APPLICATION OF ANN TO PREDICT CHLOROPHYLL-a AND SEA SURFACE TEMPERATURE IN DEMARCATION OF FISHING ZONE

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ABSTRACT

This study deals with surface water quality estimation using remote sensing to analyze two fundamental water quality parameters; chlorophyll-*a* and SST for the location of fishery zones. The Artificial Neural Network (ANN) technique has been selected in this study to develop the relationships between MODIS (Moderate Resolution Imaging Spectroradiometer) data derived satellite radiance and the water quality parameters (chlorophyll- *a* and SST) for coastal water. Based on the aggregating properties of the pelagic species, the potential zones of fish school were determined and the locations of pelagic species were identified. In the present study it was observed that the favorable ranges of chlorophyll-*a* (0.2 -0.5 mg/m^3) and SST (15 – 27 $^{\circ}$C) for various pelagic species were utilized to find out the potential fishery ground.

Key words: Artificial neural network; MODIS data; potential zones.

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1 INTRODUCTION

Satellite remote sensing is an excellent tool for monitoring of coastal waters. The periodic overpass of satellite allows the routine and cost effective collection of a variety of observations over large and often inaccessible expanses of the coastal and adjacent waters within a short period of time. The great advantage of the satellite imagery is the possibility of multi-temporal evaluation and low cost data collection compared to prolonged field sampling. The concentrations of optically active water constituents can be estimated from satellite images through the interpretation of the received radiance at the sensor at different wavelengths (Gordon and Morel, 1983). The development of numerous bio-optical algorithms provides a bridge between ocean color remote sensing and concentrations of seawater constituents and has been useful in the studies of oceanic carbon cycling to obtain estimates of phytoplankton biomass and its derived primary productivity (Platt et al., 1988; Muller-Karger et al., 1991). Application of remote sensing techniques to coastal and marine research has been now extended to the identification of Potential Fishing Zone (PFZ), estimation of primary productivity using ocean color data, mapping coastal wetlands, distinguishing coral seagrass and mangrove habitats and monitoring marine pollution. In earlier days, as the data requirements were limited and the direct methods of data acquisition were sufficient to meet the requirements. But as the technology had developed it became inevitable to acquire more information and also in a speedy manner. The use of remote sensing to provide synoptic measurements of the oceans is becoming increasingly important in fisheries research and fishing operations. Variations in ocean conditions play key roles in natural fluctuations of fish stocks and in their vulnerability to harvesting. The research and development towards this end has resulted in a modern science termed as remote sensing. Remote sensing can be defined as the acquisition of information about an object or event without being in physical contact (Butler et al., 1998). Satellite observation in the visible and near infrared allows the measurement of the oceanic chlorophyll-*a*, the principal photosynthetic pigment associated with land surface and oceanic plants. Information on the changing ocean is necessary to understand and to eventually predict the effects of the ocean on fishing ground. With the advent of satellite, these oceanographic features such as ocean color, sea surface temperature, and chlorophyll-*a* concentrations can be successfully mapped in near real time basis. This capability coupled with the knowledge oceanographic conditions affecting fishery population and historical catch data can lead towards forecasting of fish population and it's movement; and thus afford the capacity to harvest the fishery resources effectively and equally important on a sustainable basis (Mansor et al., 1998). More recently OCM (Ocean Color Monitor) derived chlorophyll and NOAA-AVHRR derived SST images have been used for fisheries resources exploitation in Arabian Sea (Solanki et al., 2003). However, one of the major problems in using SST and chlorophyll images from two different sensors is the limitation in interpretation of the bio-physical response of the oceanic surfaces. In most of the cases such as SeaWifs and OCM there is a time lag between SST and chlorophyll observation. Nammalwar et al., (2013) conducted study in three coastal districts of North Tamil Nadu and concluded that the remotely sensed data provided by INCOIS were useful tool in enhancing not only fish catch, revenue to the fishermen but also reduces the searching time, fuel cost and human effort. Gayathri et al., (2015) suggested to use microwave data for measurement of various water quality parameters as it has got the advantage of penetrating through clouds and also it gives a clear view in all weather conditions except rain. This information will be useful for identifying Potential fishing zone (PFZ).

