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Using NASA Earth Observations to Monitor Seagrass Extent and Water Quality Parameters in Southern California

DEVELOP Technical Report
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1. Abstract

Eelgrass (*Zostera marina*) is a species of submerged aquatic vegetation found in shallow bays and estuaries with soft seafloors. Eelgrass is recognized for providing ecosystem benefits, such as carbon sequestration, sediment stabilization, water clarification, and fish and wildlife habitats. However, eelgrass is impacted by both marine and terrestrial threats associated with climate change. In this project, we worked with the Southern California Coastal Water Research Project, the National Oceanic and Atmospheric Administration's National Marine Fisheries Service, and the State of California San Diego Regional Water Quality Control Board to investigate water quality parameters (i.e., chlorophyll-a concentration, sea surface temperature, and turbidity) associated with eelgrass in Newport Bay and Mission Bay, California. The team used Landsat 8 Operational Land Imager and Thermal Infrared Sensor, Landsat 9 Operational Land Imager-2 and Thermal Infrared Sensor-2, Sentinel-2 MultiSpectral Instrument, and ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station land surface temperature and cloud mask to create a time series of these water quality parameters from 2019–2023. We found that the parameters followed cyclical, seasonal patterns with turbidity and sea surface temperature peaking in the summer. We did not find that the parameters had changed significantly over longer time periods. These results will be used in a model developed by the Southern California Coastal Water Research Project to assess eelgrass ecosystem health and predict ecosystem occupancy in the future.

Key Terms

Remote Sensing, Estuaries, Southern California, Water Resources, Newport Bay, Mission Bay, Eelgrass

2. Introduction

2.1 Background Information

Eelgrass is known for the plethora of ecosystem services they provide, including carbon sequestration, coastline stabilization, sediment cycling, food web maintenance, and providing fish habitat (Hossain & Hashim, 2019). Thus, eelgrass is known to act as "ecosystem engineers" and rival tropical forests as the most productive ecosystems on Earth (Gutiérrez et al., 2011). However, eelgrass faces threats from both terrestrial and marine sources, making them susceptible to losing extent and density (Nordlund et al., 2017). *Zostera marina*, or eelgrass, is most commonly found in the soft-bottom sediments across Southern California estuaries and embayments. Due to its extensive ecosystem services, *Z. marina* is regulated at the local, state, and federal level in California (Gillett & Holt, 2023).

In 2014, the National Oceanic and Atmospheric Administration's (NOAA) National Marine Fisheries Service (NMFS) recommended a no-net loss of eelgrass habitat functioning across the state of California. This means they advocated for zero net change for eelgrass habitats to preserve the functions they provide to our ecosystems. To address this mitigation policy, the Southern California Coastal Water Research Project (SCCWRP) has been assessing eelgrass health through ground surveys and plans to create an eelgrass predicted occupancy model. However, SCCWRP would like to supplement the ground survey data with NASA Earth observations to fill spatial and temporal gaps with variables including chlorophyll-a (Chl-a), turbidity, and sea surface temperature (SST). Chl-a is the compound used in the photosynthesis process by vegetation and turbidity is a measure of water clarity in a body of water. These parameters, alongside the ground survey data collected, will be used to inform the eelgrass predictive occupancy model created by SCCWRP.

2.2 Study Area and Time Period

Due to SCCWRP's interest for their predictive model, we studied water quality parameters in Newport and Mission Bay from January 2019 to December 2023. SCCWRP is interested in modeling predicted eelgrass occupancy for a variety of bays, focusing mostly on recent years. This timespan allowed us to investigate multiple years of data, including water quality parameter's seasonality.

Newport Bay (Figure 1), located in Orange County, is the second largest estuarine embayment in Southern California. Newport Bay is one of the largest remaining natural estuaries in California, and provides shelter, food provisions, and spawning habitat for local fish, birds, and other animals in the area. Newport Bay is also used for recreation, with activities ranging from swimming to fishing (Schiff et al., 2014).

Mission Bay (Figure 1), an estuarine embayment located in San Diego, consists of salt marshes and has undergone various landscape alterations and developments throughout its history. Historically, smaller estuaries within Mission Bay have provided diverse habitats (ReWild Mission Bay, 2018). Previous studies of eelgrass in similar environments have used atmospherically corrected images of Sentinel-2 MultiSpectral Instrument (MSI) to classify eelgrass bed distribution (Gallant et al., 2021). Other studies have utilized Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) to monitor turbidity, SST, and Chl-a (Trinh et al., 2017; Dogliotti et al., 2011).



Figure 1. Study site map of Newport Bay, CA and Mission Bay, CA

2.3 Project Partners

Our team worked with multiple organizations to create a robust dataset to be used in the predictive eelgrass extent model. SCCWRP is a public research agency that develops strategies and recommendations for coastal environment preservation through scientific research in southern California. SCCWRP is interested in the data outputs of this project to train their predictive eelgrass extent model. NOAA NMFS seeks to maintain healthy ecosystems for many of our nation's most beneficial aquatic species. The State of California San Diego Regional Water Quality Control Board maintains water quality for the regions of the San Diego Bay. Each of these organizations are interested in the results of this project and how it can better inform their management.

SCCWRP has developed a system to help assess eelgrass nature that considers eelgrass' extent, health, and ecological functioning. They plan to assess each of these factors in sequence to determine the health of their ecosystems. Prior to this project, the partners used diver surveys, side-scan sonar, towed video arrays, and aerial imagery to obtain their data.

We conducted a feasibility study to determine the conditions necessary for using remote sensing data when investigating submerged aquatic vegetation (SAV) and water quality characteristics. This study determined the best algorithms to be used to calculate turbidity, SST, and Chl-a. These calculations were preformed and visualized as time series charts and animations. We also reviewed literature to recommend the conditions necessary to accurately determine eelgrass extent from remotely sensed data. The partners will use our end products to inform their occupancy model, enabling them to predict eelgrass behavior under various current and hypothetical conditions and locations. This project will allow the partners to develop a more complete understanding of where to expect eelgrass establishment and aid them in informing coastal managers of eelgrass behavior.

3. Methodology

3.1 Data Acquisition

Our team acquired data from Landsat 8 & 9 and Sentinel-2 missions available through Google Earth Engine (GEE; Table 1). We used Landsat 8 OLI/TIRS Surface Reflectance Tier 1 for the entire study period, and Landsat 9 OLI-2/TIRS-2 Surface Reflectance Tier 1 from October 2021 onward. Additionally, we obtained data from Sentinel-2 MSI for the study period. To supplement surface temperature calculations from Landsat 8 and 9 TIRS, we accessed ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) land surface temperature and cloud mask through Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). Our partners provided in situ turbidity data for validation.

