Error Analysis of *in Situ* Sea Surface Temperature Data

Edward Mendoza[1], Candice Baptiste-Sexton[2], Hannah Aizenman[3], Dr. Michael Grossberg[4]

[1]2019 High School Initiative in Remote Sensing of the Earth Systems Science & Engineering (*HIRES*) Scholar; [2]Grants and Sponsored Programs, City College of New York; [3]Department of Computer Science, City College of New York; [4]NOAA Center for Earth System Sciences and Remote Sensing Technologies and Department of Computer Science, City College of New York

Introduction

Weather and climate affect almost everything we do, from commerce to travel to agriculture, thus, monitoring and prediction are essential. For example, Sea Surface Temperature (SST) is important because we depend on SST for our measurements of the earth's atmosphere, and for predicting phenomena such as sea fog, sea breeze, and cyclone formation.[1]

Despite the advances in satellite technology, we still must reconcile inferred measurements from space with measurements in the ocean because *in Situ* (in ocean) measurements are not subject to being blocked by clouds or aerosols like satellites[2]. However, even physical sensors floating in the ocean can produce error.

This study aims to help researchers better understand the sources of *in Situ* SST error and what can be done to help reduce error frequency.

Objective

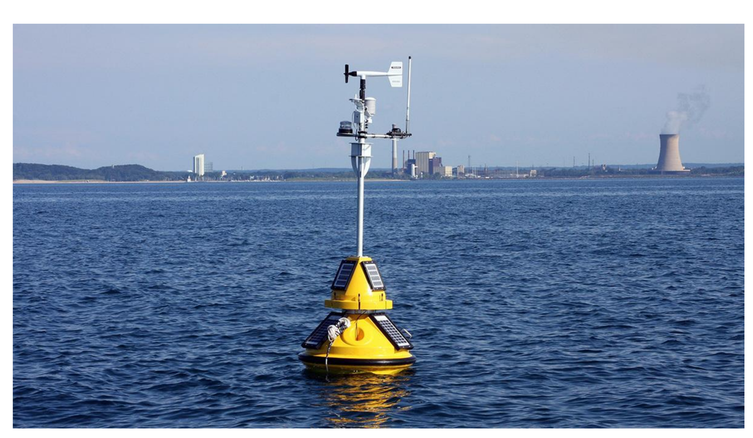
Our goal was to determine how various factors such as the season, time of day, platform usage and history influence the data by way of error bias. Our analysis was informed by the comparison of measurements collected by three individual platforms and the **Ocean Sea Surface Temperature and Sea Ice Analysis (OSTIA) SST** values. Also looked at other recorded values like air temperature and cloud coverage to see if they play a role in error formation and what could do to minimize them.

Platforms used to collect Sea Surface Temperature Data

Lihue[4] - Container Ship

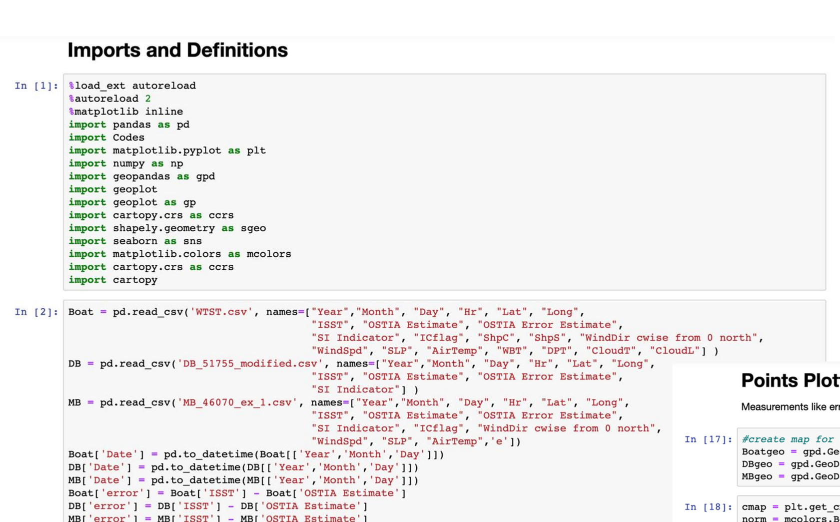
Moored Buoy[5]

