Indian J Anim Health (2022), 61(1): 84- 110
DOI: https://doi.org/10.36062/ijah.2022.12321

Research Article

Forecasting of the different hydro-climatic variables and impact of climate change on marine fish production in West Bengal, India

S. Pal[1] and V. K. Yadav[1*]

[1]Fisheries Economics, Extension and Statistics Division, ICAR- Central Institute of Fisheries Education, Mumbai – 400 061, Maharashtra, India

Abstract

The current study was conceptualized to find the future trend of different hydro-climatic variables and observe their relationship with the total marine production. The present study was conducted along the coast of West Bengal, which is considered one of the important maritime state in India. Different hydro-climatic variables data were collected on a monthly basis from August 2002 to June 2021 and forecasted up to January 2030 with different forecasting models like trend line analysis, holt winter method, exponential smoothing method, ARIMA, and finally, the relationship between various climatic variables and marine production was estimated. Sea surface temperature was found to have an average increase of 0.52 °C; rainfall is predicted to increase by an average of 1.37 mm, and salinity level is going to decrease by 0.75 ppt. Whereas the chlorophyll concentration will decrease to an average of 0.05 mg/m3, the air temperature will like to an average increase by 1°C from August 2002 to December 2019 compared to January 2021 to January 2030. The study revealed that marine production is highly dependent on the presence of chlorophyll concentration, followed by salinity, rainfall, SST, and air temperature has a very minimal role. The key finding of this study shows changing patterns of different climatic variables will greatly affect the future marine catch. The policymakers and government should strictly regulate different environment protection rules and as well as give their high concern on sustainable management.

Key words: Climate change, Fisheries production, Forecasting, Hydro-climatic variable, West Bengal

Highlights

- The current study tried to forecast different important hydro-climatic variables like sea surface temperature (SST), salinity, chlorophyll, rainfall and air temperature using different prediction models and also tried to find its significant impact on the future marine catch.
- Sea surface temperature is found to have an average increase of 0.52°C; rainfall is predicted to an average increase of 1.37 mm, and salinity level is found to have an average decrease of 0.75 ppt by the year 2030.
- The chlorophyll concentration is predicted to have an average decrease of 0.05 mg/m^3, and the air temperature will like to increase by an average of 1°C.
- The marine production along the West Bengal coast is highly dependent on the presence of chlorophyll concentration followed by salinity, rainfall and SST, whereas the air temperature has a minimal role.

INTRODUCTION

Complex and uncertain interactions between climate change and food security are the major concern for societies and ecologies (Barange *et al.*, 2018). Global assessments of predicted changes in crop production under climate change scenario with the combination of international trade dynamics suggested that disparities between nations in production and food availability will escalate in near future (Rosenzweig and Parry, 1994). The fisheries sector is one of the fastest-growing sectors in the food-producing sector, with an average annual global growth rate of 7% since 1970, compared to 2.1% for terrestrial farmed meat

*Corresponding Author, E mail: vinodkumar@cife.edu.in

production (DAHD, 2020). Currently, an estimated 59.5 million people around the world directly or indirectly depend on fisheries and aquaculture for their livelihoods (Palomares *et al.*, 2020). There are around 3 billion people around the globe who consume fisheries based products that provide 15% or more of the protein source (FAO, 2008;). Several studies indicate a 4.1% decline in the world marine fisheries production between 1930 and 2010, with some of the important fish stock ecoregions experiencing losses of up to 35% due to consistent changes among various climatic factors like sea surface temperature, salinity and air temperature etc. (Free *et al.*, 2019). These climatic variables directly or indirectly affect the feeding habitat, breeding and migration pattern, decreasing the total fisheries production worldwide (FAO, 2012; Oliver *et al.*, 2018; Cheng *et al.*, 2019). Combustion of fossil fuels, rapid population growth and industrialization are mainly responsible for the changing climate and global warming (Loaiciga *et al.*, 1996; Viner, 2002; Karmakar *et al.*, 2018). It has been estimated that about 80% of the world's power production is generated from burning fossil fuels (Krupa and Kickert, 1989; ACIA, 2004). Over the period from 1880 to 2012, the global air temperature had increased by around 0.85°C (0.65°C to 1.06°C) and showed an increasing linear pattern (Pachauri *et al.*, 2014). Again the mean global temperature is predicted to be increased by 1-7°C in the next 100 years (McCarthy *et al.*, 2001). It has been estimated that the global mean sea surface temperature for the period 2016–2035 with respect to 1986–2005 is likely to change within the range of 0.3°C - 0.7°C (Pachauri *et al.*, 2014).

India has a long coastline of 8129 km along with nine states and four union territories (CMFRI, 2019; Krishnan *et al.*, 2019). The total marine fish production of India in the year 2019-20 was 3.72 million metric tons, and the fisheries sector contributed 1.24% to the total GDP of India and 7.28% to the agricultural GDP in the financial year 2018-19 (Department of Fisheries, Govt. of India, 2020). West Bengal is one of the major contributors to total marine production in the country. The entire marine production from West Bengal in 2019-20 was 1.63 lakh tons, and it stood in the eighth position among the maritime states in India. The state has a long coastline of 158 km along with three marine districts viz. North 24 Paraganas, South 24 Parganas and East Medinipur. There were 76,981 fishermen households in the state with a total population of 3,80,138 directly or indirectly depending on the marine fisheries sector (CMFRI, 2010). Earlier studies reported that over the Bay of Bengal, air temperature from 1985 to 2000 has increased at a rate of 0.019°C per year, and if this trend continues, there is a possibility in rising of the average air temperature to around 1°C by 2050 (Hazra *et al.*, 2002). It is also observed that the comparative increase of the air temperature in 1993-2007 had a higher rate for the period 1993–2007 (Hazra *et al.*, 2010). The average Sea surface temperature (SST) trend also showed an increasing trend from 31°C to 32.6°C between 1980 and 2007 in the pre-monsoon periods, with a decadal increase of 0.5°C (Mitra *et al.*, 2009). Sea surface temperature over the northern and southern sectors of the Bay of Bengal has increased by 0.8°C and 1.0°C, respectively over 102 years (Dash *et al.*, 2007). All these climatic variables directly or indirectly impact the total marine production of the state.

The current study aims to forecast several climatic variables, i.e. air temperature, chlorophyll, sea surface temperature, rainfall and salinity, on a monthly basis. The study also tries to correlate how these climatic factors affect the total marine catch of this state, which has not been done in the earlier studies. Overall, the study tries to predict different climatic variables and simultaneously identify their potential impact on the predicted marine catch in the near future, which is unique from other relevant studies, particularly for West Bengal coast and based on recent climatic /Hydro-climatic data.

MATERIALS AND METHODS

Study area: The current study was conducted along the coast of West Bengal (Lat: 22.9868°N; Long: 87.8550°E). The state has three coastal districts (Fig. 1) viz. South 24 Parganas, North 24 Parganas, and East Medinipur, and the total marine production was 1.63 lakh tons in 2019-20.

Retrieval of the climatic variables data: The validated climatic variables data of the West Bengal coastal region were obtained from Indian National Centre for Ocean Information Services (INCOIS), Hyderabad, India, from August 2002 to June 2021. The data included the air temperature, chlorophyll, sea surface temperature, rainfall and salinity. The data of the study area were obtained from a Moderate Resolution Imaging Spectroradiometer (MODIS) sensor with a spatial resolution of 4*4 km. The L1A MODIS images of the mentioned climatic variables were processed in SeaDAS (version 7.3.1) software. The L1A MODIS images data were transformed from level L1A to L1Geo for geometric corrections, followed by L1Geo to L1B for the radiometric corrections to extract L2 products of air temperature, chlorophyll, sea surface temperature, rainfall and salinity. The corresponding marine fish landing point (Latitudes and Longitudes), ASCII file containing the value of the product was estimated and also from MODIS level 3 standard binned images archived from Asia Specific Data Research Centre. The yearly basis marine fish production data of West Bengal from 2002 to 2019 were taken from the Handbook of Fisheries Statistics and Fisheries Department, Govt. of West Bengal (Dept. of Fisheries, 2015; Department of Fisheries, Govt. of India, 2020).

