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Prediction of Fish Yields in Lakes and Reservoirs from simple Empirical Models using Artificial Neural Network (ANN) : An Review

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ABSTRACT

Prediction of reservoir yield is an important for fisheries managers to use appropriate scientific management practices to increase the fishery production. Many mathematical or applied mathematics and Artificial Neural Networks models were developed to predict fish production forecast of reservoirs. Ecology of reservoirs is dynamic, extraordinarily advanced and nonlinear in nature. There are several drivers have an effect on the fisheries, both internal and external environmental parameters. Many researchers have assessed fish yield potential based on leaner models using multiple linear regressions. Accurate modelling to predict fish yield of the reservoirs and lakes helps to understand behaviour of the system and managers can formulate appropriate management practices to improve fish yield. This paper provides an in-depth review on existing model developed from simple empirical estimation to high-level non-linear model for assessing fishery potential of lakes and reservoirs.

Keywords : Fish Yields, Artificial Neural Network, MEI, CPUE, EBP, Automata Networks

I. INTRODUCTION

Fish is nutritious food and rich in protein, minerals, vitamins and essential nutrients. As fishes are very cheap comparatively other animal proteins, many low-income groups prefer fish in their diet. Most important, the fisheries sectors play a great role in the nation building by providing nutritional health security and livelihood support to many people in the country particularly in rural area and give many ecosystem services to the mankind. India is richly endowed with vast inland open waters in form of rivers and canals (1,71,334 km(, reservoirs)3.15 million ha(, floodplain wetlands)0.24 million ha(, estuaries)0.27 million ha(and ponds and tanks (2.25 million ha) (Sinha 1999). These resources provide employment and livelihood support to many people as well as contribute more to Indian economy by foreign exchange earnings to the country. Most important, the fisheries sector plays a great role in the nation building by providing nutritional health security.

In India, reservoirs are *prime resource* in terms of both surface area and production. It offers immense scope for increasing *fish production*. More than 3 million ha of manmade reservoirs available in the country can increase the production. As populations are increasing rapidly, another blue revolution is necessary to double the fish production from these resources to meet the demand. Accurately *predicting* reservoir *yield* will help *fisheries managers to use available various scientific management practices to enhance the fishery production in the reservoir.*

Ecology of reservoirs is dynamic, very complex and nonlinear in nature. There are many drivers influencing the fisheries both internal and external environmental parameters. Many researchers have tried to assess fish yield potential based on leaner models by using multiple linear regression analysis techniques)Jowett, 1993(. These empirical models are capable of solving many linear problems, but some time it cannot give accurate results when relationships among the variables are non-linear in nature. Advance tools like neural network, fuzzy logic, wavelet transform and genetic algorithm will give better and accurate results for non-linear problems.

II. PREDICTION OF FISH YIELD USING EMPIRICAL MODEL

Many researchers predicated fish yields in lakes and reservoirs for the last 70 years using simple empirical estimation. Rawson (1952) demonstrated the first model to estimate fish yields of lakes based on mean depth. Some others also tried to assess fish yield potential from biotic and morphometric parameters)Hayes, 1957; Northcote and Larkin, 1956(. Ryder (1965) improves existing estimation further by developing morpho-edapic index)MEI(by using total dissolved solids or conductivity/depth using 23 temperate lakes. Later many researchers used other dependent variables such as lake surface area, temperature and other parameters along with MEI for prediction of fish yields in lakes and reservoirs in many countries.)e.g. Toews & Griffith, 1979; Jenkins, 1982; Schlesinger & Reglier, 1982; Machena & Fair, 1986(. Ryder (1965(applied this method in Canada. Matuszek (1978(used mean depth and total dissolved solids concentration of large North America lakes. Morpho-edaphic index along with soci-economic variables such as numbers of fisher men, boat and effort are used to predict yield of African lakes)Henderson and Welcomme, 1974(. Maximum Sustainable fish yield of Sri Lanka reservoirs were calculated)Wijayaratne and Amarasinghe, 1984; Nissanke et al., 2000(and)Hasan et al., 2001(predicted fish yield based on chlorophyll-a, Secchi depth and morpho-edaphic index in Bangaladesh.

