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Comparative Analysis of Water Quality Monitoring Procedures in a Small, Eutrophic Lake, South-Central Minnesota

Owen Lott
Minnesota State University, Mankato

Comparative Analysis of Water Quality Monitoring Procedures in a Small, Eutrophic Lake, South-Central Minnesota

By

Owen Lott

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This thesis has been examined and approved by the following members of the student's committee

Dr. Phillip H. Larson

(Committee Chair)

Dr. Bryce Hoppie

Dr. Fei Yuan

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Comparative Analysis of Water Quality Monitoring Procedures in a Small, Eutrophic Lake, South-Central Minnesota

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Abstract

Understanding the spatial and temporal distribution of water quality variables in lakes is vital for assessing their overall health. So vital in fact, that numerous government agencies are tasked with testing and maintaining a healthy public surface water supply. This study focuses primarily on the efficacy of one of such agency's procedure for monitoring surface water quality. The Minnesota Pollution Control Agency's (MPCA) procedure for water quality testing does not account for neither the spatial nor temporal variability of water quality in small Minnesota lakes, including the lake at the center of this study, Bass Lake. Currently, the MPCA assumes spatial homogeneity of water quality parameters by utilizing a singular sampling site to represent the totality of small Minnesota lakes with simple shoreline silhouettes. The MPCA's monitoring procedure is incapable of measuring the up to 54% spatial disparity in trophic state observed through in-situ sampling at different spatial positions on Bass Lake. Additionally, because the MPCA samples water from lakes on a schedule developed months in advance, they are unable to sample during the most significant periods of poor water quality. This oversite can cause them to severely underestimate the trophic state of a body of water and was demonstrated in the 2019 sampling season when only two days after an MPCA sampling event, a large algae bloom severely distorted a number of water quality parameters. This poses not only an economic concern but also, a public health concern. Bass Lake in Faribault County, Minnesota was studied repeatedly by the MPCA throughout the 1980's to the early 2000's and has had mixed results ranging from a hypereutrophic to mesotrophic lake.

Bass Lake serves as an ideal candidate for this study given its simple bathymetric topography, uncomplicated shoreline, heavily agricultural land use, and geomorphic history. Changes in water quality were measured using Carlson trophic state index values derived from Secchi disk transparency, total phosphorus, and chlorophyll-a concentration measurements derived via water sampling and laboratory testing. Additionally, this study attempts to determine the capability of multi-rotor UAV mounted multispectral imagers to determine the concentration of chlorophyll-a remotely.

CHAPTER 1: INTRODUCTION

The health of natural surface waters is important for both economic and public health reasons. Although difficult to quantify, lakes and other recreational water supplies are an incredibly valuable resource to the United States economy. The U.S. Environmental Protection Agency estimates that public waters can be valued at up to $4,500 per acre-foot (Morrison, 2013). More importantly, public proximity to lakes requires federal and state agencies to have an ongoing interest in monitoring these lakes for public health reasons. Lapses in government oversight of water monitoring procedures can have serious consequences. This was previously observed in Milwaukee, Wisconsin 1993 when a cryptosporidium oocyst epidemic infected over 400,000 people or approximately a quarter of the city's population (Mac Kenzie et al., 1994). It was concluded by Mac Kenzie et al. 1994 that sub-par water quality standards and testing were to blame for the massive surge of cases. This illustrates how citizens rely on government agencies and these agencies cannot do what is best for the general populace with inaccurate or misleading data.

Public monitoring of water quality is especially important in southern Minnesota because of the heavy agricultural land use in these areas (Heiskary, 2003). Specifically related to this land use, the widespread implementation of tile drainage systems has markedly increased runoff's ability to carry nutrients, namely phosphorus and nitrogen, out of agricultural soil and into natural drainage systems and basins (Kalita et al., 2007; Kleinman et al., 2015). These nutrients, while vital to maintaining a complex ecosystem, can also be a severe detriment when added in excess to lake systems (Rast, 1996). Specifically, high levels of phosphorus in lakes are linked to regular summer blooms of blue-green algae which can be toxic to mammals (Cottingham et al., 2015). It is important to note that a study comparing modern (circa 2000) to pre-settlement (1750 – 1800) lake water quality has determined approximately 30% of urban and agricultural region lakes in Minnesota have experienced notable increases in their total phosphorus (Ramstack et al., 2004). Additionally, this increase in total phosphorus is primarily attributed to prolonged use and accumulation of phosphorus and nitrogen rich fertilizer in agricultural soils (Bennett et al., 2001). This is particularly pertinent to the focus of this study, Bass Lake considering there are several drainage tiles draining into the lake, connecting the basin directly to surrounding agricultural land.

The Minnesota Pollution Control Agency (MPCA) is the government organization that monitors water quality in the state of Minnesota and has investigated Bass Lake extensively throughout the 1980's and into the early 2000's with mixed results. Recent complaints from current lakeshore owners have forced the MPCA back to Bass Lake to further investigate its water quality during the 2019 field season. The current MPCA monitoring requirements request only one sample be taken from the deepest part of the lake, assuming a "simple" (lacking extensive bays or doglegs) shoreline silhouette exists (Anderson et al., 2021). There are several problems with this method. Water quality in lakes is a complex equation with many different variables that the MPCA is not considering. For example, this procedure does not consider the spatial variability of a lakes water quality. One sample from one area on a lake cannot necessarily accurately reflect the health of the lake in other areas (Fig. 1.1) (Mayo et al., 1994). Additionally, MPCA sampling dates can be set months in advance, which poses a different problem; algal concentration in a lake is an incredibly dynamic variable that can change rapidly in a matter of days (Kislik et al., 2018). Given this, another primary goal of this study is to examine the efficacy of this procedure at determining a lakes water quality over time. This study also has expanded on previous research done with multirotor UAV mounted multispectral imagers, and their ability to predict chlorophyll-a concentrations remotely.

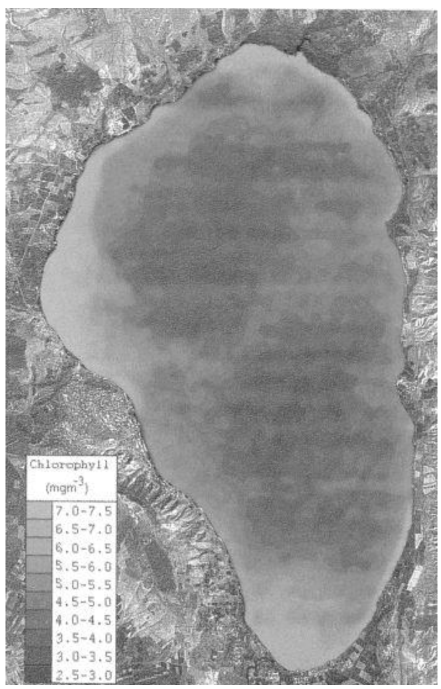

Figure 1.1: Map of the spatial distribution of chlorophyll in Lake Kinneret (Mayo et al, 1994).

In an attempt to assess the spatial and temporal accuracy of the MPCA's established protocol, this study has implemented a different monitoring strategy. Instead of one sample being used to represent the entire lake, 8 samples evenly spread across the lake were collected (Fig. 1.2). This new monitoring procedure was completed to examine the accuracy of the MPCA's assumption that relatively small, shallow lakes with a simple shoreline silhouette exhibit homogenous water quality characteristics regardless of spatial position. Additionally, a continuous in-lake sonde and weather station were fixed to a lakeshore owners dock for access to consistent snapshots of important water quality parameters, namely chlorophyll-a concentration (a parameter directly related to water quality). These continuous snapshots of lake water quality allowed observation of the temporal trends in water quality over longer periods of time. Specific weather parameter data including photosynthetic active radiation (PAR), air temperature, and wind speed/direction were also examined to see how exogenous variables might influence the spatial uniformity or nonuniformity of water quality characteristics.

This study's objectives are to: 1) compare trophic state index values determined with the MPCA's water sampling procedure to those determined with an alternate, more extensive sampling procedure; 2) measure spatial and temporal variability of algae blooms across Bass Lake; and 3) determine the efficacy of predicting chlorophyll-a concentrations using UAV gathered multispectral images.

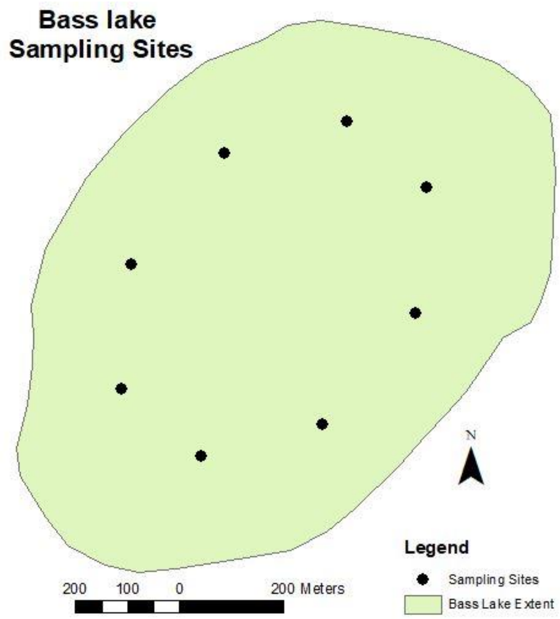

Figure 1.2: Map of Bass Lake illustrating new sampling locations used for this study.

CHAPTER 2: LITERATURE REVIEW

Eutrophication

Monitoring of surface water quality is important for both economic and public health reasons (Mac Kenzie et al., 1994; Morrison, 2013). Humans influence water quality parameters primarily by influencing rates of eutrophication in inland bodies of water. Eutrophication in freshwater systems or, increased plant productivity, is a natural part of lake evolution. When a lake is first created, it starts as an oligotrophic lake being generally devoid of the nutrients required to start a burgeoning ecosystem. However, since these areas are depressions in the landscape, they can obtain their nutrients exogenously from the environment via overland flow into the basin. This addition of nutrients and sediment over thousands of years eventually settle and fill in the lake, increasing the surface area of the photic zone, allowing photosynthesis to occur over a larger area in the lake, and enhancing its ability to support a thriving plant population. This increase in plant productivity is created by an incremental rise in available nutrients in a lake system, especially nitrogen and phosphorus. Simply put, eutrophication is a lake's shift of dependence from exogenous nutrients to utilization of existing nutrients via ecological and cycling processes (Rast, 1996). As with many natural processes, rates of eutrophication are heavily influenced by human activity, especially agricultural activity (Wang et al., 2019). Specifically, the use of phosphorus and nitrogen rich fertilizers and manure which find their way to local water systems via overland flow or by way of drainage tiles (Schindler, 2012). The addition of significant quantities of these nutrients shift the lake's primary method of acquiring nutrients from external sources to cycling these nutrients autonomously (Wang et al., 2019). Further addition of these nutrients only serves to increase the rate of eutrophication where a process that used to take place over thousands to tens of thousands of years, can now be accelerated to just a few decades time. This accelerated process is called cultural eutrophication.

Cultural eutrophication is an ongoing problem that is occurring in many areas of the world as agricultural production is increased. Consequently, the use of phosphorus and nitrogen rich fertilizers and manure is also increased. This surge in nutrients causes a drastic uptick in the populations of both algae and macrophytes as well as a decrease in water quality. In extreme cases, toxic algae blooms and hypoxic lake bottoms caused by cultural eutrophication can cause extensive problems in the aesthetic, recreational, economic, and ecological benefits that a lake would otherwise provide (Bao et al., 2015; Carmichael and Boyer, 2016). These decreases in water quality stem partially from the large algae blooms that impair water quality in lakes that lay downstream from municipal developments and agriculturally managed lands. The blooms, residing in primarily the upper water column, serve to block sunlight and once their life cycle is complete, the algae sink to the bottom of the water body, decomposing and removing oxygen from the lower water column (Smith et al., 2020). If left unchecked, large algae blooms eventually will destroy the lake ecosystem as nothing else is able to survive without the sunlight the algae blocks, or the oxygen the algae uses to decompose.

A lake’s trophic state is wholly dependent on the concentration of available nutrients in the water supply and can be classified in a few different ways. Measuring the trophic state of a lake is typically done using the average of three different characteristics, total phosphorus, chlorophyll-a concentration, and Secchi disk transparency measurements (Carlson, 1977). Using equations provided by Carlson 1977, a lakes trophic state can be determined by using what Carlson called trophic state index (TSI). These variables are converted to a number from zero - 100 where the highest numbers indicate lakes that struggle with water quality or are more eutrophic and the lowest numbers indicate nutrient deficient lakes which are more oligotrophic. Every increase in ten on Carlson's trophic state index equates to roughly a doubling of algal biomass (Carlson, 1977).

The lakes with the lowest TSI values are classified as oligotrophic lakes and are typically "young" deep lakes that have very little nutrients readily available for aquatic plant and algal uptake. This means clearer water, low phosphorus, and low algal activity which equates to lower TSI values. The next step in the eutrophic scale is mesotrophic lakes where nutrient load is increased enough to start facilitating blooms of algae in late summer. Typically, these lakes have intermediate levels of nutrients, chlorophyll, and water clarity begins to diminish. As one would suspect mesotrophic lakes tend to have higher TSI values than oligotrophic lakes. Further increasing nutrient levels will lead to increased algae bloom occurrence, reduced water clarity, and reduced water quality. These lakes would be considered eutrophic and at this point the hypolimnion may struggle to stay adequately oxygenated during peak productivity in mid – late summers (Wang et al., 2019).

Land Use Changes in the United States

Wetlands serve many important functions in the global ecosystem. These areas are defined as lowland spaces that are covered by shallow water for most if not all year (Dahl and Allord, 1997). Additionally, they act as a hydraulic transitional zone between lakes/streams and the surrounding land area. They act to filter out many nutrients and sediment being carried to waters bodies via overland flow. This is because when water enters these areas, it quickly loses velocity and deposits its suspended load carried by the flow. Once the water leaves the wetland, the sediments and nutrients are retained where they can be utilized by local fauna and hydrophytes characteristic of these semi-aquatic environments.

Early colonizers in the United States saw wetlands as disease ridden untraversable land that ultimately only served to impede their interests. Because of this, Early governments and settlers agreed that wetlands ought to be purged from the landscape to make room for agricultural and urban development. This continued from the early 1600’s until 1861 and the start of the Civil War, where wetlands now acted as a serious logistical problem since heavy machinery could not cross these areas (Dahl and Allord, 1997). Quickly after the war ended, the upper Midwest, specifically the prairie pothole region, was being farmed extensively and drainage technology, especially the widespread implementation of drainage tile, was rapidly developing to facilitate the agricultural expansion in this region (Knue, 1988). This expansion required many of the numerous prairie pothole wetlands to be drained. Moving into the early to mid-20th century, two world wars and rapid industrialization required massive expansion of agricultural production. In fact, wetland losses exceeded 50% in the prairie pothole region alone, with many regions seeing up to an 87% decrease in wetland area (Davidson, 2014). At this point there were numerous government incentives available to landowners who wished to drain and reappropriate their land for agricultural or urban development. These incentives continued until the mid-late 21st century where federal legislation such as the "Swampbuster" provision of the Food Security Act ended the federal governments incentive programs on draining and repurposing wetlands (Hofer, 1988). Not only that, but it also tied government benefits given to farmers by the USDA specifically to the conservation of wetland areas (Hofer, 1988).

Nitrogen and Phosphorus

When discussing nutrients and their effect on lake ecosystems/water quality, specifically through the lens of algal concentration, there are two specific nutrients that must be primarily considered when discussing the eutrophication of freshwater environments: nitrogen and phosphorus. This is due to Alfred Redfield's discovery of the relatively constant ratio of carbon : nitrogen : phosphorus (100 : 16 : 1) observed in saltwater algal biomass across the planet (Redfield, 1958). This work was expanded on by countless scientists in an effort to better understand the intricacies of this ratio in both freshwater and saltwater environments (Vitousek and Howarth, 1991). What is important to understand here is why this ratio ought to be better understood. Hypothetically, if the limiting nutrient is known, more pointed efforts can be made at improving the water quality of a lake or region. It is because of studies like this that phosphorus and nitrogen loads are regularly monitored by state and federal agencies to maintain adequate water quality in the interest of public and economic health (Schindler, 2012). It is also important to note that although carbon was once considered to be a primary limiting nutrient for growth of phytoplankton, the consensus has shifted to nitrogen and especially phosphorus being the most common limiting reagents in freshwater ecosystems (Sterner, 2008).

Nitrogen is a nutrient required for plant development specifically in the forms of nitrite (NO_3), nitrate (NO_2), and ammonium (NH_4). These compounds are naturally ubiquitous. Although, with the introduction of nitrogen and phosphorus rich fertilizers, nitrogen is becoming even more common in the global water cycle, theoretically increasing the occurrence and magnitude of large algae blooms (Lewis and Wurtsbaugh, 2008; Sterner, 2008). However, this is disputed by some who suggest phosphorus limitation restricts the growth of algae regardless of general availability of nitrogen (Schindler, 2012; Vitousek and Howarth, 1991). Assuming the generally accepted paradigm that nitrogen does plays an equally important role in algal biomass development, the addition of nitrogen rich fertilizers to the global nitrogen cycle can only serve to drastically increase the presence of algae in watersheds where this nutrient is added to increase crop yields. Now, because nitrogen rich compounds are water soluble, keeping these compounds confined to an agricultural area is next to impossible since rainfall events generate runoff which carries these compounds away from their originally intended destination and into local watersheds.

Phosphorus levels, like nitrogen, in many water systems are also increasing as the use of fertilizers increases. Although, phosphorus can also be sourced from a natural provenance such as the weathering of phosphorus rich rocks and minerals, atmospheric deposition, and continuous input by animals/wildlife (Heiskary, 2003). Phosphorus in freshwater environments is generally found as either organic or inorganic, organic being part of an organism where the phosphorus atom is bonded to carbon and unavailable for plant uptake and inorganic being “free” phosphorus that is available to aquatic plants and algae. Inorganic phosphorus can be created when organic phosphorus sinks to the bottom of a lake or body of water and bacterial decomposition transforms it back into inorganic phosphorus. This is then reintroduced to the upper water column when the lake bottom is disturbed, allowing for uptake by aquatic plants and algae. Additionally, it is important to note that since cyanobacteria are able to fix nitrogen from the atmosphere into ammonium, a surplus of phosphorus is usually necessary to trigger their development in leu of other species of phytoplankton (Cottingham et al., 2015; Schindler, 1977). This behavior is most important in saltwater environments where the ecosystem is often limited by nitrogen rather than phosphorus. Because of this, large cyanobacteria populations represent an integral part of saltwater ecosystems.

Nitrogen vs. Phosphorus as Limiting Nutrients

There has long been debate over which nutrient generally is more limiting in freshwater ecosystems. In estuarine and saltwater environments, it is clear that phytoplankton are at the very least co-limited by both nitrogen and phosphorus since federal efforts to reduce phosphorus pollution have succeeded, yet little to no change in planktonic activity was observed (Elser et al., 1990; Howarth and Paerl, 2008; Lewis et al., 2011; Lewis and Wurtsbaugh, 2008; Sterner, 2008). The increase in federal awareness of phosphorus as a limiting nutrient stems primarily from Schindler's series of experiments regarding primarily oligotrophic lakes in Canada, and their sensitivity to either increased phosphorus or nitrogen inputs (Schindler, 1977, 1974, 1971). In one of his more well-known experiments, a lake was split into two separate equal area bodies of water and were fertilized with either a higher ratio of phosphorus or nitrogen. His results illustrated that only the lake fertilized with a heavier concentration of phosphorus saw an increase in the production of phytoplankton (Schindler, 1977, 1971). These studies primary goals were to illustrate how cultural eutrophication could be controlled and partly due to these results, political action was taken to reduce the concentration of phosphorus not only in freshwater, but estuarine environments as well (Edmondson, 1991).

However, the so-called phosphorus paradigm has also had opponents, many of whom argue that phosphorus and nitrogen could be co-limiting in many lakes if nitrogen is not in fact the primary limiting factor (Elser et al., 1990; Sterner, 2008). It is argued by Elser that combined fertilization of both nitrogen and phosphorus has a much more consistent increase in algal biomass associated with it than fertilization of only phosphorus or nitrogen (Elser et al., 1990). He also suggests why his findings may have differed from the prevailing consensus by writing,

> *"we found considerable deficiencies in the degree to which investigators have applied sufficient replication, performed and reported statistical tests, and assessed seasonal and spatial differences in algal nutrient limitation" (Elser et al., 1990).*

Essentially suggesting poor academic rigor on the part of phosphorus proponents. Additionally, a more recent publication by Sterner suggests that a lakes limiting nutrient may be mostly related to the level of eutrophication the lake has already undergone (Sterner, 2008). His study indicates that oligotrophic lakes are more likely to be phosphorus limited while eutrophic lakes and marine systems are more likely to be nitrogen limited. He also cites a number of studies that indicate algal biomass is most effectively increased when fertilization of both phosphorus and nitrogen is employed (Sterner, 2008).

Regulations and Government Controls

Federal and state governments play an enormous role in evaluating surface water resources and determining what "clean" actually implies for such resources. On a federal level, the Federal Water Pollution Control Act or more colloquially referred to as the Clean Water Act (CWA), requires that states follow specific water quality protocols. It is these protocols that detail how much of a regulated pollutant is admissible in a body of water before the water becomes too toxic to use for its designated purpose (S. 2770 § 307 (a)). In Minnesota, these purposes are classified into 8 distinct classes (Minn. R. 7050.0140, 2017). The most relevant for this study being Class 2 waters where their purpose is defined by the state of Minnesota as:

> *Aquatic life and recreation includes all waters of the state that support or may support aquatic biota, bathing, boating, or other recreational purposes and for*

which quality control is or may be necessary to protect aquatic or terrestrial life or their habitats or the public health, safety, or welfare.

Different classifications for different purposes are important since waters being utilized for domestic consumption obviously must be held to a higher quality standard than those used for agricultural/industrial consumption. Once a body of water exceeds its threshold for one or more of a specified pollutant, it is deemed "impaired" by the state government (S. 2770 § 303 (d)). Once classified as impaired, states are required to set pollution reduction objectives termed total maximum daily loads (TMDL). These TMDLs outline a remediation plan for a body of water by specifying the maximum input of a pollutant the body of water is legally allowed to collect thereafter. A comprehensive list of these TMDLs is then sent to the United States Environmental Protection Agency (EPA) every other year for approval.

A key part of the CWA establishes the permitting system for authorized release of pollutants into public waters called the National Pollutant Discharge Elimination System (NPDES) (NPDES Compliance Inspection Manual, 2017). The permitting system, outlined in section 402 of the CWA, regulates the flow of hazardous waste from point sources into United States waters. Additionally, the CWA outlines two types of monitoring to ensure the compliance with NPDES (and other sections relating to state permit programs) in section 308. Paragraph A in section 308 of the CWA declares that the owner/operator of any point source is responsible for obtaining and abiding by their NPDES or other state permit which limits the amount of a regulated material the permit holder is permitted to discharge into public waters. To ensure their compliance, the permit holder is required to monitor and keep records of their effluent waste to prove compliance with the CWA/other state legislation. Section 308 also allows the legal entrance of state representatives (EPA or state pollution control agencies) to monitoring sites and gives access to any records regarding the point source owners monitoring data. The representative is also entitled to collect samples of any wastewater that is being also being monitored by the point source owner.

