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MODELLING THE IMPACT OF CLIMATIC VARIABLES ON DATE PRODUCTION IN PAKISTAN: AN ARIMAX-BASED FORECASTING APPROACH

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ABSTRACT

This study evaluates the advanced techniques to surge the accuracy of the date production forecasting in Pakistan. Employing ARIMAX models, this analysis focused on understanding and assessing the impact of fertilizer usage and climatic variables such as CO_2 levels (which indirectly influence the climatic variables), temperature, and rainfall. Among the tested models, ARIMA (2,2,1) was found to be the best model and has an AIC of 673.49, a BIC of 690.11 and a log-likelihood of -328.74. Results indicated that CO_2 levels (-416.37; Std. Error: 292.90), temperature (-43.49; Std. Error: 17.43), and rainfall (-0.28; Std. Error: 0.09) had significant negative impacts on date production. Fertilizer usage had a minor positive effect (0.03; Std. Error: 0.05), which was statistically insignificant. The Ljung-Box test, Q-statistic, and Jarque-Bera test were used for a diagnostics check to validate the model's reliability. This research underscores the potential of ARIMAX/SARIMAX models to analyse trends and forecast future productions accurately and provides actionable insights for policymakers and researchers to integrate diverse ecological factors into agricultural planning, ensuring optimal resource utilisation and sustainable date production practices.

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INTRODUCTION

Date palm (*Phoenix dactylifera*) has enormous economic, food, and dietary significance, specifically in arid and semi-arid areas. It supports economically to trade, employment, and rural development, and as a primary food source of income for farmers. Dates provide a staple diet for millions, with rich source of nutritional value, vitamins, minerals, and dietary fiber (Sharma et al., 2019). Date production is an important horticultural activity practiced in many regions of the world, particularly regions with favourable climatic variables to produce date fruit. Date producing countries such as Egypt known for its wide variety of dates cultivation in the Nile river valley, Saudi Arabia having with premium exports quality of date like Ajwa and Sukkari, Iran date variety with high quality Muzafati and piarom in south regions, Algeria and Tunisia famous for Deglet Noor, while Morocco have Medjhoul variety, Sudan and in Pakistan, these countries dominate in date production for global markets due to its climatic conditions and a rich history of cultivation (Siddiq et al., 2013). In Pakistan, the date fruit has cultural and nutritional value and is a vital source of income for producers (Soomro et al., 2023). As dates fruit are in high demand across the globe, optimizing resource for date production becomes essential. Accurate date production forecasting supports farmers, policymakers and other stakeholders in managing resources, preparing for markets and assessing risks (Bhatti et al., 2024). Estimation of future production levels using historical data and influential factors. Forecasting is crucial to optimizing processes, reducing post-harvest losses, and stabilizing markets in general as well as in supply chain and date production in particular. The forecasting techniques also play a role in food security by estimating the result of adversities and other disruptions that will affect date production (Sam et al., 2019).

Conventional forecasting techniques such as linear regression and moving averages have been applied in prior work, but these methods often fail to inadequate modelling of the nonlinear dynamics of date production due to multiple interacting variables and the presence of their lagged influences (Ensafi et al., 2022). Recently ARIMA became the forefront of time series forecasting techniques owing to their capacity to accommodate complex temporal patterns. More specifically, ARIMA is more suitable for datasets with time series characteristics like trends and seasonality (Ospina et al., 2023). Incorporating exogenous factors (CO_2 levels, rainfall, temperature, fertilizer use) into an ARIMAX model, this research attempts to improve date production forecasting. The aim is to get the best fit ARIMAX that has the most accuracy(Pohanková et al., 2025). Historical data are used, along with multiple ARIMAX models, to test and evaluate model fit (AIC, BIC, LogLikelihood) and prediction accuracy (MAE, MSE, RMSE). Finally, these best-performing models are evaluated on real-world applicability(Alotaibi et al., 2023).

