Modeling of Hilsa (*Tenualosa ilisha*) landings in the lower stretch of Brahmaputra River (Assam, India) under time-series framework

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ABSTRACT: For effective fisheries management of Brahmaputra River in Assam, India as well as for sustainable fishery development in the river stretch, it is significant to know the change in pattern of fish landings in previous years. Statistical modelling helps in describing the dynamics of fish landings and their short-term predictions. Thus, we attempted modeling the quarterly data series (1987–2019) on Hilsa (*Tenualosa ilisha*) landings in the Indian part of Brahmaputra River at Uzanbazar (Guwahati) using univariate forecasting techniques, viz., ARIMA (Auto-Regressive Integrated Moving Average) and NNAR (Neural Network Auto Regression). A comparative performance of fitted models was assessed based on the forecast accuracy measures. Based on comparison of forecast accuracy of models, the ARIMA model outperformed the NNAR model. Based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, an ARIMA$(1,0,0)(0,1,1)_4$ was found to be the appropriate model for describing Hilsa landings of Brahmaputra River. Under the present conditions, the forecasts by fitted ARIMA model predicted stagnation in abundance of prized Hilsa fish in the River at around 3000 kg/year for the upcoming years, which call for formulating and implementing an effective fishery management plan for conservation of its stocks. This is the first attempt on developing time-series models to forecast the Hilsa landings of Brahmaputra River in the region.

KEYWORDS: Hilsa, ARIMA, NNAR, forecast, Brahmaputra, India

INTRODUCTION

Tenualosa ilisha, commonly known as Hilsa, is an anadromous fish reported from varied riverine and estuarine ecosystems ranging from the snow fed Himalayan rivers (Ganga, Bhagirathi, Hooghly, Rupnarayan, and Brahmaputra) and their estuaries to rainfed peninsular rivers like Godavari and their estuaries, all of which drain into the Bay of Bengal. The species is also reported from rainfed peninsular rivers, like Narmada and Tapti, and their estuaries [1, 2] draining into the Arabian Sea. The Hooghly, the Ganga, and the Brahmaputra Rivers along with their tributaries contribute a significant portion of about 70% of the total Hilsa production in India [3]. The Hilsa has a great cultural and economic importance in India and Bangladesh [4, 5], and a very high consumer preference and highly prized [6]. The importance of this species can be derived from the assessment made by the Bay of Bengal Large Marine Ecosystem (BOBLME) that the economic value of Hilsa ïňĄshery is worth over US$ 2 billion. The Hilsa fishery generates employment opportunities and acts as a livelihood source for millions of people in India, Bangladesh, and Myanmar [7]. The Brahmaputra River originates in Tibet and flows through a 1625 km distance before entering India where the river runs another 918 km (278 km in Arunachal Pradesh; 640 km in Assam) and finally reaches the Bay of Bengal through Bangladesh (337 km) [8]. It is the major river draining the northeastern region of India [9–11]. The river acts as a lifeline of natural fisheries; it also plays a unique role in topography, hydrological balance, ecology demography, and economy of the region [12]. Hilsa formed a major commercial fishery in lower stretch of the Brahmaputra River in Assam [8].

In an economic system, a proper trend analysis of fish catches/landings using a time series approach is of immense value to obtain accurate and reliable forecasts. An unexpected surplus or decline in fish landings can result in a sharp fall or rise in the price of fish and consequently has significant implications on the livelihood of fishers. Fish landings observed over a period of time can be treated as a time-series process generated by a mechanism; and, in this context, the process can be studied to see the trend in landings. Statistical modelling helps in describing such trends and their short-term predictions. ARIMA, NNAR, VAR (Vector Auto Regression), Wavelet, etc., are the most frequently employed time series approaches to obtain accurate and reliable forecasts. These techniques have been widely used in fisheries by researchers [13–17]. However, the application of these approaches to understand the dynamics of fish landings in Indian rivers

is sparse and limited [18]. The proper forecast of fish landings would pave way for policy makers in formulating appropriate policy measures for riverine fisheries. The present study was attempted to model the quarterly time-series data on Hilsa landings of Brahmaputra River at Uzanbazar (Guwahati) located in Assam (India) under time-series framework.

