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Nutrient Pollution and Chlorophyll-A as a Precursor to Harmful Algal Blooms and Cyanotoxins in Rehabilitated Machado Lake, California

Michael E. Shiang
Walden University

Walden University

College of Health Sciences and Public Policy

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Michael E. Shiang

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Review Committee
Dr. Richard Jimenez, Committee Chairperson, Public Health Faculty
Dr. Paul Silverman, Committee Member, Public Health Faculty
Dr. Simone Salandy, University Reviewer, Public Health Faculty

Chief Academic Officer and Provost
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Walden University
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Abstract

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by

Michael E. Shiang

MS, California State University - Fullerton, 1999

BA, Boston University, 1976

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Algal blooms result in the formation of cyanotoxic conditions in a freshwater lake causing severe detrimental impacts to community and public health. Nitrogen, phosphorous, and ammonia stimulate the growth of phytoplankton biomass and algae, as measured by chlorophyll. This retrospective quantitative research study, grounded in the socioecological model, examined the relationship between nutrient pollutants and chlorophyll-a (Chl-a) that forecast harmful algal blooms, a precursor to cyanotoxins. A former impaired lake, Machado Lake in California, provided an ideal setting to assess relationships among nutrient indicators and Chl-a post-lake rehabilitation. Correlation and multiple regression analyses were performed to determine if a relationship existed between total nitrogen (TN), total phosphorous (TP), ammonia (NH_3), and the dependent variable Chl-a. The observational data total count was $N = 102$ for each variable. The data were transformed to approximate normality and NH_3 was recoded as dichotomous. Results revealed a positive correlation of TN and TP; however, NH_3 was negatively correlated. The regression model outcome resulted in approximately 63% of the variability of Chl-a concentration explained by the independent variables. A predictive model to forecast Chl-a was developed, potentially providing an early warning to harmful algal blooms and cyanotoxins. Implications for positive social change include protecting communities and public health by examining the precursors of harmful algal blooms and cyanotoxins to minimize risk of exposure to toxins that could potentially result in human illnesses and mortality.

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Dedication

A very warm and special feeling of gratitude to my late parents, whom impressed upon their children that education never stops. Achieving this milestone is in honor of my late mother, Flora W. Shiang, whose desire for her children was to live and strive to greater heights in our quest for knowledge. As an educator in the public school system for over 35 years, her love was unconditional and through this achievement her memory lives on. For the devotion my parents provided to their children, this accomplishment is dedicated to and in honor of them.

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I am forever indebted to those that stood alongside of me and picked me up when I needed a boost. First and foremost, I thank my committee members for their professionalism and supervision throughout these year, Dr. Richard Jimenez, my Chair providing timely, insightful direction and invaluable guidance; and Dr. Paul Silverman, second Committee member providing intuitive ways to overcome numerous challenges I encountered. A special thanks also goes to Dr. Irana Hawkins for her early-on inspiration as I started my journey. Least I not forget the university resources and those faculty members that served as role models and provided guidance throughout the years.

Secondly, this research would not have been possible without the support from Mr. Jonathan Ball, Environmental Affairs Officer, LA Sanitation & Environment, City of Los Angeles, and those staff that diligently collected the data used in my study. I am very thankful that Mr. Ball shared the same compassion in protecting public health and was willing to provide his time in making this possible.

Finally, there are many colleagues, friends, and family that were instrumental in my pursuit of this goal. Driven to achieve a higher standard and collaborating with many experts gave me great inspiration and motivation to push forward. Most importantly, those closest to me were my family whom stood by me; in particular my wife Connie, who provided everlasting encouragement throughout my journey. To all of you, I so dearly thank you!

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Chapter 1: Introduction of Study

Research of freshwater harmful algal blooms and ensuing cyanotoxic water conditions that degrade the socio-ecological environment and impair public health continues to accelerate in its frequency on a national and global scale. Over the past several years, progress has been made in the development of sustainable mitigation measures and initiatives to prevent degradation of the "lived" natural environment from harmful algal blooms that impairs and threatens public health (Kilanowski, 2017; Steffen et al., 2015). In light of global warming, there is concern over discrepancies in the literature and current research in the approaches used to assess, investigate, and mitigate the persistence of algal blooms in the nation's lakes and streams (Manning & Nobles, 2017; Wang et al., 2016; U.S. Environmental Protection Agency [EPA], 2021b). Study of climate change and planetary boundary thresholds, and geochemical variables known to affect the proliferation of harmful algal blooms leading to cyanotoxic conditions, are informative in developing appropriate platforms and analytical tools to mitigate such circumstances in the natural environment (Southern California Coastal Water Research Project [SCCWRP], 2021; U.S. EPA, 2022a). The challenging issues associated with the degradation of freshwater water resources and potential loss of open "living" space cross over several core disciplines, including socio-ecological dynamics, environmental and engineering sciences, and public health. Water-based epidemiologic studies are critically important in assessing the risks of exposure to harmful algal blooms and cyanotoxic conditions in waterways for the protection of community well-being and individual human health.

Based on a review of the literature, there is consensus within the scientific community for examination of the association, relationship, and causes of water-quality parameters as determinant factors leading to excessive harmful algal blooms. Apparent from recent research articles, scientists continue to see significant challenges in understanding how to observe, interpret, and predict conditions in which excessive harmful algal blooms will occur (Liao et al., 2021; Zhang et al., 2022; SCCWRP, 2021). For example, the continuous need for investigation of the presence of cyanotoxins resulting from harmful algal blooms can be cost prohibitive (U.S. EPA, 2021d). As cited by Howard et al. (2020) and Liao et al. (2021), each unique freshwater study may offer additional insights into investigative methods in minimizing and controlling this degraded condition in freshwater lakes. Machado Lake, the target of my research, is one such freshwater body that has recently been reconstructed and provides the opportunity to investigate and add to the current knowledge base.

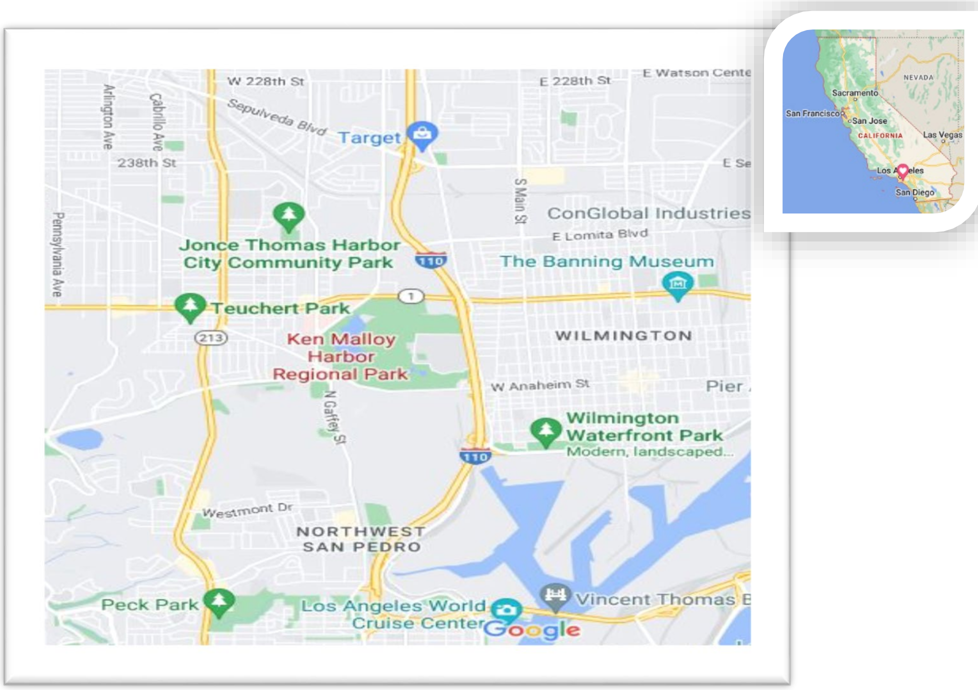
A thorough review of the literature has been made and relevant articles have been referenced and summarized in Chapter 2, providing a sound theoretical foundation and conceptual framework for this research project. In addition, an overview of scientific principles associated with key variables of study have been provided. My research design rationale, data analysis plan, and methodology are summarized in Chapter 3. Finally, the results and interpretation of my quantitative research study are provided in Chapters 4 and 5, respectively.

Background

As cited by SCCWRP (2021), local community freshwater lakes serve an essential purpose for human health and community well-being; wherein, such lakes provide beneficial uses for recreation, wildlife habitat, and water supply. The designated beneficial uses for Machado Lake include the following: REC-1, Water Contact Recreation; REC-2, Non-Contact Water Recreation; WET, Wetland Habitat; RARE, Rare, Threatened, Endangered Species; WILD, Wildlife Habitat; WARM, and Warm Freshwater Habitat. Machado Lake is an essential part of the 9,000-acre Dominguez Channel Watershed Management Area drainage system in South Los Angeles County, as shown in Figure 1.

Figure 1

Location of Study Area, Ken Malloy Regional Park and Machado Lake



Note. Images taken from Google Maps (www.google.com/maps).

As discussed in Chapter 2, the approximately 45-acre lake is situated within the 290-acre Ken Malloy Harbor Regional Park near the major routes of Pacific Coast Highway (Route 1), Vermont Avenue, and Freeway 110. On the north side of the lake is the Wilmington Drain and to the south is a roughly 60-acre seasonal freshwater marsh. An aerial view of the lake, park, and surrounding properties is provided in Figure 2, with additional facts of Machado Lake's recent reconstruction and rehabilitation projects provided in Appendix A.

Figure 2

Aerial Photo of Machado Lake and Surrounding Area

Note. From City of Los Angeles, LA-DPWBOE, 2009.

The unique qualities of post-rehabilitated Machado Lake made this an ideal setting to further conduct research associated with algal blooms and its implications to public health. In late 2000, Machado Lake was one of several lakes in California deemed "impaired" under the CWA, Section 303 (d). As a result of this impaired status, standards were established that included elements of beneficial uses of the waterbody and water-quality criteria or objectives for the purposes of protecting those uses. The standards were developed as total maximum daily loads (TMDLs) developed in 2009. Since completion of the reconstruction in 2017 (City of Los Angeles-Department of Public Works Bureau of Engineering [LA-DPWBOE], 2009), the environmental setting of Machado Lake is very much like a quasi-controlled natural environment laboratory, providing opportunity to study conditions that promote algal blooms in its natural setting. With improvements in the geomorphological aspects of this lake, many confounding factors that have typically been problematic in past research studies are, relatively speaking, in a steady-state condition today compared to pre-reconstruction times. As such, confounding variables discussed in Chapter 2 play a less critical role in assessing the relationship of variables that cause excessive algal blooms. Assuming that this assumption has merit and validity, my focus then turns to the water-based nutrient parameters that are exasperated by changing climate conditions and anthropogenic sources known to promote harmful algal blooms and subsequent cyanotoxic conditions. Over the past 5 years, water-based investigations and epidemiological studies in the United States have become more common in those states that have seen "excessive" harmful algal blooms, particularly along the east coast, southeast, southwestern states and Great Lakes region (U.S. EPA, 2021d; Centers for Disease Control and Prevention [CDC], 2021a; Alliance for the Great Lakes, 2022). Notwithstanding, similar “unhealthy” and critical exposures are occurring in many other countries with little or no monitoring or mitigation activities to abate what has become a global crisis.

There continues to be a need for researchers to further investigate the problematic issues associated with algal blooms as a precursor to harmful algal blooms and cyanotoxic conditions. Ideally, more intensive site-specific research will be conducted to fill the current lack of knowledge in using actual field-derived data to evaluate the relationship between nutrient parameters and chlorophyll measurements as an indicator of phytoplankton biomass and algae in freshwater lakes and streams. Recent observations of Machado Lake’s appearance of water color and clarity suggests that eutrophic conditions are advancing ahead of the warmest summer months. Photos taken in April 2022 and July 2022 (see Figures 3-6) reveal how the water conditions have abruptly changed over a period of about 3 months. It is apparent that the processes of eutrophication, whether in an early or late stage, are changing the appearance and health of the lake.

Figure 3

Fishing Along Southern Lake Edge, Clear Water Appearance, April 20, 2022

Figure 4

Eastern Lake Edge, Clear Water Appearance, April 20, 2022

Figure 5

Southern Lake Edge, Rich-Green Phytoplankton and Algae, July 18, 2022

Figure 6

S*treaks of Thick Biomass and Algae at Water Edge, July 18, 2022*

Note. All photos taken by Michael Shiang.

As observed during these two distinct occasions, the lake water appearance was relatively clear during the spring of 2022, as shown in Figures 3 and 4. As the summer month temperatures rise and lake water temperatures buildup, the water clarity changed from relatively clear to a light green or dark blue-green appearance indicative of increasing phytoplankton biomass and algae, as shown in Figures 5 and 6. As evidenced from these two time periods and while still early in the summer months, the lake water reveals evolving conditions for algal blooms. As such, my research of the relationship of nutrient indicators and chlorophyll furthers the understanding of these type conditions based on real-time field data collection and observations.

Problem Statement

Harmful algal blooms resulting in cyanotoxic conditions in freshwater lakes across the nation and throughout the world have been deemed a global public health crisis, not only causing impairment to the social-ecological environment, but also direct loss of animal and human life. The presence of cyanotoxins in freshwater lakes can result in human exposure through ingestion, inhalation, and or direct skin contact (CDC, 2022). Recreational activities in freshwater lakes, such as boating, swimming, or fishing contribute to these routes of exposure in highly contaminated waters. While children are more susceptible to effects of cyanotoxins than adults, the symptoms within the first 48 hours include sore throat, coughing, rash, itchy skin, blisters, headache, eye or ear irritations, and abdominal pains (CDC, 2022). More importantly, acute and long-term exposures have led to increased risk of severe illnesses and death (Cheung et al., 2013; CDC, 2021a; National Institute of Health [NIH], 2021). There is consensus among scientists and researchers that, as the scale of algal blooms continue to increase significantly around the globe (Wheeling, 2019), the need for freshwater water-based epidemiological studies will be more common if practical solutions are not found.

According to the CDC (2021a), toxins resulting from extreme algal blooms pose significant challenges in freshwater lakes and drinking water supplies, leading to human health concerns in urban areas. Without open green space and access to clean water, societal health would be at risk due to lack of physical activities, potential exposure to unhealthy and toxic lake water, and an imbalance within local habitats causing illnesses and death (Falconer & Humpage, 2005; Howard et al., 2020; SCCWRP, 2021). Knowledge of the relationships of natural and anthropogenic factors that cause harmful conditions in freshwater lakes that promote excessive algal blooms is in its early stages of research (Howard et al., 2020; U.S. EPA, 2016a). According to Howard et al. (2020), there are discrepancies in the literature related to the understanding of the issues that control algal blooms, including nutrient pollution and measurement of chlorophyll-a in determining the presence of cyanotoxins on a consistent basis. Machado Lake, now reconstructed and rehabilitated, offers the opportunity to examine the relationship between total nitrogen (TN), total phosphorous (TP), ammonia (NH_3) and chlorophyll-a (Chl-a), providing a science-based analysis to determine if one can predict the thresholds of studied variables leading to excessive algal blooms. Societal awareness of the physical conditions of the surrounding ecological environment, for the preservation of water resources, can have significant public health implications if not addressed in a timely manner.

Purpose of the Study

The overall purpose of my research is to protect community and individual health against the ill effects of harmful algal blooms and formation of cyanotoxins in water. The objective of my retrospective study was to evaluate the relationship between the nutrient indicator variables TN, TP, and NH_3 and the predictor variable Chl-a (an indicator of phytoplankton biomass and or algae) in a rehabilitated lake using correlation and multiple linear regression, after controlling for wet and dry seasons. The term correlation is synonymous to relationships, and prediction is synonymous to impact, influence, and or interaction. This quantitative evaluation was not intended to determine causal relationships. The application of each variable is further discussed in Chapters 2 and 3, providing both the approach and assumptions in determining the relationship between variables of my quantitative study.

In evaluating the predictive capability of the independent variable (IV) in relation to the dependent variable (DV), perhaps an early warning “numeric scale” would enable lake owners or stakeholders to better track increases and decreases in algal growth and cyanotoxin patterns to minimize the risk of exposures and allow for better management decision making and policy regarding mitigation and corrective-action measures.

Research Questions and Hypotheses

In keeping with my study objectives and in the context of my research questions, my interest was limited to key nutrient predictor variables and the outcome variable of chlorophyll-a. The overarching issue is whether or not, and to what extent can, the IVs predict the dependent variable for Machado Lake. The following research questions form the basis of my study. Each research question has a null and alternative hypothesis that will be evaluated.

Research Question 1 (RQ1): What is the relationship between total nitrogen (TN) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change (wet and dry season)?

$H_0$1: There is no relationship between TN and chlorophyll-*a*, when controlling for seasonal change.

H_a1: There is a relationship between TN and chlorophyll-*a*, when controlling for seasonal change.

Research Question 2 (RQ2): What is the relationship between total phosphorous (TP) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change?

$H_0$2: There is no relationship between TP and chlorophyll-*a*, when controlling for seasonal change.

H_a2: There is a relationship between TP and chlorophyll-*a*, when controlling for seasonal change.

Research Question 3 (RQ3): What is the relationship between ammonia (NH_3) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change?

$H_0$3: There is no relationship between NH_3 and chlorophyll-*a*, when controlling for seasonal change.

H_a3: There is a relationship between NH_3 and chlorophyll-*a*, when controlling for seasonal change.

Research Question 4 (RQ4): To what extent do TN, TP, NH_3 predict chlorophyll-*a* while controlling for seasonal change?

$H_0 4$: There is no predictive relationship between TN, TP, NH_3 and chlorophyll-*a*, while controlling for seasonal change.

$H_a 4$: There is a predictive relationship between TN, TP, NH_3 and chlorophyll-*a*, while controlling for seasonal change.

Theoretical Foundation

Theories and concepts that ground my study were derived from operational levels of the social ecological model (SEM) related to the dynamic interrelations among personal and environmental factors (Glanz et al., 2008). Furthermore, the concepts of planetary boundary (PB) benchmarks in understanding earth systems and their interrelationship to human health and the environment (Steffen et al., 2015) also was a dominant factor in the foundation of my research. Impairment of freshwater lakes and a dramatic increase in algal blooms has become an important national and global talking point (CDC, 2022; Lenton et al., 2008; Steffen et al., 2015). The SEM helps to identify strategies related to interpersonal, community, and societal factors when planning and implementing health promotion and prevention interventions (Glanz et al., 2008). With access to healthy freshwater lakes in the community, society will benefit when there is reduced risk of exposure to a cyanotoxic contaminated water environment. Support for my research is also derived from the understanding of PB benchmarks, specifically bio-geochemical flows and alterations in the environment caused by anthropogenic activities that degrade waterways. Societal behaviors exasperate the planet’s health, where many global citizens' current way of life and demands on earth's systems have caused an increase in acceleration of global temperatures, altering land mass use resulting in mass migrations, heat waves and wildfires, and "novel" disease outbreaks (Barnosky et al., 2011; Lenton et al., 2008; Steffen et al., 2015; Hayden, 2019). Using the principles of the PB framework, my research was grounded in the principals of earth systems and the delicate balance of nature, providing evidence that earth systems are in turmoil. If such conditions persist, conceivably freshwater waterways will be overcome with toxic blooms, causing mass extinction to living organisms (Barnosky et al., 2011; Bogardi et al., 2013; U.S. EPA, 2021a).

Researchers have identified and support the need for monitoring and prevention, as well as rehabilitation and corrective measures in providing for the protection of human health. In addressing this gap, my goal in using science-based data to evaluate the overall health and potential public health impacts of Machado Lake can add to an existing base of knowledge. Of primary concern is the nutrient factors (TN, TP and NH_3) causing lake impairment. The understanding of the relationship between nutrient pollution and chlorophyll (as an indicator of algal blooms) is fundamentally the key premise in evaluating the health of Machado lake water in reducing the negative impacts to public health.

Nature of the Study

The nature of my research was a retrospective quantitative study. The study design was grounded on the theory and concepts related to the SEM and PB framework, and related to the TN-TP-Chl-a model. Based on the elements of study as discussed in

Chapter 2, the principles of eutrophication and the need for collection of real-time water-based data to determine associations and relationships of harmful algal blooms and cyanotoxins is extremely critical moving forward. Community and individual health are directly connected to the environment, especially as it relates to risks of exposure to contaminated water.

A dataset from Machado Lake was used to perform my evaluation. This secondary dataset is from the City of Los Angeles, Water Pollution Division (WPD). In utilizing the TN-TP-Chl-a model, a correlation and linear regression analysis was performed to assess relationships of the independent variables of TN, TP, NH_3 and the dependent variable of Chl-a to determine if these relationships of variables could be used as a reliable predictive "early warning" tool of excessive algal blooms. Descriptive and inferential statistics were used to evaluate the dataset and assess data variable relationships using correlation and multivariate linear regression analyses. A more detailed discussion of the approach and analytical methods are provided in Chapter 3.

Operational Definitions

The collection of in-situ and discrete grab water-quality data in strategic locations of Machado Lake were key in deciding to use the City WPD dataset. Operationally, with approximately 4 years of data, this quantitative assessment was assessed using either daily averages or direct measurement of variable concentrations for both predictor and outcome factors. A further discussion of the instruments and methodology used in collection of data by the WPD is provided in Chapter 3.

Definitions

Select operational definitions of specific "key" terms are provided:

Bio-stimulation: related to nutrients such as nitrogen and phosphorous that stimulate organic matter and or bacteria in water.

Chlorophyll-a: generally refers to the green pigment used by plants and other organic matter in the process of photosynthesis. Also, a measure of biomass and or algae.

Cyanotoxins: relates to the presence of bacteria in water that becomes toxic to humans, animals, and wildlife. Three cyanotoxins common detected in freshwater are microcystin, anatoxin-a, and cylindrospermopsin.

Eutrophication: stages of dense growth of plant or algae in a freshwater body from urban runoff associated with nutrient loading, triggering a water body to become toxic and or results in dead zones that can no longer support life due to lack of oxygen.

Harmful Algal Blooms: is an algal bloom that causes negative or detrimental impacts through formation of natural toxins, typically referred to as cyanotoxins.

Nutrient: substances that promote the growth of organic matter or algae, as the most common nutrients from anthropogenic sources are nitrogen and phosphorous.

Phytoplankton: refers to the microscopic algae that requires sunlight to live and grow and is very common in shallow lake settings. Phytoplankton biomass is a bacteria and is commonly referred to as cyanobacteria, diatoms, and green algae.

Risk Exposure: study variables that can be quantified and used to assess the potential for human-health impacts.

Total Nitrogen: as related to biological water-assessment quantitative studies, total nitrogen is the sum of nitrate-nitrogen (NO3-N), nitrite-nitrogen (NO2-N), ammonia nitrogen (NH_3-N), and organic nitrogen.

Assumptions

The following assumptions are made in conducting my research. First, I assumed that the observed presence of algae is relatable to the stages of eutrophication. Second, I assumed that not all algal blooms are bad, harmful, or toxic in nature; however, with time and the right ambient conditions, the blooms will proliferate to become a precursor to harmful algal blooms and cyanotoxic conditions in a freshwater body. My final assumption was that the reconstructed Machado Lake offered a laboratory-like natural setting in which geomorphological and other confounders were less likely to affect the outcome of my research.

Scope and Delimitations

In addressing the relationships of nutrient variables and algal blooms in this setting, the scope of my research can further the understanding of how to control and mitigate blooms in advance of cyanotoxic conditions that potentially overwhelm the health and beneficial uses of a lake. Cyanotoxic conditions in a freshwater lake is a significant risk factor for impairment of the surrounding environment and quality of life. Use of Machado Lake data post-reconstruction allowed the development of a more comprehensive evaluation of the predictor and outcome variables, with less emphasis over other confounding factors. My research, however, was bounded by the methods of collection utilized by the City WPD, as outlined in Chapter 3. Delineation of the datasets provided by the City WPD are tied to the nutrient values in the form of TN, TP, NH_3, and chlorophyll-a. In performing my research, no human subjects were a part of the study.

Limitations

The City WPD are the originators of the dataset and have been responsible for the collection and storage of the dataset; therefore, my research was bound by the quality assurance-quality control of these parameters and processes developed by them. While the direction and strength of each relationship or association was established between the predictor variables and outcome variable, it did not address cause and effect. Despite this lake having been reconstructed, as time passes, the lake geomorphological setting also changes as a function of natural and evolutionary processes. However, the study is extremely useful and relevant as the dataset represents lake conditions immediately after reconstruction. Additional discussion of the validity and constructs of my study is provided in Chapter 3.

Significance of the Study

Recognizing exposures to harmful algal blooms and cyanotoxins in preventing human and animal illnesses and mortality gives further meaning and significance of this study. By determining the relationship between predictor and outcome variables, this study can contribute to researchers' ability to predict environmental risk factors associated with algal blooms and cyanotoxic exposures. Furthermore, the significance of determining the relationship of these study variables specific to this freshwater lake may provide "trigger or predictor" values that could potentially be used in similar lake settings. In conducting this analysis, corrective actions implemented in the early stages of eutrophication based on least costly investigative methods may be considered to prevent impairment to waterways in protecting community and human health. There is a greater sense of urgency by researchers on a national and global scale to prevent conditions in which potential cyanotoxins result. Furthermore, scientists and public health officials will be better informed in the development of applicable policy. Maintaining and protecting freshwater waterbodies for its intended use, and giving the community access to waterways for recreation, clean water sources, and sensitive habitats contribute to positive social change.

Summary

As discussed in this chapter, the importance in study of site-specific water-body conditions is of utmost importance in finding a cost-effective and simplified means to predict the natural progression of algae blooms to cyanotoxic conditions. The aim is to prevent the impairment of freshwater lakes from harmful algal blooms and to protect against exposure of unhealthy acute and chronic conditions harmful to humans, animals and critical wildlife habitat.

The logical connections between the framework and nature of my study emphasizes the concept of the interrelationship between public health and the environment. As noted by Steffen et al. (2015), the biochemical flows being observed around the globe is one of several key PB concepts that is directly related to the TN-TP and Chl-a processes causing lake impairment. Bringing engineering and epidemiology concepts together and establishing real-time trends provide critical information for making informed scientific and policy decisions. As this study and other similar research are conducted, the ability to develop a viable platform for predicting early detection and warning of excessive algal blooms and cyanotoxic conditions is of utmost importance. Early detection allows for stakeholders and regulators to take precautionary measures to protect the well-being of the local community and prevent individual exposure, illnesses, and potential mortality. As previously stated, the foundation of my research was grounded in other past research studies that were based on the SEM and PB conceptual framework. The scientific principles and background of my study as discussed in the following chapter, Chapter 2, provides a solid foundation in the research of my intended target population, Machado Lake.