Given the study areas proximity to primarily agricultural land, it is most important to discuss some of the methods of assessment used when measuring pollutant discharge off agricultural fields. Important to note, there are several different classifications of agricultural fields classified by federal and state governments. The NPDES specifically outlines regulations for animal feeding operations (AFOs) and concentrated animal feeding operations (CAFOs) ("NPDES Compliance Inspection Manual," 2017). However, this is as far as the CWA goes into regulating agricultural runoff assuming no pollutants found in the Section 401.15 "Toxic Pollutants Table" are also being transported into public waters. In fact, the CWA specifically exempts drainage ditches/tiling being used for agricultural purposes from Section 402 regulations. Meaning if a farm is not classified as an AFO/CAFO, they would be permitted to drain their land into any public water with no restrictions (S. 2770 § 404 (f)(1)(C)). There are currently no AFO/CAFO operations present in the Bass Lake watershed meaning the several drainage tiles connected to the lake are draining completely unfettered.

One of the biggest problems when enacting science based environmental legislation is the degree of certainty required to "prove" a problem exists and to what extent the problem is caused by a specific parameter. Especially since there's usually such high stakes for both environmental government agencies and private companies. Government agencies (or private companies contracted by the government) have a responsibility to maintain public health while "polluting" companies do not necessarily have that same responsibility. Regulations can cost these companies millions of dollars which provides a hefty impetus to either lobby for reductions in regulation or to disregard current environmental legislation completely (Gleason et al., 2011). Especially since establishing causal links between specific activities and their negative effect on the environment can be difficult in many situations (Houck, 2002). However, the CWA does address uncertainty of TMDL studies in Section 303 (d)(C):

> *"Each State shall establish for the waters identified in paragraph (1)(A) of this subsection, and in accordance with the priority ranking, the total maximum daily load, for those pollutants which the Administrator identifies under section 304(a)(2) as suitable for such calculation. Such load shall be established at a level necessary to implement the applicable water quality standards with seasonal variations and a margin of safety which takes into account any lack of knowledge concerning the relationship between effluent limitations and water quality."*

This section is often cited by reviewing courts when "best guesswork" is used by environmental professionals to determine the environmental impact of certain behaviors (Houck, 2002). Essentially, in many cases courts accept that scientists cannot give errorless answers to all environmental questions but educated assessments can often suffice in these kinds of legal situations.

Remote Sensing Applications on Surface Water Quality in Southern Minnesota

Before remote sensing technologies became what they are today, researchers primarily studied the effects of water quality parameters on freshwater and saltwater environments by way of in-situ water sampling. While this method is still regularly used today for its high accuracy, it has a number of disadvantages that cannot necessarily be solved easily. Its drawbacks primarily stem from the fact that it is both time intensive and financially costly (Kislik et al., 2018). Furthermore, creating monitoring strategies with high spatial and temporal resolutions is difficult because by increasing these resolutions, you are dramatically increasing the amount of time and money required to complete every survey. The size of the water body being researched also can compound these issues since high resolution studies are often impossible given a large enough lake area. Additionally, water quality characteristics, especially algal activity, are incredibly temporally dynamic which make regular sampling trips a necessity when conducting these studies (Lavigne et al., 2015; Wang et al., 2019). The MPCA attempts to solve the time intensive and financial drawbacks of in-situ water sampling by forgoing spatial accuracy in lakes with a small surface area and simple shoreline silhouette by using one water sample as a representative for the entire lake (Anderson et al., 2021). While this does partially solve how costly and time-consuming water quality monitoring can be, it leaves room for substantial error when other methods offer higher temporal and spatial accuracies while also not sacrificing time and budget.

Remote sensing via satellite imagery has become an increasingly popular way to study aquatic systems since they improve upon many of the drawbacks of in-situ sampling methodologies (Zhou and Zhao, 2011). Generally, satellites make whole-lake assessments of water quality more viable since a single image can encompass an entire waterbody. Therefore, spatial resolution is a function of the type of sensor used by the satellite rather than the amount of water samples a researcher is willing to obtain and pay to have analyzed. However, many satellites work on fixed temporal time-scales which can make consistent imaging of the same area difficult (Tóth et al., 2021). Additionally, cloud cover can completely block a sensors view of very large spatial extents (Kislik et al., 2018). Although many studies have used satellites to reliably predict important water quality parameters, namely chlorophyll concentration, the temporal problems associated with these methodologies are often cited as a severe drawback (Binding et al., 2018; Klemas, 2012; Kutser et al., 2006; Wang and Shi, 2008; Zeng et al., 2016). So, while satellite remote sensing solves some of the problems related to the current state of water quality monitoring, it is not necessarily capable of solving the temporal inadequacies in the MPCA sampling method.

Currently, a relatively new and expanding field in remote sensing is emerging as a relatively low cost, high resolution alternative to satellite imagery in the form of unmanned aerial vehicle (UAV) multispectral surveys (Kislik et al., 2018; Tóth et al., 2021). Although UAV surveys are often unable to capture the same physical extent as satellites, the spatial resolutions of such methodologies are generally much higher since UAVs fly much closer to ground level. This increase in spatial resolution will become increasingly important as the need for fine-scale data of heterogenous systems also increases (DeBell et al., 2016). Additionally, UAVs can be deployed at any time based on the need of the researcher, significantly increasing their temporal potential regardless of cloud cover. UAV surveys are becoming increasingly common because they solve many of the problems with high resolution in-situ water sampling and the temporal inaccuracies related to satellite imaging (Kislik et al., 2018). It is important to note that despite being a relatively new technology in remote sensing, high accuracies related to chlorophyll prediction are observed and likely will continue to improve as standardization of hardware and image processing methods also advances (DeBell et al., 2016; Lyu et al., 2017; Tóth et al., 2021). Were these methods to be employed by the MPCA in their water monitoring strategy, both the spatial and temporal resolution of water quality surveys could be improved at a relatively small cost. Also, because the MPCA is responsible for hundreds of impaired bodies of water around Minnesota, increasing the temporal resolution of their sampling efforts is not realistically feasible with in-situ water sampling due to the amount of time it takes to sample a large body of water. However, UAVs could potentially increase the MPCA's temporal resolution while not substantially increasing the amount of time or money required to sample a large area.

CHAPTER 3: STUDY AREA

Bass lake is located approximately 30 miles south of Mankato, Minnesota in Faribault County (Fig. 3.1). Bass Lake was chosen as the area of interest in this study for several reasons including: (1) its relatively simple bathymetric profile (Fig. 3.1), (2) its geomorphic history, and (3) the availability of historic water quality data. Because Bass Lake was likely formed after the melting of stagnant glacial ice, its bathymetry is very regular, meaning local variations in lake bottom, which otherwise would affect the distribution of nutrients (Wang et al., 2009), are not applicable considering the relatively simple bathymetry of Bass Lake. In addition, the shoreline is also very simple exhibiting no embayments and a very naturally elliptical silhouette. When a lake has a "simple" shoreline and bathymetry, the MPCA assumes uniform spatial variability of water quality across the lake and samples from a singular sampling point. Thus, one of the objectives of this study is to test this assumption on a lake with "simple" morphology like Bass Lake (Anderson et al., 2021). Bass Lake has also been sampled by the MPCA in the past. This prior sampling allows for comparison of the data compiled within this thesis to the lakes historic water quality data collected through the MPCA sampling procedure. In addition, the MPCA has returned to Bass Lake recently during the summers of 2018 and 2019 after several local complaints regarding poor water quality from local landowners. These recent investigations of the lake by the MPCA allowed for a direct comparison of sampling procedures in the summer of 2019.

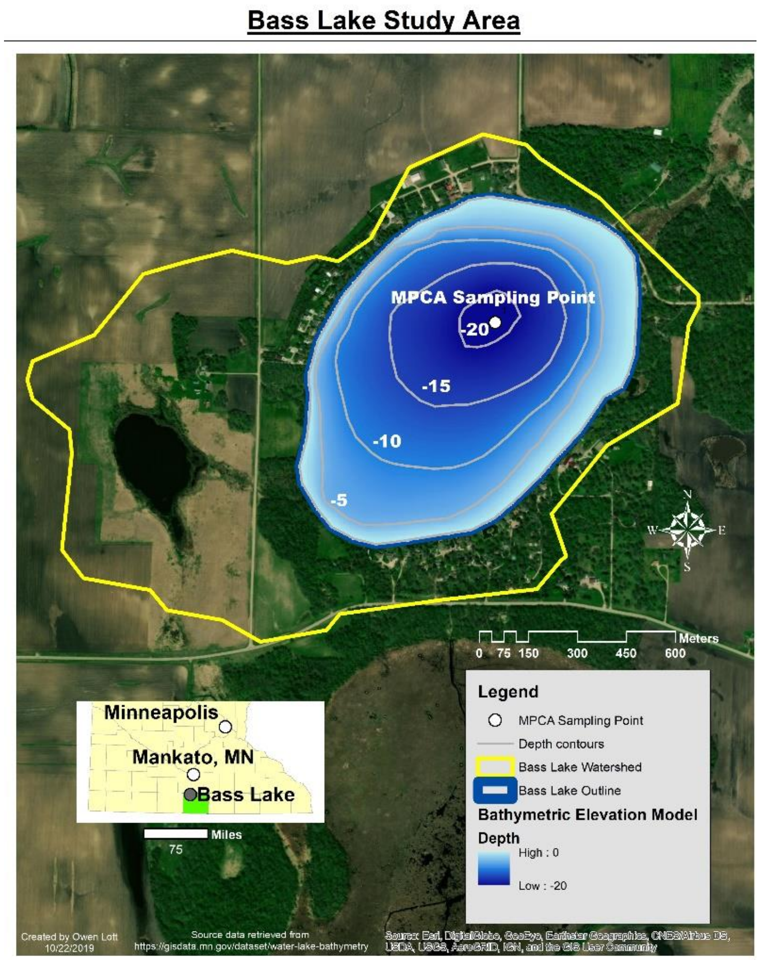

Figure 3.1: Visual depiction of Bass Lakes bathymetry and location in relation to Mankato, MN

Although the Bass Lake watershed is located in an area with a generally heavy agricultural presence, the overall land cover of the Bass Lake watershed is primarily classified as woody/emergent herbaceous wetlands. In fact, nearly 40% of the non-water area of the watershed was classified as a type of wetland by the NLCD survey in 2011. However, it is important to note that just over 41% of the non-water area is classified as cropland. This also does not paint a full picture of the effect that agriculture has on Bass Lake since there are also several drainage tiles that flow directly into the lake from the surrounding cropland. The installation of one of these drainage tiles can be viewed from Google Earth historical aerial photos (see Fig. 3.2).

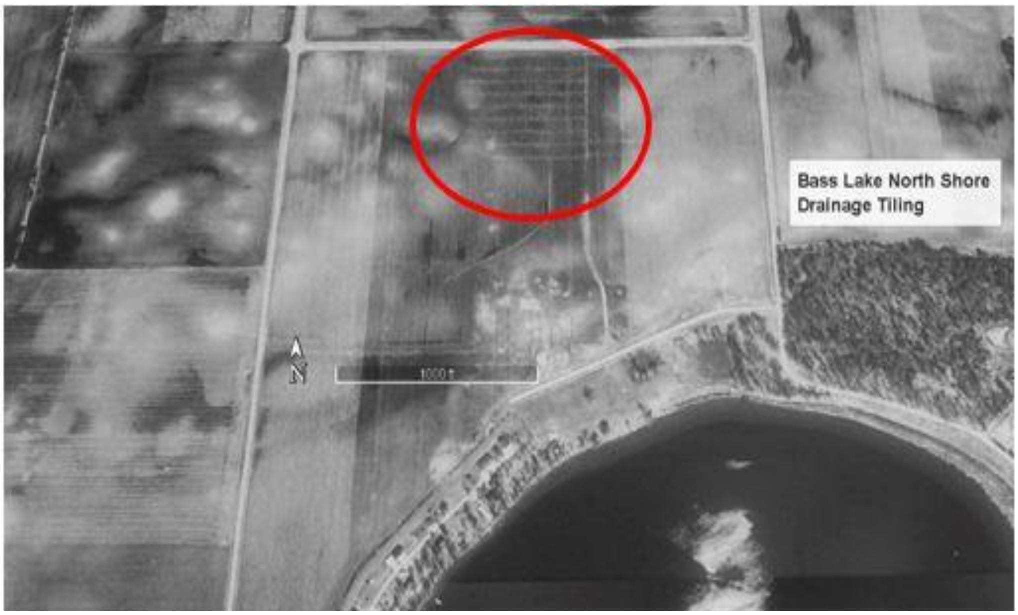

Figure 3.2: Aerial view of drainage tile installation (circled in red) during 1991 from Google Earth historic imagery.

Geomorphic History of the Area

The form of Bass Lake is important because of the MPCA's assumption of homogenous water quality across relatively small, simple lakes including Bass Lake. It is important to note that many lakes are similar in morphology to Bass Lake. This morphology is common in Minnesota because of Minnesota's glacial history. These forms are naturally susceptible to high rates of eutrophication due to the factors that caused their genesis. Since the processes which formed Bass Lake are the same processes which formed many other lakes that are morphologically similar, determining how Bass Lake was formed is important. Understanding Bass Lake's formation can help to illuminate what background rates of eutrophication might be and how humans impact the natural system. Without understanding how Bass Lake was formed, and the broader context of how the area around the lake was formed, it is impossible to say how severely humans are currently affecting the water quality of Bass Lake.

Because Bass Lake is located in such an agriculturally dominant area, it is important to discuss the geomorphic history of its watershed extent, the probable background rates of eutrophication, and how this history has affected the lake's ability to respond to heavy nutrient input. The Upper Midwest's history is marked by the many glacial advances and retreats that have occurred throughout recent glaciations. Bass Lake specifically lies in an area that was especially modified by the most recent advances and retreats of the Des Moines lobe around 12-14 ka (Patterson, 1997; Rittenour et al., 2015). The Des Moines lobe was studied extensively because of its far southward reaching margin and is important to discuss in this context because of the presence of numerous glacial landforms including ice-walled lake plains, kettle lakes, and subglacial river activity in southern Minnesota specifically around the Bass Lake area (Clayton et al., 2008; Patterson, 1997).

The relatively uncomplicated morphology of Bass Lake is due to its genesis in a stagnant ice dominated landscape following the retreat of the Des Moines Lobe. Ice-walled lake plains specifically are areas of inverted topography caused by stagnant glacial ice which at one point held a lake in place (see Fig. 3.3). As this ice melted and water drained away from the landform, the lake sediment that was deposited inside this glacial lake remained and created the characteristic inverted topography which defines the area surrounding the Bass Lake watershed (Patterson, 1997). Bass Lake itself is a kettle landform. This means that at one point, a large block of stagnant glacial ice resided in the current position of Bass Lake. As this ice melted, it left behind a basin to be subsequently filled in with water over time. These features require a regular supply of stagnant ice which was likely sourced from the Des Moines lobe during the last glaciation of Southern Minnesota. However, an important question to consider here is: What caused glacial ice to stagnate in this area? This question can be answered by looking through surficial geologic maps which indicate a large subglacial tunnel valley was likely created from meltwater off the retreating glacier. The path this subglacial water likely took is visible on soil maps of the areas surrounding Rice, Bass, and Lura lakes by following silt and clay soil units from just southwest of Bass Lake up to the northeast (see Fig. 3.4). Also, note the southwest to northeast orientation of Rice, Bass, and Lura lakes. As this subglacial river diverted water away from the existing glacier, a decrease in water pressure would then cause ice at the terminus to destabilize and stagnate. The many cycles of retreat and advance of the Des Moines lobe led to a steady source of stagnant ice in the area and prompted the formation of the numerous ice-walled lake plains and kettle lakes, currently seen in Southern Minnesota (Clayton et al., 2008).

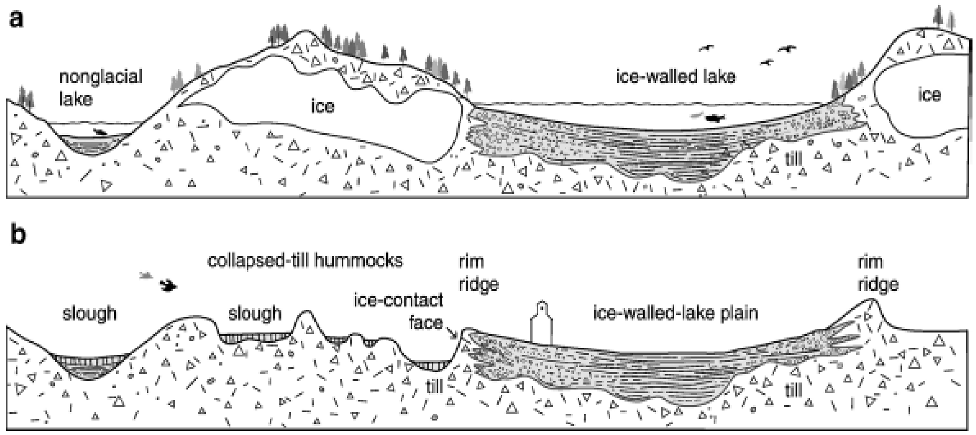

Figure 3.3: Example of how ice-walled lake plains are formed retrieved from Clayton et al. (2008).

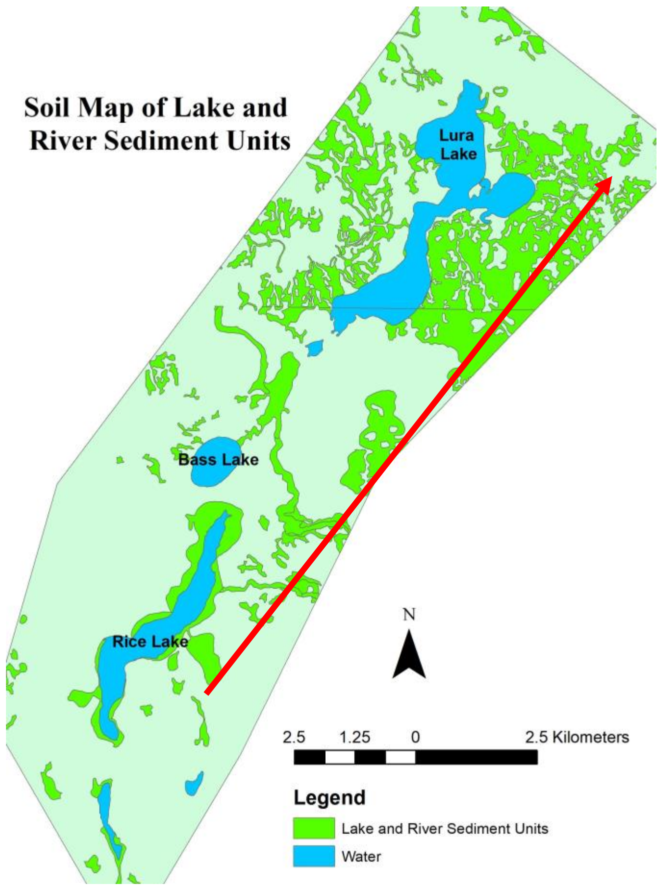

Figure 3.4: Soil map of area surrounding Bass Lake created using data taken from the National Cooperative Soil Survey.

These geomorphic landforms are incredibly important when discussing natural rates of eutrophication before Euro-American settlement since the type of sediment left behind is especially conducive to naturally eutrophic waters. This is due to ice-walled lake plains being made up of nutrient rich lake sediments which act as a natural nutrient sink and can be slowly incorporated into nearby hydraulic systems through overland flow. Additionally, wet prairie lake environments are notorious for their ability to retain nutrients in local watersheds because of abnormally long residence times which keep nutrients in place rather than regularly flushing them out and away from these lake basins (Allan et al., 1980). The long residence times allow for physical and biologic cycling processes to continually use the incoming nutrients and gradually increase the trophic state of the lake more rapidly than lakes in other areas. This process causes these lakes to be more naturally eutrophic than other areas with better drainage and lower residence times.

Because ice-walled lake plains are so full of phosphorus and nitrogen rich lake and river sediments and are often completely free of rocks and boulders, they serve as ideal agricultural centers, as is the case here in the area surrounding Bass Lake. It is important to note that since wet prairie environments are already prone to high rates of natural eutrophication, the increased nutrient load often associated with agricultural development causes incredible increases in trophic state on highly accelerated timescales (Cottingham et al., 2015). Additionally, the fact that these deposited lake and river sediments are generally very fine grained and impermeable mean that semi-regular flooding of these areas is common after large rainfalls (Clayton et al., 2008). Landowners then combat this flooding by installing tile drainage systems under their land to facilitate better drainage and ultimately create a path of direct nutrient input to local watersheds. This impact is further exacerbated by a myriad of other conventional farming practices common in the prairie pothole and wet prairie regions including drainage of wetlands for further land development, increased soil erosion from exposed and over-tilled soil, lack of buffer strips, and heavy fertilization (Gleason et al., 2011). The combination of all the above factors combined with the fact that lakes in these areas have abnormally high residence times, leads to intense rates of cultural eutrophication that is far beyond the scope of what any natural system is accustomed to.

CHAPTER 4: METHODS

GIS methods

Although the shape of Bass Lake is naturally elliptical, slight variations in the lake's shoreline made splitting the lake into equal area parts using the original lake outline via scripting not viable. To remedy this, the lake was idealized into an ellipse and split into 8 equal area sectors with a sampling site determined in ArcMap using the "Mean Center" tool for each sector (Fig. 4.1). These points were then overlaid onto an alphanumeric grid and named using the point's coordinates. The equal area sectors are where attribute data including chlorophyll-a concentration, total phosphorus, and trophic state index values were included and symbolized. The distribution of trophic state index values across time and space are what will primarily be analyzed in the results to determine the validity of the MPCA's assumption of spatial uniformity of water quality characteristics.

