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Indian Oil Sardine (*Sardinella longiceps*) Catch Prediction at Vishakhapatnam Fishing Harbor: An Artificial Neural Network Approach

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ABSTRACT

The experiment was conducted during January-September, 2024 at the Visakhapatnam Fishing Harbour, Andhra Pradesh, India to evaluate Artificial Neural Network (ANN) models to predict sardine catches by integrating key satellite-derived environmental variables. Daily catch data were collected during this period, complemented by Aqua MODIS-derived CHL-a and SST, and meteorological observations of AT and WS. A 200 km buffer zone polygon shapefile, encompassing the study area, was created using ArcGIS 10.7.1. A total of fourteen Feed Forward Neural Network models were developed and classified into With Ban (WB) and Without Ban (WOB) categories to account for the annual fishing ban from April 15 to June 14, 2024. Among these, the WOB model incorporating SST exhibited the highest predictive performance, indicating the strong influence of environmental parameter variations on sardine availability. Fluctuations in CHL-a, primarily driven by monsoon-induced upwelling and wind-mediated nutrient enrichment, were also closely associated with catch trends. Sensitivity analysis further validated model robustness, with the comprehensive WB model demonstrating reliable predictive capability despite seasonal constraints. Overall, the findings highlighted the effectiveness of ANN models in interpreting non-linear catch dynamics and emphasized their potential as valuable tools for forecasting fishery yields. The study underscored the importance of integrating environmental indicators into fisheries management to support sustainable exploitation of the Indian Oil Sardine along the Andhra Pradesh coast.

KEYWORDS: Chlorophyll a, sea surface temperature, sensitivity analysis

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Data Availability Statement: Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

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1. INTRODUCTION

Vishakhapatnam Fishing Harbour (VFH), located on the northeastern coast of Andhra Pradesh, India, spans 26 hectares along the Bay of Bengal. The Indian Oil Sardine (*Sardinella longiceps*), a dominant pelagic species, is widely distributed along the Indian coastline and constitutes a significant component of the fishery along the Andhra Pradesh coast, contributing 7.7% to the total marine fish landings in 2023 (Anonymous, 2023). Satellite-derived oceanographic and meteorological parameters are critical for addressing fisheries management challenges, including fish catch detection, stock assessment and sustainable resource management. This study investigates the influence of four environmental variables, Chlorophyll-a (CHL-a), Sea Surface Temperature (SST), Air Temperature (AT), and Wind Speed (WS) on Indian Oil Sardine abundance.

Previous research in Indian waters (Madhavan et al., 2015; Yoon et al., 2021) has demonstrated that variations in environmental conditions significantly affect fish schooling behavior and, consequently, fish availability. SST showed a strong negative relationship with Indian mackerel landings, with peak catches during cooler winter months and a sharp decline in April (Sai et al., 2025a). Overall, SST emerged as the primary environmental driver, while other variables showed weak influence. Human-induced climate change fully drives global warming, leading to rising temperatures, ocean acidification, and sea level rise that severely impact fisheries (Praneeth et al., 2025). These environmental variables, measured in surface waters, are critical predictors of sardine catch dynamics. However, the non-linear relationships between fishery resources and environmental factors pose challenges for accurate forecasting using conventional statistical methods. Pelagic fisheries exhibit considerable variability driven by both exploitation intensity and environmental fluctuations (Cisneros et al., 1996).

A wide range of modelling approaches spanning Artificial Neural Networks (ANN), Generalized Additive Models (GAM), hybrid statistical–machine learning frameworks, and spatiotemporal models have been applied globally to improve fisheries forecasting and support sustainable management. Sholahuddin et al. (2015) emphasized the importance of MSY estimation and showed that ANN–Linear Perceptron models performed comparably to traditional MLR approaches. Several coastal fisheries studies, including those by Madhavan et al. (2015a, 2015b), highlighted the effectiveness of ANN models incorporating environmental variables such as CHL-a, SST, and PAR, with seasonal architectures providing superior prediction accuracy for sardine and mackerel landings. Similar ANN-based environmental prediction frameworks were used by Wang et al. (2015) for squid and Yáñez et al. (2017) for Chilean pelagic species, achieving high accuracy and demonstrating skill in long-term projections.

