# ANN BASED ESTIMATION OF DAILY SEA SURFACE TEMPERATURE OVER ARABIAN SEA USING MODIS DATA

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**ABSTRACT:** In this study, an Artificial Neural Network (ANN) based modelling has been done to estimate daily Sea Surface Temperature (SST) using Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua datasets. A feed-forward Back-Propagation Artificial Neural Network (ANN-BP) model is implemented in this work. This ANN based SST model (MODIS-$SST_{ANN}$) was trained and tested over the Arabian Sea using 5 years of MODIS data and in-situ reference data collected by CERSAT from Coriolis data centre. The application of the tested model requires only the brightness temperatures of MODIS Aqua spectral of bands 31 and 32 at 11 and 12 µm as inputs. The modelled results were compared and analysed with the standard MODIS SST (MODIS-$SST_{STD}$) product as well as the reference data. Preliminary analysis of the obtained results show that the proposed ANN based technique performs better than MODIS SST product. The obtained results suggests that the machine learning techniques such as ANN has good potential and should be further explored in detail for estimation of SST at both near shore and offshore waters.

## 1. INTRODUCTION

Sea surface Temperature (SST) is considered as one of the fundamental geophysical variables which affect the coastal eco systems and water quality in the near shore regions. It's also a key variable which is involved in models of oceanography, climate change, marine weather etc. In the current scenario, SST is critical to assess the effects of global warming on the upper layer of ocean, which is an indicator of the health of coastal eco system (Barnes and Hu, 2013). Hence, an accurate estimation of SST is necessary for monitoring and management of seawaters. Conventionally, the SST data are collected with the help of in-situ samples measured from ships, buoys etc. With the advancement of remote sensing, continuous global monitoring of SST is achieved through a number of satellite based observations.

Satellite based SST observations started from 1981, when the National Oceanic and Atmospheric Administration (NOAA) launched Advanced Very High Resolution Radiometer (AVHRR) sensor on board (Delgado *et al.*, 2014). Following that, the National Aeronautics and Space Administration (NASA) launched Moderate Resolution Imaging Spectroradiometer (MODIS) on the satellite platforms Terra (1999-present) and Aqua (2002 – present). MODIS provides daily SST data at 1km resolution which is considered to be more accurate than AVHRR(Hosoda *et al.*, 2007; Lee *et al.*, 2010; Delgado *et al.*, 2014). Even though there are many satellites measuring SST using microwave/IR radiometers, MODIS remains one of the widely used among oceanographers due to its relatively high correlation with in-situ data, and for its almost daily coverage with 1 km resolution (Chavula *et al.*, 2009; Wang and Deng, 2017).Also, the bias of MODIS Aqua is the lowest (.1 to .3 K) compared to other platforms including MODIS Terra (Tomazic *et al.*, 2011; Wang and Deng, 2017).

Dual-window, split-window and triple window algorithms are the physically based algorithms available for the retrieval of SST data from satellite imagery(McMillin, 1975; Pichel, 1991; Walton *et al.*, 1998; Kilpatrick, Podestá and Evans, 2001; Wang and Deng, 2017). MODIS SST products are generated by the NASA Ocean Biology Processing Group (OBPG). This SST is based on a nonlinear sea surface temperature (NLSST) algorithm derived from far infrared bands(Brown and Minnett, 1999). Although this approach works well for estimating SST for global oceans, region specific algorithms will be better for the local conditions (Haines, Jedlovec and Lazarus, 2007). Previous researches show that, the MODIS SST retrievals are highly dependent on cloud conditions, and even thin clouds can create a large bias in the estimated SST values (McClain *et al.*, 1982; Walton *et al.*, 1998; Heidinger, Anne and Dean, 2002; Minnett *et al.*, 2002; Wang and Deng, 2017). Although there are a number of cloud masking algorithms with varying accuracy(Ackerman *et al.*, 1998; Hu *et al.*, 2009; Barnes and Hu, 2013), studies show that most nearshore waters are masked as clouds, which significantly prevents the detection of cold water events (Wang and Deng, 2017) . Hence, more studies have to be conducted in order to estimate SST by eliminating the data loss due to cloud cover over the study area.

