MP456
Remote Sensing Fundamentals and Applications

ANALYSIS OF DISSOLVED OXYGEN

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I Introduction

Motivation

Remote sensing has been an essential means of monitoring dynamic changes such as rainfall, wind, temperature, et al. for weather monitoring and disaster forecast.

Although water quality remains an essential element for the survival of flora and fauna, it is still monitored through in-situ monitoring stations. Even though these stations provide accurate data, their temporal and spatial resolution is inadequate. Thus, there is an opening for satellite remote sensing to develop a method to monitor water quality.

One such parameter for monitoring water quality is dissolved oxygen, which is defined as the amount of free and non-compound oxygen dissolved in the water body(Chi et al., 2020). Monitoring DO can help us predict changes in that marine ecosystem and implement remedies, considering that even a minor change can cause a significant negative impact.

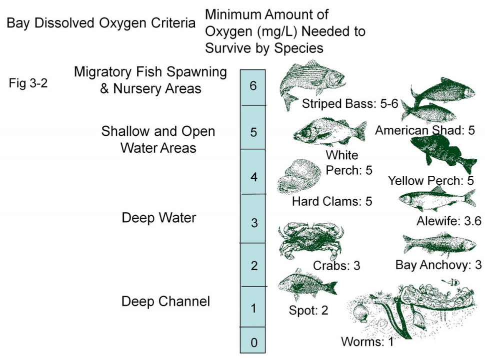


Figure 1. Requirement of DO for marine life

Literature such as Keeling et al., 2010 [?] suggests that dissolved oxygen in the open ocean has been declining in the past centuries due to natural causes or increased temperature or changes in salinity.

DO decreases exponentially with the increase in salinity(Chi et al., 2020).

In summer and winter, the temperature differential is small between day and night, affecting the convection process and hampering the mixture of upper and lower layers of the ocean; due to this and continuous consumption of DO in the lower layers can lead to hypoxic situations. The temperature differential is high in spring and autumn between day and night, allowing the layers to mix and keep the DO concentration consistent.

The traditional method of in-situ measurements is very time and labor-intensive, so this project aims to develop and verify a correlation between dissolved oxygen, temperature, salinity, and chlorophyll content.

II Data & Methodology

This project aims to develop and verify a correlation between the water parameters such as chlorophyll concentration, temperature, salinity, pH, and specific concentration with Dissolved Oxygen(DO). Therefore, we require both in-situ and remote observation to make quantitative predictions.

Here we have utilized the USGS real-time water parameters for in-situ observations and AQUA-MODIS from NASA ocean color(NASA OBPG) as the remote dataset, discussed in section II.I and II.II respectively.

For analyzing and predicting the dissolved oxygen concentration, a multiple regression model is developed using the data from 2018-01-01 to 2021-12-31, discussed in section II.III

II.I In-situ data: USGS WaterQualityWatch

Introduction

USGS provides an almost real-time environment to gather multiple parameters from water in/nearby the United States, i.e., water temperature, pH, salinity, and specific conduction.

It provides the data in tab-separated *.rdb* files with more information about the format available at waterdata.usgs.gov.

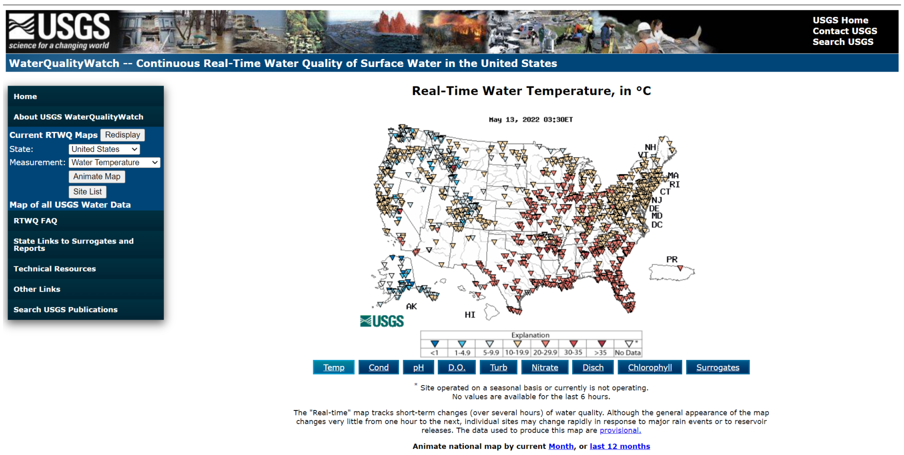


Figure 2. USGS WaterQualityWatch stations

Data processing

The location chosen for analysis is *ORIENT HARBOR AT ORIENT NY*, located at $41.13663889°N$ and $-72.30675°E$, accurate to $\pm.1s$

The rationale behind choosing this location was the easy availability of data for 2018-01-01 to 2021-12-31 and its closeness to the Atlantic ocean.

