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Hilo Bay Water Resources

Monitoring Water Quality in Hilo Bay, Hawaiʻi to Support Future Community Planning

DEVELOP Technical Report

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1. Abstract

Designated as an impaired body of water by both state and federal water quality standards, Hilo Bay, Hawaiʻi is highly susceptible to brown water, a condition where the water becomes murky and is associated with excess levels of bacteria, contaminants, and nutrients. A breakwater in Hilo Bay, which was established to protect Hilo town from tsunamis, interferes with water circulation and prolongs the presence of brown water in the bay. The State of Hawaiʻi issues brown water advisories (BWAs) following flash flood warnings, sewage spills, and other events to indicate a public health concern for those who use Hilo Bay for recreation, cultural purposes, and fishing. Due to the elevated public health risk and ecosystem disturbance that brown water poses to Hilo Bay, we partnered with the Hawaiʻi County Office of Sustainability, Climate, Equity, and Resilience (OSCER) to examine the feasibility of using Earth observations (EO) to monitor water quality in the Hilo Bay region. We leveraged data from Sentinel-2 Multispectral Instrument (MSI), Landsat 8 Operational Land Imager (OLI), Landsat 9 OLI-2, and Aqua and Terra Moderate Resolution Imagine Spectroradiometer (MODIS) instruments to identify and assess spatial and temporal patterns of two main water quality parameters, turbidity and chlorophyll-a, during BWAs. We used the Optical Reef and Coastal Area Assessment (ORCAA) tool in Google Earth Engine to process EO data and generate water quality maps and time series. Our study found that increased turbidity levels can be identified by EO data during BWAs. In addition, our map products indicated the presence of several turbidity plumes along the coast, with the highest concentration of turbidity found within Hilo Bay. While chlorophyll-a levels were relatively flat within our study region during BWAs, we found that regional chlorophyll-a patterns could be derived from MODIS chlorophyll-a data in NASA Worldview. Our study's multi-sensor approach provided valuable insights for how water quality in the Hilo Bay region can be monitored in the future.

Key Terms

remote sensing, water quality, public health, turbidity, chlorophyll-a, Sentinel, Landsat, MODIS, Google Earth Engine

Land Acknowledgment

Our team acknowledges that the ʻāina (*that which feeds*) or land on which this project has grown out of is the ancestral homeland of Kanaka Maoli (Native Hawaiians) and that it is due to their pono that we can be here today. As visitors and settler aloha ʻāina in the moku of Hilo on Hawaiʻi Island, we are deeply grateful for the generations of Native Hawaiians who have stewarded, cared for, and honored this ʻāina over the past 1,600 years.

2. Introduction

2.1 Background Information

Hilo Bay has been called the 'piko' (navel or place where life begins) of the Hilo community (Hilo Bay Muliwai Hui, 2013). The Hilo Bay watershed holds many culturally and historically important sites for both Native Hawaiians and local community members. The Hilo Bay region is home to over 50,000 residents and is in the 89th percentile for wastewater discharge in the United States, which means that community members are subject to a higher degree of risk from contaminants from on-site sewage disposal systems, like cesspools and wastewater treatment facilities (EJScreen, 2024). Poor water quality poses a public health concern for those who interact with its waters when paddling, fishing, surfing, and swimming. With Hilo as the third rainiest city in the United States, Hilo Bay receives heavy sediment run-off from the Wailuku River along with nutrients from onsite wastewater disposal systems that drain into the bay through the Wailoa River (Figure 1; Hilo Bay Muliwai Hui, 2013; Wiegner and Mead 2009). Levels of nutrients, turbidity, and fecal bacteria in the Bay have exceeded state water quality standards since the late 1970s, and in 1998 the United States Environmental Protection Agency officially listed Hilo Bay on the 303(d) list of impaired waters (Wiegner & Mead, 2009; Hilo Bay Muliwai Hui, 2013; Silvius et al. 2005). The breakwater protecting Hilo town from tsunamis obstructs circulation, increasing the residence time of contaminants in Hilo Bay (Wiegner & Mead; Hasslinger, 2020). Health concerns inhibit community members from fully utilizing Hilo Bay, as only 10% of people who use its beaches swim in it (Hasslinger, 2020; Wiegner & Mead, 2009).

Figure 1. The study area focused on the Hilo Bay region, extending from Pāpaʻikou in the North to Richardson's Beach in the southeast. The Wailoa and Wailuku rivers are the major inputs of Hilo Bay. Stream and urban land use layers were acquired through the Hawaiʻi Statewide GIS Program.

To protect the community from the potential hazards of bacteria and contaminants in the water, the Hawaiʻi Department of Health's (HDOH) Clean Water Branch (CWB) issues brown water advisories (BWAs). BWAs are issued after flash floods, heavy rainfall events, wastewater discharges or visual inspections of turbid waters. Turbidity is determined by the amount of light scattered by particulates within water, which affect the color and clarity (USGS 2018). Turbidity has been used as an indicator for sediment and other contaminants, as well as for hazardous bacteria concentrations. In Hilo Bay, concentrations of harmful bacteria like *Clostridium perfingens* and *Enterococcus* displayed a positive correlation with turbidity, making turbidity a good proxy water quality indicator when evaluating satellite data for public health concern (Wiegner et al., 2016). In addition to reducing water clarity, turbid waters from wastewater inputs can contain excess nutrients, which feed algae and produce anaerobic environments that are inhospitable for aquatic life. Chlorophyll-a, a pigment within algae, can be identified through satellite data and has been used in remotely sensed water quality monitoring.

Issuing timely and accurate BWAs poses a challenge due to the intense river flows and high-volume discharges into Hilo Bay from heavy precipitation events and Hawaiʻi Island's extreme topography (Tomlinson, 2003). Traditionally, water quality monitoring has entailed using in-situ measurements by collecting field samples that are tested in a lab for their bio-physical and chemical properties. While in-situ methods have high accuracy, they are time-consuming, expensive, and not feasible for monitoring large bodies of water and coastal regions (Duan et al. 2013). In contrast to the immense amount of time, effort, and money required for in-situ data collection, satellite remote sensing has the potential to provide an efficient and cost-effective alternative for monitoring vast water bodies like Hilo Bay (Peterson et al., 2019; Sagan et al., 2020). Previous water quality studies have successfully used Earth observations (EOs) from multispectral satellite imagery to examine water quality parameters like chlorophyll-a and turbidity at a regional scale (Kuhn et al. 2019; Dogliotti et al., 2015; Li et al., 2022; Ma et al. 2021; Mishra & Mishra, 2012).

Given the successful track record of EOs in water quality monitoring, our team studied the feasibility of using remotely sensed water quality parameters, turbidity and chlorophyll-a, to assess brown water patterns in Hilo Bay. This study leveraged EO data from Sentinel-2 Multispectral Instrument (MSI), Landsat 8 Operational Land Imager (OLI), Landsat 9 OLI-2, and Aqua and Terra Moderate Resolution Imagine Spectroradiometer (MODIS). To understand the spatial and temporal distribution of brown water patterns, we examined satellite derived measurements of turbidity and chlorophyll-a plumes before, during and after BWAs, as well as several case studies that offered further insight into the water quality of the Hilo Bay region.

2.2 Project Partners and Objectives

Our team partnered with the Hawaiʻi County Office of Sustainability, Climate, Equity, and Resilience (OSCER). Established in 2023, OSCER works to advance climate and resilience goals across Hawaiʻi Island with the goal to uplift the health of the land and people. One of the many projects OSCER seeks is enhanced monitoring methods to protect water quality and to ensure sustainability of Hilo's coastal ecosystems. Our study's primary objective was to determine the feasibility of using EOs as an efficient and cost-effective supplement to current in situ water quality monitoring methods. To do so, we analyzed water quality parameters of turbidity and chlorophyll-a, which are potential indicators for brown water and can be monitored through EOs. The team sought to generate water quality time series and maps, contrasting periods of BWAs and non-BWAs, to investigate the relationship between precipitation, turbidity and chlorophyll-a and to support end-user decision-making.

