# ASSESSING YAHARA LAKES WATER EXCLOSURE TREATMENT SYSTEM (WETS) WATER QUALITY USING SENTINEL-2 REMOTE SENSING SATELLITE

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# Abstract

This study assesses the suitability of the European Space Agency's newest generation paired satellites, Sentinel-2 A & B, in detecting spectral differences likely related to lake water quality parameters. The study evaluates differences between water inside and outside a Water Exclosure Treatment System (WETS) at Goodland County Park Beach on Lake Waubesa and Mendota County Park Beach on Lake Mendota, surrounding the Madison Metro Area within Dane County, Wisconsin between Memorial Day and Labor Day for 2019 and 2020. Previous large lake-water body studies, using various remote sensors, demonstrate reliable empirical relationships between satellite data and ground observations. The improved capabilities of the MSI (multi-spectral instrument) sensor aboard the Sentinel-2 A & B satellites allow for the best possible evaluation of the WETS small, shallow lake-water area constituents such as Secchi Disk Depth (SDD), a common measurement of water clarity, chlorophyll-a (chl-a), colored dissolved organic matters (CDOM), turbidity, and total suspended sediments (TSS). Sentinel-2 10-meter bands best support evaluating spectral differences of the small (Mendota 478 sq meters, Goodland 318 sq meters), shallow five-foot deep WETS areas. After adjusting for depth effect and differences during the uninstalled period, the visible sensor bands 2, 3, and 4 are best for detecting spectral differences. The water quality algorithms, using the 10-meter bands, detect spectral differences less prominently than the individual visible bands. Discovering spectral differences in the blue, green, and red visible bands occurred only in 2020, thus it is not known if the spectral differences inside and outside the WETS is related to the filtration of the WETS or other environment factors.

# Introduction

Lake Mendota (Mendota Beach study area) and Lake Waubesa (Goodland Beach study area) are part of the Yahara Lakes System which is a chain of five lakes connected by the 62-mile long Yahara River, located in Dane County, Wisconsin, primarily surrounding the City of Madison (Figure 1). These lakes are Mendota, Monona, Wingra, Waubesa and Kegonsa ranging in surface area from 3,985 ha to 136 ha.

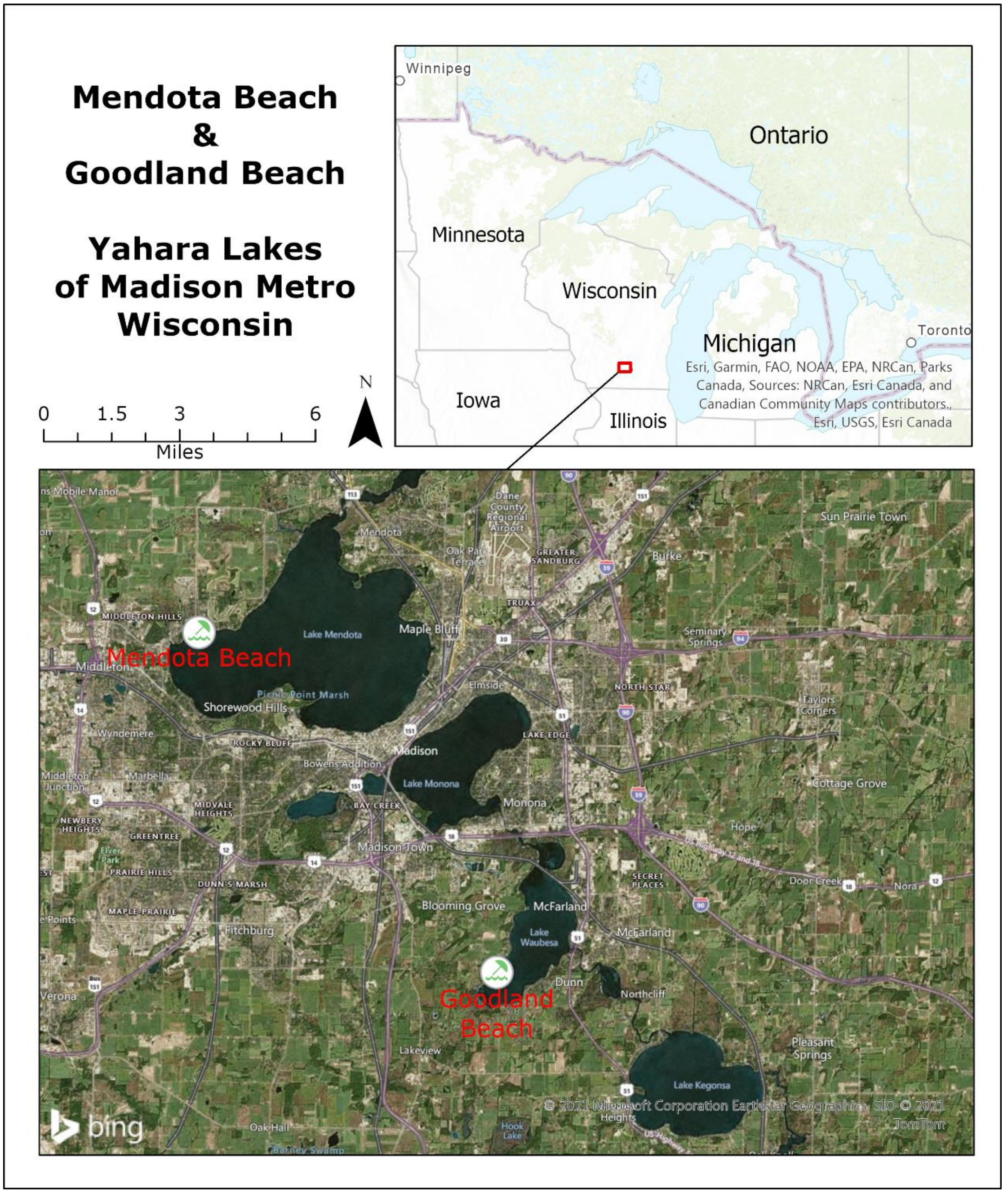



*Figure 1: Map showing locations of the studied beaches.*

This system provides recreational, aesthetic, and economic value to the county and city. Unfortunately, excessive amounts of phosphorus pollution running into the lakes, due to intense land use in the surrounding area, is causing potentially harmful blue-green algae (cyanobacteria) blooms. The excessive algae blooms not only are ugly and foul-smelling, but can be toxic to humans and animals; resulting in closed beaches, reduced opportunity for boating and fishing as well as threatening the health of local ecosystems. The trend of heavier rainfalls in recent years is increasing the amount of polluted runoff into the lakes. Tracking and attempted management of these blooms is a key objective for Dane County as is providing a safe recreation swimming space by way of filtered beach exclosures known as Water Exclosure Treatment System (WETS). Reimer, Wu, and Sorsa (2018) published positive results (reduction of E. coli and cyanobacteria) and no beach closures from testing a 2011 WETS deployment and *in situ* water quality analysis at Brittingham Beach on Lake Monona. Dane County Lake Department now deploys a varying number of WETS at beaches throughout the Yahara Lakes every summer. The WETS five-sided polypropylene exclosure protects the swimming area from contaminated offshore lake water. Within the WETS barrier, the water pumps into a portable treatment system and is filtered by ultraviolet light and a three-component sub-system:

1. A strainer removes heavy debris (aquatic plants),
2. Automated backwashing and sand filter remove the fine particles, and
3. Ultraviolet light inactivates pathogens, viruses, bacteria, and algae,

sending the backwash water to the sanitary sewer and returning clean water to the swimming area.

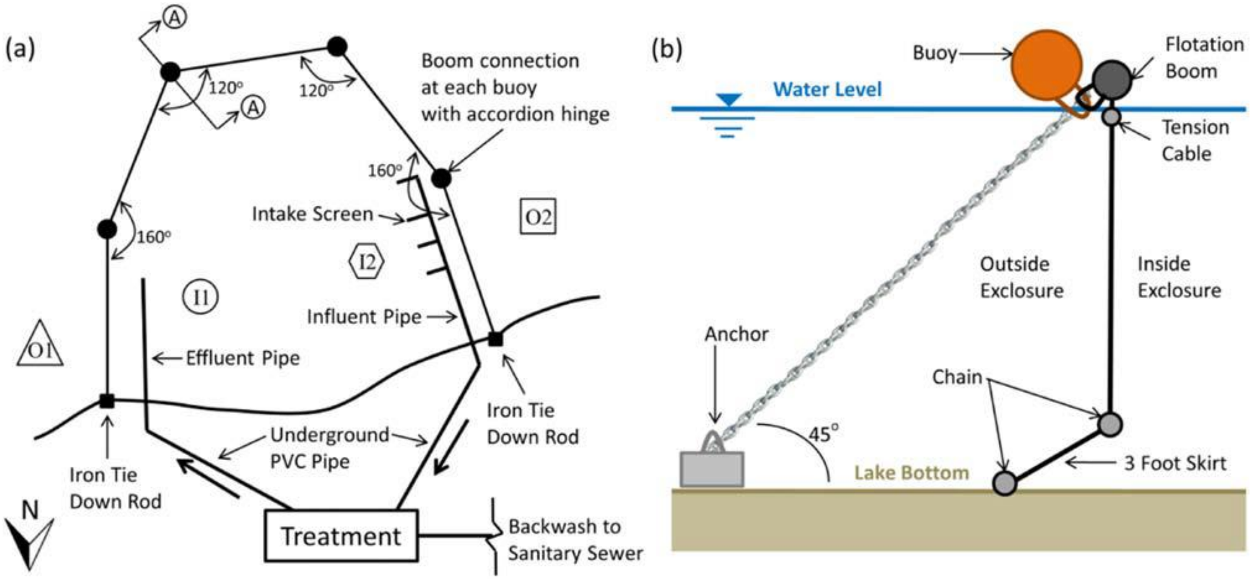



*Figure 2: (a) WETS sub-systems (b) Exclosure sub-system with anchor configuration (Reimer et al., 2018).*

Since the initial experiment, the City of Madison tests each WETS filtered swimming water, regularly, *in situ* for E. coli and cyanobacteria but no other water constituents. The purpose of this study is to determine if remote sensing can detect spectral differences between inside and outside the WETS at Mendota and Goodland Beach (Figure 3), assisting Dane County Land and Water Resources Department in monitoring the effectiveness of WETS deployments.

*Figure 3: Goodland Beach WETS, Source: Clean Lakes Alliance.*

While remote sensing, using Landsat multispectral data, of water quality has increased over the past 20-years, it is still not common practice, specifically in Dane County. This case study evaluates the suitability of using a recent generation of Earth observation satellites, Sentinel-2 A & B, for potentially improved water quality within the WETS.

Sentinel-2A and Sentinel-2B Multi-Spectral Imager (MSI) launched on 23 June 2015 and 07 March 2017, respectively, create a new opportunity in the remote sensing of inland waters water clarity. The European Space Agency (ESA) designed Sentinel-2 satellites (A & B) providing continuity to the SPOT (Satellite Pour l'Observation de la Terre, in English means, satellite to observe Earth) missions. The two Sentinel satellites are polar-orbiting, placed in the same sun-synchronous orbit, phased at 180 degrees to each other with a repeat of 10 days, combined is five days.

Different studies using multi-resolution satellites such as MODIS, MERIS, Landsat TM and ETM+, SPOT, QuickBird and Ikonos demonstrate successful monitoring of water quality including water surface temperature, water clarity, chlorophyll-a and phycocyanin concentrations, and total suspended sediments (Bonansea et al. 2019). These are powerful supporting tools for assessing temporal and spatial variations in water quality. Kloiber, Brezonik, Olmanson, et al. (2002) developed the most relevant and widely-used protocol for water clarity image processing of inland lakes using Landsat Thematic Mapper (TM) and Multi-Spectral Scanner (MSS) sensor data. The improved capabilities of the Sentinel-2 satellites enhance these common relevant protocols. These improvements include: providing medium-resolution (10 – 60 meters), an additional shorter wavelength blue band (ultra-blue), narrower near-infrared (NIR) band, 12-bit radiometric resolution, and greater signal to noise ratios.

The Sentinel-2 A or B relative orbit 26, tile 15 covers both beach areas of study. Sentinel-A and B imagery is available every five days combined (revisit frequency of each satellite is 10 days), however, not all dates were useable due to cloud cover. I selected Level 2A imagery based on cloud-free access and the start and end dates (before Memorial Day and after Labor Day) of WETS filtration; providing 15 days for 2019 and 22 days for 2020.

# Literature Review

Over the past 50 years, the study of water quality in lakes and rivers using remote sensing has expanded substantially. Topp, et al. (n.d.) examined 236 key papers, finding inland water remote sensing literature written only in the past 10-15 years. Of all the papers reviewed, twice as many studies published in the last ten years as compared to those published in the previous 28 years combined. In 2008, open access to Landsat data became available, followed by increased access to data via Google Earth Engine. After such time, 30% focused on examining drivers and impacts of water quality, compared to only 7% for the period prior. Remote sensing studies originally focused on water clarity (Secchi Disk Depth) and total suspended sediments since they are a simpler metric, due to challenges of modeling more complex spectral signatures ascribable to limited radiometric resolution of satellites. Nonetheless, many sensors both on satellites and other platforms, such as airplanes or drones, measure the qualitative parameters of water. Optically active constituents of water most commonly measured via remote sensing include:  Secchi disk depth (SDD), chlorophyll-a (chl-a), colored dissolved organic matters (CDOM), turbidity, and total suspended sediments (TSS).

Remote sensing techniques measure the amount of electromagnetic radiation at various wavelengths reflected from the water's surface and uppermost water column. Many researchers frequently use the visible (mostly blue) and near infrared bands no matter which sensor their investigation is based upon (Gholizadeh et al., 2016). Case studies have shown successful remote sensing water quality monitoring of inland water variables (surface temperature, water clarity, chlorophyll-a and phycocyanin concentrations, and total suspended sediments) using multi-resolution satellites (Bonansea et al., 2019; Lehmann et al., 2017). Most studies develop models to estimate water quality parameters by comparing the relationship between remote sensing reflectance with *in situ* measurements using statistical analysis, linear and non-linear regression, as well as mechanical and deep learning algorithms (Govedarica & Jakovljevic, 2019). The most suitable current platforms to provide water quality attribute data is Landsat 8 and Sentinel-2 A & B (Lehman et al., 2017).

As of 2020, there are two Sentinel-3 satellites, 3A & 3B, in orbit as part of the Copernicus Program. These platforms have an OLCI sensor observing 21 spectral bands simultaneously in full resolution mode with a spatial resolution of 300 meters. The lower spatial resolution negates the viability of using Sentinel-3 satellites for this study. The Sentinel-3 design is to observe water constituents in bands ranging from visible to near-infrared (400nm to 1,020nm); while Sentinel-3 is not appropriate for this study, studies show the effectiveness of observing chlorophyll, sediment, turbidity, vegetation, and more amongst large inland lakes such as Lake Balaton, Hungary (Blix et al., 2018), Baltic Lakes in Estonia, Latvia, and Lithuania (Soomets et al., 2020), and the western basin of Lake Erie, Canada (Pirasteh et al., 2020). Cazzaniga, et al. (2019) found Sentinel-3 OLCI retrieved chlorophyll-a concentration as well as Sentinel-2 MSI when evaluating Lake Trasimeno and Lake Garda in Italy. Interestingly, Ogashawara (2019), found traditional algorithms for phycocyanin and chlorophyll-a underperformed with the Sentinel-3 OLCI images of Lake Erie, United States and expressed the importance of new algorithms based on the OLCI-specific bands. Only one year later, Lyu, et al. (2020) successfully designed algorithms using Sentinel-3 OLCI images to estimate phytoplankton carbon concentration in Taihu Lake and Choahu Lake, China.

Calibration scientists developed Landsat 8 and Sentinel-2A together to offer cross-calibration of the sensors allowing use of collective data from both platforms (USGS EROS Archive, 2021; Figure 4). Sentinel-2A visible and near-infrared bands (2, 3, 4, and 8) are 10-meter spatial resolution while the 20-meter spatial resolution range captures the red-edge and SWIR bands (5, 6, 7, 8a, 11 & 12). The greatest spatial resolution of 60-meters focuses on the coastal/aerosol, water vapor, and cirrus detection bands 1, 9 & 10 respectively.

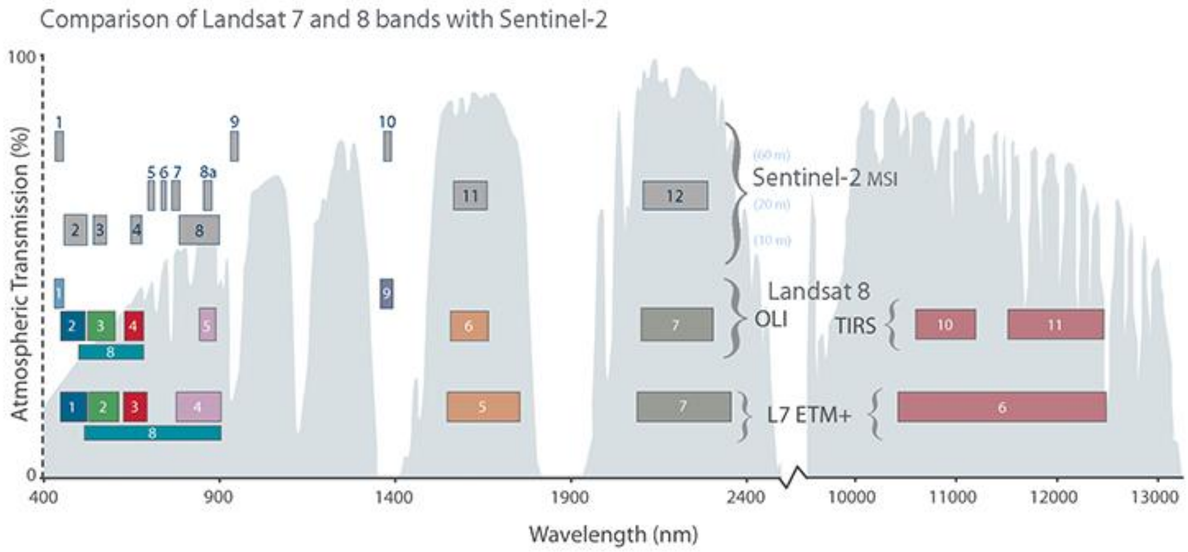



*Figure 4: Satellite band comparison between Landsat 7, Landsat 8 & Sentinel-2. https://landsat.gsfc.nasa.gov/wp-content/uploads/2015/06/Landsat.v.Sentinel-2.png*

## Secchi Disk Depth (SDD)

SDD is a widely used remote sensing metric and volunteer monitoring programs commonly measure Secchi Disk Depth (SDD) *in situ* because of its strong relationship to water constituents and quality indicators such as trophic conditions, chlorophyll-a, and total suspended solids (TSS) (Bonansea et al., 2019; Gholizadeh et al., 2016; Kloiber, Brezonik, & Bauer, 2002; Olmanson et al., 2016). An inverse correlation exists between Secchi depth and TSS (Gholizadeh et al., 2016) as well as an inverse correlation between SDD and chlorophyll levels in lakes (Olmanson et al., 2016) which makes remote sensing an ideal tool for monitoring and estimating water clarity (SDD).

Development of significant empirical algorithms to determine the relationship between the constituent concentration at time of image capture and reflectance of the spectral bands require *in situ* data on each water quality variable (Olmanson et al., 2015). Minnesota, Wisconsin, and Michigan have successfully predicted SDD and chl-a concentrations by developing the relationship between on-the-ground data and the blue, green, red, and near-infrared spectral response (Chipman et al., 2004; Gholizadeh et al., 2016; Kloiber, Brezonik, & Bauer, 2002; Olmanson et al., 2016). While many models and retrieval algorithms exist to estimate SDD, there is no one specific method or algorithm to follow because the model can vary according to water conditions (Bonansea et al., 2019). With that in mind, Kloiber, Brezonik, & Bauer, (2002) confirmed previous analysis of Landsat Thematic Mapper (TM) ratio TM3:TM1 (Red/Blue) to be the best predictor of SDD. As new platforms became available, Olmanson et al., (2016) found the best water clarity model using Landsat 8 OLI sensor data to be the blue, red, and ultra-blue bands, noted as O2, O4, and O1:

$$\ln(SD) = b_0 + b_1\left(\frac{O2}{O4}\right) + b_2 O1$$

Yet, Bonansea et al., (2019), found the best model with the Landsat 8 OLI sensor to include a combination of blue, green, and near infra-red bands:

$$SDD_{OLI} = Blue\left(\frac{Blue}{NIR}\right)\left(\frac{Green}{NIR}\right)$$

With the Sentinel-2 MSI sensor, Bonansea et al., (2019) found the best predictor of secchi disk depth to be:

$$SDD_{MSI} = \mathrm{Blue}\left(\frac{\mathrm{Green}}{\mathrm{NIR}}\right)$$

The research studies used atmospherically corrected surface reflectance values in their models.

## Chlorophyll-a (chl-a)

Chlorophyll is essential for photosynthesis hence it directly relates to algal blooms. Chl-a acts as a link between phosphorus and algal production making it a major indicator of trophic state. Chlorophyll reflects mainly green because it absorbs most energy from violet-blue and orange-red wavelengths. Gholizadeh et al., (2016) charts various spectral ratio studies for multiple sensors in identifying chlorophyll concentration. Most successful algorithms used a wavelength near 675 nm and another near 700 nm. Sensors with narrow spectral bands are not suitable for detecting chlorophyll. The comprehensive study revealed while there are several satellite sensors and aerial images capable of producing a chl-a estimate, Landsat TM and ratio of wavelengths 705/675 nm is most effective in potentially describing chl-a concentration. Yet, other multi-spectral sensors like Landsat TM, Landsat 8 OLI, and Sentinel-2 MSI have bands adequate for measuring chlorophyll (Brezonik et al., 2005; Gholizadeh et al., 2016; Toming et al., 2016).

Toming et al., (2016) found estimating chl-a using the height of the 705 nm peak provided the best results. Rather than developing new algorithms, they used well-established band ratio algorithms, shown to perform well in other sensors, to evaluate the performance of the Sentinel-2 MSI sensor. Band 5 (705 nm) is in the spectral range (700 and 720 nm) historically used in estimating chl-a concentration. Toming et al., (2016) successfully tested its chlorophyll correlation to *in situ* water samples by using band 4 (665 nm) and band 6 (740 nm) as baselines, calculated against the height of the band 5 peak.

$$Chl\text{-}a = Band\ 5 - \left(\frac{Band\ 4 + Band\ 6}{2}\right)$$

## Colored Dissolved Organic Matters (CDOM)

Studying Colored Dissolved Organic Matters (CDOM) is important for understanding aquatic ecology and carbon dynamics. CDOM affects the reflectance values in the blue and green spectral range. However, the absorbance of red light can be significant in high CDOM concentrations (Gholizadeh et al., 2016). Few water management organizations capture CDOM in their routine water monitoring even though CDOM is a critically important water quality characteristic. There is potential to fill this knowledge gap using remote sensing via satellite imagery. CDOM, usually reported as the absorptivity of filtered water at a specific wavelength, uses no standard wavelength; however, freshwater scientists typically use 420 or 440 nm (Brezonik et al., 2005; Lehman et al., 2017; Olmanson et al., 2015, 2016). Historically, researchers, including Brezonik et al., (2005) found Landsat sensors to be lacking in ability to measure high CDOM levels.

Olmanson et al., (2016) compared Landsat 7 and Landsat 8 inland lake measurements of CDOM. Based on data collected (including chlorophyll a, TSS, Mineral Suspended Solids (MSS), and SDD) from 30 Upper Midwest lakes), Landsat 8 ($a_{440}$) provided a better relationship for CDOM with the OLI sensor versus the ETM+ sensor on Landsat 7. The Landsat 8 OIL model for CDOM uses a linear regression two-variable format using green, red, and NIR, noted as O3, O4, and O5:

$$\ln(a_{440}) = b_0 + b_1\left(\frac{O3}{O5}\right) + b_2 O4$$

For Sentinel-2 MSI data, Toming et al., (2016) correlated *in situ* water samples to a green:red ratio (band3/band4) formula for CDOM.

## Turbidity and Total Suspended Sediments (TSS)

The measurement of light scattering by suspended particles defines turbidity. It scatters and absorbs the light rather than transmitting in a straight line. Chl-a and CDOM control the absorption while suspended sediments cause scattering (Gholizadeh et al., 2016). The higher the turbidity, the more suspended particles exist making it difficult for light to travel - the opposite of clarity. Due to the link with sunlight, which affects photosynthesis for algae growth, turbidity and total suspended matters are directly associated with SDD. Factors such as weather, human intervention, water column mixing, lake circulation patterns, and sediment delivery from surface runoff control Total Suspended Sediments (TSS). While turbidity and TSS highly correlate, turbidity is a good indicator of TSS but does not represent an exact measurement of TSS (Govedarica & Jakovljevic, 2019).

Clear water has high reflectance in the blue-green spectral range while absorbing at NIR and beyond. Using a single band or a ratio of two bands cultivates a relationship between spectral reflectance and turbidity. Multiple studies referenced by Govedarica and Jakovljevic (2019) recommend, in summary, the NIR band in high turbidity situations; lower concentrations (up to 15 NTU) should use the red band. Turbidity indications develop from reflectance at 700nm in remotely sensed signals (Hicks et al., 2013).

Govedaric and Jakovljevic (2019) reported two different Landsat 8 studies, and a Sentinel-2 study, exploring total suspended solids mapping. The studies showed the most effective predictors of TSS is the red to green ratios with NIR and red bands. Gholizadeh et al., (2016) references a study correlating TSS with Landsat 8 OLI sensor bands 2-5 using multiple regression models. The reflectance peak between 510 and 550 nm is successful when TSS are below 30 mg $m^{-3}$ (Olmanson et al., 2013). For higher TSS concentrations, use reflectance above 800 nm due to the overlay of chlorophyll *a* at 550 nm.

## Total Phosphorus (TP)

While phosphorus is a key contributor to the Yahara Lakes algal blooms, Total Phosphorus (TP) is not directly measurable by optical sensors. TP has an indirect relationship with water clarity (SDD) and a direct relationship to chlorophyll concentration. Also closely related to SDD, total suspended matters act as a carrier for TP with an exponential equation (Gholizadeh et al, 2016). Since TP is closely related to these parameters as well as turbidity, this provides a basis for monitoring total phosphorous dynamics. Studies reported by Gholizadeh et al (2016) suggest both SDD and chl-a concentration closely correlate to total phosphorous concentration; allowing for the indirect prediction of TP concentration.

# Methodology

The scientific method of this project employed an empirical approach using data from the latest generation of satellites, Sentinel-2 A & B from ESA (European Space Agency), in assessing the suitability of the Sentinel-2 A & B MSI sensor for detecting spectral differences in lake water quality parameters of small (Mendota 478 sq meters, Goodland 318 sq meters), shallow five-foot deep WETS areas by using 10-meter individual bands and calculated SDD and CDOM, between water inside and outside a WETS. There are three main components to my methodology:

1. Data Collection,
2. ArcGIS Pro Image Processing. And
3. Rstudio (Rcode) Data Processing,

in assessing remote sensing information, regarding water quality, to the potential effectiveness of the Water Treatment Exclosure System. The study area was Goodland County Park Beach (2844 Waubesa Avenue, Madison, WI) on the southwestern edge of Lake Waubesa and Mendota County Park Beach (5133 County Highway M, Middleton, WI) on the northwestern edge of Lake Mendota. Installation and activation of the beach exclosures occurs before Memorial Day followed by deactivation and removal, for winter storage, after Labor Day. The start and end dates for each beach is:

*Table 1: Mendota Beach WETS status dates.*

| Mendota Beach | | | | |
|---|---|---|---|---|
| **Year** | **Install** | **Activate** | **Deactivate** | **Uninstall** |
| 2020 | 05-May | 26-May | 21-Sep | 23-Sep |
| 2019* | N/A | 23-May | 29-Aug | N/A |

*Table 2: Goodland Beach WETS status dates.*

| Goodland Beach | | | | |
|---|---|---|---|---|
| **Year** | **Install** | **Activate** | **Deactivate** | **Uninstall** |
| 2020 | 06-May | 21-May | 23-Sep | 23-Sep |
| 2019* | N/A | 23-May | 27-Aug | N/A |

* 2019 actual install/uninstall and activate/deactivate dates were not available from Dane County Land and Water Resources Department therefore, the active dates for each beach are estimates based on dates of *in situ* E. coli samples taken, only during the active period, and reported by the City of Madison.

While the Sentinel-2 MSI samples 13 spectral bands ranging from 10 to 60 meters, this study will only use bands 2-Blue, 3-Green, 4-Red and 8-NIR (Near InfraRed), at 10-meter radiometric resolution, in various combinations. Refer to Table 3 and https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-2-msi for detailed Sentinel-2 MSI information.

