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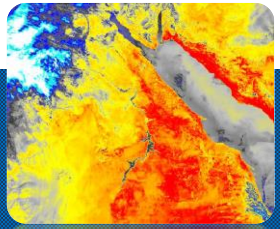

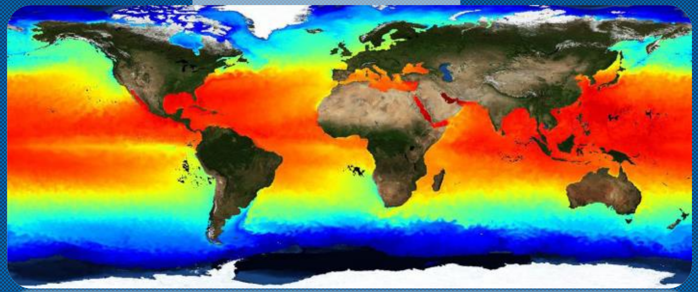

Improving the atmospheric correction algorithms for sea surface skin temperature retrievals from MODIS using machine learning methods

23rd GHRSST Science Team Meeting

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PART ONE

Introduction and Data

Significance of this study

- Satellite retrieved sea surface skin temperature (SST_{skin}) has been essential for many nearly-continuous studies.

- The missions of the two MODISs have provided continuous measurements for more than twenty years and generated a long time series of SST_{skin} with modified nonlinear SST algorithm (NLSST; Walton et al. (1998), Kilpatrick et al., (2015)).

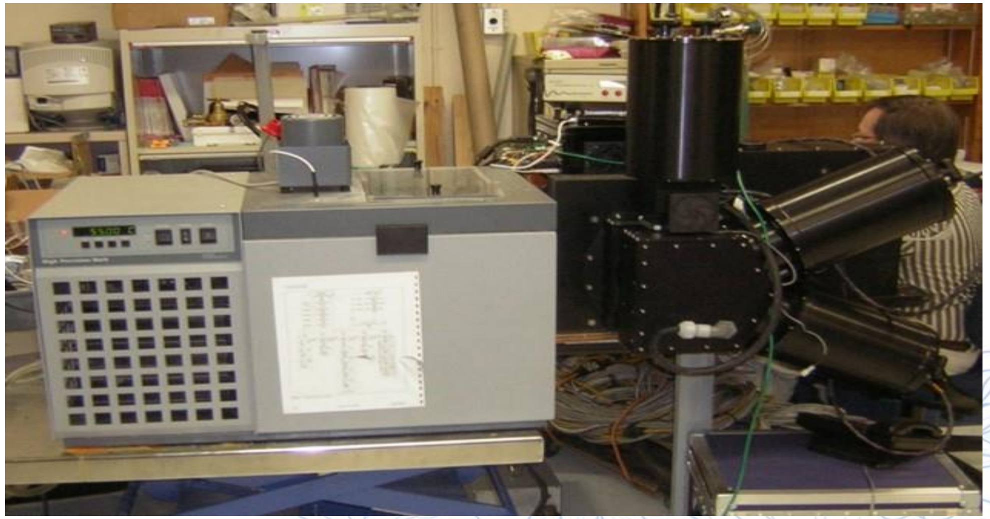
- This study used four machine learning approaches: eXtreme Gradient Boosting (XGBoost), Support Vector machine Regression (SVR), random forests (RF), and artificial neural networks (ANN), to develop improved atmospheric correction algorithms for satellite-derived SST_{skin} in the Caribbean region.

Shipboard SST dataset

The M-AERI is an accurate, self-calibrating, Fourier transform IR spectroradiometer that measures emission spectra from the sea and atmosphere (Minnett et al. 2001).

M-AERI onboard the Ronald H. Brown.

NOAA Ship R.H.B at Florida. Mar 2 2018



M-AERI is calibrated in the laboratory before and after each deployment using an external validation procedure.

Shipboard SST dataset

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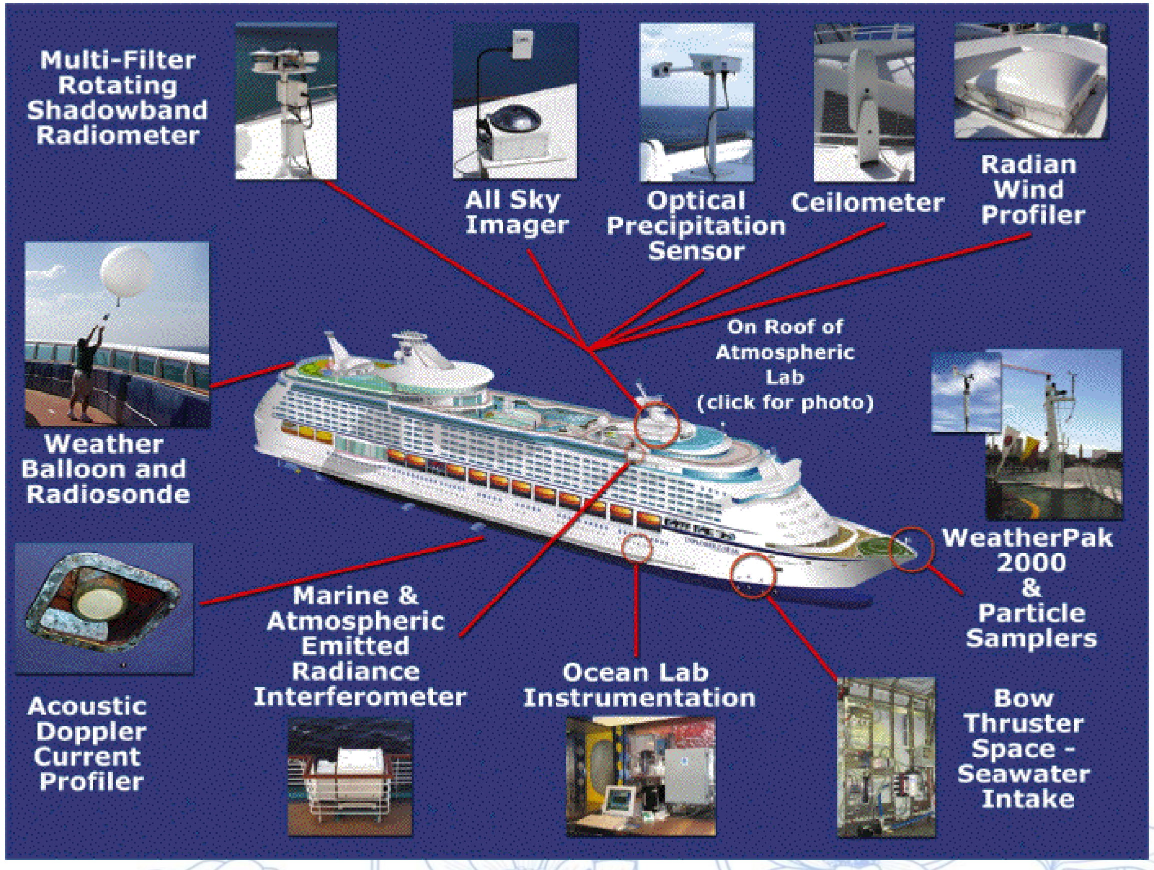