Date palms are economically, food, and dietarily important worldwide, and especially in arid and semi-arid regions where they occur (Alotaibi et al., 2023). Although date palms are not the top commercial crop, they are crucial to trade, employment and rural development especially in countries such as Pakistan. With top global producers of dates among the country are Sindh (Khairpur), Balochistan (Turbat, Panjgur), and Punjab (Dera ghazi khan) are the leading provinces where arid and semi-arid conditions favor its growth. However, this is restrained by outdated farming methods and infrastructural barriers, and marketplace constraints. Forecasts of these challenges can facilitate economic growth, secure the people's food and create jobs in the rural communities (Shiferaw et al., 2013).

Climatic variability, resource limitations, pest infestation, and failure to mechanize farm work are the main challenges date palm production faces in Pakistan. Low investment in research & Development, inadequate knowledge of the advances in agriculture among farmers compound these issues (Hussain et al., 2024). These challenges must be overcome in a multi-level approach of technology, policy support and stakeholder engagement. ARIMA and ARIMAX forecasting models are useful to face the challenges of historical data and influential factors to produce better future production levels. Therefore the allocation of resources, planning of markets and risk management to enable the optimization of the supply chain, reduction of post-harvest losses and stabilization of markets (Arowosegbe et al., 2024). Forecasting by the advancement of approaches, with ARIMA and its extended ARIMAX models, which capture the complex historical patterns and exogenous variables are climatic conditions, soil health, and advanced farming systems. Furthermore, date production optimization under climatic factors such as fertilizer usage, rainfall, temperature, and CO_2 levels by ARIMAX model. The precision and reliability of the models are evaluated with appropriate statistical metrics, which are AIC, BIC, MAE, MSE, and RMSE (Alawsi et al., 2022). These approaches contribute sophisticated statistical tools to address the stochastic nature of climatic variability for sustainable agricultural development and food security.

The determination of this exploration is to find out enhancement and improved ARIMAX models of date production to forecast exactly, taking into account important exogenous adjusting factors like fertilizer usage CO_2, temperature, and rainfall. Testing model effectiveness based on statistics using AIC, BIC, MAE, MSE and RMSE (Khosravi et al., 2021) to achieve absolute and relative accuracy along with dependability. The purpose is to determine the most appropriate predictive model which takes into account both simplicity and accuracy, and therefore grasp the essential realities for farmers, policy makers and other interested stakeholders. The investigations ultimately contribute to resource management, market strategy, and sustainable farming development as these issues stem from the impacts of climate variance and production inefficiency.

METHODOLOGY

Data Collection

This study was conducted in Pakistan and focused on analysing and forecasting Date Production. The secondary annual data for Date Production, CO2 levels, Temperature, Rainfall, and Fertilizer usage were collected from the official websites of the Agricultural Market Information System (AMIS), Pakistan Meteorological Department (PMD), and Pakistan Bureau of Statistics (PBS) from 1961 to 2022.

Model Selection

The various configurations that the study examined included different ARIMAX model, which can be differentiated in terms of the order of autoregressive terms, differenced terms, and moving average terms. The models assessed were as follows: ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (1,2,2), ARIMA (1,2,1), ARIMA (2,2,2), ARIMA (2,1,2), ARIMA (2,1,1) and ARIMA (2,2,1). All the models used endogenous variables (Y) and exogenous variables (X) that included CO_2 levels, rainfall, temperature and fertilizer usage. These variables were included because of their effects on date production.

Model Fitting

To modelling and forecasting the date production the most suitable model was found to be ARIMA (2,1,2) based on the model's performance statistics. The general form of an ARIMA (p, d, q) model is given by: The general form of an ARIMA (p, d, q) model is given by:

$$(1- \Phi_1 B - \Phi_1 B^2)(1-B)^d Y_t = (1+\theta_1 B)\epsilon_t$$

For the ARIMA (2,2,1) model used in this research, the equation can be specified as:

$$(1- \Phi_1 B - \Phi_1 B^2)(1-B)^2 Y_t = (1+\theta_1 B)\epsilon_t$$

Where:

- Y_t is the date production at time t.
- B is the backshift operator, such that $BY_t = Y_t - 1$.
- Φ_1 and Φ_2 are the parameters of the autoregressive part of the model.
- θ_1 is the parameter of the moving average part of the model.
- ϵ_t is the error term at time t.