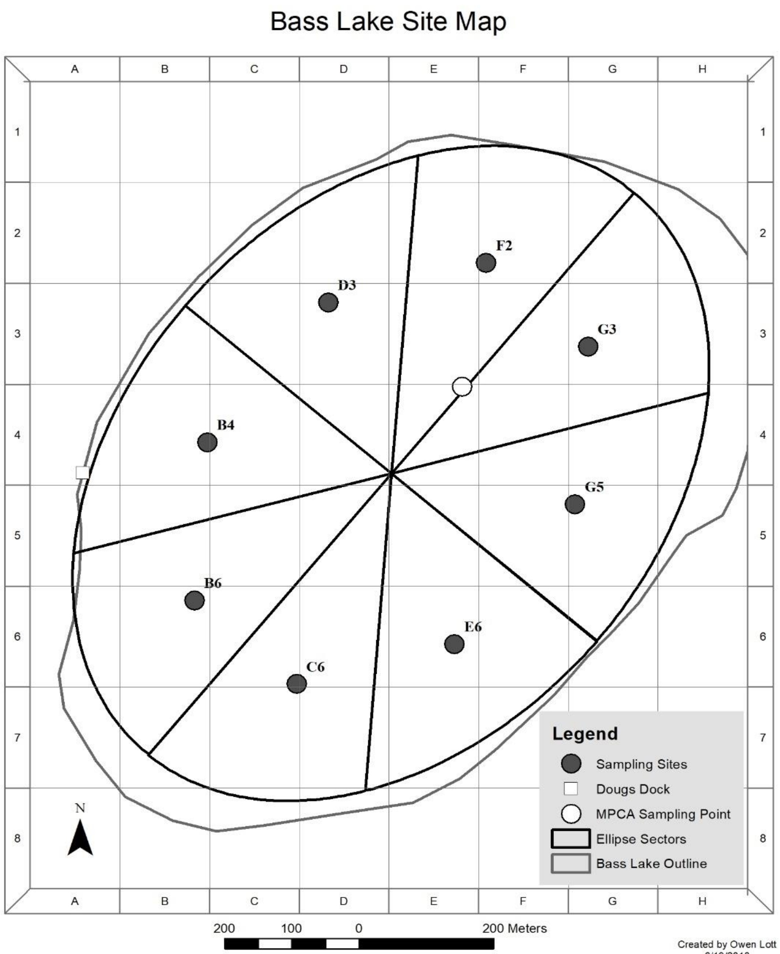

Figure 4.1: Depiction of each sampling site, the sector each site is representative of, and the idealized ellipse used to represent Bass Lake in leu of its original shoreline.

Field Methods

In this study, 2 different water sampling strategies were employed. The MPCA's water sampling technique outlined in Egge et al. (2018) was conducted first. Upon arrival to the site using a handheld GPS unit, a standard surface water sample was retrieved from the single MPCA sampling site and a Secchi disk transparency measurement was recorded. The modified sampling procedure developed for this study included navigating out to each of the 8 sampling sites at the center of each sector, taking a similar surface water sample as outlined in Egge et al. (2018), and utilizing a Hach Hydrolab DS5X or YSI 6600 V2 multi-parameter data sonde to gather temperature, specific conductivity, pH, turbidity, chlorophyll concentration, and dissolved oxygen at a depth of 20 cm and 1 m. The collected water samples were then put on ice, taken back to the university laboratory, and analyzed for chlorophyll-a concentration and total phosphorus. Laboratory measurements of chlorophyll-a and total phosphorus were required to accurately measure trophic state according to Carlson (1977).

Additionally, along with a more comprehensive sampling regiment, this study utilized a continuous in-lake sonde and weather station (Figs. 4.2 & 4.3) located along the west shoreline (Fig. 4.1) to constantly measure and report weather and water quality data. The following variables were constantly recorded every 15 minutes with the weather station and sonde; photosynthetic active radiation (PAR), wind speed/direction, air temperature, relative humidity, barometric pressure, total rain, water temperature, pH,

Figure 4.2: Image of the weather station affixed to a cooperating landowner's dock.

Figure 4.3: Image of the Hach DS5X multiparameter sonde in Bass Lake.

oxygen reduction potential, dissolved oxygen, specific conductivity, turbidity, and chlorophyll-a concentration. During sampling season, special attention was paid to chlorophyll and turbidity values. These data allowed this study to identify large algae blooms in real-time to schedule sampling events reactively rather than randomly. The reactive sampling was an important aspect to this study since the MPCA's current water sampling procedure leaves the organization totally blind to prevailing water quality conditions prior to sampling.

Chlorophyll corrections for the DS5 sonde were required in the 2020 field season while corrections for both the DS5 and YSI sondes were needed in the 2019 field season. Regressions using experimentally derived chlorophyll-a data cross plotted against raw sonde data from both the 2019 and 2020 field seasons (see Fig. 4.4) were used to manipulate sonde values for a more accurate reading (see Fig. 4.5). Note that in the 2019 field season, the transition from the DS5 to the YSI sonde is apparent around mid-summer where values become much more varied when compared to the much more consistent curve produced by the DS5.

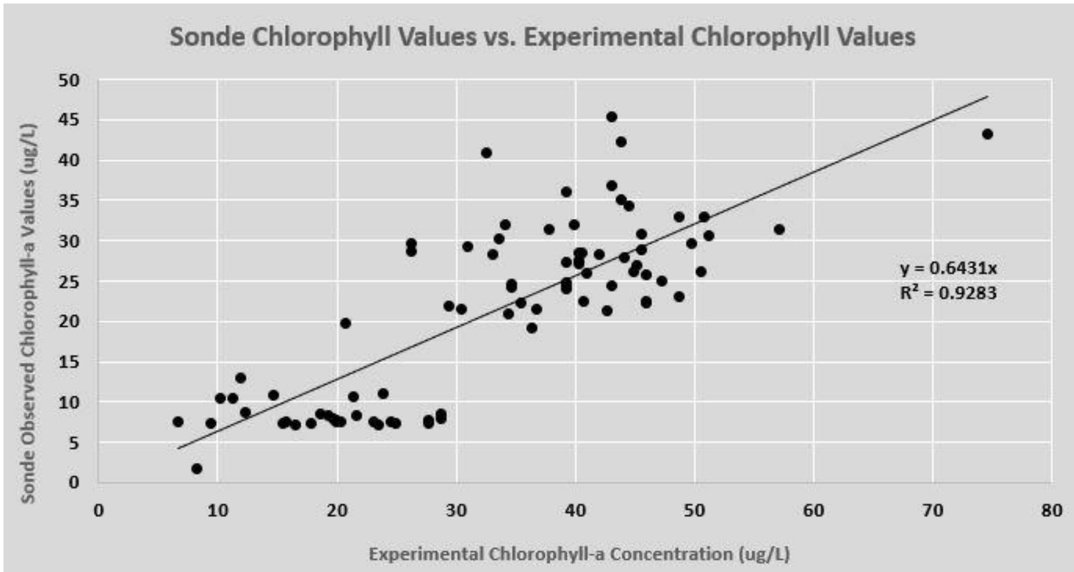

Figure 4.5: The above graph shows the relationship between the sonde observed chlorophyll-a concentration and the experimentally derived chlorophyll-a values. The trendline equation was then used to correct the sonde's reported values.

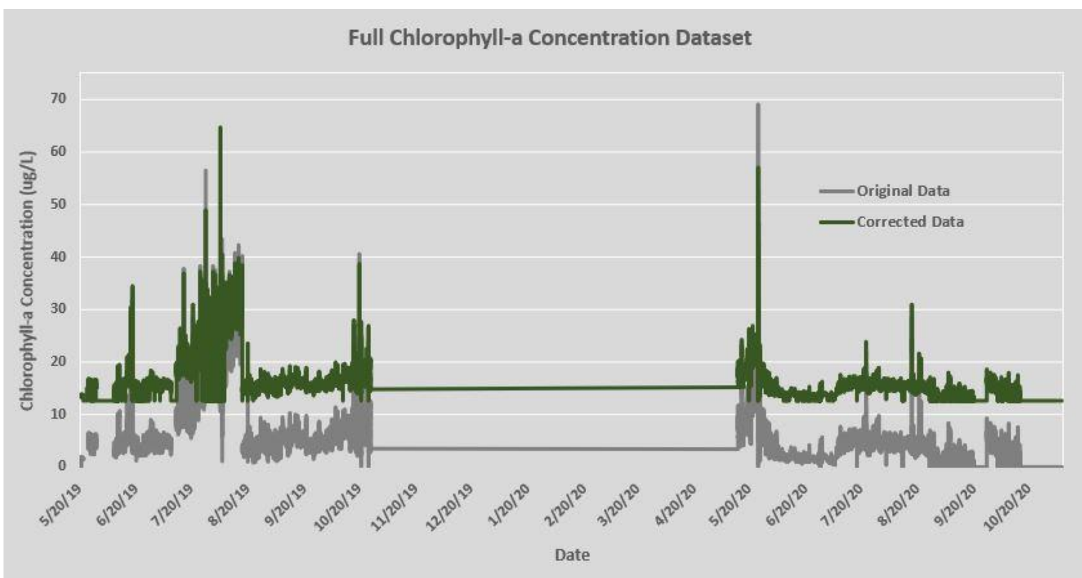

Figure 4.4: Full corrected chlorophyll-a dataset plotted with the original dataset.

The system operated for image acquisition was a Tetracam Macaw 6-band multispectral camera which was fixed to a DJI Ronin-MX professional gimbal all attached underneath a DJI Matrice 600 Pro UAV (see Figs. 6 & 7). The Tetracam's six bands were those with which the imager was factory fitted and calibrated. They include bands narrowly focused and calibrated on 710, 680, 650, 620, 560, and 490 nm. Before multispectral images were taken, flight plans were created to ensure images are being taken from the correct areas every time. To do this, the DJI program Ground Station Pro was utilized since it was the only application that allowed for the plotting of specific latitude/longitude coordinates for the UAV to fly to. Each coordinate corresponds to the point directly above every sampling site, so for each imaging mission, eight separate images were acquired. The program then flew the UAV autonomously to each point where continuous images along the flight path every 15 seconds and saved to the cameras hard drive. Once back in the lab, only the images taken directly over each sampling site were saved for later processing. These images were all processed and analyzed in ERDAS Imagine where the least distorted pixels were chosen for further analysis.

Figure 4.6: DJI Matrice 600 Pro UAV with DJ Ronin-MX gimbal mounted underneath.

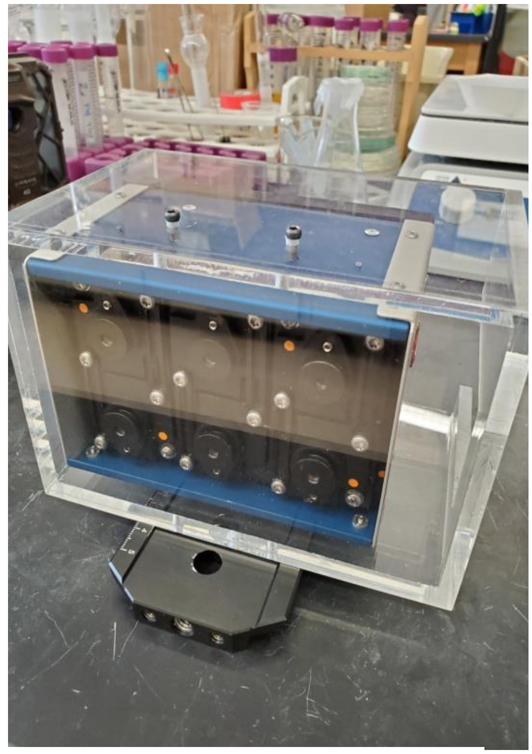

Figure 4.7: Tetracam Macaw 6-band multispectral camera.

Lab Methods

Lab methods were carried out no later than 48 hours after water sampling was completed. Sample water was refrigerated at 4°C until testing of water quality parameters was completed. The following laboratory procedures were all completed in a university lab, with university equipment, and no water samples being privately analyzed.

Chlorophyll-a Extraction

Using…

- *Tissue grinder*
- *Centrifuge*
- *Saturated magnesium carbonate solution (1.0g finely powdered magnesium carbonate to 100 mL distilled water)*
- *Aqueous acetone solution (90 parts acetone 10 parts deionized water)*
- *47 mm glass fiber filter paper*
- *Hach Spectrophotometer*
- *Cuvettes with 2.54 cm path length*
- *5 mL pipets*
- *0.1 N HCl*

This study utilized Clesceri's (1989) method for chlorophyll-a extraction. Where a filtered algae sample was macerated in a tissue grinder with 2-4 mLs of aqueous acetone solution for approximately 10 minutes, or until the filter paper was completely disintegrated. The samples were then steeped at 4^{o}C in darkness for 2 hours at minimum and 24 hours maximum. This extract was then clarified using a centrifuge for 20 minutes at 500g. If the solution remained cloudy after 20 minutes, it was placed back into the centrifuge for another 20 – 30 minutes. The now pure samples were carefully emptied into a cuvette with a 2.54 cm path length and placed into the spectrophotometer to measure optical density at 664 and 750 nm. Important to note, the destroyed filter paper should remain at the bottom of the test tube and not be carried by the solution into the cuvette. The extract was then acidified using 0.333 mLs of the 0.1 N HCl solution. Optical density at 665 and 750 nm was then recorded. Chlorophyll-a concentration was then measured using the equation 4.1 shown below.

Equation 4.1: This equation determines the concentration of chlorophyll-a in a water sample given the following parameters.

$$y = (26.7(664_b – 665_a)V_1)/V2 * L$$

Where…

- V_1 = *Volume of extract (L)*
- V_2 = *Volume of same* (m^3)
- *L = width of cuvette*
- $664_a/665_b$ = *optical densities before (a) and after (b) acidification*

Measuring the concentration of chlorophyll over each site allowed this study to determine the spatial distribution/variability of chlorophyll in Bass Lake after large algae blooms.

Equation 4.2: Determination of trophic state when given chlorophyll-a concentration (ug/L).

Additionally, a trophic state index value can be calculated using concentration of chlorophyll-a as the independent variable (Carlson, 1977). The equation for calculating trophic state index using chlorophyll-a is shown below as equation 4.2.

$$y = 30.6 + (9.81 * ln(x))$$

Phosphorus Concentration

This study utilized Hach's Method 8190 (2017) using the following supplies:

- *Total Phosphorus "Test 'N Tube" Reagent Set*
- *Deionized water*
- *DRB200 Reactor*
- *Hach Spectrophotometer*
- *Light Shield*
- *5 mL Pipet*
- *Test Tube Rack*

Phosphorus concentration (mg/L PO_4^{3-}) was derived by first preheating the DRB200 reactor to 150°C and selecting stored program #536 from the stored programs list in the Hach spectrophotometer. 5 mL of sample water was then added to a “Total and Acid Hydrolyzable Test Vial” followed by one “Potassium Persulfate Powder Pillow.” The solution then was cooked in the reactor for 30 minutes. When finished, the sample was placed on a test tube rack and allowed to cool back to room temperature. Once cooled, 2 mL of 1.54 N sodium hydroxide was added to the test tube. At this point, the tube was capped and shaken until thoroughly mixed then placed into the spectrophotometer’s 16mm cell holder. The sample was then covered to protect from outside light polluting the machines reading, and zeroed. Once zeroed, the contents of a “PhosVer 3 Powder Pillow” were added to the test tube which was then capped and shaken for 20-30 seconds. The reaction took approximately 2 minutes to complete. Once the reaction period was complete, the sample was placed again in the 16 mm cell holder, covered, and analyzed by the machine.

Determining phosphorus concentration was important for two reasons. Phosphorus is often the limiting nutrient in lakes for algal growth, meaning high phosphorus concentrations tend to suggest that the lake is able to support large algae blooms (Roelke and Buyukates, 2001). Additionally, another trophic state index value can be calculated given total phosphorus concentration using an equation from Carlson (1977). Carlson’s equation is shown below as equation 4.3.

Equation 4.3: Determination of trophic state when given phosphorus concentration (ug/L).

$$y = 14.42 * \ln(x) + 4.15$$

Trophic State Index Calculations

We can derive trophic state indexes from three different variables, two of which have already been discussed earlier in these methods (phosphorus and chlorophyll-a concentration). Secchi disk transparency can also be related to trophic state with equation 4.4 from Carlson (1977):

Equation 4.4: Determination of trophic state when given Secchi disk transparency depth (m).

$$y = 60 - 14.41 * \ln(x)$$

Where x = Secchi disk depth in meters

The three different trophic state index values determined using various water quality parameters (chlorophyll-a concentration, total phosphorus, and Secchi disk transparency) were then averaged for each site and input into ArcMap as an attribute value for each individual sector.

Image Analysis

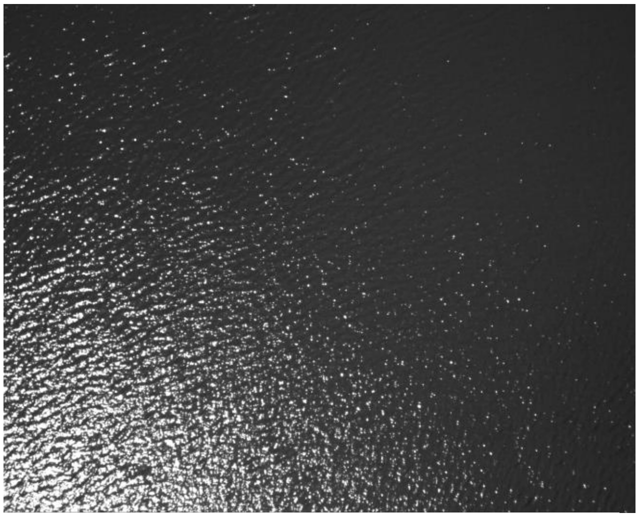

Figure 4.9: Image depicting the small waves used for image analysis on windy days.

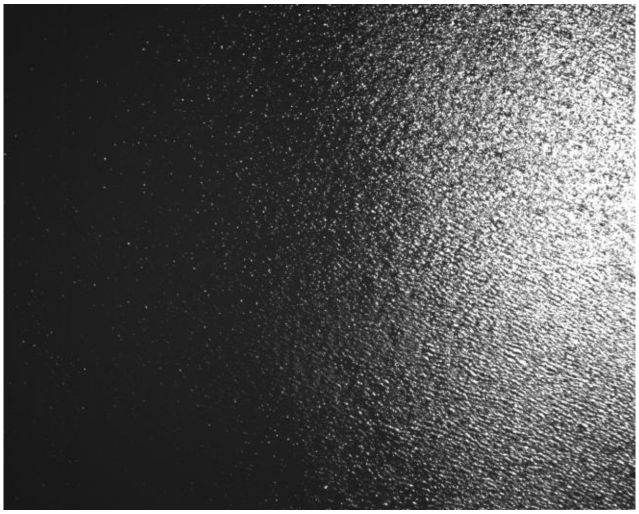

Figure 4.8: Image depicting waves that were not large enough to facilitate manual pixel sampling.

Once gathered, the images were extracted from the camera's external hard drive and input into Tetracam's image processing software, Pixelwrench for MCAW. Here, the images were geometrically corrected for the 6 – 10 cm lens offset exhibited by the Tetracam MCAW. Additionally, only the images with the correct timestamp were saved to ensure that the specific images over each sampling site were used for further processing. The geometrically corrected images were then moved into ERDAS Imagine where manual sampling of optimal pixels was conducted. Optimal pixels include those in the troughs of small waves found on Bass Lake during image acquisition (see Fig. 4.8). These pixels are prioritized since it is the darkest pixels that contain the best signal of algae in the water column being that they are the least contaminated by sky reflection or glint which is clearly visible in many of the images acquired. In fact, many images were rendered completely unusable because of such reflection/glint, and lack of waves large enough to produce dark areas suitable for manual pixel sampling (see Fig. 4.9).

Each image was analyzed using approximately 300 manually chosen pixel values across five different bands in the visible and near infrared spectrum for each site. The wavelengths of light utilized for this study were specifically chosen because of their utility in the measurement of chlorophyll-a concentration in estuarine waters (Ozbay et al., 2016). Although these bandwidths were originally used to determine chlorophyll-a concentration in saltwater, this investigation determines the efficacy of using the same bands in freshwater, while also utilizing same correction algorithm. The bands utilized in this study included three bands sensitive to chlorophyll-a absorption which were a near infrared (NIR) band at 710 nm, a 680 nm band, and a 650 nm band. It is important to note that the 650 nm 680 nm bands are the location of spectral peaks and troughs of chlorophyll-a respectively (Ozbay et al., 2016). Two additional bands located in the blue and green portions of the visible spectrum were used in the analysis to correct for suspended solids (490 nm) and color dissolved organic matter (560 nm) which may have otherwise influenced resulting pixel values. Pixel values from each band were then input

Equation 4.5: Pixel correction algorithm used to determine chlorophyll-a concentration (ug/L) using only band specific pixel values.

into the algorithm taken from Ozbay et al. (2016) averaged, and plotted against the experimentally derived chlorophyll value of the site. The equation retrieved from Ozbay et al. (2016) is shown below as equation 4.5.

$$(Avg(650 + 710) - 680)/(Avg(490 + 560))$$

CHAPTER 5: RESULTS

The primary objectives for this study were to determine the inadequacies of the MPCA's sampling method and to establish whether multispectral images can accurately determine chlorophyll-a concentration. Currently, at least two issues exist related to the spatial and temporal resolutions of their procedure. The MPCA's sampling method assumes spatial homogeneity of water quality and is temporally incapable of accounting for the dynamic nature of water quality across very short timescales. To remedy these problems, a weather station was utilized to determine the level of correspondence between specific weather parameters and the concentration/position of large algae blooms on Bass Lake. A continuous in-lake sonde was also used to remotely alert a sampler when chlorophyll-a values were abnormally high, suggesting a large algae bloom was present in the lake. Finally, an unmanned aerial vehicle (UAV) mounted multispectral imager was used alongside a more comprehensive sampling regime to determine the feasibility of implementing a monitoring protocol based on remote sensing approaches.

Weather Parameters

In addition to water quality monitoring using in-situ water samples and a continuous in-lake sonde, a weather station fixed to a lakeshore owner's dock was also used to understand what, if any, weather characteristics were correlative to predicting large algae blooms. This weather station constantly monitored and reported photosynthetic active radiation (PAR), air temperature, wind direction, and wind speed.