Chapter 2: Literature Review

On-going research established the premise that harmful algal blooms have, over the past decade, impacted public health and individual "living" space in our environment (U.S. EPA, 2022b). Concerns have grown over the on-going risks of algal blooms and our understanding of the association between short- and long-term exposures resulting in adverse health effects, including death (Fristachi et al., 2007; Loftin et al., 2016; U.S. EPA, 2021a). The need for continued research and assessment of algal blooms in fresh water lakes has become a "major" talking point, especially for those who study socio-ecological and planetary systems (Bogardi et al. 2013; NIH, 2021; U.S. EPA, 2013). The purpose of my research was to determine the relationships of water-quality parameters related to algal blooms, a precursor to harmful algal blooms and cyanotoxins, known to impair the social-ecological environment to the detriment of the community and human health.

Correlation of natural and anthropogenic factors in the environment, and research to assess the causes that promote excessive algal blooms in freshwater lakes, are in its early stages of development (Howard et al., 2020; MacLeod et al., 2014; U.S. EPA, 2021b). As indicated by the U.S. EPA, the underlying ecological and environmental conditions that promote excessive harmful algal blooms (also referred to as blue-green algae) are associated with eutrophication of the water body, producing cyanotoxins that create a "dead" water condition due to oxygen depletion (Visser et al., 2015; U.S. EPA, 2016a). As deduced from on-going research, each freshwater body (lakes, streams, rivers, wetlands) is unique in physical and chemical character. The current understanding of the site-specific prevailing conditions that promote algal blooms resulting in eutrophic or toxic conditions are not well-understood, nor well-documented in the literature (Water Education Foundation [WEF], 2021; U.S. EPA, 2022b). Analysis of shallow freshwater bodies, including Machado Lake where site-specific data was evaluated, contributes to our existing base of knowledge in protecting human health and the delicate balance of our natural environment in which we live (Kilanowski, 2017; Steffen et al., 2015; U.S. EPA, 2022b).

As studied by Howard et al. (2020), my research informed the relationship of Chl-a and nutrients, as a predictor of algal blooms. Chlorophyll-a has been a key construct in similar on-going local, national, and international research studies in assessing water-quality conditions and the presence of algal blooms (Blakey et al., 2015; California Water Quality Monitoring Council [CWQMC], 2021a). However, the existing literature has been inconsistent and conflicting where long-term monitoring data has been used to assess associations of nutrients and chlorophyll (Rome et al., 2021; Howard et al., 2020; U.S. EPA, 2021d).

According to the CDC (2021a), extreme harmful algal blooms during summer months have caused significant challenges to our lived environment and public health. Howard et al. (2020) suggested in their research that there are inconsistencies in the interpretation of water-quality parameters as determinant factors in promoting algal blooms and toxins. According to the State of California, Los Angeles Regional Water Quality Control Board (CA-RWQCB, 2022a), the physical setting of the water body, nutrient loads, and other toxic pollutants are “key” factors for on-going research to narrow down the elements controlling blooms. Researchers are in general agreement that the association of water-quality controlling factors of an algal bloom are site specific, a unique set of circumstances specific to each water body (Wang et al., 2016; U.S. EPA, 2021b). The confounding issues of chlorophyll-a and algal blooms in relation to nutrients in water needs to be further examined, as a precursor to harmful algal blooms (Howard et al., 2020, Rome et al., 2021; CA-RWQCB, 2022a). In this chapter, evaluating conditions of chlorophyll-a in water as a measure of the presence of algae and its relationship with key nutrient factors contributes to the body of knowledge and our understanding of causal factors in predicting algal blooms. This chapter sets forth the premise of my research and includes a discussion of the literature search conducted, literature review, constructs of theoretical and conceptual models in support of my research, site background and justification for my research targets, and the technical science-based principles in support of my research.

Literature Search Strategy

A search strategy was developed to retrieve relevant literature and research from numerous public, private, and academic sources, including but not limited to: Academic Search Complete, Cochrane Database of Systematic Reviews, Health and Environmental Research Online (HERO), National Academies Press, National Technical Information Service (NTIS), ProQuest, SAGE Journals, ScholarWorks, Thoreau Multi-Database Search, United Nations Public Administration Network, U.S. Department of Health and Human Services, U.S. Environmental Protection Agency, and World Health Organization. In addition, using the Google Scholar search engine helped narrow down public informational sources, specifically contemporaneous government studies and research at the local, state, and federal levels. The breadth and depth of the existing body of literature was highly varied, with research studies dating back to approximately 2000 to present day, both in the laboratory and in the field. The distinction between these varied research settings (lab verses field) identified gaps and inconsistencies in the current understanding of the controlling factors associated with excessive algal blooms. As postulated by U.S. EPA (2021b), what can be learned in the natural field environment was carefully considered in development of my research objectives and how the constructs of a theoretical framework would guide my literature review.

As my primary research question query was refined, specific relevant topical issues were targeted. Over 120 research studies, reports, and articles of interest were critiqued to assess its applicability and quality, including elements of research design, study characteristics, statistical methodology, and biases. In covering the major topical issues, my literature search strategy included key words such as: *algal blooms, harmful algal blooms, cyanobacteria, cyanotoxins, blue-green algae, chlorophyll-a, freshwater lake eutrophication, human illnesses from microcystin and cylindrospermopsin exposure, planet boundaries, social ecological model, nitrogen and phosphorous cycles, satellite imagery for algal blooms, recreational lakes and toxins in water, water-quality monitoring devices used in lakes for algae evaluation, regulatory legislation of harmful algal blooms,* and *cyanotoxins-related regulatory water advisories.*

Theoretical and Conceptual Model

Before discussing my research targets, the “blue-print” of my study was grounded by the SEM model and theory. The general constructs of this theory support individual tendencies to improve our overall health and well-being, and surrounding environment (Berkes & Folke, 1998; Glanz et al., 2008; Hayden, 2019; Steffen et al., 2015). The social-ecological theoretical model provides a foundation for my study from two perspectives, social systems and natural systems. Through Glanz et al. and Berkes and Folke’s development of the theory, researchers can advance their understanding of the components for the integration of social and natural systems. Further affirming the applicability of the SEM theoretical constructs in past research, my study is connected to a science-based evaluation of our water environment and how this could potentially lead to improved public health and relevant public health policy.

The conceptual framework of planetary boundary elements (MacLeod et al., 2014; Steffen et al., 2015) provides additional support and guidance for scientific inquiry of earth’s natural systems. Using the tenants of planetary boundary over the use of scientific data in evaluating chlorophyll-a and its association of nutrients as a predictor of algal blooms, a precursor of harmful algal blooms needs clarification in research today (Liao et al., 2021; WEF, 2021; Zhang et al., 2022). By doing so and to add to the current base of scientific knowledge, more efficient and cost-effective ways of predicting algal blooms will benefit human health and our natural environment, specifically in protecting our water resources (Visser et al., 2015; State of California – Department of Water

Resources [CA-DWR], 2022a). A further discussion of the application of this theory and conceptual framework follows in the next section.

Social-Ecological Theory and Planetary Boundaries Conceptual Framework

The social-ecological theory and model conveys that society, including all living creatures of plants and animals, must develop and thrive in a multi-layered "ecosystem" that is supported through diversity and union (Berkes and Folke, 1998; Glanz et al., 2008; Hayden, 2019). My research will employ the SEM framework in correlating and interpreting relevant site-specific lake data in addressing public health concerns. SEM grounds the discussion of societal and community needs, our need to adapt to and protect our "ever-changing" environment and individual health. As described by Glanz et al., the SEM concepts are intertwined across multiple levels in understanding health impacts and behaviors related to our surroundings.

Based on CDC's model (CDC, 2022), four levels of SEM constructs consists of individual, relationship, community, and society that must all work in unison as a multi-level program to provide primary prevention strategies for improvements in public health and the environment. While SEM strategies work across a number of different levels and seek to change personal behavior, my premise in grounding my research to this theory is that individuals will improve not only their physical well-being, but also their mental well-being when their surrounding environment is holistic in promoting active and healthy living. The importance of having a freshwater body, such as Machado Lake available for public use draws upon the main principles of this theory. Our surrounding environment and availability of water for multiple purposes in a variety of settings, such as Machado Lake is essential for life and necessary for all "living" matter.

According to the U.S. EPA (2021b), excessive blue-green algal blooms that produce cyanotoxins have been dubbed as the "silent killer". Wheeling (2019) notes that during the past "2000 Symposiums on Harmful Algae" the issue of marine blooms were front and center. Now, as Wheeling observes, a shift to freshwater blooms has dominated research. Wheeling and other researchers were concerned that climate change undercuts efforts to find fixes to these water-quality problems. If the destructive forces of climate change and global warming continue along its current trajectory, earth systems and the balance of nature will be disrupted to the point where natural disorders to our fragile ecosystem will ensue (Steffen et al., 2015). As inferred by Barnosky et al. (2011), the eventual effects of surpassing several critical PB thresholds we are experiencing today have more than likely occurred in the past, and that toxic conditions are suspected to have caused near "mass extinction of life" thousands to millions of years ago. Based on species loss and planetary boundaries being misaligned, Barnosky et al. views diversity loss as critical to understanding the phenomena of mass extinction, albeit it is difficult to grasp when dealing with the geologic time scale. In comparing past extinctions and applying what is perceived to be happening today, Barnosky et.al. advocates the need for immediate conservation measures. The associations between unusual events tied to climate change, atmospheric conditions, and ecological stressors all negatively affect conditions for our existence (CDC, 2021a; U.S. EPA, 2022a). For example, these concerns are evidenced by glacial-interglacial cycles, disturbances in atmospheric conditions, CO_2 levels rising, habitat fragmentation, pollution, and invasive species and pathogens (U.S. EPA, 2022a).

Steffen et al. (2015) reminds us that our human "footprint" is destabilizing earth systems. A comprehensive chart of PB cycles was developed through his research to help gauge the levels of environmental impacts. Conceptually, the PB outlines nine science-based areas of potential risks: (a) climate change, (b) biosphere integrity, (c) stratospheric ozone depletion, (d) atmospheric aerosol loading, (e) ocean acidification, (f) biochemical flows, (g) land-system change, (h) freshwater uses, and (i) novel entities (Steffen et al, 2015; Visser et al., 2015; Lenton et al., 2008). Steffen et al. expressed concern over how society is evolving and its impact to human health. While research and data records are available for weather and severe climatic changes throughout the world (i.e., temperature, barometric pressure, rainfall, wind direction, etc.), data is lacking on water-quality observations. Steffen et al. has viewed the PB framework as a means to focus and consolidate science-based evaluations to risks associated with human health and our surrounding environment.

Anthropogenic impact is one explanation for the destabilization of earth systems when measured against other variables outlined in the PB framework. As inferred by Wheeling et al. (2019), our well-being, livelihood, and natural environment are losing ground to the negative impacts caused by disruptions in our earth systems. Researchers that advocate PB theories assert that the nine disciplinary systems are not mutually exclusive (Bogardi et al., 2013; Steffen et al., 2015). At least four of the nine disciplinary systems are related to the conceptual framework in grounding my research. These four

PB factors are: (a) *biochemical flows* - associated with anthropogenic compounds that result in degradation to our fragile ecosystem and surround environment; (b) *nitrogen cycles* - nutrient-rich waters from application of fertilizers, septic tank drainage, urban runoff, and agricultural wastes that eventually leaches into the environment and degrades our water sources*;* (c) *climate change* - causing an increase in earth's ambient temperatures to our surface waters; and (d) *freshwater uses* - which focuses in on our ability to preserve and sustain clean sources of drinking water, and prevent degradation to our freshwater lakes, streams and waterway.

Planetary boundaries associated with adverse changes in the environment have worsened over several decades that have resulted in excessive harmful algal blooms further intensifying the imbalances in the ecological and earth systems, specifically our water environments (Loftin et al., 2016; Sobota et al., 2009). The gap recognized by Wheeling (2019) and other research scientists is to fill the need for specific real-time field studies in our natural environment that help clarify the micro-processes that effect the intensification of algal blooms in our "lived" environment.

Significance and Social Change

Over the past decade, researchers and scientists have continued to observe an increase in frequency, severity, and the worldwide geographic presence of harmful algal blooms (CDC, 2021a; U.S. EPA, 2013). As cited in the literature, the enigma of excessive algal blooms and potential for extinction of living organisms will go unabated if our understanding of the cause and effect for such occurrences is not adequately investigated (NIH, 2021; CA-OEHHA, 2022). Inferred from Berkes and Folke (1998) tenants of SEM, each research step taken provides a clue on how best to modify, control and abate the degrading conditions of our social and natural systems. Our societal “living” habits and daily needs require significant “change” to protect and improve our natural habitat (CDC, 2022; Hayden, 2019). Losing our freshwater resources is not an option; and therefore, our efforts need to be focused on algal blooms known to have caused harm to public health and our surrounding environment.

Bogardi et al. (2013) notes that there is a societal responsibility to address and fix our earth’s capacity for sustainability. Individuals need to recognize the limits of our earth’s resources, specifically water. Bogardi et al. looked at appropriation of freshwater in addition to other ecological principles in conserving water, a modified framework in developing sustainability. In doing so, their theoretical and conceptual approaches have helped in technical areas such as how fresh and drinking water is consumed by the industrial and private domestic sectors. Guided by a number of regulatory laws, degradation to our environment resulting in limited open green space and freshwater ways needs to be re-evaluated. Without local, state and federal regulations, public health and our ecosystem are at risk to further deteriorate and life as we know today would be unsustainable (Barnosky et al., 2011; Lenton et al., 2008; Steffen et al., 2015; U.S. EPA, 2021b). Societal demands need to be reassessed and technological innovation advanced in determining future appropriations in guiding policy and governance (Borgardi et al., 2013; U.S. EPA, 2021b). As cited by Borgardi et al., social change benefits will result assuming individuals have the ability to provide for earth’s sustainability. As suggested by U.S. EPA (2021a), pro-active scientific-based studies, regulations, and policy are a significant piece of the puzzle in maintaining social and environment health.

Public Health Implications

In exploring public health implications, Steffen et al. (2015) cites that our current societal behaviors continue to exasperate planet boundaries. The SEM and PB principles remind us that earth systems are in turmoil. Acceleration of greenhouse gas emissions, increasing global temperatures, altering land-mass use resulting in mass migrations, heat waves and wildfires, and “novel” disease outbreaks have caused negative impacts to public health throughout the world (Kilanowski, 2017; CDC, 2021b). If this condition persists, our freshwater waterways will become ripe for toxic blooms, leading to extinction to living organisms (Barnosky et al., 2011). Should algal blooms take over our freshwater ways, wildlife and human health as we know it today would be in peril.

Harmful algal blooms and cyanotoxic conditions have resulted in acute and chronic illnesses, and death in humans, animals, and wildlife (CWQMC, 2021b). As cited by CWQMC (2021a) and the US EPA (2022a), cyanotoxic conditions resulting from algal blooms that have appeared in our waterways continues to be a significant detriment to societal public health and requires more diligent focused research.

Justification for Research

Researchers have been studying the use of chlorophyll-a as a gauge of severity of harmful algal blooms and its production of cyanotoxins (U.S. EPA, 2022a) for some time now. However, to this day researchers continue to emphasize the lack of site-specific field-test data to improve our understanding of chlorophyll-a and algal blooms, and covariate drivers such as nutrient pollution (Blakey et al., 2015; Wang et al., 2016; U.S. EPA, 2022b). The principles of eutrophication and quantitative measurements of water quality are well-established in the literature (U.S. Geological Survey [USGS], 2022; Yao et al., 2021), but again researchers emphasize the need for more real-time field data in finding trends, associations and relationships of these bloom variables. Clearly, my research effort is to help narrow the gap in the literature of these bloom variables. Chlorophyll-a concentrations, used as an indicator of algal blooms and its relationship to nutrient pollution, is a part of the puzzle that remains inconsistent and uncertain as a predictor for harmful algal blooms. By study of relationships of these key variables will researchers and scientists be able to prevent algal blooms from overtaking our natural ecological system to the detriment of social systems and public health.

Background Study (Target Population) of Machado Lake

Over many decades, Machado Lake's degraded conditions had restricted use of this lake as a recreational, wetland habitat, and potential drinking water supply resource. This is one of many lakes in California that was cited by the U.S. EPA as being "impaired" and was in dire need of attention to restore its health. Local and state agencies were compelled to conduct scientific-based analyses of this and other local waterbodies in mitigating the damage done. Restoring and promoting a healthier condition of this lake by creating a safe habitat for wildlife and for the enjoyment of the community follows the premise of the natural, built, and social environment as key constructs to improve community and individual health.

Machado Lake, along with Wilmington Drain and its associated wetlands, is considered one of the largest coastal wetland ecosystems remaining in Southern California (City of Los Angeles-DPWBOE, 2009). It is situated in the Ken Malloy Harbor Regional Park (KMHRP), Harbor City community of Los Angeles, California (see Figure 1). The KMHRP is approximately 15 miles south of downtown Los Angeles, along Freeway 110. Machado Lake, consisting of a seasonal freshwater marsh and riparian woodland, is approximately 45 acres in size, and is a part of the larger KMHRP regional park footprint of approximately 290 acres (City of Los Angeles-DPWBOE, 2009). Approximately 50 acres are developed to include a sports complex and pool, playground areas, a multi-use synthetic turf field, picnic areas, restrooms, ranger station, maintenance yard, and a fitness zone. The remaining acreage supports a native riparian forest, a freshwater marsh, and recreational open space. The nutrient TMDL listing and beneficial uses of Machado Lake are provided in Table 1.

Table 1

TMDL Listing and Beneficial Uses of Machado Lake

Water Body	TMDL	Pollutant/Nutrient	Uses	Beneficial Use
Machado Lake	Nutrient Indicators: TN, TP, NH_3	Nitrogen Phosphorous Ammonia	Recreational Related	REC-1 REC-2
			Habitat Related	WARM WILD RARE WET

Note. Data obtained from City of LA-DPWSAN (2010). REC-1 = Water Contact Recreation, REC-2 = Non-Contact Water Recreation, WARM = Warm Freshwater

Habitat, WILD = Wildlife Habitat, RARE = Rare, Threatened, Endangered Species, WET = Wetland Habitat.

The geomorphological setting of Machado Lake and its associated Wilmington Drain is the main receptor to one of the largest drainage areas within the Los Angeles basin, capturing storm water and urban runoff from its approximately 15,500 acre watershed (City of Los Angeles-DPWSAN, 2010). The KMHRP recreational area is bordered by three major thoroughfares: Pacific Coast Highway to the north, Vermont Avenue to the west, and Anaheim Street to the south. The east side of the lake and park borders Harbor Park Golf Course and Los Angeles Harbor College. A site map and aerial photo of this study area are provided (Figures 1 and 2).

Under a Clean Water Bond issued by the State of California, Proposition O was passed in 2004 (City of Los Angeles-DPWBOE, 2009). The City of Los Angeles and numerous stakeholders worked in concert to bring “life” back to this park and lake. This is a lake that provides a local natural resource and is a key for the wellness of the local and surrounding community. While lake water quality was the primary driver of the rehabilitation project, concurrent studies also addressed water conservation, flood control measures, habitat development and protection to create meaningful open space for the community (City of Los Angeles-DPW BOE, 2009). This approximately 500 million dollar ballot measure (City of Los Angeles-DPWSAN, 2018) was passed to conduct restoration and improvements of this and other freshwater lakes throughout California. By 2017, the restoration work at KMHRP was completed. Machado Lake and its recreational areas were re-opened to the public at that time (City of Los Angeles-DPWSAN, 2018).

Variables associated with the natural and built environment that can alter the water quality in a lake are typically related to lake size and depth, receiving waters and outfalls, natural patterns of water circulation, water aeration and ambient temperatures. These covariate variables help understand the dynamics contributing to changes in water quality. As cited by Zhang et al. (2022), algae growth models are limited in their use due to the variations of the parameters noted above. Many of these models do not provide adaptability in their representation of the water body. However, with the reconstruction and rehabilitation of Machado Lake, many of these factors are no longer as critical in evaluation for my research. Post-rehabilitation of Machado Lake has resulted in a partially engineered-lined bottom, contour and reinforced walls, improved and restored catch basins and discharge outfalls, and an aeration system to continuously oxygenate the lake water. These engineered controls of the lake, enhancing the "living" aspects of the ecosystem, allows for my research to focus on chlorophyll-a and nutrients as key variables to study. These conditions will be further discussed in Chapter 3, with an expanded discussion on the specific data variables being used in my research.

Regulatory Drivers

In 1998, under Title 303(d) and the Clean Water Act (CalEPA-RWQCB, 2022c), the U.S. EPA designated this lake and other local waterbodies throughout the nation as "impaired" water bodies. These freshwater lakes were identified as degraded that created toxic conditions to the environment, impacts to surface and groundwater quality, and deterioration to the ecological setting. The consequences were direct acute and chronic impacts to public health and native wildlife (Cheung et al., 2013; Chorus, 2001; U.S. EPA, 2022a). Eutrophic conditions, algal blooms and nutrient overloading were reasons for designating Machado Lake's natural drainage as impaired. The cause of impairment, whether due to natural or anthropogenic impacts, required the City of Los Angeles to develop TMDLs for improving the water-quality conditions of the lake. These TMDLs were established in cooperation with the U.S. EPA, and were incorporated into the City's water-quality management plan. As provided in Table 2, the established TMDLs for post-rehabilitated Machado Lake set forth the amount of pollutants the lake can accept without exceeding water-quality standards.

Table 2

TMDL Nutrients and Chl-a Advisory Thresholds

Water Body	Variable	Parameter	TMDL Limit[1]
Machado Lake	IV (Nutrient Factors)	Total Nitrogen	1.0 mg/L, monthly avg.
		Total Phosphorous	0.1 mg/L, monthly avg.
		Ammonia	5.95 mg/L, monthly avg.
	DV (Algae, Biomass)	Chlorophyll-a	.02 mg/L, monthly avg.

Note. Data obtained from City of LA-DPWSAN (2010). *TMDL* = Total maximum daily load, IV = Independent variable, DV = Dependent variable, mg/L = Milligrams per liter.

With these water-quality standards and management plans in place, continuous monitoring of this lake will provide real-time data in support of its intended beneficial uses. As previously mentioned, the physical setting of any water body being investigated needs to be documented as each site is unique. A Summary Fact Sheet for Machado Lake was provided (see Appendix A).

Studies of Other Lakes

On-going research studies of other lakes in California and across the nation have provided significant background, structure and insight for my research. While the subject of algal blooms has caught the attention of the international scientific community, there were numerous similar case studies to explore right here in our own back yard. From Lake Okeechobee in Florida, Lake Erie in Michigan, to Lake Elsinore in California, on-going research and field studies have help build a base of working hypotheses for others to consider in one's research. While these lakes continue to be monitored, the efforts undertaken by local, state and federal agencies are intended to preserve and protect their respective local waterbodies so that the public can enjoy these natural water features in the community. The lakes discussed all pose risks to individual health, damage to the environment and sensitive ecosystems that would have resulted in the decline of one's quality of life, both in terms of loss of open green space and the negative impacts on the economic and sociocultural systems. These lakes and other "key" peer-reviewed research articles provided a compelling foundation for my study.

On-going research studies are reinforced through the thesis and concepts of climate change, planetary boundaries, and wide-ranging environmental factors, such as: nitrogen and phosphorous cycles, sediment leaching, redefining nutrient pollutants, influences of ambient water temperatures, areas of flooding and drought that have triggered proliferation of algal blooms and cyanotoxins (US EPA, 2013; Howard et al., 2020; Visser et al., 2015). Howard et al. and his research team conducted the first formal study under the federal statute Title 303(d) of cyanotoxins in two impaired lakes in California: Lake Elsinore and Canyon Lake. Howard et al. measured algal biomass using chlorophyll-a, and tested for the presence of four cyanotoxins: microcystin, cylindrospermopsin, anatoxin-a, and nodularin. Based on the results of their research, Lake Elsinore exceeded California recreational health thresholds for these cyanotoxins, whereas the adjacent Canyon Lake only occasionally. Howard et al. determined that there was a statistically strong correlation using chlorophyll-a and microcystin concentrations in Lake Elsinore; however, Canyon Lake did not show a similar strong correlation. While chlorophyll-a had strong correlation for microcystin, the data did not show this to be the case for the other three cyanotoxins. Researchers concluded that the use of chlorophyll-a was not a good indicator for all those algal species, and therefore, not necessarily a good indicator for harmful algal blooms and cyanotoxins. The inconsistent results in their research gave pause using chlorophyll-a for predicting toxic blooms. Inferred through Howard's research, the uncertainties need to be further investigated and potential for harmful blooms need to be better understood through continuous monitoring of the lake water. Longer periods of data need to be considered in further establishing reliable indicators for harmful algal blooms. Furthermore, Howard et al. noted legitimate concerns over the complex toxin mixtures (uncertainty in the toxicology of mixtures) in conducting studies of this nature.

During hot summer months, Lake Okeechobee in Florida appeared to constantly be under a health alert for the presence of blue-green blooms and algal toxins (Florida

Department of Health [FL-DOH], 2022). Advisories are sent out and posted to the community to take every precaution not to contact the water where visible blooms have been observed. The postings warn local residents to keep pets away from the lake shoreline, do not drink, swim, fish, or boat. The Florida Department of Environmental Protection and Department of Health monitors the water quality to keep track of any health-related illnesses. As determined by these agencies, the blue-green algae blooms will continue to flourish so long as there are hot sunny days, increased water temperatures, still lake conditions, and excessive nutrients in the water (FL-DOH, 2022). While algal blooms have been recorded throughout the year, the peak season of blue-green algal blooms continue to occur during the long hot summer months (FL-DOH, 2022). Like many similar lakes across the nation, the abundance of blue-green algae and its related harmful toxins detected in this lake has limited its use to the public each year.