Forecasting through trend line estimation: When the data is linearly distributed, the linear equation/models can be estimated by using the slope-intercept formula, but in the real world, most data is not linear. One of the methods to handle this type of data is trendline estimation, also known as best fit and least squares line estimation. In statistics, trend line analysis is often referred to as a technique for finding an underlying pattern of behaviour of observed data in time-series data. This pattern would be hidden by noise (error) partially or completely. A simple description of these techniques is trend line estimation, which is widely used and nothing but a regression analysis (Gujarati *et al.*, 2012). This technique is used to estimate the future values of time-series data by extending the trend line into the future. Creating a trend line and estimating its coefficients allows for the quantitative analysis of the underlying data, and it has the ability to both interpolate and extrapolate the data for forecast purposes with the assumption that errors have

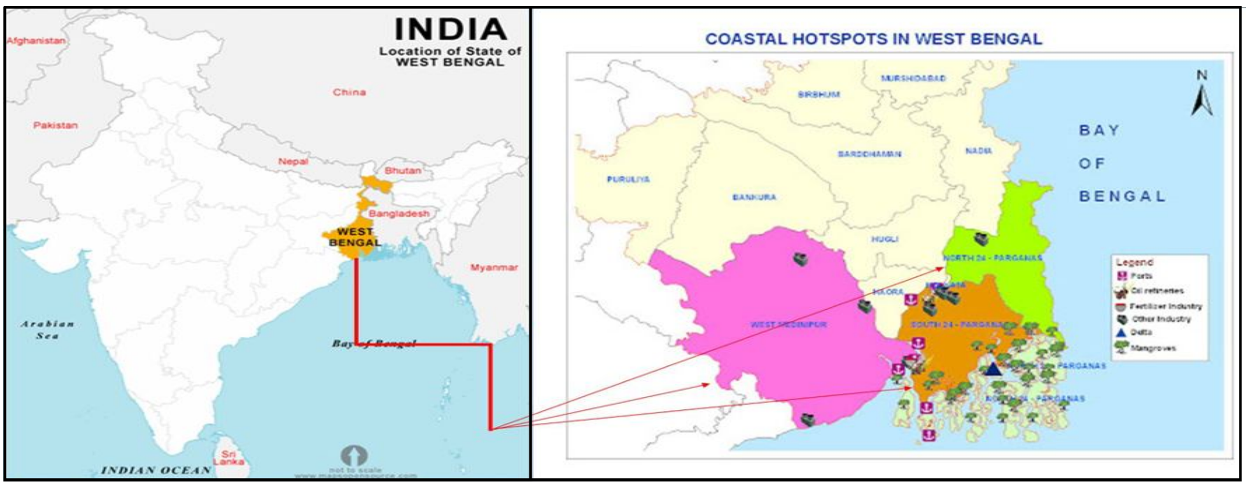

Fig. 1. Locale of the study area

zero mean and constant variance.

Forecasting through Exponential smoothing method: This is a weighted average procedure with weight declining exponentially as data become older. Here, New Forecast = Last period's forecast + α (Last period's actual demand - Last period's forecast)

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

Where, α = is a smoothing constant; F_t = predicted value, A_t = actual value

Forecasting through Holt winter additive method: Holt winter method considered all the three components of time series data i.e. base, trend, and seasonality component (denoted by E, T, and S) in case of forecasting. The parameter p denotes the number of seasonal periods in a year. ln the Holt winter additive method, the forecast for period t+n (n periods after the current period) is estimated by Gujarati *et al.* (2012).

$F_{t+n} = E_t + nT_t + S_{t+n-p}$

The values of base and trend, and the seasonal factors are updated by the following formulas.

$Et = \alpha (A_t - S_{t-p}) + (1-\alpha) (E_{t-1}+T_{t-1})$

$T_t = \beta (E_t-E_{t-1}) + (1-\beta) T_{t-1}$

$S = \gamma (A_t-E_t) + (1-\gamma) S_{t-p}$

Where α, β and γ are smoothing constant of the base, trend, and seasonal component.

Forecasting through Autoregressive integrated moving average (ARIMA) model: ARIMA model or Autoregressive integrated moving average model is the most popular and widely chosen time series forecasting model since 1970 (Gutiérrez-Estrada *et al.*, 2007; Bako *et al.*, 2013; Fattah *et al.*, 2018). It is a linear combination of time-lagged variables with the error terms. ARIMA model was introduced by Box and Jenkins (hence also known as the Box-Jenkins model) in the 1960s for forecasting time series variables. The autoregressive integrated moving average model is an extrapolation method for forecasting, and like any other such method, it requires only the time series data on the variable under forecasting (Faruk, 2010). Among the extrapolation methods, this is one of the most sophisticated methods as it incorporates the features of all such methods, does not require the investigator to choose the initial values of any variable and values of various parameters a priori, and it is robust to handle any data pattern (Mandal, 2005).

Trend and prediction of time series can be estimated by using the ARIMA model. ARIMA (p,d,q) model is a complex linear model. Here, p is the order of process AR, q is the order of process MA, and d is the order of difference. There are three parts (they do not have to contain always all of these): AR (Autoregressive) – linear combination of the influence of previous values; I Integrative) – random walk; MA (Moving average) – linear combination of previous errors. These models are very flexible, quite hard for computing and understand the results. They are linear models assuming that data are stationary and have a limited ability to capture non-stationarities and nonlinearities in series data (Khashei and Bijari, 2010). If the data are highly nonlinear and have fuzziness, advanced methods like Artificial Neural Network (ANN), Fuzzy Inference System, etc. can be taken for better prediction.

Finding the relative importance of the climatic variables with the marine production: The artificial Neural Network (ANN) method was used for finding the relative importance of different climatic variables (SST, Air temperature, chlorophyll and rainfall) with the marine fish landing. Artificial Neural Network encompasses with mathematical methods and is mainly used in forecasting and classification research. It is founded on the premise that a precise relationship between explanatory and dependent variables can be estimated using a nonlinear mathematical functional form. An intuitive way to understand artificial neural networks is through equivalence to linear regression models. Regression models estimate a linear model, which has multiplies input values called independent variables by optimal beta (β) coefficients (weights), and map the sum of the results onto output values called dependent variables that found similarity as closely as possible, the true output (Capecchi, 2010). The model, therefore, attempts to minimize the discrepancy between the actual output and estimated output, resulting in minimizing the error. This kind of regression model can be viewed as a simple Artificial Neural Network (ANN). In real ANNs, there is an additional component that permits for processing of the nonlinear aggregation of the weighted data (Gurney, 2018). This component is a nonlinear mathematical function and is located in a hidden layer. The hidden layers are the aggregates of the weighted inputs and pass the inputs to the nonlinear mathematical function to calculate a value that is transmitted to the output nodes (Gurney, 2018). To determine correct weights, the network is used to choose the random weights and calculate the resulting error, the discrepancy between the true output and the estimated output (Barbour *et al.*, 2007). The error is backpropagated through the network, where a feedback algorithm individually adjusts the weights to minimize the error. This process is iterative as the weights are updated by being passed backwards and forward until the error comes to a minimum.

Due to the unavailability of monthly basis fisheries production data, the monthly basis climatic variables data were estimated yearly by taking the average of monthly data for the periods of 2002 to 2020.

RESULTS

Forecasting of the Sea surface temperature (SST)

Forecasting of SST through trend line analysis: The trend line analysis of SST shows very high seasonality present in the time series data and very poor r^2 value (0.0053), suggesting that forecasting sea surface temperature through trend line analysis is not appropriate (Fig. 2).

Forecasting of SST through exponential smoothing method: The current study showed that (Table 1) the prediction of SST exponential smoothing method gives better result compared to trend line analysis. But it is not an appropriate model in prediction of the future SST values as the r^2 values (0.462) remains low due to the presence of seasonality of the data.

