Simultaneous Retrieval of Sea Surface Wind Speed and Sea Surface Temperature from a Multi-frequency Scanning Microwave Radiometer

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Abstract

Derivation of geophysical parameters from satellite measured brightness-temperature (T_B) is an important aspect of satellite remote sensing. Primarily, this involves development of complex inversion algorithms and empirical relations comprising T_B and *in situ* data for parameter retrieval and algorithm validation. In the present work, an Artificial Neural Network model has been attempted to simultaneously obtain sea surface wind speed (WS) and sea surface temperature (SST) utilizing T_B from 8 channels (including vertical and horizontal polarizations) of Multi-frequency Scanning Microwave Radiometer on board Indian Remote Sensing Satellite (IRS-P4) and deep sea ocean buoys in the North Indian Ocean region. The ANN obtained values are then compared with actual *in situ* observations as a test for the performance of the model. It is concluded that the ANN model is able to provide good estimates of WS and SST within acceptable error limits. The goal of the present work is to pre-establish the suitability of ANN approach for geophysical parameter retrieval from satellite measured T_B in the Indian context particularly keeping in view the forth coming satellite launches like Megha Tropiques and Oceansat-3.

1. Introduction

Sea surface Wind Speed (WS) and Sea Surface Temperature (SST) are important geophysical parameters used in the estimation of heat flux at the air-sea interface. On the global scale, these satellite derived products serve as important inputs for climate modeling, study of the earth's heat balance as well as atmospheric and oceanic circulations. They are crucial parameters to understand air-sea interactions, monsoonal forcing on oceanographic phenomena, assessing eddies, fronts and upwellings for marine navigation and tracking biological productivity (including potential fishing zones) at local scales [1, 2].

In situ observations of several parameters over vast portions of the global oceans are however significantly under-sampled, both temporally and spatially owing to measurements restricted to ships and buoys, whose ranges are limited [3]. This limitation is partially overcome in case of WS and SST owing to routine global measurements by means of space-borne radiometers offering synoptic and temporal sampling advantages. But, retrieval algorithms developed for the purpose are either based on theoretical, statistical, and empirical or combinations of these approaches which need to be fine tuned or improved. The main problem associated with algorithm development or model formulation for parameter retrieval is the complexity of physical processes involved and uncertainties associated with them. In such cases, advanced computer-based approaches like Fuzzy Logic, Genetic Algorithms, Artificial Neural Network (ANN), and Fractals can serve as alternatives to derive the required parameter from other parameters influencing it which may be available from alternate sources.

India has launched several remote sensing satellites under the series of IRS (Indian Remote Sensing) satellites. IRS-P4, launched in May 1999, carried a Multi-frequency Scanning Microwave Radiometer (MSMR) onboard, measuring brightness-temperature (T_B) at frequencies of 6.6, 10.65, 18, 21 GHz in horizontal and vertical polarizations. It is a day-night-all weather sensor, designed to measure SST, WS, atmospheric water vapour and liquid water content in the clouds [4, 5]. In the present work, an ANN based model has been formulated to retrieve WS and SST values simultaneously from IRS-P4 MSMR T_B over the North Indian Ocean (NIO). The ANN based estimations have then been compared and validated with *in situ* measurements from moored buoys.

2. Data and Methodology

IRS-P4 MSMR raw products consist of T_B of four frequencies at both polarizations. These have been collected from National Remote Sensing Centre Data Center for a one year period during 2000. Grid-1 MSMR T_B

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values in 6.6, 10.65, 18 and 21 GHz channels (with dual polarizations) are considered in the present analysis to retrieve the WS and SST with data subsets selected for our study area (Figure 1).

