ANALYSES OF TEMPORAL CHANGES IN TROPHIC STATE VARIABLES IN FLORIDA LAKES

By

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To my loving family and friends

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By

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Appropriate assessments of lake change and trends are necessary to advance limnological studies to best estimate factors driving lake change, such as climate. The citizen monitoring Florida LAKEWATCH database was used to evaluate decadal-scale trends in the trophic state variables; total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements. Two subsets of the LAKEWATCH database were used: monthly samples of the trophic state variables collected for at least 20 years for 27 Florida lakes, 193 lakes with data collected for at least 15 years. Linear regression, Kendall-Tau, and ARMA/ARIMA time series models were evaluated to detect trends in the trophic state variables for the 27 Florida lakes. Different statistical results were found among the evaluated methods. An alternative approach was developed, separating data into six categories prior to linear regression analysis, which provided similar detection of trends as ARMA/ARIMA time series models. For the 193 Florida lakes, the alternative approach detected increasing trends in total phosphorus (21%), total nitrogen (26%), chlorophyll concentrations (12%), and decreasing trends in water clarity measurements (18%). Less than 5% of the lakes experienced trends in all trophic state variables. Three clusters of lakes with similar trends in the trophic state variables were identified across the State of Florida. Patterns of phytoplankton growth and senescence (seasonal changes) were recurrent and synchronous for the examined Florida lakes. Annual elevated chlorophyll concentrations occurred June through October following annual climate cycles of air temperature and rainfall. The occurrence of extreme chlorophyll events increased in three of the 27 lakes that had the longest ($\geq$ 20 years) record. Seasonal patterns in waters classified as hypereutrophic differed from other trophic categories. The resulting assessment of lake change over multiple scales of time and space focuses future research and management efforts in the State of Florida and at a global level.

CHAPTER 1
INTRODUCTION

Concern about the functioning of the world's aquatic ecosystems has long been of interest yet research efforts have commonly focused on aquatic ecosystems as individual, unique systems. Although lakes are of global importance (Downing et al. 2006), limnological studies have historically aspired to understand functional processes within the individual lake or at a local-scale (Thienemann 1925; Naumann 1919). Individual lake and local-scale limnological studies of the past century have greatly advanced the aquatic sciences; however, as the needs of society change, there has been encouragement for limnologists to up-scale to a global level (Jumars 1990; Downing 2009) by concentrating on tractable, soluble problems to answer big environmental questions (Rigler and Peters 1995). One of the biggest environmental issues scientists, managers, and policy makers currently face is how to assess lake changes and trends over multiple scales of time and space (Williamson et al. 2009). Appropriate assessments of lake changes and trends are necessary to provide the required support for limnological studies to move forward and investigate relationships of lake changes and global factors, such as anthropogenic or climate drivers.

Lakes are constantly changing (Knowlton and Jones 2006) and the lake variables collected to measure lake change and estimate trends (e.g., trophic state variables like total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity as measured by the use of a Secchi disk) are of a random nature, highly variable temporally and spatially (Håkanson and Duarte 2008). Temporal and spatial variability are not frequently considered in lake assessments (Knowlton and Jones 2006), but consideration of such variability is important because identified directional changes and trends in lake trophic state variables may be attributed to global factors, like climate, exacerbated by global changes (see Kernan 2010). Different statistical methods exist to determine changes and trends in lake trophic state time series data, many of which account for variability (Kendall 1938; Esterby 1997; Stow et al. 1998; Burkholder et al. 2006). However, regardless of the statistical method used, the sampling frequency and duration suggested to best represent a lake's behavior range from 6 years of consecutive data (Molot and Dillon 1991) to 12 years (Howden et al. 2011) to at least 20 years (Knowlton and Jones 2006). There are limited long-term data sets that meet these suggested requirements for individual lakes, but especially for populations of lakes. To understand how to assess lake changes and trends over time, that also account for variability, alternative methods that provide analogous "statistical meaningful" (Bryhn and Dimberg 2011) results are needed.

The need to understand how to assess lake changes and trends in lake trophic state variables is of prodigious importance in the State of Florida. For example, the proposed numeric nutrient criteria by the United States Environmental Protection Agency (USEPA) for Florida's lakes (USEPA 2010), the concern of the potential effects of Florida's increasing human population (e.g., from 1900 to 2000 Florida's population has grown by almost 3000%), or the recent attribution of rising phosphorus levels to the cumulative effects of non-point sources of pollution (Figure 1-1) are current issues of concern and importance for Florida waters. The above issues, however, would be better evaluated with supportive evidence of whether Florida's lakes have experienced long-term (i.e., decadal-scale) trends. Fortunately, the Florida LAKEWATCH program has sampled over 1,500 Florida lakes since 1986 and compiled an extensive dataset

(Canfield et al. 2002) that includes a subset of 27 Florida lakes with consecutive monthly samples collected for at least 20 years and a subset of 193 Florida lakes with monthly samples collected for at least 15 years. Using these LAKEWATCH data to evaluate trophic state variables in Florida's lakes not only contributes to the understanding of how to best assess lake changes and trends, but also provides the background needed to advance scientific research, lake management efforts, and political agendas. Limnology is exclusive from many other sciences in that major research conclusions are written into public law globally (Downing 2009) (e.g., phosphorus-chlorophyll-transparency relationships (Dillon and Reigler 1975; Jones and Bachmann 1976. Therefore, the results and conclusions gained from examination of the robust, LAKEWATCH dataset are not limited to the State of Florida, but applicable to help solve global issues as well.

The examination of a long-term dataset available for a population of lakes makes it possible to examine temporal and spatial change and, thereby, relate measurable response variables such as temperature or rainfall (Williamson et al. 2009; Gaiser et al. 2009). Limnologists have recognized that lakes in their natural state are influenced by edaphic, morphometric, and climatic factors (Naumann 1919; Chandler 1944; Moyle 1956) and demonstrated strong relationships among lake trophic state variables, total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements (Sakamoto 1966; Jones and Bachmann 1976; Carlson 1977; Canfield and Bachmann 1981; Bachmann et al. 2012a). The relationship between climate factors (e.g., temperature and rainfall) and phytoplankton biomass (estimated by chlorophyll concentrations) has become of particular interest due to the projection of change in the global climate (Mann et al. 1998; Magnuson et al. 2000; IPCC 2007) and consequent changes in the patterns of phytoplankton biomass and the limnological mechanisms of lakes (Kernan et al. 2012; Jeppensen et al. 2007a, 2010). As seasonal patterns of phytoplankton biomass contribute to the intra-annual and inter-annual variability, it will be important to document and incorporate these patterns, particularly when investigating global climate change effects on lake systems.

Establishing appropriate methods to access change and trends in lake trophic state variables to understand lake variation helps overcome some of the limitations when exploring factors contributing to limnological change. In Chapter 2, various statistical methods were used to detect patterns of long-term change and trends in trophic state variables among a population of Florida lakes. The results of the evaluated methods were compared and an alternative method was proposed to detect trends. One of the proposed methods was used to evaluate the alternative hypothesis that Florida lakes, as a population, have experienced trends in total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements over a decadal period of record, described in Chapter 3. In Chapter 4, annual seasonal patterns were identified among the population of subtropical, Florida lakes and the influence of climatic factors (i.e., temperature and rainfall) and lake trophic status on the seasonal patterns were examined. Thereafter, a final discussion of how these results advance the understanding of change and trends in lake trophic state variables and also future aquatic research are provided.

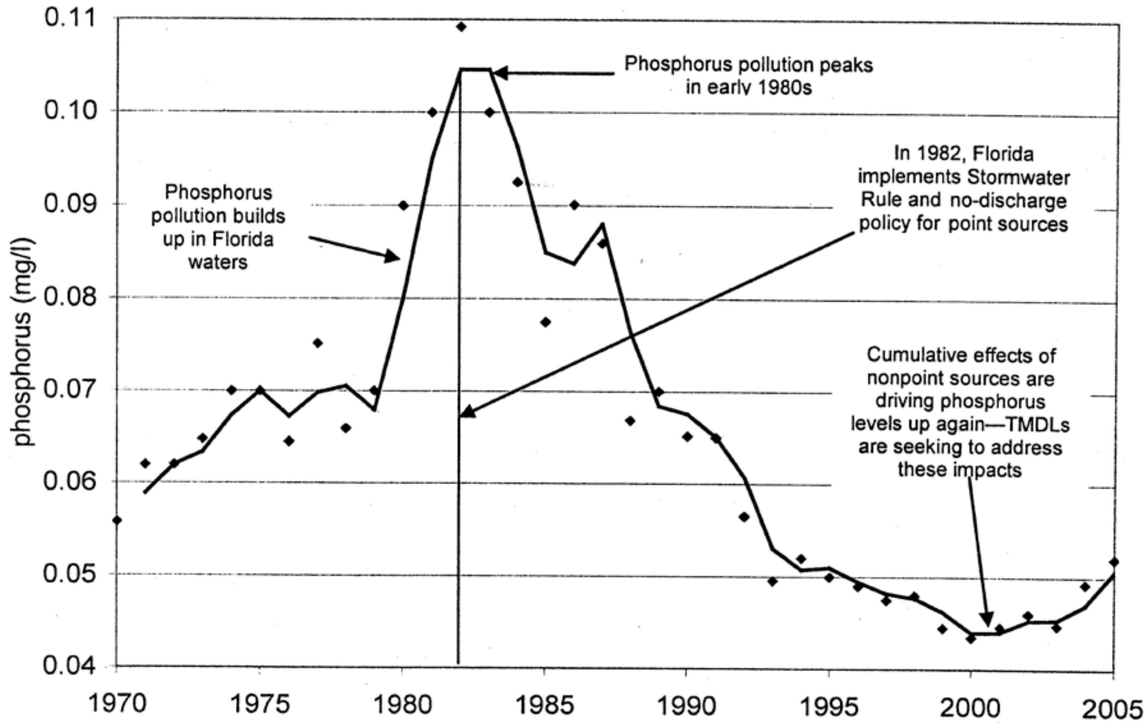


Figure 1-1. Annual mean total phosphorus concentrations (mg/L) from 1970 to 2005 for Florida water bodies from the Florida Department of Environmental Protection 303d and 305b, 2008 report.

CHAPTER 2
STATISTICAL METHODS AND AN ALTERNATIVE APPROACH TO DETECT TRENDS IN TROPHIC STATE VARIABLE TIME SERIES DATA

Background

The plight of limnologists and oceanographers is how best to detect trends in aquatic data and explain these trends to fellow scientists and non-scientists. There are many statistical methods from the basic t-test to more complicated statistical models like time series models that can be used to detect patterns of change and trends in environmental data. The problem is, however, each statistical method may provide different results (Esterby 1997; Stow et al. 1998; Kundezewicz and Robson 2004). Different statistical results are of concern because there is a potential for scientists to make erroneous conclusions that may not only hinder the advancement of science, but also corroborate unsuitable development and evaluation of public policy. It is important, as the number and power of statistical tools increase, to assess and evaluate various statistical methods to determine which are appropriate to answer ecological questions.

Environmental data, particularly aquatic data (Håkanson and Duarte 2008), are variable both temporally and spatially; the data are of a random nature (i.e., change randomly). Due to the high variability of aquatic data, statistical determination of a significant trend over a given period of record can be difficult at any reasonable confidence level and further influenced by the number of samples analyzed (Prairie 1996; Håkanson and Duarte 2008; Bryhn and Dimberg 2011). Linear regression analysis is commonly used by managers of environmental resources to detect significant trends in time series data. The assumptions of classical parametric models (i.e., normality, linearity, and independence) are not usually met by environmental data (Esterby 1997). The parametric least-squares linear regression analysis, for example, commonly violates underlying statistical assumptions (Loftis et al. 1996; Prairie 1996). Thus, nonparametric tests like the Kendall-Tau (Kendall 1938) are commonly used as these methods violate fewer statistical assumptions and supposedly better account for idiosyncrasies in environmental data. Time series models (i.e., ARMA and ARIMA models) have been recommended as a powerful statistical method to detect trends (Burkholder et al. 2006; Bendat and Piersol 2010), especially as the model accounts for extreme values, which are ubiquitous in aquatic time series data. Time series models have historically been used in economics and the social sciences (McCleary 1980), but more recently in the aquatic sciences possibly due to the increased focus to analyze time series data.

The objective of this chapter was to evaluate the statistical methods of linear regression, Kendall-Tau, and ARMA/ARIMA time series models to detect decadal-scale trends in the examined trophic state variables and to provide “statistical meaningful” (Bryhn and Dimberg 2011), alternative approach that offered a simplistic method with results comparable to a more complex statistical method. In this chapter, the term “change” was used to describe the variability of the time series data. The term “trend” implies the overall unidirectional movement (i.e., monotonic), either increasing or decreasing, of the time series data.

The statistical evaluation of long-term (i.e., monthly data collected at least 20 years) trophic state variables (i.e., total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements) provided a direct comparison of results among different statistical methods. Furthermore, the trophic state data were available for a number of Florida lakes, enhancing comparison of the statistical evaluation of patterns of change and trends. The results from this chapter refine the understanding of how to detect patterns of change and trends in time series data, which are applicable not only to the aquatic sciences, but other scientific disciplines as well. In addition, the examined dataset and similar datasets are policy-relevant (Urquhart et al. 1998) and many times these data are central to establishing standards to protect aquatic ecosystems (e.g., Bachmann et al. 2012b).

Materials and Procedures

The aquatic time series data examined included trophic state variables obtained from the Florida LAKEWATCH database. The Florida LAKEWATCH monitoring program began in 1986 with the goal to collect trophic state information for individual lakes across the State of Florida and to build a long-term data base (Canfield et al. 2002). The data collected by the LAKEWATCH citizen scientists for each trophic state variable are not significantly different from those collected by professionals (Hoyer et al. 2012). Therefore, the Florida LAKEWATCH program includes reputable data that have been collected from over 1,500 Florida lakes since 1986. A subset of the Florida LAKEWATCH database was used in this chapter. The subset included lakes with monthly samples (each month of the year was sampled) for total phosphorus, total nitrogen, chlorophyll, and water clarity (as measured by the use of a Secchi disk) collected for at least 20 years and up to 24 years. For nutrients and chlorophyll, monthly data were available for 27 Florida lakes and water clarity measurements were available for 19 Florida lakes. The number of lakes with water clarity measurements was smaller because some water clarity measurements exceeded the water depth or measurements could not be made due to the presence of aquatic macrophytes. The frequency and duration of the examined trophic state data exceeded most of the suggested data requirements to appropriately account for variance and detect trends in lake systems (Molot and Dillon 1991, Knowlton and Jones 2006, Howden et al. 2011).

Assessment

The examined population of Florida lakes ranged in trophic status from oligotrophic to hypereutrophic and encompassed the trophic states found across the State of Florida (Table 2-1; Canfield and Hoyer 1988). The analytical methods for total phosphorus, total nitrogen, and chlorophyll concentrations were consistent through time and followed the analytical procedures outlined in Canfield et al. (2002).

For each trophic state variable, a mean value for the three stations sampled on each sampling date at each lake was calculated to get a monthly mean value. An annual mean was calculated from the monthly means. Some months, however, were not sampled because stochastic events inhibited sample collection (e.g., hurricanes or droughts). Because time series model analysis requires continuous data (Box and Jenkins 1976), a missing monthly datum was replaced by the mean value calculated from the previous and following months. Data sets with less than 15% missing data can be repaired (i.e., the mean value replaced the missing datum) and time series analysis completed without introducing any substantial error (Kriendler and Lumsden 2006). All lakes examined had less than 15% missing data per each trophic state variable.

Data were analyzed with statistical packages JMP version 8.0 (SAS Institute 2007) and R, PC version 2.11.1 (R Development Core Team 2008). Coefficients of variation were calculated by dividing the standard deviation by the mean. When parametric statistics were used (i.e., linear regression and time series analyses), data were logarithmically (base 10) transformed to meet the requirements of normality

(Snedecor and Cochran 1979). All statements of statistical significance were at a probability of < 0.05.

Components of Variance

Variance component analysis was completed using JMP version 8.0 (SAS Institute 2007) on the logarithmic (base 10) transformed data to better understand the factors contributing to the observed variance at the population and individual lake levels. The amount of variance attributed to lake, year, month, station, and residual error (including laboratory error) was examined using the monthly data for the population of 27 Florida lakes. The amount of variance attributed to year, month, stations, and residual error was examined using the monthly data for the individual 27 Florida lakes.

The variance component analysis for the examined population of Florida lakes demonstrated that the majority of the variance for total phosphorus (82%), total nitrogen (86%), chlorophyll (82%), and water clarity (83%) was due to lake-to-lake differences. The majority of the remainder of the variance was either due to year-to-year differences (total phosphorus (TP) = 9%, total nitrogen (TN) = 7%, chlorophyll (CHL) = 6%, water clarity (SD) = 8%) or month-to-month differences (TP = 6%, TN = 5%, CHL = 10%, SD = 8%). Residual error, which includes station-to-station and laboratory variance, accounted for less than 5% of the total variance (TP = 3%, TN = 2%, CHL = 2%, SD = 1%) (Table 2-2).

Variance component analysis of individual sampling units (i.e., lakes) and the primary plant nutrients, phosphorus and nitrogen, demonstrated that year-to-year differences accounted for, on average, 45% (range 8% to 74%) of the variance in TP and 51% (range 17% to 72%) of the variance in TN. Month-to-month differences accounted for, on average, 39% of the variance in TP (range 21% to 61%) and 37%

(range 16% to 78%) of the variance in TN. For the biological variable chlorophyll and the physical variable water clarity, which is most closely correlated with chlorophyll, year-to-year differences accounted for, on average, 55% of the variance in CHL and 48% of the variance in SD. Month-to-month differences in CHL ranged from 22% to 85% and in SD ranged from 12% to 80% (Table 2-2).

Linear Regression

Simple least-squares linear regression analysis Equation 2-1 (Snedecor and Cochran 1980) was used to examine the relationship between the trophic state variable and time for each individual lake:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad (2\text{-}1)$$

With:

Y_i= dependent variable

X_i= independent variable

β_0 = intercept

β_1 = slope

ε_i = error term

The linear regression model was used to test whether the slope (β_1) was equal to zero. When the slope was not equal to zero (p-value < 0.05), a significant increasing trend (positive slope value) or decreasing trend (negative slope value) was determined for the time series data.

Because seasonal variation has been shown to mask long-term temporal trends in water quality variables (Hutchinson 1957) and also in Florida lakes (Brown et al. 1999), polynomial fits were used (Burns et al. 1999) to determine whether season significantly attributed to the variance in each trophic state variable when the monthly data were examined. The residuals (i.e., the difference between the actual value and the value as estimated by the polynomial fit) were used as the dependent variable and plotted over the period of record, thereby removing the variance due to seasonality. Linear regression analysis was completed using the residuals from the polynomial fit over the period of record. If there was no significant polynomial fit for the monthly data or the variance in the data were not attributed to season, then linear regression analysis was completed using monthly means as the dependent variable. Most computer software packages have the ability to conduct linear regression analysis and most ecologists are familiar with the statistical procedures and interpretation of the results.

Simple least-squares linear regression analysis of the transformed monthly data detected significant increasing monotonic trends in 63% (17 of the 27 Florida lakes) for total phosphorus, 55% (15 lakes) for total nitrogen, and 44% (12 lakes) for chlorophyll concentrations. Decreasing monotonic trends were shown for 48% (9 lakes) for water clarity measurements (Table 2-3). The coefficients of determination (R^2) from the linear regression models of the monthly data were 0.65 or less indicating the models were not predictively powerful (Prairie 1996). Although linear regression analysis detected significantly monotonic trends among the monthly times series data for many of the examined lakes (Table 2-4), the trend relationships were weak for TP (mean R^2 value = 0.22, range 0.01 to 0.62), TN (mean R^2 = 0.19, range 0.02 to 0.57), CHL (mean R^2 = 0.13, range 0.02 to 0.50), and SD (mean R^2 = 0.12, range 0.01 to 0.55). On a percentage basis, examination of monthly data among the population of lakes showed 89%, 92%, 89%, and 96% of the linear models, regressing TP, TN, CHL, and SD over the examined period of record, had R^2 values 0.65 or less suggesting a small percentage of the population, per each trophic state variable, experienced decadal-scale trends.

Simple-least squares linear regression analysis of the transformed annual data detected significant increasing monotonic trends for total phosphorus for 43% (12 lakes) of the Florida lakes, 40% (11 lakes) for total nitrogen, and 26% (7 lakes) for chlorophyll concentrations. Significant monotonic decreasing trends were observed for 37% (7 lakes) for water clarity measurements (Table 2-3). The significant monotonic trends detected by linear regression analysis using the annual mean data (Table 2-5), were weak, yet examination of annual data explained more of the variance in each trophic state variable compared to examination of monthly data (i.e., TP mean R^2 value = 0.34, range 0.03 to 0.86; TN mean R^2 = 0.31, range 0.04 to 0.81; CHL mean R^2 = 0.28, range 0.04 to 0.78; and SD mean R^2 = 0.20, range 0.01 to 0.65). A small percentage of the population of lakes, however, experienced decadal-scale trends as 89%, 92%, 89%, and 92% of the linear models regressing annual mean TP, TN, CHL, and SD data over the examined time record, had R^2 values 0.65 (Table 2-5). Interestingly, the lakes with 65% or more of the variance in the annual mean trophic state variable being explained by year, had visually identifiable linear trends as illustrated by total phosphorus concentrations in Lake Lorraine (Figure 2-1 A). The lakes with a R^2 of 0.65 or less, generally had visually identifiable trends or no visually evident trend as illustrated by Little Orange Lake (Figure 2-1 B).

Kendall-Tau

The Kendall-Tau correlation coefficient (τ) measured the association between a given trophic state variable and time (i.e., year). The nonparametric Kendall-Tau is a measure of rank correlation and uses the calculated coefficient (τ) to test for statistical dependence Equation 2-2 as outlined by Kendall (1938).

$$\tau = \frac{(\text{number of concordant pairs}) - (\text{number of discordant pairs})}{\frac{1}{2}n(n-1)} \qquad (2\text{-}2)$$

With:

τ = Kendall-Tau correlation coefficient (range $-1 \leq \tau \leq 1$)

concordant pairs = (x,y) pairs from examined X and Y variables where the ranks for both elements agree

discordant pairs = (x, y) pairs from examined X and Y variables where the ranks for the elements disagree

n = the number of observations

½ $n(n$-1) = the total number of pairs

The Kendall-Tau examined the number of pairs in different orders in the two rankings (Kendall 1938). The tau coefficient equaled 1 if the two rankings were in the same order and tau equaled -1 if the two rankings were inverted. Therefore, a positive tau value indicated a significant increase and a negative tau value indicated a significant decrease over the available record of data. The Kendall-Tau analysis offers a straightforward method yielding easy interpretation of results. Most computer programs provide the ability to complete this analysis.

The Kendall-Tau evaluation of annual mean data (Table 2-6) detected significant increasing monotonic trends for 37% (10 lakes) of the lakes for total phosphorus, 44% (12 lakes) for total nitrogen, and 22% (6 lakes) for chlorophyll concentrations. Significant decreasing monotonic trends were detected in 31% (6 lakes) of the lakes for water clarity measurements. The percentages of the population of 27 Florida lakes with significant trends detected by Kendall-Tau analysis were similar to the results of linear regression (Table 2-3).

Time Series Modeling

Time series models have historically been used in economics, stock market analysis, in the social sciences, and more recently in the aquatic sciences. Time series model analysis can be divided into two categories; harmonic analysis and regression analysis. Regression time series model analysis, specifically the class of stochastic process models provided by the autoregression integrated moving average model (Box and Jenkins 1976) was used to detect long-term trends in the trophic state variables. The time series models are useful to detect trends because a guiding principal of the Box and Jenkins (1976) approach is parsimony and consequently environmental variables can be modeled as a probabilistic function of past inputs (i.e., random variability) and outputs (i.e., time series observation) (see McCleary and Hay 1980). The major components of the time series models used in analysis account for variance due to trend, season, and residual error, Equation 2-3 (Worrall and Burt 1998).

$$Y_{time} = \text{trend} + \text{seasonal variation} + \text{residual} \qquad (2\text{-}3)$$

These components of variance are analyzed by the use of the ARMA/ARIMA time series model to understand the correlation between successive observations to help describe the evolution of the process through time (see Chatfield 2004).

Times series models were completed using the time series package in JMP, version 8.0. There were two important parameters, autocorrelation function (ACF) and the partial autocorrelation function (Partial ACF), used in time series model analysis. The ACF described the correlation between all pairs of observations in the time series with respect to time. The Partial ACF described the extent of the correlations between all successive pairs of observations. Both correlations, the ACF and the Partial ACF, are lagged correlations meaning the correlations between time series observations were shifted in time relative to one another. Lagged correlation was used in this paper because the examined trophic state variables may have delayed responses over time. The concentration of nutrients, for example, may depend on amounts of precipitation that have occurred over preceding years. All examined data were lagged by 1 unit (lag 1) across each unit of time (i.e., month or year), Equation 2-4.

$$r_1 = \frac{\sum_{i=0}^{n-1}(y_i - \bar{y})\,(y_{i+1} - \bar{y})}{\sum_{i=0}^{n}(y_i - \bar{y})^2/n} \qquad (2\text{-}4)$$

With:

r_1 = autocorrelation at lag 1

(y_1, y_2), (y_2, y_3), (y_3, y_4)…(y_{n-1}, y_n) = pairs of time series data with *n* observations

When examining annual data, for example, the ACF at a lag of 1 would describe the annual phosphorus concentration related to the previous annual phosphorus concentration. The phosphorus concentration at a lag of 10 (i.e., 11th year of record) related to the relationships established at other lag times would encompass the correlations between all the successive years and up to the 11th year.

Time series models require stationary data before model building can begin (Box and Jenkins 1970). The examined trophic state data for the individual lake were determined to be of a stationary, random process. Random processes are defined as random variables, where each point is unique at a given point in time, meaning the random process reflects properties of random variables (e.g., mean and variance). If the statistical properties of the random process do not significantly vary with time, then the process is stationary. If the process is non-stationary the random variables significantly vary with time; the majority of environmental and aquatic data are non-stationary. For the examined trophic state variable data, the Augmented-Dickey Fuller test (ADF) was used to determine whether the data were stationary. If the data (y_{time}) were non-stationary, a technique called differencing was used to remove the variance (i.e., variance due to season and/or patterns of change) making the data stationary. The removal of variance (i.e., differencing) was completed by calculating the difference between the adjacent values of all the observations in the examined data set ($\Delta y_{time\,=}$ $y_{time} - y_{time-1}$,). The integrated (I) term in the time series model denoted the data were differenced (e.g., ARIMA) versus an ARMA model denoted the data were stationary and differencing was not necessary.

The time series models were built and selected using the general principal of Box and Jenkings (1976); model parameter estimation, model identification, and diagnostic checks of the residuals of the fitted models. The autoregressive (AR) and the moving average (MA) terms were estimated from the autocorrelation function (ACF) and the partial autocorrelation function (Partial ACF). The AR and MA terms were identified from the ACF and Partial ACF plots based on visual assessment over the lagged periods of time and also by determination of the last lag term outside the associated 95% confidence interval. The last lag term outside of the 95% denoted the lag value at which the data were statistically significant and the point at which the data were no longer dependent on past values. Using significant ACF and Partial ACF lag terms, juxtaposed with the visual pattern in the lag values (e.g., sine wave, exponential decrease, or strong initial peak(s)), the time series model parameters were estimated (Figure 2-2). The Akaike's Information Criterion (AIC) was used as the model-selection criteria to determine the best-fit model for the data series. To ensure the data were best represented by the selected model, anywhere from 50 to 80 model variants were completed. The models were compared using the AIC value. The model with the AIC value closest to zero was selected as the best-fit model (Akaike 1974). The selected model was verified as a good fit by further examination of the residuals and testing for white noise using the Bartlett's Kolmogorov-Smirnov test. The selected time series model; therefore, had no pattern in the residuals or statistically significant white noise over the examined period of record.

The selected time series model tested the null hypothesis that the variance of the given trophic state variable over the examined period of record was equal to zero. If significant variance was detected over time (i.e., the p-value of the time series model was < 0.05), then the data showed significant change over time. Estimates of trend were determined by the value of the constant estimate term generated from the time series model (similar to the slope estimate for linear regression analysis). A positive constant estimate indicated an increasing trend and a negative constant estimate indicated a decreasing trend. Unlike linear regression models, time series models can detect a significant change in variance, but the constant estimate may equal zero indicating no directional, monotonic trend.

Seasonal time series models were used when monthly data were examined. Autoregressive terms were added at lag 1 and successively at lags of 12 to reflect periodic movement of season in the time series models. The lag 1 term accounted for the deviation of the current month from the previous month, while the lag 12 term accounted for the deviation of the current month from that of the same month in the previous year. The ARMA, ARIMA, and seasonal ARMA/ARIMA time series models are statistically complex and require much time and patience. There are computer packages that offer all the necessary tools to complete time series model analysis. In addition, if it is necessary to use multiple computer packages, the user will need to understand each program requiring additional time.

Time series modeling of the transformed monthly data for the population of 27 Florida lakes (Table 2-7) detected significant increasing trends in 4% (1 lake) of the lakes for total phosphorus, 15% (4 lakes) for total nitrogen, and 11% (2 lakes) for chlorophyll concentrations. Significant decreasing trends were shown for 11% (2 lakes) for water clarity measurements (Table 2-7).

Time series modeling of transformed annual means for the population of 27 Florida lakes (Table 2-8) detected increasing trends in 15% (4 lakes) of the lakes for total phosphorus, 7% (2 lakes) for total nitrogen, 15% (4 lakes) for chlorophyll concentrations, and decreasing trends in 16% (3 lakes) for water clarity measurements. The proportion of lakes showing significant trends by time series analysis was greater than expected by chance (i.e., probability of 0.05) for each trophic state variable, but the overall percentage of population of lakes with significant trends was much less than the number of trends detected by linear regression, if an $R^2 \geq 0.65$ was not used to indicate predictive power. (Table 2-8)

Time series analysis did not detect significant trends for some Florida lakes, but estimated significant change in the variance over the examined time period of record (Figure 2-3). These lakes were categorized with the lakes that had no significant trends, when summarizing for the examined population of Florida lakes (Table 2-3).