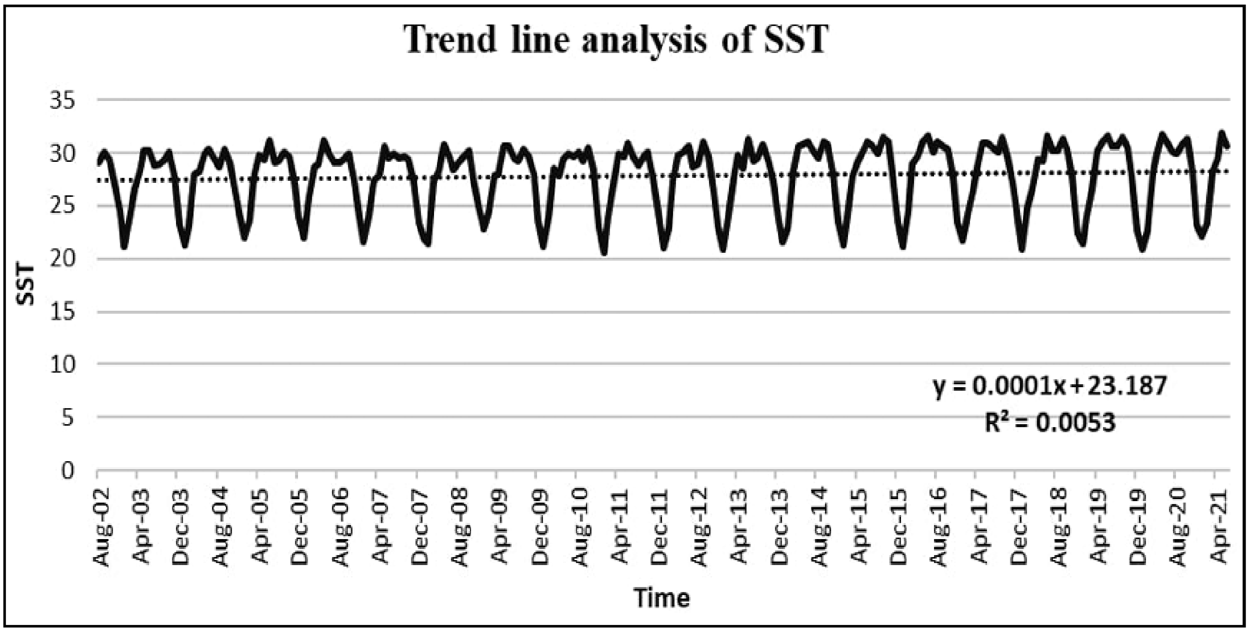

Fig. 2. Forecasting of SST through trend line analysis

Table 1. Model summary of exponential smoothing method in prediction of SST

Model	Number of Predictors	Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.	Number of Outliers
			Model Statistics										
			Model Fit statistics							Ljung-Box Q(18)			
SST-Model_1	0	-1.653E-5	0.462	2.289	7.020	1.847	23.766	5.898	1.680	494.846	17	0	0

Table 2. Model summary of Holt winter additive method in prediction of SST

Model	Number of Predictors	Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.	Number of Outliers
			Model Statistics										
			Model Fit statistics							Ljung-Box Q(18)			
SST-Model_1	0	0.666	0.954	0.676	1.933	0.525	10.285	2.273	-0.712	40.234	15	0	0

Forecasting of SST through Holt winter additive method: The study revealed that the prediction of SST using the Holt winter additive method gave an excellent result (r^2 = 0.954) as it considered the trend and seasonality factors.

Again, the error percentage i.e. Root Mean Square Error (RMSE) = 0.676, Mean Absolute Percentage Error (MAPE) = 1.933 and Mean Absolute Error (MAE) = 0.525 were also very less (Table 2). So, this method was used to predict the SST of the West Bengal coast up to January 2030.

The current study revealed that (Table 3) average sea surface temperature along the West Bengal coast will be increased by 0.53°C (1.89%) from August 2002 to December 2019 compared to January 2021 to January 2030.

Forecasting of SST using ARIMA model: The current study found that ARIMA (2,1,1)(0,1,0) was the best suitable model for forecasting the SST of the West Bengal coastal region.

The current study showed that for forecasting of SST along the West Bengal coast by Holt Winter additive method is more effective (Table 2 & Table 4) than the ARIMA model as it has more r^2 value and less error percentage i.e. less RMSE, MAPE, MAE, and higher normalized BIC value (Fig. 3).

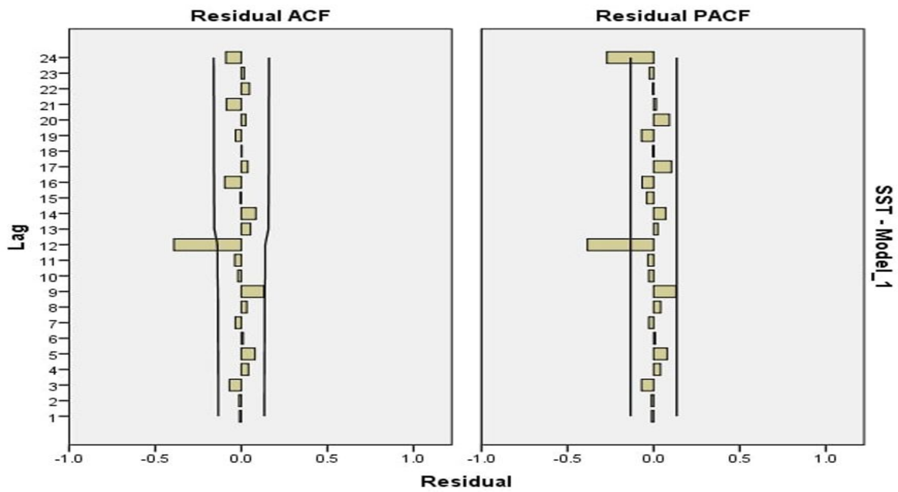

Fig. 3. Residual ACF and PACF plot in ARIMA model for predicting SST

Table 3. Predicted Sea surface temperature (SST) of West Bengal coast using Holt winter additive method

Sl. no	Year	Month	Predicted SST (°C)
1.	2021	January	21.80
2.	2021	February	24.16
3.	2021	March	27.98
4.	2021	April	29.51
5.	2021	May	30.74
6.	2021	June	31.17
7.	2021	July	30.08
8.	2021	August	29.99
9.	2021	September	30.87
10.	2021	October	30.50
11.	2021	November	28.02
12.	2021	December	24.05
13.	2022	January	21.87
14.	2022	February	24.21
15.	2022	March	28.08
16.	2022	April	29.60
17.	2022	May	30.83
18.	2022	June	31.17
19.	2022	July	30.12
20.	2022	August	30.03
21.	2022	September	30.91
22.	2022	October	30.54
23.	2022	November	28.06
24.	2022	December	24.09
25.	2023	January	21.91
26.	2023	February	24.25
27.	2023	March	28.13
28.	2023	April	29.64
29.	2023	May	30.87
30.	2023	June	31.21
31.	2023	July	30.16
32.	2023	August	30.07
33.	2023	September	30.95
34.	2023	October	30.58
35.	2023	November	28.10
36.	2023	December	24.13
37.	2024	January	21.95

Table 3., Cont. ...

Cont. Table 3.

Sl. no	Year	Month	Predicted SST (^oC)
38.	2024	February	24.29
39.	2024	March	28.17
40.	2024	April	29.68
41.	2024	May	30.91
42.	2024	June	31.25
43.	2024	July	30.20
44.	2024	August	30.11
45.	2024	September	30.99
46.	2024	October	30.62
47.	2024	November	28.14
48.	2024	December	24.17
49.	2025	January	21.99
50.	2025	February	24.33
51.	2025	March	28.21
52.	2025	April	29.72
53.	2025	May	30.95
54.	2025	June	31.29
55.	2025	July	30.24
56.	2025	August	30.15
57.	2025	September	31.03
58.	2025	October	30.67
59.	2025	November	28.19
60.	2025	December	24.21
61.	2026	January	22.03
62.	2026	February	24.37
63.	2026	March	28.25
64.	2026	April	29.76
65.	2026	May	30.99
66.	2026	June	31.34
67.	2026	July	30.28
68.	2026	August	30.19
69.	2026	September	31.07
70.	2026	October	30.71
71.	2026	November	28.23
72.	2026	December	24.25
73.	2027	January	22.07
74.	2027	February	24.41
75.	2027	March	28.29

Table 3., Cont. ...