As for this study and the selected ARIMA (2,2,1) model, the parameterization of the characteristics was derived from the historical data of date production. For example, the use of a differencing function (d=2) makes the time series mean stationary due to the assistance of differencing. Using this model later examined the effects of the other exogenous variables such as CO_2 level, temperature and rainfall on date production. The ARIMAX models were estimated with the pre-treated data with the aid of the softwares in Python. In each of the models mentioned above, all the parameters were MLE estimated. By this approach, the model's parameters effectively explain the observed data.

ARIMAX Model Equation

An ARIMAX model is used for ARIMA model by adding exogenous variables (Lee et al., 2024). The general form of the ARIMAX (p, d, q) model is expressed as:

$$\begin{aligned} y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_t + \cdots + \Phi_p y_{t-p} + \theta_1 \epsilon_{t-1} \\ + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \beta_1 x_{1,t} \\ + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \epsilon_t \end{aligned}$$

where:

- y_t is the date production at time t.
- c is a constant term.
- $\Phi_1, \Phi_2, \ldots, \Phi_p$ are the parameters of the autoregressive part.
- $\theta_1, \theta_2, \ldots, \theta_p$ are the parameters of the moving average part.
- $\epsilon t \epsilon t$ is the error term at time tt.
- $x_{1,t}, x_{2,t}, \ldots, x_{k,t}$ are the exogenous variables (e.g., CO_2 levels, rainfall, temperature, and fertilizer usage).
- $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the exogenous variables.

Model Evaluation Criteria

Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log Likelihood were used to evaluate the efficiency of each ARIMAX model. The goodness of fit of a statistical model is balanced by its complexity according to model AIC. Minimum values of AIC models have better performance, as they are closer to a more optimal balance of simplicity and accuracy (Zhao et al., 2023). Likewise, BIC is closely related to AIC but concerns a stronger penalty on the number of parameters, preferring simpler models with fewer parameters. Usually, models' efficiency with the lowest BIC values are considered better (Board et al., 2008; Harbecke et al., 2024).

The Log Likelihood measures how well a model fits the data. Higher Log Likelihood values imply a better fit, with maximum values being preferred (Dovers et al., 2024). The evaluation ensures a robust selection process by integrating these criteria for finding the most effective forecasting model.

Forecasting Performance Metrics

To assess the accuracy of our forecasting models using several widely used performance metrics. Mean Absolute Error (MAE) is simply a metric of forecast error as an average magnitude. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) follow the discipline of larger errors and, hence, are more sensitive, for which the more precise models can be identified. The reason is that MSE is the average squared error, and RMSE is the square root of MSE, which allows you to compare more easily by providing a more interpretable measure in the same units as our original data (Osorio, 2024).

The robustness of our models and generalization well is ensured by a rolling window cross-validation. Bit by bit, we separate the dataset to overlapping windows, train the model over each window, and evaluate our model over the window that comes next. However, through iteration through this process a few times, we get a sense of how well the model can learn from varying data patterns while avoiding overfitting. Moreover, this approach ensures that the models can be reliable to forecast over the subsets of the dataset (Lundstrom, 2023).