Its closeness to the Atlantic ocean made it easy to obtain the subset of data from the ocean color dataset of Sea Surface Temperature(SST) and Chlorophyll($Chlor\_a$)

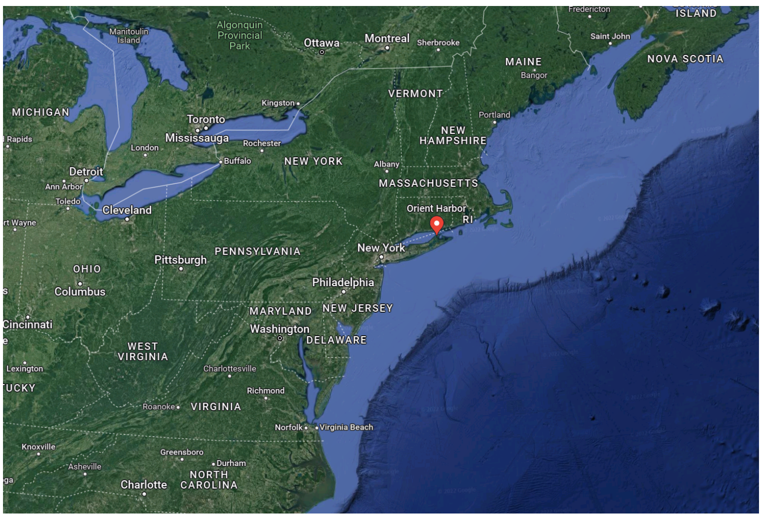


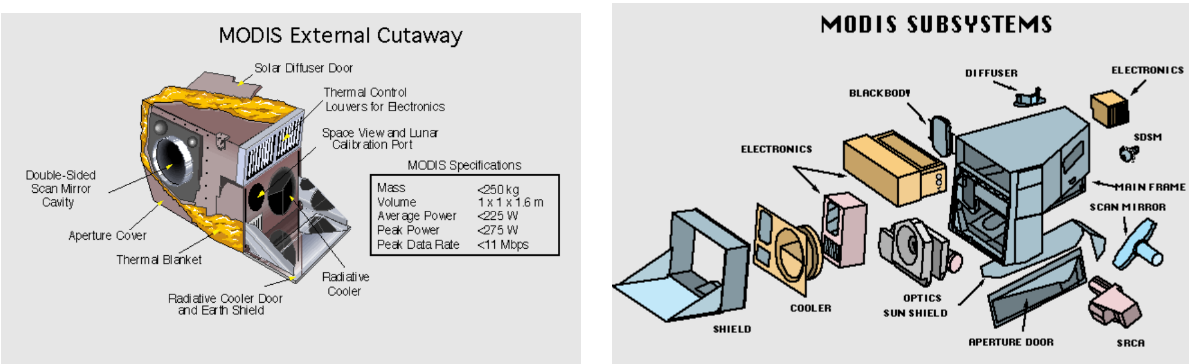
Figure 3. Satellite blown-up view

Figure 4. Satellite close-up view

NOTE:

For better results and analysis choosing multiple locations with adequate separation would be ideal, but the turbidity and water contamination may bias our analysis, so we have restricted to a single location as a proof-of-concept.

II.II Remote data: Aqua-MODIS



(a) MODIS external

(b) MODIS subsystems

Figure 5. MODIS (credits: wikipedia.org)

Introduction

MODIS (or Moderate Resolution Imaging Spectroradiometers) is an instrument onboard the Terra(EOS AM) and Aqua(EOS PM) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. MODIS is designed to provide measurements in large-scale global dynamics, including oceans, land, and cloud cover. The Scan Mirror Assembly uses a continuously rotating double-sided scan mirror to scan ±55-degrees and is driven by a motor encoder built to operate at 100 percent duty cycle throughout the 6-year instrument design life

Specification

It captures 36 spectral bands ranging in wavelength from $0.4\mu m$ to $14.4\mu m$ and at varying spatial resolutions. Together the instruments image the entire Earth every 1 to 2 days. It has a sun-synchronous, near-polar orbit of 705km with a swath of 2300km cross-track by 10km along

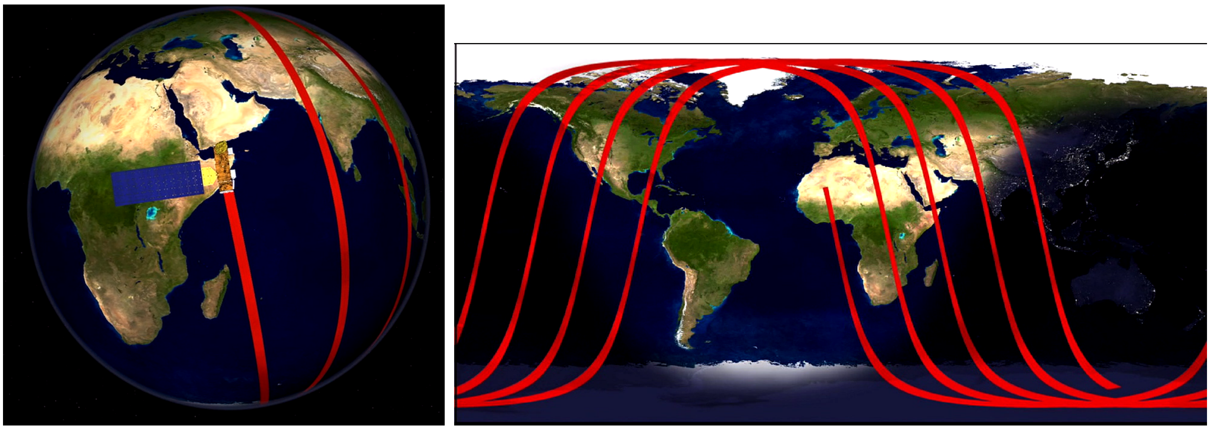


Figure 6. AQUA-MODIS orbit, credits:NASA GSFC

the track at nadir. It has a scan rate of 20.3rpm cross track. MODIS's temporal resolution is 1-2 days and was launched and designed to work for at least 6-years.

