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Forecasting quarterly landings of total fish and major pelagic fishes and modelling the impacts of climate change on Bombay duck along India's north-western Gujarat coast

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Quarterly landings or catches of total fishes and the major pelagic fish species, were forecasted using the methods and models *viz*. autoregressive integrated moving average (ARIMA), non-linear autoregressive (NAR) artificial neural network (ANN), autoregressive integrated moving average with exogenous inputs (ARIMAX), non-linear autoregressive with external (exogenous) inputs (NARX) artificial neural network. The models were also developed by considering only two important variables (differ for total fish and selected fish species) obtained from the ANN model. These simplified models proved nearly as good in their predictions. Simulated sea surface temperature (SST) for the A2 climate change scenario was used as an input for the NARX model to estimate the catches of Bombay duck over a short term (2020 – 2025) and a long term (2030 – 2050) with the last two years' (2012 – 2013) average catch of training data as a benchmark. The catches increased on average by 41 % in the short term but decreased by 17.72 % in the long term.

[Keywords: ANN, ARIMA, Bombay duck, Climate change, Forecast, SST]

Introduction

Estimating the past, current, and future quantities of the landings help in decision-making and planning for the future effectively and efficiently. The extensively used time series model for forecasting is ARIMA, short for autoregressive integrated moving average[1]. However, one of the main drawbacks of this model is the presumption of linearity, because a time series often contains non-linear components.

Another category of models, namely the ANNs, or artificial neural networks, is used when the relationships are predominantly non-linear[2-3]. To model, a series with non-linear patterns, non-linear autoregressive (NAR) ANNs are commonly employed. A number of well-known methods and models such as ARIMA, ANN, and wavelet have been used in times past by numerous researchers to forecast fish catches in the short-term[4], although environmental variables were not included in these models. Because the catches are greatly influenced by environmental variables, a modelling process that integrates them with a time series on fish catches can make the forecasts more accurate than those based on only a single parameter.

In modelling and forecasting, the ARIMAX model (short for autoregressive integrated moving average with exogenous environmental variables) is preferred over ARIMA because the former gives more accurate forecasts. Paul & Sinha[5] and Naskar *et al*.[6] used the ARIMAX model to study the influence of hydrological parameters on the abundance of hilsa, a freshwater fish in the Narmada River estuarine system, India. Non-linear autoregressive models with exogenous input (NARX models), which are based on the techniques of artificial intelligence, are commonly employed[7], when the time series data have non-linearity and the interest is to model the series with exogenous variables. Only a few studies have taken into account environmental variables in forecasting the catches of marine fish[8-9]. Because total catches and fish resources vary as the environmental variables change with the season, used quarterly landings and quarterly averages of the following exogenous (environmental) variables in building the model and for forecasting sea surface temperature (SST), diffuse attenuation coefficient for downwelling irradiance at 490 nm (Kd_490), photosynthetically active radiation (PAR), and Chlorophyll-*a* (Chl-*a*) in the present study. The importance of these four variables in the prediction of the fishery is discussed in Yadav *et al.*[10]. Although many have compared the methods and the models mentioned above in different domains with or without environmental variables, few have done so for estimating catches of fish. Damalas *et al.*[11] used the generalized additive model (GAM) for assessing the relative influence of different environmental variables on swordfish catches, and Madhavan *et al.*[8] used ANN to predict mackerel landings by taking into account three environmental variables, namely SST, Chl-*a*, and PAR.

Climate change due to the environment continues to affect marine ecosystems. The change in temperature drives the currents in the ocean, which helps in mixing the surface water with nutrient rich deeper water. This mixing of water affects the spread and plethora of plankton, which is feed for small fishes and thus affect the total catch of fish.

Predictions based on the relationships between environmental factors and resources have been made for different climate change scenarios[12-14]. Yanez *et al*.[14] used the ANN model to understand the climate change impacts on anchovy and sardine landings in Northern Chile. In the current study, the Bombay duck is chosen as a species for climate change study because it accounts for nearly 10 % of India's total catch and more than 25 % of the pelagic catch in Gujarat and about 90 % of the total catch in Gujarat and Maharashtra. To better understand the implications of climate change for those catches and to provide a reference for research on long-term strategies, simulated SST for the Climate Change Scenario A2 (2015 – 2050) obtained by the GFDL-CMIP model was used as an input for an NARX model for estimating the catches of Bombay duck for a short term (2020 – 2025) and for a long term (2030 – 2050) period. Scenario A2 is a high-greenhouse-gases-emissions scenario. As a benchmark, the average catch for the last two years (2012 – 13) of fish catch data is used.

