EXPLORING WISCONSIN LAKES' SENSITIVITY TO NUTRIENT LOADING AND PRIORITIZING LAKES FOR CONSERVATION

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ABSTRACT

Nutrients such as phosphorus and nitrogen cycle through the environment naturally. However, excessive nutrient concentrations have negative effects on aquatic ecosystems and water quality. While the importance of good water quality has become more apparent over time, and the understanding of water quality protection strategies has improved, nutrient loading continues to be a problem in many states, including Wisconsin. As such, this study aimed to support nutrient pollution management in Wisconsin lakes. The objectives of the study were to (1) model a relationship between in-lake total phosphorus (TP) and water clarity, (2) create a model that will measure lake sensitivity to phosphorus loading, (3) determine which Wisconsin lakes are most and least sensitive to phosphorus loading, and (4) create a prioritized list for lake conservation/restoration efforts based on lakes sensitivity to phosphorus loading. This study used a quantitative approach to prioritize 929 Wisconsin lakes by sensitivity to phosphorus. The model had three components: phosphorus loading sensitivity (S), sensitivity significance (SS), and lake phosphorus sensitivity significance priority score (LPSSn). A mass balance equation by Dillon and Rigler (1975) was used to determine sensitivity (S) to phosphorus loading. Next, the likelihood of reaching that phosphorus loading threshold was calculated using the sensitivity (S) and several other variables, which gave the output SS. Finally, SS was used along with clarity trend data to determine a ranked lake phosphorus sensitivity significance (LPSSn) priority score from 0-100. Lakes near TP loading thresholds received a high LPSSn score, while lakes that far exceeded TP loading thresholds scored lower. Lakes below TP loading thresholds were too few to report significant placement on the LPSSn priority score. Lakes in the Northern Lakes and Forests ecoregion scored significantly higher than the lakes in the Driftless area, Southeastern Wisconsin Till Plains, and North Central Hardwood Forests. Model results will aid decision makers in determining which waterbodies should be prioritized for conservation and water quality protection. Prioritizing Wisconsin lakes based on sensitivity to phosphorus loading and then identifying significance of that sensitivity based on land use, surface area, in-lake mean TP concentrations, and other factors will target high quality lakes near tipping points of becoming degraded.

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CHAPTER ONE: INTRODUCTION

Background

The understanding of water ecosystem services and how humans affect water quality has increased greatly over the past decades. Anthropogenic activities that increase nutrient loading into surface waters include agriculture, industrial, and urban activities (Environmental Literacy, 2015). Excess nutrients in these systems create an imbalance that shifts low nutrient systems to eutrophic systems. Since the 1960s, eutrophication has been a threat to water quality for lakes, ponds, and reservoirs (Vinçon-Leite & Casenave, 2019). Implementation of best management practices (BMP) and other conservation efforts have occurred worldwide to address nutrient loading issues. However, nutrient loading continues to be a problem that many states in the United States face, including the state of Wisconsin (EPA, 2016).

Wisconsin's agriculture and urban runoff contribute to excess nutrients in aquatic systems (Liu et al., 2009). As Wisconsin's climate changes to include more frequent and intense storms, more nutrients will be eroded and leached into ecosystems (WI DNR, n.d.(a)). Wisconsin has already experienced the negative impacts of non-point nutrient loading in both ground water and surface waters (Maxted et al., 2009). Leached nitrates have caused concern in drinking water and private wells, and increased levels of phosphorus have turned healthy waterbodies into eutrophic systems (WI DNR, 2020). Decision makers at the federal, state, and county level are continuing to address these nutrient loading issues through various programs and grants (such as). In Wisconsin, the state has been tackling the issue of non-point source pollution since 1979, including a focus on phosphorous, which as described below is essential to the health and functioning of aquatic ecosystems. In 2010, water quality protocol was implemented and updated to address both non-point and point sources for phosphorus pollution in surface waters (Radatz et al., 2018). Previously, the main regulation of phosphorus pollution was point source pollution. The 2010 protocols were set in place to minimize non-point source phosphorus pollution and to establish regulations on how water quality criteria for phosphorus will be used to create effluent limits on point source discharges (WI DNR, 2010).

Nutrients cycle through aquatic ecosystems naturally, but additional influxes from human activities can lead to detrimental imbalances in these systems. The three macronutrients that all primary producers need are carbon, nitrogen, and phosphorus. In lakes, ponds, or reservoirs, phosphorus has been identified as the key limiting nutrient for these systems (Correll, 1999). This means that even with infinite amounts of nitrogen added there will still be a plateau in primary production if phosphorus is not added (Liebig's Law of the minimum). With excess phosphorus, primary production booms. In lakes/reservoirs this primary production increase is usually seen with large plants and algae on the water's surface. Algal blooms increase turbidity in the water column and blocks sunlight that usually penetrates to the bottom of the lake, leading to decreased growth of submergent vegetation. Eventually the waterbody exhibits hypoxic conditions due to low dissolved oxygen levels. This can lead to fish kills, loss of biodiversity, and bad odors. Once damaged it is difficult to restore lake ecosystems back to their former natural state (Cook et al., 2005; Carpenter, 2005).

Waterbody sensitivity to phosphorus loading is dependent on the current amount of phosphorus in the lake, the characteristics of the lake, and surrounding land use

(Bhateria and Jain, 2016). Knowing a lake's sensitivity to phosphorus would allow for strategic conservation efforts to take place before anthropogenic eutrophication occurs and restoration is needed.

Research Purpose and Hypotheses

Phosphorus loading caused by human activities threatens to change healthy waterbodies to eutrophic systems. A model that prioritizes lake conservation and protection based on phosphorus loading thresholds and sensitivity would create a clear organization of waterbodies that require attention. While state-by-state lake prioritization models are few, one important example comes from a 2018 study by Paul Radomski and Kristen Carlson (2018). Their research created a multi-criteria decision model (MCDM) for Minnesota lakes that prioritizes lakes for conservation/restoration based on phosphorus loading sensitivity (2018). This prioritization was designed to be a tool for decision makers to use when deciding where to allocate water quality protection efforts and funds. Currently, Wisconsin does not have a comparable model that prioritizes lakes for restoration and conservation. The purpose of this research is to replicate the Radomski and Carlson 2018 study in a very similar context, by the request of UW-Extension Lakes and WI DNR. Creating such a model could prove very useful for estimating lake phosphorus sensitivity and lake phosphorus thresholds, which would allow for efficient distribution of finite water quality funds and efforts. This study used statistical modeling to evaluate lake sensitivity to phosphorous loading and prioritize lakes from low to high based on their phosphorus sensitivity. It will allow Wisconsin resource managers to identify healthy waterbodies that are near tipping points for phosphorus loading thresholds.

In the pursuit of creating a lake sensitivity model, valuable water quality datasets have been created or updated for use by DNR, UW – Extension Lakes, and other interested stakeholders. This study also established a relationship between increasing in-lake mean TP and transparency (Secchi disk depth) in Wisconsin lakes. The sensitivity model was the start to building a multi-criteria tool that assists in local and state decision making to better distribute limited water quality funds. Future research is planned to replicate other model components from the MN study to further enhance the priority score list for conservation prioritization.

The objectives of this study are to (1) model a relationship between in-lake mean total phosphorus and clarity, (2) create a model that will measure lake sensitivity to phosphorus loading, (3) determine which Wisconsin lakes are most and least sensitive to phosphorus loading, and (4) create a prioritized list for lake conservation/restoration efforts based on lakes' sensitivity to phosphorus loading.

This research aimed to answer the question: based on phosphorus loading thresholds and sensitivity, which Wisconsin lakes would most benefit from conservation and restoration efforts and funding? The previous study by Radomski and Carlson (2018), found that lakes within certain Level III ecoregions had similar sensitivities to TP loading. The ecoregions are areas of similar soil composition, topography, land use and cover, and quality/quantity of environmental resources (Omernik, 1987). Wisconsin is made up of six distinct level III ecoregions, the Northern lakes and forests, the North central hardwood forests, the Western corn belt region, the Southeastern Wisconsin till Plains, the Driftless area, and the Central corn belt region (Omernik 1987). The results from the previous study led us to our first hypothesis:

Hypothesis 1: A pattern or trend will appear for lakes sensitive to changes in water quality among a certain type of lake or in a specific ecoregion.

Another expectation was to see lakes classified as oligotrophic or mesotrophic ranked highest in the LPSSn priority score and eutrophic to hypereutrophic lakes at the lower end of the priority score. This assumption is based on the design of the model, the input variables, and the results from the MN study. This expectation directed our second hypothesis:

Hypothesis 2: Lakes near TP loading thresholds will score higher and lakes over the TP loading threshold will score lower.

CHAPTER TWO: REVIEW OF RELATED LITERATURE

This chapter addresses three key areas of the water resource management literature: (1) nutrient loading, (2) lake phosphorus models, and (3) Wisconsin water quality protection and restoration efforts.

Nutrient Loading

Sources and Land use

Phosphorus and nitrogen are limiting nutrients that can hold back the growth of primary producers in all ecosystem types. To overcome this, humans have used advancements to alter nutrient availability around the world. This has disturbed the natural balance and cycles of nitrogen and phosphorus which has led to excessive nutrient concentrations within ecosystems. A direct effect that excessive nutrient concentrations have on the natural environment is a loss of biodiversity (Isbell et al., 2013).

Increasing nutrient concentrations are attributed to human activities including agricultural, industrial, and urban land uses (Khatri and Tyagi, 2015). There are two sources of nutrient pollution, point and non-point sources. Point sources are localized inputs of nutrient pollution, such as leaking septic tanks, drainage from wastewater treatment plants, and industrial sources (Kronvang et al., 2009). Non-point sources come from dispersed sources like land runoff. Non-point sources of phosphorus pollution include urban stormwater runoff, manure and fertilizer runoff, and soil erosion from agricultural fields (Kleinman et al., 2011). The over-application of phosphorus in areas with intensive crop and livestock production have been suggested to be the most important cause of increasing phosphorus levels in soils and consequently phosphorus losses (Sharpley et al., 1994; Kleinman et al., 2011).

Forty-one percent of Wisconsin's land use is agricultural, which makes the state susceptible to nutrient loading (USDA NASS, 2012). A few criteria that are measured in the state of Wisconsin for water quality purposes include dissolved oxygen, total nitrogen, total phosphorus (TP), and sediment (WI DNR, 2020). In a Wisconsin GIS land use study, a relationship between TP in watersheds and agricultural land cover was found to be statistically significant (Liu et al., 2009). 1,203 waterbodies in Wisconsin are included on the states Impaired 303d list. From this list, 49% of these impaired waters are attributed to inputs of phosphorus from runoff (WI DNR, 2020). In the 2020 impaired waters 303d listing cycle, 111 lakes were added to the list due to phosphorus pollution while 5 lakes were delisted.

Over the past decade farmland in Wisconsin has been on the decline, but with increasing population and a need to feed and provide energy (biofuels) for the population, an increase in agricultural activity is foreseen in the state of Wisconsin (CLUE, 2010; LaBeau et al., 2014). While best management practices have been researched and implemented across the state, nutrient inputs continue to be a primary concern for water quality protection (WI DNR, 2012).

Another issue that midwestern states face are the impacts of climate change. As changes in climate and increased frequency and intensity in precipitation occur in the Upper Midwest (USGCRP, 2018), increased pulses in nutrients will have major implications for freshwater (Kaushal et al., 2014; Kleinman et al., 2006). In a long-term Wisconsin case study, researchers observed a direct relationship between increased extreme rain events and heightened phosphorus loads (Waller et al., 2021). A rise in precipitation events will directly lead to increased nutrient loading through increased runoff and erosion.

