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Research Article

Neural network models for the prediction of Indian mackerel catch using environmental variables in Visakhapatnam fishing harbour

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Artificial Neural Network (ANN) models were developed here to forecast daily catches of Indian Mackerel [*Rastrelliger kanagurta* (Cuvier, 1816)] at Visakhapatnam Fishing Harbour (VFH), located along the Bay of Bengal (BOB), Andhra Pradesh, India. The study utilised daily mackerel catch data alongside two Satellite-derived variables, Chlorophyll-*a* (CHL-*a*) and Sea Surface Temperature (SST), as well as two meteorological variables, Air Temperature (AT) and Wind Speed (WS), from January to September 2024. Fourteen Neural Network Models (NNMs) were developed to predict September 2024 (30 days) mackerel catch With Ban (WB, 7 models) and WithOut Ban (WOB, 7 models). The predicted catches were then compared with the actual catches of September 2024. Among the WB models MAC_ALL_WB (4-4-1) model performed better and MAC_SAT_WOB (2-4-1) model performed better among the 7 WOB models, achieving a low Mean Squared Error (MSE) of 0.012 and 0.009, respectively. Satellite-derived data emerged as the most influential variable for predicting mackerel catch, and it was concluded that predictions with WOB models were more accurate than those with WB models.

[**Keywords**: Air temperature, Chlorophyll-*a*, Sea surface temperature, Neural network model, Wind speed]

Introduction

In India, the pelagic fishery accounts for about 55 % of total marine production and plays a significant role in the fisheries industry. In 2023, India produced 1.93 million metric tons of pelagic fish, with Indian mackerel being one of the most common pelagic fish species accounting for 1.90 lakh tonnes of landings in 2023. The pelagic fishery accounts for 62 % of the total marine production in Andhra Pradesh, of which the Indian mackerel was the dominant pelagic species, accounting for around 15.7 % of the total landings[1]. Various satellites and sensors provide valuable spatio-temporal data to track daily changes in ocean environments. Fish catches are complex and nonlinear, and studies have qualitatively explored the links between fish capture and ocean environmental factors using satellite images[2-5]. Chlorophyll-*a* (CHL-*a*) and Sea Surface Temperature (SST) are vital satellite-derived ocean parameters that plays a crucial role in detecting and assessing fish catches[6,7]. Similarly, Air Temperature (AT) and Wind Speed (WS) are crucial meteorological parameters that vary daily. They are key indicators of regional and global climate change, which directly affect fish distribution and abundance by impacting fish metabolism and behaviour[8-10]. Hence, in this study, satellite-derived and meteorological datasets are used for mackerel prediction. Accurate forecasting of fish landings aids in making better decisions for fisheries management[11]. Although classic models like GAM (Generalized Additive Model), GLM (Generalized Linear Model), and ARIMA (Auto Regressive Integrated Moving Average) are used to predict fish catches, accurate forecasting remains challenging[12-15]. Artificial Neural Networks (ANNs) are widely used in MATLAB Software to model nonlinear data and improve the accuracy of fish catch forecasts. ANN has successfully predicted fish catches, rainfall, climate, water, tidal ranges, and PFZ[5,16-18]. This study develops an ANN model utilising two satellite-derived environmental variables (CHL-*a* and SST) and two meteorological variables (AT and WS) to predict daily mackerel catches at the Visakhapatnam Fishing Harbour (VFH) in the Bay of Bengal (BOB).