Specifically, for the monthly data, trophic state variable change was detected in 3 lakes (Table 2-7). For the annual data, there were 5, 8, 9, and 7 lakes that showed significant change for total phosphorus, total nitrogen, chlorophyll, and water clarity measurements (Table 2-8). Linear regression analysis detected no significant trend for all of the lakes where ARMA/ARIMA time series models detected significant change in the variance.

Alternative Approach

Prairie (1996) reiterated a limitation of the predictive power of linear regression analysis was the influence of the number of samples on determination of a significant relationship. Prairie (1996) suggested using intervals, determined by the intersection of the linear regression model line and the associated 95% confidence intervals (Figure 2-4), to decrease the number of samples, thereby increasing the predictive power of the linear regression analysis. The empirical derivation of the number of classes was related to the R^2 value, Equation 2-5, where an R^2 value of 0.65 and greater providing a predictively powerful linear regression model (Figure 2-4).

$$\mathrm{NC} = \frac{1.32}{\sqrt{1-R^2}} \qquad (2\text{-}5)$$

With:

NC = the number of classes

1.32 = the *t* value for a bivariate regression at a *p*-value of 0.05

R^2 = the coefficient of determination for a bivariate regression

Intervals of six classes (NC= 6 mean values) were used for the trophic state data as Bryhn and Dimberg (2011) demonstrated that aquatic environmental data have the highest R^2 values when divided into 6 classes. Linear regression analysis was then completed across the 6 calculated mean values providing an estimation of trend that was predictively powerful (Prairie 1996) and “statistically meaningful” (Bryhn and Dimberg 2011).

The proposed alternative approach, modified linear regression analysis, that included the suggestions of Prairie (1996) and Byrhn and Dimberg (2011), detected significant increasing monotonic trends in 26% (7 lakes) of the Florida lakes for total phosphorus, 26% (7 lakes) for total nitrogen, and 19% (5 lakes) for chlorophyll. Decreasing monotonic trends were shown in 37% (7 lakes) for water clarity measurements (Table 2-3). The results of this proposed modified linear regression analysis were more similar to the results of trend detection by either time series model analysis than those obtained by linear regression or Kendall-Tau analyses for the examined population of 27 Florida lakes (Table 2-3).

Discussion

It is disconcerting that the use of difference statistical methods provided different results when used to evaluate the same aquatic time series data. For instance, Florida’s human population has grown from about 9.7 million people in 1980 to over 19 million in 2010, which raises concerns about impact of anthropogenic sources of pollution on lake water quality. The results from linear regression or Kendall-Tau analyses would support the statement that population growth has adversely affected water quality as measured by the trophic state variables in the examined Florida lakes over the past 20 plus years (Table 2-3). Similar results, however, were not obtained by the use of time series modeling (Table 2-3). Rather, time series modeling showed trends of degradation in the trophic state variables for only a small proportion of the examined Florida lakes. The important point is that depending on the method of statistical analysis used, different conclusions could be reached and these conclusions may have divergent implications for science, management, and society.

Given that different conclusions could be reached depending on the statistical analyses used, ecologists need to explicitly define the experimental unit and scale of analysis to explain the results in terms of the variance when addressing aquatic systems (Duarte and Kalff 1990). For example, variance component analysis of the examined population of Florida lakes indicated that lake-to-lake differences accounted for the majority of the variance in the trophic state variables. When the variance within the individual lakes was examined, yearly (i.e., total phosphorus and total nitrogen) or monthly (i.e., chlorophyll and water clarity) differences accounted for the majority of the variance. Analogous results have been shown for a different population of Florida lakes (Brown et al. 2000). Thus, if a research objective is to address patterns of change or trend across a geographic region, like the State of Florida, inclusion of more sampling in the study would best account for temporal and spatial variance in the examined trophic state variables. Häkanson and Duarte (2008) recognized station and laboratory error as major contributors to variance in the study of single ecological units. For studies completed within a lake, station and laboratory error explain more variance in the trophic state variables and should is considered in single ecological unit studies.

The statistical assumptions of a given statistical analysis are additionally important to consider when examining aquatic data and help to understand the different results obtained by the use of different statistical analyses. A major statistical assumption of liner regression analysis, and also for the rankings of the Kendall-Tau analysis, is a linear relationship between the dependent and independent variable. In this chapter, linear regression and Kendall-Tau analyses provided a reliable assessment of trend in data that exhibited a visually identifiable linear relationship, as was the case with total phosphorus concentrations in Lake Lorraine (Figure 2-1A). However, when non-linear trends were present linear regression and Kendall Tau analyses did not provide an appropriate assessment, as was the case with total phosphorus concentrations Little Orange Lake (Figure 2-1B). Another consideration is that linear regression and Kendall-Tau analyses only account for variance in the dependent variable, while time series analysis account for variance in both the dependent and independent variable. If non-linear patterns were present, then variance in both the dependent and independent variable should be included so the number of trends is not overestimated. Due to the treatment of the dependent and independent variable and the number of lakes with non-linear relationships in the examined dataset, linear regression and Kendall-Tau analysis may have overestimated the number of trends. Furthermore, the number of samples influences statistical significant determination of a linear trend (Prairie 1996). The examined environmental data included a large number of samples ($n \geq 240$ for the monthly data and $n \geq 20$ for the annual mean data) of which linear regression and Kendall-Tau analyses detected many statistically significant trends. But, although statistically significant, the relationship of many trends was weak with data scattered from the trend line and low coefficients of determination (e.g., $R^2 = 0.10$).

The detection of trends by time series analysis may have been influenced by the violation of the parametric statistic assumption of lack of serial correlation or independence of the error terms. Such a violation is common with environmental data and can cause the standard errors to be underestimated and ultimately leads to false conclusions because the t or F test may be incorrect (Abaurrear et al. 2011). Time series model analysis includes methods to remove serial correlation (e.g., the differencing technique), but the removal of serial correlation changes the response variable (Nickerson and Madsen 2005). For example, lagged values, which are a consequence of the removal of serial correlation, make the response variable a function of the past. As response variables are generally dependent on past values, no change or trend would be detected when indeed a change or trend may have been present. In such cases, time series analysis may have underestimated the number of trends.

Understanding the differences in linear regression, Kendall-Tau, and time series model analyses is not simplistic and there are most likely additional considerations. Statistical methods are tools to help guide ecologists. The alternative, modified linear regression analysis approach, which combined statistical methods outlined by Prairie (1996) and Bryhn and Dimberg (2011), resulted in a percentage of the population of lakes with increasing and decreasing trends similar to that obtained by the use of statistically robust, yet complex ARMA/ARIMA time series modeling. The alternative approach offers a statistical took that provides predictively powerful results yet can be simply understood leading to increased application by more ecologists, including non-statisticians (Murtaugh 2007).

Comments and Recommendations

Although it is important to integrate predictively powerful statistical approaches to detect trends in aquatic time series data, it is also important to detach from the statistics every now and again. Whether statistically complex or simplistic, a statistical method may not detect a change or trend in ecological time series data. There may be certain events (i.e., stochastic, climatic, or anthropogenic) that are recognized to drastically impact an aquatic system. For example, time series analysis did not detect a significant trend in total phosphorus concentrations in Little Lake Santa Fe, but visual examination of these data showed an order of magnitude change in total phosphorus concentrations (Figure 2-3). In Little Lake Santa Fe, an order of magnitude increase in total phosphorus concentrations was due to a large forest fire, a stochastic event that an ecologist or limnologist would recognize to have substantial impacts on an aquatic system (Ruiz-Bernard 2012). Therefore, despite the numerous statistical tools available to detect trends in environmental data, it is recommended to plot and examine the data, then explore the use of statistics.

Table 2-1. Summary statistics (i.e., mean, median, minimum, maximum, and coefficient of variation) for untransformed total phosphorus (µg/L), total nitrogen (µg/L), chlorophyll concentrations (µg/L) and water clarity measurements (m) among annual mean data for the examined population of Florida lakes.

Trophic State Variable	N Lakes	Mean	Median	Minimum	Maximum	Coefficient of Variation
Total Phosphorus	27	33	18	3.7	125	42%
Total Nitrogen	27	1139	701	107.0	3729	28%
Chlorophyll	27	31	9	1.6	169	71%
Water Clarity	19	1.5	1.4	0.3	3.1	32%

Table 2-2. Results of variance component analysis and the percent of variance attributed to lake-to-lake differences, year-to-year differences, month-to-month differences, and residual error (includes station-to-station and laboratory differences) using monthly data for the population of 27 Florida lakes. Within the individual 27 Florida lakes, the mean percent of variance attributed to year-to-year differences, month-to-month differences, station-to-station differences, and residual error (laboratory differences) using monthly data are presented.

Trophic State Variable	% variance lake-to-lake	% variance year-to-year	% variance month-to-month	% variance station-to-station	% variance residual error
Population 27 lakes					
Total Phosphorus	82	9	6	.	3
Total Nitrogen	86	7	5	.	2
Chlorophyll	82	6	10	.	2
Water Clarity	83	8	8	.	1
Individual 27 lakes					
Total Phosphorus	.	45	39	6	10
Total Nitrogen	.	51	37	6	6
Chlorophyll	.	55	33	4	8
Water Clarity	.	48	46	2	4

Table 2-3. Percentage of the population of lakes with monotonic increasing trends, monotonic decreasing trends, and no trends over 20-plus years detected by the use of linear regression models, Kendall-Tau analysis, ARMA/ARIMA time series models, and the alternative approach following Prairie (1996) and Byrhn and Dimberg (2011). Monthly data and annual data were evaluated for total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements for the examined population of Florida lakes.

Trophic State Variable	N	Increasing Trend (%)	Decreasing Trend (%)	No Trend (%)
Monthly Data				
Linear Regression Model				
Total Phosphorus	27	63	22	15
Total Nitrogen	27	55	30	15
Total Chlorophyll	27	44	38	18
Water Clarity	19	13	48	39
Time Series Model				
Total Phosphorus	27	4	7	89
Total Nitrogen	27	15	4	81
Total Chlorophyll	27	11	0	89
Water Clarity	19	0	11	89
Annual Data				
Linear Regression Model				
Total Phosphorus	27	44	19	37
Total Nitrogen	27	40	4	56
Total Chlorophyll	27	26	26	48
Water Clarity	19	5	37	58
Kendall-Tau				
Total Phosphorus	27	37	19	44
Total Nitrogen	27	44	7	49
Total Chlorophyll	27	22	22	56
Water Clarity	19	5	37	58
Time Series Model				
Total Phosphorus	27	15	11	74
Total Nitrogen	27	7	4	89
Total Chlorophyll	27	15	4	81
Water Clarity	19	0	16	84
Practical Approach				
Total Phosphorus	27	26	7	67
Total Nitrogen	27	26	4	70
Total Chlorophyll	27	19	11	70
Water Clarity	19	0	32	68

*The percentage of the population of lakes reported with no trend for time series analysis included lakes with detection of significant change, but no significant monotonic trend.

Table 2-4. Linear regression analysis detection of a significant monotonic trend ($^{\times}$), slope value, and coefficient of determination (R^2) of the monthly time series logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD) data for the 27 Florida lakes. Linear regression analysis completed using the residuals of the best polynomial fit, to remove variance due to season, is denoted after the slope value ($^{\circ}$).

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Alachua	Alto	$0.001^{\times\circ}$	0.22	$0.001^{\times\circ}$	0.52	$0.001^{\times\circ}$	0.10	$-0.001^{\times\circ}$	0.35
Alachua	Little Orange	$0.002^{\times\circ}$	0.25	$0.0002^{\times\circ}$	0.02	$-0.002^{\times\circ}$	0.16	$-0.0001^{\times}$	0.12
Alachua	Little Santa Fe	$0.002^{\times\circ}$	0.43	$0.001^{\times}$	0.35	$0.001^{\times\circ}$	0.06	$-0.001^{\times}$	0.26
Alachua	Santa Fe	$0.001^{\times\circ}$	0.43	$0.001^{\times}$	0.36	$0.002^{\times\circ}$	0.27	$-0.001^{\times\circ}$	0.34
Alachua	Wauberg	$0.001^{\times\circ}$	0.23	$0.001^{\times}$	0.40	$0.001^{\times\circ}$	0.20	$-0.0004^{\times\circ}$	0.38
Hillsborough	Brant	0	0	$-0.0004^{\times}$	0.04	0.002°	0	-0.0001	0.01
Hillsborough	Magdalene	$0.0004^{\times}$	0.07	$0.0002^{\times}$	0.04	0	0	0	0.00
Lake	Beauclaire	$-0.002^{\times\circ}$	0.57	$-0.0003^{\times}$	0.05	$-0.0005^{\times}$	0.03	0	0.00
Lake	Crooked	$-0.001^{\times}$	0.19	$-0.001^{\times}$	0.10	$-0.001^{\times}$	0.08	$0.001^{\times}$	0.22
Lake	Dora East	$-0.001^{\times\circ}$	0.45	$-0.0003^{\times}$	0.08	$-0.001^{\times}$	0.09	.	.
Lake	Dora West	$-0.001^{\times\circ}$	0.30	$-0.0003^{\times}$	0.09	$-0.001^{\times}$	0.08	.	.
Lake	Grasshopper	$0.002^{\times}$	0.24	$0.001^{\times}$	0.05	$0.001^{\times}$	0.06	.	.
Lake	Harris	$0.0003^{\times}$	0.06	$-0.0003^{\times}$	0.07	$-0.001^{\times}$	0.12	$0.001^{\times}$	0.09
Lake	Lorraine	$-0.002^{\times\circ}$	0.62	$-0.001^{\times}$	0.57	$-0.004^{\times}$	0.50	.	.
Lake	Sellers	$0.002^{\times}$	0.33	$0.004^{\times}$	0.30	$0.002^{\times}$	0.36	.	.
Marion	Charles	$0.001^{\times}$	0.13	$0.001^{\times}$	0.22	$-0.001^{\times}$	0.02	-0.001	0.00
Marion	Deerback	0	0.01	0	0	$-0.001^{\times\circ}$	0.05	$-0.0003^{\times}$	0.04
Marion	Eaton	$0.001^{\times}$	0.03	$0.0003^{\times}$	0.02	0	0	0	0.00
Marion	Halfmoon	0	0	$0.001^{\times}$	0.37	$-0.001^{\times}$	0.11	$0.0003^{\times}$	0.03
Orange	Georgia	$0.001^{\times}$	0.17	$0.0004^{\times}$	0.12	$0.001^{\times\circ}$	0.10	$-0.001^{\times}$	0.27
Orange	Giles	0.0001°	0.01	0	0	$0.0005^{\times}$	0.02	-0.0005°	0.00
Orange	Ola	$0.0003^{\times}$	0.06	$0.0004^{\times}$	0.23	$0.001^{\times}$	0.13	.	.
Orange	Sarah	$-0.0004^{\times}$	0.06	$-0.0003^{\times\circ}$	0.08	$-0.003^{\times}$	0.38	.	.
Putnam	Como	$0.001^{\times}$	0.26	$0.002^{\times}$	0.35	$0.001^{\times\circ}$	0.07	.	.
Putnam	Higgenbotham	$0.0002^{\times}$	0.02	0	0	$-0.001^{\times\circ}$	0.23	0	0.01

Table 2-4. Continued

County	Lake	$L_{10}TP$ Slope	$L_{10}TP$ R^2	$L_{10}TN$ Slope	$L_{10}TN$ R^2	$L_{10}CHL$ Slope	$L_{10}CHL$ R^2	$L_{10}SD$ Slope	$L_{10}SD$ R^2
Putnam	Star	$0.001^{x\circ}$	0.22	0.001^{x}	0.3	0	0	$-0.0005^{x\circ}$	0.11
Putnam	Winnott	0.002^{x}	0.5	0.001^{x}	0.48	0.002^{x}	0.22	-0.002^{x}	0.55

Table 2-5. Linear regression analysis detection of a significant monotonic trend (^{x}), slope value, and coefficient of determination (R^2) of the annual mean time series logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD) data for the 27 Florida lakes.

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Alachua	Alto	0.009^{x}	0.47	0.104^{x}	0.75	0.009^{x}	0.22	-0.015^{x}	0.56
Alachua	Little Orange	0.024^{x}	0.32	-0.002	0.04	-0.021^{x}	0.34	-0.007^{x}	0.26
Alachua	Little Santa Fe	0.024^{x}	0.62	0.012^{x}	0.52	0.010	0.18	-0.121^{x}	0.43
Alachua	Santa Fe	0.014^{x}	0.64	0.010^{x}	0.52	0.019^{x}	0.45	-0.012^{x}	0.55
Alachua	Wauberg	0.011^{x}	0.35	0.011^{x}	0.54	0.014^{x}	0.45	-0.005	0.19
Hillsborough	Brant	0.000	0	-0.005	0.06	0.002	0	-0.002	0.01
Hillsborough	Magdalene	0.005	0.13	0.002	0.10	-0.000	0	-0.001	0.01
Lake	Beauclaire	-0.021^{x}	0.81	-0.004	0.10	-0.006	0.10	0.000	0.00
Lake	Crooked	-0.013^{x}	0.37	-0.007	0.14	-0.014^{x}	0.26	0.012^{x}	0.46
Lake	Dora East	-0.017^{x}	0.58	-0.004	0.13	-0.009	0.16	.	.
Lake	Dora West	-0.012^{x}	0.39	-0.004	0.15	-0.008	0.16	.	.
Lake	Grasshopper	0.025^{x}	0.39	0.013	0.09	0.011	0.12	.	.
Lake	Harris	0.004	0.17	-0.004	0.14	-0.014^{x}	0.41	0.009^{x}	0.22
Lake	Lorraine	-0.028^{x}	0.86	-0.014^{x}	0.81	-0.045^{x}	0.78	.	.
Lake	Sellers	0.024^{x}	0.56	0.045^{x}	0.55	0.029^{x}	0.65	.	.
Marion	Charles	0.014^{x}	0.22	0.009^{x}	0.39	-0.100	0.04	-0.002	0.01
Marion	Deerback	-0.002	0.03	-0.001	0	-0.007	0.14	-0.004	0.10
Marion	Eaton	0.007	0.10	0.003	0.04	-0.001	0	-0.000	0.00
Marion	Halfmoon	-0.001	0	0.010^{x}	0.50	-0.009^{x}	0.43	0.003	0.08
Orange	Georgia	0.009^{x}	0.34	0.005	0.23	0.012^{x}	0.28	-0.009^{x}	0.44
Orange	Giles	0.002	0.05	0.001	0	0.007	0.11	-0.006	0.15
Orange	Ola	0.003	0.14	0.005^{x}	0.52	0.012^{x}	0.40	.	.
Orange	Sarah	-0.005	0.16	-0.004	0.18	-0.033^{x}	0.65	.	.
Putnam	Como	0.016^{x}	0.42	0.018^{x}	0.57	0.010	0.15	.	.
Putnam	Higgenbotham	0.003	0.10	0.000	0	-0.017^{x}	0.56	-0.003	0.03

Table 2-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Putnam	Star	0.012^{x}	0.31	0.009^{x}	0.55	0.002	0	-0.007^{x}	0.24
Putnam	Winnott	0.018^{x}	0.71	0.011^{x}	0.63	0.018^{x}	0.44	-0.021^{x}	0.65

Table 2-6. Kendall Tau analysis detection of significant monotonic trends (^{x}) with the tau value for annual mean total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity (SD) data for the 27 Florida lakes.

County	Lake	TP Tau	TN Tau	CHL Tau	SD Tau
Alachua	Alto	0.53^{x}	0.68^{x}	0.28	-0.49^{x}
Alachua	Little Orange	0.28	0.04	-0.3	-0.33^{x}
Alachua	Little Santa Fe	0.56^{x}	0.49^{x}	0.38^{x}	-0.52^{x}
Alachua	Santa Fe	0.53^{x}	0.54^{x}	0.39^{x}	-0.60^{x}
Alachua	Wauberg	0.36^{x}	0.47^{x}	0.37^{x}	-0.23
Hillsborough	Brant	0.01	-0.21	-0.14	0.08
Hillsborough	Magdalene	0.23	0.28	-0.04	-0.08
Lake	Beauclaire	-0.66^{x}	-0.18	-0.18	-0.03
Lake	Crooked	-0.39^{x}	-0.44^{x}	-0.4^{x}	0.46^{x}
Lake	Dora East	-0.53^{x}	-0.20	-0.26	.
Lake	Dora West	-0.44^{x}	0.18	-0.22	.
Lake	Grasshopper	0.45^{x}	0.14	0.19	.
Lake	Harris	0.21	-0.24	-0.5^{x}	0.23
Lake	Lorraine	-0.74^{x}	-0.73^{x}	-0.58^{x}	.
Lake	Sellers	0.66^{x}	0.54^{x}	0.62^{x}	.
Marion	Charles	0.29	0.42^{x}	-0.19	-0.03
Marion	Deerback	-0.06	0.03	-0.18	-0.15
Marion	Eaton	0.21	0.14	-0.03	-0.01
Marion	Halfmoon	-0.04	0.53^{x}	-0.39^{x}	0.11
Orange	Georgia	0.38^{x}	0.33^{x}	0.12	-0.43^{x}
Orange	Giles	0.10	0.06	0.18	-0.29
Orange	Ola	0.29	0.45	0.44^{x}	.
Orange	Sarah	-0.23	-0.28	-0.49^{x}	.
Putnam	Como	0.49^{x}	0.5^{x}	0.1	.
Putnam	Higgenbotham	0.09	-0.01	-0.55^{x}	-0.12
Putnam	Star	0.39^{x}	0.54^{x}	-0.04	-0.44^{x}
Putnam	Winnott	0.59^{x}	0.68^{x}	0.54^{x}	-0.67^{x}

Table 2-7. Time series model (¯) denotes significant change and * denotes significant change and monotonic trend), the Akaike's Information Criterion (AIC) value, the time lag corresponding to the significant autocorrelation (AC), and the coefficient of determination (R^2) using monthly logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD) data for the 27 Florida lakes.

County	Lake	L_{10}TP Model	L_{10}TP AIC	L_{10}TP AC	L_{10}TP R^2
Alachua	Alto	ARIMA(1,1,1)	-432	48	0.49
Alachua	Little Orange	Seasonal ARIMA(2,1,2)(0,1,0)12	-268	12	0.21
Alachua	Little Santa Fe	Seasonal ARIMA(0,2,0)(1,1,1)12	-5	15	0.36
Alachua	Santa Fe	Seasonal ARIMA(0,1,0)(0,1,0)12	-285	15	0.25
Alachua	Wauberg	Seasonal ARIMA(0,0,0)(0,1,1)12 ×	-308	12	0.38
Hillsborough	Brant	Seasonal ARIMA(1,1,1)(0,1,0)12	-384	9	0.68
Hillsborough	Magdalene	Seasonal ARIMA(0,0,0)(1,1,0)12	-334	13	0.21
Lake	Beauclaire	Seasonal ARIMA(0,0,0)(0,1,0)12 ×	-252	24	0.12
Lake	Crooked	Seasonal ARIMA(0,1,0)(0,1,0)12	-180	15	0.38
Lake	Dora East	Seasonal ARIMA(0,0,0)(1,1,0)12 ×	-340	25	0.26
Lake	Dora West	Seasonal ARIMA(0,2,0)(0,1,0)12	-245	36	0.03
Lake	Grasshopper	Seasonal ARIMA(0,1,0)(1,1,0)12	8	10	0.50
Lake	Harris	ARIMA(2,2,2)	-503	13	0.30
Lake	Lorraine	Seasonal ARIMA(0,1,0)(0,1,0)12	-155	18	0.26
Lake	Sellers	Seasonal ARIMA(1,1,1,)(0,1,0)12	-42	22	0.54
Marion	Charles	Seasonal ARIMA(0,1,0)(0,1,0)12	-161	12	0.00
Marion	Deerback	ARI(1,1)	-397	4	0.00
Marion	Eaton	Seasonal ARIMA(1,1,0)(0,1,0)12	-107	11	0.27
Marion	Halfmoon	Seasonal ARIMA(1,0,1)(0,1,0)12	-406	13	0.23
Orange	Georgia	Seasonal ARIMA(1,0,1)(0,1,0)12	-356	12	0.12
Orange	Giles	Seasonal ARIMA(0,0,0)(1,1,1)12	-327	30	0.16
Orange	Ola	Seasonal ARIMA(0,0,0)(1,1,1)12 ¯	-545	7	0.02
Orange	Sarah	Seasonal ARIMA(2,1,0)(1,1,1)12	-392	20	0.12
Putnam	Como	Seasonal ARIMA(0,1,0)(0,1,0)12	-163	17	0.26

Table 2-7. Continued

County	Lake	L_{10}TP Model	L_{10}TP AIC	L_{10}TP AC	L_{10}TP R^2
Putnam	Higgenbotham	IMA(1,1)	-346	24	0.33
Putnam	Star	Seasonal ARIMA(1,1,1)(0,1,0)12	-384	14	0.22
Putnam	Winnott	Seasonal ARIMA(0,0,0)(0,1,0)12	-273	18	0.40
County	Lake	L_{10}TN Model	L_{10}TN AIC	L_{10}TN AC	L_{10}TN R^2
Alachua	Alto	Seasonal ARIMA(1,1,1)(0,1,0)12	-634	25	0.49
Alachua	Little Orange	Seasonal ARIMA(1,1,1)(0,1,0)12	-552	4	0.21
Alachua	Little Santa Fe	Seasonal ARIMA(0,1,0)(0,1,0)12	-413	17	0.36
Alachua	Santa Fe	Seasonal ARIMA(0,0,0)(1,1,0)12 $^{\times}$	-495	16	0.25
Alachua	Wauberg	Seasonal ARIMA(0,0,0)(1,1,0)12 $^{\times}$	-477	15	0.38
Hillsborough	Brant	Seasonal ARIMA(1,1,0)(0,1,0)12	-531	10	0.68
Hillsborough	Magdalene	Seasonal ARIMA(1,1,1)(1,1,0)12	-654	6	0.21
Lake	Beauclaire	Seasonal ARIMA(0,2,0)(1,1,1)12	-455	10	0.12
Lake	Crooked	Seasonal ARIMA(0,1,0)(0,1,0)12	-457	13	0.38
Lake	Dora East	I(2)	-619	10	0.26
Lake	Dora West	Seasonal ARIMA(0,0,0)(1,1,1)12 $^{\times}$	-545	9	0.03
Lake	Grasshopper	Seasonal ARIMA(0,2,0)(1,1,0)12	-11	10	0.50
Lake	Harris	Seasonal ARIMA(1,1,1)(0,1,0)12	-597	12	0.30
Lake	Lorraine	Seasonal ARIMA(0,0,0)(0,1,0)12	-464	18	0.26
Lake	Sellers	IMA(1,1)	22	15	0.54
Marion	Charles	Seasonal ARIMA(0,0,0)(1,1,1)12	-359	10	0.00
Marion	Deerback	Seasonal ARIMA(1,1,0)(1,1,0)12 $^{\times}$	-632	5	0.00
Marion	Eaton	Seasonal ARIMA(0,1,0)(0,1,0)12	-314	6	0.27
Marion	Halfmoon	Seasonal ARIMA(0,0,0)(1,1,1)12 $^{\times}$	-520	12	0.23
Orange	Georgia	Seasonal ARIMA(1,1,1)(0,1,0)12	-515	11	0.12
Orange	Giles	Seasonal ARIMA(1,1,1)(1,1,1)12	-236	27	0.16
Orange	Ola	Seasonal ARIMA(0,1,0)(0,1,0)12	-590	23	0.02
Orange	Sarah	Seasonal ARIMA(1,1,0)(1,1,1)12	-529	21	0.12
Putnam	Como	Seasonal ARIMA(0,0,0)(0,1,0)12	-199	23	0.26
Putnam	Higgenbotham	Seasonal ARIMA(1,1,0)(0,1,0)12	-478	4	0.33
Putnam	Star	Seasonal ARIMA(0,1,1)(0,1,0)12	-459	15	0.22

Table 2-7. Continued

County	Lake	L_{10}TN Model	L_{10}TN AIC	L_{10}TN AC	L_{10}TN R^2
Putnam	Winnott	Seasonal ARIMA(1,1,1)(0,1,0)12	-551	19	0.40
County	Lake	L_{10}CHL Model	L_{10}CHL AIC	L_{10}CHL AC	L_{10}CHL R^2
Alachua	Alto	Seasonal ARIMA(0,0,0)(1,1,0)12	-91	48	0.07
Alachua	Little Orange	ARIMA(1,1,2) $^{-}$	6	14	0.43
Alachua	Little Santa Fe	Seasonal ARIMA(1,1,1)(1,1,1)12	16	14	0.26
Alachua	Santa Fe	Seasonal ARIMA(0,1,0)(0,1,0)12	-78	12	0.26
Alachua	Wauberg	Seasonal ARIMA(0,0,0)(0,1,1)12 $^{\times}$	-165	24	0.25
Hillsborough	Brant	I(1)	-10	12	0.53
Hillsborough	Magdalene	Seasonal ARIMA(0,1,0)(0,1,0)12	-146	12	0.10
Lake	Beauclaire	Seasonal ARIMA(0,1,1)(0,1,0)12	-181	12	0.28
Lake	Crooked	ARI(1,1)	-11	13	0.24
Lake	Dora East	Seasonal ARIMA(0,2,0)(1,1,1)12	-210	12	0.23
Lake	Dora West	Seasonal ARIMA(0,1,0)(0,1,0)12	-273	12	0.25
Lake	Grasshopper	Seasonal ARIMA(0,1,0)(0,1,0)12	24	12	0.09
Lake	Harris	ARI(1,1)	-72	36	0.11
Lake	Lorraine	IMA(1,1)	-10	16	0.58
Lake	Sellers	Seasonal ARIMA(1,1,0)(0,1,0)12	-50	24	0.13
Marion	Charles	ARIMA(1,1,1)	187	11	0.42
Marion	Deerback	ARI(2,1)	-112	12	0.15
Marion	Eaton	ARIMA(2,1,1)	151	42	0.27
Marion	Halfmoon	ARI(1,1)	-209	24	0.08
Orange	Georgia	ARMA(1,1) $^{-}$	-58	24	0.32
Orange	Giles	ARIMA(1,1,1)	10	1	0.20
Orange	Ola	Seasonal ARIMA(0,0,0)(1,1,1)12 $^{\times}$	-97	25	0.13
Orange	Sarah	ARI(1,1)	-45	25	0.50
Putnam	Como	Seasonal ARIMA(1,1,0)(0,1,0)12	-50	13	0.06
Putnam	Higgenbotham	ARI(1,1)	-110	25	0.18
Putnam	Star	ARI(2,1)	-69	12	0.10
Putnam	Winnott	ARMA(1,1) $^{\times}$	-182	12	0.48

Table 2-7. Continued

County	Lake	L_{10}SD Model	L_{10}SD AIC	L_{10}SD AC	L_{10}SD R^2
Alachua	Alto	Seasonal ARIMA(0,0,0)(0,1,0)12	-217	36	0.12
Alachua	Little Orange	Seasonal ARIMA(1,0,1)(0,1,0)12	-349	7	0.10
Alachua	Little Santa Fe	Seasonal ARIMA(0,0,0)(0,1,1)12 [×]	-270	13	0.16
Alachua	Santa Fe	Seasonal ARIMA(0,0,0)(0,1,0)12 [×]	-349	13	0.02
Alachua	Wauberg	Seasonal ARIMA(0,1,0)(1,1,0)12	-410	13	0.22
Hillsborough	Brant	Seasonal ARIMA(0,1,0)(0,1,0)12	-371	12	0.16
Hillsborough	Magdalene	ARIMA(1,1,1)	-703	12	0.64
Lake	Beauclaire	Seasonal ARIMA(0,1,0)(1,1,1)12	-366	11	0.12
Lake	Crooked	Seasonal ARIMA(1,1,0)(1,1,0)12	-296	16	0.23
Lake	Dora East	.	.	.	.
Lake	Dora West	.	.	.	.
Lake	Grasshopper	.	.	.	.
Lake	Harris	Seasonal ARIMA(0,0,0)(1,1,0)12	-135	24	0.01
Lake	Lorraine	.	.	.	.
Lake	Sellers	.	.	.	.
Marion	Charles	ARI(1,1)	-159	5	0.30
Marion	Deerback	Seasonal ARIMA(0,1,0)(0,1,0)12	-361	12	0.16
Marion	Eaton	Seasonal ARIMA(0,1,0)(0,1,0)12	3	4	0.13
Marion	Halfmoon	Seasonal ARIMA(0,1,1)(0,1,0)12	-358	13	0.20
Orange	Georgia	Seasonal ARIMA(0,1,1)(0,1,0)12	-493	12	0.32
Orange	Giles	ARI(1,1)	-157	3	0.14
Orange	Ola	.	.	.	.
Orange	Sarah	.	.	.	.
Putnam	Como	.	.	.	.
Putnam	Higgenbotham	Seasonal ARIMA(0,1,0)(0,1,0)12	-316	6	0.21
Putnam	Star	Seasonal ARIMA(0,0,0)(0,1,0)12	-257	24	0.08
Putnam	Winnott	Seasonal ARIMA(0,2,0)(0,1,0)12	-254	15	0.28

Table 2-8. Time series model (¯) denotes significant change and * denotes significant change and monotonic trend), the Akaike's Information Criterion (AIC) value, the time lag corresponding to the significant autocorrelation (AC), and the coefficient of determination (R^2) using annual mean logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD) data for the 27 Florida lakes.