Materials and Methods

Sample data collection

Quarterly average data for a period of 1998 to 2013 on the mean value of SST, Kd, Chl-*a* and PAR in the Gujarat coastal area were obtained as ASCII file from Moderate Resolution Imaging Spectroradiometer (MODIS) level 3 standard binned images archived by the Ocean Biology Processing Group (OBPG). As complete quarter set of remotely sensed imageries value was available from the year 1998, so the quarterly landing estimate of total catch and the catch of selected fish resources (Indian Mackeral & Bombay duck) pertaining to Gujarat coastal region of India were taken from the Central Marine Fisheries Research Institute (CMFRI), Kochi. The months of the year were divided into four quarters – 1st (January to March), 2nd (April to June), 3rd (July to September), and 4th (October to December) as the fish resources landing data are available in this fashion. The model used 90 % and 10 % of the whole dataset for training and testing purposes, respectively. SST, Kd, PAR and Chl-*a* were expressed in °C, m^{-1}, Einstein/m^2/day, and mg/m^3, respectively and the fish catch landing estimation was measured in a metric ton.

Simulation SST data from the GFDL-CMIP climate model under high greenhouse gas emission climate changed scenario RCP 8.5 was collected and incorporated into the analysis of catch potential of the Bombay duck. These data were generated from a model developed by the NOAA Geophysical Fluid Dynamics Laboratory (http://www.gfdl.noaa.gov).

Sample data analysis

Autoregressive Integrated Moving Average with Exogenous Input (ARIMAX)

The ARIMAX model is a generalization of the ARIMA model, which is capable of incorporating an exogenous input variable. In statistical form, ARIMAX (p,d,q,k) model is written as equation (1).

$$Y_t = \theta_0 + \sum_{i=1}^{p} \delta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j} + \sum_{l=1}^{k} b_l F_{t-l-1} + e_t \quad \ldots (1)^{(\text{ref. 6})}$$

Where, F is the exogenous variable of order k. The p, d and q represent the order of autoregressive term, differentiation term and moving average term, respectively.

In the present manuscript, the ARIMAX-auto-regressive integrated moving average (ARIMA) with exogenous variables - SST, Kd, PAR and Chl-*a* was developed. The ARIMA and ARIMAX computations have been done in R.3.6.1 software for statistical computing. The details of ARIMA and ARIMAX can be seen in Raman *et al*.[15].

Artificial Neural Network (ANN) model

The structure of ANN (Fig. S1) consists of three distinctive layers: input layers, hidden layer and output layer. The data are initiated and processed at input and hidden layers, respectively and the outcome is brought out at output layer. Levenberg Marquardt Algorithm based back propagation learning algorithm was used in ANN and the functions used at hidden layer and output layer were sigmoid activation and linear, respectively.

Nonlinear autoregressive (NAR) Artificial Neural Network (ANN)

NAR-ANN is trained to predict a time series from the past values of that series. The Architecture of a NAR-ANN is shown in Figure 1. The p features y(t-1), y(t-2), . . . , y(t-p), are called feedback delays.

Nonlinear Autoregressive with External (Exogenous) Input (NARX)

NARX predicts series y(t) given "p" past values of series y and the external series x(t), which can be single or multidimensional. The equation of the NARX model for time series prediction is shown as below:

$$Y(t)=f(x(t-1), x(t-2)\ldots\ldots, x(t-p),y(t-1), y(t-2),\ldots\ldots\ldots y(t-p))+ e(t) \quad \ldots (2)$$

In reality, there is a salient correlation between the modeled time series and the extraneous data series. There are various environmental and climatic parameters which affect the fish catch; therefore combination of environmental and climatic parameters with time series fish catch data would provide a better forecast compared to approach of taking single fish catch time series data.

The NAR and NARX computations have been done in R.3.6.1 software. The "forecast" and "t-series" package were used in R.3.6.1 software.