Other machine learning developments include NARX models for multi-species forecasts in Indian waters (Yadav et al., 2022; Stephen et al., 2022), hybrid SARIMA–ANN models for Malaysian fisheries (Mohamed and Hasmin, 2023), CNN–LSTM and ARIMA–NN frameworks addressing multiscale forecast challenges (Zhang et al., 2022), and ANN-driven optimization of fishing effort (Kelly et al., 2023). Advanced ANN architectures, such as quartile stacking (Li et al., 2024) and dependency-aware ANN designs (Lei et al., 2024), further enhanced CPUE prediction and stock assessment reliability.

Parallel to these efforts, GAMs and related flexible models have been used effectively for habitat prediction, species distribution forecasting, and stock assessments. Notable applications include sardine distribution modelling (Kaplan et al., 2015), spatial habitat mapping of Indian fisheries (Solanki et al., 2017), global assessments of fisheries model performance (Szuwalski and Thorson, 2017), and forecasting hake distribution and bycatch risk (Malick et al., 2020; Stock et al., 2020). Recent VAST- and GAM-based assessments (Yuan et al., 2024) demonstrated strong predictive skill in data-limited fisheries, underscoring the growing value of combining environmental indicators with modern modelling tools for adaptive fisheries management. The study utilized Artificial Neural Network (ANN) models to predict sardine catches by integrating key satellite-derived environmental variables such as Chlorophyll-a, Sea Surface Temperature, Air Temperature, and Wind Speed.

2. MATERIALS AND METHODS

2.1. Study area and data sources

The study area, Vishakhapatnam Fishing Harbour (VFH), is located at coordinates 17°41’49.82”N latitude and 83°17’58.32”E longitude along the northeastern coast of Andhra Pradesh, India (Figure 1). Daily fish catch data for Indian Oil Sardine (*Sardinella longiceps*) were collected from January to September, 2024. To estimate daily CHL-a and SST, Aqua MODIS Level 2 data at 1 km resolution (Standard Mapped Images, SMI) were retrieved from NASA’s Ocean Color website (https://earth.gsfc.nasa.gov/ocean/data/ocean-color-level-1-2-browser). These data were processed using SeaDAS 8.1, an open-source software toolbox for satellite data analysis.

A 200 km buffer zone polygon shapefile, encompassing the study area, was created using ArcGIS 10.7.1. This shapefile was overlaid on processed Aqua MODIS images in SeaDAS 8.1 to extract spatially averaged CHL-a and SST values by aggregating pixel datasets within the defined region (Sai et al., 2025b, 2025c). Due to frequent cloud cover in tropical

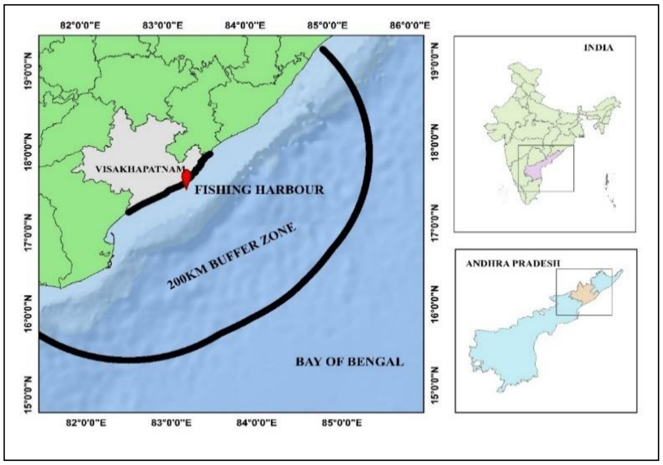

Figure 1: Study area with a 200 km buffer zone from VHF

regions like India, which can obstruct satellite sensor data collection, missing data during the study period were imputed by interpolating neighboring values in MATLAB.