Dating back to 2011, Lake Erie, Michigan experienced the largest harmful algal blooms it had in its recorded history (Alliance for the Great Lakes, 2022). Abnormal meteorological conditions and runoff of excessive nutrients from local agricultural fields created perfect conditions for the onset of algal blooms. The factors that lead to this 2011 event are no different than what has been observed today in other similar lakes, with the exception that Lake Erie (approximately 210 miles long and 55 miles wide) is considered one of the largest lakes in the continental U.S. As one of five lakes of the Great Lakes, the algal blooms in Lake Erie impact more than 11.5 million people (Alliance for the Great Lakes, 2022). The Great Lakes Now had forecasted a moderate bloom season for 2020, an improvement from previous years (Proffitt, 2020). The effects from these blooms have not only impact human health, drinking water supply, and loss of recreational space, but also the local economy. Through the collective efforts of researchers and scientists, aspects of climate change and eutrophic conditions, waste load point and non-point sources, development of predictive models, satellite imagery, and innovation in field monitoring and data collection are an acknowledgement that new strategies are needed to address on-going algal blooms (Liu et al., 2020; Manning & Nobles, 2017; National Science Foundation, 2021; O'Neil et al., 2012).

Ecological and Socioeconomics

It is important to re-emphasize the ecological and wetland systems and the role they play to societal and individual health, as these features are an integral part of the natural and built environment. Impairment of water and degradation to the environment results in negative impacts on our way of life, and the socio-economy of the community. As cited by the U.S. EPA (2022a), state and federal agencies play a dominant role in keeping our water safe for its intended purposes, whether it is for recreation or for drinking. Our local, state and federal agencies are active participants in getting the funding and resources needed to tackle this issue. Restoring and protecting our lakes and surrounding natural resources to a healthy condition will improve societal health, lifting the socio-economic status of the local community (Glanz, 2008; Kilanowski, 2017). The bottom line is that the healthier the environment and associated water resources, the healthier the individual and the higher the socio-economic status of the community (Glanz, 2008; Hayden, 2019).

Principles and Concepts

The principles and concepts discussed in the following sections provide background on “key” technical aspects of my proposed study. Understanding these technical processes were important in establishing design and methodology to guide my research, as the overall purposes of my study are exploratory and descriptive.

Eutrophication

Eutrophication is the process by which a body of water becomes so enriched and overly nourished that the dissolved nutrients in water stimulate growth of aquatic plant life, including algae. The gradual increase in nutrient concentrations will promote the aging aquatic ecosystem processes of the lake (Conley et al., 2009; O’Neil et al., 2012). During warmer weather, algae will bloom from increase urban runoff of anthropogenic chemicals from the surrounding environment. As noted by Sobota et al. (2009), the study of the temporal and spatial influx of nitrogen by anthropogenic activity during specific times of the year can potentially help reduce the magnitude of this compound in the watershed. Conversely, an increase load of nutrients into our freshwater lakes will enhance the production of algal blooms. Furthermore, dissolved oxygen (O_2) will become depleted, and the result is suffocation of life (plant and animal) in the water body (O’Neil et al., 2012). Plants and algae are all producers that carry out photosynthesis, a process by which the plant will use carbon dioxide (CO_2), sunlight, water, and minerals (i.e., nutrients such as nitrogen, phosphorous, potassium, ammonia) to produce O_2 and energy (Davis et al., 2010; Yao et al., 2021). When minerals are abundant, algal growth will be excessive, forming a translucent to opaque green matted cover over the surface of the water where very little light can penetrate down to the middle and lower sections of the water body (Yao et al., 2021). Due to a lack of sunlight, the native plant species will die off (U.S. EPA, 2021b). Furthermore, as algae die, the algal decayed mats provide an abundant source of cyanobacteria. The decomposition of microorganisms depletes the O_2 in the water further adding fuel to cyanotoxic conditions. For survival, microorganisms rely on O_2 for aerobic respiration; however, over time the microorganisms will die and decompose. This toxic condition and lack of O_2 results in the imbalance of the natural system as discussed by CA-RWQCB (2022a), where death to wildlife, fish, and possibly humans have resulted due to exposure.

Plants and algae need several prevailing conditions to grow, such as: water, sunlight and CO_2. They also need a variety of nutrients, primarily nitrogen and phosphorus. While there are natural nutrients in the soil, unfortunately there is an over-application of fertilizer, mostly of fixed nitrogen and phosphorus, used to enrich the soil in the ground. Excess treatment applications to agricultural fields and individual lawns result in nutrient overloading downstream to freshwater ponds, lakes, reservoirs and eventually to the ocean. With the increased concentration of nutrients, algae, phytoplankton, and hydrophilic plants will grow in abundance. If the conditions are right, algae and phytoplankton will explode in growth in a lake. A layer of floating algae will form a cap over the water surface, not allowing sunlight through to the middle and bottom of the lake. Without sunlight, plants below the surface cannot contribute to photosynthesis and the water conditions will no longer support life (Dodds, 2007). Typically on the bottom, bacteria and other decomposers will consume the residual organic matter, and depletion of O_2 will result in fish kills and other related toxic illnesses to living matter. The worst-case scenario is that the water body is rendered unfit to touch, unfit to drink. At that point, the ecosystem is damaged that leads to a severe loss in biodiversity and detrimental impacts to public health.

Epidemiology and Public Health Hazard

Unlike traditional public health issues, national and global research of algal blooms and cyanotoxins are in an early stage of development (Neilan et al., 2013; Carmichael & Boyer, 2016). As cited by Wheeling (2019), Lake Erie had vast blooms of algae that resulted in shut down of recreational activities after four dogs were found dead after exposed to toxic water conditions. Direct human exposures were not specifically noted, but other researchers have documented similar situations that have resulted in illnesses and death to humans. As case studies are documented, and illnesses and possible death reported, epidemiological evaluation will be warranted for chronic illnesses should a larger population set be exposed.

Our understanding of the hazards are coming into focus through contemporaneous studies being performed in many freshwater lakes and coastal waters. Fortunately, harmful algal blooms are visible to the naked eye; and therefore, precautionary or mitigation measures can be taken immediately to prevent acute exposures to humans. However, once the water becomes toxic, the potential for deadly exposures for wildlife, fish, waterfowl, and other endangered species remain a concern. The “dead” zones in the water body could result in massive fish kills or illnesses to domestic animals that are exposed when playing along the water’s edge. Epidemiological studies would be warranted if algal blooms are persistent over long periods of time and chronic illnesses are observed.

As determined by U.S. EPA (2022a), conducting an epidemiological study will require researchers to distinguish between surface water sources of chemicals verses groundwater associated with nutrients and algal blooms. Surface water and groundwater are an integral part of the hydrologic water cycle, and when groundwater is used to replenish lake water there will be significant mixing of water that needs to be taken into account in evaluating water quality and chemical sources to lakes. The direct association of algal blooms and groundwater is even more difficult to determine since there are many more sources of contaminants that impact our groundwater system. While U.S. EPA continues to research algal blooms and cyanotoxins, full-scale epidemiological studies are rare (Wang et al., 2016). However, if algal blooms go unchecked, epidemiological studies would be absolutely needed in assessing the potential for “cluster” toxic-related health conditions.

Algae and Chlorophyll

Fundamentally, algae is a plant (U.S. EPA, 2022b), typically floating on the surface of the water. Algae has a relatively simple structure, ranging from macro-algae typical of large seaweed to single-celled aquatic phytoplankton (U.S. EPA, 2022b). It is the later that is of concern in shallow freshwater lakes and other waterbodies leading to algal blooms. This single-celled algae requires three basic elements to survive: sunlight, warm temperatures, and nutrients. It is understood that algae in nature is a natural phenomenon, and that not all algae in nature is considered bad. As cited by CDC (2021a), only a relatively small percentage of algal species are considered harmful. From numerous studies being conducted around the world, the presence and distribution of harmful algal blooms is broad and the impacts are pervasive (U.S. EPA, 2021b; WHO, 2021a). From the research conducted by Howard et al., (2020), the predominant cyanotoxin species being investigated in the freshwater lakes were: microcystin, cylindrospermopsin, anatoxin-a, and nodularin. Approximately 23 classes of cyanotoxins posing serious threat to our water systems impacting wildlife and drinking water have been identified (Manning & Nobles, 2017). Manning and Nobles stated that with an increase in the number of algal bloom occurrences over the last decade, especially in the U.S., and new threats with evolving species being found in both freshwater and marine environments, there is a greater sense of urgency to find solutions and refine field techniques. Yet, Sobota et al. (2009) makes note in the lack of studies that have examined how societal actions have influenced nutrients in areas that exhibit major seasonality in water. Laboratory and field research has increased significantly to explore new and innovative ways in addressing this issue.

Algal blooms occur due to natural and anthropogenic factors that create a condition allowing algae to grow unchecked by exploiting the conditions found in the environment. The conditions that promote growth are predominantly from nutrients, basically fertilizers that end up in our waterways, rivers, lakes, and ocean. With increasing nutrient loads into our waters during summer months, proliferation of algal blooms will occur. With runoff in urban areas, whether natural or induced by anthropogenic activities, harmful algal blooms will take over our natural waterways, specifically lakes thus causing extreme damage to the environment and human and animal life.

Algal blooms are typically noted when the lake surface turns discolored, generally a greenish-blue color. This is a signal that the pigmentation concentration of chlorophyll-a has begun to grow at exceeding rapid rates. Chlorophyll-a is the most common of the greenish color pigment that absorbs energy from sunlight for photosynthesis (Blankenship, 2010). As provided in Table 3, use of Chl-a concentration for lake classification helps in assessing the health and potential amount of algae in the water.

Table 3

Observation Class and Concentrations of Chl-a

Class	Conc. Range for Chl-a	Observation of Lake Waterbody	Typical Chl-a Conc. Range
Oligotrophic	<2 ug/L	No discoloration	0 – 10 ug/L
Mesotrophic	2 to 6 ug/L	Algal Scum evident, some discoloration	11 – 20 ug/L
Eutrophic	6 to 40 ug/L	Nuisance condition, considerable discoloration	21 – 30 ug/L
Hypereutrophic	>40 ug/L	Severe, very deep discoloration	>30 ug/L

Note. From “Nutrients and Eutrophication” by USGS (2022), Water Resources. Ug/L = micrograms per liter.

As referenced in the literature (U.S. EPA, 2022b; Ortiz, 2019), chlorophyll-a is quantitatively representative of the full-spectrum of the phytoplankton organisms in the water. There is a consensus that there are three stages of a bloom that can be observed and recorded. Researchers have intuitively believed that the peak algal biomass and bloom would coincide with the peak concentration of chlorophyll-a (Blakey et al., 2015).

This may typically be the case under fixed laboratory controlled conditions, but in the field this many not hold true where there are numerous other confounding variables to take into consideration. As noted by Blakey et al. (2015) and Rome et al., (2021), while inputs of nitrogen and phosphorous are a predominant factor for initiating higher concentrations of chlorophyll-a, seasonality is also a factor not to be overlooked. Furthermore, Yao et al. (2021) assessed nitrogen cycles through decomposition of algal biomass and sedimentary samples in determining significant differences in the nitrification/denitrification processes at the interface of soil and water.

In relation to my research objectives, Ortiz (2019) quantified algae blooms based on the dynamics of algal biomass into three stages of development: 1) the pre-bloom stage biomass being very low with little change occurring on a daily basis; 2) blooming stage where a rapid increase in color was observed due to the rapid production of chlorophyll-a pigmentation; and 3) full-bloom or peak stage when the bloom observed was determined to be at its apex. Whether it was weeks or months, Ortiz et al.'s observations were that after the apex, the bloom would eventually lose its color and would begin to diminish.

Increasingly today, algal blooms are being examined from a public health perspective, as during this blooming stage that harmful algal blooms, cyanobacteria and cyanotoxins are produced. Various mitigation measures, checks and balances, must be put in place to prevent the loss of our water sources in which individuals recreate, and even more importantly use for drinking purposes. This necessitates the need to investigate and understand how and what are the determinants of harmful algal blooms, especially considering the changing climatic conditions across the U.S. and around the world. Use of improved technology as discussed by Blankenship (2010), such as satellite imagery to collect real-time field data as an early warning of pending algal blooms would be a significant game changer in protecting sensitive areas of our ecosystem and societal health. While this technology is cost-prohibitive for most research studies, finding less costly means through research and use of existing data is imperative.

Nutrients

There are numerous variables that dictate the presence and severity of an algal bloom. While nutrient pollution is generally based on a number of different compounds, our specific interest was on nitrogen, phosphorous, and ammonia as compounds identified in the literature. While there are a number of chemicals that contribute to promoting algal blooms, research continues to focus on the two most commonly found in our environment, nitrogen and phosphorous. As studied by Wang et al. (2016), the evaluation of nitrogen and phosphorous ratios of between 7.9 and 10.1 were determined to be significant in promoting algal blooms.

Typical of lakes across the country, Machado Lake being no exception, agriculture, septic systems, individuals fertilizing their yard, or public and private groups fertilizing the local park or golf course have been the main sources of nutrient pollution (City of Los Angeles-DPWSAN, 2010; U.S. EPA, 2022b; Wang et al., 2016). Fortunately, these anthropogenic sources of nutrients can be controlled with effective mitigation measures. Liao et al. (2021) considered total nitrogen as one of the primary water-quality parameters used in the Random Forest model in predicting the occurrence of algal blooms. Liao et al. focused on nutrient water quality and was able to identify thresholds for algal bloom during stages of storm events.

Cyanotoxins

As algal blooms peak, especially during the warm summer months, much of the decaying plants and algae are generating bacteria, specifically cyanobacteria (U.S. EPA, 2022b). Large quantities of cyanotoxins can be released into water bodies during or immediately following cyanobacteria blooms. While not all cyanobacteria is deemed unhealthy, some of these bacteria are known to be toxic. The cyanotoxic bacteria most commonly found in recreational freshwater lakes are microcystin and cylindrospermopsin (Howard et al., 2020; Cheung et al., 2013; Loftin et al., 2016). These cyanotoxic species can be determined through laboratory testing; however, analyses for these constituents are very costly. Unless the objective of one's research or study required these analyses, it generally would not be performed due to the excessive cost of testing. Hence, all the more reason for researchers to find reliable scientific-based and cost-effective means of alternative field methods in predicting algal blooms.

Harmful algal blooms exhibit complex temporal and spatial patterns of formation (Blakey et al., 2015; Howard et al., 2020), based on the physical attributes of the water body. Understanding those factors that affect the severity of algal blooms and their relationships with nutrients is fundamental to evaluating the presence of cyanotoxins in water (Falconer & Humpage, 2005; Howard et al., 2020).

Preliminary exposure assessment research has helped to evaluate the specific cyanotoxins produced during harmful algal blooms, specifically microcystin and cylindrospermopsin (Howard et al., 2020; NIH, 2021). As cited by Falconer and Humpage (2005), microcystin is one of the more commonly produced cyanotoxin found in freshwater. In coastal studies, Tatters et al. (2017) sampled up and down the California coast to identify cyanotoxins along the land-sea interface. In addition to microcystin and cylindrospermopsin, the marine environments of brackish waters appear to exhibit and produce other different toxins than that found in freshwater environments. Their research addresses the complications of cyanotoxin identification. Tatters et al. used over 53 sampling stations to determine the cyanobacteria genera. Tatters and his team of researchers identified a number of health concerns related to exposures from recreational swimming, shellfish consumption, and industrial discharge operations from power and desalination plants that highlights the number of sources that contribute to algal blooms along the coast. Monitoring and comprehensive assessment programs are the "key" to developing the appropriate strategies in preventing algal toxic blooms.

Routes and Risk of Exposure

The health impacts of these toxins to humans and wildlife can be significant, posing challenges to drinking and recreational waters as primary routes of exposure (Falconer & Humpage, 2005). The majority of exposures to cyanotoxins or neurotoxins result in acute illnesses. Exposure to these toxins in water have resulted in stomach illnesses, respiratory illnesses, vomiting and diarrhea and severe cases of kidney and liver damage (NIH, 2021; CDC, 2021b). The routes of exposure are generally from recreational use of waterways, aerosol spray from lake aerators or ocean waves, and more importantly potential for death for individuals with compromised immune systems. The long-term consequences of reoccurring or continuous exposures to toxins are not known (CDC, 2022).

Most state water management plans call for frequent monitoring and water testing as an essential tool in developing public health advisory notifications to ensure public safety. The U.S. EPA (2016b) has established guidance levels for toxics that may affect vulnerable populations, specifically infants and children under the age of six, and the elderly. These guidance or advisory level concentrations are not federally enforceable limits (U.S. EPA, 2016b). Falconer and Humpage (2005), examined cyanobacteria in drinking water and in case studies referenced that monitoring data for toxins in water and epidemiological studies on adverse health effects are lacking. They strongly advocated that these issues be further investigated, especially for individuals with pre-existing kidney and liver aliments, to clarify risks of exposure and the extent of health risks.

Other risk of exposure comes from the seafood we consume, such as: shellfish, clams, oysters, mussels. These bottom-dwelling crustaceans pose a real threat, as these creatures filter large volumes of water that results in an accumulation of toxic concentrations in their tissue (Guo et al., 2020; WHO, 2021b). Shellfish and fish poisoning have been well-documented in the literature, especially in subtropical and tropical regions of the world. The World Health Organization (WHO) frequently warns the public against shellfish consumption due to toxins exceeding WHO's advisory levels (WHO, 2021a).

Falconer and Humpage (2005) conducted research of cyanotoxins that have caused human poisoning in the Americas, Europe, and Australia in drinking water as a primary route of exposure. As cited by Falconer and Humpage, the risks of exposure to cyanotoxins are the neurotoxic alkaloids (anatoxins and paralytic shellfish poisons); microcystin (cyclic peptide hepatotoxins); and cylindrospermopsins (cytotoxic alkaloids). Microcystin has been the only toxin evaluated by WHO on an international basis (WHO, 2021b). Microcystin is known to cause liver damage and are an active tumor promoter (Cheung et al., 2013; Davis et al., 2010). As reported by Howard et al. (2020), guideline levels for this toxin is 1 ug/L for drinking water. Cylindrospermopsin has damaging characteristics in genotoxicity and mutagenicity, and is a potential carcinogen that causes human poisoning from drinking water (U.S. EPA, 2022a). This toxin exposure limit is also 1 ug/L (Howard et al., 2020).

Predictor of Algal Blooms

Researchers have derived formulas and models to address "tipping" points, specifically related to water and chemical cycles in the environment (Lenton et al., 2008). Lenton et al.'s research of developing prospects for early warning systems for pending destructive planetary conditions continue to be an on-going subject of concern. By using the constructs of planetary boundaries, it is hopeful that corrective measures can be implemented to slow the negative processes affecting the proliferation of harmful algal blooms and cyanotoxins. As derived from on-going research, the eutrophic stages of algal blooms are fairly well understood (Ortiz, 2019; USGS, 2022). The science and natural processes of eutrophication are also well documented in the literature. By the study of indicators and establishing predictors of algal blooms can we establish an important link in preventing eutrophication (Yao et al., 2021; Zhang et al., 2022). Algal bloom thresholds based on nutrient loading as identified by Liao et al. (2021), ties together several of the natural mechanisms in furthering our understanding of algal blooms. The bottom line is that each lake has its own signature that needs to be studied and understood. Collectively, trends and patterns may reveal alternative methods to control and or mitigate blooms in the pre-development stage.

Select lakes in California are being routinely monitored by local agencies, and their condition reported as provided in Appendix B. On the micro-scale, data collection of select variables will possibly lead to finding ways to establish a trigger point as a means of predicting algal blooms in Machado Lake. Whether this lake or other similar lakes across the nation, there may not be one single condition that could be applied universally to predict the pre-development of harmful algal blooms.

In evaluating key parameters of Machado Lake, the relationship between variables will offer insight in determining if there is a "trigger" point for occurrences of algal blooms in the lake. As cited by Lenton et al. (2008), exceeding thresholds for nutrients requires a holistic view of one's environment to prevent the initial stage of pre-bloom or pre-development of harmful algal blooms. Hence, by filling this void noted in the literature through repeated real-time lake data evaluations will researchers and scientists be able to find solutions to the benefit of the community and public health.

Summary

The designation of Machado Lake as being "impaired" lead to its restoration and rehabilitation (City of Los Angeles-DPWBOE, 2009). In doing so, the surrounding environment, local community, and public health have all benefitted. While only a relatively small percentage of algal species are considered harmful, the presence and distribution of harmful algal blooms is broad and the impacts are pervasive (U.S. EPA, 2021b). Chlorophyll-a concentrations, used as an indicator of algal blooms, and the relationship of nutrient pollution is just one part of the puzzle. As the occurrence of algal blooms continue and new threats with evolving species in freshwater environments (U.S. EPA, 2022a), the urgency to fill the void in finding more reliable field solutions are critically important (Manning and Nobles, 2017; Liao et al., 2021; Zhang et al., 2022; U.S. EPA, 2022a). Laboratory, field research and adaptive dynamic models are needed in discovering new and innovative evaluation methods to address this issue (Zhang et al., 2022).

Researchers have studied the use of chlorophyll-a as an indicator of the severity of harmful algal blooms and cyanotoxins (U.S. EPA, 2013; U.S. EPA, 2021b). Furthermore, researchers have postulated that there is a lack of site-specific field-test data provided in the literature to advance our understanding of chlorophyll-a and algal blooms, and its drivers such as nutrient pollution (Manning and Nobles, 2017; U.S. EPA, 2022a). Just as there have been different points-of-view taken on algal blooms and chlorophyll-a from lab and field research, establishing the relationship of algal blooms and nutrients with real-time field data is equally important, if not more important. The independent and dependent variables of these blooms are site-specific and do vary from one location to another. Therefore, as mentioned by Bogardi et al. (2013) and Manning and Nobles (2017), detailed and focused research is needed in the field to better understand the relationship of these variables that drive blooms to become excessive and toxic to human health in the natural environment. Researchers express the need for more field case-studies in assessing trends, associations and relationships of real-time algal bloom data (Liao et al., 2021; Manning & Nobles, 2017; Tatters et al., 2017).

Local ordinances, rules and regulations and effective public policy and education have helped to reduce the impacts to lakes and our natural environment. However, each lake or waterway where data can be collected adds to the existing body of knowledge in understanding what make algal blooms occur. As cited by Wang et al (2016), every situation is different and the site-specific conditions must be investigated.

In my stated research questions set forth in Chapter 1, clearly my effort is to help narrow the gap in the literature as my retrospective study is only a small part of the bigger picture. The intended outcome of my research is to add to the existing body of knowledge in making progress in preventing algal blooms from overtaking our natural ecological system and social systems related to public health in our “lived” environment. Our knowledge gained of critical thresholds of the research variables will be informative for future research of freshwater lakes of similar and like conditions. In the next section, Chapter 3, the relevancy of the data variables in my study have been provided through a discussion of my research design, methodology, research questions, and data analysis plan.

Chapter 3: Research Methodology

Public health concerns continue to grow over the risks of algal blooms that have detrimental impacts to human health and the socio-ecological environment (CDC, 2021a; Hayden, 2019; NIH, 2021). Research at the local, state, and federal levels have provided scientific-based evidence and documentation for nutrient pollution cycles and its association with algae (Blakey et al., 2015; U.S. EPA, 2021a; Wang et al., 2016; James et al., 2009). Over the past 10 years, research has focused specifically on eutrophic environments and chlorophyll-*a,* and their impacts on lake and stream water-quality conditions that promote cyanotoxic harmful algal blooms (U.S. EPA, 2021a; SCCWRP, 2021). Research of blooms in freshwater bodies across the nation, such as those studies conducted under the National Lake Assessments (Loftin et al., 2016; NIH, 2021; Xu et al., 2021), have established links between eutrophication, harmful algal blooms, and cyanotoxins that have caused severe damage to the environment. Furthermore, the negative impacts to human health leading to illnesses and death, and the killing of aquatic wildlife and domestic animals, are well-documented in the literature (SCCWRP, 2021; CA-DWR, 2022b; U.S. EPA, 2022c). Specific to my research statement of Machado Lake, this chapter provides further discussion of my research rationale and study questions, a data analysis plan, data validity, threats, limitations, and ethical concerns.

Purpose and Population

Inferred from national and local-based models, there continues to be epistemic uncertainty in evaluating the health of water bodies due to variations in data collection and scoping when comparing research of similar sites across the nation (USGS, 2022;

Loftin et al., 2016). As previously discussed in Chapter 2, the use of chlorophyll-*a* concentrations is critical in evaluating growth patterns of phytoplankton biomass and algae (Dodds, 2007; Conley et al., 2009; Xu et al., 2021). In understanding the problematic issues associated with algal blooms, the relationship between TN-TP-Chl-*a* covariates in promoting harmful algal blooms needs further study and modelling to fundamentally establish meaningful thresholds for ambient water-quality goals tied to a waterbody's intended beneficial use, whether recreation, aquatic wildlife, and/or for drinking-water purposes (CDC, 2022; SCCWRP, 2021; U.S. EPA, 2021a).

The subject target population of my retrospective quantitative research assessment of Machado Lake was based on use of water-quality measures: data concentration measurements of independent and dependent variables that are numeric and continuous. In principle, the assessment of the data is tied to the scientific-based criteria of eutrophication in relation, correlation, and interpretation of the relationship between the independent or predictor nutrient variables and chlorophyll-a, the outcome variable as a precursor to harmful algal blooms. As furthered discussed in sections of this chapter and as approved (IRB Approval Number 10-21-22-0366318), the study population of case variable measurements was used for descriptive, correlation, and multiple linear regression analyses.

Research Design and Rationale

Understanding processes of eutrophication in shallow lakes have been the subject of study over many years (Loftin et al., 2016; WEF, 2021); however, there remains inconsistencies and deficiencies in research in understanding the relationships of natural and anthropogenic factors that result in unsafe conditions in freshwater lakes that promote excessive harmful algal blooms (Howard et al., 2020; Xu et al., 2021; U.S. EPA, 2021a). Similar to human health research studies, environmental conditions that promote algal blooms that produce cyanobacteria and associated cyanotoxins are not-well understood, nor well-documented in the literature (Xu et al., 2021). According to the CDC (2021a), toxins resulting from extreme algal blooms pose significant challenges to drinking water supplies and health concerns in urban areas. In evaluating the relationships of TN, TP, NH_3 and chlorophyll-*a*, while controlling for seasonal changes (wet and or dry seasons), I sought to better understand the elements for forecasting of algal blooms. The importance of seasonal changes was evident in past studies conducted by Cheung et al. (2013) and Wang et al. (2016). For purposes of identifying season influences in the region related to bio-stimulation, the wet season is 6 months from October 1 to March 31, and the dry season is from April 1 to Sep 30 (State of CA–DPH, 2022). In conducting my research and in following with Howard et al. (2020), Xu et al. (2021), U.S. EPA (2021c), and others, the inconsistencies and discrepancies in field research needed to be further understood to close the gap of knowledge in the ability to control the propagation of harmful algal blooms and cyanotoxins.