*Table 3: Sentinel-2 MSI bands; study bands are in bold.*

| **Band Number** | **Spatial Resolution (m)** | **Central Wavelength (nm)** | **Bandwidth (nm)** | **Description** |
|---|---|---|---|---|
| 1 | 60 | 443 | 20 | Ultra-blue (Coastal and Aerosol) |
| **2** | **10** | **490** | **65** | **Blue** |
| **3** | **10** | **560** | **35** | **Green** |
| **4** | **10** | **665** | **30** | **Red** |

| Band Number | Spatial Resolution (m) | Central Wavelength (nm) | Bandwidth (nm) | Description |
| --- | --- | --- | --- | --- |
| 5 | 20 | 705 | 15 | Visible and Near Infrared (VNIR) |
| 6 | 20 | 740 | 15 | Visible and Near Infrared (VNIR) |
| 7 | 20 | 783 | 20 | Visible and Near Infrared (VNIR) |
| **8** | **10** | **842** | **115** | **Visible and Near Infrared (VNIR)** |
| 8a | 20 | 865 | 20 | Visible and Near Infrared (VNIR) |
| 9 | 60 | 940 | 20 | Short Wave Infrared (SWIR) |
| 10 | 60 | 1375 | 30 | Short Wave Infrared (SWIR) |
| 11 | 20 | 1610 | 90 | Short Wave Infrared (SWIR) |
| 12 | 20 | 2190 | 180 | Short Wave Infrared (SWIR) |

Sentinel Level 2A processing (https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-2-msi/processing-levels/level-2) includes a scene classification and a BOA (Bottom of Atmosphere) corrected reflectance orthoimage in coordinate system of WGS 1984 UTM Zone 15N. Via ESA's Copernicus Open Access Hub (https://scihub.copernicus.eu/dhus/#/home) I accessed imagery based on advanced search criteria:

- Sensing Period: 2019/04/01 - 2019/10/31 and 2020/04/01 - 2020/10/31
- Mission: Sentinel-2
- Satellite Platform: None selected as to retrieve A & B platforms simultaneously
- Product Type: S2MSI2A
- Relative orbit 26
- Cloud Cover: 50%

Initial search results produced tile 15 and 16 images. I determined tile 15 alone captured both study areas reducing image count approximately by half. The 2019 search produced 15 cloud-free days (Table 4) out of approximately 230 satellite tile 15 images. The 2020 search produced 22 cloud-free days (Table 5) out of approximately 243 satellite tile 15 images.

*Table 4: Sentinel-2 2019 collected cloud-free imagery dates.*

| **2019** | | | |
|---|---|---|---|
| 09-Apr | 03-Jun | 23-Jul | 27-Aug |
| 24-Apr | 08-Jun | 28-Jul | 16-Sep |
| 04-May | 13-Jun | 02-Aug | 26-Sep |
| 14-May | 08-Jul | 17-Aug | |

*Table 5: Sentinel-2 2020 collected cloud-free imagery dates.*

| **2020** | | | |
|---|---|---|---|
| 18-Apr | 12-Jun | 16-Aug | 25-Sep |
| 03-May | 17-Jun | 21-Aug | 10-Oct |
| 08-May | 27-Jun | 26-Aug | 15-Oct |
| 13-May | 22-Jul | 05-Sep | 30-Oct |
| 02-Jun | 27-Jul | 15-Sep | |
| 07-Jun | 11-Aug | 20-Sep | |

To accurately capture each WETS, I accessed aerial NAIP (National Agriculture Imagery Program) 1-meter, natural color, ortho imagery via EarthExplorer (https://earthexplorer.usgs.gov). Two separate images provided a clear view of the respective WETS study areas:

- m_4308962_sw_16_1_20170922.tif (Mendota Beach on Lake Mendota)
- m_4308961_nw_16_060_20180728.tif (Goodland Beach on Lake Waubesa)

For the years in this study, 2019 and 2020, additional information for analyses include:

- Madison Airport climate data (average wind, precipitation, and average air temperate) from 2019-05-01 to 2019-09-30 and 2020-05-01 to 2020-09-30 obtained at https://www.ncdc.noaa.gov/cdo-web/
- Lake Mendota-only water gage data from https://waterdata.usgs.gov/nwis USGS site 05428000 Lake Mendota at Madison, WI from 2019-05-01 to 2019-09-30 and 2020-05-01 to 2020-09-30
- City of Madison *in situ* E. coli measurements provided by Dane County Land and Water Resources Department taken only during WETS active period (Memorial Day to Labor Day) at each beach each year.

I created an ArcGIS Pro (ver. 2.8.3) project and geodatabase, WI_Lakes.gdb, containing two maps 2020 and 2019, for collecting information from NAIP and Sentinel 2 imagery. The project environment used all defaults except WI_Lakes.gdb was set for the Current and Scratch Workspace and WGS_1984_UTM_Zone_15N defined the Output Coordinate System. Once I collected the data, I exported to Excel spreadsheets and performed analysis using R (ver. x64 4.1.1) and RStudio (ver. 1.4.1717).

## ArcGIS Pro Image Processing

Before collecting information from the Sentinel 2 imagery, I used the NAIP images of Mendota and Goodland beach to create a line feature class of the respective WETS boundary (Mendota_WETS and Goodland_WETS).


*Figure 5: Mendota Beach WETS line feature class.*

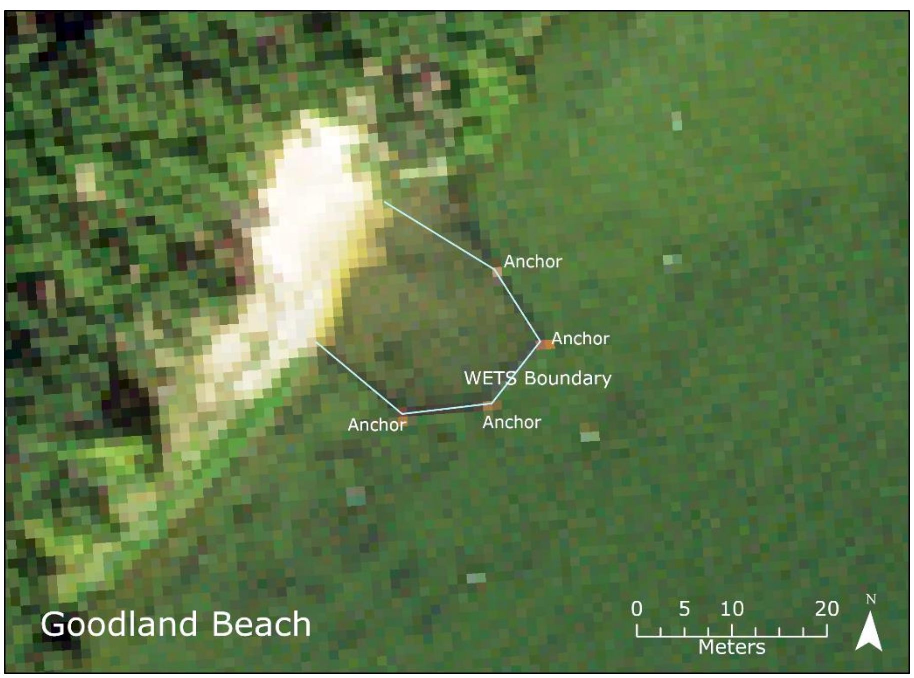



*Figure 6: Goodland Beach WETS line feature class.*

For faster processing, I added the individual 10-meter bands 2, 3, 4 and 8 for each date acquired to the map. ArcGIS automatically reassigned the sensor bands 2, 3, 4, and 8 to bands 1, 2, 3, and 4 respectively. I created a new polygon feature class (RasterClip_Polygon), in the geodatabase (WI_Lakes.gdb) containing a single rectangle polygon encompassing both beaches to use in clipping the Sentinel 2 imagery. The geoprocessing tool Batch Clip Raster allowed for clipping all the images at once using the RasterClip_Polygon as the Output Extent and selecting the option *Use Input Features for Clipping Geometry*. The tool uses the default *output raster dataset* of Clip_OutRaster_%name% and after running, adds the output datasets automatically to the map. For ease of recognition, I manually changed the name portion of each clipped raster to reflect only a four-digit date, i.e., Clip_OutRaster_T15TYH_2019**0424**T164901_B02_10m.jp2 became Clip_OutRaster_0424, etc. I applied Nearest Neighbor resampling and Color Infrared band combination each clipped raster and removed the original full-size Sentinel 2 images from the map to reduce map storage space.

*Figure 7: Clipped raster with Nearest Neighbor resampling and Color Infrared band combination.*

With the respective beach WETS feature class ordered above/before the clipped rasters and the respective beach NAIP ordered between the feature class and rasters with a 50% transparency (Figure 8), the 10-meter cells are viewable in respect to the WETS barrier and land features.

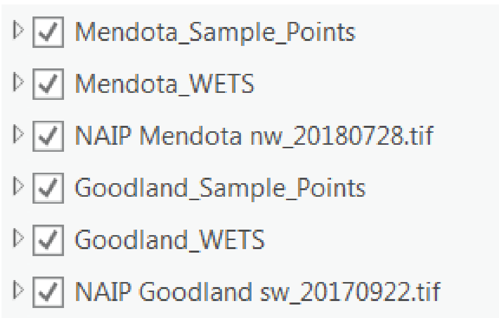



*Figure 8: ArcGIS Pro 2019 drawing order for viewing the WETS and land features.*

This view allows for the creation of sample points in a point feature class for each beach. I created Mendota_Sample_Points (Figure 9) and Goodland_Sample_Points (Figure 10) feature classes in the geodatabase, I added points by visually selecting the approximate center of each cell encompassing 95% or more inside and outside the WETS barrier, avoiding shadows and land features. Mendota_Sample_Points resulted in 12 total points, three inside and nine outside. Goodland_Sample_Points resulted in seven total points, two inside and five outside.

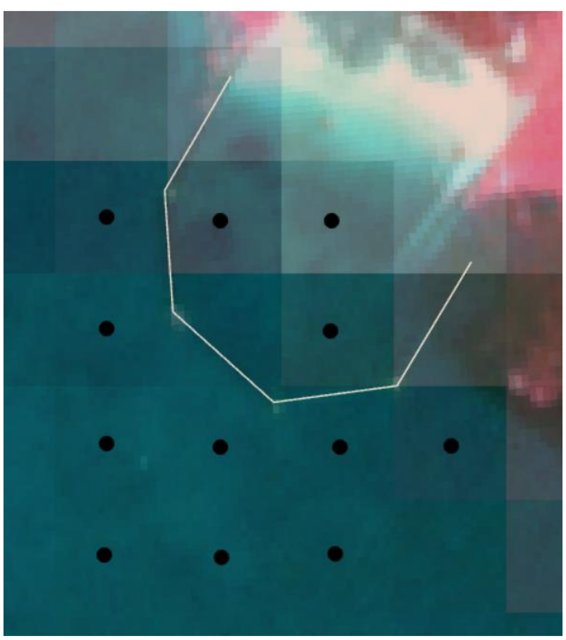


*Figure 9: Mendota WETS sample points.*

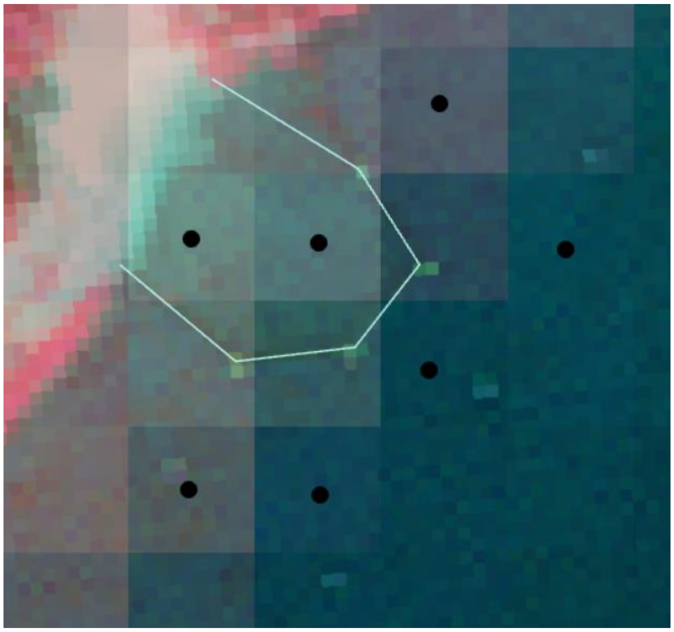


*Figure 10: Goodland WETS sample points.*

The respective Sample Points ArcGIS table consists only of the Z point and OBECTID. For ease of understanding each point within the table, I added two text fields: Location and Beach. I manually defined fields as either being inside or outside and beach name (Figures 11 and 12).

| OBJECTID * | Shape * | Location | Beach |
|---|---|---|---|
| 13 | Point Z | Inside | Mendota |
| 14 | Point Z | Inside | Mendota |
| 15 | Point Z | Inside | Mendota |
| 16 | Point Z | Outside | Mendota |
| 17 | Point Z | Outside | Mendota |
| 18 | Point Z | Outside | Mendota |
| 19 | Point Z | Outside | Mendota |
| 20 | Point Z | Outside | Mendota |
| 21 | Point Z | Outside | Mendota |
| 23 | Point Z | Outside | Mendota |
| 24 | Point Z | Outside | Mendota |
| 25 | Point Z | Outside | Mendota |

*Figure 11: Mendota sample points table.*

| OBJECTID * | Shape * | Location | Beach |
|---|---|---|---|
| 3 | Point Z | Inside | Goodland |
| 4 | Point Z | Inside | Goodland |
| 6 | Point Z | Outside | Goodland |
| 7 | Point Z | Outside | Goodland |
| 8 | Point Z | Outside | Goodland |
| 9 | Point Z | Outside | Goodland |
| 10 | Point Z | Outside | Goodland |

*Figure 12: Goodland sample points table.*

The Sample geoprocessing tool uses the sample points feature class to capture the specific cells' value for Mendota Beach 2019 and 2020 and Goodland Beach 2019 and 2020. I configured the Sample tool (found under Image Analyst Tools, Extraction), with the following parameters (Figure 13):

- Input rasters: selected all the clipped rasters (16 for 2019 and 22 for 2020)
- Input location raster or features: Mendota_Sample_Points
- Output table: Mendota_Samples
- Resampling technique: default of Nearest
- Unique ID field: default of OBJECTID.

I ran this tool again for Goodland using all the input rasters for specified year, Goodland_Sample_Points as input features and Goodland_Samples as output table. In total, the tool ran four times, twice per beach and twice per year generating four tables, two per map by location.

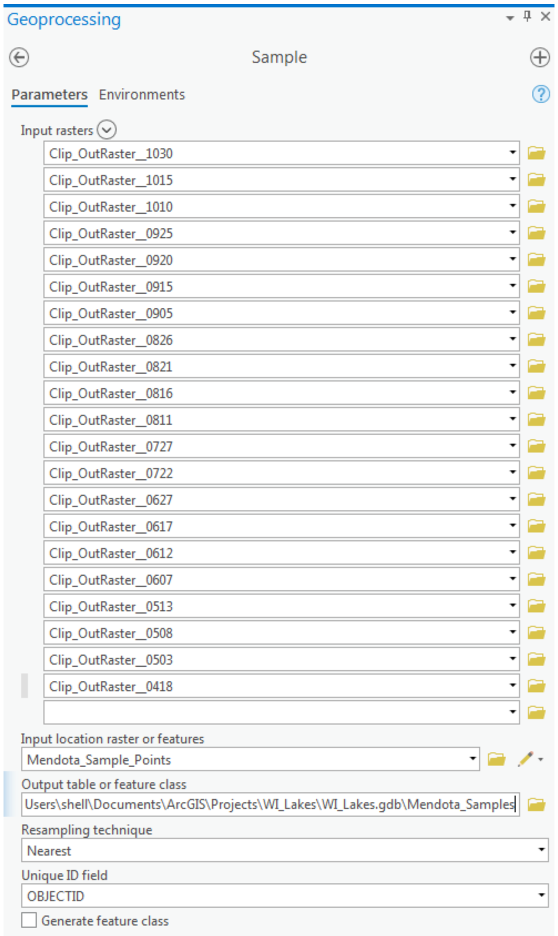



*Figure 13: Sample geoprocessing tool configuration, Mendota 2020.*

Indexing the Mendota_Sample_Points (and Goodland_Sample_Points) field within the respective Samples table for each year allowed for proper joining functionality. The Add Attribute Index tool required (Figure 14):

- Input Table: Mendota_Samples or Goodland_Samples
- Fields to Index: Mendota_Samples.Mendota_Sample_Points
- Index Name: MSP

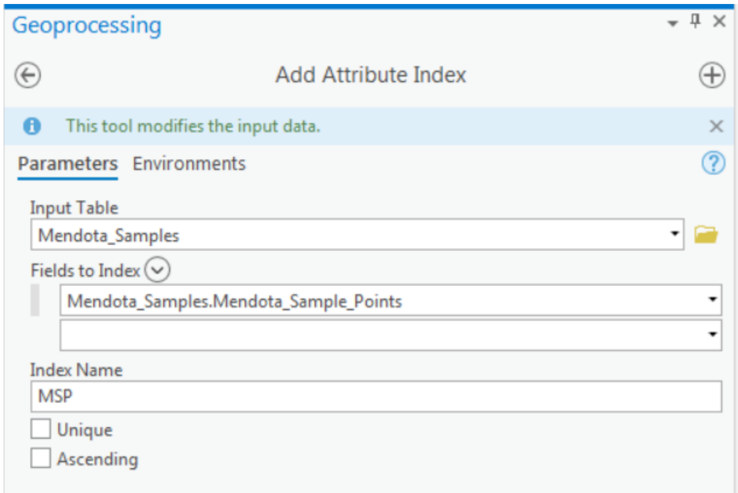



*Figure 14: Attribute Indexing in preparation for Join function.*

I individually joined the indexed tables with their respective Sample_Points feature class to include the point location (inside or outside) and the associated beach to the end of the table (Figure 15). Finally, I exported the four tables as individual sheets within a single Excel file (All_Samples.xlsx, Appendix B) for analyses within RStudio.

| Clip_OutRaster__1030_Band_4 | OBJECTID | Location | Beach |
|---|---|---|---|
| 906 | 13 | Inside | Mendota |
| 2053 | 14 | Inside | Mendota |
| 389 | 15 | Inside | Mendota |
| 209 | 16 | Outside | Mendota |
| 151 | 17 | Outside | Mendota |
| 116 | 18 | Outside | Mendota |
| 91 | 19 | Outside | Mendota |
| 141 | 20 | Outside | Mendota |
| 338 | 21 | Outside | Mendota |
| 106 | 23 | Outside | Mendota |
| 326 | 24 | Outside | Mendota |
| 75 | 25 | Outside | Mendota |

*Figure 15: Truncated Mendota_Samples table showing join results.*

## RStudio Data Processing

RStudio uses packages, tidyverse and readxl, to read, manipulate, analyze, and plot the information collected within the WI_Lakes ArcGIS project and non-satellite information such as climate, water height and E. coli. Four R scripts perform said functions.

### Read and Manipulate Data

The first script, *data_read_and_manipulate.R* reads the collected non-satellite information into respective R tables for later plotting and statistics. However, its primary function is to read and manipulate four sheets (Mendota_Samples_2020, Mendota_Samples_2019, Goodland_Samples_2020, Goodland_Samples_2019) within the All_Samples.xlsx file. Initially, the script reads the four Excel sheets and saves as four user-defined R tables. The remaining script code manipulates the data and overwrites the existing table(s) rather than creating new tables.

R prefers data to be in long format rather than wide, the code converts the new tables into long format using the *gather* function based on "Band" criteria. The original All_Samples.xlsx file has a combined Date_Band column, to create separate columns for Date and Band, the R code creates a Date column and Band column in the R tables. Creation of the Date column uses the ISOdate and substring functions against each table the Date_Band start 1, end 2 defines the month and Date_Band start 3, end 4 defines the day. The Band column creation is based on the Date_Band start 6, end 11. The code then removes the Date-Band and OBJECTID…3 column for they are no longer necessary.

Knowing which point values associate with the WETS uninstalled, inactive, or active periods, a section of code adds a status column indicating uninstalled, inactive, or active based on dates from Table 1 and Table 2.

To perform calculations, the script returns the table to wide format. Keep in mind the sensor bands of interest 2, 3, 4 and 8 appear in the ArcGIS raster table and Excel table as bands 1, 2, 3, 4 respectively. Based on the band 1, 2, 3 or 4 labeling, calculations of interest performed via R code are:

- Secchi Disk Depth
    - determined by Kloiber, Brezonik, & Bauer (2002)
    - using Landsat 7 TM 30-meter spatial resolution
    - column name Band_3div1.
    - $L7TM\ SDD = \frac{band\ 3[Red]}{band\ 1\ [Blue]}$ ArcGIS Pro has a direct band correlation
- Secchi Disk Depth
    - determined by Bonansea et al. (2019)
    - using Sentinel-2 10-meter spatial resolution
    - column name Band_SDD
    - $SDD =\ band\ 1 * \left(\frac{band\ 2}{band\ 4}\right)$ satellite correlation = $\text{Band 2[Blue]} \left(\frac{\text{Band 3 [Green]}}{\text{Band 8 [NIR]}}\right)$
- CDOM
    - determined by Toming et al. (2016)
    - using Sentinel-2 10-meter spatial resolution
    - column name Band_CDOM
    - $CDOM = \frac{band\ 2}{band\ 3}$ satellite correlation = $\frac{band\ 3\ [Green]}{band\ 4\ [[Red]}$

Upon completing calculations, the script resets the R tables for long format for analysis, plotting, and statistical calculations.

## Data Analyses

The second R script, *data analyses.R*, performs two analyses. The first analysis code creates four new tables, %name%.adj.difs (%name% is filled with Men20, Men19, Good20, Good19) and calculates the mean surface reflectance (SR) of all inside and outside values for each band and status. Example of Rows 1-3 in Men20.adj difs, Table 6:

*Table 6: Truncated example of adjusted difference table, Mendota 2020.*

| Band | Status | Inside | Outside | meanSRdifs |
|---|---|---|---|---|
| Band_1 | Active | 506.76 | 487.02 | 19.75 |
| Band_1 | Inactive | 646.00 | 634.94 | 11.06 |
| Band_1 | Uninstalled | 455.50 | 340.41 | 115.09 |

The resulting mean surface reflectance differences identify the adjusted difference for the three periods, specifically the uninstalled period of each band for use in the next analyses.

Remote sensing techniques measure the amount of electromagnetic radiation at various wavelengths reflected from the water's surface and uppermost water column.

Even though remote sensing techniques measure the amount of reflected electromagnetic radiation from the surface and uppermost water column at various wavelengths, there is some penetration into the water, especially for lower wavelengths.

Lower wavelengths are often helpful for remote sensing of water quality. However, remote sensing for water quality can be complicated in shallow water environments due to undesired lake-bottom reflection; this analysis is not interested in literal bottom surface information. This issue is address by calculating the differences between shallow and deep-water pixels as the second step of the *Data Analyses* R code script.

The second analyses in *Data Analyses.R* uses the uninstalled adjusted mean surface reflectance difference for each band to account for depth effect between inside and outside the WETS barrier. For each band and image date, the script:

1. Creates four new tables, %name%.analysis (%name% is filled with Men20, Men19, Good20, Good19) in long format and calculates the mean SR (inside mean – outside mean from the %name%long table) once for Inside and once for Outside of each image date and individual bands. Example containing the first two rows of Men20.analysis, table seven.

*Table 7: Truncated example of analysis table, Mendota 2020.*

| **Band** | **Status** | **Date** | **Location** | **meanSR** |
|---|---|---|---|---|
| Band_1 | Active | 2020-06-02 | Inside | 521.67 |
| Band_1 | Active | 2020-06-02 | Outside | 596.78 |

2. Converts table into wide format allowing for mean surface reflectance difference calculation.

3. Creates new column meanSRdifs = Inside-Outside by band and date. Example of first two rows, table five:

*Table 8: Truncated example of analysis table wide format, Mendota 2020.*

| **Band** | **Status** | **Date** | **Inside** | **Outside** | **meanSRdifs** |
|---|---|---|---|---|---|
| Band_1 | Active | 2020-06-02 | 521.67 | 596.78 | -75.11 |
| Band_1 | Active | 2020-06-07 | 532.67 | 555.78 | -23.11 |

4. Creates new column SR.adj.dif = the individual bands' meanSRdifs less the meanSRdifs for uninstalled band x in the adj.difs table. Example of first and second row of Men20.analysis, table nine:

*Table 9: Truncated example of analysis table with SR adjusted differences, Mendota 2020.*

| **Band** | **Status** | **Date** | **Inside** | **Outside** | **meanSRdifs** | **SR.adj.difs** |
|---|---|---|---|---|---|---|
| Band_1 | Active | 2020-06-02 | 521.67 | 596.78 | -75.11 | -1.90 |
| Band_ | Active | 2020-06-07 | 532.67 | 555.78 | -23.11 | -1.38 |

## Plotting

The third script *plotting.R*, plots the meanSR.adj.difs column in the %name%.analysis table for each band (1 [blue], 2 [green], 3 [red], 4 [NIR], 3div1, SDD, and CDOM), WETS status (Active, Inactive, Uninstalled) and date. The result is seven plots per year. The third script also plots the non-satellite data for each year: Lake Mendota water levels, average wind, precipitation, and average air temperature (three separate plots per year, six total) from Dane County Regional Airport. The *in situ* E. coli test results, collected by the City of Madison, are plotted by year for each beach (totaling four plots). All 40 plots appear in the results section.

### Statistical Calculations

Finally, the *statistics.R* script runs a two-sample t-test of each band between inside and outside the WETS exclosure. The process begins by copying %name%.analysis to %name%.statistics for performing statistical calculations. Based on the scatter plots, the inactive status is inconsequential therefore combined with the uninstalled status for the two-sample t-test of the individual bands and the three calculated variables (bands 3div1, SDD, and CDOM) per beach per year. Tables 11 and 12 contain the resulting *p*-values.

## Results

The methods above produce the following scatter plots:

- Mendota Beach 2019 Individual Bands
- Mendota Beach 2020 Calculated Bands and E. coli
- Goodland Beach 2019 Individual Bands
- Goodland Beach 2020 Calculated Bands and E. coli
- Water Levels and Precipitation, 2019 and 2020
- Air Temperatures and Wind, 2019 and 2020

The statistical two-sample t-test calculations produce two *p*-value tables, one for each beach, and two columns containing values for 2019 and 2020 (Tables 11 & 12).

In addition to scatter plots and *p*-values, I calculated the mean of each climate factors and water levels from May 1st to September 30th for both years (Table 10).

