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RESEARCH ARTICLE

Modeling and forecasting of egg production in India using time series models

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Zaman serisi modelleri ile Hindistan'daki yumurta üretiminin modellenmesi ve tahmin edilmesi

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Öz

Amaç: Günümüzde Hindistan'da beslenme alışkanlıkları değişmiş ve bu değişim protein tüketim alışkanlıklarını da etkilemiştir. Yumurta ürünlerinin yeme alışkanlıklarının değişmesi bunun bir göstergesidir. Nüfus artış hızı ve buna bağlı olarak yumurta talebindeki artış göz önüne alındığında, ülkelerin proteinli kümes hayvanı ürünleri üretimlerini artırmaları gerekmektedir. Bu çalışmada, hem politika yapıcılar hem de tedarikçiler için yumurta tüketim tahmini ile stratejiler geliştirebilecek sonuçlar elde edilmesi amaçlanmıştır.

Gereç ve Yöntem: Bu çalışmada, Hindistan'daki Yumurta üretimi ele alınmış ve ARIMA, BATS, TBATS ve Holt'un doğrusal eğilimi gibi birkaç zaman serisi modeli ile tahminler yapılmıştır. Yumurta üretimine ilişkin veriler 2015-2019 yılları arasında dikkate alınmıştır.

Bulgular: Holt'un Doğrusal Trend Modelinin tahmin için en uygun model olduğu tespit edildi. MAPE değerleri sırasıyla BATS, TBATS, ARIMA (1,2,2) ve Holt'un doğrusal trend modeli tarafından sırasıyla%2.137, %5.378, % 4.681 ve% 1.392 olarak elde edilmiştir. Holt'un doğrusal trend modeline göre, yumurta üretimi Hindistan'da yükseliş eğilimini sürdürüyor. Hindistan'daki Yumurta üretimi 2019-2020 ile 2023-2024 döneminde 111350,3'ten 148696,9'a yükselecektir.

Öneri: Bu çalışma, Hayvancılık sektöründeki politika yapıcılara, geleceğe yatırım yapmak için stratejiler oluşturmaları ve anlamaları için yardımcı olmaktadır. Dahası, Hindistan hükümeti tarafından yumurta ihracatı, yumurta tedariki, yumurta talebi ve yumurta fiyatları için stratejik bir plan yapmak bakımından önemlidir.

Anahtar kelimeler: BATS, TBATS, ARIMA, Holt'un doğrusal trend yöntemi, tahmin

Abstract

Aim: Eating habits have changed in India and this change has also affected protein consumption habits. The change in eating habits of egg products is an indication of this. Considering the population growth rate and the resulting increase in egg demand, the countries should increase their production of protein poultry products. Aim of the study was to obtain results for both policymakers and suppliers to develop strategies with the forecast of egg consumption.

Materials and Methods: In this study, the production of Eggs in India is considered and forecasts are made by the several time series model such as the ARIMA, BATS, TBATS, and Holt'slinear trend. The testing data for the production of the egg is considered from 2015-2019.

Results: It is detected that Holt's Linear Trend Model is the best fit model for forecasting. The MAPE values are obtained as 2.137%, 5.378%, 4.681%, and 1.392% by the best-fitted models BATS, TBATS, ARIMA (1,2,2), and Holt's Linear Trend respectively. According to Holt's linear trend Model, the Eggs production continues its upward trend in India. The Eggs production in India would be increased from 111350.3 to 148696.9 during the period 2019-2020 to 2023-2024.

Conclusion: This study might help policymakers in the Livestock sector to under standard making strategies for the future to invest in it. Furthermore, it is important to make a strategic plan for eggs export, eggs supply, eggs demand, and eggs prices by the Indian government.

Keywords: BATS, TBATS, ARIMA, Holt's linear trend method, forecasting.

Introduction

With a population of 1.2 billion, India is the fifth largest producer of chicken meat and the third largest egg producer in the world. More than half of the work force in India is employed in agriculture and this is 17.6% of the country's Gross Domestic Product (GDP). India is expected to surpass China in terms of population in the coming years. The households with middle-class are the fastest-growing part of the Indian population. Approximately 20% of the population is vegetarian, but urbanized people choose non-vegetarian diets (Mishra et al 2021). The modelling via time series is one of the significant branches in statistics and the active research area. It aims in forecasting the future outcomes of the series by studying the previous data points based on collected records and establish an appropriate model. The time series models are tools that provide information about the future and are used by many disciplines.