In the present study MODIS satellite imagery were used for the estimation of chlorophyll-*a* and sea surface temperature to demarcate the potential fishery zone for pelagic species of fish. Advantage of using MODIS satellite imagery is that two fundamental water quality parameters for the demarcation of fishery zones can be taken from a single sensor.

2. MATERIALS AND METHODS

Brief methodology used in the present study is shown in Fig. 1.

2.1 Data used

MODIS Satellite data acquired on November 19, 2005 and December 13, 2002 were used to develop the algorithms of chlorophyll-*a* and SST. Chlorophyll-*a* and SST images of same dates (November 19,2005 and December 13, 2002) were also collected for the study for multi spectral satellite images of MODIS satellite and *In situ* data of chlorophyll-*a* and SST were collected from Marine Optical Characterization Experiment (MOCE) for the same dates. To develop the neural network architecture for chlorophyll-*a* and SST, eighty data points were used for both the parameters. *In situ* data locations were depicted by creating point coverage based on location details collected from MOCE database.

2.2 Water quality parameters

The water quality parameters selected for the identification of potential fishery zones (PFZs) are follows as:

2.2.1 Chlorophyll-*a*

The chlorophyll-*a* data was obtained from the MODIS launched by NASA onboard AQUA satellite. Ocean color monitor OCM imagery was provided by Regional remote sensing service centre (RSSC), Kharagpur, West Bengal, India. OCM data were atmospherically corrected before deriving the chlorophyll concentration since a considerable percentage of the light reaching the sensor is from atmosphere and only less than 10 percent of the light is required from the ocean.

2.2.2 Sea surface temperature (SST)

Because different instruments measure SST in different ways, the term SST refers to the temperatures measured over several different depth intervals from the surface. In general Sea surface temperature is the water temperature at one meter below the sea surface. The SST images for a particular date were obtained from the MODIS launched by NASA onboard AQUA satellite (http://oceancolor.gsfc.nasa.gov).

2.3 Image pre- processing

2.3.1 Pre- processing of remote sensing data

The remote sensing data needs several steps of pre-processing before an inversing model is applied, which include radiometric correction, geometric correction and atmospheric correction. The accurate geometric correction in this study was accomplished by ground control points (GCPs). Satellite images selected for the study were geometrically corrected using OCM satellite data of Bay of Bengal as reference image. A land mask was applied on all satellite images to extract only water bodies. ERDAS imagine 8.5 and Matlab 6.5 were used for carrying out the image processing.