3. Methodology

3.1 Data Acquisition

3.1.1 Earth Observation Data and Acquisition

For our study, we used data from the NASA and United States Geological Survey (USGS) Landsat missions, NASA's MODIS mission, and the European Space Agency (ESA) Sentinel mission. Landsat 8 OLI data extends from April 2013 to June 2024, and Landsat 9 OLI-2 data extends from January 2022 to June 2024. For both missions we used Level 2, Collection 2, Tier 1 datasets available in Google Earth Engine (GEE) that included processing for atmospherically corrected surface reflectance. Data from Sentinel-2 MSI level 1C extends from December 2015 to June 2024 (Table 1). To process our data, we used the Optical Reef and Coastal Area Assessment (ORCAA) tool, a GEE script created by a previous DEVELOP team (GEE; Pippen et. al., 2019). Additionally, we collected Aqua and Terra MODIS Regional Ocean Color (OC) data Version R2022.0 from the year 2018 for this study from NASA's Ocean Biology Distributed Active Archive Center (OB.DAAC) (Table 1).

Table 1

Earth Observations used for water quality analysis of Hilo Bay

Earth Observation	Spatial Resolution	Revisit Time	Dates	Source
Aqua & Terra MODIS	1 km	1-2 days	2018	NASA (OB. DAAC)
Landsat 8 OLI	30 m	16 days	April 2013 – June 2024	NASA & USGS (GEE)
Landsat 9 OLI-2	30 m	16 days	January 2022 – June 2024	NASA & USGS (GEE)
Sentinel-2 MSI	10 m	5 days	October 2015 – June 2024	ESA (GEE)

3.1.2 Study Area and Ancillary Data

We incorporated multiple ancillary datasets to build our shapefile and acquire our Earth observation data. To delineate our study area boundaries, our county partner provided the Hilo Bay watershed extent from the United States Army Corps of Engineers (USACE) (Silvius et, al. 2005). We acquired brown water advisory dates from the State of Hawaii's Department of Health (HDOH) Clean Water Branch (CWB). We used daily precipitation totals from the Hawaiʻi Climate Data Portal (HCDP) to identify dates of interest for our study between March 2013 and June 2024 (Table 2).

Table 2

Ancillary datasets used to generate study area shapefile and analyses for turbidity patterns.

Dataset	File Type	Dates	Source
Hilo Bay Watershed Extent	Shapefile	2013	USACE

Streams	Shapefile	Updated 2022	Hawaiʻi Statewide GIS Program, Hawaii Streams from DLNR, Division of Aquatic Resources (DAR)
Land Use Districts	Shapefile	Updated 2024	Hawaiʻi Statewide GIS Program, State Land Use District Boundaries for the 8 main Hawaiian Islands
Brown Water Advisories	CSV	2013 - 2024	DOH – Clean Water Branch
Daily Precipitation (see Appendix B, Link)	CSV	2013-2024	Hawaiʻi Climate Data Portal

3.2 Data Processing

3.2.1 Brown Water Advisories

To identify dates of interest for our study, we filtered the BWA dates issued for the Hilo Bay region from March 2013 to June 2024. Between March 2013 and June 2024, we found 1,457 advisories across the entire state of Hawaiʻi. We ultimately focused on 97 BWAs that fell within our study area and time (Table A1; Table A2).

3.2.2 Available Landsat Imagery

We created a GEE script to determine the total number of viable Landsat images for our study area. We applied a cloud mask using the "QA_PIXEL" band to remove all pixels classified as clouds. This resulted in cloud-masked true color images clipped to the study region. Our team visually assessed and identified imagery with continuous pixel coverage over the Hilo Bay region, also noting their dates (Figure 2).

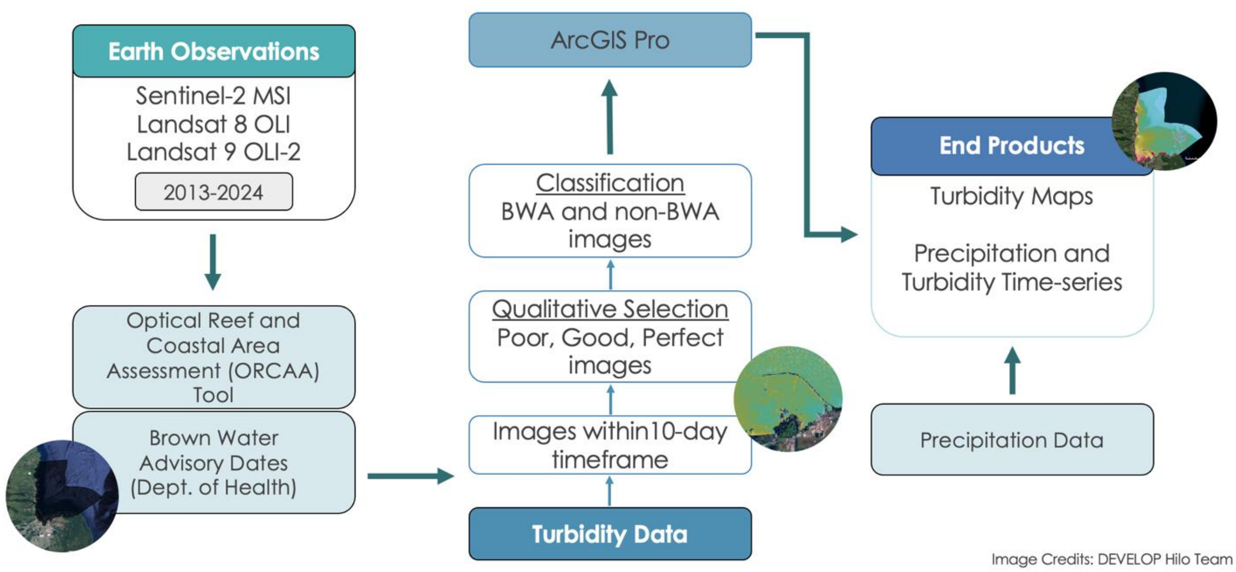

Figure 2. ORCAA Methodology to process turbidity data

3.2.3 ORCAA Tool

Our team utilized the second version of the Optical Reef and Coastal Area Assessment (ORCAA) tool. This tool was created by the Fall 2019 NASA DEVELOP Team and is publically available in GEE (Pippen et. al., 2019). The ORCAA 2.0 Tool, created and improved by previous DEVELOP teams, provided a means to analyze and visualize various water quality parameters estimated from EO data over user-supplied regions and time periods of interest. We uploaded our study area shapefile as an asset and used the user interface to run our analyses. The ORCAA 2.0 tool has pre-set image collections that integrate Landsat 8 OLI and Sentinel-2 data, as well as atmospheric corrections based on the Modified Atmsopheric correction for Inland water

(MAIN) algorithm (Page, et. al. 2019; Table 3). Our team made minor adjustments within the ORCAA 2.0 code to optimize outputs tailored for our project (Table B1; Table B2).

Table 3
Water quality parameter algorithms in ORCAA 2.0 tool

Satellite	Parameter Algorithm/ Software	Script Lines	Bands	Reference
Landsat 8 OLI	Turbidity	1420-1437	B4	Dogliotti et al. 2015
Sentinel-2 MSI	Turbidity	1439-1450	B4	Dogliotti et al. 2015
Sentinel-2 MSI	Chlorophyll-a	1453-1478	B4 (665 nm) and B5 (708 nm)	Mishra et al. 2012

3.2.4. Turbidity
We analyzed estimates of turbidity calculated from Sentinel-2 MSI data using ORCAA 2.0. We used ORCAA to visualize turbidity estimates from the least cloudy image in each 10-day period between 2013 to June 2024. We identified dates where images covered at least 25% of the study area for further analysis. We then categorized these images by visually assessing the quality of the data over the study area (Figure 3). After assessing the available imagery for the study area, we identified all BWA dates between 2015 and 2024 using data from HDOH, CWB. We intersected the categorized images with the BWA dates to determine if they were collected within BWAs or alternate conditions.

