

LAND-USE LEGACY EFFECT:
COMBINING SPATIAL AND TEMPORAL DRIVERS
IN STATISTICAL AND MECHANISTIC MODELS
OF LAKE WATER CHEMISTRY

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Fisheries and Wildlife

2010

ABSTRACT

LAND-USE LEGACY EFFECT: COMBINING SPATIAL AND TEMPORAL DRIVERS IN STATISTICAL AND MECHANISTIC MODELS OF LAKE WATER CHEMISTRY

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Lake Classification: A classification system is often used to reduce the number of different ecosystem types that governmental agencies are charged with monitoring and managing. We compare the ability of several different hydrogeomorphic (HGM) classifications to group lakes for water chemistry/clarity. We ask three questions: (1) Which approach to lake classification (regionalization, landscape position, lake-specific, or some combination) is most successful at classifying lakes for similar water chemistry/clarity? (2) Which HGM features are most strongly related to the lake classes? and, (3) Can a single classification successfully classify lakes for all of the water chemistry/clarity variables examined? We use classification and regression tree (CART) analysis of HGM features to classify six water chemistry/clarity variables from 151 minimally disturbed lakes in Michigan USA. We developed two CART models for each water chemistry/clarity variable: HGM characteristics alone and HGM characteristics combined with regionalizations and landscape position. The combined CART models had the highest strength of evidence (ω_i range 0.92-1.00) and maximized within class homogeneity (ICC range 36-66%) for all water chemistry/clarity variables except water color and chlorophyll *a*. The most successful single classification in our study was on average 20% less successful in classifying other water chemistry/clarity variables. Thus, our results show that no single classification maximizes success for all lake variables examined. Therefore, we suggest that the most successful classification is (1) specific to one response variable, and (2) capable of incorporating

information at multiple spatial scales and from a variety of different sources (regionalization and local HGM variables).

Land use legacies: The recognition of legacy effects from historical land use/land cover (LULC) is a conceptual advance that has clarified the relationship between LULC and ecosystem responses. Legacy effects can be defined as effects which perpetuate beyond an expected or perceived endpoint in time. The goal of our research was to investigate LULC legacy effects on lake water chemistry. Water chemistry and five time steps of LULC data were collected from 35 lakes in the Huron River Watershed, Michigan. We took both a correlational and mechanistic approach to represent how temporal changes in LULC influence lake water chemistry. We used principal components of LULC over time to build hierarchical regression models linking to water chemistry. We also created a mechanistic groundwater flow model to estimate spatially-explicit groundwater travel times. The groundwater travel time was used to create a legacy LULC map for subsequent regression modeling. Our correlative models show that some water chemistry characteristics show a stronger link to legacy LULC than others and may be explained by the solubility and reactivity of the chemical. Our mechanistic models offer insights about how groundwater interacts with LULC change to create legacy effects and show how naturally occurring conservative tracers can provide a basis for comparison against nutrient relationships to the landscape. By categorizing the chemistry variables by their key characteristics of solubility and reactivity, we are better equipped to explore other mechanisms that are important for the physical transport and biogeochemical transformations of these chemicals.

DEDICATION

From FCG to PhD

ACKNOWLEDGEMENTS

Thanks to the following personnel for their contributions to the development of the landscape databases: Michael Belligan, Patricia Sorrano, Mary Bremigan, Kendra Cheruvelil, Jim Breck, Howard Wandell, Gary Weissman, Stephen Bowman, Tyler Rosa, Remy Brim, Cassie Meier, Dave Meyers and Sarah Wills.

I wish to thank Erica Mize, Jason Karl, Gary Roloff, Matt Baker, and John Van Sickle for invigorating discussions about statistical design; Lidia Szabo-Kraft, Arthur Cooper, and Anthony Kendall for assistance with GIS; Dave Weed, Lauren Bailey, Bryan Burroughs, Jordan Burroughs, Emi Fergus, Jon Hansen, Geoff Horst, Justin Miller, Emily Norton, Elizabeth St James, and Dan Wieferich for assistance with field collections.

I thank my committee – Dan Hayes, Brian Maurer, Jan Stevenson, and Dave Hyndman – for their guidance during my PhD experience. Your challenges and support helped to create my success.

Dr. Horton H. Hobbs III mentored me during my time at Wittenberg University. He has been a great supporter all along the way. I am very grateful to have been a member of the Order of the Claw and the Limnuts. Some of my fondest memories are from your classes and field trips! Thank you for starting me down this path.

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CHAPTER 1: COMPARING HYDROGEOMORPHIC APPROACHES TO LAKE
CLASSIFICATION: ISSUES OF SPATIAL SCALE AND PRACTICALITY

INTRODUCTION

Ecosystem structure and function are controlled in large part by the hydrology, geology, land cover, and climate characteristics of that ecosystem. These natural landscape features have been used to identify similarities in temperate (Host et al. 1996) and tropical (Mora and Iverson 2002) forests, rangelands (Kunst et al. 2005), streams (Frissell et al. 1986) and their riparian zones (Vidon and Hill 2004), wetlands (Brinson 1993), lakes (Winter 1977, Riera et al. 2000), and coral reefs (Rodgers 2005). Brinson (1993) outlined an approach to wetland classification based on hydrologic and geomorphic features such as precipitation, groundwater flow, and landscape position. This hydrogeomorphic (HGM) approach was intended to provide a flexible classification framework based on knowledge of how HGM factors drive ecosystem structure and function. The accumulation of HGM data and the advancement of analytical techniques capable of handling complex datasets have extended the capacity of the HGM approach, making it possible to include more characteristics in the ecological classification of more ecosystem types, beyond wetland classification (Host et al. 1996).

Researchers have been classifying lakes since the early 1900's; in fact, lake classification was the major focus of the International Congress for Limnology in 1956 (Moss et al. 1994), and interest in this topic has continued to the present. Although a wide variety of approaches to classification has been adopted, one feature common to many has been to group lakes based on the statistical similarity of specified water chemistry variables. Such a classification approach has been applied to lake water chemistry data in Canada (Pitblado et al. 1980, Zimmerman et al. 1983), Northeastern U.S. (Hunsaker et al. 1986, Newton and Driscoll 1990, Young and Stoddard 1996, Momen and Zehr 1998, and Jenerette et al. 2002) and Sweden (Hakanson 1996, Hakanson 2005). However, this site-specific approach can group only those lakes for which water

chemistry data are available; therefore, it has limited application for other regions or where data are lacking.

To move beyond this limitation, we apply an HGM approach to lake classification which groups systems according to relationships between important ecosystem characteristics (e.g., lake water chemistry) and HGM features. With technological advancements in remote sensing and coordinated data collection strategies, large stores of HGM data are readily available in geographic information systems (GIS) for many areas of the world (Johnson and Gage 1997). Because an HGM-based classification can be applied to previously unsampled lakes without logistically challenging and expensive field collections, its usefulness can be extended to encompass many more lakes than can be physically sampled (Brinson 1993, Young and Stoddard 1996), thereby allowing inferences and predictions to be made for individual lakes across broad geographic regions.

Regional land classifications (e.g., regionalizations) take advantage of the wealth of HGM data to group large geographic regions based on the similarity of physiographic, climatic and terrestrial features (Omernik 1987, Bailey et al. 1994, Albert 1995). Interestingly, unlike these land classifications, few classifications of aquatic systems have taken an HGM approach (but see Hakanson 1996, Hershey et al. 1999, Higgins et al. 1998, Wolock et al. 2004). One hydrologically driven example of regionalization is the USGS hydrologic units (HUC; Seaber et al. 1987). HUCs are delineated using topographical boundaries specific to a surface drainage area and have been used as management units by many agencies. More recent examples of HGM-based hydrological regionalizations include hydrologic landscape regions (HLR, Winter 2001, Wolock et al. 2004) and ecological drainage units (EDU, Higgins et al. 2005). The concept of hydrologic landscapes provides an aquatic analog to the land-based regionalization

approaches, delineating land areas with similar HGM-drivers of surface and ground water movement and storage, specifically land-surface form, geologic texture, and climatic setting (Winter 2001, Wolock et al. 2004). Alternatively, Higgins et al. (2005) delineated EDUs by combining HUC watersheds with similar climate and landscape features. Although these regionalizations are conceptually appealing, the few studies testing such regionally-based lake classifications report that some critical lake water characteristics, such as productivity, are not always similar among lakes within these aquatic and terrestrial regions (Jenerette et al. 2002, Cheruvilil et al 2008).

The concept of lake landscape position describes the local hydrologic landscape of a system. Lake landscape position quantifies the hydrologic connectivity and spatial arrangement of various aquatic systems to infer similarity in ground and surface water hydrology (Kratz et al. 1997, Soranno et al. 1999, Riera et al. 2000, Martin and Soranno 2006). Several metrics of landscape position have been derived measuring various combinations of local hydrologic connectivity to other ecosystems (e.g., streams, lakes, wetlands). Each of these metrics of landscape position has shown significant relationships with important lake ecosystem characteristics, such as acid neutralizing capacity, dissolved organic carbon and nitrogen to phosphorus ratio (Kratz et al. 1997, Martin and Soranno 2006). However, many other measures of water clarity and productivity have not shown significant relationships with landscape position metrics (Riera et al. 2000, Quinlan et al. 2003, Martin and Soranno 2006).

Although many of the above ecological classification schemes have demonstrated some success in classifying lakes, they do so with little regard to other important HGM features. For instance, although some regionalizations successfully group lakes with similar water quality, mechanisms that act through local scale variables, such as lake morphometry, are not

incorporated into such regionalizations and are likely important for lake classification success (Cheruvelil et al. 2008). Indeed, others have emphasized the importance of including both regional and local scale variables simultaneously in analyses of stream and lake characteristics (Seelbach et al. 1997, Goransson et al. 2004, Stendera and Johnson 2006) and call for an approach that combines regional and local features (Pyne et al. 2007, Cheruvelil et al. 2008).

A combined approach, however, has inherent technical demands; it must be able to incorporate both continuous and categorical data, and account for local scale variation concurrently with regional scale phenomena. To date, the majority of statistical techniques that have been employed for classification development have used traditional linear models, such as principal components analysis and clustering (Emmons et al. 1999, Bryan 2006). Classifications created with these linear methods are limited statistically when including categorical variables, such as regionalization or landscape position. By including such spatially-explicit categories into a larger classification framework, additional variation in water characteristics may be captured that local HGM data alone may miss. In addition, although linear approaches have been found to accurately represent some ecological relationships, these approaches may not effectively represent non-linear relationships and may mask the true character of the data by forcing it to conform to a linear arrangement (De'Ath and Fabricius 2000, Robertson et al. 2006, Soranno et al. 2008). To date, few classification efforts have taken advantage of advances in statistical methods that alleviate these shortcomings (but see Zimmerman et al. 1983, Emmons et al. 1999, Olden and Jackson 2002, Robertson et al. 2006).

The goal of our study is to build an ecological classification for lake water characteristics that is built using variation in HGM features over multiple spatial scales. More specifically, we incorporate the phenomena captured by regional summaries of HGM features (i.e.,

regionalizations) with local HGM features that are intrinsic to each lake (e.g., lake morphometry). We strive to create a classification approach that: (a) maximizes within class homogeneity and between class heterogeneity for lake water characteristics, (b) is developed from natural landscape features that are temporally stable on the scale of decades to centuries, (c) minimizes the confounding effects of non-natural landscape features (e.g., human disturbances), and (d) provides an example of a broadly applicable approach for other ecosystems. We ask three questions: (1) Which approach to lake classification is most successful at grouping lakes with similar water characteristics (regionalization, landscape position, lake-specific, or some combination)? (2) Which HGM features are most strongly related to the lake classes? and (3) Can a single lake classification successfully group lakes for all of the water chemistry characteristics examined?

METHODS

Our dataset includes 151 minimally disturbed lakes in Michigan, U.S.A. that are greater than 20 hectares in area. We define minimally disturbed lakes as those with no dam or water control structure and less than 25% human land use/cover (i.e., agriculture and urban) in the cumulative catchment (detailed below). Our study lakes had only an average of 8% human land use/cover in the cumulative catchment and were surrounded mostly by forest (mean 80% forested land use/cover). We chose to limit our dataset to these lakes in order to reduce the confounding effects of human disturbances and maximize our ability to detect relationships with HGM characteristics (D'arcy and Carignan 1997, Stoddard et al. 2006).

We obtained data on lake water characteristics during the time period of 1975 through 1982 from the U.S. EPA Storet database. The Michigan Department of Environmental Quality

sampled the epilimnion of each lake during summer stratification (July, August, and September) for a wide range of limnological variables: alkalinity, water color, Secchi disk depth, total nitrogen (TN), total phosphorus (TP), and chlorophyll *a* (Chl *a*). The study lakes vary widely in all variables (Table 1.1).

Hydrogeomorphic characteristics

We created a digital HGM database for our study lakes from geospatial data including bedrock geology, surficial geology, land use/cover, and climate/hydrology. These landscape features were summarized for each lake using a 500 m buffer. Bedrock geology data were obtained from the Geologic Survey Division of the Michigan Department of Environmental Quality. Sedimentary clastic is the dominant bedrock type in Michigan and for many of our study lakes, but our dataset also includes lakes dominated by other bedrock types (Table 1.1). Surficial geology data were provided by the Michigan Natural Features Inventory and Michigan Department of Natural Resources. Outwash and moraine surficial geology types dominate the study lakes (Table 1.1). Land use/cover data were obtained from the Michigan Resource Information Service (MIRIS 2000) based on aerial photo interpretation of photos taken between 1978 and 1985. Average annual precipitation for the period 1971-2000 was obtained from the Spatial Climate Analysis Service (www.ocs.oregonstate.edu). Average annual runoff for the period 1951-1980 and mean base-flow index (BFI) were obtained from USGS (<http://water.usgs.gov>). Base-flow index provides an estimate of groundwater input relative to surface water input. Cumulative lake catchments (CUCA) were delineated to include the catchment area associated with all lakes and streams draining into the lake using 1:100,000 resolution stream hydrography data, digital elevation models (30 m resolution) and topographic

maps. Using the above data, we also delineated local catchments (LOCA) as the portion of the cumulative catchment downstream from any upstream lake greater than 0.2 km². Wetland land cover was summarized using the 500 m buffer as well as a 100 m buffer (to represent a lake's riparian zone), and for the local and cumulative lake catchments.

Lake area, perimeter, shape, mean depth, and maximum depth were gathered from bathymetric maps. Mean depth was calculated by taking the average depth of approximately 100 points evenly spaced across each bathymetric map (Omernik and Kinney 1983). Lake shape was calculated as the ratio of shoreline perimeter to the circumference of a circle of the same area (Wetzel and Likens 2000). Water residence time (WRT) was estimated as: [(lake area*mean depth) ÷ (cumulative catchment area*runoff)]. Area, shape and slope were measured for both local and cumulative catchment.

Classification frameworks

We included three regionalization frameworks: 1) USGS 8-digit hydrologic units (HUC, Seaber et al. 1987), 2) ecological drainage units (EDU, Higgins et al. 2005), and hydrologic landscape regions (HLR, Winter 2001). The location of each study lake within each region determined the class membership. Our study lakes were located within 19 HUCs, 6 EDUs, and 5 HLRs (Figure 1.1).

We included three metrics of landscape position that can be easily measured from existing data using GIS (described in brief here, see Martin and Soranno 2006 for more detailed descriptions). Lake hydrology (LH; n=7 categories) is a general measure of lake surface hydrologic connections, incorporating both connections to streams and lakes. Lake network number (LNN; n=5 categories) measures the degree of surface connectivity to other lakes. Lake

network complexity (LNC; n=4 categories) is a measure of the complexity of connections to other lakes (e.g., dendritic or linear chain).

We created two new classifications for each lake water characteristic using: 1) local HGM features for each study lake (HGM), and 2) local HGM features combined with regionalization and landscape position categories (HGM+). These classifications were created using classification and regression tree (CART) analysis. We chose to use CART models because they: 1) maximize class homogeneity, 2) do not penalize for including many independent variables, 3) handle high-order interactions among variables, and 4) accommodate both continuous and categorical data (De'ath and Fabricius 2000). All CART models were built using the recursive partitioning algorithm “rpart” in the R software system (R Development Core Team, <http://www.R-project.org>). CART trees were grown using 10-fold cross-validation and subsequently pruned using the 1-SE rule (Breiman et al 1984, Venables and Ripley 1999). Terminal nodes (i.e., lake classes) were required to have a minimum of five observations (i.e., lakes). The proportional reduction in error (PRE) for each split was summed to produce an overall PRE for each tree.

Output detailing splitting decisions from each CART tree was reviewed to assess tree stability and correlations among independent variables. Independent variables maximizing class homogeneity and PRE were always selected as the primary splitter. The top five independent variables for a primary split, measured by class homogeneity, were considered as competitor splits. The top five independent variables grouping lakes into classes similar to the primary split, measured by percent similarity, were considered as surrogate splits (R Development Core Team, <http://www.R-project.org>). We assessed tree stability using information about competitor and surrogate splits, in combination. A split was considered 1) stable if there were no competitor

splits within 3% reduction in error from the primary splitter, 2) somewhat stable/unstable if there were competitor splits within 3% reduction in error from the primary splitter but these competitors were also surrogates, or 3) unstable if there were competitor splits within 3% reduction in error from the primary splitter but these competitors were not surrogates. Therefore, given small changes in input data 1) stable trees are not likely to change in tree structure or class membership, 2) somewhat stable/unstable trees may split on different independent variables yet yield similar class membership, and 3) unstable trees would likely yield different tree structure and class membership.

Comparing classifications

We compared the success of the three regionalization frameworks, the three landscape position metrics, and our two CART models for classifying each of the six lake water characteristics included in this study. The HGM and HGM+ CART models were parameterized for each lake water characteristic independently, and thus, we could determine the success of a classification developed from one variable for another. For example, an HGM model and a HGM+ model were built specifically for alkalinity. Classification success of these two alkalinity-specific models was then assessed for each of the other lake water characteristics (e.g., water color, Secchi, TN, TP, and Chl *a*). However, because individual lakes are assigned to a category within the regionalization and landscape position classification systems, without respect to individual lake water characteristics, comparison across lake water characteristics was not appropriate.

Two model selection statistics were used to compare among the candidate classifications for each lake water characteristic. First, we took an information-theoretic approach for multi-

model comparison, using the corrected Akaike information criteria (AIC_C) for small sample sizes (Burnham and Anderson 2002), computed in SAS (version 9.1) using PROC MIXED (SAS Institute Inc.). We compared the relative support for each classification using Akaike weights (w_i). These weights sum to equal 1 and are interpreted as the probability that a model is the best model relative to others included in the analysis (Johnson and Omland 2004). Secondly, we used the intra-class correlation coefficient (ICC) to compare the ability of each of the classifications to maximize class homogeneity for each dependent variable (Donner and Koval 1980, Cheruvelil et al. 2008). We calculated the ICC from the error terms of a one-way ANOVA with random effects:

$$Y_{ij} = \gamma_{00} + r_{ij} + u_{0j}$$

where, Y_{ij} = observation of dependent variable for lake i in lake group j , γ_{00} = grand mean of the dependent variable, r_{ij} = random error term for lake i in lake group j , where $r_{ij} \sim N(0, \sigma^2)$ and σ^2 represents the within-group error in the dependent variable, u_{0j} = random error term for lake group j , where $u_{0j} \sim N(0, \tau_{00})$ and τ_{00} represents the among-group error in the dependent variable. The ICC is the amount of the total variance that is among groups:

$$ICC = \hat{\tau}_{00} / (\hat{\tau}_{00} + \hat{\sigma}^2)$$

A successful classification has a high ICC, meaning that a large amount of the variation is among the groups created from the classification, maximizing class homogeneity. All variables used in linear techniques (i.e., ANOVA) were transformed to meet normality assumptions.

RESULTS

Comparing classifications

Classification success, indicated by class homogeneity as represented by the ICC, ranged from 0% to 66% across all classification approaches and all lake water characteristics (Table 1.2). Across lake water characteristics, alkalinity was classified most successfully (ICC mean 42%, range 14% - 66%), followed by water color (ICC mean 21%, range 4% - 54%). Secchi disk depth and measures of lake productivity were classified least successfully (ICC mean <15%) with 6 classification failures (ICC = 0%).

For each lake water characteristic evaluated, we observed that one model received an Akaike weight greater than 0.9, and all other models received very low weights, less than 0.1 (Table 1.2). Thus, only one classification was supported by the data for each lake water characteristic, with supported models differing among lake water characteristics. No regionalization or metric of landscape position alone was supported as a suitable classification of our data, as AIC_C values were substantially higher than most CART models. Among all classification approaches and all lake water characteristics, CART models had the highest strength of evidence (ω_i range 0.92 - 1.00) and were the most successful at maximizing within class homogeneity (ICC range 36% - 66%). HGM+ models had more AIC_C support for a majority of lake water characteristics. Only two lake water characteristics (water color and Chl *a*) had a higher weight of evidence for HGM models. The HGM+ model for Chl *a* did not differ from the HGM model and, therefore, was not included in comparisons of model fit (indicated by “n/a” in Table 1.2).

Class homogeneity (ICC) was not always maximized by the most parsimonious model, as indicated by AIC_C (Table 1.2). According to weight of evidence, the best classification for water

color, Secchi, and TP had ICC's 12%, 4%, and 8%, lower, respectively, than the maximum ICC for that lake water characteristic.

Relationships between hydrogeomorphic features and lake classes

HGM models divided the study lakes into between 2 and 4 lake classes, capturing between 16% and 53% of the variation among lakes (Figure 1.2). Measures of lake morphometry were the most frequent classifiers across HGM models (4 of 6 models). Mean depth, in particular, was the most important feature driving HGM models of lake productivity, with water residence time and maximum depth also included in some models. Various measures of catchment morphometry were important in classifying alkalinity and water color. The proportion of the local catchment in wetlands was the most important classifier for water color and Chl *a*. Geology and climate variables were present in only one model each (Chl *a* and alkalinity, respectively).

HGM+ models divided the study lakes into between 3 and 6 lake classes, capturing between 30% and 60% of the variation among lakes (Figure 1.3). All HGM+ models (except Chl *a*) explained more variation than HGM models: alkalinity by 10%, water color by 12%, Secchi by 11 %, TN by 29%, and TP by 8%. All HGM+ models (except Chl *a*) included the regionalization framework HUC as an important classifier (Figures 1.2 and 1.3). No landscape position metrics were included as important classifiers in any of these models. As with HGM models, measures of lake morphometry were frequently important classifiers across HGM+ models (4 of 6 models), followed by catchment morphometry and wetlands (2 of 6 models each). The proportion of clastic bedrock geology type was present in the HGM+ model for TN. Climate was not included as an important splitting variable in any of the HGM+ models.

The tree structure for most lake water characteristics was similar when comparing among HGM models and HGM+ models (Figures 1.2 and 1.3). Most notably, the HGM+ model of Chl *a* did not include any regionalizations and was, therefore, identical to the HGM model. HGM and HGM+ models for Secchi and TP shared initial structure and classification variables, differing only by the addition of HUC as the last classifier. Alternatively, the HGM features driving the two CART classifications of water color were from the same broad categories; however, different variables represented these categories. More specifically, for HGM models of water color, catchment morphometry was represented by both the ratio of cumulative catchment area to local catchment area (CUCA:LOCA) and the ratio of cumulative catchment area to lake area (CA:LK), whereas in HGM+ models, catchment morphometry was represented by one variable (cumulative catchment shape, CUCA shape).

Despite these similarities, there were also some striking differences between HGM models and HGM+ models. For example, all HGM features included in the HGM model for alkalinity were completely replaced by regionalizations in the HGM+ model, with the 1st split (HUC) explaining 50% of the variation (Figures 1.2 and 1.3). In another example, the tree structure for the HGM+ model for TN is quite different than the HGM model, although lake morphometry is still important for classifying TN in both models. Catchment morphometry and bedrock geology are additional HGM features included in the HGM+ model of TN, increasing the number of classes created from 2 in the HGM model to 6 in the HGM+ model.

Evaluation of CART tree stability

Evaluating competitor and surrogate splitting options available in the detailed output from CART analyses can give a sense of the stability of a classification model. Some

classification splits can be labeled as unstable (multiple competitors with none being surrogates, further detail in Methods), thereby indicating a sensitivity of the resulting classification to the particular study lakes used to build the classification. For example, HUC is the most important classifier in the HGM+ model for TN. However, two other variables explain approximately 3% less variation than HUC and do not serve as surrogates (data not shown). Using our methods, this split can be labeled “unstable” and highly dependant on the input data. In contrast, we label the 2nd split in the TN HGM+ model as “somewhat stable” because mean depth explained only slightly less variation (approx. 2%) than maximum depth, the primary splitter at this node. In this case, however, mean depth acts as a surrogate for maximum depth since the majority (94%) of lakes would follow the same splitting path under either scenario. Therefore, this split is likely to be less dependent upon the specific dataset used in the analysis and can be considered stable. Over all 32 splits created in the CART models, 28% of splits were stable, 31% were somewhat stable/unstable, and 41% were unstable.

A single classification for all lake water characteristics

Classification success of CART models was compared across lake water characteristics to determine the model most successful at classifying lakes for all lake water characteristics. The mean ICC across water characteristics for the Secchi-HGM model ranked highest at 38% (Table 1.3). Class homogeneity varied slightly for most lake water characteristics when classified by the Secchi-HGM model in comparison to the variable-specific CART models. Homogeneity increased for water color (1%), Secchi (4%), and Chl *a* (2%), and decreased only a moderate amount for TN (6%) and TP (8%). However, the class homogeneity decreased much more for

alkalinity (50%). Simple correlations indicate that Secchi is significantly correlated to all lake water characteristics, except alkalinity (Table 1.4).

Although most lake water characteristics were significantly correlated with one another (Table 1.4), classification success varied widely when a single classification was used for all lake water characteristics (Table 1.3). For example, alkalinity was significantly correlated with water color, TP, and Chl *a* (Table 1.4). However, neither of the alkalinity CART models successfully classified any other lake water characteristic (mean ICC excluding alkalinity: HGM 6%, HGM+ 5%; Table 1.3). In another example, water color had the highest correlation with all lake water characteristics (except TP, Table 1.4), yet water color CART models ranked low for overall classification success (HGM rank 8, HGM+ rank 5; Table 1.3). Therefore, correlations among lake water characteristics did not predict classification success across lake water characteristics.