This study, which is aimed at addressing the above issue, attempts to assess the capabilities of Artificial Neural Networks in developing a new remote sensing algorithm that retrieves daily SST from MODIS Aqua (MODIS ANN-SST), followed by a comparison of the results with the existing standard long wave MODIS SST daily product (MODIS-SST$_{STD}$).

## 2. STUDY AREA

The study area considered in this work is the eastern part of Arabian Sea along the Indian coast, shown in Fig. 1. The regional differences in the physical properties of Arabian sea along different coastal stretches greatly affect the temperature and salinity distribution and sea surface emissivity(Newman *et al.*, 2005). Coastal waters of Kerala have the effect of fresh water discharge and seasonal reversing of monsoon. In Goa, the Mandovi and Zuari estuaries are some of the most complex environments in the Arabian Sea. These coasts are affected by both tides and river discharge during summer monsoon whereas during October to November (post monsoon period) the runoff decreases rapidly and becomes negligible (Qasim, 2003). The coastal waters near the Northern Karnataka is largely influenced by oceanic currents, wind forcing, and upwelling (Verlecar *et al.*, 2006; Jayaram *et al.*, 2010). The Gujrat coastline is characterized by high amount of suspended sediment concentration and a significantly high tidal activity( Misra and Balaji 2015; Misra et al. 2014). Since the study area is having different characteristics along the stretch, the efficiency of the present algorithm can be analyzed effectively in this region.

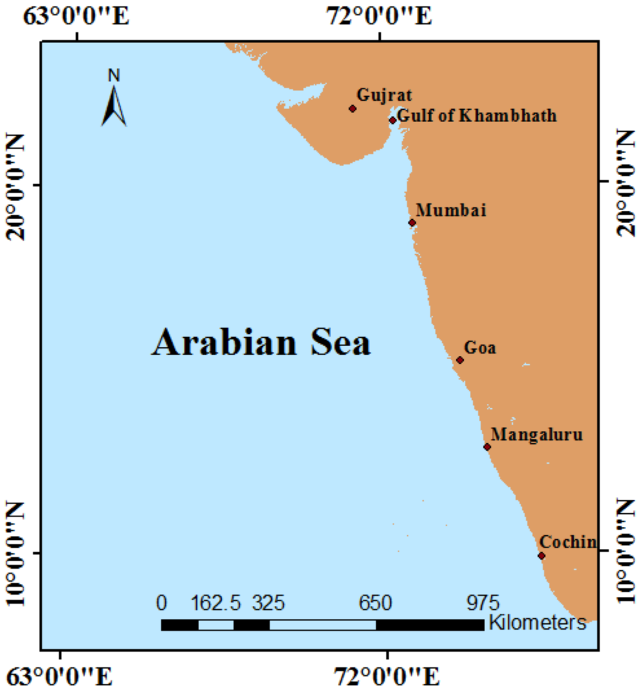


Figure 1: Location of study area – Eastern Arabian Sea along the Indian Coastline

## 3. DATASETS

The datasets used in this research are from January 2010 to December 2014 along the study area. The in-situ SST data used in this study has been collected from the *Centre ERS d'Archivage et de Traitement* (CERSAT) - French ERS Processing and Archiving Facility. CERSAT collects surface level in-situ SST data from Coriolis data centre and distributes it, in an easier-to-use format, which can be compared with the satellite SST products (http://cersat.ifremer.fr/data/tools-and-services/match-up-databases/item/298-sea-surface-temperature-in-situ-data). MODIS Aqua level 0 data was collected from NASA Ocean Color website (https://oceancolor.gsfc.nasa.gov/) for the same time period as that of the in-situ data. The MODIS standard daily long wave SST product (MODIS-SST$_{STD}$) with the same resolution is also utilized in this study to compare with MODIS-SST$_{ANN}$ results.

