Exploring Machine Learning Techniques to Estimate Cloud Free Daily Sea Surface Temperatures (SST) from MODIS Aqua across South Eastern Arabian Sea

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INTRODUCTION

- Sea surface temperature (SST) derived from Infrared radiometers often suffers from huge data loss due to cloud cover (Barton 2001, Wang and Deng 2017) and the effect is more pronounced across Arabian Sea as it is in the tropical region.
- Past studies show that the machine learning (ML) techniques provide a convenient way to work around complex problems especially for remote sensing data (Picart et al. 2018, Lary et al. 2016).
- In this study, we explore and compare four different ML models for its predictive accuracy to estimate Cloud free sea surface temperature along the south eastern parts of Arabian Sea using the MODIS Aqua datasets.

OBJECTIVES

- To estimate SST from MODIS aqua using
  - ✓ ANN
  - ✓ SVM
  - ✓ Random Forest
  - ✓ Simple Linear Regression
- To validate the results based on in-situ data and GHRSST optimal interpolated product.

STUDY AREA & DATASETS

- The study area selected for this study is the south eastern part of Arabian Sea along the Indian Coastline as shown in Fig.1
- Latitudinal extent (3º to 25º N).
- Longitudinal extend (60° to 78” E).

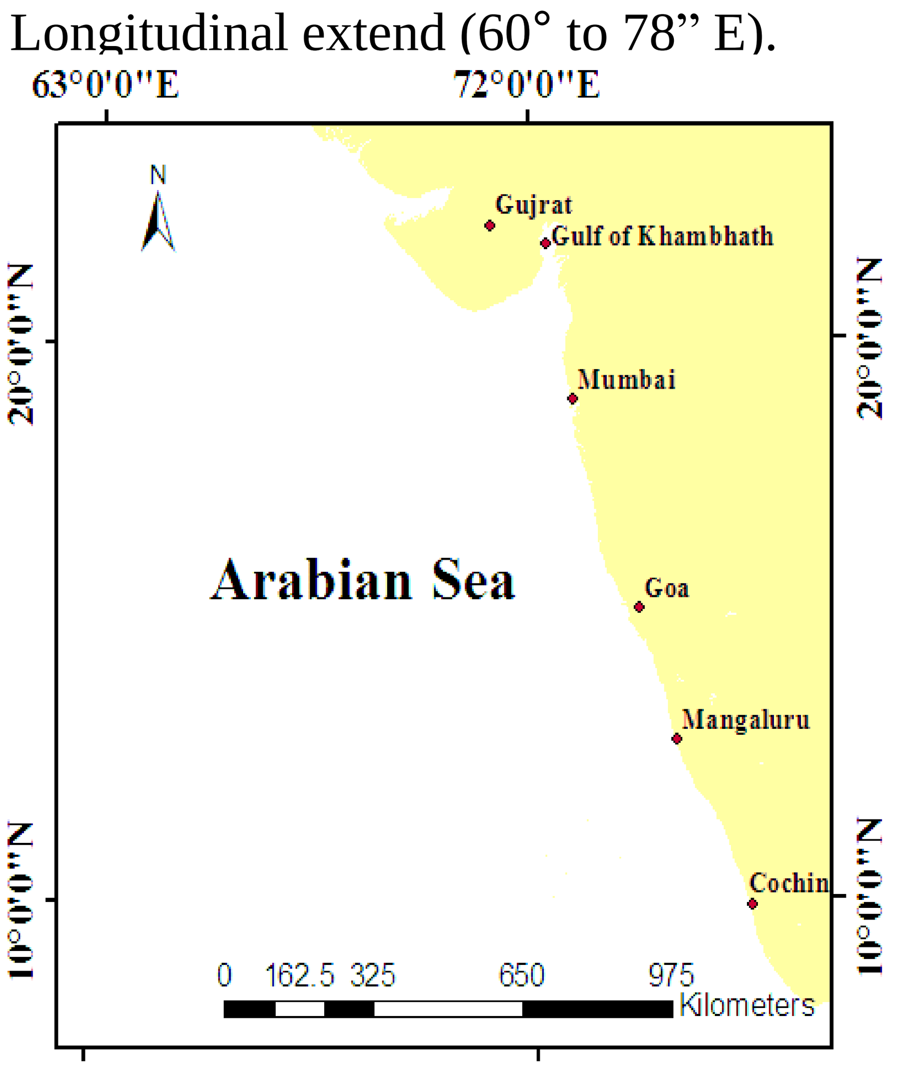

Figure 1: Location of study area – South eastern Arabian Sea along the Indian Coastline