DISCUSSION

There are three main conclusions that follow from our research questions. First, although some lake water characteristics were classified most successfully by local HGM features alone, most lake water characteristics were best classified when models included both lake-specific information and one or more regionalization. Second, lake and catchment morphometry plays a dominant role in structuring the classifications for the lake water characteristics. Third, using a single classification severely erodes the classification success for most water characteristics. Overall, because it is important for management agencies to balance the logistics and the effectiveness of classification, we suggest that the most successful classification system is (1) specific to one response variable, and (2) capable of incorporating information at multiple spatial scales and from a variety of different sources (regionalization and local HGM variables). We

found that CART models effectively modeled the complex interrelationships among our explanatory variables and are thus a useful tool for the classification of ecosystems, particularly those with multiple data types and/or non-linear relationships

Comparing classifications

Our results agree with previous studies showing that most lake water characteristics are not similar within many areas delineated by regionalizations (Jenerette et al. 2002, Cheruvilil et al. 2008). Regionalizations alone had poor classification success for all lake water characteristics, except alkalinity, which was classified well by HUCs and EDUs. Moreover, our alkalinity HGM model split on some characteristics that are more indicative of regional-scaled processes, such as climate. In another study of Michigan lakes, the authors found strong relationships between landscape position and alkalinity (Martin and Soranno 2006). However, our results show that this relationship is comparatively weak in contrast to larger-scale regionalizations. For example, landscape position (specifically, LH), explained 21% less variation than HUC in the 1st split of the alkalinity HGM+ model. These results may indicate that as the spatial scale of the classifying feature grows (LH<HUC), the explanatory power for variation in alkalinity also grows (29% LH, 50% HUC). Therefore, while landscape position does account for some variation, alkalinity may be responding to phenomena that act over larger spatial scales, such as those captured by regionalizations (Griffith et al. 1987, Cheruvilil et al. 2008).

Although models combining regionalizations with HGM features successfully classified most lake water characteristics, in some cases, the addition of regionalizations did not change or even decreased classification success. For example, the HGM and HGM+ models for Chl *a* were

the same (discussed below). In another example, although adding HUC to the model of water color increased the ICC by 8%, this increase in classification success was also accompanied by a decrease in model parsimony, as indicated by the Akaike weights. Other lake productivity and water clarity variables, however, seemed to indicate a regional phenomenon not captured through local HGM characteristics. More specifically, the best classifications for Secchi, TN, and TP all included the HUC regionalization in addition to lake morphometry features. These results agree with previous findings suggesting that local HGM features, such as lake morphometry, are strong drivers of some lake productivity and water clarity variables (e.g., Vollenweider 1968, see Brett and Benjamin 2008 for a review). However, our results also show that most of these lake water characteristics respond to additional phenomena acting at larger spatial scales that are captured in regionalizations. Therefore, our results support the conjecture that a multi-scale classification system will be most successful for classifying lake water characteristics (Hakanson 2005, Stendera and Johnson 2006, Pyne et al. 2007).

Relationships between hydrogeomorphic features and lake classes

HGM features important for splitting lake classes in CART models are similar to what we would expect based on previous studies on the relationships between lake water characteristics and lake morphometry (Fee 1979, Halsey et al. 1997) and catchment morphometry (Wolock et al. 1989, Rasmussen et al. 1989, Hakanson 2005). Overall, we found that catchment features dominated the classification of alkalinity and water color whereas measures of lake morphometry were the most important classifiers of nutrients and Secchi.

Studies have previously reported that catchment morphometry plays an important role in the variation of productivity (D'arcy and Carignan 1997, Hakanson 2005); however, none of our

classifications based solely on HGM features included any catchment morphometry features as 1st tier primary splits for productivity variables. One measure of catchment morphometry (CUCA:LOCA) was included as a 3rd tier primary split in the HGM+ model for TN. However, this variable explained little variation (6%), and was in competition with wetland presence at two spatial scales (data not shown). Moreover, catchment morphometry was not a strong competitor to split HGM models for nutrients (TN: no competitor with mean depth, TP: weak competitor explaining 15% less variation than mean depth). Inconsistencies among studies may be due in part to differences inherent in the underlying ecological relationships of the study regions. For example, our study lakes were ten times larger in surface area and spanned a wider range of mean depth, maximum depth, and water residence time than the lakes studied by D'arcy and Carginan (1997). Our study lakes were also larger and deeper with a longer WRT than the lakes studied by Hakanson (2005). Therefore, further study is required to more fully describe the relationship between catchment morphometry and lake productivity.

Wetland cover may be important for the dynamics of many lake water characteristics such as water clarity and productivity. In fact, previous studies report that wetlands act as a source of colored compounds (Detenbeck et al. 1993, Halsey et al. 1997, Prepas et al. 2001). Our results show a positive relationship between wetlands and water color (Pearson r range 0.28 to 0.43 over all spatial scales, all p -values <0.01), supporting these studies. Moreover, wetlands were the strongest classifier of water color in our study lakes, explaining more than WRT and groundwater input. These results suggest that water color in these minimally disturbed lakes may be more affected by source wetlands rather than by internal processing or by groundwater delivery, which contrasts with other studies (Rasmussen et al. 1989, Hakanson 2005, Webster et al. 2008).

Surprisingly, we also found wetland land cover to be the strongest classifier of Chl *a*, showing a positive correlation ($r = 0.34$, p -value < 0.0001). This relationship may be the result of an indirect link between wetlands and lake nutrients. Previous studies have shown that different wetland types (e.g., bog, fen) can play different roles in nutrient dynamics, with some serving as a source and others as a sink of phosphorus (Detenbeck et al. 1993, Halsey et al. 1997, Prepas et al. 2001). Our results may indicate that our study lakes are responding to the confounding roles that wetlands can play in lake productivity, by both facilitating productivity through nutrient production and by creating colored compounds that limit productivity through shading. However, finer-resolution data measuring the presence of different wetland types would be required to fully evaluate the role of wetlands in these lake dynamics.

It is also interesting to note that the water color and Chl *a* lake classes were split on a very small amount of wetlands (local catchment wetlands at 4% and 3%, respectively). One study reports that a much greater presence of wetlands in a catchment (approx. $> 50\%$) is needed before detecting significant relationships with water chemistry characteristics (Prepas et al. 2001). However, other studies report much lower thresholds (6-25%) beyond which wetland presence becomes important (Dillon et al. 1991, D'arcy and Carignan 1997, Canham et al. 2004).

We also compared wetland cover measured over four spatial scales (cumulative catchment, local catchment, 500m buffer, and 100m buffer) and found that the proportion of wetlands in the local lake catchment was the only scale represented in any of the final CART classifications (water color and Chl *a*). However, analysis tree stability shows that other spatial scales act as competitor and/or surrogate splits for all lake water characteristics (except alkalinity). In some cases, there were only small losses in explanatory power when choosing other spatial scales. For example, cumulative catchment wetland cover explained 2% and 0.5%

less than local catchment wetland cover in the HGM models for water color and Chl *a*, respectively. Moreover, cumulative catchment wetland cover had 96% and 98% classification similarity with local catchment wetland cover. Although our results show that wetland presence at the local catchment scale is the strongest classifier for our study lakes, our results support other studies finding little difference in explanatory power between wetland cover measured at different spatial scales (Gergel et al. 1999, Strayer et al. 2003, Canham et al. 2004). Therefore, additional investigations are needed to more fully understand the scale and magnitude of wetland presence important for lake ecosystem dynamics.

A single classification for all lake water characteristics

The ultimate lake classification would successfully classify lakes for all water characteristics. Our results show that such a classification likely does not exist as this approach severely erodes the success of lake classification for most water characteristics. We found that the most successful single classification (Secchi HGM CART) for the lake water characteristics that we analyzed was on average 20% less successful in classifying other water characteristics and as much as 50% less successful in classifying alkalinity. However, when compared to regionalizations, the Secchi HGM CART was on average 16% more successful in classifying characteristics and 29% better when alkalinity was not included in the analysis. Thus, our results demonstrate that no single classification scheme maximizes success for all lake water characteristics because each classification depends on a different suite of local and regional HGM variables. However, comparisons such as ours should help guide the application of different approaches to lake classification and allow for management agencies to make choices between logistical practicality and ecological robustness.

Applications to ecosystem management

Our use of detailed CART output allows for the evaluation of tree stability and splitting decisions. Alternative splitting decisions can be compared to allow for an assessment of practicality to enter into the classification process. For example, our results show that susceptibility of lakes to acidification may be adequately captured at larger spatial scales, as lakes within regions had similar alkalinity. On the other hand, management of nitrogen inputs to lakes should benefit from a more complex classification combining regionalizations and local HGM features. This increase in classification success, however, comes at the cost of increasing the number of lake classes. Management agencies can use this information to evaluate the trade-offs involved in choosing different models.

Most importantly, our approach to lake classification combines the strengths of a regionalization approach and a local HGM approach with analytical advances in multivariate statistics. Our approach can fulfill the needs of management agencies for an ecologically-based classification system which will allow for robust trend detection through time by reducing variation in natural HGM features within each class. Therefore, any resulting trend may be attributed to other factors such as changes in land use/cover or resource use (e.g., public access). The classification of other ecosystem types should also benefit from taking a multi-scale HGM approach by building upon foundational relationships between ecosystem function and hydrogeomorphic setting which can be measured over different spatial scales.

Table 1.1. Summary of lake water chemistry/clarity and hydrogeomorphic characteristics for 151 minimally disturbed lakes in Michigan USA. Variables are arranged into broad categories. Abbreviations are listed in parentheses. PCU, platinum cobalt units. CA:LK, catchment area to lake area ratio. CUCA:LOCA, cumulative catchment area to local catchment area ratio.

	units	Min.	Max.	Mean	SD
Water chemistry/clarity					
Alkalinity	mg/L	1	206	72	55
Water color	PCU	1	99	14	16
Secchi	m	0.8	7.9	3.4	1.3
Total nitrogen (TN)	µg/L	88	1044	461	192
Total phosphorus (TP)	µg/L	1.0	32.0	11.7	6.0
Chlorophyll <i>a</i> (Chl <i>a</i>)	µg/L	0.2	29.0	4.3	4.4
Bedrock geology					
Carbonate (B-Carb)	%	0.0	100.0	12.5	32.3
Clastic (B-Clast)	%	0.0	100.0	48.3	48.4
Hardrock (B-Hard)	%	0.0	100.0	20.5	38.5
Iron (B-Iron)	%	0.0	100.0	18.7	37.1
Surficial geology					
Bedrock (S-Bed)	%	0.0	100.0	3.2	16.9
Dune (S-Dune)	%	0.0	37.5	0.9	4.9
Glacial till (S-Till)	%	0.0	100.0	17.6	32.8
Lacustrine (S-Lacu)	%	0.0	100.0	9.8	27.4
Moraine (S-Mora)	%	0.0	100.0	27.7	41.2
Outwash (S-Outw)	%	0.0	100.0	36.0	42.5
Peat and muck (S-PeMu)	%	0.0	36.4	0.6	3.9
Lake morphometry					
Lake Area (LK)	km ²	0.20	70.38	2.84	9.34
Shape	unitless	1.1	6.3	1.9	0.7
Mean depth	m	1.2	21.8	4.9	3.3
Maximum depth (Max. Depth)	m	3.0	58.5	14.4	9.2
Water residence time (WRT)	year	1.2*	31.6	2.5	4.2
Local catchment morphometry (LOCA)					
Area	km ²	0.2	1759.3	52.0	182.0
Shape	unitless	1.1	3.0	1.7	0.3
Slope	%	0.6	4.9	2.4	1.0
Cumulative catchment morphometry (CUCA)					
Area	km ²	0.2	1948.3	86.0	276.7
Shape	unitless	0.0	2.6	0.6	0.4
Slope	%	0.6	5.7	2.8	1.1

Table 1.1 (cont').

CUCA:LK	ratio	0.9	2655.1	63.5	247.1
CUCA:LOCA	ratio	1.0	14.4	1.6	2.2
Climate/hydrology					
Precipitation	cm/year	72.7	90.8	81.7	4.1
Runoff	cm/year	20.3	50.8	35.8	5.5
Baseflow index (BFI)	%	55	89	71	9
Wetlands					
CUCA	%	0	25	5	5
LOCA	%	0	23	4	4
500m buffer	%	0	40	7	7
100m buffer	%	0	53	8	11

Table 1.2. Summary of model selection statistics for candidate classifications per lake water characteristic. Classification type is indicated as regionalization, landscape position, or CART. Individual classification names are indicated within each classification type. Intra-class correlation coefficients (ICC) are presented as percent of total variance that is among the classes. A high ICC indicates high within class homogeneity and thus, high classification success. The number of classes per classification model (K) is presented. ΔAIC_C is the difference between the AIC_C for each model and the minimum AIC_C for each lake water characteristic. The ΔAIC_C will equal 0 for the best model per lake water characteristic. The Akaike weights (ω_i) sum to 1 for each lake water characteristic and is interpreted as the likelihood that a given model is the best model relative to others included in the analysis. n/a, not applicable.

Lake water characteristic	Type	Name	ICC	K	AIC_C	ΔAIC_C	ω_i
Alkalinity	Regionalization	HUC	63	19	1545	30	0.00
		EDU	50	6	1586	71	0.00
		HLR	14	5	1626	111	0.00
	Landscape Pos.	LH	34	7	1598	83	0.00
		LNN	32	5	1609	94	0.00
		LNC	22	4	1617	102	0.00
	CART	HGM	56	4	1542	27	0.00
		HGM+	66	3	1515	0	1.00
Water color	Regionalization	HUC	17	19	404	43	0.00
		EDU	14	6	396	35	0.00
		HLR	15	5	403	42	0.00
	Landscape Pos.	LH	9	7	402	41	0.00
		LNN	4	5	409	48	0.00
		LNC	9	4	401	40	0.00
	CART	HGM	46	4	361	0	0.92
		HGM+	54	4	366	5	0.08
Secchi	Regionalization	HUC	0	19	522	68	0.00
		EDU	4	6	523	69	0.00
		HLR	0	5	524	70	0.00
	Landscape Pos.	LH	5	7	521	67	0.00
		LNN	2	5	524	70	0.00
		LNC	10	4	520	66	0.00
	CART	HGM	54	3	474	20	0.00
		HGM+	50	5	454	0	1.00
TN	Regionalization	HUC	13	19	182	57	0.00
		EDU	5	6	187	62	0.00
		HLR	0	5	185	60	0.00
	Landscape Pos.	LH	2	7	187	62	0.00
		LNN	0	5	185	60	0.00

Table 1.2 (cont').

TP	CART	LNC	1	4	187	62	0.00
		HGM	21	2	172	47	0.00
		HGM+	47	6	125	0	1.00
	Regionalization	HUC	13	19	291	46	0.00
		EDU	3	6	294	49	0.00
		HLR	2	5	295	50	0.00
	Landscape Pos.	LH	7	7	291	46	0.00
		LNN	0	5	293	48	0.00
		LNC	8	4	291	46	0.00
Chlorophyll <i>a</i>	CART	HGM	47	2	250	5	0.08
		HGM+	39	3	245	0	0.92
		HUC	13	19	382	27	0.00
	Regionalization	EDU	9	6	378	23	0.00
		HLR	7	5	382	27	0.00
		LH	1	7	386	31	0.00
	Landscape Pos.	LNN	0	5	384	29	0.00
		LNC	1	4	386	31	0.00
		HGM	36	4	355	0	1.00
	CART	HGM+	n/a	n/a	n/a	n/a	n/a

Table 1.3. Summary of the intraclass correlation coefficients (ICCs) for CART models across lake water characteristics. CART models are listed by the original dependant variable and type of classification. Mean ICC across lake water characteristics is computed. Rank of mean ICC is listed. See Table 2 for acronyms.

CART model	Lake water characteristic						Mean	Rank
	Alkalinity	Water color	Secchi	TN	TP	Chl <i>a</i>		
Alkalinity-HGM	56	7	5	12	5	1	14	11
Alkalinity-HGM+	66	9	0	5	5	8	16	10
Water color-HGM	1	46	22	12	12	11	17	8
Water color-HGM+	22	54	50	7	9	11	26	5
Secchi-HGM	16	47	54	41	31	38	38	1
Secchi-HGM+	25	39	50	31	29	27	34	2
TN-HGM	5	14	19	21	26	12	16	9
TN-HGM+	22	38	36	47	40	12	33	3
TP-HGM	13	31	29	24	47	23	28	4
TP-HGM+	17	28	23	18	39	24	25	6
Chl <i>a</i> -HGM	6	31	19	15	20	36	21	7

Table 1.4. Pearson product-moment correlation matrix for lake water characteristics.
 *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, NS, not significant ($p > 0.05$).

Lake water characteristic	Lake water characteristic					
	Alkalinity	Secchi	Water color	TN	TP	Chl <i>a</i>
Alkalinity	...					
Secchi	0.10 ^{NS}	...				
Water color	-0.22**	-0.66***	...			
TN	-0.02 ^{NS}	-0.45***	0.48***	...		
TP	-0.17*	-0.50***	0.53***	0.59***	...	
Chl <i>a</i>	-0.21**	-0.46***	0.52***	0.38***	0.39***	...

Figure 1.1. Map of the upper and lower peninsula of Michigan. Lakes included in the analysis are shown as solid dots. Boundaries are shown for each regionalization: A) 8-digit USGS hydrologic units (HUC), B) ecological drainage unit (EDU), and C) hydrological landscape region (HLR).

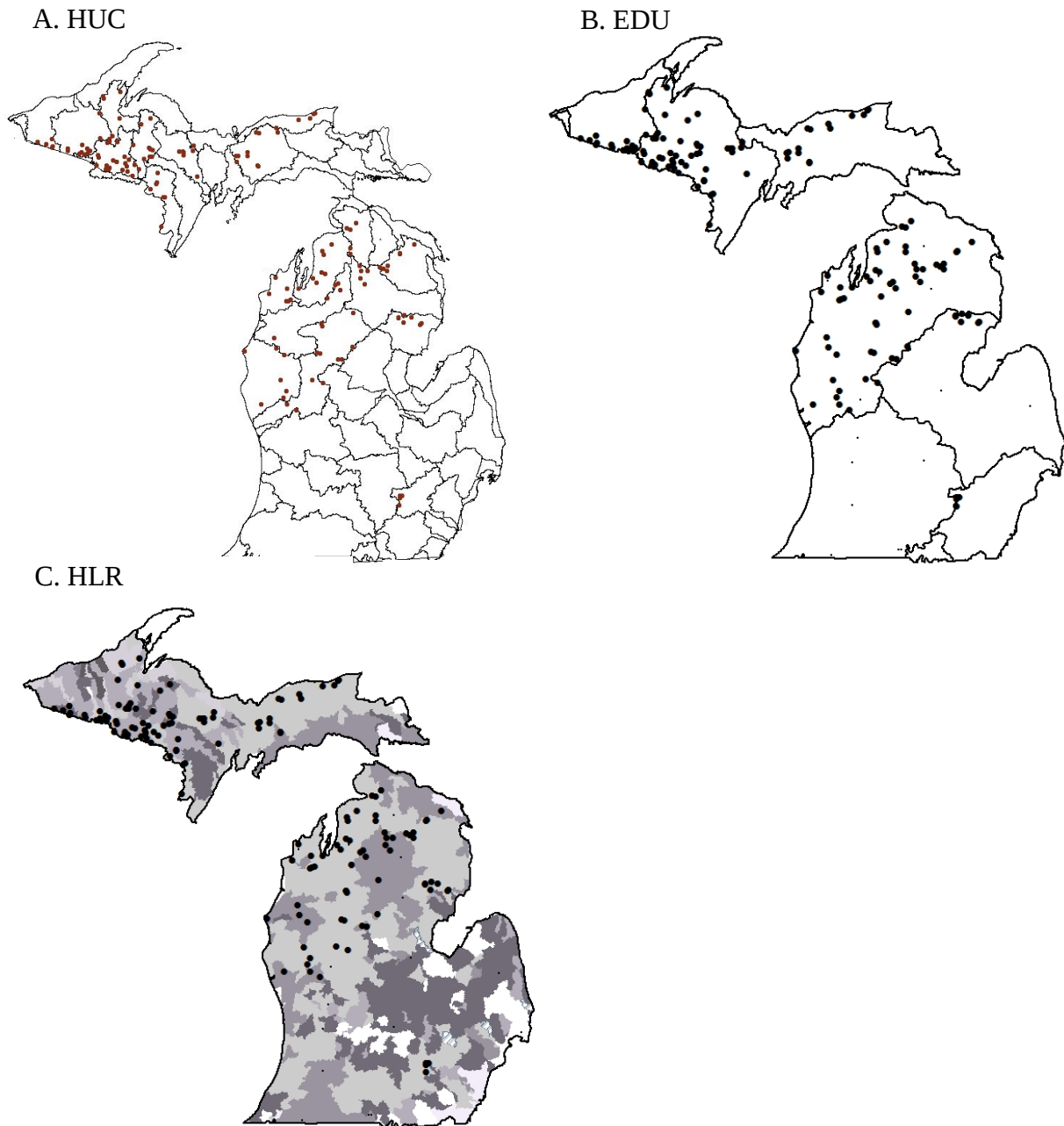
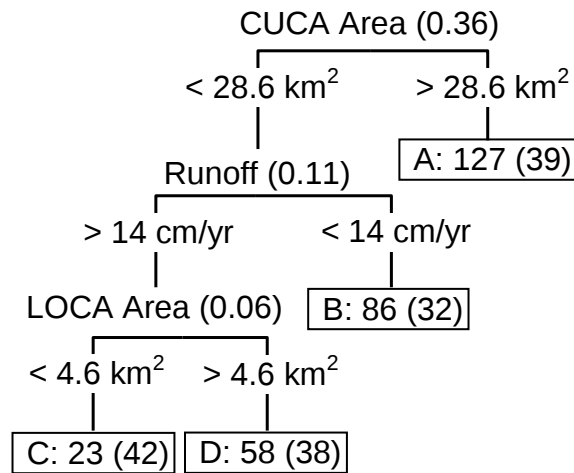
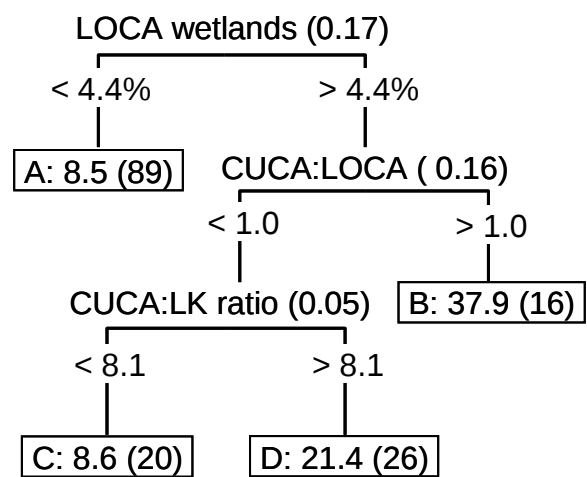


Figure1.2. Results from the CART analysis of local hydrogeomorphic features (HGM) in classifying lake water characteristics: (A) alkalinity, (B) water color, (C) Secchi, (D) TN, (E) TP, and (F) Chl *a*. Each split is labeled with the splitting variable (see Table 1 for abbreviations), and proportional reduction in error (PRE). Branches are labeled with splitting value. Terminal nodes (rectangles) represent lake classes and are labeled with an alphabetical class, class mean, and number of lakes per class (in parentheses).

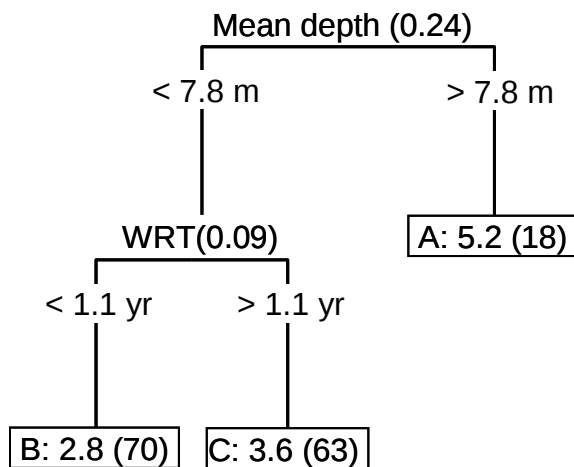
A) Alkalinity (overall PRE 0.53)



B) Water color (overall PRE 0.38)



C) Secchi (overall PRE 0.33)



D) TN (overall PRE 0.16)

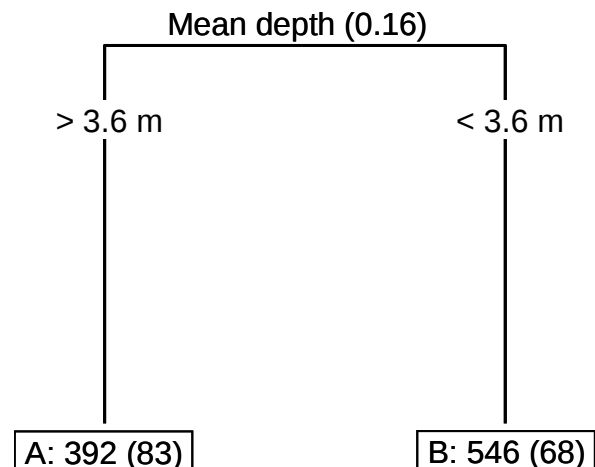
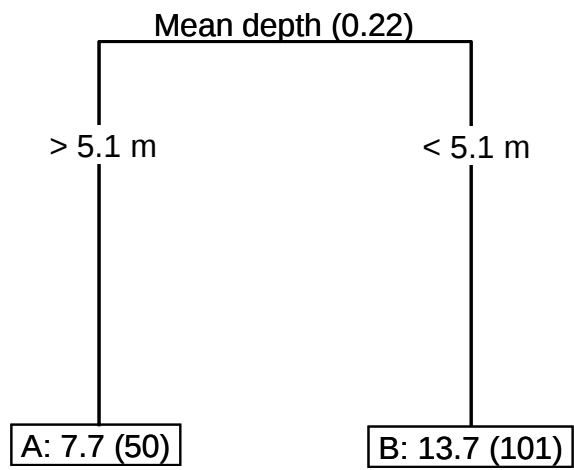


Figure 1.2 (cont').