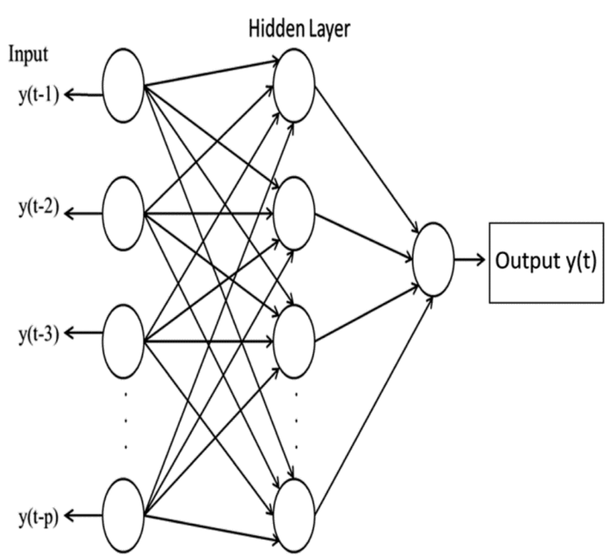

Fig. 1 — NAR-ANN Architecture

The details of these models and architectures can be seen in Paul *et al*.[5].

Results and Discussion

Fitting of ARIMA and ARIMAX models

The data series of the total catches and the catches of different fish species were stationary after taking the first-order difference. The model and parameter estimates by the best ARIMA and ARIMAX models based on minimum Akaike information criterion (AIC), root mean square error (RMSE), and model variance are shown in Tables 1 and 2.

Importance of variables in predicting total catch and selected fish species

The importance of each variable in predicting the total catches and the catches of individual species (Table S1) was determined by the connection weights algorithm using the ANN technique[16].

From Table S1, it is clear that SST and Chl-*a* are the two most important variables in predicting the total catch; SST and PAR for predicting the catches of Bombay duck; and Chl-*a* and PAR for Indian Mackerel. For references, may access Indian National Centre for Ocean Information Services (INCOIS), Hyderabad giving potential fish advisory data (total fish catch availability or assemblage) based on the environmental parameters - SST and Chl-*a*.

The method indicated that SST and PAR are the main predictors of Bombay duck catch, which is particularly sensitive to high temperatures[17-18]. The catches of Bombay duck was higher in the fourth quarter (October to December) (Fig. 2) during which the mean values of SST and PAR were low (Table S2), and the two variables are known to be positively correlated which was also reported by Madhavan *et al*.[8]. The catches of Bombay duck was higher in the fourth quarter, which is also supported by Table S3, where the maximum catch of Bombay duck was at 27.59 °C, which is close to the average value of SST (= 27.57 °C) during the 4th quarter (Table S2).

Chl-*a* and PAR are the two most important variables in predicting the catch of Indian mackerel as the species is herbivore feeding upon phytoplankton, and the growth of phytoplankton is governed by PAR. The average Chl-*a* during the study period was 2.19 mg/m^3 (Table S4). The maximum catch of Indian mackerel is at 3.01 mg/m^3 (Table S3).

The two most important variables for each case were used with NARX-NAR to forecast the quarterly landings or catches.

Table 1 — Best fitted ARIMA (or SARIMA as there is quarterly data and there are chances of seasonality) model and parameter's estimate for predicting the quarterly landing of total catch and catch of species - Indian Mackerel and Bombay duck

Total & species catch → Model and parameter ↓	Total catch	Indian mackerel	Bombay duck
Best model based on AIC value	ARIMA (3,1,0)(1,1,0)[4]	ARIMA (3,1,2)(0,1,0)[4]	ARIMA (3,1,0)(0,1,2)[4]
AR 1	**-0.6247 (0.143)**	-0.7654 (0.136)	-0.9612 (0.133)
AR 2	**-0.4146 (0.172)**	0.1751 (0.174)	-0.7323 (0.20)
AR 3	**-0.0745 (0.17)**	0.2490 (0.141)	-0.5711 (0.229)
MA 1		0.0000 (0.083)	
MA 2		-1.0000 (0.083)	
MA 3			
SAR 1	**-0.5352 (0.142)**		
SAR2			
SAR3			
SMA1			-1.2784 (0.246)
SMA2			0.4085 (0.233)
AIC Values	1248.94	881.20	1079.20
RMSE	27088.19	796.16	5155.75
Model variance	868543889	765940	32119635