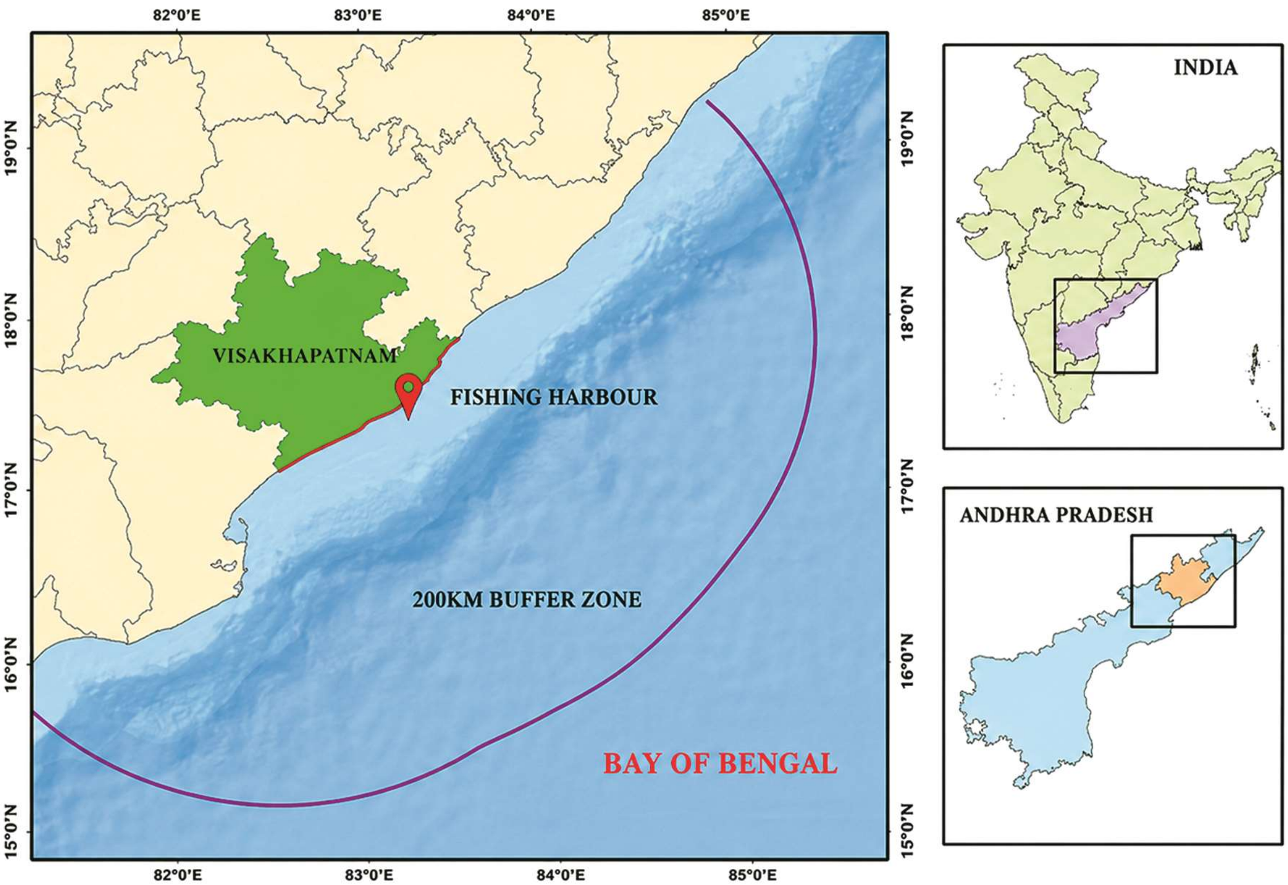

Fig. 1 — Map showing the study area and the buffer zone shows the fishing zone of 200 km

Materials and Methods

The software and tools used in this work include: the ANN tool in MATLAB R2023a, the SeaDAS 8.1, and the ArcGIS 10.7.1 version.

Study area

VFH, located in the north-eastern coastal district of Andhra Pradesh, is one of India's largest natural harbours, covering 26 hectares and facing the BOB (Fig. 1). The study area spans from latitude 17°41'49.82" N to longitude 83°17'58.32" E. The fishing zone selected for this study was up to 200 km from shore. The VFH harbour hosts 690 mechanised fishing vessels and 300 motorised and countryside crafts. Almost 580 mechanised fishing vessels are trawlers. The region is equipped with 12 jetties for berthing with a draft of 3 to 5 feet.

Data collection

The study collected three types of data: Fish catch data, satellite data, and meteorological data. The daily fish catch data obtained from January to September 2024 at VFH and the daily CHL-*a* and SST data for the above study period were extracted from Aqua MODIS Level 2/1 km resolution Standard Mapped Images (SMI), which were downloaded from NASA's Ocean Colour website (https://earth.gsfc.nasa.gov/ocean/data/ocean-color-level-1-2-browser). Daily AT and WS data were collected from the Time and Date website (timeanddate.com) and INCOIS web portal (https://incois.gov.in/), respectively.

Image processing

Firstly, daily CHL-*a* and SST, L2/1 km resolution satellite images were downloaded from NASA Ocean Color Web in the form of NetCDF format and processed using SeaDAS 8.1 open-source software. ArcGIS 10.7.1 version software was used to create a shape file with a 200 km buffer zone (polygon) in the study area, which is then superimposed on the processed images in SeaDAS 8.1, and then the spatial averages were obtained by compiling the pixel datasets (Fig. 2).

Development of Artificial Neural Network (ANN) models

The Artificial Neural Network (ANN) tool in the MATLAB programming environment is used to predict a nonlinear mackerel dataset. This study employed a feed-forward neural network with a gradient-descent back-propagation algorithm, commonly known as a multilayer perceptron. The network consists of three layers: input, hidden, and output. The input layer contains raw data, while the output layer produces the results. The hidden layer connects the input and output layers, and all layers are made up of neurons[19]. For this analysis, a total of 14 Neural Network Models (NNMs; 1-4-1, 2-4-1 and 4-4-1) were developed for the prediction of mackerel catch (Fig. 3). The predictions were categorised into two types: Prediction of mackerel catch including Ban Period as WB and prediction of mackerel catch WithOut Ban period as WOB models, as summarised in Table 1. The input layer consists of 4 neurons corresponding to the 4 input features (CHL-*a*, SST, AT, WS), the hidden layer comprises 4 neurons where the network uses weights and biases to transform the inputs, and the output layer contains a single neuron representing the target output (the targeted fish catch). Further, during training, the input and target were fed into the network, and the network was adjusted based on its trial-and-error. The training phase stopped when the maximum number of epochs was reached.