Cont. Table 3.

Sl. no	Year	Month	Predicted SST (^oC)
76.	2027	April	29.80
77.	2027	May	31.03
78.	2027	June	31.38
79.	2027	July	30.32
80.	2027	August	30.24
81.	2027	September	31.11
82.	2027	October	30.75
83.	2027	November	28.27
84.	2027	December	24.29
85.	2028	January	22.11
86.	2028	February	24.45
87.	2028	March	28.33
88.	2028	April	29.84
89.	2028	May	31.08
90.	2028	June	31.42
91.	2028	July	30.36
92.	2028	August	30.28
93.	2028	September	31.16
94.	2028	October	30.79
95.	2028	November	28.31
96.	2028	December	24.33
97.	2029	January	22.15
98.	2029	February	24.49
99.	2029	March	28.37
100.	2029	April	29.88
101.	2029	May	31.12
102.	2029	June	31.46
103.	2029	July	30.40
104.	2029	August	30.32
105.	2029	September	31.20
106.	2029	October	30.83
107.	2029	November	28.35
108.	2029	December	24.37
109.	2030	January	22.19

Forecasting of the air temperature (AT)

For forecasting the air temperature, the current study has performed different prediction models i.e. exponential smoothing model, holt winter additive method, and ARIMA modeling to identify the best prediction model of air temperature in the study area. In forecasting air temperature, ARIMA (3,1,3) (0,1,0) is best suitable among all ARIMA models.

Table 4. Model summary of ARIMA method in prediction of SST

Model Statistics													
			Model Fit statistics							Ljung-Box Q(18)			
Model	Number of Predictors	Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.	Number of Outliers
SST-Model_1	0	0.464	0.924	0.870	2.492	0.677	11.884	2.917	-0.177	47.619	15	0	0

Table 5. Comparisons of the forecasting models for predicting the air temperature

Model Statistics											
			Model Fit statistics						Ljung-Box Q(18)		
Model	Stationary R-Predictors	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.
Exponential smoothing	-5.605E-5	0.547	1.858	5.629	1.482	24.566	5.126	1.262	518.038	17	.000
Holt winter	0.562	0.917	0.79	2.08	0.55	18.50	3.641	-0.381	41.351	15	.000
ARIMA (3,1,3)	0.353	0.874	0.99	2.58	0.68	21.85	4.120	0.168	42.682	12	.000

The study found that for forecasting the air temperature along the West Bengal coast, the Holt Winter additive model is the best suitable model. It has higher r^2 values and a lower error percentage in terms of RMSE, MAPE, and MAE (Table 5).

The study revealed that the average increase of air temperature in this region was 1°C (3.72%) from August 2002 to December 2019 compared to January 2021 to January 2030 (Table 6).

Table 6. Predicted air temperature (AT) of West Bengal coast using Holt winter additive method

Sl. No	Year	Month	Predicted AT (°C)
1.	2021	January	23.15
2.	2021	February	25.19
3.	2021	March	28.71
4.	2021	April	30.55
5.	2021	May	31.58
6.	2021	June	31.99
7.	2021	July	30.30
8.	2021	August	29.78
9.	2021	September	29.88
10.	2021	October	29.23
11.	2021	November	27.03
12.	2021	December	24.48
13.	2022	January	23.36
14.	2022	February	25.16
15.	2022	March	28.14
16.	2022	April	30.01
17.	2022	May	31.33
18.	2022	June	31.54
19.	2022	July	30.30

Table 6., Cont. ...

Cont. Table 6.

Sl. No	Year	Month	Predicted AT (^{o}C)
20.	2022	August	29.78
21.	2022	September	29.88
22.	2022	October	29.22
23.	2022	November	27.03
24.	2022	December	24.48
25.	2023	January	23.36
26.	2023	February	25.15
27.	2023	March	28.13
28.	2023	April	30.01
29.	2023	May	31.33
30.	2023	June	31.54
31.	2023	July	30.29
32.	2023	August	29.77
33.	2023	September	29.87
34.	2023	October	29.22
35.	2023	November	27.02
36.	2023	December	24.47
37.	2024	January	23.36
38.	2024	February	25.15
39.	2024	March	28.13
40.	2024	April	30.00
41.	2024	May	31.33
42.	2024	June	31.54
43.	2024	July	30.29
44.	2024	August	29.77
45.	2024	September	29.87
46.	2024	October	29.21
47.	2024	November	27.02
48.	2024	December	24.47
49.	2025	January	23.35
50.	2025	February	25.15
51.	2025	March	28.12
52.	2025	April	30.00
53.	2025	May	31.32
54.	2025	June	31.53
55.	2025	July	30.28
56.	2025	August	29.76
57.	2025	September	29.86
58.	2025	October	29.21
59.	2025	November	27.01
60.	2025	December	24.46
61.	2026	January	23.35

Table 6., Cont. ...

Cont. Table 6.

Sl. No	Year	Month	Predicted AT (^oC)
62.	2026	February	25.14
63.	2026	March	28.12
64.	2026	April	30.00
65.	2026	May	31.32
66.	2026	June	31.53
67.	2026	July	30.28
68.	2026	August	29.76
69.	2026	September	29.86
70.	2026	October	29.21
71.	2026	November	27.01
72.	2026	December	24.46
73.	2027	January	23.34
74.	2027	February	25.14
75.	2027	March	28.11
76.	2027	April	29.99
77.	2027	May	31.31
78.	2027	June	31.52
79.	2027	July	30.28
80.	2027	August	29.76
81.	2027	September	29.86
82.	2027	October	29.20
83.	2027	November	27.01
84.	2027	December	24.46
85.	2028	January	23.34
86.	2028	February	25.13
87.	2028	March	28.11
88.	2028	April	29.99
89.	2028	May	31.31
90.	2028	June	31.52
91.	2028	July	30.27
92.	2028	August	29.75
93.	2028	September	29.85
94.	2028	October	29.20
95.	2028	November	27.00
96.	2028	December	24.45
97.	2029	January	23.34
98.	2029	February	25.13
99.	2029	March	28.11
100.	2029	April	29.98
101.	2029	May	31.30
102.	2029	June	31.51
103.	2029	July	30.27

Table 6., Cont. ...

Cont. Table 6.

Sl. No	Year	Month	Predicted AT (°C)
104.	2029	August	29.75
105.	2029	September	29.85
106.	2029	October	29.19
107.	2029	November	27.00
108.	2029	December	24.45
109.	2030	January	23.35

Table 7. Comparisons of the forecasting models for predicting the salinity level

Model Statistics											
			Model Fit statistics						Ljung-Box Q(18)		
Model	Stationary R-Predictors	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.
Exponential smoothing	.000	.786	.320	.774	.249	4.925	1.632	-2.255	767.034	17	.000
Holt winter	.490	.917	.200	.445	.143	3.875	1.284	-3.150	45.389	15	.000
ARIMA (2,1,2)	.577	.908	.210	.466	.150	3.737	1.238	-2.997	38.631	14	.000

Forecasting of the salinity along the West Bengal coast

Salinity is one of the key factors in fish growth. Earlier studies reported that 20 to >50% of the total fish energy budget is dedicated to osmoregulation, and increasing salinity level will lead to an increase in the metabolic rate (Bœuf and Payan, 2001). Different forecasting models have estimated the prediction of the salinity along the West Bengal coast, and the best suitable model was used for prediction.

The current study found that the best suitable ARIMA model for predicting the salinity is ARIMA (2,1,2) model, but if we compare (Table 7) all the prediction models Holt winter additive model is slightly better than the ARIMA (2,1,2) model as it has a lower error percentage in terms of RMSE (0.2), MAPE (0.445) and MAE (0.143).