Table 1

Earth observations used in this project.

Platform & Sensor	Processing Level	Acquisition Method	Data Provider	Date Range Used
Landsat 8 OLI/TIRS	Level 2 SR Collection 2 Tier 1	GEE	United States Geological Survey (USGS)	January 2019 – December 2023
Landsat 9 OLI-2/TIRS-2	Level 2 SR Collection 2 Tier 1	GEE	USGS	October 2021 – December 2023
Sentinel-2 MSI	Level 2-A	GEE	European Space Agency (ESA)	January 2019 – December 2023
ECOSTRESS	Level 2	AppEEARS	USGS	January 2019 – December 2023

3.2 Data Processing

We used GEE to generate maps of turbidity, SST, and Chl-a using Sentinel-2, Landsat 8 OLI/TIRS, and Landsat 9 OLI-2/TIRS-2 imagery. We also used ECOSTRESS to add in more SST values and investigate them at a higher resolution than Landsat. ECOSTRESS is not directly available in GEE, so we used a python script to mask out cloud areas and calculate SST in degrees Celsius.

As part of our workflow, we visualized every available image from Landsat 8 & 9 and Sentinel-2 missions in true color and selected the highest quality images by removing images with sun glint, haze, and high cloud cover. We repeated this process for each study area. This allowed us to minimize errors related to cloud cover and other atmospheric conditions. Next, we clipped the images to our study area and applied cloud and land masking. For Landsat 8 & 9 imagery we used quality assurance bands for high and medium confidence of cloud cover and cloud shadow, and for Sentinel-2 imagery we used the Scene Classification Map (SCL) band to select only the areas classified as water for our analysis. We also converted the images from bit signed integers to reflectance values using the appropriate scale factors for each dataset. We then divided images by pi to convert from surface reflectance to remote sensing reflectance values. Once we had clear and high-quality images, we created functions to calculate the water quality parameters.

To calculate turbidity, our team used the Dogliotti turbidity algorithm (Dogliotti et al., 2015). This algorithm is commonly used for calculating turbidity due to its ability to accurately estimate turbidity for a large range water types by using red and near infrared (NIR) band switching (Dogliotti et al., 2011). This algorithm was also highly recommended by our science advisors. The Dogliotti algorithm is as follows (Equation 1):

$$\mathrm{T} = \frac{\mathrm{A}_{\mathrm{T}}^{\lambda}\rho\omega(\lambda)}{\left(1-\frac{\rho\omega(\lambda)}{C^{\lambda}}\right)}(\mathrm{FNU}) \quad (1)$$

Where:

- T is turbidity calculated in Formazin Nephelometric Unit (FNU)
- $\mathrm{A_T}$ is a wavelength dependent calibration coefficient obtained by a non-linear least-square regression analysis
- C is a wavelength dependent calibration coefficient created using "standard" inherent optical properties (IOPs)
- $\rho\omega(\lambda)$ is the wavelength of the given band

Unlike other common turbidity algorithms which rely entirely on the red band, the Dogliotti algorithm switches from using the red band to the NIR in cases of high turbidity (Nechad et al., 2010; Dogliotti et al., 2015). Pixels with a value in the red band less than or equal to 0.05 would be considered low and would use the red band. Pixels with a value of 0.07 or higher would be considered high and would use the NIR band. For pixels in between 0.05 and 0.07, a weighted normalization of the red and NIR bands is calculated based on the following equation (Equation 2):

$$\mathrm{T} = (1-w)\cdot \mathrm{T}_{red} + w \cdot \mathrm{T}_{NIR} \quad (2)$$

Where:

- T is turbidity calculated in Formazin Nephelometric Unit (FNU)
- T_{red} is turbidity calculated using the red band
- T_{NIR} is turbidity calculated using the near infrared band
- w is the weight of the algorithm that changes linearly from 0 at ϱw(red) = 0.05 to 1 at ϱw(red) = 0.07

To calculate temperature, we focused on converting the thermal bands of our sensors into degrees Celsius. We chose degrees Celsius because that was what our partner SCCWRP preferred. Sentinel-2 does not have thermal bands, so we focused on Landsat 8 & 9 for this calculation. In GEE we selected the thermal band and applied the scale factor to convert the raw band to Kelvin. Then, we converted Kelvin to degrees Celsius. We also used ECOSTRESS to supplement our surface temperature data (Gorokhovich et al., 2022). We did this by converting the raw bands to Kelvin, and then from Kelvin to Celsius. Finally, we applied our cloud mask layer to get only the clearest pixels.

Measuring Chl-a concentration is effective for mapping trends in eelgrass health and growth. For this parameter we first calculated the normalized difference chlorophyll index (NDCI) that is widely used to map vegetation in remote sensing (Mishra & Mishra, 2012). This index is calculated by measuring red and near infrared bands for Landsat 8 & 9 and Sentinel-2 (Equation 3). NDCI was calculated for our study area from 2019 to 2023 and assimilated into the Mishra & Mishra algorithm for Chl-a concentration in milligrams per meters cubed (Equation 4). This equation has been applied in studies related to seagrass and turbid waters as it incorporates NDCI calibration. Constants in Equation 4 were chosen based on NDCI calibration provided in the Mishra & Mishra study.

$$NDCI = \frac{Near\ Infrared - Red}{Near\ Infrared + Red} \quad (3)$$

$$[Chl\ a] = 14.039 + (86.115\ NDCI) + (194.325\ NDCI^2) \quad (4)$$

3.3 Data Analysis

3.3.1 Time Series

Once we calculated water quality parameters for each individual image, we calculated the median value of all the pixels in each image. The median was used in our project over the mean because it is less influenced by outliers that may appear due to "edge effects", which describes the disturbance of signals at the boundary between a body of water and land, indicating that our results could be affected by their proximity to land, or possible errors in cloud masking. We then used these median values to create time series line graphs for each water quality parameter, study site, and sensor. We also overlayed certain line graphs, including all three water quality parameters and turbidity with Chl-a, to look for patterns in how our variables changed over time. We also used a python code to generate animations of our water quality parameter maps changing over time. These time series were ultimately used to reveal patterns in water quality variability over time.