MATERIALS AND METHODS

Data on Hilsa landings (in kg) collected by Guwahati Regional Centre of Indian Council of Agricultural Research- Central Inland Fisheries Research Institute (ICAR-CIFRI), Kolkata from Indian part of Brahmaputra River at the Uzanbazar Landing Center, Guwahati, Assam (26°11′44.33″ N and 91°45′23.94″ E) were used for the study. Data were divided into four quarterly groups corresponding to the seasons, viz., pre-monsoon season (March–May) representing the first quarter (Q1), monsoon season (June–August) representing the second quarter (Q2), post-monsoon season (September–November) representing the third quarter (Q3), and winter season (December–February) representing the fourth quarter (Q4). The quarterly time series data of Hilsa landings (in kg) from Brahmaputra River at Guwahati for a period of 33 years from 1987:Q1 to 2019:Q4 were utilized for the model building and the forecasting. In the present study, the entire quarterly Hilsa landing time-series comprising 132 observations (1987–2019) were split into two subsets: the train data (from 1987:Q1 to 2016:Q4) consisting of 120 data points used for model estimation and the test data of the remaining 12 observations (from 2017:Q1 to 2019:Q4) used for model validation and comparison. Further, the train data were investigated to select a suitable model for describing the dynamics of the quarterly Hilsa landing data series using seasonal ARIMA (SARIMA) and neural network forecasting techniques.

Mathematically, the general class of SARIMA model is an ARIMA model with order of non-seasonal auto regression (AR), p; order of non-seasonal differencing, d; non-seasonal moving average (MA) order, q; seasonality, s; seasonal AR order, P; order of seasonal differencing, D; and seasonal MA order, Q denoted by SARIMA$(p, d, q)(P, D, Q)_s$ and expressed in Eq. (1):

$$\varphi_P(B^s)\phi_p(B)\nabla^d\nabla_s^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (1)$$

where, Y_t is the quarterly Hilsa catches/landings at time t; $\phi_p(B)$ and $\theta_q(B)$ are polynomials in B of degree p and q, respectively; $\varphi_P(B^s)$ and $\Theta_Q(B^s)$ are polynomials in B^s of degree P and Q, respectively; $\nabla^d = (1-B)^d$, $\nabla_s^d = (1-B^s)^d$, $\phi(B) = 1-\phi_1 B-\cdots-\phi_p B^p$, $\theta(B) = 1-\theta_1 B-\cdots-\theta_q B^q$, $\varphi(B^s) = 1-\varphi_1 B^s-\cdots-\varphi_P(B^s)^P$, $\Theta(B^s) = 1-\Theta_1 B^s-\cdots-\Theta_Q(B^s)^Q$, B is back shift operator that $B^n Y_t = Y_{(t-n)}$; and $\varepsilon_t \sim \text{WN}(0, \sigma^2)$, WN indicating white noise.

The most suitable forecast model for the quarterly Hilsa landings is automatically selected from the class of ARIMA models by means of three iterative stages: (i) the identification of order of model (through differencing using Augmented Dickey Fuler-ADF unit root stationary test, distribution of autocorrelation, and partial autocorrelation function); (ii) estimation of parameters of the model (through maximum likelihood methods); and (iii) diagnostic check for the fitted models (statistically independent residuals) using Ljung and Box [19]. The popular minimization criterion (smaller is better), AIC proposed by Akaike [20] and BIC, was used for identification of best fitted SARIMA model. Finally, the forecast values for quarterly landings of Hilsa from Brahmaputra River were generated using the finalized model. Detailed information on different stages of ARIMA methodology has been described by Box et al [21].

Neural Network Auto Regression (NNAR) is a class of models used to predict time series by training the neural network using past value of the series. It is most widely used machine learning technique for modeling and forecasting the time series data containing non-linear patterns. The neural network model is consisted of three interconnected layers: simple processing units-input, output, and hidden layers. In this approach, the values of time series at previous lags are used as input in the input layer. The outputs in these models are forecast values of the time series in the output layer. There are one or more hidden layers between the input and the output layers. Each layer of nodes receives inputs from the previous layer. We used the seasonal NNAR model for the present study proposed by Hyndman and Asthasopoulos [22]. Typically, the general class of seasonal NNAR model is denoted by NNAR$(p, P, k)_m$ with order of non-seasonal lagged inputs, p; seasonal lagged inputs order, P; number of neurons in the hidden layer, k; and order of seasonality, m. In the absence of hidden layer, the NNAR$(p, P, 0)_m$ is equivalent to a SARIMA$(p, 0, 0)(P, 0, 0)_m$ but without stationarity restrictions.