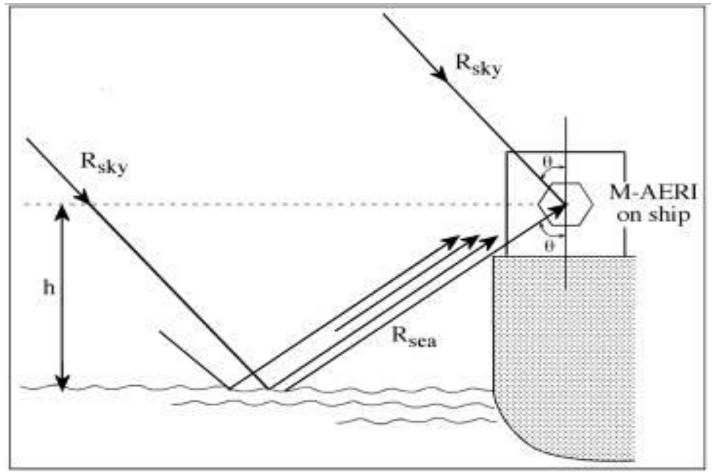
Shipboard SST dataset

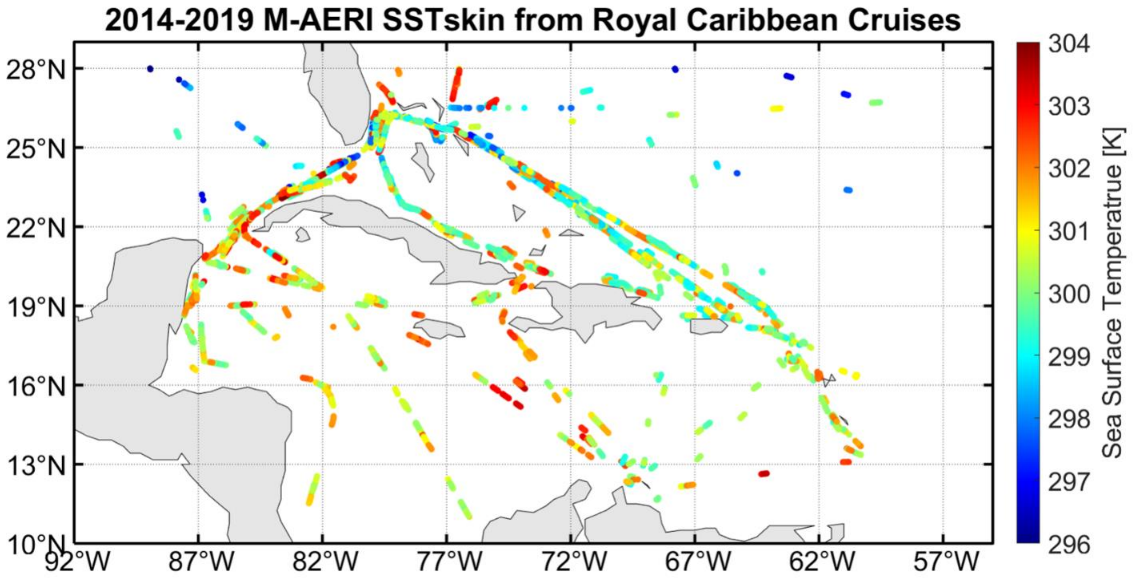
The M-AERI SST_{skin} can be retrieved from:

$$SST_{skin} = B^{-1}\left(\frac{R_{water}(\lambda,\theta) - \big(1-\varepsilon(\lambda,\theta)\big)R_{sky}(\lambda,\theta) - R_h(\lambda,\theta)}{\varepsilon(\lambda,\theta)}\right)$$

where R_{water}, R_{sky}, and R_h are the spectral radiance emitted by the sea surface, the atmosphere above the height of the instrument, and the atmosphere below the instrument, λ is the wavelength of the measured radiance, θ is the angle from vertical of the measurement, and ε is the surface emissivity. B is the Planck function. R_h includes both direct and sea-surface reflected emission.

The map shows measurements in the study area with valid matchup with MODIS as there are measurements elsewhere in this time interval.

