neural Network Architecture (MLP)

Before the data is fed into the neural network, it is scaled to facilitate training and improve performance. The values are transformed into a specific range (such as between 0 and 1, or according to a specific distribution). This is done using the following equation:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Where: x is the original value from your dataset. and x_{scaled} is the transformed, or scaled, value that will be used as input for the network. x_{min} is represents the minimum value found in your dataset. x_{max} is represents the maximum value found in your dataset.

We evaluated several possible neural network configurations to determine the optimal network architecture. To compare these configurations, we used the Sum of Squared Errors (SSE) as our primary criterion.

Through experimentation, it was found that the most appropriate model, which gives the lowest SSE value, is as follows:

- Input Layer: Contains one neuron representing the input variable to the network, which is the year.
- Hidden Layers: The number of hidden layers is defined by the parameter `hidden_layer_sizes = (100, 50)`:
 - ✓ The first hidden layer contains 100 neurons.
 - ✓ The second hidden layer contains 50 neurons.
- Activation Function: The activation function used in the hidden layers is ReLU (Rectified Linear Unit), a commonly used function that improves the efficiency of neural networks by allowing non-linear interactions between neurons.
- Output Layer: Contains one neuron representing the target variable to be predicted, which is domestic wheat consumption. A linear activation function (Identity Function) is used in the output layer, allowing continuous output values without restricting them to a specific range.

The table below shows the predicted values of wheat consumption from 2025 to 2030 using the MLPNN model

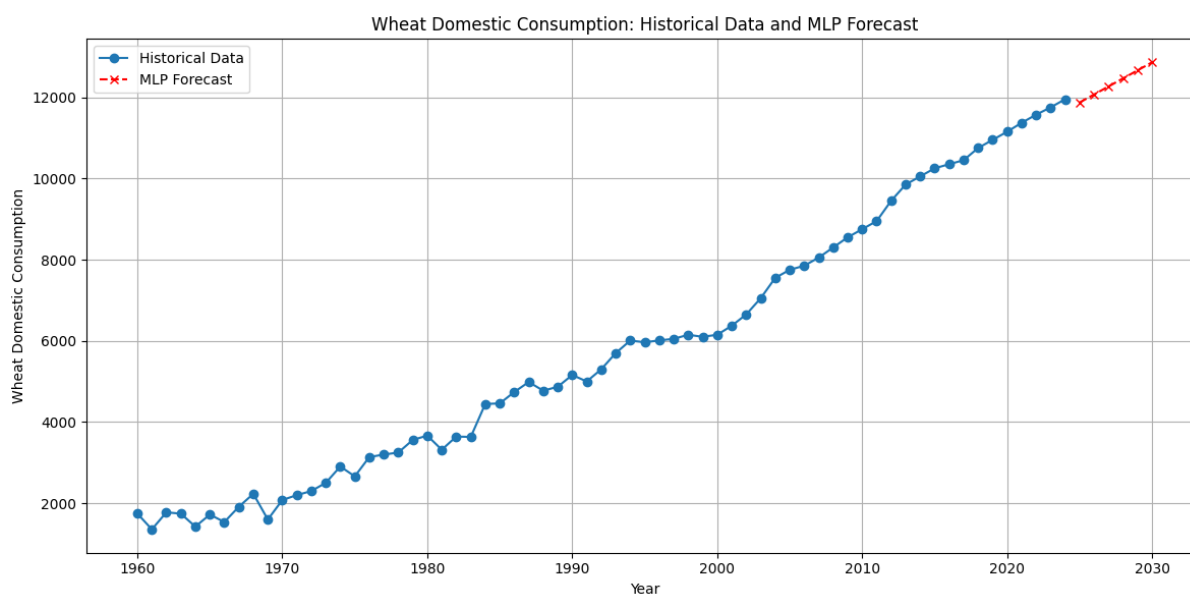
Table 4: Forecasting using the MLPNN model

Year	2025	2026	2027	2028	2029	2030
Predicted Values	11,870	12,068	12,266	12,464	12,662	12,860

Source: Prepared by the researchers

The table results show a clear pattern of increasing domestic wheat consumption over the years. From 11,870 in 2025 to 12,860 in 2030, the model indicates a steady and continuous rise, with no decline or fluctuation in consumption.