The comparative performance of the fitted models for forecasting Hilsa landings was carried out through evaluation of actual (y_t) and forecast $(\hat{y}_t)$ values by calculating mean absolute error, MAE $= (\sum|y_t - \hat{y}_t|)/n$; root mean square error, RMSE $= \sqrt{[\sum(y_t - \hat{y}_t)^2]/n}$; and mean absolute prediction error, MAPE $= (\sum|y_t - \hat{y}_t|/y_t)/n$. A model with minimum value of these statistical values was considered the best. Both of these approaches were implemented by using tseries and forecast packages in R 3.5.3 [23] for model development.

RESULTS AND DISCUSSION

Based on a preliminary assessment of temporal pattern in annual Hilsa landings, the whole period was divided into three time periods (1987–1999, 2000–2009, and
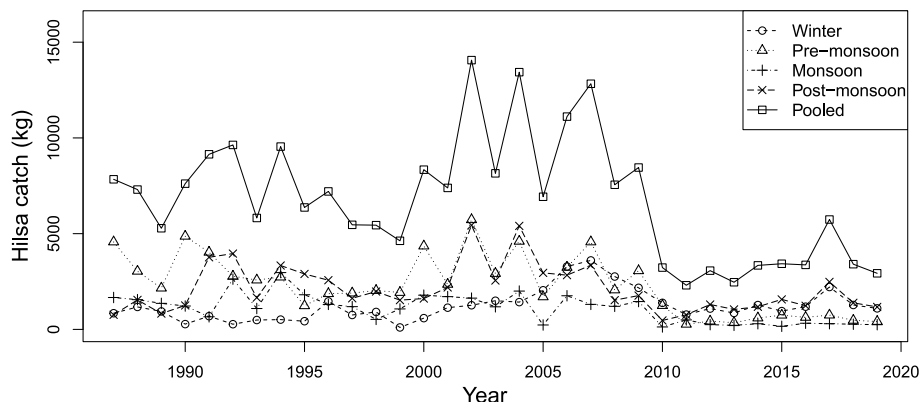
Fig. 1 Trend in seasonal and pooled landings of Hilsa in Brahmaputra River at Guwahati.
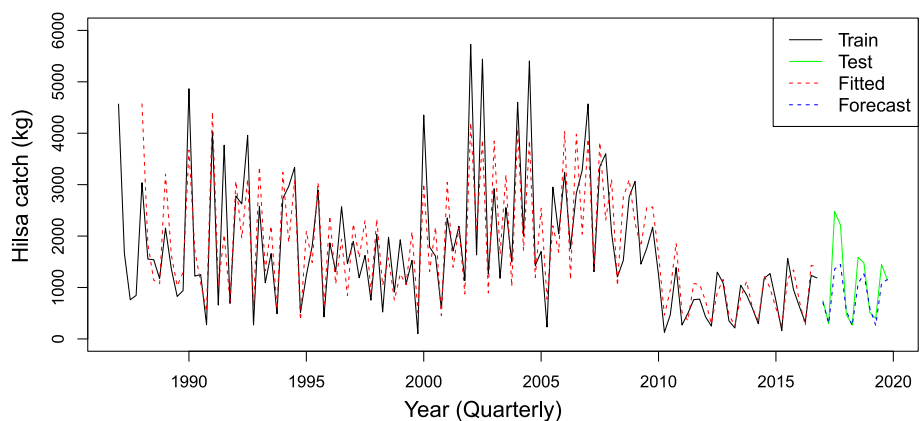

Fig. 2 Fitted and one-step ahead forecasts by SARIMA$(1,0,0)(0,1,1)_4$ model along with training and test data for Hilsa landings in Brahmaputra River at Guwahati.

2010–2019) to understand the variations in Hilsa landings between the periods (Fig. 1). The average long-term Hilsa landings was 6781.7 ± 3144.3 kg/year with the highest peak landings in 2002 (14 063 kg) and the lowest in 2010 (2305 kg). During 1987–1999, the catches were relatively stable with an average catch of 7022.1 ± 1693.2 kg/year. Following this period, a substantial increase (40%) in the average landings was observed during 2000–2009 (9825.7 ± 2749.3 kg/year) with wide fluctuations ranging from 6928 kg to 14 063 kg/year. However, unlike the other periods, the Hilsa landings declined steeply during the last

Table 1 Parameter estimates of fitted SARIMA model to forecast Hilsa landings in Brahmaputra River, Assam.