Data processing

Sea Surface Temperature (SST)

The Sea surface temperature is observed at $11\mu m$ and $4\mu m$ for day and night respectively with $4km$ and $9km$ spatial resolution. In this analysis, we have utilized the 11μ with $4km$ resolution daily data.

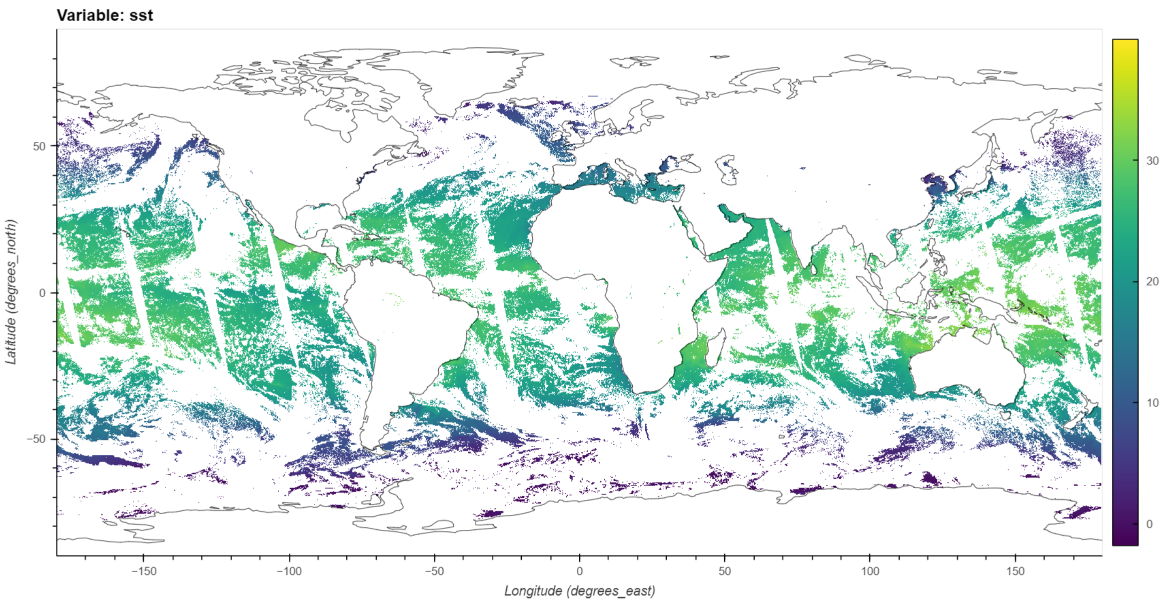


Figure 7. Sea Surface Temperature($^{\circ}C$; 11μ) 2018/01/01
Processed and plotted in python with using 'nctoolkit'; the white portions represent land mass, swaths and cloud cover.

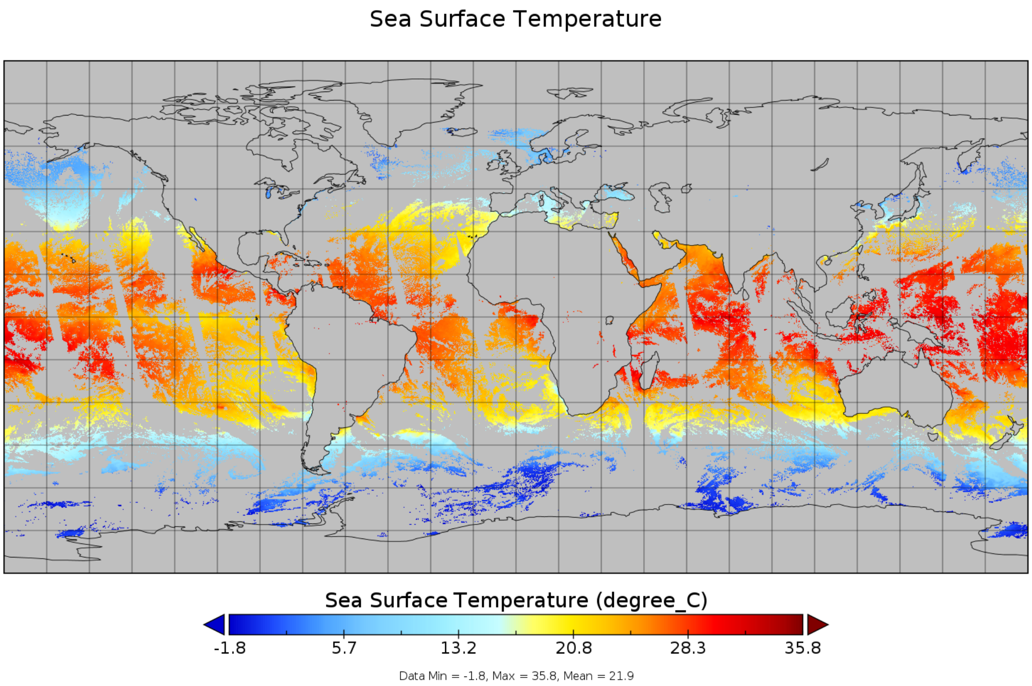


Figure 8. Sea Surface Temperature($^{\circ}C$; 11μ) 2018/01/02
Processed and plotted using NASA Panoply with interpolations enabled

Monthly averaged

The daily fluctuations vanishes when we average for a month; the remaining fluctuations are called monthly temperature anamolies.