RESULTS AND DISCUSSION

The results of this study determine the best way to forecast date production, including models, even the ARIMAX models were also considered by the respective authors. Subsequently, in Table 1, through the differential of AIC, BIC, and Log Likelihood, it was concluded that the ARIMA (2,2,1) model showcased higher results in comparison to other modulations. With an AIC of 673.49 signifying the highest fitness; the BIC obtained for the model is as low as 690.12, while has a log likelihood of -328.75 which is relatively high, at 11.74, this model proved appropriate for the of date yield according to (Beula et al., 2024; Harbecke et al., 2024). The influence of such exogenous factors as the level of light and temperature on the growth of plants was also studied during inquiry. The presence of CO_2 was noted to have a highly negative effect on the yield of dates (-416. 37, Std. Err. 292.91) and the same applies to the temperature (-43.49, Std. Err. 17. 43). The results of this study align with the studies done by (Al-Khayri et al., 2015; Swarna et al., 2024) which show that CO_2 stress and increased temperature have adverse effects on the plant growth. Rainfall was also negative to production, with a negative coefficient value equal to -0. Implicating the importance of proportionality in the utilization of fertilizer as concluded by Chandio et al., (2024) the fertilizer usage was either having no effect or less than the statistics significance level of 0.05 with a Co-efficient of 0.02 while the role of farm machinery in the increase in the yield size was relatively higher with Co-efficient of 27 (Std. Err. 0.08). More importantly, the use of Q statistic by Ljung Box (Q = 0.13) showed that there is no statistically significant level of autocorrelation at ($P < 0.05$), and the Jarque Bera results (JB = 27. 40) showed that the quantitative deviation from normality is acceptable. These indicate that variables including CO2, temperature and rainfall should be included as predictors in the mathematical models that should be used by management teams in the accuracy of date production (Bussaban et al., 2024).

The study aimed to evaluate different ARIMAX models to determine the most suitable one for forecasting the production of date using AIC and BIC criteria. The final selected model was ARIMA (2, 2, 1) due to its favorable characteristics, including the lowest AIC value of 673.49, which indicates a more parsimonious model, and a moderate BIC value of 690.12. This model demonstrated good performance when compared to other ARIMA variants. The analysis considered exogenous variables such as CO_2 levels, rainfall, temperature, and fertilizer usage, and their effects on date production. The key findings include:

CO_2 Levels: The ARIMA (2, 2, 1) model found a significant negative impact of CO_2 levels (-416.37, Std. Err. 292.91), highlighting its unfavorable role in date productivity.

Rainfall: Rainfall also negatively influenced the production of date fruit (-0.28, Std. Err. 0.09), with these results indicating adverse effects of changing rainfall patterns on date production.

Temperature: High temperature showed the most significant negative impact (-43.49, Std. Err. 17.43), confirming its critical role in affecting production of date. This finding reinforces the importance of temperature management in agricultural practices. **Fertilizer Usage**: Fertilizer had a small, positive, though statistically non-significant effect (0.03, Std. Err. 0.05), suggesting that while it is beneficial, its impact may be insufficient when other factors such as CO_2 and temperature are unfavorable. The diagnostics for the selected model supported its robustness. The Ljung-Box Q statistic of 0.13 with a p-value of 0.71 indicated no significant autocorrelation in the residuals, while the Jarque-Bera test statistic of 27.40 confirmed the normality of residuals. The findings support for incorporating multiple environmental factors, such as CO_2 levels, rainfall, and temperature, into agricultural forecasting models. Furthermore, the results underscore the importance of advanced modelling techniques in decision-making and optimizing agricultural strategies for productivity and sustainability.

Table 1. Model Comparison and Parameter Estimates for ARIMAX/SARIMAX models.