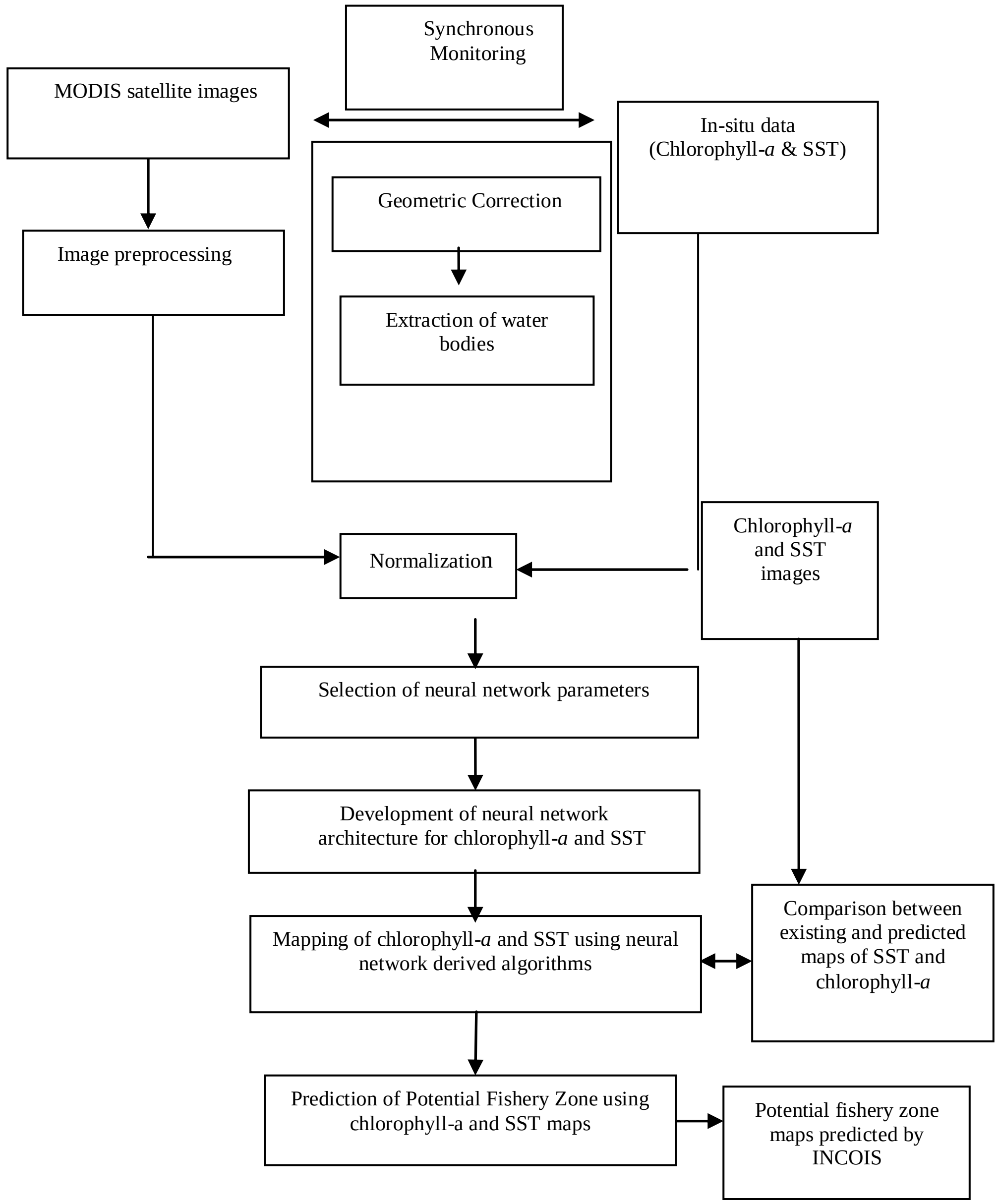

Figure 1. Brief Methodology of Study

2.4 Artificial neural network (ANN) architecture

ANN architecture development included the creation of network topology and network training under various combinations of nodes in hidden layer(s), number of hidden layers, training cycles and parameters of training function. The performance of each combination was evaluated on the basis of pre-defined performance criteria.

2.4.1 ANN training

Training neural network is essentially a non-linear least squares problem, and thus can be solved by a class of non-linear least squares algorithms. The ANN will be created, trained and implemented using Matlab 6 neural network toolbox with back propagation and the training algorithm of Levenberg-Marquardt.