[AR1:Autoregressive coefficient of order 1, AR2: Autoregressive coefficient of order 2, AR3: Autoregressive coefficient of order 3, MA1: Moving average coefficient of order 1, MA2: Moving average coefficient of order 2, MA3: Moving average coefficient of order 3, SAR1: Seasonal autoregressive coefficient of order 1, SAR2: Seasonal autoregressive coefficient of order 2, SAR3: Seasonal autoregressive coefficient of order 3, SMA1: Seasonal moving average coefficient of order 1, SMA2: Seasonal moving average coefficient of order 2, Standard error (SE) indicated in parenthesis]

Table 2 — Best fitted ARIMAX (or SARIMAX) model and parameter's estimate for predicting the quarterly landing of total catch and catch of species - Indian mackerel and Bombay duck

Total & species catch → Model and parameter ↓	Total catch	Indian Mackerel	Bombay duck
Best model-based on AIC value	ARIMA (3,1,0)(1,1,0)[4]	ARIMA (3,1,2)(0,1,0)[4]	ARIMA (3,1,0)(0,1,2)[4]
AR 1	-0.4953 (0.160)	-0.6383 (0.203)	-0.8890 (0.157)
AR 2	-0.4054 (0.176)	-0.6137 (0.218)	-0.6790 (0.228)
AR 3	0.0489 (0.173)	0.1132 (0.179)	-0.5714 (0.244)
MA 1		0.0472 (0.146)	
MA 2		0.8041 (0.16)	
MA 3			
SAR 1	-0.5536 (0.155)		
SAR2			
SAR3			
SMA1			-1.2095 (0.27)
SMA2			0.3626 (0.213)
Chl-a	-24420.52 (36647.04)	164.358 (1129.88)	-6483.622 (10095.34)
Kd	445313.4 (542078.2)	1820.968 (16011.46)	87446.61 (135704.34)
SST	-5523.788 (7422.72)	339.5515 (180.08)	-1530.986 (1592.29)
PAR	4450.952 (2097.86)	118.7936 (69.74)	1122.9694 (495.55)
AIC Values	1247.59	884.7	1079.65
RMSE	**24735.4**	786.7842	4845.291
Model variance	788593835	815993	30946745

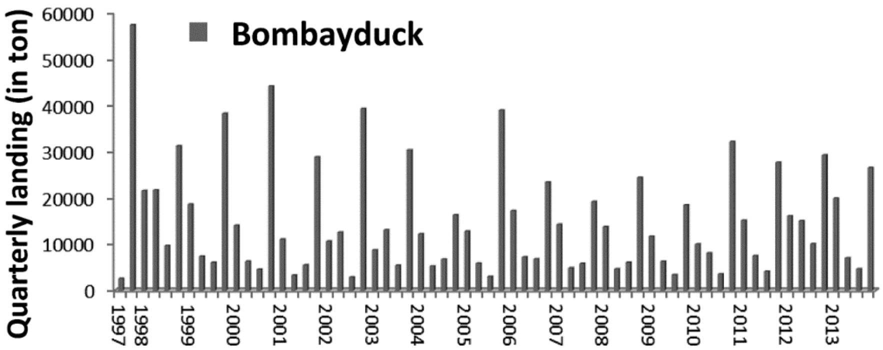

Fig. 2 — Trend of Bombay duck catch over all the quarters of the years

Table 3 — Comparisons of the forecasting results of total catch landing by ARIMA, NAR, ARIMAX, NARX, and NARX with two important variables, on last six testing data (Hold out data)

Year	Actual quarter landing	ARIMA	ARIMAX	NAR-ANN	NARX	NARX (with two important variables_sst_chl)
Q3_2012	114895	99399	100586	73985	68299	77143
Q4_2012	352986	329559	329323	297151	337807	327945
Q1_2013	238844	247122	227582	195996	195852	275380
Q2_2013	121744	172386	153868	105078	132544	138551
Q3_2013	98080	117280	116887	64017	77625	68210
Q4_2013	337994	352563	349125	289884	293569	329134
RMSE		25829.51	20004.46	41592.56	33562.23	27810.08
MAE		21935.33	18549.33	39738.44	30074.46	25811.25
Average error (%)		14.84	12.12	22.00	17.62	17.02