County	Lake	L_{10}TP Model	L_{10}TP AIC	L_{10}TP AC	L_{10}TP R^2
Alachua	Alto	I(1)	-49	1	0.03
Alachua	Little Orange	ARMA(1,1)$^{\times}$	-1	1	0.30
Alachua	Little Santa Fe	I(2)	-16	1	0.46
Alachua	Santa Fe	ARI(2,2)	-30	1	0.03
Alachua	Wauberg	ARIMA(1,1,1)$^{\times}$	-28	0	0.15
Hillsborough	Brant	ARI(1,1)	-20	1	0.01
Hillsborough	Magdalene	ARIMA(2,2,1)	-32	1	0.06
Lake	Beauclaire	MA(1)$^{\times}$	-32	2	0.50
Lake	Crooked	ARIMA(2,2,2)	-15	1	0.16
Lake	Dora East	MA(1)$^{\times}$	-34	1	0.54
Lake	Dora West	ARIMA(2,2,2)	-38	1	0.72
Lake	Grasshopper	ARIMA(1,1,1)$^{\times}$	-9	1	0.41
Lake	Harris	ARMA(2,2)$^{-}$	-53	0	0.10
Lake	Lorraine	MA(1)$^{\times}$	-23	1	0.46
Lake	Sellers	ARIMA(2,2,2)	-15	1	0.48
Marion	Charles	ARI(1,1)	-9	1	0.08
Marion	Deerback	ARMA(1,1)$^{-}$	-46	0	0.17
Marion	Eaton	MA(2)$^{-}$	-10	1	0.29
Marion	Halfmoon	ARIMA(1,1,1)	-48	1	0.13
Orange	Georgia	ARIMA(1,1,1)$^{\times}$	-38	1	0.04
Orange	Giles	ARIMA(1,1,1)	-48	0	0.06
Orange	Ola	ARIMA(2,2,1)	-44	1	0.02
Orange	Sarah	ARMA(2,2)$^{-}$	-42	1	0.23
Putnam	Como	MA(1)$^{\times}$	-20	1	0.22
Putnam	Higgenbotham	ARMA(1,1)$^{-}$	-57	0	0.02

Table 2-8. Continued

County	Lake	L_{10}TP Model	L_{10}TP AIC	L_{10}TP AC	L_{10}TP R^2
Putnam	Star	ARI(2,2)	-18	1	0.08
Putnam	Winnott	ARIMA(2,2,1)	-35	1	0.62
County	Lake	L_{10}TN Model	L_{10}TN AIC	L_{10}TN AC	L_{10}TN R^2
Alachua	Alto	ARI(1,1)	-83	2	0.77
Alachua	Little Orange	ARMA(1,1)$^{-}$	-57	0	0.06
Alachua	Little Santa Fe	MA(1)$^{\times}$	-43	1	0.38
Alachua	Santa Fe	ARIMA(2,2,2)	-47	1	0.48
Alachua	Wauberg	I(2)	-44	1	0.41
Hillsborough	Brant	ARIMA(2,2,2)	-18	1	0.08
Hillsborough	Magdalene	ARIMA(1,1,1)	-67	0	0.04
Lake	Beauclaire	ARMA(2,2)$^{-}$	-48	1	0.40
Lake	Crooked	ARIMA(2,2,2)	-43	1	0.66
Lake	Dora East	ARIM(2,2,2)$^{-}$	-50	1	0.19
Lake	Dora West	ARMA(2,2)$^{-}$	-53	1	0.20
Lake	Grasshopper	IMA(1,1)	2	1	0.21
Lake	Harris	IMA(1,1)	-49	1	0.09
Lake	Lorraine	MA(1)$^{\times}$	-48	2	0.42
Lake	Sellers	ARIMA(2,2,2)	1	1	0.58
Marion	Charles	ARMA(2,2)	-32	1	0.14
Marion	Deerback	AR(1)$^{-}$	-81	0	0.09
Marion	Eaton	ARMA(1,1)$^{-}$	-33	0	0.11
Marion	Halfmoon	ARIMA(2,2,1)	-39	1	0.20
Orange	Georgia	AR(2)$^{\times}$	-51	1	0.20
Orange	Giles	ARIMA(1,1)$^{-}$	-43	0	0.12
Orange	Ola	IMA(2,2)	-59	1	0.20

Table 2-8. Continued

County	Lake	L_{10}TN Model	L_{10}TN AIC	L_{10}TN AC	L_{10}TN R^2
Orange	Sarah	ARIMA(2,2,2)	-48	1	0.39
Putnam	Como	IMA(1,1)	-32	2	0.51
Putnam	Higgenbotham	ARMA(2,2)$^{-}$	-47	0	0.19
Putnam	Star	ARIMA(2,2,2)	-40	1	0.25
Putnam	Winnott	ARIMA(2,2,1)	-45	2	0.50
County	Lake	L_{10}CHL Model	L_{10}CHL AIC	L_{10}CHL AC	L_{10}CHL R^2
Alachua	Alto	ARMA(1,1)^{x}	-30	0	0.05
Alachua	Little Orange	IMA(1,1)	-1	1	0.03
Alachua	Little Santa Fe	ARMA(1,1)^{x}	-16	0	0.09
Alachua	Santa Fe	ARMA(1,1)^{x}	-8	1	0.16
Alachua	Wauberg	ARIMA(2,2,2)	-17	1	0.02
Hillsborough	Brant	AR(1)$^{-}$	-1	1	0.24
Hillsborough	Magdalene	ARIMA(1,1,1)	-22	1	0.07
Lake	Beauclaire	ARI(1,1)	-19	1	0.01
Lake	Crooked	ARIMA(2,2,2)	-5	1	0.23
Lake	Dora East	IMA(1,1)	-21	1	0.01
Lake	Dora West	IMA(1,1)	-27	1	0.02
Lake	Grasshopper	ARMA(2,2)$^{-}$	-10	1	0.42
Lake	Harris	ARI(2,2)	-15	1	0.14
Lake	Lorraine	MA(1)^{x}	-4	2	0.43
Lake	Sellers	MA(1)^{x}	-15	2	0.47
Marion	Charles	ARMA(2,2)$^{-}$	17	0	0.35
Marion	Deerback	AR(2)$^{-}$	-26	0	0.10
Marion	Eaton	ARMA(2,2)$^{-}$	-7	0	0.17
Marion	Halfmoon	ARIMA(2,2,2)	-27	1	0.02

Table 2-8. Continued

County	Lake	L_{10}CHL Model	L_{10}CHL AIC	L_{10}CHL AC	L_{10}CHL R^2
Orange	Georgia	ARMA(2,2)$^{-}$	-16	0	0.09
Orange	Giles	ARMA(2,2)$^{-}$	-23	0	0.12
Orange	Ola	ARIMA(2,2,2)	-21	1	0.15
Orange	Sarah	I(2)	-5	2	0.46
Putnam	Como	ARIMA(1,1,1)	-16	1	0.14
Putnam	Higgenbotham	MA(1)$^{-}$	-20	0	0.04
Putnam	Star	ARMA(1,1)$^{-}$	-27	0	0.00
Putnam	Winnott	ARI(2,2)	-6	1	0.03
County	Lake	L_{10}SD Model	L_{10}SD AIC	L_{10}SD AC	L_{10}SD R^2
Alachua	Alto	MA(1)^{x}	-38	2	0.30
Alachua	Little Orange	ARIMA(1,1,1)^{x}	-37	0	0.11
Alachua	Little Santa Fe	ARI(1,1)	-30	1	0.12
Alachua	Santa Fe	MA(1)^{x}	-44	1	0.38
Alachua	Wauberg	ARIMA(2,2,2)	-39	1	0.12
Hillsborough	Brant	ARIMA(1,1,1)	-31	1	0.06
Hillsborough	Magdalene	ARIMA(2,2,1)	-40	1	0.09
Lake	Beauclaire	AR(1)$^{-}$	-42	1	0.14
Lake	Crooked	ARIMA(2,2,1)	-26	1	0.19
Lake	Dora East	.	.	.	.
Lake	Dora West	.	.	.	.
Lake	Grasshopper	ARMA(1,1)$^{-}$	-2	1	0.52
Lake	Harris	ARIMA(1,1,1)	-18	0	0.04
Lake	Lorraine	.	.	.	.
Lake	Sellers	.	.	.	.
Marion	Charles	ARMA(2,2)$^{-}$	-17	0	0.20

Table 2-8. Continued

County	Lake	L_{10}SD Model	L_{10}SD AIC	L_{10}SD AC	L_{10}SD R^2
Marion	Deerback	ARMA(2,2)$^{-}$	-42	1	0.37
Marion	Eaton	ARMA(2,2)$^{-}$	-9	0	0.14
Marion	Halfmoon	ARIMA(2,2,2)$^{-}$	-34	1	0.03
Orange	Georgia	ARI(1,1)	-41	1	0.03
Orange	Giles	ARIMA(1,1,1)	-31	0	0.04
Orange	Ola	.	.	.	.
Orange	Sarah	.	.	.	.
Putnam	Como	.	.	.	.
Putnam	Higgenbotham	AR(2)$^{-}$	-35	0	0.01
Putnam	Star	ARIMA(2,1,2)	-35	1	0.28
Putnam	Winnott	ARI(2,2)	-20	1	0.37

Table 2-9. Modified linear regression analysis, with six categories of annual mean data, to detect significant monotonic trends (^{x}), slope value, and coefficient of determination (R^2) for logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD) data for the 27 Florida lakes.

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Alachua	Alto	0.03^{x}	0.93	0.03^{x}	0.82	0.03	0.59	-0.05^{x}	0.69
Alachua	Little Orange	0.08^{x}	0.84	0	0.09	-0.05	0.45	-0.02^{x}	0.77
Alachua	Little Santa Fe	0.08^{x}	0.67	0.05^{x}	0.71	0.05^{x}	0.73	-0.05^{x}	0.74
Alachua	Santa Fe	0.04^{x}	0.76	0.04^{x}	0.77	0.07^{x}	0.88	-0.05^{x}	0.87
Alachua	Wauberg	0.03^{x}	0.57	0.03	0.49	0.04	0.49	-0.02	0.26
Hillsborough	Brant	0	0	-0.02	0.20	0	0	0	0.01
Hillsborough	Magdalene	0.02	0.24	0.01	0.27	0	0	-0.01	0.07
Lake	Beauclaire	-0.06^{x}	0.78	-0.01	0.05	-0.01	0.04	0	0.02
Lake	Crooked	-0.04	0.48	-0.02	0.12	-0.04	0.35	0.03	0.50
Lake	Dora East	-0.05	0.54	-0.01	0.10	-0.02	0.16	.	.
Lake	Dora West	-0.03	0.29	-0.01	0.12	-0.02	0.13	.	.
Lake	Grasshopper	0.08	0.51	0.04	0.12	0.03	0.12	.	.
Lake	Harris	0.01	0.23	-0.01	0.24	-0.05	0.52	0.02	0.20
Lake	Lorraine	-0.1^{x}	0.93	-0.05^{x}	0.89	-0.14^{x}	0.82	.	.
Lake	Sellers	0.07	0.55	0.12	0.67	0.09	0.77	.	.
Marion	Charles	0.04	0.22	0.03	0.65	-0.01	0.01	-0.01	0.06
Marion	Deerback	0	0	0	0	-0.02	0.46	-0.01	0.04
Marion	Eaton	0.03	0.14	0.01	0.07	-0.01	0.02	0	0
Marion	Halfmoon	0	0	0.03^{x}	0.77	-0.03^{x}	0.70	0.01	0.04
Orange	Georgia	0.03	0.64	0.02	0.49	0.03	0.43	-0.03^{x}	0.81
Orange	Giles	0	0.11	0	0.02	0.02	0.23	-0.02	0.40
Orange	Ola	0.01	0.31	0.02	0.66	0.04^{x}	0.71	.	.
Orange	Sarah	-0.01	0.05	-0.01	0.24	-0.1	0.49	.	.
Putnam	Como	0.06	0.63	0.05	0.48	0.01	0.06	.	.
Putnam	Higgenbotham	0.005	0.06	0	0	-0.06^{x}	0.83	-0.01	0.06
Putnam	Star	0.04^{x}	0.90	0.03^{x}	0.92	0	0	-0.03	0.58
Putnam	Winnott	0.06^{x}	0.82	0.04^{x}	0.91	0.07^{x}	0.92	-0.07^{x}	0.90

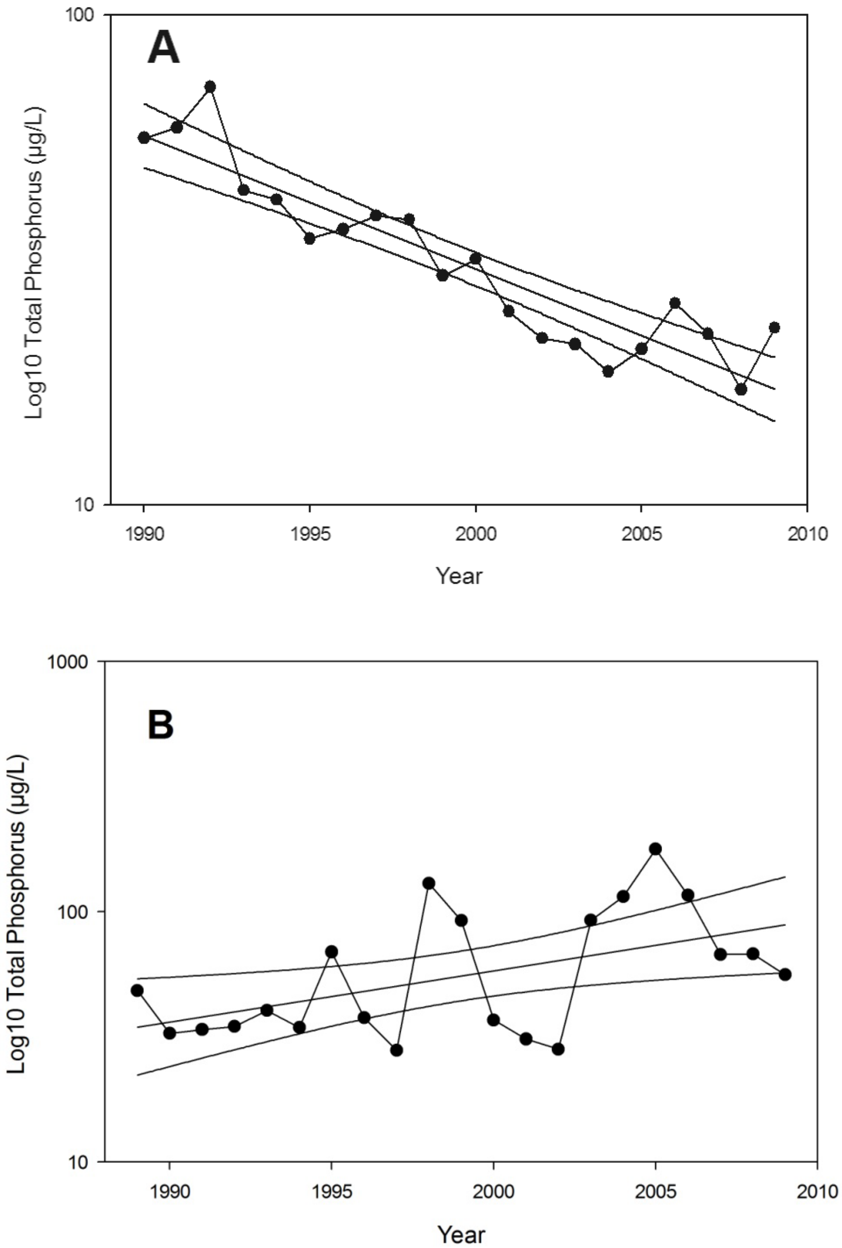


Figure 2-1. Linear regression model analysis and the associated 95% confidence intervals for annual mean total phosphorus concentrations (µg/L). A) Total phosphorus concentrations in Lake Lorraine located in Lake County, Florida ($p < 0.0001$, $R2 = 0.77$). B) Total phosphorus concentrations (µg/L) in Little Orange Lake located in Alachua County, Florida ($p = 0.03$, $R2 = 0.23$). The Kendall-Tau, ARMA/ARIMA time series models, and the proposed alternative methods detected a significant trend in total phosphorus concentrations (µg/L) in Lorraine Lake, but not in Little Orange Lake.

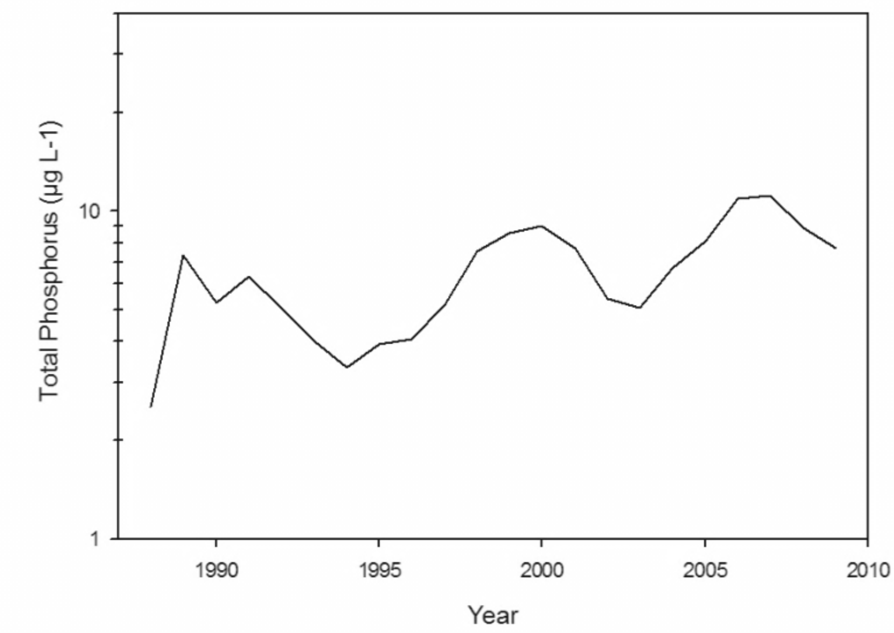


Figure 2-2. Example of a time series plot of annual mean total phosphorus concentrations (µg/L) for Lake Como (located in Putnam County, Florida) the corresponding autocorrelation function (ACF) plot, and the corresponding partial autocorrelation function (Partial ACF) plot against time with successively time units (years) lagged by one. The dotted lines on the ACF and PACF plot represent the upper and lower 95% confidence intervals. The statistically significant ACF and Partial ACF values along with the pattern of the lag terms were used to estimate the autocorrelation term (AR) and moving average (MA) terms of the time series model. The selected time series model for these data was ARIMA (1,1,1).

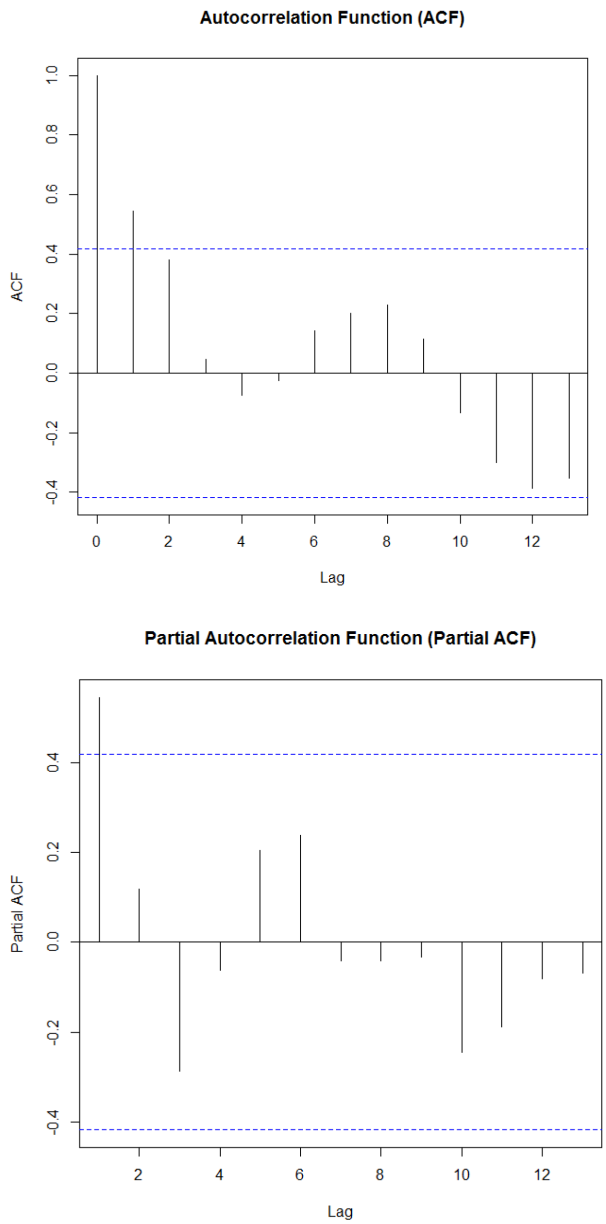


Figure 2-2. Continued

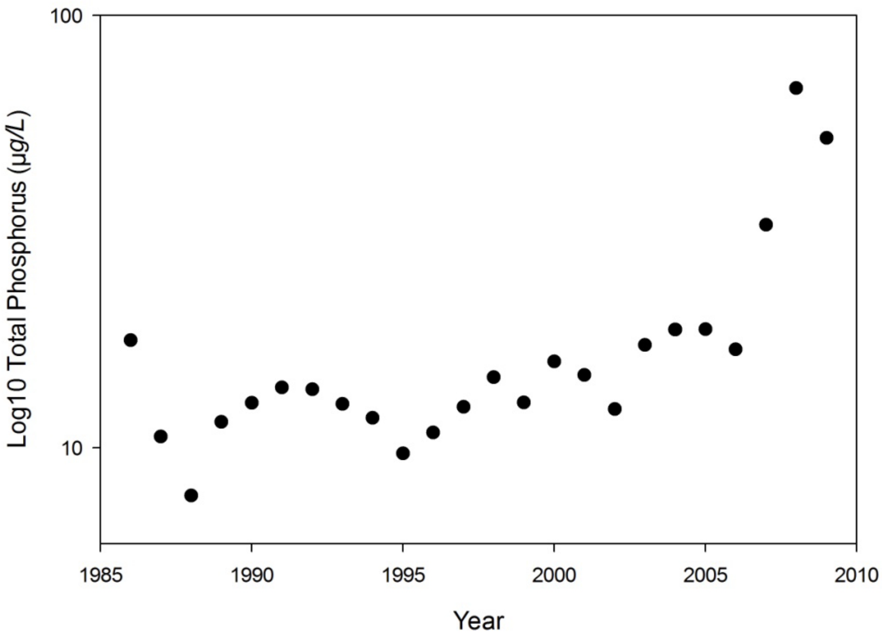


Figure 2-3. Annual mean total phosphorus concentrations (µg/L) in Little Lake Santa Fe located in Alachua County, Florida. Linear regression and Kendall-Tau analyses detected significant increasing monotonic trends in total phosphorus (µg/L), while the time series model detected a significant change in total phosphorus concentrations (µg/L), but no significant trend over the examined 24-year record (1986-2009).

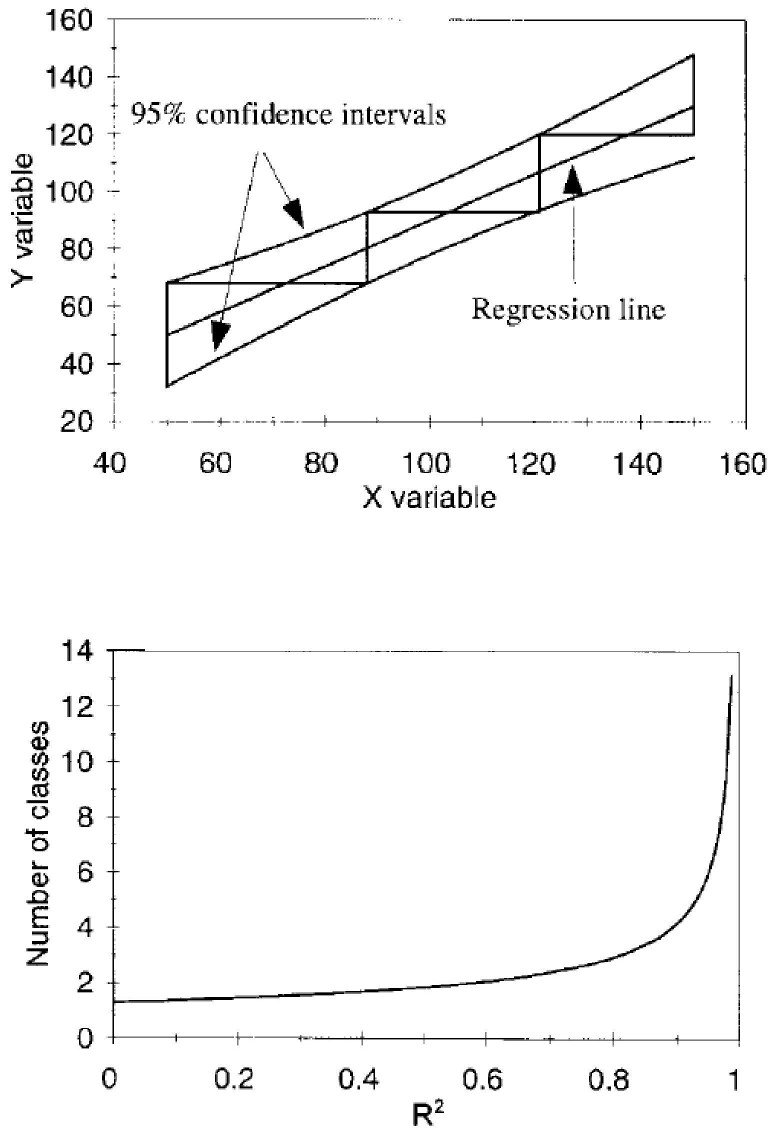


Figure 2-4. Number of classes determined (three intervals as pictured) using the bivariate linear regression model and the associated 95% confidence intervals (top figure). As the number of classes increases the coefficient of determination (R^2) values increase with a value of 0.65 noted as a predictively powerful linear regression model (bottom figure). Data and figures are from Prairie (1996).