The use of Machado Lake data for purposes of my research is to determine if a relationship exists between nutrient parameters of TN, TP and NH_3 (independent variables) and chlorophyll-*a* (dependent variable, a measure of phytoplankton biomass and correlation to algae). Depending on the strength of the relationship, measures of the independent variables may be used as a predictor of chlorophyll-*a* (dependent variable) for estimating stages of eutrophication and algal blooms (Dodds & Smith, 2017). The latter stages of eutrophication that leads to harmful algal blooms and cyanotoxic conditions, resulting in water-body dead zones, animal and human illnesses and death (CDC, 2021a), needs to be controlled.

My research design is based on the TN-TP-Chl-a model in conducting an empirical statistical quantitative analyses (Wang et al., 2016; SCCWRP, 2021). Again, the relationship between the following variables are being studied: independent variables (or predictor variables – TN, TP, NH_3); and the dependent variable (or outcome variable - chlorophyll-a). In achieving my research goals, my study method will utilize a robust secondary dataset associated with the chemical concentration measurements of TN-TP-NH_3-Chl-*a* parameters to statistically evaluate the relationship between the nutrient and chlorophyll-*a* variables.

The concepts and models cited by Howard et al. (2020), Wang et al. (2016) and Yao et al. (2021) provide a firm foundation for the basis of my research and possible future research of similar settings where monitoring data is collected. As other contemporaneous researchers have concluded and in aligning with the SEM theoretical constructs (Conley et al., 2009; Kilanowski, 2017), there needs to be more research to further our understanding of the multi-layered ecosystem and ever-changing complex environmental conditions. In doing so, appropriate corrective measures can be taken at the individual and community levels to improve and protect our water environment and individual health.

Methodology

Assessing associations and relationships has been evaluated using both descriptive and inferential statistics. Based on my research objectives, type, distribution, and nature of observations and collection methods used by the City WPD, this secondary dataset met the assumptions for use in descriptive, correlation and linear regression analyses. The dataset consisted of the key independent and dependent water-quality parameters, with all variables being numerical and continuous. The statistical analysis was performed using the SPSS software.

Descriptive Analysis

Data associations were assessed using numeric *Descriptive Statistics* to evaluate the scales (i.e., frequencies, central tendency, range and variability – mean, mode, variance, standard deviation, percentile ranks, outliers, etc.) in describing basic features of the data. Within SPSS, the generation of plots, tables and graphs were produced in describing and or establishing patterns of the dataset.

Correlation and Multiple Linear Regression

Inferential Statistics based on hypothesis tests, correlation and multiple linear regression analyses were performed in drawing conclusions about the relationships of the variables. In using SPSS, the correlation evaluation provides the strength and direction of the relationship, as either positive or negative. While the direction and strength of each relationship has been established between the predictor variables and outcome variable, it does not address cause and effect or why variables may have greater influence over the other. In using the linear regression, this analysis allowed for specific quantitative predictions that more accurately explains the relationship between the independent and dependent variables. A further discussion of the evaluation process is provided in the Data Analysis Plan section.

Secondary Data

Secondary water-quality datasets of Machado Lake were acquired from the City of Los Angeles, WPD. The benefit of use of this dataset is that the City has granted permission to access their water-quality dataset that one could not otherwise easily collect on their own. With the spatial distribution of four in-situ buoy's or monitoring points in Machado Lake that continuously collects data on a set frequency (hourly, daily, weekly, etc.), and individual records of up to four key variables results in over one million discrete data case records. The secondary datasets covered the time period of about 4 years, from approximately November 2017 through present day (year-end 2021). The datasets covering the 4 year period include: 1) Machado Lake Field Probe Monitoring data; and 2) observational and discrete water-quality data related to algal blooms. Although the frequency of measurement vary between the two datasets, the datasets do complement each other. Depending on the final evaluation for dataset use, whether a single dataset or in combination, each variable from the field in-situ probes had a minimum of 250,000 case measurements; thus, the potential total population size based on four key parameters being used could be about 1,000,000 case observations.

Once a complete dataset was obtained, a final review on its intended use and verification of specific variables was made. Assuming that the secondary dataset used had integrity and validity, there were no other anticipated field data collection needed prior to initiating my research. Notwithstanding, this dataset was refined for purposes of focusing in on my research constructs, as further discussed in Chapter 4.

Confounding Variables

Researchers have had to take into consideration a number of confounding variables that are known to impact the presence and growth of algal blooms. While confounders have been duly noted, since completion of the reconstruction and rehabilitation of Machado Lake, the physical setting improvements made have reduced and mitigated many of the previously identified geomorphological issues known to have contributed to its impairment in the past (City of LA-DPWSAN, 2018). Post reconstruction, certain physical elements such as depth, input and output controls of water flow, in-lake water circulation, and contaminated soil are not currently considered a "significant" factor, but rather these confounders are essentially static in terms of my research goals.

Instrumentation

The field in-situ instrumentation used by the City WPD for data collection has been the YDI EXO-2 Sondes dataloggers manufactured by Campbell Scientific. A compatible software program – LoggerNet has been used by the City WPD to configure the dataloggers hardware and manage data compilation (personal communication, City WPD - February 14, 2022). The YSI EXO-2 instruments are capable of long-term deployments. City staff are instructed and trained to follow the Operation and Maintenance (O&M) manuals provided with this instrumentation from the manufacturer, an important point in assessing the integrity and validity of the data.

Data Analysis Plan

In addition to a descriptive evaluation of my dataset, my quantitative study used correlation statistical analysis to assess the strength and direction of the relationship between each independent variable and the dependent variable, and through multiple linear regression the ability to use independent variables to predict the dependent variable. In using the SPSS program, the scales of measurement were interval and continuous for the following variables: independent variables (IV) of TN, TP, NH_3 and dependent variable (DV) of Chl-*a*, as a measure of phytoplankton biomass and algae. The correlation test was used to estimate the coefficient R^2 in determining the strength of correlation as either negative, positive or no relationship (absolute values of between, -1, 0, +1).

In multiple linear regression, b_1 is the estimated regression coefficient quantifying the association between the predictor X_1 and the outcome, adjusted for X_2 (b_2 is the estimated regression coefficient quantifying the association between the potential confounder and the outcome), so forth and so on. For multiple linear regression (Field, 2013; Laerd Statistics, 2022), the following equation has been used:

$$Y = b_1X_1 + b_2X_2 + b_3X_3 + b_0$$

where:

Y = Outcome or dependent variable;

X_1 = Predictor or independent variable, X_2 etc.;

b_1 = Slope of the line or estimated regression coefficient (quantifying the association between predictor and outcome variables); and

b_0 = intercept value (value of y, when X = 0).

My research data analysis plan aligns with concepts associated with the TN-TP-Chl-*a* model (Wang et al., 2016; Sutula et al., 2022) in assessing the relationship between variables associated with algal blooms. A number of steps for the conduct of my research were taken as follows:

1. Examination of the dataset and further review of the variables for reliability and validity.
2. Verification that datasets have the complete set of variables in determining TN, TP, NH_3, and chlorophyll *a.* TN is the sum of all nitrogen forms (U.S. EPA, 2021c), and can be determined as follows: $TN = TKN + NO_2 + NO_3$.
3. Re-coded the datasets to control for seasonal changes, if appropriate.
    - Wet Season = Group 1 (Oct 1 – Mar 31)
    - Dry Season = Group 2 (Apr 1 – Sep 30)
4. Conducted statistical evaluation of dataset: descriptive, correlation, multiple linear regression. Generated output of supporting tables, plots and graphs.
5. Interpretation of data output.

Once the datasets were thoroughly vetted in Steps 1 and 2, the SPSS program was used to perform the SPSS quantitative analyses of my subject variables. In addressing my research questions presented in the following section, the statistical tests to be performed were run concurrently, but handled separately for correlation and regression analysis. The multiple regression analysis followed the correlation analysis to determine if one can predict the other.

Research Questions

The use of correlation and regression is tied to the relational or predictive sphere. Hence, in keeping with my study objectives and in the context of my research questions, my interest was limited to key nutrient predictor variables and the outcome variable of chlorophyll-a. The term correlation is synonymous to relationships, and prediction is synonymous to impact, influence, and or interaction. While it is not intended to determine causal relationships, the overarching issue was whether or not and to what extent can the independent variable(s) predict the dependent variable for Machado Lake.

The following research questions form the basis of my assessment. Each research question has a null and alternative hypothesis that was examined.

Research Question 1 (RQ1): What is the relationship between total nitrogen (TN) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change (wet and dry season)?

$H_0$1: There is no relationship between TN and chlorophyll-*a*, when controlling for seasonal change.

H_a1: There is a relationship between TN and chlorophyll-*a*, when controlling for seasonal change.

Research Question 2 (RQ2): What is the relationship between total phosphorous (TP) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change?

$H_0$2: There is no relationship between TP and chlorophyll-*a*, when controlling for seasonal change.

H_a2: There is a relationship between TP and chlorophyll-*a*, when controlling for seasonal change.

Research Question 3 (RQ3): What is the relationship between ammonia (NH_3) and chlorophyll-*a* in this rehabilitated lake, after controlling for seasonal change?

H_03: There is no relationship between NH_3 and chlorophyll-*a*, when controlling for seasonal change.

H_a3: There is a relationship between NH_3 and chlorophyll-*a*, when controlling for seasonal change.

Research Question 4 (RQ4): To what extent do TN, TP, NH_3 predict chlorophyll-*a* while controlling for seasonal change?

H_04: There is no predictive relationship between TN, TP, NH_3 and chlorophyll-*a*, while controlling for seasonal change.

H_a4: There is a predictive relationship between TN, TP, NH_3 and chlorophyll-*a*, while controlling for seasonal change.

Validity of Data

As with all field studies, researchers must trust the data assuming the data collected can be verified that it has been obtained in a technically-sound manner, not faulty through use of poorly maintained equipment or biased by field research teams. Fortunately, technology has advanced to where in-situ measurements can be collected with improved reliability and validity. Inspection and training is essential to maintain this high level of confidence in the data collected in the field.

The City WPD's data collection program was vetted to evaluate whether or not the processes used in acquiring their information meets and or exceeds state and federal guidelines and industry quality assurance, quality control measures and standards. While quality assurance for the most part relates to the planning of activities associated with data collection, quality control is considered more reactive in addressing problems that may arise during the conduct of obtaining data (U.S. EPA, 2021a). In the case of field instrumentation, the end user needs to be properly trained in its use and application. Following instrumentation manuals is essential in obtaining reliable and accurate data, especially in addressing the long-term instrumentation data collection processes of operation and calibration of equipment (U.S. EPA, 2022a). A quality assurance and quality control plan is essential for purposes of verification and validation of the data collection and instrumentation processes used.

As reported by City staff (personal communication, City WPD, February 14, 2022), guidance and protocols as established in the Dominguez Channel Coordinated Integrated Monitoring Program (CIMP) are used to bring continuity to the data collection and monitoring process for Machado Lake. My research was bound to the variables and processes developed by them, and instrumentation employed. In preliminary conversations with the City WPD, it was understood that their data set is robust and the subject variables for my research are contained in the dataset. With the large case numbers available, initial steps were taken to prepare and clean, if necessary, the "raw" data prior to any statistical analyses and recode as appropriate. Cleaning or adjusting units of concentration may be necessary, especially when using in-situ instrumentation and fixed-based laboratory derived data.

Ethical Considerations

There were no readily identifiable threats or ethical concerns in the implementation of my research, as the data does not refer to human subjects. The City WPD are the originators of the dataset and have been responsible for the collection and storage of the dataset. The City WPD granted permission in a letter for the use of the data. In addition, there are no known or anticipated conflicts of interest.

Summary

The methodology and design plan lay the groundwork for answering one's research questions. My summary of the methodology presented in this chapter delineates a systematic approach for assessment of the case count dataset being provided by the City WPD. The benefit of use of this dataset was that the City has granted permission to access their water-quality dataset that one could not otherwise easily collect on their own. A correlation and multiple linear regression of the independent variables TN, TP, NH_3 and dependent variable Chl-a were used to examine their relationship for prediction of algal blooms as a proxy for harmful algal blooms and cyanotoxic water conditions in the lake water body.

The significance of my research has been to understand the associations and relationships of nutrients and chlorophyll-a to predict the potential for algal blooms leading to harmful algal blooms and cyanotoxic conditions using constructs of the TN-TP-Chl-a conceptual model. As such, an early warning precursor to harmful algal blooms may be achieved to protect human health against detrimental impacts from late stages of eutrophication impairing lake water-quality conditions (Bogardi et al., 2013; Steffen et al., 2015). Furthermore, gaining this pertinent knowledge leads to improvement in real-time proactive monitoring, data collection, and mitigation programs. While my research objectives are problematically only a small part of the larger scientific framework being undertaken today, my research will add valuable scientific-based knowledge for further development of technically-sound field methods, designing effective management strategies, and ultimately more meaningful policy.

This chapter has provided for my study design, secondary-data collection methods, and statistical procedures, evaluation of validity and integrity of data, and ethical concerns. Looking to the next section, Chapter 4 summarizes the measurement results used in the statistical, mathematical and numerical analyses performed to address my research objectives. A discussion on the associations and relationships of my quantitative study are highlighted. Rehabilitating, maintaining and protecting freshwater waterbodies for its intended use, minimizing potential exposure and human health risk, and giving the community access to such waterways for recreation, clean water sources, sensitive habitats all contributes to positive social change

Chapter 4: Results

Public concerns continue to grow over the health risks of exposure to harmful algal blooms that impact the socio-ecological environment, community, and human health (CDC, 2021a, NIH, 2021). On-going research of algal blooms and the role that nutrient pollution cycles play in promoting the growth patterns of biomass and algae need to be further studied in real-time in the open natural environment (Conley et al., 2009; Xu et al., 2021). There is sufficient evidence that freshwater lakes and open waterways have been severely damaged as a result of harmful algal blooms linked to late stages of eutrophication, with the eventual formation of cyanotoxins (State of CA-RWQCB, 2022a). According to the CDC (2021a), cyanotoxins resulting from the degradation of lake water quality, due to extreme algal blooms, pose a significant challenge in protecting freshwater habitats, recreational open space, and the drinking water supply. Researchers are in agreement that there is an urgent need to fill gaps in the literature related to the association of nutrient pollution and Chlorophyll-a in the natural environment. By investigating these nutrients in the natural environment (TN, TP, and NH_3 as key factors related to formation of algal blooms), I sought to establish meaningful thresholds in protecting the intended beneficial uses of local fresh-water lakes and water ways (Wang et al., 2016; SCCWRP, 2021). In this chapter, an analysis of these nutrient pollutant predictor variables and Chlorophyll-outcome variable interconnected to algal blooms as a precursor to harmful algal blooms has been performed and the results of this research are presented.

Overview of Research Dataset

The secondary water-quality dataset of Machado Lake was acquired from the City of Los Angeles, WPD. Several dataset files for my target population lake were reviewed and vetted for their applicability in addressing my research objectives. The datasets consisted of both in-situ probe and "grab" water-quality data, the bulk of which was coded specific to the instrumentation output (concentration values were reported in milligrams per liter, mg/L). Consolidation of the variables was considered; however, upon further examination of the in-situ datasets, I noted that many of the independent variables needed for my research were either missing or not collected. Of the datasets received from the City of Los Angeles, the most complete and reliable dataset meeting industry standards of "quality assurance and quality control" were the water "grab" samples taken at two locations from the target population (Machado Lake) post rehabilitation. From these "grab" sample datasets, four key variables needed for my research were available and these variables were analyzed by the City in the laboratory at a frequency of twice per month from late 2017 to my analysis in 2022. For my research, the dataset was trimmed to a 4-year period, from approximately November 2017 to December 2021.

The research approach and rationale for the statistical test methods used are discussed in various sections of this chapter. There was concern over the assumption of normality for my referenced dataset. While it is not uncommon that a dataset is non-parametric, appropriate options in handling the dataset needed to be considered. As discussed in this chapter, modifications to the dataset were taken to approximate normal distribution. Briefly, steps were taken to filter outliers and transform my dataset to an approximately normally distributed dataset for use in performing correlation (Pearson's Correlation) and multiple regression (Multiple Linear Regression - MLR) statistical tests. In summary, Table 4 highlights the key statistical tests used.

Table 4

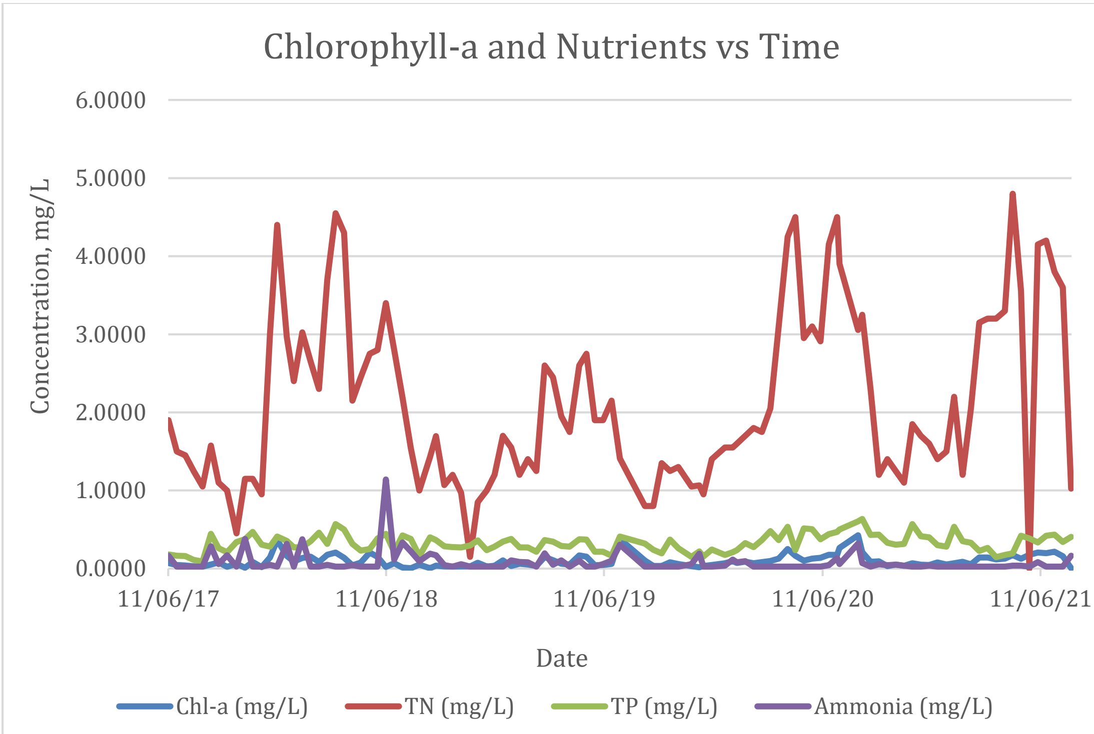
Overview of Statistical Tests

Statistic Test	Rationale
Independent t-Test	Control for Seasons – Equality of Means between Seasons
Shapiro-Wilk	Testing for Normality
Pearson's Correlation	Relationship – Strength and Direction
Multiple Linear Regression	Prediction and Regression Equation

A time-series plot of the raw data is presented in Figure 7. The time-series plot of the data shows how each variable changes in case value (concentration, mg/L) over time. The dataset represents approximately 4 years of data collected over the period of November 2017 to December 2021. The total observations of each variable is 102 cases, with no missing values. While highs and lows along the trend line are observed, these fluctuations occur somewhat randomly throughout the calendar year. A further analysis of these changes will be discussed in assessing the equality of the means between seasons. Furthermore, additional supporting data output, such as frequency tables, histograms, boxplots, and scatterplots are provided this chapter and Appendix C. A table of acronyms used are provided in Appendix D.

Figure 7

Time-Series Graph of Variables vs Time (Raw Data)



Modifications to Research Dataset

A number of steps were taken in preparing my dataset to approximate normality. These steps are described here, and further discussion is provided in other appropriate sections of this chapter. The steps include:

- Filtering outliers from my dataset, leaving 100+ observations for each independent variable and dependent variable.
- Transformation of data to SQRT and LOG10 to assess which of these transformed variable datasets better approximate normality.

- The frequency statistics of NH_3 indicates that a significant number of case values are very low and near zero (~ 0.025). With these low values, the variable was not continuous and transformation of NH_3 did not improve its approximation toward normality; therefore, this variable was recoded as dichotomous, as discussed below.

Transformation of the data required testing two methods and comparing the results in approximating normal distribution. Several outliers were filtered from the original raw dataset. Subsequently, the data was transformed using the square root (SQRT) and logarithmic (LOG10) functions to compare which transformation best exhibited near approximate normal distribution. Based on these conversions, the transformed SQRT results provided the best improvement to approximate normality, making the data more amenable to analysis. Notwithstanding, Pearson's Correlation and Multiple Linear Regression (MLR) are robust to deviations from normality (Field, 2013).

For the independent variable NH_3, the case values were observed not to be continuous and did not approximate normality after transformation; therefore, steps were taken to recode these case values into a dichotomous set of two groups, NH_3Recode 0 and 1. By recoding and changing to dichotomous, distribution and normality are no longer an issue of concern. This variable did not undergo Pearson's test as Pearson is for a continuous variable, not a dichotomous one. While NH_3 was not used in correlation, it was assessed as a dichotomous variable in the multiple regression test.

Controlling for Seasonal Changes

As originally posed in my research questions, consideration of seasonal changes as a possible controlling factor needed to be considered. An overview of the group statistics for the dependent variable Chl-a is provided in Table 5.

Table 5

Group Statistics

	Season	*N*	Mean	Std. Deviation	Std. Error Mean
Chlorophyll[a,b]	"Wet"	52	.079	.062	.009
	"Dry"	50	.091	.048	.007
SQRTChl-a	"Wet"	52	.258	.111	.015
	"Dry"	50	.291	.082	.012

Note. [a] Dependent variable, both raw (Chlorophyll) and transformed (SQRTChl-a). [b] Chlorophyll – raw data.

As cited in the literature (Fleming et al., 2002; Dodds et al., 1998), algal blooms in freshwater lakes and small water bodies are susceptible to seasonal changes. During dry hot summer months the water body can be observed to turn a slight green, indicative of algal blooms and an early warning of eutrophication (Falconer & Humpage, 2005; Dodds, 2007). As the cold winter months occur, the freshwater bodies are less prone to changes in color. In Southern California, freshwater lake conditions are subjected to very different conditions than other lakes across the nation when addressing seasonal changes. For my target water body (rehabilitated Machado Lake), seasonal changes refers to wet and dry as opposed to changes in seasonal temperatures as typically referenced in other lakes across the nation (US EPA, 2021a).

Season (wet and dry) has been examined using the Independent t-Test to address the following: *Is Season an important factor to control for in my data analysis?* Using the t-Test, the estimated mean values of Wet and Dry season of my dependent variable were compared (equal or not equal). To determine whether or not to control for seasonal changes has been based on whether there is a distinct difference among the mean values for my dependent variable (Chl-a and SQRTChl-a), wet and dry season. Depending on the outcome of the t-Test, seasonal control to my research would be applied as appropriate.

As grounded in the literature, the working hypothesis is that there would be a distinction in case values between seasons, thus controlling for season. The working hypothesis is as follows:

> $H_0$1: the statistical significance of the means of the two groups are equal [i.e., wet season mean (group1) = dry season mean (group 2)]. There is no difference in the two groups.
>
> H_a1: the means of the two groups are not equal [i.e., wet season mean (group1) ≠ dry season mean (group 2)]. There is a difference in the two groups.

The t-Test of Chl-a was performed after grouping for Season Group 1 = Wet Season (Oct 1 to Mar 31); Group 2 = Dry Season (Apr 1 to Sep 30). A comparison is provided for both the raw data (Chlorophyll) and transformed data (SQRTChl-a). While the case count was slightly different for the groups (Wet, n = 52; Dry, n = 50), this slight variation in count would not critically affect the results of the mean comparison. Based on the descriptive statistics, the wet season generally had a lower mean value, and also had a wider spread than the dry season (based on the larger standard deviation). Both the raw and transformed data between mean estimation of the groups (wet and dry) were nearly similar or otherwise deemed "equal". A more thorough analyses output of the equality of means is noted in Table 6.

Table 6

Independent t-*Test (Chl-a)*

		t-Test for Equality of Means				
		t	*df*	Sig. Two-sided *p*	Mean Difference	Std. Error Difference
Chlorophyll	Equal variance assumed	-1.117	100	.267	-.012	.011
	Equal variance not assumed	-1.122	95.752	.265	-.012	.011
SQRTChl-a	Equal variance assumed	-1.680	100	.096	-.032	.019
	Equal variance not assumed	-1.690	93.757	.094	-.032	.019

The Independent *t*-Test supports what is observed from the group statistics. The t-test for equality of means for either raw or transformed Chl-a suggests that there is no difference between the two groups representing Season (Wet and Dry). Evaluating the t-statistic of each variable (equal variances not assumed), the sig. value (two-sided) resulted in Chlorophyll ($p = .265$) and SQRTChl-a ($p = .094$), both greater than the statistic threshold of $p = .05$. The test statistic results are not statistically significant, and fail to reject the null hypothesis (H_0). Therefore, there is no difference between the two groups. Using both descriptive and the t-Test statistic, there is no reason to control for Season in evaluating my research variables.

Statistic Evaluation Results

Since there was no compelling reason to control for season, each variable's entire case count was used in addressing my research questions. My research questions are the same as provided in Chapter 3, noting that controlling for seasonal change was no longer a necessary step.

Applied Dataset

As provided in Table 7, the dataset has a total valid cases count of n = 102 for each variable. There are no missing cases. The nature of the dataset can best be described using Descriptive Statistics to approximate the character of the sample sets. A central tendency table for both the raw data and the transformed data are provided.

Table 7

Descriptive Statistics - Raw and Transformed [SQRT] Dataset

	N	Mean	Median	*SD*	Variance	Skewness	Kurtosis
Chl-a	102	.085	.069	.056	.003	.674	-.567
SQRT-Chl-a	102	.274	.263	.098	.010	.084	-.747
TN	102	2.056	1.700	1.051	1.104	.833	-.109
SQRT-TN	102	1.388	1.304	.3600	.129	.307	-.300
TP	102	.319	.315	.109	.012	.363	-.046
SQRT-TP	102	.557	.561	.098	.010	-.100	-.189
NH_3	102	.068	.025	.078	.006	2.467	6.069
NH_3Recode	102	.461	.000	.501	.251	.160	-2.014

Note. Descriptive Statistics comparison: Raw Data vs. Transformed [SQRT] data.