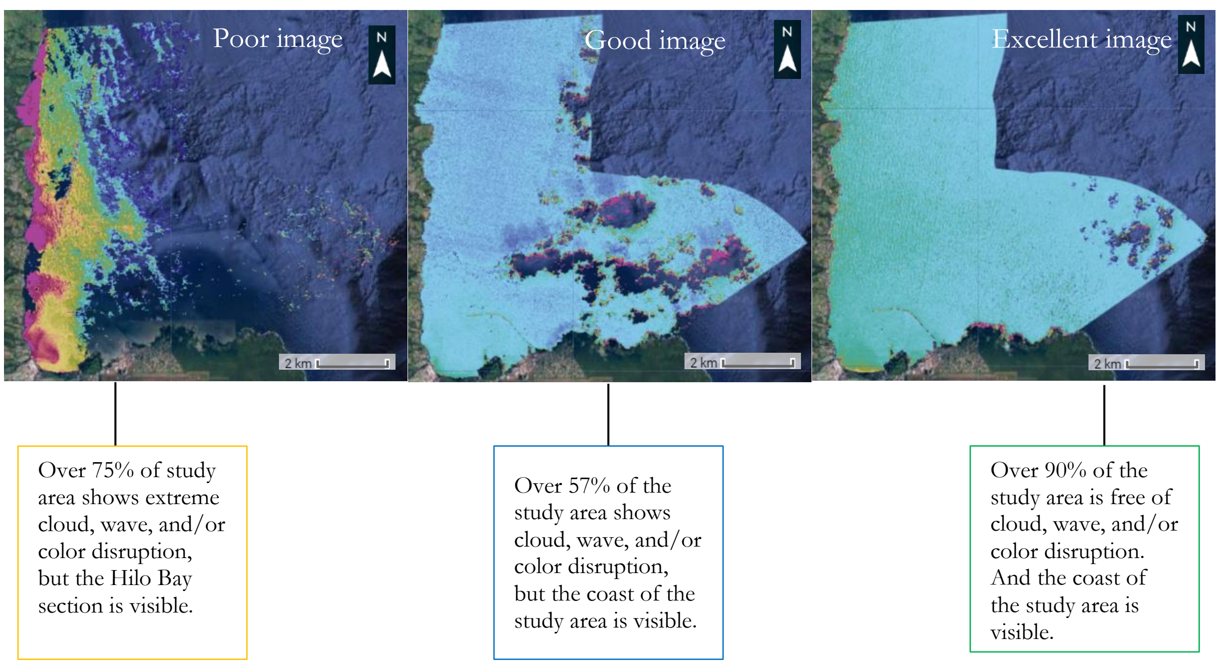

Figure 3. Criteria for selecting viable turbidity Sentinel-2 MSI imagery from ORCAA 2.0. The above images were taken from 9/5/2018, 2/17/2019, and 4/2/2020 respectively. Base map credit: *Terra Metrics 2024*

3.2.5 Chlorophyll-a
We acquired Aqua and Terra MODIS-derived chlorophyll-a data using a custom L-shaped spatial filter drawn in ArcGIS Pro 3.2.2 covering our study area. This processing step narrowed down available MODIS water pixels omitting land or breakwater pixels that could misinterpret land chlorophyll-a values for aquatic values. Pre-processed data using the chlorophyll-a algorithm from NASA's Ocean Biology Processing Group (OBPG) generated resulting chlorophyll-a values (Werdell et. al, 2023). We used Python to clean the data and

calculate average daily chlorophyll-a values for days without cloud interference over the study area and graphing software, R and Excel, were used to plot points for 2018 (Figure 4).

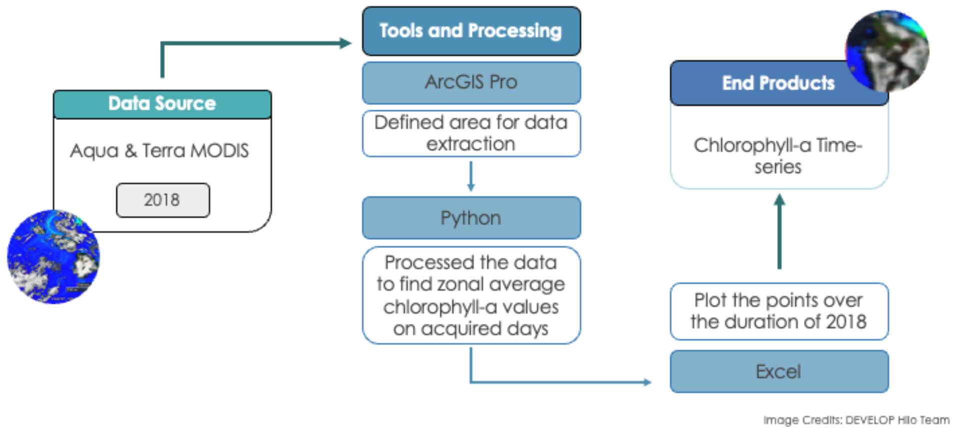

Figure 4. Methodology to process chlorophyll-a data from Aqua and Terra MODIS.

3.2.6 Precipitation

We retrieved daily precipitation data from the HCDP for three monitoring stations in our study area, Hilo International Airport (ITO; 87), Institute of Pacific Islands Forestry (IPIF; 87.9), and Piʻihonua (89.11) (Appendix B; Hawaii Climate Data Portal*, n.d.*). We selected readings one month before and after each BWA and exported the data as CSV files. We also exported Sentinel-2 MSI mean turbidity data as CSV files using the ORCAA 2.0 time-series generator.

3.3 Data Analysis

3.3.1 Precipitation and Turbidity Analysis

To understand the relationship between precipitation, turbidity, and BWAs, we analyzed three case studies: Hurricane Lane (August 2018), heavy rain (March 2021), and a sewage spill (November 2022). We consolidated the ITO, IPIF and Piʻihonua daily precipitation files within Microsoft Excel and computed the daily averages across the three stations. We then merged the daily precipitation averages with the Sentinel-2 MSI mean turbidity data and generated a set of mean turbidity time series graphs.

3.3.2 BWA Time Series

To track spatial changes, we generated another time series graph combining Sentinel-2 MSI median turbidity and median chlorophyll-a from before, during, and after a BWA occurred in February 2021. We extracted the time series graphs for these parameters using the Time Series Chart Generator of ORCAA 2.0. Then, using Microsoft Excel, we created a single graph that cross-analyzed the data, highlighting the dates assigned as BWAs.

3.3.3 Chlorophyll-a Analysis

We created time-series outputs from ORCAA 2.0 for Sentinel-2 MSI chlorophyll-a and turbidity trends surrounding a case study BWA issued from March 1, 2021 to April 19, 2021. Additionally, we used R version 4.3.3 to graph Aqua and Terra MODIS chlorophyll-a data across 2018. We used the MODIS data to examine the spatial and temporal patterns, as well as identify peak values within our study area.

4. Results & Discussion

4.1 Analysis of Results

We provided a count of the image dates selected and classified for the project. We included example images illustrating turbidity levels during a BWA and when no BWA was in effect. Additionally, we displayed images that show turbidity plumes identified along the coast during a BWA, and images that documented the progression of turbidity levels during a BWA event. The results also featured time series graphs that analyzed the relationship between turbidity mean levels and precipitation in three different cases, as well as the relationship between turbidity averages and chlorophyll-a averages during a BWA event. Finally, we presented a time series of chlorophyll-a levels specifically related to the Hurricane Lane BWA case in 2018.

