Forecasting cattle and buffalo population in India – A time series analysis

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Abstract: Cattle and buffalo are known to be the symbol of wealth in rural India from time immemorial. To ensure the attainable socio-economic benefits from cattle and buffalo reaching the rural poor through effective strategies, a more complete extrapolation of cattle and buffalo population in the country for the future using forecasting tools was attempted in this study. Data on cattle and buffalo population from 1950-51 to 2016-17 were collected from various reports of BAHS and FAO. Various time series forecasting models were employed to identify the growth patterns and to predict the future trends in bovine population. The forecasting models used were compared to identify the best fit model. From the results of the study, it could be discerned that the Damped Trend Exponential Smoothing was found to be the best fit model for cattle population and forecasted value indicated that the cattle population in the country would be almost stagnant in the next three decades. The cattle population forecast showed a slightly decreasing trend from 2010-11 with 194.184 million to 187.661, 188.177, 188.191, and 188.192 millions in 2020-21, 2030-31, 2040-41 and 2050-51, respectively. However, in case of buffaloes, the Brown Exponential Smoothing model was found to be the best fit model and the buffalo population was predicted to increase from 2000-01 and the predicted populations were 116.663, 127.787, 138.910 and 148.921 million in 2020-21, 2030-31, 2040-41 and 2050-51 respectively.

Keywords: Cattle and buffalo population, Forecasting, Time series analysis

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Introduction

Cattle and buffalo, providing food products like milk, meat and hide, have been generating productive employment and valuable income (Govt. of India, 2015-16 and Govt. of India, 2019), to the vast majority of rural households, majority of whom are small and marginal farmers, landless labourers and women. Total milk production in the country was 17 million tonnes in the year 1950-51 and since 1970s, milk production continued to rise, taking the country as the largest producer of milk in the world now by producing 13.1 per cent of world's milk, with milk production reaching 176.35 million tonnes in 2017-18 and achieving self-sufficiency in milk production (Govt. of India, 2018-19). This impressive growth could be attributed to the concerted efforts of large number of small dairy farmers, milk cooperatives, and planners who made possible crossbreeding of local low producing bovines with exotic germplasm and high producing buffaloes.

To be able to effectively plan strategies for optimizing milk production and for augmenting rural livelihood in the country, prediction of future bovine population using forecasting tools is required. Hence, this study attempted to untangle the future of Indian bovine population, considering the past and present trends.

Materials and Methods

Data on bovine population from 1950-51 to 2016-17 were collected from the reports of FAO Statistics (www.fao.org) and the reports of Basic Animal Husbandry Statistics (of different years), Dept. of Animal Husbandry and Dairying, Ministry of Agriculture and Farmers' Welfare, Govt. of India, both of various years. Different forecasting models were employed to predict the future bovine population. The results of forecasting models fitted were also compared to identify the best fit model. Among various forecasting models, Auto Regressive Integrated Moving Average [ARIMA] - p, d, q and Exponential Smoothing [ES] models were fitted.

Various combinations of ARIMA models viz., ARIMA (1,1,1), (1,1,0), (0,1,1), (0,1,0), (0,1,2), (1,1,2), (2,1,0), (2,1,1), (2,1,2), (1,2,1),

(0,2,1), (1,2,0), (0,2,0), (0,2,2), (1,2,2), (2,2,0), (2,2,1), and (2,2,2) and ES models viz., Simple ES, Holt ES, Brown ES and Damped trend ES were tried. Choudhury and James (2014) used simple exponential smoothing, double exponential smoothing, damped-trend linear exponential smoothing and ARMA models for predicting crop yields.

Then, using the best model, two kinds of forecasts were performed: sample period forecasts and post-sample period forecasts. The former was used to develop confidence in the model and the latter to generate genuine forecasts for use in planning and other purposes. Forecasting accuracy of different models was identified by using the measures of indices like Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Ahmad and Ahmad (2013) also compared the ARIMA model and Exponential Smoothing Method in making a prediction, by examining the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE).

ARIMA model

The data used in the study were non-stationary and non-seasonal. ARIMA model is a combination of an Auto Regressive (AR) process and a Moving Average (MA) process applied to a non-stationary data series. A combined model that contains p (AR) term and q (MA) term is called ARMA (p,q). If the object series is differenced 'd' times to achieve stationary, the model is classified as ARIMA (p, d, q) model as discussed by Box et al. (2007). The basic criteria for choosing the best fit of ARIMA (p, d, q) model are given in Table 1.

The general form of ARIMA model of order (p, d, q) is

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Where,

Y = Value at t^{th} year;

ε_t 's = Error terms which are independently and normally distributed with mean zero and constant variance σ^2 for $t=1, 2, \dots, n$;

μ = Constant and

ϕ_s and θ_s = Coefficients to be estimated.