CHAPTER 3
DECADAL-SCALE TRENDS IN TROPHIC STATE VARIABLES WITHIN A LARGE POPULATION OF FLORIDA LAKES

Background

Long-term data are invaluable to provide improved estimates of environmental changes and trends that offer a context in which to evaluate environmental management options (Stow et al. 1998; Hobbie 2003). Scientists, federal and state agencies, and policy makers recognize the importance of long-term monitoring data and have consequently implemented several large-scale lake monitoring programs (e.g., United States Geological Survey's National Water Quality Assessment programs, United States Department of Agriculture's National Resources Inventory, and the United States Environmental Protection Agency's National Lakes Assessment Program). Many of these lake monitoring programs; however, do not meet the sampling frequency and duration suggested to best detect changes and trends in lake trophic state variables that represent the system's behavior (i.e., 6 consecutive years (Molot and Dillion 1991) to 12 years (Howden et al. 2011) to at least 20 years (Knowlton and Jones 2006)). As lake management decisions that target improvement of water quality or nutrient control are often based on trends, assessment of long-term trophic state trends and understanding the magnitude of these trends are needed to facilitate advancement of scientific research to develop the most appropriate management plans.

The detection of trends has recently drawn much attention due to influences of mounting human pressures and climatic drivers on lake trophic state variables (e.g., Carpenter et al. 1998; Williamson et al. 2009; Adrian et al. 2009; James et al. 2011). The focus of many of these studies has been on lake responses to anthropogenic influences at the individual lake level and across small populations of lakes. There is a paucity of studies in the literature, however, that examine trends in lake changes (as measured by trophic state variables) across a large population of lakes. As global change has been projected to impact freshwater systems (Kernan et al. 2010), examination of change across many lakes provides insight that individual lake studies or studies of a few lakes may not offer. For example, if long-term trends in changes in trophic state variables are documented across many lakes or a specific grouping of lakes, then there may be dominant driving factor(s) influencing change that may be more easily recognized in the lake(s).

Limnologists have long sought to explain variation of lake systems (Hutchinson 1965) yet understanding whether lakes have changed over time prior to determination of factors driving lake change is a step that is many times overlooked. In the State of Florida, there are some well-known individual lakes with long-term data records that have been studied in great detail such as Lake Okeechobee (e.g., James et al. 2011), Lake Apopka (e.g., Bachmann et al. 1999), and Lake Annie (Gaiser et al. 2009). However, despite the State of Florida having over 7,700 lakes, of which 3,298 are named (Schafer et al. 1986), there has been only one study (Terrell et al. 2000) to use long-term records to assess lake changes across a large population of Florida lakes. The study completed by Terrell et al. (2000) included data collected by different groups, a population of 127 Florida lakes, and was completed 16 years ago. There is need for an updated and improved long-term assessment of change within a large population of Florida lakes because, in the past 16 years, the State of Florida has experienced large human population growth (about a 250% increase) and shifts in climatic patterns

(Gaiser et al. 2009) and research studies have focused on identification of factors driving change in the trophic state of Florida lakes (e.g., James et al. 2011).

The purpose of this chapter is to provide an updated and improved assessment of long-term changes in trophic state variables (i.e., total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements) across a large population of Florida lakes. Long-term trophic state data were consistently collected and analyzed by the Florida LAKEWATCH program for at least 15 years and up to 23 years for 193 Florida lakes that spanned the State of Florida (Figure 3-1). The objectives of this chapter were to 1) identify long-term trends in the lake trophic state variables for the population of 193 Florida lakes and 2) explore spatial distribution of lakes with similar identified trends in the examined trophic state variables. Due to the decadal length of the examined data (i.e., one and a half to two decades), this chapter describes trends and explores lake relationships in context of a decadal-scale of time. The robust, decadal-scale dataset provides not only a good estimation of trends in trophic state variables, but also incorporates natural variability and the inclusion of stochastic events, such as hurricanes or extreme droughts and floods.

Methods

Monthly total phosphorus (TP), total nitrogen (TN), chlorophyll concentrations (CHL), and water clarity (SD) measurements (obtained by the use of a Secchi disk) were collected by the well-established Florida LAKEWATCH program and water chemistry analyses were completed by the Florida LAKEWATCH laboratory consistent over time (Canfield et al. 2002). The Florida LAKEWATCH program began in 1986 and currently samples over 1,500 lakes across the State of Florida. A subset of the Florida LAKEWATCH database was used, which included lakes with all four trophic state variables collected for at least 15 years and up to 24 years for 193 Florida lakes (Figure 3-2). The majority of lakes were sampled monthly at 3 open-water stations and a monthly mean calculated among the stations. An annual mean was calculated from the monthly means and then used to calculate an overall mean value for the lake. The subset of data examined included 31,050 monthly samplings.

Data were analyzed with the statistical package JMP version 8.0 (SAS Institute Inc. 2007). Trends in annual mean total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements were evaluated for the 193 individual Florida lakes using a modified linear regression. The modified linear regression analysis used mean groupings of annual data, or intervals, to decrease the number of samples thereby increasing the predictive power of regression analysis (Prairie 1996). Prairie (1996) found the number of intervals was related to the coefficients of variation (R^2) and also R^2 values of 0.65 or greater increased the predictive power of linear regression analysis. Six intervals were calculated for each trophic state data time series (i.e., six mean data points, where each point represented the mean of three to four years depending on the length of the data series. Six categories were selected for use because Brhyn and Dimberg (2011) demonstrated that aquatic environmental data have the highest R^2 values when divided into six classes. Linear regression analysis was completed across the six calculated mean values providing an estimation of trend in the trophic state variable that was of high predictive power (Prairie 1996) and “statistically meaningful” (Bryhn and Dimberg 2011). To meet the requirements of parametric statistics, logarithmic (base 10) transformations were completed using annual mean values when appropriate (Snedecor and Cochran 1980) and all statements of statistical significance were at a probability level of < 0.05.

There are alternative statistical trend detection methods, such as the ARMA/ARIMA time series model, that are suggested to handle variance in a manner that does not affect statistical determination of a trend. Compared to the selected modified linear regression analysis, the ARMA/ARIMA time series analysis would have resulted in a more conservative estimate of the number of trends identified in the trophic state variables for the 193 Florida lakes. The modified linear regression model was selected to determine trends because ARMA/ARIMA time series analysis have strict data limitations (Bendat and Piersol 2010) that would have required the elimination of data and an overall reduction in the size of the dataset. The selected modified linear regression model offered an alternative method that has been shown to provide a predictively powerful statistical assessment to detect decadal-scale trends in annual mean trophic state variables (see Chapter 2).

It is important to note, the terms degradation and improvement were used in this chapter to denote the direction of the trend for each trophic state variable and for ease of explanation. The term degradation was used to describe increasing trends in total phosphorus, total nitrogen, and chlorophyll concentrations and decreasing trends in water clarity measurements. The term improvement was used to describe decreasing trends in total phosphorus, total nitrogen, and chlorophyll concentrations and increasing trends in water clarity measurements. The use of the terms, degradation and improvement, with reference to lake water quality does not imply; however, the relationship was “bad” or “good” or implie any cause-and-effect relationships (e.g., degradation in the lake trophic state variables was due to an anthropogenic source).

The spatial distribution of the Florida lakes was determined by visual identification of the geographic location of lakes with decadal-scale trends in total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements across the State of Florida. As an initial effort to understand the lakes with identified trends in one or more of the trophic state variables, the influence of natural characteristics (i.e., geology, soils, and hydrology) and nutrient characteristics (i.e., areas of Florida with high or low nutrient concentrations) were examined. The Florida Lake Regions (Griffin et al. 1997) were used as an estimate of the influence of natural characteristics and the total phosphorus zones (TP Zones) and total nitrogen zones (TN Zones) developed for the State of Florida by Bachmann et al. (2012a, 2012b) were used as an estimate of the influence of nutrient characteristics. ArcGIS 10.0 (ESRI 2011) was used to examine the lake relationships with the Florida Lake Regions, TP Zones, and TN Zones.

A one-way analysis of variance was used to quantify the amount of variance the Florida Lake Regions, TP Zones, and TN Zones attributed to each trophic state variable. The analysis was completed for the 105 Florida lakes (out of the 193 Florida lakes) where at least one trophic state variable was documented to significantly increase or decrease over the examined period of record. Specifically, examination of the Florida Lake Regions was completed by placing the lakes with identified trends in at least one trophic state variable into the respective Florida Lake Region (N=47 regions). Using an overall mean for each lake and trophic state variable, the one-way analysis of variance (ANOVA) identified the amount of variance in the given trophic state variable attributed to the Florida Lake Regions. Relationships between lakes with trophic state variable trends and TP Zones and TN Zones were examined by placing lakes into the respective total phosphorus zone (N=6 zones) and total nitrogen zone (N=5). A one-way ANOVA estimated the amount of variance in the given trophic state variable accounted for by both the TP zones and TN zones. Bachmann et al. (2012a, 2012b) developed the TP and TN zones by grouping Florida Lake Regions with similar chemical characteristics, so it was assumed the information on soils, physiography, geology, vegetation, climate, and land use/ land cover associated with the Florida Lake Regions carried over to the TP and TN zones.

Results

There was a wide range in the concentrations of total phosphorus, total nitrogen, and chlorophyll concentrations and measurements of water clarity among the 193 Florida lakes (Table 3-1) and a broad range in other physical and chemical variables; mean depth, lake area, specific conductance, and color (Table 3-2). The 193 Florida lakes encompassed all lake trophic state categories (Table 3-3) as defined by Forsburg and Ryding (1980). Specifically, for total phosphorus 35% (67 lakes) would be classified as oligotrophic (TP< 15 µg/L), 28% (54 lakes) mesotrophic (TP 15- 24.9 µg/L), 30% eutrophic (25- 99.9 µg/L), and 7% (13 lakes) hypereutrophic (≥ 100 µg/L). For total nitrogen, 13% (25 lakes) were classified as oligotrophic (< 400 µg/L), 21% (41 lakes) mesotrophic (400- 599.9 µg/L), 53% (102 lakes) eutrophic (600- 1499.9 µg/L), 12% (24 lakes) hypereutrophic (≥ 1500 µg/L). For chlorophyll concentrations, 8% (15 lakes) were classified as oligotrophic (< 3 µg/L), 33% (63 lakes) mesotrophic (3- 6.9 µg/L), 44% (86 lakes) eutrophic (7- 39.9 µg/L), and 15% (29 lakes) hypereutrophic (≥ 40 µg/L). For water clarity measurements, 7% (14 lakes) were classified as oligotrophic (> 3.96 m), 21% (40 lakes) mesotrophic (2.43- 3.96 m), 42% eutrophic (81 lakes) (0.91- 2.44 m), and 29% (56 lakes) hypereutrophic (< 0.91 m).

For the population of 193 Florida lakes, the modified linear regression analysis of the logarithmic (base 10) transformed annual mean data indicated significant increasing monotonic trends in 21% of the population of Florida lakes (40 lakes) for total phosphorus, 26% (50 lakes) for total nitrogen, 12% (23 lakes) for chlorophyll concentrations, and 4% (8 lakes) for water clarity measurements. Statistically significant decreasing monotonic trends were identified in 7% (14 lakes) for total phosphorus, 6% (12 lakes) for total nitrogen, 7% (14 lakes) for chlorophyll concentrations, and 18% (34 lakes) for water clarity measurements (Table 3-4).

For the individual 193 Florida lakes, there were 88 lakes that did not shown statistically significant increasing or decreasing trends in total phosphorus, total nitrogen, chlorophyll concentrations, or water clarity measurements over the period of record (Table 3-5). There were 9 lakes with trends of degradation in all four lake trophic state variables (Table 3-6). Other individual lakes experienced trends of degradation in three, two, or one of the examined trophic state variables (Table 3-6). There were two lakes that experienced improving trends in all four of the trophic state variables; other individual lakes exhibited trends of improvement for three, two, or one of the examined trophic state variables (Table 3-6). There was one lake (i.e., Blue North located in Polk County), with an increasing trend in total phosphorus and decreasing trends in total nitrogen and water clarity measurements, that did not fit into the denoted trend categories of degradation or improvement.

Individual lakes with similar trends of long-term degradation or improvement in the examined trophic state variables were identified across the State of Florida. Clusters of lakes with similar trends in the trophic state variables were visually identified. There were 8 lakes located in close proximity in the panhandle region of Florida that showed trends of degradation as measured by the trophic state variables. Specifically, two lakes experienced trends of degradation in all four of the trophic state variables (i.e., lakes Tallavana and Bradford), two lakes experienced trends of degradation in three of the trophic state variables (i.e., lakes Pine, Hill, and Overstreet), and three lakes showed increasing trends in total nitrogen (i.e., lakes Arrowhead, Hiawatha, and Monkey Business) (Figure 3-3A). There was one lake (i.e., Lake Hall) within this cluster of lakes that showed a decreasing trend in chlorophyll concentration. There was another cluster of lakes, located in the north-central region of Florida, which also exhibited trends of degradation in the trophic state variables. Specifically, four lakes showed trends of degradation in all four trophic state variables (i.e., lakes Little Santa Fe, Putnam, Santa Fe, and Sheelar), one lake had trends of degradation in three variables (i.e., Lake Hampton), four lakes showed degradation in two variables (i.e., lakes Alto, Cowpen, Little Johnson, and Riley), and five lakes showed degradation in one trophic state variable (i.e., lakes Bivens Arm, Deer, Putnam, Rosa, and Star). Within this cluster of lakes, however, there was one lake that experienced a decreasing trend in total phosphorus (i.e., Lake McMeekin) and one lake that experienced a decreasing trend in chlorophyll concentrations (i.e., Lake Higgenbotham) (Figure 3-3 B). The last cluster of lakes with similar trends was located in south-central Florida. This cluster of five lakes included two lakes with trends of improvement in three trophic state variables (i.e.,lakes

Holden and Ivanhoe), two lakes with trends of improvement in two variables (i.e., lakes Conway and Little Fairview), and one lake with a decrease in total nitrogen (i.e., Lake Porter) (Figure 3-3 C).

One-way analysis of variance demonstrated that for the lakes with identified trends in each trophic state variable from the examined population of 193 Florida lakes, the Florida Lake Regions explained 63% of the variance in total phosphorus, 59% in total nitrogen, 52% in chlorophyll, and 54% in water clarity. The Florida TP Zones explained 53% variance in total phosphorus, 31% in total nitrogen, and 38% in chlorophyll concentrations, and 30% in water clarity measurements. The Florida TN Zones explained 41% of the variance in total phosphorus, 52% in total nitrogen, and 34% in chlorophyll concentrations, and 33% in water clarity measurements. Bachmann et al. (2012a) also found the Florida Lake Regions to be the best predictor of lake trophic status across Florida lakes. Although the Bachmann et al. (2012a) did not complete a long-term analysis of trophic state variables among Florida lakes, their results were similar as the TP and TN zones were found to explain 40% of the variance in total phosphorus and total nitrogen in 1,387 examined Florida lakes.

Discussion

There were few lakes, a small percentage (≤ 26%) of the examined population of Florida lakes, with significant decadal-scale trends across the measured variables total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements. Considering the influence of the cumulative effects of the growing human population on freshwater systems (Carpenter et al. 1998; Carpenter and Lantrop 2008; James et al. 2011) and the subsequent projections of lake water quality to worsen in the future due to inputs of nutrients and changing climate conditions (Adrian et al. 2009; Williamson et al. 2009), the small percentage of the population of 193 Florida lakes with decadal-scale in the trophic state variables was contrary to the expectation of these statements. Other long-term trend analysis studies completed at the state-level have shown similar results; no significant trends of degradation in total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements for a population of lakes in Vermont (N=195 lakes; 11 years of data, Smeltzer et al. 1989) and in Florida (N=127 lakes; varying periods of record, Terrell et al. 2000). Bachmann et al. (2012a,b,c) examined plant nutrient and chlorophyll concentrations for 1,387 Florida lakes across varying scales of analysis (e.g., paleolimnological comparisons or natural (unaltered by human activities) lake condition comparisons) and found the majority of examined Florida lakes had not experienced changes in plant nutrients and chlorophyll concentrations. Analogous conclusions have been drawn from national lake assessments as well. For example, using a subset of lakes that were sampled as a part of the National Eutrophication Survey in the 1970s, of which many received sewage pollution, the United State Environmental Protection Agency (USEPA) (2009) demonstrated that over a 30-year period, total phosphorus concentrations did not change in 24% of the nation’s lakes (N= 800 lakes) and chlorophyll-a concentrations did not change in 51% of the same subset of examined lakes. Carlson et al. (2012) examined water clarity measurements, ranging in record from at least 5 years and up to 40 years, for 4,812 of the nation’s water bodies and determined 83% of the lakes did not significantly change over the examined period of record, respectively.

The percentage of the population of 193 Florida lakes that experienced decadal-scale trends of degradation was greater than the percentage of the population of lakes with identified decadal-scale trends of improvement in the examined trophic state variables. Although the percentage of the lakes with identified trends was small compared to the percentage of lakes with no trends, there were individual lakes that experienced decadal-scale trends of increases in total phosphorus, total nitrogen, and chlorophyll concentrations, and decreases in water clarity measurements (Table 3-4). Compared to other trend analyses of trophic state variables for Florida lakes, the percentage of the population of 193 Florida lakes with identified trends in the trophic state variables was greater than determined by both Terrell et al. (2000) and Bachmann et al. (2012a,b,c). The divergent results could be attributed to examination of different populations of Florida lakes, varying availability of data, or the length of time used to detect trends and make comparisons to other data. The different conclusions illustrate the need to consider the scale of analysis when interpreting trophic state variable trends, especially as limnologists and lake managers may interpret and value results differently depending on the scale (e.g., geological time scale versus decadal time scale).

There were 9 individual lakes out of the 193 examined Florida lakes with increasing trends in total phosphorus, total nitrogen, and chlorophyll concentrations and decreasing trends in water clarity measurements over the decadal-scale period or record. These lakes offer the opportunity for limnologists and lake managers to better understand the mechanisms driving lake change because all four of the trophic state variables exhibited decadal-scale trends. Following trophic state theory, the factors driving these trophic state variable trends, whether anthropogenic or natural factors may be more easily identified and understood in the 9 lakes compared to lakes where trends were found in one, two, or three of the other trophic state variables. Detailed examination of the two lakes out of the 193 Florida lakes that showed improving trends in all four of the trophic state variables may additionally be worthwhile to recognize why these improvements occurred and if these improvements could be replicated in other lake ecosystems. Overall, the 9 lakes with trends of degradation in the examined trophic state variables was less than 5% of the population of examined 193 Florida lakes, indicating the state of Florida lakes, as a whole, may not be as severe as hypothesized (USEPA 2000).

Another alternative to focus future research and management efforts would be to target spatial clusters of lakes with similar trophic state variable trends, either trends of degradation or trends of improvement. As this chapter demonstrated, there were three spatial clusters of lakes across the State of Florida; two clusters where the lakes had trends of degradation and one cluster where the lakes had trends of improvement. Rather than exploring driving factors within an individual lake, focus on a cluster of lakes or even the connectivity of the lake systems (i.e., the connection of lakes by other waters), incorporates a spatial aspect which may enhance the understanding of both anthropogenic and natural factors influencing lake trophic state changes and trends.

The major conclusion of this chapter is that many Florida lakes have not experienced decadal-scale trends in total phosphorus, total nitrogen, chlorophyll concentrations, and water clarity measurements. There are, however, select individual Florida lakes that have experienced concerning trends in the lake trophic state variables. Both research and lake management efforts should focus on these individual lakes and the identified clusters of lakes, to identify and understand the drivers that may be influencing these changes. If the goal is to provide a sustainable lake ecosystem for the future, then such attention and assessment of Florida’s lakes are necessary.

Table 3-1. Summary statistics (i.e., mean, median, minimum, maximum, and coefficient of variation (%)) for annual mean total phosphorus (µg/L), total nitrogen (µg/L), chlorophyll concentrations (µg/L), and water clarity measurements (m) for the population of 193 Florida lakes.

Trophic State Variable	N	Mean	Median	Minimum	Maximum	Coefficient of Variation
Total Phosphorus	193	38.4	18.3	3.8	357.5	152
Total Nitrogen	192	921	716	109	3,780	75
Chlorophyll	193	23.4	9.2	1.6	199	149
Water Clarity	191	1.92	1.58	0.32	6.69	69

Table 3-2. Summary statistics (i.e., mean, median, minimum, maximum, and coefficient of variation (%)) for supplemental data including mean depth (m), surface area (ha), specific conductance (µS), and true color (Pt-Co Units) for the population of 193 Florida lakes.

Supplemental Variable	N	Mean	Median	Minimum	Maximum	Coefficient of Variation
Mean Depth (m)	132	3.2	3	0.8	9.9	45
Surface Area (ha)	167	525	63	1	19,808	344
Specific Conductance (µS)	182	170	151	0.01	1316	91
True Color (Pt-Co Units)	193	47	22	2.2	444	139

Table 3-3. Percentage of the population of 193 Florida lakes for total phosphorus, total nitrogen, chlorophyll concentration, and water clarity measurements within each trophic state classification (i.e., oligotrophic, mesotrophic, eutrophic, and hypereutrophic) following Forsburg and Ryding (1980).

	Percent of 193 Florida lakes
Total Phosphorus	
Oligotrophic	35
Mesotrophic	28
Eutrophic	30
Hypereutrophic	7
Total Nitrogen	
Oligotrophic	13
Mesotrophic	21
Eutrophic	53
Hypereutrophic	12
Chlorophyll	
Oligotrophic	8
Mesotrophic	33
Eutrophic	44
Hypereutrophic	15
Water Clarity	
Oligotrophic	7
Mesotrophic	21
Eutrophic	42
Hypereutrophic	29

Table 3-4. Percentage of the population of Florida lakes with increasing trends, decreasing trends, and no trends detected in annual mean total phosphorus, total nitrogen, chlorophyll concentrations and water clarity measurements over a period or record of at least 15 years.

Trophic State Variable	N	Increasing Trend (%)	Decreasing Trend (%)	No Trend (%)
Total Phosphorus	193	21	7	72
Total Nitrogen	192	26	6	68
Total Chlorophyll	193	12	7	81
Water Clarity	191	4	18	78

Table 3-5. Linear regression analysis using six data points where the point reflects the mean among the six annual mean data for the logarithmic base 10 (L_{10}) total phosphorus (TP), total nitrogen (TN), chlorophyll (CHL), and water clarity measurements (SD). A significant monotonic trend (^{x}) was denoted and the corresponding slope value, and coefficient of determination (R^2) for each trophic state variable for the 193 Florida lakes.

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Alachua	Alto	0.03^{x}	0.75	0.03^{x}	0.79	0.02	0.29	-0.04	0.54
Alachua	Bivans Arm	0.06^{x}	0.74	0.06	0.59	0.06	0.28	-0.07	0.60
Alachua	Little Orange	0	0.37	-0.0008	0	-0.06	0.40	-0.02	0.34
Alachua	Little Santa Fe	0.08^{x}	0.68	0.05^{x}	0.71	0.05^{x}	0.73	-0.05^{x}	0.74
Alachua	Lochloosa	0.04	0.41	0.003	0	-0.03	0.04	0	0
Alachua	Newnan	0.05	0.45	-0.007	0.01	-0.05	0.24	0.02	0.15
Alachua	Orange	0.07	0.23	0.04	0.30	0.05	0.10	-0.05	0.50
Alachua	Santa Fe	0.04^{x}	0.76	0.04^{x}	0.77	0.07	0.88	-0.05^{x}	0.87
Alachua	Wauberg	0.03	0.57	0.03	0.49	0.04	0.49	-0.02	0.26
Bay	Powell	-0.004	0	-0.02	0.54	-0.01	0.30	0.02	0.50
Bradford	Hampton	0.03^{x}	0.70	0.03^{x}	0.84	0.06^{x}	0.85	-0.04	0.61
Brevard	Forest	0.04	0.64	0.002	0.02	0.02	0.20	-0.04^{x}	0.90
Citrus	Henderson	0.01	0.04	0.002	0	-0.002	0.01	0.01	0.02
Citrus	Hernando	0.08^{x}	0.75	0.06	0.64	0.08	0.62	-0.05	0.53
Citrus	Little Henderson	0.005	0.02	-0.001	0	-0.02	0.17	0.02	0.26
Citrus	Todd	0.08^{x}	0.72	0.07^{x}	0.81	0.1^{x}	0.90	-0.05	0.48
Citrus	Tsala Apopka	-0.02	0.25	0.02	0.18	-0.02	0.14	0.004	0.02
Clay	Asbury North	0.02	0.25	0.01	0.38	0.02	0.24	0.003	0.02
Clay	Crystal	0.004	0.01	-0.003	0.01	-0.04	0.18	0.03	0.40
Clay	Deer	0.03	0.33	0.05^{x}	0.80	0.04	0.42	-0.03	0.49
Clay	Johnson	0.04	0.55	0.05	0.64	0.06	0.45	-0.04	0.24
Clay	Kingsley	0.009	0.09	0.02	0.49	-0.03	0.38	0.01	0.25
Clay	Lily	0.05	0.40	0.03	0.22	0.08	0.56	-0.01	0.10
Clay	Little Crystal	0.04	0.60	0.02	0.30	0.04	0.34	-0.03	0.35

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Clay	Little Johnson	0.04[x]	0.73	0.07[x]	0.83	0.05	0.58	-0.07	0.54
Clay	Sheelar	0.05[x]	0.92	0.1[x]	0.91	0.12[x]	0.78	-0.05[x]	0.82
Flagler	Disston	0.03[x]	0.80	0.03[x]	0.79	-0.03	0.18	-0.01	0.09
Flagler	Ribbon North	0.02	0.58	0.01	0.38	0.06	0.52	-0.02	0.26
Gadsden	Tallavana	0.11[x]	0.88	0.08[x]	0.93	0.09[x]	0.82	-0.07[x]	0.89
Highlands	Charlotte	-0.003	0.07	0.04[x]	0.88	0.007	0.07	-0.06[x]	0.89
Highlands	Clay	0.003	0.01	0.01	0.41	-0.01	0.08	-0.01	0.14
Highlands	Francis	0	0	0.02	0.61	-0.005	0.03	0.002	0.01
Highlands	Grassy	0.04[x]	0.72	0.02	0.51	0.04	0.21	-0.02	0.13
Highlands	Huntley	-0.03[x]	0.77	-0.002	0.01	-0.11[x]	0.97	0.05[x]	0.90
Highlands	Jackson	0.02	0.16	0.01	0.22	0.03	0.09	0.02	0.31
Highlands	Josephine East	0.01	0.11	0.002	0.01	-0.008	0.08	-0.04[x]	0.86
Highlands	June	0.02	0.34	0	0	-0.02	0.25	0	0
Highlands	Lillian	-0.02	0.11	0.06[x]	0.84	-0.03	0.21	0.02	0.30
Highlands	Little Jackson	-0.001	0	0.01[x]	0.82	0.02	0.12	-0.04[x]	0.76
Highlands	Persimmon	-0.01[x]	0.85	-0.03[x]	0.81	-0.02	0.60	0.01	0.31
Highlands	Placid	0.01	0.22	0.01	0.23	0.01	0.14	-0.008	0.08
Highlands	Red Beach	0.02	0.48	0.02	0.37	0.002	0	-0.02	0.61
Highlands	Redwater	0.03	0.38	0.02	0.07	0.03	0.25	-0.05	0.33
Highlands	Sebring	-0.01	0.10	-0.01	0.26	-0.07[x]	0.83	0.03	0.35
Hillsborough	Armistead	0.05	0.60	0.02	0.46	0.09	0.54	-0.02	0.20
Hillsborough	Brant	0.01	0.02	-0.02	0.08	0.006	0	-0.01	0.03
Hillsborough	Carroll	0.02	0.33	-0.004	0.17	-0.03	0.17	0.02	0.25

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Hillsborough	Crenshaw	0.001	0	-0.006	0.06	-0.02	0.03	0.004	0.01
Hillsborough	Dead Lady	0.03	0.36	0.002	0.01	-0.009	0.01	-0.005	0.09
Hillsborough	Hiawatha	0.03	0.53	0.009	0.15	0.01	0.05	-0.03	0.57
Hillsborough	Hobbs	0.08^{x}	0.81	0.08^{x}	0.78	0.12	0.64	-0.07^{x}	0.87
Hillsborough	James	-0.01	0.04	-0.01	0.08	-0.05	0.42	-0.02	0.08
Hillsborough	Juanita	0.07^{x}	0.70	0.04	0.59	0.12^{x}	0.67	-0.07^{x}	0.92
Hillsborough	Keystone	0.03	0.55	0.02	0.43	0.04	0.34	-0.04	0.46
Hillsborough	Magdalene	0.02	0.21	0.01	0.41	-0.001	0	-0.003	0.01
Hillsborough	Wilson	0.04	0.57	-0.002	0.12	-0.01	0.40	-0.02	0.31
Lake	Beauclaire	-0.06^{x}	0.77	-0.006	0.03	-0.01	0.02	-0.006	0.04
Lake	Cherry	0.05	0.64	0.08^{x}	0.72	0.09^{x}	0.93	-0.13^{x}	0.81
Lake	Crooked	-0.04	0.48	-0.02	0.12	-0.04	0.38	0.04	0.64
Lake	Dora East	-0.06	0.62	-0.01	0.20	-0.03	0.29	.	.
Lake	Dora West	-0.04	0.44	-0.01	0.27	-0.02	0.23	.	.
Lake	Dorr	0.006	0.06	0.03^{x}	0.76	-0.03	0.48	0.001	0
Lake	East Crooked	0.02	0.44	-0.03^{x}	0.80	-0.006	0.51	-0.005	0
Lake	Emma	0.06	0.65	0.06	0.55	0.04	0.56	-0.11^{x}	0.66
Lake	Eustis	0.002	0.02	0.0003	0	-0.03	0.45	0.008	0.02
Lake	Gertrude	0.07^{x}	0.90	0.004	0.08	-0.05	0.63	-0.01	0.65
Lake	Grasshopper	0.07^{x}	0.78	0.04	0.65	0.03	0.20	-0.05	0.39
Lake	Griffin	-0.03	0.49	-0.008	0.09	-0.03	0.19	0.004	0.01
Lake	Harris	0.01	0.13	-0.01	0.13	-0.06	0.59	0.02	0.19
Lake	Joanna	0.009	0.25	0.03^{x}	0.82	0.01	0.08	0.01	0.36
Lake	Little Harris	0.02	0.22	-0.001	0	-0.006	0.01	-0.02	0.14
Lake	Lorraine	-0.09^{x}	0.91	-0.05^{x}	0.87	-0.14^{x}	0.79	.	.