4.1.1 Sentinel-2 MSI and Landsat Imagery Availability

When assessing Landsat 8 OLI and Landsat 9 OLI-2 true color images, the team found there to be 69 cloud free images between 2013 and 2024. Only 1 of these 69 viable images occurred during a BWA period (Table B1). When assessing Sentinel-2 MSI images, we found 82 viable images for the study. Out of these, 22 images coincided with BWAs, and 60 images were from non-BWA periods. Due to limited Landsat image availability, we decided to focus our study on Sentinel-2 MSI data.

4.1.2 Analysis of the Turbidity Results

After processing and analyzing the turbidity estimates, we confirmed that image-derived turbidity can serve as a reliable water quality indicator due to its consistently high levels during BWAs. Figure 5 illustrates this: it shows low turbidity levels in the Hilo Bay Region during non-BWA periods, compared to increased turbidity levels during BWAs, especially within Hilo Bay.

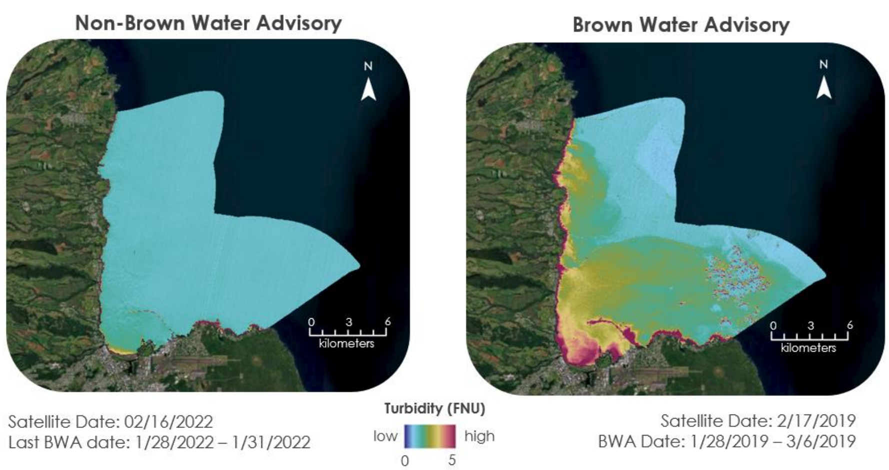

Figure 5. Sentinel-2 MSI turbidity image from a non-BWA day February 16, 2022 (left) and a BWA day February 17, 2019 (right). Base map credit: Resource Mapping Hawaiʻi, Maxar.

The team also analyzed the progression of a BWA by comparing the turbidity calculated from Sentinel-2 MSI data before a BWA (February 1 – 28, 2021), in the beginning of a BWA (March 1-14, 2021), in the middle of a BWA (March 15-31, 2021), and at the end of a BWA (April 1-19, 2021; Figure 6). The images show a gradual progression of turbidity extending north along the coast from Hilo Bay. Even though the turbidity values are relatively flat in both the first and final image, the average turbidity values increase following the BWA.

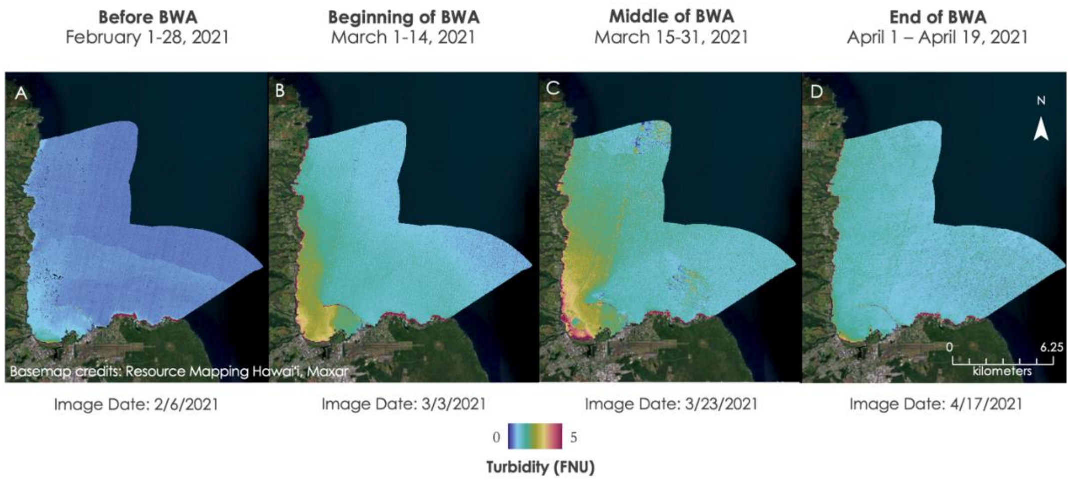

Figure 6. Time Series from Sentinel-2 MSI before, during, and after a Brown Water Advisory issued on 3/1/2021 – 4/19/2021. A turbidity plume is shown in magenta and yellow flowing outwards from the western portion of the Bay. Base map credit: Resource Mapping Hawaiʻi, Maxar.

While examining the coast, our team identified several turbidity plumes extending from the shoreline, often at river outflows. We recognized turbidity plumes not only by the prominent magenta coloration in certain areas but also by the yellow plumes extending offshore. Certain areas of magenta along the shoreline may not be reliable because they may be waves misidentified as high turbidity (Figure 7). Because of this, we also focused on yellow areas to understand the spatial distribution of turbidity. While our study did not focus on identifying exact point-source locations on land, this is an example of how sources of plumes may be identified and further analyzed in future studies.

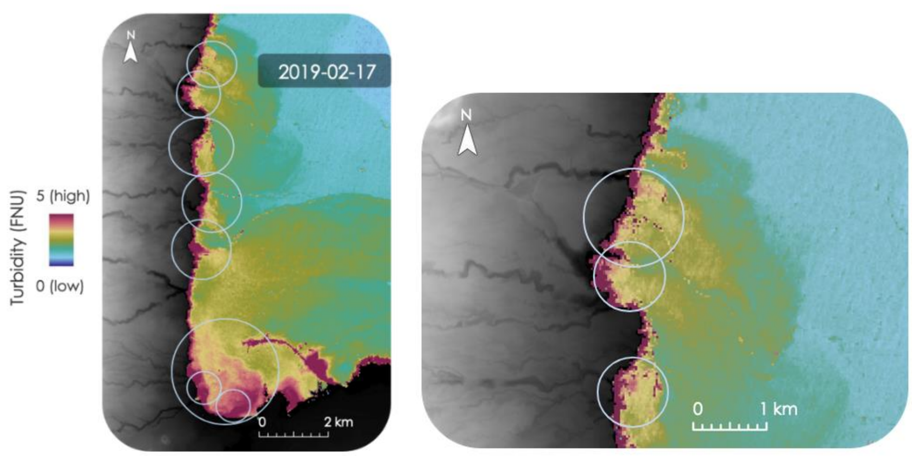

Figure 7. Example of Turbidity Plumes identification along the coast. Image taken on 02/17/2019 by Sentinel-2 MSI. Base Map credits: NOAA Office for Coastal Management and United States Geological Survey.

4.1.3 Analysis of Precipitation and Turbidity Results

The following BWA graph for August 2018, issued during Hurricane Lane, shows corresponding precipitation spikes closely followed by turbidity increases of similar magnitude (Figure 8). The BWA graph for March – April 2021 captures multiple spikes in both precipitation and turbidity levels (Figure C1; Figure C2). Finally, the November 2022 BWA shows a precipitation spike followed by a subsequent turbidity increase (Figure D2). Later in the month, during a BWA for a sewage spill, there is a marked increase in turbidity with a significant time lag after the BWA, during a period of low precipitation values. These results show that EOs can offer improved tracking of high turbidity events and better define their spatial and temporal longevity over traditional *in situ* water sampling and visual assessment methods.