Simple Exponential Smoothing

The Simple Exponential Smoothing (SES) model is a time series forecasting technique that can be defined using an additive model used to analyze data which have no trend and seasonal pattern. This is a method of estimation of forecasts of single weight or parameter. Greater weights are assigned to recent observation and smaller weights to distant observation (Sharpe et al. 2010). The model as given below:

$$F_{t+1} = F_t + \alpha(y_t - F_t)$$

New forecast value at time $t+1$ = Old forecast at time $t + \alpha$ (Error in the last forecast)

The smoothing constant (α) value is selected based on error minimization approach (Talwar and Goyal, 2019).

Brown's Linear (Double) Exponential Smoothing model

The double exponential smoothing model is used to model time series data which have trend, but not seasonality (Brown, 1963). Here, F' denotes a simple smoothed value and F'' denotes a double smoothed value:

$$F'_t = \alpha Y_t + (1 - \alpha) F'_{t-1}$$

$$F''_t = \alpha F'_t + (1 - \alpha) F''_{t-1}$$

$$\alpha_t = F'_t + (F'_{t+1} - F''_t) = 2F''_t - F'_t$$

α_t = estimated smoothed level at time t

$$b_t = \frac{\alpha}{1 - \alpha} (F'_t - F''_t)$$

b_t shows the estimated trends at the end of time period t , for m period ahead forecast is

$$F_{t+m} = \alpha_t + m b_t$$

Holt's Linear (Double) Exponential Smoothing model

Holt's method can be implemented for the time series data demonstrating a trend (Hanke and Wichern, 2008). This method is appropriate for non stationary data and to make short term forecast. In this technique, level and trend components are smoothed separately using different parameters α and β . Holt's double exponential smoothing method uses three equations one each for level, trend and forecast.

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + b_{t-1})$$

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1}$$

$$F_{t+m} = L_t + b_t m$$

where,

L_t = Level of time series at period t

b_t = trend (slope) estimate of time series at time period t

F_{t+m} = forecast at m period ahead of time t

α and β are smoothing constants for level and trend with their values lying between 0 and 1.

Damped Trend Exponential Smoothing method

The forecasts generated by Holt's linear method display a constant trend (increasing or decreasing) indefinitely into the future. Since empirical evidence indicated that this method tended to over-forecast, especially for longer forecast horizons, Gardner and McKenzie (1985) introduced a parameter that dampens the trend to a flat line sometime into the future.

The smoothing equations are,

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + \phi T_{t-1})$$

$$T_t = \gamma (L_t - L_{t-1}) + (1-\gamma)\phi T_{t-1}$$

The m-step-ahead prediction equation is

$$\hat{Y}_{t+m} = L_t + \sum_{i=1}^m \phi^i T_t$$

This is the forecast y, m-steps ahead by taking the last available estimated level state and multiplying the last available trend (slope) T_t , with ϕ = damping factor.

Results and Discussion

Among various models fitted, the model with the lowest normalized Bayesian Information Criterion (BIC) value and better model fit statistics like higher R^2 and the lowest Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) was selected as the best fit model.

Forecasting cattle population

The criteria adopted for model selection for forecasting of cattle population are given in Table 2, like the values of R^2 , RMSE, MAPE, MAE and Normalized BIC. The BIC value directly compares the information loss of models. Hence, a lower BIC value suggests a better model or best fit model. It can be discerned that the Damped Trend Exponential Smoothing was found to be

the best fit model, since its BIC value (28.209) was the lowest among all the models, along with reasonably lower values of RMSE (1247937.145), MAE (539261.451) and MAPE (0.443) and the highest R^2 value (0.984).

After this model selection, the model parameters were estimated and the results of the estimates are given in Table 3. Based on the best fit Damped Trend Exponential Smoothing model, forecasting of cattle population was carried out at two stages viz., sample period forecasts for the period from 2000-01 to 2016-17 (to develop confidence in model) and post sample period forecasts for 2020-21, 2030-31, 2040-41 and 2050-51 and the results are displayed in Table 4.

As could be seen, the Indian cattle population forecast shows that the cattle population had been slightly decreasing from 194.184 million in 2010-11 to 187.661, 188.177, 188.191, and 188.192 million numbers in 2020-21, 2030-31, 2040-41 and 2050-51, respectively. The results clearly indicate that the cattle population in the country would be almost stagnant in the next three decades. This underlines the fact that concerted programmes are required to be framed and implemented to ensure higher productivity to continue to satisfy the increasing demand for milk.