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Lake	May	0.02	0.46	0.01	0.17	0.07[x]	0.93	-0.02	0.41
Lake	Minneola	0.12[x]	0.84	0.1[x]	0.73	0.09	0.54	-0.1	0.65
Lake	Peanut Pond	-0.03	0.48	0.001	0	-0.06	0.57	0.02	0.46
Lake	Picciola	-0.03	0.35	-0.02	0.16	-0.05	0.22	0.01	0.05
Lake	Sellers	0.08[x]	0.80	0.13[x]	0.77	0.09[x]	0.77	.	.
Lake	Trout	0.04	0.40	0.04[x]	0.76	-0.04	0.12	-0.07[x]	0.79
Lake	Unity	-0.005	0.10	0.02	0.37	0.04	0.32	-0.02	0.55
Lake	Yale	0.09[x]	0.71	0.08[x]	0.89	0.18[x]	0.74	-0.12[x]	0.68
Lee	Little Murex	-0.02[x]	0.79	-0.04[x]	0.73	0.003	0.02	0.01	0.11
Leon	Arrowhead	0.02	0.23	0.06[x]	0.69	0.08	0.43	-0.01	0.03
Leon	Blairstone	0.006	0.01	0.008	0.01	-0.02	0.03	0.01	0.10
Leon	Blue Heron	0	0.03	-0.004	0.01	-0.09	0.46	0.02	0.17
Leon	Bradford	0.06[x]	0.66	0.03[x]	0.76	0.06[x]	0.67	-0.06[x]	0.89
Leon	Diane	-0.03	0.22	0.01	0.15	0.005	0	0.03	0.18
Leon	Hall	-0.03	0.49	-0.007	0.08	-0.11[x]	0.73	0	0
Leon	Hiawatha	0.05	0.61	0.04[x]	0.68	0.04	0.40	-0.02	0.18
Leon	Minniehaha	0.02	0.56	0.03	0.58	0.007	0.04	0.008	0.02
Leon	Monkey Business	0.002	0	0.03[x]	0.72	-0.03	0.11	-0.02	0.16
Leon	Overstreet	0.07[x]	0.89	0.05[x]	0.91	0.08[x]	0.85	-0.02	0.40
Leon	Petty Gulf	-0.007	0.10	0.01	0.06	-0.02	0.10	-0.007	0.02
Leon	Pine Hill	0.02	0.64	0.03[x]	0.77	0.05[x]	0.87	-0.03[x]	0.69
Marion	Charles	0.04	0.32	0.04[x]	0.76	-0.003	0.00	-0.006	0.09
Marion	Deerback	-0.008	0.06	0	0	-0.03	0.29	-0.01	0.12
Marion	Eaton	0.03	0.13	0.01	0.17	-0.001	0	0	0
Marion	Halfmoon	-0.0005	0	0.03[x]	0.69	-0.02	0.61	0.005	0.03

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Marion	Sunset Harbor	0.02	0.58	-0.004	0.03	0.007	0.14	-0.002	0.01
Marion	Weir	0.02	0.39	0.009	0.25	0.01	0.59	-0.02	0.34
Orange	Adair	-0.07	0.41	-0.02	0.49	-0.04	0.17	0.05	0.30
Orange	Bay	-0.01	0.08	0.02	0.53	0.03	0.15	-0.03	0.28
Orange	Bennett	-0.004	0.05	-0.02^{x}	0.69	-0.02	0.06	-0.005	0.01
Orange	Bessie	0.04^{x}	0.73	0.04^{x}	0.71	0.09^{x}	0.67	-0.05^{x}	0.75
Orange	Burkett	-0.008	0.07	0.006	0.03	-0.03	0.41	-0.03^{x}	0.79
Orange	Conway North	-0.005	0.04	-0.02	0.52	-0.11^{x}	0.92	0.04^{x}	0.96
Orange	Conway South	-0.004	0.05	-0.002	0.01	-0.06	0.34	0.02	0.30
Orange	Down	-0.001	0	-0.008	0.41	-0.04	0.40	0.03	0.59
Orange	Eola	-0.001	0	-0.001	0	-0.02	0.08	0.003	0.01
Orange	Estelle	0.001	0	0.002	0.01	0.004	0.02	0.03	0.53
Orange	Farrar	0.001	0.01	-0.003	0	-0.0005	0	-0.002	0.01
Orange	Formosa	-0.03	0.45	-0.01	0.20	-0.03	0.48	0.04	0.64
Orange	Georgia	0.03	0.45	0.02	0.32	0.03	0.27	-0.03	0.64
Orange	Giles	0.008	0.36	0.006	0.04	0.02	0.32	-0.02	0.60
Orange	Hickorynut	0.06^{x}	0.66	-0.03	0.29	0.12^{x}	0.75	-0.08^{x}	0.78
Orange	Holden	-0.08^{x}	0.86	-0.03	0.36	-0.1^{x}	0.68	0.06^{x}	0.69
Orange	Ivanhoe East	-0.05^{x}	0.79	-0.03	0.61	-0.1^{x}	0.77	0.08^{x}	0.76
Orange	Ivanhoe Middle	-0.03^{x}	0.78	-0.001	0	-0.04^{x}	0.80	0.03^{x}	0.73
Orange	Ivanhoe West	-0.05^{x}	0.79	-0.007	0.10	-0.09^{x}	0.73	0.08^{x}	0.87
Orange	John's	0.04	0.26	0.007	0.07	0.1^{x}	0.67	-0.04	0.33
Orange	Little Fairview	-0.05^{x}	0.77	-0.03^{x}	0.84	-0.11	0.55	0.09	0.64
Orange	Little Hickorynut	0.06^{x}	0.78	0.03^{x}	0.77	0.11^{x}	0.88	-0.07^{x}	0.92
Orange	Lurna	-0.03	0.28	-0.01	0.27	-0.04	0.25	0.02	0.17

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Orange	Marsha	0.02	0.25	0.02	0.62	0.05	0.40	-0.03	0.60
Orange	Mary Jane	0.05ˣ	0.82	0.02	0.41	0.04ˣ	0.72	-0.02	0.29
Orange	Minnehaha	-0.01	0.27	0.01	0.20	-0.01	0.04	0.003	0
Orange	Moxie	-0.01	0.14	-0.02	0.32	-0.02	0.02	-0.01	0.03
Orange	North Lotta	-0.03	0.36	-0.01	0.27	0.02	0.26	-0.02	0.35
Orange	Ola	0.01	0.30	0.02ˣ	0.74	0.04	0.58	.	.
Orange	Olympia	0.006	0.07	-0.02	0.37	-0.05ˣ	0.75	0.02	0.18
Orange	Peach	0.005	0.02	-0.03ˣ	0.74	-0.03	0.05	0.006	0.02
Orange	Porter	-0.01	0.10	-0.03ˣ	0.78	-0.002	0	-0.006	0.01
Orange	Primavista	-0.02	0.60	-0.04ˣ	0.86	-0.03	0.54	0.01	0.21
Orange	Rowena	-0.03	0.52	-0.002	0.02	-0.04	0.64	0.04	0.55
Orange	Sarah	-0.01	0.15	-0.02	0.32	-0.11	0.63	.	.
Orange	Shannon	.	.	-0.01	0.20	-0.02	0.06	0.03	0.56
Orange	South Lotta	-0.02	0.19	-0.006	0.11	0.03ˣ	0.68	-0.02	0.37
Orange	Spring	0.02ˣ	0.75	-0.01	0.27	0.006	0	-0.03	0.42
Orange	Starke	-0.02ˣ	0.83	-0.02	0.56	-0.04	0.65	0.03	0.50
Orange	Susannah	-0.03	0.48	-0.04	0.51	-0.1	0.52	0.06	0.43
Orange	Waunatta	0.02	0.62	0.05ˣ	0.79	0.11ˣ	0.73	-0.05ˣ	0.87
Orange	Willis	-0.01	0.10	-0.001	0.01	0.03	0.14	-0.006	0.05
Osceola	Alligator	0.04ˣ	0.81	0.03	0.43	0.007	0.04	-0.05ˣ	0.82
Osceola	Brick	0.06ˣ	0.73	0.04	0.60	0.01	0.13	-0.01	0.32
Osceola	Center	0.01	0.04	0.04	0.60	0.02	0.07	-0.02	0.17
Osceola	Coon	0	0	0.02	0.27	0.004	0.01	0.02	0.43
Osceola	Kissimmee	0.03	0.54	0.02ˣ	0.67	0.05	0.45	-0.02	0.53
Osceola	Lizzie	0.02	0.39	0.03	0.33	0.01	0.15	-0.04	0.56

Table 3-5. Continued

County	Lake	L_{10}TP Slope	L_{10}TP R^2	L_{10}TN Slope	L_{10}TN R^2	L_{10}CHL Slope	L_{10}CHL R^2	L_{10}SD Slope	L_{10}SD R^2
Osceola	Trout	0.01	0.07	0.02	0.32	-0.02	0.23	-0.004	0.01
Polk	Big Bass	0.01	0.11	0.04^{x}	0.69	0.05	0.57	-0.06^{x}	0.78
Polk	Blue North	0.08^{x}	0.66	-0.09^{x}	0.81	0.09	0.50	-0.08^{x}	0.69
Polk	Boca Cove	0.01	0.10	0.03^{x}	0.72	0.04	0.52	-0.06^{x}	0.78
Polk	Dexter	0.03^{x}	0.80	-0.002	0.02	0.002	0.01	0	0
Polk	Fauna	0.08^{x}	0.86	-0.002	0	-0.03	0.29	-0.02	0.26
Polk	Flora	-0.009	0.06	0.02	0.63	0.03	0.55	-0.05^{x}	0.68
Polk	Gaskin's Cut	0.01	0.10	0.03	0.61	0.04	0.39	-0.05^{x}	0.70
Polk	Little Bass	0.02	0.14	0.04	0.60	0.05	0.46	-0.06^{x}	0.75
Polk	Weohyakapka	0.05	0.64	0.04^{x}	0.87	0.08	0.53	-0.07^{x}	0.83
Putnam	Blue	-0.003	0	0.06	0.56	-0.02	0.06	0.02	0.14
Putnam	Broward	0.04^{x}	0.69	0.04^{x}	0.82	0.04	0.42	0.005	0.12
Putnam	Chipco	0.003	0.01	0.04	0.65	-0.02	0.15	0	0
Putnam	Como	0.06^{x}	0.76	0.06^{x}	0.67	0.02	0.09	.	.
Putnam	Cowpen	0.08^{x}	0.77	0.07^{x}	0.80	-0.02	0.06	-0.03	0.40
Putnam	Fanny	0.02	0.14	0.03	0.22	-0.03	0.14	0.02	0.18
Putnam	Gillis	0.005	0.02	0.04	0.22	0.02	0.23	-0.004	0.01
Putnam	Higgenbotham	0.003	0.03	0.001	0	-0.06^{x}	0.86	-0.006	0.04
Putnam	McMeekin	-0.02^{x}	0.75	0.006	0.19	-0.06	0.50	0.02	0.25
Putnam	Punchbowl	0.04^{x}	0.81	0.02	0.50	0.04	0.27	-0.04	0.59
Putnam	Riley	0.06^{x}	0.78	0.06^{x}	0.86	0.06	0.44	-0.02	0.48
Putnam	Rosa	0.002	0.01	0.05^{x}	0.85	-0.08	0.39	-0.01	0.32
Putnam	Star	0.03	0.35	0.03^{x}	0.70	-0.004	0.02	-0.02	0.36
Putnam	Winnott	0.06^{x}	0.84	0.04^{x}	0.91	0.07^{x}	0.94	-0.07^{x}	0.96
Seminole	Adelaide	0.02	0.35	0.02	0.21	0.02	0.12	-0.04^{x}	0.73

Table 3-5. Continued

County	Lake	$L_{10}TP$ Slope	$L_{10}TP$ R^2	$L_{10}TN$ Slope	$L_{10}TN$ R^2	$L_{10}CHL$ Slope	$L_{10}CHL$ R^2	$L_{10}SD$ Slope	$L_{10}SD$ R^2
Seminole	Bear	-0.002	0.01	0.04^{x}	0.90	0.05	0.60	-0.03	0.44
Seminole	Florida	-0.03	0.40	0.01	0.14	0.03	0.05	-0.03	0.40
Seminole	Little Bear	0.02	0.47	0.04^{x}	0.74	0.05	0.28	-0.04	0.36
Seminole	Mary	0.03	0.55	0.02	0.56	-0.04	0.25	-0.02	0.46
Seminole	Orienta 1	-0.003	0.01	0.001	0	-0.01	0.06	-0.03	0.26
Seminole	Orienta 2	-0.01	0.13	-0.004	0.01	-0.02	0.22	-0.02	0.11
Seminole	Rock	0.04^{x}	0.93	0.02^{x}	0.90	0.03	0.30	-0.08^{x}	0.96
Seminole	Seminary	0.01	0.53	0.02^{x}	0.74	0.006	0.02	-0.01	0.22
Seminole	Spring	-0.04^{x}	0.88	-0.05^{x}	0.90	-0.12^{x}	0.88	0.09^{x}	0.79
Seminole	Woods	-0.02	0.64	-0.01	0.16	-0.04^{x}	0.83	0	0.00
St Lucie	Margaret	0.01	0.10	0.05	0.39	0.03	0.39	-0.03	0.66
Sumter	Panasoffkee	0.08	0.61	0.04^{x}	0.78	0.08	0.55	-0.02^{x}	0.83
Volusia	Ashby	0.02	0.18	0.03^{x}	0.90	0.03	0.34	-0.03	0.56
Volusia	Beresford	0.002	0.01	-0.01	0.43	-0.01	0.15	-0.01^{x}	0.75
Volusia	Bethel	-0.02^{x}	0.80	0.02	0.21	0.07	0.45	-0.07	0.58
Volusia	Broken Arrow	0.06^{x}	0.66	0.04	0.40	0.11^{x}	0.71	.	.
Volusia	Charles	0.06^{x}	0.88	0.06^{x}	0.88	0.06	0.60	-0.07^{x}	0.91
Volusia	Harney	0.05	0.34	0.01	0.15	-0.01	0.01	-0.03	0.22
Volusia	Winnemissett	0.05^{x}	0.68	0.02	0.23	0.05	0.46	-0.02	0.11
Walton	Camp Creek	0.03	0.44	0.006	0.13	-0.003	0	-0.006	0.10
Walton	Spring	-0.003	0.02	-0.02	0.49	-0.01	0.06	0.03	0.52

Table 3-6. Number of lakes (no. of lakes) out of the examined annual mean data for 193 Florida lakes with: 1) decadal-scale increasing trends in total phosphorus (TP), total nitrogen (TN), and chlorophyll concentrations (CHL) and decreasing trends in water clarity measurements (SD) and 2) decadal-scale decreasing trends in total phosphorus (TP), total nitrogen (TN),and chlorophyll concentrations (CHL), and increasing trends in water clarity measurements (SD), and 3) no trend in any of the four trophic state variables.

No. of Lakes	Trend	No. of Lakes	Trend	No. of Lakes	Trend	No. of Lakes	Trend
9	Increase TP, TN, CHL	3	Increase TP, TN	8	Increase TP, TN	11	Increase TP
	Decrease SD		Decrease SD	2	Increase TP, CHL	17	Increase TN
		2	Increase TP, CHL	1	Increase TP	3	Increase CHL
			Decrease SD		Decrease SD	9	Decrease SD
		3	Increase TN, CHL	7	Increase TN		
			Decrease SD		Decrease SD		
2	Decrease TP, TN, CHL	5	Decrease TP, CHL	3	Decrease TP, TN	4	Decrease TP
	Increase SD		Increase SD	1	Decrease CHL	5	Decrease TN
					Increase SD	5	Decrease SD
88	No Trend						

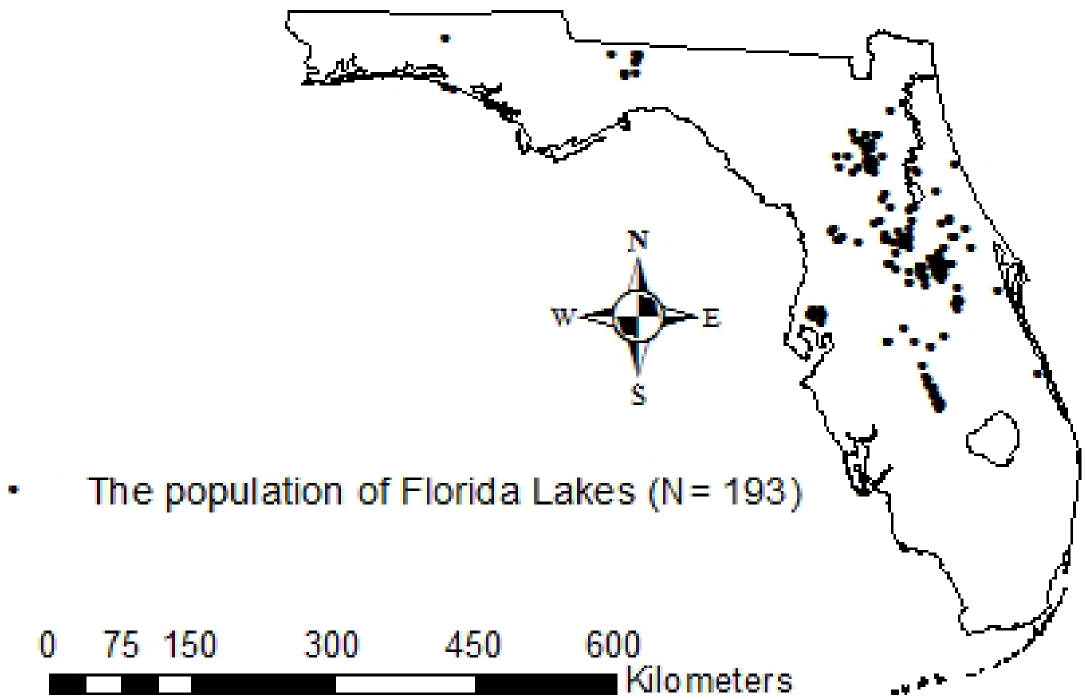


Figure 3-1. Distribution of the examined population of 193 Florida lakes.

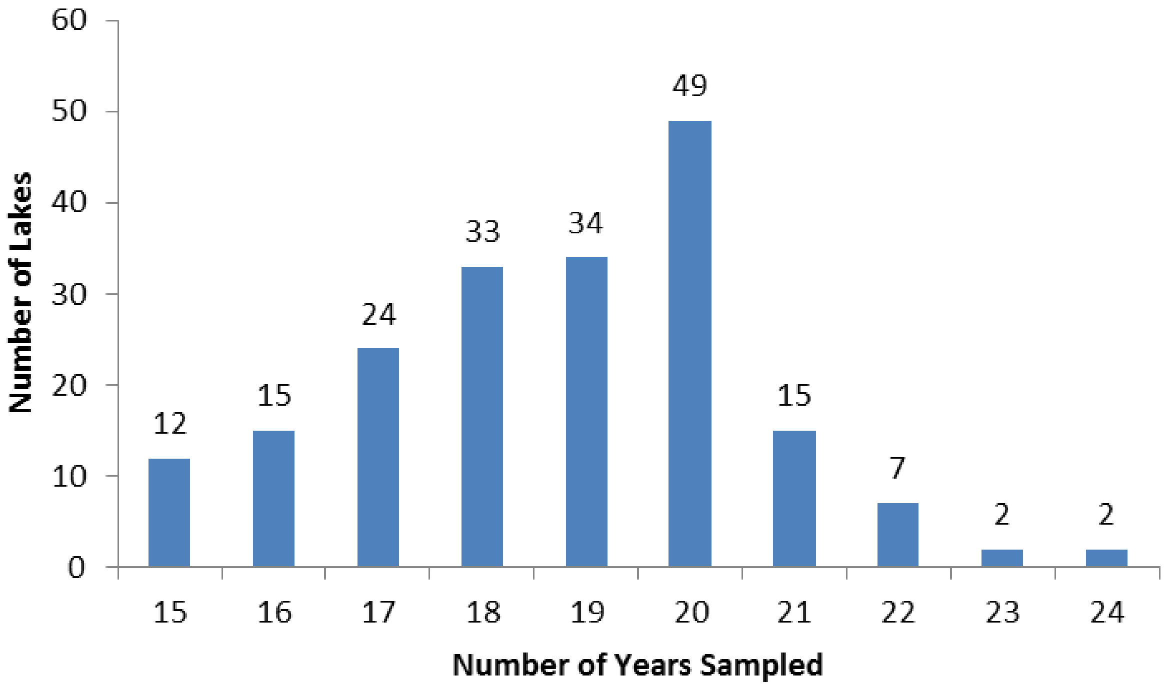


Figure 3-2. Number of years each lake was sampled (N=193 Florida lakes). The numbers above the bars denote the number of lakes that were sampled for the respective number of years.

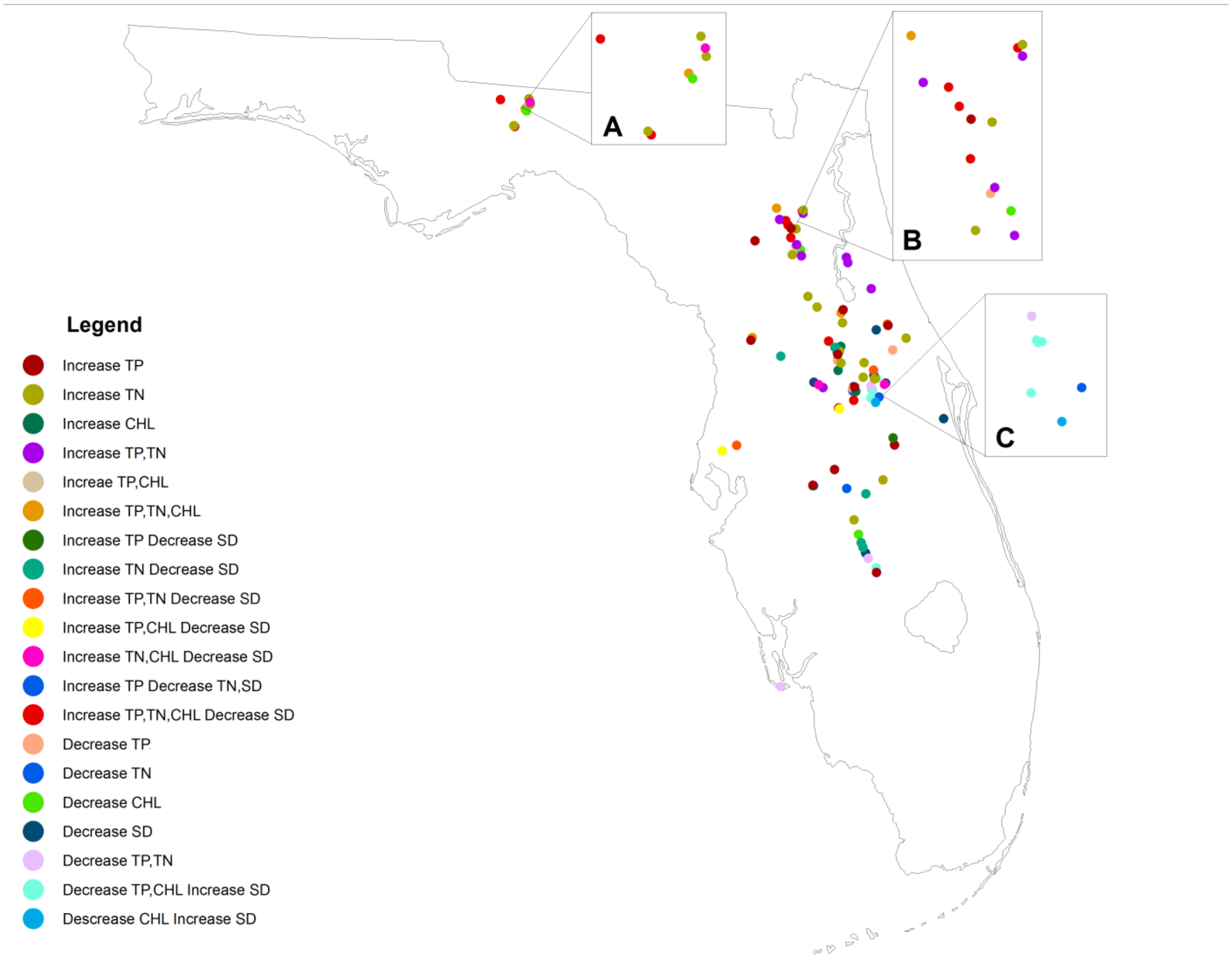


Figure 3-3. Florida lakes (N=105 lakes) with detected decadal-scale trends of degradation (i.e., increases in total phosphorus (TP), total nitrogen (TN), and chlorophyll concentrations (CHL) and decreases in water clarity (SD) measurements, and trends of improvement (i.e., decreases in TP, TN, and CHL concentrations and increases in SD). Spatial clusters of individual lakes exhibiting similar trends of degradation in one or more of the examined variables were identified (A and B) and a spatial cluster of lakes exhibiting similar trends of improvement in one or more of the variables were identified (C).

CHAPTER 4
SEASONAL PATTERNS OF PHYTOPLANKTON BIOMASS AND RESPONSES TO CLIMATE IN SUBTROPICAL, FLORIDA LAKES

Background

Primary production occurs across the biosphere following annual cycles of growth and senescence driven by the climatic system. Lake ecosystems are particularly sensitive to climate-related changes and many recent lake studies have focused on the examination of response variables like water temperature, dissolved organic carbon, or planktonic composition as indicators of climate changes (Williamson et al. 2009; Adrian et al. 2009). Phytoplankton biomass, in particular, is projected to increase (Kernan et al. 2012; Jeppesen et al. 2007a, 2010) with continuing trends of changes in climate (Mann et al. 1998, Magnuson et al. 2000, IPCC 2007). Yet, some scientists argue projections related to a changing climate do not account for the role of natural variability (Battarbee 2010). Seasonal patterns in phytoplankton biomass, which are naturally driven by climate at both a local and global-scale, are many times disregarded or the seasonal variability is even removed prior to data analyses (Bendat and Piersol 2010). The absence of identifying seasonal variability and understanding how these seasonal patterns vary among regions could have major consequences in the interpretation of linkages in phytoplankton biomass to climate.

Recurrent (i.e., how phytoplankton biomass compare from year to year) and synchronous (i.e., how phytoplankton biomass compare at a given time within a year) seasonal patterns (Clocern and Jassby 2008) have been well documented in temperate lakes. The seasonal pattern of phytoplankton in temperate lakes is generally defined by a distinct spring bloom followed by a summer depression, a subsequent fall bloom, and low levels through the winter months (Hutchinson 1967; Marshall and Peters 1989). The seasonal patterns observed in temperate lakes, however, do not necessarily reflect the annual cycles of phytoplankton biomass in all lakes. Comparatively, subtropical lakes are located at lower latitudes and sustain longer periods of warmer water temperatures. Generally, subtropical lakes are shallow in depth (i.e., < 3m), experience temporary thermal stratification, and have short water residence times (Lewis 1973; Scheffer 1998). Also, subtropical lakes do not have a period of winter ice cover as do the temperate lakes (Bachmann et al. 2012c). High levels of phytoplankton biomass experienced in subtropical lakes; therefore, would extend greater in duration over an annual cycle compared to temperate lakes. Moss (1973) determined the optimal temperature for phytoplankton growth was 23 C and above. There are many months of the year where subtropical lakes experience temperatures 23 C and greater supporting the postulation that subtropical lakes experience longer periods of high phytoplankton biomass annually compared to temperature lakes.

There is limited documentation of seasonal patterns of phytoplankton biomass in subtropical lakes (Brown et al. 1998), restricting ability to compare seasonal patterns of phytoplankton biomass across changes in latitude and longitude. The range in latitude affects phytoplankton biomass at the large-scale (e.g., across North America), especially as latitude is linked to variation in local climate conditions (Brylinsky and Mann 1973). Similarly, phytoplankton biomass (as measured by chlorophyll concentrations) vary with longitude (Soranno et al. 1999). The influence of differences in climate, associated with changes in latitude and longitude, on levels of phytoplankton biomass has not been thoroughly explored in the literature, but offers an opportunity to understand the latitude and longitudinal differences observed in phytoplankton biomass. The identification of recurrent and synchronous seasonal patterns in phytoplankton biomass in subtropical lakes facilitates the ability to explore contrasting seasonal patterns at the large-scale, across changes in both latitude and longitude.

Water is a dynamic entity, marked my measurable changes in the biology, chemistry, and physical aspects that fluctuate within a year and among years. To understand these changes, limnologists frequently classify waters. Classification by lake trophic state category is commonly used to encompass the continuum of movement towards a more biologically productive system (Carlson 1977). Chlorophyll concentrations are often used as a proxy for phytoplankton biomass (Canfield et al. 1985) and to summarize lake trophic conditions (Forsburg and Ryding 1980). There is a strong, positive relationship between chlorophyll concentrations and inter-annual variance (Knowlton et al. 1984); therefore, seasonal variation in chlorophyll concentrations has been suggested to be greater in more eutrophic or biologically rich lakes (Marshall and Peters 1989; Brown et al. 1998). Generally, the range of chlorophyll values per lake trophic state categorization (Forsburg and Ryding 1980) is smaller in temperate lakes (Marshall and Peters 1989) compared to subtropical lakes that include the whole range of chlorophyll values within a trophic category (e.g., chlorophyll concentrations of 7- 40 µg/L for eutrophic classifications). Classifying trophic state categories using the annual mean (i.e., referred to as lake-year), versus a mean value per individual lake, captures a wider range of chlorophyll values within each trophic state category and also reflects the change waters experience year to year.