The current study revealed that (Table 8) salinity level along the West Bengal coast will decrease by an average of 0.75 ppt (2.32%) from August 2002 to December 2019 compared to January 2021 to January 2030

Table 8. Predicted salinity level of West Bengal coast using Holt winter additive method

Sl. No	Year	Month	Salinity (ppt)
1.	2021	January	32.36
2.	2021	February	32.48
3.	2021	March	32.48
4.	2021	April	32.32
5.	2021	May	32.14
6.	2021	June	31.85
7.	2021	July	31.67
8.	2021	August	31.47
9.	2021	September	31.26

Table 8., Cont. ...

Cont. Table 8.

Sl. No	Year	Month	Salinity (ppt)
10.	2021	October	31.15
11.	2021	November	31.30
12.	2021	December	31.54
13.	2022	January	31.89
14.	2022	February	32.17
15.	2022	March	32.42
16.	2022	April	32.46
17.	2022	May	32.36
18.	2022	June	31.99
19.	2022	July	31.61
20.	2022	August	31.41
21.	2022	September	31.20
22.	2022	October	31.09
23.	2022	November	31.23
24.	2022	December	31.48
25.	2023	January	31.83
26.	2023	February	32.11
27.	2023	March	32.36
28.	2023	April	32.40
29.	2023	May	32.30
30.	2023	June	31.93
31.	2023	July	31.55
32.	2023	August	31.35
33.	2023	September	31.14
34.	2023	October	31.03
35.	2023	November	31.17
36.	2023	December	31.42
37.	2024	January	31.77
38.	2024	February	32.05
39.	2024	March	32.30
40.	2024	April	32.34
41.	2024	May	32.24
42.	2024	June	31.86
43.	2024	July	31.49
44.	2024	August	31.29
45.	2024	September	31.08
46.	2024	October	30.97

Table 8., Cont. ...

Cont. Table 8.

Sl. No	Year	Month	Salinity (ppt)
47.	2024	November	31.11
48.	2024	December	31.36
49.	2025	January	31.71
50.	2025	February	31.99
51.	2025	March	32.24
52.	2025	April	32.27
53.	2025	May	32.18
54.	2025	June	31.80
55.	2025	July	31.43
56.	2025	August	31.23
57.	2025	September	31.02
58.	2025	October	30.91
59.	2025	November	31.05
60.	2025	December	31.30
61.	2026	January	31.65
62.	2026	February	31.92
63.	2026	March	32.17
64.	2026	April	32.21
65.	2026	May	32.12
66.	2026	June	31.74
67.	2026	July	31.36
68.	2026	August	31.17
69.	2026	September	30.96
70.	2026	October	30.85
71.	2026	November	30.99
72.	2026	December	31.24
73.	2027	January	31.59
74.	2027	February	31.86
75.	2027	March	32.11
76.	2027	April	32.15
77.	2027	May	32.05
78.	2027	June	31.68
79.	2027	July	31.30
80.	2027	August	31.10
81.	2027	September	30.90
82.	2027	October	30.78
83.	2027	November	30.93

Table 8., Cont. ...

Cont. Table 8.

Sl. No	Year	Month	Salinity (ppt)
84.	2027	December	31.17
85.	2028	January	31.52
86.	2028	February	31.80
87.	2028	March	32.05
88.	2028	April	32.09
89.	2028	May	31.99
90.	2028	June	31.62
91.	2028	July	31.24
92.	2028	August	31.04
93.	2028	September	30.83
94.	2028	October	30.72
95.	2028	November	30.87
96.	2028	December	31.11
97.	2029	January	31.46
98.	2029	February	31.74
99.	2029	March	31.99
100.	2029	April	32.03
101.	2029	May	31.93
102.	2029	June	31.56
103.	2029	July	31.18
104.	2029	August	30.98
105.	2029	September	30.77
106.	2029	October	30.66
107.	2029	November	30.80
108.	2029	December	31.05
109.	2030	January	31.40

Table 9. Comparisons of the forecasting models for predicting the rainfall

	Model Statistics											
			Model Fit statistics							Ljung-Box Q(18)		
Model	Stationary R-Predictors	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.
Exponential smoothing	-1.8E-5	0.421	3.25	44290.9	2.25	9260979	9.24	2.38	236.68	17	0.00
Holt Winter	0.762	0.857	1.62	11878.4	1.13	2551138	5.11	1.04	10.50	15	0.78
ARIMA (3,2,2)(2,1,1)	0.868	0.751	2.20	18446.7	1.56	3487685	8.61	1.80	19.60	10	0.033

Forecasting of the rainfall along the West Bengal coast

Earlier studies (Moss *et al.*, 2001; Welcomme *et al.*, 2010) have reported that heavy rainfall and increased water level reduce marine fish catch and significantly decrease the catch per unit effort (CPUE). The present study tried to forecast future rainfall by choosing the best-fit prediction model.

The present study found (Table 9) that although the Holt winter method gave a better result in terms of less error percentage in predicting the rainfall of the study area, but the overall model is not significant. So, for forecasting the rainfall along with the West Bengal coast study, the ARIMA (3,2,2)(2,1,1) model is the best suitable prediction model.

The present study found that (Table 10) the average increase of the rainfall along the West Bengal coast will be 1.37 mm (32.5%) from August 2002 to December 2019 compared to January 2021 to January 2030.

Forecasting of the chlorophyll along the West Bengal Coast Chlorophyll is the primary pigment for the photosynthesis of marine algae in the oceanic environment. The concentration level of chlorophyll is often considered an index of biological productivity and is also used as the key indicator for fisheries production (Yadav *et al*., 2020). The present study tried to identify the best-fit chlorophyll prediction model along the West Bengal coast.

The current study found that ARIMA (3,2,1)(3,1,3) is the best suitable model for predicting the chlorophyll data (Table 11).

The average decrease of the chlorophyll level (0.05 mg/ m^3) from August 2002 to December 2019 compared to January 2021 to January 2030 in ocean water showed serious threats to the aquatic habitat, including fish production (Table 12).

Table 10. Predicted rainfall of West Bengal coast using ARIMA model

Sl. No	Year	Month	Rainfall (mm)
1.	2021	January	1.27
2.	2021	February	1.48
3.	2021	March	1.79
4.	2021	April	2.83
5.	2021	May	5.74
6.	2021	June	9.09
7.	2021	July	12.23
8.	2021	August	10.75
9.	2021	September	9.46
10.	2021	October	5.17
11.	2021	November	1.53
12.	2021	December	1.33
13.	2022	January	1.39
14.	2022	February	1.62
15.	2022	March	1.97
16.	2022	April	3.03
17.	2022	May	5.97
18.	2022	June	9.24
19.	2022	July	12.33
20.	2022	August	10.85
21.	2022	September	9.55
22.	2022	October	5.27
23.	2022	November	1.62

Table 10., Cont. ...

Cont. Table 10.

Sl. No	Year	Month	Rainfall (mm)
24.	2022	December	1.42
25.	2023	January	1.49
26.	2023	February	1.72
27.	2023	March	2.06
28.	2023	April	3.13
29.	2023	May	6.06
30.	2023	June	9.33
31.	2023	July	12.42
32.	2023	August	10.94
33.	2023	September	9.65
34.	2023	October	5.36
35.	2023	November	1.72
36.	2023	December	1.51
37.	2024	January	1.58
38.	2024	February	1.81
39.	2024	March	2.15
40.	2024	April	3.22
41.	2024	May	6.16
42.	2024	June	9.43
43.	2024	July	12.51
44.	2024	August	11.03
45.	2024	September	9.74
46.	2024	October	5.45
47.	2024	November	1.81
48.	2024	December	1.61
49.	2025	January	1.67
50.	2025	February	1.90
51.	2025	March	2.25
52.	2025	April	3.31
53.	2025	May	6.25
54.	2025	June	9.52
55.	2025	July	12.61
56.	2025	August	11.13
57.	2025	September	9.83
58.	2025	October	5.55
59.	2025	November	1.90
60.	2025	December	1.70

Table 10., Cont. ...

Cont. Table 10.

