Application of Deep Neural Network in Estimating SST from INSAT-3D Imager

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1. Abstract

The present study demonstrates the application of a machine learning technique, deep neural network (DNN), for the estimation of sea surface temperature from INSAT-3D Imager observations. The quality assessment of the estimated SST is carried out with concurrent in-situ SST measurements. The error standard deviation is observed to be better than 0.6K with consistent negative biases.

2. Introduction

Sea surface temperature (SST) plays a key role in monitoring and regulating the earth's climate change. The accurate information of SST is also required to understand the various physical oceanic processes. Moreover, it is also used as a primary input for important applications like identification of the potential fishery zones, etc. Therefore, the availability of high quality SST is extremely important. The present paper illustrates the application of a machine learning technique, deep neural network (DNN), to estimate SST from INSAT-3D Imager's split-window observations.

3. Data used

- INSAT-3D Imager L1B data products (Brightness Temperatures, geo-location, satellite zenith angle, etc.) downloaded from https://www.mosdac.gov.in.
- In-situ measurements of SST acquired from iQuam portal of NOAA available at https://www.star.nesdis.noaa.gov/sod/sst/iquam.
- Forecast SST fields from Numerical Weather Prediction Model: Global Forecasting System (ftp://nomads.ncdc.noaa.gov/GFS/)

4. Methodology

- To establish the DNN, a matchup dataset is prepared by collocating the split-window observations of INSAT-3D Imager and in-situ measurement of SST for the years 2017-2020.
- CDF matching is applied to correct the observed biases in INSAT-3D observations with respect to simulations.
- Further, 70% of the matchup data is randomly selected for training the DNN, whereas, the rest 30% is used for testing.
- DNN Architecture: input layer, 3 hidden layers and output layer, **ReLu** activation function and **adam** optimizer.

  Input layer consists of the following variables:

  Julian day, longitude, latitude, TIR-1 BT, (TIR1-TIR2) BT, SST_{fct}*(TIR1-TIR2), satellite zenith angle, acquisition time in hour

  The Output layer has only one variable SST taken from iQuam.