The variables in the dataset include: Chl-a, TN, TP, NH_3, and each of the four transformed (SQRT) variables. The level of measurement of each variable represents a discrete measurement (units in milligrams per liter, [mg/L]) and was continuous and interval, with the exception of NH_3Recode that was recoded as dichotomous.

The central tendency data for both the raw and transformed data include: mean, median, standard deviation, variance, skewness, and kurtosis. The continuous variables are best described in the following manner. The mean (average) for Chl-a, TN, TP and NH_3 were .085, 2.056, .319, and .068, respectively. The median for Chl-a, TN, TP and NH_3 were .069, 1.700, .315, and .025, respectively. The measure of spread or variability described by the variance (dispersion or spread of values around the mean) and standard deviation (square root of the variance) are: Chl-a (.003, .056); TN (1.104, 1.051); TP (.012, .109); and NH_3 (.006, .078). For comparison, the respective SQRT outcome of each variable has also been provided (see Table 8).

Research Questions and Hypotheses

The two primary statistical tests used are to: 1) establish the relationship (strength and direction) of the predictor variable to the outcome variable (Pearson's Correlation); and 2) whether one variable can predict the other (MLR). Use of Pearson's Correlation applies directly to RQ 1, 2, and 3, and use of multiple regression applies to RQ 4. In summary, taking the first three RQs in combination, the follow-on research question is:

Research Questions (RQ1 through RQ3: What is the relationship between each of the independent variables (IV_1 - TN, IV_2 – TP, IV_3 - NH_3) and the dependent variable (DV – Chl-a) in rehabilitated Machado Lake?

Where:

$H_0 1$ - $H_0 3$: There is no relationship between variables.

$H_a 1$ - $H_a 3$: There is a relationship between variables.

Research Question (RQ4): To what extent do the independent variables TN, TP and NH_3 predict the dependent variable Chl-a?

Where:

$H_0 4$: There is no predictive relationship between variables.

$H_a 4$: There is a predictive relationship between variables.

Test Assumptions

A key assumption to the tests performed is that the values of the dataset are normally distributed, or approximately normally distributed. As mentioned earlier, the original raw dataset was not normally distributed and thus transformed. Comparing the outcome of using techniques of SQRT, and LOG10, it was concluded that use of SQRT transformation was closer to approximating normal distribution. In support of this analysis, histograms of the transformed data for SQRTChl-a, SQRT-TN and SQRT-TP are provided in Figures 8 through 10.

Figure 8

Histogram of SQRTChl-a

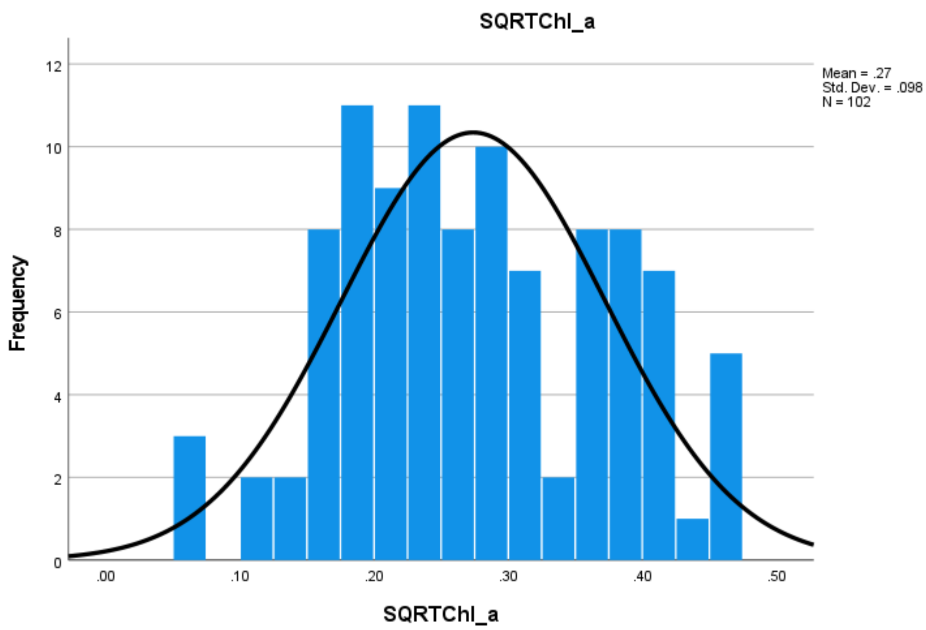


Figure 9

Histogram of SQRT-TN

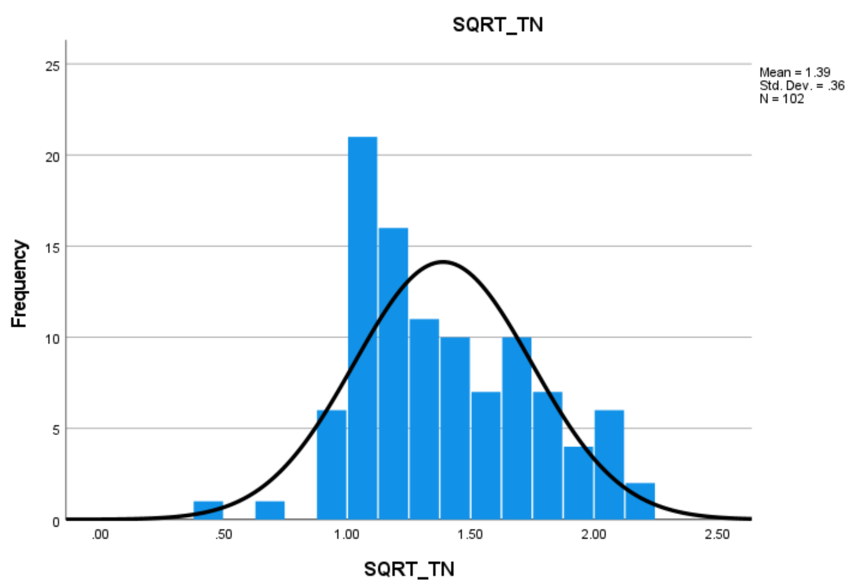
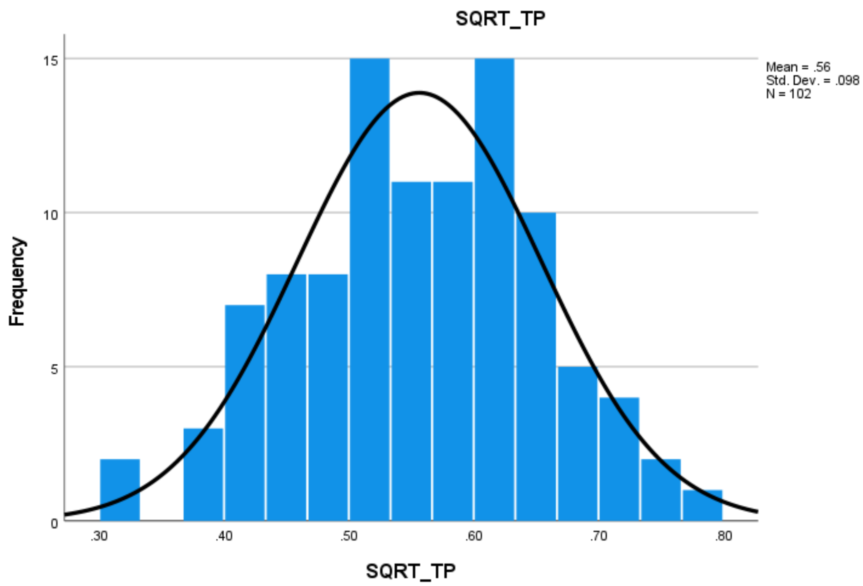


Figure 10

Histogram of SQRT-TP



In addition to transformation, other assumption tests taken into consideration in evaluating variables include, but not limited to: continuous scale variables; homoscedasticity; multicollinearity; and no outliers or unusual data points. The exception on the use of these assumption tests was the independent variable NH_3, which was recoded as NH_3Recode.

Test for Normality

The normality test is an essential step prior to use in Pearson's Correlation and Multiple Linear Regression. The normality test was applied using the transformed variables as noted in Table 8.

Table 8

Tests of Normality

	Kolmogorov-Smimov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
SQRTChl-a	.075	102	.175	.976	102	.056
SQRT-TN	.105	102	.008	.964	102	.007
SQRT-TP	.040	102	.200*	.996	102	.987

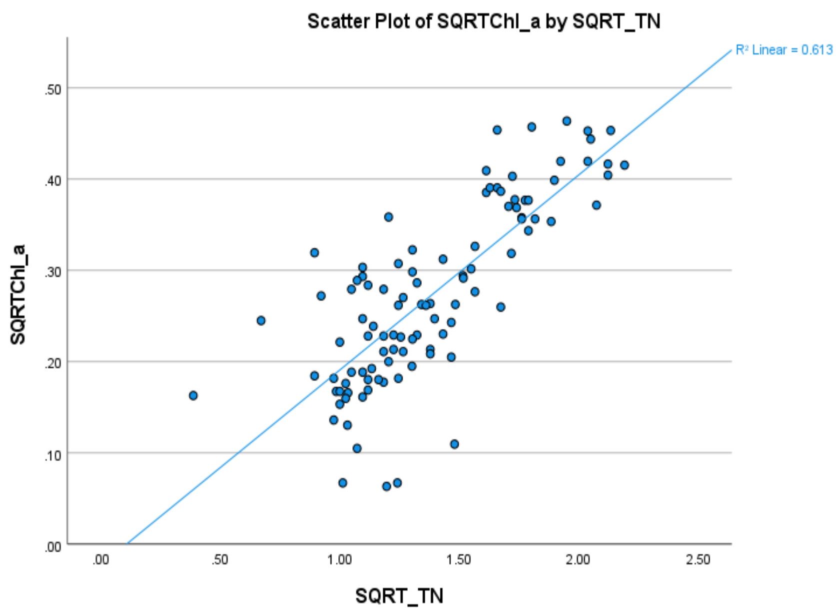
Note. [a] Lilliefors Significance Correction. * This is the lower bound of the true significance.

Shapiro-Wilk's sig-value for each variable is determined to test its statistical significance for normality. The significance threshold for assumption of normality is not met if the sig. value is $< .05$ (test of significance at the $p = .05$ level). If not met, the result is statistically significant (null rejected) and the data is not normally distributed. If sig. $> .05$, then the assumption of normality is NOT violated and it suggests that the variable is normally distributed.

Based on the test statistic results, SQRTChl-a ($p = .056$) and SQRT-TP ($p = .987$) were normally distributed; whereas, SQRT-TN ($p = .007$) was not normally distributed. For comparison purposes and while the test statistic for SQRT-TN was not met, the descriptive statistic (scatterplot and skewness) output suggests that this variable approximates normal distribution. A scatterplot of SQRTChl-a by SQRT-TN as provided in Figure 11, supports this position.

Figure 11

Scatterplot of SQRTChl-a by SQRT-TN



The scatterplot suggests a linear relationship between SQRTChl-a and SQRT-TN variables. Based on visual inspection, the linear relationship of the variables are positive, as SQRT-TN increases, so does SQRTChl-a. Additionally, the SQRT-TN skewness (.307) falls within the suggested tolerance limits of -1 to +1, providing support for approximating normality. Contrary to the Shapiro-Wilk test output, the descriptive statistics for SQRT-TN reinforces the position that there is a positive approximately normal relationship between variables.

Pearson's Correlation

The purpose of running Pearson's Correlation is to measure the strength and direction of the association between two variables. Since Pearson's Correlation coefficient is fundamentally tied to conducting the Multiple Linear Regression, the correlation statistic has been discussed in greater detail in the next section.

As with all statistical tests, a number of assumptions need to be examined. The basic premise for this test is that the variables are continuous (interval or ratio), and are normally distributed. The normality test related to Shapiro-Wilk test output resulted in SQRTChl-a and SQRT-TP approximating normal distribution; whereas, SQRT-TN was not. However, as discussed above, the SQRT-TN descriptive statistics of skewness and kurtosis supports the premise that there is an association between variables.

Correlation and Multiple Linear Regression

In conducting both correlation and regression tests, the statistic method tests if the coefficients from the regression function have a significant impact on my dependent variable (SQRTChl-a). A review of the descriptive statistics for the variables are provided in Table 9. Each mean and standard deviation are provided for the transformed variables of SQRTChl-a, SQRT-TN, SQRT-TP and NH_3Recode.

Table 9

Descriptive Statistics [SQRT and ReCode] for Correlation and Regression

	Mean	Std. Deviation	*N*
SQRTChl-a	.274	.098	102
SQRT-TN	1.39	.360	102
SQRT-TP	.557	.098	102
NH_3Recode	.461	.501	102

Note. Dependent Variable: SQRTChl-a.

The descriptive statistics output references that the dependent variable SQRTChl-a has an average value is .28, with a standard deviation of .10. The three independent variable average mean values of SQRT-TN, SQRT-TP and NH_3Recode were 1.39, .56 and .46, with a corresponding standard deviation of .36, .10 and .50, respectively.

As noted in Table 10, the correlation between the dependent variable SQRTChl-a and the independent variables was statistical significant for SQRT-TN (<.001) and SQRT-TP (.001), but not statistically significant for NH_3Recode (.093).

Table 10

Correlations [SQRT]

		SQRT-Chl-a	SQRT-TN	SQRT-TP	NH_3Recode
Pearson Correlation	SQRT-Chl-a	1.00	.783	.312	-.132
	SQRT-TN	.783	1.00	.293	-.011
	SQRT-TP	.312	.293	1.00	.000
	NH_3Recode	-.132	-.011	.000	1.00
Sig.(1-tailed)	SQRT-Chl-a		<.001	.001	.093
	SQRT-TN	<.001		.001	.456
	SQRT-TP	.001	.001		.499
	NH_3Recode	.093	.456	.499	
N	SQRT-Chl-a	102	102	102	102
	SQRT-TN	102	102	102	102
	SQRT-TP	102	102	102	102
	NH_3Recode	102	102	102	102

The Pearson's coefficient of independent variable SQRT-TN and dependent variable SQRTChl-a was .783, slightly above .7. This was a positive finding as an indication that these two key variables, one independent and one dependent, are nicely correlated. As for NH_3Recode, the statistical significance outcome was not unexpected.

In assessing the output of the MLR model, an examination of the ANOVA and Model Summary tables provides an evaluation of the regression statistical significance and effect size. The ANOVA output, provided in Table 11, has an *F* statistic ($F = 57.03$) and sig. value of p = <.001, suggesting that it is statistically significant; and therefore, the model's three independent variables (SQRT-TN, SQRT-TP, NH_3Recode) predict the dependent variable (SQRTChl-a). The regression model indicates that with the sig. = <.001, there is statistical significance and the null hypothesis is rejected. In accepting of the alternative hypothesis, the combination of the three independent variables does have a relationship with the dependent variable. At the model level, no distinction is given for which of the independent variables may be more influential in affecting the outcome variable.

Table 11

ANOVA – Regression Model

Model [a]		Sum of Squares	*df*	Mean Square	*F*	Sig.
1 of 1	Regression	.621	3	.207	57.027	<.001[b]
	Residual	.356	98	.004		
	Total	.977	101			

Note. [a] Dependent Variable: SQRTChl-a. [b] Predictors: (Constant), SQRT-TN, SQRT-TP, NH_3Recode.

Furthermore, the Model Summary provided in Table 12 indicates R^2 and Adj. R^2 are > .3, suggesting that there is a good fit to the regression model line (Field, 2013).

Table 12

MLR Model Summary

Model [b]	*R*	*R* Square	Adj. *R* Square	Std. Error of the Estimates	Durbin-Watson
1 of 1	.797[a]	.636	.625	.060	1.965

Note. [a] Predictors: (Constant), SQRT-TN, SQRT-TP, NH_3Recode. [b] DV: SQRTChl-a.

Evaluating the effect size (see Table 12), the Adj. R^2 value (Adj. $R^2 = .63$) implies that 63% of the variability of the dependent variable Chl-a concentration is explained by the combination of the independent variable's concentrations (SQRT-TN, SQRT-TP), with a statistical significance p = <.001. On the other hand, 37% of the variability of the dependent variable is contributed by other outside factors. With a sig. = < .001, there is statistical significance and at the model level the independent variables do have a relationship with the dependent variable. In summary, the model's independent variables statistically significantly predict the dependent variable, as follows: Chl-a, $F(3, 98) = 57.03$, $p < .001$.

Examining the output at the variable level in Table 13, the coefficients of the variables are provided. The output of statistical significance (sig. – value) were SQRT-TN = < .001, SQRT-TP = .16, and NH_3Recode = .05. Using the $p < .05$, both SQRT-TN and NH_3Recode were statistically significant, and SQRT-TP was not statistically significant. What this suggests is that this variable (SQRT-TP) by itself does not have a relationship with SQRTChl-a, but when SQRT-TP is combined with SQRT-TN, together these variables have a statistically significant relationship with SQRTChl-a. While these two independent variables (SQRT-TN and SQRT-TP) have a positive influence on the dependent variable, the NH_3Recode variable has a negative influence. For every unit increase of NH_3Recode, there is a decrease of SQRTChl-a by -.02.

Table 13

Coefficients [SQRT] - Regression Model

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	*t*	Sig.
1 of 1	(Constant)	-.052	.038		-1.387	.169
	SQRT-TN	.206	.017	.755	11.838	<.001
	SQRT-TP	.092	.064	.091	1.428	.156
	NH_3Recode	-.024	.012	-.124	-2.030	.045

An analysis of the Unstandardized Coefficient B reveals that if SQRT-TN goes up by one unit (1 mg/L), then the dependent variable SQRTChl-a will increase by .21 units (while holding all other independent variables constant). The Unstandardized Coefficient B of SQRT-TP indicates that if SQRT-TP goes up by one unit, then SQRTChl-a will increase by .09, a relatively small amount compared to TN. Since the concentration units of all my variables are the same, the output values of the Unstandardized Coefficients B hold true (all unit values on the same scale), and thus there is no need to interpret the Standardized Coefficients Beta (Field, 2013).

In summarizing the output at the variable level, the coefficient of SQRT-TP (sig., $p = .156$) was not significant; however, collectively and in combination with the other independent variables of SQRT-TN ($p = <.001$) and NH_3Recode ($p = .045$), they are contributing to the observed changes in unit concentration of SQRTChl-a. The complete summation of the results of the regression model is provided in Table 14.

Table 14

Multiple Linear Regression Results for Chl-a

		95% CI for B					
Chl-a	B	*LL*	*UL*	Std. Error	Std. Coef. ß	R^2	$Adj.R^2$
Model 1 of 1						.636	.625
(Constant)	-.052	-.127	.023	.038			
SQRT-TN	.206	.172	.241	.017	.755		
SQRT-TP	.092	-.036	.219	.064	.091		
NH_3Recode	-.024	-.048	-.001	.012	-.124		

Note. Dependent Variable: SQRTChl-a. Predictors: (Constant), SQRT-TN, SQRT-TP, NH_3Recode. B = unstandardized regression coefficient. CI = confidence interval. *LL* = lower limit. *UL* = upper limit. ß = standardized regression coefficient. R^2 = coefficient of determination. Adj. R^2 = adjusted coefficient of determination.

An analysis of the dichotomous independent variable, NH_3Recode, is interpreted differently than that of the continuous independent variables. The Unstandardized Coefficient B for NH_3Recode is -.024, a negative slope coefficient in group comparison. This result indicates that the predicted NH_3 for the high-valued group (Group 1) is -.024 units less than the low-valued group (Group 0), when all other independent variable values are held constant. This value was applied in the estimation of a prediction equation model.

Regression Model for Prediction

Taking into account the theoretical importance in using all three independent variables in the developing a predictive equation, the predictive equation is as follows:

Equation 1: Predicted Chl-a = $b_0 + (b_1 \times IV_1) + (b_2 \times IV_2) + (b_3 \times IV_3)$

b_0 = intercept

b_1, b_2, b_3…slope of the IV

IV_1 = Total Nitrogen

IV_2 = Total Phosphorous

IV_3 = NH_3 or Ammonia

Using B from our regression output, the following predictive equation is derived:

Equation 2: DV = -.052 + .206*(SQRT-TN) + .092*(SQRT-TP) - .024*(NH_3Recode)

As future data is collected, this preliminary predictive model regression equation can be refined. In interpreting the relationships between these independent variables and the dependent variable, it can be inferred that SQRT-TN is the most influential independent variable among the nutrients used in my research in predicting SQRTChl-a concentrations. While other external factors do exist that will influence Chl-a (by about 37%), the model Adj. R^2 (.63 or 63%) was exceptionally high and that this equation is a reasonable tool for forecasting of Chl-a under similar conditions.

Summary

An understanding of the relationships between nutrient pollutant variables and Chl-a as the indicator of algal blooms, have been examined. The unique history and setting of Machado Lake offers this rare opportunity to assess what associations between predictor variables and outcome variable are at work for managing risk of exposure to harmful algal blooms. My research is based on numeric continuous data obtained from the City of Los Angeles from Machado Lake, post rehabilitation. The relationship between my independent and dependent variables are well grounded in theory and existing literature of SEM Theory and constructs of PB (Hayden, 2019; Steffen et al., 2015). In review, the following interpretation from my research are:

- The equality of means for the dependent variable SQRTChl-a, wet and dry seasons were equal. The analysis of the Independent t-Test output supports not having to control for Seasonal changes.
- The results of the normality test determined that SQRTChl-a and SQRT-TP were approximately normally distributed; however SQRT-TN ($p = .007$) was not. Upon further examination of this variable's descriptive statistics of scatterplot and skewness, the descriptive output supports the dataset approximating normality.
- Pearson's Correlation coefficient demonstrates that both SQRT-TN and SQRT-TP have a positive correlation with the dependent variable SQRTChl-a. The coefficient for SQRT-TN was $r = .783$, indicating a very good degree of correlation between the independent and dependent variable.
- At the model level, the MLR output was statistical significant such that SQRT-TP combined with SQRT-TN have a significant relationship with the dependent variable, SQRTChl-a ($p = <.001$). Two of the three independent variables had a significant relationship with the dependent variable.
- The regression analysis indicated that the independent variables (specifically, TN) accounted for approximately 63% of the variation in SQRTChl-a.

The positive relationship of the independent variable SQRT-TN is the one nutrient pollutant that is the most influential over the dependent variable, SQRTChl-a. While the relationship of SQRT-TP is also positive, it is relatively minor compared to the strength of the relationship of SQRT-TN. On the other hand, NH_3Recode negatively impacted the case value concentrations of SQRTChl-a. In addition to our understanding of the relationships established between the predictor variables and the outcome variable, a preliminary predictive regression equation has been developed for forecasting purposes.

As discussed in Chapter 5, researchers seek scientific-based options to forecast early stages of algal blooms, thus offering sufficient time to prepare corrective actions and prevent blooms from causing detrimental impairment to the environment and human health. Our ability to control and prevent nutrient pollutants, specifically TN from entering into a water body would reduce the presence of algal blooms. Further research studies in the field will continue to add to our existing knowledge base and fill the gap that exists in the literature for the need of real-time data evaluations derived from our natural environment.

Chapter 5: Discussion, Conclusions, and Recommendations

Through this statistical evaluation of my research variables associated with nutrient pollutants and Chl-a, the outcomes have contributed to a broader understanding of what associations between variables are occurring in the natural environment. The results of my research helps fill this void in evaluating "predictor" values to forecast potential impairment to our fresh water resources. My research statistics align with what has been determined from other recent research in the literature, specifically supporting the interactions between nutrient pollution and algal blooms as determined from the measurement of Chlorophyll-a.

As evident in the literature (Blakey et al., 2015; Wang et al., 2016; SCCWRP, 2021), there is a greater sense of urgency in preventing occurrences in which harmful algal blooms and cyanotoxins flourish. It is recognized that more scientific-based evidence is needed from contemporaneous field research studies to fill the current gap in the literature, specifically the understanding of the nature of my study variables in a natural setting in preventing human illnesses and mortality. Securing community access to waterways for recreation, maintaining clean water sources, and protecting sensitive habitats all contribute to improved human health and positive social change.

Summary and Interpretation of Findings

The primary purpose of my research was to further understand in this unique setting of Machado Lake the relationships between the TN, TP and NH_3 as predictor variables to the outcome variable Chl-a, an indicator of algal blooms. While laboratory analyses require a high level of test frequency and have become increasing more costly, research studies from different locations in the field are needed. In the natural environment, research of the interrelationships between nutrient variables (independent variables of TN, TP and NH_3 to predict the dependent variable, Chl-a) fill this gap between field and lab research. The results of my study align with the theory (TN, TP and Chl-a cycles) cited in literature that helps explain the role that nutrient pollutants have over algal blooms. Adding to our current base of knowledge from past studies, the following findings from my research of data representing Machado Lake are:

1. Research Questions - RQ1 through RQ3: What is the relationship between each of the independent variables (TN, TP, NH_3) and the dependent variable (Chl-a) in rehabilitated Machado Lake?

The Pearson's Correlation coefficient statistic (r) provided an analysis of the relationship (strength and direction) between my independent variables and dependent variable. Both SQRT-TN and SQRT-TP were positively correlated, with SQRT-TN (r = .783) more highly correlated than TP (r = .312). The variable NH_3 was recoded, and therefore was not tested using Pearson's statistic test.

2. Research Question - RQ4: To what extent do the independent variables TN, TP and NH_3 predict the dependent variable Chl-a?

Using multiple linear regression, an evaluation of the regression statistical significance and effect size was determined. Based on the ANOVA output (F = 57.03, p = <.001), the three independent variables at the model level do predict the dependent variable. It is the combination of these variables that the model level addresses without distinction as to which independent variable may be more influential in affecting the outcome variable. At the variable level, it was not expected that all the independent variables would show a relationship. The *p* value for SQRT-TP (.156) was not statistically significant, and therefore this variable statistic suggests no relationship with the dependent variable. Despite this result for SQRT-TP, it did have a positive Pearson's correlation statistic (.312).