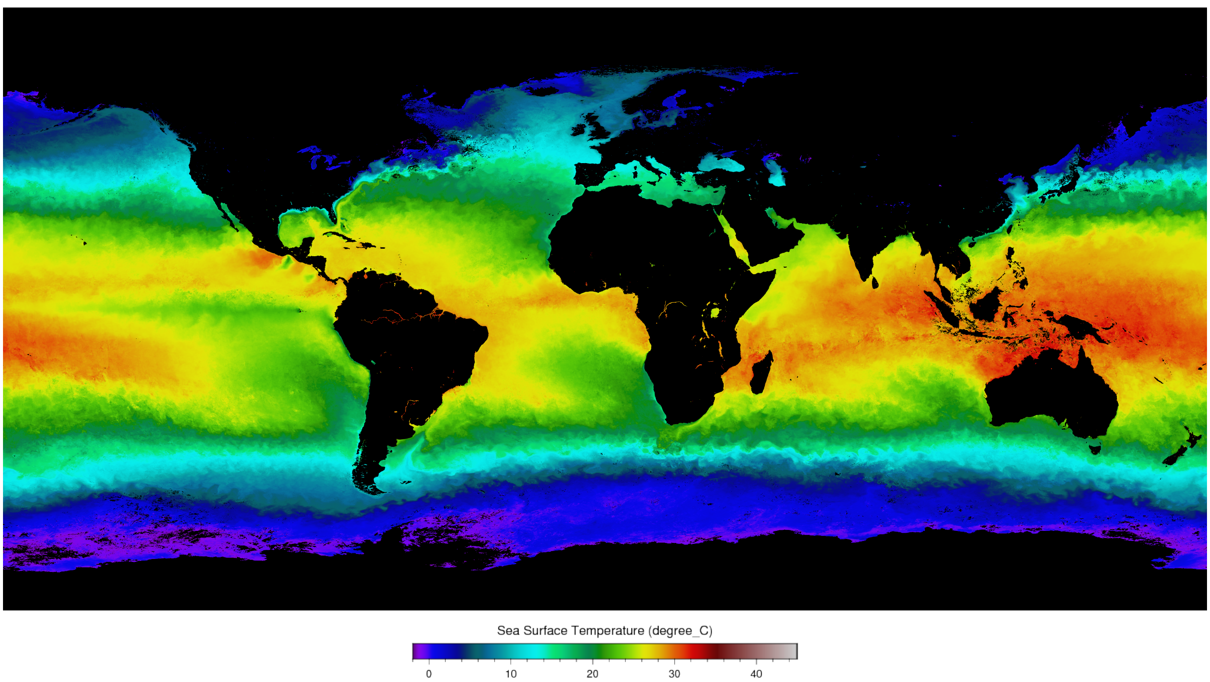


Figure 9. Montly averged temperatures for January 2018

Chlorophyll

The chlorophyll content cannot be directly measured using remote methods, so in this analysis the chlorophyll-A is computed using the NASA OCI algorithm.

This algorithm returns the near-surface concentration of Chlorophyll-A(chlor_a) in $mg\ m^{-3}$, calculated using an empirical relationship derived from in-situ measurements of chlor_a and remote sensing reflectances (R_{rs}) in the blue-to-green region of the visible spectrum.

In this analysis, we have utilized the $4km$ spatial resolution daily dataset.