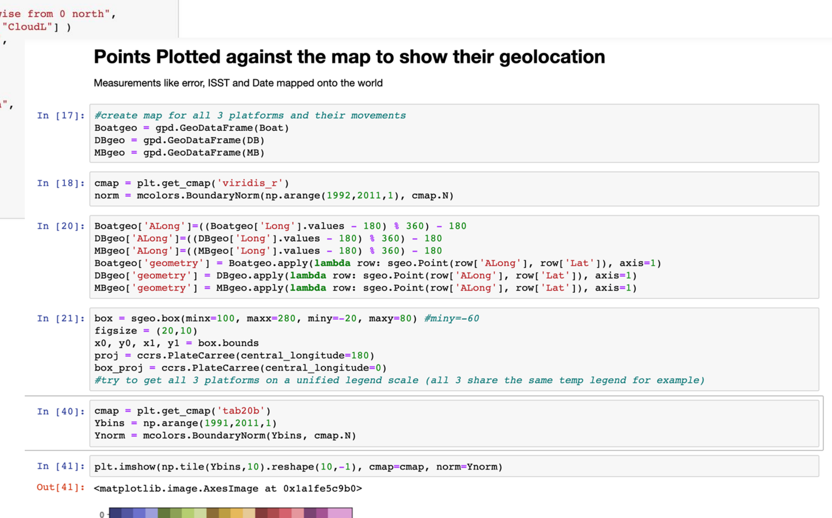
Drifting Buoy[6]



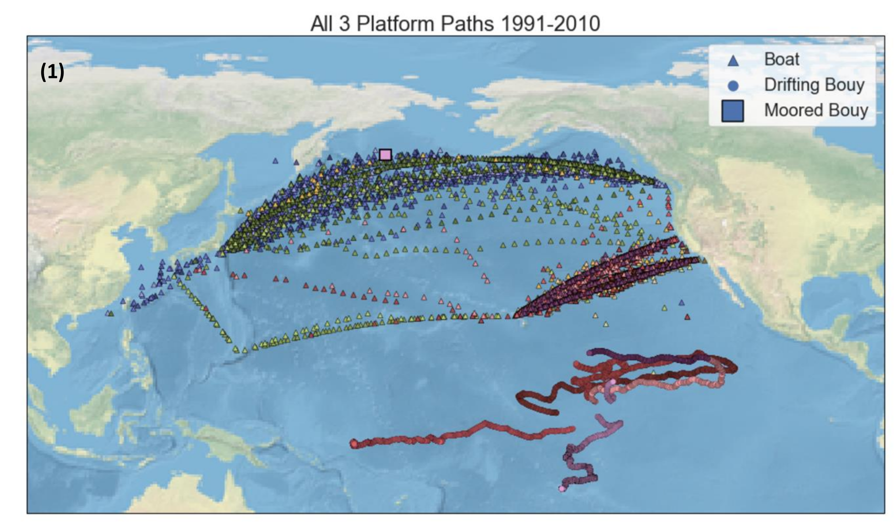
Methods

1. Data were taken from 3 individual platforms pictured above, the Lihue, and both Moored and Drifting Buoys.
2. We used **Python** as our programing language because of its versatility and easy interface
3. We fed our data into Python and used **Matplotlib** to make scatter plots to visualize trends
4. We then defined error as the difference between the **estimated SST** values and the **actual SST** measurements recorded.
5. Furthermore, we used libraries like **Pandas** and **Seaborn** to plot the points onto real world maps by giving them Geometry, via **Geopandas**, which converts the longitude and longitude values into geographical coordinates.