*Table 10: Mean climate factors from 05-01 to 09-30 of each study year.*

| **Factor** | **2019** | **2020** |
|---|---|---|
| Lake Mendota Water Levels | 10.5 feet | 10.6 feet |
| Airport Precipitation | 0.17 inches | 0.16 inches |
| Airport Temperature | 66° F | 66° F |
| Airport Wind Speed | 6.1 mph | 6.4 mph |

## *P*-Value Statistic Tables

*Table 11: Mendota Beach two-sample t-test.*

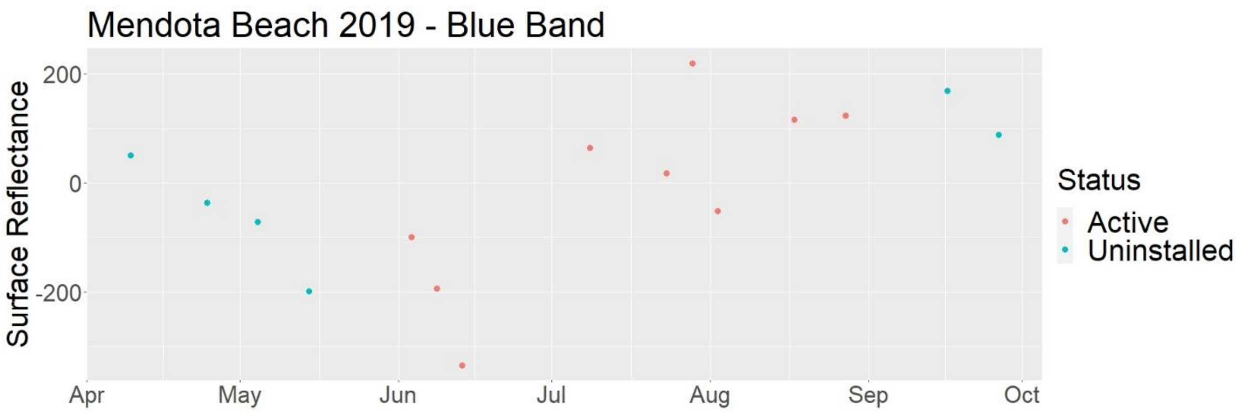
| Mendota Beach *p*-values<br>Significance: **High *p*-value < 0.05**<br>Moderate *p*-value is 0.05 – 0.10 | | | |
|---|---|---|---|
| **Band** | **2019** | **2020** | **% Change** |
| Band 1 | 0.846 | 0.107 | 87.3% |
| Band 2 | 0.801 | 0.121 | 84.9% |
| Band 3 | 0.774 | 0.166 | 78.6% |
| Band 4 | 0.848 | 0.081 | 90.4% |
| Band 3div1 | 0.873 | 0.509 | 41.6% |
| Band SDD | 0.881 | 0.469 | 46.7% |
| Band CDOM | 0.866 | 0.881 | -1.7% |
| Average 2019 to 2020 Change | | | 61.1% |

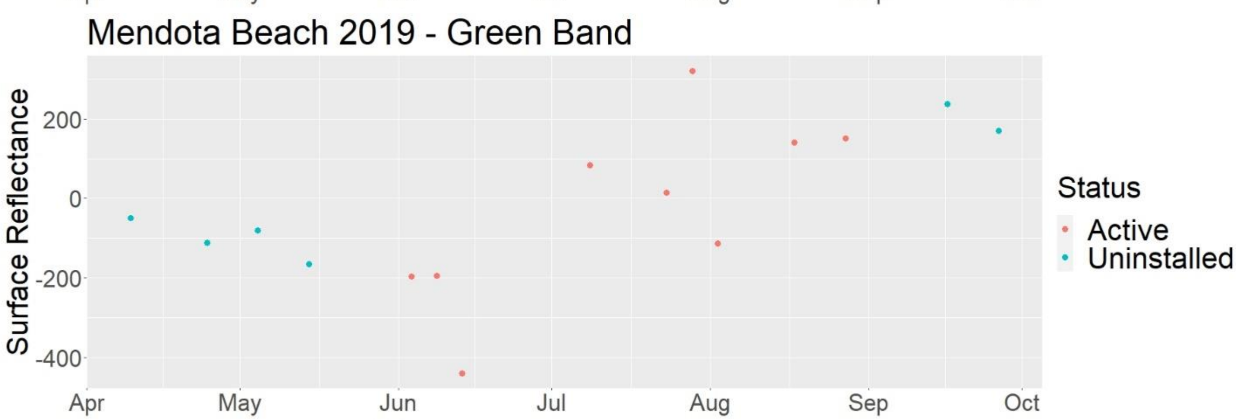
*Table 12: Goodland Beach two-sample t-test.*

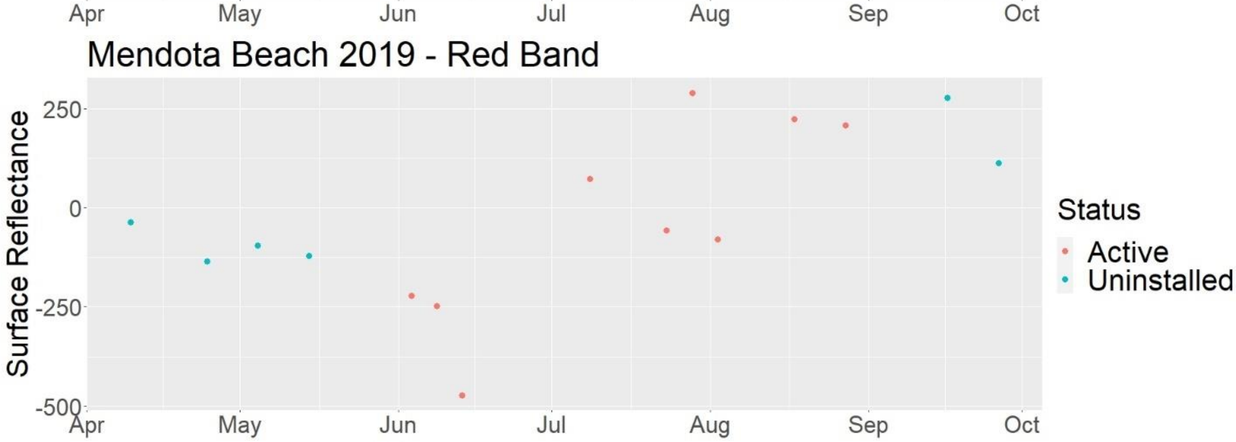
| Goodland Beach *p*-values<br>Significance: **High *p*-value < 0.05**<br>Moderate *p*-value is 0.05 – 0.10 | | | |
|---|---|---|---|
| **Band** | **2019** | **2020** | **% Change** |
| Band 1 | 0.220 | **0.028** | 87.1% |
| Band 2 | 0.146 | **0.020** | 86.6% |
| Band 3 | 0.304 | **0.011** | 96.5% |
| Band 4 | 0.241 | 0.286 | -18.9% |
| Band 3div1 | 0.394 | 0.177 | 55.2% |
| Band SDD | 0.893 | 0.866 | 3.0% |
| Band CDOM | 0.148 | 0.893 | -501.9% |
| Average 2019 to 2020 Change | | | -27.5% |

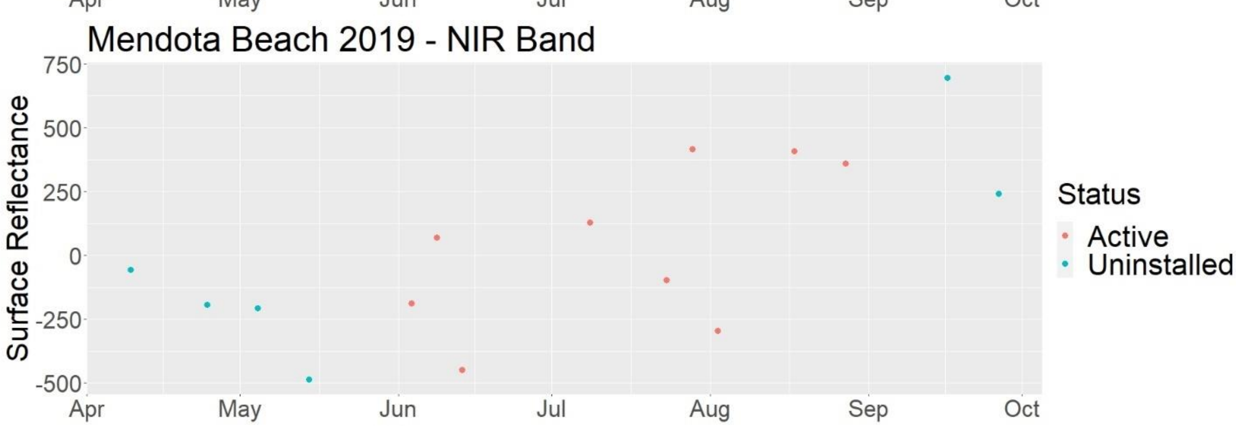
Hypotheses: Significant detection of spectral differences between inside and outside the WETS based on the adjusted surface reflectance (SR.adj.dif)