E) TP (overall PRE 0.22)



F) Chl *a* (overall PRE 0.30)

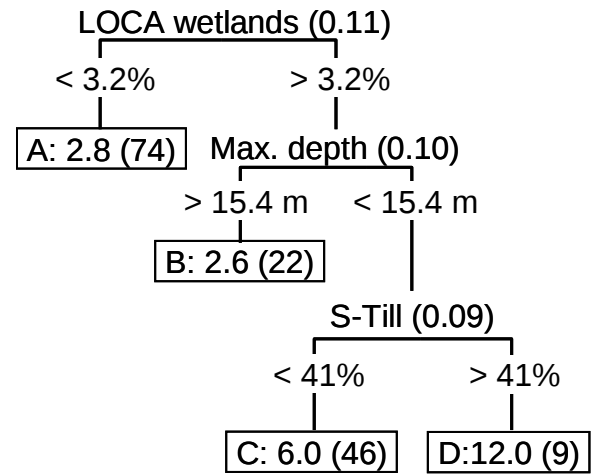
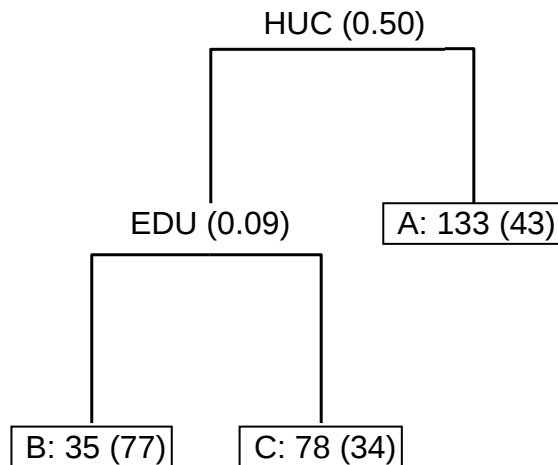
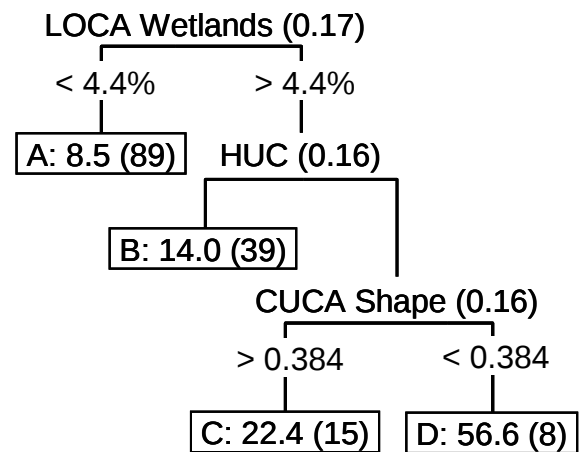


Figure 1.3. Results from the CART analysis combining regionalization, landscape position and local hydrogeomorphic features (HGM+) in classifying lake water characteristics: (A) alkalinity, (B) water color, (C) Secchi, (D) TN, (E) TP, and (F) Chl *a*. Each split is labeled with the splitting variable (see Table 1 for abbreviations), and proportional reduction in error (PRE). Branches are labeled with splitting value. Branches split using categorical variables (e.g., HUC, EDU) are detailed in appendices. Terminal nodes (rectangles) represent lake classes and are labeled with an alphabetical class, class mean, and number of lake per class (in parentheses).

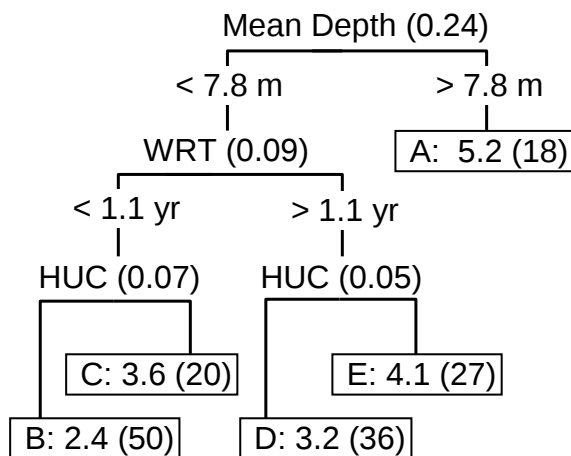
A) Alkalinity (overall PRE 0.59)



B) Water color (overall PRE 0.49)



C) Secchi (overall PRE 0.45)



D) TN (overall PRE 0.46)

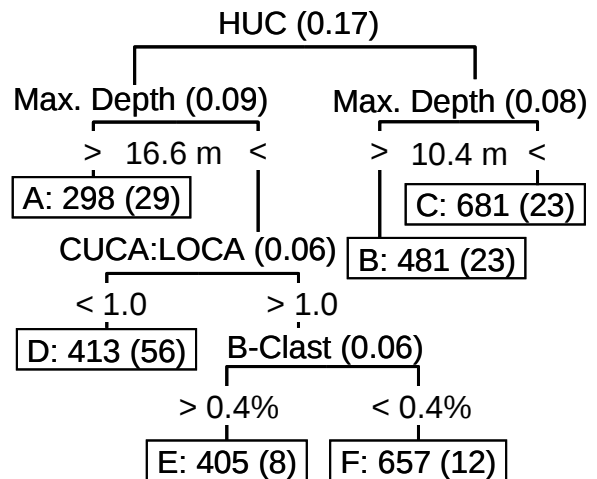
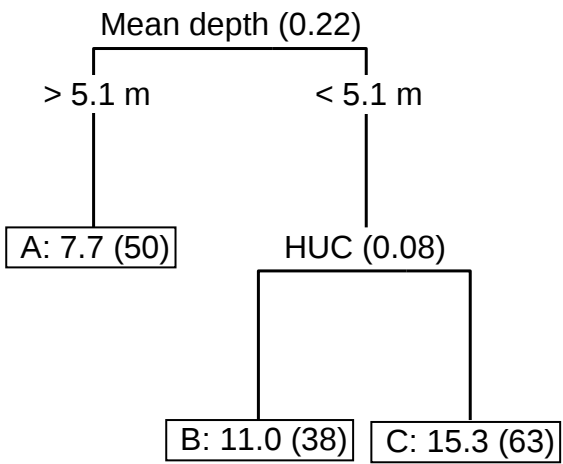
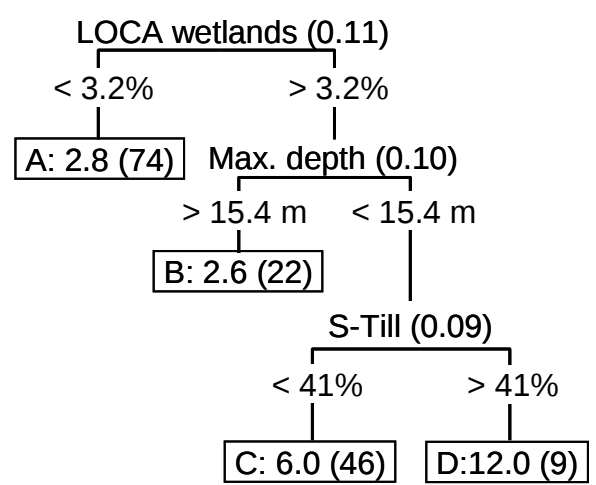


Figure 1.3 (cont').

E) TP (overall PRE 0.30)



F) Chl *a* (overall PRE 0.30)



APPENDIX

Appendix 1. Additional figures for Chapter 1

Figure 1.4. Details of HUC and EDU categorical splits in the alkalinity HGM+ model (refer to Figure 3): A) first node splitting further into class A and towards classes B and C, and B) second node splitting further to classes B or C. Grey areas indicate HUCs which split to the left. Striped areas indicate HUCs which split to the right.

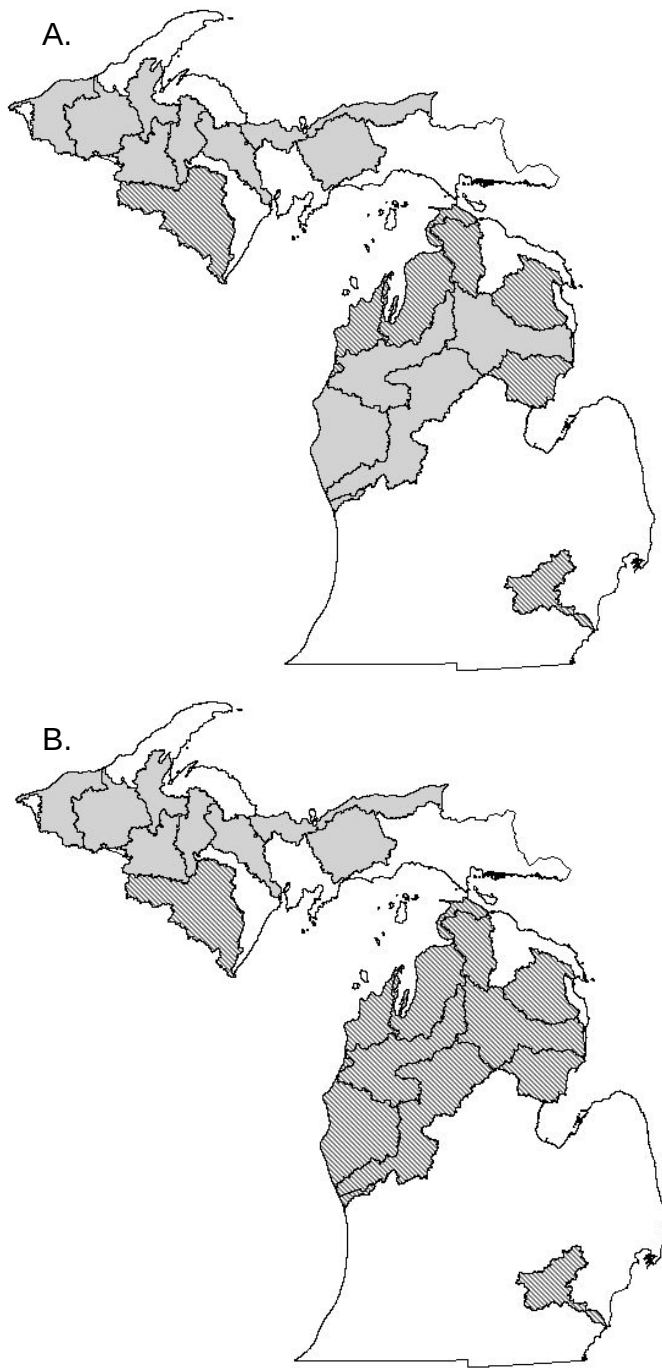


Figure 1.5. Details of HUC categorical split in the water color HGM+ model (refer to Figure 3). Black areas indicate HUCs which were not represented at the node. Grey areas indicate HUCs which split to the left into class B. Striped areas indicate HUCs which split to the right towards classes C and D.

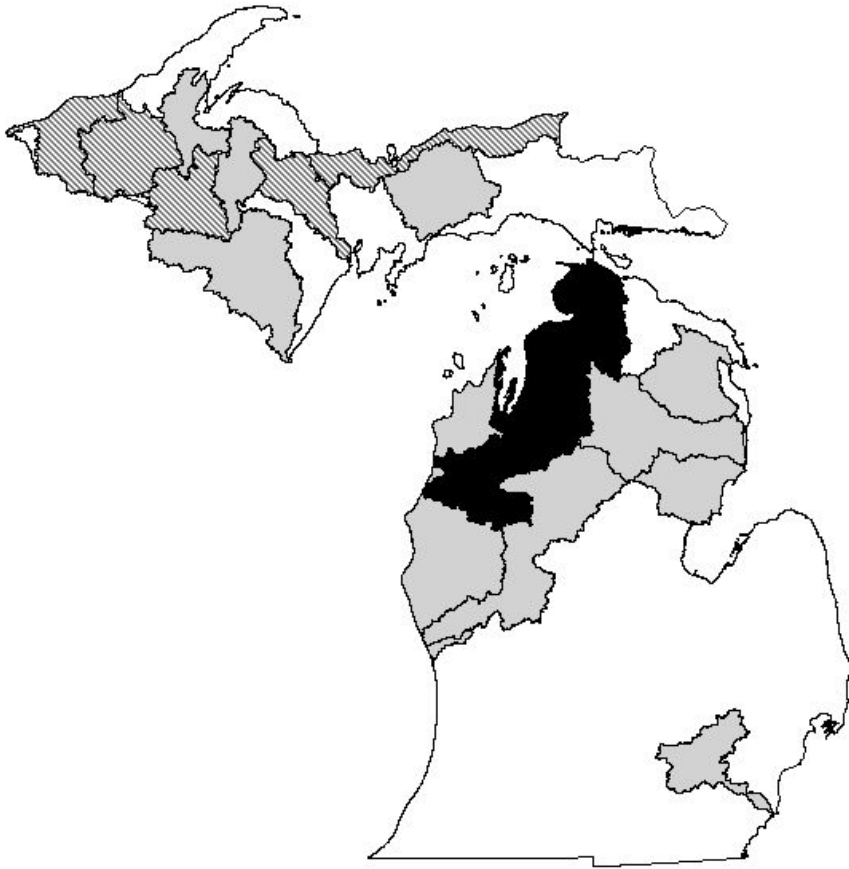


Figure 1.6. Details of HUC categorical splits in the Secchi HGM+ model (refer to Figure 3): A) left split from WRT splitting further to classes B and C, and B) right split from WRT splitting further to classes D and E. Black areas indicate HUCs which were not represented at the node. Grey areas indicate HUCs which split to the left into classes B or D. Striped areas indicate HUCs which split to the right into classes C or E.

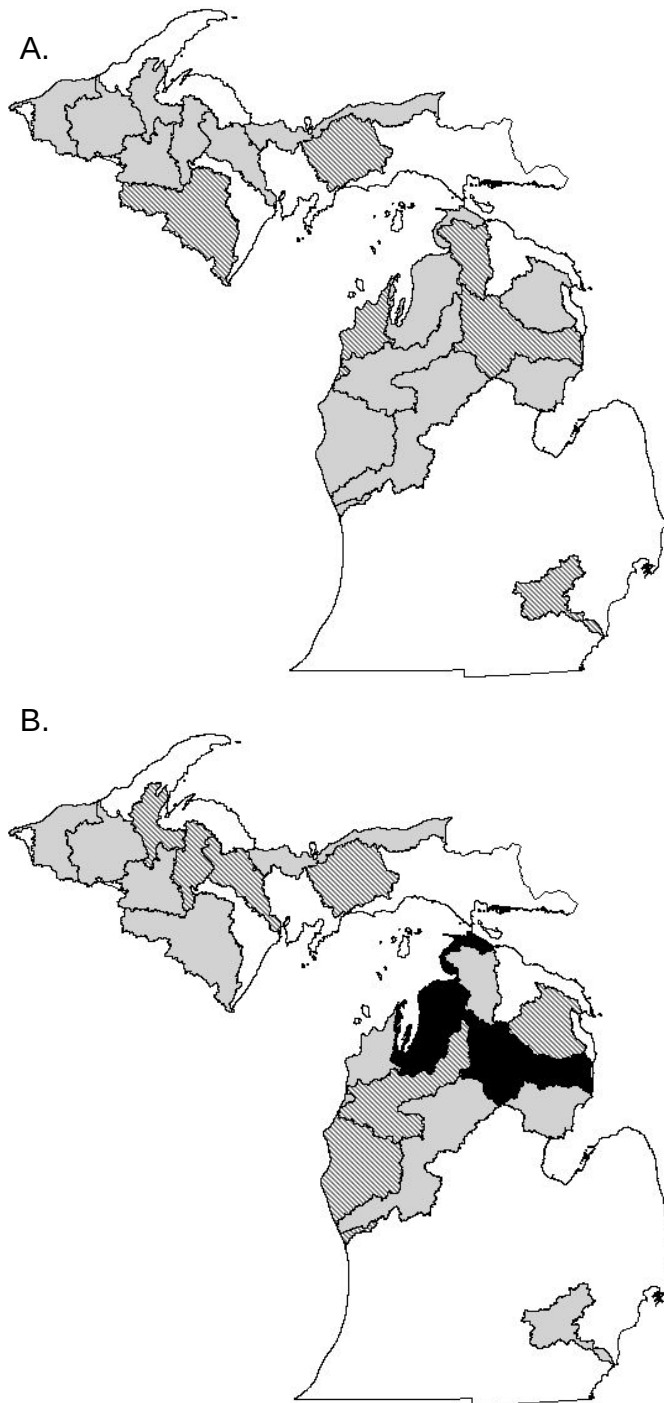


Figure 1.7. Details of HUC categorical split in the TN HGM+ model (refer to Figure 3). Grey areas indicate HUCs which split to the left towards classes A, D, E, and F. Striped areas indicate HUCs which split to the right towards classes B and C.



Figure 1.8. Details of HUC categorical split in the TP HGM+ model (refer to Figure 3). Grey areas indicate HUCs which split to the left into class B. Striped areas indicate HUCs which split to the right into class C.



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CHAPTER 2: THE LAND-USE LEGACY EFFECT - ADDING TEMPORAL CONTEXT TO UNDERSTANDING LAKE WATER CHEMISTRY

INTRODUCTION

The conversion of land to serve human purposes can alter lake ecosystems. In particular, many human activities drive lake eutrophication through direct (e.g. sewage and industrial wastes) and indirect (e.g. agricultural run-off) inputs of excess nutrients (Dillon and Kirchner 1975, Omernik 1976, Holtan et al. 1988). Although many studies have related land use/cover to lake and stream characteristics, much variation remains to be explained (Allan 2004, Declerck et al. 2006). For example, agriculture is a known source of nitrogen and phosphorus to aquatic systems. However, large differences exist in nutrient export to streams among watersheds dominated by agriculture (Arbuckle and Downing 2001, Vanni et al 2001, Knoll et al. 2003) as well as forest (Findlay et al. 2001, Brett et al. 2005). In contrast, some studies report finding no relationship between riverine nutrient concentrations and watersheds with contrasting land cover (Pellerin et al. 2004, Burcher and Benfield 2006). Such inconsistencies indicate that the scientific understanding of ecosystem response to land use/cover (LULC) is still developing (Allan 2004).

The recognition of legacy effects from historical LULC is an important conceptual advance that has clarified the relationship between LULC and ecosystem responses in terrestrial (Foster et al. 1998, Foster et al. 2003, Chauvat et al. 2007), and aquatic systems (Harding et al. 1998, McTammany et al. 2007). Legacy effects can be defined as effects which perpetuate beyond an expected or perceived endpoint in time. In other words, an ecosystem response to LULC disturbance depends on contemporary LULC cover as well as effects from prior LULC that are still propagating through the system. Harding et al. (1998) provide a prominent example of legacy effects in aquatic systems. They found that historic LULC had a stronger relationship with stream macroinvertebrate and fish community diversity than current LULC and called for further research investigating land use legacy effects.

The value of adding a temporal component to analyses of LULC impacts has been discussed in many studies (Allan 2004, Pellerin et al. 2004, Opperman et al. 2005, Goodman et al. 2006, Burcher and Benfield 2006, Davies and Jackson 2006, Foy and Lennox 2006). Specifically, Goodman et al. (2006) report no differences in stream macroinvertebrate community diversity between forested and clear-cut sites, which they attributed to legacy effects from previous agricultural land use. In another example, Foy and Lennox (2006) indicated that a land-use legacy effect may be the mechanism driving increasing riverine phosphorus export despite temporally stable LULC and reductions in point source phosphorus input. Legacies have been suggested to play roles in other small scale (Reed-Anderson et al. 2000, Tomer and Burkhart 2003, Schilling and Spooner 2006) as well as global nutrient budgets (Bennett et al. 2004).

Despite the many studies that suggest the importance of legacy effects, few studies have been designed explicitly to investigate these temporal effects of LULC changes on aquatic systems. Moreover, studies that have addressed legacies have thus far focused on biological endpoints, such as measures of community diversity. Because aquatic biological communities integrate environmental stresses over their lifetime and respond indirectly to some aspects of LULC change, measuring the effects of land use legacies on water chemistry may provide a more direct mechanistic link to aquatic ecosystem condition.

There are at least three potential mechanisms for land-use legacy effects in lakes: 1) import through surface water runoff, 2) delayed import through groundwater pathways, and 3) internal recycling from lake sediments. Knowledge of biogeochemical cycles can help differentiate among these mechanisms. Differences in biogeochemical activity and therefore cycling periods will likely produce different signals in the data for dissolved versus particulate

substances and for reactive versus conservative ions. Phosphorus tends to adsorb to soil, being delivered primarily as particulate matter through surface run-off (Wetzel 1983). In contrast, nitrogen is highly mobile, readily dissolved, and delivered through both surface and groundwater pathways (Wetzel 1983). Therefore, differences between nitrogen and phosphorus legacy signals may indicate differences between surface and groundwater delivery. Furthermore, because lake systems retain a majority of water column nutrients and export a majority of conservative ions (Larsen et al. 1981, Kling et al. 2000), comparing the legacy signals of conservative ions to those of nutrients can help differentiate between external delivery and internal recycling.

The goal of our research was to investigate temporal LULC effects (i.e. legacy effects) on lake water chemistry to increase understanding of how changes in LULC over time influence lake ecosystem responses, such as eutrophication. We used multiple linear regression, where the response variable was one of a suite of water chemistry variables and the predictor variables were time-specific LULC represented by principal components. We then compared model fit and model predictive ability between models using LULC from a single time, and legacy models, which use LULC from multiple time periods. By comparing the legacy signals from a wide range of limnological variables, we can better understand the processes that differentiate the legacy signal among these chemicals.

METHODS

Study area

This study was conducted within the Huron River Watershed (HRW) in Michigan (Figure 2.1). This watershed is approximately 2,359 km² in size and ranges from 390m to 173m in elevation. The HRW contains numerous rivers, streams and lakes supporting a diverse

assemblage of aquatic species (Hay-Chmielewski et al. 1995). Due to close proximity to major metropolitan areas, such as Detroit and Ann Arbor, and the development of interstate highways, many people live, work, and enjoy the recreational opportunities the area provides. The watershed has undergone extensive LULC change over the past century, shifting from an agrarian to suburban society (Hay-Chmielewski et al. 1995, Rutledge and Lepczyk 2002). However, numerous natural areas have been maintained in various publicly owned parks. These characteristics make the HRW a prime area to investigate legacy effects as the watersheds cover a range of LULC trajectories.

Description of data

Water samples were collected from 35 lakes in the HRW during 2008 spring mixing. Lakes were chosen based on their accessibility, including both private and public lakes, and ranged in size from 0.05 to 2.6 km². All water samples were taken from 1m below the surface at the deepest portion of the lake. Samples were analyzed for a range of limnological attributes. Cation (calcium, magnesium, potassium, and sodium) and anion (chloride, nitrate, and sulfate) concentrations were determined using membrane-suppression ion chromatography (Wetzel and Likens 2000). Silica concentrations were determined using the molybdate colorimetric method (Wetzel and Likens 2000). Total nitrogen concentrations were determined using the 2nd derivative of the absorbance curve at 224 nm following persulfate digestion. Ammonia concentrations were determined following the indophenol-blue method. Soluble reactive phosphorus (SRP) and total phosphorus (TP) concentrations were determined spectrophotometrically following persulfate digestion method.

Water chemistry variables were organized into *a priori* groups based largely on biological reactivity and solubility (Appendix 1). Phosphorus species were the most highly reactive variables in our study (Wetzel 1983). Nitrogen species are also highly reactive, but less so than phosphorus due to the relative abundance of nitrogen versus phosphorus (Wetzel 1983). We group Ca, Si, and SO₄ together under the heading of “reactive variables” due to their role as micronutrients in the metabolisms of macrophytes, diatoms, and bacteria, respectively (Wetzel 1983). Conservative ions (i.e. Cl, K, Na, and Mg) play a much smaller role in biological metabolism and therefore are influenced more by external supply than internal conversions (Wetzel 1983).

Land use/cover data (30m resolution) were available from five time steps (1938, 1955, 1968, 1978, and 1996), classified into six categories (urban, agriculture, open, forest, water, and wetland) based a modified version of the Anderson et al. (1976) LULC classification scheme. All data were compiled into a multi-temporal GIS database for analysis (full details in Rutledge 2001). Briefly, digitized land use/cover data for 1978 were provided by the Michigan Department of Natural Resources Michigan Resource Information System (MIRIS) and served as a base for digitizing all other time steps. Aerial photos from each of the other time steps were scanned (150 dpi) to create digital images. These images were then registered and rectified to the 1978 data using the placement of county roads. Land use/cover polygons were then digitized. This technique increased the consistency of polygon locations. Even though LULC data from more recent times were available for the study area, the source images and LULC classification techniques made the datasets incomparable to our historical data. The proportion of each land use/cover type during each time step was calculated for the surface drainage area (watershed) of each study lake.

Statistical analyses

The relationship between time-specific land use/cover and lake water chemistry was analyzed using a combination of principal components analysis and multiple regression. Principal components (PC) analysis on the covariance matrix of the six LULC types was used to reduce the dimensionality of the data, reduce collinearity among the LULC variables, and summarize the LULC composition for lake watersheds for each time step. Land use/land cover composition for the watershed of each lake ($n = 35$) entered the PC analysis separately for each time step, totaling 175 observations entering into the PC analysis (35 lakes by 5 time steps). The six LULC types were combined via PC analysis to represent each lake watershed for each time period, preserving changes in watershed composition through each of the five time steps as well as differences among watersheds. This approach to PC analysis of LULC shows differences in watershed LULC between lakes and between times, highlighting different LULC trajectories.