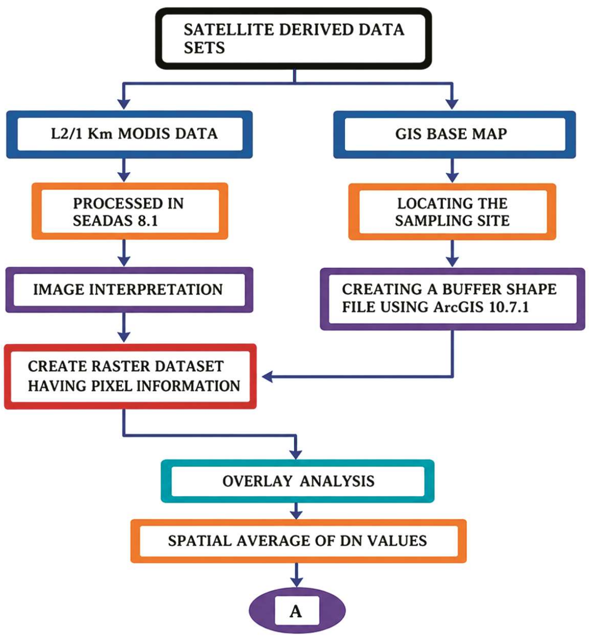

Fig. 2 — Methodology for DN value extraction from satellite images

Prediction of mackerel catches With Ban (WB)

For the prediction of mackerel catch in WB models, the closed-season catch data (from April 15th to June 14th) was first predicted and incorporated

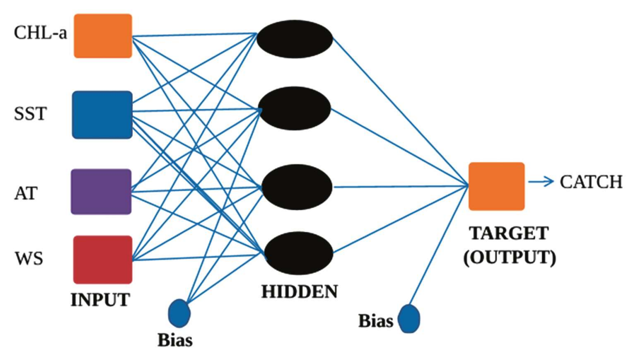

Fig. 3 — Schematic representation of four-layered feed-forward neural network (4-4-1)

Table 1 — Feed forward neural network models for WB and WOB period with results of sensitivity analysis

Models	Sensitivity analysis						EPOCH	RANK
	R	R^2	MSE	RMSE	MAE	MODEL		
WB models								
MAC_CHL_WB	0.349455	0.122119	0.026177	0.161795	0.1481649	01:04:01	6	7
MAC_SST_WB	0.337856	0.114146	0.016107	0.126914	0.0982945	01:04:01	8	3
MAC_AT_WB	0.312632	0.097739	0.0173	0.131528	0.0172996	01:04:01	4	4
MAC_WS_WB	0.251927	0.063467	0.017797	0.133407	0.1032792	01:04:01	7	5
MAC_MD_WB	0.126632	0.016036	0.020006	0.141443	0.1125611	02:04:01	10	6
MAC_SAT_WB	0.571915	0.327087	0.013325	0.115434	0.0977391	02:04:01	9	2
MAC_ALL_WB	0.58312	0.340029	0.012704	0.112712	0.0963594	04:04:01	15	1
WOB models								
MAC_CHL_WOB	0.30608	0.093685	0.019684	0.140301	0.1231013	01:04:01	4	6
MAC_SST_WOB	0.30404	0.09244	0.017253	0.131353	0.101612	01:04:01	8	3
MAC_AT_WOB	0.279922	0.078356	0.018591	0.13635	0.1187029	01:04:01	2	5
MAC_WS_WOB	0.183507	0.033675	0.018279	0.135202	0.1136162	01:04:01	6	4
MAC_MD_WOB	-0.02317	0.000537	0.024218	0.155621	0.1249704	02:04:01	9	7
MAC_SAT_WOB	0.473363	0.224073	0.00988	0.099398	0.0993976	02:04:01	10	1
MAC_ALL_WOB	0.512925	0.263092	0.016191	0.127243	0.1084903	04:04:01	17	2

