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NPZf_c: An ecological relation-based fish catch prediction model using Artificial Neural Network

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Original Article

Abstract

Quantifying interactions of organisms of the various trophic levels is important in understanding the dynamics of aquatic ecosystems. Concerning fish, as both ecologically and commercially important components of natural aquatic ecosystems, predicting their catch in relation to primary producers provides insight into sustainable management. This paper describes a novel model NPZfc, for encompassing nutrients, phytoplankton, zooplankton and fish, which can predict planktivorous fish catch. Unlike the existing models, which deal with the interactions within the system through mathematical equilibrium, the proposed model uses an artificial neural network (ANN) to automatically learn inter-dependencies between different related variables and predict the fish catch of a water body using a limited dataset. The efficiency of the model was enhanced by refining the input variables. Here biomass of plankton species population (phytoplankton and zooplankton) was specifically selected from feeding ecology studies of target fish species as input variable. The study involving two of the commercially important fish species, Etroplus suratensis and Nematalosa nasus, in Chilika lagoon showed that the model can predict with high accuracy from limited input data. The root mean square error (RMSE) is satisfactory, ranging from 12.55 t for N. nasus to 16.13 t for E. suratensis. Higher accuracy and better predictive ability with a smaller dataset make this ANN-based NPZfc model promising for wider expansion with future research integrating multi-year and cross-system data to enhance the model's transferability and predictive reliability across diverse environmental conditions.

Keywords: *ANN, machine learning, fisheries management, Chilika Lagoon, plankton modelling, fish catch prediction*

Introduction

The increasing demand for natural resources and accounting for their sustenance has constantly drawn attention to simulating the real world. Scientific models are widely used methods for substituting real-world systems into numerical relations. It allows experimenting with different inputs and analysing how the end product is affected. As aquatic ecosystems account for the highest natural resources, ecosystem models have been persistently used for their management (Slobodkin, 1960; Odum and Odum, 2000). The models range from using the simplest parameters like nutrients and plankton (Franks, 2002) to complex organisms including humans (Wandersee *et al*., 2012). Models have also been proposed for understanding inter and intra-interactions between abiotic and biotic components (Fulton, 2010; Rose *et al*., 2010). However, less effort has been taken to quantify this interactive understanding. Machine learning (ML) tools are known for their use in modelling patterns within data by automatically learning the parameters of the systems (Theodoridis and Koutroumbas, 1999; Pal and Mitra, 2004) including in ecological modelling (Reichstein *et al*., 2019). Artificial Neural Network (ANN) is one such ML tool trying to model biological neural networks (Yegnanarayana, 2009) and follows a simple principle of learning from examples without specifying any task-specific rules. As a result, ANN has been successfully used in systems where mathematical relations are hard to observe from the data (Kuo-lin *et al*., 1995). This motivated us to use ANN in the prediction of forage fish catch from NPZ values.

The study was conducted in Asia's largest coastal lagoon, Chilika, a Ramsar site. Fisheries in the lagoon contribute 71%

of the ecosystem's economic value (Kumar, 2003) and generate significant international revenue (Mohanty *et al*., 2008). Chilika is well known for its biodiversity, reflected in its high ecosystem health grades based on water quality, fisheries, and biodiversity metrics (Pattnaik, 2013). The biodiversity assessment considered bird richness, benthic diversity, dolphin abundance, and phytoplankton diversity (Pattnaik, 2013). Previous studies have attempted to predict fish catch potential in Chilika using MLP models (Mishra and Ojha, 2021), but these did not account for nutrient flow through the food chain, a key aspect of ecosystem dynamics. Although interest in studying the trophic status of the lagoon and its relation to fisheries dates back decades, no substantial advancements have been made since the early work of Jhingran (1963) (Mohanty and Adhikary, 2013; Jhingran, 1963). No attempts have yet been made to model the complex relationships among nutrients, plankton, and fish in Chilika using a predictive approach that elucidates system dynamics. Developing such an ecological model can improve our understanding of dynamic changes in both biotic and abiotic components and assist in the management of the fisheries of the lagoon (Ghoroghi *et al*., 2023). In this study, we present a novel approach that leverages species-specific plankton biomass as input to an ANN-based model for predicting forage fish catch. Unlike currently available mathematical models, this is the first application of ANN to model NPZ interactions for forage fish prediction in Chilika Lagoon, focusing on the actual dietary composition of target fish species to enhance predictive accuracy. The findings of this study will serve as proof of concept for future work on ANN aimed at developing more generalised and robust predictive models across diverse ecological systems.