We built regression models to test the effects of land-use legacies for each water chemistry variable following a chronological hierarchy of LULC following the general form:

$$y_i = \beta_0 + \beta_{1,t} PC1_t + \beta_{2,t} PC2_t + \beta_{3,t} PC3_t + \varepsilon_i$$

where, y_i is the value of water chemistry variable i , $\beta_{1,t}$ is the coefficient for PC axis 1 in time step t (1996 to 1938), and $PC1_t$ is the value of PC axis 1 at timestep t (1996 to 1938). Model building continued until all time steps were included in a single regression model (max 15 independent variables) as shown below:

$$\text{Model 1: } y_i = \beta_0 + \beta_{1,1} PC1_{1996} + \beta_{2,1} PC2_{1996} + \beta_{3,1} PC3_{1996} + \varepsilon_i$$

$$\text{Model 2: } y_i = \beta_0 + \beta_{1,1}PC1_{1996} + \beta_{2,1}PC2_{1996} + \beta_{3,1}PC3_{1996} + \beta_{1,2}PC1_{1978} + \\ \beta_{2,2}PC2_{1978} + \beta_{3,2}PC3_{1978} + \varepsilon_i$$

...

$$\text{Model 5: } y_i = \beta_0 + \beta_{1,1}PC1_{1996} + \beta_{2,1}PC2_{1996} + \beta_{3,1}PC3_{1996} + \beta_{1,2}PC1_{1978} + \\ \beta_{2,2}PC2_{1978} + \beta_{3,2}PC3_{1978} + \beta_{1,3}PC1_{1968} + \beta_{2,3}PC2_{1968} + \beta_{3,3}PC3_{1968} + \\ \beta_{1,4}PC1_{1955} + \beta_{2,4}PC2_{1955} + \beta_{3,4}PC3_{1955} + \beta_{1,5}PC1_{1938} + \beta_{2,5}PC2_{1938} + \\ \beta_{3,5}PC3_{1938} + \varepsilon_i$$

By building the regression models in this way, our approach recognizes the contribution from all time periods and makes the explicit assumption that current LULC is a stronger driver of lake water chemistry than older LULC. It was not our intent to interpret the effect of individual LULC types over time, as represented by individual regression coefficients, but rather we focused on the aggregate effect over time (see Appendix 2). We used Akaike Information Criteria (AIC), AIC weights (ω_i) and the coefficient of determination (R^2) (following Burnham and Anderson 2002) to compare the performance among the five models for each water chemistry variable. We also used AIC weights to compare models built from two PC's to models built from 3 PC's (Appendix 3). All analyses were computed using 3 PC's in SAS using PROC PRINCOM and PROC REG (SAS).

RESULTS

Changes in land use/cover

Averaged across all lake watersheds, the largest changes in LULC occurred in the agriculture and urban categories (Fig. 2.2). Agriculture predominated in 1938, comprising an average of 40% of the study watersheds. Over time, agriculture steadily declined in area to represent only about 15% of the watershed areas by 1996. As agriculture declined, urban LULC steadily increased from less than 5% in 1938 to over 20% by 1996. Wetland LULC type also declined steadily from 12% to 8% over the study period. Both forest and open LULC types increased initially, reaching 23% and 21% of the watershed areas in 1968 and 1978, respectively. However, these LULC types then decreased for the remainder of the study period, comprising 20% and 19%, respectively, of the watershed areas by 1996 (Fig. 2.2).

The first three PC's explained approximately 89% of the variation in the dataset (Table 2.1). The first PC represented almost half of the variation in the dataset and was weighted most heavily by agriculture and urban LULC types (Table 2.1). The pattern of urban expansion and agricultural contraction, seen using average watershed LULC (Fig 2.2), can also be seen using a multivariate representation of the LULC data (Fig. 2.3). Agriculture dominated the landscape in 1938, shifting steadily to urban dominance between 1955 and 1968 (Fig 2.3). The second PC was weighted most heavily on urban and forest (Table 2.1), and showed a slight shift between forest and urban LULC between 1938 and 1968 (Fig. 2.3), as the pace of urban growth exceeded that of forest (Fig. 2.2). A more dramatic shift in forest and urban LULC types occurred between 1968 and 1996, as the growth of urban increased as forest waned. The third PC was weighted most heavily on open and forest LULC types (Table 2.1). The pattern of LULC change represented with the third PC is more complex than what was seen in the first two PC's. Open areas were slightly more prevalent than forest in 1938, switching to forest prevalence for 1955 and 1968. Forest and open areas were roughly equal for the last two time steps of the study.

Plotting the change in LULC of each lake watershed over time showed that our dataset included lakes that vary in initial conditions, rate of change, and final composition (Appendix 4). The individual trajectories of LULC change represented by the first PC were nearly parallel, showing a change from agriculture to urban dominance. However, some of the lakes changed more rapidly than others, some changed more than others, and some changed very little. The second PC showed a narrower range of initial conditions than the first PC, but also showed largely parallel trajectories for the majority of the lakes with few divergences. The trajectory of the third PC was more erratic than the other two PCs, representing more lake to lake variation in the timing of shifts in open and forest LULC.

Comparing regression models

The regression models using only current LULC provided the best model fit only for phosphorus species (Fig. 2.4). The explanatory power, as measured by R^2 , for these models ranged from 19% to 64%, but had low Akaike weights (mean 8%) for all other water chemistry variables. Our results showed that legacy models provided a better model fit for all other lake water characteristics. Including additional information about historical LULC in regression models always improved explanatory power (Fig. 2.5), but did not always improve model fit enough to account for the added complexity (Fig. 2.4). The explanatory power of the simplest model for TP and SRP (the 1996-only model) was only 25% and 22%, increasing to 45% and 35%, respectively, when all of the time steps were included (Fig. 2.5). Among the five regression models evaluated, the only model supported by Akaike weights for TP or SRP was the 1996-only model (Fig. 2.4).

All other lake water characteristics were best modeled by some combination of current and past LULC data (Fig. 2.4). All species of nitrogen were best modeled by including historical LULC information through the 1978 time step (Fig. 2.4), increasing the explanatory power from 18-27% for the current-LULC-only regression approach to 38-43% for the model including 1978 (Fig. 2.5). Calcium, silica, and sulfate were also best modeled by a 1978 legacy model (Fig. 2.4), accounting for 47-62% of the variation in the data (Fig. 2.5). Other legacy models for these variables also received some support by AIC weights. The 1968 legacy models for calcium and silica were supported by AIC weights of 0.27 and 0.25, respectively.

Conservative ions showed the longest legacy effect and the highest explanatory power of all water chemistry characteristics in our study. The best model for potassium included historical LULC information through the 1955 time step (Fig. 2.4), accounting for 93% of the variation in the data (Fig. 2.5). Explanatory power increased the most (approximately 30%) when 1978 LULC was added to the regression model, but continued to increase through the addition of 1955 (Fig. 2.5). Chloride, magnesium, and sodium were best modeled by the full legacy model that included LULC information for all time steps back to 1938 (Fig. 2.4). Although the 1996-only model for sodium was also supported with an AIC weight of 0.23, the full legacy model received the majority of support, with an AIC weight of 0.59. The 1938-legacy models of chloride, magnesium, and sodium improved explanatory power by 21%, 35%, and 20%, respectively, over the 1996-only model (Fig. 2.5). These models accounted for 82-85% of the variation in the data (Table 2.2).

All regression models show a roughly linear relationship (Appendix 5).

DISCUSSION

Among key ecological principles essential in sustainable land planning, Dale et al. (2000) describe the relevance of ‘time’ in terms of ecological legacies, time-lag feedbacks, and future constraints. Our study sought to quantify this temporal component of ecosystem response to land conversion (i.e. land use legacy effect). The method we used shows both the presence and timescale of legacy effects in models relating LULC to most lake water characteristics. Furthermore, by comparing lake water characteristics with vastly different biogeochemical cycles, our study gives mechanistic insight into legacies. We report finding the first evidence of land use legacy effects in lakes.

The traditional approach to studying ecosystem responses to LULC compares LULC from a single time period to a measure of ecosystem response from a similar time period. A legacy approach simply modifies the traditional approach by adding historical LULC to models. We found that taking a legacy approach improved model fits for total and dissolved nitrogen, reactive ions, and conservative ions. However, the added complexity inherent to legacy models did not substantially improve explanatory power for total and soluble reactive phosphorus. These results seem to support a conclusion that phosphorus responds most strongly to the most recent LULC. Another plausible explanation is that lake phosphorus concentrations are governed more by internal recycling from lake sediments rather than delivery pathways (Stauffer 1987, Soranno et al. 1996). The low explanatory power for our models of phosphorus also indicates that other mechanisms, such as internal recycling, should be considered in future analyses of phosphorus. Results from other studies linking watershed landscape context to phosphorus also show that external landscape factors fail to predict lake phosphorus well (Riera et al. 2000, Martin and Soranno 2006, Martin et al. In Review).

In contrast to phosphorus, legacy effects were more apparent for nitrogen species. Nitrogen is also a highly reactive nutrient; however, nitrogen is readily held in multiple biologically available forms and remains dissolved much more easily than phosphorus. Previous studies provide evidence that nitrogen species are delivered primarily as dissolved forms through subsurface hydrologic pathways (Jordan et al. 1997, Vanni et al. 2001), whereas phosphorus binds to soils and is delivered primarily through surface runoff (Jordan et al. 1997, Johnes and Heathwaite 1997). Differences in the rate of delivery between these two routes, surface delivery being fast and subsurface delivery being slow, provide another potential mechanistic explanation for differences in legacy timescales for nitrogen and phosphorus. Carpenter and Turner (2000) discuss how interactions between the proverbial tortoises and hares of ecological processes work to structure ecosystem responses. Our results provide empirical evidence supporting the importance of both slow (soil saturation) and fast (surface runoff) processes in structuring lake ecosystem response to external nitrogen loads.

By grouping our water chemistry variables into *a priori* groups based on biological reactivity, we are able to show that the level of biological reactivity can also be used to understand differences in legacy timescales. As major nutrients for aquatic primary producers, phosphorus and nitrogen have high levels of reactivity. Calcium (Alstad et al. 1999), silica (Martin-Jezequel et al. 2000) and sulfate (Holmer and Storkholm 2001) are also important in biological processes, but less than nitrogen (Wetzel 1983). On the other hand, Cl, K, Mg, and Na are grouped as conservative ions given their low relative reactivity in aquatic ecosystems (Wetzel 1983). Our results indicate that legacy timescales are negatively related to biological reactivity: highly reactive elements, such as nutrients have relatively short legacy timescales and conservative ions have the longest legacy timescales. From these results, we can estimate that the

signal from nitrogen and reactive ions are still apparent from historical LULC occurring 30 years ago. In comparison, conservative ion concentrations, which are not as strongly linked to biological metabolism, are still responding to historical LULC from 70 years ago. It is possible that if LULC data were available prior to 1938, many of the conservative ions would have shown an even longer legacy. The few biogeochemical studies of legacy effects have found similar legacy timescales for nutrients (Harding et al. 1998, Chauvat et al. 2007) and conservative ions (Boutt et al. 2001).

We also see an increase in explanatory power as reactivity decreases, with forms of phosphorus explained poorly (R^2 22 and 25%), nitrogen explained fairly well (R^2 37-43%), reactive ions explained well (R^2 47-62%), and conservative ions explained extremely well ($R^2 > 80\%$). Kling et al. (2000) found that biological reactivity was positively related to the coefficient of variation calculated from multiyear sampling on ten lakes, with higher reactivity showing higher interannual variability. This high variability may also explain differences in explanatory power of the legacy models, in that high interannual variability of a variable in a lake will likely reduce the predictability (hence model power) for that variable.

Management Implications

A recent renewal of interest in eutrophication (Conley et al. 2009, Smith and Schindler 2009, Wagner and Adrian 2009) and calls for nutrient reductions (Carpenter 2008) echo the calls of the past (Edmonson et al. 1956, Edmonson 1970, Schindler 1974). Many management strategies, such as changes in land use policies and reductions in point source inputs, have been put into place to reduce anthropogenic effects on lakes (Schindler 2006). Setting realistic expectations is important part of the management cycle and failure to recognize legacy impacts

may lead to unachievable expectations. While the occurrence of legacy effects may be more widely known or accepted, the quantification of legacy timescales is important for setting realistic goals for the restoration of ecosystem services (Chauvat et al. 2007). Our study shows a nitrogen legacy signal from more than a decade prior. On the other hand, our study did not show a legacy effect for phosphorus. Therefore, management actions aimed at reducing nitrogen impacts may take longer to show improvements than actions aimed at reducing phosphorus impacts. The long legacy that conservative ions exhibited may also be indicative of the legacy timescale of other soluble substances, such as persistent toxic chemicals

In conclusion, relationships between LULC and lake water characteristics go beyond that which is currently being measured. It is essential to include the temporal context of LULC in modeling important ecosystem dynamics. By adding an analysis of conservative ions to the suite of limnological variables, we were able to show differences in inferred legacy mechanisms that would have otherwise been missed. Furthermore, ecosystem responses to future changes in land cover and/or climate are likely linked to historic landscape context.

Table 2.1. Eigenvectors and proportional variance explained from principal components analysis of land use/cover types. Extreme values for each PC are indicated in bold.

	PC1	PC2	PC3	PC4	PC5
Agriculture	-0.8663	-0.1345	-0.0426	-0.0509	-0.2457
Urban	0.3302	-0.7274	-0.0216	-0.4412	0.0075
Forest	0.1567	0.5363	0.5599	-0.4196	-0.1779
Water	0.2239	-0.1552	0.2985	0.7826	-0.2399
Open	0.2416	0.3533	-0.7711	0.0099	-0.2355
Wetland	-0.0862	0.1276	-0.0231	0.1191	0.8916
Eigenvalue	0.043	0.024	0.013	0.007	0.003
% variance explained	48%	27%	14%	7%	4%

Table 2.2. Regression statistics for best models. Dependant variables are listed under broad categories. Details of regression models include: time step(s) represented in final model, number of regression parameters fit (p), Akaike Information Criteria (AIC), Akaike weight (ω_i), and coefficient of determination (R^2).

Dependant	Regression model	p	ω_i	R^2
Phosphorus				
TP	96	3	0.872	0.255
SRP	96	3	0.930	0.216
Nitrogen				
TN	96+78	6	0.639	0.376
NO ₃	96+78	6	0.788	0.400
NH ₄	96+78	6	0.722	0.435
Reactive Ions				
Ca	96+78	6	0.494	0.496
Si	96+78	6	0.611	0.471
SO ₄	96+78	6	0.672	0.616
Conservative Ions				
Cl	96+78+68+55+38	15	0.926	0.850
K	96+78+68+55	12	0.870	0.933
Mg	96+78+68+55+38	15	0.968	0.847
Na	96+78+68+55+38	15	0.593	0.815

Figure 2.1. Map showing the Huron River Watershed within the state of Michigan, including detailed hydrography features along with outlines for the cities of Ann Arbor and Ypsilanti. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation.

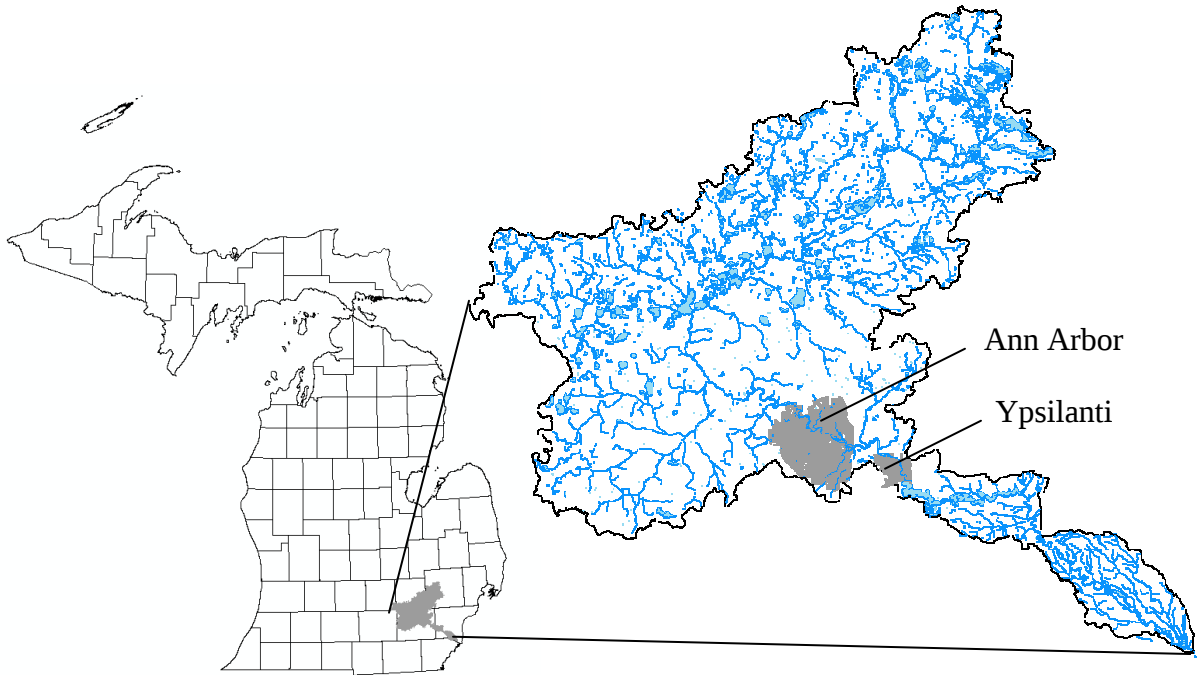


Figure 2.2. Average proportion of each land use/cover type for the study lakes calculated for each time step in the study. Solid fine line represents agriculture. Solid heavy line represents urban. Dashed fine line represents forest. Dashed heavy line represents open. Dotted fine line represents water. Dotted heavy line represents wetland.

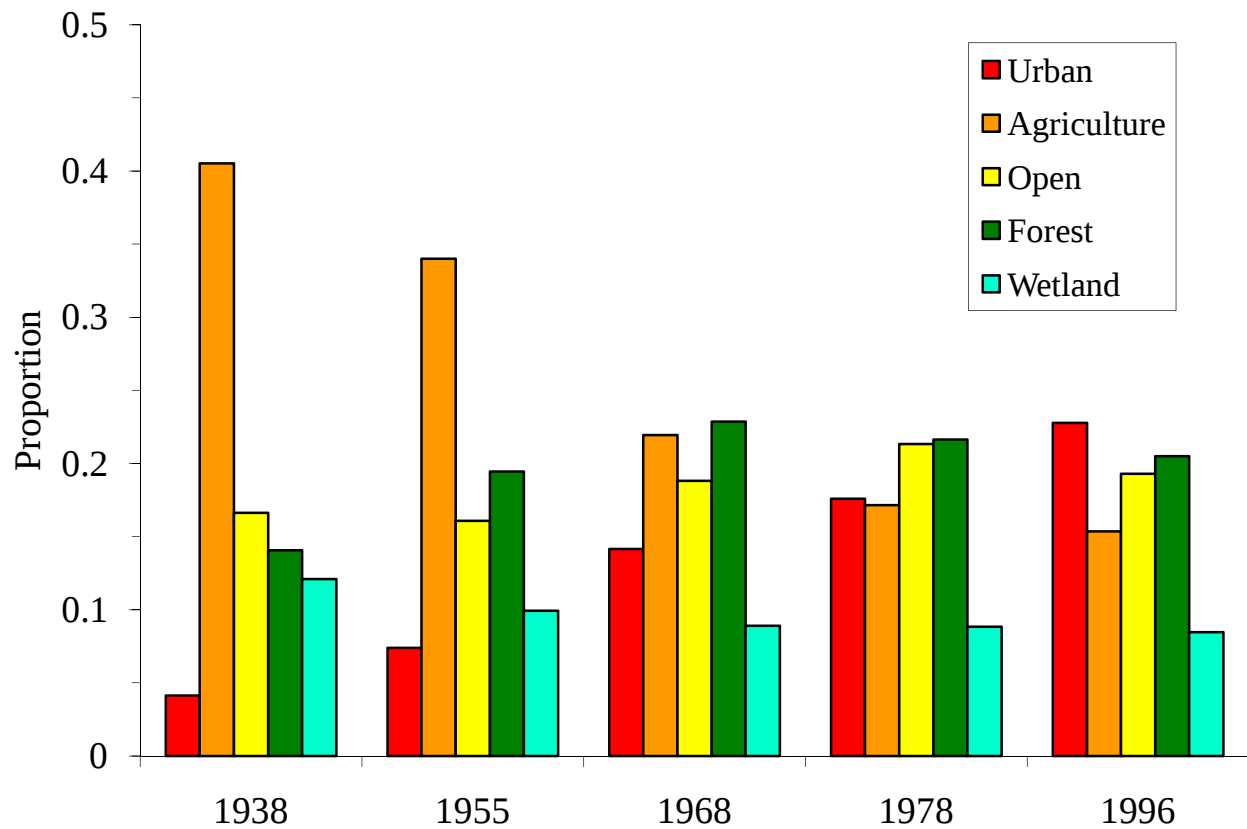


Figure 2.3. Change in land use/cover over time represented by principal component 1 (PC1), principal component 2 (PC2), and principal component 3 (PC3). Each dot represents the average score for that time step.

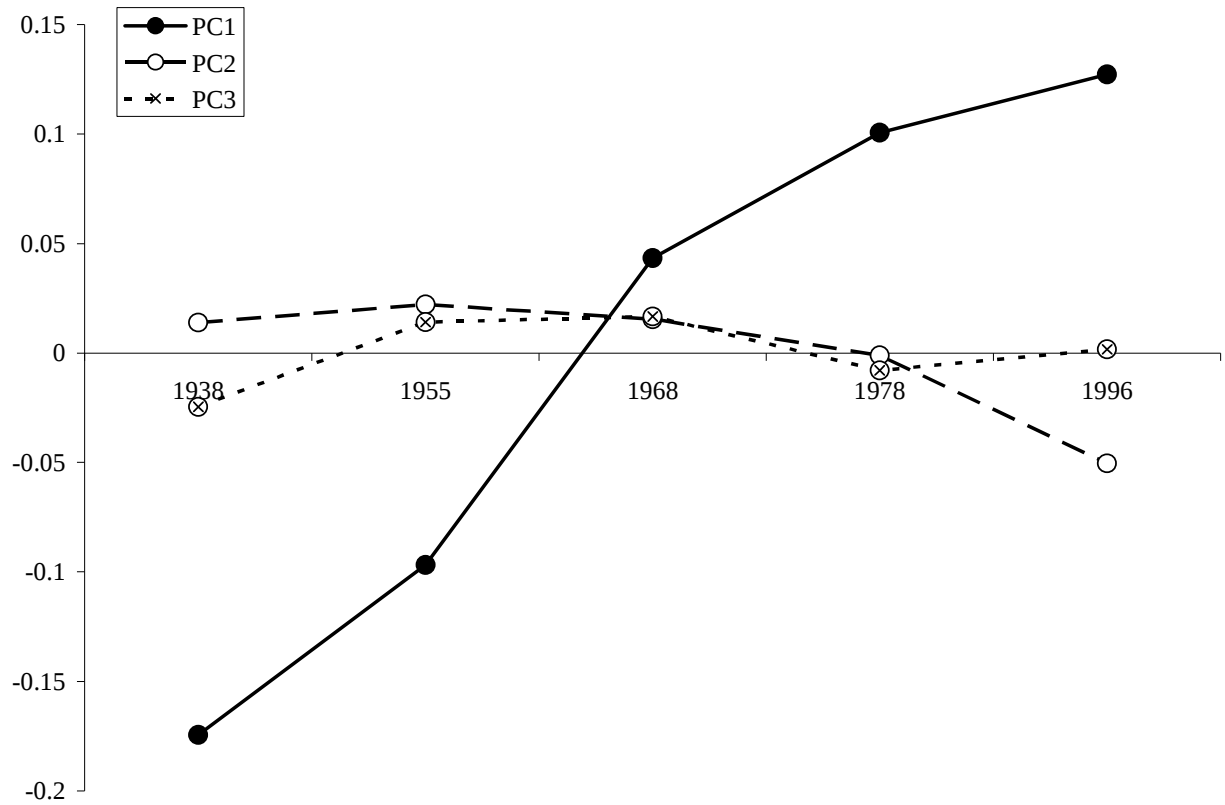


Figure 2.4. Akaike weights (ω_i) from chrono-sequence of regression models. (A) TP, solid circles with heavy solid line; and, SRP, open circles with dashed line. (B) TN, solid circles with heavy solid line; NO_3 , open circles with dashed line; and, NH_4 , X inside circle with dotted line. (C) Ca, open circle with heavy solid line; Si, open triangle with dashed line; and, SO_4 , open square with dotted line. (D) Cl, open with circle heavy solid line; K, open triangle with dashed line; Mg, open square with dotted line; and, Na, open diamond with fine solid line.