Phosphorus Loading effects on Lakes

While nutrient loading can pose problems in all manner of surface and subsurface waters, it is especially important for lakes, ponds, and reservoirs, as these water bodies have longer residence times and thermal stratification (Vinçon-Leite & Casenave, 2019). Longer residence time combined with thermal stratification will cause lower phosphorus output rates than the rate of phosphorus being input, resulting in higher phosphorus concentrations in the system (Brusseau et al., 2019). As phosphorus concentrations continue to increase in a waterbody, so does the chance of it becoming a eutrophic system. Human induced eutrophication has been observed in numerous aquatic ecosystems due to human activities that increase phosphorus loads (Correll, 1998; Smith et al., 1999). The amount of phosphorus that can be added to a waterbody before it reaches its phosphorus loading threshold is dependent on the retention time, depth, water source, and other lake characteristics. These other characteristics will be discussed further in Section 2 (Lake phosphorus models) of the review on literature, below. Identifying phosphorus loading thresholds can prevent waterbodies from crossing into nearly irreversible trophic state changes.

Influxes of phosphorus will increase the primary production of the lake. This can be beneficial to a lake, up to a certain point. Increased primary production of certain plants in a waterbody can be advantageous to fish biomass but rapid changes in trophic state will result in a loss of biodiversity and desirable fishes (Jones and Lee, 1986; Isbell et al., 2013). Eutrophication is a cascade of events spurred by increased lake fertility

(MEII, 1998). The most noticeable effect of rapid eutrophication is increased algal blooms. Increased amounts of algal production and algal blooms tint the water green and decrease light penetration to the plants below. Once the algae die and begin to decay, bacteria begin to consume the decaying matter and the oxygen. This results in hypoxia and over time many species will disappear from the ecosystem (MEII, 1998). Algal blooms are toxic to animals and can cause harmful health effects and result in death (Hudnell, 2010). Humans rarely die from toxic blooms but can become ill (Stewart et al., 2006). Along with being toxic, increased algal blooms and reduced water clarity are undesirable for recreational purposes and property values (USGS, 2019). To mediate damage done by human induced eutrophication, the U.S. spends nearly $2.2 billion annually (Dodds et al., 2009).

Human activities affect the quality of water and humans are also influenced by degradation of lake ecosystems. Lakes with limited clarity are perceived to be of lesser quality than lakes with greater transparency. Poor water quality closely effects the recreational value and desirability of lakes (Keeler et al., 2015). Recreational users prefer waterbodies with clearer water (Noehner, et al., 2018). In a 2009 study aimed to estimate potential economic losses caused by eutrophication, Dodds et al. estimated that recreational losses ranged from $0.37-1.16 billion per year and lakefront property value loss ranged from $0.3-2.8 billion annually (Dodds et al., 2009). Lake property values were found to be higher on lakes that have greater water clarity as compared to property on lakes with less clear water (Gibbs and Halstead, 2002); with every 1-meter loss in Secchi Depth, property values decrease by15.6% (Krsysler et al., 2003). Recent studies and best management practices have begun to look at lake property owners' influence and perception of the waterbody that they live nearby.

The consequences of human induced eutrophication justify the need for protection. Furthermore, reversing eutrophication caused by human activities is no easy feat (Cook et al., 2005; Carpenter, 2005). TP loading is often from non-point sources, especially in areas with a large amounts of agricultural land cover. Non-point source reduction strategies can be more challenging than that of point sources (Carpenter et al., 1998; Weiner and Matthews, 2003). Even after external nutrient loads are reduced to impaired waters, restoration is difficult due to internal TP cycling (Søndergaard et al., 2003; Huser et al., 2016). Management of phosphorus loading is complex and will require a collective effort to reduce inputs from scientists, policy makers, and citizens.

Lake Phosphorus Models

Phosphorus models are important tools that identify sources of phosphorus loading and demonstrate how lake characteristics affect TP retention, cycling, and outputs. These models are numerous and differ in inputs and complexity. Several studies have been done to assess which characteristics most impact in-lake phosphorus concentrations (Brett and Benjamin, 2008; Cheng et al., 2010). Phosphorus model inputs include but are not limited to mean lake depth, areal phosphorus loading rate, water clarity, hydraulic inflow rate, phosphorus retention, and areal hydraulic loading (Brett and Benjamin, 2008). A strong foundation for lake phosphorus modeling has been laid by R. Vollenweider.

Vollenweider's research (1969, 1975, 1976) provides a basis for lake phosphorus retention and concentration models that include physical/hydraulic lake characteristics for model inputs as a basic mass-balance approach. Since, models have developed from Vollenweider's to include more specific assumptions and complex inputs to account for variability among lakes. For example, the Jenson model (2006) estimates in-lake phosphorus concentrations specifically for shallow lakes.

Research conducted by the Minnesota DNR (MDNR) created a multi-criteria decision model (MCDM) that prioritized Minnesota lakes for conservation based on three models (Radomski and Carlson, 2018). The three models in this MCDM were a hedonic model, values-based phosphorus model, and a biological uniqueness model. The values-based model from this MDNR research was replicated in this study for Wisconsin lakes, with the research methods closely following the MDNR study.

The values-based model from the MDNR study was an additive and multiplicative benefit function that ranked lakes based on a resulting lake phosphorus sensitivity significance prioritization (LPSSn). The model had three components: (1) lake's TP sensitivity, (2) TP loading sensitivity significance, and (3) lake phosphorus sensitivity significance priority score. The first component included inputs of in-lake mean TP concentration, Secchi disk transparency depth (SDT), hydraulic inflow rate, lake volume, and flushing rate (Radomski and Carlson, 2018). In a 2008 study, these lake characteristic variables were tested to determine which variables were most important in determining lake TP concentrations and retention (Brett and Benjamin, 2008). The MN study used the best suited lake characteristics in a mass balance equation by Cheng et al. and increased TP loading to determine lake sensitivity to phosphorus loading (Cheng et al., 2010; eq 6). This was then reported as a loss of Secchi disk depth in inches per 100 pounds of TP added. For the Wisconsin replication of this model a different mass balance equation was used, based on work by Dillon and Rigler which was located in the Wisconsin Lake Monitoring Suite of models (WiLMS; Dillon Rigler, 1976).

The second component of the MDNR values-based model identified the likelihood of reaching lake phosphorus sensitivity thresholds with additional watershed and lake characteristic variables. These inputs included the sensitivity from the first component along with surface area, watershed disturbance, predicted TP loads, TP load thresholds, and in-lake mean TP concentrations. The final component took half of a clarity trend score and then added the sensitivity significance score, which resulted in a lake phosphorus sensitivity significance priority score. This priority score was normalized between 0 and 100 to create a prioritization list that ranked high quality lakes near TP loading thresholds at the top of the list and gave a lower rank to lakes that exceeded TP loading thresholds. For the Wisconsin version of the values-based model, this research used all variables and methods from the second and third/final model components.

TP sensitivity varies among lakes and is dependent on many factors including lake characteristics, circulation, and temperature (Bhateria and Jain, 2016). Phosphorus load criteria were set for Wisconsin in 2010, in the form of TMDLs for impaired watersheds. These criteria are useful to repair impaired watersheds but do not cover site specific lakes that differ in the amount of phosphorus that can be absorbed without affecting the ecosystem balance. A model that determines phosphorus sensitivity allows for more lake specific phosphorus criteria values and thresholds.

Wisconsin Water Quality Protection and Restoration

Phosphorus inputs can appear in watersheds from both point and non-point sources. Wisconsin has been addressing non-point sources with several programs that date back to 1979 (WI DNR, 2010). The most recent non-point program is the *Performance standards and prohibitions for both agricultural and urban nonpoint sources* program, which began in 2002 and was updated in 2010. This plan works at the local level with the county land conservation department and focuses on agricultural and urban non-point sources.

In 2010, WI DNR implemented new water quality protocol to address both non-point and point sources for phosphorus pollution in surface waters (Radatz et al., 2018). This revision created maximum thresholds for phosphorus in watersheds which includes procedures and permits for both point and non-point sources. To help manage non-point pollution runoff, the WI DNR, Wisconsin Department of Agriculture, and Trade and Consumer Protection in 2017 allocated $21 million dollars in state and federal funds (WI DNR, 2018).

In July 2019, Governor Tony Evers claimed that it would be "the year of clean water." He granted $32.65 million in the state budget for improving water quality throughout the state and $750,000 annually to farmers to participate in best management practices (Spaeth-Bauer, 2019). This budget was granted for the sole purpose of increasing quality of groundwater and drinking water but will also be reflected in overall water quality protection.

In 2018, WI DNR, Water Quality Bureau, and Lakes Partnership created the *Healthy lakes and rivers plan.* It was created to keep the healthy waters in Wisconsin healthy. Across the nation the number one stressor to lake health is attributed to the loss of lakeshore habitat (Toshner, 2019). It focuses on best management practices and acts as a guide to private and public shoreline parcel owners on how to take care of their properties habitat to prevent degradation to the waterbody they occupy. In 2020, 18 Healthy Lake grants were awarded totaling $165,000. Taking preventative measures and starting inexpensive protection will help keep these waterbodies clean and will avoid future spending on restoration projects. These programs and grants are a few examples of efforts and funding that Wisconsin has put forth to protect the state's waterbodies from nutrient loading.

Summary

In Wisconsin, value and consideration for water quality has greatly increased in the past decades. Understanding how human activities influence aquatic ecosystems has created an awareness for how we can implement BMP and preventative measures to protect these systems. Restoration and conservation funding will continue to be a necessary tool to keep improving and protecting the quality of Wisconsin's water. Models are used in many water resource scenarios and a multi-criteria decision model would aid decision makers in allocating conservation funds. Targeting lakes that would benefit the most from restoration and water quality protection projects based on water quality data would ensure a positive, appropriate use of water quality funds.

CHAPTER THREE: METHODS

Methodology

This study used a quantitative approach to estimate lake phosphorus loading sensitivity through mass balance equations, regression analysis, and a prioritization model.

Data

Data was taken from the WI DNR Surface Water Integrated Monitoring System (SWIMS). The SWIMS database houses chemistry, physical, and biological data for surface waters in Wisconsin. Another valuable source of data was the WI Lake Character spreadsheet. This spreadsheet was created in 2016 and holds lake characteristic data for 5,345 lakes and reservoirs. The WI Lake Character spreadsheet also contains TP loading estimates for 914 lakes calculated using the Pollution Load Ratio Estimation Tool (PRESTO). The analysis for this study was limited to 929 Wisconsin lakes that had all necessary variables (Figure 1). These lakes were selected based on available clarity, total phosphorus concentration, and lake characteristics data, with clarity measured by Secchi disk transparency depth (SDT). A Secchi disk is an 8-inch disk with alternating black and white sections. It is lowered into the water column until it can no longer be seen. The depth of disappearance is the measured Secchi depth, which can vary based on suspended sediments, color of the water, and algae (NALMS, n.d.).

Within the overall workflow for this research, one important step was to estimate the relationship between SDT and in-lake TP using linear regression. Since this particular analysis contained only two variables, it was possible to utilize a slightly larger dataset, with a total of 1,217 lakes used to quantify the SDT vs. TP relationship (Figure 2).