Algae in freshwater lakes are primarily photoautotrophic organisms, deriving their energy from solar radiation via photosynthesis (Wetzel, 2001). Since algae are dependent on this energy, careful measurements of PAR are helpful since increases in algal biomass can potentially be attributed to long periods of high light conditions (Lester et al., 1988). Generally speaking, PAR has a high daily variance since during the night there is no sun and midday the sun is directly overhead. However, there are a number of factors that can influence the daily variation of PAR values. For example, overcast skies drastically decrease the amount of sunlight that reaches the Earth’s surface. Relatively short-term weather phenomena play the largest role in affecting these daily and weekly PAR cycles. Additionally, PAR values can change significantly over much longer cyclic periods depending on season and location. Since Bass Lake is located at a relatively high latitude, the amount of sunlight it receives gradually decreases as you move from summer into autumn and increases from spring into summer. Figures 5.1 and 5.2 depict average daily PAR for Bass Lakes 2019 and 2020 field seasons respectively. In Figures 5.1 and 5.2,

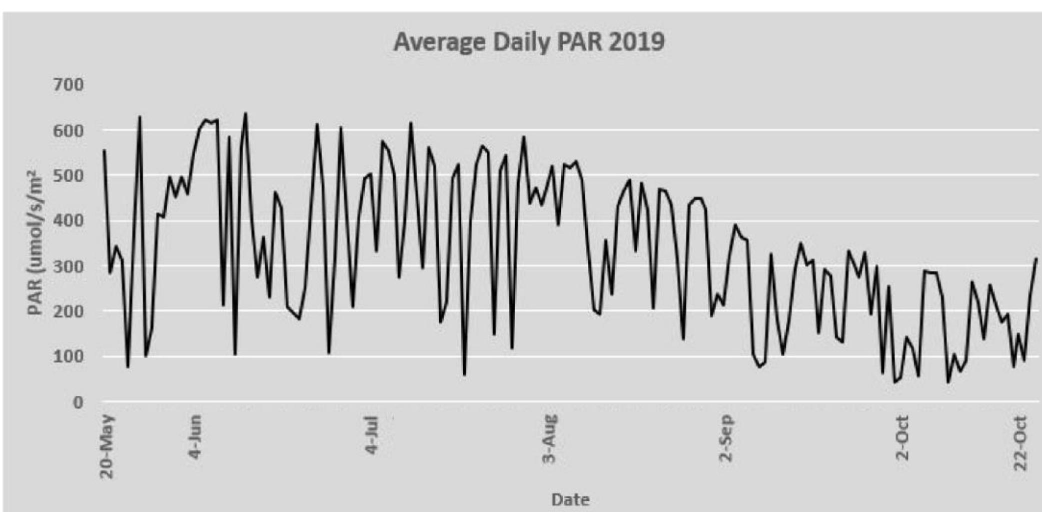

Figure 5.1: Average daily PAR in 2019 field season.

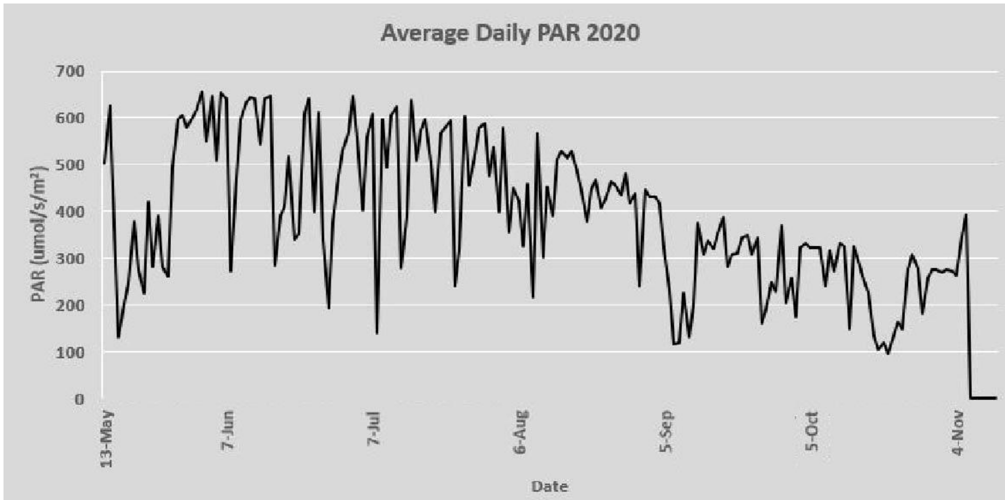

Figure 5.2: Average daily PAR in 2020 field season.

both the highly variable short-term PAR values and the long-term trend of gradually decreasing sunlight as the season progresses are observed.

Water temperatures greater than 25°C affect the growth of algae in freshwater primarily by interrupting cycling processes that mix lake water and would otherwise leave algae beneath the photic zone (Aleya et al., 2011). Strong thermal stratification inhibits this mixing and allows algae to remain in the upper water column where photosynthesis is most efficient (Lester et al., 1988). So, when water temperature rises, thermal stratification increases, and this promotes further growth in algal biomass. Additionally, algae replicate much faster in warmer water. This has to do with the production of enzymes and algae's ability to convert nutrients into usable forms (Singh and Singh, 2015). Water temperature is increased by high air temperatures in a couple ways: (1) by conduction and (2) by convection. Conduction in this case is simply the transfer of energy between the relatively high energy (high temperature) air molecules and the relatively low energy (low temperature) water molecules through direct contact of the surface of the water and air. Alternatively, since wind can cause mixing in the upper water column, convective currents arise from mixing created by wind (Chorus, 1999). Essentially, as wind blows across the surface of the water, it blows this warmer upper water column across the surface of the lake where it is replaced by the cooler water underneath. However, without wind these convective currents quickly die since the system is much more stable with the less dense warmer water on top of the denser cooler water.

Daily trends for air temperature are similar to PAR in that it generally peaks at max sunlight around midday and is at its lowest at night. This is because the more sunlight an area gets, the more energy that is available to warm the air in that area. Although increases in PAR values do generally correlate to increases in temperature, there are regional weather phenomena that can affect air temperature regardless of the amount of sunlight present in an area. For example, wind direction plays a large role in forecasting air temperature since south winds are generally much warmer than north winds. So, while consistently high PAR values do lead to higher air temperatures, there are other factors that can influence air temperature to a higher degree than PAR. Alternatively, water temperature is directly correlated to air temperature. This is because lakes have no external heating mechanism other than the air above them. Therefore, you can never have water that is hotter than the air above it for very long. Although the high specific heat of water allows it to retain energy at a far greater rate than is exhibited by the air overlying the water, warm water will eventually transfer its heat to overlying masses of cooler air. Conversely, colder water will absorb heat from the air until it is a similar temperature as the air above. Continuously, during both years of this investigation, the weather station and in-lake sonde collected concomitant air and water temperatures. Results for both air temperatures and water temperatures are shown below as Figures 5.3 and 5.3. It is important to note that in both parameters, water/air temperature are plotted as average daily temperatures.

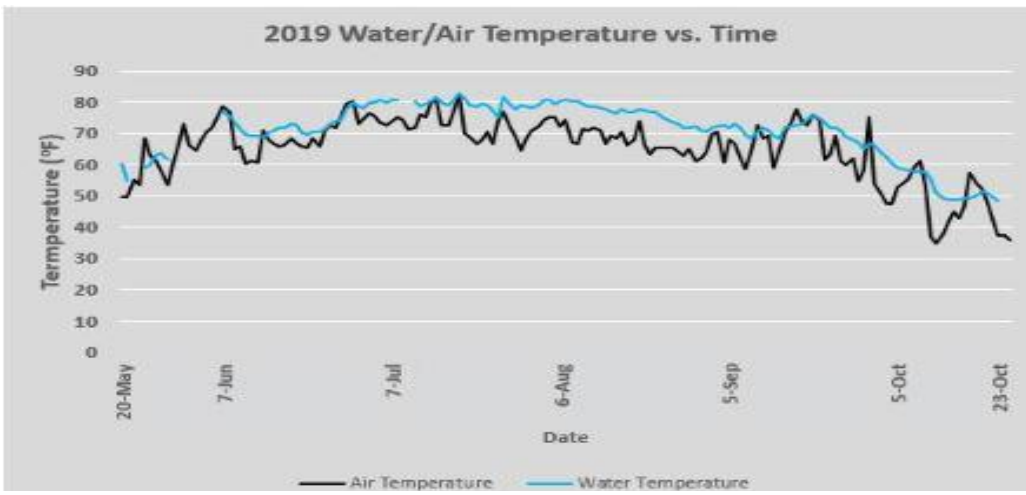

Figure 5.4: Illustration of the relationship between water temperature and air temperature in the year 2019.

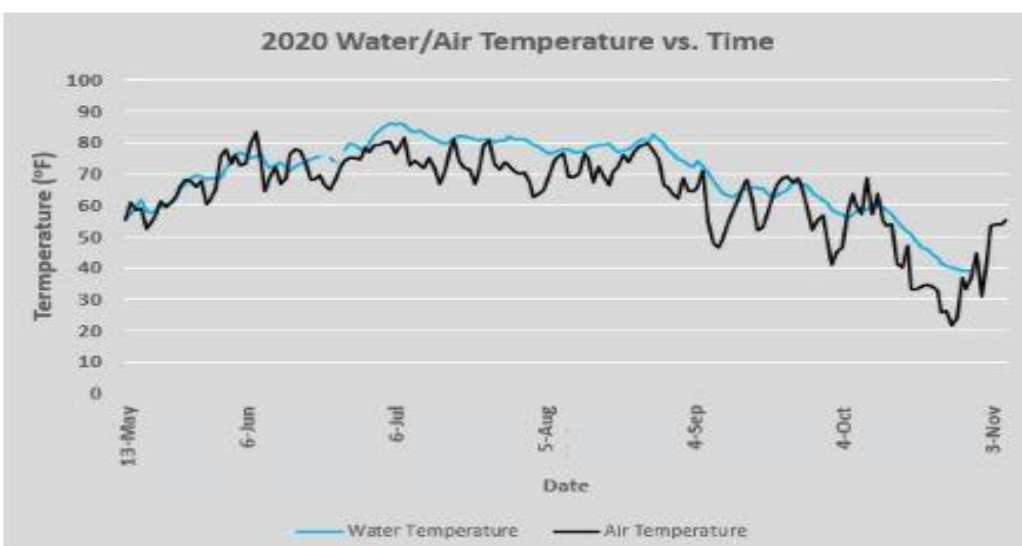

Figure 5.3: Illustration of the relationship between water temperature and air temperature in the year 2020.

Both water temperature and PAR play an important role in the growth of algae. Without any sunlight, photosynthesis cannot occur, and reproduction is impossible. Conversely, too much sunlight results in photoinhibition which damages chloroplasts and temporarily reduces the ability of algae to create the carbohydrates they use for survival (Chisti, 2007). Although the PAR levels required for photoinhibition are species specific, green algae tends to prefer irradiances as high as 2400 and as low as 400 umol $m^{-2}s^{-1}$ while cyanobacteria prefer a slightly lower irradiance range of 200 – 2000 umol $m^{-2}s^{-1}$ (Singh and Singh, 2015). Like PAR, water temperature also affects the growth of algae by influencing cellular chemical composition, the uptake of nutrients, and the fixation of CO_2 (Singh and Singh, 2015). Again, ideal temperature ranges are species specific and often result in different species of algae dominating a certain system through different seasons (Jonker and Faaij, 2013). However during summer, green algae and cyanobacteria are the most common species of algae because of their tolerance to both high temperatures and irradiances (Singh and Singh, 2015). The optimal temperatures for green algae tends to be approximately 15 – 30^{o}C, and 25 – 30^{o}C for cyanobacteria (Singh and Singh, 2015). Using temperature and PAR results from the weather station and sonde, the total time this optimum temperature and irradiance for both cyanobacteria and green algae was determined. Of the total 335 days recorded, 22% of this time was ideal for growth of green algae and 13% for cyanobacteria.

Wind speed and more importantly, direction, play a critical role in determining the position of large algae blooms on lakes (Chorus, 1999). Even relatively low wind speeds (2-3 m/s) in a consistent direction are capable of blowing the upper water column in the same direction as the wind (Chorus, 1999). This process plays a large role in the spatial position of algae due to photosynthesis increasing the buoyancy of the organism and resulting in diurnal migrations up the water column. This algae-enriched upper water column can then be blown to downwind sites on the lake resulting in heavy concentration of algae in these areas. This process is explained visually in Figure 5.5 below. The weather station used in this study was able to capture both wind speed and direction every 15 minutes. Using these data, the wind roses seen in Figures 5.6 and 5.7 were created for the 2019 and 2020 field seasons respectively. Note that a plurality of the wind blowing across Bass Lake is coming from the southeast at relatively high speeds. Alternatively, low speed westerly winds are also common in this area.

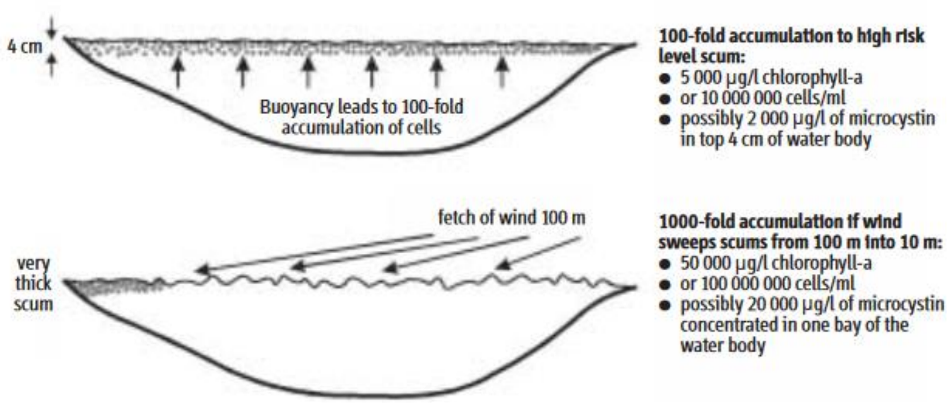

Figure 5.5: Illustration of how wind affects the spatial distribution of algae across a lake retrieved from Chorus (1999).

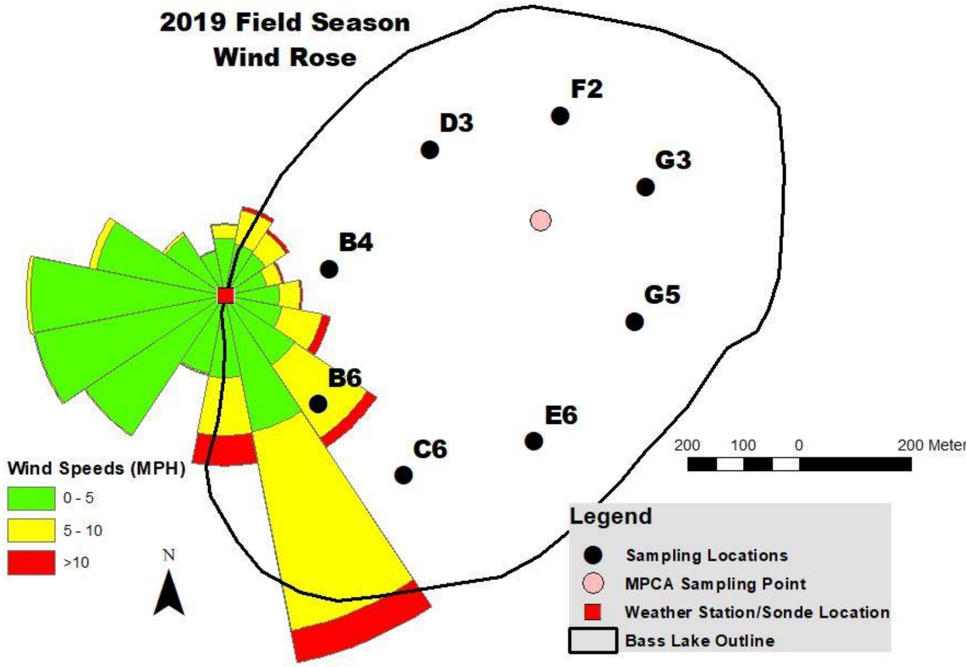

Figure 5.6: Visual depictions of how fast and in what direction wind is blowing across Bass Lake in the 2019 field season.

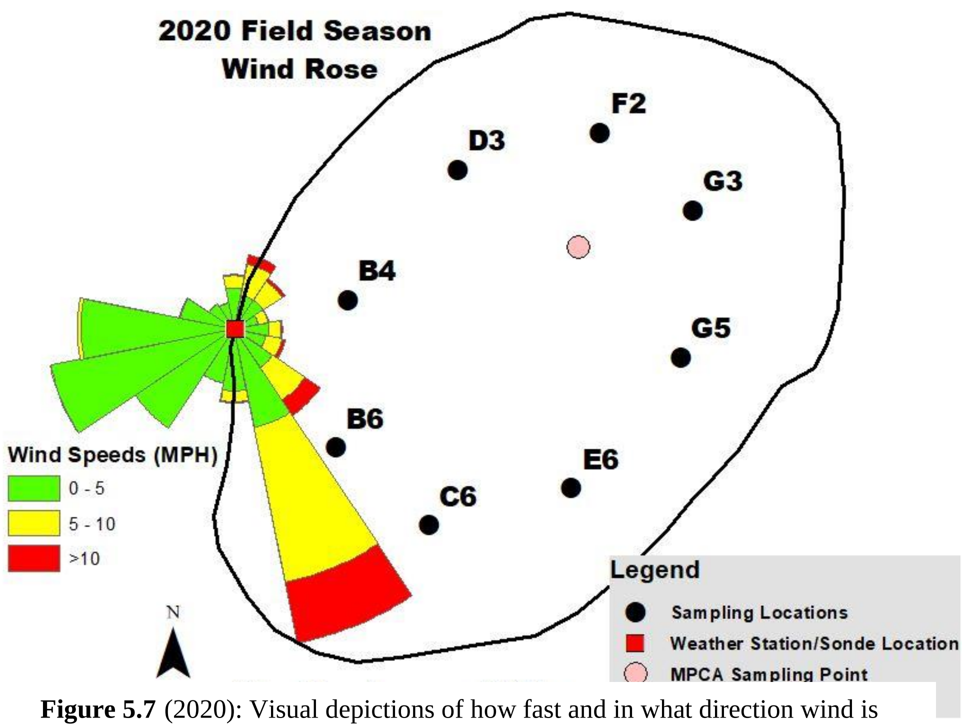

Figure 5.7 (2020): Visual depictions of how fast and in what direction wind is blowing across Bass Lake in the 2020 field season.

State Weather Data

The Minnesota Department of Natural Resources offers the ability to look at the average daily temperature, wind speed, and wind direction using automated weather stations named Automated Surface Observing Systems (ASOS). These systems are located around the country and are maintained by the National Weather Service (NWS) and the Federal Aviation Administration (FAA). Although many of these stations exist throughout Minnesota, many do not offer historic records of all weather parameters and instead only report rainfall accumulation. However, the stations maintained by the FAA which are located at or near airports offer a far more comprehensive daily weather report for the area. Using the data recorded from the FAA's weather station at the Mankato Regional Airport, located approximately 30 miles north of Bass Lake, a direct comparison between this study's average daily temperature results and the FAA's was created (see Figs. 5.8 and 5.9). Additionally, Figures 5.10 and 5.11 depict the FAA's wind direction and speed records as a wind rose. However, it is important to note that these wind data are also daily averages and exhibit much lower temporal resolution than the data reported by the weather station on Bass Lake.

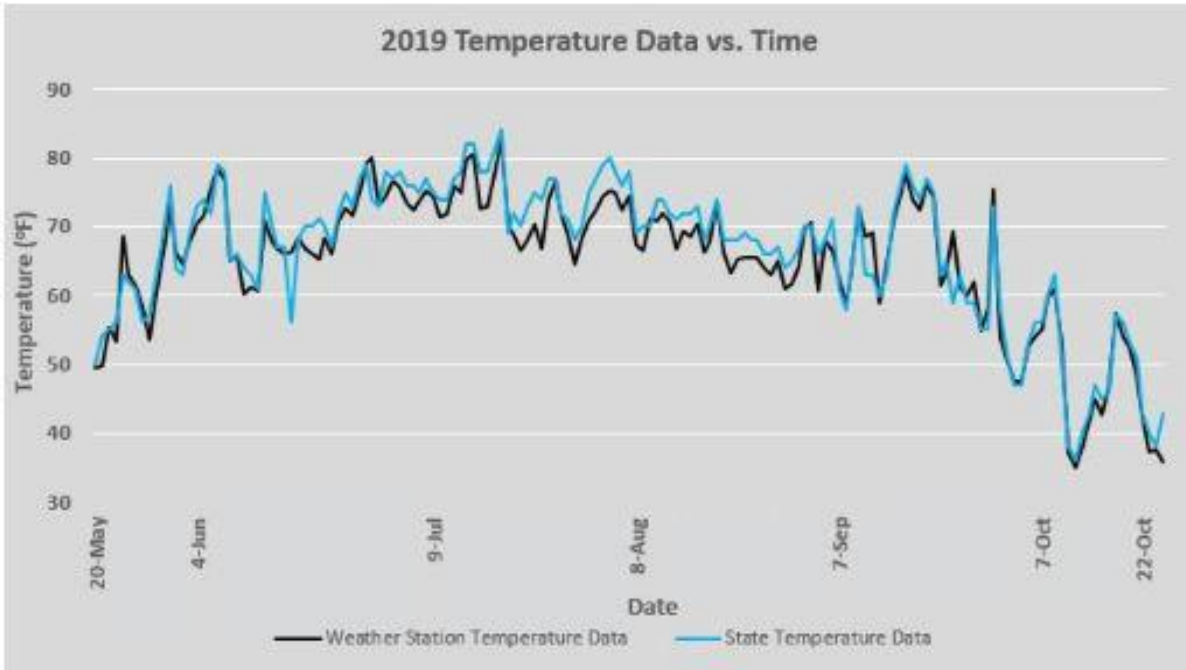

Figure 5.9: 2019 temperature data plotted from both the weather station located on Bass Lake and data collected the FAA weather station at Mankato Regional Airport.

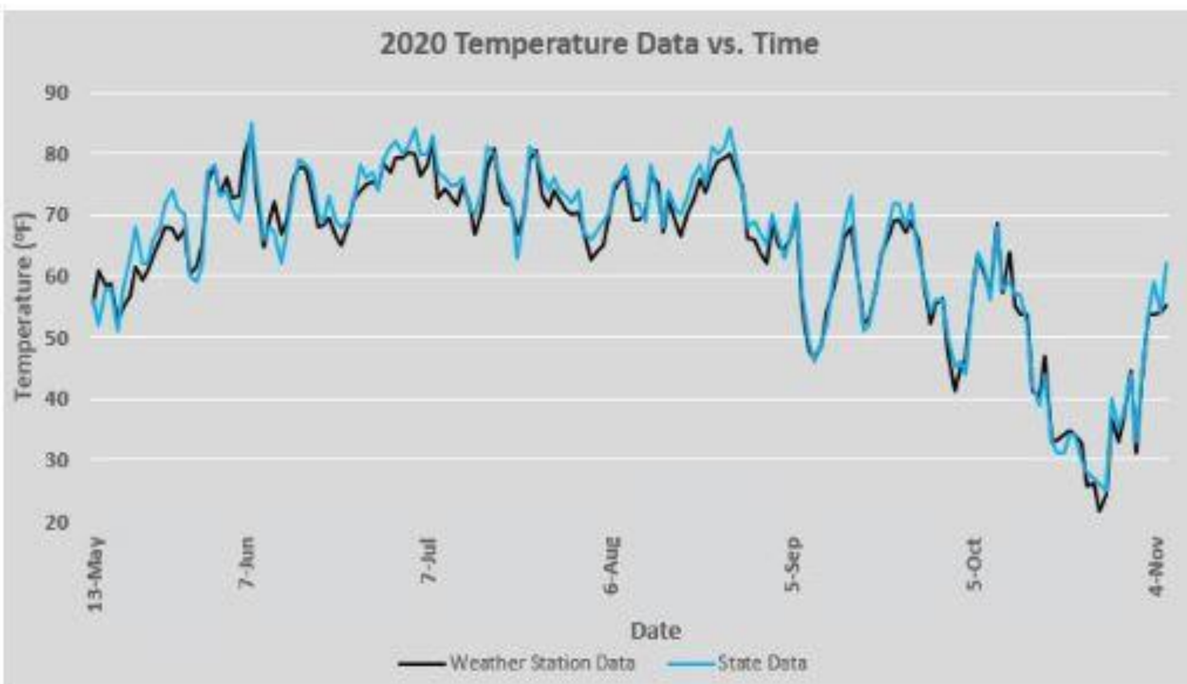

Figure 5.8: 2020 temperature data plotted from both the weather station located on Bass Lake and data collected the FAA weather station at Mankato Regional Airport.

