EXPLORING RELATIONSHIPS BETWEEN IN-STREAM CONDITIONS AND ECOLOGICAL HEALTH WHILE ASSESSING LANDUSE AND CLIMATE SCENARIOS

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ABSTRACT

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Human disturbances can have significant impacts on physicochemical and biological conditions of streams. A good understanding of the relationships among these factors will help decision makers in sustainable management of the ecosystems. To address these issues, the following research objectives were developed: 1) bridge the gap between hydrologic models and ecological conditions using the Soil and Water Assessment Tool, 2) identify influential in-stream variables to explain fish and macroinvertebrate measures, 3) compare fuzzy logic techniques with statistical approaches to describe and model ecological health, 4) use in-stream variables obtained from SWAT to predict the impacts of different landuse and climate scenarios, and evaluate the effectiveness of best management practices, in regards to aquatic health. A high resolution SWAT model was built for the Saginaw River basin of Michigan, and flow and water quality outputs were linked with measured biological data. Results indicate that SWAT models can be an effective tool to produce in-stream variables, explaining 21% to 57% of variation (R^2) in ecological measures. Fuzzy logic methods are effective approach to model ecological health and outperformed other statistical methods tested here. Average annual flow rate had the strongest correlation with IBI, whereas nutrient concentrations showed the largest influence on all other ecological measures. Results suggest that efforts to model historic baseline conditions and to provide context for stream health assessments should include both pre-settlement land use and climate conditions. Meanwhile, the conservation practice, native grass, showed the most improvement to stream health, followed by residue management and no-tillage.

This thesis is dedicated to my family and friends for their much needed love and support.

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LIST OF ABBREVIATIONS

%INTOL	Percent Intolerant Individuals (Fish)
ACBOD	Average annual carbonaceous biochemical oxygen demand concentration (mg/L)
ACHLA	Average annual Algal biomass (chl - a) concentration (mg/L)
ADO	Average annual dissolved oxygen concentration (mg/L)
AFLOW	Average annual flow (cms)
AMinP	Average annual mineral phosphorus concentration (mg/L)
ANFIS	adaptive neural-fuzzy inference system
ANH4	Average annual ammonium concentration (mg/L)
ANo2	Average annual nitrite concentration (mg/L)
ANo3	Average annual nitrate concentration (mg/L)
AOrgN	Average annual organic nitrogen concentration (mg/L)
AOrgP	Average annual organic phosphorus concentration (mg/L)
APercBase	% Average annual water yield contributed by groundwater (%)
ASED	Average annual sediment concentration (mg/L)
ATN	Average annual total nitrogen concentration (mg/L)
ATP	Average annual total phosphorus concentration (mg/L)
BMP	Best Management Practice
CCSM	Community Climate System Model
CDL	Crop Data Layer
CEAP	Conservation Effects Assessment Project
CrossArea	Cross-sectional area of reach (m^2)
EPT	Ephemeroptera, Plecoptera, and Trichoptera

EPTtaxa	Total number EPT tax
Family IBI	Family index of Biological Integrity (Macroinvertebrates)
GIS	Geographic Information Systems
HBI	Hilsenhoff Biotic Index (Macroinvertebrates)
HRU	Hydrologic Response Unit
HUC	Hydrologic Unit Code
IBI	Index of Biological Integrity (Fish)
MNFI	Michigan Natural Features Inventory
MSE	Mean Square Error
MUSLE	Modified Universal Soil Loss Equation
N	Nitrogen
NCAR	National Center for Atmospheric Research
NED	National Elevation Dataset
NHDPlus	National Hydrography Dataset plus
NSE	Nash-Sutcliffe Efficiency
P	Phosphorus
PBIAS	Percent Bias
PLSR	partial least squares regression
R^2	Coefficient of determination
RMSE	Root mean square error
SCBOD	Average seasonal carbonaceous biochemical oxygen demand concentration (mg/L)
SCHLA	Average seasonal Algal biomass (chl - a) concentration (mg/L)
SDO	Average seasonal dissolved oxygen concentration (mg/L)

