Dhaka Univ. J. Sci. 74(2): 219–224, 2026 (July)
ISSN 1022-2502, E-ISSN 2408-8528
DOI: https://doi.org/10.3329/dujs.v74i2.84119

Comparison of ARIMA Model and Exponential Smoothing for Forecasting the Production of Jackfruit in Bangladesh

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(Received: 2 September 2025; Accepted: 5 February 2026)

Abstract

Jackfruit, the national fruit of Bangladesh, has the potential to meet both domestic demand and export value. In light of its significance for Bangladesh and other tropical nations, this study aims to anticipate Bangladesh's jackfruit production using the best-fitting ARIMA model by comparing it with an exponential smoothing technique. Using the data from 1971-72 to 2022-23, the ARIMA (1,2,1) model, selected via AIC metrics and validated through residual diagnostics, outperformed Holt's exponential smoothing in RMSE and MAPE comparisons. The results show that the exponential smoothing method is not as good at fitting the jackfruit production data as the ARIMA (1,2,1) model. Therefore, we use the ARIMA (1,2,1) model to forecast Bangladesh's jackfruit production for the ensuing ten years. The forecasted graph indicates linear growth in Bangladesh's jackfruit output over the next ten years.

Keywords: ARIMA, AIC, Holt's Exponential Smoothing, Forecasting, Bangladesh.

I. Introduction

Agriculture is the pillar of Bangladesh's rural economy. By providing food security and boosting this country's GDP through exports, agriculture has played a vital role for a long time. Fruits comprise 20% to 25% of the agricultural output for home use. Bangladesh produces a wide variety of fruits, including guava, pineapple, jackfruit, bananas, and mangoes. The country exports fruits such as bananas, jackfruit, and mangoes to several nations, accounting for between 5% and 7% of its total agricultural export revenue. The national fruit of Bangladesh, jackfruit, plays a key role in food security and rural development. It is distributed to the Middle East, Europe, and North America, where many South Asians reside. Bangladesh's climate and fertile loam soil support year-round jackfruit cultivation, with the main growing areas in the Rajshahi, Natore, and Chapai Nawabganj districts. Locals use the jackfruit seeds in curries or grind them into flour. Moreover, jackfruit meets local demand and supports exports of chips, jams, and canned products. Trade agreements, seasonal availability, foreign market demand, and other factors influence export quantities. Overall, although Bangladeshi jackfruit exports may not be as large as those of some other fruits, such as mangoes, there remains a sizable market for Bangladeshi jackfruit exports, and efforts are being made to further grow and expand this market. To meet the demand for domestic consumption as well as to implement a beneficial export strategy, it is important to predict the forecasted values of jackfruit production in Bangladesh.

Significant research has focused on forecasting fruit production using the ARIMA model and exponential smoothing techniques in South Asian countries, including Bangladesh. Ramadhan et al.[1] employed time series modeling to analyze coconut production, finding ARIMA (0,1,0) most suitable for productivity projection, while identifying Holt's exponential model as appropriate for acreage projection. Girija Devi[2] and Loidang Devi determined ARIMA (1,1,2) superior to compound growth rate and exponential smoothing methods for estimating pineapple production in Manipur. Similarly, Ullah et al.[3] applied ARIMA (1,1,0) to forecast peach production in Pakistan, projecting declining trends for future years. In comparing multiple forecasting approaches for Turkey's grain production, Ozlem Akay et al. [4] identified the ARIMA model as the most effective, while Akin and Eyduran[5] found Holt's exponential smoothing optimal for predicting Turkey's strawberry harvest area. Hamjah[6] successfully employed the Box-Jenkins ARIMA methodology to forecast seasonal rice production in Bangladesh, determining that ARIMA (2,1,2), ARIMA (2,1,2), and ARIMA (1,1,3) performed best for Aus, Aman, and Boro rice varieties, respectively.[7] The same researcher later concluded that for forecasting the production of other fruits in Bangladesh, ARIMA (2,1,3), ARIMA (3,1,2), and ARIMA (1,1,2) were most suitable for guava, bananas, and mangoes, respectively. Badar et al.[8] used the same ARIMA model to analyze the area, yield, production, and future trends of major food crops, including rice, wheat, and maize in Pakistan. The most suitable ARIMA models for forecasting the area and production of apples in Himachal Pradesh, as determined by the findings of Sharma et al.[9], were ARIMA (1,1,4) and ARIMA (1,1,2). Hossain et al.[10] projected three different types of pulse pricing in Bangladesh using the ARIMA model based on monthly data from 1998 to 2000: motor, mash, and mung.