2.4.2 Development of ANN model

Multi layer perceptron (MLP), neural network model with three layers, using back- propagation learning algorithm was used in the present study. The main steps for development of ANN models include pre-processing (normalization), development of neural network architecture and use of trained network for simulation and prediction. In this study Levenberg-Marquardt algorithm was applied to determine the weights in the network. The normalization was performed using linear scaling of the raw data (chlorophyll-*a*, SST and spectral reflectance data) between 0 and 1.Total *in situ* dataset were divided into training (60) and validation sets (20) in such a way that both sets are statistically consistent. Multilayer perceptron used in the present study was composed of three layers: input layer, hidden layer, and output layer. The digital number values of bands number 8 -16 (ocean color sensitive bands of MODIS) were used as input for chlorophyll-*a* and bands number 20 -26 (temperature sensitive bands) for SST based on the spectral reflectance characteristics of the parameters. The second (hidden) layer had a varying number of neurons, where each input parameter was multiplied by its connection weights and all the inputs to the neurons were summed and passed through the nonlinear sigmoid function. The third (output) layer receives the output of the hidden layer in which it was processed through the neurons again. In the present study ANN training was carried out for different number of hidden neurons (2-10) as well as different learning rates (0.005, 0.01 & 0.1) and different combinations of learning momentum. Based on RMSE (Root Mean Square Error) optimum network architecture was selected for each parameter. Based on the chlorophyll-*a* and SST maps, PFZ were located and compared with the PFZ located by INCOIS(Indian National Centre for Ocean information services) for the same spatial and temporal details.

A conceptual model was used for the present study to derive the potential fishing zones (PFZs) taking MODIS true colour, chlorophyll-*a* and SST data (Fig. 2). The details of the results obtained in the present investigation are discussed in this section. The details of the PFZ derived on the basis of algorithm developed for chlorophyll-*a* and SST are also presented here.

2.4.3 Selection of MODIS bands for algorithm development

Different bands of MODIS were selected for algorithm development of the bio-optical parameters (chlorophyll-*a* and SST) based on the reflectance characteristics. The details of bands selected and their correlation with *in situ* data for each parameter are discussed in the following section. DN values of bands 8 to 16 of MODIS data were taken as input for developing the algorithm of neural network for chlorophyll-*a*. The DN values of bands 12, 13 and 14 were found to be zero for all the observations of chlorophyll-*a*. Hence DN values of five bands (bands 8 -11 and 15) were taken for the study. Hence it demands the application of advanced computation like ANN to derive the accurate output (chlorophyll-*a*) by combining all the ocean color sensitive bands of MODIS.