## Mendota Beach 2019 Individual Bands Scatter Plots

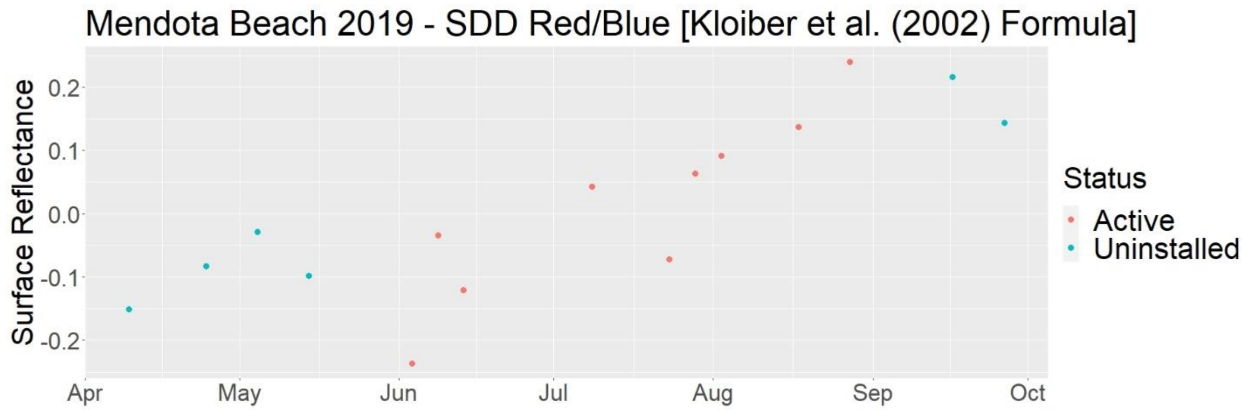


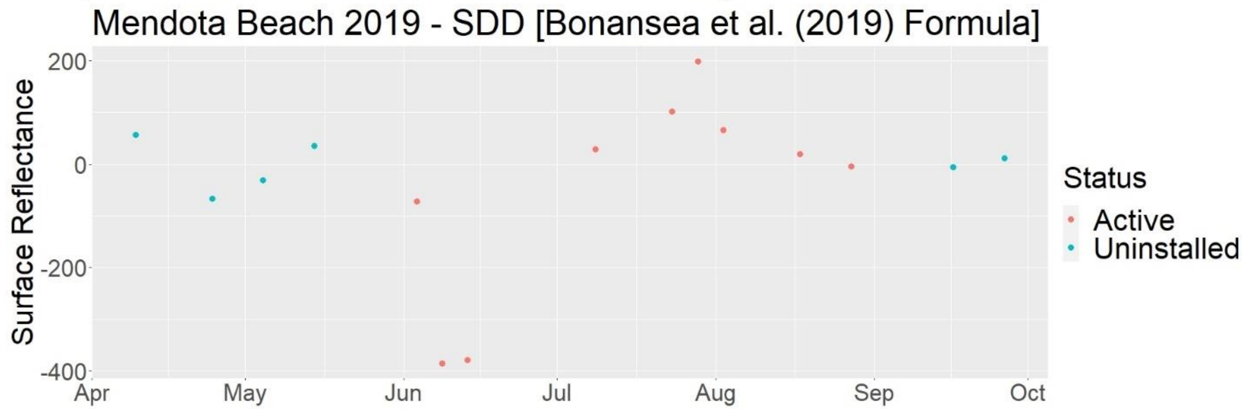



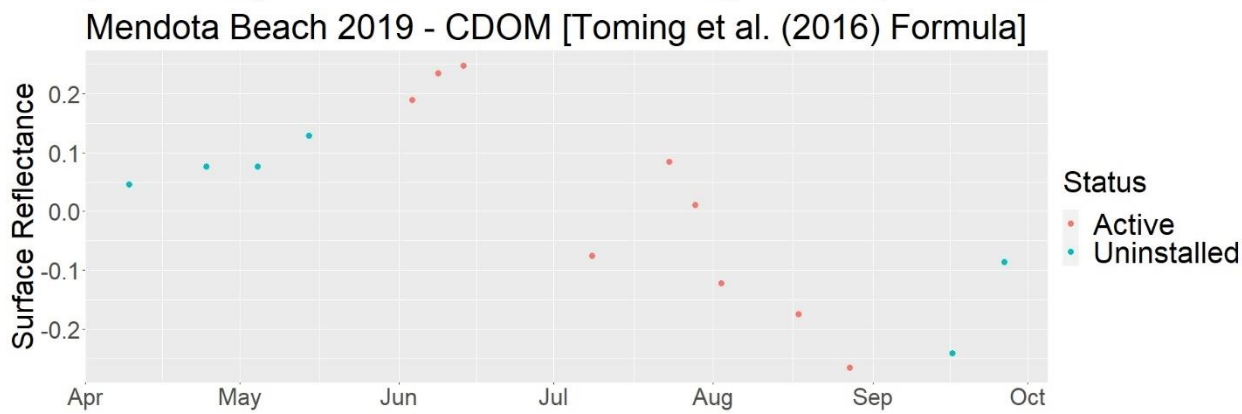



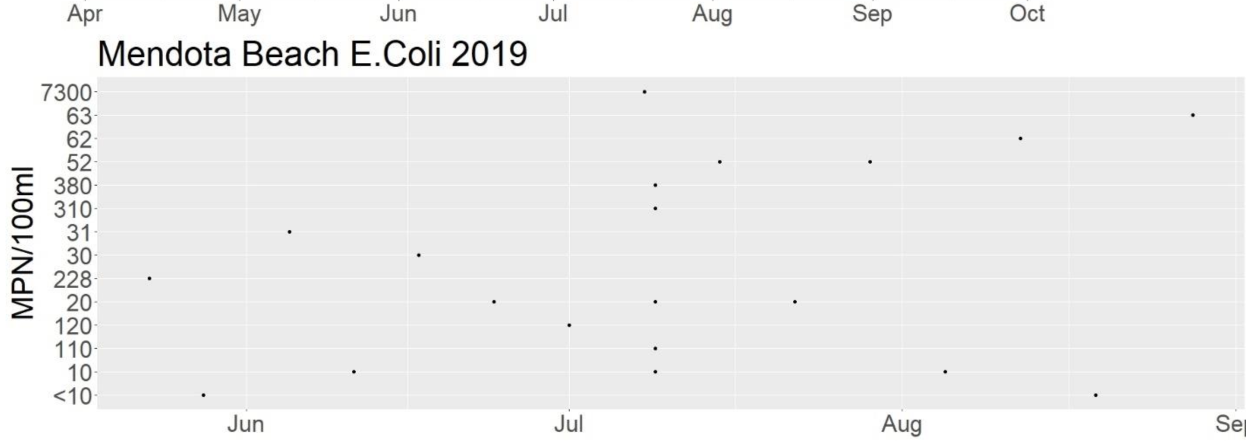



## Mendota Beach 2019 Calculated Bands and E. coli Scatter Plots

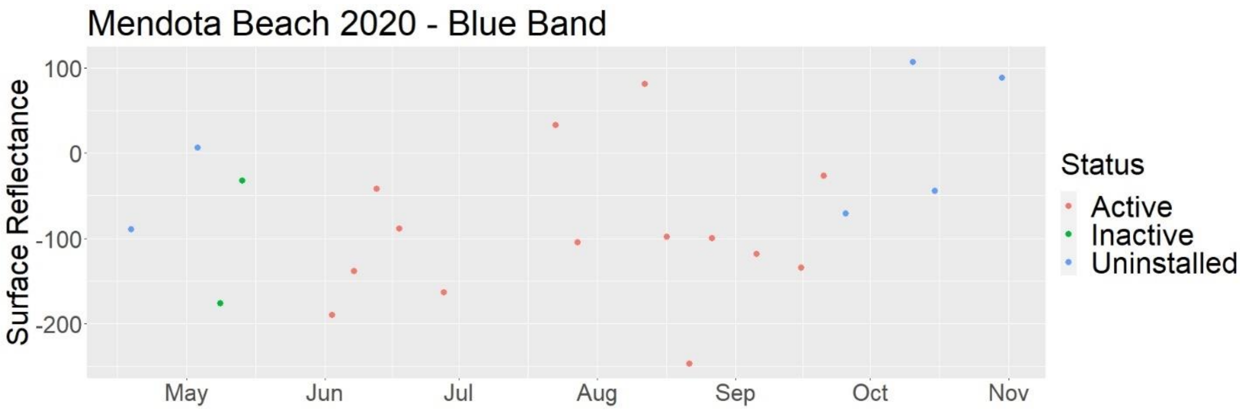


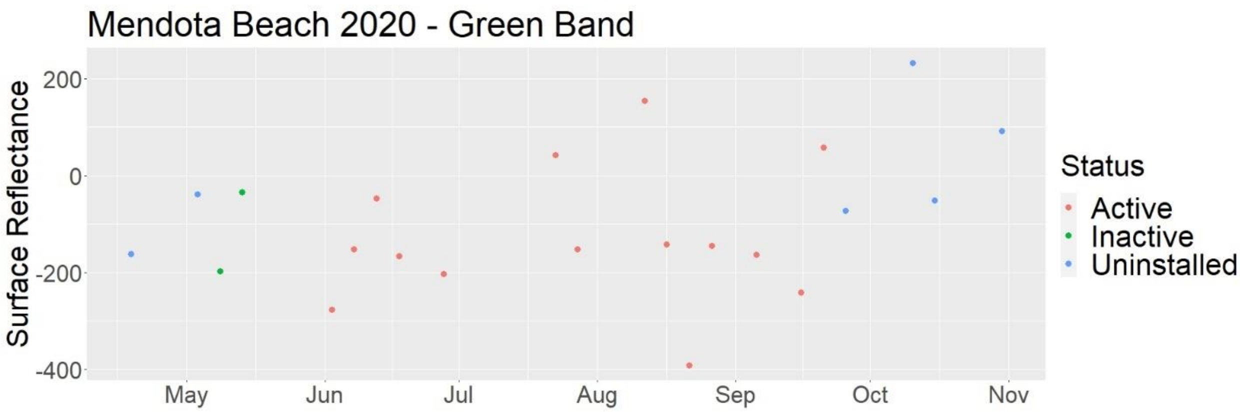



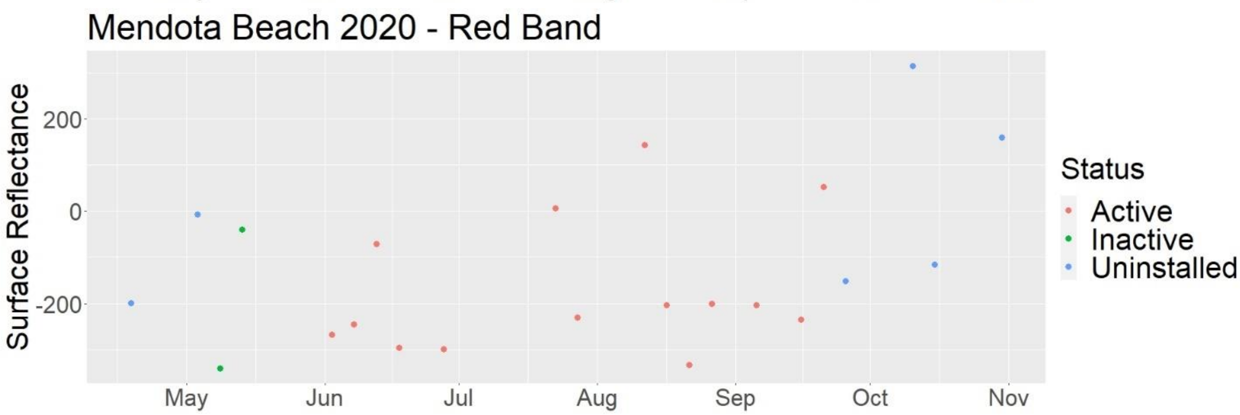



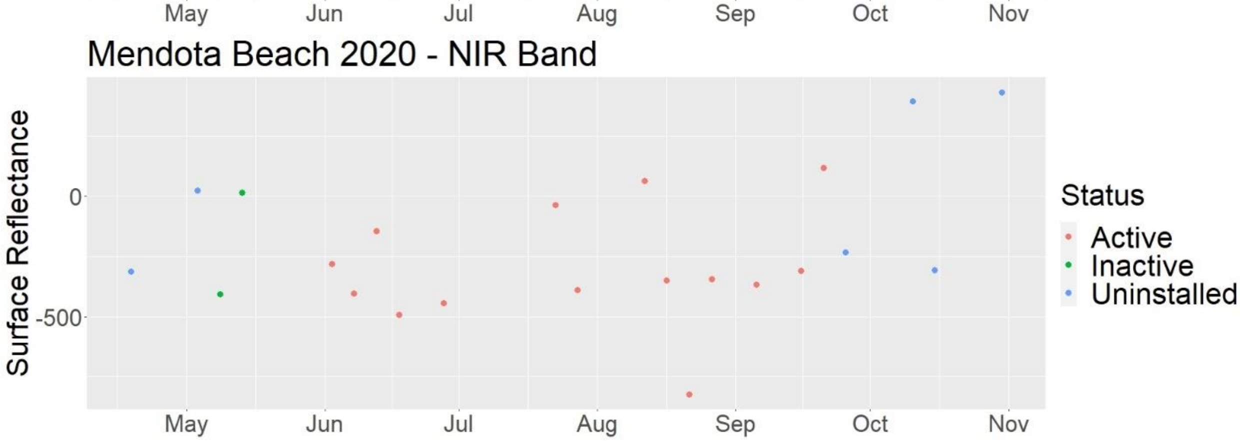



## Mendota Beach 2020 Individual Bands Scatter Plots

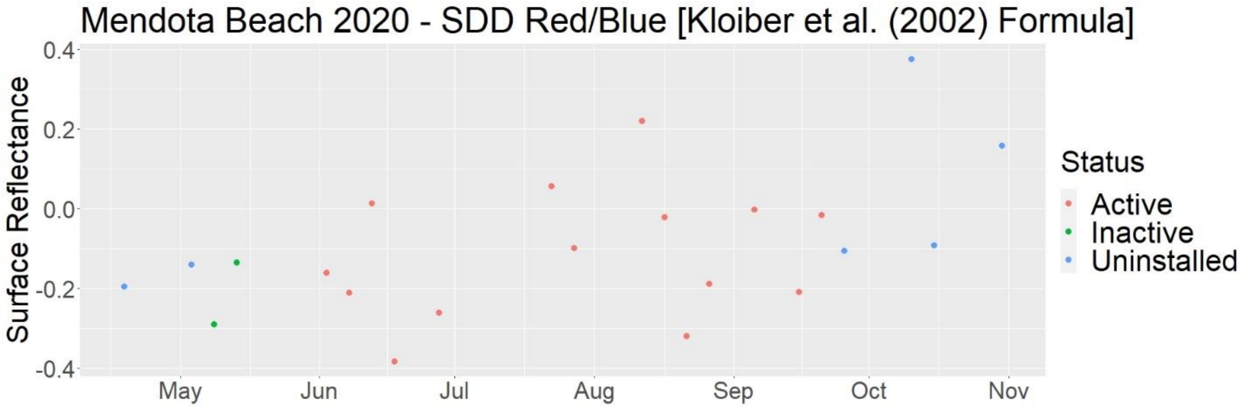


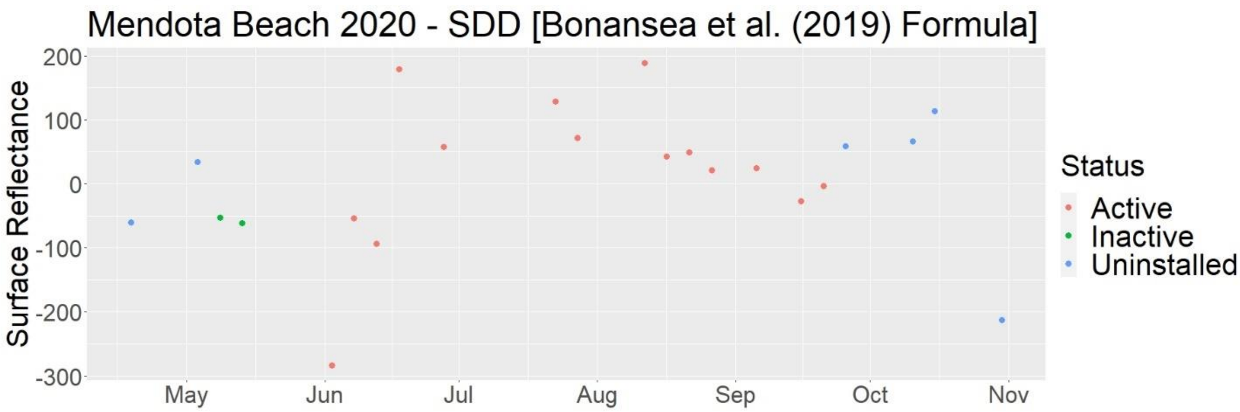



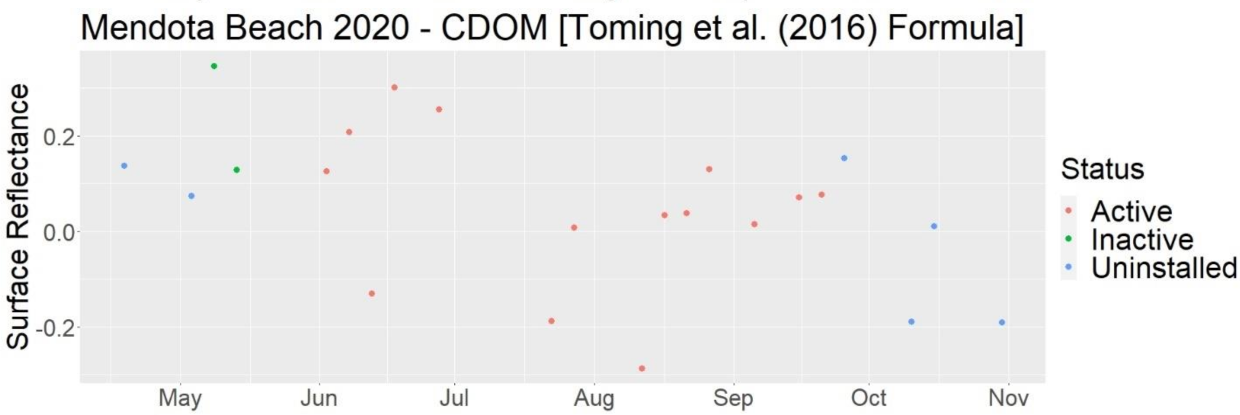



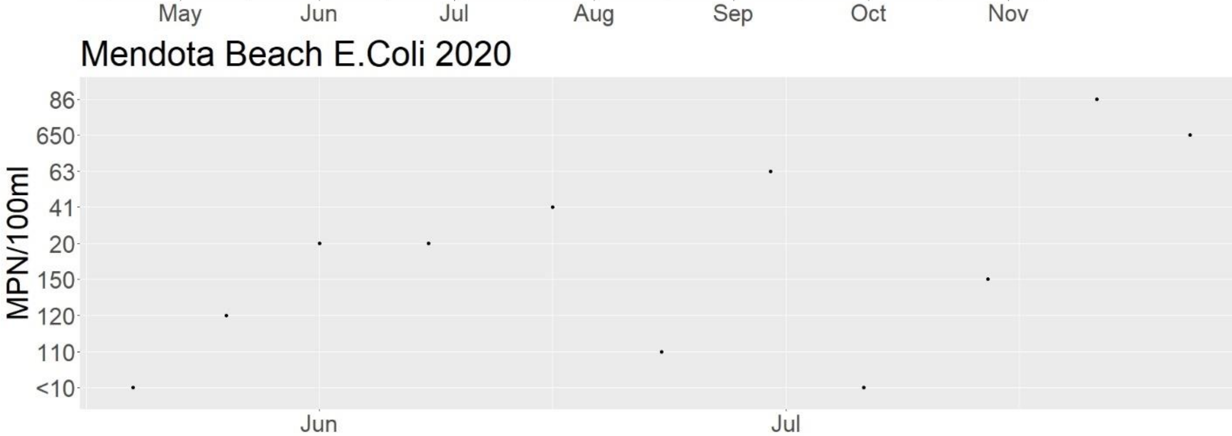



## Mendota Beach 2020 Calculated Bands and E. coli Scatter Plots

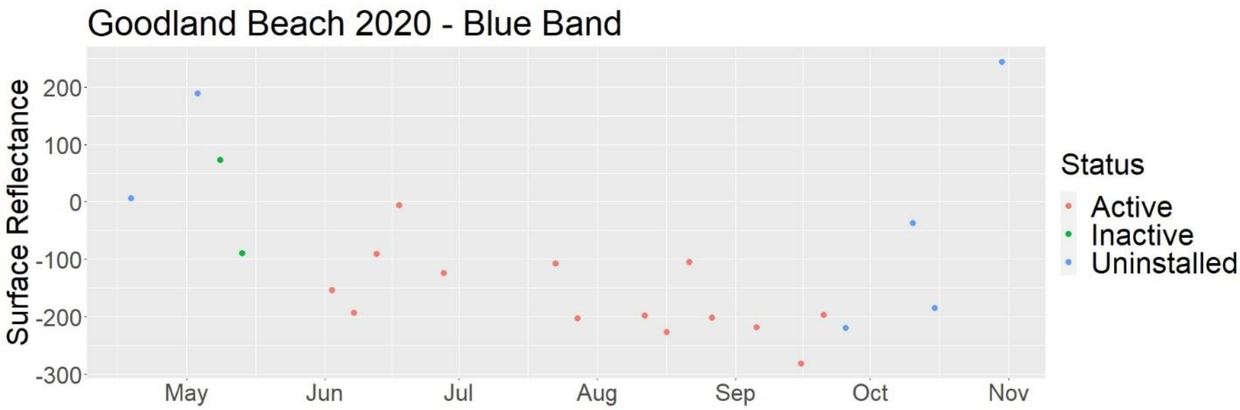


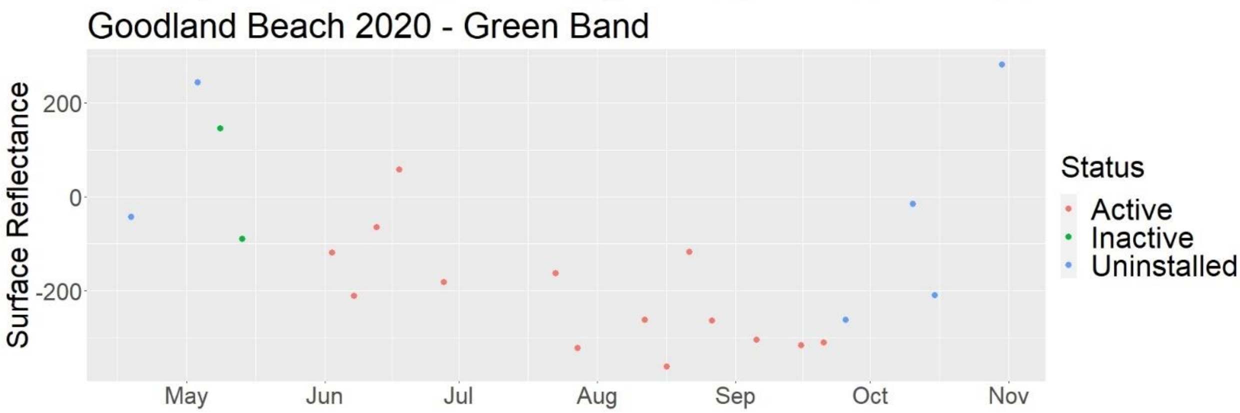



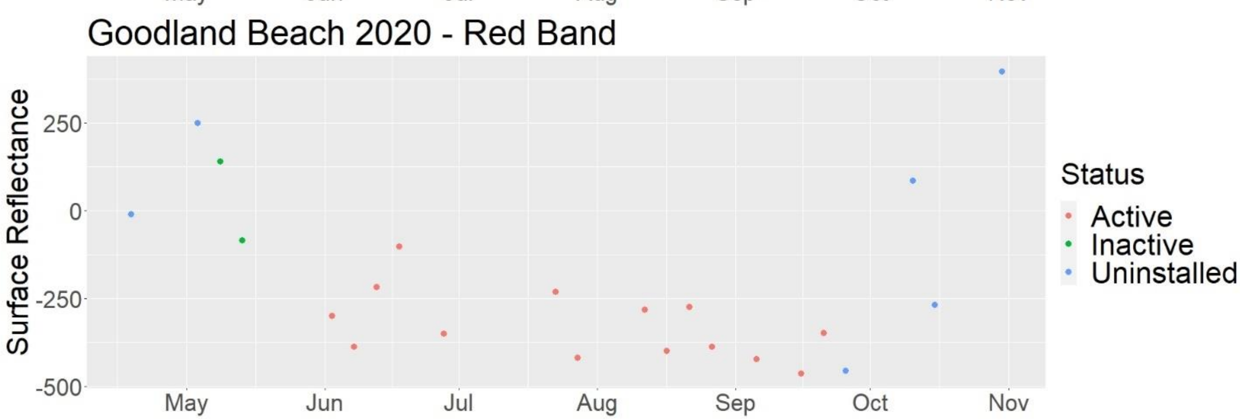



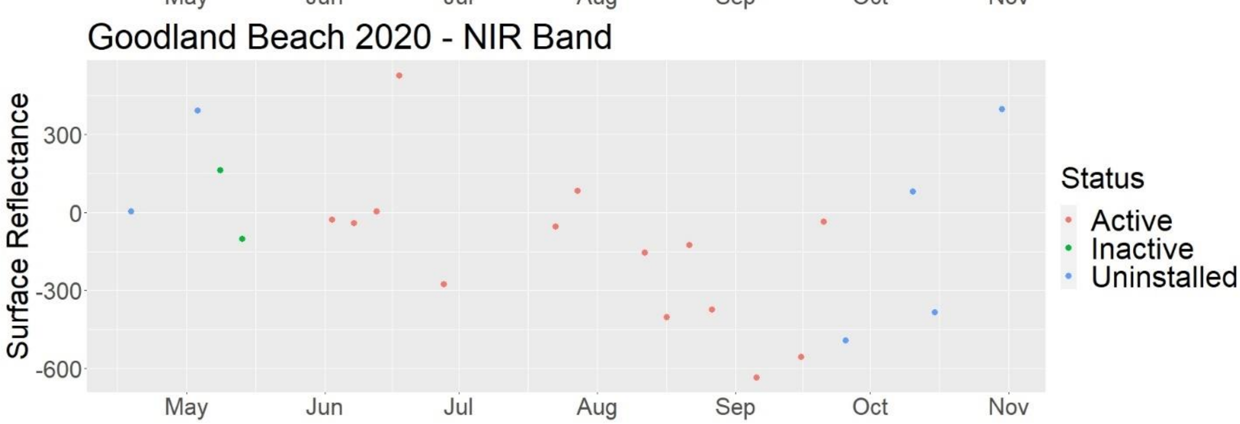



## Goodland Beach 2020 Individual Bands Scatter Plots

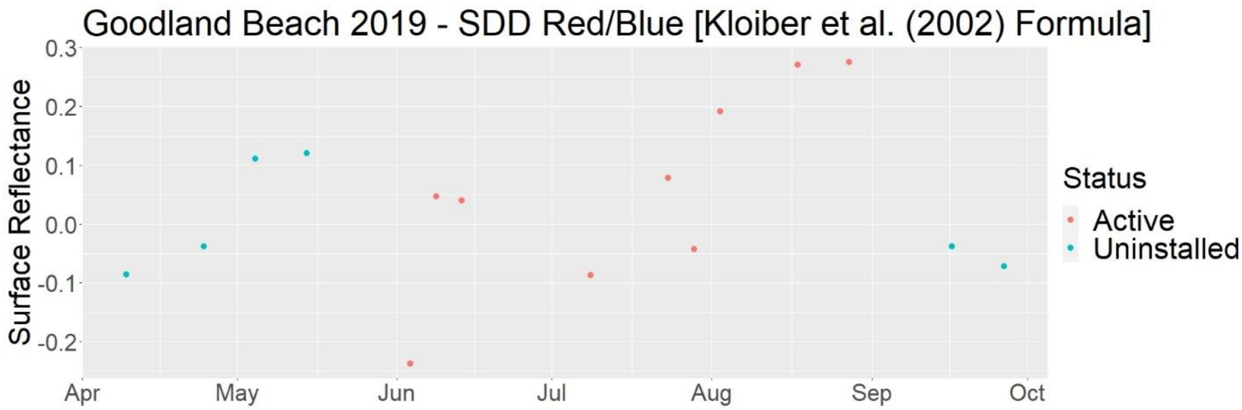


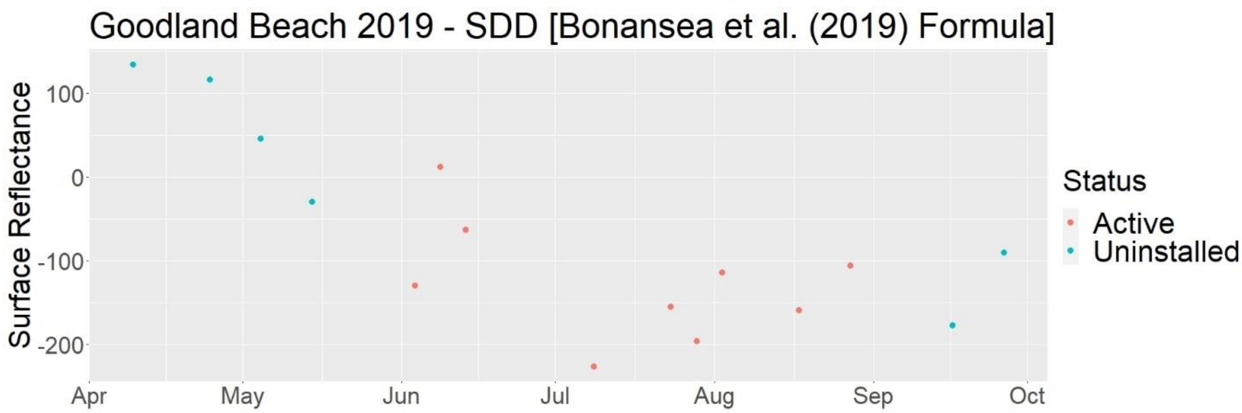



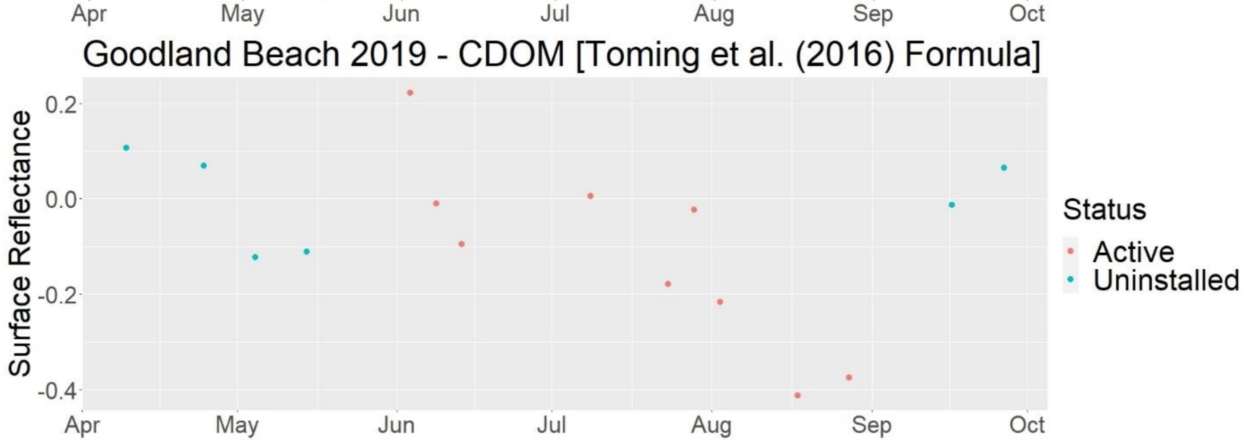



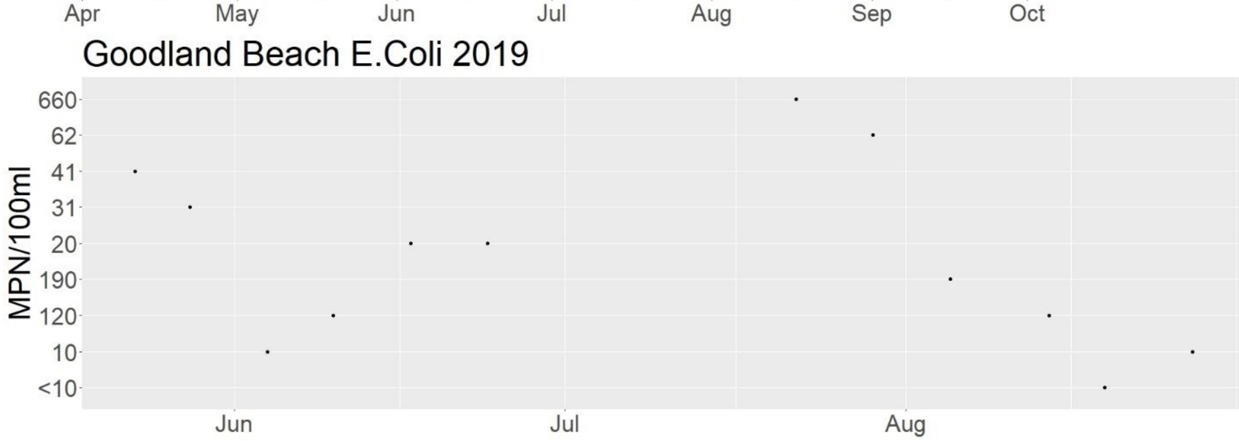



## Goodland Beach 2019 Calculated Bands and E. coli Scatter Plots

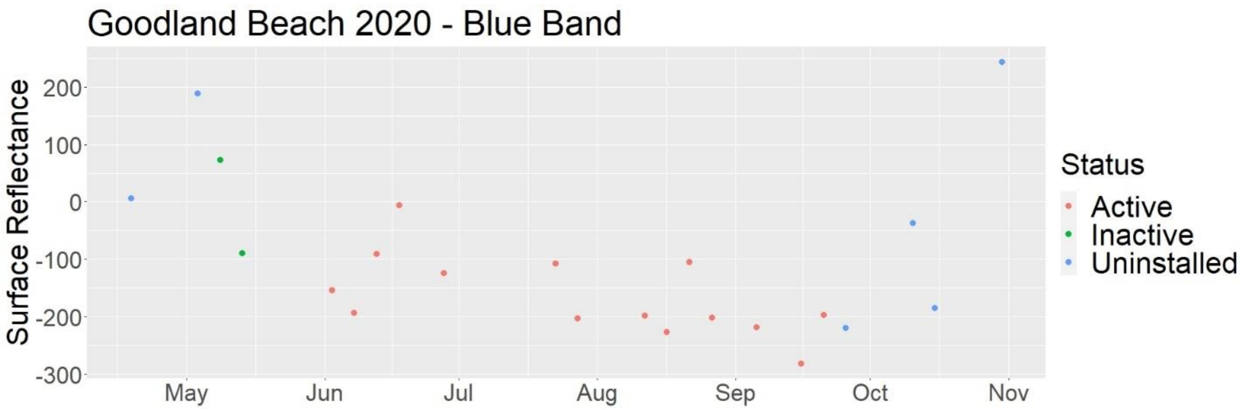


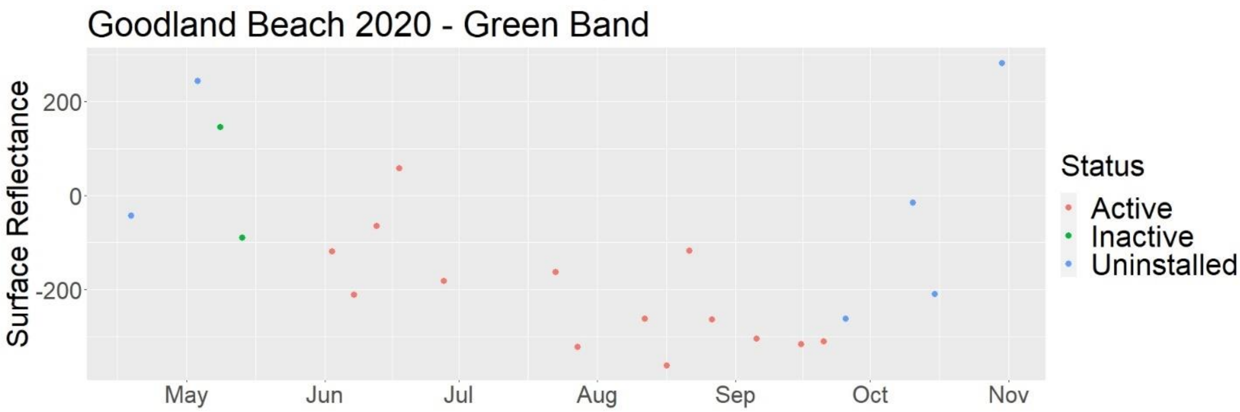



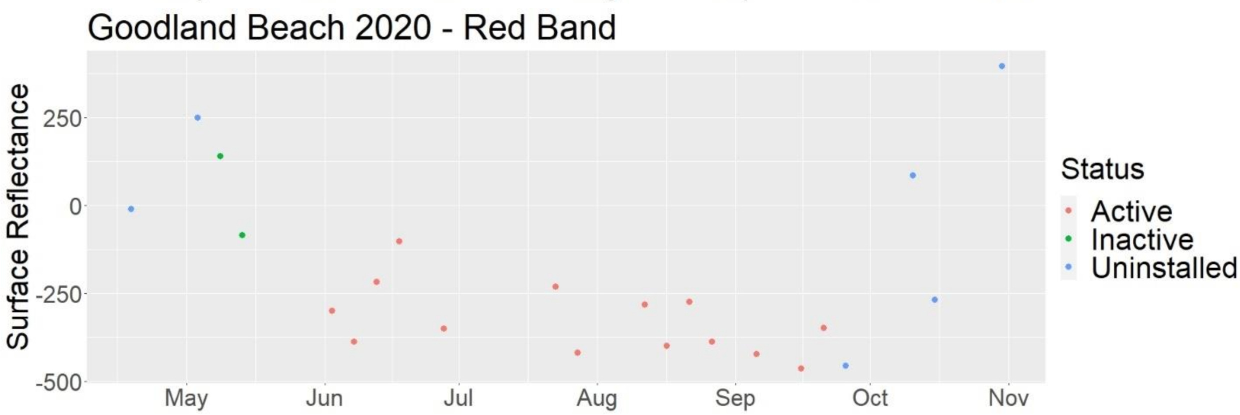



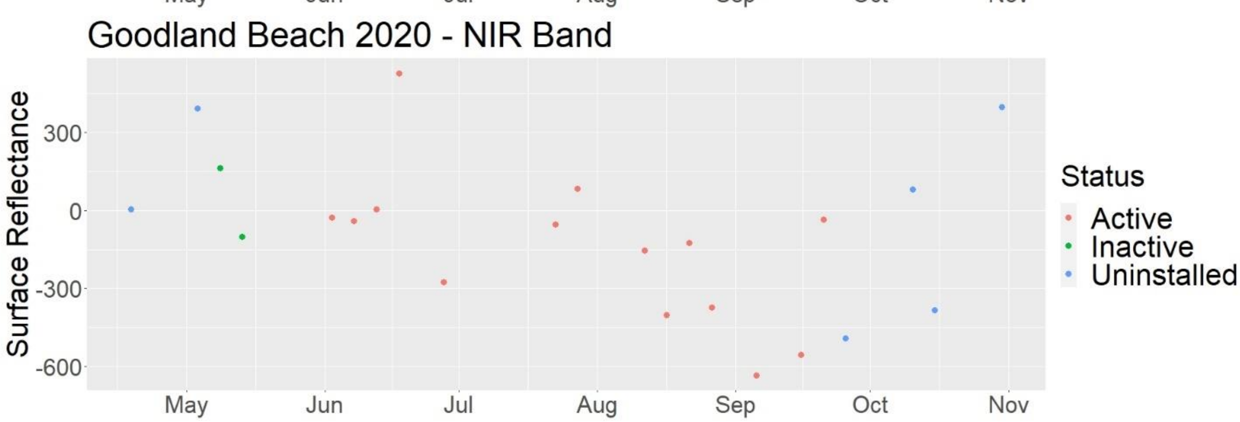



## Goodland Beach 2020 Individual Bands Scatter Plots

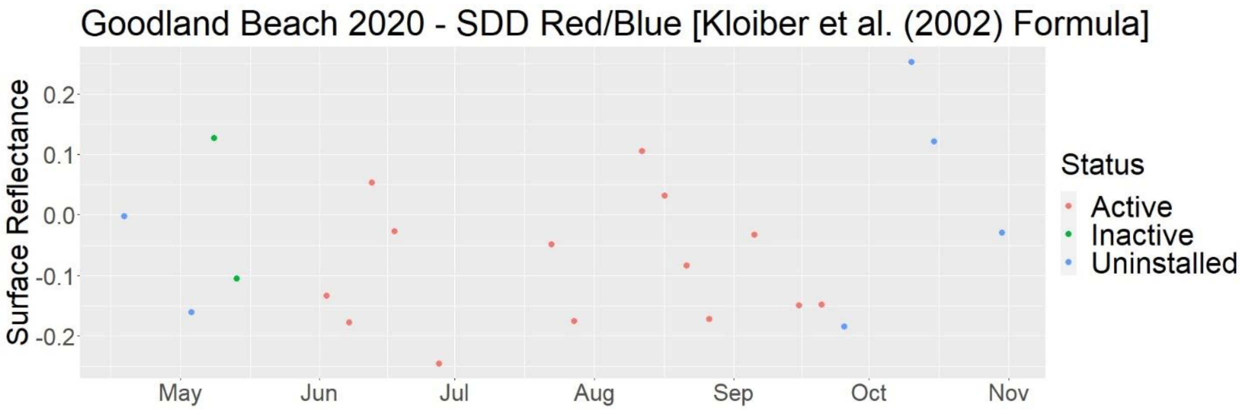


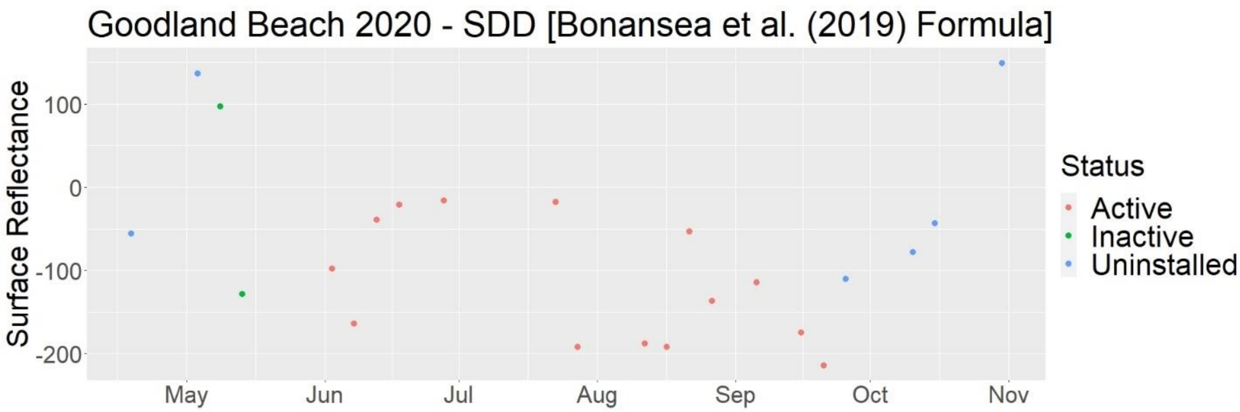



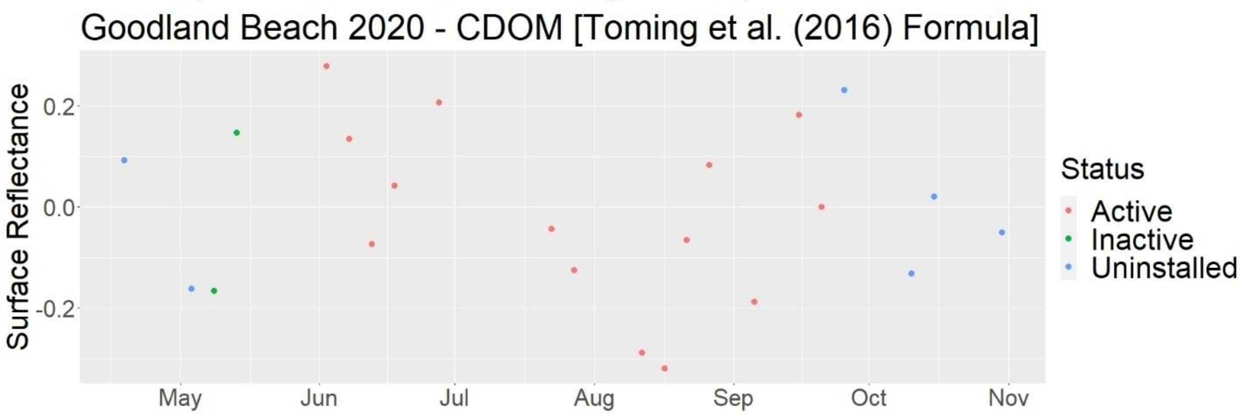



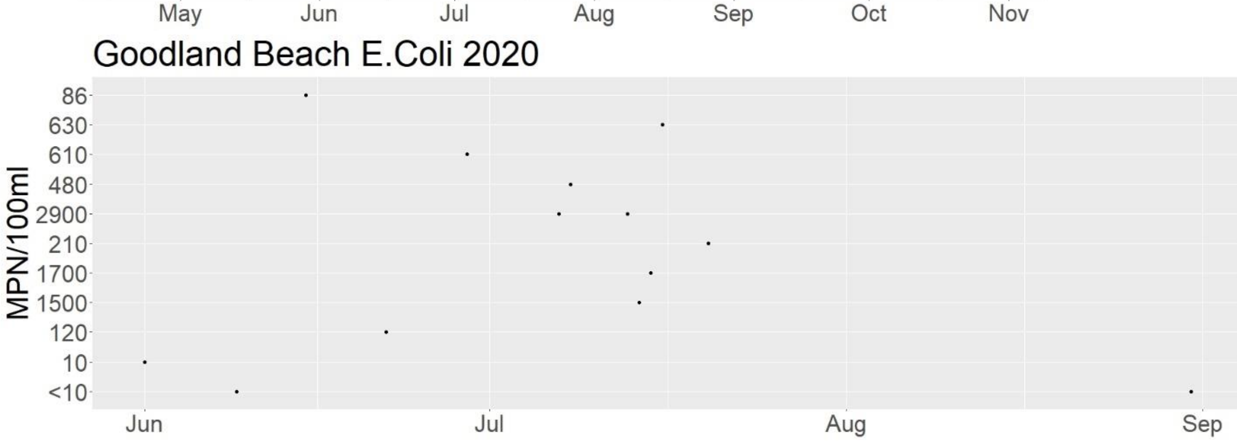



## Goodland Beach 2020 Calculated Bands Scatter Plots

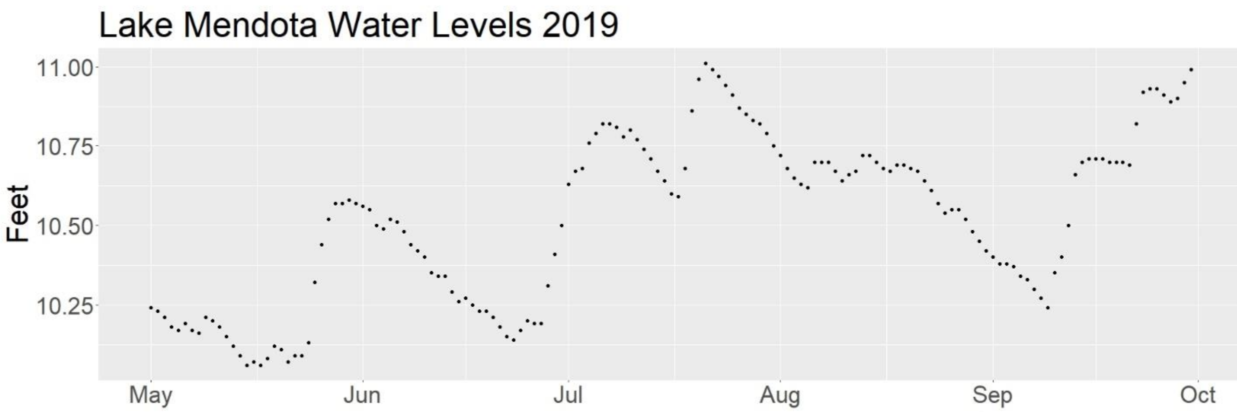


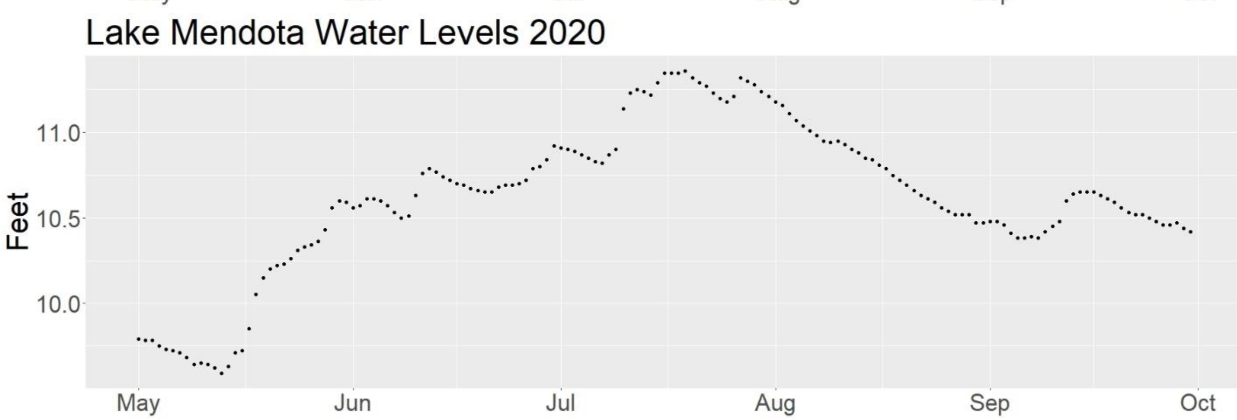



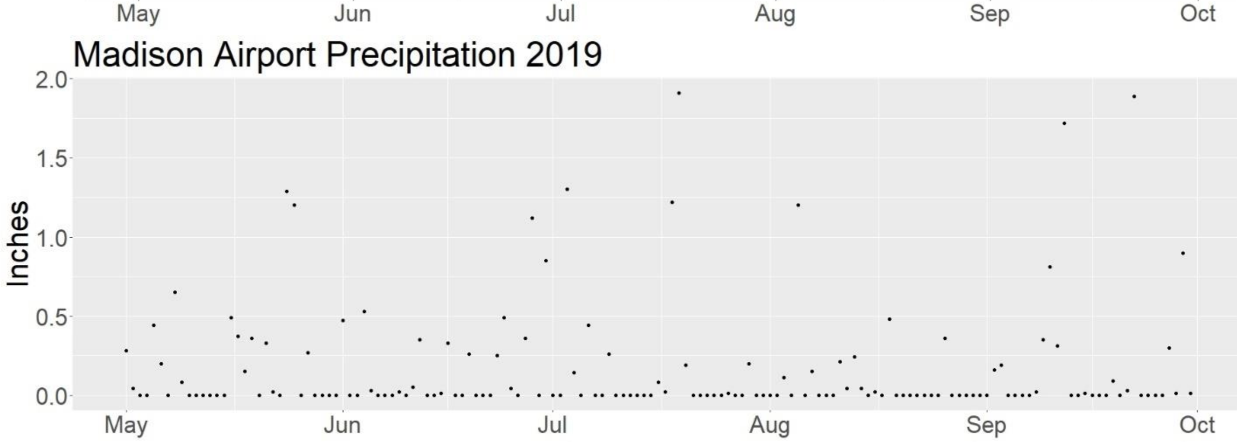



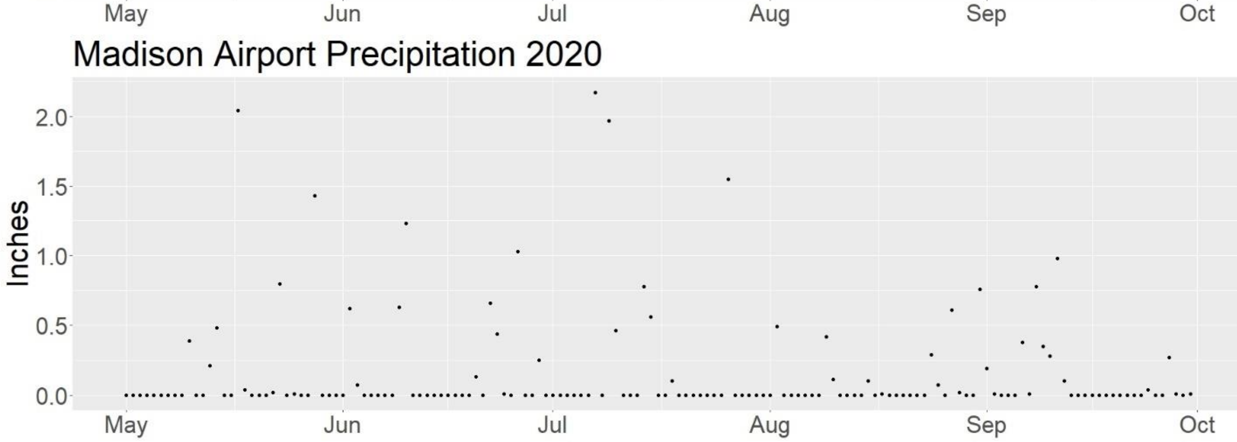



## Water Levels and Precipitation Plots 2019 and 2020



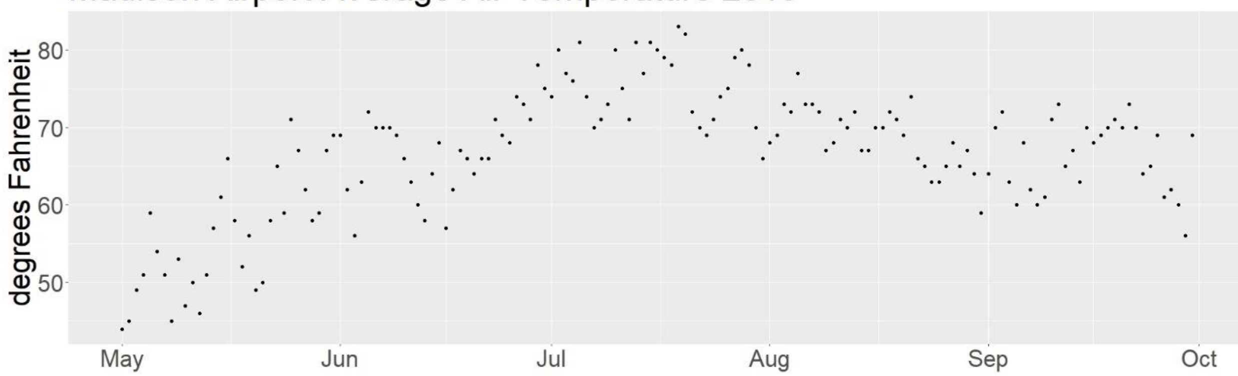



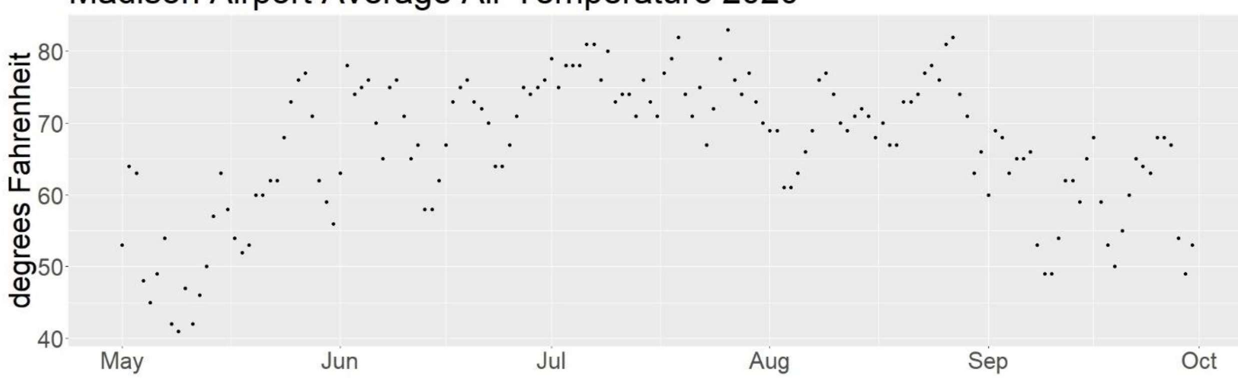



## Air Temperature and Wind Plots 2019 and 2020

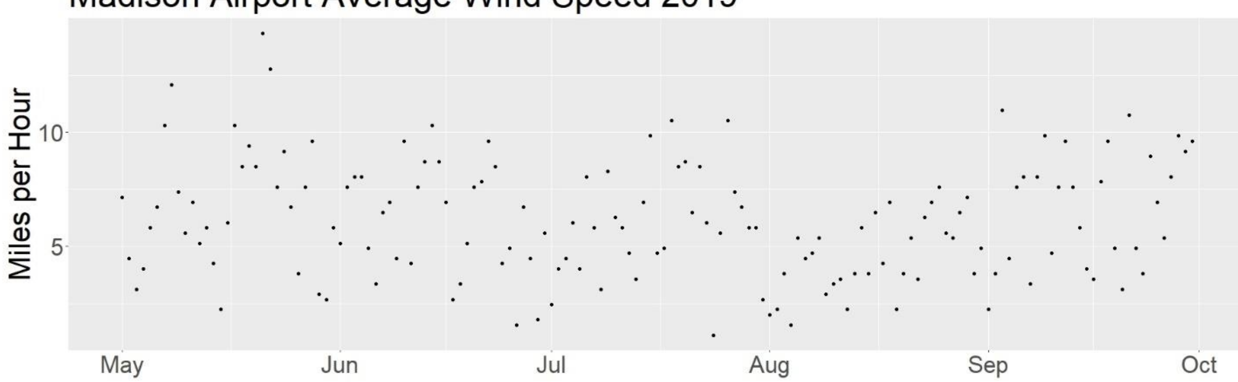
Madison Airport Average Air Temperature 2019



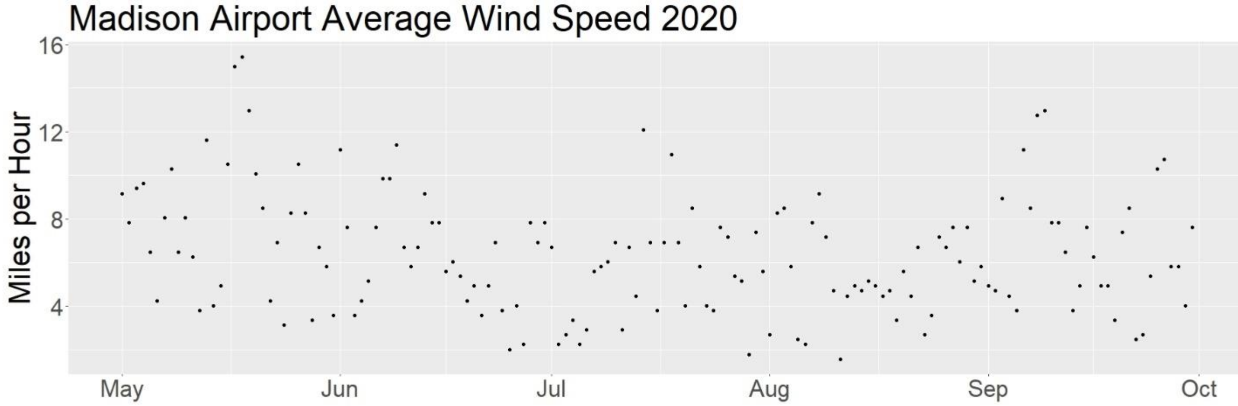

Madison Airport Average Air Temperature 2020




Madison Airport Average Wind Speed 2019




Madison Airport Average Wind Speed 2020



# Discussion

While there is no *in situ* data specific to this study available for ground truthing against the Secchi Disk Depth and Colored Dissolved Organic Matter calculated spectral reflectance, the data indicates two overall interesting comparisons, site-to-site and year-to-year. In general, the scatter-plot comparison of the WETS active and inactive/uninstalled and *p*-value findings indicates the calculated variables, Landsat 7 SDD, Sentinel-2 SDD, and CDOM are not as sensitive as the visible individual blue, green and red bands. Even near infrared (NIR) is less sensitive than the visible spectrum except for Mendota 2020. Mendota 2020 NIR is the only sensitive band of all bands measured and calculated for 2019 and 2020. The visible blue, green, and red individual bands are the only bands showing sensitivity for 2020 at Goodland Beach. The visible spectrum is more sensitive to the differences possibly because of dead organic or suspended inorganic material present inside versus outside the exclosure. The visible spectrum is also sensitive to cyanobacteria blooms and/or floating algal mats which grow due to the invasiveness of aquatic organisms, like zebra mussels and spiny water fleas altering phosphorus availability and native food webs (Clean Lakes Alliance, 2020).

## Site-to-Site

The scatter plots and the *p*-value tables indicate enhanced detectable differences of Goodland WETS over Mendota WETS. Goodland is a smaller exclosure with only two data sample points which may be influencing the results. It is also possible, the WETS filtration system, being equal at each beach, performs better on a smaller exclosure. A potential environmental factor for this influence is that Goodland WETS lies between two locks, Tenney Lock (Lake Mendota Dam) and Babcock Lock (Lake Waubesa Dam). The Yahara River flows freely through Lake Mendota before encountering Tenney Lock, located at the outlet of Lake Mendota; the river continues flowing through Lake Monona and Lake Waubesa before entering Babcock Dam at the outlet of Lake Waubesa. Lock functionality may contribute to the turbidity and suspended solids in each lake.

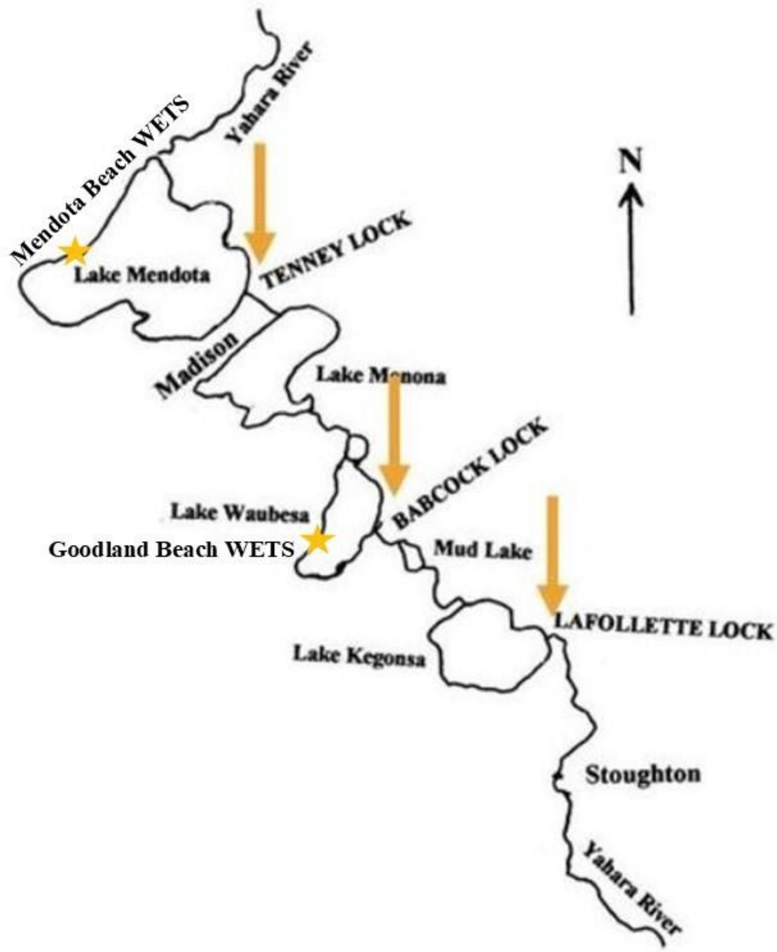



*Figure 16: Yahara River locks with WETS locations. https://openchannelyaharadams.weebly.com/*

The exclosure area at both beaches is shallow (approximately five feet) requiring additional calculations to adjust for depth effect, yet tainted radiometric signals is possible. Due to the sediment removal project, Suck the Muck, on creeks upriver from Lake Mendota there is possibly a different bottom-of-the-lake composite causing signal contamination in Mendota WETS versus Goodland WETS. Lake Mendota is five times larger than Lake Waubesa, so the Mendota exclosure may experience a greater impact by stronger longshore currents and/or wind-wave induced mixing.

## Year-to-Year

It is worth noting, the significant relative difference in water quality (if the reflectance data is indeed capturing water quality differences between inside and outside the WETS) of both locations from 2019 to 2020 in the scatter plots and the *p*-values. Possibly the Suck the Muck projects are starting to have an impact on water quality as determined by visible spectrum surface reflectance. If the outside lake water is high water quality reflectance, then the inside water quality may also be high quality regardless of the purification system influence.

In 2019, Lake Mendota water levels spiked numerous times due to frequent and intense rainfall causing an influx of suspended solids and 171,000 pounds of phosphorous (Swanson, 2021) from land runoff throughout the watershed, while 2020 water levels peaked once in July with 7.59 total inches but retained a similar precipitation mean as 2019. The chronic precipitation, followed by low waves and warm temperatures in 2019 allowed for greater algal growth resulting in higher near IR surface reflectance in the individual bands, yet the spectral difference between inside and outside the WETS at both beaches remains insignificant.

Dane County Land and Water Resources Department maintains approximate five-foot water level between Lake Mendota and Lake Monona via the Tenney Lock, therefore water flow from dam activity may affect turbidity. Another human activity is a sediment dredging project in the Yahara River at Lake Monona (downstream of Lake Mendota) in 2020. Even though the dredging is removing excess phosphorus it creates sediment disturbance also potentially reducing clarity in Lake Waubesa (Goodland WETS).

The year 2020 significant relative difference in water quality over 2019 produced interesting electromagnetic spectrum results between Mendota and Goodland WETS. The Mendota WETS area NIR band is the only band to present statistically significant mean differences between inside and outside the exclosure. While Goodland WETS presented statistically significant differences in bands blue, green, and red.

The detectable spectral differences in 2020 give rise to considering factors as to why one year is sensitive to spectral reflectance and the other is not. Swanson (2021), reports significantly fewer days of strong cyanobacteria in 2020 versus 2019 and water clarity is similar between both years based on turbidity tube measurements.

# Conclusion

The Sentinel-2 10-meter bands 2 (blue), 3 (green), and 4 (red) best support evaluating spectral differences of the small, shallow WETS areas. Calculated constituents 3div1 (red/blue), SDD, and CDOM, using combinations of 10-meter bands blue, green, red and NIR are less sensitive in detecting spectral differences between inside and outside the WETS. An overall site to site evaluation of both years indicates Mendota Beach has less detectable difference across all bands than Goodland Beach. Goodland Beach is more radiometrically sensitive for both years in the visible bands yet are only statistically significant in 2020. Mendota Beach only expressed radiometric sensitivity 2020 and statistically significant in NIR.

Viewing 2019 in its entirety, there are no spectral differences between inside and outside the WETS at either study site. Various speculated events occurred in 2019 which may explain why in 2020 Mendota WETS saw a 61% overall change in detectable spectral differences in water quality over the non-detectable 2019 and Goodland came in with a negative change percentage of spectral differences over 2019 due to the barely detectable spectral difference of CDOM in 2020. While both green and red bands had statistically significant detectable spectral differences in 2020, 2019 had higher spectral difference in green while 2020 had a higher spectral difference in red, resulting in a large change in CDOM at Goodland from 2019 to 2020.