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While extensive research utilizes the ARIMA model and, to a slightly lesser extent, Holt's exponential smoothing for forecasting, gaps still exist. No previous work has compared these models for forecasting jackfruit production. This research aims to do so by predicting jackfruit production over the next ten fiscal years. These forecasts are essential for planning, formulating, and implementing policies related to food distribution, import-export decisions, and food procurement.

II. Objectives of the Study

- To develop an ARIMA model to predict Bangladesh's jackfruit production.
- To develop Holt's exponential smoothing to predict Bangladesh's jackfruit production.
- To compare the fitted ARIMA model with the exponential smoothing for forecasting jackfruit production in Bangladesh.
- To predict jackfruit production for the next 10 years using the best fitted model.

III. Methodology

Autoregressive Integrated Moving Average (ARIMA) process:

If, in a time series with a need for differencing d times towards stationarity, applied an ARMA (p, q), then the original series is called an ARIMA (p, d, q) process. Here, p is the number of autoregressive terms, d is the number of differencing steps needed to make the series stationary and q is the number of moving average terms.

The model for ARIMA (1, 1, 1) can be expressed as:

$$W_t = \theta + \alpha_1 W_{t-1} + \beta_0 v_t + \beta_1 v_{t-1},$$

where

- W_t is the first difference of the series of Y_t
- θ is a constant term
- v_t and v_{t-1} are white noise terms

Exponential Smoothing

A popular forecasting technique for smoothing univariate time series data is exponential smoothing. The process involves giving past observations exponentially diminishing weights. More recent data are given larger weights, whereas farther-off observations are given weights that decrease exponentially.

Three varieties of exponential smoothing exist. Single exponential smoothing is the first kind and is unaffected by trends or seasonality. It foresees the latest forecast.The following is the mathematical formula for single exponential smoothing:

$$U_t = \alpha Y_t + (1-\alpha) U_{t-1},$$

where

- Y_t is the real record at time t
- U_t is the smoothed statistics
- α is the smoothing constant, which varies from 0 to 1.

Double exponential smoothing, often known as Holt's approach, is the most effective way to handle data that shows trends since it uses two smoothed constants, α and β. The double exponential smoothing formulations are as follows:

$$M_t = \alpha Y_t + (1-\alpha)(M_{t-1} + N_{t-1})$$

$$N_t = \beta(M_t - M_{t-1}) + (1-\beta) N_{t-1}$$

$$\hat{Y}_t = M_{t-1} + N_{t-1},$$

where

- N_t is the trend at time t
- $\hat{Y}_t$ is the predicted value of the series at time t
- M_t is the level at time t
- α and β are the weights (or smoothing constant) for the level and the trend respectively.

Triple exponential smoothing, also called Holt Winter's approach, is a statistical technique that uses three parameters (α, β, and γ) to account for a series' trend and seasonality.

Akaike Information Criterion (AIC) and log-likelihood

Selecting the model that minimizes

$$\text{AIC} = -2 \log (\text{maximum likelihood}) + 2k$$

is advised by Akaike's Information Criterion. If the model includes an intercept or constant term, k = p + q; otherwise, k = p + q. Higher values for log-likelihood are favored.

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error can be defined as the average of all the percentage errors for a particular data collection, calculated without taking into account the sign. The Mean Absolute Error Percentage (MAPE) is expressed as:

$$\textbf{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{B_t - G_t}{B_t} \right| \times 100\%,$$

where

- B_t is the real observed value at time t
- G_t is the forecasted value at time t.