Figure 4: Graphical representation of the original and predicted values using the MLPNN model



Source: Prepared by the researchers

4.3.SVM Model:

-Interpretation of SVR Model Outputs for Forecasting Domestic Wheat Consumption :

Before applying the SVM model, several key hyperparameters that affect the model's performance were selected to enhance its accuracy in predicting domestic wheat consumption in the coming years. These hyperparameters help determine the model's flexibility and its ability to generalize to new data.

The Support Vector Regression (SVR) model with the RBF (Radial Basis Function) kernel was used to forecast domestic wheat consumption for the period from 2025 to 2030. This choice is due to the potentially complex and nonlinear relationships among the influencing factors, making SVR more suitable for future forecasts because of its high accuracy and low error.

The model relies on the RBF kernel, which is particularly appropriate for handling nonlinear relationships between variables.

- **Hyperparameters**

Kernel = 'rbf': The purpose of using the RBF kernel is to map the data from a low-dimensional space to a higher-dimensional space. This allows the model to detect nonlinear patterns that may exist in the data. Therefore, this kernel is suitable when the relationship between the independent variables (inputs) and the dependent variable (consumption) is nonlinear.

Regularization parameter (C) = 100: This parameter controls the trade-off between training accuracy and model complexity. A high value of C (100) means that the model prioritizes achieving the lowest possible training error, even at the cost of flexibility. This may lead to overfitting if the data contains noise. On the other hand, a lower C value would allow the model to tolerate small errors, reducing the risk of overfitting. In this case, with a high C value of 100, the SVR model focuses on minimizing error as much as possible, resulting in higher accuracy.

Epsilon (ϵ) = 0.1: This defines the width of the margin around the regression function where no penalty is given for prediction errors. With $\epsilon = 0.1$, any prediction error less than 0.1 is ignored. Increasing epsilon would make the model more tolerant to small errors and less sensitive to noise.

Gamma = 'scale': This parameter determines how much influence a single training example has on the final decision. The 'scale' option calculates gamma based on the number of features in the dataset. This helps the model adapt automatically to the data structure, ensuring good performance. The choice of Gamma = 'scale' allows for automatic adjustment based on the data, reducing the risk of bias.

The table below shows the predicted values of domestic wheat consumption from 2025 to 2030 using the SVR model.