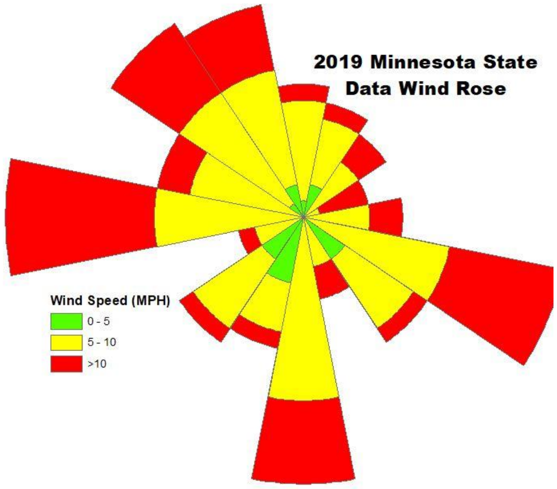

Figure 5.10: 2019 wind rose depiction of daily average wind speed and direction data taken from FFA records at the Mankato Regional Airport.

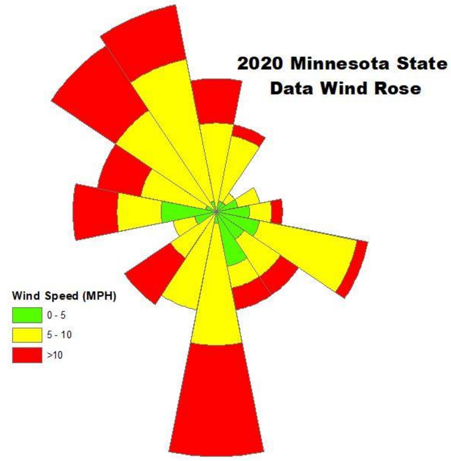

Figure 5.11: 2020 wind rose depiction of daily average wind speed and direction data taken from FFA records at the Mankato Regional Airport.

Individual Water Quality Characteristics

This study is primarily focused on water quality using trophic state as a defining variable. However, it is important to note that since trophic state is calculated using a composite of secchi disk transparency, total phosphorus, and chlorophyll-a concentration values, each of these parameters ought to be individually examined briefly for a holistic look at the overall water quality of Bass lake. Table 5.1 outlines the basic statistics of these variables alongside both this study's trophic state results and the MPCA's.

Table 5.1: Basic statistics of water quality parameters across both 2019 and 2020 sampling seasons.

	MEAN	**STANDARD DEVIATION**	**MINIMUM**	**MAXIMUM**	**RANGE**
TP (MG/L)	0.038	0.030	0.003	0.140	0.136
CHLOROPHYLL-A (UG/L)	27.00	14.86	1.40	74.60	73.20
SECCHI DISK DEPTH (M)	0.65	0.13	0.44	1.08	0.64
TROPHIC STATE	60.84	7.66	33.90	70.10	36.20
MPCA TROPHIC STATE	60.82	5.64	52.69	68.73	16.05

Spatial Variation of Trophic State

Trophic state is not a spatially homogenous variable. In larger lakes, the MPCA attempts to accommodate this condition by utilizing two or more sampling sites (Anderson et al., 2021); however, the agency uses only one sampling location within the relatively small shallow lakes like the one that is the focus of this study. Figures 5.12 and 5.13 graphically illustrate the spatial differences in trophic state observed in both the 2019 and 2020 field seasons. Appendix A includes the raw data used to create the spatial maps depicted in Figures 5.12 and 5.13. Disparities in trophic state between lake sectors were as high as 55% and of the 11 total sampling trips taken in 2019 and 2020, 6 of these trips (see Figs. 5.12 and 5.13) showed at least a 20% difference in trophic state between sectors. Additionally, trophic state from the MPCA site differed from the others by 5.6% on average. However, disparities over 10% were not uncommon occurring approximately once in every 7 samples.

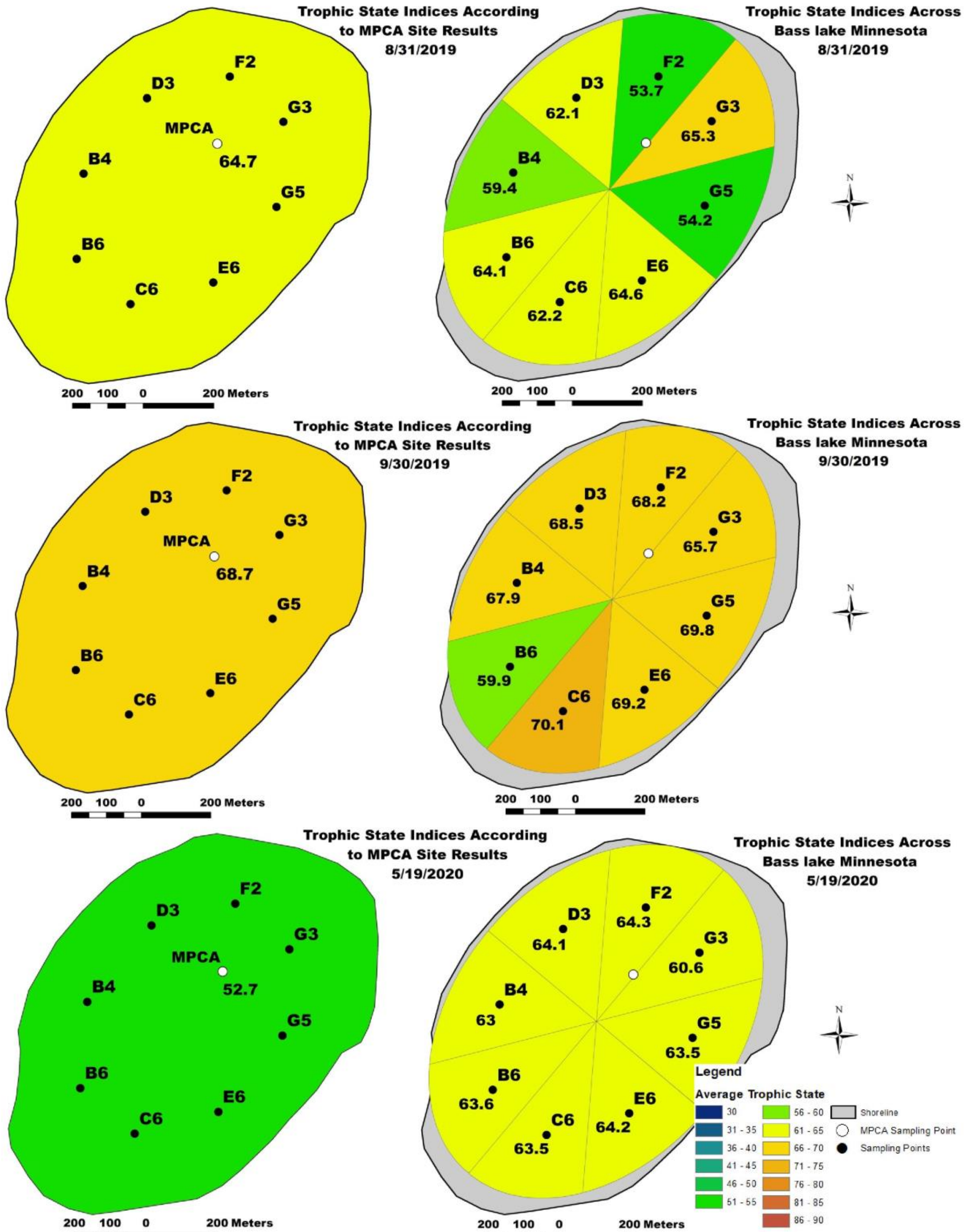

Figure 5.12: Graphic depictions of the spatial variability in trophic state on Bass Lake throughout the 2019 and 2020 field seasons.

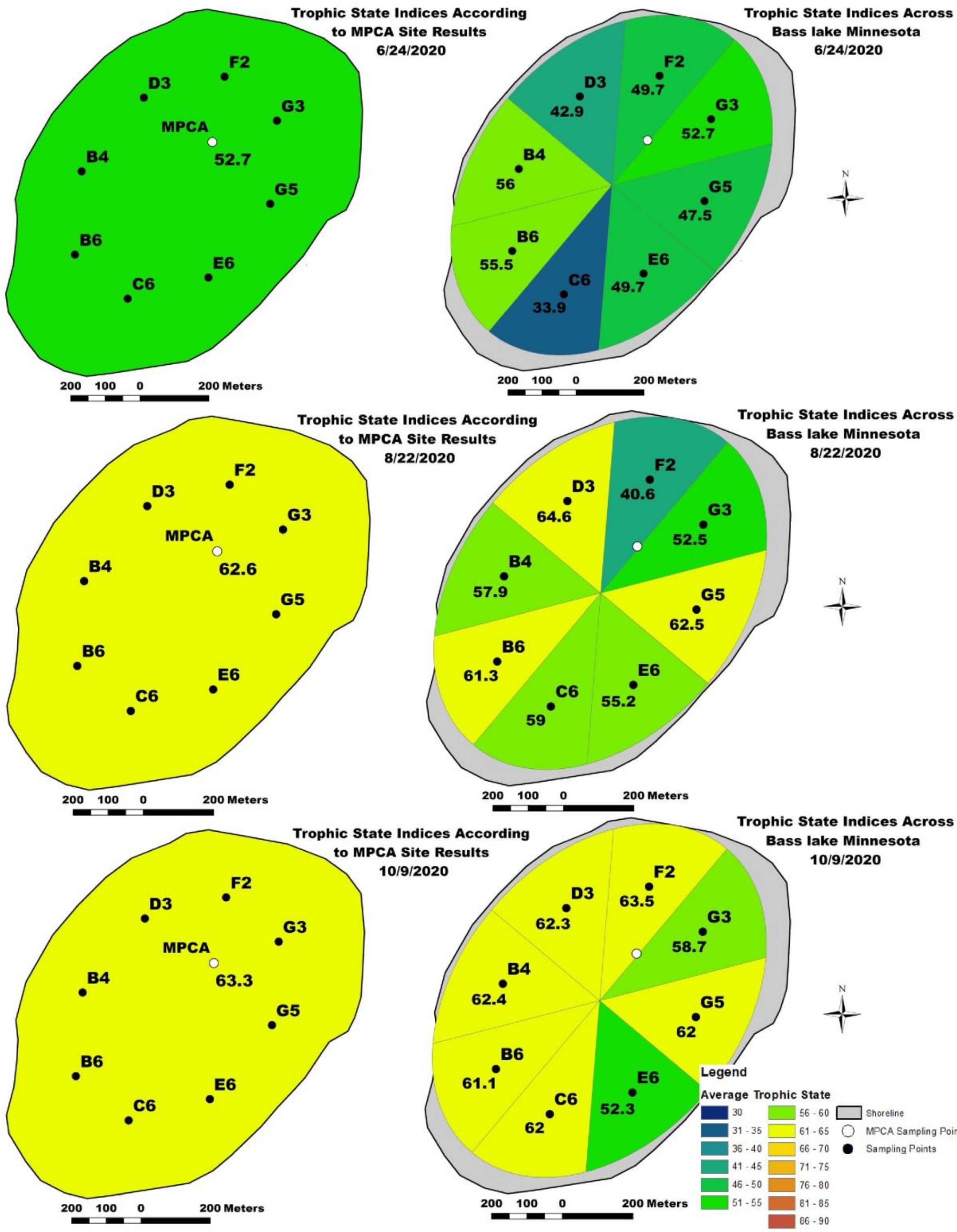

Figure 5.13: Graphic depictions of the spatial variability in trophic state on Bass Lake throughout the 2019 and 2020 field seasons.

Multispectral Image Analysis

The final objective of this study was to determine how accurately a UAV mounted multispectral imager is capable at determining chlorophyll-a concentration remotely. Of the 40 images acquired, five were lost to data corruption leaving a total of 35 images. Manually selected pixels in each of these images were corrected for instrumental and environmental distortion; they were then averaged and plotted against the experimentally derived chlorophyll-a values for each sampling site. Figure 5.14 illustrates the results and depicts two separate series of data. In this figure, the black colored points are the data used to create the linear trendline depicted on the chart. The red colored points are data excluded from the analysis since they were all taken during the same sampling trip (7/15/2020) and had completely undermined the existing trend observed with the rest of the data. Because these images were taken on the same day, it is likely that an operational or instrumental error caused these data to deviate significantly from their expected values. It is important to note that on no other sampling day did was a similar anomaly observed where all images taken at each site departed so noticeably from the primary trend of the rest of the data. The removal of these data improved the coefficient of determination of the plot from 0.05 to 0.4196.

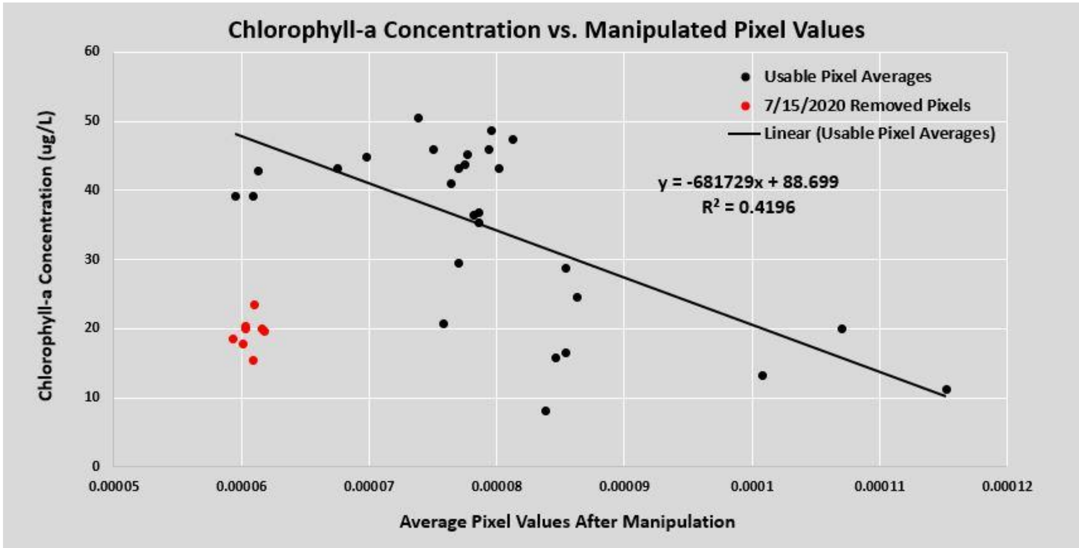

Figure 5.14: Plot describing the trend between averaged pixel value (after manipulation) against experimental chlorophyll-a values derived from in-situ water sampling.

Figure 5.15 outlines the path that the UAV flew during each flight. Additionally, image tiles are placed over each sampling point where they were originally taken. These photos are scaled, so the size of each image reflects the real-world field of view on Bass Lake. Below Figure 5.15, Figure 5.16 is a close-up on each of these RGB composite images.

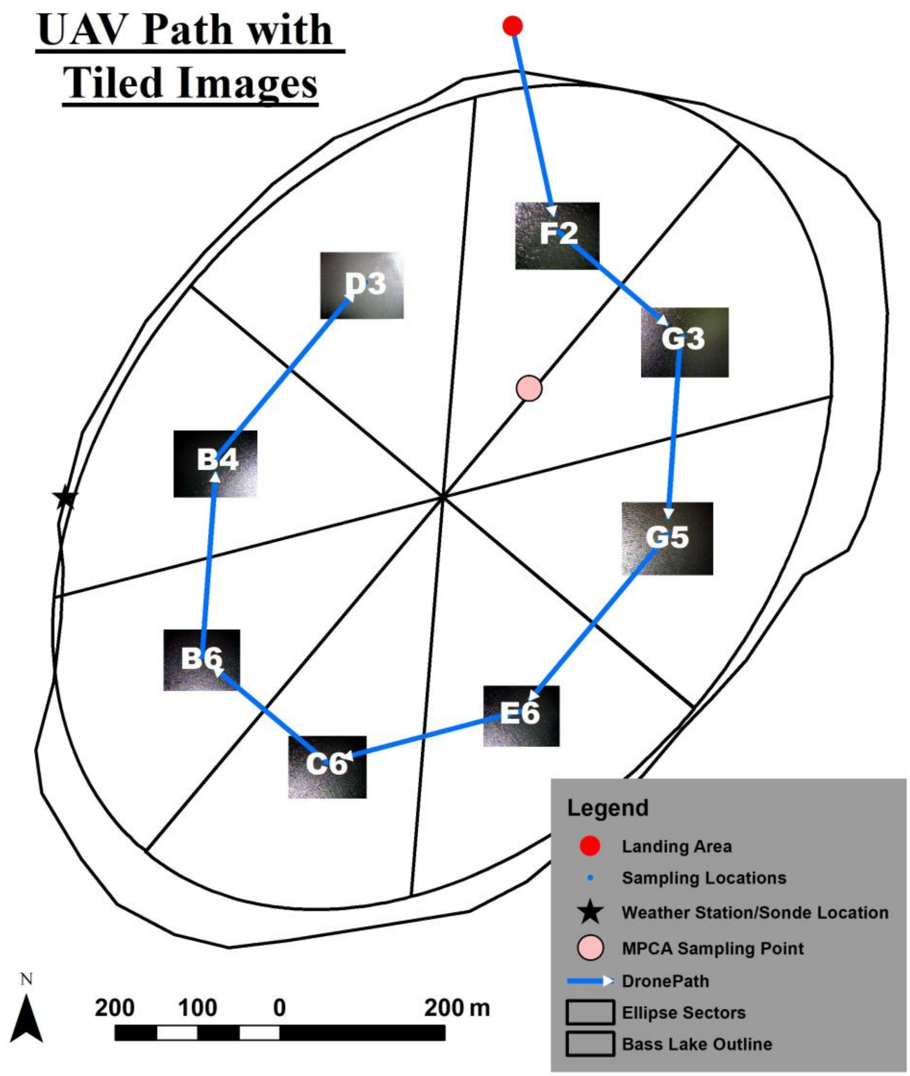

Figure 5.15: Shows the path of the UAV across all 8 field sites and illustrates the size of the field of view being imaged by the camera.

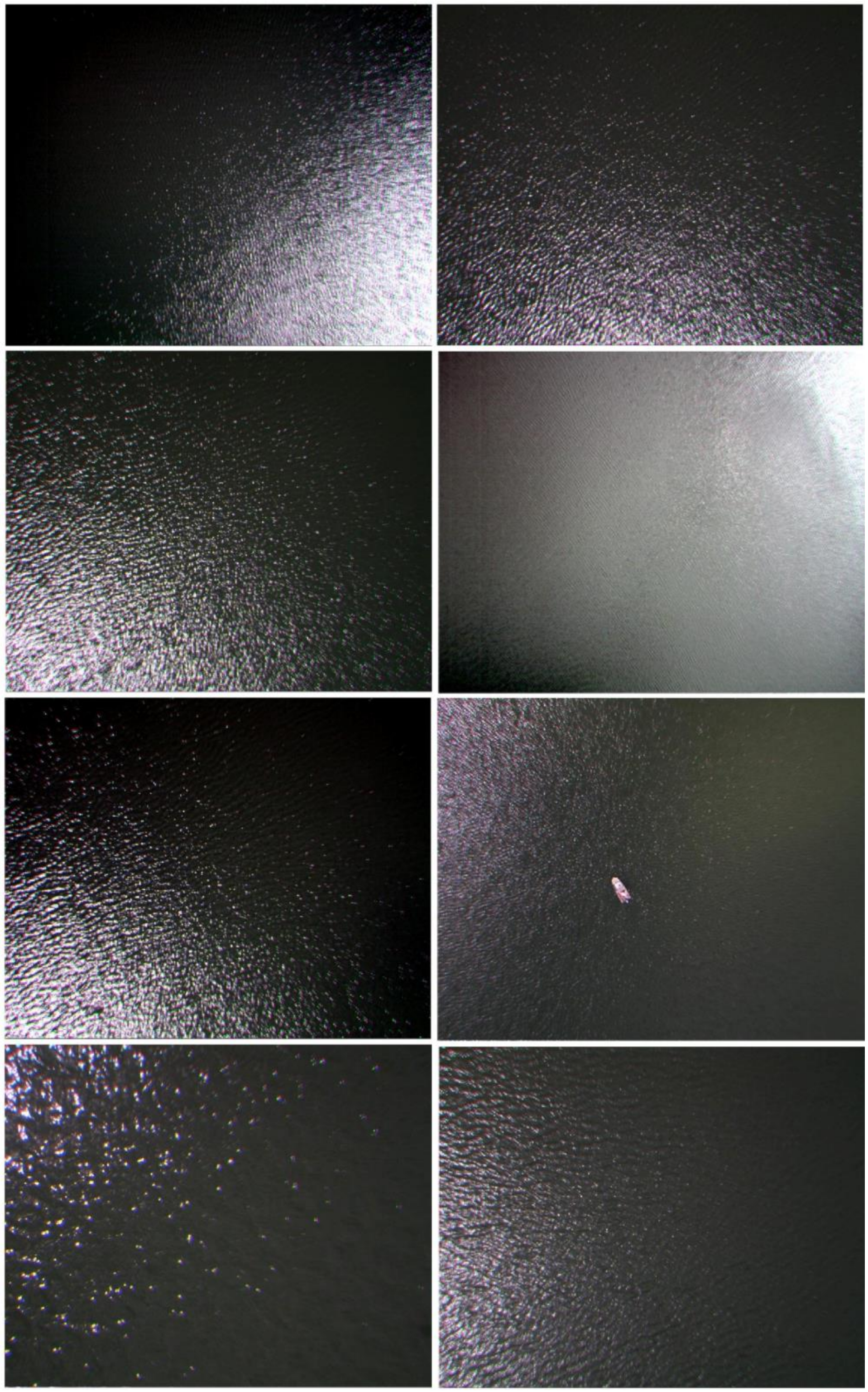

Figure 5.16: RGB composite images of field sites taken just after the 6/24/2020 sampling trip.