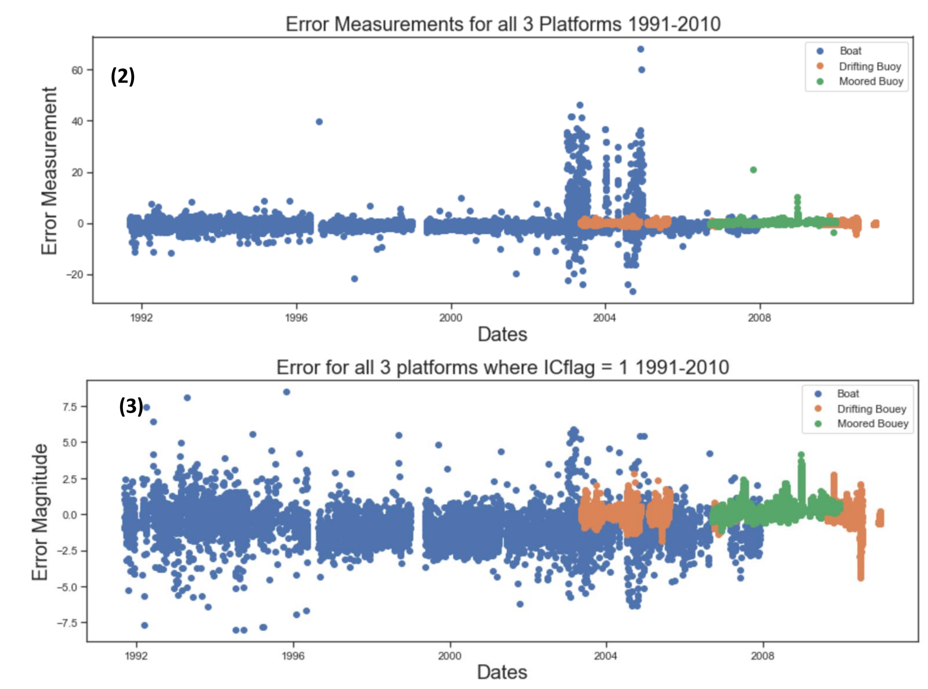




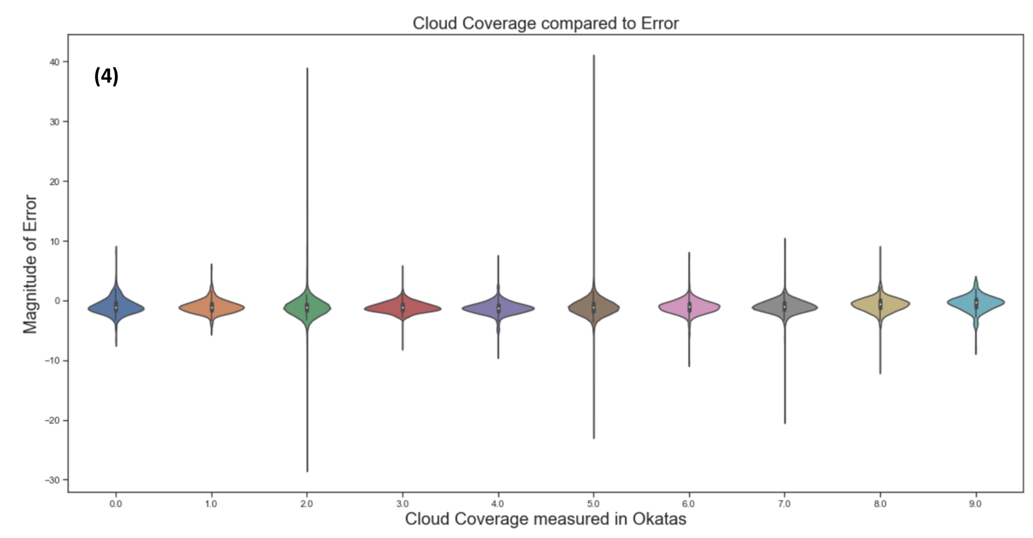
Results



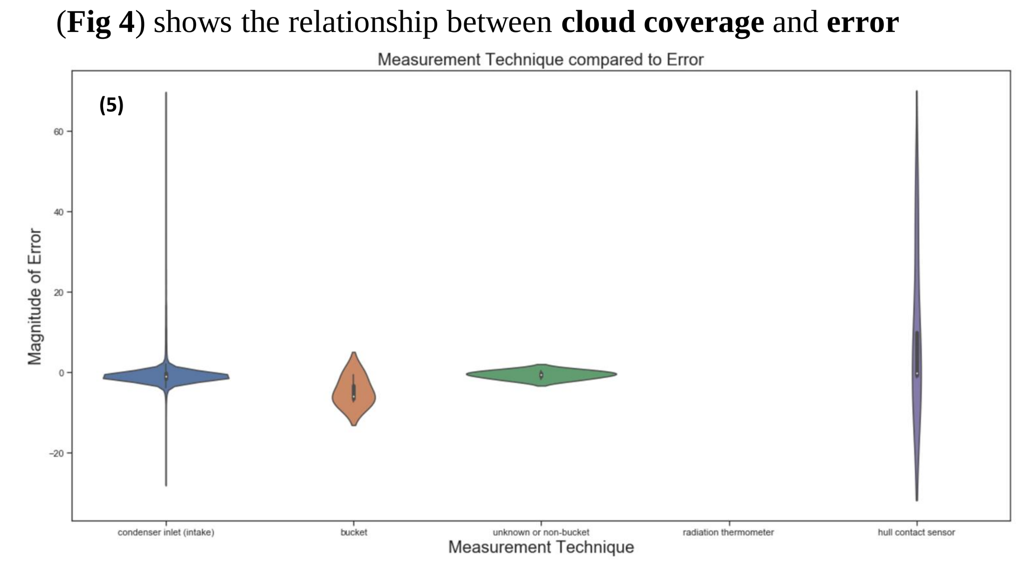
(**Fig 1**) Shows the **path** of the **3 platforms** over 1991-2010