Table 5: Forecasting Using the SVR Model

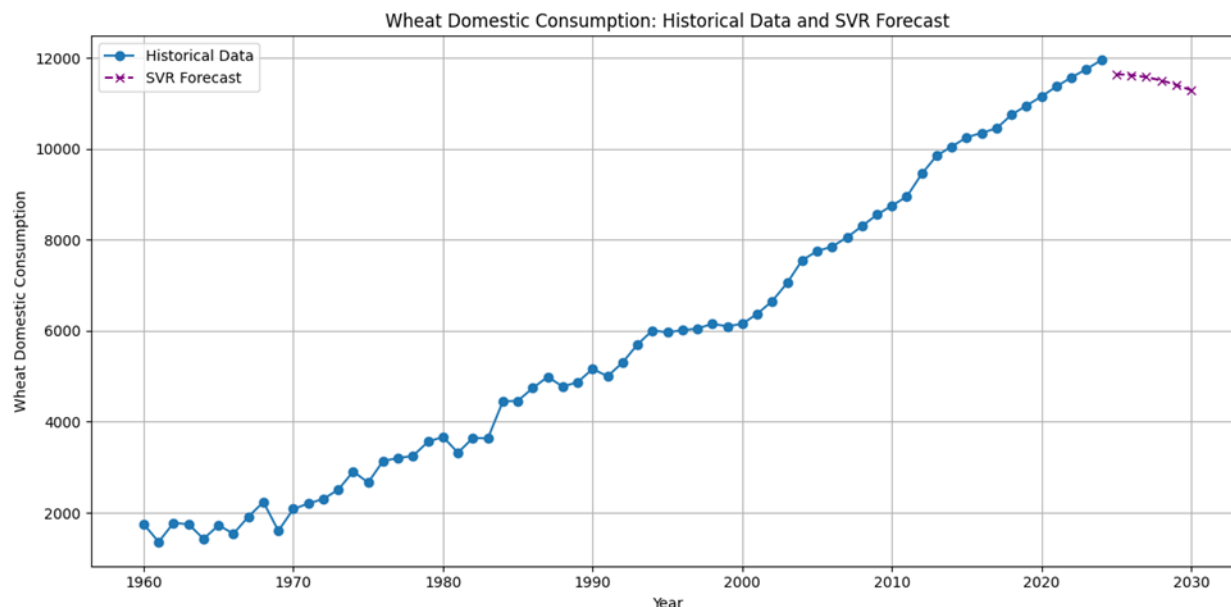
Year	2025	2026	2027	2028	2029	2030
Predicted Values	11,640	11,621	11,575	11,503	11,407	11,287

Source: Prepared by the researchers.

The table results show that wheat consumption in Algeria is gradually and steadily declining, from 11,640 thousand tons in 2025 to 11,287 thousand tons in 2030. This consistent decrease suggests that the model has captured a long-term downward trend in consumption, which may be attributed to a combination of economic factors or national agricultural strategies, including new agricultural policies and shifts in consumption patterns.

The graph displays the original and predicted data using the SVR model for domestic wheat consumption from 1960 to 2023.

Figure 5: Graphical representation of the original and predicted values of the SVR model.



Source: Prepared by the researchers.

4.5. Comparison between the three models:

To compare the ARIMA, MLPNN, and SVR models, three performance accuracy metrics were used: MSE (Mean Square Error), RMSE (Root Mean Square Error), and MAPE (Mean Absolute Percentage Error). The results are shown in the table below:

Table 6: Comparison results between the ARIMA, MLPNN, and SVR

Model	MSE	RMSE	MAPE (%)
ARIMA	126,396.71	355.52	8.29
MLPNN	116,143.00	340.80	7.13
SVR	39,486.12	198.71	4.33

Source: Prepared by the researchers.

4.6. Discussion of Findings and Contribution:

The findings of this study confirm the relevance and growing importance of machine learning techniques in forecasting agricultural consumption, particularly in the context of supply chain management. By applying and comparing three models ARIMA, MLPNN, and SVM to forecast domestic wheat consumption in Algeria, the study demonstrates the superior performance of machine learning algorithms, especially SVM, in handling nonlinear and complex patterns in time series data.

The results presented in the comparison table show that the SVR model clearly outperformed the other models across all three evaluation criteria. It recorded the lowest Mean Squared Error (MSE) of 39,486.12, reflecting minimal differences between predicted and actual values. Its Root Mean Squared Error (RMSE) was 198.71, indicating high

predictive precision in units of wheat consumption (thousand tons). Additionally, the Mean Absolute Percentage Error (MAPE) stood at 4.33%, a remarkably low error rate that demonstrates excellent forecasting accuracy.

The MLPNN model ranked second in performance with MSE = 116,143.00, RMSE = 340.80, and MAPE = 7.13%, confirming that neural networks can capture data patterns more effectively than ARIMA, though still less accurately than SVR. In contrast, the ARIMA model recorded the highest error rates (MSE = 126,396.71, RMSE = 355.52, and

MAPE = 8.29%), indicating significant discrepancies between predicted and actual values. These findings underscore the limitations of ARIMA in modeling complex and nonlinear relationships, especially in datasets affected by volatility and structural shifts.