Root Mean Square Error (RMSE)

It provides an average value of the sizes of the errors between the actual and anticipated values. RMSE is calculated as follows:

$$\textbf{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(B_t - G_t)^2},$$

where

- B_t is the real observed value at time t
- G_t is the forecasted value at time t.

IV. Data and Variables

Data on yearly jackfruit production from 1971-72 to 2022-23 has been obtained from the Statistical Yearbook of Bangladesh[11] and Yearbook of Agricultural Statistics[12], published by the Bangladesh Bureau of Statistics (BBS). The only variable considered here is jackfruit production.

V. Results and Discussions

Three tests have been carried out to check the stationarity of the data: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

According to the ADF test in Table 1, the data remain non-stationary after the first difference. However, the PP test and KPSS test indicate that the data become stationary after the first difference at 5% level of significance. Because of these contradictory outcomes, the second difference is used, and stationarity is obtained according to all three tests. Also, log transformation is used before taking the difference to make the variance stationary.

Table 1. Different unit-root tests.

	p-value		
	Original data	After 1st difference	After 2nd difference
ADF test [H_0: The data is non-stationary]	0.5838	0.1421	0.01
PP test [H_0: The data is non-stationary]	0.7711	0.01345	0.01
KPSS test [H_0: The data is stationary]	0.01	0.1	0.1

ACF and PACF plots of the 2nd differenced data havebeen used to select the number of MA and AR terms, respectively. From Figure 1 and 2, not a single spike is outside the confidence band at any lag. Therefore, AICand log-likelihood values have been used to choose a suitable ARIMA model.

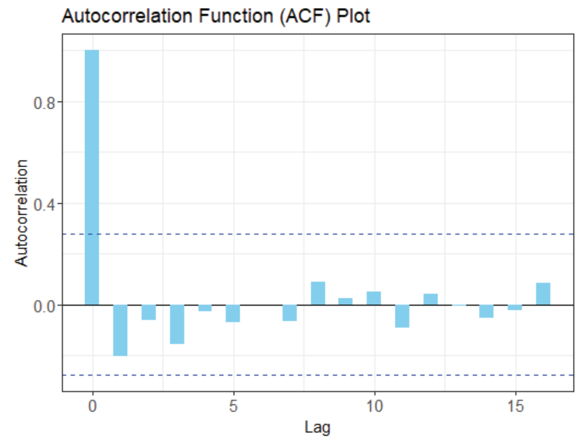

Fig. 1. ACF plot

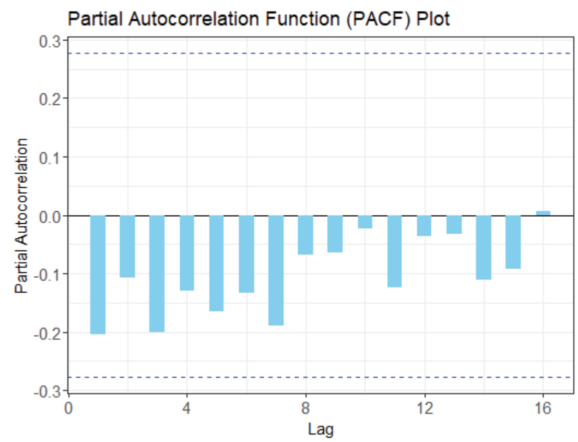

Fig . 2. PACF plot

Table 2 shows ARIMA (1,2,1) is the best fitted model to this data since it has the lowest AIC value and higher log-likelihood value. The ARIMA (1,2,1) trend line is shown in Figure 3.