Table 4 — Comparisons of the forecasting results of Indian Mackerel landing by ARIMA, NAR, ARIMAX, NARX, and NARX with two important variables, on last six testing data

Year	Actual quarter landing	ARIMA	ARIMAX	NAR-ANN	NARX	NARX (with two important variables_chl_par)
Q3_2012	469	610	643	182	265	324
Q4_2012	1528	2550	2440	1853	1623	1726
Q1_2013	1938	3404	2217	1751	1791	1523
Q2_2013	565	1232	1056	819	910	703
Q3_2013	573	555	686	247	325	312
Q4_2013	2229	2771	1489	2366	2356	2136
RMSE		811.63	538.71	262.20	211.70	233.90
MAE		642.66	451.5	252.66	194.33	208.33
Average error (%)		53.01	41.83	33.35	27.88	23.23

Fitting of NAR and NARX models

The model for predicting the total catch and selected pelagic fishes was examined at various delays with varying numbers of hidden nodes. In most cases, a neural network model with four delays and five nodes in the hidden layer performed better than the other competing models in NAR and NARX neural network structures. All four exogenous (environmental) variables were predicted quarterly for the next five years by using NAR-ANN methods (not shown here) and were used in the NARX model.

The values predicted by the NARX model and the actual values of the total catch and selected pelagic fishes are represented in a graphic form in Figures S2 (a – c).

Validation of models for hold-out data

One-step-ahead forecasts from the 3rd quarter of 2012 to the 4th quarter of 2013 (the last six data points) as given by the fitted models are given in Tables 3 – 5. The forecasts of these models were compared using RMSE, MAE, and average error percentage. The NARX model proved more accurate than any other model in all cases except for the total catch, for which ARIMAX proved superior.

As can be seen in Tables 3 – 5, ARIMAX performed better than ARIMA in most cases (except

Table 5 — Comparisons of the forecasting results of Bombay duck landing by ARIMA, NAR, ARIMAX, NARX, and NARX with two important variables, on last six testing data

Year	Actual quarter landing	ARIMA	ARIMAX	NAR-ANN	NARX	NARX (with two important variables_SST & PAR)
Q3_2012	10072	5791	6164	6206	6263	10700
Q4_2012	29265	28944	29976	29157	26187	33063
Q1_2013	19921	15490	14811	15373	13397	17572
Q2_2013	7025	10287	9970	11877	8581	5955
Q3_2013	4684	6367	6616	8159	6037	6813
Q4_2013	26518	29139	30416	26905	27026	24662
RMSE		3120	3403.18	3449.76	3441.29	2215.71
MAE		2766.5	3084	2872.45	2804.66	1971.49
Average error (%)		26.348	27.45	34.38	22.33	16.44

in predicting the total catch and that of Bombay duck – in which both the models either performed equally well or ARIMAX performed better, and NARX performed better than NAR. This indicates that the inclusion of environmental variables makes the forecasts more accurate. Also, seasonal variations in total catch and in those of Bombay duck were captured more accurately by ARIMAX (or SARIMAX). Despite such non-linearity in the data, ARIMAX performed better than or nearly as well as NARX. Lastly, NARX with two important variables performed slightly better than or almost equally well as NARX with all the four environmental variables.

Forecasting of total catch and catch of selected pelagic fishes

As the developed models ARIMAX and NARX had good accuracy on hold out data, these models were used for forecasting the total catch and catch of selected pelagic fishes. The predicted landings were compared with the landing estimation given by CMFRI, Kochi, to check the reliability of models. Using the values of all the endogenous (time-series data of fish catch landing) and exogenous variables (environmental variables) as forecast by the NAR-ANN method, the NARX method was used to forecast the total catch and the catch of selected pelagic fishes in each quarter. Also, it was found that Chl-*a* (29.7 %) and SST (23.7 °C) has the most important role in predicting the total catch (Table S1). Hence SST and Chl-*a* were taken in the ARIMAX model in predicting the quarterly landing of the total catch, and it was found that the model was equally better than the model taking all the four variables (SST, Chl-*a*, Kd, and PAR) (Table 6). The values of total catch and selected pelagic fishes for five years (20 quarters) are shown in Tables 7 and 8, respectively.