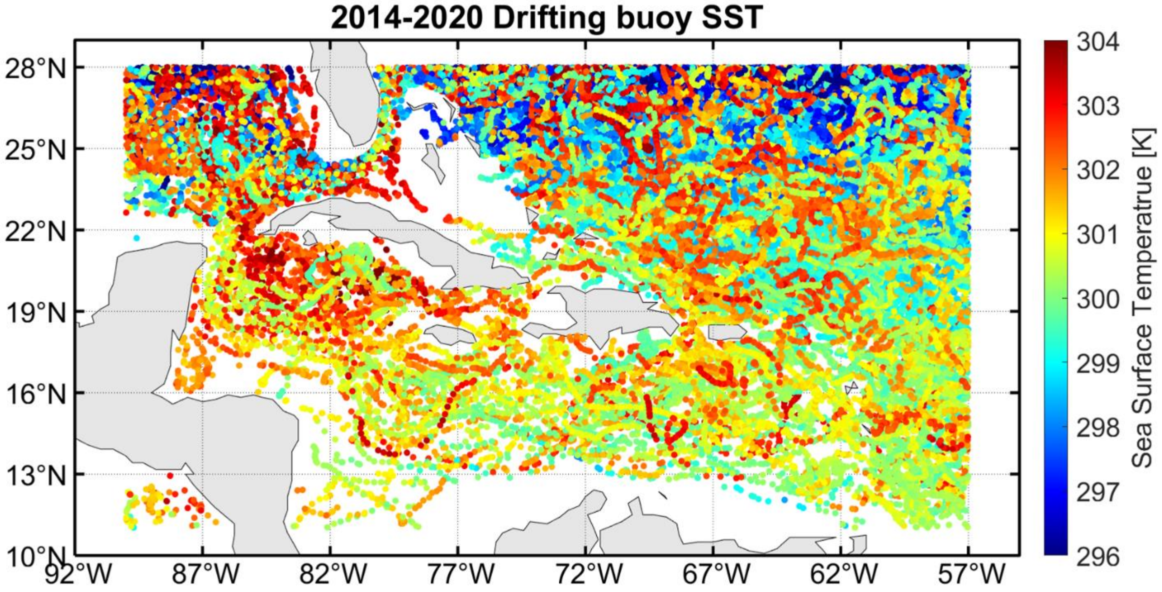




Minnett, P. J., et al. "The marine-atmospheric emitted radiance interferometer: A high-accuracy, seagoing infrared spectroradiometer." *Journal of Atmospheric and Oceanic Technology* 18.6 (2001): 994-1013.

Drifting buoys SST dataset

The data is from GDP Drifter Data Assembly Center (NOAA). NOAA established the in situ sea surface temperature (SST) Quality Monitor (iQuam) to support the validation (Cal/Val) of satellite and blended SST products (Xu and Ignatov, 2016). IQuam consists of quality-controlled measurements from drifters, moored buoys and ships.

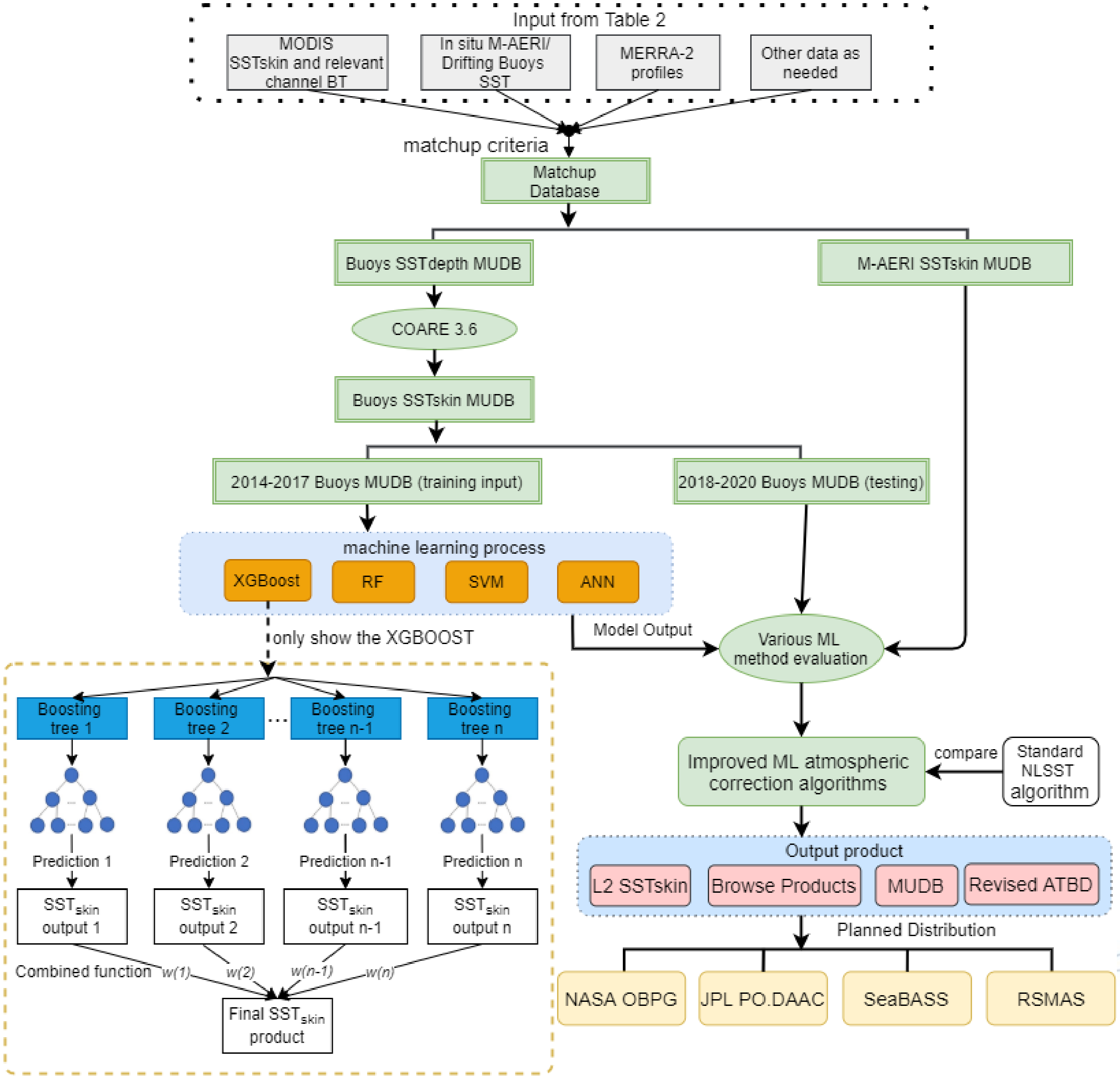


MERRA-2 dataset

- NASA Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2) contains global oceanic and atmospheric variables such as aerosol optical depth, SST and air temperature.

Data Name	Variable	Spatial resolution	Time resolution
inst1_2d_asm	2m Temperature 2m Specific Humidity Sea Surface Temperature 10m V (northward wind) 10m U (eastward wind)	0.5° *0.625°	1-hourly

Gelaro, Ronald, et al. "The modern-era retrospective analysis for research and applications, version 2 (MERRA-2)." Journal of Climate 30.14 (2017): 5419-5454.