Table 2. AIC and log-likelihood values for ARIMA (p, 2, q) model

Model	AIC	Log-likelihood
ARIMA (0,2,1)	1230.34	-613.17
ARIMA (0,2,2)	1228.79	-611.39
ARIMA (1,2,0)	1230.72	-613.36
ARIMA (1,2,1)	**1224.25**	**-609.12**
ARIMA (1,2,2)	1226.17	-609.08
ARIMA (2,2,0)	1232.45	-613.22
ARIMA (2,2,1)	1226.13	-609.06
ARIMA (3,2,1)	1227.05	-608.52

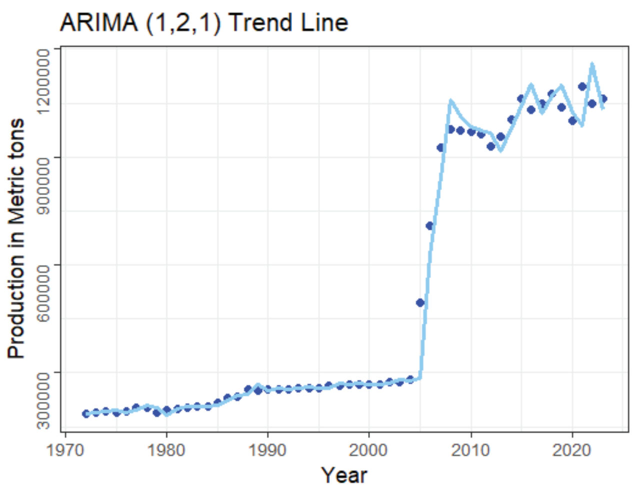

Fig. 3. ARIMA (1,2,1) trend line

In Figure 4, Holt's double exponential smoothing model is fitted to the data since the data shows no seasonality, only trends. Then, the performances of both models are compared using MAPE and RMSE values.

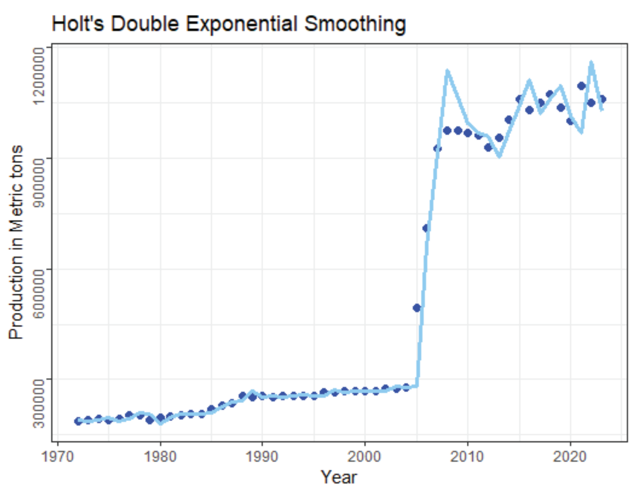

Fig. 4. Holt's double exponential smoothing model

Table 3 shows that the double exponential smoothing model does not yield a competitive result when compared to the ARIMA (1,2,1) model, which has lower MAPE and RMSE values.

Since the ARIMA (1,2,1) model fits the data better and the model diagnostic test satisfies all the criteria, it is used to predict jackfruit production over the next 10 years, or the fiscal years 2023-24 to 2032-33. According to Table 4, the jackfruit production is expected to rise from 1076604 metric tons in 2023-24to 1223824 metric tons in 2032-33.

Table 3. Comparison between ARIMA (1,2,1) and Holt's double exponential smoothing model

Model	MAPE	RMSE
ARIMA (1,2,1)	3.7891	45118.36
Holt's double exponential smoothing	4.1053	50230.96

Table 4. Forecasted values of jackfruit productions using ARIMA (1, 2, 1) model

Year	Point Forecast	95% Confidence Interval
2023-24	1076551	(985533.1, 1167569)
2024-25	1091845	(921106.0, 1262584)
2025-26	1107733	(862174.0, 1353293)
2026-27	1123960	(809575.8, 1438344)
2027-28	1140379	(762772.8, 1517985)
2028-29	1156907	(720880.2, 1592934)
2029-30	1173498	(683031.8, 1663964)
2030-31	1190124	(648486.2, 1731762)
2031-32	1206770	(616641.4, 1796899)
2032-33	1223428	(587018.8, 1859837)

The projected graph shown in Figure 5 suggests that during the next 10 years, Bangladesh's jackfruit production will show an upward trend.