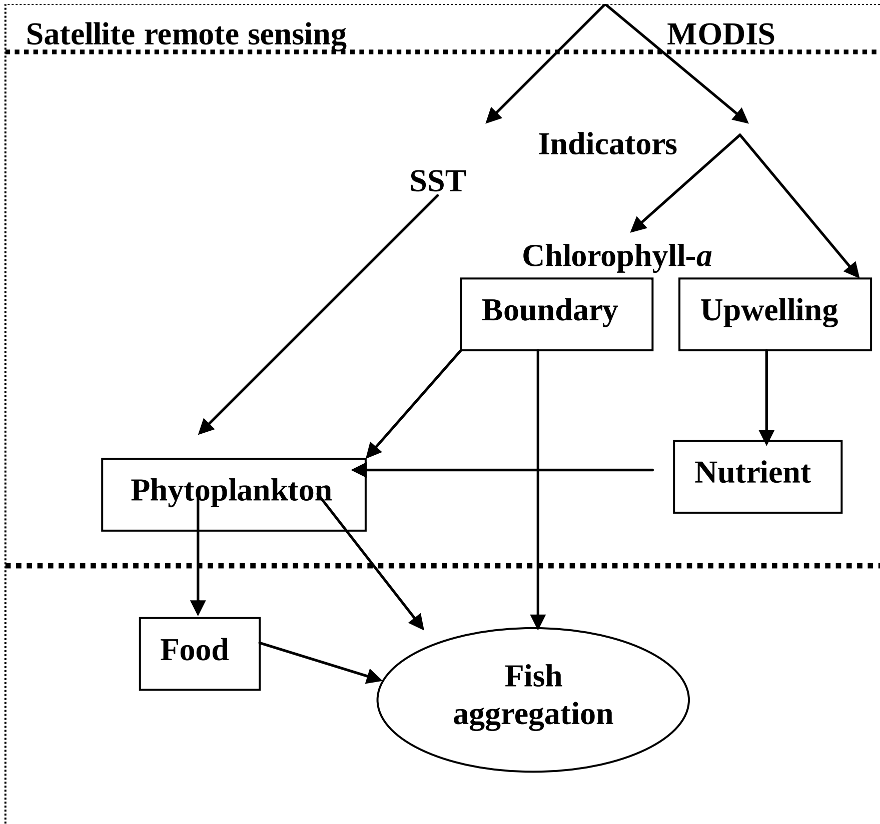

Figure 2. Conceptual fish forecasting model

3. RESULTS AND DISCUSSION

3.1 Development of ANN algorithm

The performance of different network architectures (variables: hidden neurons & training parameters) and selection of optimum network architecture for retrieval of chlorophyll-a and SST from MODIS onboard AUQA satellite images are discussed in this section.

3.1.1 Algorithm for chlorophyll-*a*

Neural network was trained using the training data set (60 data points) of chlorophyll-*a* and the corresponding DN values of the selected MODIS bands . The performance of different networks (RMSE) for different combinations of network training parameters and hidden neurons is shown in Table 1

Table1.Performance of networks (chlorophyll-*a*) with different number of hidden neurons for learning rate of 0.01 and learning momentum equal to mu_inc=5 & mu_dec=0.5.

No. of neurons	MSE		No. of epochs	Full dataset RMSE (^{0}C)
	Training	Validation		
2	0.11	0.018	45	0.95
3	0.121	0.021	75	0.77
4	**0.108**	**0.015**	**47**	**0.57**
5	0.113	0.019	34	0.68
6	0.117	0.017	32	0.67
7	0.12	0.021	57	0.75
8	0.13	0.022	69	0.84
9	0.154	0.024	39	0.92
10	0.163	0.027	86	0.98

The network trained with learning momentum equal to mu_inc=10 & mu_dec=0.1 was found to be poor compared to the other two selected learning momentum values (mu_inc=5 & mu_dec=0.5; mu_inc=1.1 & mu_dec=0.9) for all learning rates (0.005, 0.01 & 0.1) (Fig. 3).

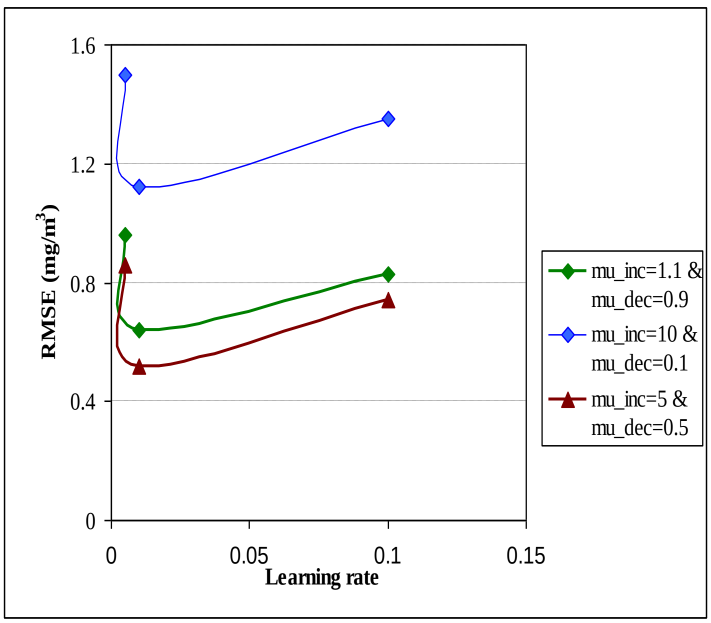

Figure 3. Performance of networks with four hidden neurons with different learning parameters for chlorophyll-a