A time series contain a trend, seasonal, cyclic, and random components. A trend component moves up or down over an extended period. The cyclical component refers to longer cycles than seasonal components, and the seasonal component does not correspond to any of the three classes mentioned above (Hamilton1994). Additionally, the seasonality denominates to recurring and predictable trends and patterns after a certain period. Traditional times series methods such as Naïve (Makridakis et al 2008), Drift (Hyndman and Athanasopoulos 2018), simple exponential smoothing (SES) (Snyder et al 1999), Holt (Kendall and Ord 1990) Holt with drift (Fildes 1992), ETS (Error, trend, seasonal) (Hyndman and Khandakar 2007) and ARIMA (Ediger and Akar 2007) are utilized to model time series with univariate. ETS and SARIMA models (Jeong et al 2014) are failed to build satisfyingly if there are seasonal and complex patterns in the time series but they are well-known time series methods to deal with a single seasonal pattern. Some variants of these methods are useful for tackle seasonality, but it is enforced to be periodic. A time series with a complex seasonal pattern is a joint event. Considering this fact, the aim of this study was improving the utmost efficient short-term univariate forecasting model utilizing various time series models in literature ARIMA, Holts Winter, Exponential Smoothing and new techniques like BATS and TBATS (Exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components) to predict complex time series by using egg production data of India.

Looking at egg production time series, it is one of the most affected series with seasonal and cyclic variations in addition to trend, hence this study aim of the study above at forecasting the egg production of India using various time series models which are ARIMA, Holt's Winter, BATS, TBATS, to capture accurately complex seasonal and cyclic variations.

Material and Methods

Data was collected on egg production in India from 1980-2018. (Ministry of Agriculture & Farmers Welfare, Govt. of India & Past Issues)

The current investigation data which was used in fitting the models, divided into two sets of years, with training data accounting for 90% of the data set ("1979-1980", "2014-2015") and testing data accounting for 10% of the data set in the data from (2015-2016 To 2018-2019) for validation. The analyses are conducted by RStudio: Integrated Development for R. RStudio, Inc., Boston; R 4.0.3 (RStudio Team (2020).

BATS and TBATS models

TBATS is an improvement modification of BATS that allows multiple seasonal in correct cycles. TBATS has the following equation (De Livera et al 2011). Figure 1 is represented BATS and TBATS models.

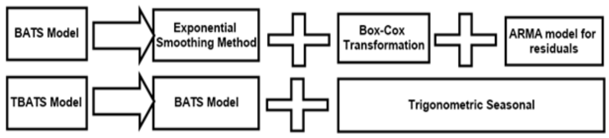

Figure 1: BATS and TBATS model

The first equation (1) is a Box-Cox transformation, error is modeled by ARMA

$$Y_t^{(\eta)} = \begin{cases} \dfrac{y_t^{(\eta)} - 1}{\eta} \quad \eta \neq 0 \\ \log y_t, \eta = 0 \end{cases} \quad (1)$$

The second Equation (2) represents the seasonal *M* pattern

$$Y_t^{(\eta)} = l_{t-1} + \xi Z_{t-1} + \sum_{i=1}^{T} s_{t-\rho_i}^{(i)} + d_t \quad (2)$$

Global trends and local trends are given by Equations (3), (4), and (5)

$$l_t = l_{t-1} + \xi Z_{t-1} + \alpha d_t \quad (3)$$

$$b_t = \xi b_{t-1} + \beta d_t \quad (4)$$

$$s_t^{(i)} = s_{t-\rho_i}^{(i)} + \gamma_i d_t \quad (5)$$

Equation (6) error can be modeled by ARMA

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad) \quad (6)$$

The smoothing parameters are given by α,β,γ_i for i=1…T and ξ is the dampening parameter (Taylor 2003). For seasonal data the following equations representing Trigonometric exponential smoothing models,

$$s_t^{(i)} = \sum_{j=1}^{k_i} a_{j,t}^{(i)} \cos\left(\psi_j^{(i)} t\right) \tag{7}$$