The effect size (Adj. R^2 = .63) suggests that approximately 63% of the variability of the dependent variable is explained by the independent variables; wherein 37% of the variability of the dependent variable is caused by other factors. Given that Machado Lake was rehabilitated, the relatively low effect size of the other factors (37%) is not a surprise. While nutrient pollutant interactions and levels of association may differ under varying conditions in the environment, the relationships established in my research between variables do support the theoretical premises in the literature. With a large effect size reported (Adj. R^2 = .63) such that 63% of the variability of the dependent variable is explained by the combined independent nutrient variables, provides justification that these nutrients need to be managed, controlled, and if possible eliminated to keep harmful algal blooms in check.

Limitation of Findings

A number of assumptions were made regarding the dataset acquired from the City of Los Angeles, WPD to insure integrity and validity. An inquiry was made over the protocols established in the collection and test methods used in compiling the dataset provided for my research analysis. As reported and discussed with the City of Los Angeles, the use of well-established industry standards for sampling and reporting, as well as testing protocols by a certified laboratory assured that the dataset is verifiable at a number of different audit levels, and it met state and federal guidance standards for quality assurance and quality control. Assuming these standards and protocols were rigorously followed throughout the collection period, the dataset would have integrity and validity for its use in research.

The use of transformed data does have limitations (Field, 2013). The SQRT transformation could result in missing values or biases (Field, 2013). Fortunately, there were no negative numbers in my raw dataset that resulted in missing values. The primary reason to have transformed the dataset was to improve the variable's normality distribution. Depending on one's research objectives, back transformation of findings could potentially be a limitation that should be taken into account. Use of the predictive model to forecast algal and harmful algal blooms in the natural environment assumes that the geomorphological setting is nearly similar to my research setting, thus reducing the effects of cofounders in one's research study.

Social-Ecological Theory and Risk Assessment

The presence of harmful algal blooms and evolving cyanotoxins resulting in imbalances in the environment and water impairment impacting public health has really taken hold in our daily conversations (US EPA, 2021b; Alliance for the Greater Lakes, 2022). The acceleration of greenhouse gases, increases in global temperatures, heat waves and extreme cold causing altering land mass use, and novel diseases are negatively impacting our public health (CDC, 2021a; Steffen et al., 2015). An important theoretical pillar to my research, Steffen (2015) reiterates that the biochemical flows associated with climate change and PB principals are directly related to the TN-TP-Chl-a cycle processes as a primary reason for lake impairment.

Through the constructs of the Social-Ecological Theory model, the understanding is to improve the dynamic interactions in our personal daily lives and the environmental factors that degrade our freshwater lakes. Intertwined in this theory associated with individual's relationship with our surrounding community is how collectively each person must protect against exposure (acute and chronic illnesses) to unhealthy cyanotoxic conditions that cause harm in recreational waters, wildlife habitat, and drinking water. The outcome of my research provides a field method to forecast algal blooms in addressing issues of risk assessment, and ultimately finding cost-effective solutions to prevent the propagation of algae blooms, harmful algal blooms and cyanotoxic conditions. Owners, operators, and stakeholders ultimately need to find sustainable solutions in preventing the propagation of harmful algal blooms and resulting cyanotoxic conditions in their localized water bodies. As my research is just one aspect of the larger picture in our understanding of the relationships associated with nutrient pollutants and algal blooms in the natural environment, it also provides reason for new "engineering-based" theories tied to epidemiologic concepts in establishing applicable and relevant policy. From a public health perspective, being pro-active and taking the necessary measures will help to minimize risk to exposure, illnesses and potential mortality.

Application of Study to Global Health Risk Practices

The SEM and PB principles remind us that earth systems are in turmoil. If this condition persists unchecked, our freshwater waterways will be ripe for toxic blooms, poisoning our source of fresh water (Barnosky et al., 2011). Whether the concern is domestic or global, our societal "living" habits and daily needs require significant "change" to improve our natural habitat and protect our natural resource (CWQMC, 2021b; US EPA, 2022a; Hayden, 2019). On a broader scale, further research is needed to develop a viable platform for predicting early detection and warning of excessive harmful algal blooms and cyanotoxic conditions. Global efforts are needed in the development of new technology that could potentially be a launching point for additional collaboration in addressing harmful algal blooms. Our collective efforts for early detection allows for stakeholders and regulators to take precautionary measures in protecting the well-being of the local community and individual exposure to illnesses. Through continued research (local stakeholders, state and federal agencies), pro-active scientific-based studies will continue to build upon the foundation for establishing new innovative data-intensive field programs in maintaining social, environment and public health.

Implications for Positive Social Change

It is apparent that in order to prevent occurrences of harmful algal blooms, changes in our daily habits are necessary (Hayden, 2019). It begins with changes to human-induced impacts in our communities and individual behaviors that have created these observed imbalances in nature (US EPA, 2022a). The anthropogenic sources of nutrient pollution, especially in an urban setting need to be better controlled in mitigating conditions that result in toxic environmental conditions to humans and wildlife. Changes in societal behaviors in protecting the environment and local water bodies for its intended use will promote positive social change. The sources of nutrient pollution need to be reduced, if not eliminated, and more controls on runoff that enters our shallow lakes and waterways from major agricultural activities and industries to the individual that applies fertilizers to their lawn need to be curbed. Having clean water, whether for recreation, habitat or for drinking water purposes, should not be taken for granted.

Education and localized community efforts are needed to effect change at the societal level. Through education, we will be able to further our understanding of the impacts on our daily livelihood and activities to maintain the well-being of the community and individual public health. Achieving a balance requires that we all do our part in keeping our water safe for not only our generation, but for generations to come. It is not a right, but rather a privilege to have this available resource that undoubtedly promotes positive social change.

Recommendations for Future Research

Our deficiencies in research requires a concerted effort to collect contemporaneous field data in understanding the relationships of these nutrient pollutants and other co-variates in the natural environment. Existing models can be updated and refined, and new models developed as more freshwater bodies and lakes are studied. While each water body is unique, there will be opportunity to consolidate the results of researcher’s data and study findings in support of a national platform to predict and forecast the stages of impending harmful algal blooms. As additional field data is compiled, it may be possible to develop a series of nomograms based on unique water body physical and geomorphological setting and nutrient pollutant contributions in improving predictive models for future use.

While researchers strive to prevent such occurrences from ever taking place; unfortunately, blooms and toxins will more than likely continue to persist. The challenge is to develop and implement sustainable solutions tied to research in the field, and assuring that there is uniformity and consistency on how information is communicated. Scientifically-based water-quality standards and establishing sustainable water-management programs to protect our water resource needs to be a priority, starting with policy that affects farmlands on use of fertilizers, industry of chemical usages, local municipalities that maintain storm water and sewer systems, and an individual’s footprint that degrades the environment.

Conclusion

The outcome of my research reveal that there exists a statistically significant linear relationship between the concentrations of Chl-a - TN, and to a lesser degree Chl-a – TP. Since rehabilitation of Machado Lake, its reconstruction provided a laboratory-like natural environment in which data collected pertaining to nutrient pollutants and Chlorophyll-a allowed for field-data relationships to be established. My research aligns with the theoretical framework of the TN, TP and Chl-a cycles (and other nutrients) as supported in the literature.

Research of harmful algal bloom is in its infant stages in terms of our understanding of what is happening in the natural environment. Through comprehensive field studies, we can provide for a better understanding of the natural environment associations of our predictive variables to guide us in our decisions. Through continued study of these relationships will researchers and scientists be able to prevent algal blooms from overtaking our natural systems, a detriment to our social systems and community public health. We all need to do our part, embrace cultural and anthropogenic changes in finding the balance needed to protect our precious water resources and our individual well being.

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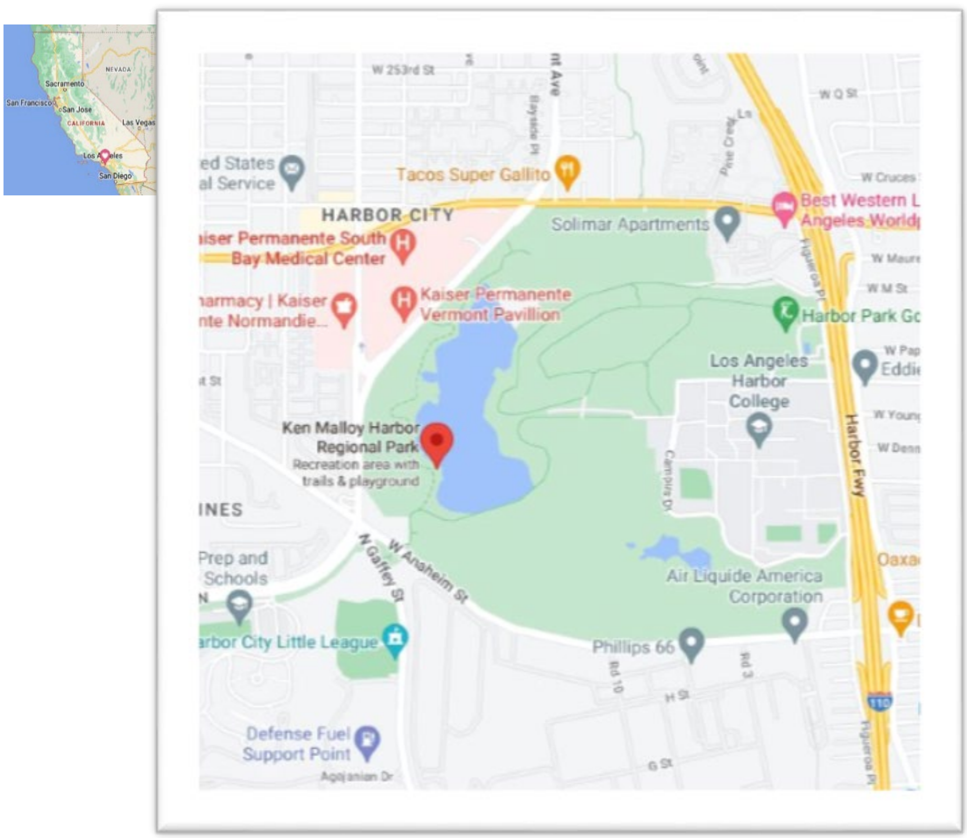
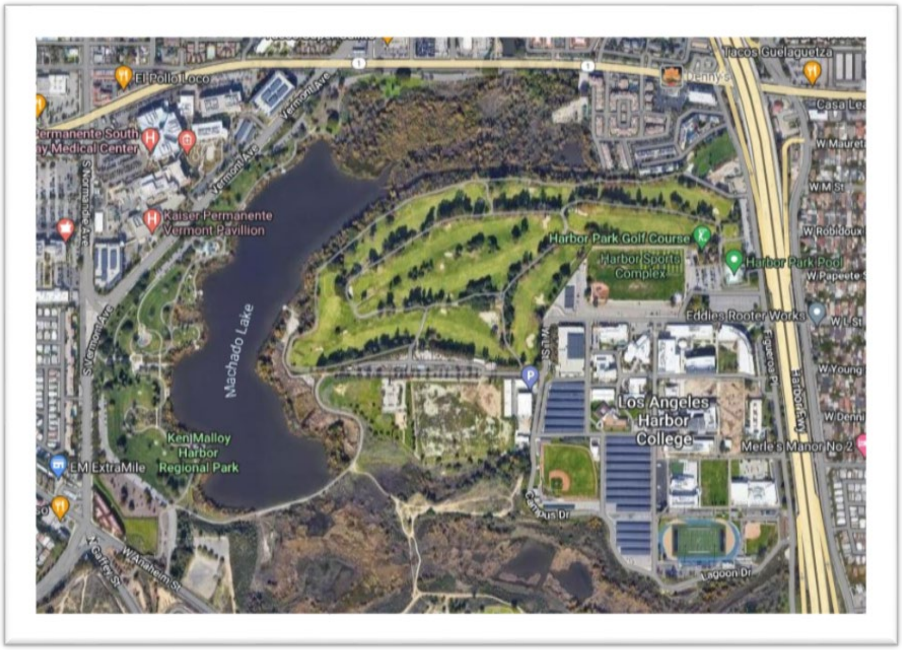
Appendix A: Ken Malloy Harbor Park and Machado Lake

Machado Lake is located within the Ken Malloy Harbor Regional Park (KMHRP) in the Harbor City and Wilmington communities of Los Angeles County, California, as shown in Exhibit A-1. The KMHRP is approximately 290 acres in which the 45-acre Machado Lake is situated (LA-DPWBOE, 2009). While Machado Lake is the target subject of my research, the importance of understanding the socio-ecological interactions that occur in the surrounding park and urban area setting are vital factors that impact our individual and community health.



Note: Google Maps, August 2022.

Figure A-1. *General Location Map of Ken Malloy Harbor and Machado Lake.*



Note: Google Maps, August 2022.

Figure A-2. *Aerial Photo of Machado Lake and Surrounding Area*

Note: *Photos by Michael Shiang - April 2022.*

Figure A-3. *View across Machado Lake to the southwest.*

Figure A-4. *At Dam along the south end of Lake, view to the northwest.*

The KMHRP is owned and operated by the City of Los Angeles, Department of Recreation and Parks (RAP). As reported by LA-DPWBOE, 2009), in-coming stormwater that is conveyed through the Wilmington Drainage area is owned by the Los Angeles County Flood Control District (LACFCD), and maintained by the Los Angeles County Department of Public Works (LACDPW). This Wilmington watershed basin that drains into Machado Lake covers an approximate area of 112 acres.

As early as 1998, Machado Lake was cited by the U.S. EPA as being impaired under the Clean Water Act, Title 303(d). In 2008, the State Regional Water Quality Control Board adopted Resolution 2008-006, a basin plan amendment to address eutrophic, algae and nutrient conditions. Under Proposition O in 2010, the owners and stakeholders undertook an 80 to 100 million dollar restoration project to rehabilitate the park and lake, and established Total Mass Discharge Limits (TMDLs) standards to protect the quality of the lake water. A brief summary of the geomorphological features of the reconstructed park and lake, as provided in Exhibit A-5, includes:

Table A-1. *Fact Sheet*

Machado Lake		Ken Malloy Harbor Park
Lake size = 45 acres. Depth = Reconstructed 6 feet. Wetland and Wildlife Habitat. Inlet Drainage = Wilmington Channel. Outlet Drainage = Wetland. Bottom = Sealed with Bio-layer Cap. Shoreline Edge = Block wall, Cobble Stone.		Park Size = 245 acres. Fishing Pier and Dam Constructed. Vegetation and Habitat Improvements. Restoration of walkways, playground, picnic areas, and open space. Adjacent to Park: Regional Hospital, Residential, Golf Course, Chemical and Oil Storage Facility.

In order to comply with the new orders for rehabilitation of the lake, the planning and reconstruction of the lake took place over an approximately seven year period, from March 2010 to April 2017 (LA-DPWBOE, 2009). The main purpose of the project was to improve water-quality conditions of the lake, maintain TMDL compliance, and provide for the enhancement of the natural environment and park recreational facilities for the community (CA-DPWSAN, 2018). In achieving these goals, the reconstruction and rehabilitation activities included, but was not limited to:

- Dredging over 239,000 cubic yards of lake sediment;
- Sealing the base of the lake with AquaBlok bio-layer cap;
- Installing an oxygenation system, and dam structure;
- Constructing storm drainage improvement systems at inlets for storm water treatment.

Appendix B: Freshwater Harmful Algal Blooms - California

The following report was obtained from the Office of Information Management and Analysis, State Water Resources Control Board. This report related to Freshwater Harmful Algal Blooms includes both monitoring and event responses, and are available on the agencies website at: mywaterquality.ca.gov/habs. Attached is the September 2022 FHAB Report.

Note: Public report, retrieved from https://mywaterquality.ca.gov/habs.

Table B-1. *Freshwater Harmful Algal Bloom Report – September 2022*

Freshwater Harmful Algal Bloom (FHAB) reports updated in last 7 days

Office of Information Management and Analysis
State Water Resources Control Board
mywaterquality.ca.gov/habs

List created on: 09/23/2022
View FHABs web map for report details

For more information, contact:
cyanoHAB.reports@waterboards.ca.gov

The list below includes both routine monitoring and event response bloom reports updated by Water Boards staff in the last 7 days. Other water bodies may have previously reported FHABs or currently posted FHAB advisory signs. Check the FHABs report web map for information about all reports.

Report Updated On	Waterbody	Landmarks	Current Advisory	County	Regional Board	Report#
09/16/2022	Big Break Regional Shoreline	Boat launch	**Danger**	Alameda	Region 5 - Central Valley	3282
09/16/2022	Quarry Lakes; Lago Los Osos area	Lago Los Osos area	**Danger**	Alameda	Region 2 - San Francisco Bay	3293
09/22/2022	Tahoe Keys Lagoons	Venice / Alpine Drive	**Danger**	El Dorado	Region 6 Lahontan	3661
09/22/2022	Clear Lake	Soda Bay Cove (CLV7)	**Danger**	Lake	Region 5 - Central Valley	3321
09/16/2022	San Luis Reservoir	Dinosaur Point Boat Launch	**Danger**	Merced	Region 5 - Central Valley	3470
09/16/2022	San Luis Reservoir	Pacheco Pumping Plant	**Danger**	Merced	Region 5 - Central Valley	3226
09/23/2022	Pinto Lake	Pinto Lake Boat Launch (PLS5)	**Danger**	Santa Cruz	Region 3 - Central Coast	3296
09/22/2022	Clear Lake	Buckingham Park (BP)	**Warning**	Lake	Region 5 - Central Valley	3236
09/22/2022	Clear Lake	Redbud Park (RED01)	**Warning**	Lake	Region 5 - Central Valley	3242
09/16/2022	Mcleod Lake	by Joan Darrah Promenade (ML)	**Warning**	San Joaquin	Region 5 - Central Valley	3267
09/23/2022	Lake Del Valle	Lake Del Valle East Beach	**Caution**	Alameda	Region 2 - San Francisco Bay	3509
09/23/2022	Lake Del Valle	Lake Del Valle West Beach	**Caution**	Alameda	Region 2 - San Francisco Bay	3508
09/23/2022	Lake Temescal	East Bay Regional Parks	**Caution**	Alameda	Region 2 - San Francisco Bay	3290
09/16/2022	Lake Chabot (Alameda Co)	lake-wide	**Caution**	Alameda	Region 2 - San Francisco Bay	3281
09/16/2022	Lake Merritt	Lake Merritt Boating Center	**Caution**	Alameda	Region 2 - San	3657

09/16/2022	Lake Merritt	Lake Merritt Ampitheater	**Caution**	Alameda	Region 2 - San Francisco Bay	3726
09/16/2022	Lake Merritt	Lake Merritt at Lakeshore Ave. near Boden Way	**Caution**	Alameda	Region 2 - San Francisco Bay	3494
09/19/2022	West Canal	at Clifton Court Intake (WCI)	**Caution**	Contra Costa	Region 5 - Central Valley	3211
09/19/2022	Old River	at Clifton Court Intake (ORI)	**Caution**	Contra Costa	Region 5 - Central Valley	3210
09/19/2022	False River	near San Joaquin River (FAL)	**Caution**	Contra Costa	Region 5 - Central Valley	3183
09/16/2022	Contra Loma Reservoir	at Regional Park	**Caution**	Contra Costa	Region 5 - Central Valley	3288
09/22/2022	Tahoe Keys Lagoons	Carson Court	**Caution**	El Dorado	Region 6 Lahontan	3673
09/16/2022	Lake Tahoe	Connolly Beach	**Caution**	El Dorado	Region 6 Lahontan	3627
09/16/2022	Lake Tahoe	Mouth of Upper Truckee River as it enters Lake Tahoe	**Caution**	El Dorado	Region 6 Lahontan	3674
09/16/2022	Lake Tahoe	Kiva Beach	**Caution**	El Dorado	Region 6 Lahontan	3447
09/16/2022	Lake Tahoe Keys	Venice Drive	**Caution**	El Dorado	Region 6 Lahontan	3652
09/16/2022	Big Lagoon	Lagoonwide	**Caution**	Humboldt	Region 1 - North Coast	3224
09/22/2022	Clear Lake	Lily Cove (LC01)	**Caution**	Lake	Region 5 - Central Valley	3471
09/22/2022	Clear Lake	Cache Creek Shady Acres (SHADY01)	**Caution**	Lake	Region 5 - Central Valley	3316
09/22/2022	Clear Lake	Jago Bay (JB)	**Caution**	Lake	Region 5 - Central Valley	3295
09/22/2022	Clear Lake	Oaks Arm, Center of the Lake (DWR Site CL-4)	**Caution**	Lake	Region 5 - Central Valley	3246
09/22/2022	Clear Lake	Lakeport 1st Street Ramp (LPTNT)	**Caution**	Lake	Region 5 - Central Valley	3241
09/22/2022	Clear Lake	Keeling Park (KP01)	**Caution**	Lake	Region 5 - Central Valley	3240
09/22/2022	Clear Lake	Clearlake Oaks near Water Intake (CLOAKS01)	**Caution**	Lake	Region 5 - Central Valley	3238
09/22/2022	Clear Lake	Austin Park (AP01)	**Caution**	Lake	Region 5	3234

09/23/2022	Quail Lake	Quail Lake outlet	**Caution**	Los Angeles	Region 6 Lahontan	3396
09/23/2022	Pyramid Lake	Pyramid Lake, Vaquero Swim beach	**Caution**	Los Angeles	Region 4 - Los Angeles	3400
09/23/2022	Pyramid Lake	Pyramid Lake, Emigrant Landing Swim beach	**Caution**	Los Angeles	Region 4 - Los Angeles	3399
09/23/2022	Pyramid Lake	Pyramid Lake, oulet	**Caution**	Los Angeles	Region 4 - Los Angeles	3398
09/16/2022	O'Neill Forebay	Boat Launch	**Caution**	Merced	Region 5 - Central Valley	3444
09/16/2022	O'Neill Forebay	OutleUCheck 13	**Caution**	Merced	Region 5 - Central Valley	3274
09/16/2022	O'Neill Forebay	Gianelli Pumping Plant	**Caution**	Merced	Region 5 - Central Valley	3273
09/22/2022	Baker Pond	Baker Pond	**Caution**	Riverside	Region 8 - Santa Ana	3732
09/22/2022	Gunnerson Pond	Gunnerson Pond	**Caution**	Riverside	Region 8 - Santa Ana	3731
09/20/2022	North Natomas Regional Park	Park pond	**Caution**	Sacramento	Region 5 - Central Valley	3725
09/19/2022	Three Mile Slough	near San Joaquin River (TSL)	**Caution**	Sacramento	Region 5 - Central Valley	3184
09/22/2022	San Dieguito River	San Dieguito River in Arroyo Preserve	**Caution**	San Diego	Region 9 - San Diego	3495
09/20/2022	Cedar Creek	Cedar Creek at the falls	**Caution**	San Diego	Region 9 - San Diego	3327
09/16/2022	Lake Henshaw	Open water near buoy line and at shoreline	**Caution**	San Diego	Region 9 - San Diego	3285
09/16/2022	Lake Henshaw	end of fishing dock	**Caution**	San Diego	Region 9 - San Diego	3284
09/19/2022	Victoria Canal	near Union Point (VCU)	**Caution**	San Joaquin	Region 5 - Central Valley	3212
09/19/2022	Grant Line Canal	near Old River (GLC)	**Caution**	San Joaquin	Region 5 - Central Valley	3209
09/19/2022	Old River	Downstream of the ORT Barrier (ODM)	**Caution**	San Joaquin	Region 5 - Central Valley	3208
09/19/2022	Old River	at Mountain House (ORM)	**Caution**	San Joaquin	Region 5 - Central Valley	3207
09/19/2022	Old River	between Franks Tract and San Joaquin River	**Caution**	San Joaquin	Region 5 - Central	3180

09/19/2022	Holland Cut	near Franks Tract (HOL}	**Caution**	San Joaquin	Region 5 - Central Valley	3188
09/19/2022	Middle River	near Mildred Island (HLT}	**Caution**	San Joaquin	Region 5 - Central Valley	3186
09/19/2022	Turner Cut	near San Joaquin River (TRN)	**Caution**	San Joaquin	Region 5 - Central Valley	3185
09/19/2022	Fisherman's Cut	near San Joaquin River (FCT)	**Caution**	San Joaquin	Region 5 - Central Valley	3182
09/16/2022	Buckley Cove	near Buckley Cove Boat Launch (BC)	**Caution**	San Joaquin	Region 5 - Central Valley	3261
09/16/2022	San Joaquin River	Stockton Rod and Gun Club (SJ)	**Caution**	San Joaquin	Region 5 - Central Valley	3264
09/16/2022	San Joaquin River	Windmill Cove (WC)	**Caution**	San Joaquin	Region 5 - Central Valley	3262
09/16/2022	Smith Canal	near American Legion Park (SC)	**Caution**	San Joaquin	Region 5 - Central Valley	3263
09/16/2022	McLeod Lake	Morelli Park (MP)	**Caution**	San Joaquin	Region 5 - Central Valley	3266
09/22/2022	Santa Margarita Lake	Santa Margarita Lake at Marina, main launch	**Caution**	San Luis Obispo	Region 3 - Central Coast	3430
09/16/2022	Lower Klamath Wildlife Refuge	West Sheepy Lake	**Caution**	Siskiyou	Region 1 - North Coast	3179
09/23/2022	Quarry Lakes	East Bay Regional Park	**Algal mat alert sign**	Alameda	Region 2 - San Francisco Bay	3287
09/16/2022	Silver Fork American River	Silver Fork American River at Silver Fork Rd.	**Algal mat alert sign**	El Dorado	Region 5 - Central Valley	3727
09/23/2022	Merced River	El Portal	**Algal mat alert sign**	Mariposa	Region 5 - Central Valley	3737
09/23/2022	Merced River	Pohono Bridge	**Algal mat alert sign**	Mariposa	Region 5 - Central Valley	3734
09/23/2022	Merced River	Happy Isles Bridge	**Algal mat alert sign**	Mariposa	Region 5 - Central Valley	3733
09/23/2022	South Fork Merced River	Wawona campground	**Algal mat alert sign**	Mariposa	Region 5 - Central Valley	3735
09/23/2022	Russian River	Comminsky Station Road	**Algal mat alert sign**	Mendocino	Region 1 - North Coast	3667
09/23/2022	South Fork Eel River	Standish-Hickey State Recreation Area	**Algal mat alert sign**	Mendocino	Region 1 - North Coast	3523
09/23/2022	South Fork Eel River	Cooks Valley	**Algal mat alert sign**	Mendocino	Region 1 - North	3543

09/22/2022	San Luis Rey River estuary	San Luis Rey River estuary at the mouth	**Algal mat alert sign**	San Diego	Region 9 - San Diego	3660
09/21/2022	Scott River	Indian Scotty Campground	**Algal mat alert sign**	Siskiyou	Region 1 - North Coast	3729
09/21/2022	Scott River	Jones Beach	**Algal mat alert sign**	Siskiyou	Region 1 - North Coast	3730
09/23/2022	Russian River	Syar	**Algal mat alert sign**	Sonoma	Region 1 - North Coast	3347
09/23/2022	Russian River	Alexander Valley Road	**Algal mat alert sign**	Sonoma	Region 1 - North Coast	3344
09/16/2022	Lake Merritt	Lake Merritt shoreline between 1200 and 1400 Lakeshore Avenue	**NA - refer to Report Details**	Alameda	Region 2 - San Francisco Bay	3609
09/16/2022	Dyer Reservoir	Outlet	**None**	Alameda	Region 5 - Central Valley	3272
09/23/2022	Lake Anza	lake-wide	**None**	Contra Costa	Region 2 - San Francisco Bay	3283
09/16/2022	Clifton Court Forebay	Inlet	**None**	Contra Costa	Region 5 - Central Valley	3275
09/22/2022	Tahoe Keys Lagoons	Lucerne Court F	**None**	El Dorado	Region 6 Lahontan	3479
09/22/2022	Tahoe Keys Lagoons	White Sands Drive	**None**	El Dorado	Region 6 Lahontan	3711
09/22/2022	Clear Lake	West of Sulphur Bank Mercury Mine (SBMMEL01)	**None**	Lake	Region 5 - Central Valley	3323
09/22/2022	Clear Lake	Rodman Slough (RODS)	**None**	Lake	Region 5 - Central Valley	3322
09/22/2022	Clear Lake	County Park (CP)	**None**	Lake	Region 5 - Central Valley	3319
09/22/2022	Clear Lake	Horseshoe Bend (HB)	**None**	Lake	Region 5 - Central Valley	3318
09/22/2022	Clear Lake	Glenhaven (GH)	**None**	Lake	Region 5 - Central Valley	3317
09/22/2022	Clear Lake	Lower Arm, Center of the Lake (DWR site CL-3)	**None**	Lake	Region 5 - Central Valley	3250
09/22/2022	Clear Lake	Upper Arm, Center of the Lake (DWR site CL-1)	**None**	Lake	Region 5 - Central Valley	3243
09/22/2022	Clear Lake	Elem Indian Colony (ELEM01)	**None**	Lake	Region 5 - Central Valley	3239
09/22/2022	Clear Lake	Tule Boat Launch (The Point) (BVCL6)	**None**	Lake	Region 5 - Central	3235

09/22/2022	Clear Lake	Lucerne Harbor Park (LUC01)	None	Lake	Region 5 - Central Valley	3233
09/23/2022	Castaic Lake	Castaic Lake, oulet	None	~~Los Angele~~ s	Region 4 - Los Angele s	3403
09/23/2022	Castaic Lake	Castaic Lake, Lagoon Swim beach	None	Los Angele s	Region 4 - Los Angele s	3402
09/23/2022	Castaic Lake	Castaic Lake, boat launch	None	Los Angele s	Region 4 - Los Angele s	3401
09/22/2022	Silverwood Lake	Silverwood Lake outlet	None	San Bernardino	Region 6 Lahontan	3452
09/19/2022	Mokelumne River	near San Joaquin River (MOK)	None	San Joaquin	Region 5 - Central Valley	3181
09/16/2022	Lower Klamath Wildlife Refuge	Stateline Boat Ramp	None	Siskiyou	Region 1 - North Coast	3178
09/22/2022	Sonoma Creek	below Adobe Cyn. Rd. and Godspeed Trail	None	Sonoma	Region 2 - San Francisco Bay	3599

Appendix C: SPSS Output - Supporting Documentation

The following appendix of IBM SPSS statistical output is provided to those readers who may find it useful in their own research. The information presented herein are snip-its from the software program. Therefore, this presentation of information is not intended to be compliant with the latest APA 7 format. Tables and figures provided are grouped by the major statistical analysis performed.