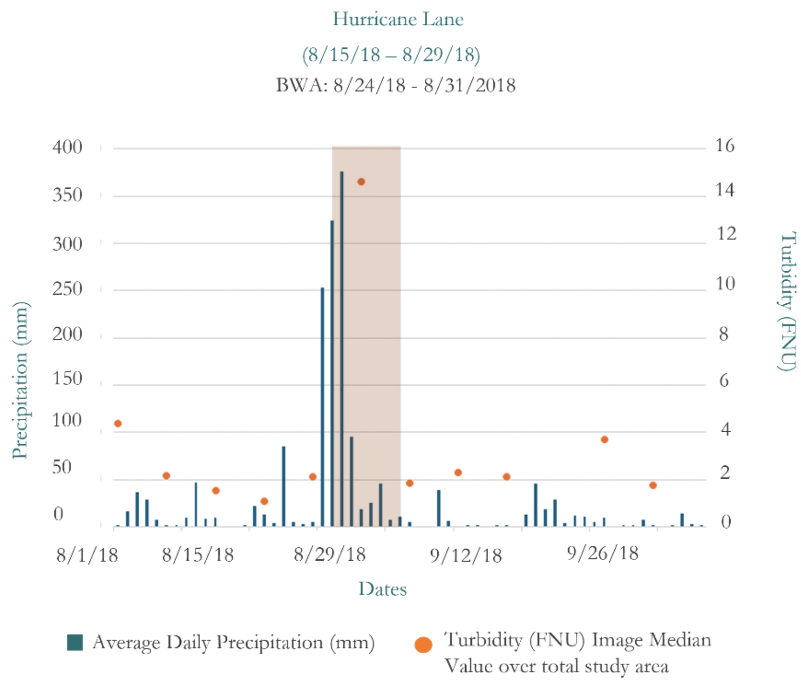

Figure 8. The BWA graph for August – September 2018 with precipitation and turbidity spikes.

4.1.4 Analysis of the Time series of the Parameters During a BWA

The ORCAA 2.0 Sentinel-2 MSI time series for turbidity and chlorophyll-a during a BWA between February – April 2021 indicated that the highest turbidity values occurred simultaneously with the issued BWA, marked by the brown box (Figure 9). In contrast, chlorophyll-a values remained relatively stable during this period, suggesting an independent relationship between turbidity and chlorophyll-a during a BWA scenario.

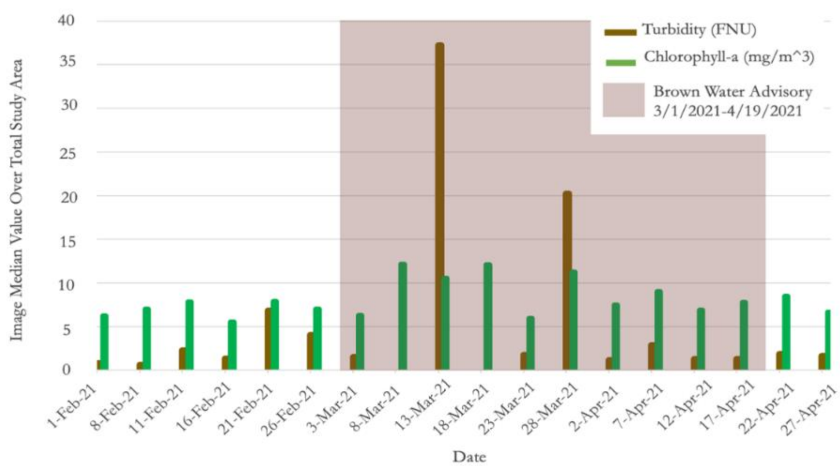

Figure 9. Comparison of chlorophyll-a (mg/m^3) and turbidity (FNU) before, during, and after a Brown Water Advisory issued from March 1, 2021, to April 19, 2021.

4.1.5 Analysis of the Chlorophyll-a Results

Sentinel-2 MSI did not provide detailed spatial variation for chlorophyll-a patterns. Despite a lower spatial resolution than Sentinel-2 (10 m), MODIS chlorophyll-a data (30 m) provided better temporal variation in chlorophyll-a patterns for the year 2018. The plotted data showed maximums for MODIS data aboard Aqua and Terra satellites occurring after Hurricane Lane, which was a Category 5 hurricane that struck the Hawaiian Islands between August 22 to August 26 of 2018 (Figure 10). Accompanying images, which can be found on the OB.DAAC, support the spatial changes with heightened chlorophyll-a values visible on the east side of Hawai'i Island near Hilo Bay.

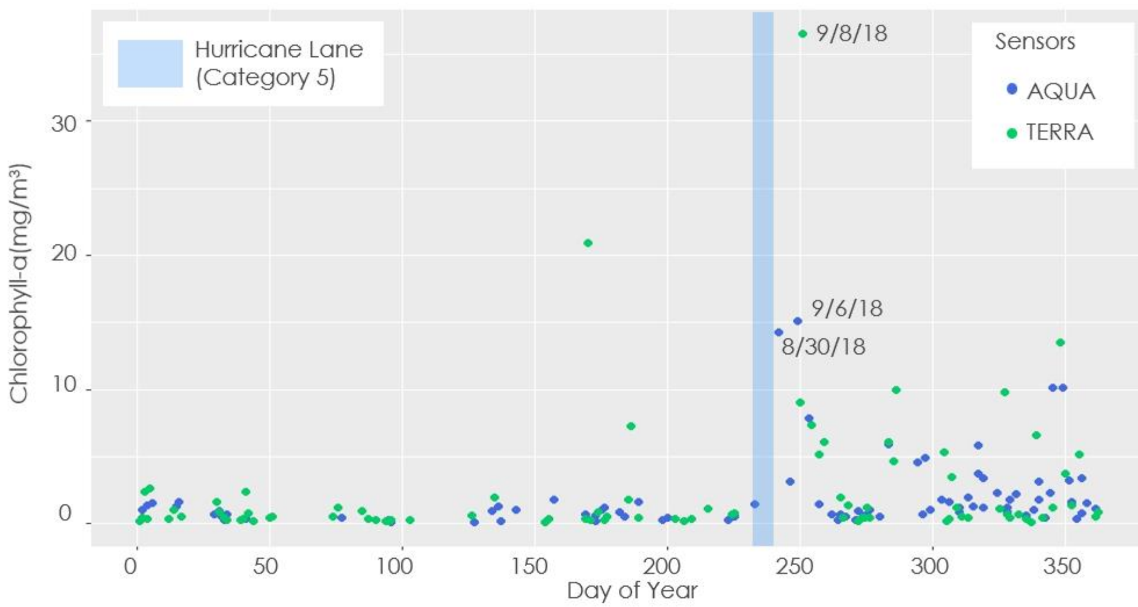

Figure 10: Chlorophyll-a values from Aqua and Terra MODIS during 2018 showed peaks occuring after Hurrican Lane and increased values for the rest of the year.

4.2 Errors & Uncertainties

The errors and uncertainties faced in this study include the issues found in optically complex environments of coastal zones; the consistent cloud cover in Hilo; lengthy satellite revisit time; and the turbidity units used within the ORCAA tool. Coastal zones are categorized as optically complex environments for collecting Earth observation data because up to 90% of the signal received by satellite instruments comes from the atmosphere and less than 10% of the signal is reflected from the water or bottom surface (Torres-Pérez & McCullum, 2020). This makes it critical to have an accurate atmospheric correction. The performance of the atmospheric correction algorithm Modified Atmospheric Correction for INland waters (MAIN) has not been assessed or validated, creating even more uncertainty regarding its accuracy (Valenti et al., 2019). Several studies agree that more work needs to be done to advance atmospheric correction, as it poses an obstacle to achieving accurate results (Sagan et al. 2020; Zhu et al. 2022).