Forecasting buffalo population

The criteria adopted for model selection for forecasting of buffalo population are given in Table 5, like the values of R^2 , RMSE, MAPE, MAE and Normalized BIC. From the table, it can be found out that the Brown Exponential Smoothing model was found to be the best fit model, since the BIC value was found to be the lowest (26.606), with the high R^2 value of 0.996. RMSE (577912.272), MAPE (0.445) and MAE (336752.723) were also lower in this model. The model parameter was estimated and the results of the estimate are given in Table 6.

Based on the best fit Brown Exponential Smoothing model, forecasting of buffalo population was carried out at two stages

Table 1 Criteria for choosing the appropriate forecasting model

Selection Criterion	Notation
Bayesian Information Criterion = $n \log(\text{MSE}) + K \log n$	BIC
Coefficient of Determination = $1 - \frac{\text{Error sum of square}}{\text{Total sum of squares}}$	R^2
Root Mean Square Error = $\sqrt{\frac{1}{n-k} \sum \hat{\epsilon}_t^2}$	RMSE
Mean Absolute Error = $\frac{1}{n} \sum_{t=1}^n \hat{\epsilon}_t $	MAE
Mean Absolute Percent Error = $\frac{1}{n} \sum_{t=1}^n \left \frac{\hat{\epsilon}_t}{y_t} \right \times 100$	MAPE

Where k = Number of parameters in the statistical model; n = Sample size; y_t = Observed value; and $\hat{\epsilon}_t$ = Difference between the observed and estimated values.

viz., sample period forecasts for the period from 2000-01 to 2016-17 (to develop confidence in model) and post sample period forecasts for 2020-21, 2030-31, 2040-41 and 2050-51. Results are displayed in Table 7. From the forecasted values, it is evident that buffalo population is increasing linearly. The actual value of buffalo population during 2000-01 was found to be 93.831 million against the predicted value of 93.762 million.

The buffalo population was predicted to be increasing from 2000-01 and the predicted populations were 116.663, 127.787, 138.910 and 148.921 million in 2020-21, 2030-31, 2040-41 and 2050-51 respectively. The increasing trend of buffalo population in the

past, present and future could be attributed to the higher fat content of its milk which fetches higher price. This inherent characteristic of buffalo must have adequately persuaded the farmers to rear more and more buffaloes over time.

While Prasad et al. (2004) found the average annual growth rates of cattle and buffaloes in India as 0.67 and 1.63 per cent, respectively during the period 1951-92, Prabu et al. (2012) found a positive growth of cattle during 1997 and 2003 census periods also in the country. Borah and Halim (2014) too found a positive average annual growth rate of cattle (1.83 per cent) in India.

Table 2 Criteria for model selection for cattle population

Model	R ²	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.982	1279634.152	0.449	848577.423	28.343
ARIMA (1,1,0)	0.982	1356200.215	0.529	1003762.456	28.459
ARIMA (0,1,1)	0.982	1356200.231	0.529	1003762.478	28.459
ARIMA (0,1,0)	0.968	1689753.124	0.721	1372901.548	28.826
ARIMA (0,1,2)	0.981	1333415.456	0.508	964140.245	28.498
ARIMA (1,1,2)	0.982	1297745.153	0.445	842705.654	28.517
ARIMA (2,1,0)	0.982	1286037.456	0.452	855883.968	28.426
ARIMA (2,1,1)	0.983	1258719.012	0.464	876411.743	28.456
ARIMA (2,1,2)	0.984	1271794.014	0.457	862154.756	28.549
ARIMA (1,2,1)	0.982	1301902.245	0.420	795006.123	28.454
ARIMA (0,2,1)	0.979	1367974.365	0.347	654400.431	28.479
ARIMA (1,2,0)	0.979	1368205.348	0.346	652181.654	28.480
ARIMA (0,2,0)	0.979	1356819.489	0.339	639172.698	28.389
ARIMA (0,2,2)	0.979	1376650.564	0.372	703860.124	28.566
ARIMA (1,2,2)	0.980	1382529.154	0.374	707267.423	28.648
ARIMA (2,2,0)	0.979	1379807.469	0.352	665399.000	28.570
ARIMA (2,2,1)	0.980	1380997.324	0.379	715601.123	28.646
ARIMA (2,2,2)	0.982	1325554.781	0.427	808053.465	28.638
Simple ES	0.966	1751810.123	0.756	1444439.146	28.824
Holt ES	0.981	1331488.154	0.340	641808.135	28.347
Brown ES	0.981	1318859.215	0.335	631730.131	28.256
Damped trend ES	0.984	1247937.145	0.443	539261.451	28.209

Table 3. Estimates of the best fit Damped Trend Exponential Smoothing model for cattle population