Table 1: Datasets used in this study

Data	Period	Source
In-situ SST data	2006-2015	Centre (CEERS Centre d'Archivage et de Traitement RSAT)
MODIS L0 data	2006-2015	NASA Ocean Color group
Bathymetry	2009	General Bathymetric Chart of the Oceans (GEBCO)
GHRSST MODIS Aqua L2 P Product	2014-2015	PO.DAAC - NASA

METHODOLOGY

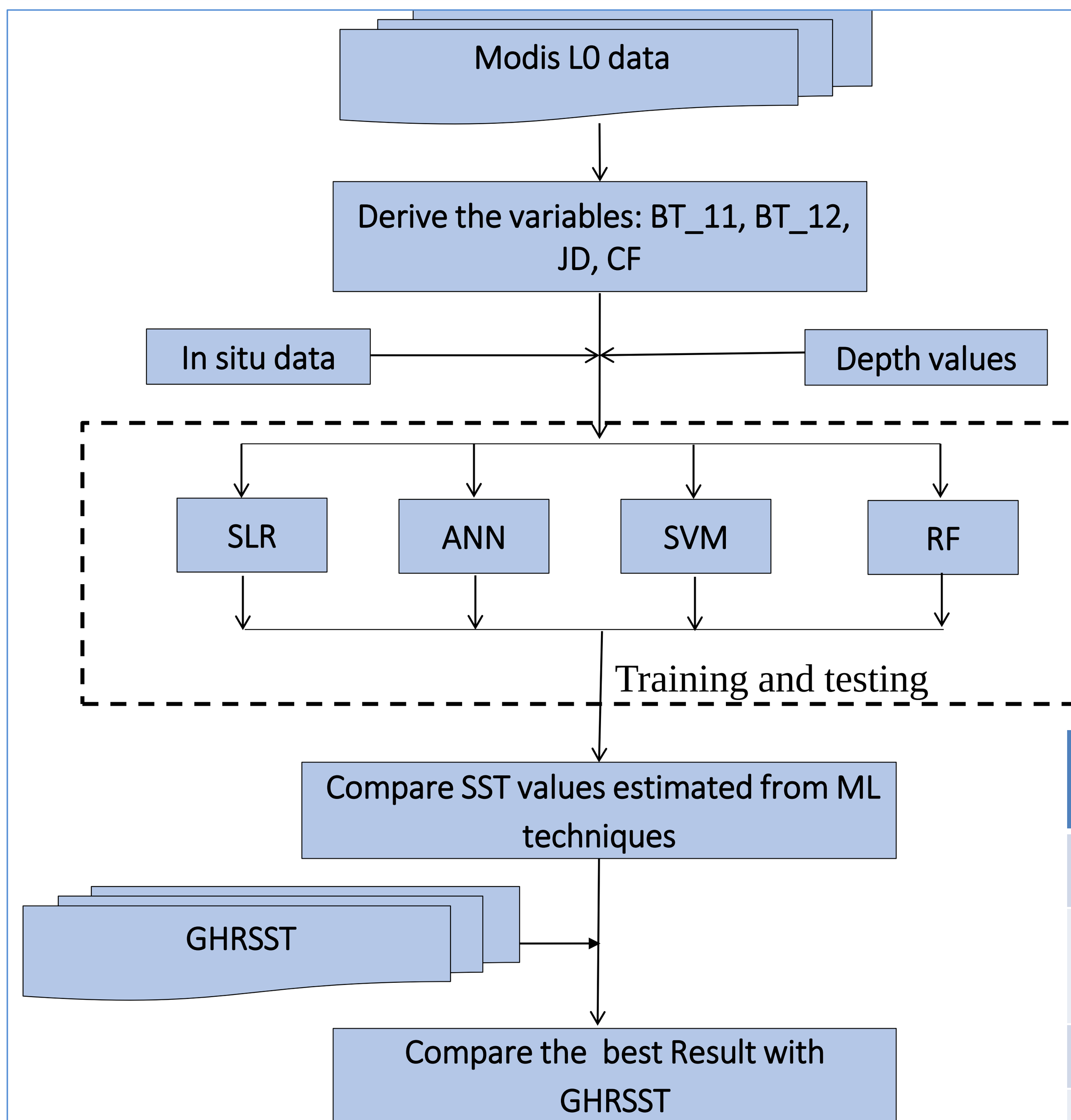

Fig 2: Framework of the methodology followed for estimation of SST using ML techniques