The equation that describes the relationship between chlorophyll-a concentration and pixel values is seen in Figure 5.14. Sampled pixel values were input back into Figure 5.14's equation to determine the efficacy of determining chlorophyll-a concentrations using the Tetracam MACAW and correction algorithm provided by Ozbay et al. (2016). These results are shown in Appendix B. Additionally, using these pixel derived chlorophyll-a concentrations, calculations of trophic state were made and plotted against the water sample derived trophic state values in Figure 5.17. Using these values, trophic state determined via pixel value deviated from the sample derived trophic state by approximately 4.1% on average. The highest deviation observed was on 6/24/2020, at site G5, where a 20.8% overestimate of trophic state was reported by the image. It is important to note that only seven images reported trophic state deviations higher than 5%. Although the number of images used in this analysis is low, the range in trophic states observed by this study in 2020 was relatively high. The fact that this procedure was able to accurately differentiate relatively low trophic states (50-55) from comparatively high trophic states (65-70), is remarkably promising.

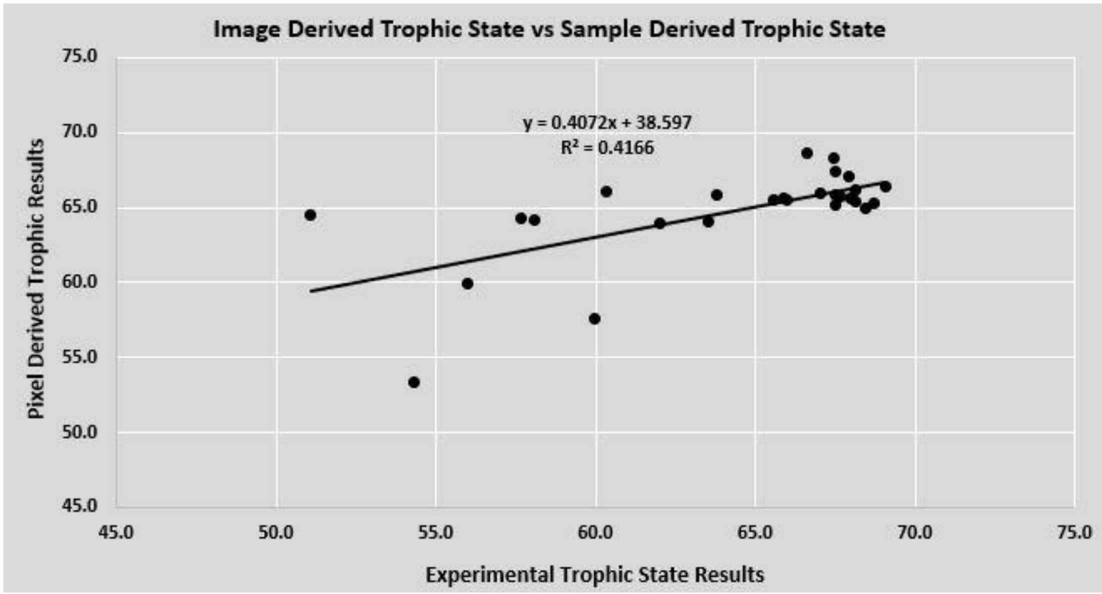

Figure 5.17: Plot of pixel derived trophic state vs. sample derived trophic state values.

Verifying the Accuracy of Secchi Disk Transparency, Total Phosphorus, and Chlorophyll-a Concentration Values Measured for this Study

Water quality results obtained by the laboratory instruments used in this study were directly compared to specific water quality parameters (Secchi disk transparency, total phosphorus, and chlorophyll-a concentration) determined by the MPCA to ensure their accuracy. During the 2019 field season, the MPCA conducted a parallel study of Bass Lake which gave a reference point for water quality parameter values developed in this study. Both the MPCA's results and the results of this study are listed in Table 5.2

where the right shows the MPCA data, and the left shows the parallel data collected for this study.

Table 5.2: Table compares the results obtained from this study's sites to the MPCA site. Variables SD, TP, and Chlorophyll-a stand for Secchi disk transparency measurement, total phosphorus, and chlorophyll-a concentration respectively.

Date	SD (m)	TP (mg/L)	Chlorophyll-a (ug/L)
6/19/2019	1.08	0.037	24.88
7/31/2019	0.63	0.056	45.55
8/31/2019	0.72	0.065	33.11
9/30/2019	0.48	0.078	48.7

Date	MPCA SD (m)	MPCA TP (mg/L)	MPCA Chlorophyll-a (ug/L)
6/13/2019	1.4	0.036	20.4
7/31/2019	0.7	0.051	31
8/29/2019	0.8	0.058	33.6
9/25/2019	0.6	0.068	42.2

Water quality characteristics measured in this study generally fall within the range of standard values for lakes in the "Western Corn Belt Plains" region of Minnesota (Heiskary et al., 1987). Heiskary notes that normal ranges of chlorophyll-a concentration and TP for this region are approximately 10 – 100 ug/L and 0.01 – 1 ug/L, respectively. Given this of information, both the results of this study and the MPCA are possible. The small differences between the results of this study and the MPCA are attributable to differences in sampling time, place, technique, and laboratory practices. Algae are dynamic organisms and without having access to the same exact water sample, seemingly large differences between separate sampling entities are not uncommon. Even with access to the same water, the MPCA's quality control samples differed by up to 15% from the originals illustrating exactly how unrealistic it is to expect low error tolerances (*Historic MPCA Water Quality Reports*, 2019). Heiskary and Wilson, (2008) also outlines the typical interquartile range of summer Secchi disk transparency measurements for the western corn belt plains to be anywhere from 0.5 to 1 meter which also characterizes the majority of this study's observations.

CHAPTER 6: DISCUSSION

Water quality is heavily influenced by weather parameters like photosynthetic active radiation (PAR) and wind speed/direction, and without the broader context that these weather parameters provide, meaningful interpretations of water quality parameters are impossible. For example, while high concentrations of algae and cyanobacteria can be attributed to nutrient loading (Schindler, 1974), they can also be attributed to abnormally warm and sunny periods (Singh and Singh, 2015). Additionally, wind plays a huge role in determining the spatial position of algae on a lake. Without an idea of how weather affects water quality parameters, there is no way to accurately associate increases/decreases in water quality to causal mechanisms. This is one of the key distinctions between the sampling method implemented in this study and the method employed by the MPCA. While the MPCA does have an idea of what is going on with certain water quality parameters in Bass Lake, their generalized assumptions inherent in their sampling strategy results in potential for error in their data – which may explain their inconsistent results for measured water quality parameters, notably chlorophyll-a, since 1981 (*Historic MPCA Water Quality Reports*, 2019). Here, parameters capable of influencing water quality rather than only the water quality itself were assessed. This allows for a more complete picture of the driving forces controlling water quality on a lake.

<u>Temperature, Photosynthetic Active Radiation, and Wind's effect on the Distribution of Water Quality Parameters</u>

When examining water quality over multiple sampling seasons, it is important to also explore how external variables can affect water quality characteristics. In this case, weather parameters, specifically air temperature, illustrate how the years 2019 and 2020, compare broadly to temperature trends in the last five years. Temperature data from 2015-2018 were retrieved from the FAA's weather station at the Mankato Regional Airport. These data were used to determine whether the years 2019 or 2020 exhibited statistically different temperatures from the past five years from May through October. In neither 2019 nor 2020 were statistically significant temperature differences observed at a significance level higher than 0.05 (P = 0.48 and P = 0.13 respectively). This is simply to say that 2019 and 2020 did not exhibit any exceptional temperature patterns which could have had influence on the usual behavior of algae in Bass Lake.

In addition to the average daily temperature data gathered from the years 2015 – 2018, average monthly temperature maps were used to further illustrate the normality of temperature data observed by this study in the years 2019 and 2020. These maps used average monthly temperature data from the years 1981 – 2010. An example of these maps is shown in Figure 6.1 where a star illustrates the location of Bass Lake (MN DNR, 2017). It is important to point out that Bass Lake resides in one of the warmest regions of Minnesota during the early spring and summer. This is noteworthy since land plants germinate more quickly when soil temperature increases (Egley, 1995). The quicker land plants can germinate, the quicker they are able to start using the nitrogen and phosphorus in the surrounding area and prevent these nutrients from entering local watersheds. Table 6.2 outlines monthly temperature data in 1981 – 2010 compared to average monthly temperature observed by this study in 2019 and 2020. Air temperature has stayed consistent, differing by only 3% in 2019 and 5% in 2020 on average. This disparity should not have had any serious effect on water quality parameters in the years 2019 and 2020.

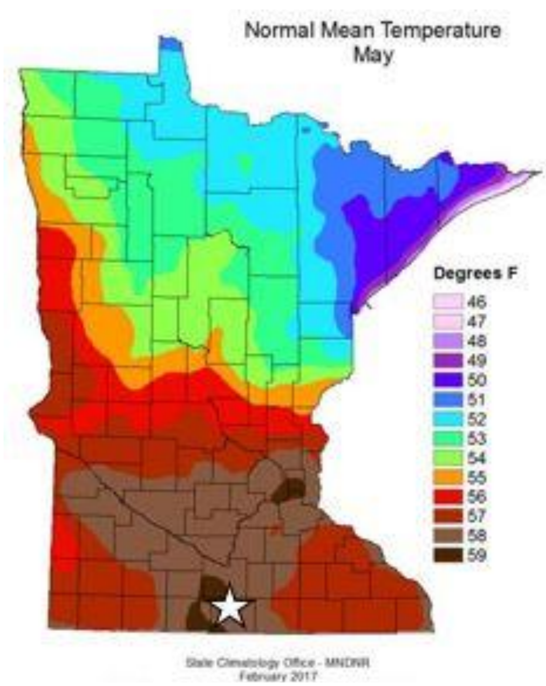

Figure 6.1: Map of Minnesota split by county depicting the average monthly temperatures of May by location.

Table 6.1: Average monthly temperatures of the Bass Lake area using data gathered from the MN DNR in the years 1981 – 2010 as well as monthly temperature data gathered by a weather station located on Bass Lake in the years 2019 and 2020.

Month	Average Temperature 1981 - 2010	Average Air Temperature 2019	Average Air Temperature 2020
May	58	59.4	61.3
June	68	69.9	72.9
July	72	72.9	74.6
August	69	68.4	71.4
September	61	66.7	60.7
October	48	47.4	43.5

Conversely, photosynthetic active radiation (PAR) values throughout the summer months (June – August) do appear to have impacted chlorophyll-a concentration in Bass

Lake. Figure 6.2 plots average daily chlorophyll-a concentration with average daily PAR. In this graph there are 3 notable spikes where chlorophyll-a had increased by 15% or greater. These periods of relatively high chlorophyll-a are circled in green on Figure 6.2. During these times, average daily PAR values were over 20% higher than average PAR values for the entire period of June – August. It is important to note that PAR is most likely to have its biggest effect on chlorophyll-a concentration during the summer months due to thermal stratification of the lake and lack of internal cycling mechanisms (Foy et

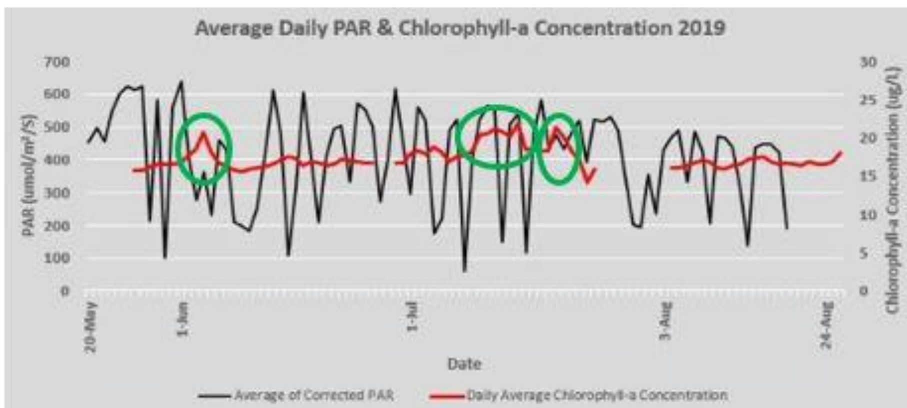

Figure 6.2: Average daily PAR and chlorophyll-a concentration on the same timeline. Green circles indicate periods of relatively high chlorophyll-a concentration

al., 1976). PAR tends to have a decreased effect on algal populations in the early spring and fall due to turnover events which force mixing of the lake and subsequently replenish key nutrients to the upper water column which keep chlorophyll concentrations high regardless of the generally decreased PAR values during these periods (Rigler, 1964).

As described in Chapter 5, wind can play a very important role in water quality studies by heavily concentrating certain areas of a lake in algae. Although this phenomenon was visually observed during many sampling trips, these areas of high chlorophyll-a concentration were located adjacent to the shoreline and did not extend far enough into open water to be observed at any of the nine sampling sites used in this study. However, during one such event, a grab sample was collected along the north shoreline to illustrate how concentrated these algae had become after only two days (10/8/2020 – 10/9/2020) of consistent wind direction. Figure 6.3 visualizes the wind speed/direction of the days just before and during the sampling trip. Figure 6.4 is an RGB image taken by another researcher approximately 300 meters west of the grab sample location along the north shore just one day prior to this study's sampling trip (10/8/2020) (Von-Korff, 2021). Figure 6.5 shows the southernmost field site (B6) directly compared using aerial photos of the large bloom that was concentrated on the north end of Bass Lake. Using an NDVI model, chlorophyll-a concentrations as high as 133 ug/L were reported by Von-Korff (2021). In the case of this study's more northeastern sampling location and later sampling date of 10/9/2020, chlorophyll-a concentration was over ten times greater (492 ug/L) than the average across all other sampling sites (42.3 ug/L). The southeast wind, which is omnipresent during this two-day period, is likely to blame for this event since it was able to blow the upper water column northward and lead to heavy enrichment of algal concentrations in the area.

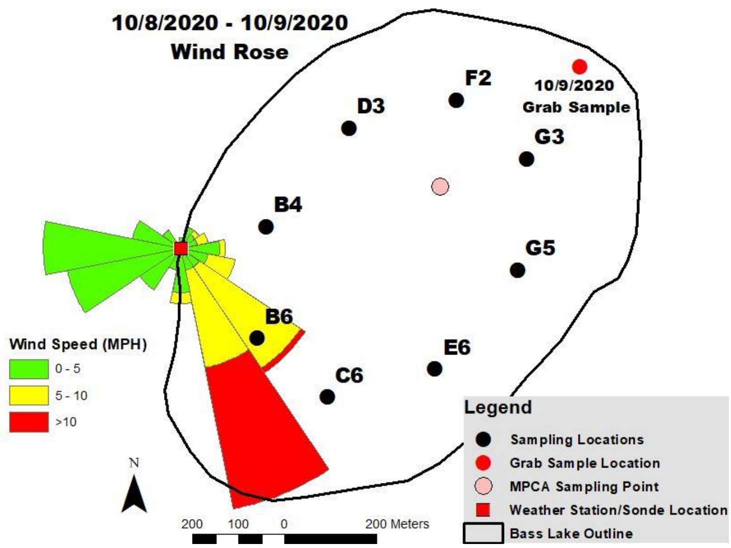

Figure 6.4: Map of Bass Lake with wind rose depicting a heavily prevalent southwest wind direction through a 2-day period (10/8/2020 – 10/9/2020).

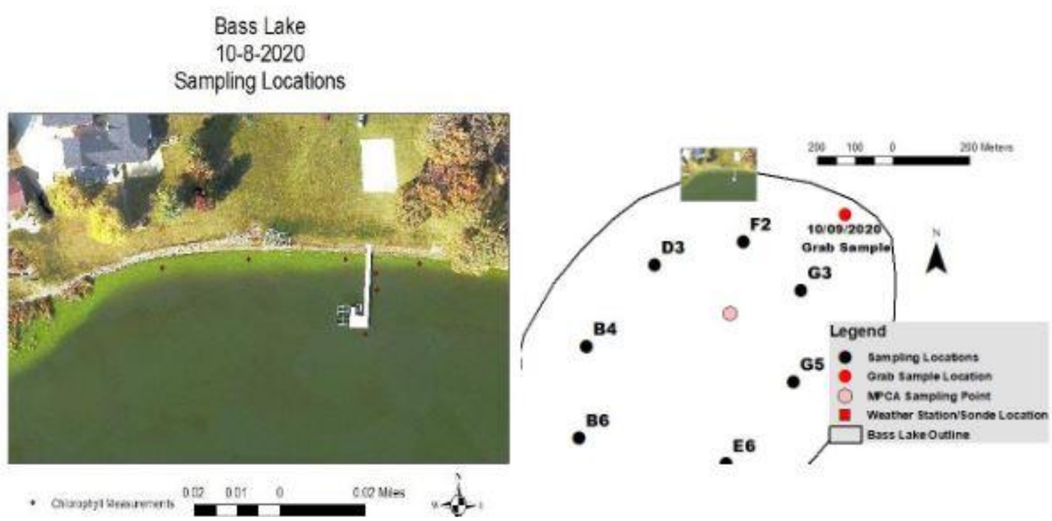

Figure 6.3: RGB image (left) retrieved from Von-Korff (2021) depicts the north shore of Bass Lake on 10/08/2020. The right image depicts where the RGB photo was taken in relation to the location of the grab sample obtained for this study.

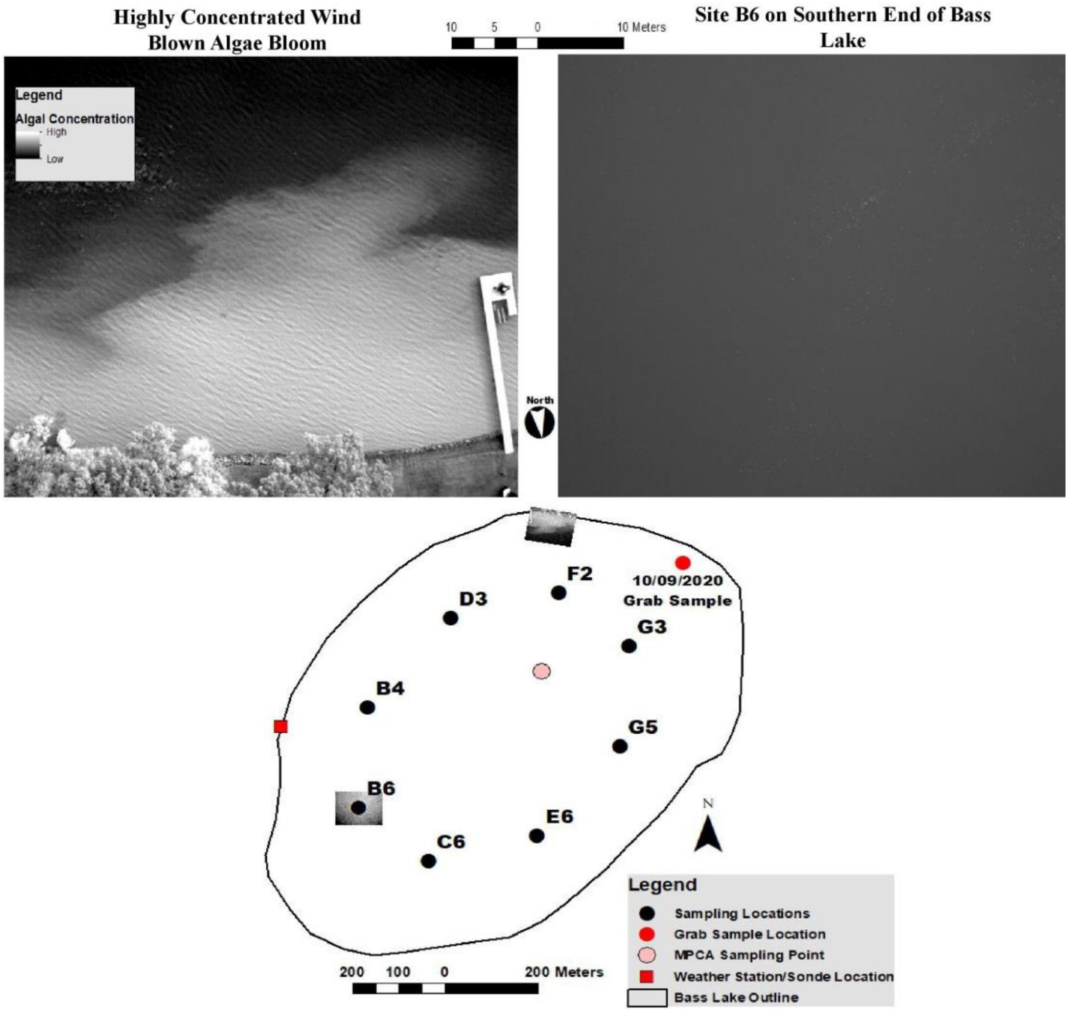

Figure 6.5: The images above are an illustration of winds effect on algae in Bass Lake. These aerial photos were taken 5 minutes apart at different ends of the same lake on 10/09/2020. These images are taken from a NIR band where lighter colors reflect a higher concentration of algae. The right image was taken over the site B6 while the left image was taken over the north shore of Bass Lake on 10/09/2020. The map just under the photos depicts where each of these images was taken.

Watershed Characteristics and Their Effect on Water Quality

Table 6.2: Series of watershed characteristics, what their effect on the uniformity of water quality should be, and how it was observed to actually affect water quality in Bass Lake.

Watershed Characteristic	**Uniformity/Nonuniformity of Water Quality Parameters**	**Observed Outcome**
Bathymetric Topography	Bowl shaped bathymetric topography should promote spatial uniformity of water quality parameters.	Surficial water quality varies significantly over space.
Shoreline Silhouette	Highly elliptical Shoreline should not affect the uniformity of water quality parameters.	Small variations in shoreline act as a sink for pollutants.
Land Use	Large agricultural presence in the surrounding area with numerous drainage tiles draining directly into the lake promotes nonuniformity of water quality parameters.	Observed areas close to shore do have significant differences in water quality compared to the rest of the lake.
Geomorphic History	Ice-walled lake plains leave behind fertile lake sediments rich in nutrients (Clayton et al., 2008) that eventually find their way into local watersheds via overland flow and through drainage tiles promoting Nonuniformity of water quality parameters.	Observed areas close to shore do have significant differences in water quality compared to the rest of the lake.
Heavy Boat Traffic	Heavy boat traffic promotes mixing and uniformity of water quality characteristics (Anthony and Downing, 2003).	Despite sampling on several weekends where boat traffic is highest, large spatial disparities in water quality were still observed.

Table 6.3 outlines how different characteristics of Bass Lake's watershed should affect the spatial and temporal uniformity of Bass lake's water quality parameters versus how they were observed to affect the water quality in Bass Lake. The bathymetric topography in Bass Lake is as simple and idealized as a real-world example can be (see Fig. 3.2). This near perfect bowl shape should have next to no effect on the spatial uniformity of water quality parameters (Wang et al., 2009) and despite that, there are obvious water quality discrepancies between different areas on the surface of the lake. In the same vein, the shoreline silhouette of Bass Lake is remarkably elliptical which should not have a serious effect on the distribution of nutrients in Bass Lake. Yet, the small variations that are present in the shoreline of Bass Lake, namely the small bay-like

elongation of Bass Lake's elliptical profile in its northeast, appear to act as a sink for algae and other pollutants. This concentration of algae was observed during the 10/09/2020 sampling trip where a large bloom was sampled in this northeastern area. Additionally, this phenomenon can also be seen in Figure 6.6 which shows an aerial photo of Bass Lake from 2006, where the northeast quadrant of the lake visually appears to be significantly more impaired than the rest of the lake. Also note, the source of this impaired water appears to be where the drainage tile pictured in Figure 3.2 drains into the lake.