Overall framework of the proposed study. The yellow dot box shows a schematic diagram illustrating the process of the XGBoost algorithm, an optimized distributed gradient boosting method.

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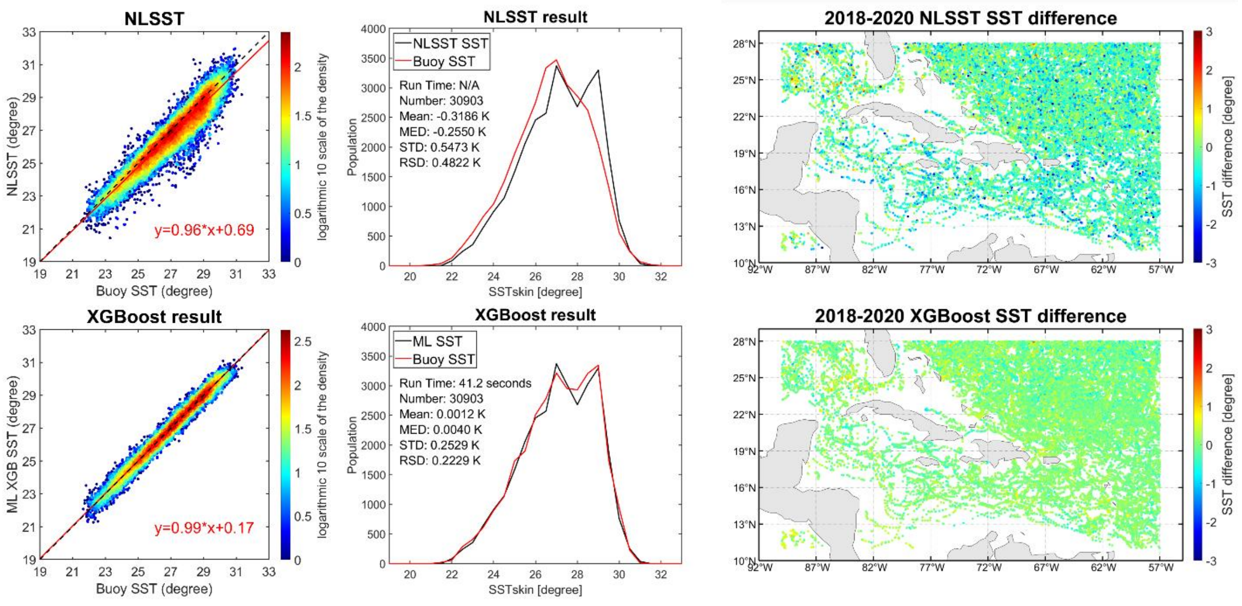
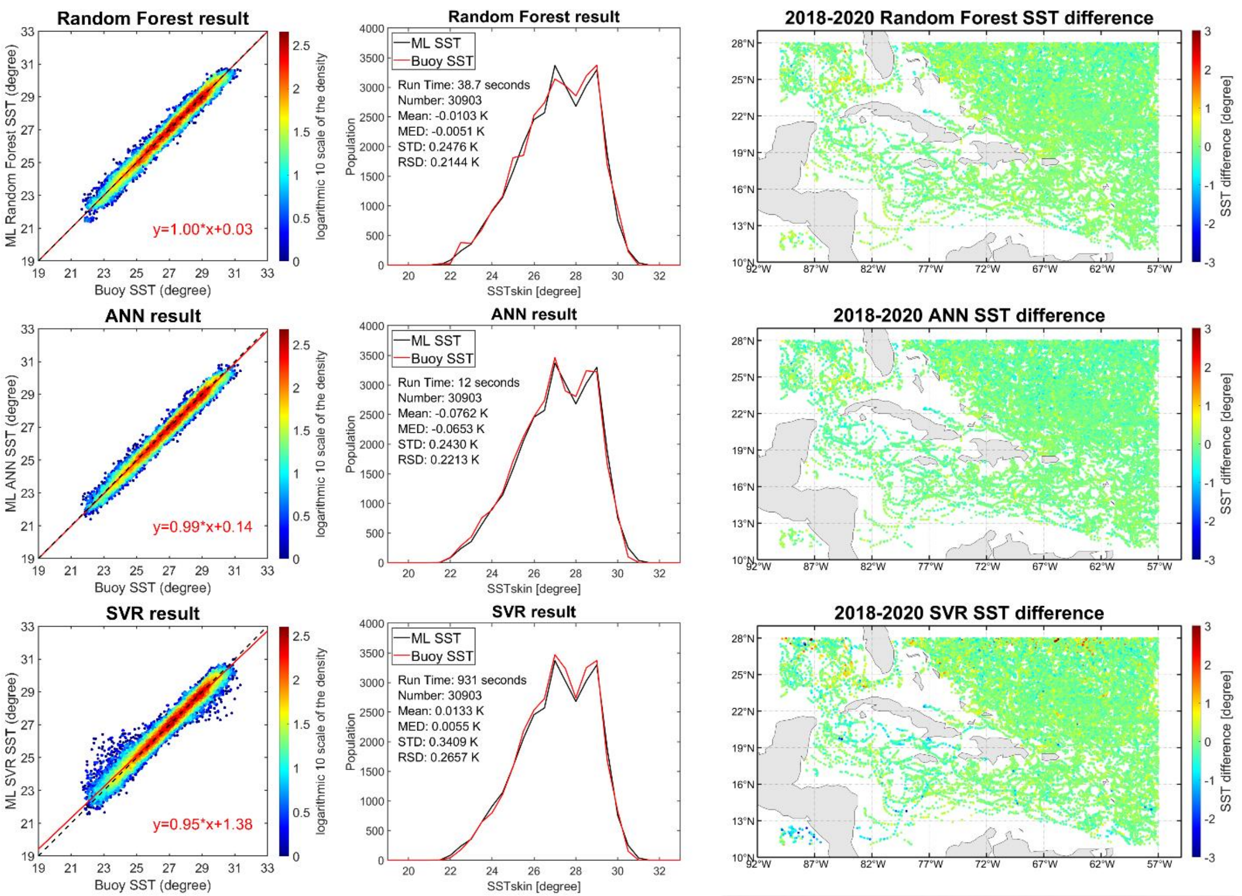
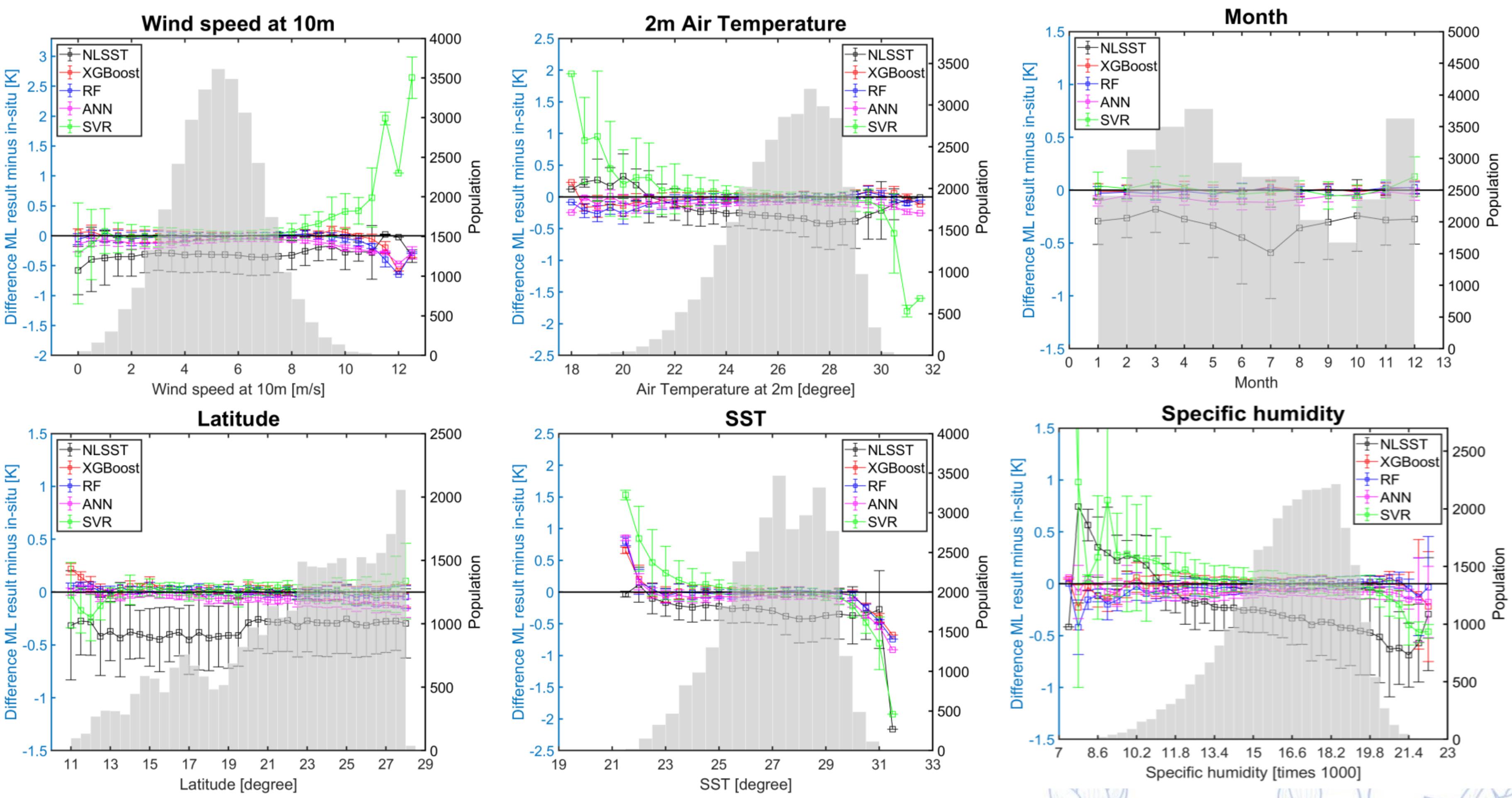
PART TWO