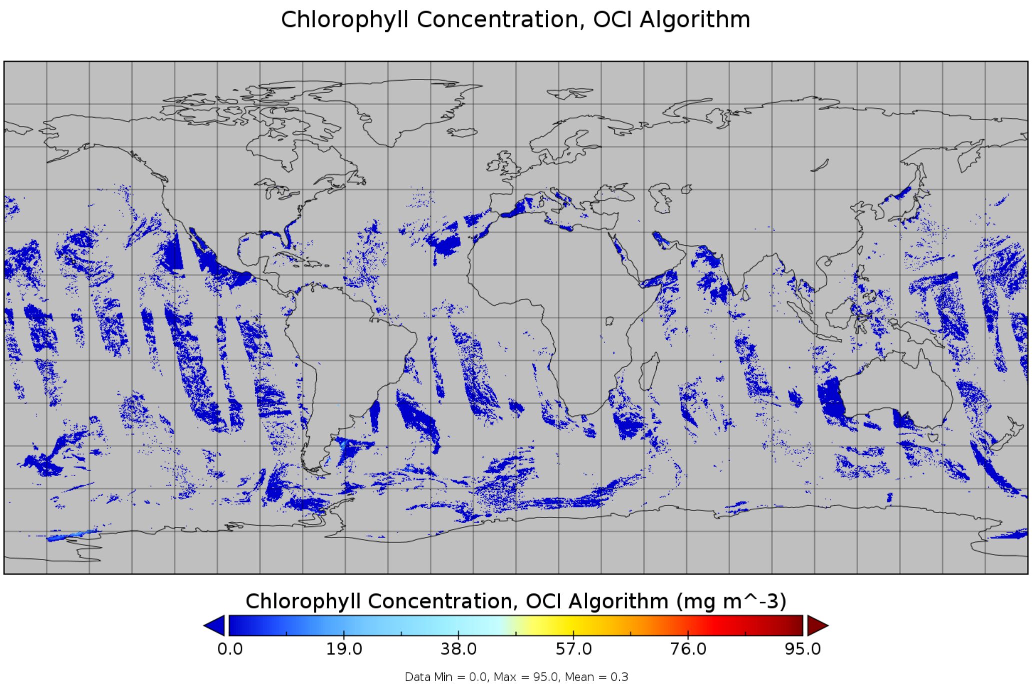


Figure 10. Chlorophyll-A 2018/01/04
Processed and plotted using NASA Panoply with interpolations enabled

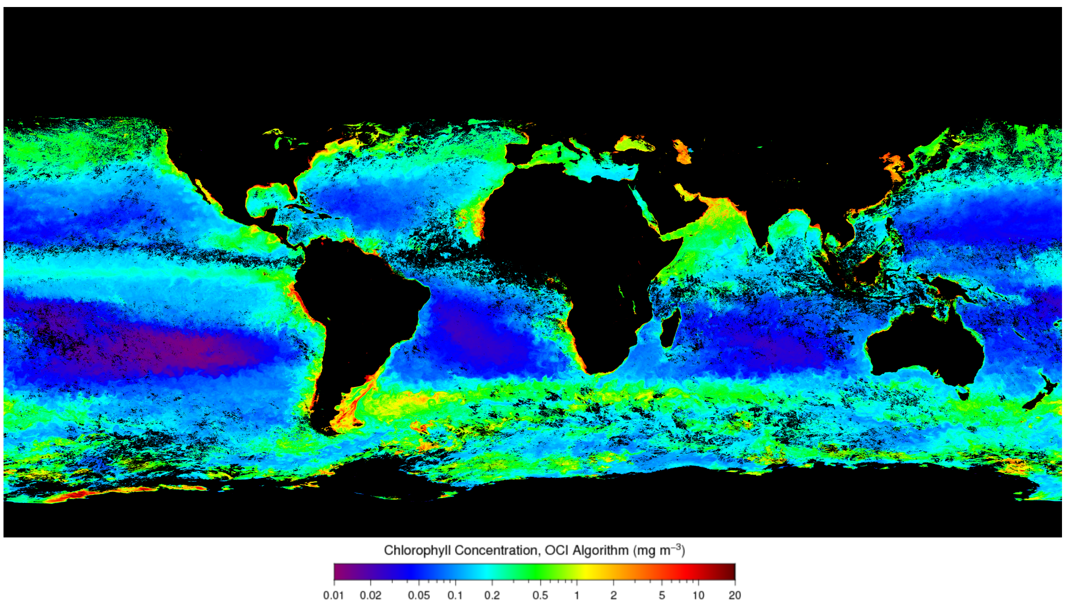


Figure 11. Montly averged chlorophyll-a (OCI) for January 2018

II.III Methodology

The in-situ data source is *ORIENT HARBOR AT ORIENT NY*, but the remote data is worldwide with 4km resolution. Therefore, we limit our remote data to a polygon around the monitoring station. To reduce complexity, we choose this polygon to be a box with a latitudes range of $[40,\ 41.250]°N$ and a longitudes range of $[-73,\ -71]°E$; this box encompasses an area of 25000 km^2 (refer to Fig 8).

The remote data subset is spatial averaged to account for fluctuations inside the box.

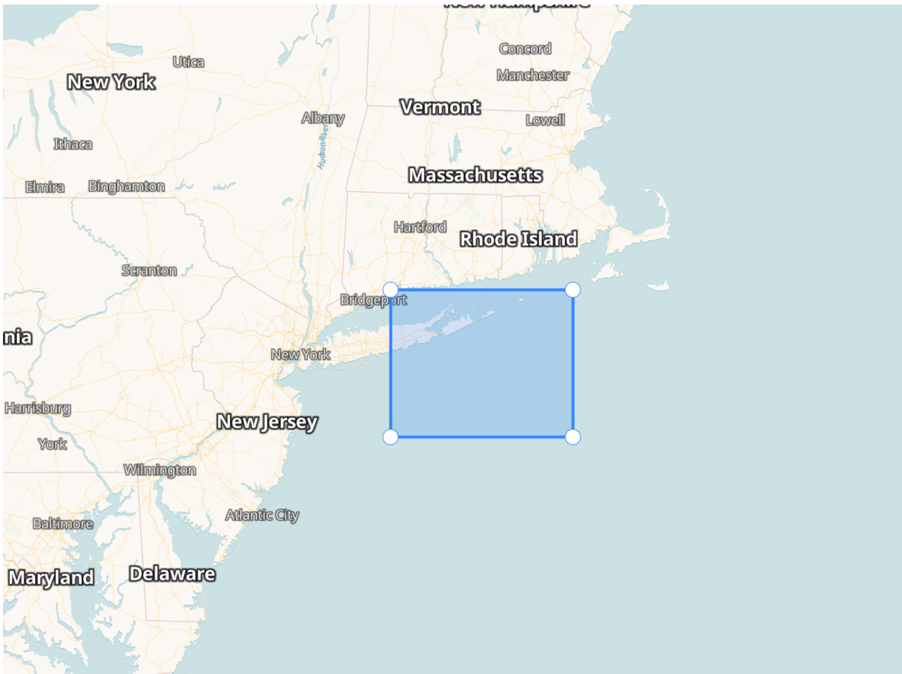


Figure 12. Subset for remote data

After gathering the data, we use the supervised machine learning algorithm called the **Multiple Linear Regression** to develop a relationship.