SFLOW	Average seasonal flow (cms)
SMinP	Average seasonal mineral phosphorus concentration (mg/L)
SNH4	Average seasonal ammonium concentration (mg/L)
SNo2	Average seasonal nitrite concentration (mg/L)
SNo3	Average seasonal nitrate concentration (mg/L)
SOrgN	Average seasonal organic nitrogen concentration (mg/L)
SOrgP	Average seasonal organic phosphorus concentration (mg/L)
SPercBase	% Average seasonal water yield contributed by groundwater (%)
SSED	Average seasonal sediment concentration (mg/L)
STATSGO	State Soil Geographic Database
STN	Average seasonal total nitrogen concentration (mg/L)
STP	Average seasonal total phosphorus concentration (mg/L)
StreamGrad	Stream segment gradient (m/m)
SWAT	Soil and Water Assessment Tool
USDA	United States Department of Agriculture
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey

INTRODUCTION

With over 3.5 million miles of rivers and streams within the United States (USEPA, 2011a) and given the numerous benefits and services provided by them, these freshwater ecosystems are of great importance to humans and much attention has been given to their protection. Land- use changes, climatic changes, and other stressors can have a profound effect on water resources. Among these stressors, agriculture practices, specifically, have a large influence on streams and rivers, effecting water quality, water quantity, and geomorphology (Dale and Polasky, 2007; Zimmerman et al., 2003; Webb et al., 2008). This in not only observed at field scale, but also large scale assessments identify agriculture as a leading source of current water quality problems, through practices such as fertilizer, manure, and pesticide applications and sediment inputs from increased erosion and runoff (Heimlich, 2003).

These effects to our streams can be further reflected in the aquatic organisms and ecological health of the system. Alterations to flow regimes (Poff et al., 1997), changes in water temperature (Wehrly et al., 2003), increases in sediment (Wood and Armitage, 1997) and nutrient (Miltner, 2010) concentrations, and changes to physical habitat and stream geomorphology (Rowe et al., 2009; Sullivan et al., 2004), have all been shown to influence the aquatic organisms within river systems. Being that the ecological health of the stream cannot be directly measured, biological indicators, such as fish or macroinvertebrates, are often used to represent different communities' responses to stressors (Karr, 1991; MDEQ, 1997; Barbour et al., 1999).

Overall, the relationships between environmental variables, such as nutrients, and macroinvertebrates or fish measures need to be further investigated (Wang et al., 2007; Weigel and Robertson, 2007). In addition, there is a need to forecast the impacts that anthropogenic activities have on stream health and fish distributions (Diebel et al., 2010). The first challenge when linking disturbance and stream condition data to biological data is the lack in availability of high resolution and complete datasets (Wang et al., 2008; Sutela et al., 2010). The use of biophysical models can play an important role in successfully estimating this data otherwise nonexistence. Few studies, however, have examined the use of models to help fill this gap. Meanwhile, efforts are currently under way, through the Conservation Effects Assessment Project (CEAP), to quantify the ecological benefits of best management practices (BMPs) and conservation practices through modeling applications and tools (Maresch et al., 2008; Shields et al., 2006). The second challenge is finding a suitable modeling technique or method that can capture the complex relationships between stream conditions and ecological components (Wang et al., 2008; Sutela et al., 2010). Alternative soft computing methods, such as fuzzy logic, may be a possible solution to address this challenge (Marchini, 2011).

The overall goal of this research is to provide foundation for linking watershed models to ecological health to better understand and further document the relationships involved between environmental variables and biological integrity within a large watershed in Michigan. In addition, this study investigates the consequences of agricultural practices on ecological health and aims at providing critical information to support decision making regarding landuse management.

The specific objectives of this study are to:

- Bridge the gap between hydrologic models and ecological conditions using the Soil and Water Assessment Tool (SWAT) to generate high resolution flow and water quality data

- Identify the influential in-stream variables and their relationship to macroinvertebrate and fish indices and metrics, ultimately indicating the overall ecological health

- Employ and compare soft computing techniques and statistical analysis to describe and model the relationships among stream health, flow, and water quality variables.