$$a_{j,t}^{(i)} = a_{j,t-1}^{(i)} + k_1^{(i)} d_t \tag{8}$$

$$\beta_{j,t}^{(i)} = \beta_{j,t-1}^{(i)} + k_2^{(i)} d_t \tag{9}$$

The smoothing parameters are $k_1^{(i)}$ and $k_2^{(i)}$

$\psi_j^{(i)}=2\pi j/\rho_i$ This is an extended, modified single source of error version of single seasonal multiple sources of error representation presented by (Hannan et al 1970, Harvey 1990, Durbin and Koopman 2012)

$$a_{j,t}^{(i)} = s_{j,t}^{(i)} \cos\left(\psi_j^{(i)} t\right) - s_{jt}^{*(i)} \sin\left(\psi_j^{(i)} t\right) \tag{10}$$

$$\beta_{j,t}^{(i)} = s_{j,t}^{(i)} \sin\left(\psi_j^{(i)} t\right) - s_{jt}^{*(i)} \cos\left(\psi_j^{(i)} t\right) \tag{11}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{12}$$

where

$$s_{jt}^{(i)} = s_{j,t-1}^{(i)} \cos\psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin\psi_j^{(i)} + \left[k_1^{(i)} \cos(\psi_j^{(i)} t) + k_2^{(i)} \sin(\psi_j^{(i)} t)\right] d_t \tag{13}$$

$$s_{jt}^{*(i)} = -s_{j,t-1} \sin\psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos\psi_j^{(i)} + \left[k_2^{(i)} \cos(\psi_j t) - k_1^{(i)} \sin(\psi_j t)\right] d_t \tag{14}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{15}$$

Equations (16) and (17) are seasonal patterns modeled by the Fourier model.

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\psi_j^{(i)} + s_{j,t-1}^{*(i)} \sin\psi_j^{(i)} + \gamma_1^{(i)} d_t \tag{16}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} \sin\psi_j^{(i)} + s_{j,t-1}^{*(i)} \cos\psi_j^{(i)} + \gamma_2^{(i)} d_t, \tag{17}$$

The notation of TBATS $(p,q,\{\rho_1,k_1\},\{\rho_2,k_2\},\dots,\{\rho_T,k_T\})$ is used for these trigonometric models.

Holt's linear trend method

This method is an exponentially weighted moving average, a means of smoothing out random variability with a number of advantages: (1) the data have a declining weight that's extremely important that; (2) very simple to calculate; and (3) the most important for data set is that minimal data is needed. (Holt 2004) had given three equations for forecast, level, and trend.

Forecast Equation

$$\hat{X}_{t+\rho\backslash t} = M_t + \rho\theta_t \tag{18}$$

Level Equation

$$M_t = \upsilon\,\chi_t + (1-\omega)(M_{t-1} + \theta_{t-1}) \tag{19}$$

Trend Equation

$$b_t = \gamma^*(M_t - M_{t-1}) + (1-\gamma^*)\theta_{t-1} \tag{20}$$

ARIMA model

ARIMA models are used for the series that are non-stationary but are made stationary with the operation of the difference of the series (Tekindal 2016). Several model options take the data into account when selecting an ARIMA model that is most suitable but with limited parameters. (Yonar et al 2020, Tekindal et al 2020, Arıkan et al 2018, Çevrimli et al 2020). ARIMA model consists of three parts. The first part is (AR) that is Autoregressive, the second part is (I) integrated and the third part is (MA) Moving Average so that model is named that Autoregressive Integrated Moving Average (ARIMA). Sometimes data of time series not required integrated part to decline the seasonality and in that case ARIMA model represented as ARMA (p,q) model. In this model, p is the order of the autoregressive part (AR) and q is the order of the moving average (MA) and integrated part is equal to zero ARIMA(p,0,q) that represented as ARMA(p,q).

Equation (1) The autoregressive model of order p is written as AR(p)

$$X_t = K + \sum_{i=1}^{p} \omega_i X_t + \varepsilon_t \tag{21}$$

where $\omega_1,\omega_2,\dots,\omega_p$ are the parameters of the model, Kis a constant and sometimes the constant term is avoided is white noise.