into the dataset spanning from January 1st to August 31st 2024. Daily data for four input variables (CHL-*a*, SST, AT, and WS) from January 1st to April 14th (105 days) were used as input, and daily catch data for mackerel from January 1st to April 14th (105 days) were used as the target for ANN training. After the training phase, the input variables for a 61-day period during the closed season (April 15th to June 14th) were used in the ANN for testing. After testing, the output was obtained as predicted catch for the closed season. To retrieve the predicted catch for the month of September, the ANN was again trained with 4 input variables for eight months from January 1st to August 31st (244 days) as input and fish catch data of all the eight months from January 1st to August 31st (244 days), including the predicted closed season catch of 61 days into the ANN as a target. After training, the predicted September month catch is obtained by providing the September month input variables data for testing. After testing with several numbers of epochs, the predicted catch data was obtained as output, corresponding to the predicted September 2024 catch for the WB models.

Prediction of mackerel catches WithOut Ban (WOB)

In the case of WOB predictions, the ANN was trained with the daily data for four input variables from January 1st to April 14th and June 15th to August 31st (183 days), and fish catch data from January 1st to April 14th and June 15th to August 31st (183 days) as the target. The predicted catches of the September 2024 WOB models were obtained by providing the environment data of the September month to the ANN for testing. The predicted September month catch WOB arrived after testing.

Methods of evaluation

Different error measures were used to evaluate the ANN's performance and identify the best model. The Coefficient of Correlation (R) measures the relationship between actual and predicted values. The Coefficient of Determination (R^2) indicates the proportion of total variation in the observed data. Other measures include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). In this study, the model with the lowest MSE, ideally close to zero, was considered the best. These errors were calculated using the following formulae[17].

1) $$R = \frac{n\sum Yi\widehat{Yi} - (\sum Yi)(\sum \widehat{Yi})}{\sqrt{n(\sum_{Yi} 2) - (\sum Yi)^2}\sqrt{n(\sum_{\widehat{Yi}} 2) - (\sum \widehat{Yi})}}$$

2) $$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2$$

3) $$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Yi - Y\hat{i})^2}{n}}$$

4) $$\text{MAE} = \frac{n\sum_{i=1}\left|Yi - Y\hat{i}\right|}{n}$$

Results

The results obtained from the fishery data, satellite data, meteorological data, and ANN data WB and WOB are discussed with relevant studies in this section.

Fishery data

During the study period, the mackerel catches varied from 50 to 2100 kg, with inter-month fluctuations. The highest catches were observed in March (pre-monsoon) and July (monsoon), while the lowest day catches were observed in April and June (monsoon). These variations might be due to seasonal shifts and environmental conditions. Similar observations were made along the Tiruchendur coast of the Bay of Bengal by Pitchaikani & Lipton[20], who noted that the maximum catches of sardines and Indian mackerel occurred during the post-monsoon period. Further, investigations by Manjusha *et al.*[21], Krishnakumar *et al.*[22], Rajesh *et al.*[23], and Chellappan *et al.*[24] reported the highest annual landings of sardines and mackerels during the post-monsoon and monsoon seasons, as well as during or immediately after the upwelling season along the Kerala coast (1967 – 2007), Mangalore coast (1995 – 2004), Karnataka coast (2007 – 2016), and Maharashtra coast (2007 – 2019).

Satellite data

The present study revealed a gradual increase in the monthly average MODIS-derived CHL-*a* concentration from January to July 2024 (0.16 to 0.73 mg/m³). From Figure 4(a), it can be observed that the highest CHL-*a* concentration was recorded on 19th July 2024 (2.3 mg/m³); whereas the lowest CHL-*a* concentration was recorded on January 1st, 2024 (0.05 mg/m³), because seasonal monsoon winds can bring nutrient-rich water to the surface, promoting phytoplankton