3.3.2 Accuracy Assessment

We compared our satellite derived turbidity (FNU) results to in situ turbidity data from six data logging stations provided by SCCWRP (Figure B3) for Newport Bay. To do this, we filtered the in situ data to our study period and only included surface-level depth measurements, to ensure consistency with our remotely sensed imagery. Additionally, we omitted any in situ turbidity values over 10 in situ turbidity, as it was determined that the provided data had outlier values above 10 in situ turbidity (Figure B1). We then paired the in situ measurements with the nearest satellite acquisition within a 0–4 day range using R. This was done to ensure there was enough data to conduct the accuracy assessment, since the satellites' acquisition frequency impedes to have a one-to-one correspondence with the in situ measurements acquisition dates. Next, we extracted satellite derived turbidity using GEE and the station locations provided by SCCWRP with a 30 m buffer and took the mean of all pixels within. This allowed us to compare the differences in turbidity measurements from the remotely sensed imagery and the in situ data. We then calculated the root mean square (RMS) and mean average error (MAE) values in R, allowing us to determine the accuracy of the turbidity values from Sentinel-2, Landsat 8 OLI, and Landsat 9 OLI-2. Although the values are expressed in different turbidity units, existing literature suggests that these units are equivalent to each other, avoiding any need for conversion (Schloss, 2002).

3.3.3 Eelgrass Extent Mapping

Our team considered multiple methods for eelgrass extent mapping. We conducted a literature review to understand the possibilities and limitations of SAV mapping in aquatic environments using remotely sensed data. Based on the literature, we determined that accurately mapping eelgrass extent would not be possible within the timeline of this project, and with the available data we had. We decided to instead make recommendations outlining the conditions and methods required to complete this objective in the future.

From the reviewed literature, we identified studies that are successful in mapping seagrass using remote sensing and the commonalities that facilitate the mapping process. This included water body type, water depth, clarity, machine learning methods, and equations that yielded significant results in the literature. We then compiled these results to outline the best potential workflow to produce eelgrass extent maps for the study areas.

4. Results & Discussion

4.1 Analysis of Results

Our data displays cyclical patterns in turbidity and SST for both Mission Bay and Newport Bay (Figures 2 and 3). Chl-a did not exhibit these seasonal trends (Figures 4 and 5). We did not observe long term changes in any parameters for either location (Figures 2 and 3).

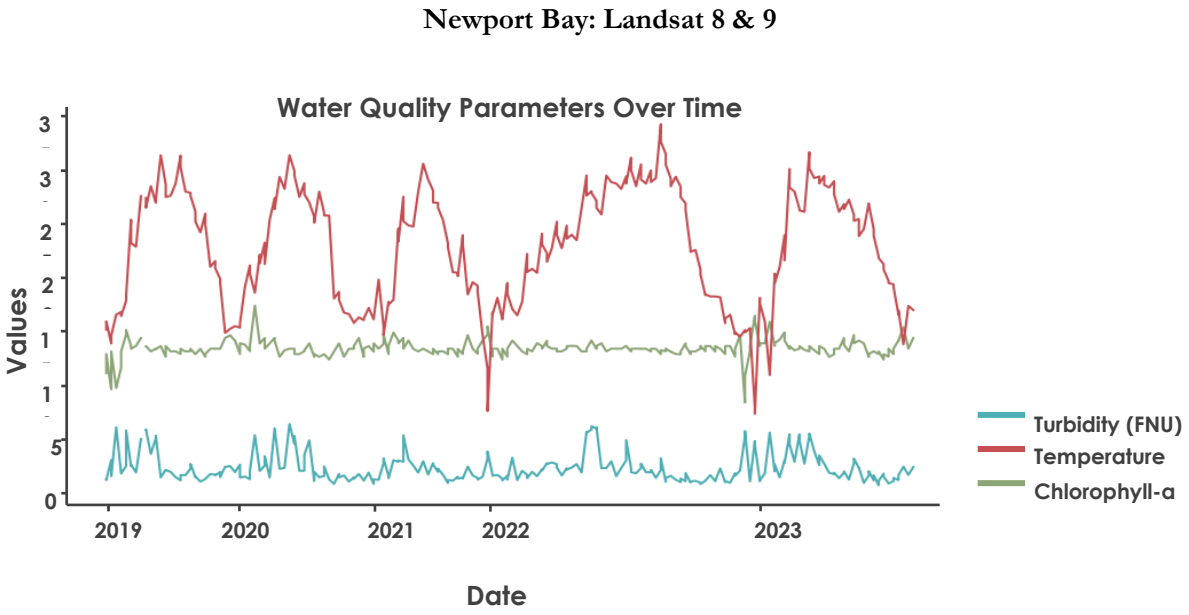


Figure 2. Chart of water quality parameters over time for Newport Bay using data from Landsat 8 & 9.

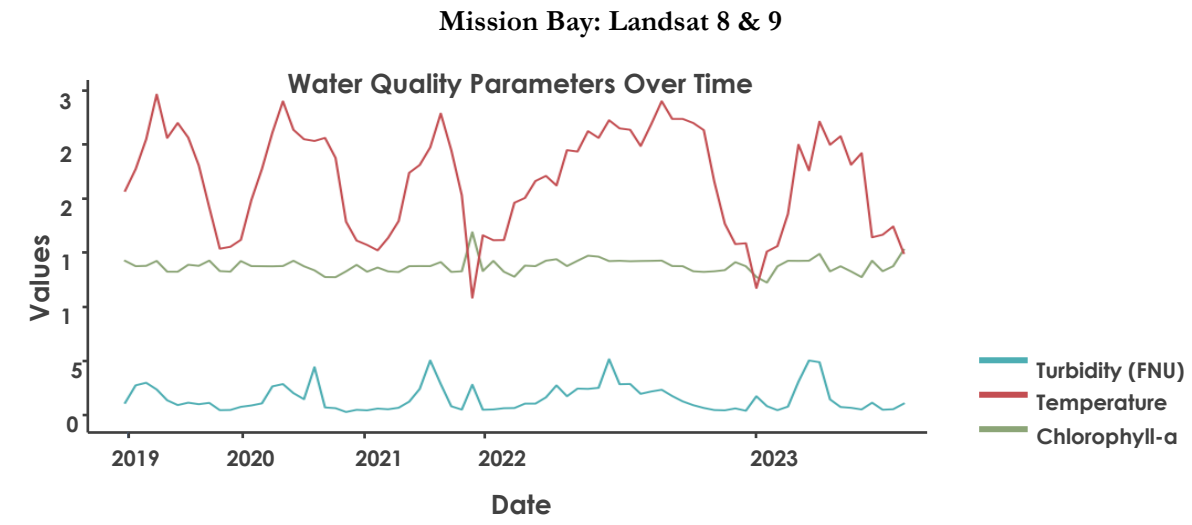


Figure 3. Chart of water quality parameters over time for Mission Bay using data from Landsat 8 & 9.