Figure 6.6: Aerial photo taken from Google Earth of Bass Lake in 2006 depicting clear nonuniform water quality conditions especially in the northeastern quadrant of Bass Lake.

There is prolific agricultural development in the area surrounding Bass Lake. Additionally, numerous active drainage tiles exist which deliver agricultural runoff directly into the lake almost completely unfettered. This obviously affects the uniformity of water quality parameters in Bass Lake and is consistent with observations of poorer water quality in other corn belt lakes (Kalita et al., 2007). Specifically related to Bass Lake, these poorer water quality conditions were regularly observed close to the shoreline where these drainage tiles enter the lake. In addition to Figure 6.6, Figure 6.7 below offers another historic aerial photo of Bass lake in 2016 where a bloom is clearly visible and circled in red on the western shoreline. Although the exact cause of this bloom is impossible to surmise at this point, it is likely that drainage tiles or some sort of human development caused this highly localized algae bloom.

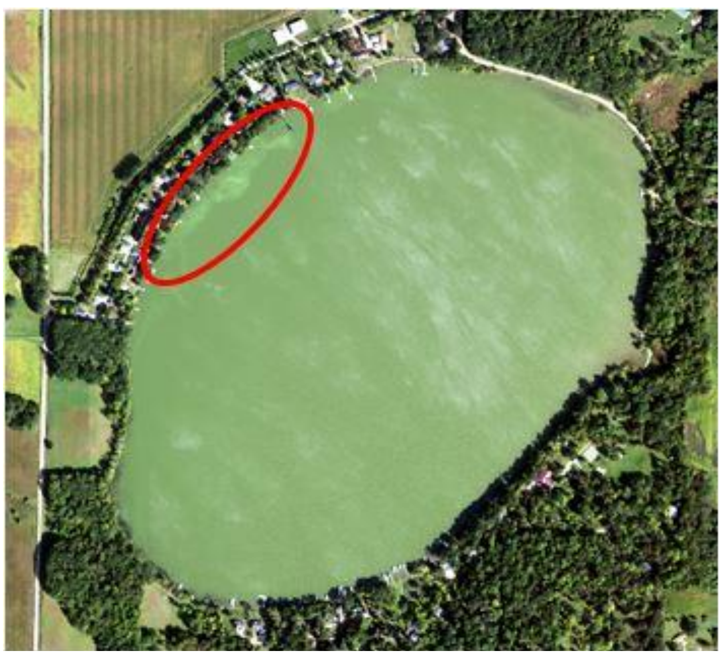

Figure 6.7: Image retrieved from Google Earth depicting a large algae bloom (outlined in red) along Bass Lake's western shoreline during 2016.

The ice-walled lake plains common to this area are incredibly rich in nutrients (Clayton et al., 2008). These nutrients, while ideal for agricultural development, do find their way into local watersheds through overland flow and through the drainage tiles that are now present in the Bass Lake area. In fact, the reason why these drainage tiles exist in the first place is explained by the geomorphic history of the area. Ice-walled lake plains are thick deposits of former lake and river sediment which make them high in nutrients but also very fine grained and generally impermeable. This impermeability means that flooding of these areas after rainfall events is common and is what requires agricultural developers to install these drainage tiles into their land. Additionally, wet prairie lake environments generally have abnormally long residence times (Allan et al., 1980). These longer residence times allow more time for nutrients to cycle in the lake and consequently increase trophic state more rapidly than normal. While this might not necessarily influence the spatial variability of water quality parameters, it certainly plays a role in long term temporal trends of water quality in Bass Lake.

Finally, the boat traffic on Bass Lake, particularly during Friday through Sunday is significant. Conceptually, boats do mix water (Anthony and Downing, 2003), and this would suggest that recreational boating might lead to more uniformity of water quality parameters. However, the results of this study do not support this assertion and instead strongly contradict it. Figures 5.12 and 5.13 show the most disparate sampling days between the MPCA site and the 8 sites used in this study. Half of these sampling days were on a weekend day where boat traffic was at its peak. Additionally, other research suggests heavy boat traffic actually has diminishing effects on water quality due to resuspension of deposited sediment (Anthony and Downing, 2003; Garrad and Hey, 1987).

Water Quality as a Spatially Dynamic Variable

The biggest point of contention between the sampling method employed by this study and the MPCA's sampling method is that the MPCA relies too heavily on a single water sample to verify the water quality in a lake that is hundreds of acres across. Currently, in lakes with simple shoreline silhouettes and no bays, the MPCA allows one sample to be used as a representative for water quality in the entire lake (Anderson et al., 2021). This assumption of homogenous water quality is not extended to all lakes in Minnesota. In fact, the MPCA acknowledges that bayed lakes require additional sampling sites since significant spatial differences in water quality are present between the primary water body and these bay areas (Anderson et al., 2021). This acknowledgement is central to this study since it is feasible that this idea ought to encompass all Minnesota lakes regardless of size/shape.

Figure 6.8 shows how the MPCA's results compare to the results of this study. This plot depicts the results of the MPCA site's trophic state against the trophic states observed across the entire lake. Each color is used to represent its own site and the different markers (triangle or diamond) are used to plot either year (2019 or 2020). An important observation here is the horizontal line of points just under the 55-horizontal gridline. These points come from two separate days of sampling. During these two sampling trips (5/19/2020 and 6/24/2020), the trophic state at the MPCA site was 52.7. This trophic state evaluation at the MPCA site over two separate sampling trips is what this seemingly misplaced line of points represents. It also perfectly illustrates how extremely varied water quality can be depending on sampling position in the lake. Since each different color point characterizes its own sampling site, and the MPCA site value is 52.7, the fact that there are points that stretch from (33.9, 52.7) to (64.1, 52.7) make the MPCA assertion that water quality is spatially homogenous incredibly tenuous. To state this a different way, the MPCA's trophic state evaluation of 52.7 on the days 5/19/2020 and 6/24/2020, is simultaneously underestimating the trophic state of Bass Lake by 18% and overestimating the trophic state by 56% depending on where the sample is taken from. Note that this graph is simply used to illustrate the obvious incongruence between the results of this study and the results of the MPCA.

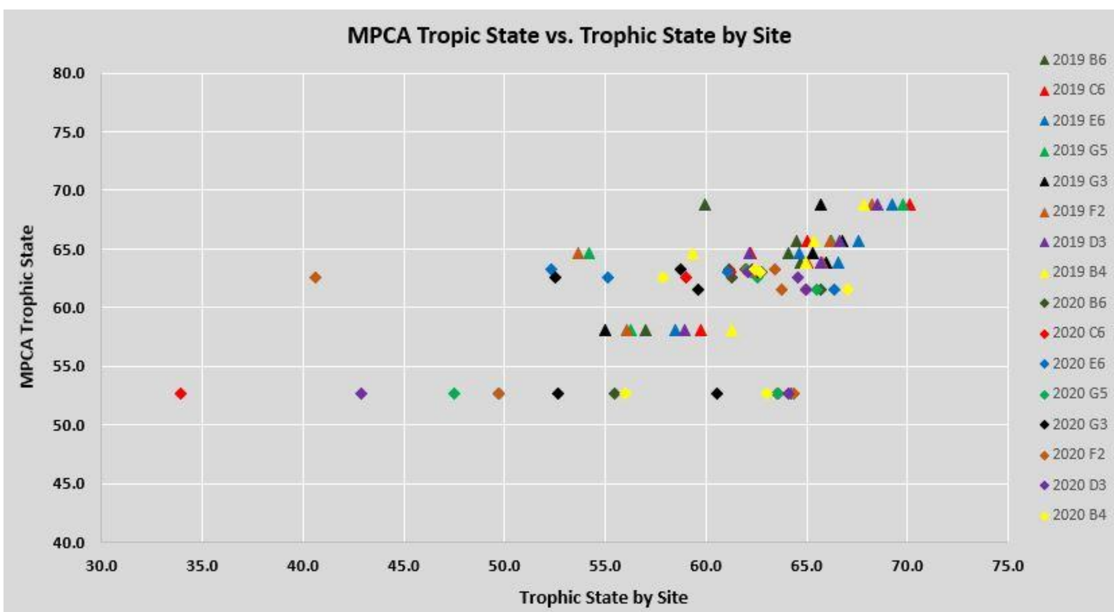

Figure 6. 8: Trophic state indices determined by the MPCA procedure plotted against trophic state indices determined from each MNSU study sampling site on the same day. All sites are shown as the same color and each year is plotted either with a triangle for the year 2019 or diamond for the year 2020.

If the water quality in Bass Lake was genuinely homogenous on any given day of the year, there would be no difference in trophic state values among any two samples from any two sites from any two areas of the lake. With the exception of early season water conditions in April and May, this is simply not the case. Figures 5.12 and 5.13 further illustrate that fact by depicting days where water quality varied by at least 20% between lake sectors. These results are especially poignant because they illustrate that spatial variability in small, eutrophic lakes that are similar to Bass Lake are actually common and potentially significant. The existing practice of acquiring a single sample from the location overlying the deepest point in the lake is not necessarily reflective of the distribution of water quality in the lake or even the average quality of the entire lake. The sampling trip on 5/19/2020 (see Fig. 5.15) perfectly illustrates the shortcomings of this method. For example, a trophic state of 52.7 was reported at the MPCA site, 15% lower than the lowest value from the other 8 sites and 20% lower than the mean. Although the MPCA did not sample in 2020, this sampling event illustrates just how variable water quality can be over a small area and why the MPCA sampling method can have unintentionally misleading consequences.

It is also important to consider Carlson's trophic state index scale and how imprecise it is when contrasting results in a 1:1 comparison. Carlson's scale ranges from zero to 100 so the difference between a trophic state of 50 and 55 would not seem to indicate a very meaningful distinction. However, it is important to consider the trophic state variability in a lake across a larger temporal scale. Realistically speaking, no lake will ever be so oligotrophic that it scores zero on Carlson's scale and in the same sampling season be so eutrophic that it scores 100 (Schindler, 1974). What this suggests is that small differences in trophic state observed across a body of water might be much more significant than Carlson's scale would suggest. To account for this, the same maps created in Figures 5.12 and 5.13 were re-symbolized as percent difference maps illustrating the offset between this study's results across all 8 sampling sites and the MPCA's single sample site. Additionally, to account for Bass Lake's trophic state variability over time, the trophic state values utilized by Figures 5.12 and 5.13 were normalized using the total observed range in trophic state values between the 2019 and 2020 field seasons rather than relying on Carlson's fixed range of 100. Between both sampling seasons, the maximum trophic state observed at a specific site was 70.1 and minimum 33.9, offering a total range of 36.2. Now, if the difference between a trophic state of 50 and 55 is again considered and normalized using the total observed range of trophic state values seen on Bass Lake, the distinction nearly triples from 5% using Carlson's zero – 100 scale, to approximately 14% using the calculated range of 36.2. The normalized values illustrated in Figure 6.9 paint a much different picture than the 1:1 comparisons shown in Figures 5.12 and 5.13.

Another concern related to Carlson's TSI scale is that its values are logarithms. This means that relatively small differences in trophic state equate to much larger differences in the parameter it reflects. Again, consider the difference between a trophic state of 50 and 55. The chlorophyll-a concentrations that would reflect these values are 7.2 and 12 ug/L respectively, meaning it would require a 66% increase in chlorophyll-a concentration to increase the trophic state of a body of water by five. In fact, every increase of five in Carlson's scale equates to a 66% increase in chlorophyll-a concentration. Referring back to the raw differences in trophic state values depicted in Figures 5.12 and 5.13, the up to 54% difference between the MPCA's and this study's trophic state evaluations is significant.

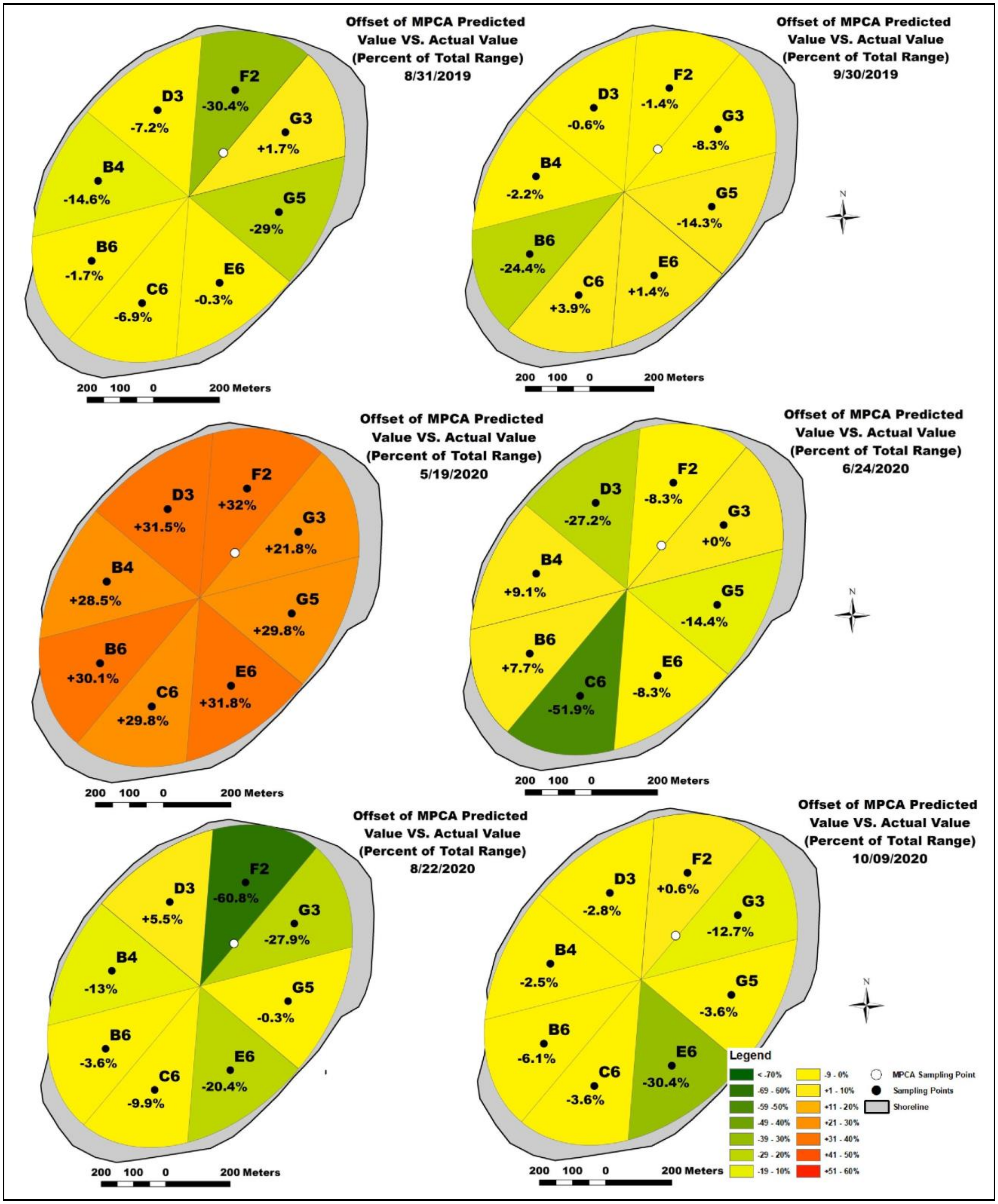

Figure 6.9: Spatial variation of water quality in Bass Lake symbolized as percent of the total range in trophic state values seen in Figures 5.12 and 5.13.

The general trend of Figure 6.9 mirrors that of Figures 5.12 and 5.13. However, the differences between the MPCA results and this study's are accentuated because of the comparatively small range of trophic state values observed in Bass Lake throughout the 2019 and 2020 field seasons are used instead of Carlson's full range. Simply put, the range of numbers that are never observed are removed from the analysis. When these ranges are removed by normalizing the difference in values to the total observed range of values, then the heterogenous distribution of water quality across these simple lakes is more realistically presented.

Water Quality as a Temporally Dynamic Variable

Being able to effectively manage every lake in Minnesota requires the MPCA to schedule sampling events months in advance to ensure there is enough time to adequately sample every lake on their docket in the 6-8-month sampling season. What this means is they are always unfamiliar with what the general conditions of the water will be when they go to sample a lake. Because water quality is known to change significantly during short duration of time (Kislik et al., 2018), the timing of sampling events is vitally important. Figures 6.10 and 6.11 illustrate exactly why this timing is so critical. On 6/13/2019, the MPCA sampled water that reflected baseline levels of chlorophyll-a. However, had their sampling event been scheduled only 3-4 days later, when the amount of chlorophyll-a in the water abruptly doubled, their perception of the lake would have been completely different. The lack of consistent, continuous observation on monitored lakes presents a large logistical challenge for the MPCA because any single, randomly selected sampling date may not be representative of the quality of water for the monthly, weekly, or even daily time period that is corresponding to their sampling event. This is further reiterated by the fact that the MPCA has repeatedly visited Bass Lake during 17 separate field seasons since 1981 and has observed both highly eutrophic and completely normal water quality characteristics for the area (Heiskary et al., 1987; *Historic MPCA Water Quality Reports*, 2019).

Figure 6.10 plots chlorophyll-a concentration vs. time and highlights dates of peak algal activity. To illustrate The MPCA's temporal shortcoming, Figure 6.11 plots one of the MPCA sampling dates on an excerpt of Figure 6.10 where only 3 days after an MPCA sampling trip, the concentration of chlorophyll-a abruptly doubles. The lack of continuous data and reliance on historic water quality data imposes a condition of chance into the MPCA's existing protocol. The new results from Bass Lake illustrate the fact that rapid responses to evolving water quality are necessary to more thoroughly characterize the overall quality of water in small, eutrophic lakes with respect to time.

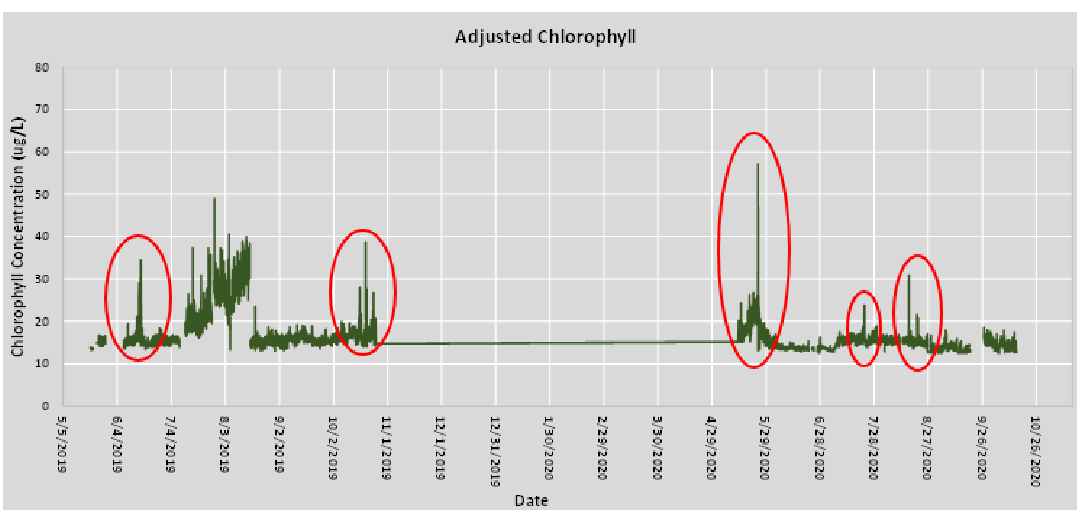

Figure 6.10: Graph of corrected chlorophyll-a concentration across both sampling seasons as reported by the continuous in-lake sonde utilized by this study. Periods of high chlorophyll-a concentration are circled in red.

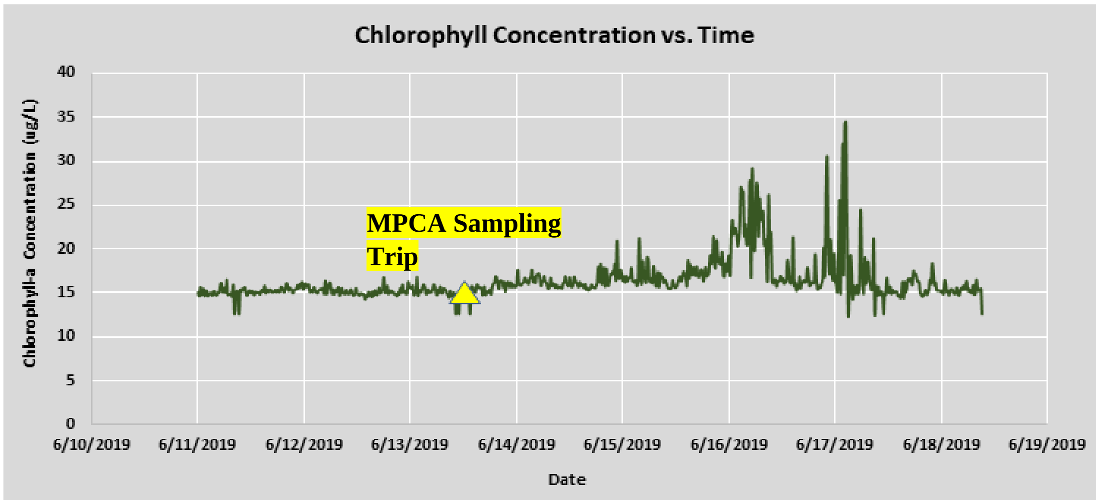

Figure 6.11: Excerpt of Figure 6.10 showing the presence of a large algae bloom just after an MPCA sampling date.

The water quality trends observed over the two years this study took place were fairly consistent over time. During the late spring – early summer and late summer – early fall, lake turnover events caused thorough mixing of Bass Lake and lead to peak algal activity during this time (see Fig. 6.10). Although this phenomenon was not observed by the sonde in the fall of 2020, the sampling event which took place on 10/09/2020 explained why the continuous in-lake sonde was unable to accurately portray how the turnover event affected the water quality in Bass Lake. What happened was, consistent southern winds over two days blew the upper water column northward and lead to heavy enrichment of important water quality parameters (TP and chlorophyll-a) along the northern shoreline (see Fig. 6.5 and 6.6). Given the sondes spatial position along the western shoreline, it was impossible for the sonde to see the decreased water quality. Note that Figures 5.12 and 5.13 depict days where water quality across the eight different sites utilized by this study differed from the MPCA site by 20% or more. Every one of these sampling days took place in these late spring – early summer and late summer – early fall time periods. It appears that the spatial distribution of water quality is most spatially disparate in the time leading up to and during these turnover events.