- All the inputs were normalized before training and testing.
- All tested ML techniques were trained using the datasets collected for the years 2006-2014. **10 fold cross validation** method was used for training.
- The results were tested independently using the datasets collected during 2015

Table 2: Description of the variables used for training and testing of the ML models

Variable Name	Description
BT_11	Brightness temperature at 11 µm
BT_12	Brightness temperature at 12 µm
Depth	Bathymetric values
JD	Julian day
Cloud factor (CF)	Indicates the presence of Cloud (CF =0, No cloud; CF=1 , Cloudy)

RESULTS

1. Performance of machine learning techniques

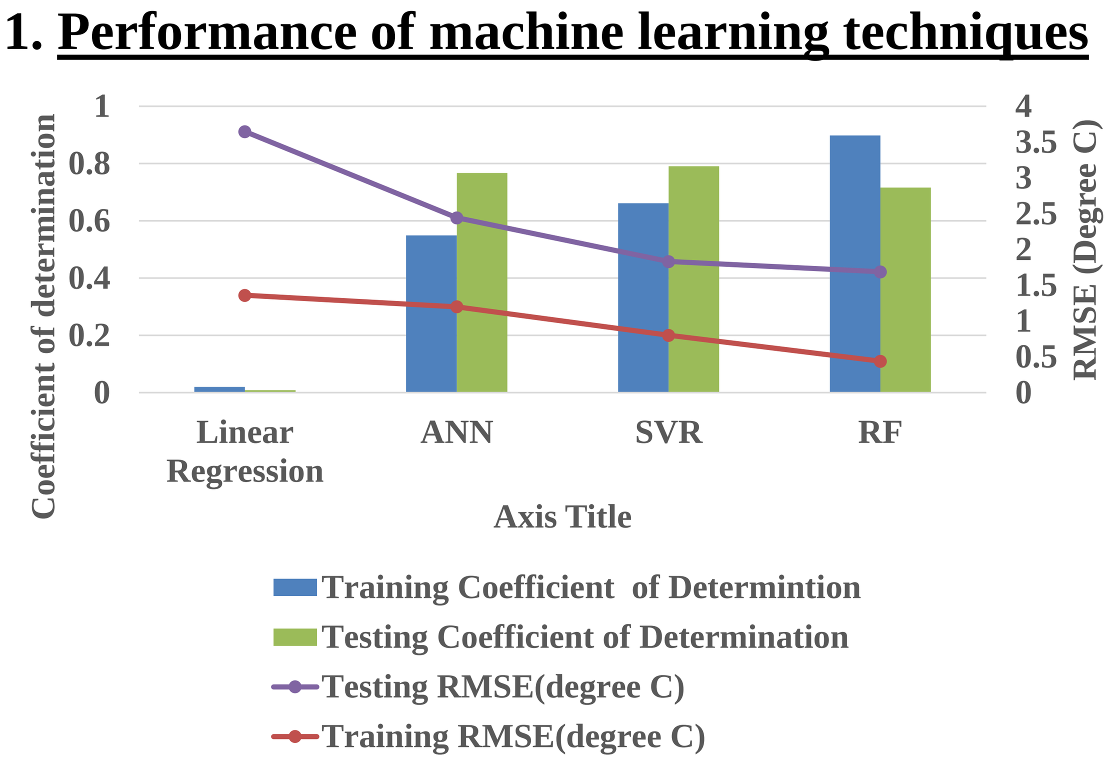

Fig 3: Performance of the machine learning techniques during training and testing with respect to the in situ reference data