This result supports the concept of failure of network to converge to local minimum in the error surface due to rapid change in the learning rates. In the case of learning momentum mu_dec=0.5 & mu_inc=5 and mu_dec=0.9 & mu_inc=1.1 all the networks found to have similar performance characteristics. Based on the performance value (RMSE), network trained with learning rate of 0.01 and learning momentum of mu_dec=0.5 & mu_inc=5 was found to be more accurate (RMSE=0.52 mg/m^3) compared to other networks. The generalization capability of the network trained using the selected network parameters was checked using the validation data records (20 data points) of chlorophyll-*a*.The observed chlorophyll-*a* values were found to be highly correlated to predicted chlorophyll-a values (R^2=0.9769) retrieved through empirical neural network developed (Fig. 4).

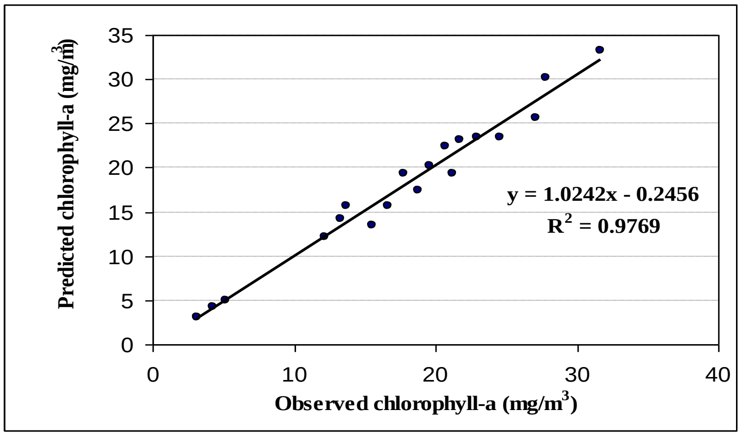

Figure4. Comparison between observed and predicted chlorophyll-*a* concentration

A paired sample t-test was carried out to identify the significant difference between observed and predicted chlorophyll-*a* values. According to the analysis there was no significant difference between chlorophyll-*a* predicted using the empirical neural networks and the observed values (t=0.43; p> 0.05) at 95% confidence interval.

3.1.2 Algorithm for SST

Neural network was trained using the training data set (60 data points) of SST and the corresponding DN values of the selected MODIS bands). The performance of different networks (RMSE) for different combinations of network training parameters and hidden neurons is shown in Table 2.

Table 2. Performance of networks (SST) with different number of hidden neurons for earning rate of 0.01 and learning momentum equal to mu_inc=5 & mu_dec=0.5.

No. of neurons	MSE		No.of epochs	Full dataset RMSE (mg/m^3)
	Training	Validation		
2	0.138	0.02	22	0.87
3	0.137	0.018	34	0.82
4	0.126	0.02	15	0.74
5	0.121	0.016	18	0.62
6	**0.119**	**0.012**	**20**	**0.52**
7	0.123	0.016	65	0.65
8	0.124	0.019	48	0.78
9	0.132	0.02	67	1.1
10	0.134	0.021	54	1.15

The network trained with learning momentum equal to mu_inc=10 & mu_dec=0.1 was found to be poor compared to the other two selected learning momentum values (mu_inc=5 & mu_dec=0.5; mu_inc=1.1 & mu_dec=0.9) for all learning rates (0.005, 0.01 & 0.1) (Fig. 5).