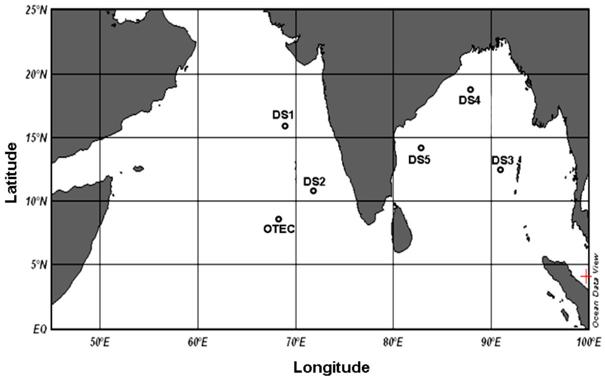

Figure 1: Study area and moored buoy locations

WS and SST datasets recorded by deep sea moored buoys (DS1, DS2, DS3, DS4, DS5 and OTEC) have been collected from National Institute of Ocean Technology during the corresponding period. Circles in Figure 1 show the location of these buoys. The details of instrumentation on these moorings and their observations are given in [6]. These buoy datasets have been used to develop and validate the ANN algorithm for the retrieval of WS and SST from MSMR T_B. The nearest MSMR observations lying within the search radius of 150 km around the buoy locations and a time interval of 3 hours or less with respect to data buoy measurements have been considered as coincident for validation purpose. The buoy measures WS at a height of ~3 m from the sea surface. These were converted to equivalent winds at 10 m height to match up with the IRS-P4 MSMR measurements following a logarithmic wind profile as given in Equation (1) where, U_z is the mean wind speed (m/s) at height z, and U_{10} is the wind speed (m/s) at 10 m height [6].

$$U_{10} = U_z \left(\frac{10}{z} \right)^{1/7} \tag{1}$$

After adopting this methodology, concurrent and collocated database (n = 918) was constructed on moored buoys' recorded WS, SST and MSMR recorded T_B in the 6.6, 10.65, 18 and 21GHz frequencies in vertical and horizontal polarization modes during January-December 2000 over the NIO. This datasets have been used for further ANN analysis. The details of the ANN formulation are presented below.

2.1 Artificial Neural Network Analysis

ANN has been widely used in various meteorological and oceanographic studies [7, 8] and in developing satellite retrieval procedures [8, 9]. An ANN is a massive parallel-distributed computer model consisting of simple processing units called artificial neurons which are interconnected through activation links modulated by synoptic weights. The resulting network has a natural propensity to store experimental knowledge through learning or training [10]. Some of the popular formulations of ANN models are Multi Layer Perceptron, Radial Basis Functions (RBF), and Conjugate Gradient Descent models [10, 11]. In the present work, multiple ANNs were generated by systematic variation of architecture involving input and hidden layer nodes**.** After evaluating the performance of several ANN models on the basis of statistical summary and network performance, a RBF based two outputs ANN model has been finalized for WS and SST retrieval. The ANN model which in general is of the form of equation (2), in the present case consists of one input layer with eight neurons, one hidden layer with 44 hidden neurons and one output layer consisting two neurons, where X_i and Y_q are the components of the input and output vectors respectively, and A and B are fitting parameters. ϕ is the activation function, n and m are the number of inputs and outputs, respectively, and k is the number of neurons in the layer [11].

$$Y_q = A_{q0} + \sum_{j=1}^{k} A_{qj} \Phi(B_{j0} + \sum_{i=1}^{n} B_{ji} X_i), \quad q = 1,2,...,m \tag{2}$$

In the present analysis, the input (independent) parameters are MSMR T_B values in 6.6, 10.65, 18 and 21 GHz channels (with dual polarizations) and the dependent parameters (outputs) are the buoy WS and SST for each input set. As per the requirement of ANN formulation, the total 918 collocated and concurrent observations have been randomly segregated into Training, Verification and Prediction sets. 50% (459 observations) have been used for training the ANN model, 25% (229 sets) for verification, and 25% (230 sets) for ANN prediction and validation of the predicted results. A random selection eliminates the introduction of any systematic bias into the model.

3. Results and Discussions

The performance of the ANN model was evaluated by comparing 25% (n=230) ANN determined MSMR WS and SST values with collocated oceans buoy observations, that were not a part of training and verification steps of ANN model formulation. The comparison indicated a correlation (R) of 0.56 (0.52) and root mean square error (RMSE) of 1.97 m/s (0.75 °C) for ANN obtained MSMR-WS (SST) values and buoy observations. The scatters between ANN estimations and buoys are provided in Figure 2 and the statistical analyses in Table 1.