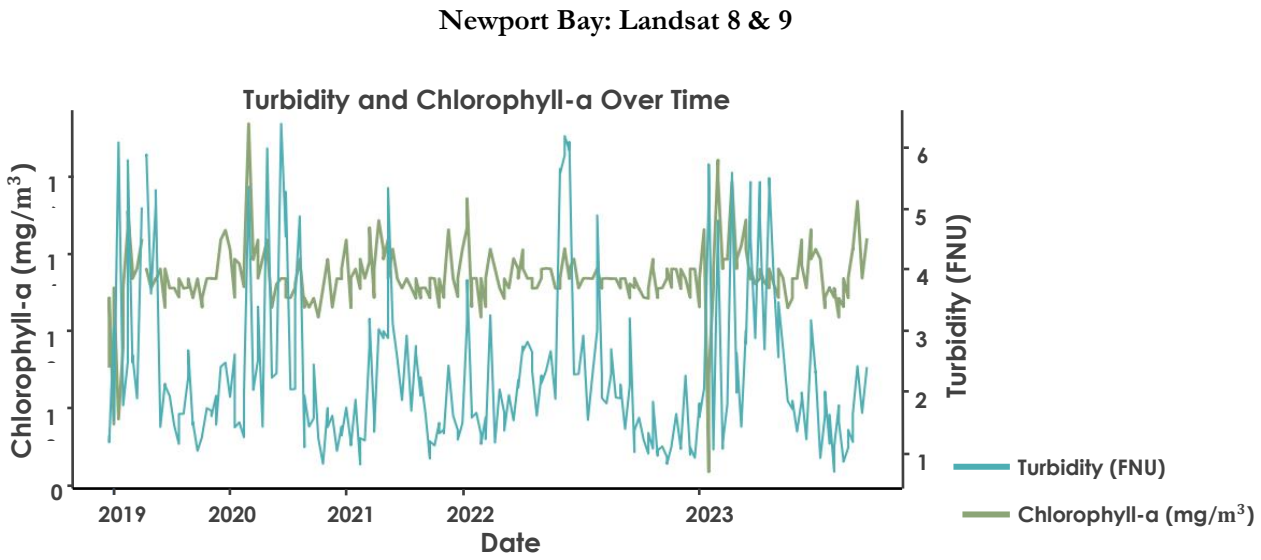


Figure 4. Chart of turbidity and chlorophyll-a over time for Newport Bay using data from Landsat 8 & 9.

Mission Bay: Landsat 8 & 9

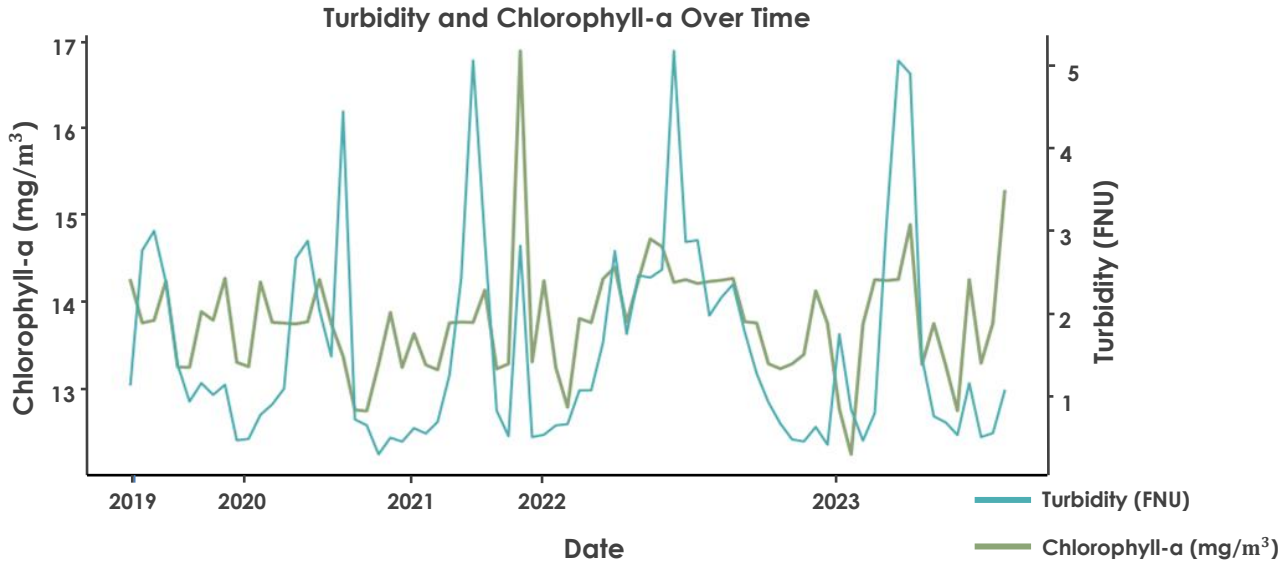


Figure 5. Chart of turbidity and chlorophyll-a over time for Mission Bay using data from Landsat 8 & 9.

The median turbidity value of all the pixels in each image calculated from Landsat 8 and 9, and Sentinel-2 in Newport Bay ranges from about zero to seven FNU (Table 2). Median turbidity in Mission Bay calculated from Landsat 8 and 9 ranges from about zero to five FNU but ranges roughly from zero to three FNU when calculated from Sentinel-2. For all satellites at both locations, turbidity is generally higher in the summer months than the winter months (Table A1).

Table 2
Median Turbidity (FNU) Value Ranges.

	Minimum Turbidity	Maximum Turbidity
Newport Bay: Landsat 8 & 9	0.7059	6.3934
Newport Bay: Sentinel-2	0.5794	6.6719
Mission Bay: Landsat 8 & 9	0.3148	5.1753
Mission Bay: Sentinel-2	0.0393	3.0155

Furthermore, an accuracy assessment was conducted to assess the precision of using Landsat 8 OLI, Landsat 9 OLI-2, and Sentinel-2 to measure turbidity in Newport Bay. The root mean square error (RMSE) values for both the Sentinel-2 and Landsat satellites were ~2.25, and the mean average error (MAE) for the Landsat satellites was found to be over ~1.8 while for the Sentinel-2 satellite the MAE was ~1.4 (Table 3). The RMSE and MAE values being very close to one another for the Landsat and Sentinel-2 is indicative of the consistency of satellite derived turbidity values from various multispectral instruments. However, the RMSE and MAE values suggest a general disagreement between in situ measurements and satellite derived turbidity, though this is likely a result of having little in situ values to compare the satellite imagery with. When considering Figure B2, we can also see that the geographic placement of the turbidity station may influence the accuracy assessment. For example, station 'UNBCHB' is located near a roadway which may have resulted in higher turbidity values from edge effects.

Table 3
Calculated error values of satellite derived turbidity.