- Demonstrate the applications of SWAT to model beyond sampled locations and forecast conditions by predicting historical reference conditions under pre-settlement land-use and climate data as well as determine the effectiveness of large scale best management practice implementation.

LITERATURE REVIEW

1.1 Overview

This review discusses stream health and integrity, along with the aquatic organisms that can serve as indicators. Because fish and macroinvertebrates are commonly used indicators (MDEQ, 1997; Flinders et al., 2008; Barbour et al., 1999; Infante et al., 2008; Karr, 1991), they will be discussed specifically, including frequently used indices. The review then describes how agriculture can impact streams and reviews its effects on flow, sediments, nutrients, pesticides, water temperature, dissolved oxygen, and other channel characteristics. It continues by connecting the first two sections and shows how water quality, quantity, and other characteristics, influenced by agriculture, can affect aquatic organisms and ecological health. It also looks at methodological approaches that have been taken to make this connection. Furthermore, the use of agricultural conservation practices to reduce the impacts on streams and aquatic species is reviewed along with the Conservation Effects Assessment Project (CEAP) and its efforts to quantify the effects of these practices on ecological integrity. The review ends with a look at potential models and how they can play a role in these efforts.

1.2 Stream / Ecological Health and Integrity

Ecological health is a term that is not so clear cut and has been defined in many different ways, making it difficult to measure and quantify (Karr, 1999). In general, the health of the stream refers to a condition of the stream when it is flourishing, resilient, sustainable, and maintains its societal values (Meyer, 1997). Associated with stream health, although different, is the term integrity (Karr, 1996). Integrity refers to a quality or condition that is compared to an original condition (Karr, 1996). . Biological Integrity, as defined by Karr and Dudley (1981) is the ability of a system to support "a balanced, integrated, adaptive community of organisms having a species composition, diversity, and functional organization comparable to that of natural habitat of the region" (Karr, 1991). The definition, as later explained by Karr (1999), involves three main principles; temporal and spatial scale, elements of biodiversity and processes, and the aspect that "living things are embedded in dynamic evolutionary and biogeographic contexts". Biological integrity, along with physical and chemical integrity, makes up ecological integrity (Karr, 1996). Both "ecological health" and "integrity" are terms frequently used by agencies and are included in legislation and laws, including the Clean Water Act (Karr, 1991).). These definitions make integrity a valuable approach at looking at how human disturbances have affected streams and rivers ecologically. To determine the integrity of a system, we review measurements of the condition of a system, indicators within the system, and the indexes that involve them.

1.2.1 Indicators

There exist numerous biological monitoring methods to measure and quantify the ecological condition of a stream system. Using biological indicators is a highly accepted technique in seeing how different communities respond to water quality issues and can often be efficient in situations where physical habitat (Flinders et al., 2008) and low levels of pollutants may be otherwise hard to detect (Barbour et al., 1999; Flinders et al., 2008). Common biota used as indicators in aquatic systems are fish and macroinvertebrates (MDEQ, 1997; Flinders et al., 2008; Barbour et al., 1999; Infante et al., 2008; Karr, 1991), while others like periphyton, macrophytes, and diatoms are not as frequently used. Periphyton, however, have been shown to be informative indicators because of their short life, their location at the base of the food web, and their connection to fish and macroinvertebrates (Griffith et al., 2009; Hill et al., 2010; Barbour et al., 1999).