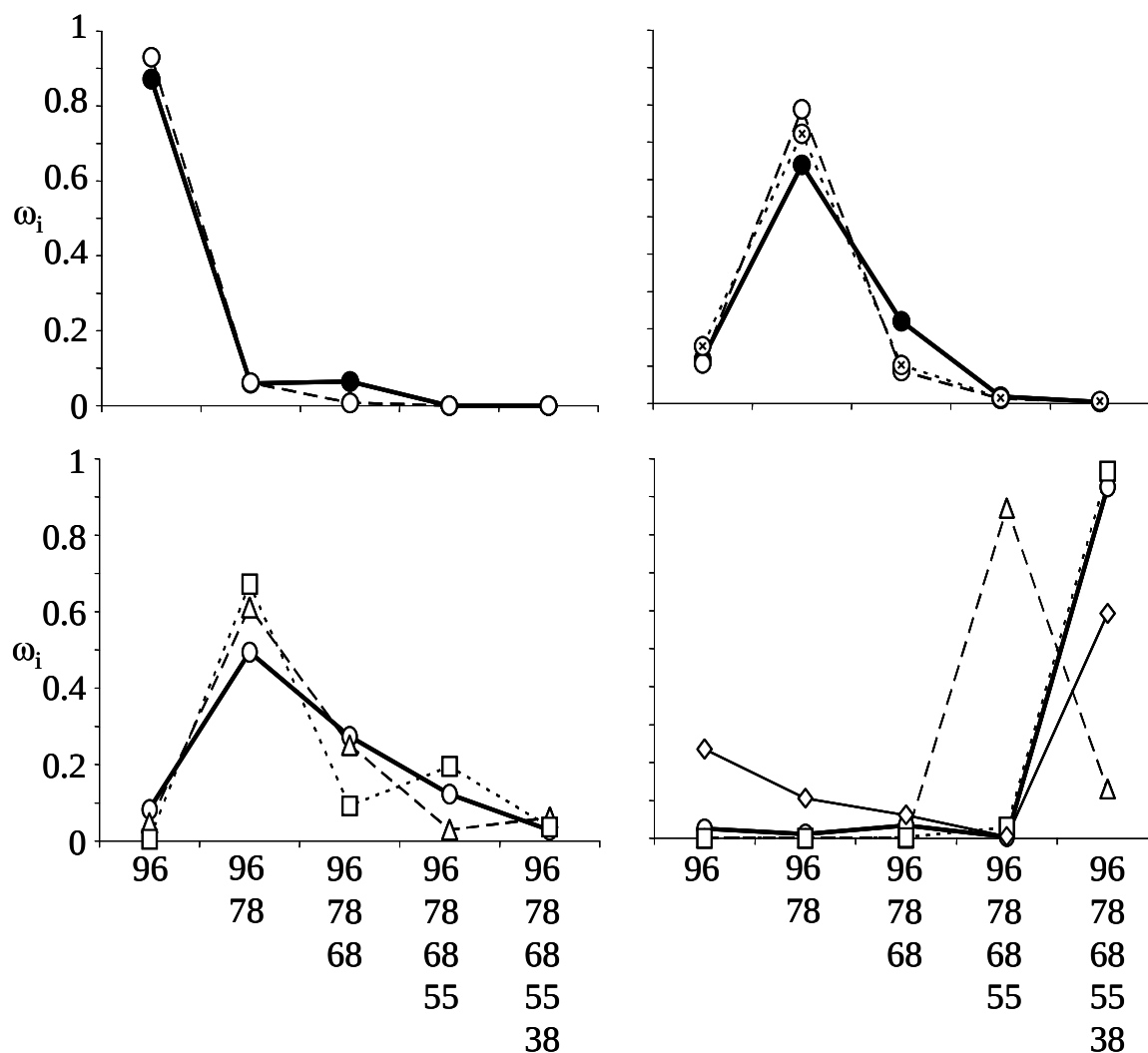
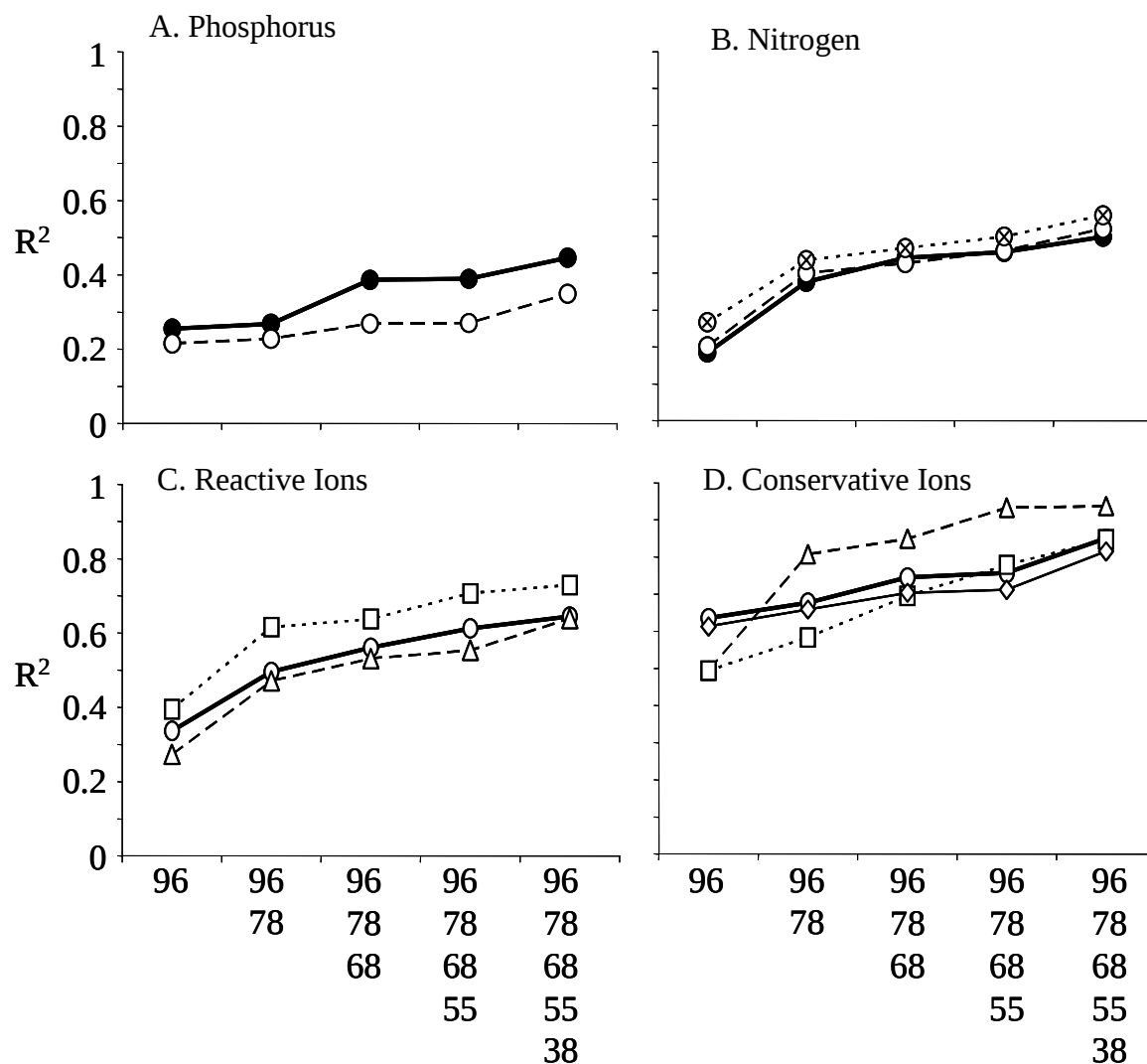


Figure 2.5. Coefficient of determination (R^2) from chrono-sequence of regression models. (A) TP, solid circles with heavy solid line; and, SRP, open circles with dashed line. (B) TN, solid circles with heavy solid line; NO_3 , open circles with dashed line; and, NH_4 , X inside circle with dotted line. (C) Ca, open circle with heavy solid line; Si, open triangle with dashed line; and, SO_4 , open square with dotted line. (D) Cl, open with circle heavy solid line; K, open triangle with dashed line; Mg, open square with dotted line; and, Na, open diamond with fine solid line.



APPENDIX

Appendix 2. Additional information for Chapter 2.

Table 2.3. Characteristics of the study lakes including water chemistry variables as categorized into *a priori* groups and lake area. Minimum, maximum, mean, and coefficient of variation are shown for each variable.

Lake characteristic	Minimum	Maximum	Mean	CV
Lake area (km ²)	0.06	2.60	0.65	0.93
Phosphorus				
TP (µg/L)	5.4	45.0	24.1	0.37
SRP (µg/L)	0.33	3.45	1.15	0.56
Nitrogen				
TN (mg/L)	0.53	1.85	0.94	0.30
NO ₃ (mg/L)	0.00	1.03	0.20	1.20
NH ₄ (µg/L)	3	143	36	0.96
Reactive Ions				
Ca (mg/L)	16	92	52	0.38
Si (mg/L)	0.00	5.61	1.53	0.88
SO ₄ (mg/L)	1.9	88.4	26.1	0.83
Conservative Ions				
Cl (mg/L)	2	242	66	0.90
K (mg/L)	0.58	7.53	2.09	0.57
Mg (mg/L)	3.9	24.7	15.4	0.26
Na (mg/L)	0.9	77.3	24.0	0.88

Table 2.4. Regression coefficients from best models as reported in Table 2.2.

	Ca	Cl	K	Mg	Na	NH ₄	NO ₃	Si	SO ₄	SRP	TN	TP
Intercept	49	-44	1.4	17	-15	37	0.352	1.2	22	1.3	1.1	27
PC1_96	-42	-705	-13	4.7	-228	-416	-6.4	-13	135	-1.0	-8.3	-27
PC2_96	-145	-377	-11	-4.2	-129	-175	-2.2	-14	-61	1.1	-3.6	-2.4
PC3_96	335	491	14	24	352	-731	0.5	1.5	527	0.4	-0.6	-12
PC1_78	-23	1362	13	7.2	451	503	5.5	11	-212		7.2	
PC2_78	147	5.6	11	-23	34	159	1.7	20	73		3.1	
PC3_78	-353	338	-8.5	-11	-60	751	-0.2	-6.6	-536		1.2	
PC1_68		-657	1.0	-11	-241							
PC2_68		298	-3.3	27	107							
PC3_68		-681	-2.6	-13	-232							
PC1_55		590	-4.1	-20	245							
PC2_55		-603	1.8	-27	-267							
PC3_55		436	-0.1	-23	169							
PC1_38		-746		19	-284							
PC2_38		255		33	70							
PC3_38		-471		37	-200							

Figure 2.6. Comparisons between regression results using 2 PCs and 3 PCs for calcium, chloride, potassium, magnesium, sodium, ammonium, nitrate, silica, sulfate, soluble reactive phosphorus (SRP), total nitrogen (TN), and total phosphorus (TP). Akaike weights (y-axis) were computed across regression results for each water chemistry variable from both 2 PCs and 3 PCs to total ten regression models.

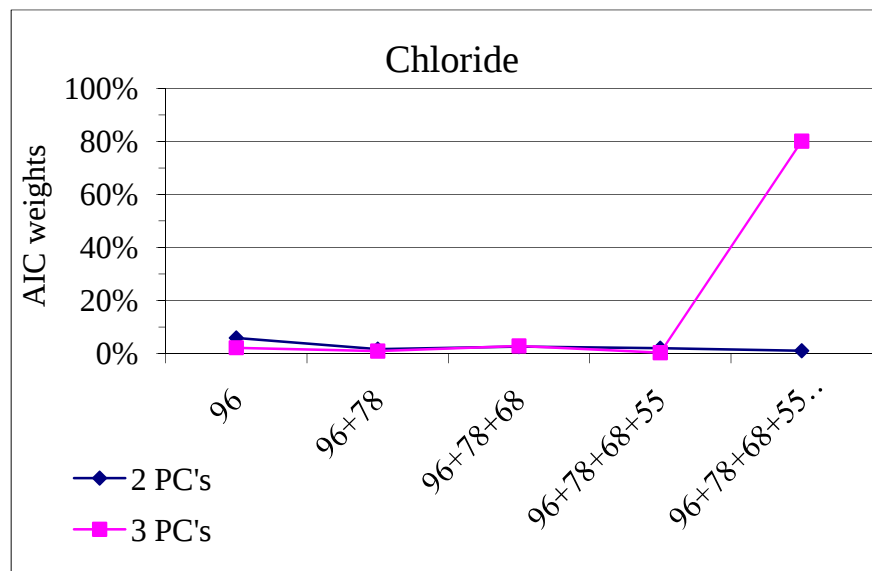
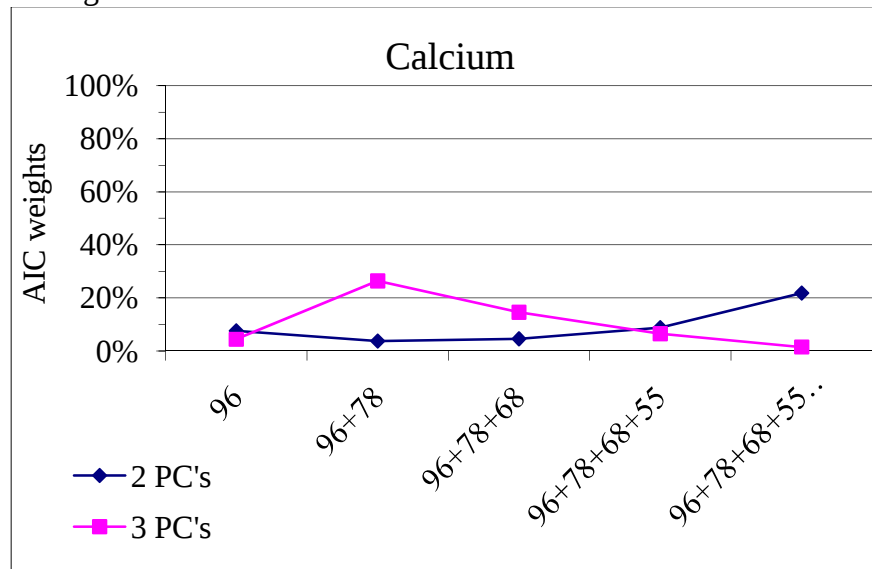


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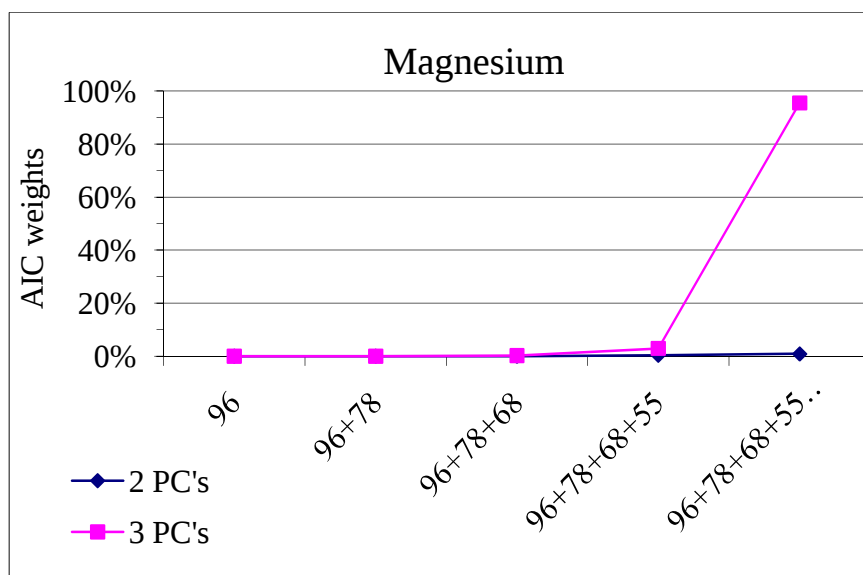
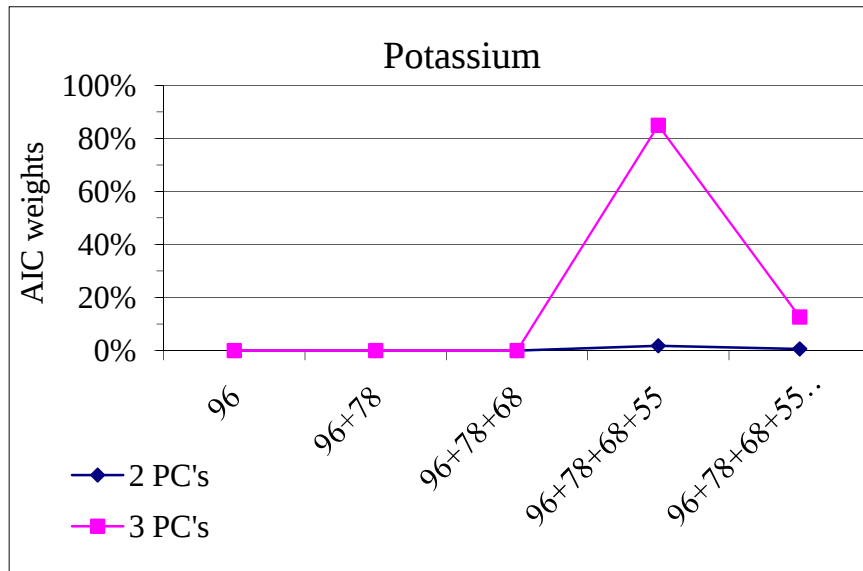


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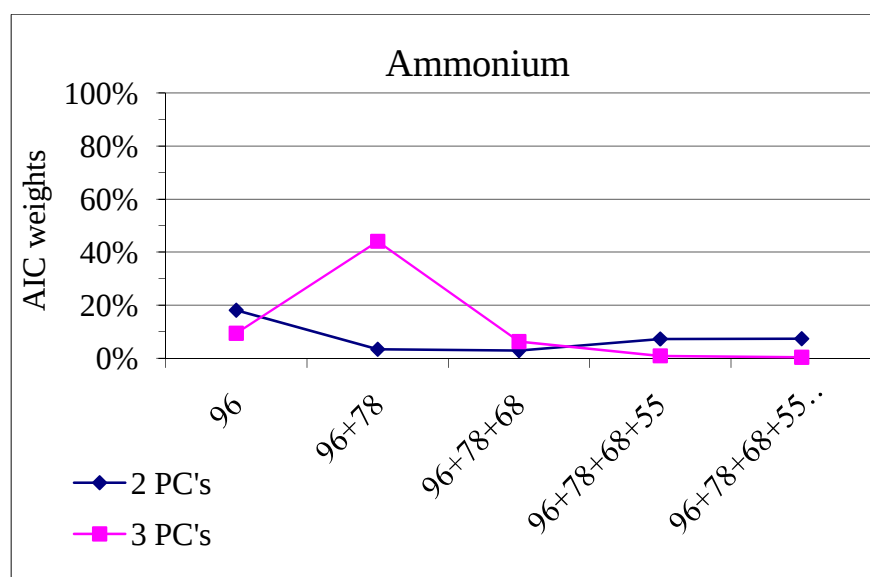
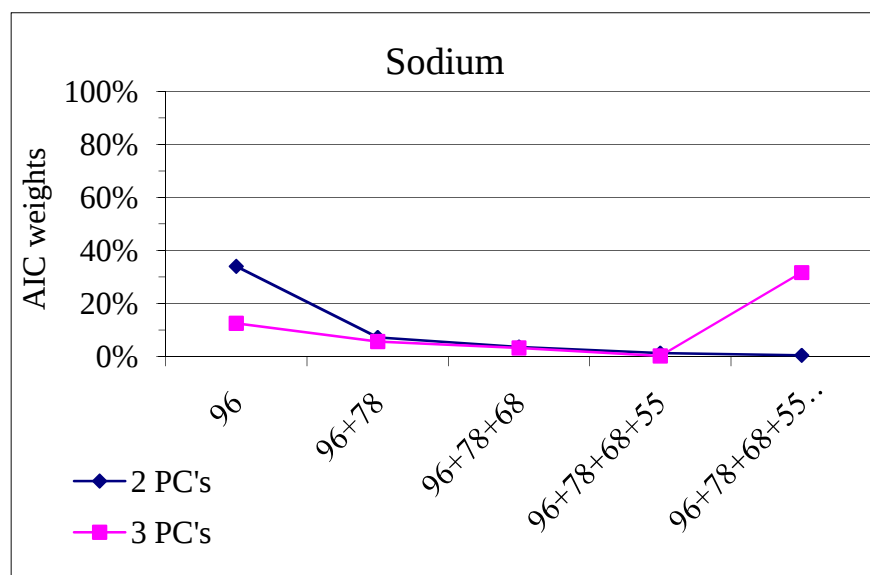


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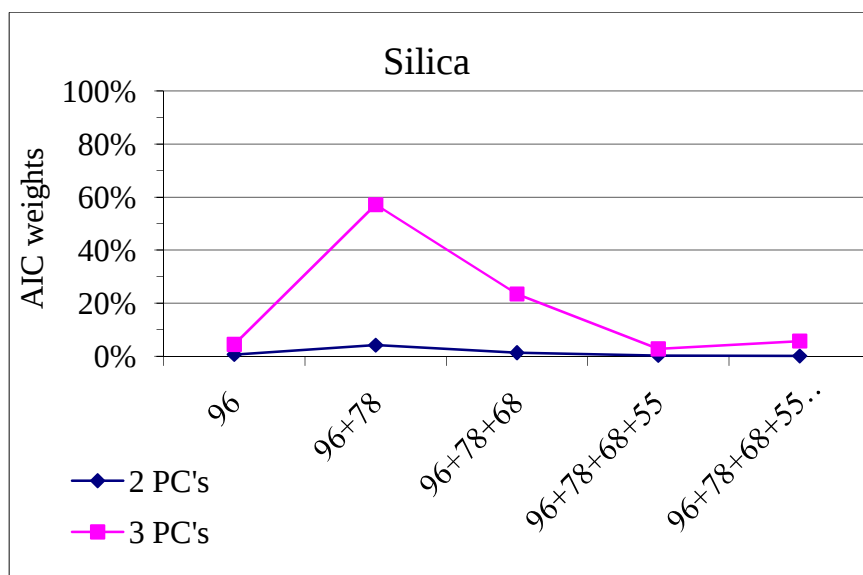
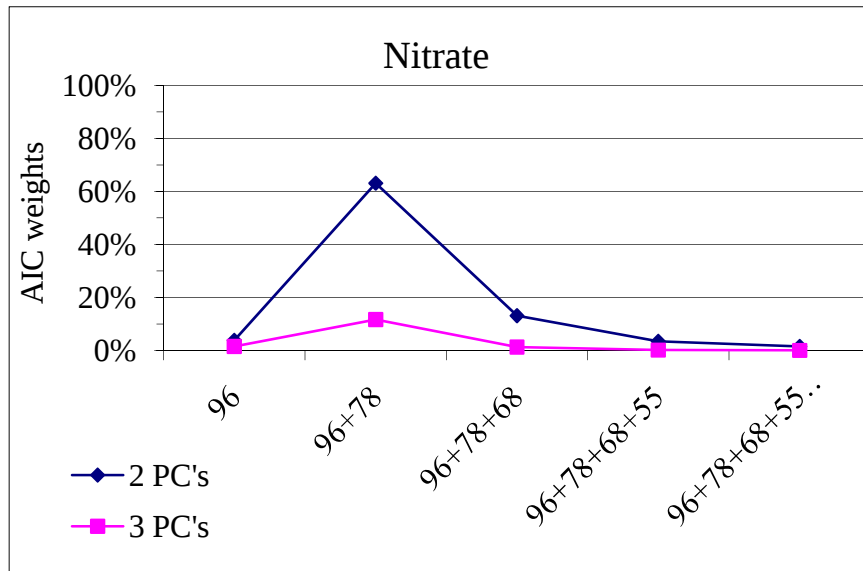


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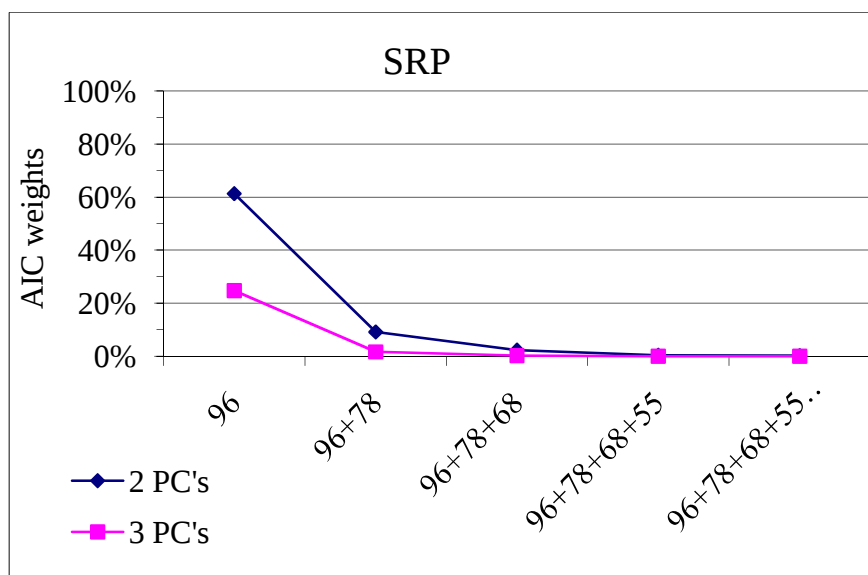
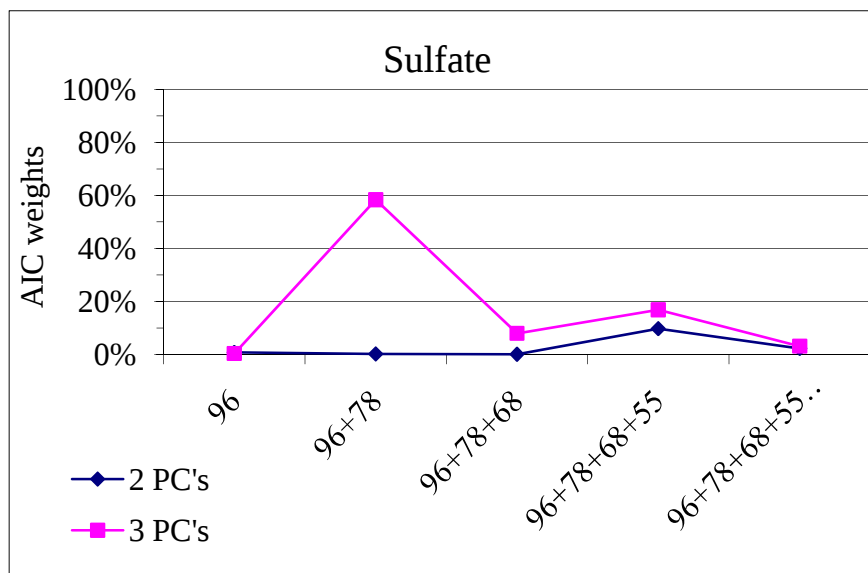


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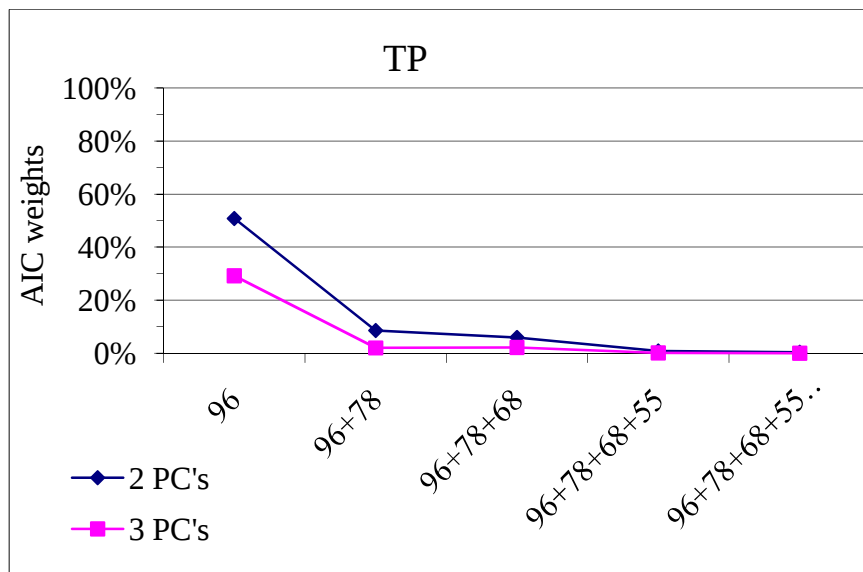
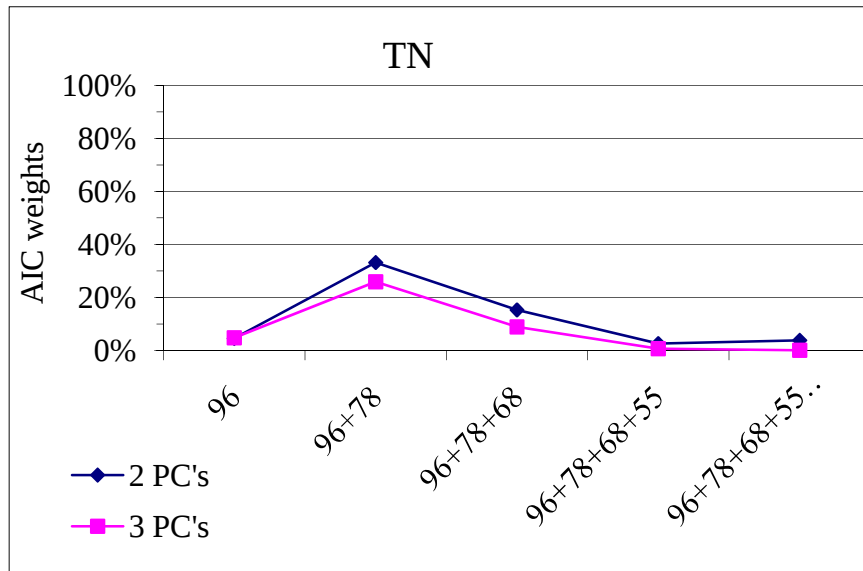


Figure 2.7. Change in LULC over time as represented in multivariate space. Each line represents the LULC trajectory of a lake in the study. Each of the first three PC's are shown.