Material and methods

Study area

The study was conducted in Chilika Lagoon, located between 19°28'and 19°54' N and 85°6' and 85°35' E on the east coast of India. This coastal lagoon exhibits estuarine characteristics due to the combined influence of precipitation, freshwater influx from the Mahanadi River distributaries, and seawater intrusion from the Bay of Bengal. Chilika is recognised as Asia's largest brackish water lagoon, supporting rich biodiversity and significant fisheries. The lagoon's dynamic salinity gradients and ecological diversity make it an ideal setting for studying nutrient–plankton–fish interactions.

Field sampling and plankton biomass estimation

Simultaneous nutrient and microplankton samples were collected at monthly intervals using standard methods (Eaton *et al*., 2005). A 20-micron net was used to collect microplankton samples, and their biomass (mgC/l) was estimated using their biovolume. Biovolumes, estimated based on geometric shapes, were then converted to carbon in picograms following Menden-Deuer and Lessard (2000).

The formulae used for the estimation of the biovolume are the following.

Diatoms: pgC/cell = 0.288 * volume0.811

Other protist plankton groups: pgC/cell = 0.216 * volume0.939

Microplankton species confirmed from the feeding ecology analysis of the target fish species (Mukherjee *et al*., 2016, 2017) were exclusively used for calculating input variable (microphytoplankton and microzooplankton) biomass.

Fish catch data

Planktivorous fish species catch data corresponding to the sampling period were obtained from the Chilika Development Authority through a concurrent study. The catch was measured in tonnes and used as the dependent variable in the model.

Artificial Neural Network modelling

Model Architecture and Training: The model NPZf_c approached the use of three variables: *viz;* nutrients (N), microphytoplankton (P), and microzooplankton (Z) to predict catch of the planktivorous fish species (f_c) in tonnes. A supervised machine learning technique, the ANN, was used to develop a predictive model. The ANN consisted of three input neurons (nutrients, microphytoplankton, microzooplankton), one hidden layer with three neurons, and one output neuron representing the predicted fish catch (Fig. 1). The three hidden neurons were selected by hyperparameter tuning with 2 to 10 hidden neurons. We selected three neurons as it provided the best possible results. Supplementary bias nodes were added to the hidden and output layers.

The state of neurons was calculated as the weighted sum of received signals from the preceding layer as $y_k = f_0 \{b_k + S_j w_{jk} * f_h(b_j + w_{ij} * x_i)\}$

where, y_k = output signals, x_i = input signals, w_{ij} = weight between input neuron *i* to hidden neuron *j*, b_j = bias associated with the hidden layer, b_k = bias associated with output layer, f_0 = activation function for output layer and f_h = activation function for the hidden layer.

The activation function of a neuron defines the output of

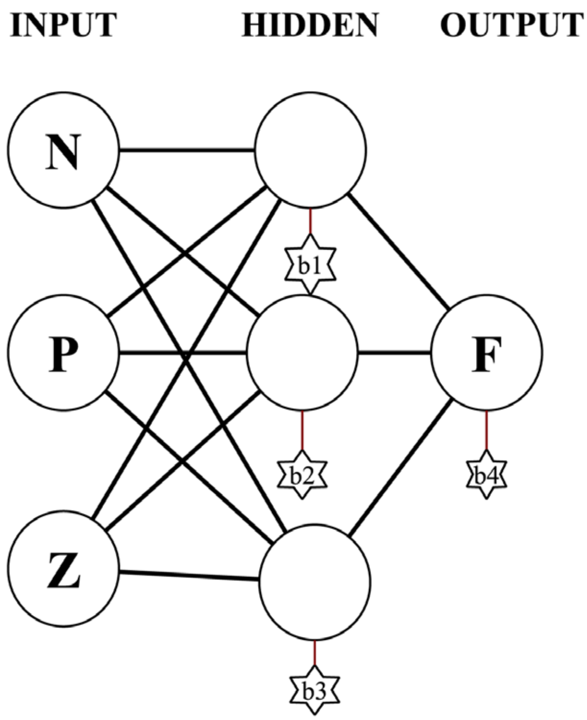

Fig. 1. Neural network design of the model, with three input nodes and one hidden layer of three nodes. N = Nutrients, P = Microphytoplankton, Z = Microzooplankton, F = Fish. b1, b2, b3 and b4 are the biases obtained from each node