The sections in this appendix are as follows:

- **Exhibit C-1.** *Descriptive Statistics for Core Values*
- **Exhibit C-2.** *Independent* t-*Test*
- **Exhibit C-3.** *Pearson's Correlation*
- **Exhibit C-4.** *Multiple Linear Regression*

Exhibit C-1. *Descriptive Statistics for Core Values*

Descriptive Statistics

	Mean	Std. Deviation	N
SQRTChl_a	.2739	.09834	102
SQRT_TN	1.3884	.35985	102
SQRT_TP	.5565	.09768	102
NH3Recode	.4608	.50092	102

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	NH3Recode, SQRT_TP, SQRT_TN[b]	.	Enter

a. Dependent Variable: SQRTChl_a

b. All requested variables entered.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Chlorophyll	102	100.0%	0	0.0%	102	100.0%
TN	102	100.0%	0	0.0%	102	100.0%
TP	102	100.0%	0	0.0%	102	100.0%
NH3	102	100.0%	0	0.0%	102	100.0%

Descriptives

			Statistic	Std. Error
Chlorophyll	Mean		.084608	.0055148
	95% Confidence Interval for Mean	Lower Bound	.073668	
		Upper Bound	.095548	
	5% Trimmed Mean		.082049	
	Median		.069250	
	Variance		.003	
	Std. Deviation		.0556971	
	Minimum		.0040	
	Maximum		.2150	
	Range		.2110	
	Interquartile Range		.0904	
	Skewness		.674	.239
	Kurtosis		-.567	.474
TN	Mean		2.055784	.1040321
	95% Confidence Interval for Mean	Lower Bound	1.849413	
		Upper Bound	2.262156	
	5% Trimmed Mean		1.998638	
	Median		1.700000	
	Variance		1.104	
	Std. Deviation		1.0506725	
	Minimum		.1500	
	Maximum		4.8000	
	Range		4.6500	
	Interquartile Range		1.5625	
	Skewness		.833	.239
	Kurtosis		-.109	.474
TP	Mean		.319118	.0107432
	95% Confidence Interval for Mean	Lower Bound	.297806	
		Upper Bound	.340429	
	5% Trimmed Mean		.315997	
	Median		.315000	
	Variance		.012	
	Std. Deviation		.1085011	
	Minimum		.0900	
	Maximum		.6350	
	Range		.5450	
	Interquartile Range		.1463	
	Skewness		.363	.239
	Kurtosis		-.046	.474
NH3	Mean		.067500	.0076746
	95% Confidence Interval for Mean	Lower Bound	.052276	
		Upper Bound	.082724	
	5% Trimmed Mean		.054962	
	Median		.025000	
	Variance		.006	
	Std. Deviation		.0775100	
	Minimum		.0250	
	Maximum		.3800	
	Range		.3550	
	Interquartile Range		.0556	
	Skewness		2.467	.239
	Kurtosis		6.069	.474

Descriptives

			Statistic	Std. Error
SQRTChl_a	Mean		.2739	.00974
	95% Confidence Interval for Mean	Lower Bound	.2546	
		Upper Bound	.2932	
	5% Trimmed Mean		.2744	
	Median		.2632	
	Variance		.010	
	Std. Deviation		.09834	
	Minimum		.06	
	Maximum		.46	
	Range		.40	
	Interquartile Range		.16	
	Skewness		.084	.239
	Kurtosis		-.747	.474
SQRT_TN	Mean		1.3884	.03563
	95% Confidence Interval for Mean	Lower Bound	1.3177	
		Upper Bound	1.4590	
	5% Trimmed Mean		1.3824	
	Median		1.3038	
	Variance		.129	
	Std. Deviation		.35985	
	Minimum		.39	
	Maximum		2.19	
	Range		1.80	
	Interquartile Range		.56	
	Skewness		.307	.239
	Kurtosis		-.300	.474
SQRT_TP	Mean		.5565	.00967
	95% Confidence Interval for Mean	Lower Bound	.5373	
		Upper Bound	.5757	
	5% Trimmed Mean		.5567	
	Median		.5612	
	Variance		.010	
	Std. Deviation		.09768	
	Minimum		.30	
	Maximum		.80	
	Range		.50	
	Interquartile Range		.13	
	Skewness		-.100	.239
	Kurtosis		-.189	.474
SQRT_NH3	Mean		.2333	.01138
	95% Confidence Interval for Mean	Lower Bound	.2107	
		Upper Bound	.2559	
	5% Trimmed Mean		.2183	
	Median		.1581	
	Variance		.013	
	Std. Deviation		.11492	
	Minimum		.16	
	Maximum		.62	
	Range		.46	
	Interquartile Range		.13	
	Skewness		1.732	.239
	Kurtosis		2.393	.474
NH3Recode	Mean		.4608	.04960
	95% Confidence Interval for Mean	Lower Bound	.3624	
		Upper Bound	.5592	
	5% Trimmed Mean		.4564	
	Median		.0000	
	Variance		.251	
	Std. Deviation		.50092	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		1.00	
	Skewness		.160	.239
	Kurtosis		-2.014	.474

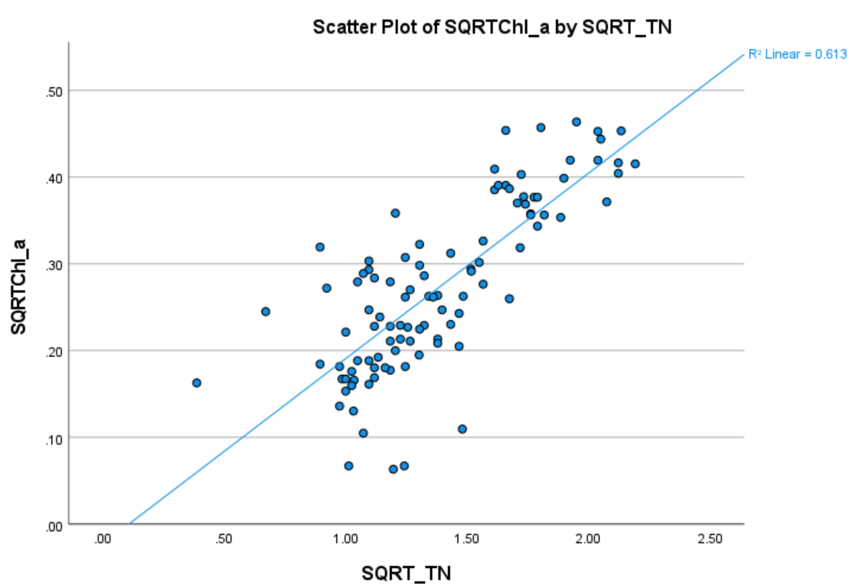
Exhibit C-2. *Independent* t-*Test*

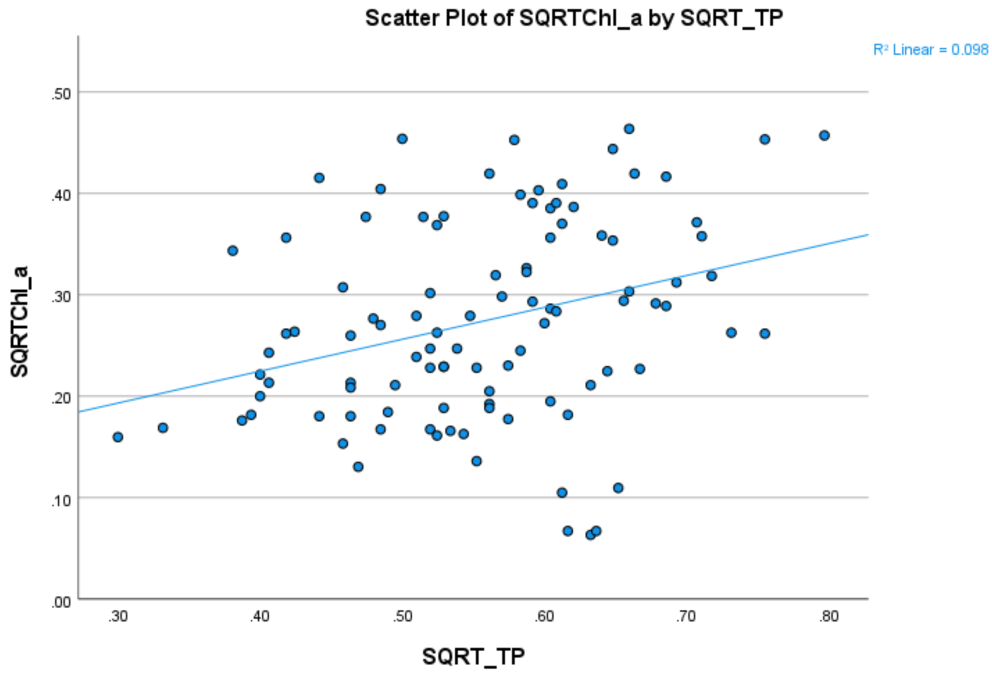
Group Statistics

	Season	N	Mean	Std. Deviation	Std. Error Mean
Chlorophyll	"Wet"	52	.078577	.0620177	.0086003
	"Dry"	50	.090880	.0480868	.0068005
SQRTChl_a	"Wet"	52	.2580	.11063	.01534
	"Dry"	50	.2905	.08154	.01153

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance		Mean	Std. Error	95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Difference	Difference	Lower	Upper
Chlorophyll	Equal variances assumed	3.454	.066	-1.117	100	.133	.267	-.0123031	.0110183	-.0341631	.0095570
	Equal variances not assumed			-1.122	95.752	.132	.265	-.0123031	.0109641	-.0340674	.0094613
SQRTChl_a	Equal variances assumed	5.569	.020	-1.680	100	.048	.096	-.03244	.01931	-.07074	.00586
	Equal variances not assumed			-1.690	93.757	.047	.094	-.03244	.01919	-.07055	.00567





SPSS Output

Case Processing Summary

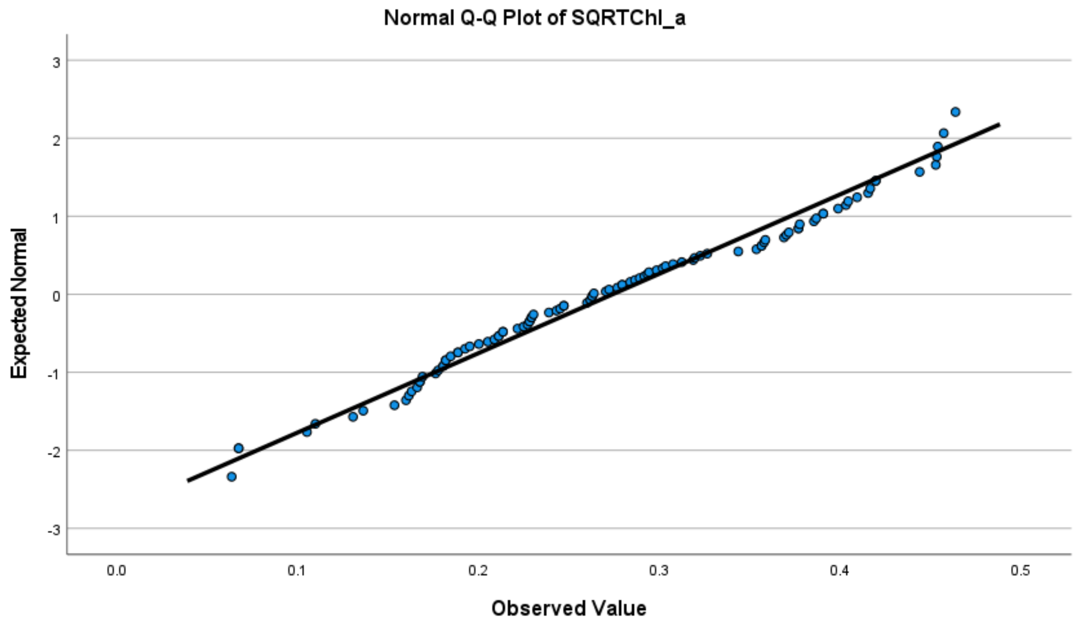
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
SQRTChl_a	102	100.0%	0	0.0%	102	100.0%
SQRT_TN	102	100.0%	0	0.0%	102	100.0%
SQRT_TP	102	100.0%	0	0.0%	102	100.0%

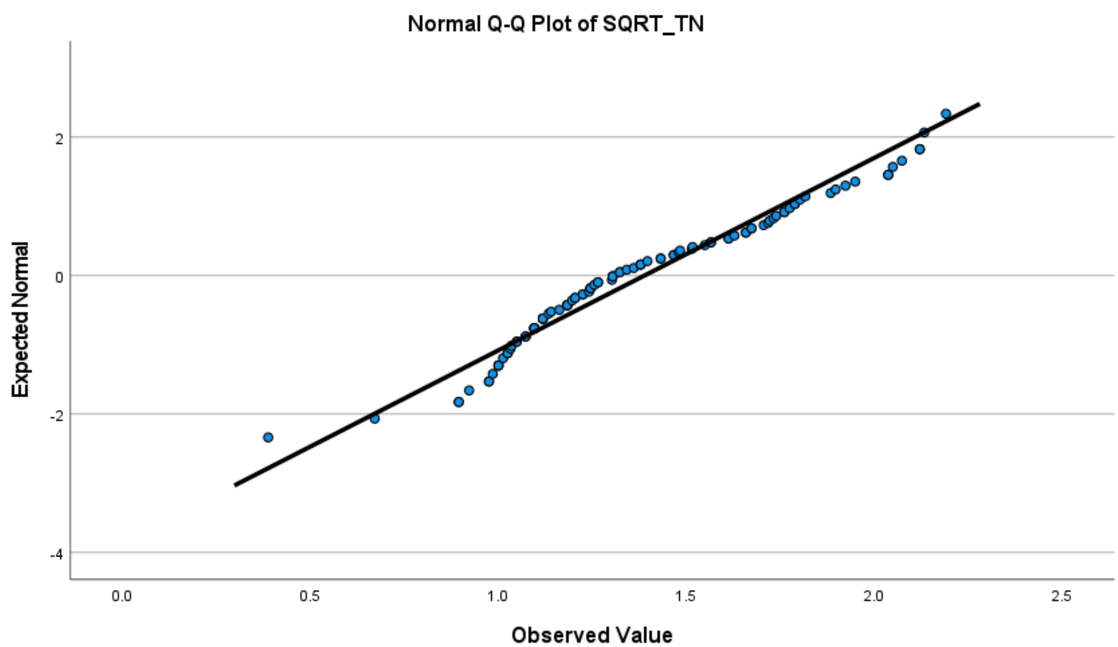
Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SQRTChl_a	.075	102	.175	.976	102	.056
SQRT_TN	.105	102	.008	.964	102	.007
SQRT_TP	.040	102	.200*	.996	102	.987

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction


Normal Q-Q Plot of SQRTChl_a
Expected Normal
Observed Value
3
2
1
0
-1
-2
-3
0.0
0.1
0.2
0.3
0.4
0.5


Normal Q-Q Plot of SQRT_TN
Expected Normal
Observed Value
2
0
-2
-4
0.0
0.5
1.0
1.5
2.0
2.5

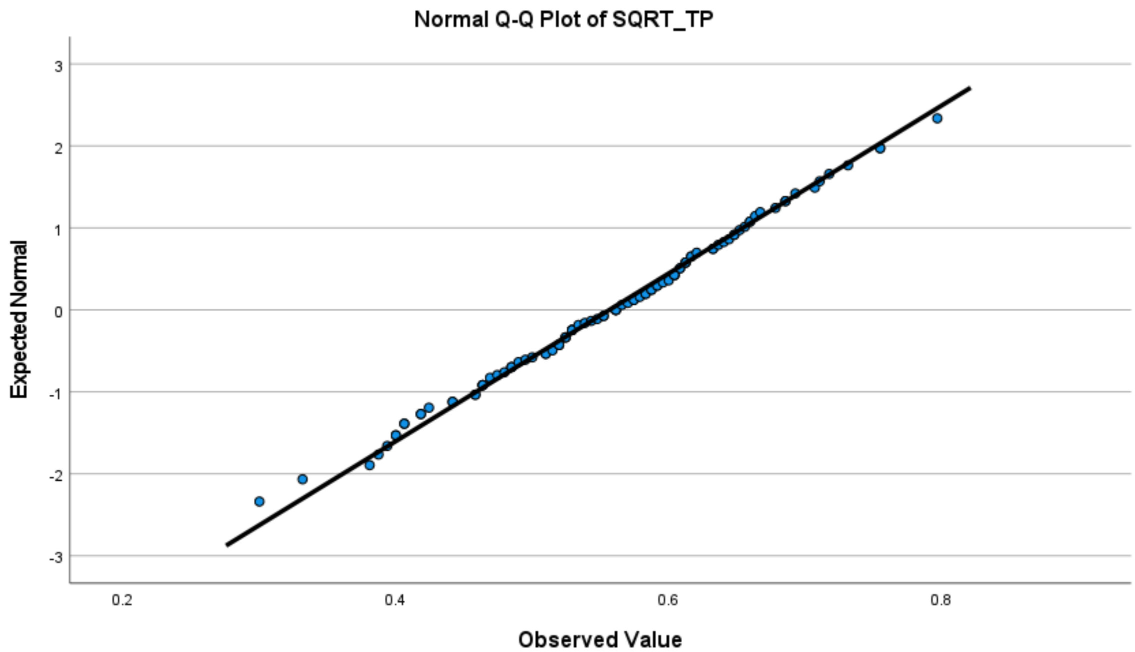

Normal Q-Q Plot of SQRT_TP
Expected Normal
3
2
1
0
-1
-2
-3
0.2
0.4
0.6
0.8
Observed Value

Exhibit C-3. *Pearson's Correlation*

SPSS Output

Case Processing Summary

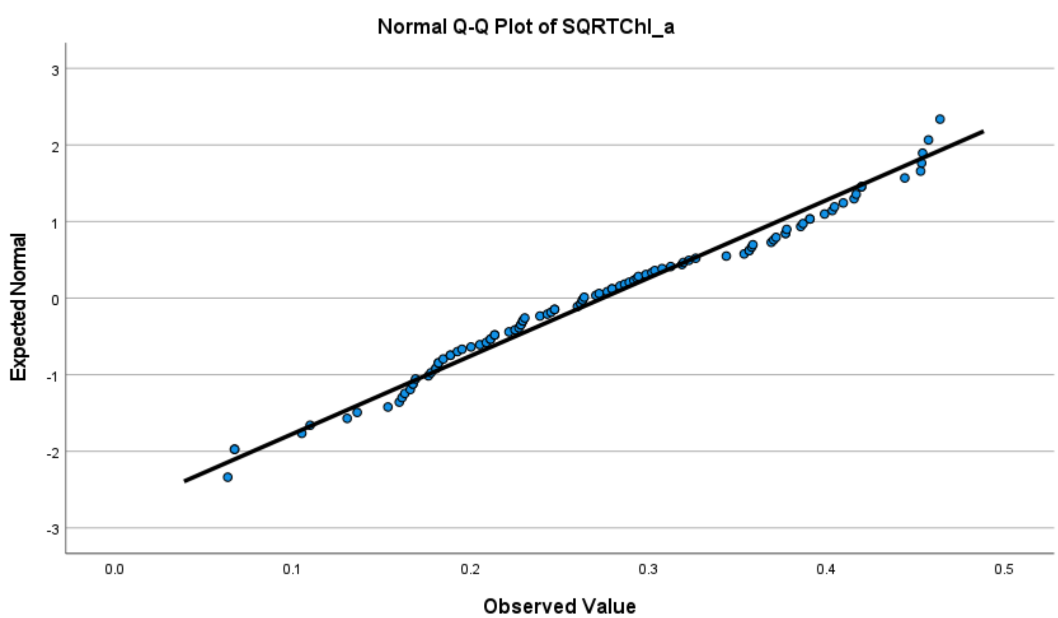
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
SQRTChl_a	102	100.0%	0	0.0%	102	100.0%
SQRT_TN	102	100.0%	0	0.0%	102	100.0%
SQRT_TP	102	100.0%	0	0.0%	102	100.0%

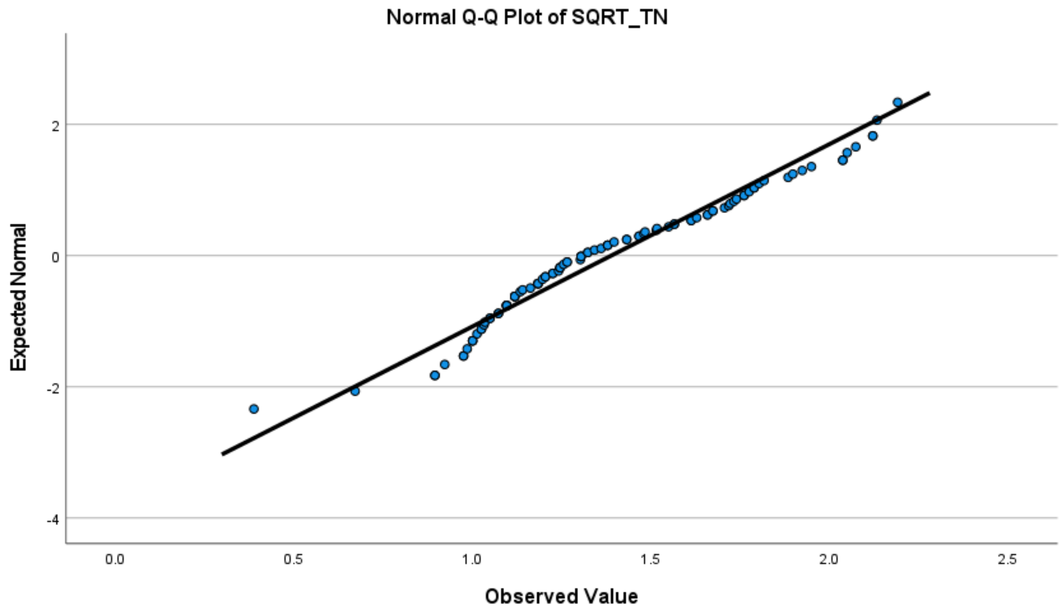
Tests of Normality

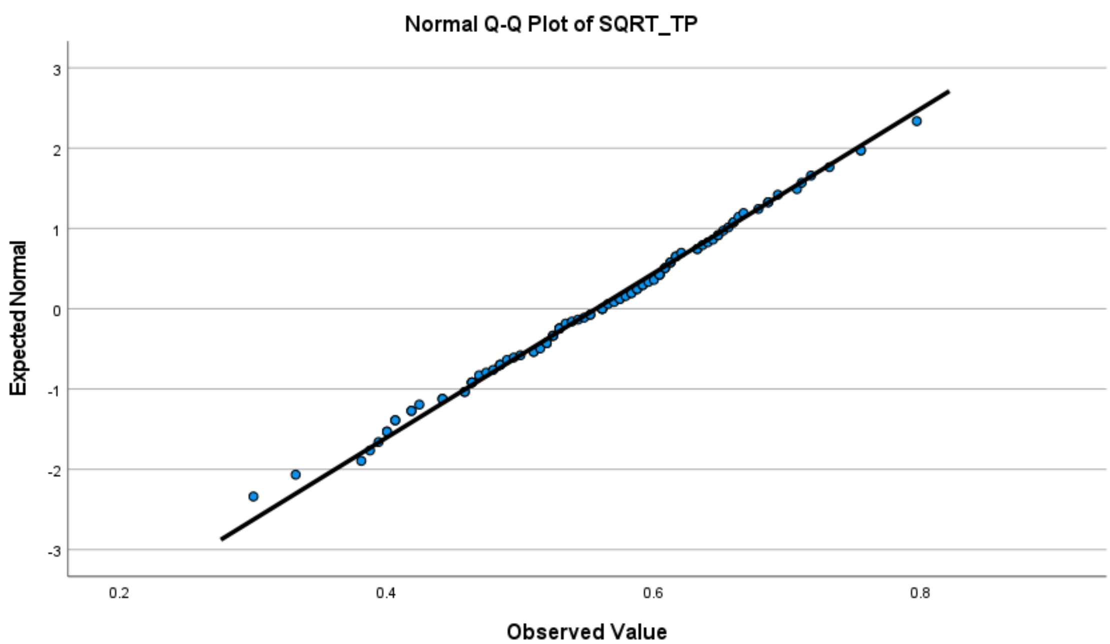
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SQRTChl_a	.075	102	.175	.976	102	.056
SQRT_TN	.105	102	.008	.964	102	.007
SQRT_TP	.040	102	.200*	.996	102	.987