## 4. METHODOLOGY

The images were processed using the SeaWiFS Data Analysis System (SeaDAS), which is a comprehensive image analysis package developed by NASA for processing, displaying, analysing Ocean Color data. MODIS Aqua day time thermal infrared bands 31 (11 µm) and 32 (12 µm) level 2 products with 1 km resolution were used in this study. The band brightness temperature values were normalised as given in Eqn (1), in order to reduce the systematic errors.

$$\tilde{R}_i = \frac{R_i - \min(R_i)}{\max(R_i) - \min(R_i)} \quad (1)$$

where $\tilde{R}_i$ refers to the normalised brightness temperature of bands 31 and 32, where i refers to the band designation and $R_i$ denotes the brightness temperature. The other variables, viz. min( $R_i$ ) and max ( $R_i$ ), are the minimum and maximum of the values for the band i found in the selected time period of this study. The satellite data and in-situ data were collocated using the pixel extraction tool available in SeaDAS.

A feed forward back propagation Artificial Neural Network model available in MATLAB toolbox, was utilised in this algorithm to produce the results. The inputs are the brightness temperature values of the bands 31 and 32 and output is given as the in-situ SST data collected from CERSAT. The algorithm was trained using 20 hidden neurons between the input and output layers. The in-situ and satellite data collected from 2010 to 2014 were used for constructing the model. Of the total data, 70% were used for training, 15% were used for validation, and the remaining 15% were used for testing. The training set which involves the majority of data is used for fitting the model and the validation set is used for computing the prediction error. The model with the least validation error is chosen and that is verified again with the independent test dataset. For analysing the results, statistics such as coefficient of determination ($R^2$), Root Mean Square Error (RMSE), mean and median were used.

## 5. RESULTS AND DISCUSSIONS

### 5.1 Development of MODIS-SST$_{ANN}$ algorithm

The ANN based model was developed by considering the points with cloud contamination. The model was developed using the in-situ and corresponding MODIS Aqua brightness temperature values of band 31 and 32 during the time period 2010 -2014 along the study area. The performance of MODIS-SST$_{ANN}$ model while training and validation against the in-situ SST is plotted and shown in Figs.2a & Fig 2b respectively.