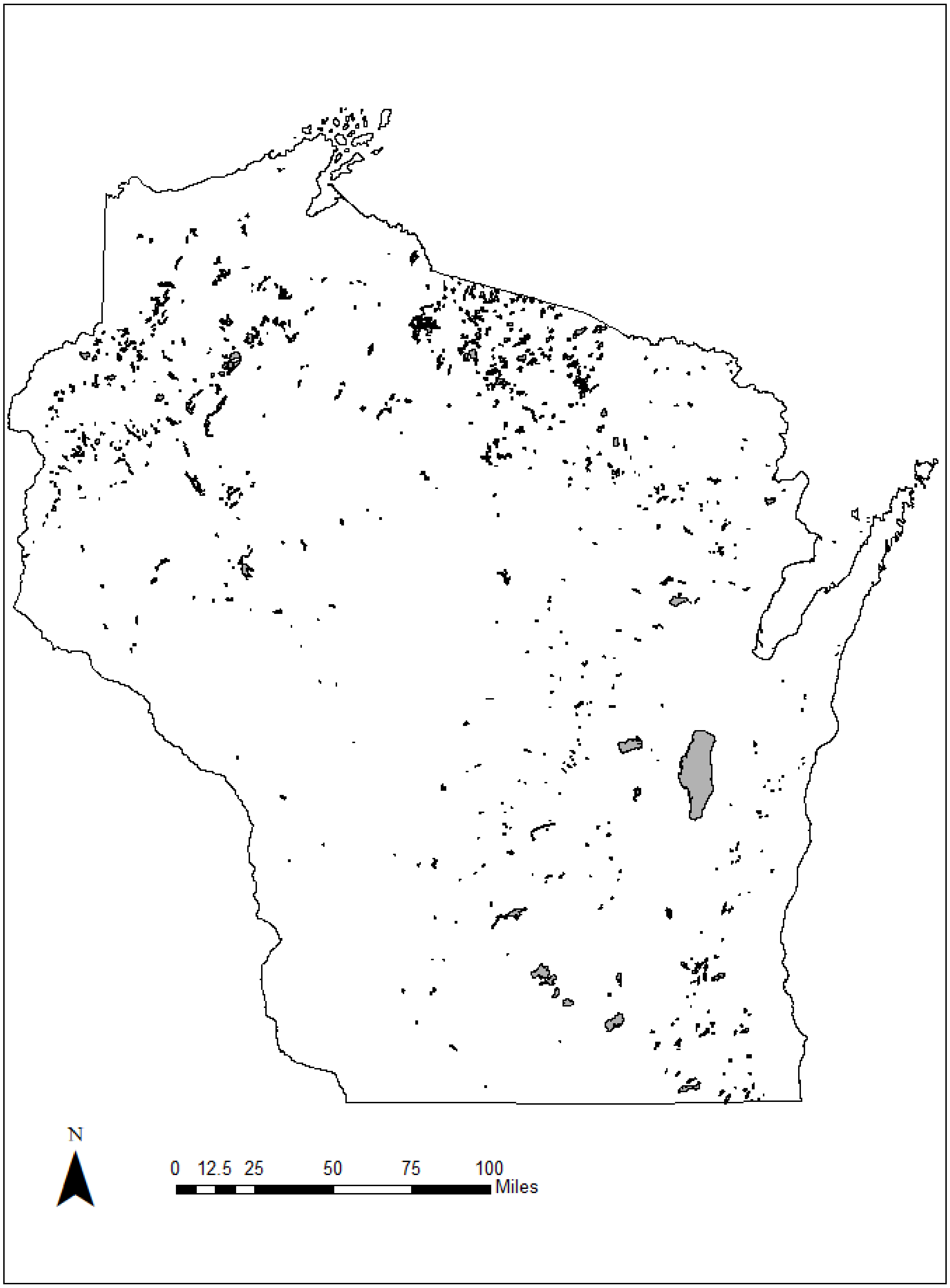

Figure 1. Locations of 929 lakes used in model analysis.

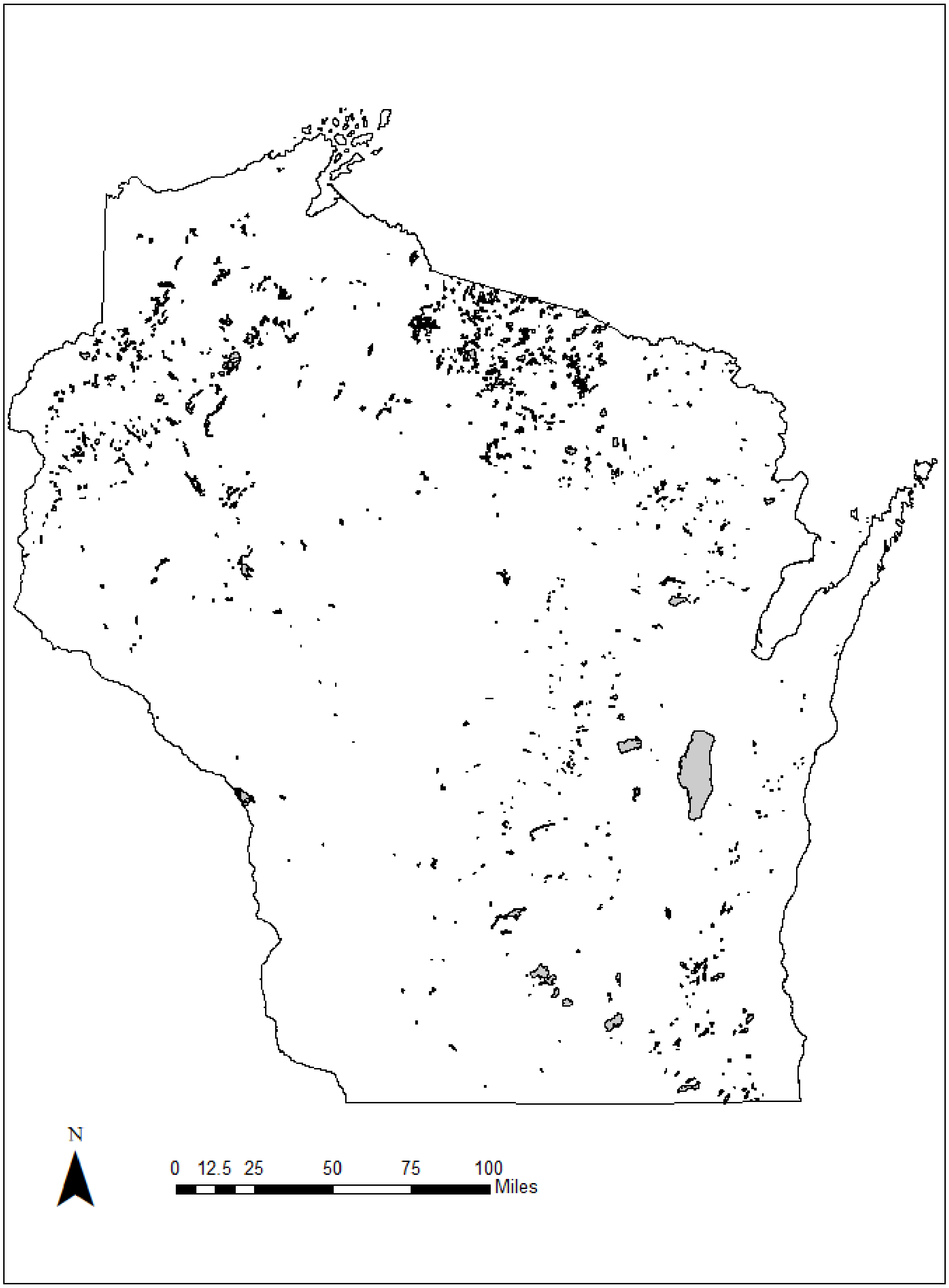

Figure 2. Locations of 1217 lakes used in the SDT v. TP regression analysis.

The total phosphorus concentration data and clarity data used in this research focused on Wisconsin summer conditions, from the months of June to mid-September, and available data ranged from the years 2000-2020. Total phosphorus summer mean concentrations were averaged across all available years, as was measured SDT, to produce one TP and one SDT value for each lake.

Lake morphometry, watershed characteristics, and other lake attributes were taken from the WI DNR 'Lake character spreadsheet' (2016). The variables used from this spreadsheet included mean lake depth (z), retention time (t), volume (V), hydraulic inflow rate (Q), surface area (A), phosphorus loading (L), drainage area (DA), and land cover. Following the methods of Radomski and Carlson, these lake characteristic variables were used in a multiple regression analysis to predict TP loading. These variables were also used in various parts of the model to find phosphorus sensitivity and sensitivity significance. Where lake volume was not available, volume was estimated by dividing Q by t (Brett and Benjamin, 2008). Mean depth was available for most lakes but when it was not present it was estimated by dividing V by A (Brett and Benjamin, 2008). Disturbed land (D) in the watershed was estimated by adding the area of developed land and cultivated land use classes (USGS, 2006) divided by the drainage area.

Other variables used in the model that were computed using the SWIMS data and WI Lake Character spreadsheet data included mix stratify ratios, TP loading thresholds, and trophic state indices. Mix stratify ratios were calculated using the WI DNR's equation:

(1) $$(MaxDepth-0.1)/(LOG(SurfaceArea)).$$

Values greater than 3.90 are considered stratified and less than 3.90 are considered mixed (WI DNR, n.d.). These classifications were then used when assigning TP loading thresholds to lakes for model analysis. TP loading thresholds were assigned based on waterbody type (lake/pond or reservoir/flowage), waterbody source (drainage, seepage, etc.), and mix stratify classifications. These TP thresholds (Table 1) were created for Wisconsin's Phosphorus Water Quality Standards for statewide P criteria. Assigning TP thresholds was an important step for use in the Sensitivity Significance model (SS), which is explained further in the research methods section below.

Table 1. TP thresholds by waterbody type created by WI DNR for statewide P criteria.

Waterbody Type	Applicable Criteria (ug/L
Reservoir or Flowage:	
Stratified	30
Not stratified	40
Lakes or Ponds:	
Stratified, seepage	20
Stratified, drainage	30
Non-stratified, drainage	40
Non-stratified, seepage	40

Trophic state indices were computed based on Chlorophyll-a, in-lake TP, and SDT data, using Carlson's 1977 TSI equations (1977). These equations are used in the Wisconsin Consolidated Listed Methods (WisCALM) and produce easy to understand numerical outputs (Carlson and Simpson, 1996). The output for each of these TSI equations was averaged to give each lake a single TSI value. TSI values and their corresponding trophic status can be found in Table 2. The single averaged trophic state index was used to analyze the performance of the lake phosphorus priority score model (LPSSn). The intended result of the model was to identify high quality lakes at greatest risk of becoming degraded. The expectation was to see lakes classified as oligotrophic or mesotrophic ranked highest in the LPSSn priority score and eutrophic to hypereutrophic lakes at the lower end of the priority score.

Table 2. Trophic state indices and their corresponding classification.

TSI	Trophic State
<30-40	Oligotrophic (O)
40-50	Mesotrophic (M)
50-60	Eutrophic (E)
>60	Hypereutrophic (HE)

Research Methods

A three-component model (Figure 3) was created to reflect the value-based prioritization model from the Radomski and Carlson study *Prioritizing lakes for conservation in lake-rich areas* (2018). Methods follow closely to that of the Radomski and Carlson study, however, based on consultation and collaboration with university faculty and WI DNR, some small modifications have been made to better suit the unique context of Wisconsin lakes. The first step in the workflow established a relationship between SDT and in-lake mean TP concentration. This was done using linear regression analysis in R. Establishing this relationship was an important first step because this linear regression equation was a required input in the first component of the model. The data for this step included 1,217 lakes spread across Wisconsin (Figure 2).