The study objectives were to evaluate seasonal patterns of phytoplankton biomass or chlorophyll variability to 1) identify recurrent and synchronous seasonal patterns, 2) determine whether seasonal patterns differ among waters classified by trophic state category, 3) examine the influence of the climatic factors, temperature and rainfall, on seasonal patterns of phytoplankton biomass, and 4) determine if the frequency of occurrence of extreme chlorophyll events has changed over the years of record.

Methods

Datasets

Two datasets were used in this chapter. The first dataset included continuous monthly chlorophyll concentrations (January to December) for 27 Florida lakes. The 27 Florida lakes were obtained from the Florida LAKEWATCH database and ranged in record from 20 to 24 years. The second dataset, which included monthly chlorophyll concentrations for 193 Florida lakes ranging in record from 15 to 24 years, was also obtained from the Florida LAKEWATCH database. The 27-lake database was used for all analyses presented in this chapter. The 193-lake database was used only to compare seasonal patterns in chlorophyll concentrations to the 27-lake database. The 193-lake database was not selected for use in other analyses because there were missing monthly data and the major objective of the chapter was to understand inter- and intra-seasonal patterns among the years of record. The examined 27 lakes provided a representative subset of Florida lakes that ranged in chlorophyll concentrations (Table 4-1); therefore, the 27-lake dataset provided enhanced analyses of seasonal patterns in subtropical lakes. The analytical methods for chlorophyll, for both the 27-lake and 193-lake datasets, did not correct for pheophytins; therefore, the estimates of chlorophyll were considered total chlorophyll concentrations (Canfield et al. 2002). Both the Florida LAKEWATCH sampling and chlorophyll analytical methods were consistent over time (Canfield et al. 2002). Total chlorophyll concentrations (µg/L) were used to estimate phytoplankton biomass.

Approach to Identify Seasonal Patterns in Phytoplankton Biomass

Although there are many ways to identify seasonal patterns in phytoplankton biomass (Clocern and Jassby 2008), three approaches were used. The first approach examined the variability attributed to season by ARMA/ARIMA time series model analysis. The second approach identified the month in which maximum chlorophyll values occurred each year, a common approach used to understand seasonal patterns across ecological systems; subtropical lakes (Brown et al. 1998), temporal lakes (Marshall and Peters 1989), coastal and pelagic oceanic systems (Clocern and Jassby 2008), and terrestrial vegetation systems (Myneni et al. 1998). The third approach identified the number of extreme chlorophyll events that occurred each month within each year of examination. Extreme events included elevated chlorophyll concentrations and did not include low extreme chlorophyll values because a component of the chapter was to identify whether climate-related factors increased chlorophyll concentrations in subtropical lakes.

The three approaches used to identify seasonal patterns were also completed categorizing waters by the annual mean chlorophyll concentration into the trophic state categories outlined by Forsburg and Ryding (1980). The trophic state classification by the annual mean chlorophyll concentration was referred to as lake-year. Trophic state classification of waters by lake-year allowed an estimate of changes in chlorophyll concentrations by trophic category both within and among years.

Statistical Analyses

The JMP software (version 8.0)was used for all statistical analyses (SAS 2007) and all statements of statistical significance were determined at a probability of < 0.05. Monthly chlorophyll means were determined by averaging the three, open-water stations sampled by Florida LAKEWATCH on the same day for the individual month. Annual chlorophyll means were determined by averaging the 12 monthly means. The data were evenly distributed throughout the year as each of the 27 lakes had 12 consecutive months of chlorophyll data per year for 20-plus years. There were a few missing values due to restricted sampling. In such cases, a missing monthly datum was replaced by the calculated mean from the month prior and following the missing datum. For the 193-lake dataset, the number of missing datum was great; therefore, the data presented include missing monthly datum. Chlorophyll concentrations were not normally distributed for the 27 Florida lakes or the majority of the 193 Florida lakes (KSL Goodness-of-Fit Test). Because the goal of the paper was to examine patterns in seasonal variability, logarithmic transformations were not completed unless required for statistical analysis (i.e., ARMA/ARIMA time series modeling).

Identification of seasonal patterns was completed using the three outlined approaches. The goal of the first approach was to identify seasonal patterns from examination of the variance that attributed to season and removed prior to application of ARMA/ARIMA time series model analysis. Time series models identify variance that is attributed to a seasonal component and display this variance through a plot called a spectral density plot. The spectral density plot represents a function of the period and frequency of the chlorophyll concentrations with the integral of the plot equal to the variance exhibited by the examined variable over the entire period of record (i.e., 240-

252 total chlorophyll observations for each individual Florida lake). Time series models must meet the requirements of parametric statistics, so logarithmic transformed (base 10) chlorophyll concentrations were used in this analysis (Snedecor and Cochran 1980). To determine whether the chlorophyll variance had a periodic component (i.e., the variance was attributed to season), the Fisher's Kappa Statistic was used to test the null hypothesis that the data were from a normal distribution (JMP 2007). If the Fisher's Kappa Statistic showed there was a period component in the variance of the chlorophyll concentrations, the spectral density plot was additionally examined to visually determine if the variance was attributed to season. A peak at 12 (i.e., 12 months) indicated the variance in the chlorophyll data series was attributed to season. Typically, the variance identified by the spectral density plot of the time series analysis is the variance that is removed prior to ARMA/ARIMA time series model analysis.

The goal of the second approach used to identify seasonal patterns in chlorophyll concentrations was to examine the monthly variance within the individual lake and compared the monthly variances among the years of record. The monthly mean percent (mean %) difference from the annual mean was calculated for the individual lake. Specifically, the monthly mean % differences were determined by subtracting the annual mean value from the monthly mean, dividing this value by the annual mean, and multiplying by 100. A positive % difference indicated the mean chlorophyll concentration for the month was greater than the annual mean for the respective year. A negative % difference indicated the mean chlorophyll concentration for the month was greater than the annual mean for the respective year. The monthly mean % difference was summarized among years and then among the 27 Florida lakes by month. The 95%

confidence intervals were calculated around the monthly mean. A one-way analysis of variance was used (the residuals for each lake were homoscedastic) to determine whether a significant difference existed among the mean % difference among the months of the year using the summarized data for the 27 Florida lakes.

The goal of the third approach used to identify seasonal patterns was to evaluate the frequency of occurrence of extreme chlorophyll values. Extreme chlorophyll values were defined as 1) the maximum chlorophyll value that occurred in each month of each year of record and 2) a mean chlorophyll value that exceeded the grand mean by double in value for each month and year of record. The frequency of occurrence of the maximum chlorophyll values and the frequency of occurrence of the chlorophyll values exceeding the grand mean by double were summarized by month among years for the 27 Florida lakes (Brown et al. 1998). Histograms illustrating the frequency of occurrence of the maximum chlorophyll values and the chlorophyll values exceeding the grand mean by double were generated to identify the months with a higher probability of experiencing extreme chlorophyll values, respectively.

Due to the continuous and lengthy record of the examined dataset, more extreme chlorophyll concentrations were likely captured. Pareto distributions (Pareto 1897) were used to describe whether there was a change in the occurrence of extreme chlorophyll events over the 20 plus-year record of examination. Pareto distributions, which have great potential to describe a wide range of aquatic variables (Vidondo et al. 1997), use a semi-logarithmic (base 10) plot where the slope of the regression line corresponds to the probability function. The percent number of records greater than x (the corresponding chlorophyll concentration) represented the dependent variable and was plotted against the corresponding logarithmic (base 10) chlorophyll value (x) that represented the independent variable. Linear regression analysis was fit to these data and the slope value determined. The slope value was determined for every year of record for the individual 27 Florida lakes. The annual slope values were plotted against the corresponding year and linear regression analysis was used to determine whether there was a trend in the slope values over the examined period of record for the individual lake. If linear regression analysis indicated a significant increasing trend in the annual slope values, then it was concluded that there was an increase in the frequency of occurrence of extreme chlorophyll concentrations over the examined period of record. If linear regression analysis of the annual slope values indicated a significant decreasing trend, then it was concluded that there was a decrease in the frequency of occurrence of extreme chlorophyll concentrations over the examined period of record.

Climate Relationships

In-lake water temperature data (i.e., monthly or annual data) were not available for the examined Florida lakes. Water temperatures have been correlated with air temperatures across Florida lakes (Coenen 2005); therefore, air temperature data were used. Monthly mean air temperature data were obtained from the Florida Climate Center (http://climatecenter.fsu.edu/) with the closet location of collection to the individual lake. The long-term mean (i.e., 24-year period), and the associated 95% confidence intervals, were calculated among the 27 Florida lakes for each month of the year. The 24-year period corresponded to the longest record of trophic state variable collection and used to make consistent water temperature comparisons among the 27 Florida lakes. The long-term monthly means were determined monthly to examine the relationship with the monthly mean chlorophyll concentrations among the 27 Florida lakes.

The rainfall data were gathered by the monthly sum of rainfall (cm) and obtained from the Florida Climate Center using the closest location of collection to the individual lake. The sum of rainfall data obtained matched the month of trophic state variable collection for the individual, 27 Florida lakes. The long-term mean (i.e., the length of years depends on the record for the individual lake) was calculated for the individual lake for each month of the year. The long-term, mean chlorophyll concentration was also calculated for the individual lake for each month of the year. The long-term monthly sum of rainfall and the long-term monthly chlorophyll concentrations were compared for the individual, 27 Florida lakes. Comparisons between temperature and rainfall data were not completed for the 27 Florida lakes because the location of the collection sites for temperature and rainfall data varied for some of the individual 27 Florida lakes.

Results

Magnitude of Phytoplankton Biomass

The chlorophyll concentration database of 27 Florida lakes included 19,836 individual measurements, 6,612 monthly mean measurements, and 551 lake-years, providing a comprehensive inventory of phytoplankton biomass for subtropical Florida lakes. The distribution of the monthly mean chlorophyll concentrations for the 27 Florida lakes ranged three orders of magnitude with 75% of the measurements below 23 µg/L. The distribution of chlorophyll concentrations for the 551 lake-years of chlorophyll data (i.e., annual means) also ranged three orders of magnitude with 75% of the values below 24 µg/L, but the annual maximum chlorophyll values were about half (292 µg/L) that observed among the monthly mean values (436 µg/L).

Variability of Seasonal Patterns across Florida Lakes

Seasonal period components were identified with spectral density analysis in the chlorophyll concentrations for each of the 27 Florida lakes. Seasonal patterns were identified in the chlorophyll variance, which would have been removed prior to ARMA/ARIMA time series modeling, for 21 of the 27 subtropical, Florida lakes (Table 4-3). The seasonal patterns were statistically identified by the Fisher's Kappa Test of variance and also visually identified by a peak (i.e., high variance) of the chlorophyll concentrations at 12 months (Figure 4-1). There were six lakes with no seasonal pattern in the chlorophyll concentration time series, meaning the variance was not statistically different from zero and there was no visual peak at 12 months.

Examination of the mean % difference in monthly chlorophyll concentrations refined identification of seasonal patterns in the variability of chlorophyll concentrations by quantifying monthly changes over an annual cycle (Figure 4-2). The monthly mean % difference among the 27 Florida lakes ranged from -18% (January) to 19% (September). The cooler months (i.e., November through May) had lower chlorophyll concentrations (negative % mean difference), while the warmer months (June through October) had higher chlorophyll concentrations (positive % mean difference). A one-way analysis of variance (ANOVA) with multiple comparisons showed August and September monthly mean % differences were significantly different from all other months of the year among the 27 Florida lakes.

The frequency of occurrence of extreme maximum chlorophyll events provided an alternative detection of seasonal patterns in the variability of chlorophyll concentrations. Among the population of examined Florida lakes, the months with the higher number of maximum chlorophyll events occurred during the months of June through October (Figure 4-3), identical to the months with the positive % mean differences in monthly chlorophyll concentrations. The highest frequency of maximum chlorophyll events occurred in October. The same seasonal pattern was also present among all Florida lakes when chlorophyll concentrations were characterized using a more conservative estimate of an extreme chlorophyll value. The conservative estimate, the frequency of occurrence of chlorophyll values that exceeded the doubling of the grand mean of an individual lake, also showed the higher frequency of events during the months June through October, with September having the highest number of values that exceeded the grand mean by double (Figure 4-3).

Variability of Seasonal Patterns by Lake-year Trophic State Category

The annual seasonal patterns of monthly chlorophyll concentrations were different in hypereutrophic lake-year classifications. Seasonal patterns were evident as positive monthly % mean differences in chlorophyll concentrations occurred during the months of June through October across oligotrophic lake-years classifications (N=79 lake-years), mesotrophic (N=171 lake-years), and eutrophic (N= 197 lake-years) (Figure 4-4 A-C). The seasonal pattern in lake-years classified as oligotrophic, mesotrophic, and eutrophic visually exhibited the same seasonal curve exhibited among the 27 Florida lakes. The monthly % mean differences in chlorophyll concentrations of the hypereutrophic lake-years (N= 104 lake-years) similarly have high chlorophyll concentrations in October, but the annual curve was bimodal with chlorophyll concentrations peaking in April and in October (Figure 4-4 D).

The magnitude of chlorophyll concentrations varied among the lake-year trophic state classifications. The range of monthly % mean difference in oligotrophic lake-years ranged from -16% (February) to 19% (September), from -21% (January) to 26%

(September) in mesotrophic lake-years, from -20% (January) to 23% (August) in eutrophic lake-lakes, and from -12% (January) to 9% (October) in hypereutrophic lake-years. The range of the monthly % mean differences in oligotrophic and hypereutrophic lake-years was smaller than the monthly % mean difference in mesotrophic and eutrophic lake-year classifications. Not only does this result suggest mesotrophic and eutrophic lake-year classifications experience a wider range of chlorophyll concentrations on an annual basis, but also eutrophic lake-year classifications had more months with statistically higher mean % differences in chlorophyll concentrations. Specifically, for oligotrophic, mesotrophic, and the eutrophic lake-years, the mean % differences were above the annual mean during the warmer months of June through October and below the annual mean during the remaining months (Figure 4-4 A-C). The ANOVA and a multiple comparison tests showed the months August and September (oligotrophic), September (mesotrophic), and June, July, August, and September (eutrophic) had mean % difference in chlorophyll significantly different from the other months. The monthly % mean difference in the hypereutrophic lake-years exceeded the annual mean for half the year (i.e., March, April, August, September, October and November) and was below the annual mean for the half the year (i.e., January, February, May, June, July, and December). The ANOVA and multiple comparison tests showed the % mean difference in chlorophyll concentrations in January was significantly less than other months.

The frequency of extreme events, which showed seasonal patterns, also differed across trophic lake-years classifications. The frequency of maximum value extreme events varied annually among months in oligotrophic, mesotrophic, and eutrophic lake-years with the highest frequency of events occurring during the months June through October (Figure 4-5 A and 4-5 B). The month with the highest frequency of maximum chlorophyll events shifted later in the year with a shift towards a more biologically productive system. Specifically, the highest frequency of maximum chlorophyll values occurred in June in oligotrophic lake-years, September in mesotrophic lake-years, and October in eutrophic lake-years (Figure 4-5 A-C). Hypereutrophic lakes did not follow the patterns of the occurrence of extreme chlorophyll events exhibited in the other trophic categories. Instead, the highest frequency of maximum chlorophyll values occurred in April, which exceeded the number of events occurring in any other month by double (Figure 4-5 D).

A similar distinction of seasonal patterns of extreme events was shown when extreme events were defined as the chlorophyll value that exceeded the grand mean by double. Oligotrophic, mesotrophic, and eutrophic lake-years had high frequencies of extreme chlorophyll events during June through October (Figure 4-5 A-C). The month with the highest number of extreme events, exceeding the grand mean by double, differed from the months with the highest number of maximum chlorophyll events (Figure 4-5 A-C). The highest number of extreme events that exceeded the grand mean by double occurred in October in oligotrophic lake-years and in September in mesotrophic and eutrophic lake-years. The frequency of extreme doubling events in hypereutrophic lake-years showed the same pattern as the number of extreme maximum events, with the most extreme events occurring in May (Figure 4-5 D).

Temporal Shifts in the Occurrence of Extreme Chlorophyll Events

The occurrence of extreme chlorophyll events, based on the results of the Pareto analysis, did not change annually over the past two decades in the majority (N= 23 lakes) of the examined Florida lakes (Table 4-2). Neither extended periods of higher phytoplankton biomass nor an increase in extreme chlorophyll events were identified in 23 lakes. However, a significant lessening of the annual slope value across the years of record was determined from the Pareto analysis in three lakes (i.e., lakes Deerback, Harris, Sarah), indicating these three lakes experienced an increase in the occurrence of extreme chlorophyll concentrations over the past two decades. A significant increase in the slope value occurred in one lake (i.e., Lake Lorraine) indicated a decrease in the occurrence of extreme chlorophyll events over the past two decades.

Climate Relationships

Monthly temperature showed the same annual pattern as chlorophyll concentration where months of higher temperature corresponding to months of higher chlorophyll concentrations (i.e., June through October) and the months of lower temperature corresponding to months of lower chlorophyll concentrations (i.e., November through May) (Figure 4-6).

The amount of rainfall was related to seasonal patterns in chlorophyll concentrations with months of higher rainfall corresponded to higher chlorophyll concentrations (i.e., June through October) and months of lower rainfall corresponded to lower chlorophyll concentrations (i.e., November through May). There were some lakes where month(s) of high rainfall were followed by high chlorophyll concentrations 1-3 months thereafter, a lagged effect (Figure 4-7). Overall, among the 27 Florida lakes, there were three groupings of the rainfall-chlorophyll patterns: 1) monthly chlorophyll concentrations either increased with increased monthly rainfall amounts (N= 19 lakes), 2) monthly chlorophyll concentrations decreased with increased monthly rainfall amounts (N=5 lakes), or 3) there was no distinct pattern between monthly chlorophyll and rainfall (N=3 lakes).

Discussion

Seasonal patterns in chlorophyll concentrations, used as an estimate of phytoplankton biomass, followed cycles of phytoplankton biomass growth and senescence that were recurrent from year to year and synchronous across the examined population of subtropical, Florida lakes. The magnitude of chlorophyll concentrations varied among the individual lakes and there was high inter-annual variance around the mean within the individual lake.

There may be some apprehension that a subset of 27 Florida lakes was not representative of subtropical, Florida lakes. Examination of annual seasonal patterns in chlorophyll concentrations using a larger population of 193 subtropical, Florida lakes showed a similar annual seasonal pattern as observed across the 27 Florida lakes (Figure 4-8). The difference in the annual seasonal pattern being the period of higher chlorophyll values (i.e., positive mean % differences) was extended by one month (i.e., June through November) among the population of 193 Florida lakes versus June through October as identified among the population of 27 Florida lakes. The additional month of observed higher chlorophyll concentrations may be due to the expanded geographic range of lakes or an artifact of an unequal dataset. The 193-lake dataset did not have consistent monthly samples or the number of years sampled compared to the 27-lake dataset. The number of years sampled was found to be of greater importance when identifying seasonal patterns. The inter-annual variance around the monthly mean was larger for the population of 193 lakes, yet the range of chlorophyll values observed among the 27 lakes was larger than observed among the 193 lakes. Specifically, the mean coefficient of variation among the 193 lakes was 43% and ranged from 23% to 76% across the lakes, whereas the mean coefficient of variation among the 27 lakes was 33% and ranged from 21% to 84%.

These results suggested that more extreme chlorophyll events were captured with the inclusion of more years of sampling. Therefore, the 27 Florida lakes were not only representative of subtropical, Florida lakes, but also the consistent (i.e., monthly) and lengthy (i.e., greater than 20 years) dataset provided sound identification of seasonal patterns in phytoplankton biomass. Overall, the 193- and 27-lake datasets showed an extended period of phytoplankton growth (i.e., high chlorophyll concentrations) over an annual cycle from July through October.

Understanding the temporal and spatial structure of seasonal variability in the chlorophyll concentrations of subtropical Florida lakes was best described by the annual climate cycle. The climatic influence on seasonal dynamics is well documented in lakes with phytoplankton responses directly linked to changes in solar radiation and temperature (Wetzel 2001). The 27 examined Florida lakes were located in the humid subtropical climate zone (using the Köppen climate zones) characterized by monthly average temperature above 18 C and a rainy season from June through September (Henry 1998). The annual seasonal patterns in the examined lakes reflected the climatic characteristics of the subtropical region with higher phytoplankton biomass persisting over an extended period of the year (i.e., June through October) that closely followed annual mean monthly air temperature (Figure 4-6). Terrestrial plants in Florida have an all year-growing season (USDA 2012), meaning that depending on the plant species, something is always growing in Florida. This idea transfers to aquatic systems as warmer lakes have prolonged growing seasons with a greater probability of prolonged algal blooms, or extreme chlorophyll events (Jeppesen et al. 2007b). In the examined Florida lakes, maximum chlorophyll concentrations were found to occur at any time during the year over the examined period of record. The highest monthly chlorophyll concentrations, however, consistently occurred during the months where the air temperature exceeded 23 C, an ideal temperature for phytoplankton growth (Moss 1973). These months (i.e., air temperature exceeding 23 C) corresponded to months of higher solar radiation, indicating the seasonal patterns in subtropical lakes, like temperate lakes (Wetzel 2001), are driven by annual solar radiation and temperature cycles.

There is contradicting evidence that temperature variation within the State of Florida affects annual seasonal patterns in phytoplankton biomass. Beaver et al. (1998) suggested lake biological processes differ across temperature differences observed in the State of Florida, from north Florida to south Florida (e.g., annual mean maximum temperatures in Jacksonville and Key West differ by ± 0.6 C, Coenen 2005). Examination of a large population of Florida lakes, however, did not find any significant changes in annual chlorophyll concentrations due to temperature changes across Florida's latitudinal gradient (Coenen 2005). Brown et al. (1998) further suggested that even light and temperature conditions were similar throughout the year and across Florida lakes. The results of this chapter showed the influence of temperature on seasonal patterns, but the temperature had a greater influenced on chlorophyll concentrations over an annual cycle than latitude differences across the State of Florida. Other temperature driven seasonal patterns support this conclusion as well. For example, temperature driven seasonal patterns in dissolved oxygen and consequent fish kills have been documented across the State of Florida over an annual cycle (Hoyer et al. 2009).

Rainfall cycles climatically described the annual variability in the chlorophyll concentrations for the examined subtropical, Florida lakes. High rainfall events have been linked to increased input of nutrients, sediments, and dissolved organic carbon in many lake systems (Deevey 1988; Gaiser et al. 2009), but the response of phytoplankton biomass to rain driven fluctuations in nutrients, sediments, and dissolved organic carbon is not consistent among lakes. When rainfall and phytoplankton biomass relationships were examined on an annual basis among the 27 examined Florida lakes, phytoplankton biomass consistently responded to high rainfall amounts with high biomass levels over the 20-plus year record in many of the examined subtropical, Florida lakes (Figure 4-7). An inverse relationship of phytoplankton biomass and rainfall was identified in five of the lakes; months with low phytoplankton biomass and high rainfall (Figure 4-7). The different annual relationships of phytoplankton biomass and rainfall may be driven by differences in the water entering an individual lake from the surrounding watershed, both surface water and groundwater. The observed differences in the phytoplankton and rainfall relationships among the 27 Florida lakes may also be a result of flushing rates. The amount of water that enters a lake per a given amount of time could be high, inhibiting phytoplankton use of available nutrients or could be low, promoting phytoplankton use of available nutrients (Vollenweider 1968). Overall, on an annual basis, the identified relationships between monthly rainfall amounts and monthly phytoplankton biomass provided an understanding of seasonal patterns that may become important if climate patterns change in the future.

The lake trophic state concept explained contrasting annual seasonal patterns identified across the examined Florida lake-years. Seasonal patterns of chlorophyll concentrations and the occurrence of extreme chlorophyll events (i.e., maximum chlorophyll concentrations and values exceeding the grand mean by double) among oligotrophic, mesotrophic, and eutrophic classified lake-years were similar, following the temperature and rainfall patterns (Figures 4-6 and 4-7). Seasonal patterns of hypereutrophic lake-years, however, did not follow the seasonal pattern exhibited by the other lake-year trophic categories. Rather, the seasonal patterns in hypereutrophic lake-years were more typical of seasonal patterns observed in a temperate lake with peak chlorophyll concentrations occurring in April and October like the spring and fall overturn of temperate lakes. The mechanisms driving the phytoplankton biomass peaks turn over events in the spring (i.e., April/May) and fall (i.e., September/October) are initiated by an upwelling of hypolimnetic phosphorus and disruption of the thermocline (Nürnberg 1985; Marshall and Peters 1989). Although temporary stratification (Lewis 1973) does occur in some Florida lakes, lake mechanisms associated with stratification most likely do not drive the chlorophyll peaks observed in the Florida hypereutrophic lake-years as the examined Florida lakes are shallow (< 3m) and polymictic.

Differences in temperate and subtropical limnological mechanisms are well acknowledged (Hutchinson 1957; Scheffer 1998), yet it is difficult to resolve the reason for contrasting seasonal patterns in the hypereutrophic lake-years with the available data for the examined lakes. One explanation that could be supported by data was the effect of wind resuspension of bottom sediments. Relationships of chlorophyll and nutrients have been shown to follow wind patterns in Florida lakes (Carrick et al. 1993; Havens et al. 1999; Bachmann et al. 2000) and the bottom sediments of productive systems are nutrient rich as these systems accumulate large amounts of organic material, marked by the large nutrient-rich flocculent layers (Brenner et al. 1996). Although the resuspension of bottom sediments could limit light availability, it has been shown this effect is lessened in productive Florida systems by the shallow lake depth, low concentration of light-attenuating inorganic particles, or high concentrations of soluble nutrients in the sediments that simulate phytoplankton growth (Havens et al. 1999). Wind driven resuspension of the bottom sediments may explain the observed annual April and October peaks in chlorophyll concentrations across hypereutrophic lake-years because April and October are months with historically high wind velocities (NOAA 1996).

An increase in extreme chlorophyll concentrations has been suggested to occur across aquatic ecosystems as changing global climatic patterns are projected to increase growing conditions (Vitovesk et al. 1997). The three lakes, where an increase in occurrence of extreme chlorophyll concentrations was identified over the past two decades, would support this hypothesis. Despite the strong link recognized between the seasonal influence of the phenological traits temperature and rainfall on seasonal patterns of phytoplankton biomass, the Pareto analysis showed no change in the frequency of occurrence of elevated chlorophyll concentrations over the years of record in 23 (85%) of the examined subtropical, Florida lakes. One consideration relevant to the importance of regional climate on shifts in the occurrence of extreme chlorophyll events is that the Florida phytoplankton levels reach maximum capacity, meaning phytoplankton reach a threshold of self-shading and light limitation (Agustí et al. 1990). At levels of maximum capacity, the percent biomass contribution of phytoplankton to the community plateaus, which is dependent on the algal species and trophic state of the Florida lake (Duarte et al. 1992), and offers a future consideration for future examination of the shifts in the occurrence of extreme chlorophyll events over a period of record.

It is evident that seasonal patterns in Florida lakes are affected by climate as estimated by temperature and rainfall. With the exception of the annual seasonal patterns identified by hypereutrophic lake-year category, the annual seasonal patterns in phytoplankton biomass do not follow the typical, annual seasonal patterns of temperate lakes with peaks in phytoplankton biomass occurring with the spring and fall turnover events. Subtropical lakes demonstrate an extended growing period of phytoplankton biomass (i.e., June through October) where extreme chlorophyll events could occur during any month of the year. Comparisons between subtropical and temperate annual seasonal patterns in phytoplankton biomass indicate differences occur at the large-scale and latitudinal and longitudinal considerations should be considered. This study further highlights the importance of defining seasonal patterns and incorporates, not remove the variance due to seasonal patterns. Understanding that natural seasonal variability is an important determinant of recurrent and synchronous lake dynamics and that this seasonal variability may differ depending on the scale of analysis will enhance the understanding of limnology.

Table 4-1. Summary statistics of monthly chlorophyll samples (µg/L) collected over a 20 plus-year period for 27 Florida lakes.

County	Lake	N samples	Mean Chlorophyll	Minimum Chlorophyll	Maximum Chlorophyll	Standard error	Coefficient of Variation
Alachua	Alto	252	11.3	2.7	57.3	0.4	54
Alachua	Little Orange	240	18.5	2.7	148.7	1.0	83
Alachua	Little Santa Fe	276	9.7	1.0	54.7	0.5	78
Alachua	Santa Fe	276	8.1	1.3	37.3	0.3	71
Alachua	Wauberg	240	96.2	29.7	240.3	2.9	46
Hillsborough	Brant	240	21.2	1.7	216.0	1.4	100
Hillsborough	Magdalene	240	4.3	1.0	12.0	0.1	45
Lake	Beauclaire	240	169.1	38.7	435.7	4.5	41
Lake	Crooked	240	8.6	2.0	36.0	0.4	68
Lake	Dora East	240	160.4	26.0	344.7	3.8	36
Lake	Dora West	240	148.3	45.0	310.7	3.1	32
Lake	Grasshopper	240	2.8	1.0	14.7	0.1	77
Lake	Harris	240	56.6	4.0	121.3	1.5	42
Lake	Lorraine	240	23.4	1.7	105.0	1.4	90
Lake	Sellers	240	1.6	0.1	7.7	0.1	69
Marion	Charles	240	6.4	0.3	296.7	1.3	314
Marion	Deerback	252	4.7	1.0	21.7	0.2	55
Marion	Eaton	240	5.8	1.0	41.7	0.3	94
Marion	Halfmoon	240	9.1	2.0	20.7	0.2	36
Orange	Georgia	252	5.2	0.1	28.3	0.2	57
Orange	Giles	240	32.2	4.3	125.3	1.3	64
Orange	Ola	240	4.1	1.0	14.0	0.1	54
Orange	Sarah	240	13.5	2.0	59.0	0.6	66
Putnam	Como	252	2.5	0.7	10.0	0.1	55
Putnam	Higgenbotham	240	3.3	1.0	14.3	0.1	57
Putnam	Star	252	7.0	1.3	30.0	0.3	58
Putnam	Winnott	240	4.1	1.0	31.3	0.2	81

Table 4-2. Linear regression analysis of slope values by year. The annual slope values were derived from determination of the percent number of records greater than a given chlorophyll concentration against the corresponding logarithmic (base 10) transformed chlorophyll concentration. Significant liner relationships indicate a change in the frequency of occurrence of extreme chlorophyll concentrations over the examined period of record for the individual 27 Florida lakes.