$$y = \beta_0\ +\ \beta_1 x_1\ +\ \beta_2 x_2\ +\ \cdot\ \cdot\ \cdot\ +\ \beta_n x_n \tag{1}$$

We have utilized pH, salinity, field temperature, remote temperature and specific conductance as our input parameters, so our equation will become

$$DO = \beta_0\ +\ \beta_1 pH\ +\ \beta_2(\text{salanity})\ +\ \beta_3(\text{field temperature})\ +\ \beta_4(\text{MODIS SST})\ +\ \beta_5(\text{specific conductance}) \tag{2}$$

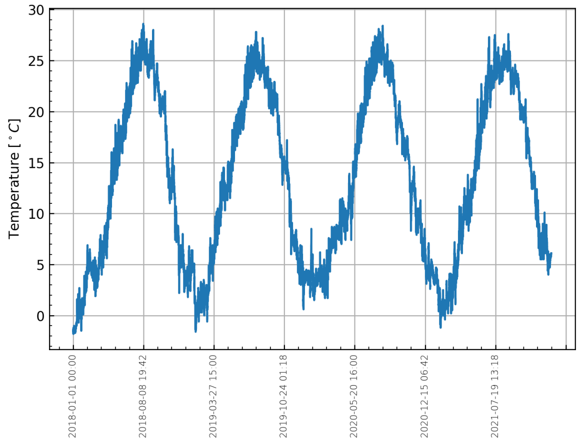
We split our dataset into two sets, labeled for supervised learning and unlabled data for testsing with 0.8 and 0.2 ratio respectively.

III Analysis

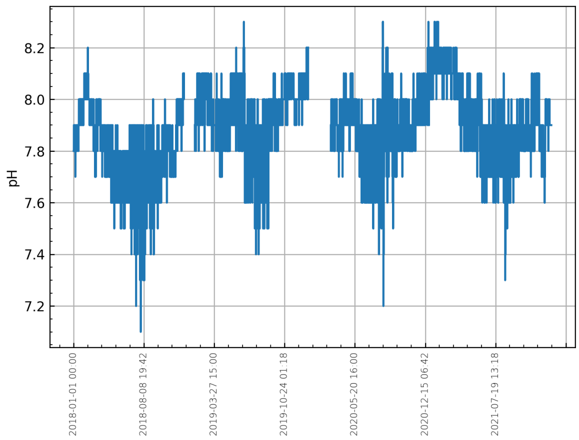
III.I Field data

Time-series data for field data from *ORIENT NY* monitoring station; the data is collected at intervals of 6mins, with no data available represented by NaN.

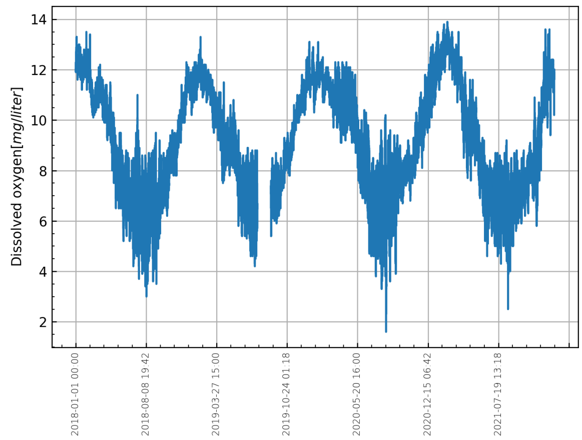
As represented in Fig.13a, the temperature shows a seasonal pattern at a frequency of 6-8 months, representing the gap between summer and winter seasons. Other parameters pH, dissolved oxygen, specific conductance and salinity also follows a similar pattern with frequency around 6-months.



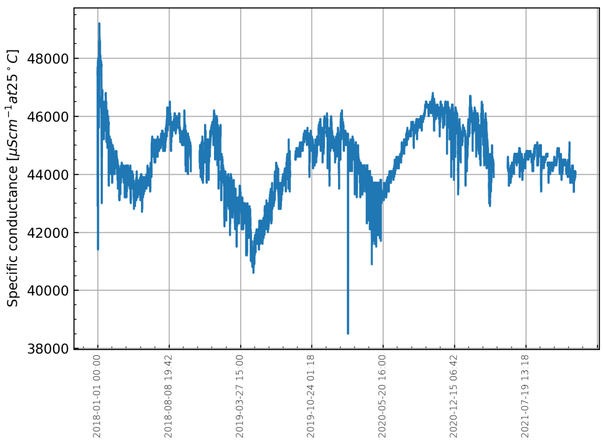
(a) Temperature



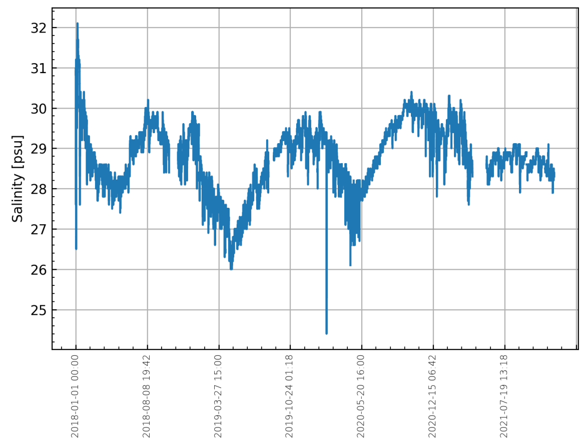
(b) pH



(c) Dissolved oxygen(mg/L)