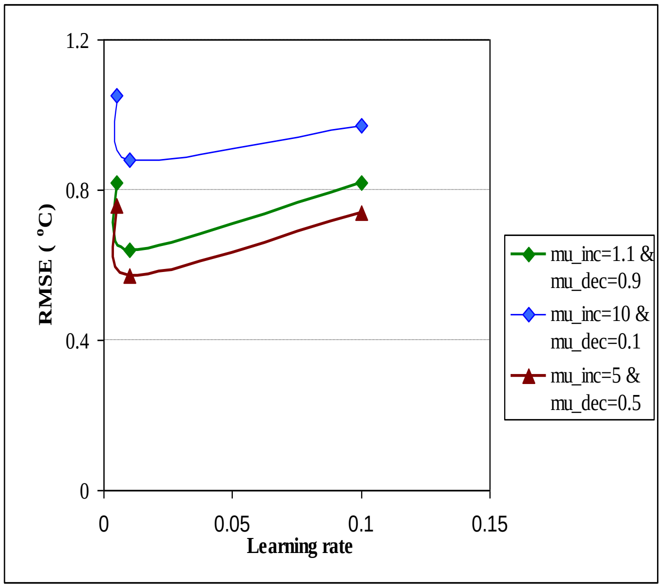

Figure5. Performance of networks with four hidden neurons with different learning parameters for SST

This result supports the concept of failure of network to converge to local minimum in the error surface due to rapid change in the learning rates. In the case of learning momentum mu_dec=0.5 & mu_inc=5 and mu_dec=0.9 & mu_inc=1.1 all the networks found to have similar performance characteristics.
Based on the performance value (RMSE), network trained with learning rate of 0.01 and learning momentum of mu_dec=0.5 & mu_inc=5 was found to be more accurate (RMSE=0.57 ^{o}C) compared to other networks. The generalization capability of the network trained using the selected network parameters was checked using the validation data records (20 data points) of SST.
The observed SST values were found to be highly correlated to predicted SST values (R^2=0.93) retrieved through empirical neural network developed (Fig. 6). A paired sample t-test was carried out to identify the significant difference between observed and predicted SST values. According to the analysis there was no significant difference between SST predicted using the empirical neural networks and the observed values (t=0.33; p> 0.05) at 95% confidence interval.

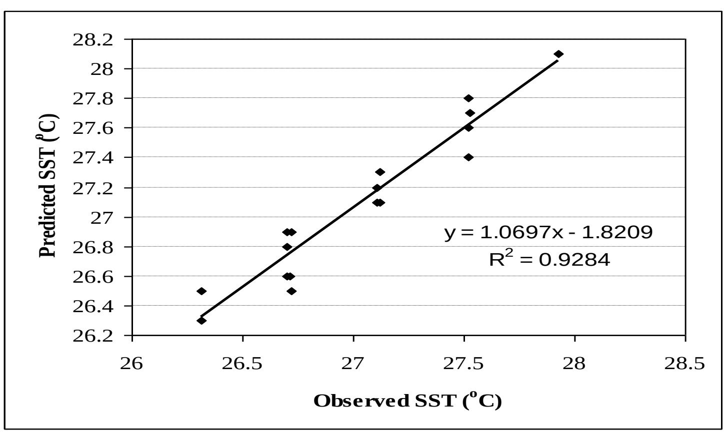

Figure 6. Comparison between observed and predicted SST concentration

3.2 Comparison between existing (NASA images) and predicted maps (ANN derived) of chlorophyll-*a* and SST

The algorithms of chlorophyll-a and SST developed using ANN were used to retrieve the chlorophyll-a and SST values from multi-spectral images of MODIS. NASA derived chlorophyll-*a* and SST maps of the same period were used to compare with the predicted maps. Multi-spectral MODIS onboard AQUA satellite data of November 19, 2005 and December 13, 2002 were used to create the maps of chlorophyll-*a* and SST maps through ANN developed algorithms.
Chlorophyll-*a* and SST images created using ANN developed algorithms were compared with the existing chlorophyll-a and SST maps of the same period. The study shows that the chlorophyll-a maps created are more accurate compared with that of existing chlorophyll-a maps especially for low chlorophyll-a concentration. In the case of SST maps no significant difference was observed between the existing and created SST maps. This indicates the capability of the existing SST algorithm to retrieve the SST values effectively from the MODIS data.
The chlorophyll-*a* maps created revealed that ANN has the capability to retrieve the chlorophyll-a concentration more effectively than conventional algorithm. The outcomes of the study are presented in (Fig. 7).