that neuron based on the weighted sum of its inputs; that is, it transforms the neuron's activation level into an output signal. Among the many activation function types (Bishop, 1995), the hyperbolic tangent function (tanh) was used for both the hidden and output layers in this study.

The tanh activation function is $\tanh(x) = 2 * \sigma(2x) - 1$ where $\sigma(x)$ is the sigmoid function.

The range of the tanh function is [-1, 1] which provides a stronger gradient. The error function used here with back-propagation was the least square error. The number of hidden nodes was optimized by testing networks with 1 to 10 nodes, selecting the configuration with the best statistical performance. Only one hidden layer was used, as it provided acceptable results, consistent with previous findings (Kurkova, 1992).

Normalisation and statistical evaluation: The dataset was split into training (80%) and testing (20%) samples, randomly selected for each of the ten simulations. All input variables [nutrients (nitrate-N in ppm), microphytoplankton (units/l), and microzooplankton (number/l)] and output [fish catch (t)] were normalised using a natural logarithm transformation. A $\ln(x)$ transformation was applied to reduce skewness and bring values closer to a normal distribution. Output values of the test set were de-normalised before statistical analysis. All machine learning algorithms were simulated and analysed in Mathematica 11 (using inbuilt functions), on an Intel Core i5 processor with 12 GB RAM using Linux OS. Fig. 2. shows the detailed steps of the process involved.

Results

The model generated considered the transfer of energy at each trophic level in terms of biomass. The total microphytoplankton carbon biomass was calculated as 2.96×10^{-3} mgC/cell and microzooplankton was calculated as 1.28×10^{-3} mgC/cell. The monthly average microphytoplankton abundance of the species measured for biovolume ranged from 20 units/l in December to 19711 units/l in April and microzooplankton ranged between 1 no./l in October and 1992 no./l during May (Table 1). The biomass trend showed by microzooplankton followed that of microphytoplankton, wherein the gradual

Table 1. Monthly average abundance of plankton enumerated for biovolume

Abundance	Feb	Mar	Apr	May	Jun	Aug	Sep	Oct	Nov	Dec
Microphytoplankton (Units/1)	1458	8082	19711	3856	383	279	3259	37	91	20
Microzooplankton (no./1)	16	11	660	1992	99	18	695	1	9	14