	Root mean square error (RMSE)	Mean average error (MAE)
Landsat 8 & 9	2.2525	1.7685
Sentinel-2	2.2512	1.4237

The median SST value of all the pixels in each image for Newport Bay calculated from Landsat 8 and 9 ranges from about eleven to thirty-five degrees Celsius, and from ECOSTRESS ranges from roughly five to thirty-six degrees Celsius (Table 4). Median SST for Mission Bay calculated from Landsat 8 and 9 ranges from about eleven to thirty degrees Celsius, and from ECOSTRESS ranges from roughly six to thirty-three degrees Celsius. SST also shows seasonal patterns, with peaks in the summer months for all satellites at both locations (Table A2).

Table 4
Median Temperature (Degrees Celsius) Value Ranges.

	Minimum Temperature	Maximum Temperature
Newport Bay: Landsat 8 & 9	11.3140	34.4574
Newport Bay: ECOSTRESS	5.2700	36.0300
Mission Bay: Landsat 8 & 9	10.7821	29.6965
Mission Bay: ECOSTRESS	5.5700	33.0900

The medians of Chl-a values of all the pixels in each image for Newport Bay, calculated from Landsat 8 and 9, ranges from about eight to seventeen mg/m^3 (Table 5). The same parameter calculated from Sentinel-2 ranges from about six to fifteen mg/m^3. Median Chl-a in Mission Bay calculated from Landsat 8 and 9 images ranges from roughly twelve to seventeen mg/m^3, and calculated from Sentinel-2 ranges from about five to seventeen mg/m^3. Chl-a does not show seasonal patterns, nor drastic changes over long time periods (Table A3).

Table 5
Median Chlorophyll-a (mg/m^3) Value Ranges.

	Minimum Chlorophyll-a	Maximum Chlorophyll-a
Newport Bay: Landsat 8 & 9	8.3727	17.3716
Newport Bay: Sentinel-2	6.4584	14.9514
Mission Bay: Landsat 8 & 9	12.2349	16.8765
Mission Bay: Sentinel-2	4.9559	16.9832

4.3 Feasibility Analysis

We found that accurately mapping Eelgrass extent was not feasible for our study area. Spectral signals in optically complex waters are affected by suspended sediments, phytoplankton, and dissolved organic matter (Uudeberg et al., 2019). Vahtmäe et al., 2023 determined that a depth restriction of 1.5–2m yielded the most effective results for seagrass mapping. They were able to achieve accurate results by using both empirical and physics-based approaches. While it may be possible to determine presence of vegetation, identifying species requires a high spectral resolution in optically complex waters (Wilson et al., 2020). We determined the most ideal water conditions for SAV extent mapping to be less than 2 m deep, with very low turbidity, such as those found in tropical waters. We recommend using machine learning techniques such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN; Mederos-Barrera et al., 2022). Additionally, supplementing remotely sensed data with in situ data and using the highest resolution imagery available will yield the most accurate results.

Possible limitations of our study include lack of in situ data, imperfect atmospheric correction methods for water applications, and the possible influence of edge effect. The only in situ data for accuracy assessment we received was for turbidity in Newport Bay. This means that we cannot verify the accuracy of our results for the other parameters and for Mission Bay. We also relied on agency delivered surface reflectance products which are not optimized for water targets.

Standard atmospheric correction methods are not as effective in turbid waters (Dogliotti et al., 2011). Although we made comparisons and chose the data product with the best-known atmospheric correction, this could have affected our results. Another considerable issue is the possible influence of "edge effect" on our data.

The results of this project are valuable in informing our partner's data model that will be used to predict eelgrass health in bays along the California coast. The three water quality parameters calculated in this study, turbidity, SST, and Chl-a, will be used as inputs in our partner's model. Furthermore, supplemental tutorials will help guide our partners to be able to recreate our study with other study sites in order to expand the scope of their analysis. While the results of our study are informative, it is important to note that not every water quality parameter calculated had been ground validated due to a lack of ground data for both sites as well as each water quality parameter. A more thorough ground truthing procedure would be beneficial in ensuring that the output data is as accurate as possible before inputting it in the model.

Furthermore, while our partners were interested in the possibility of using Earth observations to map eelgrass extent and other SAV, we determined that this would not be feasible for this project. We were able to provide recommendations to our partners on the requirements needed for successful remotely sensed mapping of SAV. However, the requirements needed are strict and may not be applicable to our partner's study sites. The goal of replacing ground measurements for eelgrass extent mapping with remotely sensed eelgrass extent mapping may not be feasible for our partners at this time.

4.3 Future Recommendations

We recommend our partners to obtain more in situ data on each water quality parameter to better calibrate and ground truth the predicted occupancy model that our partners will create. As previously mentioned, our accuracy assessment was limited due to only having in situ data for one water quality parameter at one of our study sites. This would be an important step, for example, when mapping seagrass extent as the algorithms used to calculate Chl-a does not differentiate Chl-a from eelgrass or forms of algae. We would also recommend for our partners to apply their model to other study sites in coastal Southern California to make more comparisons on water quality parameters to draw their conclusions.

5. Conclusions

Our project used satellite derived imagery from Landsat 8 OLI/TIRS, Landsat 9 OLI-2/TIRS-2, and Sentinel-2 MSI to assess the feasibility of utilizing Earth observations as a means of measuring water quality parameters in estuarine systems. Our team was able to calculate turbidity, SST, and Chl-a from remotely sensed imagery in both Newport and Mission bays and create time series to analyze their change over time. Turbidity and SST both peaked in summer months, while Chl-a showed no seasonal trends. There were no long-term changes across our study period for any of the water quality parameters. Furthermore, the accuracy assessment conducted by our team found that there was general consistency between the date-matched in situ turbidity measurements and satellite-derived turbidity values.

Additionally, our project investigated the feasibility of eelgrass extent mapping using remotely sensed imagery in order to replace our partners current ground measurements. While we determined that this task would not be feasible for our study sites, we were able to provide recommendations to our partners about the requirements needed to increase the success of creating eelgrass maps from remotely sensed data. This includes study sites with low turbidity, high spatial resolution imagery, less than two meters of water depth,

and even implementation of machine learning techniques. This information can be used by our partners to determine if any of their areas of interest meet these criteria and would be a good candidate for an eelgrass extent mapping project in the future.

The water quality data collected from this project will be used by our partners to inform their predictive eelgrass occupancy models. These models seek to provide valuable insight into eelgrass' relationship with the coastal ecosystem and ultimately seek to inform policy and decision makers on the best practices to protect eelgrass. This will ensure that eelgrass can continue providing ecosystem services and the contributions it offers to the community including carbon sequestration, habitat for marine life, sediment stabilization, and water purification.