Others have found that phytoplankton production can predict fish yield more accurately (Oglesby, 1977) or total phosphorus and macro benthos biomass/mean depth found to be the best predictors of fish yield better than MEI (Hanson and Legget,1982). Surface area alone or Lake Shoreline development is useful predictor variables of fishyield in North American lakes (Youngs and Heimbuch, 1982). Hrbacek)1969(found that significant correlation between primary production and carp yield in European ecosystems. Melack)1976(and Toews and Griffith)1979(reported that primary production is an estimator of fish yield. Stocking densities of fingerlings in inland reservoirs can be calculated based on estimation of potential fish production using morpho-edaphic index)MEI( )Welcomme, 1976(. Surface area can alone be the best predictor of fish yield reported by researchers from North American lakes)Youngs and Heimbuch, 1982(.

Models have been developed using reservoir depth, volume and area for estimation of fishery yield)Rawson, 1952; Jenkins and Morais, 1971; Moreau and De Silva, 1991(. Downing et al., (1990) reported annual phytoplankton production correlated (r^2= 0.79) than MEI, total phosphorus concentration and macro benthos biomass/mean depth, were the best univariate predictors of fish yield (r^2= 0.84 and r^2= 0.48, respectively). Hanson and Leggett (1982(reported catchment land use patterns are key parameters for fish yield prediction of reservoir)De Silva et al., 2001(. Rawson)1938(grouped lake productivity parameters in three groups i.e climatic, morphometric, and edaphic

A. *Potential Fish Yield from Morphological parameters*

Reservoir area, volume, depth, and shoreline development or gradient is some of the key morphological parameters to assess the productivity)Ryder, 1978). The mean depth alone a single most important parameter to assess the fish yield (Rawson, 1952; Henderson and Welcomme, 1974; Ryder et al., 1974; Mehner et al. 2007(. Henderson & Welcomme (1974) first applied Ryder's morphoedaphic index to tropical fisheries in African lakes and derived relationship from 17 fully exploited lakes where more than 1 fisherman fishing km^{-2} lake area. Oglesby)1977(reported that mean depth was not relevant variable for assessing fish yield, where lake having more than 25m deep. Schlesinger & Regier)1982(found that fish yield - MEI relationships accurate only to lakes within regional level and generalizing the relationship need to include other dependent variable such as mean annual air temperature into the model. Hanson & Legget)1982) developed many equations based on total dissolved solids)TDS(and total phosphorus concentration)TP) which was highly correlated and much better predictor of fish yield. Downing *et al.*)1990(has reported based on his study that fish production is closely correlated with annual phytoplankton production (R^2 = 0.79), mean total phosphorus concentration (R^2 = 0.67), and annual average fish standing stock (R^2 = 0.67) but least correlated with the morphoedaphic index ($p>0.05$). Schneider & Hadrich, (1989) reported that fish landings varied proportion to lake area.

Moreau & De Silva (1991) developed fish yield model using multiple regression for lakes and reservoirs of Sri Lanka, Thailand and Philippines using area and effort. Moreau & De Silva (1991) also tested a number of models using predictor variables catchment/lake area ratio, mean depth, transparency, total alkalinity, chlorophyll a concentration, primary productivity and fishing effort. Crul(1992) correlated with catch (t y^{-1}) and area (km^2) for 46 lakes and 25 reservoirs in Africa.

Brämick, U and Roland (2003) estimated fish yield potential based on data of 786 lakes in north-east Germany using primary production and total phosphorus. Relationship between fish yield potential and total phosphorus or chlorophyll a or primary production of phytoplankton have been published and reviewed (Nurnberg 1996; Knösche, R., & Barthelmes, D. 1998). John A. Downing and Céline Plante(2011) estimated annual fish production using independent variables temperature, phosphorus concentration, chlorophyll a concentration, primary production, and pH .Knösche, R., & Barthelmes, D. (1998) estimated lake fisheries yield from primary plankton production or total phosphorus. John Mark HansonandWilliam Leggett (2011) reported that total phosphorus concentration and macro benthos biomass/mean depth best predictor than morphoedaphic index. Kolding, J., & Van Zwieten, P. A. (2012) reported water-level fluctuation and mean depthis a simple estimatorfor fish productivity in tropical lakes and reservoirs.

Wijeyaratne and Amarasinghe (1987) showed that maximum sustainable yield (MSY) in several reservoirs of Sri lanka were correlated with the morphoedaphic index. Amarasinghe *et al.* (2002) have shown catchment features like ratio of catchment, land use patterns and reservoir capacity are important predictor variables in Sri Lankan.