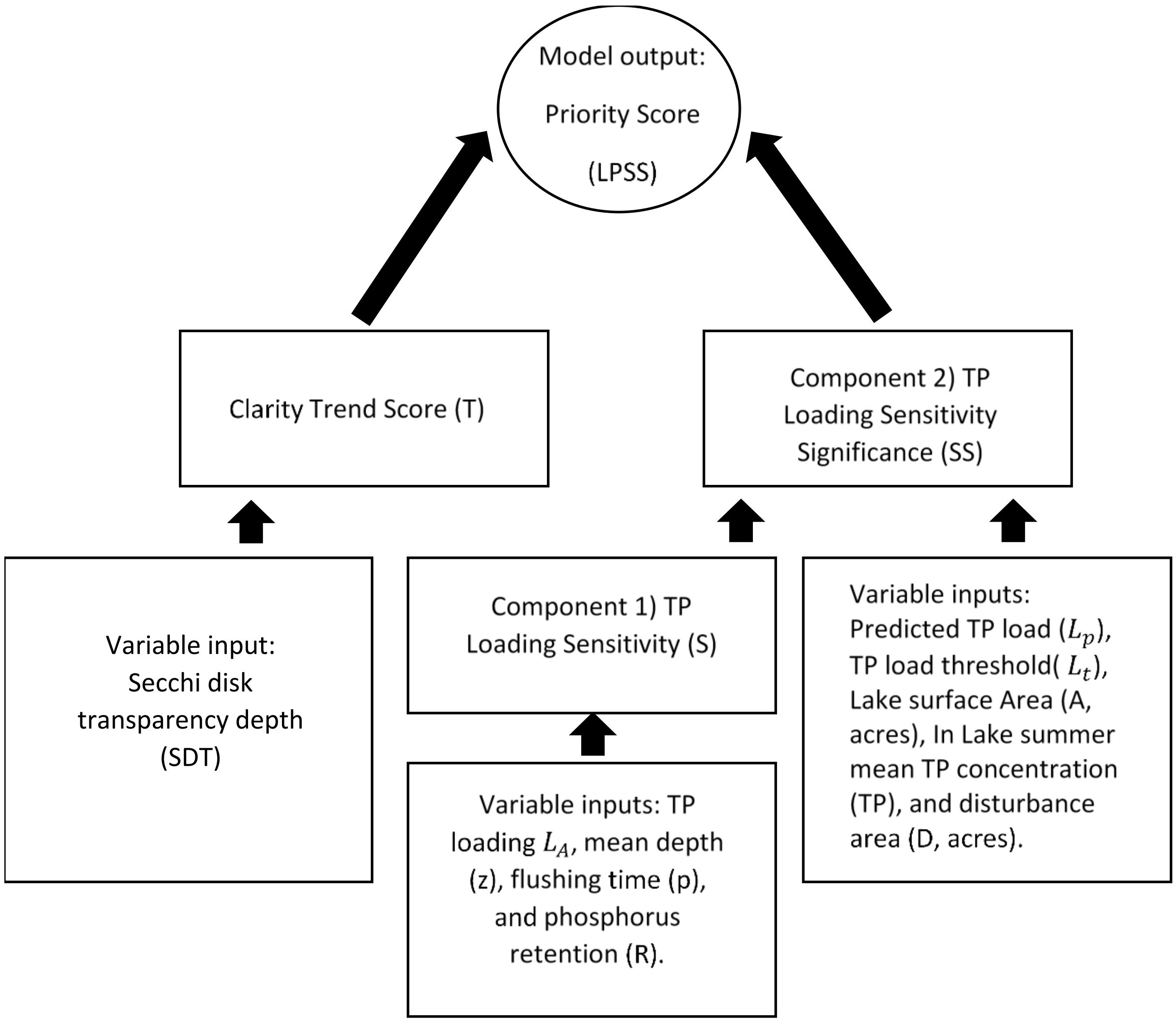

Figure 3. Conceptual framework of three component model with variable inputs.

The first component of the model estimated annual TP loading and lake sensitivity to TP loading. In a 2008 study by Brett and Benjamin, a suite of models was created to determine which lake characteristics were most connected to lake phosphorus concentration and phosphorus retention. From this suite of models, the model that best fit the available data was used to predict annual TP loading for a subset of Wisconsin lakes (n =298). The best model used lake volume (V), hydraulic inflow rate (Q), in-lake summer mean total phosphorus concentration (TP_{lake}), and mean lake depth (z) as fixed effects. This model was validated using predicted annual TP loading data for 298 lakes from the PRESTO. data found in the WI Lake character spreadsheet. The estimated annual TP loading was then used in a natural lakes mass-balance equation by Dillon and Rigler (1975; equation 2). This mass-balance equation predicts TP_{lake} as a function of Areal loading (L_A), phosphorus retention (R), mean depth (z), and flushing rate (p). R was estimated using the equation $1 - \frac{TP_{lake}}{TP_{in}}$ (Radomski and Carlson, 2018). Where TP_{lake} is the measured total phosphorus concentration in a lake and TP_{in} is the predicted TP load converted to units of concentration. Sensitivity (S) to additional loading was determined by increasing predicted TP loads by 45.36 kg (100 lbs.). This increased load was added to predicted TP loads and entered in the mass-balance equation which then predicted the change to TP_{lake}. This change in TP_{lake} was entered into the linear regression equation from step one to determine loss of SDT. The sensitivity was then expressed as a loss of SDT in inches per 45.36 kg of TP added (Radomski and Carlson, 2018).

(2) $$TP_{lake} = L_A(1 - \frac{R}{zp})$$

The second component of the model created a significance score, TP loading sensitivity significance (SS), to determine the likelihood that this increase in phosphorus would occur. Values from this output can take-on a wide range from 0 to greater than 50,000. Lakes that have low SS values are not sensitive to increased phosphorus loads and likely already exceed TP load thresholds. Lakes that receive high values are extremely sensitive to increased TP loading and would generally be labeled as lakes to protect. This component used the sensitivity score (S), predicted TP load (L_p), TP load threshold(L_t), lake surface Area (A, acres), in-lake summer mean TP concentration (TP), and area disturbed in the lake's watershed (D, acres). If the predicted TP load (L_p) to TP load threshold(L_t) ratio was less than or equal to one, then equation 2 was used. If the predicted TP load (L_p) to TP load threshold(L_t) ratio was greater than one, then equation 3 was used. Equation 3 normalizes the TP load (L_p) to TP load threshold (L_t) ratio between 0 and 1. The results of a 2013 MN study indicated that lake TP concentrations could be significantly altered by watershed disturbance that exceeded a threshold of 40% (Cross and Jacobson). Therefore, the third equation also used a normal probability density function with a mean of 0.4 and standard deviation of 0.2 and was then normalized between 0 and 1 (D_n). The normal probability density function places higher significance on watersheds that had disturbance greater than 40%.

(3) $$SS = S * \frac{A}{TP} * \frac{L_p}{L_t} * D$$

(4) $$SS = S * \frac{A}{TP} * [1 - \frac{\frac{L_p}{L_t} - Min\left(\frac{L_p}{L_t}\right)}{Max\left(\frac{L_p}{L_t}\right) - Min\left(\frac{L_p}{L_t}\right)}] * D_n$$

The final part of the model used the normalized sensitivity significance (SS_n, component two), and one-half of the decreasing water clarity trend score (T) to create the priority score (equation 4).

(5) $$Priority\ score = 0.5 * T + SS_n$$

The clarity trend score (T) assigned a score of 0 or 0.5. T is based on the p-value from a Mann-Kendall statistical test. Lakes with at least 8 years of data were analyzed. From the 929 lakes, 261 lakes did not have enough data to be analyzed. 20 lakes had an increasing water clarity trend, and 27 lakes had a decreasing trend. Following the methods of Radomski and Carlson, lakes that showed a significant negative trend, were given a value of 0.5, otherwise, lakes were given a value of 0 (Radomski and Carlson, 2018). The priority score was then normalized between 0 and 100. All normalizations and rescaling followed equation 6, where X is the original value and X' is the normalized value.

(6) $$\left(\frac{X-Min(X)}{Max(X)-Min(X))}\right) * ((\mathrm{U}+\mathrm{L})+\mathrm{L}) = \mathrm{X'}$$

Once the final model output was completed, the in-lake mean TP, Sensitivity (S), and lake phosphorus priority score (LPSSn) data was analyzed using a Kruskall-wallis test to test for significant differences among Level III ecoregions. A Kruskall-Wallis test was used instead of an ANOVA because the data did not meet the assumption of normality and the data across the five ecoregions had varying sample sizes. If significant differences were identified a Post-hoc Dunn's multiple comparisons test was used to find specific differences between each ecoregion.

Table 3. Study Variables

Measure	Unit	Source	Relationship
Priority Score	Index of 0-100	Model output - Radomski & Carlson (2018)	Summation of normalized TP loading sensitivity significance (SS_n) and decreasing water clarity trend score (T).
Decreasing water quality trend score (T)	Unitless; Either a score of 0 for no negative trend or 0.5 for evidence of a negative trend.	Mann-Kendall test performed on water Clarity.	Results of a test for a monotonic clarity trend over 8 years of data.
Water Clarity (SDT)	Secchi disc depth (m)	WI DNR Satellite Clarity	Used to calculate trend score (T).
TP Loading Sensitivity (S)	Loss of SDT in inches per 45.36 kg of TP added.	Component one model output – Radomski & Carlson (2018)	First component variable in the model to find the priority score.
TP Loading (L)	kg $year^{-1}$	WI DNR – 'WI Lake character spreadsheet'	Used to calculate TP loading sensitivity (S).
TP Concentration (TP_{lake})	µg L^{-1}	WI DNR SWIMS	Used to calculate TP loading sensitivity (S).
Hydraulic inflow rate (Q)	$m^3 s^{-1}$	WI DNR – 'WI Lake character spreadsheet'	Used to calculate TP loading sensitivity (S).
Lake volume (V)	m^3	WI DNR – 'WI Lake character spreadsheet'	Used to calculate TP loading sensitivity (S).
Lake depth (d)	meters	WI DNR – 'WI Lake character spreadsheet'	Used to calculate TP loading sensitivity (S).
Flushing rate (p)	$year^{-1}$	WI DNR – 'WI Lake character spreadsheet'	Used to calculate TP loading sensitivity (S).
TP Sensitivity Significance (SS)		Component two model output – Radomski & Carlson (2018)	Second component variable in the model to find priority score. Following variables

Table 3. Study Variables continued

Predicted TP load (L_p)	µg L^{-1}	WI DNR – 'WI Lake character spreadsheet'	required to calculate TP loading and SS.
TP load threshold(L_t)	µg L^{-1}	WI DNR – Loading thresholds for different waterbody types.	
Lake surface Area (A)	m^2	WI DNR – 'WI Lake character spreadsheet'	
In Lake summer mean TP concentration (TP_{lake})	µg L^{-1}	WI DNR SWIMS	
Disturbance in watershed (D)	m^2	WI DNR – 'WI Lake character spreadsheet'	Amount of cultivated plus developed land divided by the entire watershed.

CHAPTER FOUR: RESULTS

The regression analysis between in-lake summer mean TP concentrations and SDT performed best when both variables were log transformed. The relationship between increasing log transformed TP concentrations and decreasing log transformed SDT was a strong, negative linear relationship with an R^2 of 0.6818 (Figure 4). This relationship between in-lake summer mean TP and SDT was used later in the first component of the model to predict a lake's sensitivity to phosphorus loading, expressed as a loss of Secchi disk transparency depth when 45.36 kg (100 lbs.) of TP was added.

Establishing a multiple regression equation to predict TP loading values for all study lakes (n = 929) was an important step in the analysis. Without this regression equation only 298 lakes with prior established TP loading values would have been available for the remaining analysis. A linear log-log regression model was the best model to predict TP loading. The predictor variables included hydraulic inflow rate, lake volume, mean lake depth, and lake mean TP concentration (Multiple R^2= 0.851; adjusted R^2= 0.849; Table 4; Figure 5). The resulting predictor variable inputs were the same as the the MN study, with one additional variable, mean lake depth. The observed values were obtained from the Lake character spreadsheet and were created by the PRESTO. The average absolute percent difference between the observed and fitted values was 9.75% (standard deviation = 7.83%). Using this multiple regression equation, predicted TP loading for all lakes were added to the database for use in the first component of the model, TP Sensitivity (S).

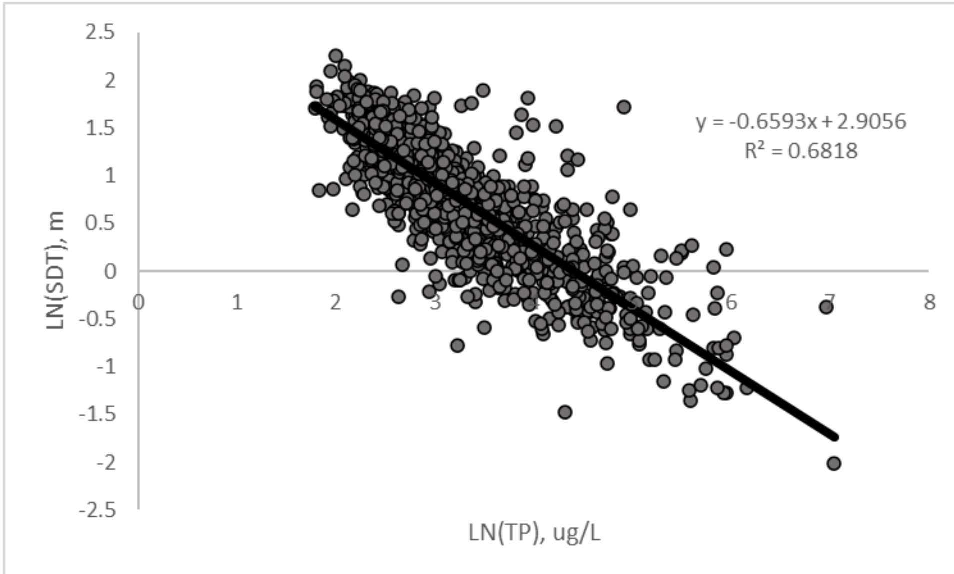

Figure 4. The linear regression between in-lake summer mean TP concentrations and mean Secchi disk transparency.