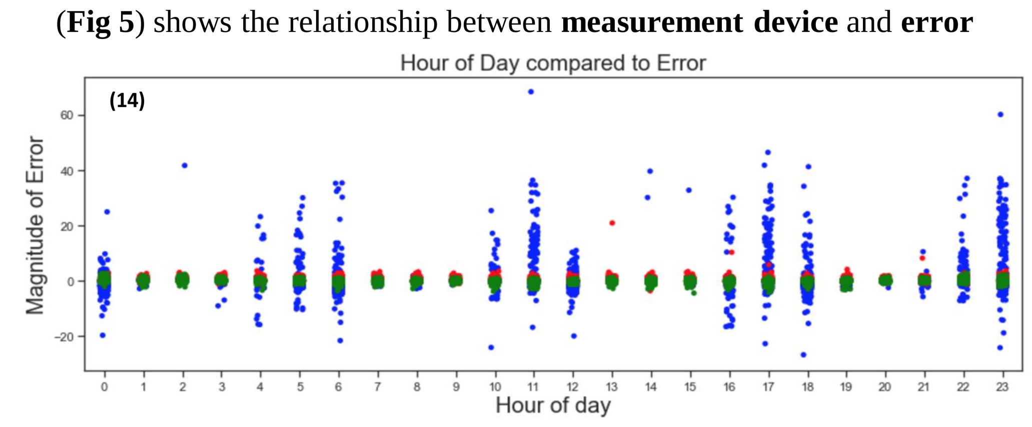
(**Fig 2**) shows the **error unfiltered** by the ICOADS, while (**Fig 3**) show the measurements that **passed the filter**. The filter was able to reduce the maximum error from 68 to 8, resulting in over **80% decrease** in error.



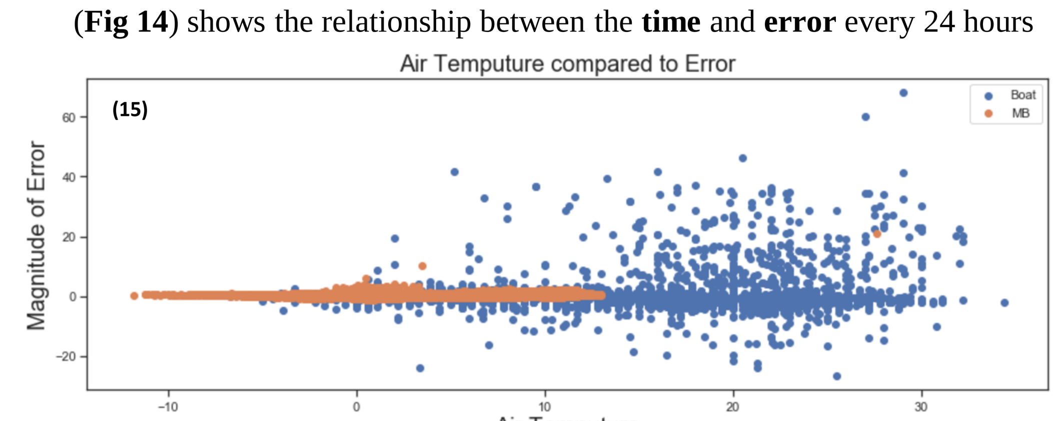
(**Fig 4**) shows the relationship between **cloud coverage** and **error**