(d) Specific conductance($\mu S/cm$)

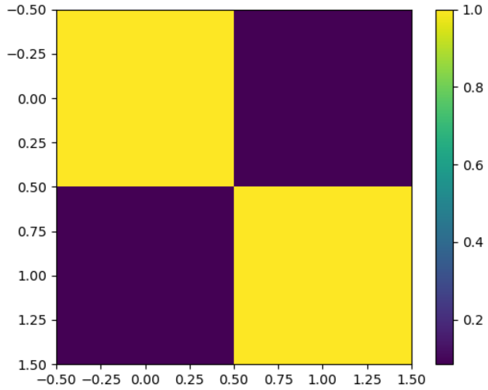


(e) Salinity(psu)

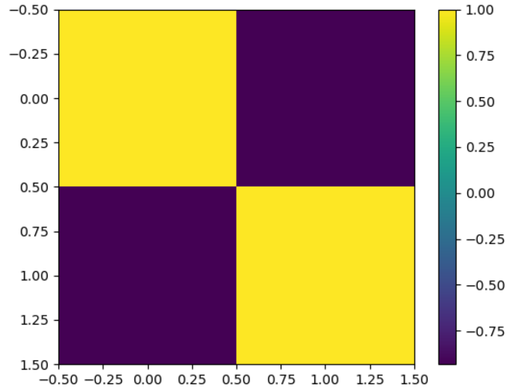
Figure 13. Orient Harbour New York, US

Correlation with dissolved oxygen

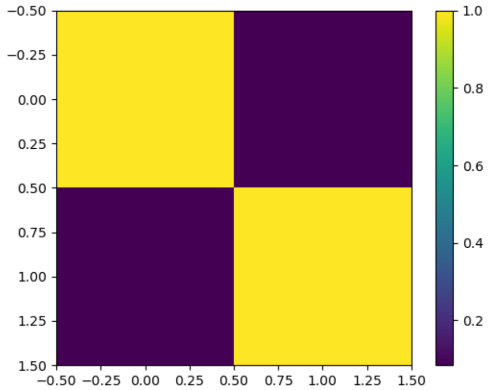
By using our field data we can compute correlations matrices to solidfy our understanding of correlations between dissolved oxygen and pH, dissolved oxygen and specific conductance et al. Through these correlation matrices we can verify that our parameters have a positive correlation with the concentration of dissolved oxygen.



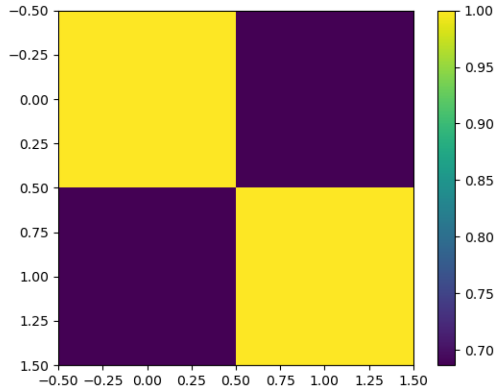
(a) Dissolved oxygen and salinity



(b) Dissolved oxygen and temperature



(c) Dissolved oxygen and specific conductance

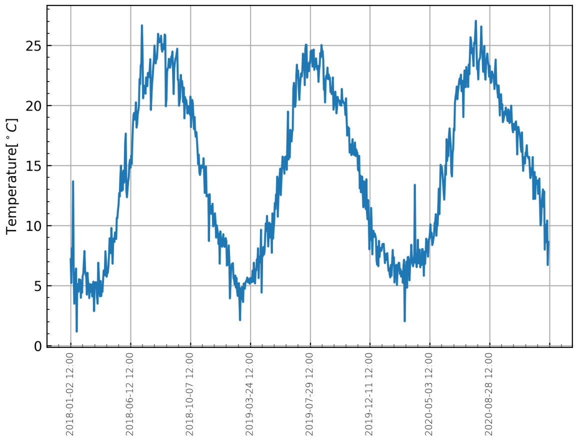


(d) Dissolved oxygen and pH

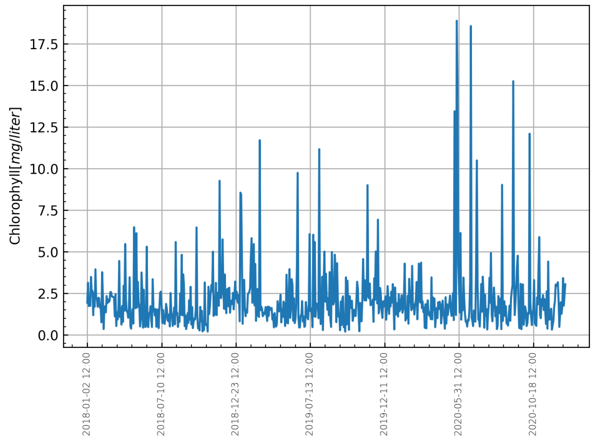
Figure 14. Correlation matrics with dissolved oxygen