Cloud interference, wave action, and algorithms not calibrated to our study area also produced uncertainty in our analysis of turbidity and chlorophyll-a levels in the region. Due to cloud interference, less than 25% of available Landsat images during the study period were usable for our study area. This limited availability of imagery was exacerbated by 16-day revisit times for Landsat 8 OLI and Landsat 9 OLI-2. In addition, ORCAA consistently misidentified wave action and whitecaps as high turbidity within the Hilo Bay Region, suggesting additional operational controls may be required to produce high quality turbidity maps. Chlorophyll-a algorithms also produce low confidence values in shallow, coastal waters which likely affected the accuracy produced by the ORCAA tool (Blondeau-Patissier et al. 2014).

A challenge that may impact partner implementation of this study is related to the turbidity units used by ORCAA. While Nephelometric Turbidity Units (NTU) is a more widely adopted unit of measure for turbidity within the United States and is based on Environmental Protection Agency (EPA) standards, ORCAA algorithms are calibrated to FNU instead. While these units are similar, they are not identical, which means that our partners may need a separate model calibration for projects requiring compliance with EPA standards. Despite the challenges and the degree of uncertainty within our study's results, our results provide promising evidence that Earth observations can be used to inform future water quality monitoring in the Hilo Bay Region.

4.3 Feasibility & Partner Implementation

Through an assessment of available Sentinel-2 and Landsat 8 turbidity imagery, our team found it feasible to visually identify turbidity plumes in Hilo Bay and along the coast with EO data. This study found higher concentrations of turbidity within Hilo Bay at the mouths of the Wailuku and Wailoa Rivers, with smaller turbidity plumes extending along the coast north of Hilo, most frequently at the mouth of other rivers and stream. Knowing where turbidity plumes are consistently located in Hilo Bay and along the coast can support OSCER's decision-making regarding what water sampling locations should be prioritized on a regular basis following heavy rainfall or water treatment failures. Our team produced time-series charts with the ORCAA tool to assess temporal variability of turbidity values before, during, and following BWAs. When assessing the temporal variability of turbidity, we found turbidity values increased during BWAs but found no known correlation between turbidity and chlorophyll-a levels. When assessing chlorophyll-a levels within the Hilo Bay region, we found the values to show little spatial and temporal variation. Because of this, chlorophyll-a plumes and their spatial variability could not be easily identified within our study region. As a result, we explored Aqua and Terra MODIS chlorophyll-a values from NASA Worldview along the windward (East) side of Hawai'i Island for the year 2018, before, during, and after Hurricane Lane. When expanding beyond our study area to the broader coastal region, variability in chlorophyll-a values became more apparent. While this method of assessing chlorophyll-a levels comes at a lower spatial resolution, the frequent revisit time of Aqua and Terra satellites makes close to real-time water quality monitoring possible.

4.3.1 Future Work

Our team sees two main pathways for future studies: refining water quality monitoring of turbidity and chlorophyll-a in the coastal zone or shifting focus to identify land-based point-source locations contributing to heightened turbidity and chlorophyll-a values using EO data. To further refine water quality monitoring, the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) instrument and Visible Infrared Imaging Radiometer Suite (VIIRS) instrument may provide fruitful avenues for further investigation. While our study focused on the feasibility of monitoring turbidity and chlorophyll-a levels within the Hilo Bay region, future studies could refine the analyses of the land-water boundary by including land cover classification and topographic data in the watershed and coastal region to identify point-source locations for turbidity plumes (Figure D1). Further investigation is also needed to determine the links between precipitation and EO information.

5. Conclusions

The persistent issue of brown water in the Hilo Bay region highlighted the need for understanding spatial and temporal patterns of water quality parameters, specifically turbidity and chlorophyll-a. This study demonstrated the viability of using Earth observations to monitor water quality in the Hilo Bay region. We found a considerable increase in turbidity during most BWAs analyzed when compared with non-BWA water quality data. We also found Sentinel-2 MSI data to be more suitable than Landsat 8 OLI data for analyzing turbidity in the Hilo Bay region due to greater data availability. While turbidity in the Hilo Bay region was most concentrated in Hilo Bay, smaller plumes extending off the coast were also visible in several turbidity maps and coincided with BWAs. Further analysis of Sentinel-2 MSI turbidity data can be used to identify point-source locations of turbidity inputs by analyzing data across different BWAs and identifying consistently visible turbidity plumes.

While we found no observable correlation between chlorophyll-a and turbidity, we did, however, see the outflow of the Wailoa River as a consistent location for chlorophyll-a concentrations, as seen from Sentinel-2 MSI chlorophyll-a data. When compared with turbidity data, chlorophyll-a levels from Sentinel-2 MSI were relatively flat within the extent of our study region. When zooming out beyond the extent of our study area, we found Aqua and Terra MODIS chlorophyll-a data to be a promising avenue for near real-time (daily) chlorophyll-a monitoring of the larger coastal region. The time-series we produced using NASA Worldview Aqua and Terra MODIS chlorophyll-a data for the year 2018 shows that chlorophyll-a levels increased after Hurricane Lane. This methodology could be employed in future water quality monitoring following serious weather events.

The maps and charts our team produced provide a view into water quality in the Hilo Bay region from 2013 to 2024. The methodology outlined in this study can be reproduced to monitor turbidity within the Hilo Bay region in the future during both non-BWA time periods and BWAs, as well as to monitor chlorophyll-a levels in the broader region. All data and tools used are open-access and can be used by the County of Hawaiʻi, other researchers, and community scientists alike to further understand water quality dynamics in the Hilo Bay region in the past, present, and future. In addition to generating maps and charts for this study, we also created a community brochure for outreach, education, and community engagement to keep community members in-the-know on this important issue regarding local water quality.

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Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Aeronautics and Space Administration.

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7. Glossary

ArcGIS Online: a cloud-based mapping and analysis solution. Use it to make maps, to analyze data, and to share and collaborate
ArcGIS Pro 3.2.2: a desktop GIS software developed by ESRI
BWAs: Brown water advisories
Chlorophyll-a: Chlorophyll-a allows plants to photosynthesis and is used to measure algae growing in a waterbody
EO: Earth observation; Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time

CWB: Clean Water Branch; protects the public health of residents and tourists who enjoy playing in and around Hawaii's coastal and inland water resources
HCDP: Hawaiʻi Climate Data Portal; a centralized resource for access to high-quality, up-to-date access to climate data, research, and visualization tools
HDOH: Hawaiʻi Department of Health; a state agency of Hawaiʻi, functions under the leadership of the Director and Deputy Director, and includes attached offices and agencies.
Landsat 8 OLI: Landsat 8 is a satellite launched on February 11, 2013, with one of its two sensors being the Optical Land Imager.
MODIS: Moderate Resolution Imagine Spectroradiometer, a sensor on NASA satellites Aqua, Terra
OB. DAAC: NASA's Ocean Biology Distributed Active Archive Center
NASA Worldview: an online platform where satellite data can be viewed around the world
OSCER: Office of Sustainability, Climate, Equity & Resilience
Python: a programming language used in our study
R: a programming language for statistical analysis and data visualization used for our study
Sentinel-2 MSI: Sentinel-2 Multispectral Instrument
Turbidity: Turbidity is determined by the amount of light scattered by particulates within water affecting the color and clarity (USGS 2018) and has been used as an indicator for sediment and other contaminants.
USACE: US Army Corps of Engineers