Sl. No	Year	Month	Rainfall (mm)
61.	2026	January	1.77
62.	2026	February	2.00
63.	2026	March	2.34
64.	2026	April	3.41
65.	2026	May	6.34
66.	2026	June	9.61
67.	2026	July	12.70
68.	2026	August	11.22
69.	2026	September	9.93
70.	2026	October	5.64
71.	2026	November	2.00
72.	2026	December	1.79
73.	2027	January	1.86
74.	2027	February	2.09
75.	2027	March	2.43
76.	2027	April	3.50
77.	2027	May	6.44
78.	2027	June	9.71
79.	2027	July	12.79
80.	2027	August	11.31
81.	2027	September	10.02
82.	2027	October	5.73
83.	2027	November	2.09
84.	2027	December	1.89
85.	2028	January	1.95
86.	2028	February	2.18
87.	2028	March	2.53
88.	2028	April	3.59
89.	2028	May	6.53
90.	2028	June	9.80
91.	2028	July	12.89
92.	2028	August	11.40
93.	2028	September	10.11
94.	2028	October	5.83
95.	2028	November	2.18
96.	2028	December	1.98
97.	2029	January	2.05

Table 10., Cont. ...

Cont. Table 10.

Sl. No	Year	Month	Rainfall (mm)
98.	2029	February	2.28
99.	2029	March	2.62
100.	2029April	3.69	
101.	2029	May	6.62
102.	2029	June	9.89
103.	2029	July	12.98
104.	2029	August	11.50
105.	2029	September	10.21
106.	2029	October	5.92
107.	2029	November	2.27
108.	2029	December	2.07
109.	2030	January	2.14

Table 11. Comparisons of the forecasting models for predicting the chlorophyll concentration

Model Statistics											
			Model Fit statistics						Ljung-Box Q(18)		
Model	Stationary R-Predictors	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.
Exponential smoothing	0.017	0.170	0.032	16.785	0.025	78.090	0.083	-6.88	106.839	17	0
Holt winter	0.715	0.672	0.020	10.899	0.016	42.408	0.066	-7.756	15.060	15	0.447
ARIMA (3,2,1)(3,1,3)	0.856	0.507	0.025	12.817	0.019	66.534	0.077	-7.10	24.545	8	0.002

Table 12. Predicted chlorophyll concentration level along West Bengal coast using ARIMA model

Sl. No	Year	Month	Chlorophyll (mg/m^3)
1.	2021	January	0.217
2.	2021	February	0.217
3.	2021	March	0.168
4.	2021	April	0.128
5.	2021	May	0.127
6.	2021	June	0.138
7.	2021	July	0.125
8.	2021	August	0.118
9.	2021	September	0.121
10.	2021	October	0.168
11.	2021	November	0.168
12.	2021	December	0.184
13.	2022	January	0.188
14.	2022	February	0.175

Table 12., Cont. ...

Cont. Table 12.

Sl. No	Year	Month	Chlorophyll (mg/m^3)
15.	2022	March	0.127
16.	2022	April	0.112
17.	2022	May	0.099
18.	2022	June	0.108
19.	2022	July	0.114
20.	2022	August	0.111
21.	2022	September	0.115
22.	2022	October	0.152
23.	2022	November	0.162
24.	2022	December	0.176
25.	2023	January	0.174
26.	2023	February	0.166
27.	2023	March	0.126
28.	2023	April	0.097
29.	2023	May	0.093
30.	2023	June	0.110
31.	2023	July	0.109
32.	2023	August	0.100
33.	2023	September	0.105
34.	2023	October	0.149
35.	2023	November	0.151
36.	2023	December	0.161
37.	2024	January	0.166
38.	2024	February	0.159
39.	2024	March	0.107
40.	2024	April	0.089
41.	2024	May	0.081
42.	2024	June	0.091
43.	2024	July	0.101
44.	2024	August	0.096
45.	2024	September	0.099
46.	2024	October	0.138
47.	2024	November	0.140
48.	2024	December	0.157
49.	2025	January	0.158
50.	2025	February	0.147
51.	2025	March	0.109
52.	2025	April	0.082
53.	2025	May	0.075
54.	2025	June	0.090
55.	2025	July	0.089
56.	2025	August	0.083

Table 12., Cont. ...

Cont. Table 12.

Sl. No	Year	Month	Chlorophyll (mg/m^3)
57.	2025	September	0.087
58.	2025	October	0.127
59.	2025	November	0.134
60.	2025	December	0.144
61.	2026	January	0.145
62.	2026	February	0.139
63.	2026	March	0.092
64.	2026	April	0.067
65.	2026	May	0.062
66.	2026	June	0.076
67.	2026	July	0.081
68.	2026	August	0.073
69.	2026	September	0.077
70.	2026	October	0.118
71.	2026	November	0.118
72.	2026	December	0.132
73.	2027	January	0.136
74.	2027	February	0.126
75.	2027	March	0.081
76.	2027	April	0.059
77.	2027	May	0.051
78.	2027	June	0.062
79.	2027	July	0.066
80.	2027	August	0.061
81.	2027	September	0.065
82.	2027	October	0.103
83.	2027	November	0.109
84.	2027	December	0.122
85.	2028	January	0.122
86.	2028	February	0.113
87.	2028	March	0.071
88.	2028	April	0.044
89.	2028	May	0.038
90.	2028	June	0.053
91.	2028	July	0.054
92.	2028	August	0.046
93.	2028	September	0.050
94.	2028	October	0.091
95.	2028	November	0.094
96.	2028	December	0.104
97.	2029	January	0.108
98.	2029	February	0.100
99.	2029	March	0.051

Table 12., Cont. ...

Cont. Table 12.

Sl. No	Year	Month	Chlorophyll (mg/m^3)
100.	2029	April	0.030
101.	2029	May	0.022
102.	2029	June	0.033
103.	2029	July	0.039
104.	2029	August	0.033
105.	2029	September	0.036
106.	2029	October	0.075
107.	2029	November	0.077
108.	2029	December	0.091
109.	2030	January	0.093

Trend line analysis and forecasting of marine fish production in West Bengal

The study found (Fig. 4) that marine fish production in West Bengal shows a linear trend. Total marine fish production was highest in the year 2010-11 (1.94 lakh tons) and showed the lowest in 2012-13 (1.47 lakh tons). Marine fish production shows a decreasing trend after 2010-11, and changes in the hydro-climatic variables are mostly responsible.

Due to the limitations of fish production data, the study only forecasts for the upcoming three years of the marine landing of West Bengal. For forecasting, the ARIMA (3,0,2) model found the most appropriate method. The current study revealed that (Table 13) there is a possibility of increasing marine production in the upcoming three years.

Relative importance of climatic variables with the marine production

Due to data constraints, Artificial Neural Network (ANN) did not give a good result in terms of prediction. Still, it provides an idea about the relative importance of the hydrological climatic variables with the marine fish landing along the West Bengal coast.

The study found that (Table 14 and Fig. 5) marine production along the West Bengal coast is highly dependent on the abundance of chlorophyll (100%), followed by salinity (74.5%), rainfall (59.9%) and sea surface