The results of this study are hopeful for future work considering the major limitations of studying shallow, small lake-water areas (course spatial resolution relative to exclosure size), adjusting for lake-bottom reflectance, short temporal range with multiple cloudy days reducing the availability of cloud-free days, low radiometric resolution, and various environmental influences. During the initial two-sample t-tests, there was an error in the Sentinel-2 SDD and CDOM band equations due to an incorrect band correlation between the sensor bands (2, 3, 4, and 8) and the respective ArcGIS Pro bands (1, 2, 3, and 4). The incorrect equations produced significant t-test results in SDD for 2019 and 2020 in Goodland and in CDOM at Mendota in 2020; this suggests that future analyses should explore additional band ratios not previously reported in the literature to be significant in detecting water quality differences. Increased image frequency and availability with additional specialized bands for detecting specific water quality parameters, and higher than 10-meter resolution, would greatly improve the results of future studies.

# Acknowledgments

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# Appendix A: Remote Sensing Files

## NAIP

Mendota: m_4308961_nw_16_060_20180728.tif

Goodland: m_4308962_sw_16_1_20170922.tif

## Sentinel 2A&B

To understand the filename structure, visit:

[https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-2-msi/naming-convention](https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-2-msi/naming-convention)

### 2019

S2A_MSIL2A_20190424T164901_N0211_R026_T15TYH_20190424T235956.SAFE

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S2A_MSIL2A_20190514T164901_N0212_R026_T15TYH_20190514T211202.SAFE

S2A_MSIL2A_20190603T164901_N0212_R026_T15TYH_20190603T211257.SAFE

S2A_MSIL2A_20190613T164901_N0212_R026_T15TYH_20190613T210848.SAFE

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S2B_MSIL2A_20190916T164929_N0213_R026_T15TYH_20190916T223826.SAFE

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### 2020

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S2B_MSIL2A_20200612T164849_N0214_R026_T15TYH_20200612T211134.SAFE
S2B_MSIL2A_20200722T164849_N0214_R026_T15TYH_20200722T211602.SAFE
S2B_MSIL2A_20200811T164849_N0214_R026_T15TYH_20200813T161525.SAFE
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# Appendix B: Excel Data Files

## Mendota – 2019 reflectance values from Sentinel-2 imagery (All_Samples.xlsx)

| OBJECTID | Mendota_Sample_Points | OBJECTID | Location | Beach | X | Y |
|---|---|---|---|---|---|---|
| 1 | 13 | 13 | Inside | Mendota | 787224.6346 | 4778894.699 |
| 2 | 14 | 14 | Inside | Mendota | 787234.5352 | 4778894.699 |
| 3 | 15 | 15 | Inside | Mendota | 787234.3957 | 4778884.938 |
| 4 | 16 | 16 | Outside | Mendota | 787235.2324 | 4778874.619 |
| 5 | 17 | 17 | Outside | Mendota | 787224.6346 | 4778874.619 |
| 6 | 18 | 18 | Outside | Mendota | 787234.8141 | 4778865.137 |
| 7 | 19 | 19 | Outside | Mendota | 787224.774 | 4778864.858 |
| 8 | 20 | 20 | Outside | Mendota | 787214.5946 | 4778885.078 |
| 9 | 21 | 21 | Outside | Mendota | 787214.5946 | 4778894.978 |
| 10 | 23 | 23 | Outside | Mendota | 787214.5946 | 4778874.898 |
| 11 | 24 | 24 | Outside | Mendota | 787245.0788 | 4778874.732 |
| 12 | 25 | 25 | Outside | Mendota | 787214.3826 | 4778865.045 |

| 0409_Band_1 | 0409_Band_2 | 0409_Band_3 | 0409_Band_4 | 0424_Band_1 | 0424_Band_2 | 0424_Band_3 | 0424_Band_4 |
|---|---|---|---|---|---|---|---|
| 586 | 636 | 590 | 783 | 325 | 523 | 448 | 322 |
| 717 | 758 | 825 | 1086 | 325 | 546 | 522 | 398 |
| 547 | 551 | 506 | 629 | 389 | 498 | 396 | 353 |
| 517 | 585 | 500 | 618 | 350 | 559 | 418 | 280 |
| 552 | 594 | 506 | 622 | 344 | 518 | 372 | 261 |
| 495 | 602 | 500 | 584 | 374 | 545 | 404 | 276 |
| 523 | 585 | 509 | 576 | 360 | 525 | 377 | 273 |
| 526 | 600 | 455 | 648 | 355 | 507 | 409 | 286 |
| 543 | 561 | 450 | 692 | 311 | 503 | 408 | 291 |
| 539 | 613 | 469 | 612 | 359 | 544 | 395 | 281 |
| 545 | 579 | 509 | 660 | 353 | 548 | 449 | 333 |
| 552 | 600 | 491 | 584 | 336 | 497 | 391 | 269 |

| 0504_Band_1 | 0504_Band_2 | 0504_Band_3 | 0504_Band_4 | 0514_Band_1 | 0514_Band_2 | 0514_Band_3 | 0514_Band_4 |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 516 | 702 | 589 | 441 | 1158 | 1316 | 1266 | 1450 |
| 599 | 799 | 708 | 731 | 1250 | 1428 | 1356 | 1760 |
| 485 | 675 | 526 | 399 | 1310 | 1312 | 1256 | 1623 |
| 566 | 670 | 478 | 467 | 1396 | 1362 | 1204 | 1782 |
| 553 | 676 | 489 | 398 | 1564 | 1400 | 1192 | 1960 |
| 663 | 772 | 551 | 640 | 1572 | 1472 | 1282 | 2001 |
| 618 | 742 | 550 | 493 | 1612 | 1614 | 1340 | 2228 |
| 535 | 667 | 507 | 357 | 1180 | 1272 | 1146 | 1484 |
| 511 | 667 | 500 | 365 | 1048 | 1214 | 1142 | 1287 |
| 580 | 700 | 518 | 438 | 1396 | 1408 | 1194 | 1832 |
| 563 | 676 | 497 | 543 | 1350 | 1372 | 1204 | 1804 |
| 551 | 711 | 540 | 469 | 1530 | 1570 | 1320 | 2083 |

| 0603_Band_1 | 0603_Band_2 | 0603_Band_3 | 0603_Band_4 | 0608_Band_1 | 0608_Band_2 | 0608_Band_3 | 0608_Band_4 |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 1168 | 1274 | 1138 | 1732 | 447 | 647 | 532 | 758 |
| 1200 | 1266 | 1208 | 1960 | 556 | 982 | 846 | 1437 |
| 1224 | 1274 | 1074 | 1700 | 276 | 483 | 333 | 619 |
| 1276 | 1334 | 1158 | 1714 | 434 | 693 | 547 | 567 |
| 1276 | 1396 | 1176 | 1694 | 543 | 711 | 549 | 558 |
| 1268 | 1364 | 1184 | 1718 | 717 | 908 | 771 | 679 |
| 1290 | 1412 | 1208 | 1722 | 731 | 925 | 807 | 692 |
| 1232 | 1318 | 1144 | 1712 | 517 | 745 | 544 | 541 |
| 1200 | 1266 | 1072 | 1718 | 435 | 702 | 510 | 536 |
| 1284 | 1412 | 1240 | 1728 | 649 | 844 | 651 | 517 |
| 1232 | 1294 | 1128 | 1742 | 525 | 692 | 524 | 715 |
| 1310 | 1448 | 1242 | 1718 | 727 | 909 | 754 | 605 |

| 0613_Band_1 | 0613_Band_2 | 0613_Band_3 | 0613_Band_4 | 0708_Band_1 | 0708_Band_2 | 0708_Band_3 | 0708_Band_4 |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 227 | 387 | 286 | 354 | 521 | 673 | 502 | 837 |
| 277 | 337 | 291 | 382 | 677 | 977 | 895 | 1250 |
| 327 | 493 | 455 | 448 | 557 | 627 | 490 | 980 |
| 604 | 707 | 621 | 554 | 561 | 706 | 429 | 894 |
| 725 | 927 | 785 | 738 | 502 | 564 | 373 | 688 |
| 743 | 885 | 790 | 712 | 469 | 512 | 331 | 436 |
| 739 | 913 | 789 | 753 | 445 | 499 | 332 | 377 |
| 462 | 637 | 520 | 467 | 488 | 569 | 370 | 587 |
| 359 | 544 | 429 | 408 | 494 | 560 | 386 | 598 |
| 530 | 664 | 557 | 470 | 474 | 531 | 343 | 442 |
| 491 | 642 | 551 | 528 | 519 | 670 | 420 | 1244 |
| 548 | 722 | 605 | 550 | 436 | 494 | 317 | 367 |

| 0723_Band_1 | 0723_Band_2 | 0723_Band_3 | 0723_Band_4 | 0728_Band_1 | 0728_Band_2 | 0728_Band_3 | 0728_Band_4 |
|---|---|---|---|---|---|---|---|
| 443 | 536 | 411 | 629 | 651 | 916 | 804 | 1192 |
| 534 | 749 | 582 | 835 | 881 | 1340 | 1256 | 1842 |
| 415 | 526 | 419 | 656 | 550 | 645 | 602 | 943 |
| 435 | 496 | 358 | 593 | 444 | 576 | 429 | 675 |
| 420 | 490 | 340 | 521 | 470 | 561 | 439 | 611 |
| 442 | 479 | 359 | 540 | 401 | 464 | 364 | 512 |
| 397 | 460 | 325 | 486 | 405 | 489 | 391 | 459 |
| 376 | 479 | 335 | 534 | 472 | 603 | 431 | 652 |
| 423 | 488 | 335 | 561 | 534 | 676 | 504 | 802 |
| 397 | 495 | 325 | 481 | 414 | 498 | 366 | 554 |
| 408 | 473 | 359 | 647 | 407 | 541 | 389 | 1056 |
| 420 | 482 | 309 | 476 | 427 | 443 | 373 | 466 |
| **0802_Band_1** | **0802_Band_2** | **0802_Band_3** | **0802_Band_4** | **0817_Band_1** | **0817_Band_2** | **0817_Band_3** | **0817_Band_4** |
| 296 | 505 | 371 | 570 | 613 | 869 | 763 | 1188 |
| 390 | 660 | 640 | 807 | 854 | 1178 | 1230 | 2026 |
| 328 | 513 | 335 | 771 | 522 | 669 | 545 | 930 |
| 393 | 653 | 398 | 933 | 522 | 641 | 430 | 780 |
| 346 | 612 | 372 | 766 | 499 | 628 | 419 | 653 |
| 335 | 505 | 307 | 564 | 543 | 678 | 434 | 619 |
| 335 | 545 | 302 | 585 | 525 | 672 | 434 | 579 |
| 399 | 626 | 382 | 971 | 499 | 614 | 435 | 672 |
| 352 | 432 | 296 | 595 | 526 | 701 | 467 | 781 |
| 348 | 585 | 331 | 689 | 493 | 647 | 432 | 608 |
| 369 | 631 | 386 | 1117 | 499 | 659 | 438 | 1128 |
| 330 | 500 | 290 | 491 | 520 | 675 | 417 | 548 |
| **0827_Band_1** | **0827_Band_2** | **0827_Band_3** | **0827_Band_4** | **0916_Band_1** | **0916_Band_2** | **0916_Band_3** | **0916_Band_4** |
| 347 | 631 | 522 | 820 | 439 | 771 | 648 | 1224 |
| 722 | 1094 | 1186 | 1630 | 666 | 1064 | 1210 | 2067 |
| 227 | 418 | 319 | 503 | 351 | 605 | 351 | 846 |
| 284 | 451 | 303 | 363 | 296 | 485 | 295 | 404 |
| 274 | 445 | 284 | 297 | 318 | 472 | 284 | 319 |
| 315 | 493 | 271 | 312 | 259 | 441 | 238 | 309 |
| 296 | 497 | 296 | 266 | 255 | 448 | 233 | 244 |
| 220 | 388 | 241 | 321 | 276 | 452 | 274 | 383 |
| 232 | 425 | 261 | 322 | 322 | 557 | 328 | 618 |
| 258 | 413 | 229 | 269 | 279 | 455 | 262 | 288 |
| 318 | 493 | 347 | 844 | 289 | 448 | 285 | 961 |
| 283 | 500 | 280 | 233 | 258 | 457 | 240 | 228 |

| 0926_Band_1 | 0926_Band_2 | 0926_Band_3 | 0926_Band_4 |
|---:|---:|---:|---:|
| 351 | 685 | 483 | 702 |
| 532 | 963 | 897 | 1294 |
| 306 | 555 | 318 | 468 |
| 280 | 487 | 282 | 332 |
| 262 | 468 | 263 | 274 |
| 243 | 428 | 221 | 256 |
| 266 | 426 | 235 | 219 |
| 290 | 471 | 276 | 350 |
| 310 | 517 | 318 | 408 |
| 280 | 433 | 249 | 227 |
| 280 | 463 | 303 | 559 |
| 265 | 416 | 242 | 190 |