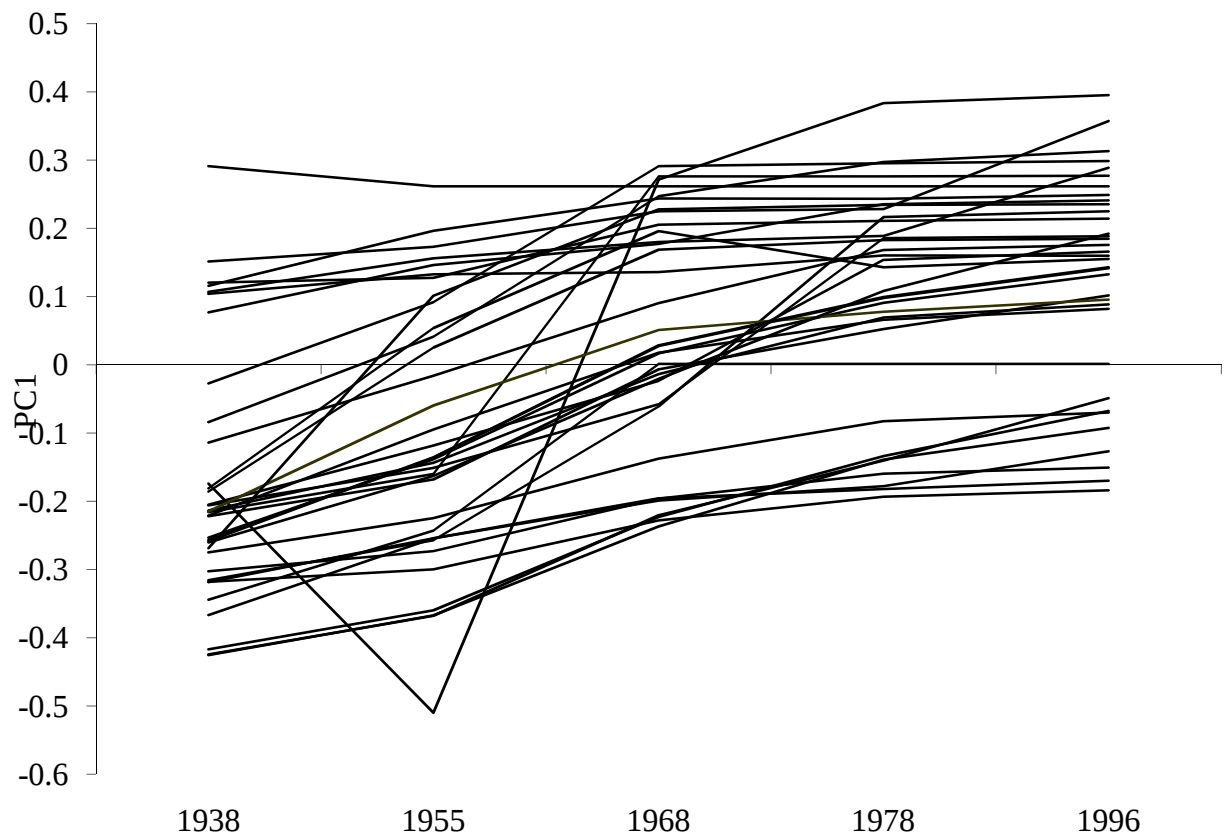


Figure 2.7 (cont').



Figure 2.7 (cont').



Figure 2.8. Regression diagnostics for best models as reported in Table 2.2. Observed values (y-axis) are plotted against values predicted from the regression equation (x-axis).

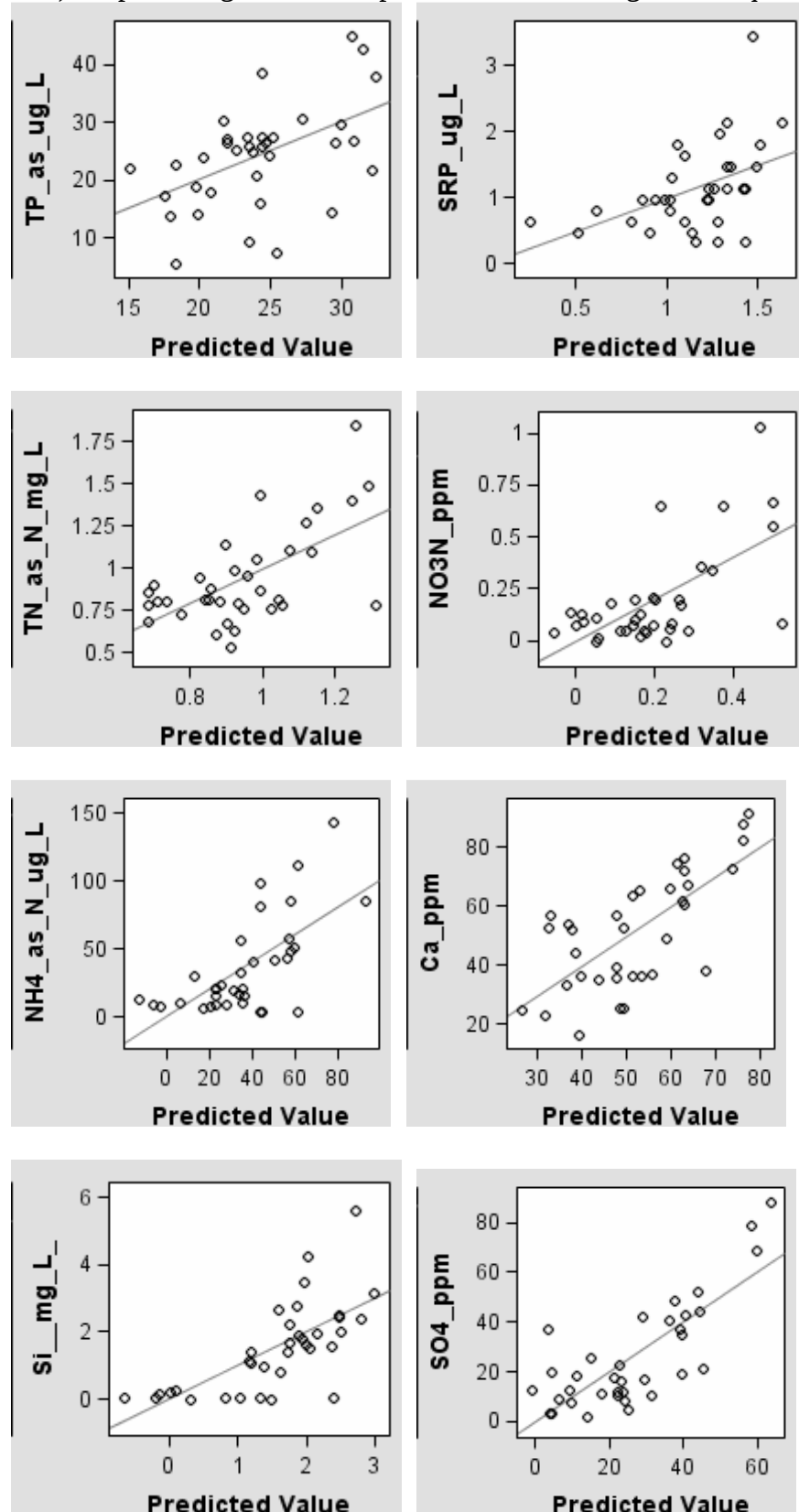
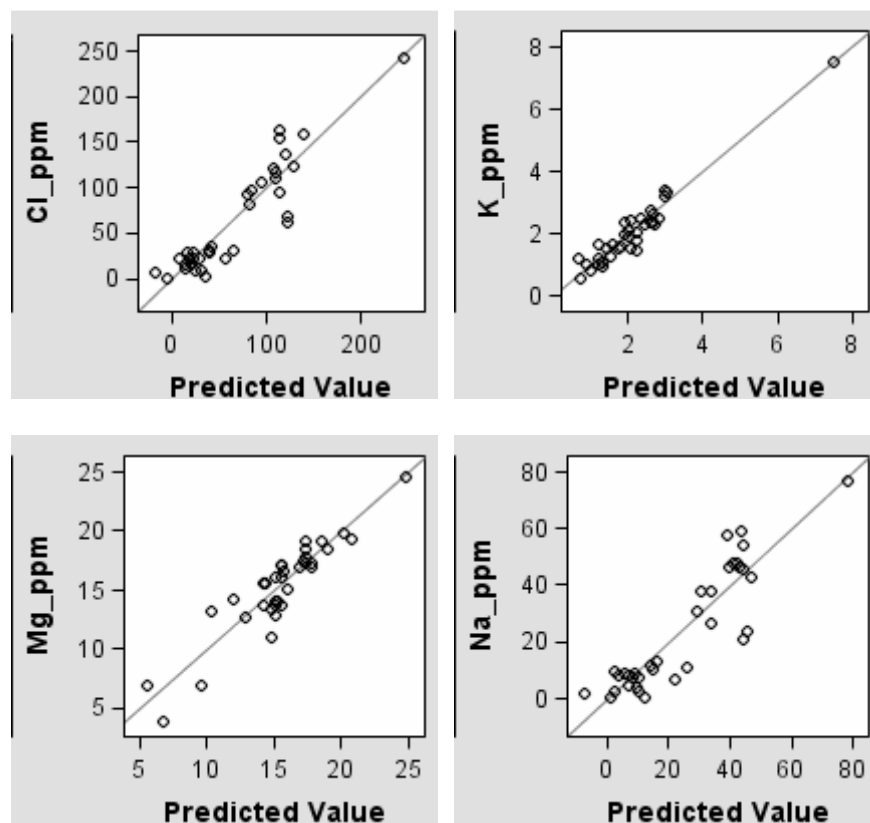


Figure 2.8 (cont').



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CHAPTER 3: THE LAND-USE LEGACY EFFECT - A MECHANISTIC INVESTIGATION
OF HOW GROUNDWATER DELIVERY, WETLAND PROCESSING, AND
RIPARIAN DYNAMICS AFFECT LAKE WATER CHEMISTRY

INTRODUCTION

There have been numerous studies linking land use/land cover (LULC) to ecosystem responses. The typical approach involves correlating current LULC within a specified area to current ecosystem condition(s). The main difference among these studies is the way in which the contributing zone has been delineated, including fixed-distance (Strayer et al. 2003, King et al. 2005) and flow distance buffers around a sampling station (Brazner et al. 2007), fixed-distance buffers around a stream (Hunsaker & Levine 1995, Van Sickle et al. 2004, Floyd et al. 2009) with varying distance upstream of a station (Sponseller et al. 2001, Frimpong et al. 2005), and, finally, different variations on “watersheds” (Soranno et al. 1996, Hollister et al. 2008). Regardless of spatial scale, these approaches assume that materials originating from different cover types are delivered to the ecosystem over the same time period that the LULC is measured. This is likely a reasonable assumption for surface delivery. Burcher (2009) estimated that the maximum travel time for overland flow from precipitation was on the order of days. However, groundwater delivery often takes longer than a decade and can exceed a century (Pint et al. 2003, Pijanowski et al. 2007). Therefore, it is likely that much of the water delivered through groundwater pathways is not representative of the current LULC. In systems where groundwater provides the dominant source of water, this temporal mismatch can obscure relationships between LULC and ecosystem responses.

While there have been several studies that highlight the importance of representing groundwater geochemistry (Wayland et al. 2003) and transport delays in models of aquatic ecosystem response (Baker et al. 2006, Fraterrigo & Downing 2008, Kelly et al. 2008), few have linked the dynamics of changing LULC to a mechanistic understanding of flow paths and travel times (Boutt et al. 2001, Wayland et al. 2002). Pijanowski et al. (2007) coupled a land

transformation model with a groundwater travel time model to produce a temporally adjusted mosaic of LULC that they term the land-use legacy map. They found large discrepancies between current LULC and legacy LULC in their study watershed. For example, there was only a 22% agreement in urban LULC type between current and legacy maps. Additionally, 11% of their study area that was currently in a human dominated LULC type (i.e., urban and agriculture) was assigned to forested cover type in the legacy map. Using a legacy map of LULC, as described above, should improve models of ecosystem response to LULC.

In addition to groundwater flow paths, wetland processing and riparian zone dynamics modify how current LULC impacts aquatic ecosystem condition. Peterjohn and Correll (1984) showed that riparian forests can effectively capture surface and subsurface nutrient fluxes from adjacent agricultural land to stream systems. In recent reviews of riparian buffer characteristics, Zhang et al. (2009) and Yuan et al. (2009) agree that buffer width and composition are important in determining the flux of non-point pollutants. Other studies have shown that stream and lake water chemistry characteristics are related to wetland extent and proximity (Osborne & Wiley 1988, Johnston et al. 1990, Detenbeck et al. 1993). However, the appropriate spatial scale for wetland measurement, whole watershed proportion versus proportion within a specified distance, remains an active area of inquiry (Gergel et al. 1999, Xenopoulos et al. 2003, Moreno-Mateos et al. 2008).

The goal of this study is to combine the knowledge of groundwater delivery, wetland and riparian processing in mechanistic and statistical models to better understand the relationship between LULC and lake water chemistry characteristics. We created a mechanistic groundwater flow model to estimate spatially-explicit groundwater travel times for a watershed to surface water bodies. We used this information to create a legacy LULC map, which accounts for delays

in materials delivered via groundwater pathways from past LULC. Three approaches for incorporating wetland processing were compared: 1) wetland extent, 2) area of wetland connected to rivers, and 3) length of wetland connected to rivers. Riparian processes are incorporated by adding measures of riparian LULC to the mechanistic groundwater legacy model. We use regression models to relate lake water chemistry variables to various LULC representations.

We applied these modeling approaches to twelve water chemistry variables, ranging from nutrients to conservative ions, to better understand the roles that biological reactivity and solubility play in connections between LULC and aquatic ecosystem function. We expect that:

- 1) chemicals of high solubility (e.g. SRP, NO_3^-) will have a stronger relationship with groundwater flow paths than chemicals of low solubility (e.g. TP), which will be more dependent upon surficial transport processes, such as retention in riparian zones, than groundwater flow paths;
- 2) chemicals of low biological reactivity (e.g. conservative ions) will have a stronger link to groundwater flow paths than chemicals of high biological reactivity (e.g. nitrogen and phosphorus), which will be more dependent on wetland processing than groundwater flow paths.

METHODS

Study Area

This study was conducted within the 2,359 km² Huron River Watershed (HRW) in Michigan (Figure 3.1), which ranges from 390m to 173m in elevation. The HRW contains numerous rivers, streams and lakes supporting a diverse assemblage of aquatic species (Hay-

Chmielewski et al. 1995). Due to close proximity to major metropolitan areas, such as Detroit and Ann Arbor, and the development of interstate highways, many people live, work, and enjoy the recreational opportunities of the area. The watershed has undergone extensive LULC change over the past century, shifting from an agrarian to suburban society (Hay-Chmielewski et al. 1995, Rutledge and Lepczyk 2002). However, numerous natural areas have been maintained in publicly owned parks.

Water chemistry data

Water samples were collected from 35 lakes in the HRW during 2008 spring mixing. Lakes were chosen based on their accessibility, including both private and public lakes ranging in size from 0.05 to 2.6 km². All water samples were taken from 1m below the surface at the deepest portion of the lake and analyzed for major ions and nutrients. Cation (calcium, magnesium, potassium, and sodium) and anion (chloride, nitrate, and sulfate) concentrations were determined using membrane-suppression ion chromatography (Wetzel and Likens 2000). Silica concentrations were determined using the molybdate colorimetric method (Wetzel and Likens 2000). Total nitrogen concentrations were determined using the 2nd derivative of the absorbance curve at 224 nm following persulfate digestion. Ammonia concentrations were determined following the indophenol-blue method (Wetzel and Likens 2000). Soluble reactive phosphorus (SRP) and total phosphorus (TP) concentrations were determined spectrophotometrically following persulfate digestion.

Water chemistry variables were organized into *a priori* groups based largely on biological reactivity and solubility (Appendix 3.1). Phosphorus species were the most highly reactive variables in our study; nitrogen species are also highly reactive, but less so than

phosphorus due to the relative abundance of nitrogen versus phosphorus (Wetzel 1983). We grouped Ca, Si, and SO₄ together as “reactive variables” due to their role as micronutrients in the metabolism of macrophytes, diatoms, and bacteria, respectively (Wetzel 1983). Conservative ions (i.e. Cl, K, Na, and Mg) play a much smaller role in biological metabolism and are thus influenced more by external supply than internal conversions (Wetzel 1983).

Land use/cover data

Land use/cover data (30m resolution) from five available time steps (1938, 1955, 1968, 1978, and 1995) were classified into six categories (urban, agriculture, open, forest, water, and wetland) based a modified version of the Anderson (1976) LULC classification scheme (Figure 3.2). All data were compiled into a multi-temporal GIS database for analysis (full details in Rutledge 2001). Briefly, digitized land use/cover data for 1978 from the Michigan Resource Information System (MIRIS) served as a base for digitizing all other time steps. Aerial photos from each of the other time steps were scanned (150 dpi) to create digital images that were then registered and rectified to the 1978 data using the placement of county roads. Land use/cover polygons were then digitized.

Groundwater travel time calculation and modeling

We modeled groundwater travel times following procedures similar to Boutt et al. (2001) and Pijanowski et al. (2007). This approach is based on Darcy’s Law of groundwater flow:

$$Q = -KAi$$

where, Q is discharge in m³/day, K is hydraulic conductivity in m/day, A is the cross sectional area in m², and i is the hydraulic gradient. Groundwater flow velocity (v , m/day) is calculated as:

$$v = \frac{Q}{An}$$

where n is porosity. Travel time is then calculated by dividing the flow length by flow velocity.

We used the Groundwater Modeling System preprocessor (BYU 1994) to facilitate the discretization of geospatial data for input to MODFLOW-2000 (Harbaugh et al. 2000) to solve for the groundwater flow equations. We used a one-layer model, with 180,000 cells with approximately 109 x 109 m dimensions. We used elevations from USGS 1/3rd arc second National Elevation Dataset (NED, resolution approx. 10m) to represent surface topography. We also used the NED surface elevations to model stream coverage using procedures and tools in ArcInfo 8.3 (ESRI, Inc): FILL SINKS, FLOW DIRECTION, and FLOW ACCUMULATION. The location of stream cells were defined according to a threshold of 15,000 cells using the STREAM DEFINITION tool, which produced stream cell locations comparable to known hydrography features. Stream cells were combined with cells along lake edges to create a complete representation of hydrography features. These features were modeled as drains in the groundwater model. Bedrock elevations were provided by MSU Department of Geography (D. Lusch personal communication).

Recharge was estimated using measured flows from the Ypsilanti USGS gauge on the Huron River (#4174800) for 1974-1994. Low flow values for each year in this period of record were averaged and divided by the drainage area, providing the recharge estimate of 0.00138 m/d (49 cm/yr). This is roughly 55% of the mean annual precipitation measured in the near-by city of Ann Arbor.

Static water levels from 15,581 wells recorded in the Michigan Department of Environmental Quality Statewide Groundwater Database, called Wellogis, were used to

interpolate water table elevations across an initial model boundary (HRW plus 1km buffer). We filtered this dataset to only include wells with the following characteristics: 1) physically located within the model boundary, 2) reported surface elevation within 2m of NED surface elevation at that location, and 3) casing deeper than the reported static water level. This groundwater surface was then used to delineate a groundwater sourced area for all river cells upstream of Ypsilanti, as all of the study lakes were located upstream of Ypsilanti. We use the term sourced area in parallel to how watershed is used for surface water drainage. Therefore, the groundwater sourced area represents the area contributing groundwater to a particular point (e.g. study lake). The modeled groundwater sourced area, which we will refer to as the Huron River Groundwater Sourced Area (HRGW), was then used as the model boundary for the MODFLOW-2000 groundwater model. The interpolated static water levels were also used as starting heads in the model.

A digital version of the Farrand and Bell (1982) map detailing the location of surficial geology types was obtained from the Michigan Geographic Data Library (<http://www.mcgi.state.mi.us/mgdl>). The area within the HRGW has some variation in surficial geology types, but is dominated by glacial outwash and end moraine deposits (Figure 3.3).

Hydraulic conductivity (K) values for each surficial geology type were optimized using PEST 10.0 (Doherty 2004) (Figure 3.3). Simulated groundwater elevations were in reasonable agreement with observations from the Wellogic database (Figure 3.4). We found that wells with high residual values were surrounded by other wells with groundwater elevations similar to the modeled values, had low influence on the R^2 when removed, and therefore were kept in the well dataset despite being clear outliers. Groundwater flow velocities and travel times were calculated following Darcy's Law, as described above, from the simulated groundwater

elevations and optimized hydraulic conductivity values, using FLOWDIRECTION and FLOWLENGTH tools in ArcGIS (Pijanowski et al. 2007).

Creating the legacy map

The legacy map was created by combining simulated groundwater travel times with interpreted historical LULC categories for each model cell. Groundwater travel times were calculated using Darcy's Law, as described above. The calculated travel times (Figure 3.5 – step 1) were grouped around available LULC data (Figure 3.5 – step 2), with 1996 being the most recent land cover map available in this area. The mid-point between the LULC time steps was used to define category thresholds. For example, there is an eighteen year gap between the 1996 and 1978 LULC maps, thus we assigned LULC from the 1996 time step to all model cells with a groundwater travel time of zero (1996) to nine years earlier (1987). These reclassified travel times (Figure 3.5 – step 2) were then combined with the LULC maps developed from air photo analysis for particular years to produce the legacy LULC map (Figure 3.5 – step 3). Therefore, the legacy map is a spatially explicit representation of the LULC, corresponding to groundwater delivery to each study lake. Finally, we compared the legacy LULC to the 1996 LULC, highlighting areas where the two differ (Figure 3.5 – step 4).

Statistical analyses

The relationships between LULC and lake water chemistry variables were analyzed using multiple linear regression, implemented in PROC REG (SAS). Each water chemistry variable was regressed against the proportional cover of the six LULC classes within the study lake groundwater sourceheds, following the equation:

$$y_i = \beta_0 + \beta_{urb}x_{urb} + \beta_{ag}x_{ag} + \beta_{open}x_{open} + \beta_{for}x_{for} + \beta_{water}x_{water} + \beta_{wet}x_{wet} + \varepsilon_i$$

where, y_i is the value of water chemistry i ; β_0 is the constant (y-axis intercept); β_p is the regression coefficient for x_p ; x_p is the proportional cover of LULC p ; and ε_i is the error associated with the model of y_i . The proportion of each LULC type within the sourcesheds was determined for the 1996 time step (current LULC) and the legacy map (GW legacy).

We modified the general regression equation (above) to incorporate wetland and riparian processes. Wetland processes were represented by replacing the single regression parameter describing wetlands (x_{wet}) with two terms for wetlands: 1) proportional area of wetlands that border drain cells (x_{conwet}), and 2) proportional area of wetlands that are unconnected to drain cells ($x_{unconwet}$), following the form:

$$y_i = \beta_0 + \beta_{urb}x_{urb} + \beta_{ag}x_{ag} + \beta_{open}x_{open} + \beta_{for}x_{for} + \beta_{water}x_{water} + \beta_{conwet}x_{conwet} + \beta_{unconwet}x_{unconwet} + \varepsilon_i$$

Connected and unconnected wetlands were summarized within two spatial extents: 1) proportion within the groundwater sourceshed that represents processing by wetland area, and 2) proportion within a 30m river buffer that represents processing along the wetland length.

Riparian processes were incorporated by adding parameters to the general regression equation for the proportional cover of each of the six LULC classes as represented in 1996 within a 50m river buffer. Therefore, the regression equations modeling overland flow has six LULC types measured over two extents, equaling twelve regression parameters, as follows:

$$y_i = \beta_0 + LEGACY[\beta_{urb}x_{urb} + \dots + \beta_{wet}x_{wet}] + RIPARIAN[\beta_{urb}x_{urb} + \dots + \beta_{wet}x_{wet}] + \varepsilon_i$$

We used Akaike Information Criteria (AIC), AIC weights (ω_i) and the coefficient of determination (R^2) (following Burnham and Anderson 2002) to compare the parsimony and explanatory power of each model. Specifically, to understand if groundwater pathways are the dominant mechanism for legacy effects, we compared results from: 1) current LULC models, 2) GW legacy models, and 3) a correlative estimation of legacy land cover (as described fully in Chapter 2). Briefly, the correlative legacy models use regression to relate LULC, as represented through principal components analysis, to water chemistry variables. These models were built sequentially, starting with the most recent LULC then adding the next most recent LULC and so on until each of the five time steps of LULC were included in the model. For the current study, we limited our comparison to only the correlative models with highest support as demonstrated by AIC weights.