Ideally, both fish and macroinvertebrates should be measured together because they can react differently, vary in sensitivity to different stressors, and mirror conditions at different scales (Griffith et al., 2009; Lammert and Allan, 1999; Infante et al., 2008; Flinders et al., 2008; Karr, 1981). Previous research from Infante and others (2008) showed weak community concordance between fish and macroinvertebrates within their study region, suggesting that certain landscape factors may be more stressful for certain organisms and/or the scale at which influences may differ between organisms. More specifically, it has been shown that fish tend to respond to broader scale factors like flow and land use, due to their range of movement and lifespan (Lammert and Allan, 1999; Barbour et al., 1999; Plafkin et al., 1989). Conversely, macroinvertebrates seem to be influenced more by local habitat, including substrate (Lammert and Allan, 1999). This can be attributed to invertebrates living much of their lives within the hyporheic zone of streams and their connection with the stream bed with little migration (Power et al., 1999; Barbour et al., 1999). Flinders and others (2008) further supported this when they found that watershed land-use predicted a higher percentage of fish community variation more consistently than that of macroinvertebrates.

1.2.1.1 Fish as Indicators

Fish have several benefits when it comes to biological monitoring and being used as indicators. Karr (1981) explained that fish cover many trophic levels, including piscivores, herbivores, omnivores, and insectivores, which allows them to be a good representation of the system and its interactions. This is also achieved by being at the top of the aquatic food chain (Karr, 1981). Fish are advantageous because of their long lives and mobility, allowing for observation of long term effects, as well as influences from larger, broader scales (Karr, 1981; Babour et al., 1999). Because of fishes' ability to often persist and recover from environmental strain (Rowe et al., 2009), stress and toxicity effects can be observed, through missing taxa and growth and reproductive variations (Karr, 1981). From a sampling stand point, fish are easy to collect and identify. Their life history information is often known, along with distributions and environmental requirements (Barbour et al., 1999). Not only does the public relate to reports and information about fish, but the information collected is directly applicable to fisheries (Karr, 1981; Barbour et al., 1999).

1.2.1.1.1 Index of Biological Integrity

One common index recognized and used by many (Lammert and Allan, 1999) to measure biological integrity is the Index of Biotic Integrity (IBI) which was introduced by James Karr (1981). The IBI uses a set of metrics that cover hierarchical aspects of a system, from the individual through the whole ecosystem (Karr, 1991). The original 12 metrics, intended for the Midwest United States, are broken up into three main components including species richness and composition, trophic composition, and fish abundance and condition. Within species richness and composition, six metrics focus on quantifying native, benthic, water-column, long-lived, intolerant, and tolerant species. With the trophic composition component, three metrics look at percentages of omnivores, insectivores, and piscivores. The last three metrics, within fish abundance and condition, quantify number of individuals, hybrids, and individuals with diseases or abnormalities (Karr, 1991). After metrics are measured, they are scored by a comparison to how the site would be expected to be found if undisturbed; this is usually done with a 1, 3, or a 5, 5 being the best. Totaling the metric scores obtains a final IBI score, which can be represented by a class that can range from very poor to excellent (Karr, 1981). Over the years, others have used alternative metrics and made appropriate modifications to the IBI to properly assess specific sites (Cooper et al., 2009; Roth et al., 1996; Lammert and Allan, 1999; Wang et al., 2006; MDEQ, 1997; Wehrly et al., 2003; Lyons et al., 1996; Lyons, 1992). Several IBIs have been created for the various regions of North America and specific states (Barbour et al., 1999). Furthermore, indexes that are modified for stream type based on temperature also exist; an example being the coldwater and warmwater IBIs (Lyons et al., 1996; Lyons, 1992). Streams are often classified as being a cold, cool, or warm water streams, leading to the species and faunal assemblages they support (MDEQ, 1997; Lyons et al., 2009). With warmwater streams supporting more diversity and species richness (Karr, 1981; Lyon et al., 2009), just as important, coldwater streams may not be represented well, using the same metrics. By adjusting metrics to fit species and measures that are realistic to the site, more accurate estimations and scores can be obtained. In past studies, underestimations of biotic integrity were obtained where warmwater or coldwater indexes were used for streams that were classified as coolwater (Lyons et al., 2009). The MDEQ (1997) survey protocols also call for different metrics to be used, anticipating the absence of many species in coldwater streams, and highlighting the presence of others, like salmonids.