County	Lake	Slope	R^2
Alachua	Alto	0.38	0
Alachua	Little Orange	1.66	0.05
Alachua	Little Santa Fe	2.85	0.08
Alachua	Santa Fe	2.8	0.04
Alachua	Wauberg	-0.18	0
Hillsborough	Brant	-5.5	0.10
Hillsborough	Magdalene	3.42	0.06
Lake	Beauclaire	-3.5	0.04
Lake	Crooked	-2.68	0.11
Lake	Dora East	-7.24	0.07
Lake	Dora West	-3.74	0.01
Lake	Grasshopper	0.1	0
Lake	Harris	-8.6[x]	0.25
Lake	Lorraine	6.35[x]	0.42
Lake	Sellers	13.75	0.16
Marion	Charles	-0.24	0
Marion	Deerback	-4.58[x]	0.21
Marion	Eaton	-0.71	0.04
Marion	Halfmoon	2.244	0.05
Orange	Georgia	2.243	0.05
Orange	Giles	-1.61	0.04
Orange	Ola	-2.86	0.04
Orange	Sarah	-4.42[x]	0.23
Putnam	Como	-2.1	0.03
Putnam	Higgenbotham	-3.48	0.06
Putnam	Star	-1.7	0.04
Putnam	Winnott	4.4	0.11

Table 4-3. Statistical identification of periodic component of variability in chlorophyll concentrations by spectral density analysis, generated by the time series model analysis, by the Fisher's Kappa Test (p-values listed). Visual identification (Y= yes and N= no of a peak at 12 months in the chlorophyll variance indicated the individual Florida lake exhibited a seasonal periodic component across the examined period of record.

County	Lake	Fisher's Kappa p-value	Visual Peak
Alachua	Alto	0	Y
Alachua	Little Orange	0	Y
Alachua	Little Santa Fe	0	Y
Alachua	Santa Fe	0	Y
Alachua	Wauberg	0	Y
Hillsborough	Brant	0	Y
Hillsborough	Magdalene	0	N
Lake	Beauclaire	0	N
Lake	Crooked	0	N
Lake	Dora East	0	Y
Lake	Dora West	0	Y
Lake	Grasshopper	0	Y
Lake	Harris	0	N
Lake	Lorraine	0	N
Lake	Sellers	0	Y
Marion	Charles	0	Y
Marion	Deerback	0	Y
Marion	Eaton	0	Y
Marion	Halfmoon	0.001	Y
Orange	Georgia	0	Y
Orange	Giles	0.005	N
Orange	Ola	0	Y
Orange	Sarah	0	Y
Putnam	Como	0	Y
Putnam	Higgenbotham	0	Y
Putnam	Star	0	Y
Putnam	Winnott	0	Y

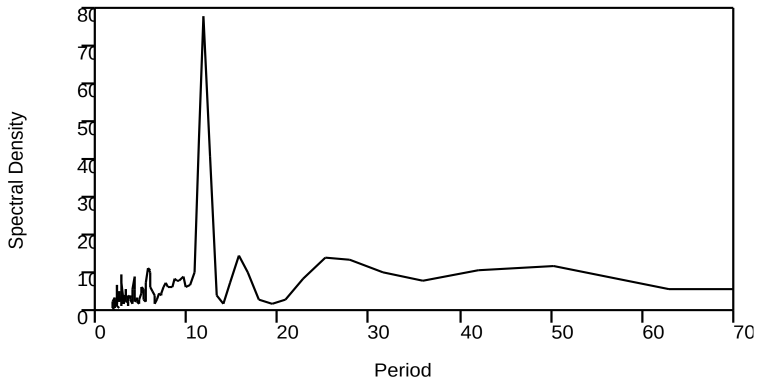


Figure 4-1. Spectral density plot generated from time series model analysis for monthly chlorophyll concentrations over a 21-year period in Lake Alto located in Alachua County, Florida. The peak, at a period of 12, indicates there is a seasonal component in the chlorophyll concentrations in Lake Alto.

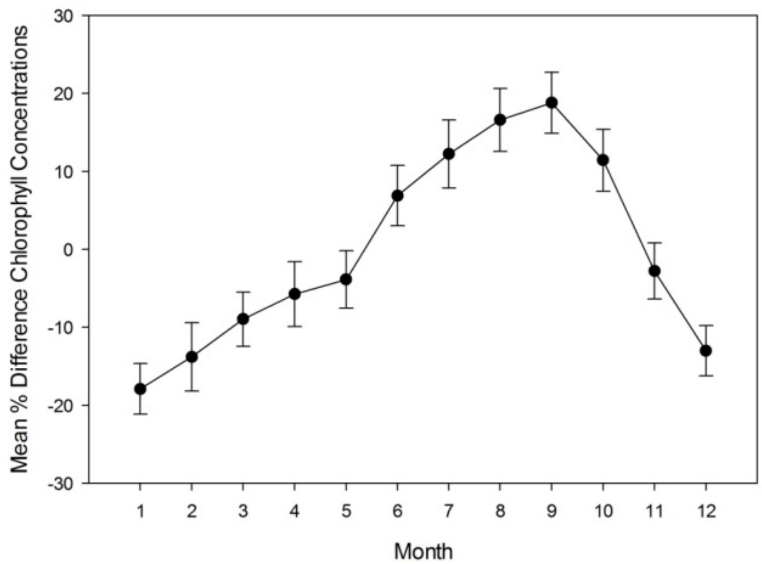


Figure 4-2. Mean percent (%) difference of monthly chlorophyll concentrations over an annual cycle for 27 subtropical, Florida lakes. The bars represent the 95% confidence intervals around the mean of the monthly mean % difference in chlorophyll concentrations from the annual mean. Positive differences indicate concentrations greater than the mean and negative differences indicate concentrations less than the mean.

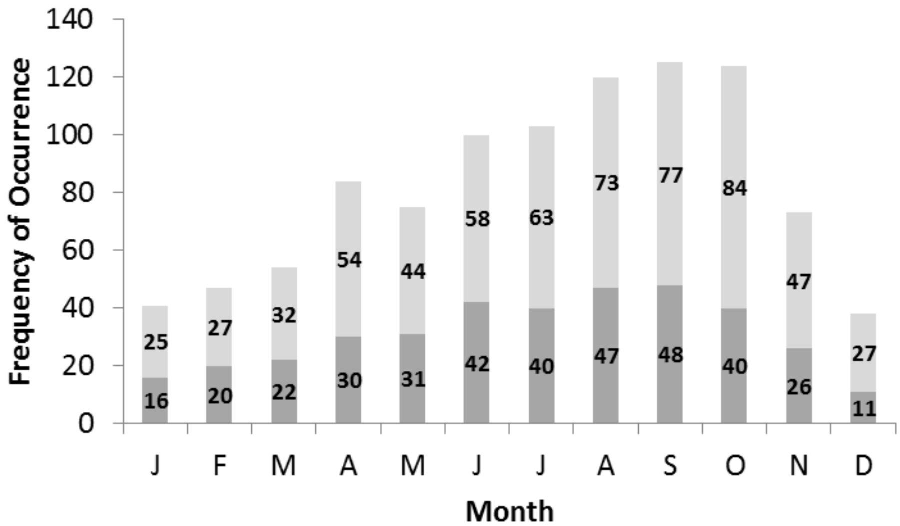


Figure 4-3. Frequency of occurrence of extreme chlorophyll events represented as the maximum chlorophyll concentrations (light grey bars) and the chlorophyll concentrations exceeding two times the grand mean (dark grey bars) summarized for each month among the years sampled for the 27 Florida lakes (N = 611 total maxima values and N = 373 values exceeding the grand mean by double).

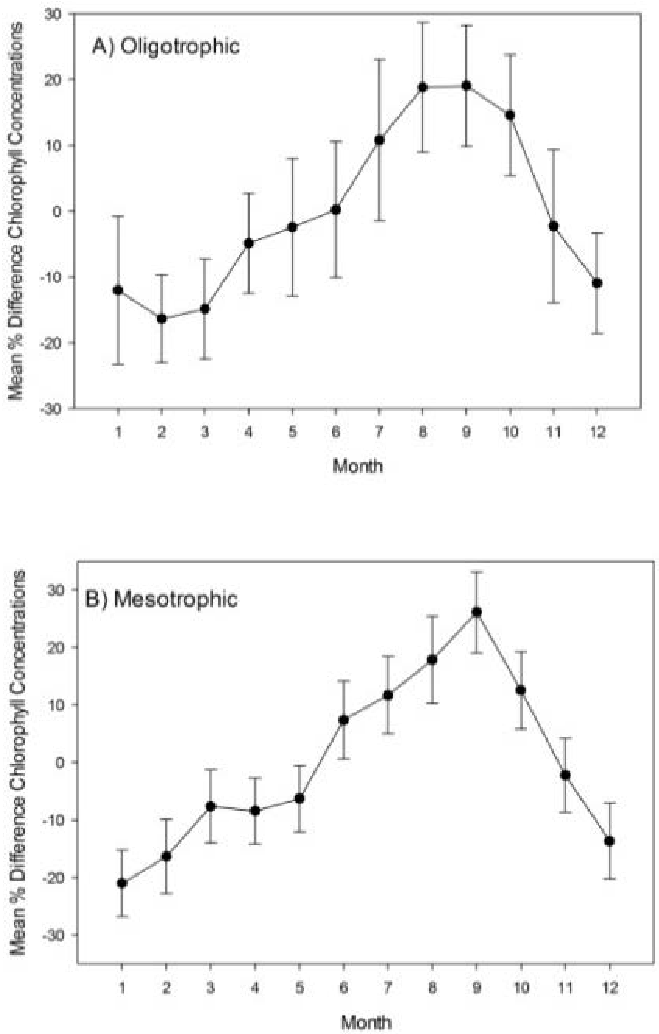


Figure 4-4. Mean percent (%) difference of monthly chlorophyll concentrations calculated over an annual cycle by classification into lake-year trophic state categories A) oligotrophic, B) mesotrophic, C) eutrophic, and D) hypereutrophic classification. The bars represent the 95% confidence intervals associated with the mean for the monthly mean % difference in chlorophyll concentrations.

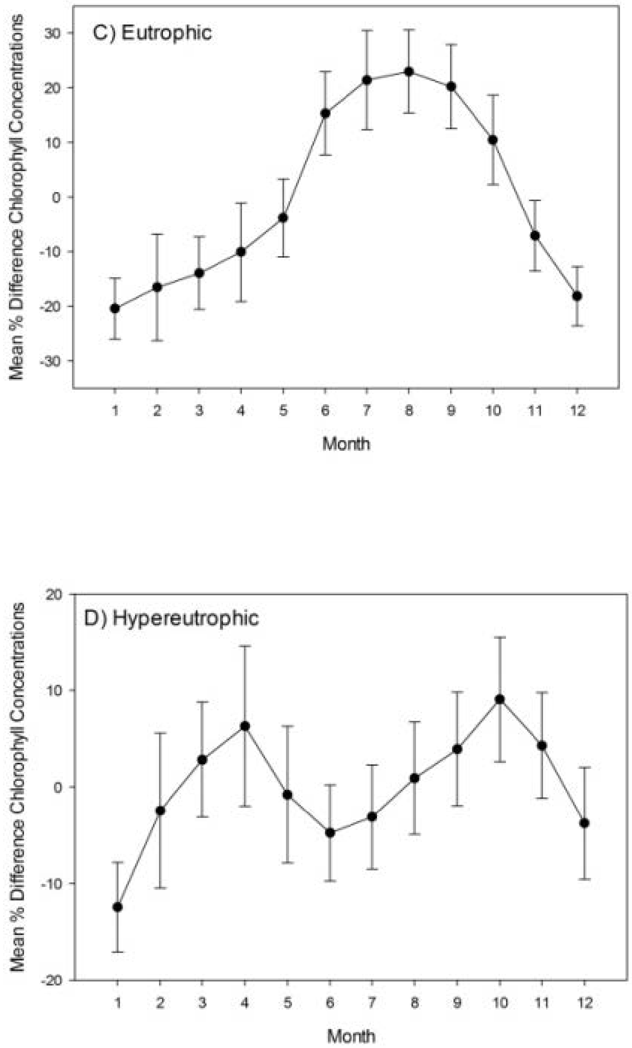


Figure 4-4. Continued

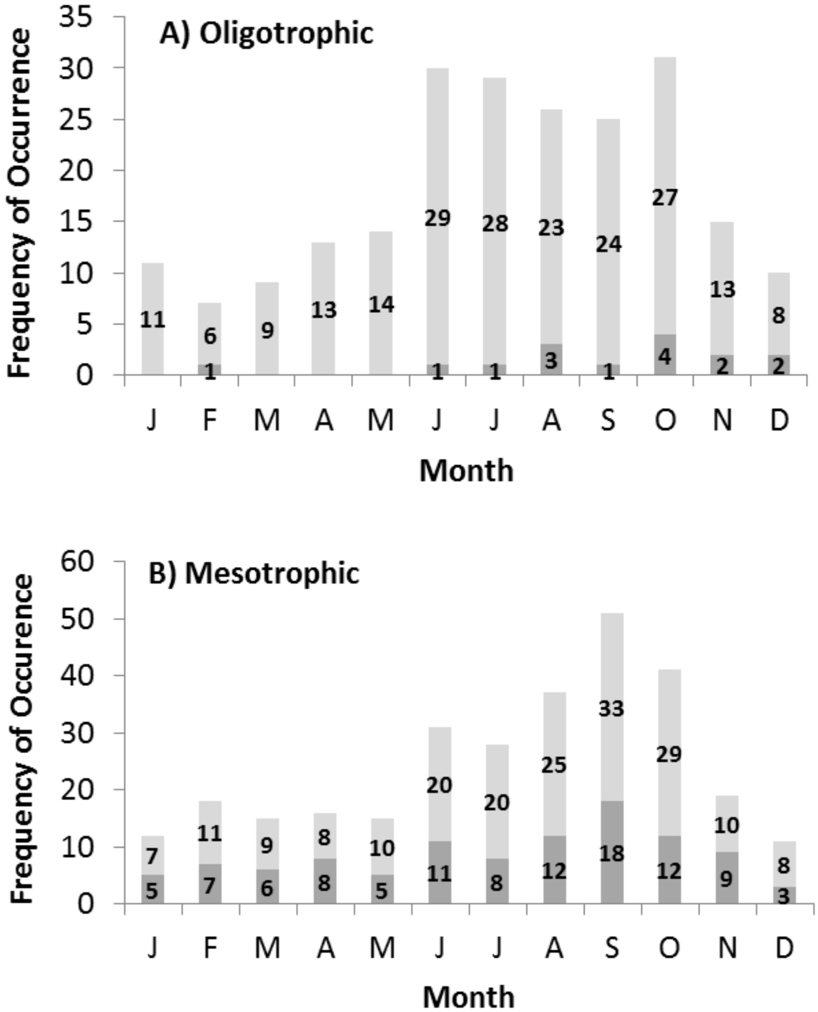


Figure 4-5. Frequency of occurrence of extreme chlorophyll events represented as the maximum chlorophyll concentrations (light grey bars) and the chlorophyll concentrations exceeding the grand mean by double (dark grey bars) summarized for each month among the years sampled by classification into lake-year trophic categories A) oligotrophic (N= 948 total lake-years), B) mesotrophic (N= 2051 total lake-years), C) eutrophic (N=2365 total lake-years), and D) hypereutrophic (N=1248 total lake-years.

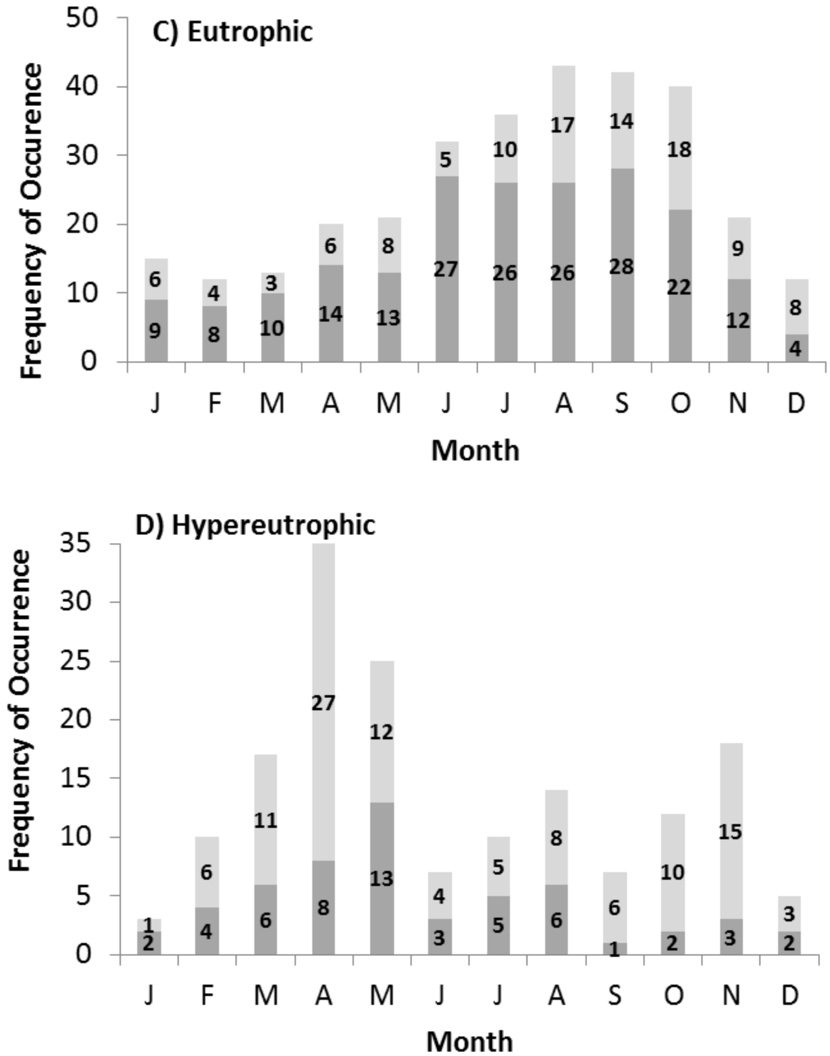


Figure 4-5. Continued

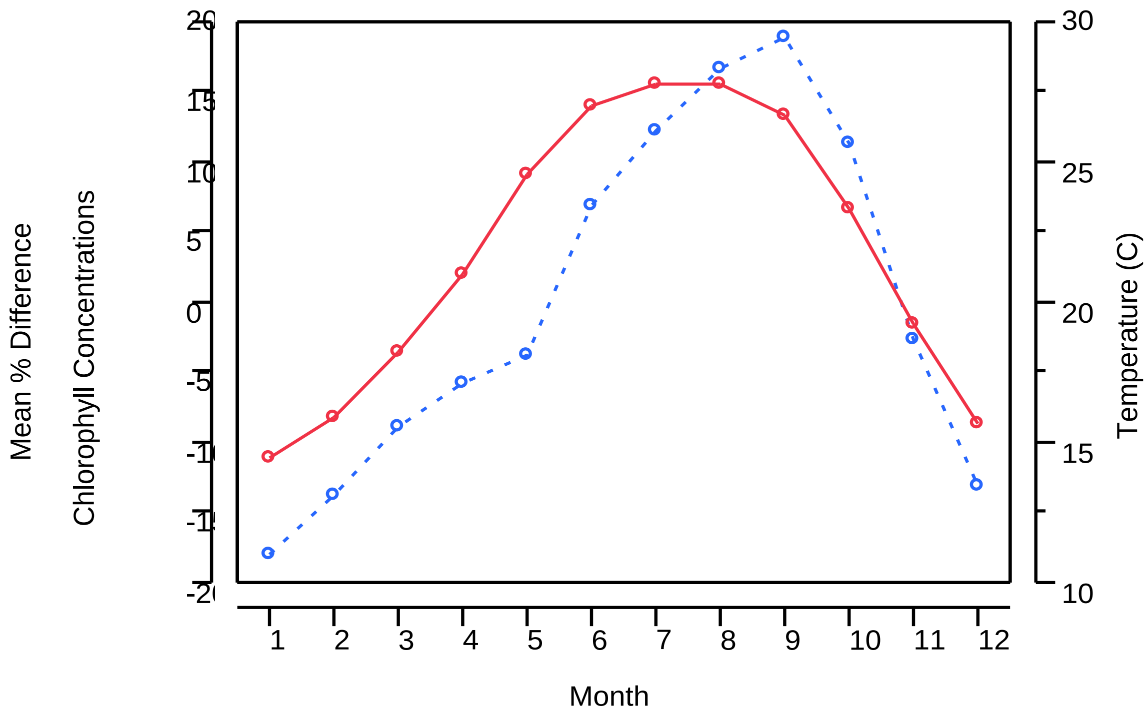
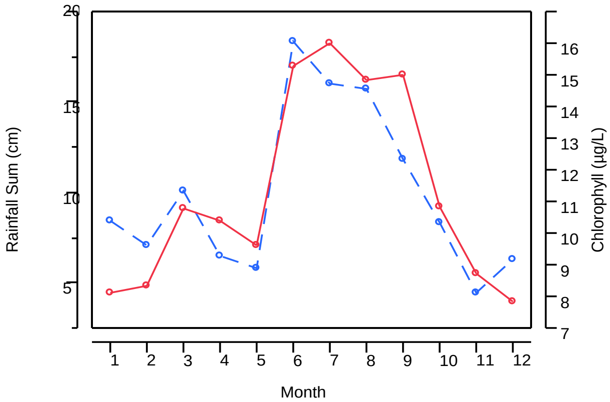


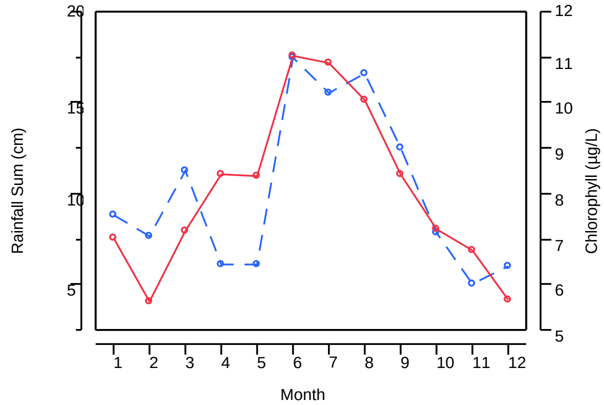
Figure 4-6. Monthly air temperature (C) data averaged over a 24-year period for the five nearest collection sites (solid line) and the corresponding mean % difference of monthly chlorophyll concentrations over an annual cycle (dotted line) for the examined 27 Florida lakes.

Figure 4-7. Average monthly rainfall sum (cm) (dotted line) and the average monthly chlorophyll concentrations (µg/L) (solid line) calculated among the annual data for the individual Florida lake, which are represented as Lake Name (County of location).

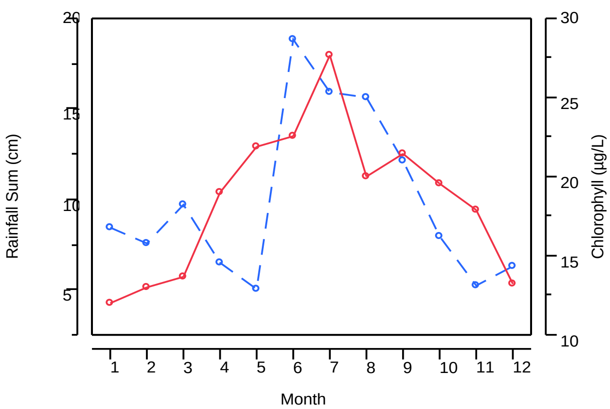
Alto (Alachua)



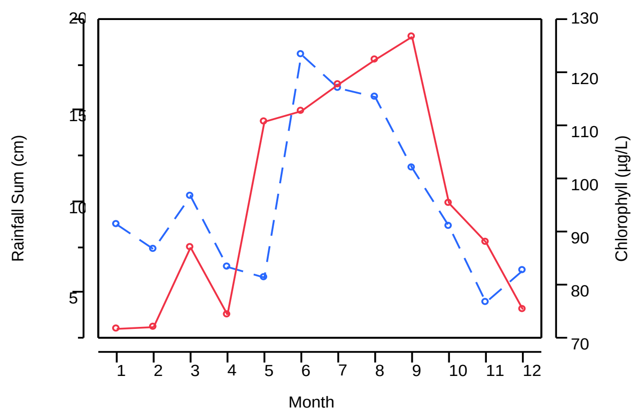
Santa Fe (Alachua)



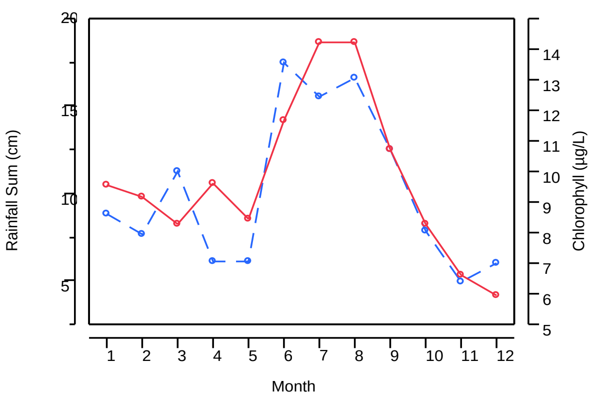
Little Orange (Alachua)



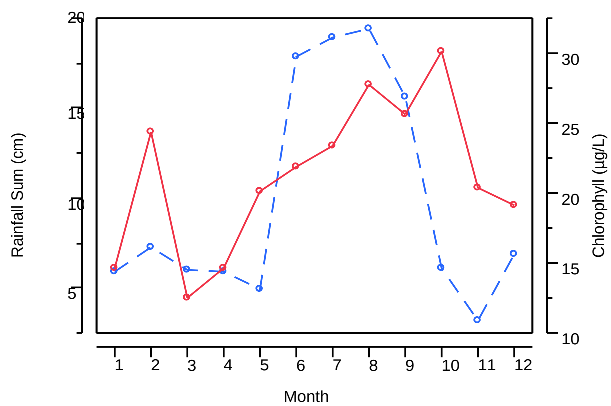
Wauberg (Alachua)

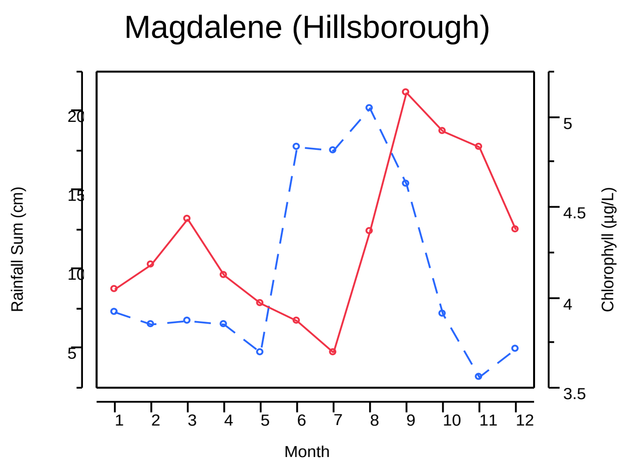


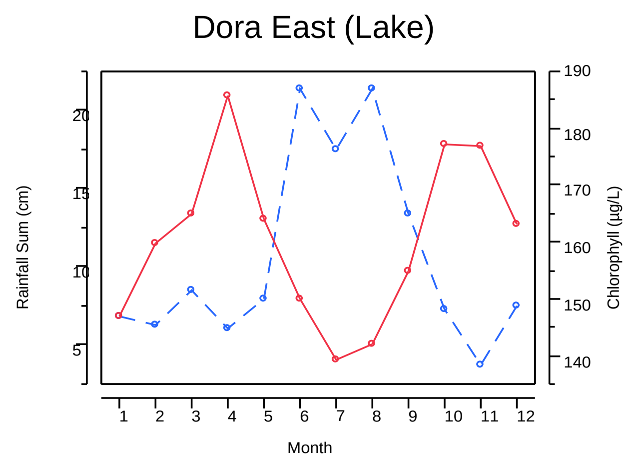
Little Santa Fe (Alachua)

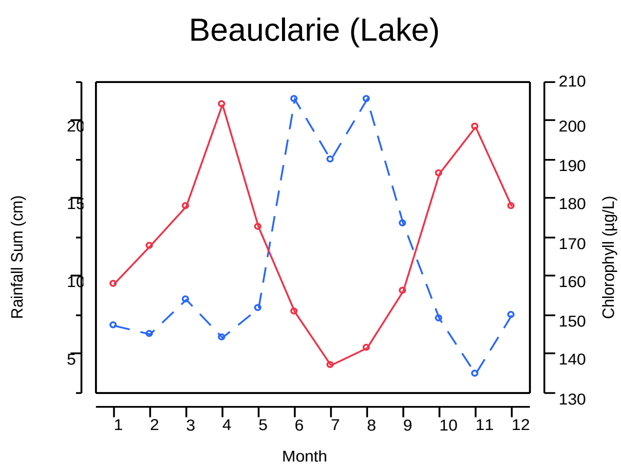


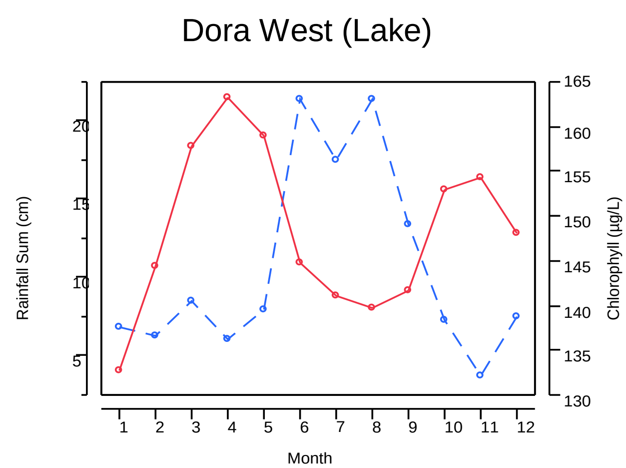
Brant (Hillsborough)