Daily AT data were sourced from the Time and Date website (https://www.timeanddate.com/), while daily WS data were obtained from the Indian National Centre for Ocean Information Services (INCOIS) web portal (https://incois.gov.in/).

2.2. Implementation of artificial neural network

A total of 14 Feed Forward Neural Network (FFNN) models, with architectures 1-4-1, 2-4-1, and 4-4-1, were developed in the MATLAB programming environment to predict Indian Oil Sardine (*Sardinella longiceps*) catches at VFH. The predictions were categorized into two models: With Ban (WB), which included the fishing ban period (April 15 to June 14, 2024), and Without Ban (WOB), which excluded the ban period. A Feed Forward Neural Network comprises multiple neurons operating in parallel, organized into layers: an input layer, one or more hidden layers and an output layer. The input layer receives raw data, analogous to sensory neurons in biological systems, enabling non-linear data processing. Each layer processes the output from the preceding layer, with the final layer producing the model's output. The high interconnectivity among neurons allows information storage and the network's adaptability enables it to adjust to environmental changes through iterative training, improving predictive accuracy with each epoch (Sarkar et al., 2020).

2.2.1. Model configuration and training

The FFNN models were configured with an input layer containing neurons corresponding to four environmental variables: CHL-a, SST, AT, and WS. The hidden layer consisted of interconnected neurons that applied weights and biases to transform the inputs, while the output layer contained a single neuron representing the predicted sardine catch. During training, the network was presented with input-target pairs, and weights and biases were adjusted through a trial-and-error process. Training ceased when the maximum number of epochs was reached, ensuring the model learned the underlying patterns in the non-linear sardine catch dataset effectively.

2.2.2. Prediction methodology for with ban (WB) models

For the WB model, which includes the fishing ban period from April 15 to June 14, 2024, the ANN was used to predict Indian Oil Sardine (*Sardinella longiceps*) catches at VFH. Initially, the ANN was trained to estimate catches during the ban period using daily data of four environmental variables, CHL-a, SST, AT and WS from January 1 to April 14, 2024 (105 days) as inputs, with corresponding daily sardine catch data (105 days) as the target. After training, the model was tested with input variables from April 15 to June 14, 2024 (61 days), yielding predicted catches for the closed season. To predict September 2024 catches, the ANN was retrained using eight months of input data (January 1 to August 31, 2024; 244 days) and catch data for the same period, including the predicted 61-day ban period catches, as the target. The model was then tested with September 2024 environmental data, and after evaluating multiple epoch configurations, the predicted September catches for the WB model were obtained.

2.2.3. Prediction methodology for without ban (WOB) models

For the WOB model, which excludes the fishing ban period, the ANN was trained using daily data of the four environmental variables (CHL-a, SST, AT, and WS) from January 1 to April 14 and June 15 to August 31, 2024 (183 days), with corresponding sardine catch data for the same period as the target. To predict September 2024 catches, the trained model was tested with September 2024 environmental data. After testing, the predicted September catches for the WOB model were derived, with model performance optimized through multiple epoch iterations.

2.3. Methods of evaluation

Different error measures were used to evaluate the performance of the ANN and identify the best model (Abrahart and See, 2000). In this study, the Coefficient of Correlation (R) measures the relationship between actual and predicted values, and the Coefficient of Determination (R^2) indicates the proportion of total variation in the observed data. Mean Square Error (MSE) is used to measure the average of the squares of the error between predicted and actual values during the calibration and validation phase of NNM:

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

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

Where: n is the number of data points. *yi* is the observed value. *y^i* is the predicted value by the model.