Equation (2) the moving average model of order (q) is written as MA (q),

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i\,\varepsilon_{t-i} \tag{22}$$

$$V_t = K + \emptyset_1 V_{t-1} + \emptyset_2 V_{t-2} + \dots + \emptyset_p V_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_p e_{t-p} \tag{23}$$

After this, the Ljung Box test was used to test whether or not the autocorrelations for the errors or residuals are non zero (Young 1977, Frain 1992, Kirchgässner et al 2012, Chatfield 2019). The statistical packages used for model building is R.

Results

The model considers the forecasting of the production of Eggs in India, which are identified by the ARIMA, BATS, TBATS, and Holt's Linear Trend. The data is divided into two sets of the year are training data 90 % of the data set ("1979-1980", "2014-2015") and testing data 10% of data set in the data from (2015-2016 To 2018-2019). After transforming the series into a stationary series, the ARIMA model was estimated. The stationary series is the one whose values differ over time only around a constant mean and constant variance. There are numerous ways to do this. The well-known method is to check stationarity by examining the graphs time plots of the data. Fig.1 revealed that the series were nonstationary. Non-stationarity in the mean is corrected through appropriate differencing of the series. For this, the descriptive study of the eggs production is also given in Table 1 below which defines the mean, max, and min, standard deviation, skewness, kurtosis.

From table 1, we find that: from 1979-1980 To 2018-2019, the eggs production in India has increased during the period from (9523) to (103318). The average eggs production in India is (40199). Kurtosis value is (2.5) indicates the data follows a platykurtic distribution which shows a tail that's thinner than a normal distribution which means the number of outliers will not be large. Followed by a positive value of skewness (0.80) which indicates there is some probability of increasing in the eggs production in India.

The data on production of the eggs in India was shown in the table from Table 2 to Table 10. These tables show the different forecasting of the data which are analyzed by the different methods like BATS, TBATS, ARIMA and Holt's Linear Trend. There is the data of Eggs which is testing by all the above-mentioned methods which give the 10% of the testing on Eggs in the form of RMSE, MSE & MAPE (Table 8). From, the eggs production in India: BATS is the best-suited model (0.037, {0,0}, 1, -), In this model, Box-Cox transformation =0.037, the order of ARMA error is (0, 0), the damping parameter = 1 (essentially doing nothing) (Table 2).

Table 1. Descriptive statistics of eggs production in India

Eggs production in India	Mean	Minimum	Maximum	Standard deviation	Skewness	Kurtosis
	40199	9523	103318	26029.16	0.800	2.572

Table 2. BATS Model fitted for of eggs production in India on training data 90 % of data set ("1979-1980","2014-2015")

Eggs production in India	Parameters						Prediction error	
	Lambda	Alpha	Beta	Damping parameter	AR coefficients	MA coefficients	Sigma	AIC
BATS (0.037, {0,0}, 1, -)	0.0372	0.984	-0.009	1	-	-	0.052	638.561

Table 3. TBATS Model fitted for of eggs production in Indiaon training data 90 % of data set("1979-1980","2014-2015")

Eggs production in India	Parameters			Gamma-1 values	Gamma-2 values	Sigma	AIC
	Alpha	Beta	Damping parameter				
TBATS (1, {0,0}, 1, {<6,2>})	0.746	0.250	1	-0.0001	-0.0004	1.185.119	658.593

From Table 3, the Eggs production in India: TBATS is the best-suited model (1, {0,0}, 1, {<6,2>}) In this model, Box-Cox transformation =1, (doing nothing), the order of ARMA error is (0, 0), the damping parameter = 1 (essentially doing nothing). The parameter for the level smoothing is represented by Alpha, and the parameter for the trend smoothing is represented by Beta, α and β are bounded by0-1, the high values mean fast learning and lesser values means lower learning (Table 3). It becomes obvious that the finest values of the level and the trends are 0.999 for level for the series (Eggs Production in India) meaning fast learning in the year-to-year Eggs Production in India, and 1e-04 for trend for the series (Eggs Production in India), which means slow learning for the trend (Table 4).