These predicted values were compared with the actual values (those released by the Central Marine Fisheries Research Institute for 2014, 2015, and 2016

Table 6 — Best fitted ARIMAX (or SARIMAX) model and parameter's estimate for predicting the quarterly landing of the total catch

Total catch → Model and parameter ↓	Using SST, Chl-*a*, Kd & PAR	Using SST & Chl-*a*
Best model-based on AIC value	ARIMA (3,1,0)(1,1,0)[4]	ARIMA (3,1,2)(0,1,0)[4]
AR 1	-0.4953 (0.160)	-0.6797 (0.152)
AR 2	-0.4054 (0.176)	-0.5129 (0.193)
AR 3	0.0489 (0.173)	-0.059 (0.176)
MA 1		
MA 2		
MA 3		
SAR 1	-0.5536 (0.155)	-0.57 (0.159)
SAR2		
SAR3		
SMA1		
SMA2		
Chl-a	-24420.52 (36647.04)	11434.13 (9516.18)
Kd	445313.4 (542078.2)	
SST	-5523.788 (7422.72)	-7250.426 (7188.4)
PAR	4450.952 (2097.86)	
AIC Values	1247.59	1249
RMSE	24735.4	25977.6
Model variance	788593835	832778282

Standard error (SE) indicated in parenthesis

(www.cmfri.org.in/gj2014, www.cmfri.org.in/gj2015, and www.cmfri.org.in/gj2016)[19], and the results are shown in Tables S5 and S6.

The results (Table S5) indicates that the model ARIMAX with input SST and Chl-*a*, gives a very close estimate of the total catch for all the three the years (2014, 2015 and 2016), with CMFRI released report (Note that the CMFRI data are annual aggregates and this study compared the total of the four quarters as forecast to the year's actual value). This also can be noted that the performance of

Table 7 — Forecasted landing (in metric ton) of the total catch for next 5 years (20 quarters) using different inputs in the ARIMAX model

Year	Using SST, Chl-*a*, Kd & PAR	SST & Chl-*a*
Q1_2014	119159	91675
Q2_2014	373800	302698
Q3_2014	165944	193079
Q4_2014	101813	177324
Q1_2015	158015	129556
Q2_2015	391394	319610
Q3_2015	191406	209025
Q4_2015	123193	190759
Q1_2016	183612	151169
Q2_2016	409928	332363
Q3_2016	191008	229352
Q4_2016	133209	206963
Q1_2017	187479	165529
Q2_2017	420496	347963
Q3_2017	229216	242300
Q4_2017	153715	220367
Q1_2018	213959	178689
Q2_2018	439787	361691
Q3_2018	213626	261938
Q4_2018	167226	236447

Table 8 — Forecasted landing (in metric ton) of the catch of selected pelagic fishes (using NARX model with all 4 environmental variables) for next 5 years (20 quarters)

Year	Indian mackerel	Bombay duck
Q1_2014	2258	18080
Q2_2014	1549	3697
Q3_2014	1511	8625
Q4_2014	2264	21076
Q1_2015	3049	14069
Q2_2015	1591	9296
Q3_2015	1626	4742
Q4_2015	1628	20482
Q1_2016	2597	12447
Q2_2016	1612	8256
Q3_2016	1526	7074
Q4_2016	1976	16997
Q1_2017	2557	11905
Q2_2017	1586	12635
Q3_2017	966	9956
Q4_2017	2025	12704
Q1_2018	2855	11300
Q2_2018	1517	11902
Q3_2018	1665	10968
Q4_2018	2244	11726

ARIMAX with all 4 variables and with selected 2 variables (SST and Chl-*a*) are very close.

As can be seen from Table S6, the forecast for the year 2014 as the total of the four quarters is close to the actual value. From the second year onwards, the