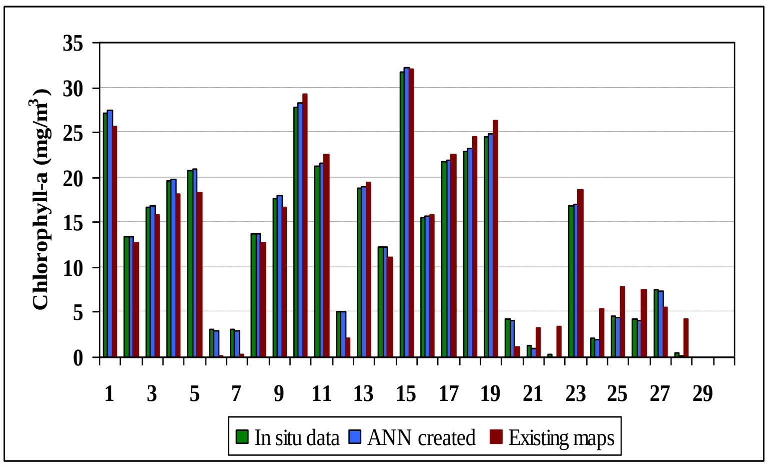

Figure7. Comparison of in situ, ANN created and existing chlorophyll-*a* maps

3.3 Prediction of potential fishery zones (PFZs)

The chlorophyll-*a* and SST maps created using ANN from November 19, 2005 MODIS AQUA satellite data were used to predict the potential fishery zones of pelagic species of Bay of Bengal. Based on the aggregating properties of the pelagic species, the potential zones of fish schooling were determined. In this study the location of pelagic species (catfish, pomfret, sardine, mackerel) were identified through the integrated analysis of chlorophyll-*a* and SST maps. The favorable ranges of chlorophyll-*a* (0.2 -0.5 mg/m^3) and SST (15 – 27 $^{\circ}$C) for various pelagic species were utilized to reveal the potential fishery ground. The derived PFZ based on this information were compared with that of INCOIS derived PFZ for the same spatial and temporal details.

Based on the study more PFZ sites were identified than that of INCOIS for the same region and time. This is due to the lack of incorporation of other constraints affecting the PFZ like distance from the harbour, wind speed, bathymetric details and many more. The most advantageous using the MODIS imagery is that the chlorophyll-*a* and SST images can be derived from the satellite image that were taken from the same platform and the time difference error between set of images can be omitted.

CONCLUSIONS

The capabilities of ocean remote sensing technology, combined with conventional data collection techniques, provide a powerful tool for the efficient and cost effective exploitation and management of living marine resources. The potential capabilities of satellite remote sensing accompanied with ANN, facilitate the development of accurate algorithms for chlorophyll-a and SST from MODIS satellite data. The obtained results showed that neural network can be effectively used to retrieve the chlorophyll-a (RMSE = 1.52 mg/m^3) and SST (0.57 ^oC) from MODIS satellite data. The study showed that neural network model for chlorophyll-*a* outperforms the OC3 algorithm for lower chlorophyll-a concentration values. The locations of PFZ identified in the study coincides with the INCOIS derived locations of PFZ for pelagic species. The study demonstrates the possibility, accuracy, potential and effectiveness of integration of MODIS satellite data and ANN capabilities to reveal the potential fishery grounds of pelagic species of Bay of Bengal.

Therefore, it can be said that most of the PFZ (potential fishery zone) locations derived by INCOIS coincide with the outcomes of the present study.

The present investigation can be extended further by carrying out proper validation techniques using the in situ fish catch data i.e. catch per unit effort (CPUE). In this study the PFZ located were compared only with the PFZ forecasted by INCOIS as it demands less attention compared to that of the algorithm development using MODIS bands. Hence, there is a future scope in the same area with the adoption of the MODIS algorithms for SST and chlorophyll-*a* developed through ANN.

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