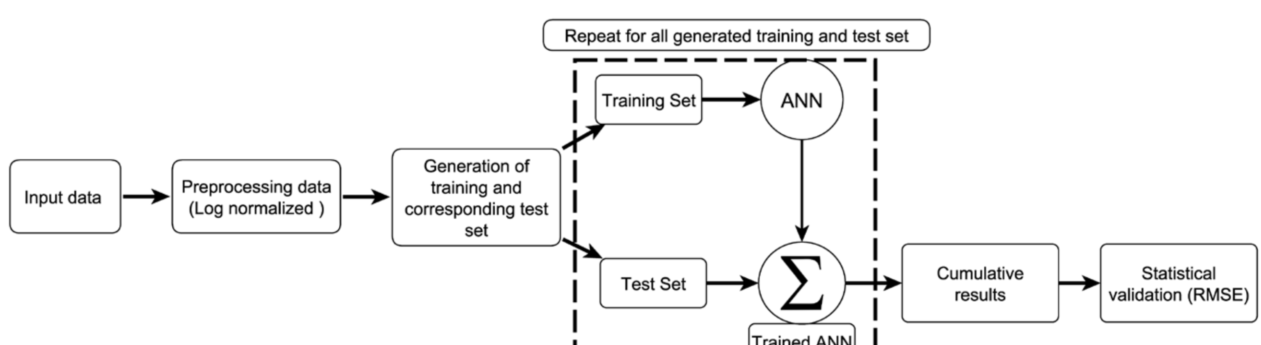

Fig. 2. Steps followed in the NPZf_c model

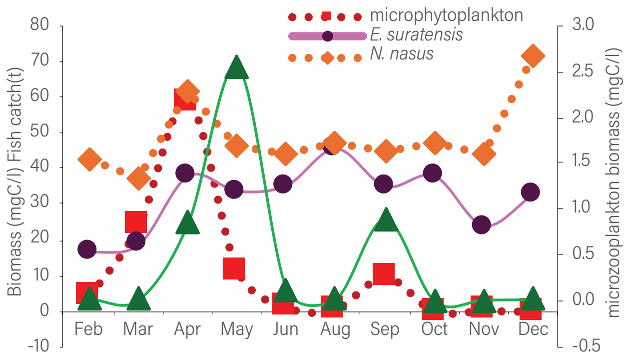

Fig. 3. Monthly variation in biomass of plankton, *E. suratensis* and *N. nasus*

increase in phytoplankton from February to April was followed by an increase in zooplankton from March to May (Fig. 3). The transfer of this biomass to the next trophic level was studied through the feeding ecology of two important forage fishes of Chilika viz. *E. suratensis* (Mukherjee *et al*., 2017) and *N. nasus* (Mukherjee *et al*., 2016). *E. suratensis* catch gradually increased and reached its peak in August when both the plankton groups showed a drop in biomass (Fig. 3). A Further decline in the fish catch of September showed a corresponding increase in biomass of both groups of plankton. The catch trend of *N. nasus* also showed a similar relation to that of *E. suratensis*, wherein its catch increased with a decrease in plankton abundance (Fig. 3). It is only during April that *N. nasus* catch increased with microphytoplankton and a corresponding decrease in microzooplankton abundance. This fish species was found to have a very specific need for microzooplankton during the month which is discussed in detail by Mukherjee *et al*. (2016). The fishing effort in the lagoon did not exhibit measurable change during this period. Thus, the possibility of plankton growth based on the available nutrients of the environment and the corresponding growth of planktivorous fish using them as food could be established for both species.

Table 2 provides the values of the predictor or input variables of the model used along with the fish catch. It comprised 10 months of sampling data with nitrate (mg/l) as nutrient, microphytoplankton (mgC/l), microzooplankton (mgC/l) and catch (t) of planktivorous fishes the *E. suratensis* and *N. nasus*. The predicted catches (*i.e*., the output from the model) with the corresponding actual catches of all of the test samples are given in Fig.4a and 4b for *E. suratensis* and *N. nasus* respectively. Corresponding numerical values are mentioned in Tables 3 and 4. In the case of *E. suratensis*, 13 values (65%) remained higher and 7 lower (35%) predictions. Of these 65% higher predicted values, three values were almost perfect predictions, (0.93 t, 0.63 t, 1.13 t) remaining within a difference of 1t. For *N. nasus*, the higher and lower predicted values remained equal in percentage (50%), of which four values were near perfect (1.56 t, 1.71 t, -1.71 t and 1.93 t). The values for all 20 samples are given in Table 3 for *E. suratensis* and Table 4 for *N. nasus* for reference.

Root mean square errors (RMSEs) were calculated to find the variations amongst the actual and predicted values of fish catch of both species. Root mean square errors are more sensitive to occasional very large errors in predicted values as they tend to square the errors in the calculations. The mean absolute error (MAE) was also used to complement the idea of goodness of fit. The error values were also converted into

Table 2. Input data of *E. suratensis* used for training and testing the model

Months	Feb	Mar	Apr	May	Jun	Aug	Sep	Oct	Nov	Dec
Nitrate (mg/l)	0.35	0.44	0.14	0.03	0.49	0.57	0.45	0.05	0.47	1.03
Microphytoplankton (mgC/l)	4.33	23.99	58.5	11.45	1.14	0.83	9.68	0.11	0.27	0.06
Microzooplankton (mgC/l)	0.02	0.01	0.85	2.56	0.13	0.02	0.89	0	0.01	0.02
E. suratensis catch (t)	xx	18.54	37.62	33.42	35.06	45.28	34.74	37.64	23.82	32.42
N. nasus catch (t)	42.26	37.41	61.26	46.66	44.07	47.45	44.72	47.31	43.73	71.54