1.2.1.1.2 Modified Index of Well Being

The Modified Index of Well Being (MIWB) was created to resolve the issues with the first Index of Well Being that often gave misleading results and is considered to be a sensitive and consistent index to environmental stressors (Yoder, 1987; Barbour et al., 1999). This index however, is made up of the same computational steps, with the elimination of certain species when computing. Problems with the first index were often skewed due to tolerant species being dominant and abundant, masking lack of diversity and other structural problems (Yoder, 1987). The MIWB is made up of four estimates, two measuring diversity and two measuring abundance, including relative number of all species, relative weight of all species, Shannon Diversity Index of relative number of species, and the Shannon Diversity Index of relative weight. Modifications to the original index includes highly tolerant species, exotics, and hybrids being eliminated from the numbers and biomass estimates, while still being acknowledged within the Shannon Diversity Index (Yoder, 1987). The estimates are put into a basic formula, resulting in a final score (Barbour et al., 1999; Yoder, 1987). Higher scores for the MIWB reflect healthier communities and better environmental conditions (Covert, 1997). When reviewing the literature, very rarely was the MIWB used compared to Karr's (1981) Index of Biotic Integrity. When comparing results across agencies in a particular study, Covert (1997) found that IBI values were less varied and consistent compared to the MIWB. The MIWB is often a complimentary index to the IBI and can react faster to severe impacts and recovery within a lotic system (Yoder and Smith, 1999).

1.2.1.2 Macroinvertebrates and Indicators

Frequently, macroinvertebrates have also been used to evaluate stream conditions and integrity. Because of their smaller migration habits and sessile lifestyle, macroinvertebrates can be efficient at reflecting localized sites and habitats (Barbour et al., 1999; Flinders et al., 2008; USEPA, 2009c). They often respond quickly to stressors due to sensitive life stages, complex life cycles, and varying pollution tolerances. While this allows macroinvertebrates to be affected by short-term environmental conditions (Barbour et al., 1999), they also tend to live for periods longer than a year (USEPA, 2009c; Barbour et al., 1999), making it possible to observe affects over extended periods of time. Macroinvertebrates represent a range of trophic levels and being that they are an important food source for fish (Barbour et al., 1999); they act as a link in the food web connecting multiple organisms (USEPA, 2009c). As for sampling, macroinvertebrates, much like fish, are generally easy to collect and identify. There is a great deal of background information available, as well (Barbour et al., 1999; USEPA, 2009c). Over the years there have been numerous indexes and metrics used in identifying and measuring stream conditions and integrity using macroinvertebrates. Macroinvertebrate indexes provide useful information about the condition of the community (Ohio EPA, 1989) by evaluating elements and processes (Barbour et al., 1999), along with reflecting the health and integrity of a stream. There are two main informative types: multi-metric indexes, that have several metrics that measure and cover specific attributes of the assemblage; and pollution-tolerance indexes, which are based on taxon-specific tolerance values (Fore et al., 1996). There are many variations of these indexes that have been presented for different regions and conditions. Below, are some of the more common and basic ones.

1.2.1.2.1 Invertebrate Community Index

The Invertebrate Community Index (ICI) is a commonly used multi-metric index, which was created by the Ohio EPA. Being based off of Karr's fish IBI, the ICI is made up of ten metrics reflecting the structure and composition of the community. The ten original metrics include total number of taxa, number of Mayfly taxa, number of Caddisfly taxa, number of Dipteran taxa, percent Mayfly composition, percent Caddisfly composition, percent Tribe Tanytarsini Midge composition, percent other Dipteran and non-insect composition, percent tolerant organisms, and number of qualitative EPT taxa. These metrics are then given a score of 6, 4, 2, or 0, based on a comparison with undisturbed reference sites, and summed up to a final ICI value (DeShon, 1995; Ohio EPA, 1989). However, before being summed up, metrics may be scaled to the relative attributes of the sample and the drainage area of the stream (Lammert and Allan, 1999; Ohio EPA, 1989). Like most indexes, the ICI may be modified to take into account regional variation and the levels at which identification is being done. An example of this is where Lammert and Allan (1999) used a modified ICI, by omitting midges and tolerant species metrics, in determining the influence of land cover and structure on biotic integrity in Michigan's River Raisin watershed.