Parameter	ARIMA(1, 1, 1)	ARIMA(1, 1, 2)	ARIMA(1, 2, 2)	ARIMA(2, 2, 2)	ARIMA(2, 1, 1)	ARIMA(2, 2, 1)	ARIMA(2, 1, 2)
AIC	683.66	681.73	679.38	679.25	679.49	673.49	680.34
BIC	698.32	698.49	693.93	696.00	696.00	690.12	699.19
Log Likelihood	-334.83	-332.87	-332.69	-331.62	-331.19	-328.75	-331.17
CO_2	-287.70	-287.56	-417.14	-287.20	-287.74	-416.37	-416.39
CO_2 Std. Err.	260.86	329.60	315.53	263.17	266.68	292.91	294.10
Rainfall	-0.21	-0.17	-0.21	-0.31	-0.32	-0.28	-0.33
Rainfall Std. Err.	0.13	0.14	0.13	0.09	0.09	0.09	0.09
Temperature	-21.42	-38.47	-16.11	-47.79	-46.39	-43.49	-50.96
Temperature Std. Err.	16.99	23.41	16.93	18.56	17.48	17.43	20.48
Fertilizer	0.05	0.07	0.03	0.04	0.03	0.03	0.02
Fertilizer Std. Err.	0.05	0.05	0.04	0.04	0.05	0.05	0.05
ar. L1	0.09	-0.76	-0.27	-0.58	-0.76	-0.30	-0.57
ar. L2	-	-	-	-0.48	-0.76	-0.41	-0.50
ma. L1	-0.44	0.55	-1.00	0.38	0.62	-1.00	-0.63
ma. L2	-	-0.45	-	-	0.39	-0.37	-
sigma2	4107.72	3712.69	4273.85	3671.22	3605.54	3685.40	3569.42
Ljung-Box (L1) (Q)	0.04	0.08	0.60	0.05	0.33	0.13	0.00
Prob(Q)	0.85	0.77	0.44	0.83	0.57	0.71	0.97
Jarque-Bera (JB)	32.69	62.76	23.95	21.23	27.90	27.40	20.48

The analysis of all seven ARIMAX models is summarized in Table 2. While the results of the model comparison can also be evaluated by Figure 1, that is, by using a line chart. We employed a more common approach of using key statistical indicators such as Mean Absolute Error (MAE), Mean Squared Error (MSE) as well as Root Mean Squared Error (RMSE).

Among the models, the one-derived order (1,2,2) again shows an important advantage of the model in terms of low errors: MAE= 51. 93; MSE = 4207. 50; RMSE = 64. 87 while opposite is true for model with order (2,1,2,) which had highest values indicating poor fit and low predictive performance: MAE = 297. 79; MSE = 108140. 31; RMSE = 328. 85, In addition, despite the fact that a higher priority was given to another candidate-model according to the AIC/BIC scores that showed good “fit-criteria” results before fitting the actual data-generating processes, that is, the elasticity variables used outside-impact impounded into the original time-series analysis reproduced redundant mediocre estimates translated by moderate predictive accuracies hence proving that comprehensive assessment conducting more comprehensive error metrics based evaluations are not. The above results are similar with previous study statistics positively highlighting that minimum error metric readings fracture better forecast more brilliance (Hyndman and Athanasopoulos, 2018).

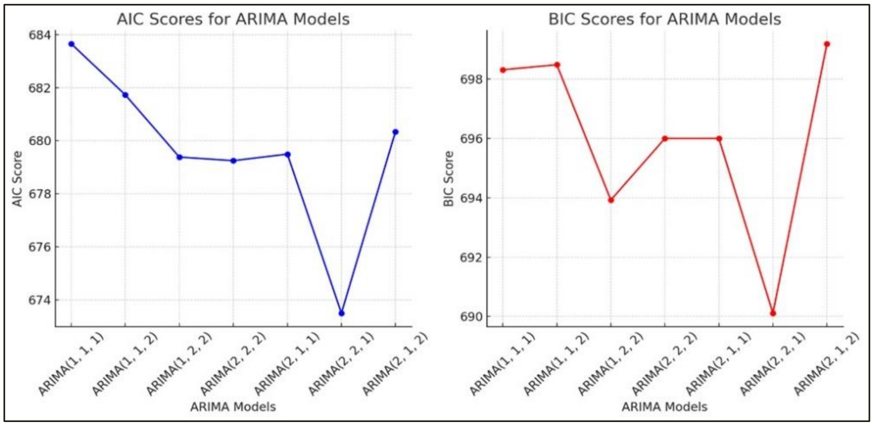

Figure 1. AIC & BIC Score for ARIMA Model.