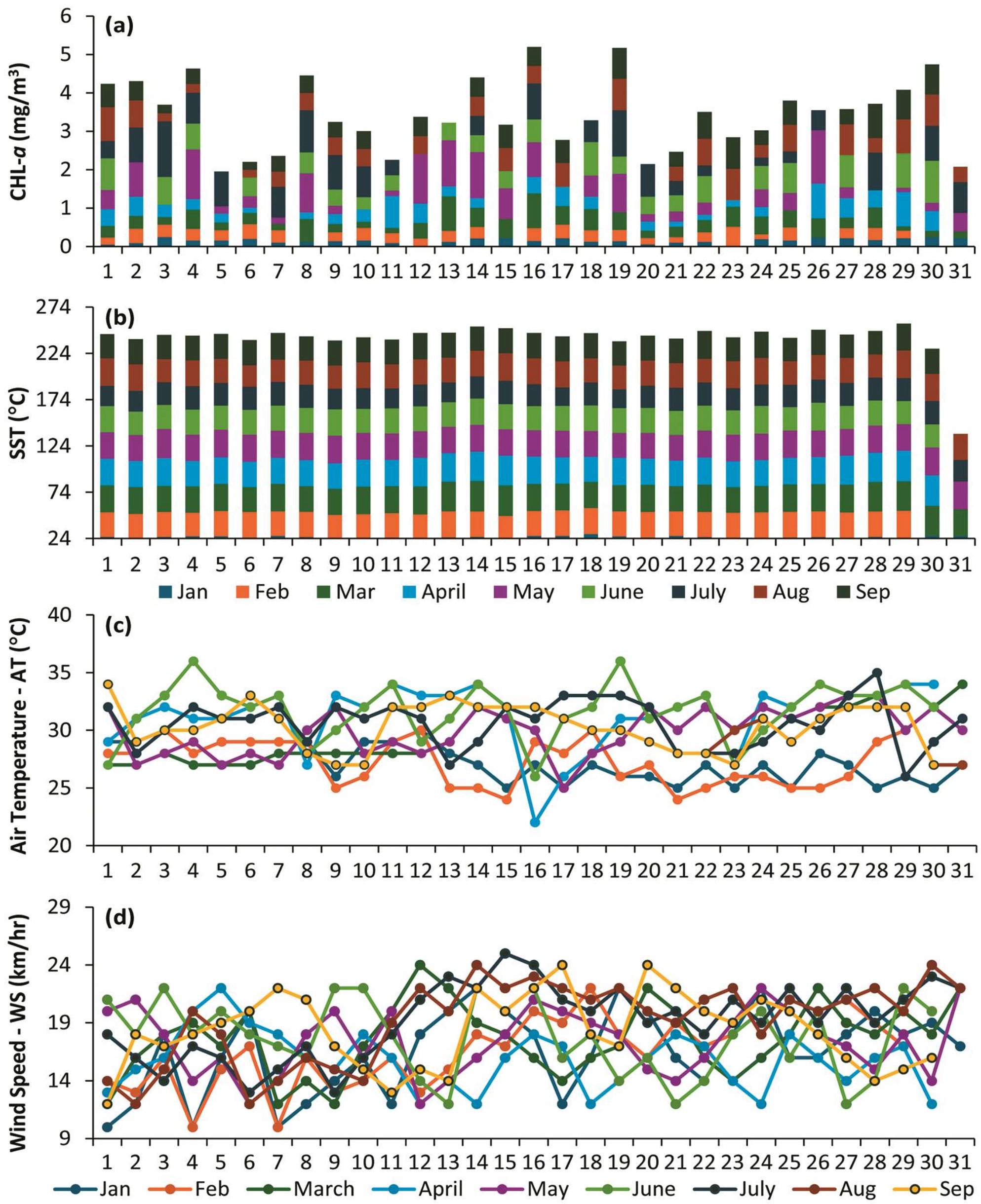

Fig. 4 — Month-wise daily data of a) Aqua MODIS CHL-*a*, b) Aqua MODIS SST, c) AT, and d) WS, in the study area

growth. This pattern aligns with previous studies by Das *et al*.[25], who reported a gradual increase in MODIS CHL-*a* concentrations from April to November 2022 along the Visakhapatnam coast. Similarly, a study by Pitchaikani & Lipton[20] shows that average CHL-*a* concentrations ranged from 2 to 7 mg/m³ along the Tiruchendur coast, Tamil Nadu, from 2008 to 2010. Furthermore, during 2009 – 2011 CHL-*a* concentration varied from 0.04 to 13.87 µg/L with the maximum concentration (13.87 µg/L) occurred during the winter monsoon and the minimum (0.04 µg/L) was recorded at the start of the summer monsoon[26]. Compared to the range observed by Azmi *et al*.[27] MODIS-derived CHL-*a* concentration (0.3 to 3.9 mg/m³) during the monsoon season at the Mumbai coast (2003 – 2012), the present study observed CHL-*a* concentrations range at Vizag coast is very less (0.5 to 1.45 mg/m³) due to the absence of direct river inflows into the Bay of Bengal as river inflow brings nutrient loads, which in turn boost phytoplankton growth and increase chlorophyll concentrations.

The SST range in the study area varied from 20.10 °C to 32.99 °C, reflecting typical seasonal variation in the region. SST plays a major role in the pelagic fishery because it regulates the rate of photosynthesis in aquatic ecosystems. In the present study, the highest SST was noted in April 2024 (32.99 °C) and the lowest SST in July 2024 (20.10 °C) (Fig. 4b). Similar results were observed by Pitchaikani and Lipton[20] at Tiruchendur coast, where the SST ranged from 25.20 °C to 30.4 °C, with peaks in May and June and minimum values from October to December. In addition, the SST range varied from 23.50 °C to 33.90 °C, with the highest SST occurring during the pre-monsoon season and the lowest during the southwest monsoon along the Kanyakumari coast, Tamil Nadu[28]. Further, Jitendra Kumar *et al.*[29] noted that the highest in-situ SST at the Mangalore coast was recorded in May (32.2 °C), and the lowest was in October (28.5 °C).

