Geoprogramming & Geovisualization Final Proposal

Background & Goal:

Harmful algal blooms (HABs) have been increasingly present in Iowa lakes, which in turn threatens drinking water availability and state income through recreational opportunities. Given that HABs can produce microcystin, a toxin that can cause liver and kidney failure and cancer, there is an increased human health risk (Gu et al., 2022; US EPA, 2013). Current projections suggest that HAB events will increase with warming temperatures, and 2023 was a record-breaking year for HAB advisories in Iowa (Gu et al., 2022; US EPA, 2013). Currently, in Iowa, 39 state-owned beaches are monitored by water sampling once a week, limiting the capacity to make informed risk assessments across the state throughout the summer. Environmental groups have stated that increased monitoring is needed to limit human exposure (IDNR, 2022; Peikes, 2021; Schechinger, 2021), but budget constraints limit the ability to increase monitoring across more lakes. There is a critical need to lower costs and time while improving our capacity for detecting and managing HAB dynamics across time and space.

Satellite remote sensing has been leveraged worldwide for rapid HAB assessment, capturing HAB spatial and temporal variability at a rate that is impossible with *in-situ* techniques. Furthermore, the annual mean cost savings of a satellite platform for retrieval of chlorophyll-a alone has been estimated to be $42 million a year (Papenfus et al., 2020). However, current work targets large freshwater lakes (e.g., Lake Erie) or oceans (e.g., Florida coast), which is not translatable to the smaller freshwater lakes common in Iowa and the Midwest because of the need to capture near-shore HABs (Binding et al., 2021; Hill et al., 2020). Inland waters are also optically complex systems in comparison to coastal and ocean monitoring, making established techniques non-transferable. This research expands the use of satellite remote sensing for detecting, assessing, and monitoring HABs in freshwater inland lakes with a focus on generating a near-daily product that could inform public health initiatives. We will develop a remote sensing methodology that fuses imagery from multiple satellite sensors, enhancing our capability to monitor HABs almost daily across a lake. This multi-sensor approach equips Iowa water managers with the spatio-temporal trends that can provide insight into the dynamics of HABs. However, to complete this overarching aim in future research, we must first assess the capacities of a suite of satellites in retrieving chlorophyll-a.

Here, I propose to use satellite remote sensing to predict chlorophyll-a in Big Spirit Lake in Iowa with PlanetScope, Sentinel-2, and Sentinel-3 for a single date in 2023. I plan to attain the overall objective by pursuing the following specific aims:

1. **Determine the spatial resolution most appropriate for capturing the spatial variability of HABs.**
2. **Assess the correlation between field-verified chlorophyll-a and the Normalized Differenced Chlorophyll Index (NDCI) from a suite of satellite remote sensing platforms.**

Data Collection & Methods:

In-Situ Data:

The presence of microcystin is the main concern for public health, but microcystin does not possess a spectral or optical signature that remote sensing can measure. Therefore, proxies such as chlorophyll-a and phycocyanin are used to monitor microcystin concentrations, as they have been shown to correlate with microcystin toxin presence (Buley et al., 2022; Marion et al., 2012). Chlorophyll-a is a pigment in algae that photosynthesizes sunlight into organic compounds and is a commonly applied measure of water's eutrophic condition as algae biomass grows (Zhang et al., 2017). However, chlorophyll-a is not a perfect measure of HAB risk, as it is present in many algal species that do not produce toxins (Ogashawara, 2020). Phycocyanin, a secondary pigment found in HAB species such as *Microcystin aeruginosa*, has been the target for many recent studies as it provides the capacity to distinguish toxin-producing algal species. We conducted four field campaigns in Big Spirit lake through the 2023 season to gather the *in-situ* chlorophyll-a lab-verified values needed for future empirically-driven machine learning approaches. Data assessed here is from campaign four on 9/11/2023. Each campaign used a small boat to collect 40 water samples following State Hygenic Lab (SHL) protocol. At each collection site, sub-centimeter resolution Global navigation satellite system (GNSS) locations were taken with a Trimble DA2 at each site to identify corresponding imagery pixels. The in-situ values collected on 9/11/2023 had chlorophyll-a values verified via the SHL. These values will be point-based data used to verify pixel values from the remotely sensed data.

Remotely Sensed Imagery:

Three sensors are used in this project, as they have varying spatial resolutions and band placements. We have selected these three sensors because they capture the trade-off between spatial and temporal resolution (Figure 1). Sentinel-2, with a revisit time of 5 days and spatial resolution of 20 meters, has been used in recent HAB analysis (Beal et al., 2024). Sentinel-3 was designed for water applications, but specifically for ocean watercolor, so it collects imagery approximately daily but with 300 m spatial resolution (Donlon et al., 2012). The PlanetScope SuperDove satellite constellation has a nearly daily revisit time and a spatial resolution of 3 m but remains untested as data has only recently become available to the public. These remote sensing platforms were selected for their synergistic capabilities: Sentinel-2's moderate spatial resolution and more appropriate spectral bands, Sentinel-3's frequent revisits and ideal spectral bands, and PlanetScope's high spatial and temporal resolution. Sentinel data is freely available from the Copernicus open-access hub, and PlanetScope data from the Planet Explorer open-access hub.