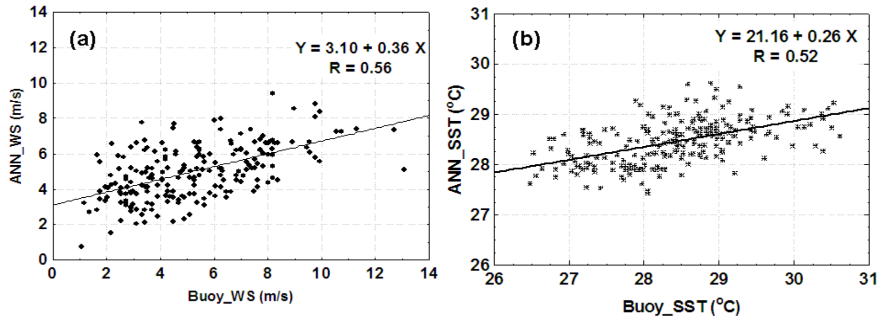

Figure 2: Scatters of ANN-based MSMR estimations and collocated buoy observations for (a) WS, and (b) SST

Table 1: Statistical analysis of ANN-based MSMR WS and SST estimations, and corresponding buoy observations for a set of 230 observations

Parameter	ANN_WS vs. Buoy_WS	ANN_SST vs. Buoy_SST
RMSE	1.97 (m/s)	0.75 (°C)
Correlation	0.56	0.52
Slope	0.36	0.26
Intercept	3.10	21.16
Bias	-0.25 (m/s)	0.04 (°C)

Histograms on bias of the ANN based values calculated by subtracting buoy observations from ANN based estimations for the two parameters (figures not shown) indicate that on an average 69% of ANN determined MSMR WS observations are with in an error of $\pm$2 m/s and 89% with in $\pm$3 m/s when compared with buoy. Similarly in case of SST, 85% of observations lie within $\pm$1 °C and 95% are within $\pm$1.5 °C error as compared to buoy SST.

Figure 3 presents the monthly averaged variations of WS and SST for the ANN estimations and corresponding buoy observations during 2000. The ANN based WS and SST values match reasonably well with buoy observations as seen in the figure. High WS was observed during the southwest monsoon where as higher SST was during the pre-summer monsoon months of April and May. The potential of the ANN approach in deriving geophysical parameters like WS and SST simultaneously from microwave radiometer measured T_B is quite evident from the present analysis. This also strengthens the scope of applications of microwave radiometry in monitoring extreme weather events on real-time basis.

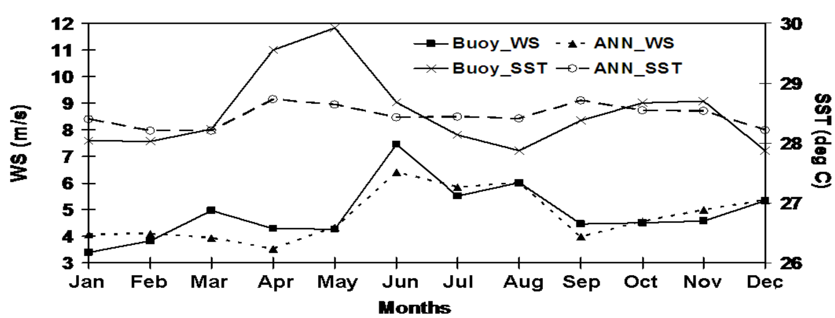

Figure 3: Monthly mean values of WS and SST from Buoy and MSMR_ANN during 2000.

4. Conclusions

The ANN model was found to be successful in retrieving WS and SST simultaneously from T_B values of MSMR multiple channels. The model estimated values were compared with *in situ* buoy observations and were found to be well within acceptable limits of error. The present work involving only a year long data set consisting of 918 collocated cases and that too during 2000 for IRS-P4 MSMR is meant to demonstrate the utility of the ANN approach in obtaining WS and SST simultaneously from T_B of MSMR. However, more collocated *in situ* observations for training would further improve the performance of ANN algorithm. A similar technique may also be used for other microwave radiometers provided more collocated *in situ* observations over the global oceans are available covering larger spatial and temporal extents. It may be noted that even though microwave radiometers can be utilized to obtain SST even under cloudy conditions unlike infrared channels which are suitable only under clear sky conditions owing to the limitations of infrared remote sensing, the accuracy of SST derived from the microwave sensor is less and with poor spatial resolution.

5. Acknowledgements

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6. References

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