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9. Appendices

Appendix A: *Available Imagery*

Table A1

Landsat 8 OLI viable image dates from 2013-2024

Year	**Viable Image Dates** (with applied cloud mask)	**Year**	**Viable Image Dates** (with applied cloud mask)	**Year**	**Viable Image Dates** (with applied cloud mask)
2013	6/17/2013	2017	1/3/2017	2020	4/1/2020
	9/5/2013		2/4/2017		12/29/2020
	11/24/2013		4/9/2017	2021	3/3/2021
	12/10/2013		5/27/2017		4/20/2021
2014	1/27/2014		7/14/2017		7/9/2021
	6/20/2014		8/15/2017		10/29/2021
	7/6/2014		8/31/2017	2022	1/17/2022
	9/24/2014		10/2/2017		2022-04-07
	11/11/2014		11/3/2017		7/28/2022
2015	1/30/2015		12/5/2017		8/29/2022
	5/6/2015	2018	2/7/2018		9/30/2022
	5/22/2015		5/14/2018	2023	4/10/2023
	7/9/2015		12/8/2018		4/26/2023
	8/10/2012	2019	1/25/2019		5/12/2023
	10/13/2015		2/26/2019		8/16/2023
2016	1/1/2016		5/17/2019		10/19/2023
	3/5/2016		7/20/2019		11/20/2023
	5/8/2016		9/22/2019	2024	None
	7/11/2016		10/24/2019		
	9/29/2016				
	10/15/2016				

Table A2

Landsat 9 OLI-2 viable image dates from 2022 – 2024

Viable Image Dates (with applied cloud mask)	**Year**
2022	1/9/2022
	2/10/2022
	6/2/2022
	8/21/2022
	11/9/2022
	12/27/2022
2023	1/12/2023
	3/17/2023
	8/8/2023
	10/27/2023
2024	None

Appendix B: *Usable BWA Dates for Acquiring Satellite Imagery*

Table B1

Brown water advisory useful imagery dates for Sentinel-2 MSI

TURBIDITY					
Brown Water Advisory Date			**Sentinel-2 Date**	**ORCAA Quality image**	**Note**
Type of BWA	**Start**	**Closure**			
Heavy rain	8/23/2016	8/30/2016	8/26/2016	Poor	One section works
Heavy rain	8/30/2016	9/13/2016	9/5/2016	Good	Doesn't show much turbidity
Heavy rains	12/14/2016	12/21/2016	12/14/2016	Poor	Show something
Heavy rain	10/30/2017	12/31/2017	11/4/2017	Good	Has clouds disturbance
Heavy rain	10/30/2017	12/31/2017	12/24/2017	Excellent	Has some clouds disturbance
Heavy rain	1/1/2018	1/5/2018	1/3/2018	Excellent	Doesn't show much turbidity
Hurricane lane	8/24/2018	9/4/2018	8/31/2018	Good	Good visualization
Hurricane lane	8/24/2018	9/7/2018	9/5/2018	Poor	Good visualization
Heavy rain	9/4/2018	12/31/2018	11/9/2018	Good	Good visualization
Rough ocean conditions	1/28/2019	3/6/2019	2/17/2019	Good	Good visualization
Rough ocean conditions	1/28/2019	3/6/2019	1/28/2019	Poor	One section works
Heavy rain	1/8/2020	1/22/2020	1/3/2020	Excellent	Good
Heavy rain	1/8/2020	1/22/2020	1/18/2020	Poor	The bay section works
Heavy rain	4/2/2020	4/28/2020	4/2/2020	Excellent	Has one cloud small section
Undetermined	10/14/2020	10/20/2020	10/14/2020	Excellent	Has some clouds disturbance
Heavy rain	3/1/2021	4/19/2021	3/3/2021	Excellent	Good visualization
Heavy rain	12/13/2021	12/22/2021	12/18/2021	Poor	One section works
Broken air feed line	11/24/2022	11/29/2022	12/23/2022	Excellent	Doesn't show much turbidity
Heavy rain	3/6/2023	4/10/2023	3/8/2023	Excellent	Doesn't show much turbidity
Heavy rain	7/19/2023	7/28/2023	7/26/2023	Poor	Has many waves disturbance
Heavy rain	11/30/2023	1/4/2024	12/28/2023	Good	Doesn't show much turbidity
Heavy rain	2/27/2024	3/19/2024	3/2/2024	Good	Weird colors

Table B2

Brown water advisory useful imagery dates

TURBIDITY			
Not a Brown Water Advisory Date			Note
Year	Date	ORCAA Quality image	
2016	11/4/2016	Good	One section works
2017	1/3/2017	Excellent	Excellent
2017	2/12/2017	Excellent	Excellent
2017	7/7/2017	Good	Has waves disturbance
2017	8/16/2017	Good	Has waves disturbance
2017	9/5/2017	Good	Has clouds disturbance
2017	9/25/2017	Excellent	Good
2018	1/13/2018	Good	Must adjust color
2018	2/2/2018	Good	Good
2018	3/29/2018	Good	Must adjust color
2018	9/10/2018	Good	Show something interesting
2019	3/29/2019	Excellent	Not BWE image
2019	5/18/2019	Poor	has many waves disturbance
2019	7/27/2019	Poor	has many waves disturbance
2019	9/10/2019	Poor	has many waves disturbance
2019	10/5/2019	Good	Not BWE image
2020	2/17/2020	Excellent	Good
2020	5/17/2020	Poor	has many waves disturbance
2020	6/26/2020	Poor	has many waves disturbance
2020	7/1/2020	Poor	has many waves disturbance
2020	9/4/2020	Excellent	Excellent
2020	9/19/2020	Excellent	Has some clouds disturbance
2020	9/29/2020	Excellent	Good visualization
2020	10/9/2020	Excellent	Excellent
2020	11/8/2020	Good	Has some clouds disturbance
2020	11/13/2020	Good	Has some clouds disturbance
2020	12/31/2020	Good	Has some clouds disturbance
2021	2/6/2021	Good	Some missing pixels
2021	4/17/2021	Good	has some waves disturbance
2021	4/27/2021	Poor	has many waves disturbance
2021	6/1/2021	Poor	has many waves disturbance
2021	8/20/2021	Poor	Waves, not turbidity visual
2021	8/15/2021	Good	Some waves disturbance

2021	9/4/2021	Poor	Waves and clouds
2021	9/14/2021	Excellent	Not much turbidity
2021	10/4/2021	Excellent	Not much turbidity
2021	10/29/2021	Good	Some waves disturbance
2021	11/3/2021	Excellent	Excellent
2021	11/28/2021	Good	The coast section works
2022	1/7/2022	Excellent	Some empty spaces for clouds
2022	1/17/2022	Good	Some empty spaces for clouds
2022	2/1/2022	Poor	Some empty spaces for clouds
2022	2/16/2022	Excellent	Some turbidity
2022	3/13/2022	Good	Not covers the central bay
2022	6/21/2022	Poor	Bad color in some areas
2022	9/29/2022	Good	Not covers the central bay
2022	10/14/2022	Excellent	Excellent
2023	1/12/2023	Excellent	Not BWE image
2023	2/1/2023	Good	Adjust color
2023	2/8/2023	Excellent	Excellent
2023	5/12/2023	Poor	has many waves disturbance
2023	9/29/2023	Poor	Not covers the central bay
2023	10/14/2023	Excellent	Excellent
2023	11/3/2023	Excellent	Excellent
2023	11/13/2023	Poor	has many clouds disturbance
2024	2/1/2024	Excellent	Excellent
2024	3/2/2024	Excellent	a little dark
2024	5/11/2024	Good	Weird color
2024	7/5/2024	Poor	Weird color