Meteorological data

In the present study, the monthly AT ranged from 24 °C to 34 °C. The highest AT was recorded during the pre-monsoon months of March (33.2 °C) and April (33 °C), while the lowest AT was observed during the monsoon period in July (24 °C) (Fig. 4c). Similar patterns were reported by Anitha Kumari *et al.*[28] along the Kanyakumari coast, where AT ranged between 24.7 °C to 33.7 °C, while Jitendra Kumar *et al.*[29] noted monthly AT between 26.5 °C to 29.3 °C along the Mangalore coast. But in the east Mediterranean region of Turkey, the AT ranged from 17.8 °C to 42.2 °C[(ref. 30)]. Along the Sitakunda coast, the AT ranged from 24.64 °C to 26.96 °C[(ref. 31)] whereas along the Kota Kinabalu, Malaysia it ranged from 26 °C to 28.6 °C[(ref. 33)]. From the study, it is evident that AT varies across different regions, climatic zones, and seasonal weather patterns, and is directly correlated with fish catch because mackerel shows a preference for warm water. In general, warm-water fish species tend to flourish in warm conditions[32].

An increase in WS enhances upwelling which in turn enhances fish catch[33,34]. In the present study, maximum mackerel catches were observed during the periods of elevated WS (Fig. 4d), as high mackerel catches occurred in July (25 km/hr). This study is in concurrence with the study by Pitchaikani *et al.*[20] from BOB. During the southwest monsoon, increased WS enhances upwelling, which significantly influences fish productivity.

Sensitivity analysis of artificial neural network models

A total of 14 NN forecasting models meticulously developed and trained with sampling data. Through a comprehensive, sensitive analysis, the most proficiently trained model was selected based on the lowest MSE. Among the WB and WOB models, the MAC_ALL_WB and MAC_SAT_WOB models achieved the lowest Mean Squared Error (MSE) values of 0.012 and 0.009, respectively (Table 1). In the WB - NNM modelling, the combination of Chl-*a*, SST, WS, and AT performed well and positively correlated. On the other hand, the WOB-NNM modelling revealed that the CHL-*a* and SST combination performed well. Compared with the present study, the modified NNM model developed by Wang *et al.*[18] for neon flying fish in the Northwest Pacific Ocean using satellite-derived environmental variables, emerged as the most significant predictor, with an MSE value of 0.62. A low MSE value indicated a well-trained model, and the difference between observed and predicted catches being close to zero, as illustrated in Figures 5 and 6. The present study suggests that including multiple environmental variables enhances the model's predictive power.

The MAC_ALL_WB model from the present study achieved an R^2 of 0.34, indicating 34 % accuracy (Table 1). A MODIS-based non-seasonal NN predictive model STS_MO_MAC_SP_NS, is a best performed one with an R^2 value of 0.2777 for monthly mackerel catches at Nagapattinam[17]. Comparative analysis by Wang *et al.*[37] in the South China Sea for the spatiotemporal distribution of fishing grounds and its relationship with marine environment using a Generalized Additive Model (GAM) yielded an R^2 value of 0.36 with a relative contribution of 40 %. These results are closely aligned with the present study. This implies that the combination of satellite and meteorological variables enhances the daily mackerel prediction.

In the present study, the MAC_ALL_WB model achieved a moderate correlation coefficient of R = 0.583, indicating 58 % predictive efficiency between the input variables and daily mackerel catches. Similarly, study by Yoon *et al.*[5] yielded a positive correlation coefficient of R = 0.745 to while predicting daily mackerel catches in near shore and offshore areas of South Korea, using a Deep Neural Network (DNN) model by utilising meteorological data, including rainfall, relative humidity, salinity, and pressure, along with satellite data such as SST, Wave Height (WH), and Sea Surface Wave Velocity (SSWV). In contrast, Welliken *et al.*[38] reported a very strong correlation (R = 0.934) between CHL-*a* and