Table 4. A summary of the linear regression model to predict TP loading.

Source of variation	Coefficient	SE	t	p
Intercept	4.715	0.296	15.92	0.000
logTP_Lake	0.754	0.064	11.69	0.000
logQ	0.942	0.034	28.08	0.000
logz	0.486	0.096	5.092	0.000
logTP_Lake*logV	-0.049	0.010	-4.869	0.000

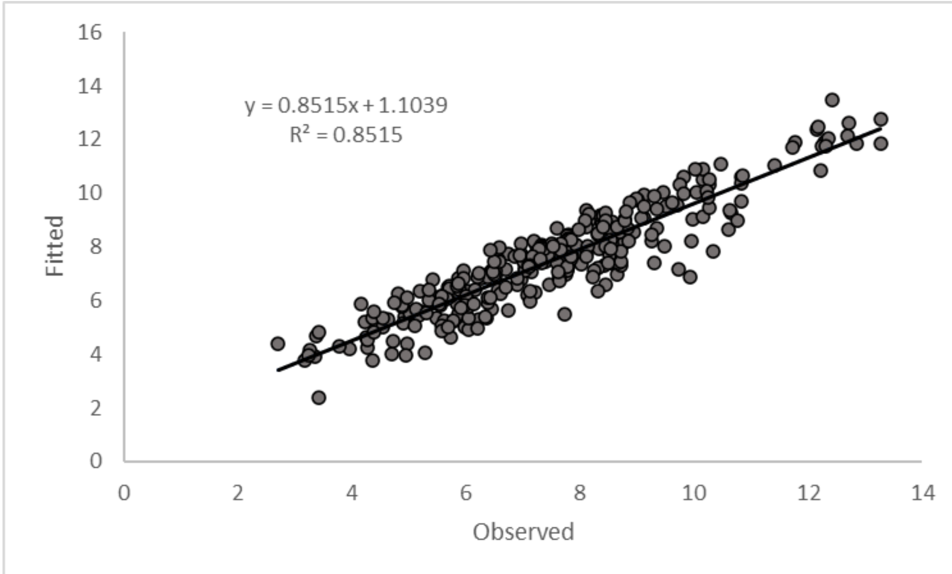

Figure 5. Fitted vs. observed values for the linear regression with log-transformed response variables, n= 298.

Model Components

The results of the sensitivity score (S) ranged in values from 1.76 to 588.4 inches of Secchi disk depth transparency (SDT) loss. The average value of S was 71.2 inches lost per 100 lbs of TP added. Lakes that had high predicted TP loading values were less sensitive to additional TP loading and had lower losses of clarity. While lakes with low predicted TP loading values were more sensitive to additional loading and had high S indices.

The normalized sensitivity significance score (SSn) had a range of values from the minimum zero to the maximum 916.9, with an average of 20.5. High SSn values had low watershed disturbance, generally below 20%. Lakes with high SSn values had a more concentrated range for in-lake summer mean TP concentrations from 20-30 ug/L. The range for in-lake summer mean TP concentrations for low SSn was much more widespread. Low SSn values displayed in-lake summer mean TP concentrations that ranged from 14-350 ug/L. SSn values that were low had watershed disturbance values equal to or above 40%. Generally, lakes that had low values from the subsequent index had low values of SSn, especially if the watershed disturbance was greater than or equal to 40%.

The normalized Lake phosphorus sensitivity significance priority score (LPSSn) was designed to range from 0 to 100. The average LPSSn score was 2.24. As expected, the LPSSn index produced high values for oligotrophic lakes that were near total phosphorus thresholds and low values for hypereutrophic lakes with large watershed disturbance and high estimated phosphorus loading. Similar to the MN study, lakes with large watersheds were more likely to have low priority score indices. Most lakes with high indices for sensitivity (S) scored high in the LPSSn indices. Those lakes that scored high in the S index but low in the LPSSn index had a watershed disturbance greater than 40%.

Ecoregion Analysis

The Level III ecoregions are areas of similar environmental resources and land cover (Omernik, 1987). Lakes in each ecoregion are generally alike, while lakes between different ecoregions generally have differences in lake morphology and watershed land cover. When looking at the Priority list in order, there was a noticeable number of top ranked lakes from the Northern Lakes and Forests ecoregion and the bottom ranked lakes were located in both North Central Hardwood forests and Southeastern Wisconsin Till Plains. When the LPSSn score was mapped out for each lake, there were obvious differences among the ecoregions. Unlike the Radomski and Carlson study, there were no obvious trends of high LPSSn scores in transitional zones throughout the state.

The Kruskall-Wallis test indicated that in-lake mean summer TP concentrations, S indices, and priority score (LPSSn) varied across Ecoregions (Table 5; alpha = 0.05). For each of the three variables a post-hoc Dunn's multiple comparisons test using a Bonferroni-adjusted alpha level of 0.010 (0.05/5) was used to compare all pairs of groups.

Table 5. Kruskall-Wallis test results, alpha = 0.05.

	In-lake TP concentrations (ug/L)	Sensitivity index (S)	Priority Score index (LPSSn)
Kruskal-Wallis H	82.041	90.166	324.176
df	4	4	4
p-value	0.000	0.000	0.000

For in-lake TP, the Northern Lakes and Forests ecoregion was significantly different from the Driftless area (adj. p = 0.00), North Central Hardwood Forest (adj. p = 0.00), and Southeastern Wisconsin Till Plains (adj. p = 0.00), but not the Western Corn Belt Region (adj. p = 0.352; Table 6; Figure 6). The Driftless area was also significantly different from all other ecoregions (adj. p = 0.00), besides the Western Corn Belt Region (adj. p = 1.00). The North Central Hardwood Forest and Southeastern Wisconsin Till Plains were not significantly different from each other or the Western Corn Belt Region (adj. p = 1.00).

Table 6. Dunn's multiple comparison test for in-lake TP concentration across Ecoregions using a Bonferroni-adjusted alpha level of 0.010 (0.05/5).

Comparison	Z	Unadjusted p-value	Adjusted p-value
Driftless Area – North Central Hardwood Forests	5.104	<0.000	<0.000
Driftless Area - Northern Lakes and Forests	7.238	<0.000	<0.000
North Central Hardwood Forests – Northern Lakes and Forests	5.054	<0.000	<0.000
Driftless Area – Southeastern Wisconsin till Plains	4.595	<0.000	<0.000
North Central Hardwood Forests – Southeastern Wisconsin Till Plains	-0.632	0.527	1.000
Northern Lakes and Forests – Southeastern Wisconsin Till Plains	-4.791	<0.000	<0.000
Driftless Area – Western Corn Belt Plains	-0.119	0.905	1.000
North Central Hardwood Forests – Western Corn Belt Plains	-1.554	0.120	1.000
Northern Lakes and Forests – Western Corn Belt Plains	-2.106	0.0352	0.352
Southeastern Wisconsin Till Plains – Western Corn Belt Plains	-1.456	-1.452	1.000

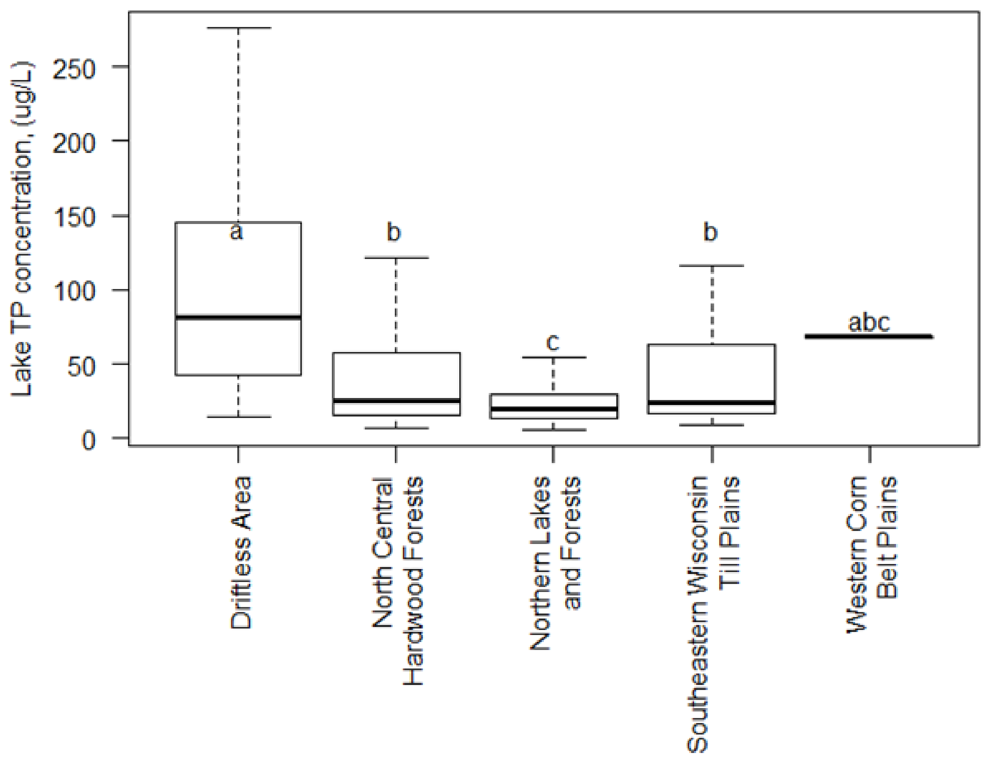

Figure 6. Box plots of lake summer mean TP grouped by level III ecoregion. The whiskers are no longer than 1.5 times the interquartile range, and the line within the box ins the median.

The sensitivity score (S) followed the same pattern as the other two variables. All ecoregions were not significantly different from the Western Corn Belt Region (adj. p = 0.770). The Driftless area was significantly different from the Northern Lakes and Forests (adj. p = 0.00), North Central Hardwood Forest (adj. p = 0.001), and Southeastern Wisconsin Till Plains (adj. p = 0.006). The Northern Lakes and Forests was also significantly different from all other ecoregions (adj. p = 0.00). The North Central Hardwood Forest and Southeastern Wisconsin Till Plains were not significantly different from each other (adj. p = 1.00).

Table 7. Dunn's multiple comparison test for Sensitivity score (S) across Ecoregions using a Bonferroni-adjusted alpha level of 0.010 (0.05/5).