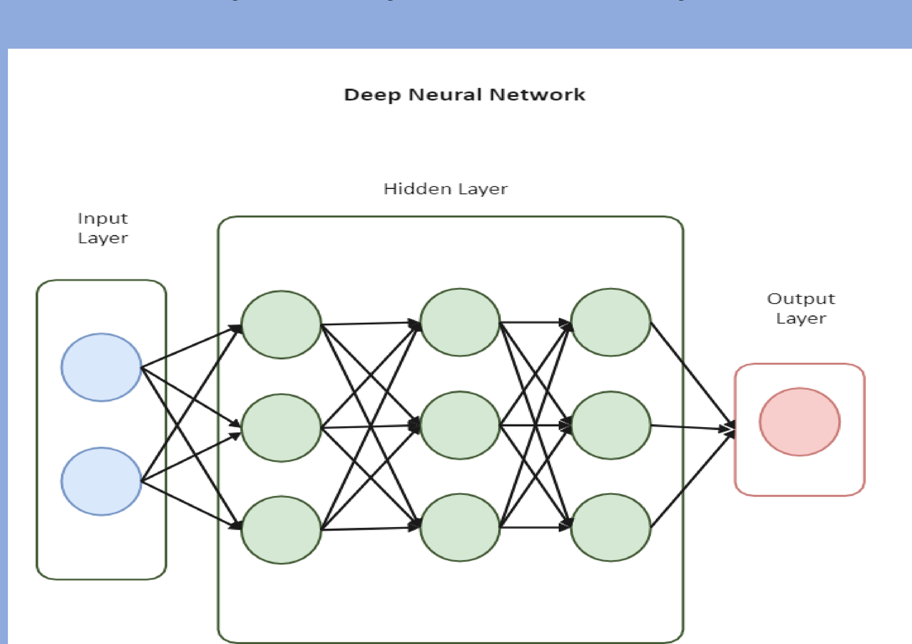


Figure: Typical DNN structure with 3 hidden layers

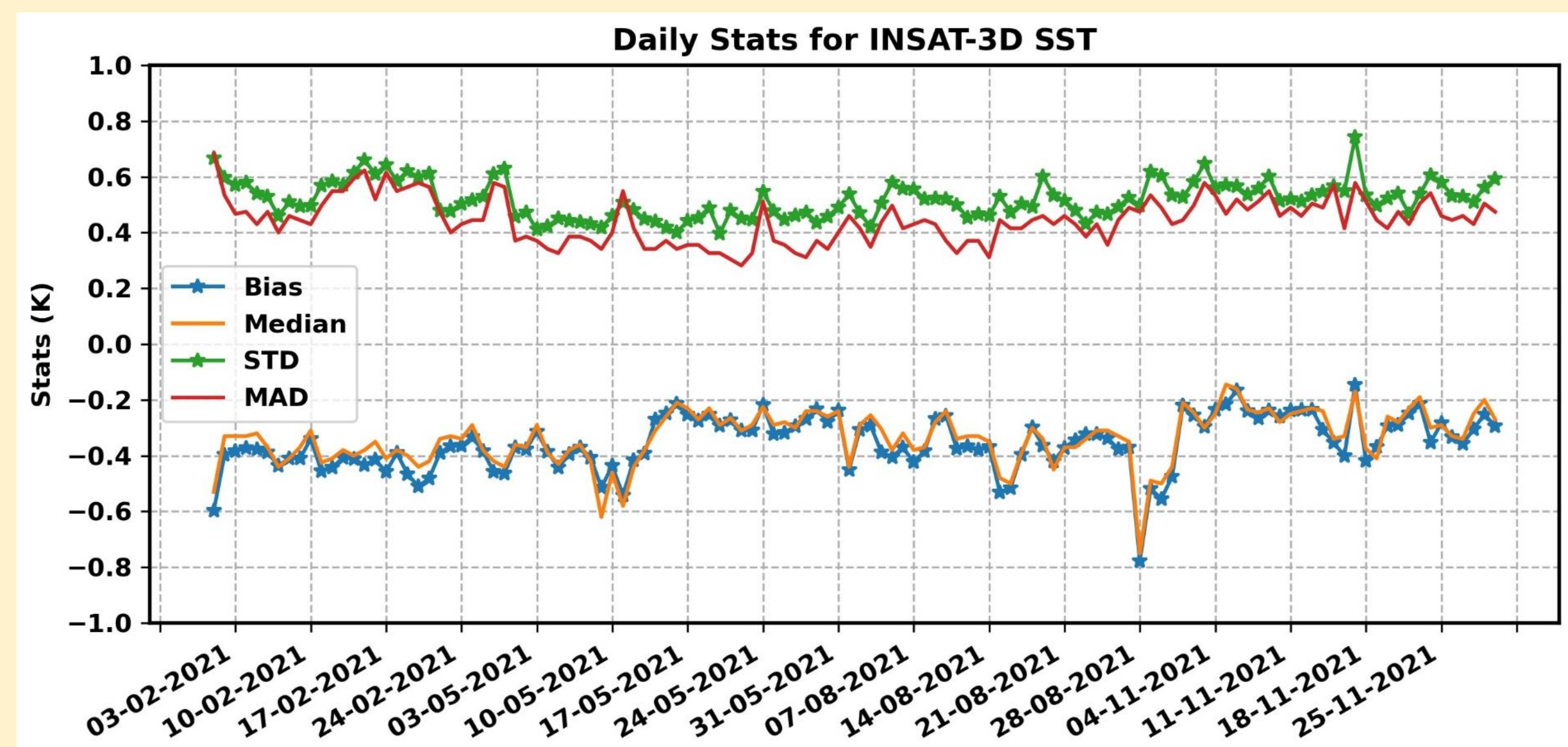
- Independent testing of the established DNN by using it on February, May, August and November months of 2021 INSAT-3D observations to retrieve SST.
- These months are chosen to cover the seasonal variations that occurs in SST.