UAV Challenges and Future Improvements in Method

An important goal of this study is the improvement of water quality through the improvement of water quality monitoring methods. Currently, monitoring water resources is both cost and time prohibitive. To attempt to solve this problem, this study utilized a 6-band multispectral camera mounted underneath a multirotor UAV. Ideally, this system allowed for the “sampling” of water remotely by examining pixel values from multiple bands once the flight mission was complete. Because this sampling process is far less involved than in-situ water sampling, it drastically decreases the amount of time it takes to sample a large area. The time it takes to actively sample water across this study’s 8 field sites ranged from approximately 1 – 2 hours depending on weather conditions and the efficiency of the sampler. In contrast, the UAV was able to fly to each site, take its images, and return in less than 20 minutes, making this method a far more efficient way to measure specific water quality parameters across a vast area. Additionally, while the initial cost is substantial, this system would quickly pay for itself since each water sample taken by the MPCA costs anywhere from 300-500 dollars to analyze at a private lab. Alternatively, the UAV, camera, and image processing software costs very little to operate and as drones become more and more common, the initial cost will likely shrink as well (Ferro-Famil and Pottier, 2016).

Despite numerous challenges with image acquisition, processing, and pixel sampling, the multispectral image analysis used in this study produced a curve predicting chlorophyll-a concentration far more accurately than expected. One of the primary issues foreseen before starting the image processing procedure was the time at which water sampling would finish to subsequently fly the UAV and gather images. Generally, water sampling would be completed anytime from 11:00AM – 3:00PM meaning sky reflection and glint were at their peak (see Fig. 5.19) and appeared to completely wash out many of the images taken, leaving a significant portion of the image completely unreadable. To correct for this, manual pixel sampling of the darkest pixels in the troughs of waves were collected to drown out as much specular and sky reflection as possible. Although the trend illustrated by Figure 5.17 is weak, it is important to note these data only account for the 2020 field season leaving only 35 usable data points. Even so, the fact that these data were riddled with problems from the start, and still able to produce any meaningful correlation is remarkable. Significantly more data over multiple sampling seasons would be needed to verify the accuracy of this curve. Additionally, ironing out the many problems with the image acquisition method like sampling when sun angle is lower or during overcast skies would presumably increase the number of usable pixels in each image, making image processing a far more forgiving endeavor.

Although the coefficient of determination among the values of chlorophyll-a from laboratory analyses and those from aerial images is 0.4166, the calculated trophic state evaluations that result from these methods are highly comparable. Remotely sensed and laboratory chlorophyll-a values varied on average by 24.1%. However, this deviation only equates to an approximately 4% average variance in trophic state, or a flat difference of about two on Carlson's scale. Consequently, the images acquired by the multispectral imager appear to be an acceptable proxy for the samples that were acquired from single points in the lake and subsequently analyzed in the laboratory (Gordon and Morel, 2012; Ha et al., 2017; Rundquist and Han, 1997; Zeng et al., 2016). Although acquiring contiguous images of the entire lake was never intended to be part of this research, the accurate representation of trophic state within the eight 100m by 75m areas imaged during each flight facilitates an expanded assessment of spatial variability of water quality within the lake. This extended view confirms the calculated value of whole-lake, averaged trophic state and reinforces the contention that spatial heterogeneity in water quality parameters does exist within small, midwestern lakes similar to Bass Lake. Not only is the contention of heterogenous water quality reinforced by remotely sensed pixel values, but remote sensing could also amplify the spatial capability of in-situ water monitoring procedures. With calibrated pixel data, whole-lake assessments of trophic state at very high spatial resolutions are possible using methods similar to this study and Tóth et al. (2021).

Conclusions

This study's primary objective was to identify the potential pitfalls of the MPCA's water sampling method. Currently, the MPCA method fails to account for three important variables: The broader external parameters which can influence water quality characteristics, the spatial distribution of water quality across small lakes with relatively simple shoreline silhouettes, and the temporally dynamic nature of algal blooms which drastically change trophic state indicators on weekly timescales. Additionally, a secondary goal was to improve water monitoring methods through the use of UAV's and multispectral imaging.

The external parameters measured in this study were primarily weather related however, some specific watershed characteristics were also examined. Temperature data from the years 2019 and 2020 were compared to historic temperature data and were found to not have had any discernable effect on the water quality in Bass Lake. Higher average daily PAR values, especially during the summer months of 2019, did appear to weakly correlate to marked increases in chlorophyll-a concentration. However, wind speed and direction played a much clearer role in affecting the spatial position of all trophic state indicators tested in this study. The heavy enrichment of chlorophyll-a observed during the sampling event on 10/09/2020 along the northern shoreline and after consistent south winds, is clear evidence of wind's effect on water quality in Bass Lake. During this period, chlorophyll-a concentration was measured to be ten times greater than the average value across the other nine sampling sites.

In addition to weather parameters, certain watershed characteristics of Bass Lake were also examined to determine external factors which played a role in the water quality of Bass Lake. The relatively simple and elliptical nature of Bass Lake's shoreline is one of the factors that made it so attractive for this study since it was unlikely that such a simple shoreline would have had any discernable effect on the uniformity of water quality characteristics. However, despite Bass Lake's comparatively simple shoreline silhouette, small variations in Bass Lake's shoreline, specifically the elongation of its elliptical profile in the northeast quadrant, were observed to act as a sink for large algal blooms. Not only was this observed during the 2020 sampling season, but it is also depicted in historic photos which clearly demonstrate a lack of spatial homogeneity. Additionally, because the surrounding land use of the area is primarily agricultural, there are numerous drainage tiles that drain directly into Bass Lake. This direct path of nutrient input also plays a role in the spatial heterogeneity of water quality parameters and is likely the cause of a localized bloom along the western shoreline of Bass Lake in 2016. Finally, the heavy boat traffic experienced on Bass Lake, which was originally thought to have promoted nutrient mixing and subsequent uniformity of water quality, appeared to have either no effect or even increased the spatial heterogeneity of water quality in the lake. Despite sampling on a number of weekends, when boat traffic was highest, half of the most disparate results were observed during these periods.

Because the MPCA uses only a single water sample to represent small Minnesota lakes, their sampling method does not capture the spatial differences in water quality across the entire lake. This is demonstrated by this study in several ways, chief of which being that the MPCA was able to simultaneously overestimate and underestimate the water quality in Bass Lake. During 5/19/2020 and 6/24/2020, the MPCA site used by this study garnered a trophic state status of 52.7. However, the other 8 field sites used in this study ranged from trophic states as low as 33.9 and as high as 64.1. Were the MPCA's assumption of spatial homogeneity of water quality in small Minnesota lakes to be true, regardless of where Bass Lake was sampled from, the trophic state should have remained consistent across spatial position. In total, there were six sampling trips where trophic state at one of the 8 field sites used in this study deviated by at least 20% from the MPCA value. Additionally, Carlson's trophic state index compounds this problem since its large range of values is wholly gratuitous for its applications. No lake will ever be so oligotrophic that it will score zero on Carlson's scale and in the same season be so eutrophic that it scores 100. When only the trophic state values observed in Bass Lake are used in the analysis, the MPCA site underestimated trophic state by up to 61% and overestimated trophic state by up to 32% in the same sampling season.

As a result of the MPCA being required to schedule sampling events in months in advance, they are never familiar with what the general conditions of water quality will be or have been when they go to sample a lake. Since water quality parameters can change drastically under remarkably short timescales, the time at which the MPCA is able to capture samples is incredibly important. However, since the MPCA is unaware of what the prevailing water conditions are, they are vulnerable to drastically underestimate how poor the water quality can get. This was specifically observed in this study when on 6/13/2019, the MPCA sampled water from Bass Lake. Then, only two days later, a large algae bloom doubled the amount of chlorophyll-a observed from the in-lake sonde utilized by this study. This is simply to say that because of the MPCA's random sample times, they are unable to know when the best time to sample water from a lake will be.

Recommendations

This method of determining chlorophyll-a concentration via multispectral analysis shows promise in improving both the spatial and temporal accuracies of water monitoring methods especially on small eutrophic lakes in southern Minnesota. This is due to the fact it is far more feasible to fly over multiple areas of a lake and process those images rather than physically sampling from multiple areas and analyzing that water in a lab. Additionally, because simply flying a UAV over sampling sites is significantly less time consuming than in-situ water sampling, improving temporal accuracy through added sampling days would be far more logistically achievable. Also, the high number of these relatively small, shallow lakes in Minnesota makes high resolution in-situ water sampling exceedingly cost and time prohibitive. Were multispectral analysis to be included in water monitoring strategies, the cost of accurately observing the vast number of these lakes would be much lower and far more financially achievable, especially for a government institution with increasingly finite resources (Tóth et al., 2021). Additionally, other researchers were able to predict chlorophyll-a using UAV systems at a much higher accuracy (R = 0.88 – 0.96) than this study was able to (Tóth et al., 2021). Refinement of these remote sensing procedures will leave very little to no discernable deviation in trophic state between in-situ sampling and remotely sensed values.

Although this study only employed methods attempting to remotely determine chlorophyll-a, there are several cases where phosphorus concentration and water clarity have also been reliably predicted using satellite remote sensing technologies (Binding et al., 2018; Kislik et al., 2018; Klemas, 2012; Kutser, 2004; Kutser et al., 2006). This would suggest that similar methods could be used with UAVs to calculate trophic state using all three water quality parameters completely remotely.

How Can the MPCA Improve their Sampling Procedure?

Although the sampling method employed by this study is in some ways better than the MPCA approach, in some ways it is much worse especially regarding the amount of time it takes to sample a single lake. Since the MPCA only requires one sample for Bass Lake, they can be on and off the lake in less than 15 minutes. The method employed by this study required at minimum an hour to effectively sample the 8 sites in addition to the MPCA site. This is an incredibly important variable to consider when you are an organization responsible for the health of every impaired body of water in Minnesota. So, although this study's method may have a far higher spatial resolution, it comes at great cost. Additionally, standardization of this process would be incredibly difficult on lakes with a more complex shoreline silhouette. Adding additional field sites to Bass Lake was not especially complicated since the shoreline was already naturally elliptical. Furthermore, the idealized ellipse used in this study was able to cover over 90% of the lake area with almost no land inclusion. However, most lakes in Minnesota have a far more complex shape and splitting them into equal area sectors is a much less feasible solution if not impossible in most cases.

Tackling the MPCA's temporal challenge is an even more complicated issue since there are a number of obstacles at play; (1) The issues cannot be remedied by simply increasing the number of sampling events over time, (2) The MPCA cannot realistically be expected to have access to the amount of data that this study was given, and (3) There are numerous logistical challenges for a large-scale organization that make increasing temporal accuracy much more difficult.

Because of the dynamic nature of algal concentration in Minnesota lakes, increasing the number of sampling days still leaves plenty of room for error. Figures 6.11 and 6.12 illustrate just how high this resolution would need to be increased in order to completely "solve" this problem. Instead of randomly scheduling sampling trips 4-6 times per field season, the MPCA would need to sample water at least every 2 days to have a high enough resolution to reliably capture every bloom. Obviously, this would be a completely unrealistic and entirely wasteful standard to set for every impaired lake in Minnesota. So, instead of pressuring the MPCA to sample more, perhaps it would be more conducive to consider when the MPCA samples water and how they could choose more appropriate times to sample, something this study had considered and implemented in its monitoring strategy.

By mounting a sonde and weather station to a dock, this study was able to continuously monitor the water quality of the lake using chlorophyll-a as a proxy for overall water quality. In this study, when chlorophyll-a was high, a sampling trip was scheduled. This meant an opportunity was never missed to sample water when water quality was at its worst. Also, it offered something verifiable to aim for rather than scheduling sampling dates randomly with little to no knowledge of what the prevailing water conditions had been. However, the MPCA is responsible for countless acres of water and the expectation that they be able to monitor each of these water bodies with the same level of scrutiny that this study was able to is admittedly impractical. Additionally, having to juggle the general water quality of hundreds of lakes/streams all at once would be a huge organizational dilemma. For example, if many lakes were experiencing poor water quality at the same time, how would the MPCA decide which lake gets monitored that day or week and which lakes do not? What if the water quality does not ever deteriorate to a level which you deem necessary to sample? Who is going to regularly drive out to each lake to clean and maintain equipment? Every solution has numerous downstream consequences and although the MPCA does implement this strategy on some impaired lakes and rivers, expecting them to expand this process to all impaired water bodies is unrealistic.

Lastly, the logistical issues that come with monitoring thousands of lakes compound the temporal and spatial issues. Any accurate water monitoring process is an expensive and time consuming one. Consumable testing supplies, analyzing water samples using a private laboratory, boats, gas, labor, and time is just a taste of the number of variables being juggled by the MPCA at any given time, and every new lake added to their monitoring docket adds more and more variables to consider. Adding additional sampling sites to each lake to improve spatial resolution drastically increases the amount of time spent on each lake. This then decreases the amount of time they would otherwise have available to revisit the same lake to improve their temporal resolution. By trying to solve one problem you create new problems for a government organization that does not have infinite resources.

One solution that could potentially solve certain logistical challenges would be to involve local landowners in monitoring the lake they live on for the MPCA. This has already been partially implemented on some lakes where citizens will send Secchi disk transparency measurements to MPCA employees. In theory, this program could be expanded to encompass both water sampling and Secchi disk transparency measurements, meaning the MPCA would not have to visit public lakes to sample water anymore. However, this creates an entirely new set of challenges. Most importantly, training would be required to ensure the water samples being retrieved are acceptable and to ensure they know exactly where on the lake to sample from. Additionally, water samples need to be quickly frozen or analyzed after capture to maintain the accuracy of the data being collected. This presents another logistical problem since now not only do these landowners have to collect the samples, but they must also drop samples off somewhere for the MPCA to collect them. There is simply no panacea to the MPCA's problems here, a solution to one problem will always have a cast of other problems to take its place.

A Possible Future of Water Monitoring Procedures

Because increasing the MPCA's temporal and spatial resolutions using in-situ water samples might be realistically impossible, an important question to consider is: given the deficiencies inherent in the MPCA's sampling method on small Minnesota lakes, would the resources used by the MPCA be better spent elsewhere? To answer that question, consider the scale of what the MPCA has accomplished despite certain oversights in their monitoring procedure. They are responsible for over 32,000 individual monitoring stations across the entire state of Minnesota. The sheer volume of water under the MPCA's jurisdiction requires the organization to take certain liberties to ensure every lake in Minnesota is monitored at all. Although there are theoretical improvements that could be made to the MPCA's procedure, it is not as though the MPCA is completely incapable of obtaining useful data. This is illustrated by the fact that through the MPCA's extensive monitoring station network, they have evaluated over 2,900 lakes to be impaired. Without these monitoring stations, no impairment determinations could have been made, and no steps could have been taken to remediate bodies of water in poor health. Although the MPCA sampling procedure on small Minnesota lakes with a simple shoreline silhouette is far from perfect, it is capable of providing useful data to government officials and should not be discounted.

We should also consider that as remote sensing technology advances, the MPCA could employ the use of UAVs and multispectral imagers to dramatically increase the temporal and spatial resolutions of their monitoring strategy while drastically decreasing the costs associated with large-scale monitoring of the entire state of Minnesota. Unfortunately, because this field is relatively new, standardization of these methods has yet to be established, but recent studies have proven to be incredibly promising at reliably predicting trophic state indicators remotely. So, while there are current issues in the MPCA's procedure, it is likely these issues will be solved as monitoring technology and methods continue to improve.

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Appendices

Appendix A: Shows Secchi disk (SD) transparency depth in meters, the trophic state index based on secchi disk depth (TSI SD), total phosphorus in mg/L (TP), the trophic state index based on total phosphorus (TSI TP), concentration of chlorophyll in ug/L (Chl-a), trophic state index based on chlorophyll concentration (TSI Chl-a), and finally the mean trophic state index based on the 3 calculated trophic state indices. The BD abbreviation indicates a phosphorus value that was below the detection of the lab instrument used in this study (< 0.054 ug/L).

Date	*Site*	*SD (m)*	*TSI (SD)*	*TP (ug/L)*	*TSI (TP)*	*Chl-a (ug/L)*	*TSI (Chl-a)*	*AVG TSI*
8/31/2019	**MPCA**	**0.72**	**64.7**	**0.065**	**64.4**	**33.11**	**64.9**	**64.7**
	B6	0.7	65.1	0.065	64.4	26.28	62.7	64.1
	C6	0.68	65.6	0.071	65.7	12.61	55.5	62.2
	E6	0.7	65.1	0.065	64.4	31.01	64.3	64.6
	G5	0.69	65.3	0.006	31.0	37.84	66.2	54.2
	G3	0.71	64.9	0.065	64.4	39.24	66.6	65.3
	F2	0.72	64.7	0.006	31.0	34.16	65.2	53.7
	D3	0.75	64.1	0.047	59.6	26.28	62.7	62.1
	B4	0.74	64.3	0.022	48.7	33.64	65.1	59.4
9/30/2019	**MPCA**	**0.48**	**70.6**	**0.078**	**66.9**	**48.70**	**68.7**	**68.7**
	B6	0.5	70.0	0.013	40.7	50.50	69.1	59.9
	C6	0.51	69.7	0.099	70.5	57.10	70.3	70.1
	E6	0.58	67.8	0.109	71.7	45.60	68.1	69.2
	G5	0.57	68.1	0.112	72.1	50.80	69.1	69.8
	G3	0.44	71.8	0.040	57.5	43.80	67.7	65.7
	F2	0.54	68.9	0.078	66.9	49.80	68.9	68.2
	D3	0.53	69.1	0.093	69.5	40.30	66.9	68.5
	B4	0.5	70.0	0.065	64.4	51.20	69.2	67.9
5/19/2020	**MPCA**	**0.55**	**68.6**	**0.050**	**60.5**	**6.70**	**49.3**	**52.7**
	B6	0.59	67.6	0.068	65.1	16.50	58.1	63.6
	C6	0.54	68.9	0.044	58.6	27.70	63.2	63.5
	E6	0.56	68.4	0.059	63.0	23.10	61.4	64.2
	G5	0.58	67.8	0.047	59.6	27.70	63.2	63.5
	G3	0.53	69.1	0.025	50.6	24.50	62.0	60.6
	F2	0.57	68.1	0.053	61.4	28.70	63.5	64.3
	D3	0.6	67.4	0.053	61.4	28.70	63.5	64.1
	B4	0.6	67.4	0.047	59.6	24.90	62.1	63.0
6/24/2020	**MPCA**			**BD**		**9.50**	**52.7**	**52.7**
	B6			0.003	21.6	12.60	55.5	55.5
	C6			0.059	63.0	1.40	33.9	33.9
	E6			0.140	75.4	7.00	49.7	49.7
	G5			BD		5.60	47.5	47.5
	G3			0.124	73.7	9.50	52.7	52.7
	F2			0.013	40.7	7.00	49.7	49.7
	D3			0.003	21.6	3.50	42.9	42.9
	B4			0.019	46.5	13.30	56.0	56.0
8/22/2020	**MPCA**	**0.61**	**67.1**	**0.022**	**48.7**	**68.30**	**72.0**	**62.6**
	B6	0.63	66.7	0.025	50.6	39.20	66.6	61.3
	C6	0.57	68.1	0.013	40.7	45.90	68.1	59.0
	E6	0.62	66.9	0.006	31.0	43.10	67.5	55.2
	G5	0.63	66.7	0.028	52.3	48.70	68.7	62.5
	G3	0.58	67.8	0.003	21.6	45.90	68.1	52.5
	F2	0.56	68.4	0.000	-14.9	47.30	68.4	40.6
	D3	0.63	66.7	0.047	59.6	42.70	67.4	64.6
	B4	0.62	66.9	0.019	46.5	20.70	60.3	57.9
10/9/2020	**MPCA**	**0.6**	**67.4**	**0.034**	**55.1**	**42.00**	**67.3**	**63.3**
	B6	0.68	65.6	0.028	52.3	35.40	65.6	61.1
	C6	0.65	66.2	0.025	50.6	50.50	69.1	62.0
	E6	0.6	67.4	0.003	21.6	44.90	67.9	52.3
	G5	0.62	66.9	0.028	52.3	40.30	66.9	62.0
	G3	0.6	67.4	0.013	40.7	45.90	68.1	58.7
	F2	0.55	68.6	0.031	53.8	45.20	68.0	63.5
	D3	0.59	67.6	0.028	52.3	41.00	67.0	62.3
	B4	0.65	66.2	0.034	55.1	36.80	66.0	62.4
	NE Bloom	0.24	80.6	0.384	90.0	492.00	91.4	87.3

Appendix B: Table of sample derived chlorophyll-a concentration/trophic state and pixel derived chlorophyll-a concentration/trophic state

Date/Site	*Sample Derived Chlorophyll-a (ug/L)*	*Sample Derived Trophic State*	*Pixel Derived Chlorophyll-a (ug/L)*	*Pixel Derived Trophic State*	*% Difference in Chlorophyll-a Concentration*	*% Difference in Trophic State Evaluations*
6/24 B4	13.3	56.0	20.0	60.0	33.3	6.6
6/24 B6	20.0	60.0	15.7	57.6	27.0	4.1
6/24 C6	11.2	54.3	10.1	53.3	10.6	1.9
6/24 D3	15.8	57.7	31.0	64.3	49.2	10.3
6/24 E6	16.5	58.1	30.5	64.1	46.0	9.4
6/24 G5	8.1	51.1	31.5	64.5	74.4	20.8
6/24 G3	24.5	62.0	29.8	63.9	17.8	3.0
6/24 F2	28.7	63.5	30.4	64.1	5.6	0.9
8/22 D3	42.7	67.4	46.9	68.3	8.8	1.3
8/22 B6	39.2	66.6	48.1	68.6	18.4	2.9
8/22 E6	43.1	67.5	42.7	67.4	1.0	0.1
8/22 G5	48.7	68.7	34.4	65.3	41.6	5.2
8/22 B4	20.7	60.3	37.0	66.0	44.2	8.7
8/22 G3	45.9	68.1	34.6	65.4	32.9	4.3
8/22 F2	47.3	68.4	33.3	65.0	42.1	5.3
9/26 B6	36.4	65.9	35.4	65.6	3.1	0.5
9/26 C6	29.4	63.8	36.2	65.8	18.7	3.1
9/26 D3	43.8	67.7	35.9	65.7	22.1	3.0
9/26 F2	43.1	67.5	34.0	65.2	26.6	3.5
9/26 G3	43.1	67.5	36.2	65.8	19.1	2.6
10/9 G3	45.9	68.1	37.6	66.2	22.2	3.0
10/9 F2	45.2	68.0	35.7	65.7	26.5	3.5
10/9 E6	44.9	67.9	41.1	67.1	9.1	1.3
10/9 D3	41.0	67.0	36.6	65.9	12.0	1.7
10/9 C6	50.5	69.1	38.3	66.4	31.7	4.1
10/9 B6	35.4	65.6	35.1	65.5	0.9	0.1
10/9 B4	36.8	66.0	35.1	65.5	4.8	0.7