Comparison	Z	Unadjusted p-value	Adjusted p-value
Driftless Area – North Central Hardwood Forests	-3.745	<0.000	0.001
Driftless Area - Northern Lakes and Forests	-6.451	<0.000	<0.000
North Central Hardwood Forests – Northern Lakes and Forests	-6.585	<0.000	<0.000
Driftless Area – Southeastern Wisconsin till Plains	-3.447	<0.000	0.006
North Central Hardwood Forests – Southeastern Wisconsin Till Plains	0.314	0.753	1.000
Northern Lakes and Forests – Southeastern Wisconsin Till Plains	5.681	<0.000	<0.000
Driftless Area – Western Corn Belt Plains	0.000	0.999	1.000
North Central Hardwood Forests – Western Corn Belt Plains	1.051	0.293	1.000
Northern Lakes and Forests – Western Corn Belt Plains	1.768	0.077	0.770
Southeastern Wisconsin Till Plains – Western Corn Belt Plains	1.001	0.0317	1.000

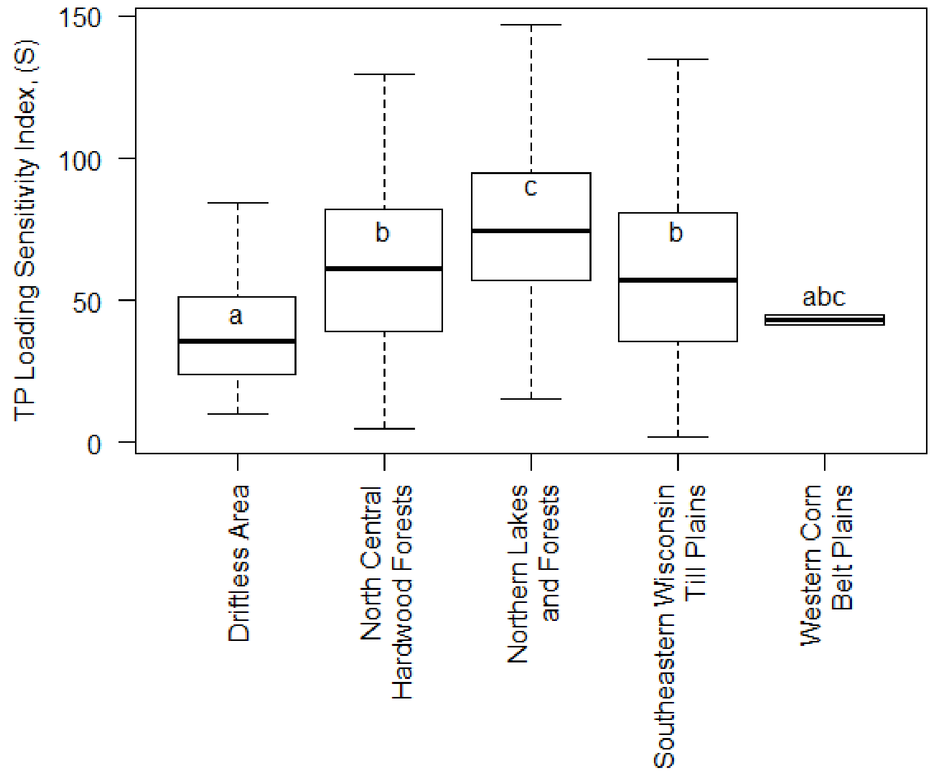

Figure 7. Box plots of TP loading sensitivity index (S) grouped by level III ecoregion. The whiskers are no longer than 1.5 times the interquartile range, and the line within the box ins the median.

For the priority score (LPSSn), the Driftless area was significantly different from the Northern Lakes and Forests (adj. p = 0.00), North Central Hardwood Forest (adj. p = 0.00), and Southeastern Wisconsin Till Plains (adj. p = 0.021), but not the Western Corn Belt Region (adj. p = 1.00). The Northern Lakes and Forests was also significantly different from all other ecoregions (adj. p = 0.00), besides the Western Corn Belt Region (adj. p = 0.062). The North Central Hardwood Forest and Southeastern Wisconsin Till Plains were not significantly different from each other or the Western Corn Belt Region (adj. p = 1.00).

Table 8. Dunn's multiple comparison test for Priority score (LPSSn) across Ecoregions using a Bonferroni-adjusted alpha level of 0.010 (0.05/5).

Comparison	Z	Unadjusted p-value	Adjusted p-value
Driftless Area – North Central Hardwood Forests	-3.471	<0.000	0.005
Driftless Area - Northern Lakes and Forests	-9.191	<0.000	<0.000
North Central Hardwood Forests – Northern Lakes and Forests	-14.20	<0.000	<0.000
Driftless Area – Southeastern Wisconsin till Plains	-3.078	0.002	0.021
North Central Hardwood Forests – Southeastern Wisconsin Till Plains	0.523	0.600	1.000
Northern Lakes and Forests – Southeastern Wisconsin Till Plains	12.08	<0.000	<0.000
Driftless Area – Western Corn Belt Plains	0.211	0.833	1.000
North Central Hardwood Forests – Western Corn Belt Plains	1.191	0.233	1.000
Northern Lakes and Forests – Western Corn Belt Plains	2.737	<0.000	0.062
Southeastern Wisconsin Till Plains – Western Corn Belt Plains	1.111	0.267	1.000

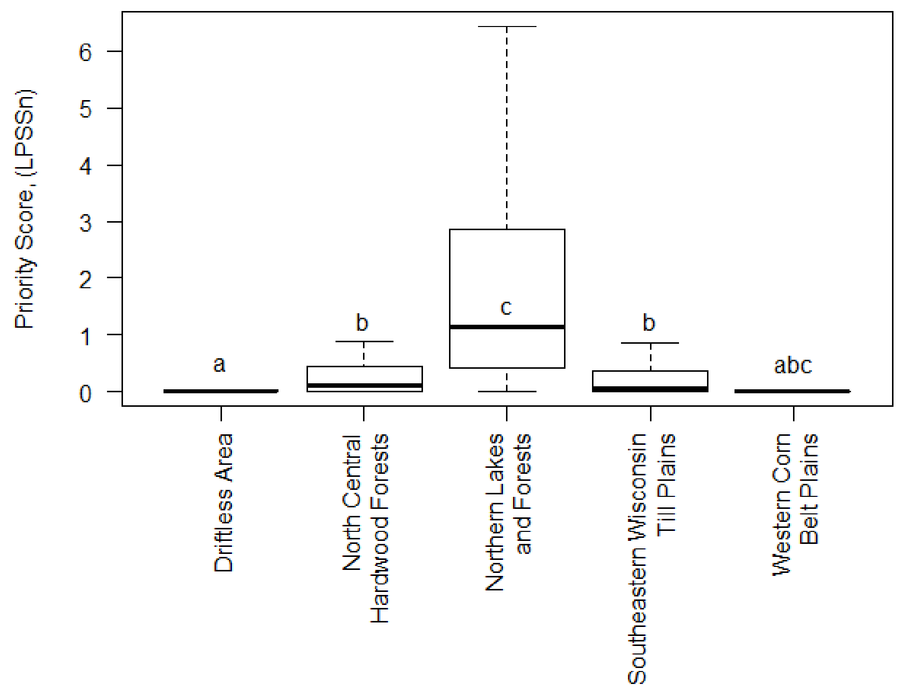

Figure 8. Box plots of priority score (LPSSn) grouped by level III ecoregion. The whiskers are no longer than 1.5 times the interquartile range, and the line within the box ins the median.

Table 9. Dunn's multiple comparisons test using a Bonferroni-adjusted alpha was used to compare all pairs of groups.

Variable tested	TP Lake Group	LPSSn Group	S Group
Driftless Area	a	a	a
North Central Hardwood Forest	b	b	b
Northern Lakes and Forests	c	c	c
Southeastern Wisconsin Till Plains	b	b	b
Western Corn Belt Plains	abc	abc	abc

Priority Score List

Lakes that scored high in the priority score (LPSSn) had predicted TP loading values near the WI designated thresholds and measured in-lake mean TP concentrations below these thresholds (Table 10). Lakes that had a low LPSSn had predicted TP loading values that far exceeded the designated loading thresholds (Table 11). The majority of top ranked lakes were found in the Northern Lakes and Forests ecoregion, while the bottom ranked lakes were mainly found in the Southeastern WI Till Plains and North Central Hardwood Forest regions. The top ranked lakes had TSI classification of oligotrophic and the bottom ranked lakes had a TSI classification that ranged from mesotrophic to hypereutrophic. The bottom 15 lakes were searched in the WI DNR impaired waters search tool and lakes in the bottom 15 that were classified as hypereutrophic in this study were listed as impaired for excess algal growth from phosphorus pollution and were assigned a low priority score by WI DNR.

Other differences between the top 15 lakes and the bottom 15 lakes included mean lake depth (z) and surface area (A). The top ranked lakes generally had a deeper mean depth ranged from 4.7-12.8 meters with a mean of 8.8 meters. The bottom ranked lakes mean depth ranged from 0.9-8.3 with a mean of 3.5 meters. For surface area, the top ranked lakes ranged from 4.2-52.3 square kilometers with a mean of 15 square kilometers. The bottom ranked lakes had a range from 0.044-4.9 square kilometers and a mean of 0.8 square kilometers for surface area. Since these variables were used in the first and second component of the model it was expected that these values would be an important factor in the overall model.

Table 10. Top 15 lakes by lake phosphorus sensitivity significance priority score (LPSSn).

WBIC	Waterbody Name	TP Lake (ug/L)	TSI	Predicted TP Load (ug/L)	S	LPSSn	Level III Ecoregion
2323000	Fence Lake	8.57	O	36.42	157.82	100.00	Northern Lakes and Forests
2390800	Lac Courte Oreilles	11.47	O	32.74	146.76	92.21	Northern Lakes and Forests
1542700	Tomahawk Lake	12.18	O	41.56	131.93	57.34	Northern Lakes and Forests
793600	Delavan Lake	27.92	O	99.05	588.41	55.32	Southeastern Wisconsin Till Plains
2294900	Turtle Flambeau Flowage	29.25	O	33.28	77.52	54.95	Northern Lakes and Forests
2391200	Grindstone Lake	12.80	O	39.13	133.98	50.57	Northern Lakes and Forests
805400	Lake Mendota	21.90	O	45.23	93.14	46.60	Southeastern Wisconsin Till Plains
396500	Lake Lucerne	7.90	O	38.21	165.83	33.11	Northern Lakes and Forests
2900200	Lake Owen	9.33	O	37.16	147.22	30.54	Northern Lakes and Forests
2322800	Crawling Stone Lake	10.86	O	41.63	142.79	29.99	Northern Lakes and Forests
2395600	Round Lake	17.00	O	51.92	109.71	29.75	Northern Lakes and Forests
1623800	Twin Lakes	16.23	O	46.39	112.41	29.71	Northern Lakes and Forests
2496300	Shell Lake	14.63	O	40.81	113.81	26.05	North Central Hardwood Forests
2106800	Long Lake	20.42	O	45.67	99.84	25.67	Northern Lakes and Forests
1593100	Star Lake	10.30	O	39.47	135.96	25.53	Northern Lakes and Forests

Table 11. Bottom 15 lakes by lake phosphorus sensitivity significance priority score (LPSSn).

WBIC	Waterbody Name	TP Lake (ug/L)	TSI	Predicted TP Load (ug/L)	S	LPSSn	Level III Ecoregion
77600	Boot Lake	350.10	HE	1246.53	10.91	0.00	Southeastern Wisconsin Till Plains
2089500	Tenmile Lake	232.50	HE	215.12	15.21	0.00	Northern Lakes and Forests
850300	Okauchee Lake	18.36	M	51.97	103.99	1.60E-05	Southeastern Wisconsin Till Plains
68600	Round Lake	176.84	E	964.18	7.07	3.14E-05	Southeastern Wisconsin Till Plains
299200	Grass Lake	15.35	M	66.82	77.24	3.42E-05	North Central Hardwood Forests
2628800	White Ash Lake	54.37	E	116.01	39.27	6.60E-05	North Central Hardwood Forests
994800	Lake George	27.00	M	109.54	25.67	8.10E-05	Southeastern Wisconsin Till Plains
750300	Browns Lake	20.57	M	55.16	54.56	8.56E-05	Southeastern Wisconsin Till Plains
353200	McGee Lake	14.00	M	71.84	82.09	1.09E-04	North Central Hardwood Forests
1878800	Rusk Lake	29.00	E	196.56	25.08	1.12E-04	Northern Lakes and Forests
2136200	Fairchild Pond	180.00	E	374.89	21.13	1.28E-04	North Central Hardwood Forests
2128100	Altoona Lake	119.88	E	110.54	28.19	1.51E-04	North Central Hardwood Forests
77300	Becker Lake	206.24	HE	607.84	20.87	1.55E-04	Southeastern Wisconsin Till Plains
2054200	Dead Lake	249.00	HE	362.67	18.47	1.72E-04	Driftless Area
264500	Ottman Lake	24.10	M	105.85	27.70	1.76E-04	North Central Hardwood Forests

CHAPTER FIVE: DISCUSSION AND CONCLUSIONS

Overall, the multi-stage model in this study performed as intended: it identified high-quality lakes at greatest risk of becoming degraded or further degraded. The findings from the sensitivity component of the model identified lakes near TP loading thresholds that would lose significant amounts of clarity in the water column if additional TP loading occurred. Lakes that had low in-lake TP concentrations were more sensitive to TP loading than lakes with higher amounts of in-lake TP concentrations. Subsequently, lakes that were near TP loading thresholds were ranked highest in the priority score and lakes that greatly exceeded TP loading thresholds and had high watershed disturbance were ranked lower. These results are similar to that of the MN study and confirm Hypothesis 2 for this research. These findings have important implications for resource managers; in particular, prevention of additional TP loading to lakes that were ranked high on the priority score list via watershed protection should be prioritized to prevent losses in water clarity, which could be environmentally harmful, economically harmful, and essentially irreversible. Additionally, with further precision the sensitivity values could be used as lake specific TP loading thresholds.