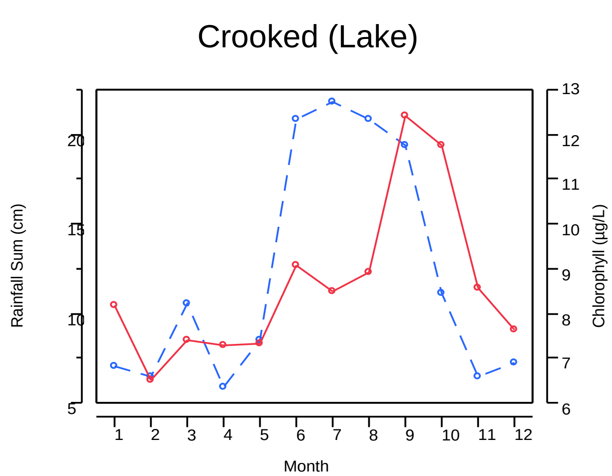


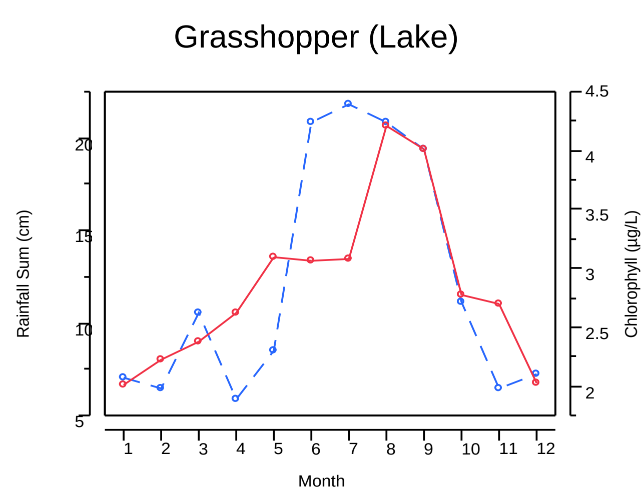

Magdalene (Hillsborough)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
3.5
4
4.5
5
1 2 3 4 5 6 7 8 9 10 11 12
Month


Dora East (Lake)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
140
150
160
170
180
190
1 2 3 4 5 6 7 8 9 10 11 12
Month

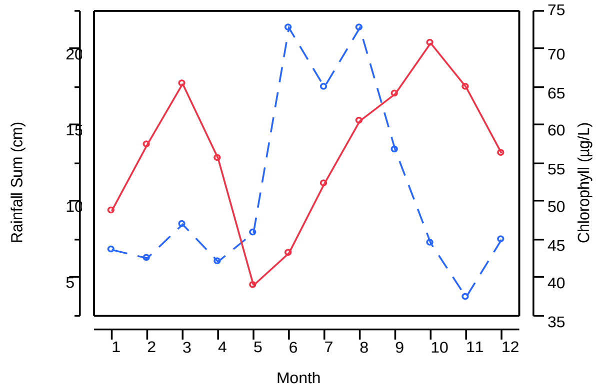

Beauclarie (Lake)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
130
140
150
160
170
180
190
200
210
1 2 3 4 5 6 7 8 9 10 11 12
Month


Dora West (Lake)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
130
135
140
145
150
155
160
165
1 2 3 4 5 6 7 8 9 10 11 12
Month

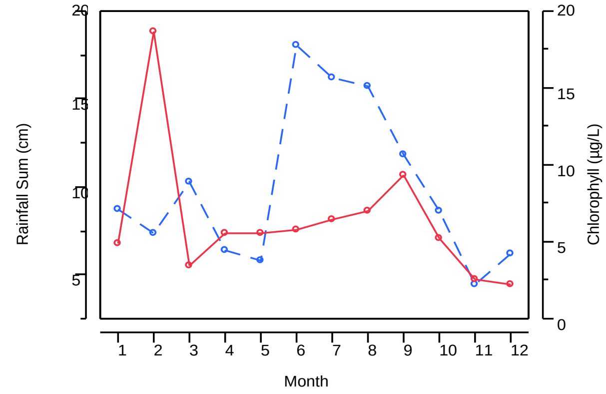

Crooked (Lake)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
6
7
8
9
10
11
12
13
1 2 3 4 5 6 7 8 9 10 11 12
Month


Grasshopper (Lake)
Rainfall Sum (cm)
5
10
15
20
Chlorophyll (µg/L)
2
2.5
3
3.5
4
4.5
1 2 3 4 5 6 7 8 9 10 11 12
Month

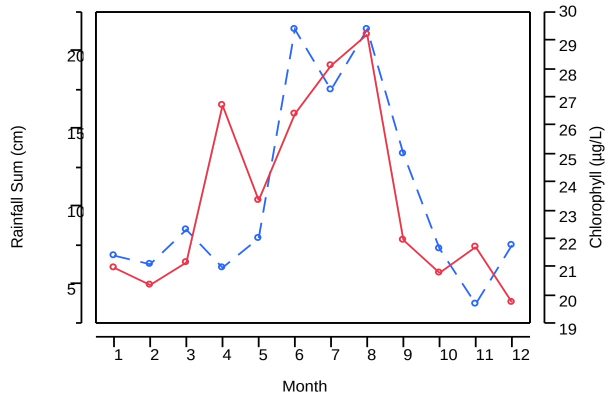
Harris (Lake)



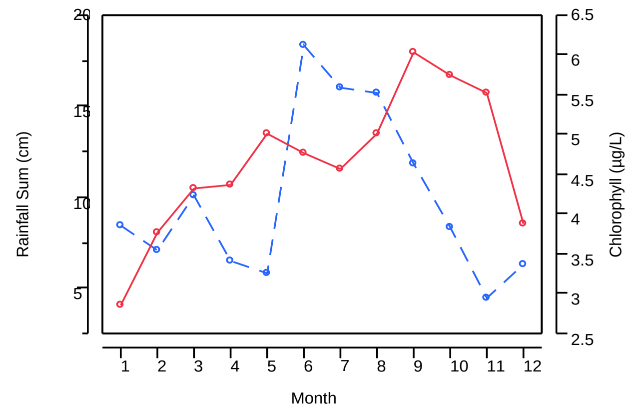
Charles (Marion)



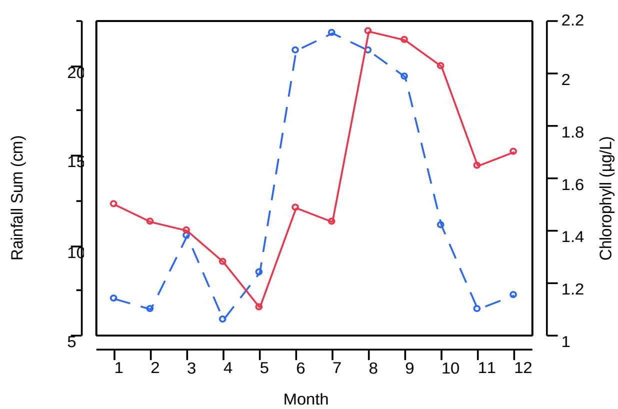
Lorriane (Lake)



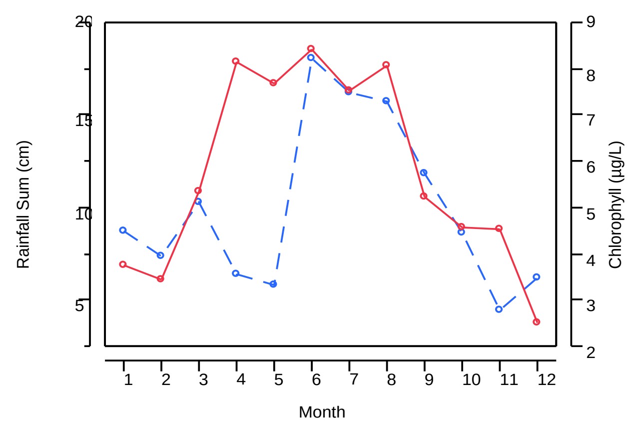
Deerback (Marion)

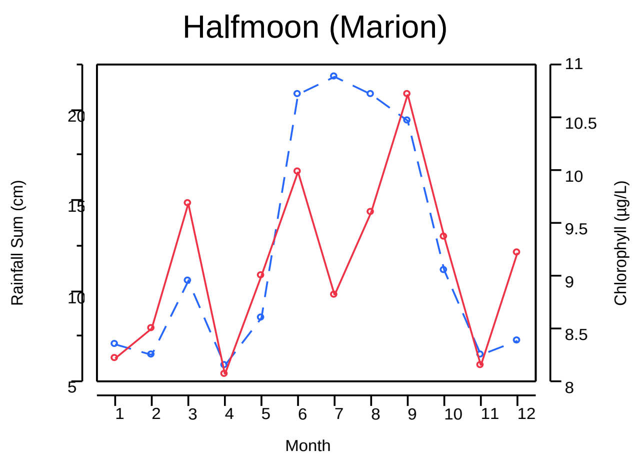


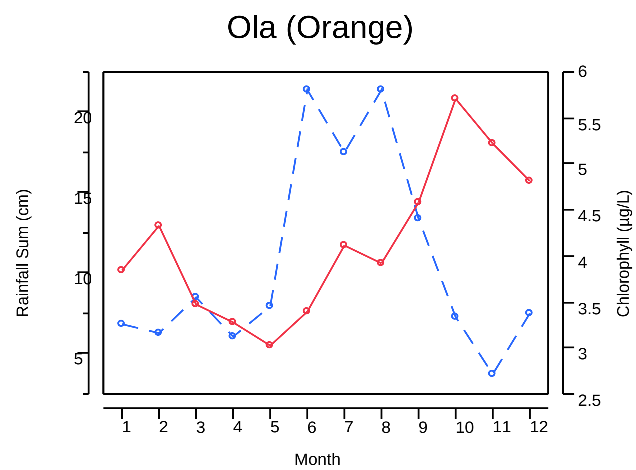
Sellers (Lake)

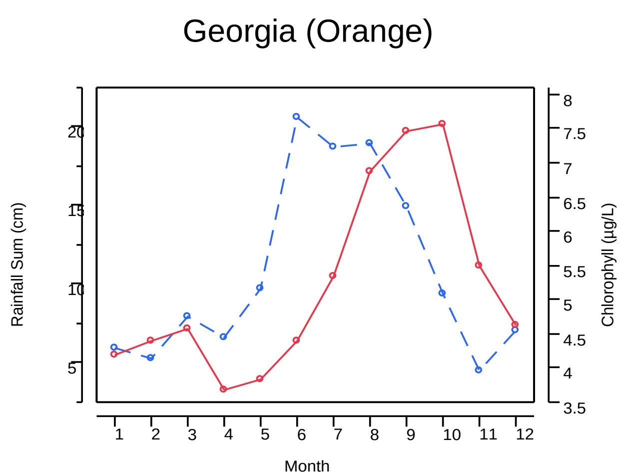


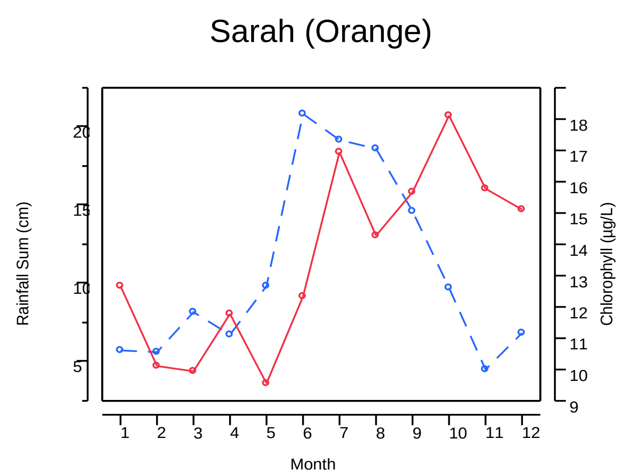
Eaton (Marion)

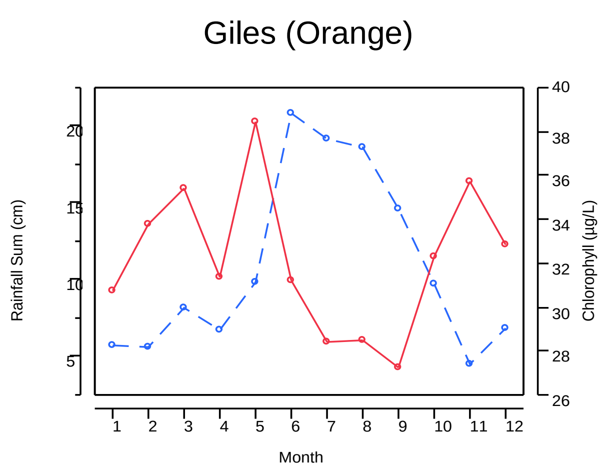


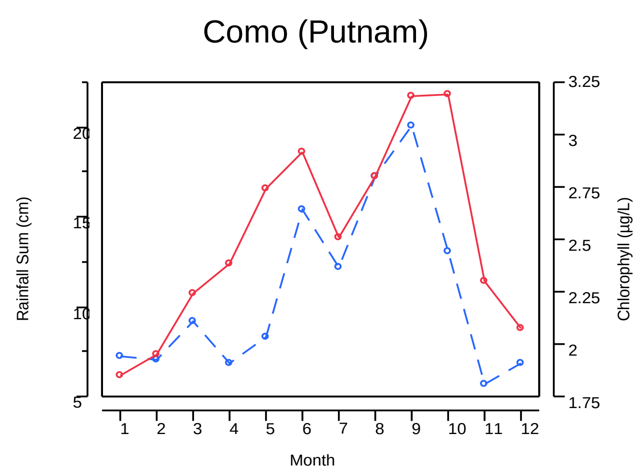

Halfmoon (Marion)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month

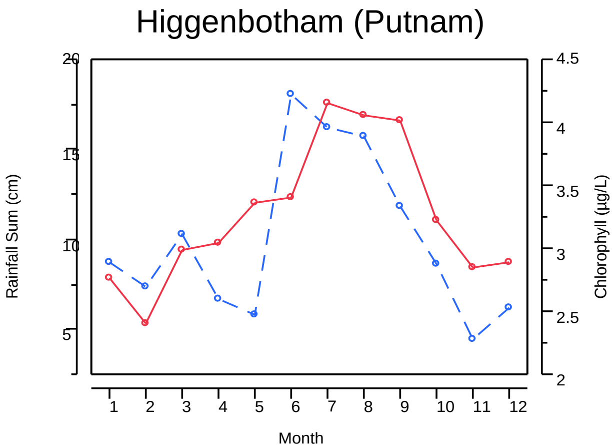

Ola (Orange)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month

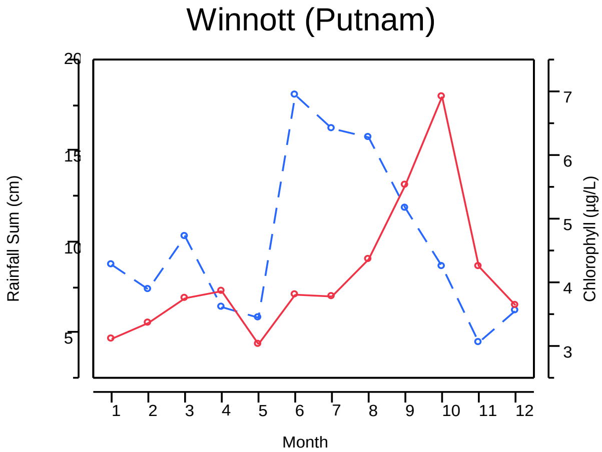

Georgia (Orange)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month

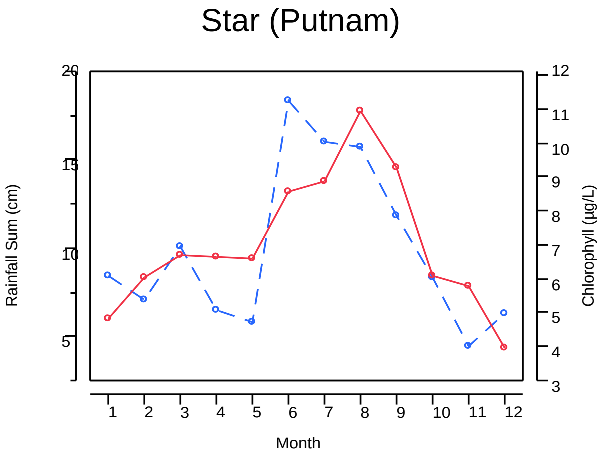

Sarah (Orange)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month


Giles (Orange)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month


Como (Putnam)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month


Higgenbotham (Putnam)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month
20
15
10
5
4.5
4
3.5
3
2.5
2
1 2 3 4 5 6 7 8 9 10 11 12


Winnott (Putnam)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month
20
15
10
5
7
6
5
4
3
1 2 3 4 5 6 7 8 9 10 11 12


Star (Putnam)
Rainfall Sum (cm)
Chlorophyll (µg/L)
Month
20
15
10
5
12
11
10
9
8
7
6
5
4
3
1 2 3 4 5 6 7 8 9 10 11 12

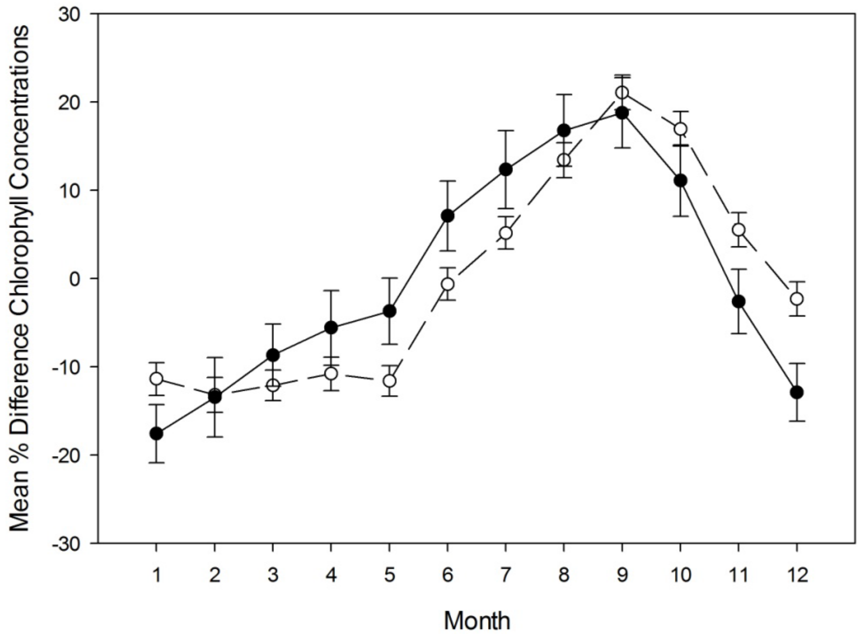


Figure 4-8. Mean percent (%) difference of monthly chlorophyll concentrations over an annual cycle for a population of 193 Florida lakes (open circles connected by dotted line) and the population of 27 Florida lakes (closed circles connected by solid line). The bars represent the 95% confidence intervals around the mean of the monthly mean % difference in chlorophyll concentrations from the annual mean.

CHAPTER 5
SUMMARY, RECOMMENDATIONS, AND MAJOR CONCLUSIONS

Summary and Recommendations

Freshwater lakes are sensitive to changes in the environment, such as nutrient loading or climatic events, and the response of the lake provides the ability to identify and understand the impact of changes in the surrounding watershed and landscape (Carpenter et al. 2007; Adrian et al. 2009; Schindler 2009). One of the biggest issues scientists, environmental managers, and policy makers currently face is how to assess changes over multiple scales of time and space (Williamson et al. 2009). Using a robust, long-term dataset composed of lake trophic state variables, statistical methods, ranging from simplistic to complex, were used to identify lake trophic state trends and proposed alternative trend detection methods (Chapter 2). A simple alternative approach, which provided comparable results to the more complex statistical models, was developed to determine trends in the trophic state variables and to examine spatial clusters of lakes with identified trends for a large population of Florida lakes (Chapter 3). Components of lake variability were examined by identification of seasonal patterns in phytoplankton biomass and the influence of climate factors, temperature and rainfall, on seasonal patterns (Chapter 4). The results from the above inquiries contributed to improving assessments of lake change in Florida over multiple scales of time and space. Improved assessments of lake change provide a platform to enhance future studies that target understanding the linkages of anthropogenic and natural factors to lake change.

Evaluation of simple least-squares linear regression, Kendall Tau, and ARMA/ARIMA time series models produced different results of trend detection when the same data were analyzed (Chapter 2). The ARMA/ARIMA time series models are suggested to best account for variance around the mean and also extreme values, common characteristics of aquatic time series data. Compared to the other evaluated statistical methods, ARMA/ARIMA time series models provided a conservative estimate of lakes exhibiting decadal-scale trends in the examined trophic state variables and population of 27 Florida lakes. The ARMA/ARIMA time series models, however, are statistically complexity and have strict data requirements. Therefore, an alternative, modified linear regression method was developed, offering a “statistical meaningful” (Bryhn and Dimberg 2011) and predictively powerful approach (Prairie 1996) that provided similar results as the ARMA/ARIMA time series model analysis. The divergent determination of long-term trends in lake trophic state variables, using various statistical analyses, elucidates the point that statistical methods are tools useful to guide interpretation. Lakes are variable in nature and sometimes statistical determination of trends may not capture the variability in a data time series appropriately. Thus, it is important to plot and examine data prior to using statistical tools.

The examination of long-term trends in lake trophic state variables is essential to describe a lake’s behavior, but frequently not completed for a large populations of lakes. Determination of long-term trends within and among lakes facilitates a context in which future limnological studies and evaluation of environmental management options can be accomplished. A comprehensive evaluation of trophic state variable trends for a large population of 193 Florida lakes was completed (Chapter 3). Due to postulated worsening conditions of freshwater systems in response to shifts in global climate (Kernan 2010), trends of degradation (i.e., increases in total phosphorus, total nitrogen, and chlorophyll concentrations and decreases in water clarity measurements) were expected to be documented in a number of the 193 examined Florida lakes over the decadal-scale (≥ 15 years) period of record (Chapter 3). For the population of 193 Florida lakes, increasing trends in total phosphorus (21%), increasing trends in total nitrogen (26%), increasing trends in chlorophyll concentrations (12%), and decreasing trends in water clarity measurements (18%) were determined using the alternative modified linear regression method (Chapter 2). Trends of improvement (i.e., decreases in total phosphorus, total nitrogen, and chlorophyll concentrations, and increases in water clarity measurements) were found in 7%, 6%, 7%, and 4% of the population of examined Florida lakes, respectively. The major conclusion is that not many of the examined Florida lakes experienced decadal-scale trends in total phosphorus, total nitrogen, chlorophyll concentrations, or water clarity measurements.

The lakes with identified decadal-scale trophic state trends (Chapter 3) should be recognized and offer a valuable opportunity to focus future research and management efforts. For example, the nine lakes where trends of "degradation" were documented in all of the four trophic state variables or the three spatial clusters of lakes with similar trends among the trophic state variables (Chapter 3) should help to focus research and management efforts. Directing research and management efforts to "lakes of interest" or "clusters of lakes of interest," where decadal-scale trends in the trophic state variables have been documented, would enhance allocation of time, money, and resources.

The dynamic nature of lakes cofounded by the codependence of limnological mechanisms limits recognition of the factors influencing identified change in lakes. The influence of seasonal patterns in phytoplankton biomass, an important aspect of lake variability, is often disregarded or even removed prior to statistical trend analysis. For the population of 27 Florida lakes with at least 20 years of consistent monthly data, seasonal patterns in phytoplankton biomass (chlorophyll concentrations were used as an estimate of phytoplankton biomass) were identified (Chapter 4). The seasonal patterns in phytoplankton biomass were found to follow cycles of phytoplankton biomass growth and senescence that were recurrent and synchronous (Chapter 4). Annual elevated chlorophyll concentrations occurred June through October, an extended length of the year compared to the peak growing period of phytoplankton biomass in temperate lakes (Marshall and Peters 1989). There were contrasting seasonal patterns, which were best explained by the classification of waters by lake-year trophic category of chlorophyll concentrations (Forsburg and Ryding 1980). Oligotrophic, mesotrophic, and eutrophic classified waters experienced patterns of elevated chlorophyll concentrations during June through October. Hypereutrophic classified water, however, showed the largest range in chlorophyll concentrations with elevated chlorophyll concentrations occurring in April and October. The reason for the difference in the seasonal patterns observed in the hypereutrophic classified waters was not determined, but warrants an important question to address. The overall results do illustrate the contribution of seasonal components to lake variability and the importance of incorporating seasonal variability into lake assessments and statistical analyses.

Incorporation and interpretation of seasonal variability in lake assessments depends on the scale of analysis. Annual seasonal patterns of phytoplankton biomass, as measured by chlorophyll concentrations, are driven by annual climate cycles of solar radiation (Wetzel 2001), air temperature (Chapter 4), and rainfall (Chapter 4). Climate patterns vary with latitude and longitude suggesting seasonal patterns of phytoplankton biomass would vary at the large-scale of analysis, along changes in latitude and longitude. Latitudinal and longitudinal variation is essential to recognize when comparing seasonal patterns of phytoplankton biomass across lakes. For example, examination of Florida lakes, indicated fluctuations of monthly chlorophyll values followed monthly air temperature changes with the higher chlorophyll levels occurring during the months where temperatures exceeded 23 C (Chapter 4), as temperatures of 23 C and above are optimal for phytoplankton growth (Moss 1973). Due to varying latitude, Florida lakes experience longer annual periods of phytoplankton growth versus temperature lakes where air temperatures do not reach or exceed 23 C for as many months, meaning a decreased annual period of phytoplankton growth, comparatively.

The influence of climate warming conditions on phytoplankton has increased in interest because changing temperatures are anticipated to alter levels of phytoplankton production and community structure in lakes (Hering et al. 2010). Warming temperatures have already been documented to change the limnology of lakes, such as the documented shift in patterns of ice out occurring earlier in the year (Magnuson et al. 2000). The influence of warming temperatures on seasonal patterns of phytoplankton biomass may be of a greater magnitude for lakes located in northern latitudes over southern latitudes. The identification of annual seasonal patterns in phytoplankton biomass, link of seasonal patterns to annual temperature and rainfall patterns, and lack of determination of an increase in the occurrence of extreme chlorophyll events (i.e., only three of the 27 Florida lakes experienced an increase in the occurrence of extreme chlorophyll events over the past 20-plus years) provide anecdotal evidence of a potentially greater impact of climate warming on seasonal patterns of phytoplankton in northern latitude lakes. It would be interesting, therefore, to see whether the same results were obtained in lakes located in more northern latitudes.

Overall, the research completed outlines an alternative, modified linear regression method to detect decadal-scale trend in trophic state variable time series data, offers suggestions as to where to focus future research efforts, and provides a framework to address global factors driving lake changes. These contributions, however, would not have been possible without the involvement of citizen scientists whose efforts developed an excellent, robust long-term database of trophic state variables available for a large population of lakes. The involvement of citizen scientists, like the Florida LAKEWATCH volunteers, allows scientists to answer broad ecological questions that may otherwise not have been possible (Ecological Society of America 2012). The use of citizen scientists to monitor and gather long-term databases are invaluable to science and society.

Major Conclusions

1- Different statistical methods used to detect trends in time series data provide different results.

2- For the population of 193 Florida lakes, increasing decadal-scale trends were detected for total phosphorus (21%), total nitrogen (26%), and chlorophyll concentrations (12%), and decreasing decadal-scale trends for water clarity measurements.

3- Annual patterns in phytoplankton biomass were found to follow cycles of phytoplankton biomass growth and senescence that were recurrent and synchronous with elevated concentrations occurring in June through October.

4- Hypereutrophic classified waters showed a wide range of chlorophyll concentrations with elevated concentrations occurring in April and October, which differed from waters classified as oligotrophic, mesotrophic, or eutrophic with elevated concentrations in June through October.

5- Annual patterns of phytoplankton biomass follow monthly air temperatures with higher chlorophyll concentrations occurring during the months exceeding 23 C.

6- Annual patterns of phytoplankton biomass showed either similar or inverse relationships to monthly rainfall patterns.

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BIOGRAPHICAL SKETCH

Dana Bigham received her Bachelor of Science degree in zoology and biological aspects of conservation in 2001 from the University of Wisconsin- Madison. As an undergraduate, she worked at the University of Wisconsin Ophthalmology Department laboratory assisting in eye melanoma research. Dana also had the opportunity to work as a field research assistant examining two evolutionary distinct stickleback (Gasterosteidae sp.) in British Columbia lakes. Before returning to graduate school, Dana worked for the Department of Wisconsin Natural Resources completing macrophyte surveys of Wisconsin lakes. In 2008, Dana completed a Master of Science degree at the University of Florida in Fisheries and Aquatic Sciences. Her thesis examined concentrations of the cyanobacterial toxin, microcystin, across Florida lakes and more specifically in the Harris Chain of Lakes, located in Lake County, Florida. Thereafter, Dana began her dissertation research examining temporal changes in trophic state variables for a large population of Florida lakes. As a graduate student, Dana was an active member in various societies, serving on the board of directors for the North American Lake Management Society and the Florida Lake Management Society. Dana received her Doctor of Philosophy from the University of Florida in December 2012.