Results

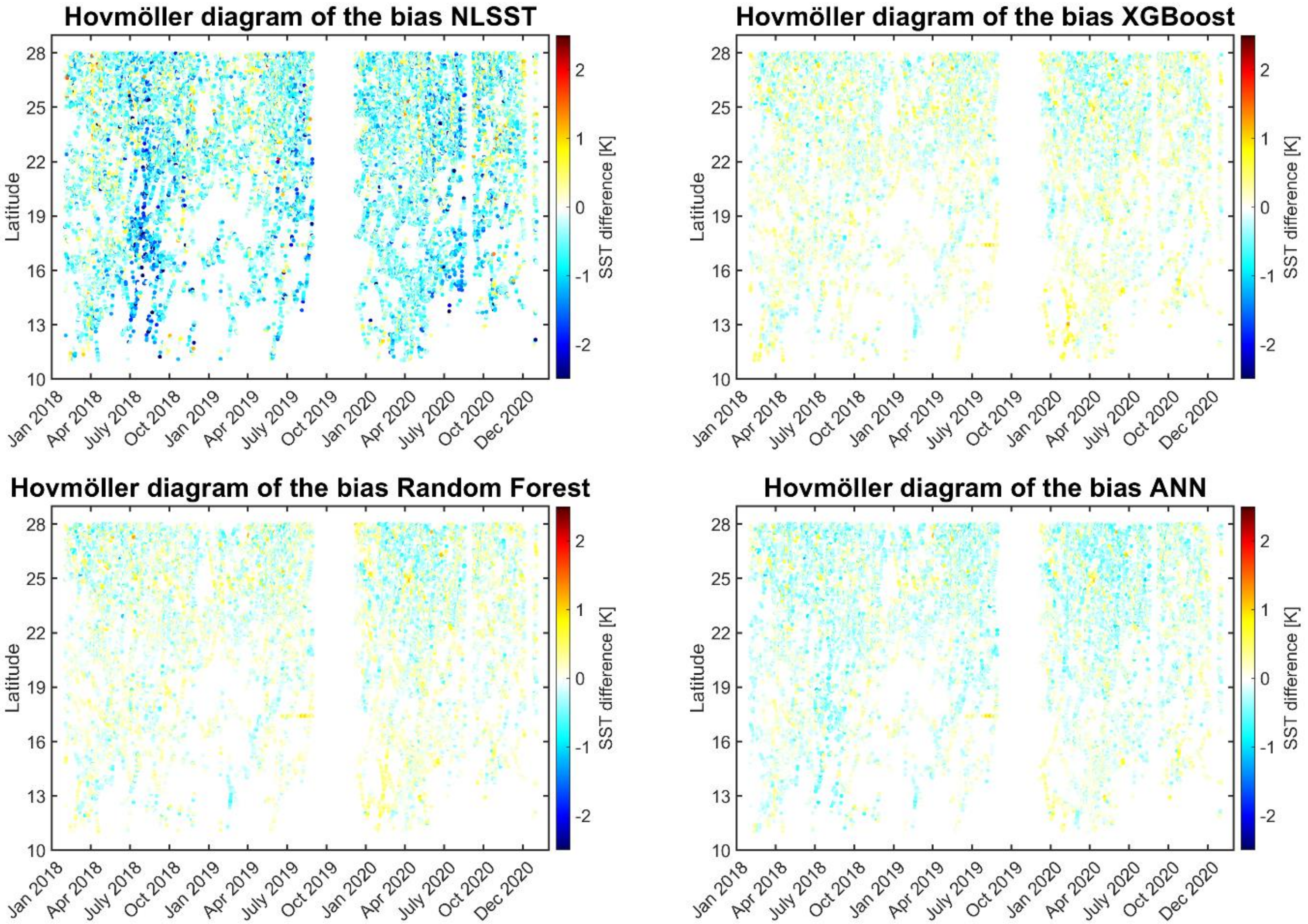




Left: Scatter plot of ML output SST against the drifting buoy measured SST. The dashed line is the 1:1 line and the red line is the least-squares linear fit. Middle: Histograms of ML output and measured SST as a function of the measured SST. Right: Differences between the ML output and measured SST. The colors indicate the difference, as shown on the right in degrees.

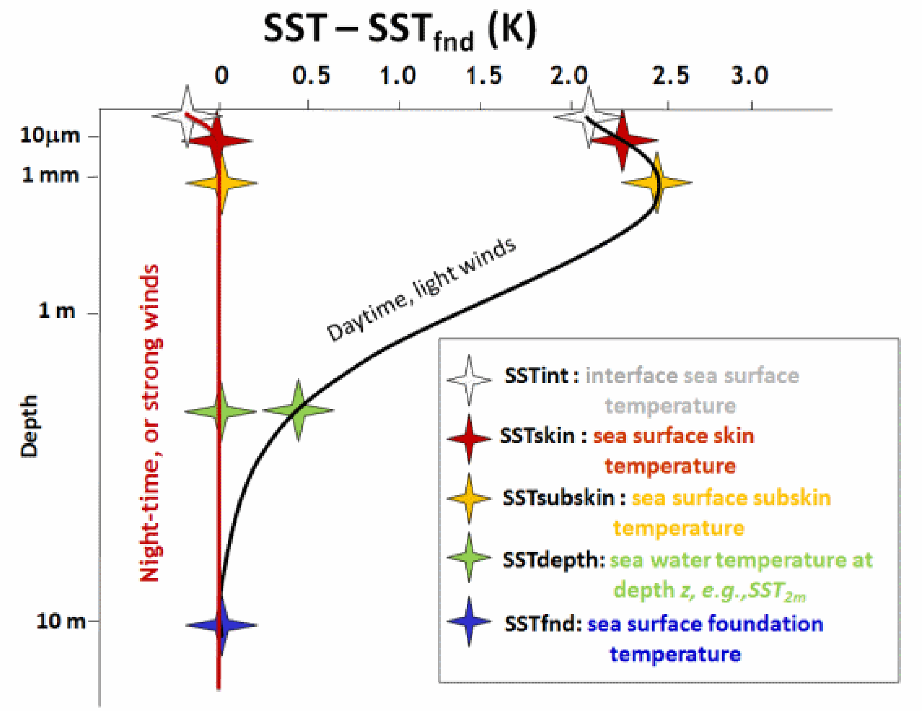


ML output minus drifting buoy measured SST as functions of wind speed, 2m air temperature, latitude, SST, month, and relative humidity. The error bars indicate the variance of the difference, and the error dot is the mean of the difference. The gray bars show the population within each x-axis interval.

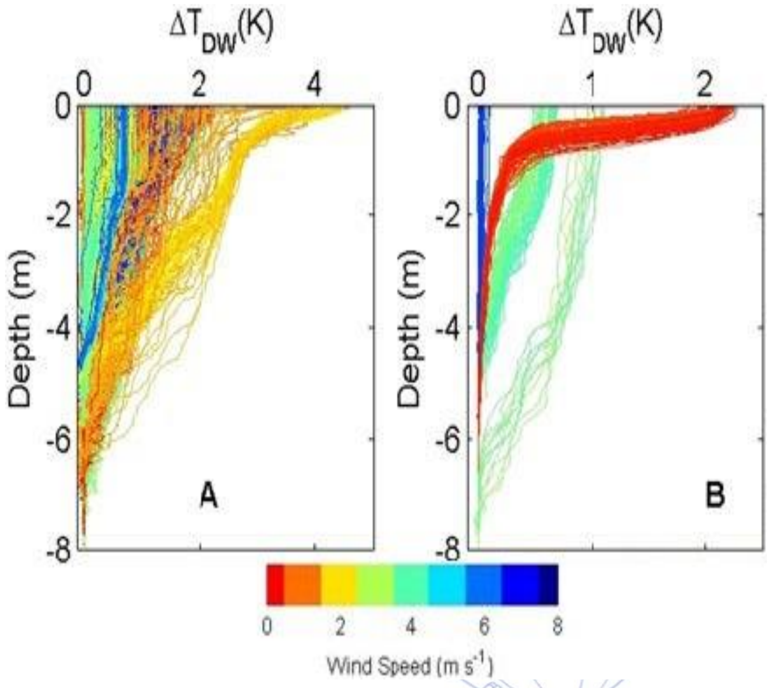


Hovmöller diagram shows the time and latitude evolutions of the bias from NLSST and three ML outputs. Because the drifting buoy data from July 2019 to Jan 2020 were not available, there is a gap between them. The color represents SST difference. The buoys data was not available during Oct 2019 so there are gaps.