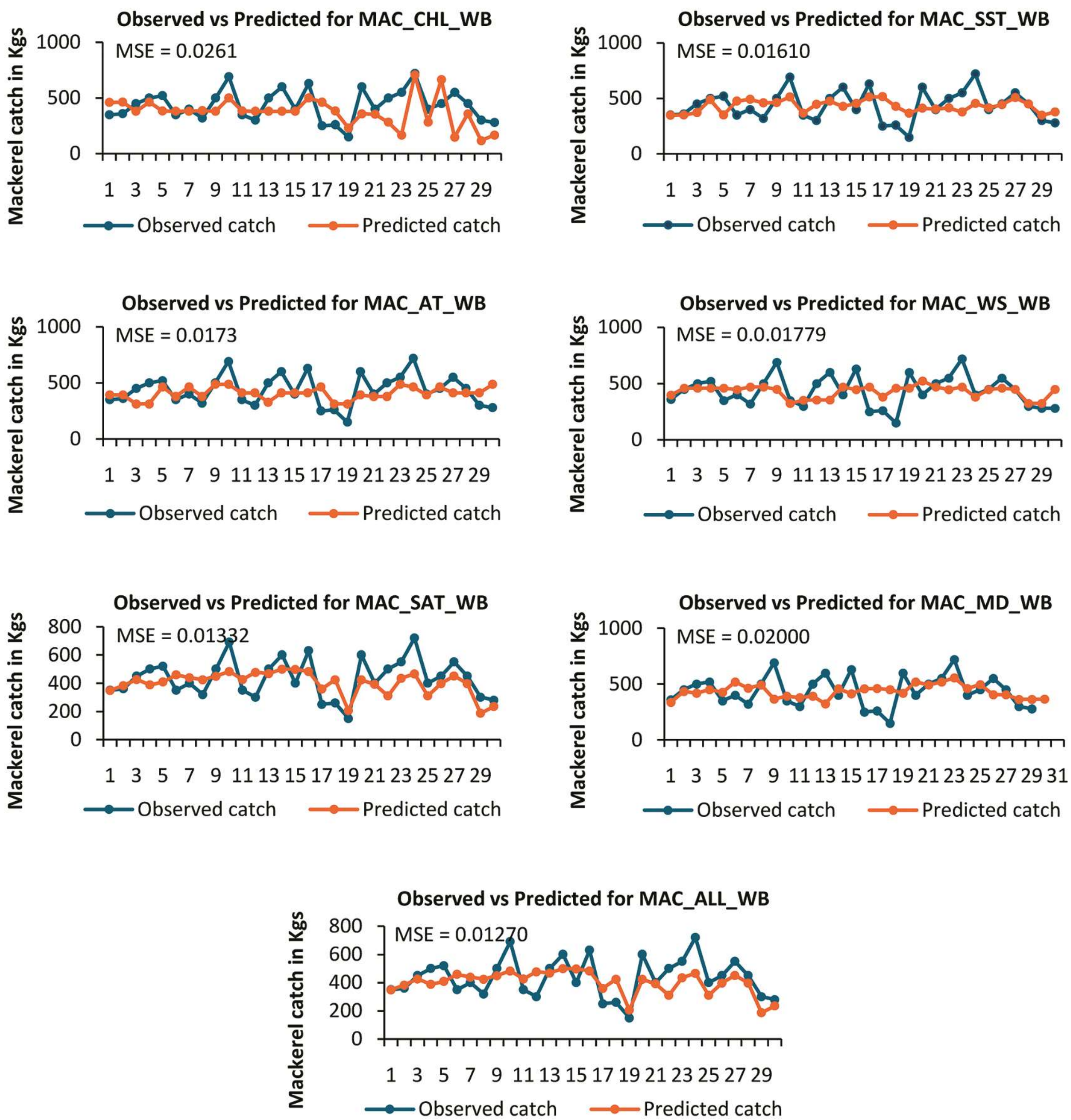

Fig. 5 — Observed *vs.* predicted catches of mackerel for With Ban (WB) period

mackerel catches using neural network analysis in the Arafura Sea. The significant disparity in *R* values between the two studies may be attributed to differences in environmental variables and study areas.

The current study demonstrates that the MAC_ALL_WB model offers superior accuracy, with low RMSE and MAE values (0.112712 and 0.096359, respectively). Conversely, the model MAC_MD_WB recorded a low *R* value of 0.12663, ranking 6th. The RMSE and MAE values for the model MAC_MD_WOB are relatively low (RMSE = 0.15562, MAE = 0.12497); however, this model shows a negative correlation (R = -0.0232) between the predicted mackerel catches and the observed catches (Table 1). Among all the predictive models, MAC_MD_WB and MAC_SAT_WOB models performed better with the average number of epochs (10); while the MAC_ALL_WB and MAC_ALL_WOB models achieved better error values with a high number of epochs (17 and 15).