These comparative results reinforce the central contribution of this paper: while ARIMA remains useful for modeling stationary linear data, machine learning techniques particularly SVM are more capable of adapting to dynamic, nonlinear consumption patterns in agriculture. Unlike most previous studies that focused on forecasting in energy, finance, or weather sectors, this study provides a novel application of ML techniques in agricultural demand forecasting linked to supply chain management, especially within the Algerian context where such integration is lacking in the literature.

Therefore, this research not only advances methodological knowledge but also delivers practical insights for policymakers and supply chain stakeholders aiming to enhance food security and reduce dependency on imports through more accurate and forward-looking planning.

5. Conclusion:

Supply chain management (SCM) is a key factor that significantly influences the efficiency of business operations in today's increasingly volatile and challenging economic environment. SCM plays a pivotal role in ensuring the smooth flow of goods and resources across the various stages of production and distribution. Modern supply chains have become more complex than ever due to rapid changes in demand and market conditions. Consequently, enhancing forecasting and strategic planning has become critical to ensuring business sustainability and mitigating risks related to inventory shortages or surpluses.

This study has demonstrated that improving forecasts using machine learning techniques can significantly enhance the sustainability of supply chains. By increasing the accuracy of predictions, organizations can minimize risks associated with inventory imbalances such as material shortages or excess stock thereby reducing operating costs and improving overall efficiency. Furthermore, these technologies enable companies to respond more swiftly to changes in demand and labor market dynamics, ensuring agility and responsiveness.

By comparing machine learning models such as the Multilayer Perceptron Neural Network (MLPNN) and the Support Vector Machine (SVM) with the traditional ARIMA model for forecasting domestic wheat consumption, the study found that machine learning models are more effective in handling nonlinear and volatile data. The SVM model outperformed the others based on accuracy metrics such as MSE, RMSE, and MAPE. While the ARIMA model may be effective in certain contexts, its limitations in predicting nonlinear and complex patterns make it less suitable for long-term forecasting. These findings reinforce the need to adopt more advanced techniques, such as machine learning, to address contemporary forecasting challenges.

Recommendations:

Leveraging machine learning techniques to enhance forecasting can significantly improve supply chain management strategies not only by boosting local production and reducing reliance on imports but also by strengthening food security and economic stability. These models can enhance coordination among various stakeholders in the supply chain, including suppliers, distributors, and manufacturers. Improved coordination leads to cost reductions and more efficient logistics, enhancing the competitiveness of organizations in volatile markets.

Additionally, the use of advanced forecasting models can help reduce information gaps among different parties in the supply chain, enabling timely and informed decision-making. This improved coordination ensures the efficient use of resources and supports sustainable operations amid rapid economic changes.

The application of machine learning models to supply chain management represents a crucial step toward securing future business sustainability. Given the current economic challenges, including global market volatility, the adoption of such technologies is essential for enhancing competitiveness and developing the local economy. Therefore, organizations are encouraged to invest more in these models to ensure effective responsiveness to ongoing market changes, contributing to improved resilience and long-term sustainability.

Future Work:

Future research should aim to enhance the effectiveness of machine learning models in supply chain management and improve the accuracy of forecasts. Specific directions include:

- Utilizing deep learning techniques such as Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) to improve forecasting in supply chain management, by evaluating their effectiveness in handling complex and nonlinear data.
- Collecting and analyzing large-scale datasets across various sectors such as procurement, logistics, and transportation to ensure accurate representation of the dynamic economic environment and improve model performance.
- Focusing on the integration of mathematical and machine learning models by developing hybrid solutions that combine traditional methods like ARIMA with machine learning techniques such as SVM and MLPNN. These hybrid models can offer more accurate forecasts tailored to the diverse needs of supply chains.

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