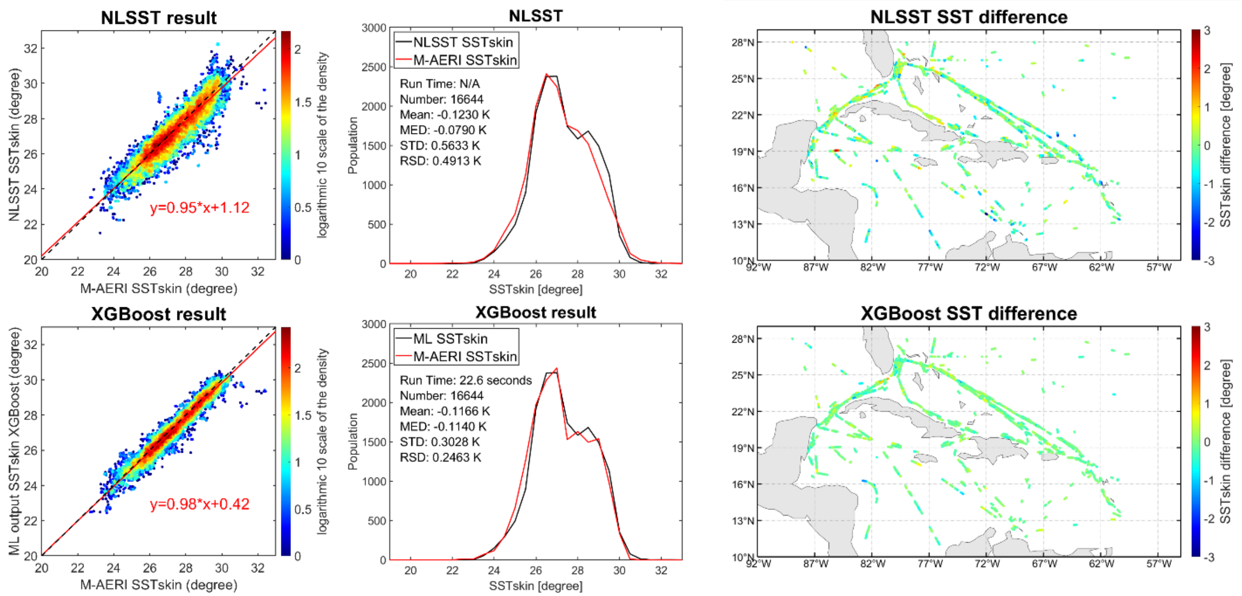
Due to the diurnal warming effect, in a skin-to-skin temperature comparison, SST_{skin} values from various ML methods are directly compared with M-AERI SST_{skin}.

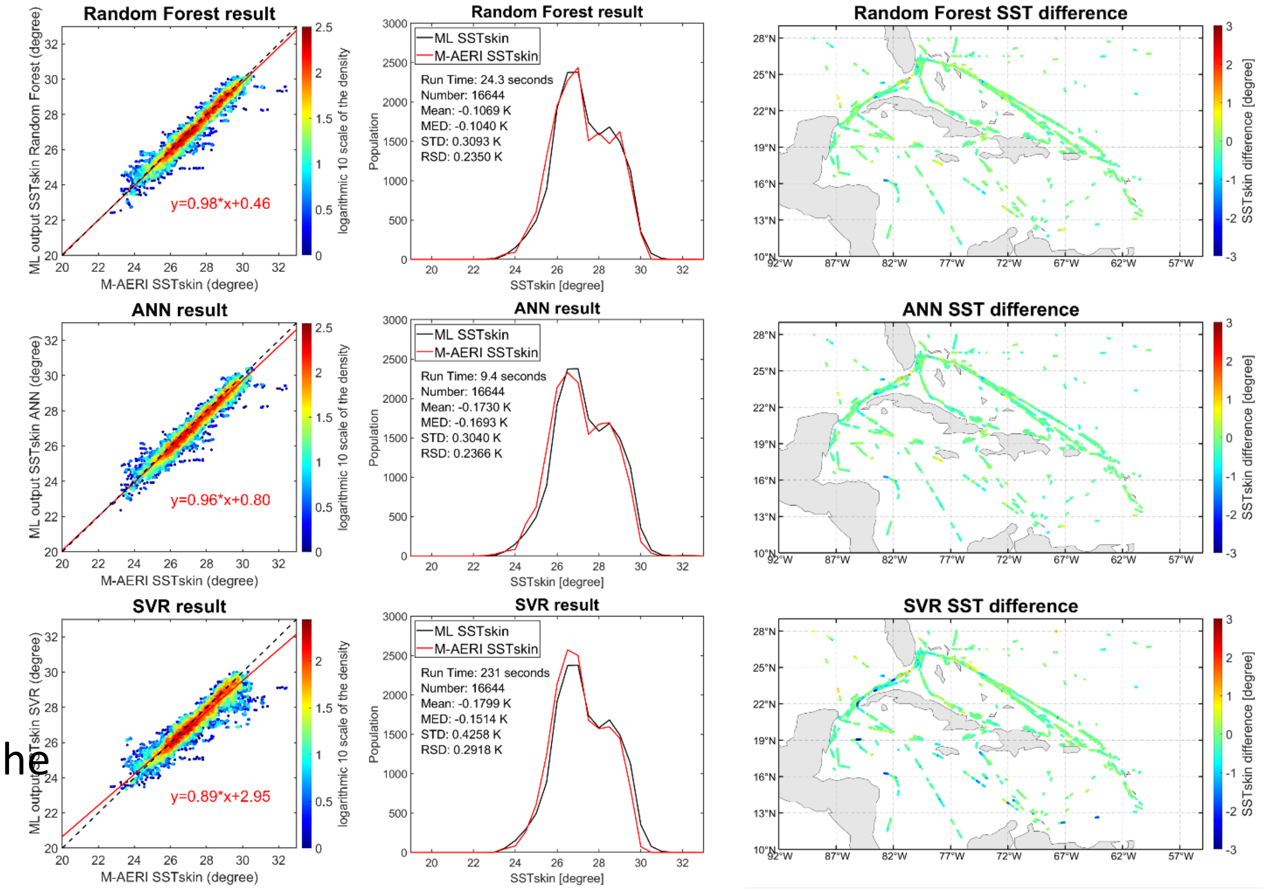


Donlon, et al. (2007). The Global Ocean Data Assimilation Experiment High-resolution Sea Surface Temperature Pilot Project. *Bulletin of the American Meteorological Society, 88, 1197-1213*