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7. Glossary

AppEEARS – Application for Extracting and Exploring Analysis Ready Samples
Atmosphere Correction – removing scattering and absorption effects from the Earth's atmosphere from remote sensing imagery.
Chl-a – Chlorophyll-a, a form of chlorophyll used in photosynthesis.
Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time.
ECOSTRESS – ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station.
Eelgrass - (Zostera marina) is a species of submerged aquatic vegetation (SAV) found in shallow bays and estuaries with soft seafloors.
FNU – Formazin Nephelometric Unit.
GEE – Google Earth Engine.
Ground Truthing/Ground Validation – Accuracy assessment of remotely sensed data through the use of data taken in situ
In situ – in the original place, data collected from the ground at the location.
Machine Learning – The use of computer systems to perform complex tasks and make decisions without explicit human instructions
MAE – mean average error.
MSI – MultiSpectral Instrument.
NDCI – Normalized Difference Chlorophyll Index.
NTU – Nephelometric Turbidity Units.
OLI – Operational Land Imager.
Optically complex water – waters easily affected by suspended sediments, phytoplankton, and dissolved organic matter.
RMSE – root mean square error.

SAV – submerged aquatic vegetation.
SST – sea surface temperature.
TIRS – Thermal Infrared Sensor.
Turbidity – Measure of water clarity in a body of water.

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9. Appendices

Appendix A: Water Quality Parameters

Table A1
Turbidity graphs.

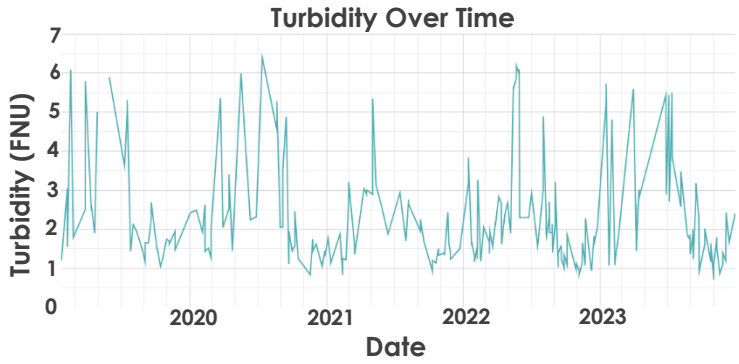
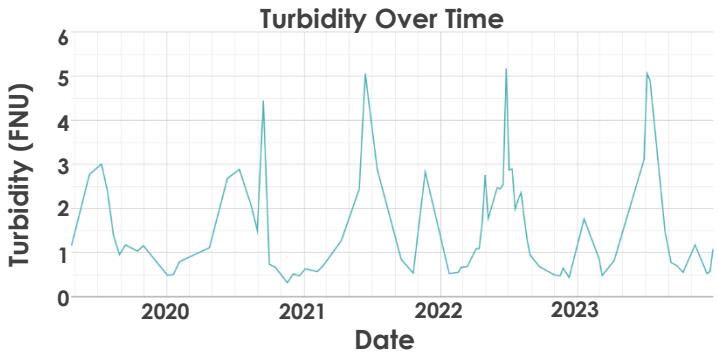
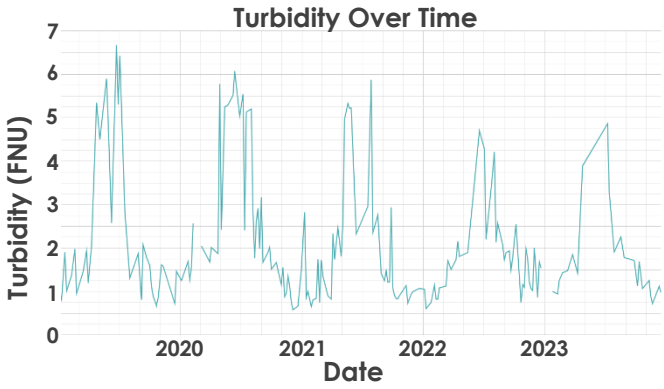
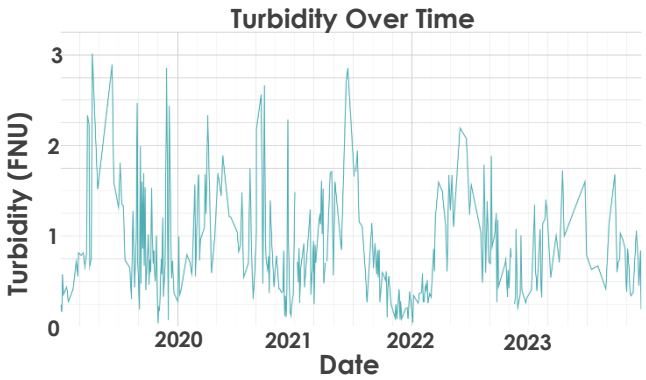
Newport Bay – Landsat 8 & 9	Mission Bay – Landsat 8 & 9
	
Newport Bay – Sentinel-2	**Mission Bay – Sentinel-2**
	

Table A2

Temperature graphs.