The correlative legacy models represented legacy effects through a correlational “black box”, in that no specific mechanisms were specified. In comparison, GW legacy models specified groundwater pathways as the dominant mechanism for legacy effects. The current LULC models represented the traditional approach linking LULC to ecosystem responses and hypothesizes that historical LULC has no consequence for our study lakes. Comparisons were also made with models measuring wetland and riparian processes. Hypotheses inherent to the models were: wetland presence throughout the entire lake watershed was important to lake water chemistry (wetland extent tested); the entire area of riparian wetlands was important to lake water chemistry (wetland area tested); only the area of riparian wetland in immediate contact with the river was important to lake water chemistry (wetland length tested); the LULC within only the riparian zone was important to lake water chemistry (riparian LULC only tested); there is an additive effect of riparian LULC to the watershed LULC (legacy + riparian tested) .

RESULTS

Groundwater travel time

Modeled groundwater travel times in the HRGW ranged from <1 yr to >400 years, encompassing each of the six time classes of available LULC data (Figure 3.6). Just over half of the HRGW has a groundwater travel time between 0-9 years, following the surface drainage network in the watershed. The longest travel times occurred in the central and northeastern portions of the HRGW. In general, the groundwater travel times in the study lake groundwater sourcesheds match those of the larger HRGW, but have more area within the 0-9 yr travel time category than the overall watershed (Figure 3.6).

Characterizing LULC

Urban and agriculture land cover dominated the HRGW in 1996, with open and forested land cover types comprising most of the remaining area (Figure 3.7A). The legacy LULC map shows agriculture as the dominant land cover, followed by urban, forest and open cover types (Figure 3.7B). The largest differences between the two LULC maps were in human dominated cover types, as agriculture increased by approximately 5% and urban decreased by approximately 4% of the model area, when legacy LULC was used.

The 1996 LULC within the studied groundwater sourcesheds also show an urban dominance (Figure 3.7A), however forest was the second most common LULC type in the groundwater sourcesheds, and there was 12% less agriculture cover than in the HRGW as a whole. Legacy LULC within the studied groundwater sourcesheds had almost equal

representation of forest, urban, and open LULC types, and agriculture was still underrepresented relative to the HRGW (Figure 3.7).

Overall differences in LULC composition between 1996 and the legacy map within the HRGW and the groundwater sourcesheds were relatively small (Figure 3.8), with only 10.5% of the area of the HRGW where legacy LULC differed from current LULC. This is mainly due to the high hydraulic conductivities of the sediments, coupled to the relatively small size of the watershed. Differences in the studied sourcesheds were even less, at 8.5%.

Relationships with lake water chemistry

Current LULC and GW legacy models had similar explanatory power (Figure 3.9). Across all water chemistry variables, the R^2 values from these models differed by a maximum of 4% (TN, NH_4 , and SO_4) but were within 1.4% of each other on average. In general, models showed a pattern of high correlation with lower-reactivity soluble ions, such as Cl, K, Mg, and Na, and decreasing correlation for more biologically reactive chemicals such as nitrogen and phosphorus

Correlative legacy models received most support from AIC weights for 9 out of 12 of the water chemistry variables (Figure 3.9). Correlative legacy models for TP, NO_3 , and Si explained 8-11% more variation than current LULC or GW legacy models. However, there were larger differences between the models for all other water chemistry variables. The correlative legacy model explained on average 21% more variation than the GW legacy or current LULC models for all other water chemistry variables, ranging between 19% and 28% more for TN and K, respectively. Models using current LULC or legacy LULC received more AIC support for NH_4 ,

Ca, and SO₄, and explained 11%, 21%, and 7% more variation, respectively, than the correlative legacy models. Overall, these results provide evidence that adding a mechanistic representation of land cover through delayed groundwater delivery was not sufficient to capture legacy effects for most water chemistry variables in our study lakes.

Adding different measures of wetlands (all wetland, wetland area, and wetland length) to the GW legacy model changed the explanatory power of most models very little, changing R^2 less than 3% in most cases (Figure 3.10). However, the explanatory power increased by 14% and 11% for TP and SRP, respectively, when wetland connections were specified in the regression. Interestingly, the method for representing wetland processing differed between TP and SRP; adding the length of connected wetland performed better for the TP model, whereas the area of connected wetland performed better for SRP. Overall, our comparison of different ways to represent wetlands shows that there was little difference for most water chemistry variables. However, forms of phosphorus did show a stronger relationship to LULC when wetland connections were included in the regression.

Because wetland length provided similar or slightly better model fits for most water chemistry variables, we only show results for GW legacy models using this term in our analyses of riparian zones. However, wetland area was used in the GW legacy models for SRP.

In comparison to adding wetland processing to the GW legacy model, adding factors representing riparian processes increased R^2 values for every water chemistry variable (Figure 3.11). Models combining GW legacy with riparian processes improved R^2 values by 15% on average and up to 26% (Si) and 43% (SRP) from models of GW legacy alone. Many of these models received more AIC support than correlative legacy models (6 out of 12), with the largest

increase in R^2 for SRP (46% over correlative legacy). However, some nutrients (TP, TN, and NO_3) and conservative ions (K and Mg) were still better described by correlative legacy models than GW legacy combined with riparian processes.

Models including riparian LULC alone have little support from AIC weights and had R^2 values similar to or lower than GW legacy for most water chemistry variables. Only SRP and Si show more explanatory power with riparian only models versus GW legacy models. Differences between GW legacy and riparian only models were greater for conservative ions than nutrients.

DISCUSSION

Legacy effects have been shown to be important in terrestrial (Foster et al. 1998, Foster et al. 2003, Chauvat et al. 2007), stream (Harding et al. 1998, McTammany et al. 2007), and lake (Martin et al. Chapter 2) ecosystems. These studies have all used a correlational approach, relying solely on statistical relations to detect legacy effects. This study moves beyond a simple correlational approach by combining temporal and spatial changes in LULC with a mechanistic model of groundwater flow paths to create a process-informed representation of legacy LULC. We show how this legacy map can be used to connect changes in LULC to important ecosystem characteristics, such as water chemistry in lakes. We also incorporate other mechanisms known to be important, such as wetland and riparian processes, for a more complete analysis of the relationships between LULCs and lake ecosystem dynamics. This mechanistic approach is generalizable across ecosystem types and will likely increase the accuracy and predictability of other models linking LULC with ecosystem responses.

This study shows how delays in groundwater travel time can be successfully coupled with changes in LULC as a mechanism for land use legacies. Unfortunately, our study area was

not the ideal location for groundwater legacies to play a major role. Rapid changes in LULC occurred in the HRW between 1938 and 1968 (Martin et al. Ch2), a time period represented by only 17% of the groundwater sourced. LULC largely stabilized during the time represented by the majority of the groundwater, showing only small declines in agriculture (2%) and increases in urban (5%) area. Therefore, it is not surprising that our results show little difference in explanatory power between legacy LULC and current LULC. Legacy effects through groundwater delivery would be more apparent in 1) areas where groundwater travel times are long enough to “reach back further in time”, or 2) areas where LULC is currently undergoing rapid conversions within areas of shorter delivery times.

Wetland processing

Wetlands are a particularly important land cover type in biogeochemical cycles, greatly altering the chemistry of water from input to output (Howard-Williams 1985). However, there is no consensus about the most appropriate method for representing the impact of wetland processing within the landscape. Most studies have measured wetland extent as the proportional cover within an area, usually a watershed. Whigham et al. (1988) offer an early meta-analysis showing the variable nature of nitrogen and phosphorus removal along a gradient of increasing wetland extent. Since then, other methods for measuring wetlands have been used, such as proportional cover within a specified distance of the target ecosystem (Johnston et al. 1990, Weller et al. 1996, King et al. 2005). We add to this research by offering a comparison of three measures of wetland influence: watershed extent, area of river connected wetland, and length of river connected wetland.

Our results agree with previous studies that show a stronger relationship between phosphorus and riparian wetlands in comparison to wetlands located further from receiving bodies (Johnston et al. 1990, Weller et al. 1996). Furthermore, our analyses provide evidence that wetland area and wetland length are important in different ways for nutrient cycling. Models including the area of connected wetland had higher explanatory power for dissolved phosphorus (SRP) whereas models including the length of connected wetland had higher explanatory power for total phosphorus (TP, Figure 3.10). Given that dissolved forms move more freely through groundwater pathways, it makes sense that the entire area of a connected wetland will influence SRP. On the other hand, overland flow has been found to be the primary transport mechanism for particulate forms, such as TP (Banner et al. 2009, Hoffman et al. 2009b). Therefore, the length of riparian wetlands may act as a barrier reducing overland transport. This agrees with previous studies which show that overland flow is reduced considerably by wetlands (Weller et al. 1996) and that the spatial arrangement of riparian zones, particularly gaps between patches that function to reduce flow, is important for material flux (Weller et al. 1998).

In contrast to phosphorus, our analyses of nitrogen show that all three measures of wetland presence had similar model explanatory power. Groundwater pathways allow for the transport of dissolved substances over long distances. Because nitrogen is transported in dissolved forms primarily through subsurface pathways (Peterjohn & Correll 1984, Walsh and Kunapo 2009), wetland proximity may be less important for nitrogen concentrations in lakes. Previous studies report that nitrogen removal in wetlands varies with hydrologic flushing, showing low removal in periods of high flow (Johnston et al. 1990, Jordan et al. 2003). Because our samples were taken in the spring, it is possible that frequent rain events flushed nitrogen through the system (Inamdar et al. 2009).

In addition to nutrients, which are commonly included in analyses of wetland processing, we compare the ability of wetland measures to explain patterns in a variety of other water chemistry variables. Our results show no appreciable difference in predictive capacity for models of reactive and conservative ions when wetlands are measured by extent, connected area or connected length. These results are in agreement with those from Johnston et al. (1990), who found that specific conductance, a surrogate for dissolved ions, was related to measures of both wetland extent and proximity.

Riparian zones

Riparian zone dynamics are another mechanism affecting the relationship between LULC and ecosystem responses. Riparian LULC has been shown to be important for both surface and subsurface transport of materials to streams and lakes (Peterjohn and Correll 1984, Gregory et al. 1991, Groffman et al. 2002, Groffman et al. 2004). We show that some lake water chemistry variables were predicted as well from either catchment scale LULC or riparian LULC, and in some cases, riparian LULC had higher explanatory power than catchment LULC. Specifically, the riparian only model of SRP showed greater explanatory power over the GW legacy model. Because SRP shows a stronger relationship with wetland area than wetland length, we believe that this is more an indication of wetland effects on SRP than riparian effects in general. On the other hand, the riparian only model of Si shows a riparian signal not present in the GW legacy models investigating wetlands. Recent work shows that biological processing of Si by plants is an important source of Si to freshwater systems (Derry et al. 2005, Struyf et al. 2009). Therefore, it is possible that the relationship between riparian LULC and Si we observe is due to biogeochemical cycling by riparian vegetation (Struyf et al. 2009).

Riparian zones are recognized primarily for reducing nonpoint source pollution (Gregory et al. 1991, Groffman et al. 2002, Craig et al. 2008). Results from our comparison of individual mechanisms (GW legacy, wetland processing, and riparian LULC) with models combining these mechanisms provides further evidence that riparian zones are important to relate LULC to aquatic ecosystem characteristics. We show that when mechanisms are combined to offer a more holistic view, the explanatory power of the models increased.

Our study also provides a comparison across water chemistry variables not often included in studies relating LULC to aquatic ecosystem dynamics. In fact, we only found two other studies reporting results linking conservative ions to landscape features (Ryszkowski et al. 1999, Wayland et al. 2002). In a study of biogeochemical barriers within agriculture fields, termed shelterbelts, Ryszkowski et al. (1999) show the utility of using Ca and Mg as conservative tracers for comparison with concentrations of nutrients under trees that have been planted as windbreaks. Our results relating conservative ions to catchment and riparian LULC show that diffuse transport of these chemicals through groundwater pathways overwhelms a weaker relationship found with riparian zones. Future studies of landscape connections to aquatic ecosystems can benefit from the use of naturally occurring conservative ions as tracers.

To date, there have been numerous methods proposed to incorporate riparian zones, that mainly focus on defining the most appropriate spatial extent of measurement (Baker et al. 2006, van Sickle and Johnson 2008). In contrast, our emphasis was to model the impact of the riparian zone (however it is defined) jointly with groundwater and wetland influences. Our results support the early sentiment of Gregory et al. (1991) who say:

“The importance of riparian zones far exceeds their minor proportion of the land base because of their prominent location within the landscape and the intricate linkages between terrestrial and aquatic ecosystems.”

We built our models hierarchically by adding riparian processes to the model of GW legacies in an attempt to mathematically express the important role of riparian zones.

Conclusions

This study investigated the roles of groundwater pathways, wetland processing and riparian zone dynamics for relationships with lake water chemistry. We offer insights about how groundwater interacts with land transformation to create legacy effects. We combine groundwater flow dynamics with other mechanisms known to influence relationships between LULC and lake water chemistry, namely wetland and riparian zone processing, to offer a more complete model of land-water interfaces. Our results show that incorporating all of these mechanisms is important for modeling lake water chemistry and that looking at them individually can lead to misinterpretations (e.g., SRP with riparian versus wetland) and lower predictive power overall. Through the use of naturally occurring conservative tracers, we provide a basis for comparison against nutrient relationships to the landscape. By categorizing the chemistry variables by their key characteristics of solubility and reactivity, we are better equipped to explore other mechanisms that are important for the physical transport and biogeochemical transformations of these chemicals.

Table 3.1. Size and water chemistry characteristics of study lakes, including minimum, maximum, mean, and coefficient of variation. Phosphorus species include total phosphorus (TP), and soluble reactive phosphorus (SRP). Nitrogen species include total nitrogen (TN), nitrate (NO_3), and ammonia (NH_4). Reactive ions include calcium (Ca), silica (Si), and sulfate (SO_4). Conservative ions include chloride (Cl), potassium (K), magnesium (Mg), and sodium (Na).

Lake characteristic	Minimum	Maximum	Mean	CV
Lake area (km^2)	0.06	2.60	0.65	0.93
Phosphorus				
TP ($\mu\text{g/L}$)	5.4	45.0	24.1	0.37
SRP ($\mu\text{g/L}$)	0.33	3.45	1.15	0.56
Nitrogen				
TN (mg/L)	0.53	1.85	0.94	0.30
NO_3 (mg/L)	0.00	1.03	0.20	1.20
NH_4 ($\mu\text{g/L}$)	3	143	36	0.96
Reactive Ions				
Ca (mg/L)	16	92	52	0.38
Si (mg/L)	0.00	5.61	1.53	0.88
SO_4 (mg/L)	1.9	88.4	26.1	0.83
Conservative Ions				
Cl (mg/L)	2	242	66	0.90
K (mg/L)	0.58	7.53	2.09	0.57
Mg (mg/L)	3.9	24.7	15.4	0.26
Na (mg/L)	0.9	77.3	24.0	0.88

Figure 3.1. Map showing the Huron River Watershed within the state of Michigan, including detailed hydrography features along with outlines for the cities of Ann Arbor and Ypsilanti.

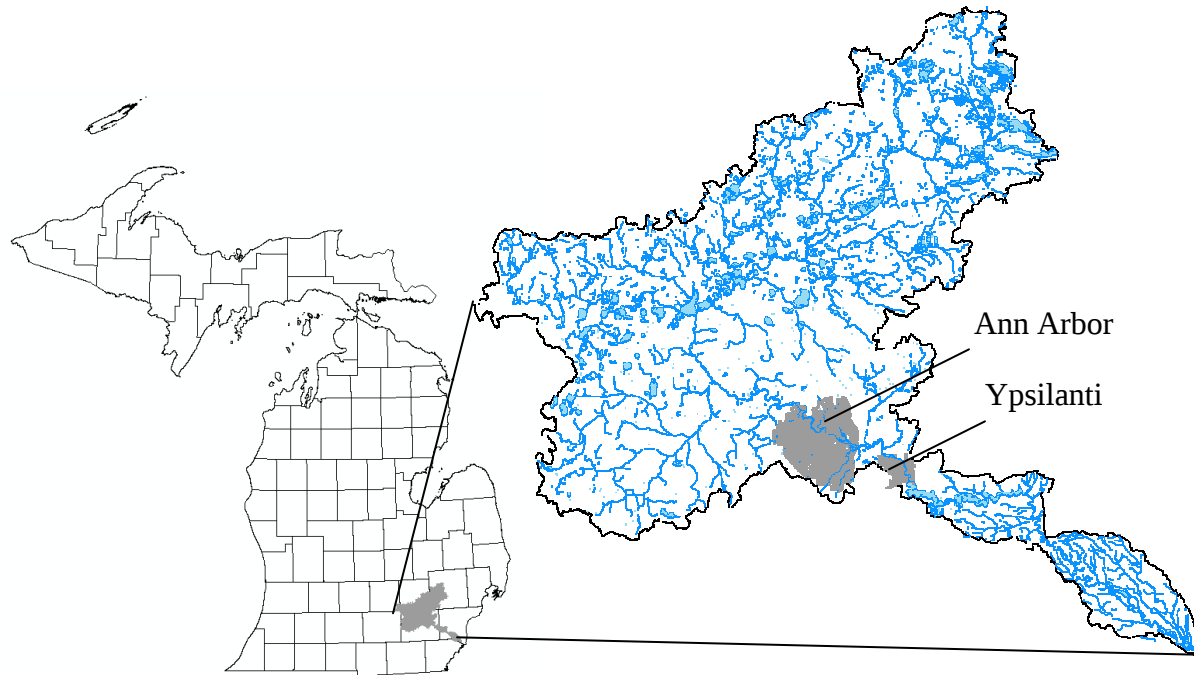


Figure 3.2. Map showing land use/cover (LULC) from 1938, 1955, 1968, 1978, and 1996 within the Huron River Watershed.

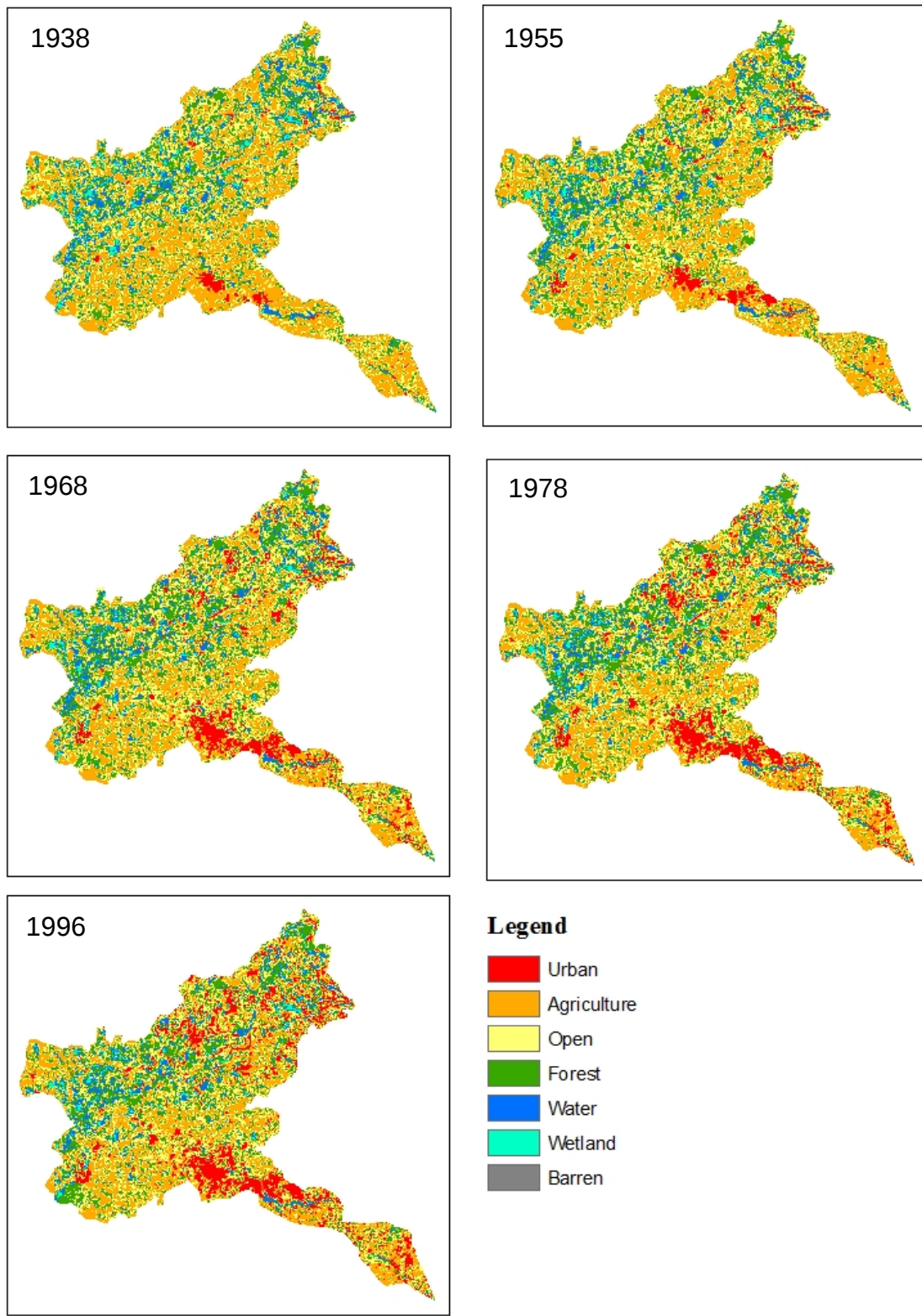
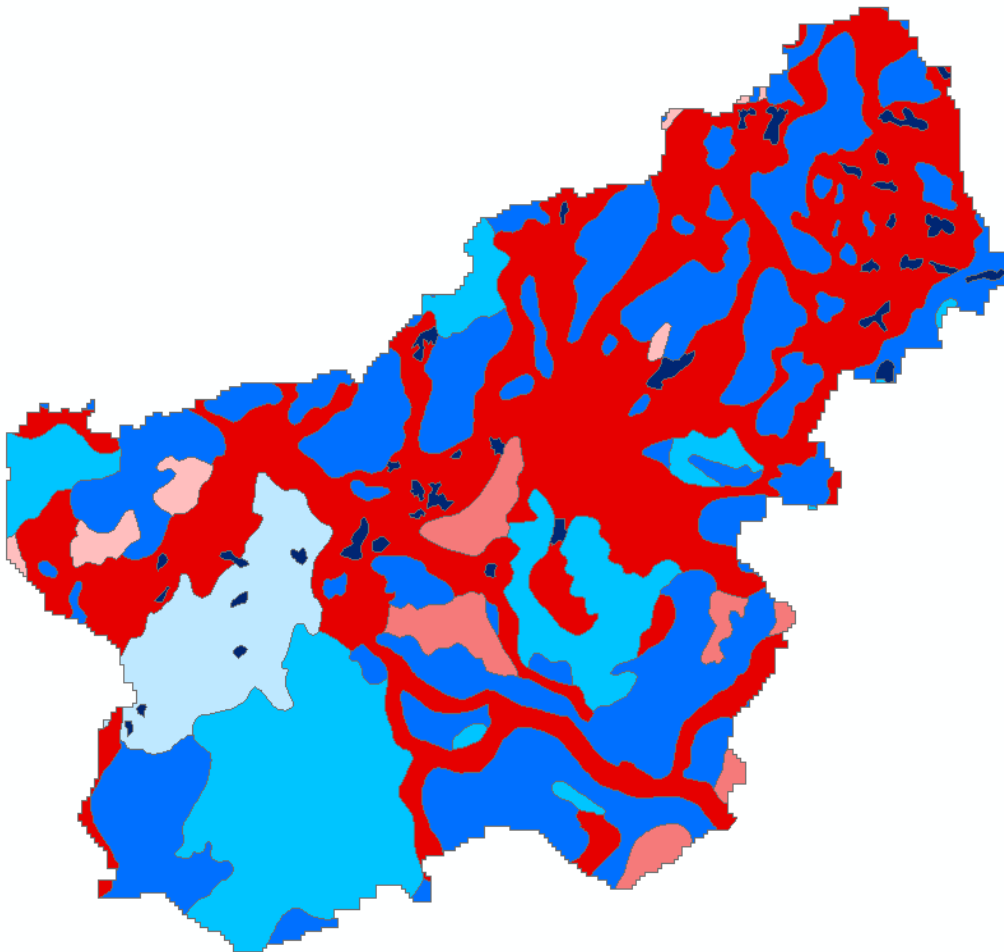


Figure 3.3. Surficial geology zones and optimized hydraulic conductivity (K, m/d) values used in the final model. Glacial Outwash = glacial outwash sand and gravel and postglacial alluvium. Ice Contact = ice contact outwash sand and gravel. Percent of each type within the Huron River groundwater sourceshed (HRGW) upstream of Ypsilanti, and the mean percent for the study lake groundwater sourcesheds are shown. The HRGW is dominated by glacial outwash. The study lakes had similar geology as the HRGW, in general.



Surficial geology type	K (m/d)	% within HRGW	Mean % within lake groundwater sourcesheds
Glacial Outwash	7.3	39.9	46.9
Glacial Till - Fine	8.2	3.2	0.9
Glacial Till - Coarse	9.4	1.2	1.0
Ice Contact	9.4	5.8	24.9
End Moraine	14.6	31.4	15.6
Glacial Till - Medium	14.6	16.8	7.7
Water	500	1.6	2.9

Figure 3.4. Observed versus predicted water levels (m) recorded for 15,581 wells used to estimate values for hydraulic conductivity (K). The line of best fit and coefficient of determination are shown.