Goodland 2019 reflectance values from Sentinel-2 imagery (All_Samples.xlsx)

| OBJECTID | Goodland_Sample_Points | OBJECTID | Location | Beach | X | Y |
|---|---|---|---|---|---|---|
| 1 | 3 | 3 | Inside | Goodland | 798425.0196 | 4767384.792 |
| 2 | 4 | 4 | Inside | Goodland | 798435.133 | 4767384.503 |
| 3 | 6 | 6 | Outside | Goodland | 798424.8371 | 4767364.997 |
| 4 | 7 | 7 | Outside | Goodland | 798435.1549 | 4767364.584 |
| 5 | 8 | 8 | Outside | Goodland | 798443.8218 | 4767374.489 |
| 6 | 9 | 9 | Outside | Goodland | 798454.5523 | 4767383.981 |
| 7 | 10 | 10 | Outside | Goodland | 798444.6472 | 4767395.537 |

| 0409_Band_1 | 0409_Band_2 | 0409_Band_3 | 0409_Band_4 | 0424_Band_1 | 0424_Band_2 | 0424_Band_3 | 0424_Band_4 |
|---|---|---|---|---|---|---|---|
| 1017 | 1316 | 1700 | 2374 | 670 | 1096 | 1162 | 1469 |
| 678 | 877 | 834 | 955 | 342 | 547 | 412 | 260 |
| 529 | 666 | 749 | 1028 | 274 | 427 | 374 | 309 |
| 421 | 497 | 454 | 538 | 246 | 333 | 255 | 221 |
| 422 | 521 | 507 | 563 | 205 | 318 | 258 | 243 |
| 446 | 596 | 521 | 537 | 254 | 437 | 294 | 218 |
| 539 | 753 | 748 | 985 | 371 | 621 | 479 | 341 |
| **0504_Band_1** | **0504_Band_2** | **0504_Band_3** | **0504_Band_4** | **0514_Band_1** | **0514_Band_2** | **0514_Band_3** | **0514_Band_4** |
| 743 | 1128 | 1330 | 1882 | 594 | 852 | 888 | 1340 |
| 426 | 683 | 478 | 523 | 466 | 509 | 353 | 437 |
| 303 | 508 | 450 | 498 | 489 | 511 | 331 | 632 |
| 237 | 327 | 201 | 256 | 437 | 477 | 280 | 538 |
| 249 | 337 | 209 | 262 | 455 | 448 | 279 | 503 |
| 295 | 454 | 258 | 198 | 446 | 436 | 270 | 408 |
| 368 | 601 | 459 | 554 | 432 | 560 | 459 | 466 |
| **0603_Band_1** | **0603_Band_2** | **0603_Band_3** | **0603_Band_4** | **0608_Band_1** | **0608_Band_2** | **0608_Band_3** | **0608_Band_4** |
| 1364 | 1538 | 1426 | 2690 | 788 | 1202 | 1140 | 3660 |
| 1332 | 1450 | 1324 | 2164 | 657 | 907 | 833 | 1797 |
| 1356 | 1432 | 1314 | 2112 | 404 | 577 | 500 | 1384 |
| 1332 | 1406 | 1288 | 2004 | 298 | 394 | 296 | 469 |
| 1326 | 1418 | 1296 | 1982 | 400 | 529 | 416 | 637 |
| 1356 | 1400 | 1312 | 1968 | 350 | 428 | 305 | 494 |
| 1284 | 1392 | 1248 | 2254 | 380 | 514 | 372 | 2084 |

| 0613_Band_1 | 0613_Band_2 | 0613_Band_3 | 0613_Band_4 | 0708_Band_1 | 0708_Band_2 | 0708_Band_3 | 0708_Band_4 |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 324 | 648 | 495 | 2101 | 666 | 785 | 781 | 1830 |
| 167 | 263 | 223 | 480 | 474 | 572 | 353 | 870 |
| 92 | 205 | 111 | 386 | 508 | 562 | 413 | 806 |
| 103 | 183 | 117 | 244 | 517 | 564 | 372 | 610 |
| 169 | 268 | 183 | 334 | 508 | 616 | 394 | 589 |
| 200 | 287 | 205 | 300 | 490 | 613 | 374 | 470 |
| 175 | 294 | 189 | 699 | 546 | 628 | 396 | 973 |
| **0723_Band_1** | **0723_Band_2** | **0723_Band_3** | **0723_Band_4** | **0728_Band_1** | **0728_Band_2** | **0728_Band_3** | **0728_Band_4** |
| 554 | 828 | 725 | 2673 | 794 | 966 | 1114 | 2376 |
| 390 | 537 | 427 | 1062 | 446 | 611 | 458 | 1162 |
| 429 | 568 | 386 | 993 | 456 | 596 | 458 | 835 |
| 411 | 543 | 342 | 698 | 474 | 609 | 451 | 585 |
| 399 | 519 | 313 | 623 | 485 | 637 | 499 | 591 |
| 411 | 552 | 343 | 589 | 485 | 642 | 466 | 539 |
| 397 | 565 | 332 | 1521 | 462 | 609 | 422 | 1516 |
| **0802_Band_1** | **0802_Band_2** | **0802_Band_3** | **0802_Band_4** | **0817_Band_1** | **0817_Band_2** | **0817_Band_3** | **0817_Band_4** |
| 453 | 788 | 789 | 2149 | 485 | 844 | 824 | 2702 |
| 290 | 465 | 332 | 828 | 347 | 542 | 408 | 1090 |
| 392 | 636 | 401 | 1158 | 346 | 553 | 315 | 958 |
| 386 | 614 | 354 | 888 | 318 | 506 | 283 | 497 |
| 343 | 542 | 325 | 845 | 299 | 446 | 266 | 495 |
| 363 | 606 | 370 | 787 | 311 | 506 | 273 | 377 |
| 382 | 561 | 353 | 1481 | 355 | 594 | 297 | 1668 |
| **0827_Band_1** | **0827_Band_2** | **0827_Band_3** | **0827_Band_4** | **0916_Band_1** | **0916_Band_2** | **0916_Band_3** | **0916_Band_4** |
| 539 | 931 | 744 | 3240 | 394 | 777 | 484 | 2009 |
| 344 | 560 | 553 | 1368 | 265 | 418 | 252 | 909 |
| 285 | 477 | 295 | 1207 | 264 | 408 | 228 | 550 |
| 245 | 383 | 221 | 285 | 254 | 367 | 189 | 278 |
| 218 | 334 | 198 | 363 | 243 | 355 | 198 | 268 |
| 244 | 409 | 224 | 329 | 214 | 400 | 199 | 242 |
| 260 | 422 | 234 | 2064 | 246 | 383 | 210 | 996 |

| 0926_Band_1 | 0926_Band_2 | 0926_Band_3 | 0926_Band_4 |
|---|---|---|---|
| 393 | 705 | 629 | 1672 |
| 282 | 327 | 226 | 691 |
| 222 | 335 | 241 | 468 |
| 238 | 326 | 220 | 367 |
| 220 | 332 | 234 | 341 |
| 252 | 345 | 233 | 330 |
| 243 | 332 | 228 | 977 |

Mendota 2020 reflectance values from Sentinel-2 imagery (All_Samples.xlsx)

| OBJECTID | Mendota_Sample_Points | OBJECTID | Location | Beach | X | Y |
|---|---|---|---|---|---|---|
| 1 | 13 | 13 | Inside | Mendota | 787224.6346 | 4778894.699 |
| 2 | 14 | 14 | Inside | Mendota | 787234.5352 | 4778894.699 |
| 3 | 15 | 15 | Inside | Mendota | 787234.3957 | 4778884.938 |
| 4 | 16 | 16 | Outside | Mendota | 787235.2324 | 4778874.619 |
| 5 | 17 | 17 | Outside | Mendota | 787224.6346 | 4778874.619 |
| 6 | 18 | 18 | Outside | Mendota | 787234.8141 | 4778865.137 |
| 7 | 19 | 19 | Outside | Mendota | 787224.774 | 4778864.858 |
| 8 | 20 | 20 | Outside | Mendota | 787214.5946 | 4778885.078 |
| 9 | 21 | 21 | Outside | Mendota | 787214.5946 | 4778894.978 |
| 10 | 23 | 23 | Outside | Mendota | 787214.5946 | 4778874.898 |
| 11 | 24 | 24 | Outside | Mendota | 787245.0788 | 4778874.732 |
| 12 | 25 | 25 | Outside | Mendota | 787214.3826 | 4778865.045 |

| 0418_Band_1 | 0418_Band_2 | 0418_Band_3 | 0418_Band_4 | 0503_Band_1 | 0503_Band_2 | 0503_Band_3 | 0503_Band_4 |
|---|---|---|---|---|---|---|---|
| 419 | 571 | 548 | 444 | 756 | 941 | 924 | 1164 |
| 439 | 636 | 674 | 696 | 955 | 1196 | 1244 | 1904 |
| 395 | 613 | 525 | 410 | 607 | 794 | 723 | 856 |
| 392 | 595 | 498 | 339 | 642 | 805 | 650 | 759 |
| 379 | 569 | 485 | 287 | 672 | 848 | 691 | 747 |
| 390 | 572 | 470 | 300 | 668 | 828 | 666 | 720 |
| 400 | 572 | 489 | 311 | 668 | 833 | 682 | 716 |
| 400 | 569 | 496 | 304 | 667 | 826 | 724 | 753 |
| 387 | 575 | 502 | 354 | 583 | 811 | 686 | 852 |
| 400 | 575 | 498 | 299 | 688 | 832 | 710 | 747 |
| 382 | 564 | 481 | 338 | 614 | 774 | 634 | 919 |
| 395 | 579 | 498 | 321 | 653 | 833 | 674 | 740 |

| **0508_Band_1** | **0508_Band_2** | **0508_Band_3** | **0508_Band_4** | **0513_Band_1** | **0513_Band_2** | **0513_Band_3** | **0513_Band_4** |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 583 | 868 | 702 | 641 | 791 | 1044 | 950 | 1112 |
| 472 | 807 | 558 | 786 | 937 | 1284 | 1282 | 1788 |
| 475 | 686 | 612 | 535 | 618 | 829 | 787 | 831 |
| 512 | 726 | 595 | 489 | 681 | 873 | 753 | 713 |
| 615 | 829 | 712 | 598 | 685 | 908 | 740 | 689 |
| 466 | 688 | 560 | 435 | 712 | 911 | 749 | 679 |
| 578 | 810 | 697 | 577 | 688 | 921 | 751 | 652 |
| 670 | 895 | 802 | 643 | 749 | 930 | 786 | 745 |
| 651 | 888 | 740 | 619 | 661 | 842 | 730 | 768 |
| 628 | 847 | 736 | 584 | 745 | 936 | 794 | 696 |
| 385 | 580 | 481 | 436 | 650 | 793 | 707 | 833 |
| 637 | 854 | 733 | 569 | 716 | 913 | 791 | 666 |
| 0602_Band_1 | 0602_Band_2 | 0602_Band_3 | 0602_Band_4 | 0607_Band_1 | 0607_Band_2 | 0607_Band_3 | 0607_Band_4 |
| 525 | 750 | 632 | 676 | 575 | 872 | 593 | 569 |
| 620 | 762 | 832 | 1028 | 509 | 758 | 541 | 566 |
| 420 | 607 | 441 | 546 | 514 | 700 | 485 | 429 |
| 550 | 752 | 569 | 499 | 545 | 714 | 455 | 375 |
| 603 | 785 | 610 | 493 | 570 | 753 | 458 | 380 |
| 611 | 829 | 641 | 485 | 561 | 716 | 499 | 420 |
| 641 | 848 | 658 | 495 | 591 | 786 | 541 | 397 |
| 604 | 795 | 644 | 525 | 545 | 727 | 493 | 446 |
| 530 | 668 | 550 | 540 | 530 | 735 | 531 | 502 |
| 659 | 855 | 653 | 479 | 604 | 739 | 499 | 408 |
| 498 | 717 | 527 | 663 | 498 | 686 | 458 | 419 |
| 675 | 854 | 653 | 507 | 558 | 749 | 514 | 380 |
| 0612_Band_1 | 0612_Band_2 | 0612_Band_3 | 0612_Band_4 | 0617_Band_1 | 0617_Band_2 | 0617_Band_3 | 0617_Band_4 |
| 392 | 635 | 462 | 552 | 700 | 829 | 689 | 669 |
| 539 | 766 | 733 | 1028 | 606 | 874 | 646 | 635 |
| 328 | 480 | 296 | 308 | 654 | 760 | 619 | 637 |
| 368 | 497 | 296 | 255 | 613 | 792 | 644 | 583 |
| 346 | 452 | 251 | 207 | 627 | 807 | 629 | 579 |
| 371 | 517 | 312 | 239 | 595 | 709 | 596 | 623 |
| 320 | 468 | 260 | 188 | 570 | 807 | 542 | 634 |
| 332 | 480 | 288 | 256 | 745 | 853 | 728 | 668 |
| 356 | 444 | 274 | 345 | 669 | 828 | 722 | 688 |
| 347 | 484 | 274 | 216 | 608 | 790 | 730 | 639 |
| 332 | 509 | 289 | 489 | 568 | 755 | 654 | 600 |
| 343 | 465 | 250 | 171 | 642 | 794 | 656 | 653 |

| **0627_Band_1** | **0627_Band_2** | **0627_Band_3** | **0627_Band_4** | **0722_Band_1** | **0722_Band_2** | **0722_Band_3** | **0722_Band_4** |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 577 | 692 | 607 | 863 | 339 | 484 | 391 | 678 |
| 602 | 731 | 606 | 979 | 589 | 848 | 777 | 1233 |
| 540 | 698 | 590 | 881 | 400 | 473 | 402 | 450 |
| 639 | 755 | 645 | 850 | 368 | 428 | 274 | 397 |
| 611 | 677 | 547 | 778 | 339 | 405 | 246 | 337 |
| 591 | 647 | 542 | 734 | 283 | 336 | 226 | 247 |
| 584 | 637 | 538 | 741 | 287 | 344 | 209 | 215 |
| 550 | 691 | 570 | 814 | 247 | 320 | 204 | 280 |
| 533 | 637 | 535 | 839 | 270 | 355 | 214 | 315 |
| 696 | 771 | 664 | 886 | 290 | 342 | 216 | 237 |
| 711 | 842 | 740 | 1051 | 300 | 384 | 234 | 558 |
| 678 | 780 | 696 | 871 | 267 | 368 | 212 | 209 |
| 0727_Band_1 | 0727_Band_2 | 0727_Band_3 | 0727_Band_4 | 0811_Band_1 | 0811_Band_2 | 0811_Band_3 | 0811_Band_4 |
| 216 | 347 | 249 | 354 | 375 | 617 | 504 | 836 |
| 231 | 374 | 264 | 401 | 597 | 986 | 1068 | 1322 |
| 214 | 322 | 211 | 308 | 228 | 351 | 268 | 495 |
| 207 | 279 | 169 | 215 | 191 | 313 | 201 | 295 |
| 198 | 298 | 164 | 202 | 215 | 337 | 192 | 226 |
| 212 | 294 | 181 | 193 | 190 | 257 | 140 | 195 |
| 230 | 336 | 202 | 210 | 203 | 278 | 165 | 169 |
| 209 | 312 | 187 | 260 | 218 | 310 | 198 | 290 |
| 196 | 274 | 175 | 294 | 222 | 350 | 227 | 417 |
| 206 | 332 | 176 | 199 | 212 | 271 | 163 | 207 |
| 209 | 280 | 169 | 312 | 187 | 322 | 185 | 827 |
| 222 | 348 | 202 | 206 | 194 | 285 | 148 | 155 |
| 0816_Band_1 | 0816_Band_2 | 0816_Band_3 | 0816_Band_4 | 0821_Band_1 | 0821_Band_2 | 0821_Band_3 | 0821_Band_4 |
| 211 | 389 | 264 | 282 | 1032 | 575 | 353 | 1188 |
| 243 | 452 | 438 | 548 | 906 | 730 | 536 | 1352 |
| 295 | 426 | 249 | 456 | 957 | 686 | 308 | 1395 |
| 230 | 353 | 241 | 297 | 1003 | 825 | 439 | 1518 |
| 209 | 359 | 213 | 211 | 1014 | 791 | 404 | 1614 |
| 220 | 350 | 194 | 210 | 1084 | 977 | 576 | 1606 |
| 220 | 383 | 207 | 175 | 1110 | 977 | 529 | 1635 |
| 270 | 370 | 272 | 306 | 1200 | 718 | 358 | 1637 |
| 251 | 371 | 255 | 333 | 1134 | 617 | 330 | 1428 |
| 228 | 382 | 235 | 207 | 1162 | 926 | 407 | 1782 |
| 228 | 386 | 237 | 482 | 1001 | 797 | 455 | 1648 |
| 237 | 382 | 214 | 176 | 1162 | 1116 | 476 | 1744 |

| **0826_Band_1** | **0826_Band_2** | **0826_Band_3** | **0826_Band_4** | **0905_Band_1** | **0905_Band_2** | **0905_Band_3** | **0905_Band_4** |
|---:|---:|---:|---:|---:|---:|---:|---:|
| 537 | 686 | 492 | 624 | 225 | 367 | 300 | 347 |
| 525 | 753 | 667 | 735 | 271 | 492 | 489 | 623 |
| 522 | 683 | 474 | 642 | 174 | 329 | 197 | 300 |
| 511 | 641 | 462 | 518 | 176 | 286 | 183 | 227 |
| 528 | 697 | 474 | 501 | 217 | 351 | 226 | 249 |
| 512 | 653 | 439 | 449 | 147 | 313 | 174 | 173 |
| 525 | 683 | 457 | 465 | 325 | 475 | 315 | 352 |
| 512 | 641 | 448 | 512 | 180 | 332 | 236 | 232 |
| 492 | 630 | 430 | 578 | 168 | 335 | 211 | 353 |
| 508 | 690 | 468 | 457 | 244 | 410 | 260 | 207 |
| 505 | 596 | 451 | 569 | 184 | 287 | 180 | 450 |
| 518 | 695 | 460 | 459 | 396 | 500 | 389 | 270 |
| 0915_Band_1 | 0915_Band_2 | 0915_Band_3 | 0915_Band_4 | 0920_Band_1 | 0920_Band_2 | 0920_Band_3 | 0920_Band_4 |
| 547 | 659 | 536 | 822 | 748 | 943 | 834 | 1289 |
| 589 | 756 | 706 | 1170 | 904 | 1360 | 1328 | 1903 |
| 613 | 734 | 653 | 917 | 695 | 830 | 736 | 1009 |
| 597 | 730 | 557 | 735 | 705 | 797 | 642 | 796 |
| 597 | 763 | 633 | 751 | 702 | 783 | 618 | 735 |
| 616 | 758 | 532 | 684 | 700 | 797 | 602 | 706 |
| 571 | 763 | 557 | 690 | 680 | 802 | 617 | 691 |
| 616 | 762 | 579 | 787 | 691 | 798 | 622 | 740 |
| 603 | 766 | 574 | 788 | 667 | 791 | 648 | 788 |
| 616 | 815 | 605 | 772 | 691 | 782 | 623 | 655 |
| 600 | 747 | 568 | 1024 | 707 | 773 | 617 | 1169 |
| 604 | 767 | 579 | 697 | 700 | 808 | 611 | 651 |
| 0925_Band_1 | 0925_Band_2 | 0925_Band_3 | 0925_Band_4 | 1010_Band_1 | 1010_Band_2 | 1010_Band_3 | 1010_Band_4 |
| 336 | 535 | 423 | 535 | 489 | 735 | 714 | 975 |
| 413 | 736 | 673 | 968 | 760 | 1176 | 1400 | 2013 |
| 365 | 500 | 400 | 407 | 352 | 561 | 556 | 613 |
| 332 | 471 | 369 | 349 | 280 | 398 | 305 | 289 |
| 318 | 483 | 368 | 337 | 315 | 442 | 324 | 281 |
| 317 | 448 | 333 | 309 | 294 | 371 | 267 | 235 |
| 326 | 469 | 356 | 290 | 300 | 400 | 284 | 217 |
| 340 | 455 | 338 | 337 | 342 | 382 | 278 | 285 |
| 346 | 473 | 373 | 388 | 332 | 421 | 314 | 449 |
| 326 | 477 | 355 | 303 | 323 | 370 | 230 | 207 |
| 321 | 491 | 392 | 621 | 316 | 413 | 323 | 491 |
| 314 | 457 | 352 | 282 | 298 | 382 | 241 | 197 |

| 1015_Band_1 | 1015_Band_2 | 1015_Band_3 | 1015_Band_4 | 1030_Band_1 | 1030_Band_2 | 1030_Band_3 | 1030_Band_4 |
|---|---|---|---|---|---|---|---|
| 234 | 492 | 463 | 249 | 276 | 389 | 479 | 906 |
| 232 | 534 | 471 | 561 | 753 | 1112 | 1264 | 2053 |
| 183 | 394 | 302 | 215 | 235 | 424 | 373 | 389 |
| 151 | 345 | 234 | 123 | 227 | 362 | 263 | 209 |
| 183 | 357 | 251 | 119 | 230 | 367 | 277 | 151 |
| 106 | 299 | 180 | 90 | 211 | 388 | 266 | 116 |
| 113 | 332 | 211 | 107 | 232 | 386 | 290 | 91 |
| 152 | 303 | 260 | 160 | 199 | 314 | 241 | 141 |
| 160 | 344 | 276 | 159 | 172 | 257 | 183 | 338 |
| 180 | 335 | 253 | 140 | 239 | 397 | 263 | 106 |
| 130 | 336 | 247 | 239 | 214 | 325 | 257 | 326 |
| 135 | 320 | 214 | 110 | 228 | 400 | 259 | 75 |

Goodland 2020 reflectance values from Sentinel-2 imagery (All_Samples.xlsx)

| OBJECTID | Goodland_Sample_Points | OBJECTID | Location | Beach | X | Y |
|---|---|---|---|---|---|---|
| 1 | 3 | 3 | Inside | Goodland | 798425.0196 | 4767384.792 |
| 2 | 4 | 4 | Inside | Goodland | 798435.133 | 4767384.503 |
| 3 | 6 | 6 | Outside | Goodland | 798424.8371 | 4767364.997 |
| 4 | 7 | 7 | Outside | Goodland | 798435.1549 | 4767364.584 |
| 5 | 8 | 8 | Outside | Goodland | 798443.8218 | 4767374.489 |
| 6 | 9 | 9 | Outside | Goodland | 798454.5523 | 4767383.981 |
| 7 | 10 | 10 | Outside | Goodland | 798444.6472 | 4767395.537 |

| 0418_Band_1 | 0418_Band_2 | 0418_Band_3 | 0418_Band_4 | 0503_Band_1 | 0503_Band_2 | 0503_Band_3 | 0503_Band_4 |
|---|---|---|---|---|---|---|---|
| 915 | 1072 | 1466 | 2218 | 976 | 1604 | 1744 | 2740 |
| 294 | 628 | 487 | 921 | 324 | 418 | 480 | 1225 |
| 352 | 513 | 518 | 651 | 268 | 547 | 480 | 992 |
| 287 | 423 | 287 | 365 | 78 | 96 | 88 | 209 |
| 312 | 420 | 372 | 344 | 95 | 221 | 115 | 210 |
| 307 | 522 | 378 | 318 | 201 | 394 | 261 | 175 |
| 323 | 483 | 414 | 620 | 256 | 473 | 402 | 833 |
| **0508_Band_1** | **0508_Band_2** | **0508_Band_3** | **0508_Band_4** | **0513_Band_1** | **0513_Band_2** | **0513_Band_3** | **0513_Band_4** |
| 754 | 1290 | 1340 | 2396 | 1130 | 1520 | 1722 | 2482 |
| 340 | 526 | 631 | 1000 | 682 | 835 | 798 | 1498 |
| 229 | 408 | 304 | 687 | 738 | 879 | 841 | 1180 |
| 125 | 200 | 136 | 318 | 667 | 783 | 656 | 870 |
| 147 | 260 | 178 | 231 | 727 | 821 | 741 | 828 |
| 181 | 343 | 268 | 246 | 770 | 945 | 775 | 836 |
| 276 | 495 | 375 | 670 | 661 | 808 | 749 | 1208 |
| **0602_Band_1** | **0602_Band_2** | **0602_Band_3** | **0602_Band_4** | **0607_Band_1** | **0607_Band_2** | **0607_Band_3** | **0607_Band_4** |
| 688 | 1034 | 973 | 2641 | 533 | 964 | 744 | 2486 |
| 393 | 530 | 420 | 969 | 375 | 431 | 365 | 850 |
| 476 | 586 | 487 | 838 | 325 | 520 | 348 | 629 |
| 413 | 453 | 410 | 540 | 361 | 472 | 289 | 457 |
| 439 | 451 | 411 | 550 | 447 | 505 | 383 | 483 |
| 371 | 426 | 363 | 411 | 376 | 436 | 388 | 404 |
| 361 | 487 | 349 | 1290 | 314 | 509 | 338 | 1034 |

| 0612_Band_1 | 0612_Band_2 | 0612_Band_3 | 0612_Band_4 | 0617_Band_1 | 0617_Band_2 | 0617_Band_3 | 0617_Band_4 |
|---|---|---|---|---|---|---|---|
| 655 | 998 | 852 | 2374 | 669 | 1042 | 859 | 3184 |
| 323 | 412 | 420 | 1112 | 608 | 878 | 804 | 1383 |
| 357 | 436 | 482 | 842 | 335 | 410 | 305 | 636 |
| 279 | 310 | 210 | 371 | 314 | 400 | 290 | 351 |
| 293 | 344 | 212 | 336 | 374 | 508 | 316 | 601 |
| 258 | 285 | 182 | 305 | 361 | 485 | 329 | 469 |
| 299 | 375 | 217 | 1310 | 429 | 603 | 464 | 1199 |
| **0627_Band_1** | **0627_Band_2** | **0627_Band_3** | **0627_Band_4** | **0722_Band_1** | **0722_Band_2** | **0722_Band_3** | **0722_Band_4** |
| 579 | 791 | 736 | 2146 | 572 | 825 | 929 | 2879 |
| 384 | 510 | 397 | 756 | 391 | 637 | 386 | 1473 |
| 338 | 419 | 366 | 636 | 335 | 515 | 367 | 1268 |
| 304 | 378 | 276 | 498 | 305 | 483 | 284 | 805 |
| 338 | 413 | 302 | 519 | 321 | 438 | 303 | 854 |
| 295 | 399 | 289 | 483 | 264 | 432 | 232 | 506 |
| 338 | 448 | 388 | 970 | 309 | 496 | 291 | 2188 |
| **0727_Band_1** | **0727_Band_2** | **0727_Band_3** | **0727_Band_4** | **0811_Band_1** | **0811_Band_2** | **0811_Band_3** | **0811_Band_4** |
| 459 | 764 | 574 | 2536 | 481 | 883 | 878 | 2050 |
| 386 | 560 | 403 | 1123 | 308 | 459 | 278 | 1061 |
| 367 | 599 | 335 | 743 | 313 | 546 | 328 | 607 |
| 395 | 584 | 315 | 611 | 298 | 471 | 228 | 418 |
| 344 | 576 | 311 | 579 | 317 | 466 | 262 | 346 |
| 310 | 539 | 278 | 365 | 301 | 500 | 238 | 324 |
| 300 | 522 | 338 | 905 | 324 | 579 | 286 | 1322 |
| **0816_Band_1** | **0816_Band_2** | **0816_Band_3** | **0816_Band_4** | **0821_Band_1** | **0821_Band_2** | **0821_Band_3** | **0821_Band_4** |
| 403 | 677 | 573 | 1829 | 559 | 973 | 777 | 2200 |
| 245 | 477 | 372 | 483 | 360 | 408 | 355 | 1010 |
| 264 | 522 | 266 | 458 | 301 | 433 | 294 | 847 |
| 283 | 540 | 271 | 315 | 268 | 362 | 239 | 410 |
| 279 | 508 | 274 | 382 | 277 | 360 | 219 | 377 |
| 264 | 538 | 296 | 287 | 282 | 386 | 221 | 303 |
| 250 | 480 | 286 | 818 | 282 | 397 | 264 | 1180 |
| **0826_Band_1** | **0826_Band_2** | **0826_Band_3** | **0826_Band_4** | **0905_Band_1** | **0905_Band_2** | **0905_Band_3** | **0905_Band_4** |
| 601 | 899 | 710 | 2121 | 313 | 626 | 481 | 1150 |
| 554 | 717 | 579 | 832 | 215 | 356 | 284 | 457 |
| 470 | 647 | 450 | 702 | 194 | 372 | 215 | 296 |
| 512 | 674 | 440 | 587 | 200 | 370 | 224 | 289 |
| 496 | 658 | 440 | 633 | 200 | 377 | 203 | 241 |
| 540 | 679 | 460 | 608 | 181 | 377 | 198 | 210 |
| 462 | 601 | 412 | 1184 | 222 | 381 | 220 | 617 |

| 0915_Band_1 | 0915_Band_2 | 0915_Band_3 | 0915_Band_4 | 0920_Band_1 | 0920_Band_2 | 0920_Band_3 | 0920_Band_4 |
|---|---|---|---|---|---|---|---|
| 556 | 850 | 689 | 1652 | 677 | 968 | 915 | 2643 |
| 439 | 645 | 469 | 889 | 547 | 696 | 576 | 1454 |
| 498 | 645 | 453 | 722 | 527 | 706 | 538 | 1011 |
| 532 | 664 | 462 | 652 | 547 | 702 | 522 | 708 |
| 480 | 637 | 458 | 716 | 487 | 714 | 503 | 744 |
| 480 | 656 | 460 | 676 | 529 | 750 | 488 | 661 |
| 490 | 617 | 415 | 831 | 542 | 735 | 457 | 1764 |
| **0925_Band_1** | **0925_Band_2** | **0925_Band_3** | **0925_Band_4** | **1010_Band_1** | **1010_Band_2** | **1010_Band_3** | **1010_Band_4** |
| 397 | 654 | 506 | 1539 | 792 | 1184 | 1418 | 2588 |
| 239 | 387 | 265 | 432 | 473 | 636 | 729 | 1296 |
| 233 | 348 | 260 | 438 | 408 | 575 | 478 | 968 |
| 273 | 340 | 229 | 290 | 380 | 457 | 321 | 385 |
| 245 | 350 | 242 | 318 | 369 | 464 | 343 | 362 |
| 245 | 380 | 240 | 232 | 363 | 462 | 335 | 389 |
| 278 | 391 | 273 | 571 | 414 | 564 | 503 | 1678 |
| **1015_Band_1** | **1015_Band_2** | **1015_Band_3** | **1015_Band_4** | **1030_Band_1** | **1030_Band_2** | **1030_Band_3** | **1030_Band_4** |
| 289 | 618 | 802 | 1627 | 866 | 1278 | 1688 | 2711 |
| 102 | 276 | 182 | 260 | 703 | 915 | 1028 | 1798 |
| 84 | 260 | 171 | 241 | 346 | 604 | 623 | 1497 |
| 121 | 216 | 145 | 153 | 225 | 299 | 225 | 309 |
| 90 | 240 | 168 | 171 | 162 | 263 | 191 | 162 |
| 104 | 231 | 141 | 131 | 201 | 308 | 220 | 210 |
| 91 | 234 | 214 | 414 | 362 | 498 | 587 | 1576 |