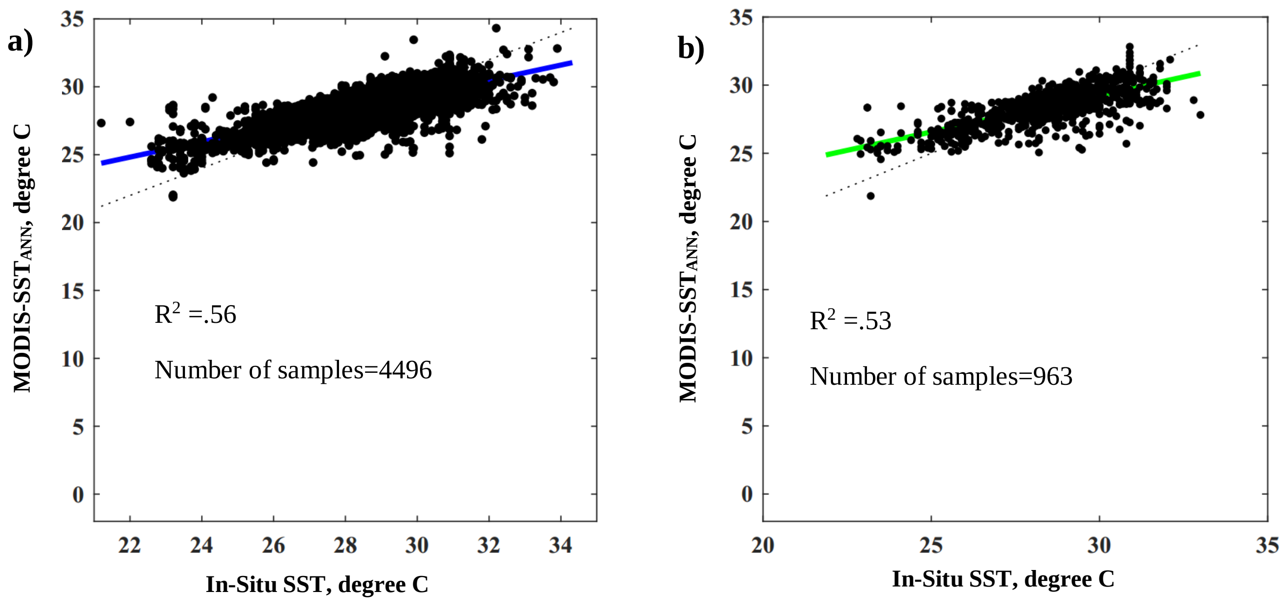


Figure 2: Performance of the MODIS-SST$_{ANN}$ model during (a) training and (b) validation.

Fig. 2 shows that the MODIS-SST$_{ANN}$ is having a coefficient of determination of 0.56 during training and 0.53 during validation. From Table 1, it can be observed that the mean and median values of MODIS-SST$_{ANN}$ and as well as in-situ SST are closely matching with a negligible deviation in the order of $10^{-1}$. Also, the RMSE of the present algorithm is around 0.8$^{o}$C for both the training and validation data. From the overall statistics, it can be observed that, although coefficient of determination is relatively low for the ANN model, the error in the estimates is also less (<1$^{o}$C).

Table 1: Statistical measures for SST derived using MODIS-SST$_{ANN}$ with respect to in-situ data during training and validation of the model.

| **Training data** | | | **Validation data** | | |
|---|---|---|---|---|---|
| **Statistical Indicators** | **In-situ SST** | **MODIS-SST$_{ANN}$** | **Statistical Indicators** | **In-situ SST** | **MODIS-SST$_{ANN}$** |
| $R^2$ | N/A | 0.56 | $R^2$ | N/A | 0.53 |
| RMSE ($^{o}$C) | N/A | 0.83 | RMSE | N/A | 0.86 |
| Mean($^{o}$C) | 28.4748 | 28.48 | Mean | 28.4191 | 28.40 |
| Median ($^{o}$C) | 28.6 | 28.67 | Median | 28.52 | 28.64 |

### 5.2 Testing of MODIS-SST$_{ANN}$ Model

In order to ensure the consistency of the developed model, it was tested with independent datasets as discussed in sec.4. The obtained results are shown in Fig. 3 and the corresponding statistics are given in Table 2.