From table 5, The Model ARIMA (1,2,2) is seen as best fitted model for eggs production in India. In Table 5 and 6, the best-fitted models on training data set ("1979-1980","2014-2015"), based on, lowest values of ME, RMSE, MAE, MPE, MAPE, MASE and ACF1, BATS model is the best model for the series (Eggs Production in India). In other words, the forecasting accuracy by the BATS model is very high and outperform the forecasting accuracy of the other models, because the most values of the accuracy criteria (RMSE, MPE, and ACF1) were lower than the values of the accuracy criteria of other Models for the series (Eggs Production in India).

Table 4. Holt's linear trend model fitted for of eggs production in India on training data 90 % of data set ("1979-1980","2014-2015")

Eggs production in India	Box-Cox transformation	Smoothing parameters		Initial states		Sigma	AIC
	Lambda	Alpha	Beta	L	B		
	-0.1034	0.9999	1.00E-04	58.967	0.0214	0.0129	-178.367

Table 5. ARIMA Model fitted for of eggs production in India on training data 90 % of data set ("1979-1980","2014-2015")

Model	AR (1)	MA (1)	MA (2)
ARIMA (1,2,2)	0.6827	-17.859	0.8994

Table 6. Holt's Linear Trend, BATS, TBATS, ARIMA model fitted for Eggs production in India on testing data 10% of data set ("1979-1980","2014-2015")

Model	RMSE	MSE	MAPE
BATS	3.021.285	9128162	2.14%
TBATS	6.176.329	38147036	5.38%
Holt's linear trend	1.376.373	1894404	1.39%
ARIMA (1,2,2)	5691.2	32389752	4.68%

Table 7. Fitted Holt's linear trend, BATS, TBATS, ARIMA Model fitted for eggs production in India on trainingdata90 % of data set (2015-2016 To 2018-2019)

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
BATS	12.182	1.139.162	784.007	0.004	2.555	0.398	-0.255
TBATS	304.867	1.185.119	803.889	0.521	3.096	0.408	-0.032
Holt's linear trend	-217.590	1.218.055	885.007	-0.218	2.615	0.449	-0.196
ARIMA (1,2,2)	269.034	1.164.778	694.152	0.847	2.122	0.352	-0.079

Table 8. MAPE BATS, TBATS, Holt's linear trend and ARIMA on testing eggs production in India on testing data 10 %of data set from 2015-2016 to 2018-2019

Year	Eggs production in India by using BATS model			Eggs production in India by using TBATS model		
	Actual	Forecasted	Error	Actual	Forecasted	Error
2015-2016	82929	82958.43	0.04%	82929	81530.94	1.69%
2016-2017	88139	87668.98	0.53%	88139	85187.95	3.35%
2017-2018	95217	92636.52	2.71%	95217	88747.19	6.80%
2018-2019	103318	97874.47	5.27%	103318	93314.68	9.68%
	MAPE		2.14%	MAPE		5.38%
Year	Eggs production in India by using Holt's linear trend model			Eggs Production in India by using ARIMA(1,2,2)		
	Actual	Forecasted	Error	Actual	Forecasted	Error
2015-2016	82929	84086.75	1.40%	82929	82095.16	1.01%
2016-2017	88139	90133.9	2.26%	88139	85856.08	2.59%
2017-2018	95217	96664.47	1.52%	95217	89719.26	5.77%
2018-2019	103318	103721.03	0.39%	103318	93652.24	9.36%
	MAPE		1.39%	MAPE		4.68%

Table 9. Forecasting from BATS, TBATS, and Holt's linear trend on testing eggs production in India from (2019-2020 to 2023-2024)

Date	BATS	TBATS	Holt's linear trend	ARIMA(1,2,2)
2019-2020	103397	97679.7	111350	97632.9
2020-2021	109219	100739	119603	101646
2021-2022	115356	104098	128537	105681
2022-2023	121824	107756	138212	109732
2023-2024	128640	111315	148697	113793

The best-fitted models on testing data set (2015-2016 To 2018-2019) based on, lowest values of RMSE, MSE and MAPE, Holt's Linear Trend model is the best model for the series (Eggs Production in India), (Tables 7 and 8). In other words, the forecasting accuracy by the Holt's Linear Trend model is very high and outperform the forecasting accuracy of the other models, because the most values of the accuracy criteria (RMSE, MSE, and MAPE) were lower than the values of the accuracy criteria of other models for the series (Eggs Production in India). The best model for forecasting the egg production which lowest MAPE error for India holt's linear trend that is the model which has the lowest error (Table 9). The results from BATS model represent that the egg production will be upward. The Eggs production in India will increase from 111350.3 to 148696.9 during the period 2019-2020 to 2023-2024.