Ramakrishna (1990) reported that catchment has a positive impact on the Indian reservoirs productivity, provided the catchment is moderately fertile (Natarajan, 1976, 1977, 1979; Jhingran, 1986).

Vollenweider (1969) reported that Flushing rate (inflow/storage capacity) is important variable for fish production as it regulates nutrient loading.

B. Potential Fish Production from Primary Production

Oglesby)1977(has derived relationships between fish and summer standing crop of phytoplankton. Jones & Hoyer)1982(, correlated sport fish harvests with summer chlorophyll a in US reservoirs and lakes. Liang *et al.*,)1981(derived relationship between net fish yield and gross primary production in sub-tropical Chinese lakes and ponds. Relative fish biomasses expressed as gillnet CPUE were found correlated to chlorophyll a, total phosphorus, total nitrogen and total organic matter in a large number of Argentinean lakes and reservoirs)Quiros, 1990(.

Xiong (1996), shown that 15 factors such as mean depth, catchment area, water temperature, precipitation, dissolved oxygen content, total phosphorus, phytoplankton biomass and the number of stocked fingerlings responsible for fish yield.

C. Fish Yields from Socio-economic Variables

Fishing effort, number of fishermen or number of boats or units of fishing gear are important predictor socio-economic variables for predict fish yield (Henderson & Welcomme, 1974; Bayley, 1988).

TABLE – I. LIST OF MODELS DEVELOPED TO PREDICT FISH YIELDS IN LAKES AND RESERVOIR

Author(s)	**Predictor variable**	**Remarks**
Rawson (1952)	Mean depth	Fish yield prediction of Lakes
Crul(1992)	Area	Establishedrelation-ship between catch and area from 46 lakes and 25 reservoirs in Africa
Rawson,1952; Jenkins and Morais, 1971; Moreau and De Silva, 1991; Bernascek, 1997	Depth, Volume and Area	Models have been developed based on morphometric features
Ryder (1965)	Total dissolved solids or conductivity divided by mean depth	Morpho-edaphic Index (MEI) predictive yield model for lakes and reservoir
D. R. Toews and J. S. Griffith (1979)	Morphoedaphic-index(MEI)	Predicted fish yield using 31 African lakes.
Schlesinger & Regier (1982)	Air temperature and MEI	Prediction of fish yield from reservoirs having less than 25 m depth
Oglesby (1977) and Biro & Vőrős (1988)	Chlorophyll -a	Predictive yield model
Ryder (1978)	Reservoir area, Volume, Depth, and Shoreline development or gradient	Predict the reservoir or lake productivity
Biro&Vőrős (1988) and Moreau & De Silva (1991)	Ratio of surface area to catchment area (CA)	Predicting the fish yields of lakes and reservoirs in Sri Lanka
Nissanka, Amarasinghe & De Silva (2000)	Ratio of the CA to reservoir capacity	Better predictor variable for fish yield
Hrbacek (1969)	Primary production	Reported highly significant

		relationship between primary production and carp yield from European ecosystems.
Melack (1976), Toewsand Griffith (1979) and Plante&Lalonde (1990)	Gross primary production	Useful estimator of fish yield based on data of African lakes.
Hanson and Legget(1982)	Total phosphorus	Better predictors of fish yields than the MEI
Jenkins and Morais (1971); Youngs and Heimbuch (1982)	Surface area alone	Opined that surface area can alone be the predictor of fish yield of North American lakes
Henderson and Welcomme(1974)	Electrical conductivity	Studies based on Africa and Srilanka
Morpau and De Silva (1991)	Watershed area and Mean depth	Asian reservoir
Ramakrishniah(1990), Ramakrishniah el al. 1998)	C/A radio along with MEI	Modified MEI model incorporating the drainage parameter, the ratio of catchment to reservoir area (C/A), (based on 19 Indian reservoir)
S. S. De Silva*et. al.*(2001)	Catchment parameters i.e forest cover (FC) and shrub-land (SL) to reservoir surface area (RA) and/or reservoir capacity (RC)	GIS Model using 11 reservoirs of Sri Lanka
Amarasinghe*et al.* (2002)	Ratios of forest cover and/or shrub cover to reservoir capacity or reservoir area	Prediction of fish yield
Downing *et al.* (1990)	Phyto-plankton production, Total Phosphorus concentration , Annual average fish standing stock	Prediction of fish yield
Xiong(1996)	Phyto-plankton primary production	Methodology developed to predict silver carp and bighead carp production(China)
Xiong (1996)	Mean depth, Catchment area, Water temperature , Precipitation, Dissolved oxygen content, Total phosphorus, Phyto-plankton	Reported major factors influencing fish yield