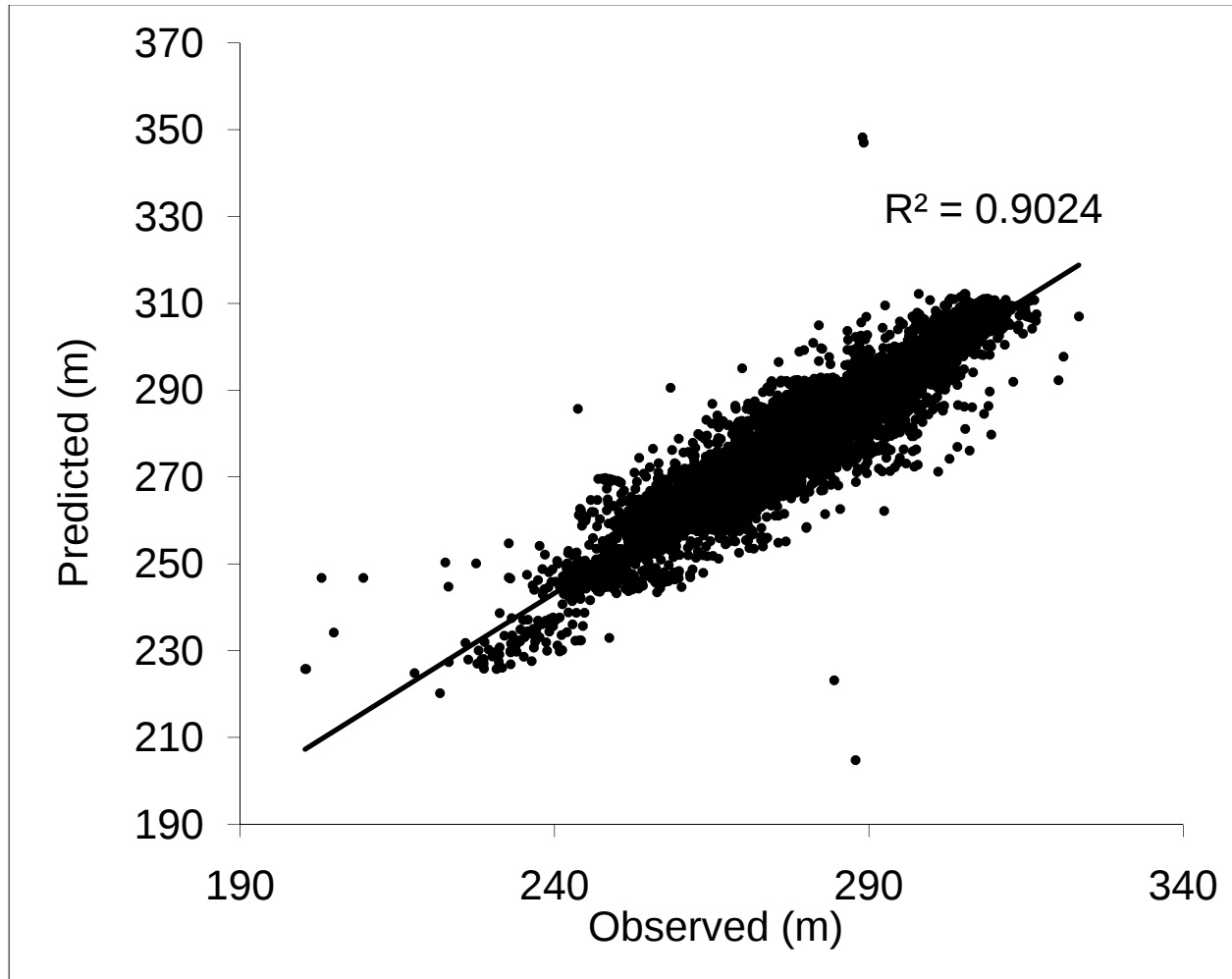


Figure 3.5. Steps to create a land use legacy map. Step 1: The simulated groundwater travel times in years were calculated for each model location down gradient to a discharge point (e.g. river) using Darcy's Law, as detailed in Methods. Step 2: Groundwater travel time year was reclassified to bracket times with available LULC data (in this case, 1996, 1978, 1968, 1955, 1938, or Pre-1900). Step 3: LULC type for each cell was assigned using time categories from step 2. Step 4: LULC from 1996, showing areas that differ with the legacy LULC with black cross-hatching.

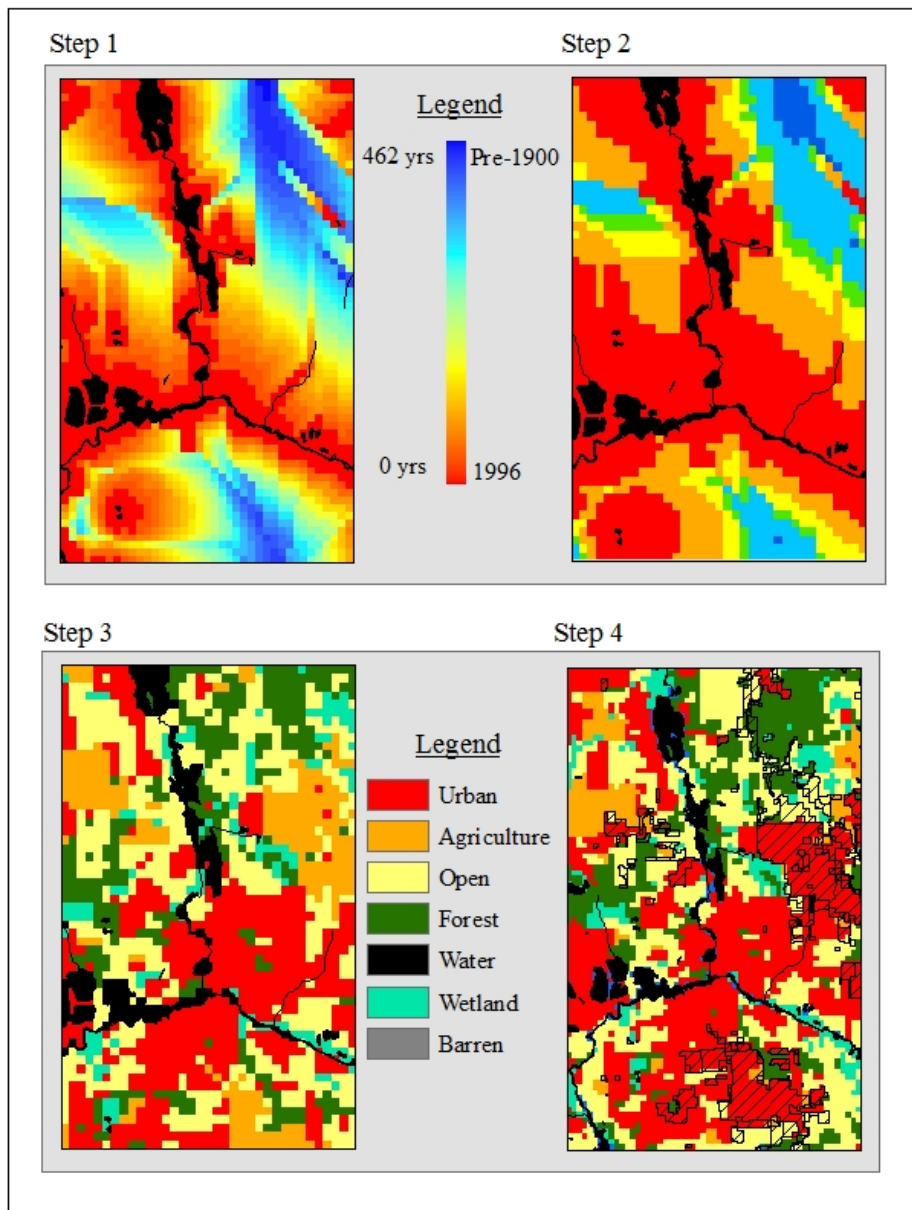
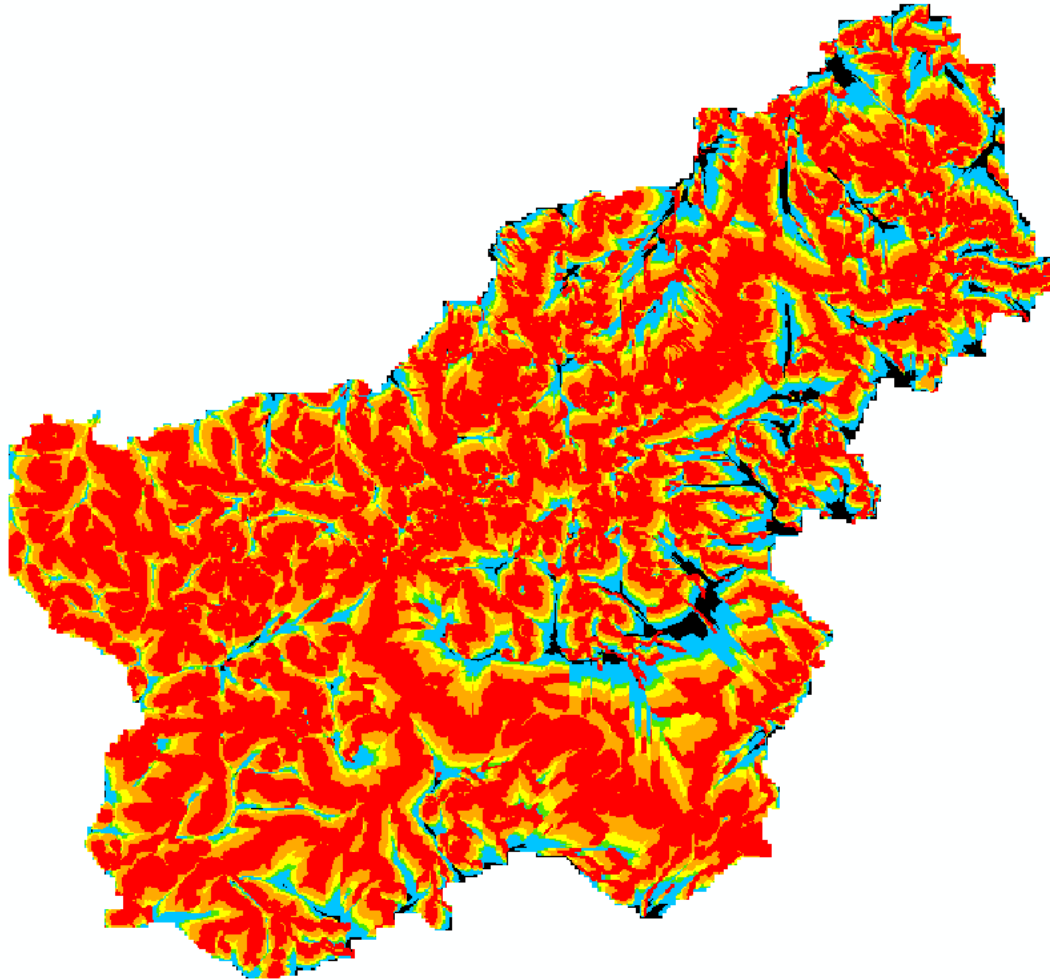


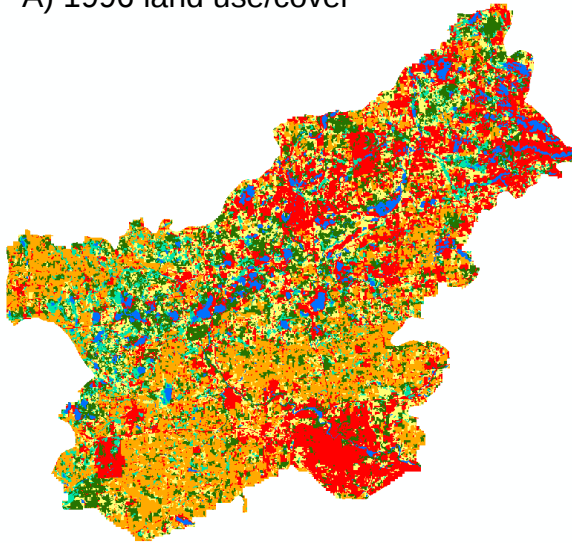
Figure 3.6. Groundwater travel times reclassified to represent the 5 time steps of land cover data. Time classes span from midpoint to midpoint around a specified year. Percent of each groundwater travel time category within the Huron River groundwater sourcedshed (HRGW), and the mean percent for the study lake groundwater sourcedsheds are shown. The HRGW is dominated by groundwater needing less than 10 years to travel from it's source to a surface water delivery pathway. The study lakes had similar groundwater travel times as the HRGW, in general.



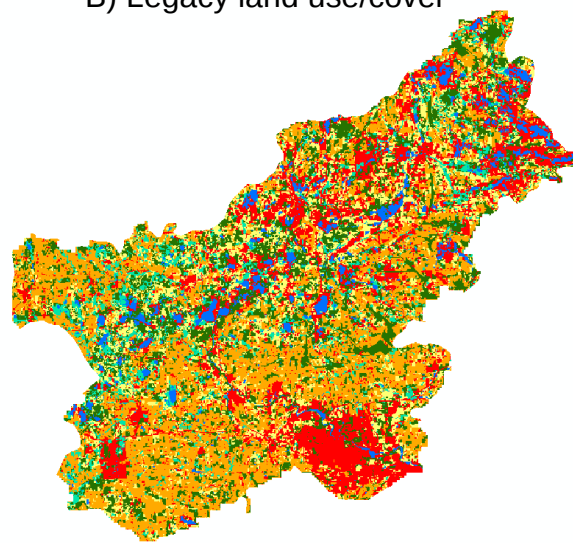
	Groundwater travel time	Assigned to time step	% within HRGW	Mean % within lake groundwater sourcedsheds
■	0-9 years	1996	53.1	62.1
■	9-23 years	1978	22.5	19.1
■	23-34 years	1968	8.8	6.9
■	34-41 years	1955	3.6	2.9
■	41-96 years	1938	9.6	7.1
■	>96 years	Pre-1900	2.4	1.8

Figure 3.7. Land use/cover within the model area showing A) 1996 and B) legacy land use/cover. Percent of each LULC type within the Huron River groundwater sourcedshed (HRGW), and the mean percent for the study lake groundwater sourcedsheds are shown. Maximums are shown in bold. The HRGW is dominated by urban LULC type in 1996, but agriculture dominates in the legacy map. The study lakes had similar LULC representation as the HRGW, in general.

A) 1996 land use/cover



B) Legacy land use/cover



1996			Legacy	
	% within HRGW	Mean % within lake groundwater sourcedsheds	% within HRGW	Mean % within lake groundwater sourcedsheds
Urban	27.0	22.2	22.8	18.9
Agriculture	25.4	13.7	29.7	16.3
Open	17.2	18.6	16.3	18.5
Forest	17.9	20.9	19.1	22.2
Water	5.1	14.4	5.1	13.9
Wetland	7.4	10.3	7.0	10.1

Figure 3.8. Areas within the Huron River groundwater sourcedshed (HRGW) with differences between 1996 LULC and legacy LULC. The model boundary is indicated with the bold black line. Study lake groundwater sourcedsheds are indicated with dark grey lines and light grey shading. Red areas indicate where legacy land cover differs from 1996 land cover (10.5% of the area within the HRGW, 8.4% of the area within the study lake groundwater sourcedsheds).

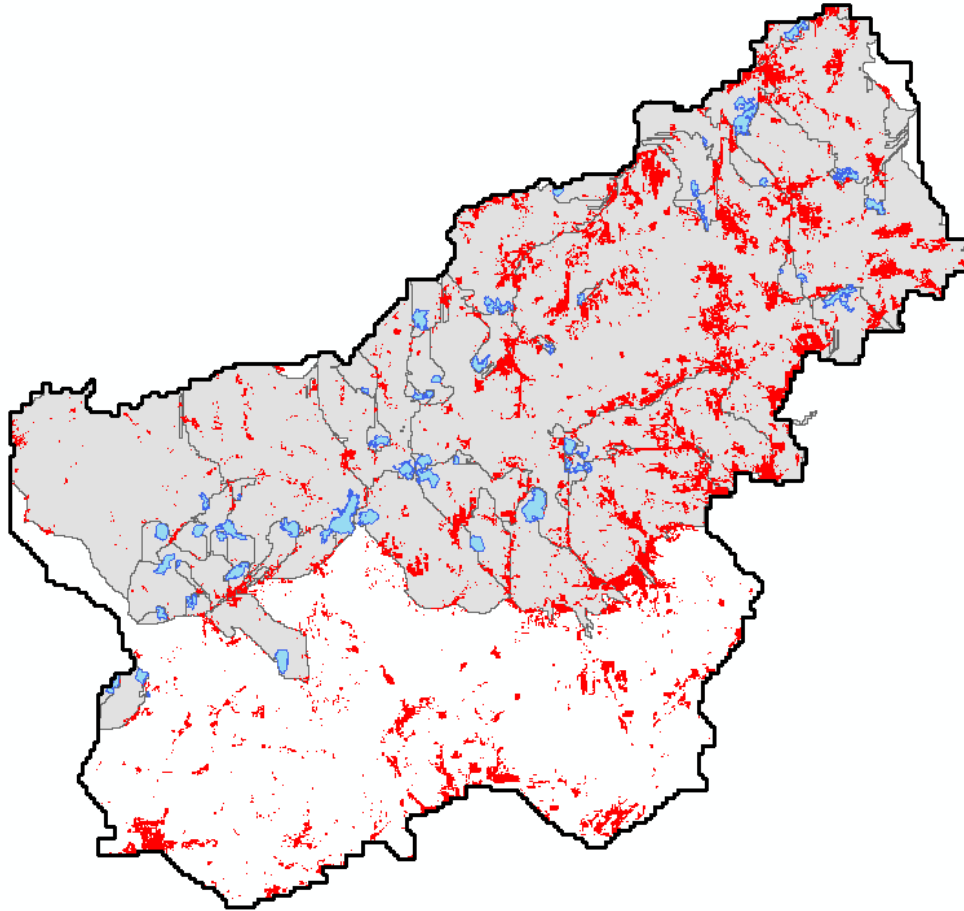


Figure 3.9. Coefficients of determination (R^2) from regression models of total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), nitrate (NO_3), ammonia (NH_4), silica (Si), calcium (Ca), sulfate (SO_4), chloride (Cl), potassium (K), magnesium (Mg), and sodium (Na) using correlative legacy models from Chapter 2, LULC characterized by the current time step (current LULC), and LULC characterized by the legacy map. Asterisks indicate model chosen by AIC weights.

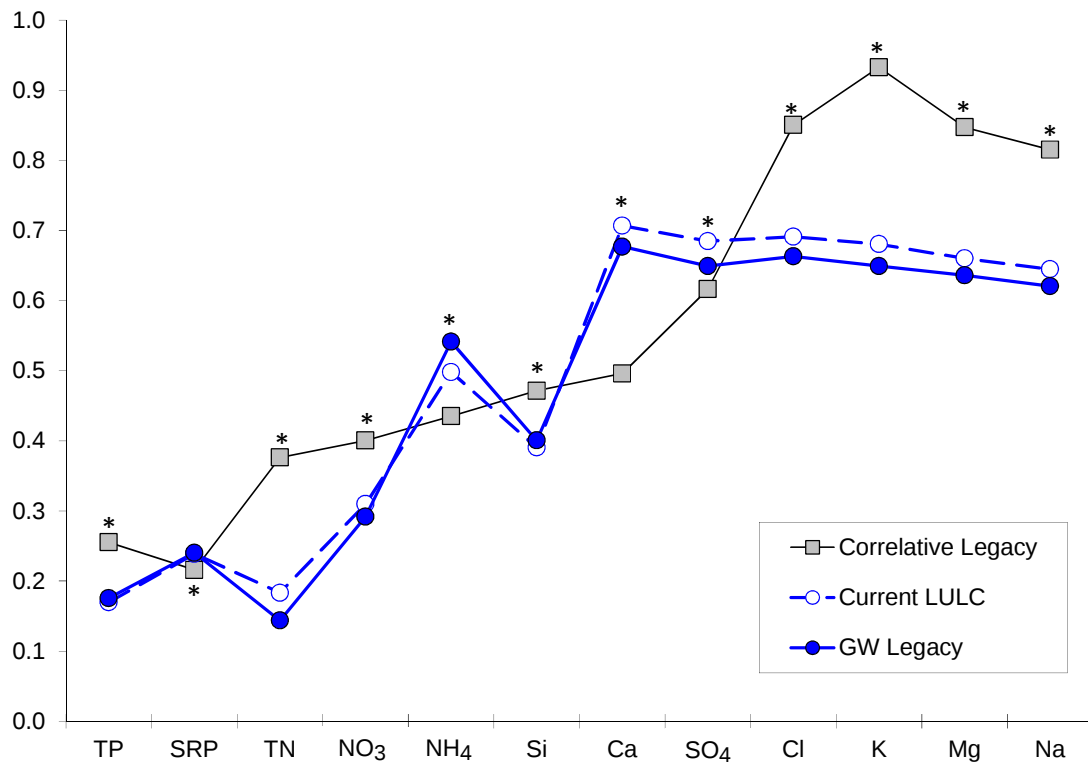


Figure 3.10. Coefficients of determination (R^2) from regression models of total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), nitrate (NO_3), ammonia (NH_4), silica (Si), calcium (Ca), sulfate (SO_4), chloride (Cl), potassium (K), magnesium (Mg), and sodium (Na) using LULC characterized by the GW legacy models measuring wetlands in three ways: all wetlands in the watershed (GW legacy), area of wetland connected to rivers, and length of wetland connected to rivers. Wetland area includes the entire area of the wetland polygons which connect to rivers. Wetland length differs from wetland area by only accounting for the area of the connected wetland polygons within a 50m buffer of rivers.

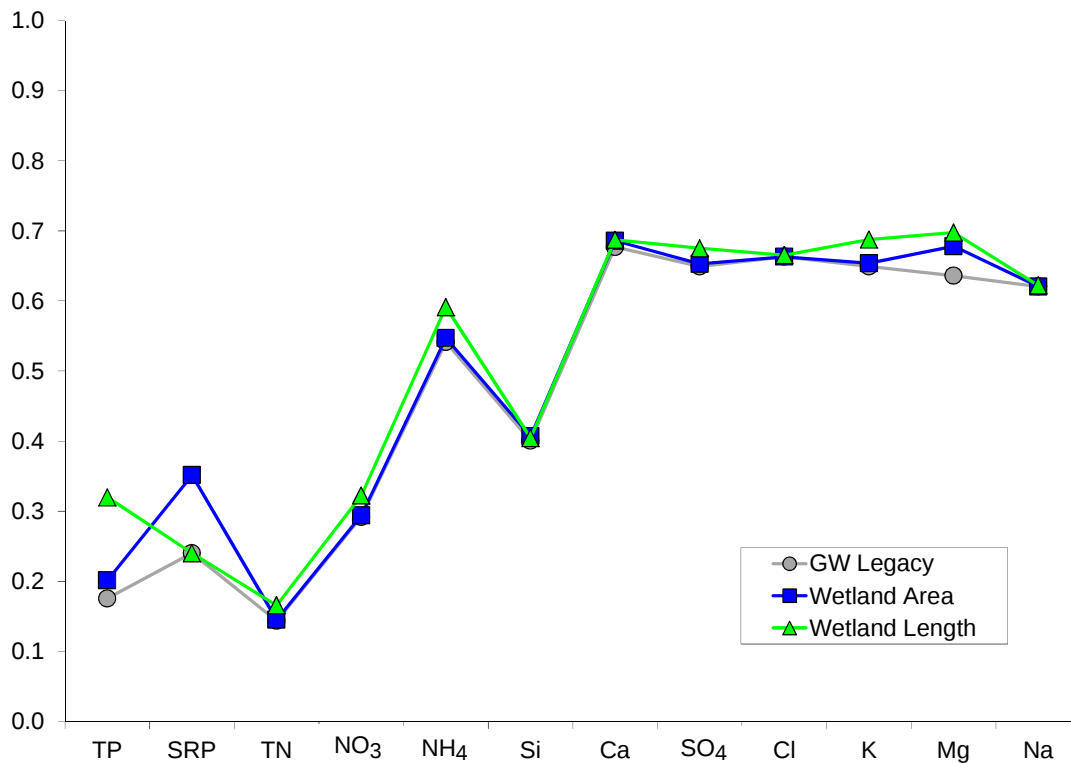
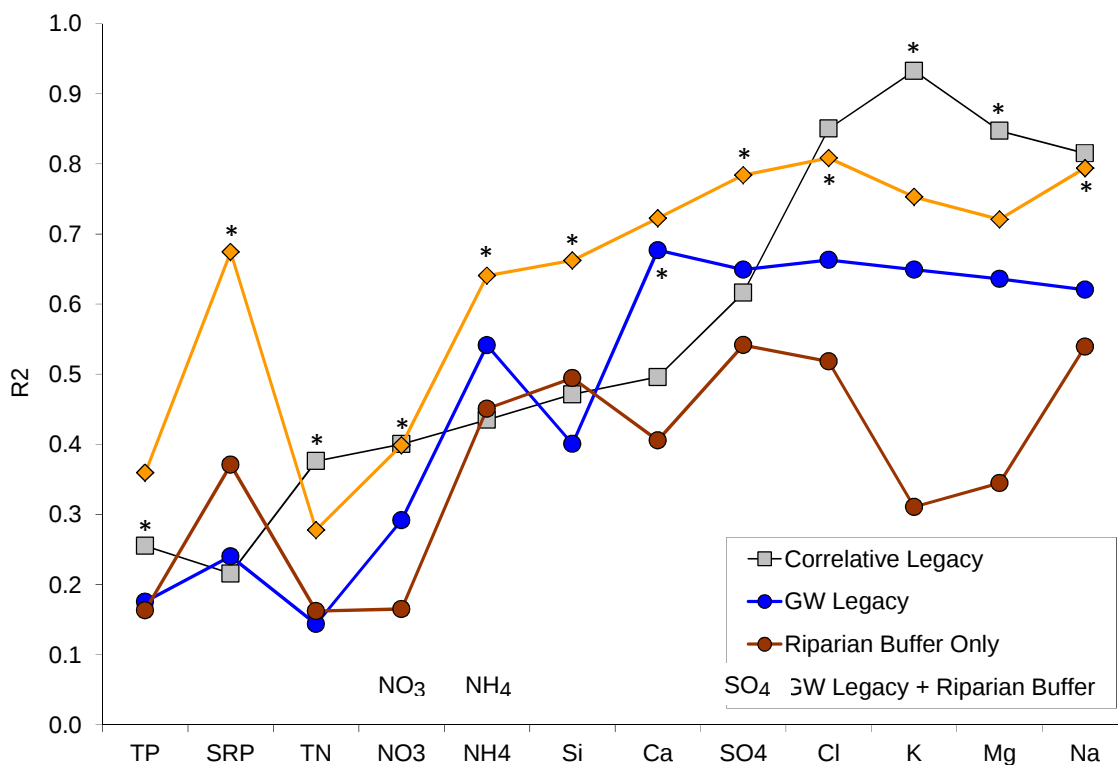


Figure 3.11. Coefficients of determination (R^2) from regression models of total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), nitrate (NO_3), ammonia (NH_4), silica (Si), calcium (Ca), sulfate (SO_4), chloride (Cl), potassium (K), magnesium (Mg), and sodium (Na) using correlative legacy models from chapter 2, LULC characterized by the legacy map, LULC within the 50m riparian zone buffer only, and legacy LULC combined with LULC from the 50m riparian zone buffer. Asterisks indicate model chosen by AIC weights. The asterisk for nitrate indicates the correlative legacy model.



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