Radomski and Carlson found general patterns among the MN ecoregions which led to Hypothesis 1, that a pattern or trend will appear among the Wisconsin ecoregions for lake phosphorus sensitivity and priority score rankings. Compared to the other ecoregions, the lakes in the Northern lakes and forests (NLF) ecoregion were significantly more sensitive to phosphorus loading. Correspondingly, lakes in NLF ecoregion had significantly higher priority score than the North Central Hardwood Forests, Driftless Area, and the Southeastern Wisconsin Till Plains. The top ranked lakes were oligotrophic lakes primarily located in the Northern Lakes and Forests ecoregion (Table 11).

The ecoregions exhibit differences in land cover, environmental resources, quantity of lakes, and differences in lake trophic states. Top and bottom ranked priority score lakes varied by ecoregion due to these distinct differences between the ecoregions. The Northern lakes and forests (NLF) ecoregion is made up of primarily nutrient poor sandy and loamy glacial till (Omernik, 1987). The soil and the lower temperatures inhibit agriculture, which results in the land cover being mainly woodland, wetland, and forest. 69% of Wisconsin's lakes are located in the Northern lakes and forests ecoregion. Lakes in the NLF are clear and generally have a low trophic state (Omernik, 1987). NLF lakes range from oligotrophic to mesotrophic with a few eutrophic lakes. With low watershed disturbance and low trophic states, due to low TP concentrations, these lakes are more sensitive to additional phosphorus, which generally ranks them at the top of the priority score list.

Lakes within the North central hardwood forests (NCHF) and Southeastern Wisconsin till plains (SWTP) were not significantly different from one another for amounts of in-lake TP concentration, TP sensitivity, and LPSSn. The NCHF is a transitional area with a mix of land cover and topography. It is a combination of forests, wetlands, cropland, pasture, and dairy operations (Omernik, 1987). The NCHF ecoregion has 20% of Wisconsin lakes. Lakes in the NCHF have higher trophic states ranging from eutrophic to hypereutrophic. Moving further south, the Southeastern Wisconsin till Plains (SWTP) land usage is mainly cropland with a much flatter topography and greater variety in soils. The number of lakes in this ecoregion continue to decrease and contains 7% of lakes in the state. Lakes in these two ecoregions were less sensitive to phosphorus loading than the Northern lakes and forest ecoregion, likely due to land cover.

The remaining lakes in Wisconsin are largely found in the Driftless area (4%) and are mostly reservoirs with generally high trophic states (Omernik, 1987). The major land uses in the Driftless area are livestock and dairy operations, which has had a negative impact on water quality in streams (Omernik, 1987). In the Dunn's multiple comparison test the Driftless area had significantly higher values for in-lake mean TP, and lower values for sensitivity and LPSSn priority score than that of the NCHF, SWTP, and NLF.

The two smallest ecoregions in the state, the Western Corn belt plains (WCBP) and Central Corn belt (CCB), contain less than 0.5% of Wisconsin's lakes. The land use for the WCBP and CCB are very similar to each other with high amounts of agriculture and livestock. The soils are fertile and are one of the most productive areas for corn and soybeans in the world. The Western corn belt plains are listed as a major environmental concern due to livestock concentrations and fertilizer runoff which has led to contamination in ground and surface waters (Omernik, 1987). In this study only two lakes of the 929 were from the Western corn belt plains. This is likely the reason that for all Dunn's multiple comparison tests no ecoregion was found to be significantly different from the Western corn belt plains.

A few of the lakes in the Top 15 ranked lakes seemed out of place, namely Delavan Lake and Lake Mendota. These two lakes are currently listed on the impaired waters 303d list for excess algal growth and are classified as eutrophic systems (WI DNR, 2020). In the 2020 listing cycle Lake Mendota exceeded the designated P criteria and Delavan Lake in the 2021 listing cycle nearly exceeded the P criteria (WI DNR, 2020). TP concentration data used for this study ranged from years 2000-2020. Summer TP concentration data was averaged across all available years, which for these two lakes likely resulted in an overall lower summer mean TP concentration than the values that are currently being measured in these waterbodies. This would explain why their TSI classification was determined as oligotrophic in this research. Additional consideration for these two waterbodies ranking higher in the priority score is due to their large volumes. The model used mean lake depth and surface area in two components of the model, which placed high importance on these variables in the overall model. The lake sensitivity priority score model objective was to identify high quality lakes at risk of becoming degraded or further degraded. Lake Mendota and Delavan Lake fall in the objective of identifying high quality lakes at risk of being further degraded.

Limitations and Recommendations

This lake phosphorus sensitivity priority score model was limited by available water chemistry and lake characteristic data. With additional lake characteristic data and in-lake TP measurements this model would be able to prioritize are greater amount of Wisconsin lakes. I would recommend using a more comprehensive model, such as WiLMS, to get more accurate predictions of phosphorus loading lake by lake. For practical use of this prioritization list, Radomski, Carlson, and myself, recommend making the draft list available for peer review. Insights from reviewers would bring in more information on Wisconsin lakes and would result in an even more accurate and useful list.

This study is the first model of a three component multi-criteria decision model (MCDM). The 2018 MN study used this values-based model along with a hedonic model that assessed the cost and benefits of restoration projects, and a unique biological communities model that put priority on lakes with unique communities (Radomski and Carlson, 2018). These additional model outputs would greatly enhance the results of the priority score list by including additional parameters. Future research for prioritization modeling by specific lake type and/or waterbody source would increase the precision of the lake phosphorus sensitivity significance priority score. There are a wide range of models that suit certain lake types, i.e. – shallow lakes, reservoirs, two-story lakes, etc. Models that are more specific would allow for more accurate thresholds and sensitivities to be predicted. Another interesting direction for future research would be create separate prioritization models for the distinct ecoregions. As addressed earlier, the ecoregions have differing land uses, topography, number of lakes, and trophic states. Creating prioritization among the ecoregions would allow for different model inputs that best suite a specific ecoregion and highlight lakes in each ecoregion that require protection.

Management Implications

Prioritizing Wisconsin lakes based on sensitivity to phosphorus loading and then identifying significance of that sensitivity based on land use, surface area, in-lake mean TP concentrations, and other factors will aid in the proper distribution of limited water quality funds and efforts. The results of this research align with the objective of the model and follow the Minnesota (MN) values-base model results of the 2018 Radomski and Carlson study (2018). Further findings from the MN study found that restoration costs were often higher than the cost of protection through conservation efforts, such as conservation easements (Radomski and Carlson, 2018). Focusing funding on conservation of healthy waters over restoration of impaired waterbodies might therefore be a more efficient use of efforts and funding. Restoring impaired waters with phosphorus loading issues has its drawbacks: (1) restoration efforts can be made more difficult by internal TP cycling (Huser et al., 2016), (2) TP loading is often from non-point sources that have more challenging reduction strategies (Carpenter et al., 1998; Weiner and Matthews, 2003), and (3) restoring lakes to their natural state is difficult (Cook et al., 2005; Carpenter, 2005). This is not to say that restoration efforts of impaired waters are unimportant, but that ideally conservation and protection should be used before restoration becomes necessary. The results of this research indicate where those conservation and protection efforts can provide the greatest added value.

This model, which prioritizes Wisconsin lakes for conservation and protection, can be used to identify lakes that require attention and preservation practices before restoration is necessary. Keeping healthy waters healthy through conservation practices will prevent degradation of lakes, avoid costs of future management, avert the negatives of eutrophication, and prevent losses in property and recreational value. In a 2010 study, Kashian and Kasper found that property values on degraded Wisconsin lakes were lower by $128 to $402 per shoreline foot in relation to non-eutrophic lakes (Kashian and Kasper, 2010).

Lakes that are highly sensitive to phosphorus loading and are at high risk of being degraded should employ watershed protection plans and regular assessments to reduce non-point source pollutions. Implementation of best management practices (BMP) are proven to decrease the amount of phosphorus pollution runoff from agricultural land (USDA, 2006). However, further improvements of BMPs are needed to make these strategies effective. Better understanding of agronomic behavior and including farmers in the development of transport BMPs could lead to an increase in adoption and overall effectiveness of this form of water quality protection (Shepard, 2000). Hesitancy to adopt BMPs could be lessened with financial support and assistance through cost-share programs. Ultimately, decreasing the amount of surplus phosphorus on the landscape at a regional scale would provide a long-term solution (Sharpley et al 2006). To limit phosphorus loading in urban settings, reduction of watershed P inputs is required (Hobbie et al., 2017). Restriction of P fertilizers, proper disposal of dog waste, and removal of plant matter, would decrease the amount of P that is exported by stormwater runoff. Increased infiltration in urban settings to reduce phosphorus transport into streets would help decrease P runoff into stormwater drains.

Shoreland property owners can also take matters into their own hands, to keep their waterbody healthy, by participating in best practices that divert/filter runoff, prevent erosion, and create habitat. Additionally, WI DNR offers competitive ‘Healthy Lakes and Rivers’ grants for eligible applicants.

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APPENDIX I. Definitions

Eutrophication – excess nutrient richness in a waterbody that occurs naturally over time. Increased nutrient inputs causes a dense growth of plant life that eventually results in the waterbody having very available low oxygen. Anthropogenic runoff and erosion increase nutrient inputs which decreases the time for a system to turn eutrophic from centuries to decades or shorter.

Multi-criteria decision model (MCMD) – a model that incorporates valuable features; for this research, valuable features include physical lake characteristics and water quality data.

Impaired Waterbody – Waters that do not meet applicable water quality standards for its classification and intended use. Listed in the statewide 303(d) report to the Environmental Protection Agency (EPA) by regulation of the Clean Water Act (CWA).

APPENDIX II. Acronyms

Geographic Information Systems (GIS)

Multi-criteria decision model (MCMD)

Surface Water Integrated Monitoring Systems (SWIMS)

Total Phosphorus (TP)

Secchi disk transparency (SDT)

Wisconsin (WI)

Wisconsin Department of Natural Resources (WI DNR)

Minnesota (MN)

APPENDIX III. Key Terms and Variables

Flushing rate – the amount of time it takes to replace the volume of the lake.

Hydraulic inflow rate – the volume of water that enters a waterbody over a given time.

Multi-criteria decision model (MCMD) – a model that incorporates valuable features; for this research, valuable features include physical lake characteristics and water quality data.