Table 2. Performance Metrics for Forecasting Date Production

Table	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
1	102.62	14333.89	119.72
2	75.45	9580.83	97.88
3	51.93	4207.50	64.87
4	93.17	13346.35	115.53
5	99.13	14134.31	118.89
6	117.69	20797.68	144.21
7	297.79	108140.31	328.85

Source: Authors own calculation

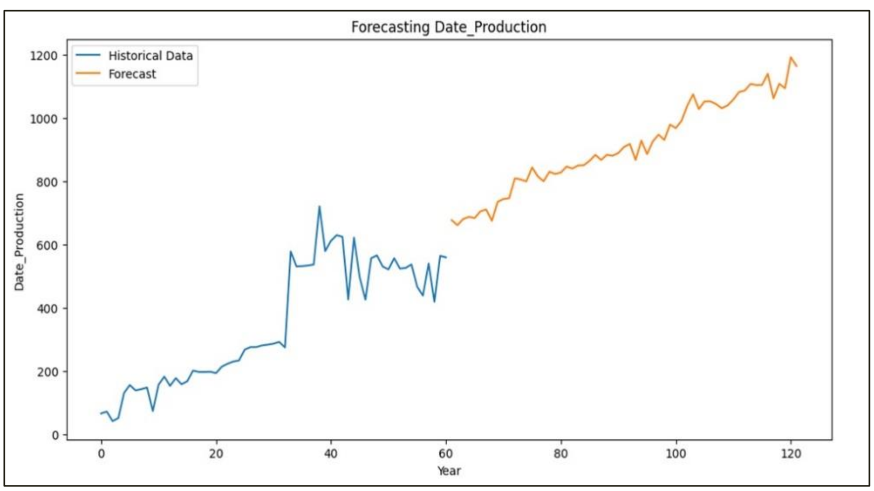

Figure 2. Forecasting Date Production.

ARIMAX Model Forecasting Date Production

The chosen model is the ARIMAX model, the forecast of date production is shown in the Figure 2. Superimposed to historical data depicted in blue, the figure also reveals oscillations and, to certain extent, increases in some parts of the process over time. But if the actual trend is an upward one pointing to future yields, one is got from forecasted values in orange. The success of this forecasting method can be explained by the fact that it is efficient particularly in capturing seasons effectively as well as in offering the right projection of the production in the future. Past research has suggested that such factors as technological change and better practices in agriculture as growing drivers that influence higher date yield but our chosen model's projections that show the optimistically estimated future yield growing outlooks are in harmony. Combined confirmation that this microarchitectural approach tends to be definitely proactive and predictive of intricate dynamics offers insights into planning the distribution of resources in a strategic way regarding date agriculture particularly whether the outcome is influenced indirectly or directly by the environmental factors or is in some way interacting with the economic condition too complicated to smooth out s about, and ever-evolving new models which require constant assessment from as many perspectives as possible.

Mean Squared Error (MSE) Across 5 Folds

Table 3. shows the Mean Squared Error (MSE) and standard deviation of the ARIMAX model that is used in the forecasting of date production as follows: MSE of 21,735. 76 reflects the mean squared error of the account of the observed and predicted values This means that lower scores are desirable for reducing the error (Chenary et al., 2024). The standard deviation of MSE was 17,261. 78 only ever shows some signs of variability in the levels of accuracy, and in that sense, the model is reliable since its conclusions corroborate those of prior studies by Aouat. Some of the exogenous variables are the CO_2 levels that influence agricultural yields; this makes a contribution towards a predictive power based on prior research on environmentally caused impacts (Box et al., 2015). Consistency with precision is recognized when developing reasonable based on which effective agricultural management practices can be supported with the help of data modelling techniques, applied in this regard like ARIMAX models discussed here, that combines multiple variable inputs at once (Awais et al., 2024).