Table 3. Goodness of fit *E. suratensis* model assessed through statistical tests

Test sample	1	2	3	4	5	6	7	8	9	10
Predicted (t)	44.93	33.81	21.37	42.17	59.68	15.19	62.78	19.20	49.14	25.84
Actual (t)	33.42	34.7	45.3	34.7	32.4	18.5	32.4	33.4	35.1	34.7
Test sample	11	12	13	14	15	16	17	18	19	20
Predicted (t)	16.11	63.48	8.00	34.43	6.21	17.76	20.09	14.89	22.11	17.41
Actual (t)	18.54	35.1	37.6	35.1	37.6	37.6	18.5	37.6	34.7	18.5
RMSE (t)	16.13 ±	2.72								
MAE	0.58									

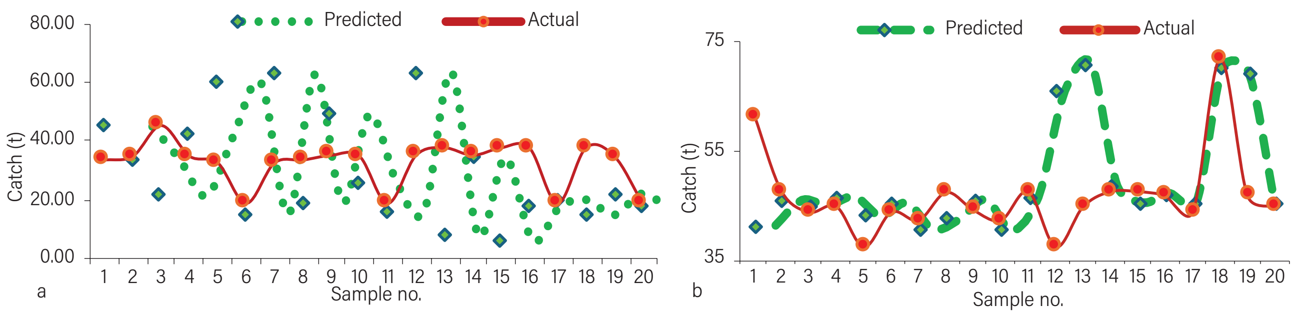

Fig. 4. Predicted and actual catch of fishes (a) *E. suratensis* and (b) *N. nasus* generated from 20 test sets used for validation of the model

Table 4. The goodness of fit for *N. nasus* model, assessed through statistical tests

Test sample	1	2	3	4	5	6	7	8	9	10
Predicted (t)	41.30	45.89	44.92	46.56	42.97	45.44	40.55	42.45	46.02	40.32
Actual (t)	61.26	47.45	43.73	44.72	37.41	43.73	42.26	47.31	44.07	42.26
Test sample	11	12	13	14	15	16	17	18	19	20
Predicted (t)	46.46	65.77	70.86	48.43	45.43	47.14	45.44	69.95	69.19	45.09
Actual (t)	47.45	37.41	44.72	47.45	47.45	46.66	43.73	71.54	46.66	44.72
RMSE (t)	12.55±	1.26								
MAE	0.99									

RMSE = Root Mean Square Error MAE = Mean Absolute Error

percentages to better visualise the differences. The RMSE values of *E. suratensis* were16.13± 2.72 and MAE 0.58 t. The RMSE value of *N. nasus* was 12.55 t±1.26 and MAE was 0.99 t.

Discussion

The production of an ecosystem depends upon the energy flow through each trophic level, making fish production as an end product inherently dependent on its source of energy. Chilika Lagoon supports high biodiversity and a complex trophic chain, with plankton dynamics exhibiting distinct spatio-temporal variations (Srichandan *et al.*, 2015; Mukherjee *et al.*, 2018). These variations have a considerable effect on the forage fish population, which in turn has motivated ecologists to develop compartment models (Kumar and Kumari, 2015; Franks, 2002). The present study explored the potential of linking plankton dynamics and feeding ecology to develop a predictive fish catch model.