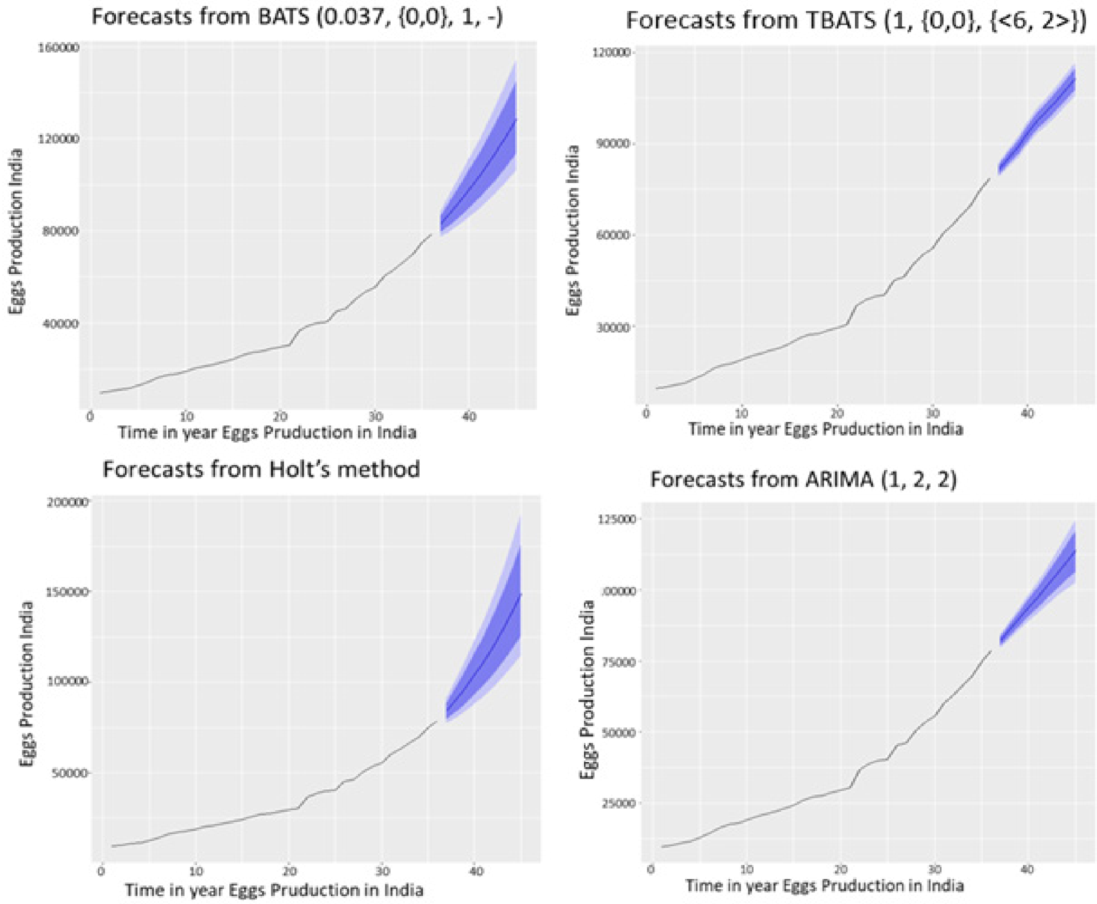

Figure 2 The forecasting values from ("2019-2020" to "2023-2024"), using BATS, TBATS and Holt'slinear trend models and ARIMA

Discussion

This research used well-known time series methods to deal with a single seasonal pattern like ARIMA Model, Holt's linear trend Model and some of the newest techniques like BATS and TBATS in order to predict complex time series by using egg production data of India. The results showed that Holt's Linear Trend Model was the best fit model for forecasting when compared to ARIMA, BATS, TBATS models. Moreover, The MAPE values were obtained as 2.137%, 5.378%, 4.681%, and 1.392% by the best-fitted models BATS, TBATS, ARIMA (1,2,2), and Holt's Linear Trend respectively.