Model	Parameter	Estimate	Std error	*t*-value	*p*-value
SARIMA$(1,0,0)(0,1,1)_4$	Seasonal MA1	−0.648	0.087	7.43	<0.0001
	Non-seasonal AR1	0.326	0.199	2.98	0.0029
Out of sample forecasts of Hilsa landings (kg) by fitted SARIMA model					
Forecast (year/quarter)[†]	Q1	Q2	Q3	Q4	Total
2020	555.19	307.35	1041.16	1116.07	3019.77
	(90.55, 2406.63)	(49.53, 1795.74)	(181.68, 4317.44)	(183.99, 4418.75)	
2021	528.47	267.23	1093.24	1148.53	3037.47
	(82.98, 2744.41)	(45.44, 1970.76)	(166.31, 5053.13)	(168.42, 5164.85)	
2022	534.64	285.38	1024.03	1106.27	2950.32
	(76.35, 3098.71)	(41.87, 2154.11)	(152.88, 5826.01)	(154.82, 5948.67)	

[†] Values in parentheses indicates 95% confidence interval of forecasts.

decade of 2010–2019 to an average of 3424.9 ± 934.2 kg/year. This showed that average Hilsa landings of Brahmaputra River at Guwahati during 2010–2019 declined by almost 58% compared with the average Hilsa landings in the previous two decades from 1987 to 2009. Earlier studies have revealed that average catch of Hilsa during 1973–79 was 22.1 kg/day and declined to 2.9 kg/day during 1996–98; and the percentage contribution of this species to the total fish catch of Brahmaputra declined from 11.2% to 2.1% during the period with an overall decline of 81% in its catch [24]. Debnath et al [25] observed that contribution of Hilsa landings in this centre declined from 9.71% in 1975 to a meagre 1.87% in 2010. Recently, small-sized miscellaneous group of fish have started dominating (40–50%) the total catch; and *Aspidoparia morar*, a minor carp (mean total length 94.77 ± 0.79 mm), has emerged as single most dominant species in this landing centre [26] indicating less favorable habitat conditions for major fishes including Hilsa [8, 24]. The decline in catch might be due to recruitment overfishing (catching of brooders) and growth overfishing (catching of juveniles) during the course of their upstream and downstream migration, respectively both in Indian and Bangladesh stretch of the river (although the recent situation has improved significantly in Bangladesh owing to stringent regulatory measures). Over exploitation is a perfect example of 'tragedy of the commons', where numerous stakeholders exploit a common resource, thereby leading to its depletion [27, 28]. It is reported that anthropogenic activities, impact of climate change, and siltation of river bed followed by rising river basins had destroyed and disturbed the migration routes and spawning grounds of the species. As a result, the Hilsa production from freshwater ecosystems has declined around 20%, with 3 fold increase in catch from marine waters. Thus, a gradual shifting in the catch of the species across ecosystems have been noticed [29]. Moreover, we noted that from 2011–2012 onwards the Hilsa landings was considerably the highest during the post-monsoon season followed by the winter season (Fig. 1). Bhaumik [30] stated that catch rate of Hilsa in Hooghly River is high during the time of their spawning migration and during the period when the spent fish returning to sea. Similar trend was noticed in Brahmaputra River, with high catch rate noticed during the post-monsoon, when the individuals undertaking spawning migration upstream to rivers; and during the winter and the pre-monsoon, when juveniles migrating back to sea. High catch during the post-monsoon and the winter may also be due to upstream migration (twice) of the species in rivers of India and Bangladesh as observed by Raja [31].

SARIMA model was built using train data (1987:Q1 to 2016:Q4) and validated through test data (2017:Q1 to 2019:Q4) using Box-Jenkin's technique.

Table 2 Comparison of accuracy measure of forecasts.

Model	Training data			Test data		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
SARIMA	479.7	615.2	37.2%	276.5	438.6	19.2%
NNAR	351.4	532.5	30.8%	483.4	641.2	42.1%

ADF test applied for stationarity testing of quarterly Hilsa landings data gave a *p*-value greater than 0.05, thereby the time-series data under study were considered to be non-stationary. Accordingly, we applied seasonal differencing of order 1 to the original data series. The first seasonal differenced series of original Hilsa landings data were found to be stationary as *p*-value for ADF test did not exceed 0.05. Furthermore, the ACF and the PACF were estimated to identify the order of SARIMA models. Out of the 8 models developed to forecast Hilsa landings of Brahmaputra River at Guwahati, the model with minimum Akaike Information Criterion (AIC) was selected for the purpose. In our study, a SARIMA model with a non-seasonal auto-regression and seasonal moving average, that is $\text{SARIMA}(1,0,0)(0,1,1)_4$ model on the basis of minimum AIC value (215.11), was considered the best model. The estimated SARIMA model parameter values and their significance are given in Table 1. Training and test data along with fitted and one-step ahead forecast by $\text{SARIMA}(1,0,0)(0,1,1)_4$ model are presented in Fig. 2.