A detailed study of the feeding ecology of *N. nasus* and *E. suratensis* (Mukherjee *et al.*, 2016, 2017) has established them as planktivorous fishes. This relationship was used to build a model that traces energy transfer from nutrients to microphytoplankton, then to microzooplankton, and finally to planktivorous fish. The relationship between these four compartments provided a platform to build a predictive model, which we termed the NPZf_c model (Nutrient- Phytoplankton- Zooplankton- fish catch), using artificial neural networks (ANNs).

Traditional mathematical NPZ models are effective for predicting aquatic system dynamics that are otherwise hard to measure (Franks, 2002; Kumar and Kumari, 2015). However, our approach focused on predicting and quantifying the final outputs based on related inputs, leveraging the strengths of statistical and machine learning methods. While various species of forage fishes are confirmed as specialised, preferential, or generalised feeders (Mukherjee *et al.*, 2016, 2017), using the entire plankton community as input would be inappropriate for accurate modelling.

To address this, we adopted a diet-specific modelling approach. Out of the 233 plankton species recorded in Chilika (Mukherjee *et al.*, 2018), only the biomass of the 85 species recorded from the diets of the target fish species was used as input for the model. This contrasts with generic environmental modelling, which typically uses total plankton biomass as an input variable.

The ANN-based NPZf_c model proved effective at capturing the nuanced relationships between environmental variables and fish catch, even with relatively small observational datasets (Pasini, 2015). Neural networks have previously shown efficacy in modelling phytoplankton production (Scardi, 1996; Mattei *et al.*, 2018), succession (Olden, 2000), and bloom prediction (Kang *et al.*, 2012), as well as in relating environmental variables to fish catches (Iglesias *et al.*, 2004; Gutie´rrez-Estrada *et al.*, 2009). The lake-resident *E. suratensis*, being non-migratory, is particularly well-suited for modelling based on environmental variables (Fig. 3). *N. nasus*, although migratory, has specific dietary preferences that also support accurate prediction (Fig. 3). Thus, our results indicate that predictive models based on such parameters require a detailed catch structure of the target fish species and are best suited for resident species of an ecosystem.

The model showed a good fit with very small data feeds for both fish species. For *E. suratensis*, the predicted catch values matched the actual catch values for 45% of the test dataset, with exact matches for 25%. The RMSE value was 16.13 t. For *N. nasus*, 55% of predictions were within about 1 t of the actual catch, and the RMSE was even lower at 11.14 t (2%). Overall, *N. nasus* showed slightly better predictability than *E. suratensis*, likely due to its more specialised plankton feeding habits. *E. suratensis* on the other hand is known for its occasional omnivorous feeding behavior (Emmanuel *et al*., 2019) leading to slightly lower predictability with the model's focus on diet-specific plankton input. The sensitivity analysis indicated that nutrients and microzooplankton were the most influential features for predicting *E. suratensis* catch whereas microphytoplankton were comparatively the more influencing feature for *N. nasus* catch.

When compared with Support Vector Regression (SVR) that generated MAE of 6.29 for *N. nasus* and 12.12 for *E. suratensis*, the proposed ANN-based NPZf_c model demonstrated strong predictive performance for both species, indicating that the relationships established between nutrients, microphytoplankton, microzooplankton, and planktivorous fish were appropriate for developing a predictive model of fish catch. Thus, the proposed model offers a robust alternative to traditional ML models. As the model is trained and evaluated exclusively on data from the Chilika Lagoon, its potential to perform reliably across other ecosystems, or under markedly different years or seasonal regimes within the same system, warrants further exploration.

An ecosystem that supports the livelihoods of more than 0.2 million people (Pattnaik, 2013) highlights the importance of fish catch prediction as a tool for sustainable fisheries management. Accurate predictions can inform not only ecological and ecosystem management but also socio-economic planning. Since planktivorous fish serve as prey for higher trophic levels, the model can be adapted to predict catches of carnivorous fish by analysing prey species and their corresponding catch. This modelling framework is flexible and can be modified for species-specific or holistic approaches to predicting related fish species, provided that the requisite ecological data are available. Beyond fish quantification, the NPZf_c model can be applied to predict any environmental process with well-defined and measurable parameters.