Model	Parameters	Estimate	SE	t	Sig.
Damped trend ES	Alpha (Level)	1.000	0.292	3.420	0.001
	Gamma (Trend)	1.000	0.946	1.050	0.295
	Phi (Trend damping factor)	0.701	0.199	3.510	0.001

Table 4 Forecasts of cattle population (in million)

Year	Actual	Predicted	LCL(95%)	UCL(95%)	Residual
2000-01	191.924	192.591	190.088	195.095	-0.667
2010-11	194.184	194.673	192.170	197.176	-0.488
2020-21	-	187.661	177.929	197.394	-
2030-31	-	188.177	161.331	215.023	-
2040-41	-	188.192	150.548	225.836	-
2050-51	-	188.192	142.963	233.422	-

Table 5 Criteria for model selection for buffalo population

Model	R ²	RMSE	MAPE	MAE	BIC
ARIMA (1,1,1)	0.999	567161.153	0.501	381150.716	26.788
ARIMA (1,1,0)	0.999	569149.589	0.520	393204.556	26.722
ARIMA (0,1,1)	0.999	577715.345	0.539	410116.112	26.752
ARIMA (0,1,0)	0.999	563598.589	0.596	401268.973	26.789
ARIMA (0,1,2)	0.999	565862.894	0.512	425689.178	26.987
ARIMA (1,1,2)	0.999	602589.241	0.536	394568.156	26.897
ARIMA (2,1,0)	0.999	586947.235	0.548	375984.679	26.698
ARIMA (2,1,1)	0.999	614859.245	0.591	389125.279	26.746
ARIMA (2,1,2)	0.999	598674.259	0.459	412689.265	26.823
ARIMA (1,2,1)	0.999	547785.295	0.437	338227.316	26.723
ARIMA (1,2,0)	0.999	625475.653	0.436	323676.971	26.914
ARIMA (0,2,1)	0.999	545105.745	0.439	342153.624	26.639
ARIMA (0,2,0)	0.999	598647.258	0.612	396587.415	26.789
ARIMA (0,2,2)	0.999	602146.359	0.658	412689.345	26.989
ARIMA (1,2,2)	0.999	576298.345	0.589	402356.246	26.874
ARIMA (2,2,0)	0.999	563897.156	0.754	396589.125	27.215
ARIMA (2,2,1)	0.999	587569.217	0.753	435689.456	27.198
ARIMA (2,2,2)	0.999	589246.256	0.659	482678.159	28.234
Simple ES	0.996	1265498.454	1.459	1140561.574	28.174
Holt ES	0.999	571353.153	0.466	357039.178	26.655
Brown ES	0.996	577912.272	0.445	336752.723	26.606
Damped Trend ES	0.999	576353.100	0.492	376768.763	26.745

Table 6 Estimate of the best fit Brown Exponential Smoothing model for buffalo population

Model	Parameter	Estimate	SE	t	Sig.
Brown ES	Alpha (Level and Trend)	0.671	0.065	10.31	0.000

Table 7 Forecasts of buffalo population (in million)

Year	Actual	Predicted	LCL (95%)	UCL (95%)	Residual
2000-01	93.831	93.762	92.605	94.921	0.068
2010-11	107.375	107.757	106.600	108.916	-0.382
2020-21	-	116.663	112.815	120.513	-
2030-31	-	127.787	109.455	146.120	-
2040-41	-	138.910	100.185	177.636	-
2050-51	-	148.921	87.957	209.886	-

Thirunavukkarasu and Rajarathinam (2014), while forecasting milled rice production in India using data from 1960-61 to 2013-14, found that the most appropriate models were the ARIMA, Brown's model and Damped model. Chaudhari and Tingre (2015), while forecasting egg production in India, based on data from 1979-80 to 2010-11, found that the model which had minimum normalized BIC value (i.e., ARIMA (0,1,0)) was found to be the best model for predicting Indian egg production. Celik (2016) used Holt, Brown and Damped Trend exponential smoothing methods for forecasting production of cereals in Turkey based on the data from 1965 to 2015. Celik and Sengul (2016), while predicting the number of poultry in Turkey from 2016 to 2025 found that Damped exponential smoothing method was the best model for predicting the number of turkeys.

Conclusions

Cattle population would be almost stagnant in the next three decades. This underlines the fact that concerted programmes are required to be framed and implemented to ensure higher productivity to continue to satisfy the increasing demand for milk. However, the buffalo population would increase linearly in the future, due to the much preferred higher fat content of its milk which fetches higher price, adequately persuading the farmers to rear more and more buffaloes. Provision of adequate quality inputs like feed, fodder and health cover needs to be continuously provided to further augment the productivity among cows and to satisfy the increasing demand from the increasing number of buffaloes, if milch bovines are to be continuously exploited to ensure food security and improved rural livelihood in the country.

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