3. RESULT AND DISCUSSION

3.1. Chlorophyll-a and sea surface temperature

CHL-a concentration in the Bay of Bengal is a critical indicator of plankton productivity, which is directly correlated with fish availability, particularly for Indian Oil Sardine (*Sardinella longiceps*) at Vishakhapatnam Fishing Harbour (VFH). Monthly mean CHL-a concentrations, as depicted in Figure 2, increased from January to July, 2024, ranging from 0.16 to 0.73 mg/m³, followed by moderate levels (>0.53 mg/m³) in August and September, 2024 within the 200 km buffer zone surrounding VFH. These variations in CHL-a are attributed to regional temperature shifts and the southwest monsoon, which induces nutrient-rich upwelling, thereby enhancing plankton productivity. Previous studies have reported elevated CHL-a concentrations during the winter monsoon in the northern Indian Ocean and along the southwest coast of the Bay of Bengal (Yoder, 2000; Shanthi et al., 2015). The observed fluctuations in CHL-a result from the combined effects of water circulation, wind-driven upwelling and nutrient enrichment from river runoff, which elevate chlorophyll levels (Kumar et al., 2007; Ali et al., 2021). These findings corroborate the current results, indicating that CHL-a concentration is closely linked to sardine availability, with seasonal variability driving changes in CHL-a levels.

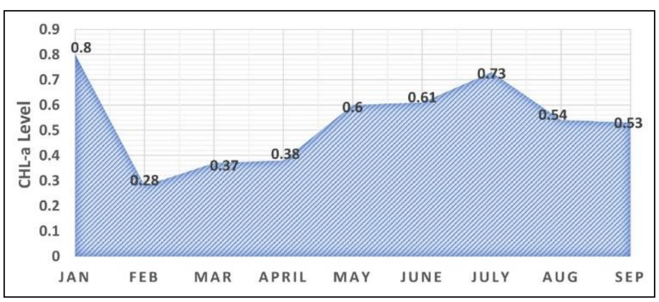

Figure 2: Average mean monthly chlorophyll a level in the study area

SST is a key determinant of marine species distribution, including the Indian Oil Sardine (*Sardinella longiceps*) at VFH. SST values were derived from brightness temperature data using the MODIS dataset. As shown in Figure 3, SST within the 200 km buffer zone around VFH ranged from 20.1°C to 32.99°C during the study period. This variability is attributed to seasonal fluctuations along the Bay of Bengal coast, consistent with findings from previous studies (Selvin Pitchaikani and Lipton, 2012; Azmi et al., 2015; Jitendra Kumar et al., 2016; Anitha Kumari et al., 2023). SST significantly influences marine fish productivity, as highlighted by Belgum et al. (2022), who underscored its critical role in shaping marine ecosystem dynamics. These results suggest that SST variations are essential for understanding seasonal patterns in marine species distribution and their relationship with sardine catch in the study area.

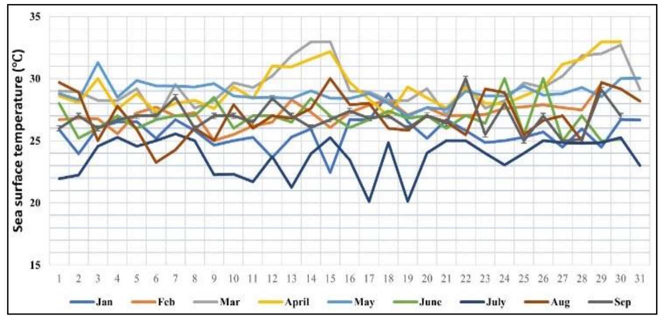

Figure 3: Average daily sea surface temperature (SST) from January to September in the study area

3.2. Air temperature (AT) and wind speed (WS)

AT exhibited significant seasonal variation during the study period at VFH. The highest AT, recorded at 33.2°C in March, coincided with pre-monsoon conditions characterized by intense sunshine and hot air. Conversely, the lowest AT of 24°C was observed in July during the monsoon season, attributed to cloudy skies and monsoon influences. These fluctuations align with findings by Ho et al. (2011), which suggest that peak sardine landings often correspond with lower AT. However, the current study indicates that sardine landings peaked across both high and low AT ranges, as illustrated in daily AT fluctuations shown in Figure 4. Additionally, Park et al. (2024) and Ozbek et al. (2021) reported that higher AT is associated with increased rainfall or precipitation, which can impact pelagic fish landings. The present results confirm that AT variations, influenced by regional climatic zones and seasonal weather patterns, are directly correlated with sardine catch, highlighting its role in modulating fish availability.