5. Validation

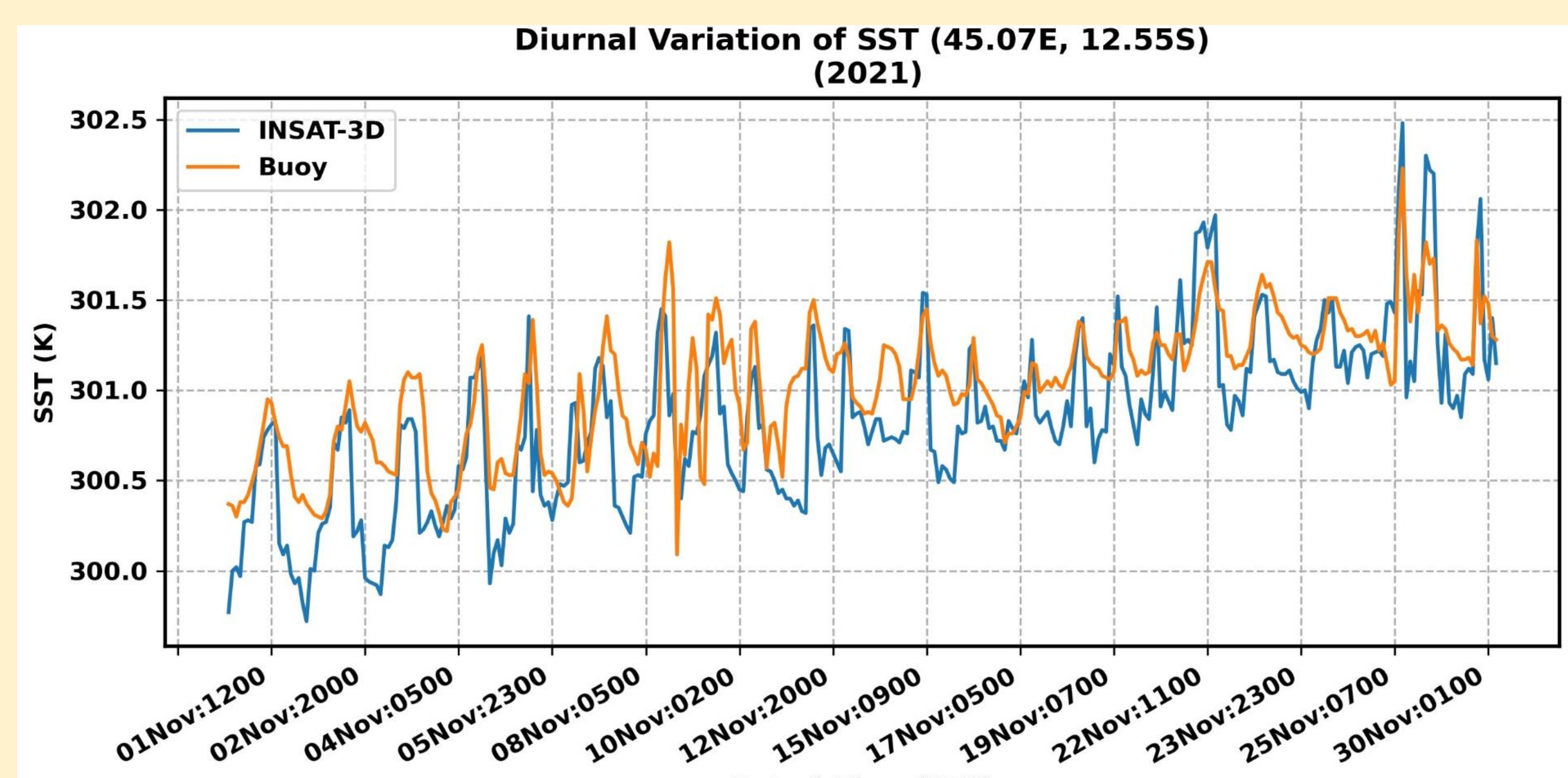
- The estimated SST from INSAT-3D Imager observations is validated with in-situ SST measurements.
- The matchup dataset has been prepared by collocating both the observations. The collocation criterion: $\Delta x=0.04^0$, Δt=15 minutes

6. Results

Comparison with in-situ



Diurnal variation with Buoy SST



7. Conclusions

- A machine learning technique DNN is utilized for SST retrieval from INSAT-3D Imager observations.
- A preliminary assessment of the retrieved SST with in-situ measurements shows an accuracy better than 0.6K.
- A good match was observed between the diurnal variation in the retrieved SST with buoy SST located at 45.07E, 12.55S.
- The study concludes that DNN based retrieval algorithm can produce excellent SST from INSAT-3D Imager.

8. Acknowledgements

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9. Reference

- Haghbin et al., "Applications of soft computing models for predicting sea surface temperature: a comprehensive review and assessment", *Progress in Earth and Planetary Science* **8**, 4 (2021), https://doi.org/10.1186/s40645-020-00400-9.