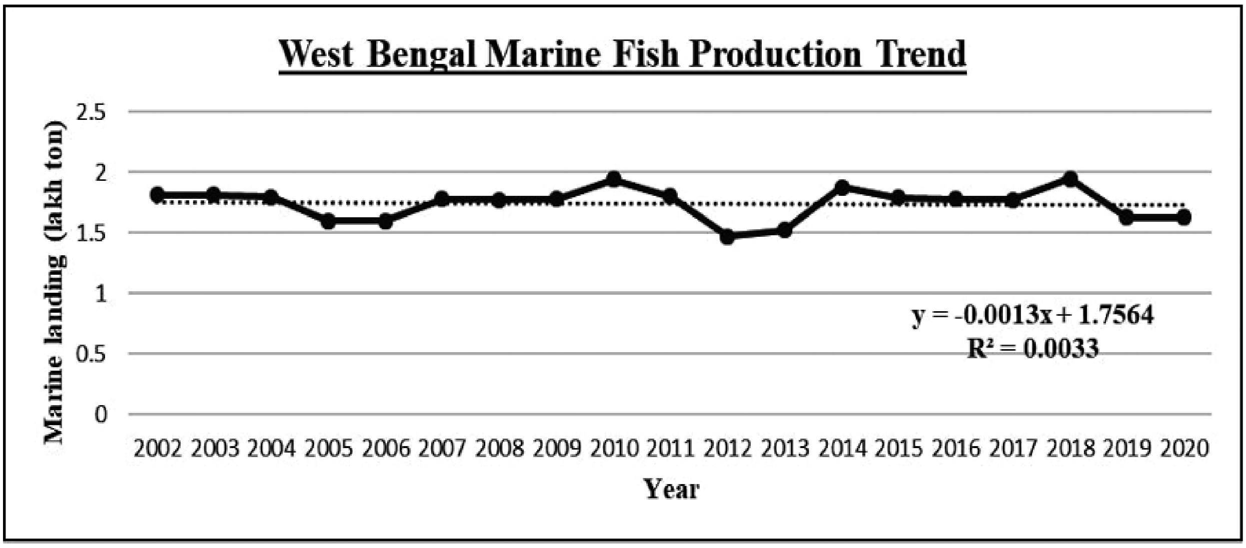

Fig. 4. Marine fish production trend in West Bengal

Table 13. Predicted marine fish landing in West Bengal

Sl no	Year	Predicted Marine landing (lakh tons)
1.	2021-22	1.701
2.	2022-23	1.765
3.	2023-24	1.781

Table 14. Relative importance of the different climatic variables in marine production

	Independent variable importance	
	Importance	Normalized importance
Air temperature (°C)	0.005	1.3%
Chl (mg/m3)	0.378	100.0%
Rainfall (mm)	0.226	59.9%
SST	0.110	29.0%
Salinity (ppt)	0.281	74.5%

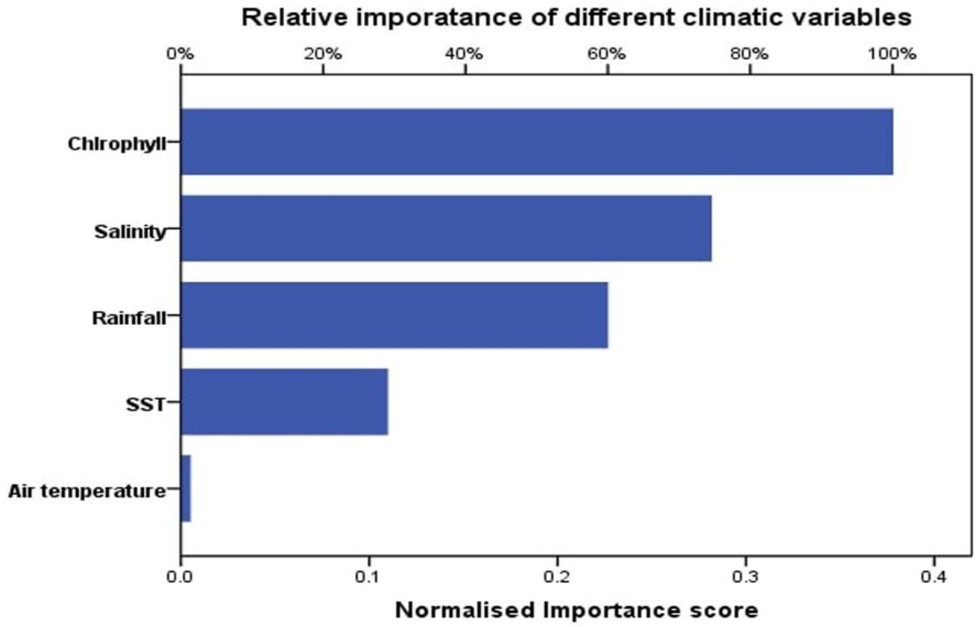

Fig. 5. Graphical representation of the relative importance of different climatic variables

temperature (29%). Whereas, air temperature (1.3%) does not significantly influence marine production along the coast.

DISCUSSION

The current study found that the average increase of SST from August 2002 to December 2019 compared to January 2021 to January 2030 will be 0.53°C (1.89%), which is a major threat to marine production along the coast. A similar kind of study (Mitra *et al.*, 2009) also found the decadal increase of SST in this region from 1980 to 2007 was 0.5°C, which supports the present study. The study also revealed that the average increase of air temperature during this time period would be 1°C, which will directly or indirectly affect the coastal livelihood and also tend to decrease the marine catch by changing the feeding habitat, migration pattern, and breeding habitat. Thus, the current study reported that both the air temperature (AT) and sea surface temperature (SST) along the West Bengal coast would like to be increased in the near future, and global warming and the climate change might be the possible reason behind it. Another study (Hazra *et al.*, 2002) also found that in the Bay of Bengal region, the growth rate of the air temperature from 1985 to 2000 was 0.195°C, and there is a probability of a more rapid increase in the air temperature, which supports the current study. In the case of salinity, the present study found that the average salinity level will decrease in this period. There is an inverse relationship between salinity and temperature. This relationship has been established in this study as the air temperature (AT) and sea surface temperature (SST) have increased, resulting in decreased salinity levels, which supports the current observation. This is due to the global warming and the melting of polar ice resulting in heavy influents on the river waters (freshwater) again due to several cyclones. In recent years, heavy rainfall has hit this coast and increased the average precipitation rate. The rainfall from August 2002 to December 2019 compared to January 2021 to January 2030 will be increased by 32.5%. This will leads to a decrease in the CPUE of this maritime state. A similar kind of study (Mandal, 2005) also found the decadal increase of rainfall in this area was 0.98 mm, which supports the current study. Whereas, the average chlorophyll concentration will be decreased by 0.05 mg/m^3. Sea surface temperature (SST) also showed an increasing trend, and as low SST is favourable for chlorophyll growth, which supports the current study. The decreasing trend of the chlorophyll level in seawater will hamper the growth of the microalgae, and due to the insufficiency of the food, the marine production on this coast will be reduced. The current study also revealed that as the concentration of chlorophyll is forecasted to decrease, it might affect marine fish production in the near future. Again, increasing the trend of salinity level, sea surface temperature and rainfall may significantly decrease the total marine fish production along the West Bengal coast.

Continuous rising of sea surface temperature, salinity, air temperature, rainfall, and decreasing chlorophyll show a major threat to future marine landing, mainly resulting from several anthropogenic activities. Government and policymakers should give a serious look at the illegal constructions along the coastal belt, deforestation activities, and mangrove conservations policy. The taxation system for polluting the water bodies like rivers and canals may be implemented to reduce ocean pollution. Sustainable management of marine capture fisheries should be followed to reduce the threat of future marine catch. Several rules and regulations like the environment protection act, CRZ regulation, biodiversity act, wildlife protection act, water prevention and control of pollution act, banning season should be strongly implanted to protect the marine habitat. A mass awareness campaign must be organized by several NGOs, government, and other authorities to spread the awareness of the harmful effect of climate change among the local communities. The government and policymakers should create alternative livelihood opportunities to stop illegal fishing activities and decrease the tendency of juvenile fish catch. The present study also suggests the future scope for a better understanding of the relationship between several hydro-climatic variables and total marine catch, with the availability of good quality marine fish production time-series data.

Conflict of interest: Authors have no conflict of interest in this study.

Author's contribution: SP: Contributed to the preparation of the paper, such as conceptualization, data collection, data analysis, and drafting of the manuscript; VKY: Contributed to overall supervision and guidance on the manuscript revision.

ACKNOWLEDGEMENT

The authors are thankful to the ICAR-Central Institute of Fisheries Education, Mumbai, and the Indian National Centre for Ocean Information Services, Hyderabad for providing the data, necessary support, and facilities to carry out the study.