WS during the study period ranged from a maximum of 35 km h^{-1} in July, during the southwest monsoon season, to a minimum of 10 km h^{-1} in April, during the pre-monsoon

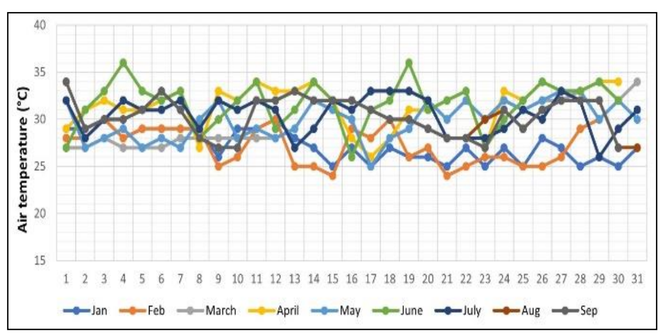

Figure 4: Average daily air temperature (AT) from January to September in the study area

season. As depicted in Figures 5 and 6, high sardine landings at VFH were positively correlated with elevated wind speeds. This observation is consistent with Ho et al. (2022), who noted that stormy winds induce vertical mixing, transporting nutrients to the euphotic zone and enhancing surface layer productivity. Furthermore, upwelling driven by high WS brings cooler, nutrient-rich waters to the surface, improving survival rates of sardine larvae (Lloret et al., 2004). Previous studies by Selvin Pitchaikani and Lipton (2012), Muskananfola et al. (2021) and Abdulla et al. (2023) have similarly reported that increased WS during the southwest monsoon amplifies upwelling, significantly boosting fish productivity along the Indian coast. These findings underscore the critical role of WS in driving nutrient availability and supporting sardine landings at VFH.

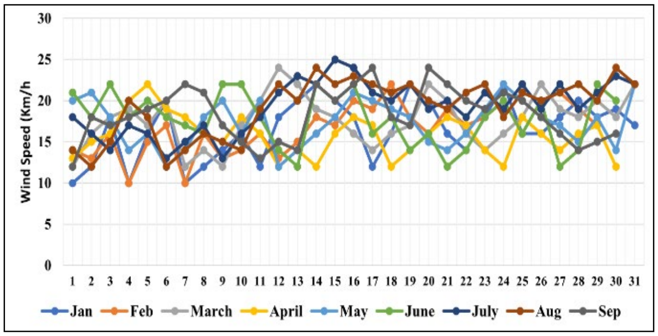

Figure 5: Average daily wind speed (WS) from January to September in the study area

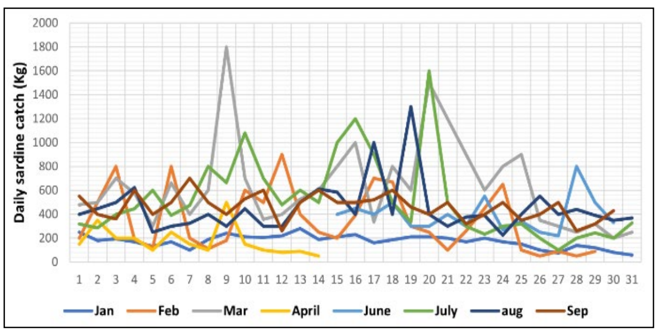

Figure 6: Daily sardine catches at Vishakhapatnam Fishing Harbour (VFH)

3.3. Sardine prediction comparison in artificial neural network models (NNMs)

In this study, multi-layered Feed Forward Neural Network (FFNN) models with a Back Propagation training algorithm were employed to predict Indian Oil Sardine (*Sardinella longiceps*) catches at VFH due to their simple architecture and effective error minimization capabilities. Previous research in Indian and international waters (Ganchev et al., 2004; Yanez et al., 2010; Madhavan et al., 2015; Naranjo et al., 2015; Wang et al., 2015; Yoon et al., 2020) has demonstrated that Neural Network Models (NNMs) outperform other predictive models, such as Multiple Linear Regression (MLR) for simple fisheries data, Auto-Regressive Integrated Moving Average (ARIMA) for time-series forecasting, and Generalized Additive Models (GAM) with limited predictive power, in capturing non-linear fish catch dynamics.