1.2.1.2.2 Benthic Index of Biological Integrity

The Benthic index of Biotic Integrity is another multi-metric index, which was based off Karr's IBI for fish that has been used commonly and was developed by Kerans and Karr (1994). This index focuses on taxa richness, composition, and biological process. All metrics represent attributes that are reactive to human disturbances (Fore et al., 1996). They are compared with undisturbed sites and given a score of 1, 3, or 5. These scores are then added up to give a final B-IBI value. There are thirteen original metrics involved in this index including, total taxa richness, intolerant snail and mussel species richness, mayfly richness, caddisfly richness, stonefly richness, relative abundance of Corbicula, oligochaetes, omnivores, filterers, grazers, and predators, proportion of individuals in two most abundant taxa, and total abundance. With the metrics, total taxa richness and total abundance, statistical comparisons can be made among sites (Kerans and Karr, 1994). Modifications also are needed and have been made for this index, depending on local conditions and sampling methods. Fore and others (1996) modified and created a B-IBI for the Pacific Northwest that used metrics that were similar to those of Kerans and Karr's (1994) that responded to logging. In addition, Lammert and Allan (1999) modified metrics and scoring criteria to work for the River Raisin watershed in Michigan, based on taxonomic differences in the area.

1.2.1.2.3 Biotic Index

The Biotic Index (BI) that was presented by Hilsenhoff (1987), also known as the HBI, is an index based on the tolerance values of organic pollution for species and genera (Hilsenhoff ,1988; Barbour et al., 1999). Biotic indexes can target different types of stressors and the tolerance values derived, determine the accuracy of the index (Lenat, 1993). The tolerance values are multiplied by the number of individuals in that taxa, summed up across taxa, and then a weighted average pollution tolerance is derived (Lenat, 1993; Fore et al., 1996; Lammert and Allan, 1999). The sites with higher BI scores, which are scaled from 0 to 10, are determined to be more degraded by pollution (Lammert and Allan, 1999). As mentioned previously, different modifications have been made to the index based on tolerances to the pollutions of concern, differences in season, stream size, and geographic regions (Lenat, 1993; Davis, 1995). Not only has this index continued to be used and modified individually, but it has also been incorporated into multi-metric indexes as well (Davis, 1995).

1.2.1.3 Habitat Indexes

With physical habitat being the fundamental driver of fish communities and structure (Lammert and Allan, 1999), often agencies will use habitat indexes as well. With this evaluation, habitat restraints on the biological potential of a stream can be determined. Having habitat conditions combined with water quality conditions can allow for a better understanding of the limiting factors of a system (MDEQ, 1997). Habitat characteristics that have been shown to be of importance in influencing faunal assemblages include velocity, depth, water temperature, substrate, woody debris, in stream and stream side cover, and diversity of pools, riffles, runs, and bends (Infante et al., 2008; Barbour et al., 1999; Rowe et al., 2009).

1.2.1.3.1 Qualitative Habitat Evaluation Index

The Qualitative Habitat Evaluation Index (QHEI) is a habitat index that was developed to give a measure of macrohabitat based on physical and functional factors that can affect fish communities (Rankin, 1989; Miltner and Rankin, 1998). There are six components that make up the QHEI; type and amount of substrate; type and amount of in-stream cover; channel morphology, including sinuosity, development, channelization, and stability; Riparian zone width and bank erosion; pool, glide, riffle, and run quality; and Gradient. These metrics are scored based on comparison with streams that have high biological diversity and integrity and summed up for a QHEI value (Rankin, 1989).