According to Holt's linear trend Model, the Eggs production continues its upward trend in India. The Eggs production in India would be increased from 111350.3 to 148696.9 during the period 2019-2020 to 2023-2024. The comparison between the four different time-series models in terms of yearly data short forecasting accuracy, the Holt's Linear Trend model was found to be the best method for short-term forecasts. These findings further support the idea that there was linear trend in the data of the series (eggs production in India) and that is why the Holt's Linear Trend model was the best choice. The findings of the current study are consistent with those of Michel & Makowski (2013) in which they utilized eight models to forecast wheat yield, and they found that Holt's Linear Trend models were better performance as compared to others. Kumari et al. (2014) utilized many exponential smoothing models to forecast rice productivity and they found that Holt's linear trend model was the best model compared to exponential smoothing models. Khayati (2015) found that Holt's linear trend model was the best model to forecast the productivity of potatoes, artichoke and pepper.

Oni and Akanle (2018) compared Holt's linear trend model with others Exponential Smoothing Models for forecasting cassava production, and they found that Holt's linear trend model was better than Exponential Smoothing Models.

The primary conclusion is that using a new forecasting method did not provide more robust forecasts than traditional ones in all cases, there are more factors that have effects on the accuracy of forecasting models including frequency of the data, complexity of data, number of observations, the seasonality in time series, cyclic variations of time series, stationarity of time series, trending behaviour of time series, the long of out-sample forecast and randomness of the data. Some authors such as Gil-Alana et al (2008) andFranses and Van Dijk (2005) have speculated that simpler models perform better for short horizons while, complex models should be preferred for longer forecasting horizons. In future investigations, it might be possible to use a different approach in forecasting, for example: Using Prophet model which takes into account non-linear trends and it is robust to missing data and shifts in the trend, and handles outliers well. And compare it with Neural Network Autoregressive model (NNAR) for complex non-linearity nature of the data series. However, more research on this topic needs to be undertaken, by applying hybrid forecasting models, besides multivariate time series forecasting models.

After developing the best fitted time series model, forecasting is carried out for Eggs production in India, the data is divided into two sets of the year are 90 % of data set ("1979-1980","2014-2015") and testing data 10% of data set in the data from ("2015-2016" To "2018-2019") and the data from ("2019-2020" to "2023-2024"), are used as out-sample forecast, satisfied that the residuals of all selected models are found to be approximately stationary and white noise. The forecasting values with 95% confidence limit from ("2019-2020" to "2023-2024"), using best-fitted models for eggs production are shown in Figure 2 The blue color line of both figures indicated the forecasted values, which lie within the 95% upper and lower confidence limit. All predicated figures tend to be close to the observed values, which confirms the good prediction of selected models. From the forecasted figures (using Holt's linear trend model) which is the best model in our study, it can be seen that eggs production will increase continually in India, and it will range between 125000 to 175000.

In the projection model, every model is showing a different error rate. In the present investigation; MAPE measure, from training data, the best model with the least MAPE error is Holt's linear trend Model. We conclude that Holt's linear trend model is better than BATS Model, TBATS Model, and ARIMA model in the eggs production forecasting in India. According to Holt's linear trend model, the eggs production continues its upward trend in India.

Conclusion

The eggs production plays a central role in the development of the Livestock sector which is an important activity of Indian Agriculture GDP. India is the third biggest country in the world in terms of Eggs production. The Eggs production in India will increase from 111350.3 to 148696.9 during the period 2019-2020 to 2023-2024. This study helps policymakers in the livestock sector to understand and making strategies for the future to invest towards it. Moreover, it is important to make a strategic plan for eggs export, eggs supply, eggs demand, and eggs prices by the Indian government.

Conflict of Interest

The authors did not report any conflict of interest or financial support.

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An ethical statement was received from the author that the data, information and documents presented in this article were obtained within the framework of academic and ethical rules and that all information, documents, evaluations and results were presented in accordance with scientific ethics rules.

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