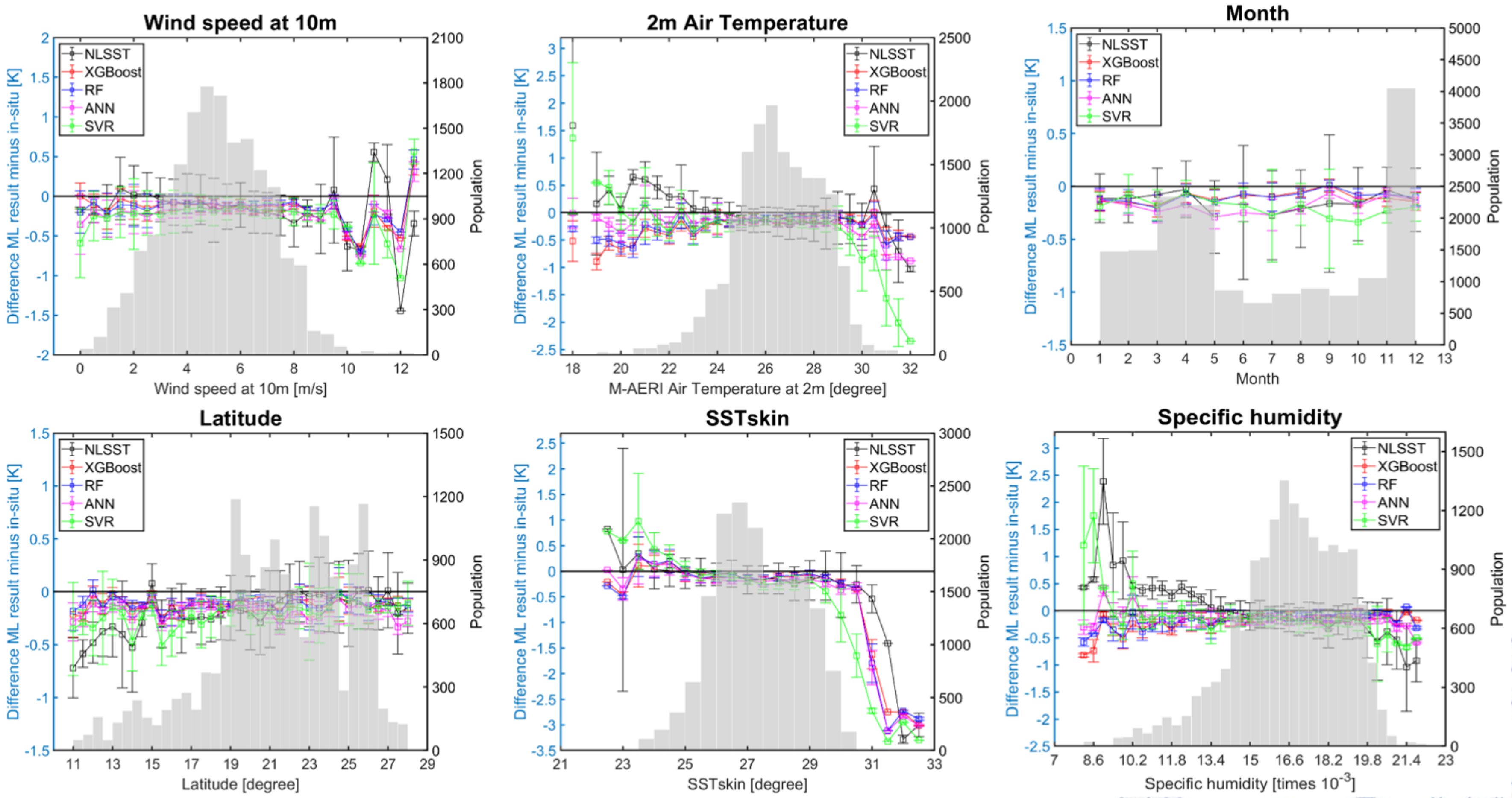


Upper ocean temperature profiles colored by wind speed at the time of the profile (A). A smoothed subset showing the clear wind-speed dependence (B). From Gentemann et al., (2009).





For ML output with M-AERI SST_{skin} measurements. We used the drifting buoys data to train the ML model, the output SST_{skin} was calculated with the ML output SST, diurnal warming, and COARE 3.6 cool skin model to get the SST_{skin}.



For ML output minus M-AERI SST_{skin} measurements.

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PART THREE

Conclusions & Future Work

Conclusions:

- A set of satellite and in-situ measurements, including SST, the atmospheric state and surface radiation, taken on research cruises, from surface moorings and drifting buoys was used to train the machine learning models.

- The reliability and shortcomings of various machine learning methods were assessed through comparisons with SST_{skin} derived from shipboard and other in situ measurements.

- Overall comparisons show encouraging results: the biases of various machine learning approaches vary between -0.076 K to 0.013 K; with the XGBoost showing the best correlation in a statistical analysis of in situ SST measurements.

- This study contributes to improving our understanding of the key environmental properties and will reduce uncertainty in earth science and climate research.

Future Work:

- We will expand the ML method to global oceans.

- The impact of other factors, such as different kinds of aerosol layers, sea salt sprays, etc. should be further explored with ML method.

- Such approaches as developed here can be applied to infrared satellite radiometers such as VIIRS on the Suomi-NPP and NOAA-20, SLSTR on Copernicus Sentinel-3 A/B satellites to improve the SST_{skin} retrievals.

THANK YOU!

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