Predicting Chlorophyll-a:

$$NDCI = \frac{Red\ Edge\ 1 - Red}{Red\ Edge\ 1 + Red}$$

Equation 1

In the future, we plan on assessing more spectral indices, a multiple-instance learning algorithm, and a random forest machine learning approach. However, this project is meant to assess a single spectral index, the Normalized Difference Chlorophyll Index (NDCI). The NDCI uses the red-edge bands available on the Sentinel platforms (Eq. 1). The literature shows that these bands strongly relate to chlorophyll-a (Caballero et al., 2020).

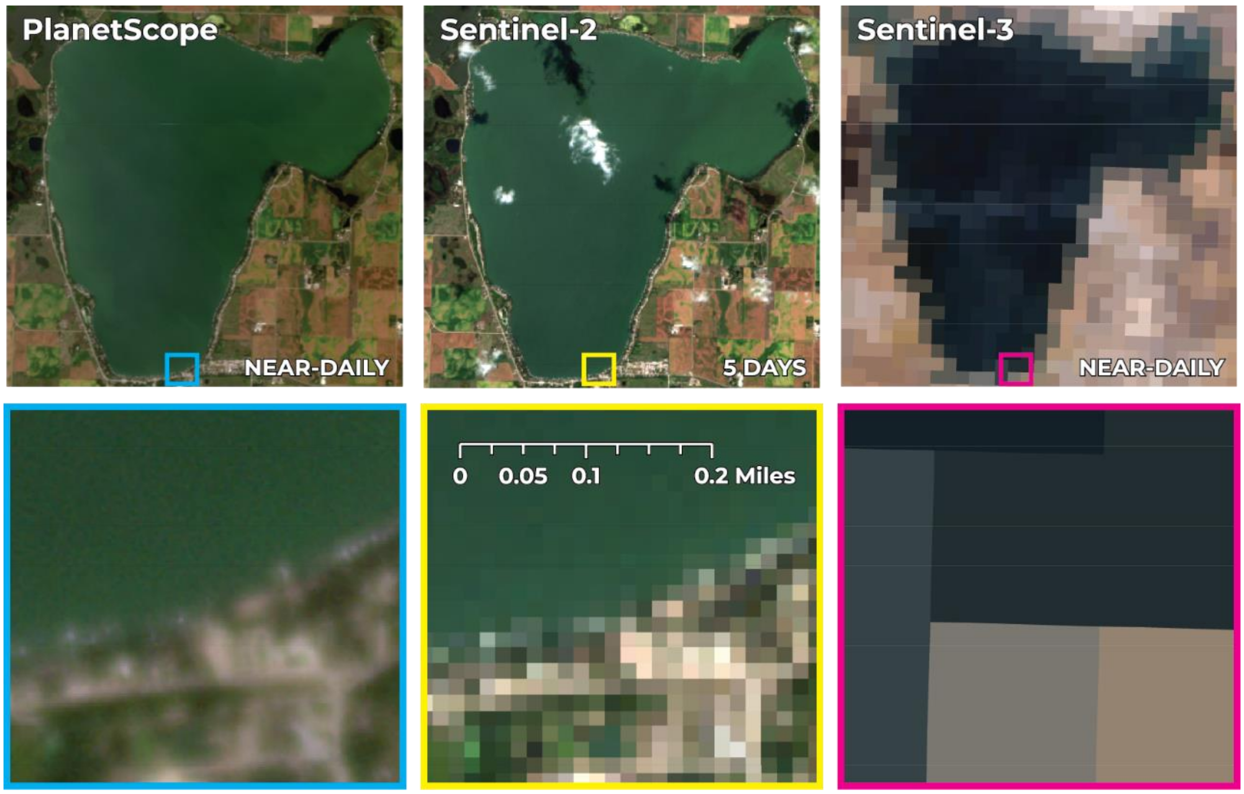

Figure 1. In Sept. 2023, Big Spirit Lake in NW Iowa had a HAB that was imaged with PlanetScope (~3m pixel size), Sentinel-2 (20m), and Sentinel-3 (300m) sensors. Inset shows Orleans Beach. While daily imagery is critical for monitoring, Sentinel-3 limits the ability to capture near-shore HABs.

Related Research:

In-situ monitoring of HABs is time-consuming, costly, and fails to capture the spatial and temporal variability of algal blooms. In response, remote sensing has been leveraged worldwide to improve the ability for rapid HAB assessment, such as HabNet for Florida coasts (Hill et al., 2020), the Great Lakes Alliance for Remote Sensing (GLARS, 2024), and Environment and Climate Change Canada's Earth Observation lake watch platform (Binding et al., 2021). Furthermore, the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Coastal Ocean Science (NCCOS) has developed a HAB monitoring and forecasting used for the Gulf of Mexico, Maine, Lake Erie, Pacific Northwest, and Californian and Floridian coasts (NCCOS, 2023). These programs are cost-effective solutions that use spectral indices calculated from satellite remote sensing to retrieve spatially variable water quality status. For example, Kislik et al., (2022) found that NCDI for two small reservoirs on the California/Oregon border had an accuracy of R^2 = 0.84 for chlorophyll-a retrieval. No monitoring platform exists for the Midwest, and no satellite remote sensing of chlorophyll-a has been completed for Iowa; in completing the overarching goal of this research, this work could launch Iowa and the Midwest into an unprecedented era of predictive analysis, early warning, and mitigation strategies for HABs.

Model Workflow:

Figure 2. Current model workflow demonstrating where data is coming from through model analysis and final objectives.

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