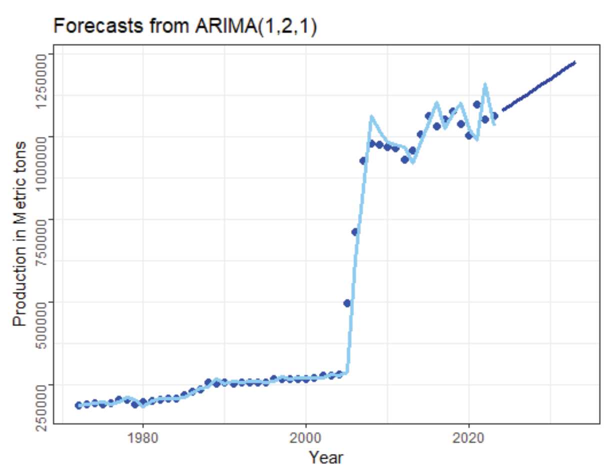

Fig. 5. Forecast from ARIMA (1,2,1) model

VI. Conclusion

In this study, the ARIMA model and the exponential smoothing model are fitted to Bangladesh's annual jackfruit production data. The ARIMA (1,2,1) is found to be the best fitted ARIMA model to the data with respect to AIC and log-likelihood values. Also, Holt's double exponential smoothing model is found suitable for the data since the data has no seasonality, only trends. The two models are then compared using their respective MAPE and RMSE values. However, as compared to the ARIMA (1,2,1)model,Holt's double exponential smoothing modeldoes not suit the data any better.

This research enriches the present literature. Moreover, the present study will be a good reference for further studies.

References

1. Ramadhan, A.J., T. Biswas, S. Roy, S.R. Anjanawe, D. Rawat, B. Kumari, and Z. Albadran, 2024., Modeling and Forecasting of Coconut Area, Production, and Productivity Using a Time Series Model, BIO Web of Conferences, **97**,. 00113.https://doi.org/10.1051/bioconf/20249700113

2. Devi, C.G., and S.L.Devi , 2022. *Estimation of Pineapple* Productionin Manipur-A Statistical Approach, The Journal of Research ANGRAU, **50(**3), 128-138.

3. Ullah, A., D.Khan, and S. Zheng, 2018. Forecasting of peach area and production wise econometric analysis,Journal of Animal & PlantSciences, **28**(4), 1121-1127.

4. Akay, Ö., G.Bozkurt, and G.Yüksel, 2017. *Prediction of grain products in Turkey*, Journal of Mathematics and Statistics, **13**(3), 220-230.http://doi.org/10.3844/jmssp.2017.220.230

5. Akın, M., and S.P.Eyduran, 2017. Forecasting harvest area and production of strawberry using time series analyses, Journal of Agricultural Faculty of Gaziosmanpaşa University, **34**(3), 18-26.https://doi.org/10.13002/jafag4298

6. Hamjah, M.A., 2014. *Rice production forecasting in Bangladesh: An application of Box-Jenkins ARIMA model*, Mathematical theory and modeling, **4(4),** . 1-11.

7. Hamjah, M.A., 2014. *Forecasting major fruit crops productions in Bangladesh using Box-Jenkins ARIMA model*, J Econ Sustain Dev, **5**(7).

8. Badar, N., H.Fatima, A.Jabbar, and M.Asif, 2015. *Major food crops production and yield forecast in Pakistan*, Pakistan Journal of Agricultural Research, **28(3)**.

9. Sharma, A., O.K.Belwal, S.K.Sharma, and S.Sharma, Forecasting area and production of apple in Himachal Pradesh using ARIMA model, International Journal of Farm Sciences, 2014. **4(4)**, 212-224.

10. Hossain, Z., Q.A. Samad, and Z.Ali, 2006. ARIMA model and forecasting with three types of pulse prices in Bangladesh: a case study, International Journal of Social Economics, **33**(4), 344-353.https://doi.org/10.1108/03068290 610651652

11. Bangladesh Bureau of Statistics, Statistical Yearbook of Bangladesh,2011.

12. Bangladesh Bureau of Statistics, Yearbook of Agricultural Statistics,2023.