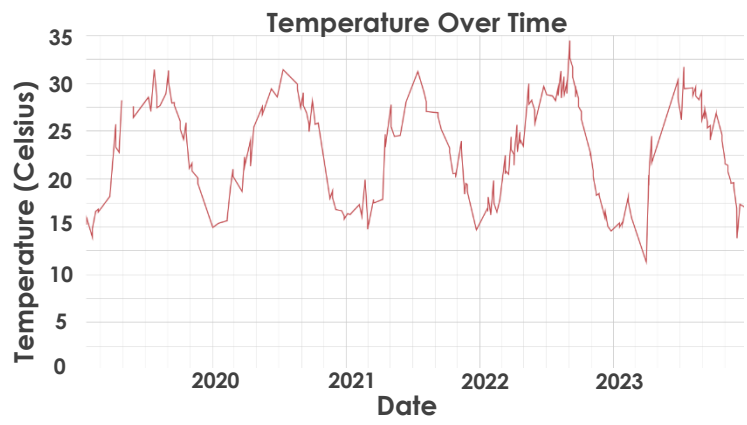
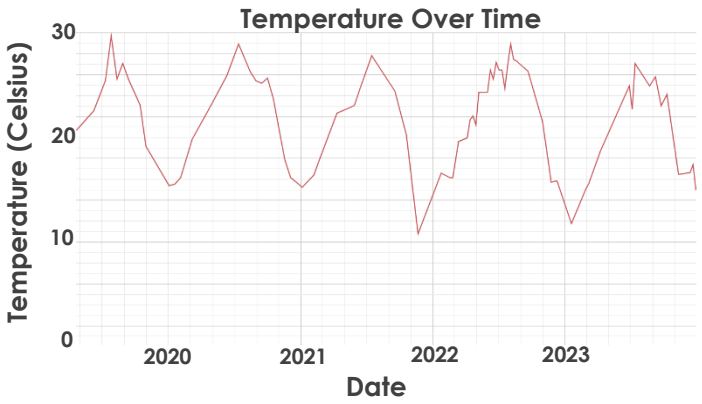
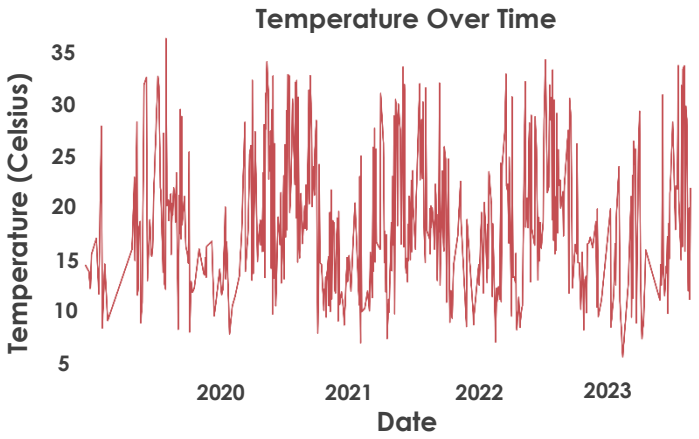
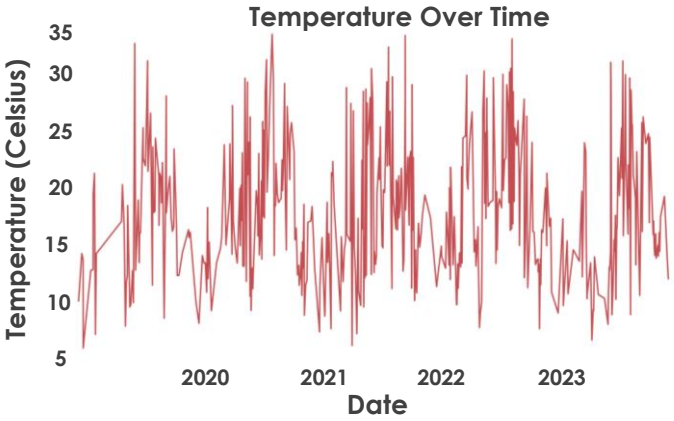
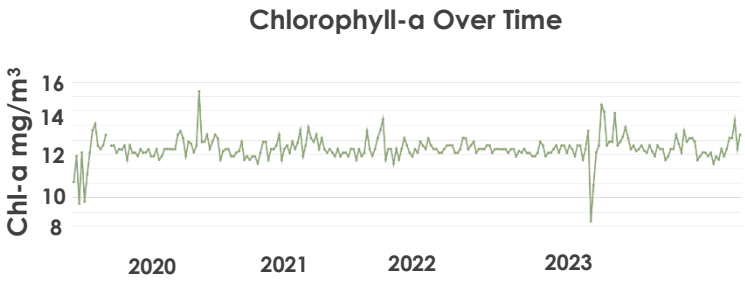
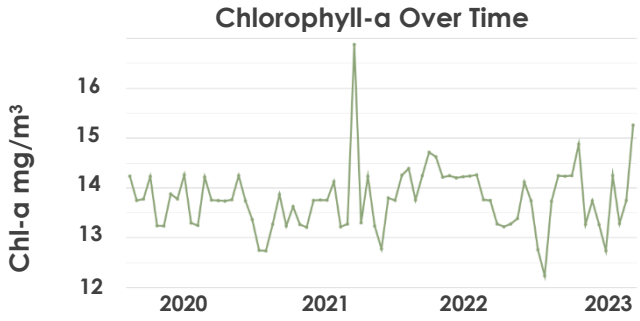
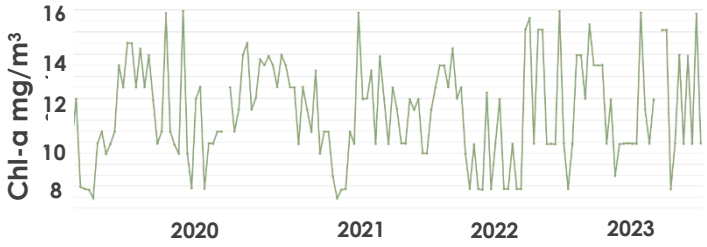
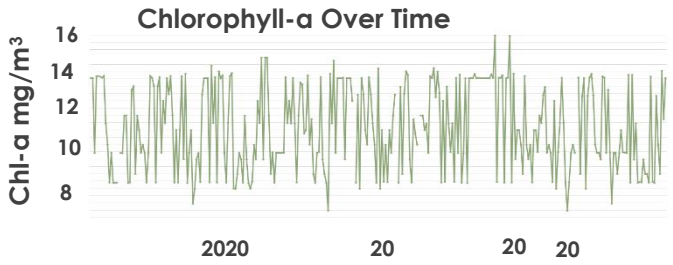
Newport Bay – Landsat 8 & 9	Mission Bay – Landsat 8 & 9
	
Newport Bay – ECOSTRESS	Mission Bay – ECOSTRESS
	

Table A3

Chlorophyll-a graphs.

Newport Bay – Landsat 8 & 9	Mission Bay – Landsat 8 & 9
	
Newport Bay – Sentinel-2	Mission Bay – Sentinel-2
	

Appendix B: Accuracy Assessment

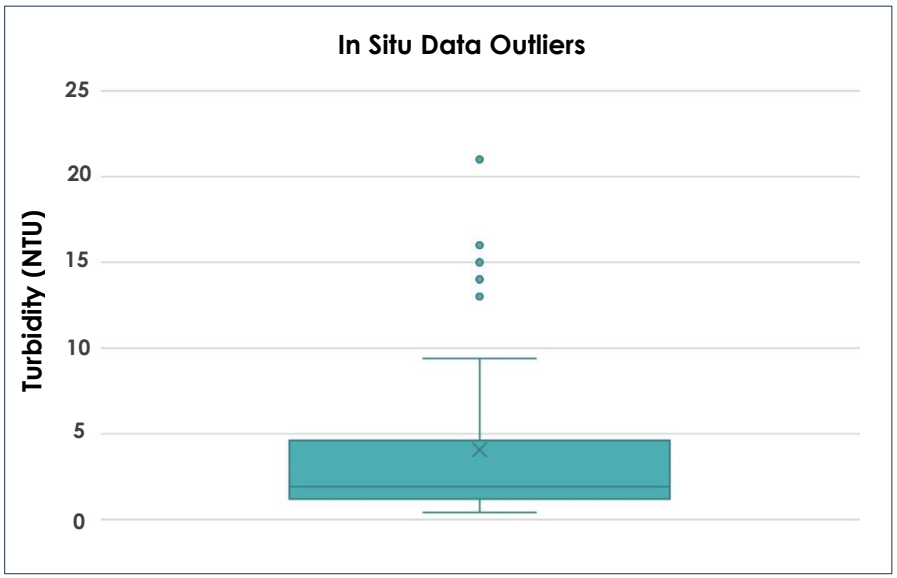


Figure B1. Box and whisker plot showing the in situ turbidity data outliers.