## E. coli - Mendota

| **2019 - Mendota** | | |
|---|---|---|
| Date | Test | Result |
| 8/28/2019 | E Coli | 63 |
| 8/19/2019 | E Coli | <10 |
| 8/12/2019 | E Coli | 62 |
| 8/5/2019 | E Coli | 10 |
| 7/29/2019 | E Coli | 52 |
| 7/22/2019 | E Coli | 20 |
| 7/15/2019 | E Coli | 52 |
| 7/9/2019 | E Coli | 10 |
| 7/9/2019 | E Coli | 110 |
| 7/9/2019 | E Coli | 380 |
| 7/9/2019 | E Coli | 20 |
| 7/9/2019 | E Coli | 310 |
| 7/8/2019 | E Coli | 7300 |
| 7/1/2019 | E Coli | 120 |
| 6/24/2019 | E Coli | 20 |
| 6/17/2019 | E Coli | 30 |
| 6/11/2019 | E Coli | 10 |
| 6/5/2019 | E Coli | 31 |
| 5/28/2019 | E Coli | <10 |
| 5/23/2019 | E Coli | 228 |

| 2020 - Mendota | | |
|---|---|---|
| Date | Test | Result |
| 7/27/2020 | E Coli | 650 |
| 7/21/2020 | E Coli | 86 |
| 7/14/2020 | E Coli | 150 |
| 7/6/2020 | E Coli | <10 |
| 6/30/2020 | E Coli | 63 |
| 6/23/2020 | E Coli | 110 |
| 6/16/2020 | E Coli | 41 |
| 6/8/2020 | E Coli | 20 |
| 6/1/2020 | E Coli | 20 |
| 5/26/2020 | E Coli | 120 |
| 5/20/2020 | E Coli | <10 |

## E. coli - Goodland

| **2019 - Goodland** | | |
|---|---|---|
| Date | Test | Result |
| 5/23/2019 | E Coli | 41 |
| 5/28/2019 | E Coli | 31 |
| 6/4/2019 | E Coli | 10 |
| 6/10/2019 | E Coli | 120 |
| 6/17/2019 | E Coli | 20 |
| 6/24/2019 | E Coli | 20 |
| 7/22/2019 | E Coli | 660 |
| 7/29/2019 | E Coli | 62 |
| 8/5/2019 | E Coli | 190 |
| 8/14/2019 | E Coli | 120 |
| 8/19/2019 | E Coli | <10 |
| 8/27/2019 | E Coli | 10 |

| **2020 - Goodland** | | |
|---|---|---|
| Date | Test | Result |
| 6/1/2020 | E Coli | 10 |
| 6/9/2020 | E Coli | <10 |
| 6/15/2020 | E Coli | 86 |
| 6/22/2020 | E Coli | 120 |
| 6/29/2020 | E Coli | 610 |
| 7/7/2020 | E Coli | 2900 |
| 7/8/2020 | E Coli | 480 |
| 7/13/2020 | E Coli | 2900 |
| 7/14/2020 | E Coli | 1500 |
| 7/15/2020 | E Coli | 1700 |
| 7/16/2020 | E Coli | 630 |
| 7/20/2020 | E Coli | 210 |
| 8/31/2020 | E Coli | <10 |

## Climate (Wind, Rain, Temperature) - 2019

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 5/1/2019 | 7.16 | 0.28 | 44 |
| 5/2/2019 | 4.47 | 0.04 | 45 |
| 5/3/2019 | 3.13 | 0 | 49 |
| 5/4/2019 | 4.03 | 0 | 51 |
| 5/5/2019 | 5.82 | 0.44 | 59 |
| 5/6/2019 | 6.71 | 0.2 | 54 |
| 5/7/2019 | 10.29 | 0 | 51 |
| 5/8/2019 | 12.08 | 0.65 | 45 |
| 5/9/2019 | 7.38 | 0.08 | 53 |
| 5/10/2019 | 5.59 | 0 | 47 |
| 5/11/2019 | 6.93 | 0 | 50 |
| 5/12/2019 | 5.14 | 0 | 46 |
| 5/13/2019 | 5.82 | 0 | 51 |
| 5/14/2019 | 4.25 | 0 | 57 |
| 5/15/2019 | 2.24 | 0 | 61 |
| 5/16/2019 | 6.04 | 0.49 | 66 |
| 5/17/2019 | 10.29 | 0.37 | 58 |
| 5/18/2019 | 8.5 | 0.15 | 52 |
| 5/19/2019 | 9.4 | 0.36 | 56 |
| 5/20/2019 | 8.5 | 0 | 49 |
| 5/21/2019 | 14.32 | 0.33 | 50 |
| 5/22/2019 | 12.75 | 0.02 | 58 |
| 5/23/2019 | 7.61 | 0 | 65 |
| 5/24/2019 | 9.17 | 1.29 | 59 |
| 5/25/2019 | 6.71 | 1.2 | 71 |
| 5/26/2019 | 3.8 | 0 | 67 |
| 5/27/2019 | 7.61 | 0.27 | 62 |
| 5/28/2019 | 9.62 | 0 | 58 |
| 5/29/2019 | 2.91 | 0 | 59 |
| 5/30/2019 | 2.68 | 0 | 67 |
| 5/31/2019 | 5.82 | 0 | 69 |
| 6/1/2019 | 5.14 | 0.47 | 69 |
| 6/2/2019 | 7.61 | 0 | 62 |
| 6/3/2019 | 8.05 | 0 | 56 |
| 6/4/2019 | 8.05 | 0.53 | 63 |
| 6/5/2019 | 4.92 | 0.03 | 72 |
| 6/6/2019 | 3.36 | 0 | 70 |
| 6/7/2019 | 6.49 | 0 | 70 |
| 6/8/2019 | 6.93 | 0 | 70 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 6/9/2019 | 4.47 | 0.02 | 69 |
| 6/10/2019 | 9.62 | 0 | 66 |
| 6/11/2019 | 4.25 | 0.05 | 63 |
| 6/12/2019 | 7.61 | 0.35 | 60 |
| 6/13/2019 | 8.72 | 0 | 58 |
| 6/14/2019 | 10.29 | 0 | 64 |
| 6/15/2019 | 8.72 | 0.01 | 68 |
| 6/16/2019 | 6.93 | 0.33 | 57 |
| 6/17/2019 | 2.68 | 0 | 62 |
| 6/18/2019 | 3.36 | 0 | 67 |
| 6/19/2019 | 5.14 | 0.26 | 66 |
| 6/20/2019 | 7.61 | 0 | 64 |
| 6/21/2019 | 7.83 | 0 | 66 |
| 6/22/2019 | 9.62 | 0 | 66 |
| 6/23/2019 | 8.5 | 0.25 | 71 |
| 6/24/2019 | 4.25 | 0.49 | 69 |
| 6/25/2019 | 4.92 | 0.04 | 68 |
| 6/26/2019 | 1.57 | 0 | 74 |
| 6/27/2019 | 6.71 | 0.36 | 73 |
| 6/28/2019 | 4.47 | 1.12 | 71 |
| 6/29/2019 | 1.79 | 0 | 78 |
| 6/30/2019 | 5.59 | 0.85 | 75 |
| 7/1/2019 | 2.46 | 0 | 74 |
| 7/2/2019 | 4.03 | 0 | 80 |
| 7/3/2019 | 4.47 | 1.3 | 77 |
| 7/4/2019 | 6.04 | 0.14 | 76 |
| 7/5/2019 | 4.03 | 0 | 81 |
| 7/6/2019 | 8.05 | 0.44 | 74 |
| 7/7/2019 | 5.82 | 0 | 70 |
| 7/8/2019 | 3.13 | 0 | 71 |
| 7/9/2019 | 8.28 | 0.26 | 73 |
| 7/10/2019 | 6.26 | 0 | 80 |
| 7/11/2019 | 5.82 | 0 | 75 |
| 7/12/2019 | 4.7 | 0 | 71 |
| 7/13/2019 | 3.58 | 0 | 81 |
| 7/14/2019 | 6.93 | 0 | 77 |
| 7/15/2019 | 9.84 | 0 | 81 |
| 7/16/2019 | 4.7 | 0.08 | 80 |
| 7/17/2019 | 4.92 | 0.02 | 79 |
| 7/18/2019 | 10.51 | 1.22 | 78 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 7/19/2019 | 8.5 | 1.91 | 83 |
| 7/20/2019 | 8.72 | 0.19 | 82 |
| 7/21/2019 | 6.49 | 0 | 72 |
| 7/22/2019 | 8.5 | 0 | 70 |
| 7/23/2019 | 6.04 | 0 | 69 |
| 7/24/2019 | 1.12 | 0 | 71 |
| 7/25/2019 | 5.59 | 0 | 74 |
| 7/26/2019 | 10.51 | 0.01 | 75 |
| 7/27/2019 | 7.38 | 0 | 79 |
| 7/28/2019 | 6.71 | 0 | 80 |
| 7/29/2019 | 5.82 | 0.2 | 78 |
| 7/30/2019 | 5.82 | 0 | 70 |
| 7/31/2019 | 2.68 | 0 | 66 |
| 8/1/2019 | 2.01 | 0 | 68 |
| 8/2/2019 | 2.24 | 0 | 69 |
| 8/3/2019 | 3.8 | 0.11 | 73 |
| 8/4/2019 | 1.57 | 0 | 72 |
| 8/5/2019 | 5.37 | 1.2 | 77 |
| 8/6/2019 | 4.47 | 0 | 73 |
| 8/7/2019 | 4.7 | 0.15 | 73 |
| 8/8/2019 | 5.37 | 0 | 72 |
| 8/9/2019 | 2.91 | 0 | 67 |
| 8/10/2019 | 3.36 | 0 | 68 |
| 8/11/2019 | 3.58 | 0.21 | 71 |
| 8/12/2019 | 2.24 | 0.04 | 70 |
| 8/13/2019 | 3.8 | 0.24 | 72 |
| 8/14/2019 | 5.82 | 0.04 | 67 |
| 8/15/2019 | 3.8 | 0 | 67 |
| 8/16/2019 | 6.49 | 0.02 | 70 |
| 8/17/2019 | 4.25 | 0 | 70 |
| 8/18/2019 | 6.93 | 0.48 | 72 |
| 8/19/2019 | 2.24 | 0 | 71 |
| 8/20/2019 | 3.8 | 0 | 69 |
| 8/21/2019 | 5.37 | 0 | 74 |
| 8/22/2019 | 3.58 | 0 | 66 |
| 8/23/2019 | 6.26 | 0 | 65 |
| 8/24/2019 | 6.93 | 0 | 63 |
| 8/25/2019 | 7.61 | 0 | 63 |
| 8/26/2019 | 5.59 | 0.36 | 65 |
| 8/27/2019 | 5.37 | 0 | 68 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 8/28/2019 | 6.49 | 0 | 65 |
| 8/29/2019 | 7.16 | 0 | 67 |
| 8/30/2019 | 3.8 | 0 | 64 |
| 8/31/2019 | 4.92 | 0 | 59 |
| 9/1/2019 | 2.24 | 0 | 64 |
| 9/2/2019 | 3.8 | 0.16 | 70 |
| 9/3/2019 | 10.96 | 0.19 | 72 |
| 9/4/2019 | 4.47 | 0 | 63 |
| 9/5/2019 | 7.61 | 0 | 60 |
| 9/6/2019 | 8.05 | 0 | 68 |
| 9/7/2019 | 3.36 | 0 | 62 |
| 9/8/2019 | 8.05 | 0.02 | 60 |
| 9/9/2019 | 9.84 | 0.35 | 61 |
| 9/10/2019 | 4.7 | 0.81 | 71 |
| 9/11/2019 | 7.61 | 0.31 | 73 |
| 9/12/2019 | 9.62 | 1.72 | 65 |
| 9/13/2019 | 7.61 | 0 | 67 |
| 9/14/2019 | 5.82 | 0 | 63 |
| 9/15/2019 | 4.03 | 0.01 | 70 |
| 9/16/2019 | 3.58 | 0 | 68 |
| 9/17/2019 | 7.83 | 0 | 69 |
| 9/18/2019 | 9.62 | 0 | 70 |
| 9/19/2019 | 4.92 | 0.09 | 71 |
| 9/20/2019 | 3.13 | 0 | 70 |
| 9/21/2019 | 10.74 | 0.03 | 73 |
| 9/22/2019 | 4.92 | 1.89 | 70 |
| 9/23/2019 | 3.8 | 0 | 64 |
| 9/24/2019 | 8.95 | 0 | 65 |
| 9/25/2019 | 6.93 | 0 | 69 |
| 9/26/2019 | 5.37 | 0 | 61 |
| 9/27/2019 | 8.05 | 0.3 | 62 |
| 9/28/2019 | 9.84 | 0.01 | 60 |
| 9/29/2019 | 9.17 | 0.9 | 56 |
| 9/30/2019 | 9.62 | 0.01 | 69 |

## Climate (Wind, Rain, Temperature) - 2020

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 5/1/2020 | 9.17 | 0 | 53 |
| 5/2/2020 | 7.83 | 0 | 64 |
| 5/3/2020 | 9.4 | 0 | 63 |
| 5/4/2020 | 9.62 | 0 | 48 |
| 5/5/2020 | 6.49 | 0 | 45 |
| 5/6/2020 | 4.25 | 0 | 49 |
| 5/7/2020 | 8.05 | 0 | 54 |
| 5/8/2020 | 10.29 | 0 | 42 |
| 5/9/2020 | 6.49 | 0 | 41 |
| 5/10/2020 | 8.05 | 0.39 | 47 |
| 5/11/2020 | 6.26 | 0 | 42 |
| 5/12/2020 | 3.8 | 0 | 46 |
| 5/13/2020 | 11.63 | 0.21 | 50 |
| 5/14/2020 | 4.03 | 0.48 | 57 |
| 5/15/2020 | 4.92 | 0 | 63 |
| 5/16/2020 | 10.51 | 0 | 58 |
| 5/17/2020 | 14.99 | 2.04 | 54 |
| 5/18/2020 | 15.43 | 0.04 | 52 |
| 5/19/2020 | 12.97 | 0 | 53 |
| 5/20/2020 | 10.07 | 0 | 60 |
| 5/21/2020 | 8.5 | 0 | 60 |
| 5/22/2020 | 4.25 | 0.02 | 62 |
| 5/23/2020 | 6.93 | 0.8 | 62 |
| 5/24/2020 | 3.13 | 0 | 68 |
| 5/25/2020 | 8.28 | 0.01 | 73 |
| 5/26/2020 | 10.51 | 0 | 76 |
| 5/27/2020 | 8.28 | 0 | 77 |
| 5/28/2020 | 3.36 | 1.43 | 71 |
| 5/29/2020 | 6.71 | 0 | 62 |
| 5/30/2020 | 5.82 | 0 | 59 |
| 5/31/2020 | 3.58 | 0 | 56 |
| 6/1/2020 | 11.18 | 0 | 63 |
| 6/2/2020 | 7.61 | 0.62 | 78 |
| 6/3/2020 | 3.58 | 0.07 | 74 |
| 6/4/2020 | 4.25 | 0 | 75 |
| 6/5/2020 | 5.14 | 0 | 76 |
| 6/6/2020 | 7.61 | 0 | 70 |
| 6/7/2020 | 9.84 | 0 | 65 |
| 6/8/2020 | 9.84 | 0 | 75 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 6/9/2020 | 11.41 | 0.63 | 76 |
| 6/10/2020 | 6.71 | 1.23 | 71 |
| 6/11/2020 | 5.82 | 0 | 65 |
| 6/12/2020 | 6.71 | 0 | 67 |
| 6/13/2020 | 9.17 | 0 | 58 |
| 6/14/2020 | 7.83 | 0 | 58 |
| 6/15/2020 | 7.83 | 0 | 62 |
| 6/16/2020 | 5.59 | 0 | 67 |
| 6/17/2020 | 6.04 | 0 | 73 |
| 6/18/2020 | 5.37 | 0 | 75 |
| 6/19/2020 | 4.25 | 0 | 76 |
| 6/20/2020 | 4.92 | 0.13 | 73 |
| 6/21/2020 | 3.58 | 0 | 72 |
| 6/22/2020 | 4.92 | 0.66 | 70 |
| 6/23/2020 | 6.93 | 0.44 | 64 |
| 6/24/2020 | 3.8 | 0.01 | 64 |
| 6/25/2020 | 2.01 | 0 | 67 |
| 6/26/2020 | 4.03 | 1.03 | 71 |
| 6/27/2020 | 2.24 | 0 | 75 |
| 6/28/2020 | 7.83 | 0 | 74 |
| 6/29/2020 | 6.93 | 0.25 | 75 |
| 6/30/2020 | 7.83 | 0 | 76 |
| 7/1/2020 | 6.71 | 0 | 79 |
| 7/2/2020 | 2.24 | 0 | 75 |
| 7/3/2020 | 2.68 | 0 | 78 |
| 7/4/2020 | 3.36 | 0 | 78 |
| 7/5/2020 | 2.24 | 0 | 78 |
| 7/6/2020 | 2.91 | 0 | 81 |
| 7/7/2020 | 5.59 | 2.17 | 81 |
| 7/8/2020 | 5.82 | 0 | 76 |
| 7/9/2020 | 6.04 | 1.97 | 80 |
| 7/10/2020 | 6.93 | 0.46 | 73 |
| 7/11/2020 | 2.91 | 0 | 74 |
| 7/12/2020 | 6.71 | 0 | 74 |
| 7/13/2020 | 4.47 | 0 | 71 |
| 7/14/2020 | 12.08 | 0.78 | 76 |
| 7/15/2020 | 6.93 | 0.56 | 73 |
| 7/16/2020 | 3.8 | 0 | 71 |
| 7/17/2020 | 6.93 | 0 | 77 |
| 7/18/2020 | 10.96 | 0.1 | 79 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 7/19/2020 | 6.93 | 0 | 82 |
| 7/20/2020 | 4.03 | 0 | 74 |
| 7/21/2020 | 8.5 | 0 | 71 |
| 7/22/2020 | 5.82 | 0 | 75 |
| 7/23/2020 | 4.03 | 0 | 67 |
| 7/24/2020 | 3.8 | 0 | 72 |
| 7/25/2020 | 7.61 | 0 | 79 |
| 7/26/2020 | 7.16 | 1.55 | 83 |
| 7/27/2020 | 5.37 | 0 | 76 |
| 7/28/2020 | 5.14 | 0 | 74 |
| 7/29/2020 | 1.79 | 0 | 77 |
| 7/30/2020 | 7.38 | 0 | 73 |
| 7/31/2020 | 5.59 | 0 | 70 |
| 8/1/2020 | 2.68 | 0 | 69 |
| 8/2/2020 | 8.28 | 0.49 | 69 |
| 8/3/2020 | 8.5 | 0 | 61 |
| 8/4/2020 | 5.82 | 0 | 61 |
| 8/5/2020 | 2.46 | 0 | 63 |
| 8/6/2020 | 2.24 | 0 | 66 |
| 8/7/2020 | 7.83 | 0 | 69 |
| 8/8/2020 | 9.17 | 0 | 76 |
| 8/9/2020 | 7.16 | 0.42 | 77 |
| 8/10/2020 | 4.7 | 0.11 | 74 |
| 8/11/2020 | 1.57 | 0 | 70 |
| 8/12/2020 | 4.47 | 0 | 69 |
| 8/13/2020 | 4.92 | 0 | 71 |
| 8/14/2020 | 4.7 | 0 | 72 |
| 8/15/2020 | 5.14 | 0.1 | 71 |
| 8/16/2020 | 4.92 | 0 | 68 |
| 8/17/2020 | 4.47 | 0.01 | 70 |
| 8/18/2020 | 4.7 | 0 | 67 |
| 8/19/2020 | 3.36 | 0 | 67 |
| 8/20/2020 | 5.59 | 0 | 73 |
| 8/21/2020 | 4.47 | 0 | 73 |
| 8/22/2020 | 6.71 | 0 | 74 |
| 8/23/2020 | 2.68 | 0 | 77 |
| 8/24/2020 | 3.58 | 0.29 | 78 |
| 8/25/2020 | 7.16 | 0.07 | 76 |
| 8/26/2020 | 6.71 | 0 | 81 |
| 8/27/2020 | 7.61 | 0.61 | 82 |

| DATE | AWND | PRCP | TAVG |
|---:|---:|---:|---:|
| 8/28/2020 | 6.04 | 0.02 | 74 |
| 8/29/2020 | 7.61 | 0 | 71 |
| 8/30/2020 | 5.14 | 0 | 63 |
| 8/31/2020 | 5.82 | 0.76 | 66 |
| 9/1/2020 | 4.92 | 0.19 | 60 |
| 9/2/2020 | 4.7 | 0.01 | 69 |
| 9/3/2020 | 8.95 | 0 | 68 |
| 9/4/2020 | 4.47 | 0 | 63 |
| 9/5/2020 | 3.8 | 0 | 65 |
| 9/6/2020 | 11.18 | 0.38 | 65 |
| 9/7/2020 | 8.5 | 0.01 | 66 |
| 9/8/2020 | 12.75 | 0.78 | 53 |
| 9/9/2020 | 12.97 | 0.35 | 49 |
| 9/10/2020 | 7.83 | 0.28 | 49 |
| 9/11/2020 | 7.83 | 0.98 | 54 |
| 9/12/2020 | 6.49 | 0.1 | 62 |
| 9/13/2020 | 3.8 | 0 | 62 |
| 9/14/2020 | 4.92 | 0 | 59 |
| 9/15/2020 | 7.61 | 0 | 65 |
| 9/16/2020 | 6.26 | 0 | 68 |
| 9/17/2020 | 4.92 | 0 | 59 |
| 9/18/2020 | 4.92 | 0 | 53 |
| 9/19/2020 | 3.36 | 0 | 50 |
| 9/20/2020 | 7.38 | 0 | 55 |
| 9/21/2020 | 8.5 | 0 | 60 |
| 9/22/2020 | 2.46 | 0 | 65 |
| 9/23/2020 | 2.68 | 0 | 64 |
| 9/24/2020 | 5.37 | 0.04 | 63 |
| 9/25/2020 | 10.29 | 0 | 68 |
| 9/26/2020 | 10.74 | 0 | 68 |
| 9/27/2020 | 5.82 | 0.27 | 67 |
| 9/28/2020 | 5.82 | 0.01 | 54 |
| 9/29/2020 | 4.03 | 0 | 49 |
| 9/30/2020 | 7.61 | 0.01 | 53 |

## Water Levels Lake Mendota USGS site 05428000 - 2019

| Date | Feet |
|---:|---:|
| 5/1/2019 | 10.24 |
| 5/2/2019 | 10.23 |
| 5/3/2019 | 10.21 |

| Date | Feet |
|---|---|
| 5/4/2019 | 10.18 |
| 5/5/2019 | 10.17 |
| 5/6/2019 | 10.19 |
| 5/7/2019 | 10.17 |
| 5/8/2019 | 10.16 |
| 5/9/2019 | 10.21 |
| 5/10/2019 | 10.2 |
| 5/11/2019 | 10.18 |
| 5/12/2019 | 10.15 |
| 5/13/2019 | 10.12 |
| 5/14/2019 | 10.09 |
| 5/15/2019 | 10.06 |
| 5/16/2019 | 10.07 |
| 5/17/2019 | 10.06 |
| 5/18/2019 | 10.08 |
| 5/19/2019 | 10.12 |
| 5/20/2019 | 10.11 |
| 5/21/2019 | 10.07 |
| 5/22/2019 | 10.09 |
| 5/23/2019 | 10.09 |
| 5/24/2019 | 10.13 |
| 5/25/2019 | 10.32 |
| 5/26/2019 | 10.44 |
| 5/27/2019 | 10.52 |
| 5/28/2019 | 10.57 |
| 5/29/2019 | 10.57 |
| 5/30/2019 | 10.58 |
| 5/31/2019 | 10.57 |
| 6/1/2019 | 10.56 |
| 6/2/2019 | 10.55 |
| 6/3/2019 | 10.5 |
| 6/4/2019 | 10.49 |
| 6/5/2019 | 10.52 |
| 6/6/2019 | 10.51 |
| 6/7/2019 | 10.48 |
| 6/8/2019 | 10.44 |
| 6/9/2019 | 10.42 |
| 6/10/2019 | 10.4 |
| 6/11/2019 | 10.35 |
| 6/12/2019 | 10.34 |

| Date | Feet |
|---:|---:|
| 6/13/2019 | 10.34 |
| 6/14/2019 | 10.29 |
| 6/15/2019 | 10.26 |
| 6/16/2019 | 10.27 |
| 6/17/2019 | 10.25 |
| 6/18/2019 | 10.23 |
| 6/19/2019 | 10.23 |
| 6/20/2019 | 10.21 |
| 6/21/2019 | 10.18 |
| 6/22/2019 | 10.15 |
| 6/23/2019 | 10.14 |
| 6/24/2019 | 10.17 |
| 6/25/2019 | 10.2 |
| 6/26/2019 | 10.19 |
| 6/27/2019 | 10.19 |
| 6/28/2019 | 10.31 |
| 6/29/2019 | 10.41 |
| 6/30/2019 | 10.5 |
| 7/1/2019 | 10.63 |
| 7/2/2019 | 10.67 |
| 7/3/2019 | 10.68 |
| 7/4/2019 | 10.76 |
| 7/5/2019 | 10.79 |
| 7/6/2019 | 10.82 |
| 7/7/2019 | 10.82 |
| 7/8/2019 | 10.81 |
| 7/9/2019 | 10.78 |
| 7/10/2019 | 10.8 |
| 7/11/2019 | 10.77 |
| 7/12/2019 | 10.74 |
| 7/13/2019 | 10.71 |
| 7/14/2019 | 10.67 |
| 7/15/2019 | 10.64 |
| 7/16/2019 | 10.6 |
| 7/17/2019 | 10.59 |
| 7/18/2019 | 10.68 |
| 7/19/2019 | 10.86 |
| 7/20/2019 | 10.96 |
| 7/21/2019 | 11.01 |
| 7/22/2019 | 10.99 |

| Date | Feet |
|---:|---:|
| 7/23/2019 | 10.97 |
| 7/24/2019 | 10.94 |
| 7/25/2019 | 10.91 |
| 7/26/2019 | 10.87 |
| 7/27/2019 | 10.85 |
| 7/28/2019 | 10.83 |
| 7/29/2019 | 10.82 |
| 7/30/2019 | 10.79 |
| 7/31/2019 | 10.75 |
| 8/1/2019 | 10.72 |
| 8/2/2019 | 10.68 |
| 8/3/2019 | 10.65 |
| 8/4/2019 | 10.63 |
| 8/5/2019 | 10.62 |
| 8/6/2019 | 10.7 |
| 8/7/2019 | 10.7 |
| 8/8/2019 | 10.7 |
| 8/9/2019 | 10.67 |
| 8/10/2019 | 10.64 |
| 8/11/2019 | 10.66 |
| 8/12/2019 | 10.67 |
| 8/13/2019 | 10.72 |
| 8/14/2019 | 10.72 |
| 8/15/2019 | 10.7 |
| 8/16/2019 | 10.68 |
| 8/17/2019 | 10.67 |
| 8/18/2019 | 10.69 |
| 8/19/2019 | 10.69 |
| 8/20/2019 | 10.68 |
| 8/21/2019 | 10.67 |
| 8/22/2019 | 10.64 |
| 8/23/2019 | 10.61 |
| 8/24/2019 | 10.57 |
| 8/25/2019 | 10.54 |
| 8/26/2019 | 10.55 |
| 8/27/2019 | 10.55 |
| 8/28/2019 | 10.52 |
| 8/29/2019 | 10.48 |
| 8/30/2019 | 10.45 |
| 8/31/2019 | 10.42 |

| Date | Feet |
| ---: | ---: |
| 9/1/2019 | 10.4 |
| 9/2/2019 | 10.38 |
| 9/3/2019 | 10.38 |
| 9/4/2019 | 10.37 |
| 9/5/2019 | 10.34 |
| 9/6/2019 | 10.33 |
| 9/7/2019 | 10.3 |
| 9/8/2019 | 10.27 |
| 9/9/2019 | 10.24 |
| 9/10/2019 | 10.35 |
| 9/11/2019 | 10.4 |
| 9/12/2019 | 10.5 |
| 9/13/2019 | 10.66 |
| 9/14/2019 | 10.7 |
| 9/15/2019 | 10.71 |
| 9/16/2019 | 10.71 |
| 9/17/2019 | 10.71 |
| 9/18/2019 | 10.7 |
| 9/19/2019 | 10.7 |
| 9/20/2019 | 10.7 |
| 9/21/2019 | 10.69 |
| 9/22/2019 | 10.82 |
| 9/23/2019 | 10.92 |
| 9/24/2019 | 10.93 |
| 9/25/2019 | 10.93 |
| 9/26/2019 | 10.91 |
| 9/27/2019 | 10.89 |
| 9/28/2019 | 10.9 |
| 9/29/2019 | 10.95 |
| 9/30/2019 | 10.99 |