	biomass and Number of stocked fingerlings	
Henderson & Welcomme, 1974; Bayley, 1988	Fishing effort (number of fishermen) or number of boats or units of fishing gear	Socio-economic variable to predict fish yield
John A. Downing and Céline Plante (2011)	Temperature, Lake phosphorus concen-tration, Chlorophyll-a concen-tration, Primary production, and pH.	Estimated annual production of fish populations
Jeppe Kolding and PaulA.M.van Zwieten(2012)	Water-level fluctuation and mean depth	Simple robust indicator of fish productivity in tropical lakes
C Nissanka; U S Amarasinghe; and S S De Silva	Chlorophyll a, Dissolved phosphorus and Total phosphorus, Alkalinity to mean depth (MEIa) and Conductivity to mean depth and CA/RC ratios	All these parameters were found positively influence with fish yield in reservoirs
Dillon &Rigler (1974), Oglesby (1977) Liang et al. (1981) Bulon&Vinberg (1981) Hanson&Leggett (1982) Peters (1986) Leach et al. (1987) Downing *et al.* (1990) Qutros (1990 & 1991) Barthelmes (1992) Downing&plante (1993) Nurnberg (1996) Knosche&Barthelmes(1998)	Total phosphorus (TP), Chlorophyll-a or Primary production of phytoplankton (PP)	Empirically derived relations between Fish Yield Potential (FYP)or Fish Biomass(FB).
Reiner Knösche and D. Barthelmes (1998)	Primary plankton production (PP) or Total phosphorus	The most promising limnological parameters for fish yield estimation
JeppeKoldingandPaul A.M.van Zwieten(2012)	Water-level fluctuation and mean depth	Reported simple and robust indicator of fish productivity in tropical lakes and reservoirs
Hoyer (1982)	chlorophyll a	Correlated sport fish harvests in US reservoirs

III. ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial Neural Networks (ANNs) are mathematical models designed to mimic the information processing functions of a network of neurons in the brain (Hinton1992; Jensen 1994). Humans and animals are processing information by neurons. Computer algorithms mimic the way biological systems are functioning called artificial neural networks. The brain is a highly complex, nonlinear and parallel processing system computing many times faster than digital computer. It is widely used in many disciplines for modelling. An artificial neural network is highly popular because of similarity in biological systems and has anability to learn from experiences and improving its performance. It is a very powerful tool for modelling non-linear and complex, imprecise and noisy data. It has an ability to manipulate large amounts of data and generalize results.

A. Prediction of Fish Yields in Lakes and Reservoirs using Artificial Neural Network

ANN have been used in many ecological modeling, phytoplankton production (Scardi, 1996), fish species richness prediction (Brosse, Set al., 1998), and prediction of density and biomass of various fish populations (Baran et al., 1996; Lek et al., 1996a,b; Mastrorillo*et. al*., 1997). Many authors have reported that ANN predicts more accurate than multi leaner regression (Ehrman et al .1996; Lek*et. al*. 1996b; Scardi1996).

Laë, R., Lek, S., & Moreau, J. (1999) predicted fish yield of African lakes using Artificial neural networks using six input variables such as catchment area, maximum area, fishing effort, conductivity, depth, altitude and latitude. The structure of the feed forward neural network is six input neuron with one hidden layer of five neurons, sigmoid functions, and backpropagation algorithm for the training of the ANNs. The result shows that correlation coefficients between the estimated and observed values were significantly very high.

Zhang, H., & Zimba, P. V. (2017) developed multi-layer neural networks to assess effects of estuarine freshwater fluxes on fish abundanceusing artificial neural network. The predictor variable consists of inflow, evaporation, precipitation and annual catch rate of fish species of Nueces Estuary. The network was trained using Levenberg-Marquardt back propagation algorithm. Maravelias, C. D., Haralabous, J., & Papaconstantinou, C. (2003) predicted distributions of demersal fish species in the Mediterranean Sea using ANN. The input variables are biomass/abundance ratio, depth of the water column, latitude and longitude, and monthlysampling of675 sample stations of North Aegean Sea.Error back-propagation (EBP) algorithm is used to learn the network.