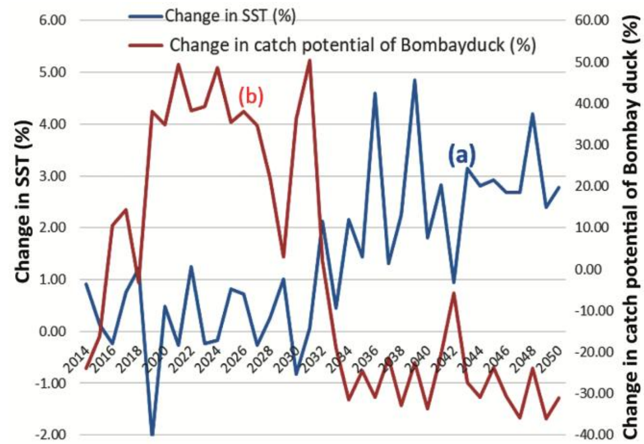

Fig. 3 — Change in (a) SST (in %) and (b) catch potential of Bombay duck (in %); with respect to the last 2 years (2012-2013) average

forecast values were not as close to the actual values. This deviation might be due to some seasonal abnormality, extraneous factors, change in fishing effort, etc., which could not be captured in the developed model. These findings show the potential of accurate forecasts of total catch and selected pelagic fishes in decision-making and for short-term management of fisheries.

Potential catches of Bombay duck under climate change scenario A2

The NARX method was chosen because it had proved better for predicting the catches of Bombay duck, and was used along with the values of SST as simulated under the climate change scenario A2. The percentage changes in SST with respect to the average value for the last two years (2012-2013) are shown in Figure 3. The scenario is a high-greenhouse-gas-emissions scenario (RCP8.5), as set out by the Intergovernmental Panel on Climate Change (IPCC). The present study predicts the trends and variations in the catches for both the short term (2020 – 2025) and long term (2030 – 2050) (Fig. 3), although the long-term predictions showed large fluctuations.

On average, the catches of Bombay duck are likely to increase by 41 % in the short term and decrease by 17.72 % in the long term scenario. The decrease is probably due to the greater fluctuations of SST in the percentages for the long term.

The average SST for 2030 – 2050 is 27.49 °C, whereas that for 2020 – 2025 is 26.96 °C, which means that it is the higher temperature that is mainly responsible for the declining catches of Bombay duck. The Gujarat coast consists of two gulf regions, the

Gulf of Kutch and Gulf of Khambhat. The impact of climate change and especially the change in SST in the gulf is entirely different as compared to the open seas. As these gulfs are shallow and the anthropogenic activities are also very high, which impacts the SST.

The generalized additive model of predicting the catches of Bombay duck (Fig. S3) based on SST supports the predicted decline in catches during 2030 – 2050, given the higher average temperature of 27.49 °C. Details of GAM are given by Guisan *et al*.[20].

Conclusion

All the methods were tested using hold-out data and the inclusion of environmental variables made the forecasts more accurate. Also, NARX-ANN performed better than ARIMAX in all cases, with one exception: ARIMAX proved superior in predicting the total catches, probably because it captures seasonal variations more accurately. Of the four climatic variables, SST and Chl-*a* were the two most important variables for predicting the total catches; SST and PAR for Bombay duck, and Chl-*a* and PAR for the Indian mackerel.

Taking the two most important variables was better than or as good as taking four variables, probably because the network learns faster if training data are limited, and network performance will be better with fewer parameters, but more training data for each parameteras usually happens in ANN modelling. The total catch and selected pelagic fishes were forecasted for the next five years (20 quarters), and the forecast values for the first three years (2014, 2015, and 2016) were compared with actual data. The two values (predicted and actual) were very close, at least for the first year (the forecast value was a total of four quarters, whereas the actual value was aggregate for the year). With a larger data set for training, the forecasts would have been even more accurate.

Taking the average of the last two years to catch data as a benchmark, the catches of Bombay duck under the climate change scenario A2, on average, will increase by 41 % in the short term and decrease by 17.72 % in the long term. However, these results and analyses can be refined by incorporating data from remote sensing and from climate change scenarios at higher resolutions. In summary, the present study have shown that climate change may lead to substantial changes in the quantities of the catch of Bombay duck and that further research can help in devising better management strategies to adapt to climate change.

Supplementary Data

Supplementary data associated with this article is available in the electronic form at http://nopr.niscair.res.in/jinfo/ijms/IJMS_50(07)557-565_SupplData.pdf

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Conflict of Interest

The authors would like to declare that there are no conflicts of interest to publish this research papers in the journal.

Author Contributions

The authors like to certify that, the first author (VK) of this paper had contributed towards the preparation of the paper such as conceptualization, data collection, data analysis, and drafting of the manuscript; the second author (SJ) contributed in guidance and editing of the contents; and the third author (JA) contributed in overall supervision and guidance on the manuscript revision.

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