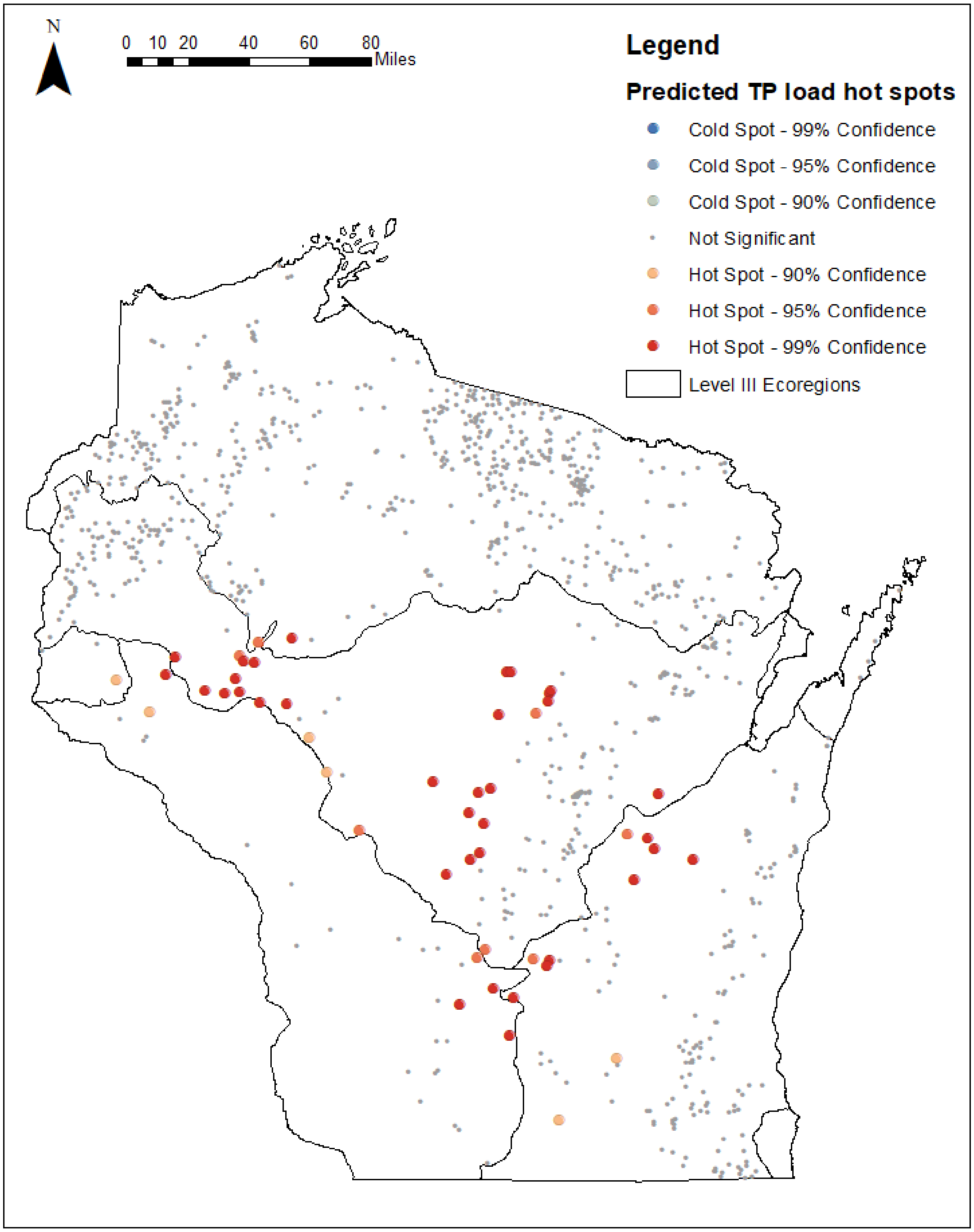
Secchi Disc – A Secchi disc is an opaque white and black disc that is dropped down into the water column and measures the clarity of the water. Once the Secchi disc is not visible in the water, that depth measurement is taken.

Satellite Clarity – measurement of water clarity (Secchi disc depth, ft) measured by satellite.

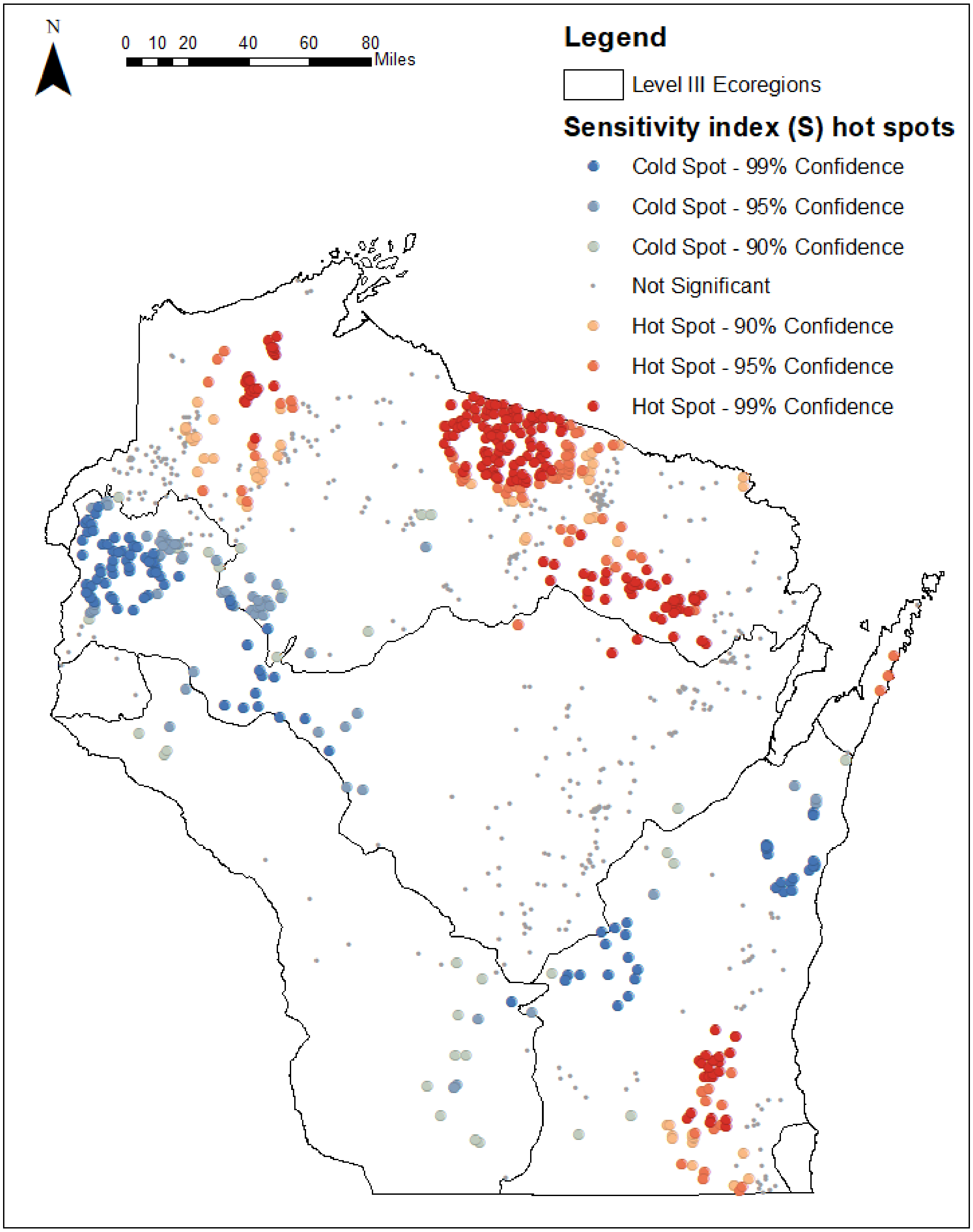
Total phosphorus concentration – the amount of total phosphorus divided by the total volume, mg/L.

Total phosphorus loading – the mass (kg) amount of total phosphorus that enters a waterbody from the surrounding watershed annually.

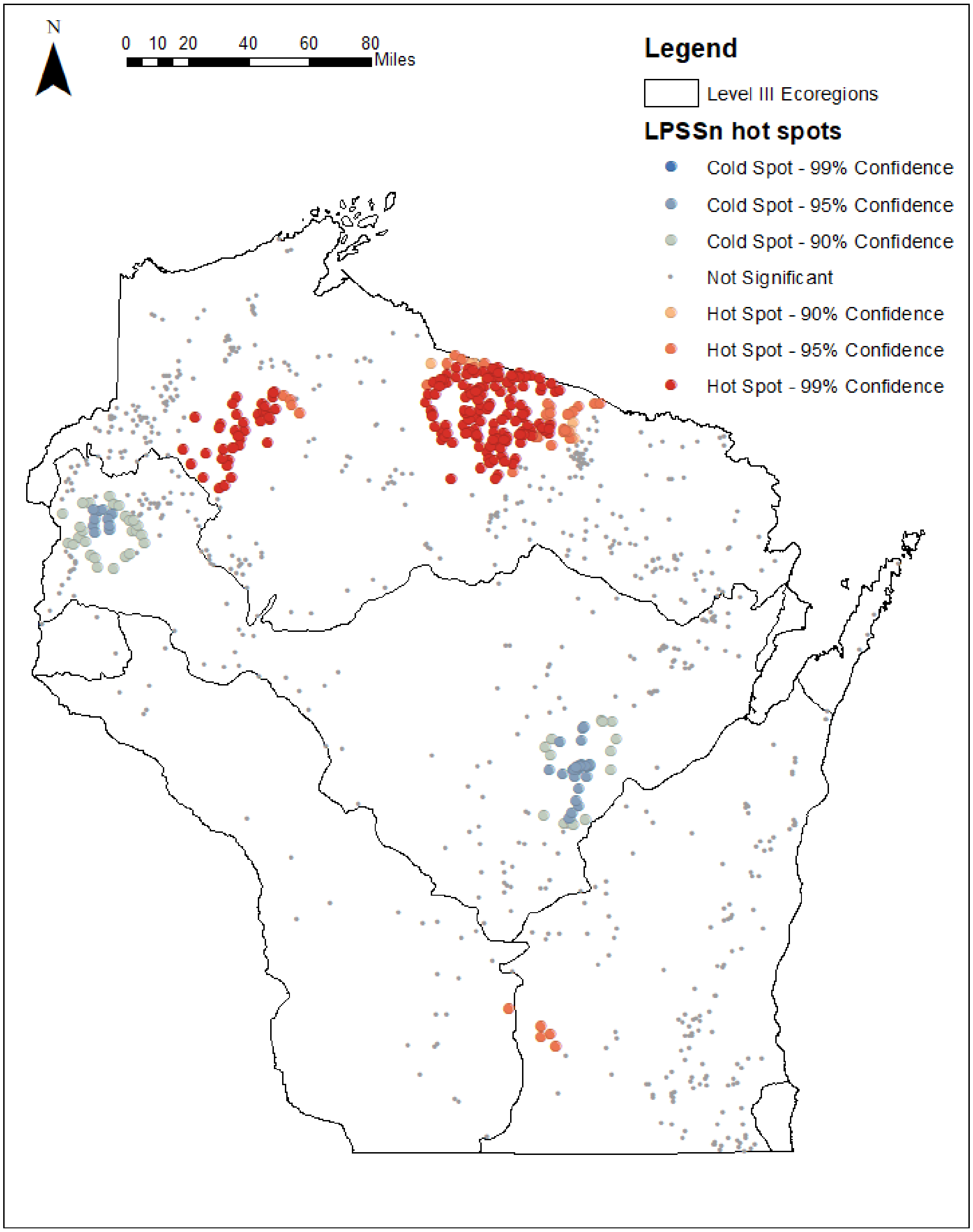
APPENDIX IV. Predicted TP loading (ug/L) cluster hot spots.



APPENDIX V. Hot spot analysis for Sensitivity index (S)



APPENDIX VI. Hot spot analysis for Lake phosphorus sensitivity significance priority score (LPSSn)


N
0 10 20 40 60 80
Miles
Legend
Level III Ecoregions
LPSSn hot spots
Cold Spot - 99% Confidence
Cold Spot - 95% Confidence
Cold Spot - 90% Confidence
Not Significant
Hot Spot - 90% Confidence
Hot Spot - 95% Confidence
Hot Spot - 99% Confidence

APPENDIX VII. Lake phosphorus sensitivity significance priority score (LPSSn) list.

Overall really great job and very interesting.

1. Please review my comments, they will direct my questions
2. Why are the WI till plains showing up at all in table 10?