III.II AQUA-MODIS data

Fig.15 represents the time-series data from the spatially averged AQUA-MODIS dataset for SST and Chlorophyll-A for our geofenced location of *ORIENT NY*



(a) SST($11\mu m$; $°C$)

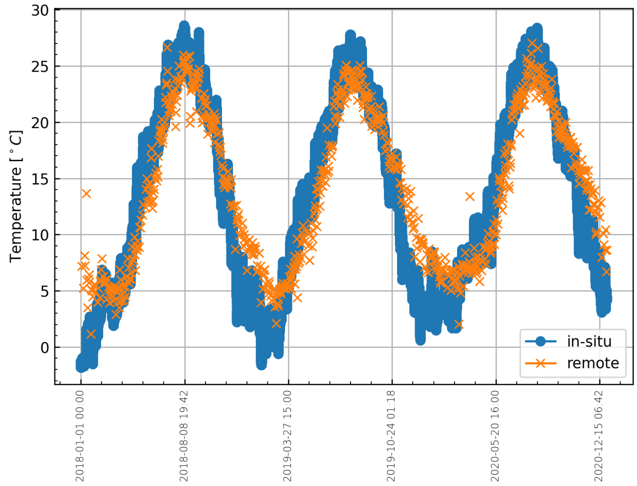


(b) Chlorophyll-A(mg/m^3)

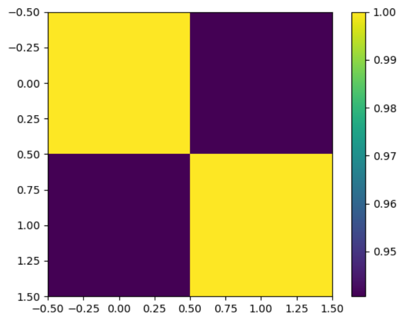
Figure 15. AQUA-MODIS

III.III Verification

By plotting a correlation matrix between the field sea temperature and MODIS sea surface temperature we can make sure they are consistent with each other thus reduceing the possibility of an error. we verify our correlation of in-situ measured temperature and remotely observed SST.



(a) In-situ sea temperature vs MODIS SST



(b) Correlation matrix

Figure 16. Verification of in-situ temperature and AQUA-MODIS SST($11\mu m$)

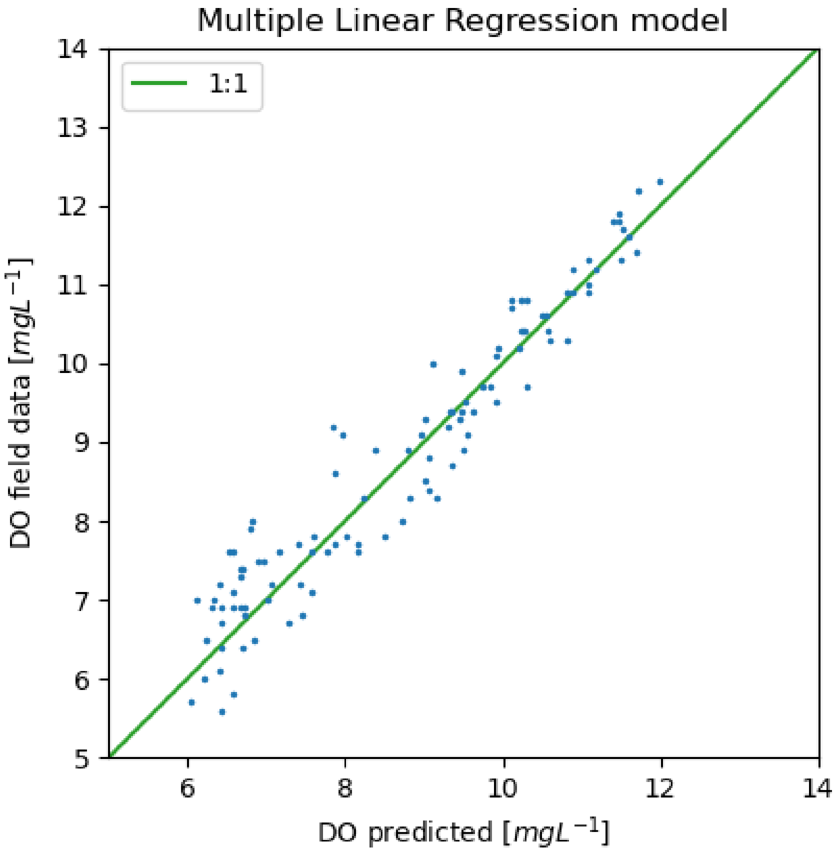


Figure 17. Model test

Fig.17 suggests a good correlation with predictions and test labels of the data. We find that there is 24% error associated with our predictions which could be reduced by using more longer and vivid datasets.

IV Conclusion

In this study, DO measurements of Orient NY monitoring station and MODIS data was used to develop and validate the multiple linear regression model.

As discussed in section III, the MLR model predicts with adequate accuracy which could be improved by adding data from multiple sources with multiple water characteristics.

All codes for extraction and processing of data are available at devanshshukla99/Analysis-of-DO.

V References

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