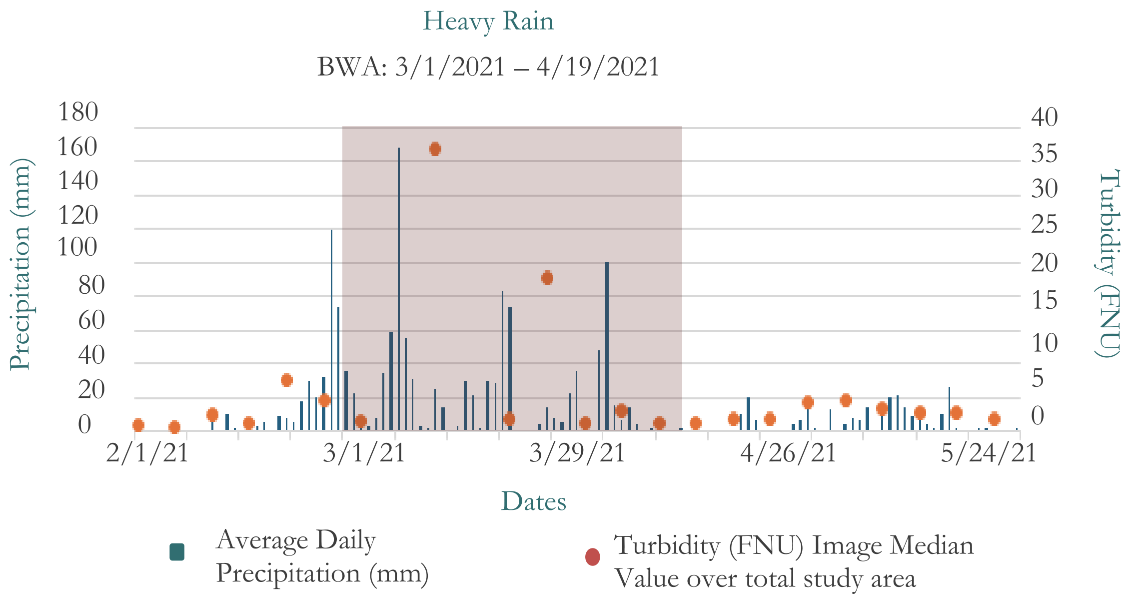

Figure C1. March – April 2021 BWA, Turbidity and Precipitation Graph

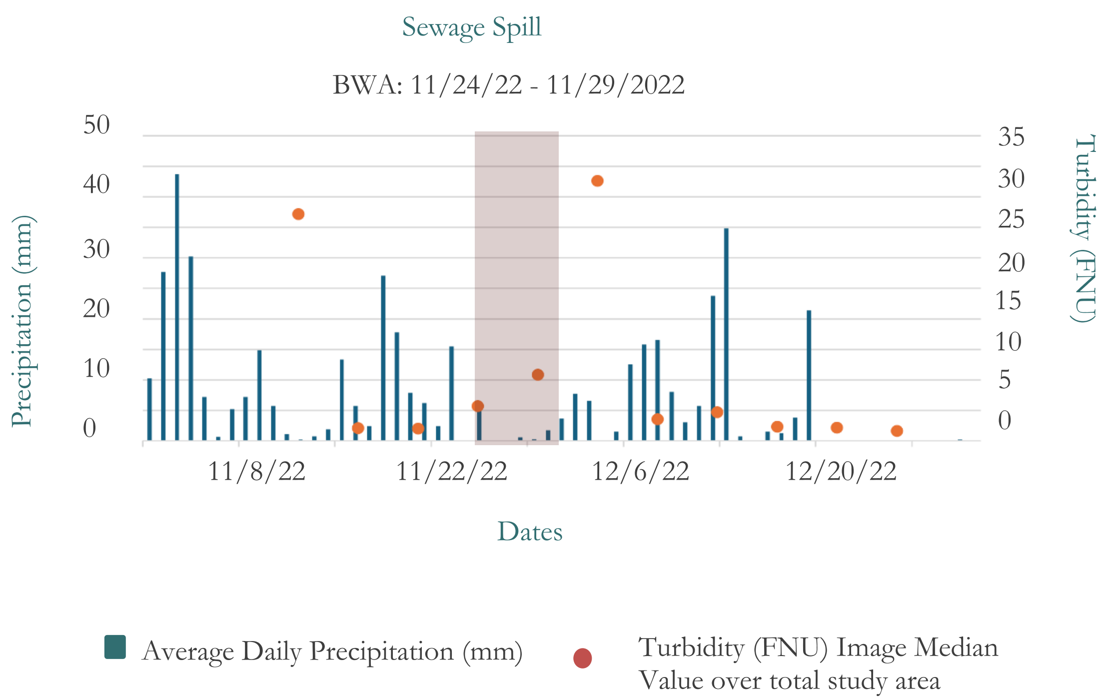

Figure C2. November – December 2022 BWA, Turbidity and Precipitation Graph

Appendix D: *Impervious Surface Cover in Hilo Town*

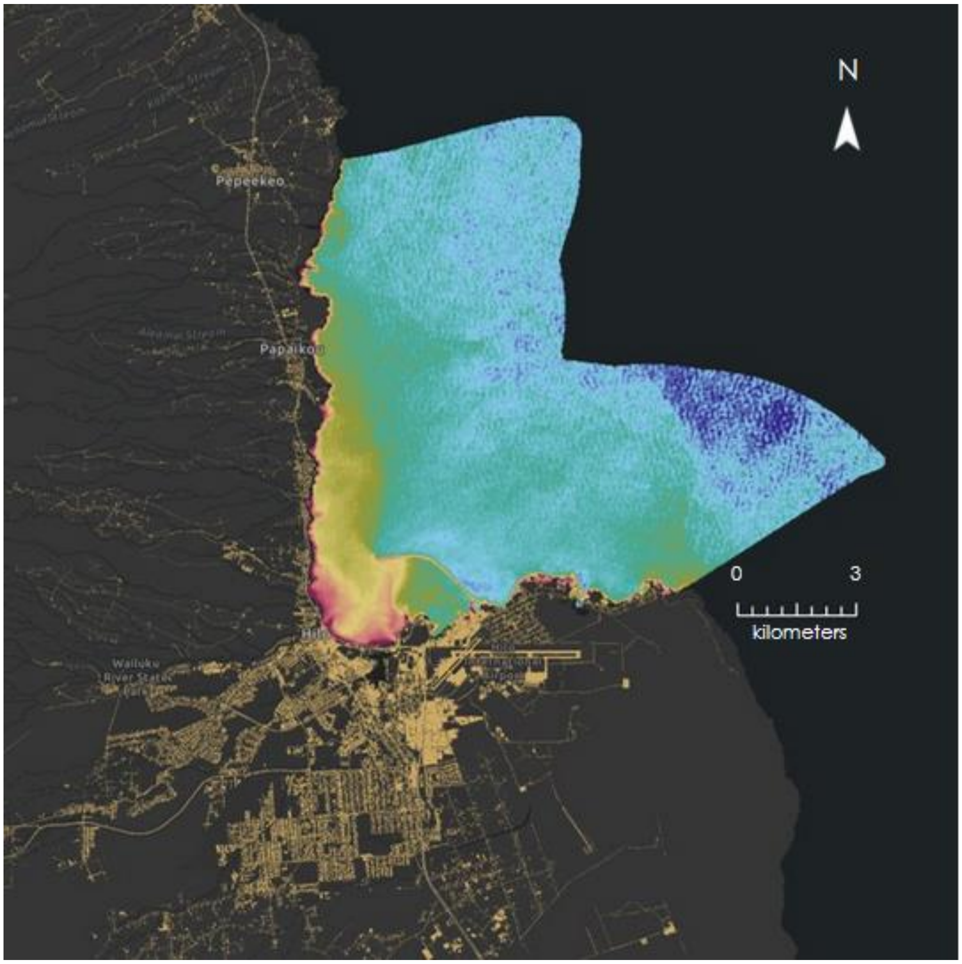

Figure D1. Hilo town's impervious surfaces with turbidity displayed in the Hilo Bay region.