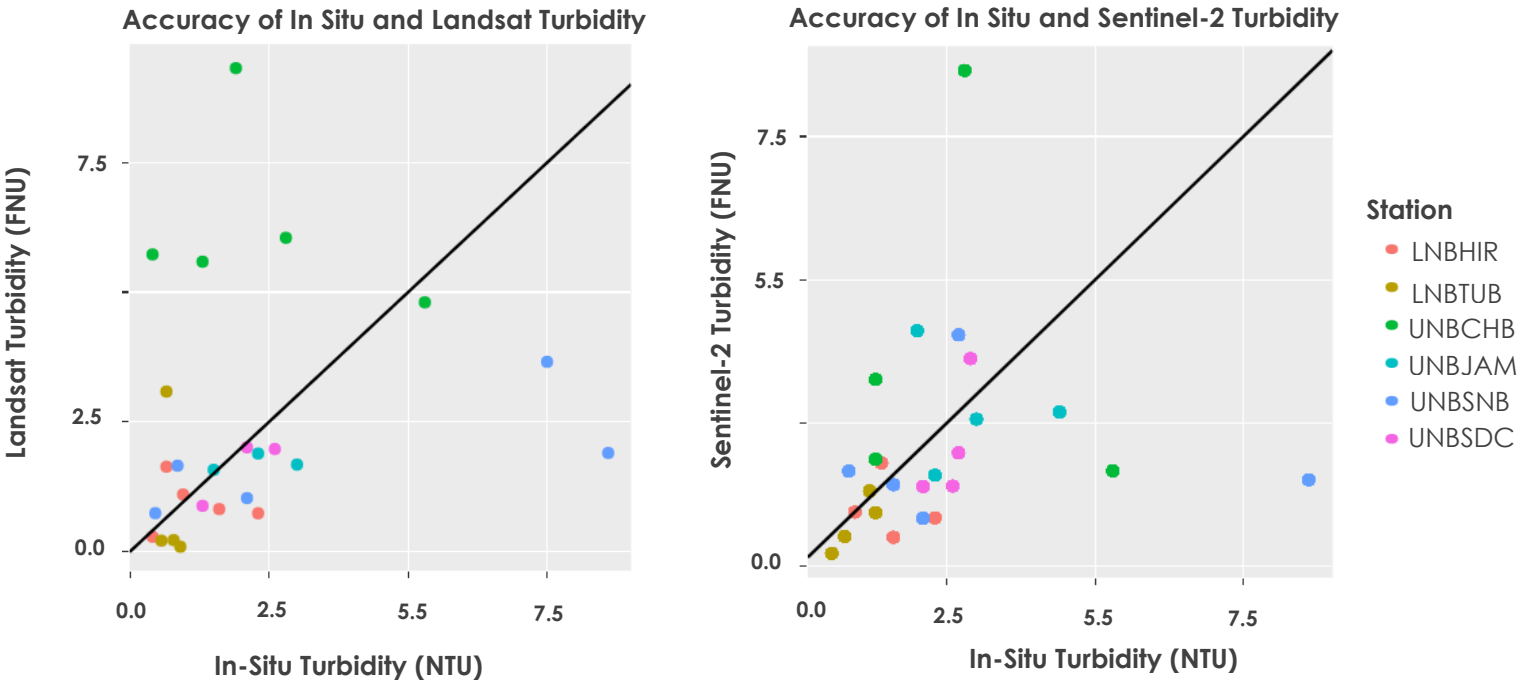


Figure B2. Scatterplots of the accuracy assessment conducting comparing the in situ turbidity (NTU) values to the satellite derived turbidity (FNU) values. The points were colored by station name (Figure B3).

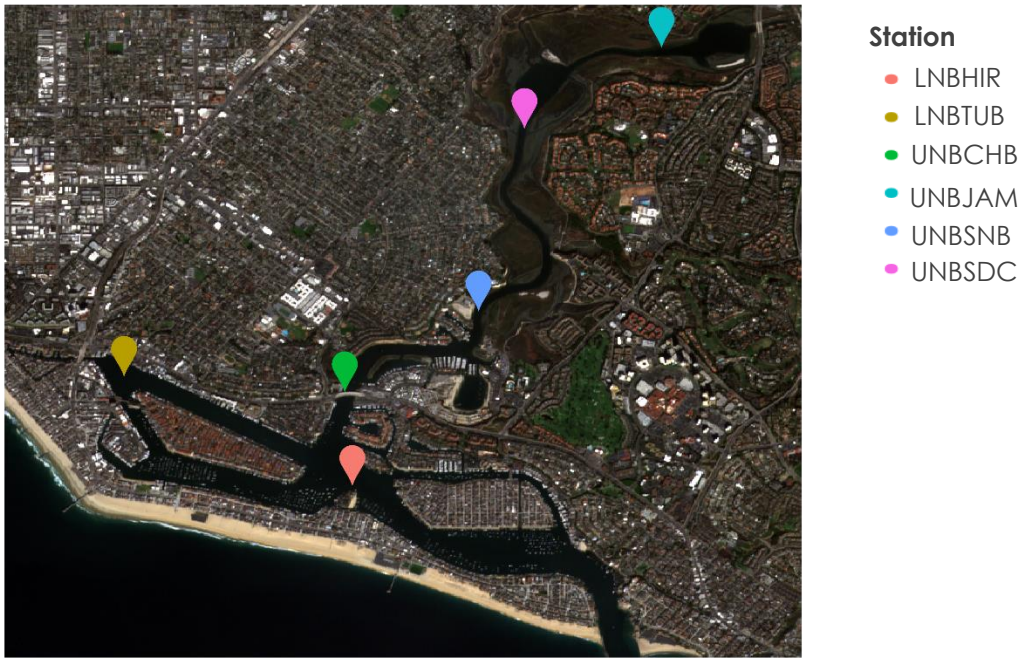


Figure B3. Map of turbidity data logging stations.