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction



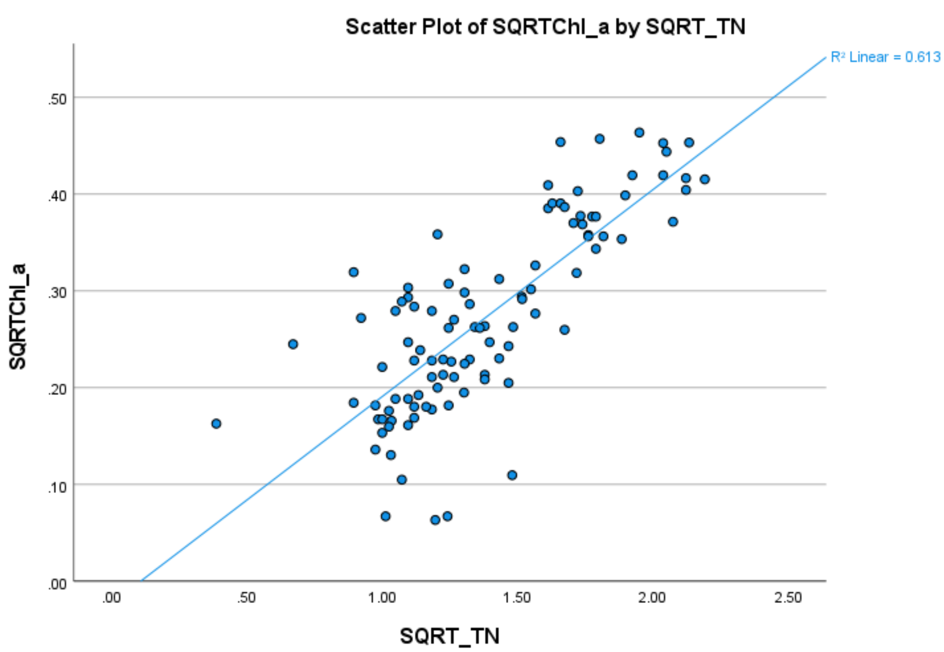

Normal Q-Q Plot of SQRT_TN
Expected Normal
2
0
-2
-4
0.0
0.5
1.0
1.5
2.0
2.5
Observed Value

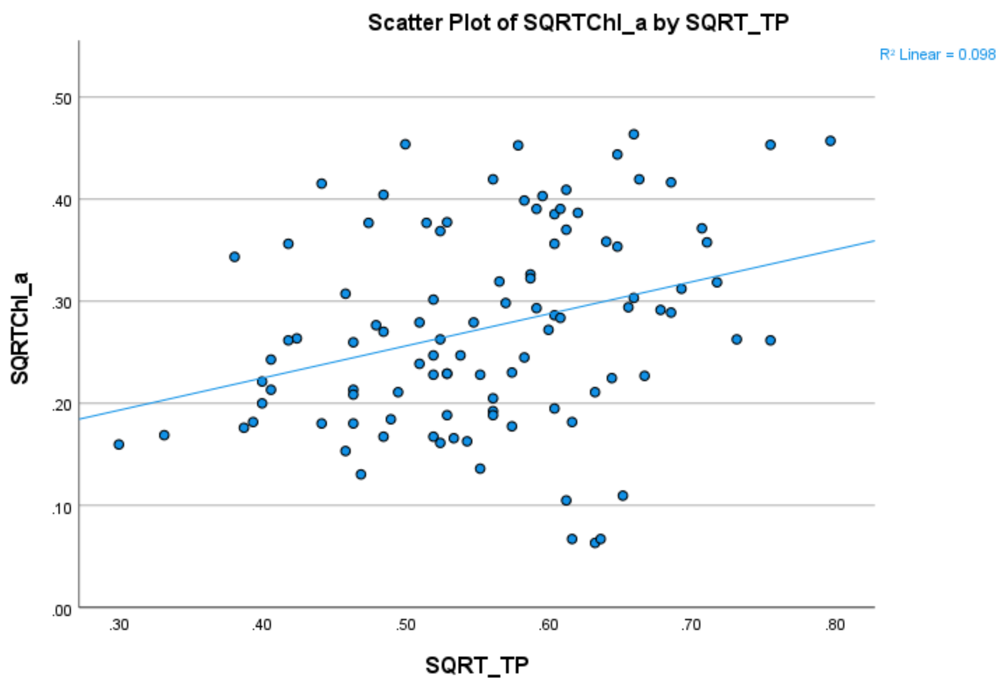

Normal Q-Q Plot of SQRT_TP
Expected Normal
3
2
1
0
-1
-2
-3
0.2
0.4
0.6
0.8
Observed Value

Correlations

		SQRTChl_a	SQRT_TN	SQRT_TP
SQRTChl_a	Pearson Correlation	1	.783**	.312**
	Sig. (2-tailed)		<.001	.001
	N	102	102	102
SQRT_TN	Pearson Correlation	.783**	1	.293**
	Sig. (2-tailed)	<.001		.003
	N	102	102	102
SQRT_TP	Pearson Correlation	.312**	.293**	1
	Sig. (2-tailed)	.001	.003	
	N	102	102	102

**. Correlation is significant at the 0.01 level (2-tailed).




Scatter Plot of SQRTChl_a by SQRT_TP
R² Linear = 0.098
SQRTChl_a
.50
.40
.30
.20
.10
.00
.30
.40
.50
.60
.70
.80
SQRT_TP

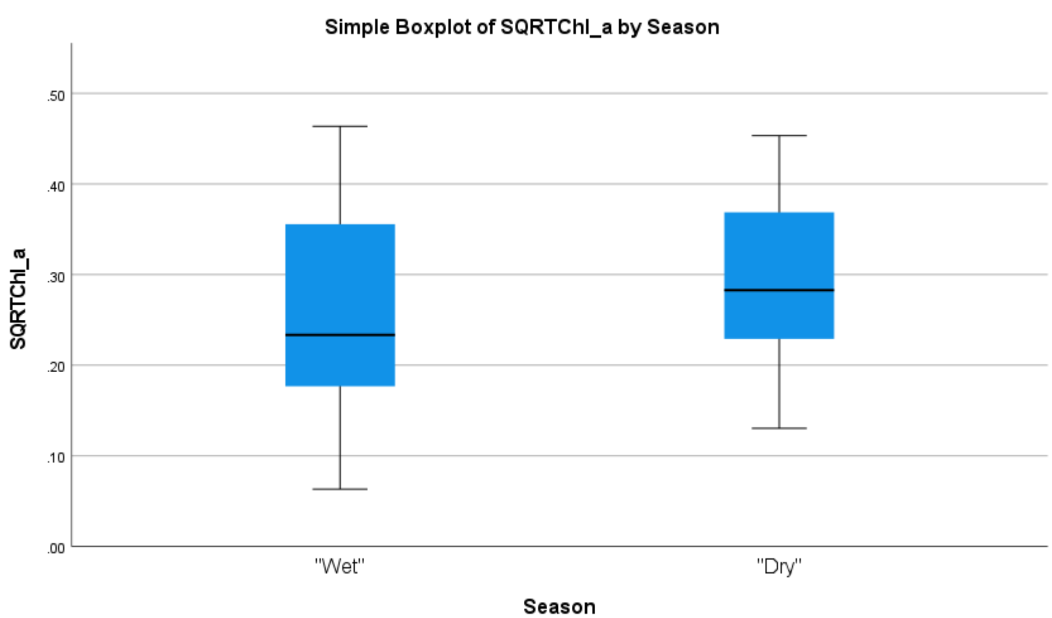
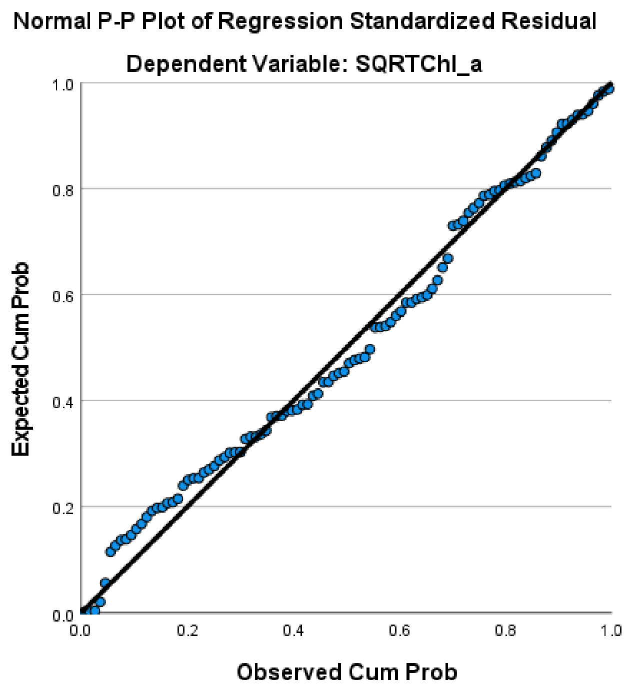
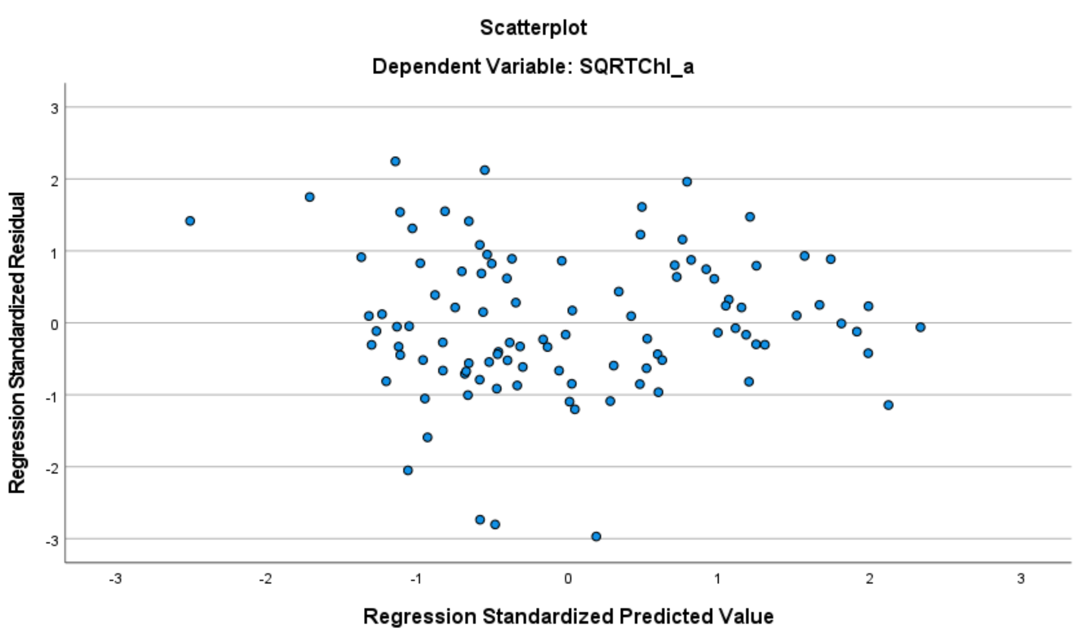

Simple Boxplot of SQRTChl_a by Season
SQRTChl_a
.50
.40
.30
.20
.10
.00
"Wet"
"Dry"
Season

Exhibit C-4. *Multiple Linear Regression*





Descriptive Statistics

	Mean	Std. Deviation	N
SQRTChl_a	.2739	.09834	102
SQRT_TN	1.3884	.35985	102
SQRT_TP	.5565	.09768	102
NH3Recode	.4608	.50092	102

Correlations

		SQRTChl_a	SQRT_TN	SQRT_TP	NH3Recode
Pearson Correlation	SQRTChl_a	1.000	.783	.312	-.132
	SQRT_TN	.783	1.000	.293	-.011
	SQRT_TP	.312	.293	1.000	.000
	NH3Recode	-.132	-.011	.000	1.000
Sig. (1-tailed)	SQRTChl_a	.	<.001	<.001	.093
	SQRT_TN	.000	.	.001	.456
	SQRT_TP	.001	.001	.	.499
	NH3Recode	.093	.456	.499	.
N	SQRTChl_a	102	102	102	102
	SQRT_TN	102	102	102	102
	SQRT_TP	102	102	102	102
	NH3Recode	102	102	102	102

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	NH3Recode, SQRT_TP, SQRT_TN[b]	.	Enter

a. Dependent Variable: SQRTChl_a

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.797[a]	.636	.625	.06025	1.965

a. Predictors: (Constant), NH3Recode, SQRT_TP, SQRT_TN

b. Dependent Variable: SQRTChl_a

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.621	3	.207	57.027	<.001[b]
	Residual	.356	98	.004		
	Total	.977	101			

a. Dependent Variable: SQRTChl_a

b. Predictors: (Constant), NH3Recode, SQRT_TP, SQRT_TN

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-.052	.038		-1.387	.169	-.127	.023					
	SQRT_TN	.206	.017	.755	11.838	<.001	.172	.241	.783	.767	.722	.914	1.094
	SQRT_TP	.092	.064	.091	1.428	.156	-.036	.219	.312	.143	.087	.914	1.094
	NH3Recode	-.024	.012	-.124	-2.030	.045	-.048	-.001	-.132	-.201	-.124	1.000	1.000

a. Dependent Variable: SQRTChl_a

Collinearity Diagnostics[a]

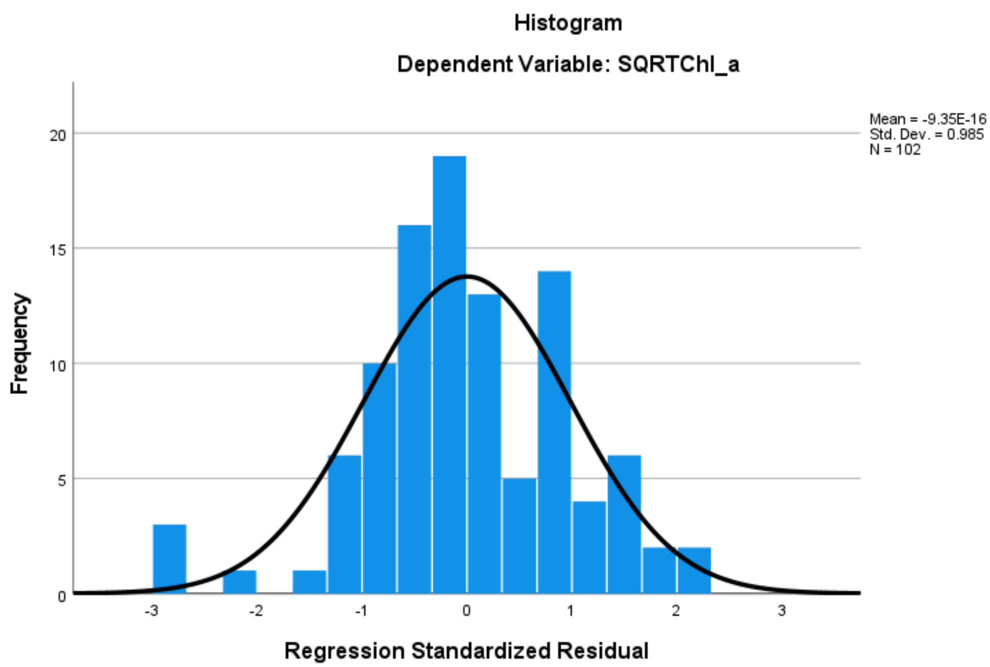
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	SQRT_TN	SQRT_TP	NH3Recode
1	1	3.485	1.000	.00	.00	.00	.03
	2	.462	2.746	.00	.01	.00	.96
	3	.038	9.542	.09	.98	.14	.01
	4	.015	15.365	.90	.01	.85	.01

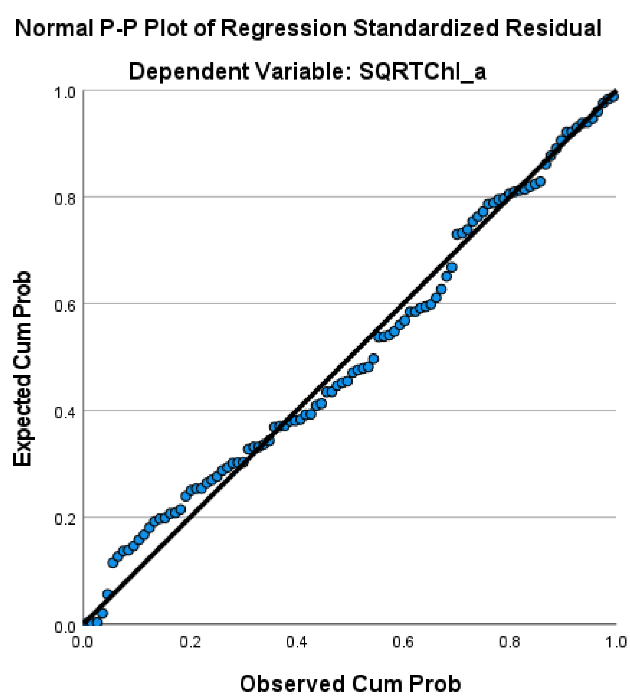
a. Dependent Variable: SQRTChl_a

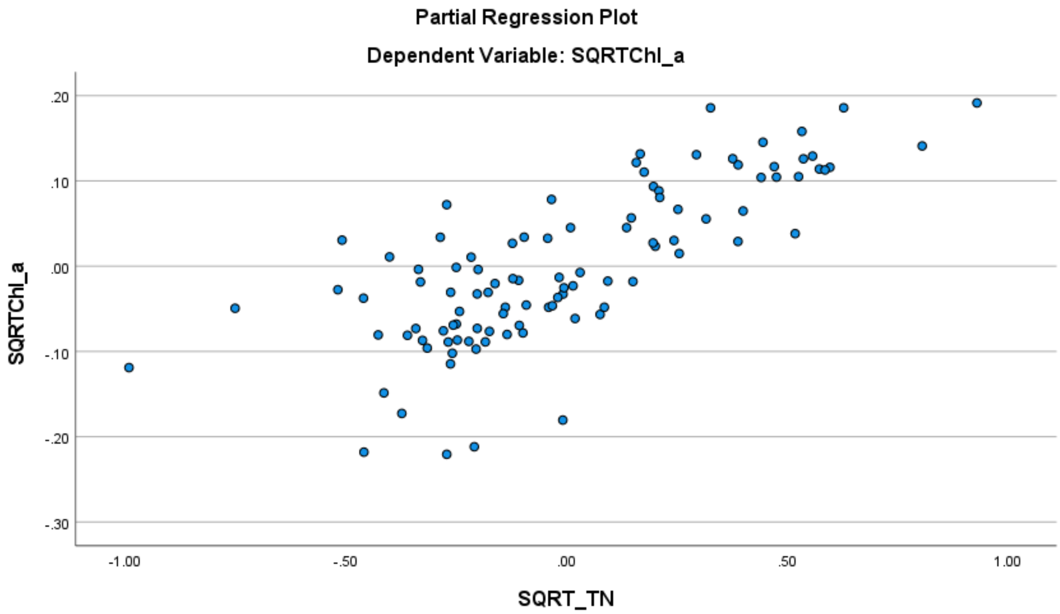
Residuals Statistics[a]

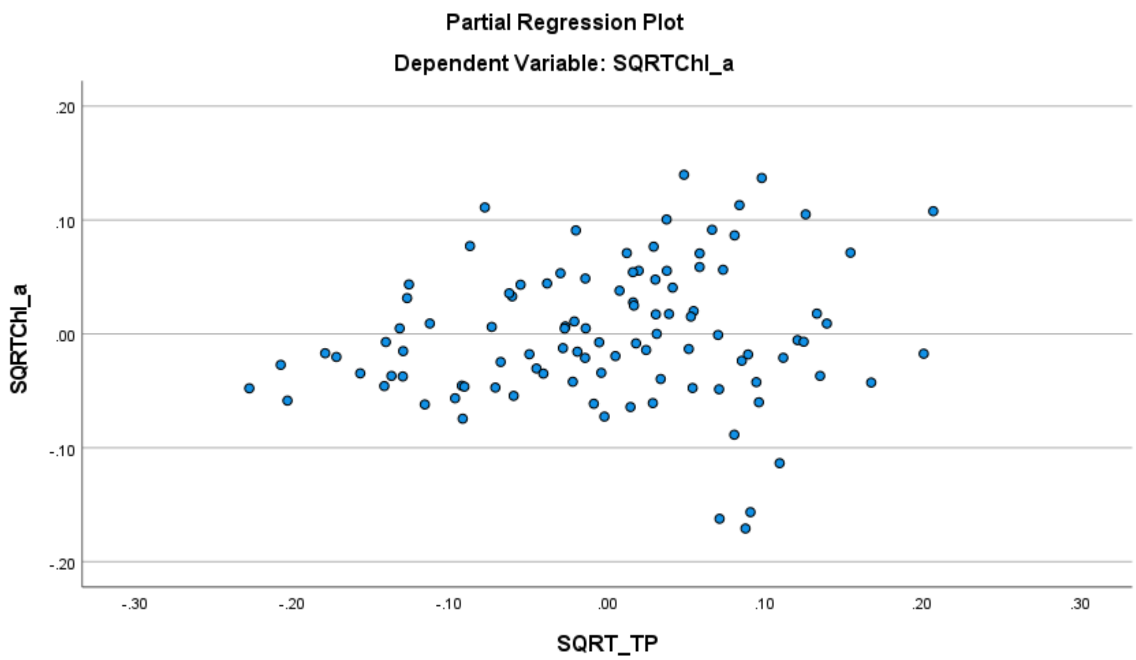
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.0774	.4569	.2739	.07842	102
Std. Predicted Value	-2.506	2.334	.000	1.000	102
Standard Error of Predicted Value	.008	.020	.012	.003	102
Adjusted Predicted Value	.0678	.4573	.2738	.07870	102
Residual	-.17890	.13531	.00000	.05935	102
Std. Residual	-2.969	2.246	.000	.985	102
Stud. Residual	-3.016	2.292	.001	1.004	102
Deleted Residual	-.18457	.14092	.00011	.06171	102
Stud. Deleted Residual	-3.150	2.344	-.001	1.019	102
Mahal. Distance	.883	9.864	2.971	1.834	102
Cook's Distance	.000	.072	.010	.016	102
Centered Leverage Value	.009	.098	.029	.018	102

a. Dependent Variable: SQRTChl_a


Histogram
Dependent Variable: SQRTChl_a
Mean = -9.35E-16
Std. Dev. = 0.985
N = 102
Frequency
0
5
10
15
20
-3
-2
-1
0
1
2
3
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SQRTChl_a
Expected Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob


Partial Regression Plot
Dependent Variable: SQRTChl_a
SQRTChl_a
SQRT_TN
.20
.10
.00
-.10
-.20
-.30
-1.00
-.50
.00
.50
1.00


Partial Regression Plot
Dependent Variable: SQRTChl_a
SQRTChl_a
SQRT_TP
.20
.10
.00
-.10
-.20
-.30
-.20
-.10
.00
.10
.20
.30

Appendix D: List of Acronyms

AGL	Alliance for the Great Lakes
BMP	Best Management Practice
CA-OEHHA	State of CA – Office of Environmental Health Hazard Assessment
CARE	Comprehensive Cleaning and Rapid Engagement Program
CCR	California Code of Regulations
CWQMC	California Water Quality Monitoring Council
CWA	Clean Water Act
IBM SPSS	IBM Statistical Package for Social Sciences
LADPW	Los Angeles Department of Public Works
LADPWBOE	City of LA Dept. of Public Works Bureau of Engineering
LADPWSAN	City of LA Dept. of Public Works Sanitation Department
LARWQCB	Los Angeles Regional Water Quality Control Board
LASAN	City of Los Angeles Bureau of Sanitation
MFAC	Minimum Frequency of Assessment and Collection Program
MS4	Municipal Separate Storm Sewer System
NOAA	National Oceanic and Atmospheric Administration
NIH	National Institute of Health
NSF	National Science Foundation
NRDC	National Resources Defense Council
RAP	Department of Recreation and Parks
RCRA	Resource Conservation and Recovery Act

SCCWRP	Southern CA Coastal Water Research Project
SWAMP	Surface Water Ambient Monitoring Program
SWPPP	Storm Water Pollution Prevention Plan
SWRCB	State Water Resources Control Board
TMDL	Total Maximum Daily Load
TMRP	Trash Monitoring and Reporting Plan
USEPA	United States Environmental Protection Agency
USGS	United States Geological Society
WDR	Waste Discharge Report
WHO	World Health Organization
WLA	Waste Load Allocation
WPD	Watershed Protection Division