Ablation study

To systematically optimise and interpret the NPZf_c ANN architecture for predicting planktivorous fish catch, we conducted a series of ablation studies targeting three key model components: activation function, input feature selection, and the number of hidden neurons.

Effect of different activation functions*:* We evaluated the effect of different activation functions on model performance by training separate models using the hyperbolic tangent (tanh), Rectified Linear Unit (ReLU), and Sigmoid functions for both hidden and output layers. Performance was compared using the root mean square error (RMSE) for both target species, *N. nasus* and *E. suratensis*. The tanh activation function consistently outperformed both ReLU and Sigmoid across both species. For *N. nasus*, RMSE values were 12.55 (tanh), 13.774 (ReLU), and 12.9216 (Sigmoid). For *E. suratensis*, RMSEs were 16.13 (tanh), 20.568 (ReLU), and 18.8925 (Sigmoid). Thus, tanh was selected for all layers due to its superior predictive accuracy.

Hidden neuron numbers: To identify the optimal model complexity and avoid overfitting, we systematically varied the number of hidden neurons in the single hidden layer from 1 to 10. For each configuration, the model was retrained and evaluated using RMSE. Model performance varied with the number of hidden neurons. For *E. suratensis*, RMSE was lowest at 11.79 with 3 hidden neurons, increasing slightly with more neurons. These results suggest that 3 hidden neurons provide optimal model complexity, balancing predictive accuracy (Table 5).

Input feature sensitivity

To determine the relative importance of each input variable (nutrients, microphytoplankton, microzooplankton), we performed a leave-one-feature-out sensitivity analysis. For each run, one feature was omitted from the input set, the model

Table 5. Root Mean Square Error (RMSE) of the NPZf_c model for *E. suratensis* and *N. nasus* as a function of the number of hidden neurons in the single hidden layer

No of hidden neurons	1	2	3	4	5	6	7	8	9	10
E. suratensis	13.56	13.42	11.79	13.6	13.87	13.51	14.03	13.81	13.81	13.49
N. nasus	22.05	13.42	12.67	12.43	18.11	15.25	14.6	16.17	14.64	13.29

was retrained, and the resulting RMSE was compared to that of the full model. This approach quantifies the contribution of each feature to predictive accuracy. The analysis for *N. nasus* produced RMSEs of 13.71 (nutrient omitted), 13.49 (phytoplankton omitted), and 13.90 (zooplankton omitted). For *E. suratensis*, the corresponding RMSEs were 19 (nutrient omitted), 17.28 (phytoplankton omitted), and 19 (zooplankton omitted). These results indicate that, for both species, all three features contribute to model performance, with zooplankton being most critical for *N. nasus* and phytoplankton for *E. suratensis*.

This study, thus, underscores the importance of machine learning, particularly ANNs, in developing ecological models capable of predicting outcomes, measuring changes, and revealing key biological relationships through automated learning. As classical neural network methods have provided promising results, more advanced deep learning techniques may further improve fish catch predictions. With the advent of advanced sensors (Dyomin *et al.*, 2021; Yang and Compton, 2023), larger and more detailed biomass datasets can be collected to support these data-intensive AI models, enabling even more accurate and robust predictions. Since the model is trained and evaluated solely on data from the Chilika Lagoon, its robustness across different ecosystems remains untested. This currently restricts the model's generalizability and limits its immediate applicability for broader ecological or fisheries management purposes. Future efforts should focus on incorporating multi-year and cross-system data to evaluate the model's transferability and strengthen its predictive confidence under varying environmental contexts.

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Author contributions

Conceptualization: MM; Methodology: MM, VVRS, SK; Data Collection: MM, VVRS; Data Analysis: MM, SK; Writing Original Draft: MM; Writing Review and Editing: MM, VVRS, SK; Supervision: VVRS, SK.

Data availability

The data are available and can be requested from the corresponding author.

Competing interests

The authors declare that they have no conflict of financial or non-financial interests that could have influenced the outcome or interpretation of the results.

Ethical statement

No ethical approval is required as the study does not include activities that require ethical approval or involve protected organisms/ human subjects/ collection of sensitive samples/ protected environments.

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