2. Comparison of the Performance between RF and GHRSST

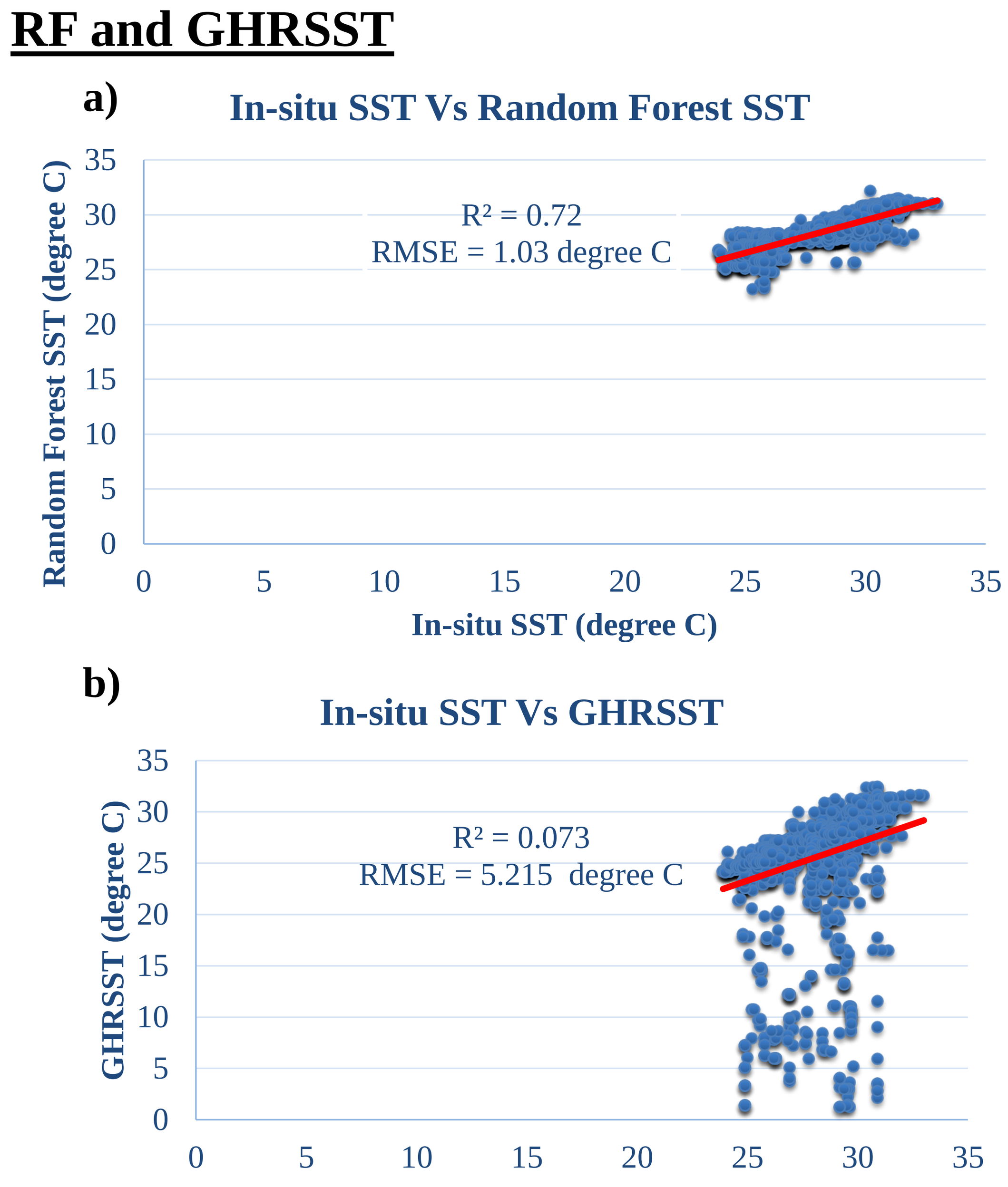

Fig 4: Comparison of SST between in situ reference data and (a) estimates from RF technique and (b) estimates from GHRSST

CONCLUSIONS

- Random forest technique is performing better than other machine learning techniques used in this study. It should be noted that the computational time is very less while using random forest technique which makes it useful for operational purposes.
- Support vector regression model performs as second best followed by Artificial Neural Networks and Simple linear regression.
- The RF based estimate of SST is more accurate compared to the OI product from GHRSST for the present study.
- Future research shall be geared towards further improvement of results by including more number of variables.

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