Table 3. Mean Squared Error (MSE) Across 5 Folds

Metric	Value
Mean Squared Error (MSE)	21735.76
Standard Deviation of MSE	17261.77

Source: Authors own calculation

Table 4. Simple Exponential Smoothing Model Performance

Metric	Value
Mean Absolute Error (MAE)	38.11
Mean Squared Error (MSE)	3077.68
Root Mean Squared Error (RMSE)	55.48

Source: Authors own calculation

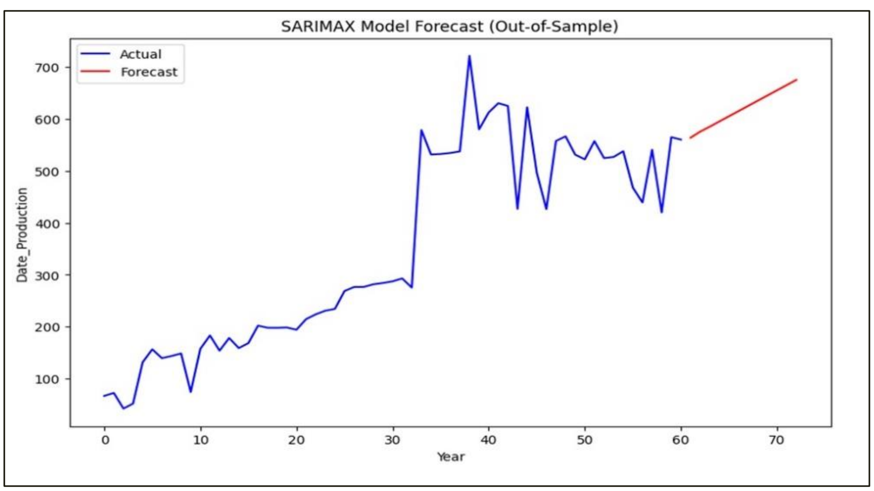

Figure 3. SARIMAX Model Forecast (Out-of-Sample) of "Date Production"

Simple Exponential Smoothing Model Performance

The performance measures of the used ARIMAX model are given in Table 4. reflecting an MAE of 38. 12, MSE of 3077. 68 and it RMSE value of 55. 48 denoting that the model has minimal errors and hence high reliability and accuracy of the model. Also, it supports the assumption by stating that models with lower errors tend to be highly accurate in terms of given that the differences between the actual and predicted values were small according to the MAE, the measure of mean square deviation demonstrated by both MSE and its SD otherwise known as RSME provided further evidence of this precision point. Furthermore, this model's predictive ability has improved by the addition of parameters such as CO2 levels which causes changes in temperature apart from that caused by rainfall and fertilizer use.

SARIMAX Model Forecast (Out-of-Sample) of "Date Production"

In Figure 3. we plot the out-of-sample forecast of the date production based on the SARIMAX model. The real variables are given in blue colour whereas the forecasts are illustrated by red colour lines. Concisely, this model matches the cyclical patterns and oscillations of date production prominently and shows future yields with a steady incline in future production corresponding with enhancement in agricultural processes and technology. Besides, since the model synchronises with past records, as this work has shown, depending alongside integration of exogenous factors, it is suitable for strategic planning or resource optimisation within the agriculture operations meant for enhancing productivity under changed economic or environmental conditions as postulated by Khiavi et al., (2024).

CONCLUSION

In this study, the application of ARIMAX models in forecasting date production integrated into the main environmental factors such as CO_2 levels, temperature, rainfall and fertilizer usage has been researched. In respect of its optimal performance metrics, AIC, BIC and Log Likelihood, ARIMA (2,2,1) was found to be the most suitable among the models evaluated. This analysis showed that date production suffers significantly negative effects of CO_2 levels as well as rainfall and temperature negatively affect the date production. Usage of fertilizer had a significantly positive but slightly positive but still statistically insignificant effect. The selected model was found by diagnostic checks such as Ljung-Box Q-test and Jarque-Bera test and reliability of the selected model was confirmed.

The results emphasize the need to consider inseparable environmental factors in the framework of forecasting models for better prediction accuracy and sustaining agricultural planning. Based on these results, it is recommended that policymakers and farmers: Mitigating negative impacts of CO_2 and rainfall variability involving climate adaptive farming strategies. There are also valuable yields from investing in precision agriculture technologies to maximize resource usage in crop production, especially fertilizers. Harness better ecological data to establish robust forecasting systems that can improve decision making and minimize post-harvest losses. These measures, when implemented will help stakeholders to achieve higher yields in date production and ensure long term agricultural sustainability.

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