## Water Levels Lake Mendota USGS site 05428000 - 2020

| Date | Feet |
|---:|---:|
| 5/1/2020 | 9.79 |
| 5/2/2020 | 9.78 |
| 5/3/2020 | 9.78 |
| 5/4/2020 | 9.75 |
| 5/5/2020 | 9.73 |
| 5/6/2020 | 9.72 |
| 5/7/2020 | 9.71 |
| 5/8/2020 | 9.68 |
| 5/9/2020 | 9.64 |
| 5/10/2020 | 9.65 |
| 5/11/2020 | 9.64 |
| 5/12/2020 | 9.62 |
| 5/13/2020 | 9.59 |
| 5/14/2020 | 9.63 |
| 5/15/2020 | 9.71 |
| 5/16/2020 | 9.72 |
| 5/17/2020 | 9.85 |
| 5/18/2020 | 10.05 |
| 5/19/2020 | 10.15 |
| 5/20/2020 | 10.2 |
| 5/21/2020 | 10.22 |
| 5/22/2020 | 10.23 |
| 5/23/2020 | 10.26 |
| 5/24/2020 | 10.31 |
| 5/25/2020 | 10.33 |
| 5/26/2020 | 10.34 |
| 5/27/2020 | 10.36 |
| 5/28/2020 | 10.43 |
| 5/29/2020 | 10.56 |
| 5/30/2020 | 10.6 |
| 5/31/2020 | 10.59 |
| 6/1/2020 | 10.56 |
| 6/2/2020 | 10.57 |
| 6/3/2020 | 10.61 |
| 6/4/2020 | 10.61 |
| 6/5/2020 | 10.6 |
| 6/6/2020 | 10.57 |
| 6/7/2020 | 10.53 |
| 6/8/2020 | 10.5 |

| | |
|---|---|
| 6/9/2020 | 10.51 |
| 6/10/2020 | 10.63 |
| 6/11/2020 | 10.76 |
| 6/12/2020 | 10.79 |
| 6/13/2020 | 10.77 |
| 6/14/2020 | 10.74 |
| 6/15/2020 | 10.72 |
| 6/16/2020 | 10.7 |
| 6/17/2020 | 10.69 |
| 6/18/2020 | 10.67 |
| 6/19/2020 | 10.66 |
| 6/20/2020 | 10.65 |
| 6/21/2020 | 10.65 |
| 6/22/2020 | 10.68 |
| 6/23/2020 | 10.69 |
| 6/24/2020 | 10.69 |
| 6/25/2020 | 10.7 |
| 6/26/2020 | 10.72 |
| 6/27/2020 | 10.79 |
| 6/28/2020 | 10.8 |
| 6/29/2020 | 10.84 |
| 6/30/2020 | 10.92 |
| 7/1/2020 | 10.91 |
| 7/2/2020 | 10.9 |
| 7/3/2020 | 10.89 |
| 7/4/2020 | 10.87 |
| 7/5/2020 | 10.85 |
| 7/6/2020 | 10.83 |
| 7/7/2020 | 10.82 |
| 7/8/2020 | 10.87 |
| 7/9/2020 | 10.9 |
| 7/10/2020 | 11.14 |
| 7/11/2020 | 11.23 |
| 7/12/2020 | 11.25 |
| 7/13/2020 | 11.24 |
| 7/14/2020 | 11.22 |
| 7/15/2020 | 11.29 |
| 7/16/2020 | 11.35 |
| 7/17/2020 | 11.35 |
| 7/18/2020 | 11.35 |
| 7/19/2020 | 11.36 |

| | |
|---|---|
| 7/20/2020 | 11.32 |
| 7/21/2020 | 11.29 |
| 7/22/2020 | 11.27 |
| 7/23/2020 | 11.23 |
| 7/24/2020 | 11.2 |
| 7/25/2020 | 11.18 |
| 7/26/2020 | 11.21 |
| 7/27/2020 | 11.32 |
| 7/28/2020 | 11.3 |
| 7/29/2020 | 11.28 |
| 7/30/2020 | 11.24 |
| 7/31/2020 | 11.21 |
| 8/1/2020 | 11.18 |
| 8/2/2020 | 11.16 |
| 8/3/2020 | 11.11 |
| 8/4/2020 | 11.07 |
| 8/5/2020 | 11.04 |
| 8/6/2020 | 11.01 |
| 8/7/2020 | 10.98 |
| 8/8/2020 | 10.95 |
| 8/9/2020 | 10.94 |
| 8/10/2020 | 10.95 |
| 8/11/2020 | 10.93 |
| 8/12/2020 | 10.9 |
| 8/13/2020 | 10.88 |
| 8/14/2020 | 10.85 |
| 8/15/2020 | 10.84 |
| 8/16/2020 | 10.81 |
| 8/17/2020 | 10.79 |
| 8/18/2020 | 10.75 |
| 8/19/2020 | 10.72 |
| 8/20/2020 | 10.69 |
| 8/21/2020 | 10.66 |
| 8/22/2020 | 10.63 |
| 8/23/2020 | 10.61 |
| 8/24/2020 | 10.59 |
| 8/25/2020 | 10.56 |
| 8/26/2020 | 10.54 |
| 8/27/2020 | 10.52 |
| 8/28/2020 | 10.52 |
| 8/29/2020 | 10.52 |

| | |
|---|---|
| 8/30/2020 | 10.47 |
| 8/31/2020 | 10.47 |
| 9/1/2020 | 10.48 |
| 9/2/2020 | 10.48 |
| 9/3/2020 | 10.46 |
| 9/4/2020 | 10.41 |
| 9/5/2020 | 10.38 |
| 9/6/2020 | 10.38 |
| 9/7/2020 | 10.39 |
| 9/8/2020 | 10.38 |
| 9/9/2020 | 10.42 |
| 9/10/2020 | 10.45 |
| 9/11/2020 | 10.48 |
| 9/12/2020 | 10.6 |
| 9/13/2020 | 10.64 |
| 9/14/2020 | 10.65 |
| 9/15/2020 | 10.65 |
| 9/16/2020 | 10.65 |
| 9/17/2020 | 10.63 |
| 9/18/2020 | 10.61 |
| 9/19/2020 | 10.59 |
| 9/20/2020 | 10.56 |
| 9/21/2020 | 10.53 |
| 9/22/2020 | 10.52 |
| 9/23/2020 | 10.52 |
| 9/24/2020 | 10.5 |
| 9/25/2020 | 10.48 |
| 9/26/2020 | 10.46 |
| 9/27/2020 | 10.46 |
| 9/28/2020 | 10.47 |
| 9/29/2020 | 10.44 |
| 9/30/2020 | 10.42 |

# Appendix C: R Scripts

## data_read_and_manipulate.R

```
#Creators: Erik Schiefer and Shelly Bruhn
#Last Update: 11/15/2021

#install.packages("tidyverse") #line only needed if tidyverse package is not already installed
#install.packages("readxl") #line only needed if readxl package is not already installed

#load packages being used in this R code
library(tidyverse); library(readxl)

#read excel sheet of Sample geoprocessing output table into an R data frame (tibble)
Men20 = read_excel("All_Samples.xlsx", sheet = "Mendota_Samples_2020")
Men19 = read_excel("All_Samples.xlsx", sheet = "Mendota_Samples_2019")
Good20 = read_excel("All_Samples.xlsx", sheet = "Goodland_Samples_2020")
Good19 = read_excel("All_Samples.xlsx", sheet = "Goodland_Samples_2019")

#the following code is all about manipulating the data into a more usable form
#for R analyses, long data table formats are much preferable than wide
#these two pages (among many others) have great descriptions of some of the functions used:
#https://dplyr.tidyverse.org/articles/dplyr.html
#https://open.oregonstate.education/computationalbiology/chapter/reshaping-and-joining-data-frames/

#convert to a long format using gather()
Men20 = gather(Men20, Date_Band, SR, contains("Band"))
Men19 = gather(Men19, Date_Band, SR, contains("Band"))
Good20 = gather(Good20, Date_Band, SR, contains("Band"))
Good19 = gather(Good19, Date_Band, SR, contains("Band"))

#create a Date column using ISOdate() and substring functions
Men20$Date=ISOdate(year = 2020, month = substr(Men20$Date_Band,1,2), day = substr(Men20$Date_Band,3,4))
Men19$Date=ISOdate(year = 2019, month = substr(Men19$Date_Band,1,2), day = substr(Men19$Date_Band,3,4))
Good20$Date=ISOdate(year = 2020, month = substr(Good20$Date_Band,1,2), day = substr(Good20$Date_Band,3,4))
Good19$Date=ISOdate(year = 2019, month = substr(Good19$Date_Band,1,2), day = substr(Good19$Date_Band,3,4))

#create a Band column
Men20$Band=substr(Men20$Date_Band,6,11)
Men19$Band=substr(Men19$Date_Band,6,11)
```

```
Good20$Band=substr(Good20$Date_Band,6,11)
Good19$Band=substr(Good19$Date_Band,6,11)

#remove temporary columns
Men20 = select(Men20, !c(Date_Band, OBJECTID...3))
Men19 = select(Men19, !c(Date_Band, OBJECTID...3))
Good20 = select(Good20, !c(Date_Band, OBJECTID...3))
Good19 = select(Good19, !c(Date_Band, OBJECTID...3))

#add a 2020 Status column (hard coded here; 2020 from Dane County Land and Water Resources Dept)
Men20 = mutate(Men20, Status = case_when(Date < "2020-05-04" ~ "Uninstalled",
                                         Date < "2020-05-26" ~ "Inactive",
                                         Date < "2020-09-21" ~ "Active",
                                         Date >= "2020-09-23" ~ "Uninstalled"))

Good20 = mutate(Good20, Status = case_when(Date < "2020-05-05" ~ "Uninstalled",
                                           Date < "2020-05-20" ~ "Inactive",
                                           Date < "2020-09-22" ~ "Active",
                                           Date >= "2020-09-23" ~ "Uninstalled"))

#add a 2019 Status column (hard coded here; based on in situ E. Coli samples from Dane County LWRD)
Men19 = mutate(Men19, Status = case_when(Date < "2019-05-22" ~ "Uninstalled",
                                         Date <= "2019-08-28" ~ "Active",
                                         Date >= "2019-08-29" ~ "Uninstalled"))

Good19 = mutate(Good19, Status = case_when(Date < "2019-05-22" ~ "Uninstalled",
                                           Date < "2019-08-28" ~ "Active",
                                           Date >= "2019-08-28" ~ "Uninstalled"))

#make table wider so band ratios or other band calculations can be made
Men20 = spread(Men20, Band, SR)
Men19 = spread(Men19, Band, SR)
Good20 = spread(Good20, Band, SR)
Good19 = spread(Good19, Band, SR)

#Secchi Disc Depth using Landsat TM; see band ratios in Kloiber et al (2002)
Men20$Band_3div1=Men20$Band_3/Men20$Band_1
Men19$Band_3div1=Men19$Band_3/Men19$Band_1
Good20$Band_3div1=Good20$Band_3/Good20$Band_1
Good19$Band_3div1=Good19$Band_3/Good19$Band_1
```

```
#Secchi Disc Depth using Sentinel 2 10-meter bands; see band ratios in Bonansea et al (2018)
Men20$Band_SDD=Men20$Band_1*(Men20$Band_2/Men20$Band_4)
Men19$Band_SDD=Men19$Band_1*(Men19$Band_2/Men19$Band_4)
Good20$Band_SDD=Good20$Band_1*(Good20$Band_2/Good20$Band_4)
Good19$Band_SDD=Good19$Band_1*(Good19$Band_2/Good19$Band_4)

#CDOM using Sentinel 2 10-meter bands; see band ratios in Toming et al (2016)
Men20$Band_CDOM=Men20$Band_2/Men20$Band_3
Men19$Band_CDOM=Men19$Band_2/Men19$Band_3
Good20$Band_CDOM=Good20$Band_2/Good20$Band_3
Good19$Band_CDOM=Good19$Band_2/Good19$Band_3

#put back in long format for plotting and analyses
Men20long = gather(Men20, Band, SR, contains("Band"))
Men19long = gather(Men19, Band, SR, contains("Band"))
Good20long = gather(Good20, Band, SR, contains("Band"))
Good19long = gather(Good19, Band, SR, contains("Band"))

# ****************************************************************************************

# WATER LEVELS OF LAKE MENDOTA
WL20 = read_excel("Water_Level_2020.xlsx", sheet = "Height_Feet")
WL20 = select(WL20, !c(agency_cd, site_no))
WL19 = read_excel("Water_Level_2019.xlsx", sheet = "Height_Feet")
WL19 = select(WL19, !c(agency_cd, site_no))

# CLIMATE AT MADISON AIRPORT - Average Wind, Precipitation and Average Temperature
CLMT20 = read_excel("Climate_2020.xlsx", sheet = "CLIMATE")
CLMT19 = read_excel("Climate_2019.xlsx", sheet = "CLIMATE")

# IN-SITU E. COLI TESTS Units= MPN/100ml
Men_EC20 = read_excel("Mendota_EColi.xlsx", sheet = "2020")
Men_EC19 = read_excel("Mendota_EColi.xlsx", sheet = "2019")
Good_EC20 = read_excel("Goodland_EColi.xlsx", sheet = "2020")
Good_EC19 = read_excel("Goodland_EColi.xlsx", sheet = "2019")
```

## data_analyses.R

```
#Creators: Erik Schiefer and Shelly Bruhn
#Last Update: 10/19/2021

library(tidyverse)

#Get mean SR differences between inside and outside point locations, by status, by band
#This is done to get adjustment differences during uninstalled period
Men20.adj.difs = summarise(group_by(Men20long, Band, Status, Location), meanSR = mean(SR))
Men20.adj.difs = spread(Men20.adj.difs, Location, meanSR)
Men20.adj.difs = mutate(Men20.adj.difs, meanSRdifs=Inside-Outside)

Men19.adj.difs = summarise(group_by(Men19long, Band, Status, Location), meanSR = mean(SR))
Men19.adj.difs = spread(Men19.adj.difs, Location, meanSR)
Men19.adj.difs = mutate(Men19.adj.difs, meanSRdifs=Inside-Outside)

Good20.adj.difs = summarise(group_by(Good20long, Band, Status, Location), meanSR = mean(SR))
Good20.adj.difs = spread(Good20.adj.difs, Location, meanSR)
Good20.adj.difs = mutate(Good20.adj.difs, meanSRdifs=Inside-Outside)

Good19.adj.difs = summarise(group_by(Good19long, Band, Status, Location), meanSR = mean(SR))
Good19.adj.difs = spread(Good19.adj.difs, Location, meanSR)
Good19.adj.difs = mutate(Good19.adj.difs, meanSRdifs=Inside-Outside)

#Get mean SR differences between inside and outside locations, by date, status, band
#This is done to adjust the ratio of depth effect for each band of the uninstall periods
Men20.adj.difs = summarise(group_by(Men20long, Band, Status, Location), meanSR = mean(SR))
Men20.adj.difs = spread(Men20.adj.difs, Location, meanSR)
Men20.adj.difs = mutate(Men20.adj.difs, meanSRdifs=Inside-Outside)

Men19.adj.difs = summarise(group_by(Men19long, Band, Status, Location), meanSR = mean(SR))
Men19.adj.difs = spread(Men19.adj.difs, Location, meanSR)
Men19.adj.difs = mutate(Men19.adj.difs, meanSRdifs=Inside-Outside)

Good20.adj.difs = summarise(group_by(Good20long, Band, Status, Location), meanSR = mean(SR))
Good20.adj.difs = spread(Good20.adj.difs, Location, meanSR)
Good20.adj.difs = mutate(Good20.adj.difs, meanSRdifs=Inside-Outside)

Good19.adj.difs = summarise(group_by(Good19long, Band, Status, Location), meanSR = mean(SR))
Good19.adj.difs = spread(Good19.adj.difs, Location, meanSR)
```

```
Good19.adj.difs = mutate(Good19.adj.difs, meanSRdifs=Inside-Outside)

#Get mean SR differences between inside and outside locations, by date, status, band
#This is done to adjust the ratio of depth effect for each band of the uninstall periods
Men20.analysis = summarise(group_by(Men20long, Band, Status, Date, Location), meanSR = mean(SR))
Men20.analysis = spread(Men20.analysis, Location, meanSR)
Men20.analysis = mutate(Men20.analysis, meanSRdifs=Inside-Outside)
Men20.analysis = mutate(Men20.analysis,SR.adj.dif = case_when(
  Band == "Band_1" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_1", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_2" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_2", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_3", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_4" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_4", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3div1" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_3div1", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_SDD" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_SDD", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_CDOM" ~ meanSRdifs - filter(Men20.adj.difs, Band == "Band_CDOM", Status ==
"Uninstalled")$meanSRdifs))

Men19.analysis = summarise(group_by(Men19long, Band, Status, Date, Location), meanSR = mean(SR))
Men19.analysis = spread(Men19.analysis, Location, meanSR)
Men19.analysis = mutate(Men19.analysis, meanSRdifs=Inside-Outside)
Men19.analysis = mutate(Men19.analysis, SR.adj.dif = case_when(
  Band == "Band_1" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_1", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_2" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_2", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_3", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_4" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_4", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3div1" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_3div1", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_SDD" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_SDD", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_CDOM" ~ meanSRdifs - filter(Men19.adj.difs, Band == "Band_CDOM", Status ==
"Uninstalled")$meanSRdifs))

Good20.analysis = summarise(group_by(Good20long, Band, Status, Date, Location), meanSR = mean(SR))
Good20.analysis = spread(Good20.analysis, Location, meanSR)
Good20.analysis = mutate(Good20.analysis, meanSRdifs=Inside-Outside)
Good20.analysis = mutate(Good20.analysis, SR.adj.dif = case_when(
  Band == "Band_1" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_1", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_2" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_2", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_3", Status == "Uninstalled")$meanSRdifs,
```

```
  Band == "Band_4" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_4", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3div1" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_3div1", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_SDD" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_SDD", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_CDOM" ~ meanSRdifs - filter(Good20.adj.difs, Band == "Band_CDOM", Status ==
"Uninstalled")$meanSRdifs))

Good19.analysis = summarise(group_by(Good19long, Band, Status, Date, Location), meanSR = mean(SR))
Good19.analysis = spread(Good19.analysis, Location, meanSR)
Good19.analysis = mutate(Good19.analysis, meanSRdifs=Inside-Outside)
Good19.analysis = mutate(Good19.analysis, SR.adj.dif = case_when(
  Band == "Band_1" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_1", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_2" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_2", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_3", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_4" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_4", Status == "Uninstalled")$meanSRdifs,
  Band == "Band_3div1" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_3div1", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_SDD" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_SDD", Status ==
"Uninstalled")$meanSRdifs,
  Band == "Band_CDOM" ~ meanSRdifs - filter(Good19.adj.difs, Band == "Band_CDOM", Status ==
"Uninstalled")$meanSRdifs))
```

## plotting.R

```
#Creators: Erik Schiefer and Shelly Bruhn
#Last Update: 11/13/2021

library(tidyverse)

#meanSR.adj.dif column from %name%.analysis table (MAIN ANALYSIS)

# MENDOTA 2020
ggplot(filter(Men20.analysis, Band == "Band_1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - Blue Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men20.analysis, Band == "Band_2"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - Green Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men20.analysis, Band == "Band_3"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - Red Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men20.analysis, Band == "Band_4"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - NIR Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")
```

```
ggplot(filter(Men20.analysis, Band == "Band_3div1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - SDD Blue/Red [Kloiber et al. (2002) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men20.analysis, Band == "Band_SDD"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - SDD [Bonansea et al. (2019) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men20.analysis, Band == "Band_CDOM"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2020 - CDOM [Toming et al. (2016) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

# MENDOTA 2019
ggplot(filter(Men19.analysis, Band == "Band_1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - Blue Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men19.analysis, Band == "Band_2"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - Green Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")
```

```
ggplot(filter(Men19.analysis, Band == "Band_3"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - Red Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men19.analysis, Band == "Band_4"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - NIR Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men19.analysis, Band == "Band_3div1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - SDD Blue/Red [Kloiber et al. (2002) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men19.analysis, Band == "Band_SDD"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - SDD [Bonansea et al. (2019) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Men19.analysis, Band == "Band_CDOM"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Mendota Beach 2019 - CDOM [Toming et al. (2016) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")
```

```
# GOODLAND 2020
ggplot(filter(Good20.analysis, Band == "Band_1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - Blue Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good20.analysis, Band == "Band_2"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - Green Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good20.analysis, Band == "Band_3"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - Red Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good20.analysis, Band == "Band_4"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - NIR Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good20.analysis, Band == "Band_3div1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - SDD Blue/Red [Kloiber et al. (2002) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")
```

```
ggplot(filter(Good20.analysis, Band == "Band_SDD"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - SDD [Bonansea et al. (2019) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good20.analysis, Band == "Band_CDOM"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2020 - CDOM [Toming et al. (2016) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

# GOODLAND 2019
ggplot(filter(Good19.analysis, Band == "Band_1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - Blue Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good19.analysis, Band == "Band_2"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - Green Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good19.analysis, Band == "Band_3"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - Red Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")
```

```
ggplot(filter(Good19.analysis, Band == "Band_4"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - NIR Band") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good19.analysis, Band == "Band_3div1"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - SDD Blue/Red [Kloiber et al. (2002) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good19.analysis, Band == "Band_SDD"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - SDD [Bonansea et al. (2019) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

ggplot(filter(Good19.analysis, Band == "Band_CDOM"), aes(Date,SR.adj.dif,color=Status)) +
  geom_point() +
  stat_summary(fun = "mean", size = 3, geom = "point") +
  ggtitle("Goodland Beach 2019 - CDOM [Toming et al. (2016) Formula]") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Surface Reflectance")

# WATER LEVELS OF LAKE MENDOTA
ggplot((WL20), aes(Date,Feet)) +
  geom_point() +
  ggtitle("Lake Mendota Water Levels 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b")

ggplot((WL19), aes(Date,Feet)) +
  geom_point() +
```

```r
  ggtitle("Lake Mendota Water Levels 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b")

#AVERAGE WIND MEASURED AT MADISON AIRPORT
ggplot((CLMT20), aes(DATE,AWND)) +
  geom_point() +
  ggtitle("Madison Airport Average Wind Speed 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Miles per Hour")

ggplot((CLMT19), aes(DATE,AWND)) +
  geom_point() +
  ggtitle("Madison Airport Average Wind Speed 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Miles per Hour")

#PRECIPITATION MEASURED AT MADISON AIRPORT
ggplot((CLMT20), aes(DATE,PRCP)) +
  geom_point() +
  ggtitle("Madison Airport Precipitation 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Inches")

ggplot((CLMT19), aes(DATE,PRCP)) +
  geom_point() +
  ggtitle("Madison Airport Precipitation 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "Inches")

#AVERAGE AIR TEMPERATURE MEASURED AT MADISON AIRPORT
ggplot((CLMT20), aes(DATE,TAVG)) +
  geom_point() +
  ggtitle("Madison Airport Average Air Temperature 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "degrees Fahrenheit")
```

```
ggplot((CLMT19), aes(DATE,TAVG)) +
  geom_point() +
  ggtitle("Madison Airport Average Air Temperature 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "degrees Fahrenheit")

# IN-SITU E.COLI TESTS Units= MPN/100ml
ggplot((Men_EC20), aes(Date,Result)) +
  geom_point() +
  ggtitle("Mendota Beach E.Coli 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "MPN/100ml")

ggplot((Men_EC19), aes(Date,Result)) +
  geom_point() +
  ggtitle("Mendota Beach E.Coli 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "MPN/100ml")

ggplot((Good_EC20), aes(Date,Result)) +
  geom_point() +
  ggtitle("Goodland Beach E.Coli 2020") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "MPN/100ml")

ggplot((Good_EC19), aes(Date,Result)) +
  geom_point() +
  ggtitle("Goodland Beach E.Coli 2019") +
  theme(text = element_text(size = 32), axis.title.x = element_blank(), legend.text = element_text(size = 32)) +
  scale_x_datetime(date_breaks = "1 month", date_labels = "%b") +
  labs(y = "MPN/100ml")
```

## statistics.R

```
#Creators: Erik Schiefer and Shelly Bruhn
#Last Update: 10/27/2021

library(tidyverse)

#Copy each analysis table to perform statistical analysis
Men20.statistics = data.table::copy(Men20.analysis)
Men19.statistics = data.table::copy(Men19.analysis)
Good20.statistics = data.table::copy(Good20.analysis)
Good19.statistics = data.table::copy(Good19.analysis)

#Replace Inactive status with Uninstalled
Men20.statistics$Status[Men20.statistics$Status == "Inactive"] <- "Uninstalled"
Men19.statistics$Status[Men19.statistics$Status == "Inactive"] <- "Uninstalled"
Good20.statistics$Status[Good20.statistics$Status == "Inactive"] <- "Uninstalled"
Good19.statistics$Status[Good19.statistics$Status == "Inactive"] <- "Uninstalled"

#Compute t-test for each band and the three calculated variables per beach per year

#Mendota 2020
Band = filter(Men20.statistics, Band == "Band_1")
Men20.B1 <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.B1
Band = filter(Men20.statistics, Band == "Band_2")
Men20.B2 <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.B2
Band = filter(Men20.statistics, Band == "Band_3")
Men20.B3 <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.B3
Band = filter(Men20.statistics, Band == "Band_4")
Men20.B4 <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.B4
Band = filter(Men20.statistics, Band == "Band_3div1")
Men20.B3div1 <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.B3div1
Band = filter(Men20.statistics, Band == "Band_SDD")
Men20.BSDD <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.BSDD
Band = filter(Men20.statistics, Band == "Band_CDOM")
```

```
Men20.BCDOM <- t.test(SR.adj.dif ~ Status, data = Band)
Men20.BCDOM

#Mendota 2019
Band = filter(Men19.statistics, Band == "Band_1")
Men19.B1 <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.B1
Band = filter(Men19.statistics, Band == "Band_2")
Men19.B2 <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.B2
Band = filter(Men19.statistics, Band == "Band_3")
Men19.B3 <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.B3
Band = filter(Men19.statistics, Band == "Band_4")
Men19.B4 <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.B4
Band = filter(Men19.statistics, Band == "Band_3div1")
Men19.B3div1 <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.B3div1
Band = filter(Men19.statistics, Band == "Band_SDD")
Men19.BSDD <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.BSDD
Band = filter(Men19.statistics, Band == "Band_CDOM")
Men19.BCDOM <- t.test(SR.adj.dif ~ Status, data = Band)
Men19.BCDOM

#Goodland 2020
Band = filter(Good20.statistics, Band == "Band_1")
Good20.B1 <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.B1
Band = filter(Good20.statistics, Band == "Band_2")
Good20.B2 <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.B2
Band = filter(Good20.statistics, Band == "Band_3")
Good20.B3 <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.B3
Band = filter(Good20.statistics, Band == "Band_4")
Good20.B4 <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.B4
Band = filter(Good20.statistics, Band == "Band_3div1")
Good20.B3div1 <- t.test(SR.adj.dif ~ Status, data = Band)
```

```
Good20.B3div1
Band = filter(Good20.statistics, Band == "Band_SDD")
Good20.BSDD <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.BSDD
Band = filter(Good20.statistics, Band == "Band_CDOM")
Good20.BCDOM <- t.test(SR.adj.dif ~ Status, data = Band)
Good20.BCDOM

#Goodland 2019
Band = filter(Good19.statistics, Band == "Band_1")
Good19.B1 <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.B1
Band = filter(Good19.statistics, Band == "Band_2")
Good19.B2 <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.B2
Band = filter(Good19.statistics, Band == "Band_3")
Good19.B3 <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.B3
Band = filter(Good19.statistics, Band == "Band_4")
Good19.B4 <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.B4
Band = filter(Good19.statistics, Band == "Band_3div1")
Good19.B3div1 <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.B3div1
Band = filter(Good19.statistics, Band == "Band_SDD")
Good19.BSDD <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.BSDD
Band = filter(Good19.statistics, Band == "Band_CDOM")
Good19.BCDOM <- t.test(SR.adj.dif ~ Status, data = Band)
Good19.BCDOM

mean(WL19$Feet)
mean(WL20$Feet)
mean(CLMT19$PRCP)
mean(CLMT20$PRCP)
mean(CLMT19$TAVG)
mean(CLMT20$TAVG)
mean(CLMT19$AWND)
mean(CLMT20$AWND)
```