We considered the same train data and test data used in the SARIMA model for building the NNAR model also. A three layer feed forward neural network model was used to predict quarterly landings of the data series under study. A linear activation function was used in the input and output layers, whereas a sigmoid function in the hidden layer. Back propagation learning algorithm was used to compute a gradient descent with respect to weights. In this study, a feed-forward neural network model 4-2-1 with four lagged inputs (three non-seasonal and one seasonal), two neurons at the hidden layer, and one output corresponding to estimate of the Hilsa landings performed better among the competing NNAR models. Training and test data along with fitted and one-step ahead forecasts by seasonal NNAR model have been presented in Fig. 3.

The adequacy of the fitted models was performed by goodness-of-fit checks. A model is assumed to be statistically adequate if residuals obtained are statistically independent. We applied L-Jung and Box Chi-square test [19] to the residuals of the fitted model on training data. The *p*-value for both of the fitted models exceeded 0.05, thereby ensured that residuals were normally distributed. Thus, both of the fitted models were appropriate and able to capture the dependence in Hilsa landing data series.
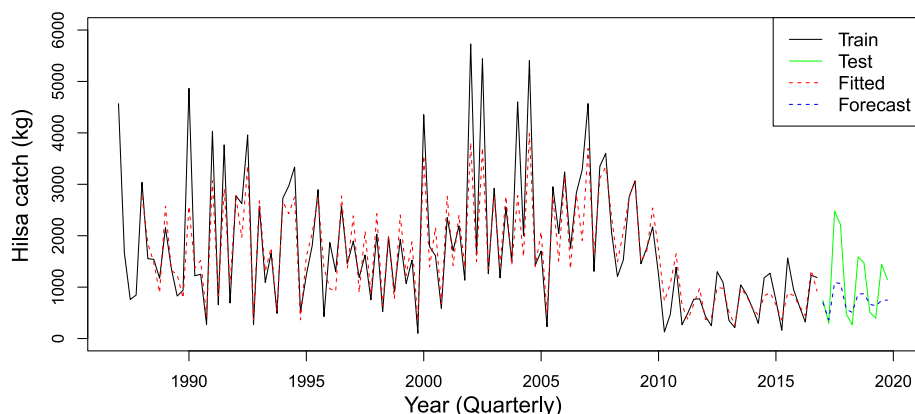
Fig. 3 Fitted and one-step ahead forecasts by seasonal NNAR model along with training and test data for Hilsa landings in Brahmaputra River at Guwahati.

Besides, both of the fitted models were used for forecasting over test data period from 2017 to 2019. The predictive capabilities of the two methods were checked by comparing their forecasted values against the actual values for the test data. Comparative statistics, viz., MAE, RMSE, and RMAPE were computed for forecast evaluation of the fitted models (Table 2). For training data set, it was observed that NNAR model performed better than SARIMA model as the comparative statistical values were lower. Both of the models performed more or less in a similar way for the training data set. However, NNAR model gave a poorer forecast than the SARIMA model resulting in a higher MAPE for the test data period (2017–2019). Mini et al [13] found that the NNAR model did not perform well in comparison to the SARIMA model for test data in modeling CPUE series. The values of MAPE for the SARIMA and the NNAR models were computed as 19.2% and 42.1%, respectively. The higher MAPE values for the fitted models may be attributed to the random fluctuations in the observed Hilsa landings as well as the drastic decline in the landings since 2009. Thus, if a strong deviation from the past pattern occurs, the prediction ability of a seasonal NNAR model was limited as compared with the SARIMA model. Based on the comparative statistical values, we concluded that the SARIMA model outperformed the seasonal NNAR model in forecasting capabilities. Similar observations were made for forecasting shrimp and fish landings in Songkhla Lagoon in Thailand [15]. Finally, the fitted SARIMA$(1,0,0)(0,1,1)_4$ model was used for out of sample forecasts of Hilsa landings in Brahmaputra River for the period from 2020:Q1 to 2022:Q4 (Table 1).

The study found that annual Hilsa landings will stagnate at around 3000 kg during 2020–2022. The forecast of fish landings would pave way for formulating and implementing effective fishery management plan for conservation of its stocks. However, the developed model could be further improved through integration of hydrological, environmental and meteorological variabilities.

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