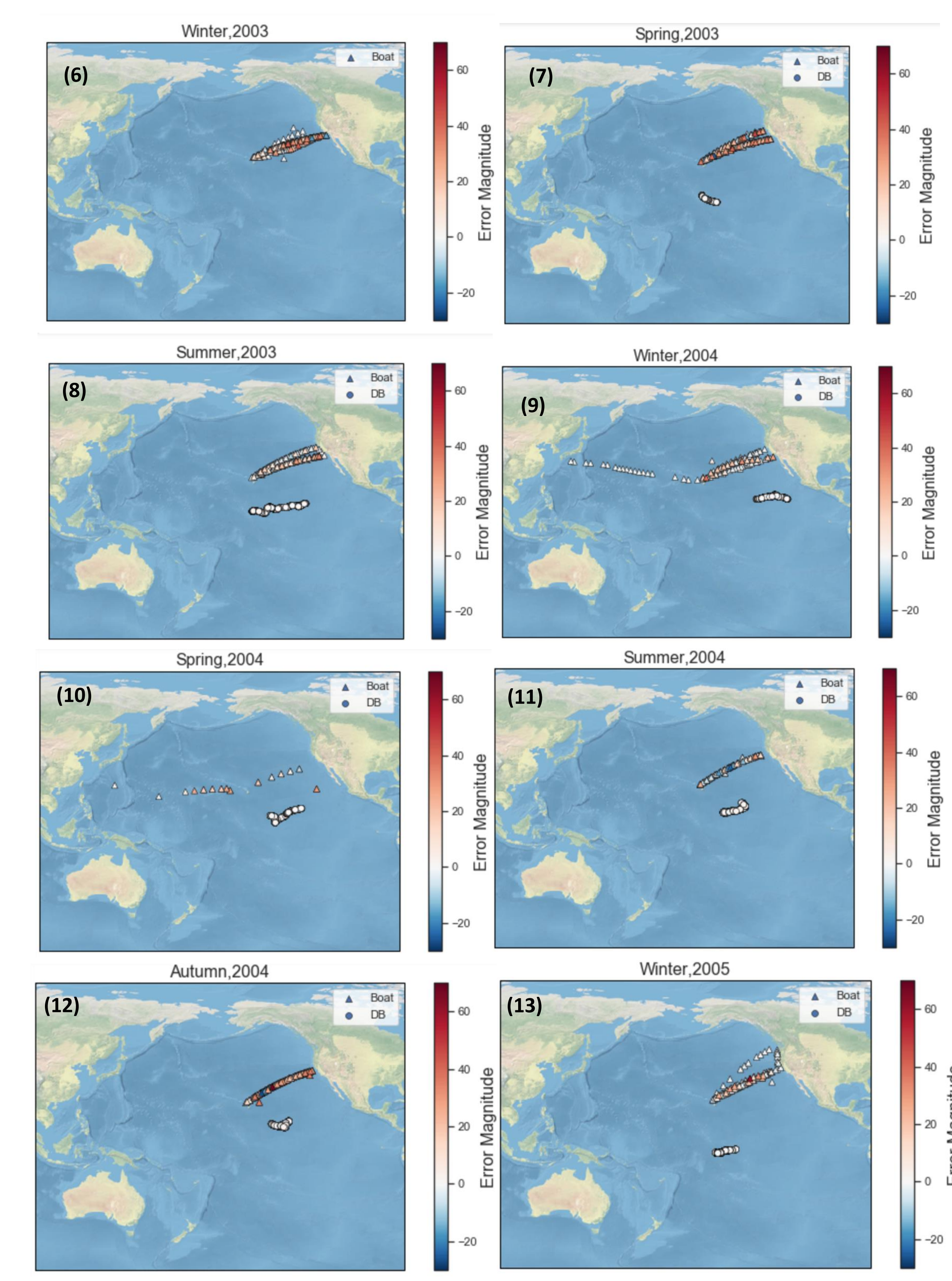
(**Fig 5**) shows the relationship between **measurement device** and **error**



(**Fig 14**) shows the relationship between the **time** and **error** every 24 hours



(**Fig 15**) shows the relationship between the **Air Temperature** and **error**



(**Fig 6-13**) Timelapse from **Winter 2003** to **Winter 2005** showing the **errors** made per **season** per **platform**. This shows the **biggest spike** in **error** over the **shortest amount** of **time** belonging to the **Boat**.

Conclusions

- From the scatter plots and world maps, we can see that most variables have **negligible effects** on the error.
- **Ships** are the most **unreliable** platform, as they show larger instances of error and have been documented as having more problems with their measurement techniques[3].
- The **ICOADS** filter has proven to be **very effective**, because our analysis shows that it filters most of the error.

References

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