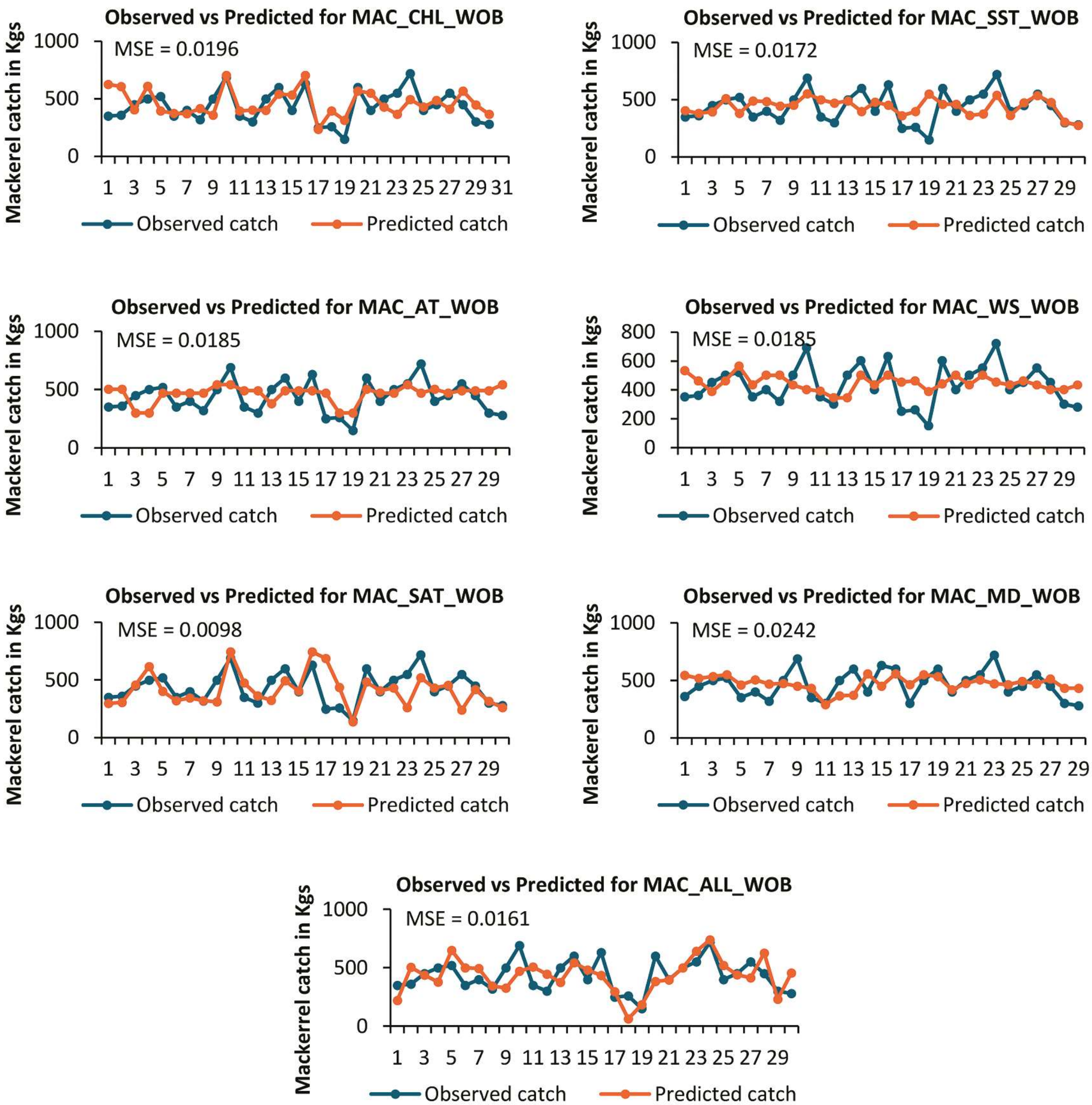

Fig. 6 — Observed *vs.* predicted catches of mackerel for WithOut Ban (WOB) period

Conclusion

In the current findings, the MAC_ALL_WB and MAC_SAT_WOB models achieved the lowest Mean Squared Error (MSE) values of 0.012 and 0.009, respectively. These models are the most effective for predicting daily mackerel catches based on environmental variables. A sensitivity analysis revealed a moderate correlation between the predicted and observed catch in MAC_ALL_WB model with 58 % correlation and MAC_SAT_WOB model with 47 % correlation, highlighting the importance of all environmental parameters, such as CHL-*a*, SST, AT, and WS in MAC_ALL_WB model, and highlighting the importance of satellite-derived parameters, such as CHL-*a*, SST, in the MAC_SAT_WOB model for forecasting mackerel catches. Hence, it can be concluded that predictions with WOB models were more accurate than those with WB models.

However, more research is required to get a deep understanding of the extent and nature of the relationships between environmental variables and mackerel landings in the VFH. This crucial information helps fishermen and fisheries departments improve catch predictions, promote sustainable practices, and maintain ecosystem health. To understand the complexities and daily nonlinearities, further studies are required on the nature of uncertainty associated with mackerel's food and feeding habits, and on the physiological changes that influence the ocean environment.

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Conflict of Interest

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

Ethical Statement

The evidence used by the authors is from their own original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere. The paper properly credits the meaningful contributions of co-authors. All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

Author Contributions

MN, KV, JVS & SS: Conceptualization of the study, data collection, and data analysis. PAP, OS, & TP: Supervision, validation, review, drafting and preparation of the manuscript.

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