REFERENCES

ACIA, (Arctic Climate Impact Assessment), 2004. Impacts of a warming Arctic-Arctic climate impact assessment. ACIA Overview report. Cambridge University Press, pp 140

Bako HY, Rusiman MS, Kane IL and Matias-Peralta HM, 2013. Predictive modeling of pelagic fish catch in Malaysia using seasonal ARIMA models. Agric For Fish, 2(3): 136-140, doi: 10.11648/j.aff.20130203.13

Barange M, Bahri T, Beveridge MC, Cochrane KL and Funge-Smith S, 2018. Impacts of climate change on fisheries and aquaculture-synthesis of current knowledge, adaptation and mitigation options. In Fisheries and Aquaculture. Food and Agriculture Organization

Barbour B, Brunel N, Hakim V and Nadal JP, 2007. What can we learn from synaptic weight distributions? Trends Neurosci, 30(12): 622-629, doi: 10.1016/j.tins.2007.09.005

Bœuf G and Payan P, 2001. How should salinity influence fish growth? Comp Biochem Physiol C Toxicol Pharmacol, 130(4): 411-423, doi: 10.1016/s1532-0456(01)00268-x

Box GEP and Jenkins GM, 1970. Time Series Analysis Forecasting and Control, Holden-Day, San Francisco

Capecchi V, 2010. Applications of mathematics in models, artificial neural networks and arts: mathematics and sociology. Springer, Dordrecht London

Cheng L, Abraham J, Hausfather Z and Trenberth KE, 2019. How fast are the oceans warming? Science 363(6423): 128-129, doi: 10.1126/science.aav7619

CMFRI, 2010. Marine Census 2010, West Bengal. ICAR-Central Marine Fisheries Research Institute, Kochi, http://eprints.cmfri.org.in/id/eprint/8998 [20.12.2021]

CMFRI, 2019. Annual Report 2019. Central Marine Fisheries Research Institute, Kochi, India. Available at http://eprints.cmfri.org.in/14753/1/CMFRI%20Annual%20Report%202019.pdf [20.12.2021]

DAHD, 2020. Annual Report 2019-20. Department of Animal Husbandry and Dairying Ministry of Fisheries, Animal Husbandry and Dairying Government of India. Available at https://dahd.nic.in/sites/default/filess/Annual%20Report%202019-20.pdf [20.12.2021]

Dash SK, Jenamani RK, Kalsi SR and Panda SK, 2007. Some evidence of climate change in twentieth-century India. Clim change, 85(3): 299-321, doi: 10.1007/s10584-007-9305-9

Department of Fisheries, Govt. of India, 2015. Handbook of Fisheries Statistics.Government of West Bengal

Department of Fisheries, Govt. of India, 2020. Handbook on Fisheries Statistics. Ministry of Fisheries, Animal Husbandry & Dairying Government of India, New Delhi. Available at https://dof.gov.in/sites/default/files/2021-02/Final_Book.pdf [20.12.2021]

FAO, 2008. Food and Agriculture Organization of the United Nations; 2009. The state of world fisheries and aquaculture

FAO and World Fish Centre, 2008. Small-scale capture fisheries: A global overview with emphasis on developing countries: A preliminary report of the Big Numbers Project

FAO, 2012. The state of world fisheries and aquaculture. Opportunities and challenges. Food and Agriculture Organization of the United Nations

Faruk DÖ, 2010. A hybrid neural network and ARIMA model for water quality time series prediction. Eng Appl Artif Intell, 23(4): 586-594, doi: 10.1016/j.engappai.2009.09.015

Fattah J, Ezzine L, Aman Z, El Moussami H and Lachhab A, 2018. Forecasting of demand using ARIMA model. Int J Eng Bus Manag, 10(2): 1847979018808673, doi: 10.1177/1847979018808673

Free CM, Thorson JT, Pinsky ML, Oken KL and Wiedenmann J, 2019. Impacts of historical warming on marine fisheries production. Science, 363(6430): 979-983, doi: 10.1126/science.aau1758

Gujarati DN, Porter DC and Gunasekar S, 2012. Basic Econometrics. Tata McGraw-Hill Education

Gurney K, 2018. An Introduction to Neural Networks, CRC Press, doi: 10.1201/9781315273570

Gutiérrez-Estrada JC, SilvaC, Yáñez E, Rodríguez N and Pulido-Calvo I, 2007. Monthly catch forecasting of anchovy *Engraulis ringens* in the north area of Chile: non-linear univariate approach. Fish Res, 86(2-3): 188-200, doi: 10.1016/j.fishres.2007.06.004

Hazra S, Ghosh T, Das Gupta R and Sen G, 2002. Sea level and associated changes in the Sundarbans. Sci Cult, 68(9-12): 309-321

Hazra S, Samanta K, Mukhopadhyay A and Akhand A, 2010. Temporal change detection (2001–2008) of the Sundarban. Unpublished Report, WWF-India. Available in http://www.iczmpwb.org/main/pdf/ebooks/WWF_FinalReportPDF.pdf [20.12.2021]

Karmakar S, Purkait S, Das A, Samanta R and Kumar K, 2018. Climate change and Inland fisheries: impact and mitigation strategies. J Exp Zool India, 21(1): 329-335

Khashei M and Bijari M, 2010. An artificial neural network (p, d, q) model for time series forecasting. Expert Syst Appl, 37(1): 479-489, doi: 10.1016/j.eswa.2009.05.044

Krishnan P, Ananthan PS, Purvaja R, Joe Jeevamani JJ, Amali Infantina J *et al*., 2019. Framework for mapping the drivers of coastal vulnerability and spatial decision making for climate-change adaptation: A case study from Maharashtra, India. Ambio, 48: 192-212, doi: 10.1007/s13280-018-1061-8

Krupa SV and Kickert RN, 1989. The greenhouse effect: impacts of ultraviolet-B (UV-B) radiation, carbon dioxide (CO2), and ozone (O3) on vegetation. Environ Pollut, 61(4): 263-393, doi: 10.1016/0269-7491(89)90166-8

Loaiciga HA, Valdes JB, Vogel R, Garvey J and Schwarz H, 1996. Global warming and the hydrologic cycle. J Hydrol, 174(1-2): 83-127, doi: 10.1016/0022-1694(95)02753-X

Mandal BN, 2005. Forecasting sugarcane production in India with ARIMA model. Inter Stat, October, 2005

McCarthy JJ, Canziani OF, Leary NA, Dokken DJ and White KS, 2001. Climate Change 2001: Impacts, Adaptation, and Vulnerability: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, UK

Mitra A, Gangopadhyay A, Dube A, Schmidt AC and Banerjee K, 2009. Observed changes in water mass properties in the Indian Sundarbans (northwestern Bay of Bengal) during 1980–2007. Curr Sci, 97(10): 1445-1452

Moss RH, Brenkert AL and Malone EL, 2001. Vulnerability to climate change: A quantitative approach. Prepared for the US Department of Energy

Oliver ECJ, Donat MG, Burrows MT, Moore PJ, Smale DA *et al*., 2018. Longer and more frequent marine heatwaves over the past century. Nat Commun, 9(1): 1324, doi: 10.1038/s41467-018-03732-9

Pachauri RK, Allen MR, Barros VR, Broome J, Crame W *et al*., 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC

Palomares MLD, Froese R, Derrick B, Meeuwig JJ, Nöel S-L *et al*., 2020. Fishery biomass trends of exploited fish populations in marine ecoregions, climatic zones and ocean basins. Estuar Coast Shelf Sci, 243(11): 106896, doi: 10.1016/j.ecss.2020.106896

Rosenzweig C and Parry ML, 1994. Potential impact of climate change on world food supply. Nature, 367: 133-138, doi: 10.1038/367133a0

Viner D, 2002. A qualitative assessment of the sources of uncertainty in climate change impacts assessment studies, in: Climatic Change: Implications for the Hydrological Cycle and for Water Management. Springer, pp 139-149

Welcomme RL, Cowx IG, Coates D, Béné C, Funge-Smith S *et al*., 2010. Inland capture fisheries. Philos Trans R Soc Lond B Biol Sci, 365(1554): 2881-2896, doi: 10.1098/rstb.2010.0168

Yadav VK, Jahageerdar S and Adinarayana J, 2020. Use of different modeling approach for sensitivity analysis in predicting the catch per unit effort (CPUE) of fish. Indian J Geo-Mar Sci, 49(11): 1729-1741

Received – 29.12.2021, Accepted – 25.03.2022, Published- 17.05.2022 (Online), 01.06.2022 (Print)

Section Editor: Prof. S. K. Das, Member, Editorial Board