The performance of WB and WOB models is presented in Table 1. Among the WB models, the SAR_MD_WB model exhibited the best performance for predicting sardine catch, achieving an MSE of 0.019. For the WOB models,

Table 1: Sensitivity analysis result for WB and WOB models

WB Models		R	R2	MSE	Model	EPOCH	Rank
1.	SAR_CHL_WB	0.43878	0.192528	0.030747	01:04:01	6	7
2.	SAR_SST_WB	0.341391	0.116548	0.022476	01:04:01	8	3
3.	SAR_AT_WB	0.138605	0.019211	0.025555	01:04:01	4	6
4.	SAR_WS_WB	0.270571	0.073209	0.023889	01:04:01	7	5
5.	SAR_MD_WB	0.278274	0.077437	0.019360	02:04:01	10	1
6.	SAR_SAT_WB	0.461439	0.018493	0.023388	02:04:01	9	4
7.	SAR_ALL_WB	0.525369	0.276013	0.021066	04:04:01	15	2
8.	SAR_CHL_WOB	0.367272	0.134889	0.015039	01:04:01	4	2
9.	SAR_SST_WOB	0.238593	0.056927	0.013975	01:04:01	8	1
10.	SAR_AT_WOB	0.13371	0.017878	0.019729	01:04:01	2	5
11.	SAR_WS_WOB	0.233456	0.054502	0.034583	01:04:01	6	7
12.	SAR_MD_WOB	0.237677	0.056490	0.016839	02:04:01	9	3
13.	SAR_SAT_WOB	0.372018	0.138397	0.018226	02:04:01	10	4
14.	SAR_ALL_WOB	0.448209	0.200892	0.025155	04:04:01	17	6

the SAR_SST_WOB model was the most effective, with an MSE of 0.013, indicating that SST is a critical predictor of sardine catch compared to other environmental variables in both WB and WOB models. These findings align with studies by Yanez (2010) and Madhavan et al. (2015), which identified SST as an indispensable parameter for forecasting sardine abundance using NNMs. Conversely, Akohi and Komatsu (1996) found that favorable conditions for sardine availability along the northeastern coast of Japan occur when SST is lower and zooplankton density is high. In comparison, a modified NNM developed by Wang et al. (2015) for neon flying fish in the Northwest Pacific Ocean, using satellite-derived environmental variables, achieved an MSE of 0.62, underscoring the superior predictive accuracy of low MSE values, where the difference between observed and predicted catches approaches zero.

Sensitivity analysis revealed that the SAR_AT_WOB model had a predictive capability with an R^2 value of 0.238. In contrast, the LTS_MER_SAR_SST_NS model by Madhavan et al. (2015) demonstrated a higher R^2 of 0.57, indicating greater predictive power. The SAR_ALL_WB and SAR_ALL_WOB models in the current study showed improved R values with higher epoch counts (15 and 17), as increasing epochs allows the models to iteratively adjust weights, minimizing prediction errors. However, excessive epochs may lead to overfitting, where the model captures noise rather than meaningful patterns. To mitigate this, internal validation, as recommended by Yanez et al. (2017), was employed to ensure robust model training without overfitting.

4. CONCLUSION

Forecasting sardine catches around VFH using Neural Network Models integrated with environmental variables proved effective, with the SAR_SST_WOB model showing the best performance (MSE 0.013).

5. ACKNOWLEDGEMENT

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