Baran, P*et.al*.(1996) developed stochastic models to predict trout population density or biomass on a mesohabitat scale using neural networks. Backpropagation algorithm was used to train habitat variables width, gradient, mean depth, coefficient of variation of depth, mean bottom velocity, coefficient of variation of bottom velocity, froude number, area of cover, area of shelter, pool deep water area and elevation. The result shows that the back propagation neural network estimatedmore accuratelythan the multiple regression.

Brosse, S. *et. al*. (1999) predicted fish spatial occupancy and abundance in a mesotrophic reservoir using Artificial Neural Network.The input databased on 306 observations collected using electrofishing. The relationships between physical parameters and the abundance fish species are studied. Eight independent environmental variables depth, distance from the bank, slope of the bottom, flooded vegetation cover, percentage of boulders, percentage of pebbles, percentage of gravel and percentage of mud are used to quantify fish density. Structure of the network is feed-forward with eight input neurons, one hidden layer with 10 nodes with bias and aoutput layer (8-10-1). The network was trained using back-propagation algorithm to predict accurately with minimum error.

Scardi, M., et.al (2008) evaluated ecological integrity of streams and rivers using an expert system based fish assemblage model. Twenty-seven environmental parameters along with fish assemblage composition of 63 locations in Latium streams and rivers were used in this study. Neural network was trained using most popular error back-propagation algorithm. Aoki, I., and Komatsu, T. (1997) predicted the winter catch of young Japanese sardine *(Sardinopsmelanostictus)* from climatic, hydrological and biological parameters in the Joban-Boso Seas of the Pacific coast of central Japan using neural network. A feed-forward three layers an input, hidden and an output layer is used. Predictor variables are hydrological and biotic parameters. Hydrological parameters consist of southern limit of the Oyashio, path type of Kuroshio, northern limit of the Kuroshio Extension, sea surface temperature in the northeastern sea area of Japanand sea surface temperature in the fishing ground. Zooplankton, climatic southern oscillation index, far east zonal index and east sea index are biological parameters. The network trained by back-propagation algorithm to predictchanges in the sardine abundance.

Joy, M. K., & Death, R. G. (2004) developed predictive model and spatial mapping of decapod assemblages using combination of GIS and neural networks. Single hidden-layer feed forward multi-layer perceptron trained by back propagation error algorithm are used in this network. Catchment area, average catchment elevation, elevation upstream end of reach, average catchment slope, average annual catchment rainfall, average catchment air temperature, estimated river flow, reach length, latitude, stream order, catchment rainfall, distance from the coast, lake catchment area, catchment land use proportion and catchment geology proportions (surface rock) are input variables. The decapod was predicted with high degree of accuracy from geospatial landscapepredictor variables.

Olden, J. D., & Jackson, D. A. (2001). Developed fish–habitat models for nine fish species using Artificial Neural Networks. The study was conducted using data of 128 lakes from the Madawaska river drainage and 32 lakes from the Oxtongue river drainage of Canada. The habitat input variables are area, maximum depth, shoreline perimeter, elevation, total dissolved solids, pH, summer stratification (0, 1) and littoral-zone predator (0, 1). Artificial neural networks predicted accurately abundance as well as occurrence of fish species.

Kılıç, H., *et. al* (2007) developed ANN models to predict primary production of reservoir by using preprocessing technique of an Automata Networks (AN) to find suitable variables for subsequent ANN modeling. The AN based preprocessing followed by a ANN application predicted primary productivity accurately using Chl-a. The correlation coefficient as high as 0.83 and RMSE was as low as 2.69g/l was achieved withdouble hidden layer structure with 10 neurons.

Kuo, J. T., Hsieh, M. H., Lung, W. S., & She, N. (2007) predict reservoir water quality using Artificial Neural Network with back-propagation algorithm. The input variables are dissolved oxygen (DO), total phosphorus (TP), chlorophyll-*a* (Chl-*a*), and secchi disk depth (SD). Results show that correlation coefficients between predicted values and measured data are 0.7 with reasonable accuracy.

IV. CONCLUSION

Prediction of reservoir and lakes fish yield is the important factor for the fishery managers to improve the decision-making processes of reservoir fishery management and use appropriate management practices to enhance the fish production. There is extensive literature available over the past decade on prediction of fish yield in reservoir and lakes both in linear and non-linear models. Many authors reported that Artificial Neural Network model is giving high level of accuracy than Multilinear Regression Model.

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