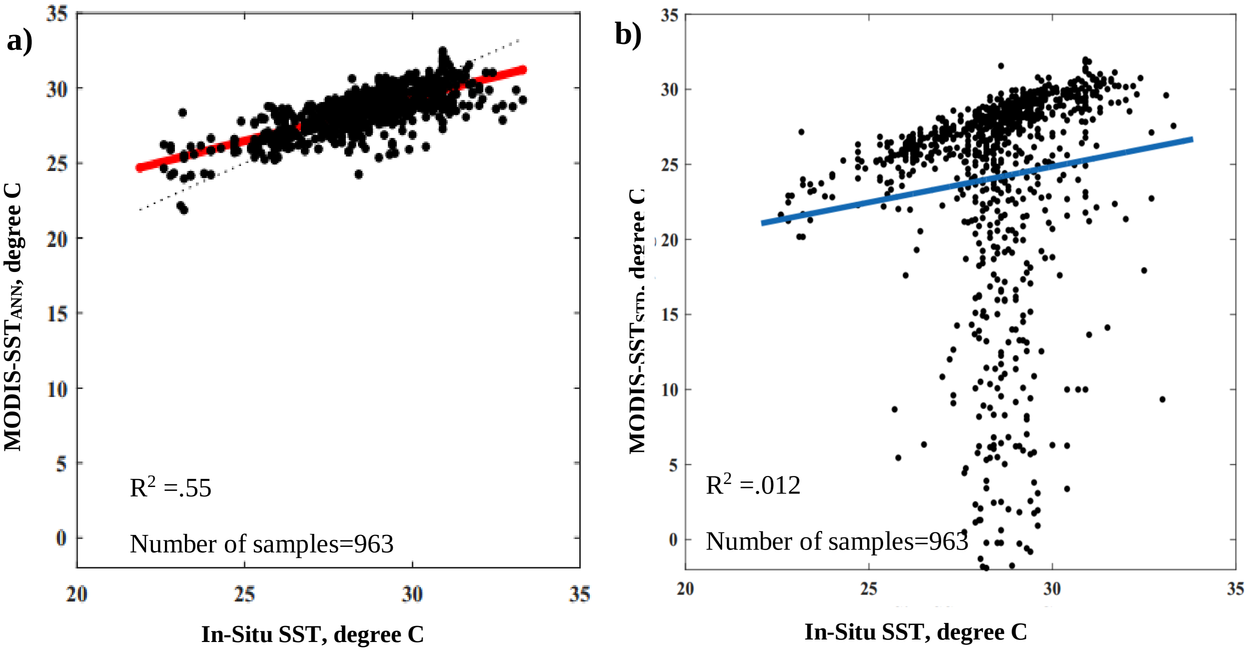


Figure 3: Comparison of the results obtained while testing the MODIS-SST$_{ANN}$ and MODIS-SST$_{STD}$ estimates with respect to in-situ data. a) MODIS-SST$_{ANN}$ vs In-situ SST. b) MODIS-SST$_{STD}$ vs In-situ SST

The coefficient of determination as well as RMSE of MODIS SST$_{STD}$ show poor values compared to MODIS-SST$_{ANN}$ (Table 2). The mean and median computed from MODIS-SST$_{STD}$ estimates show large difference from the in-situ mean and median values. It should be noted that the mean of MODIS-SST$_{STD}$ is 24.13$^{o}$C and its median is 26.78 $^{o}$C (Table 2) and this higher difference between mean and median signifies that the MODIS-SST$_{STD}$ is more skewed towards lower values compared to the in-situ and MODIS-SST$_{ANN}$. This is due to the underestimation of the MODIS-SST$_{STD}$ as shown in Fig.3b. It has been already proven in many studies that the physical based approaches to estimate SST from IR radiometers fail in cloudy conditions (McClain *et al.*, 1982; Walton, 2000). Since the cloudy data has not been masked in this study, the MODIS-SST$_{STD}$ is performing relatively poor.

Table 2: Statistical measures for SST derived using MODIS-SST$_{ANN}$, MODIS-SST$_{STD}$ with respect to In-situ data for testing.

| **Statistical Indicators** | **In-situ SST** | **MODIS-SST$_{STD}$** | **MODIS-SST$_{ANN}$** |
|---|---|---|---|
| $R^2$ | N/A | 0.012 | 0.55 |
| RMSE($^{o}$C) | N/A | 7.21 | 0.86 |
| Mean($^{o}$C) | 28.49 | 24.13 | 28.47 |
| Median ($^{o}$C) | 28.6 | 26.78 | 28.65 |

At the same time it should be noted that the ANN based model is also producing relatively low $R^2$ in training, validation and testing stages. This can be attributed to the difference in coastal and deep sea water characteristics, which were not considered in the present study. Newman et al. (2005) pointed out that, due to the strong gradients and temperature and salinity dependence of sea surface emissivity in the coastal regions, algorithms developed for deep waters may not work for coastal waters. Therefore, further research have to be carried out to improve the MODIS-SST$_{ANN}$ algorithm by separately considering the nearshore and offshore waters for a longer time period to prove the consistency of the model.

## 6. SUMMARY

An ANN based model was constructed to estimate daily SST from MODIS Aqua over Arabian Sea for the period 2010 -2014. In-situ data used in this study for training, validation and testing were collected by CERSAT from Coriolis data centre. The comparison between the MODIS-$SST_{ANN}$ and MODIS-$SST_{STD}$ shows that the ANN based algorithm performs better. Even though the statistics such as RMSE, mean and median are giving good results, the $R^2$ value of MODIS-$SST_{ANN}$ is relatively low during training testing and validation. This might have occurred since the present study didn't consider the nearshore and offshore waters separately. Hence, further research have to be carried out by segregating the coastal and deep sea waters using longer time period data to improve the results.

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