1.2.1.4 Michigan DEQ GLEAS Procedures

In their survey protocols and procedures, the Michigan Department of Environmental Quality, Great Lakes and Environmental Assessment Section (GLEAS) have outlined a standardized evaluation of nonpoint source impacts, developed specifically for Michigan. These protocols involve evaluations of the habitat quality of a stream along with the biological integrity based on fish and macroinvertebrate community metrics (MDEQ, 1997).

The Macroinvertebrate score is similar to that of the ICI (DeShon, 1995) and is composed of nine metrics that are scored based on a comparison of an excellent site and summed up for a final score. The nine metrics include total number of taxa, representing diversity; total number of mayfly taxa, caddisfly taxa, and stone fly taxa, all of which are in the EPT group and sensitive to pollution and disturbance; Percent mayfly composition; percent caddisfly composition; percent contribution of the dominant taxon, an indication of community balance; percent isopods, snails, and leeches, which are highly tolerant; and percent surface dependent taxa, which are indicators of dissolved oxygen levels (MDEQ, 1997). These metrics have been used by many; including Cooper and others (2009) when looking at sediment contamination and faunal communities in urbanized watersheds.

The fish index within these protocols works like most of the indexes with metrics that are scored based on ideal conditions and totaled for a final fish score. If sites have fewer than 50 fish or extensive amounts of fish have anomalies, the site will be considered below acceptable quality. Cold water streams will be judged by macroinvertebrates, with salmonid numbers determining designation. The ten metrics that compose the index are; number of darter species, which are sensitive to habitat degradation; number of sunfish species, which are responsive to habitat structure and cover; number of sucker species, an intolerant species to habitat and chemical degradation; number of intolerant species; percent omnivores, who can dominate degraded sites; percent insectivores, who can respond to degradation; percent piscivores, which are indicators of a healthy and diverse community; percent tolerant species; and percent lithophilic spawners, who rely on gravel for spawning and can be largely impacted by sediments (MDEQ, 1997). This index is not only used by itself but also has been integrated into the IBI as seen by Lammert and Allan (1999).

1.3 Agricultural Influences on Streams

Because of the importance of having healthy streams with healthy biological integrity, it is essential to recognize and be able to assess the impacts of anthropogenic activities, such as agricultural practices. Agriculture makes up a large portion of the land-use in the United States. We use approximately 20% of total land for the production of crops and a quarter of private land is used for grazing (USEPA, 2009a). Recently, due to urbanization and the conversion of farmland through development, land area designated for cultivation has shown some decline (USEPA, 2009a). This decline, however, does not relieve the risks to our natural resources. Difficulties in reducing these risks will continue with future conditions in climate change, water supply challenges, and production of biomass for alternative fuel (Maresch et al., 2008). Agricultural practices can have a large influence on our water resources and often results in alterations in flow (Dale et al., 2007; Shields et al., 2006; Rowe et al., 2009; Poff et al., 1997);

increases in sediments (Rowe et al., 2009; Dale and Polasky, 2007; Zimmerman et al., 2003; Wohl and Carline, 1996; Diana, 2006); an excess of nutrients (Bernot et al., 2006) and pesticides (Gillium, 2007); increases in water temperature (Poole, 2001; Caissie, 2006; Webb, 2008); and changes in stream morphology (Sullivan et al., 2004; Rowe et al., 2009).

1.3.1 Agriculture and Flow

Flow is a primary function of lotic systems and has been shown to be altered by different land covers. Agriculture, through topography, geology, and vegetative cover, or lack thereof, can influence flow patterns (Poff et al., 1997) and critical components of flow (Shields et al., 2006). For example, increases in agricultural land-use can often lead to increases in both magnitude and frequency of storm flows (Shields et al., 2006). Diana and others (2006) also observed a decrease in flow stability associated with agriculture in southeastern Michigan. With natural vegetation often lacking in agricultural areas, there is little to act against overland flow and runoff. This combined with artificial drainage, like tiles, that rapidly discharge water into channels, illustrates processes in which agriculture can have an effect on flow (Rowe et al., 2009). Irrigation and water withdrawal is another activity tied to agriculture that shapes flows and infiltration patterns (Dale and Polasky, 2007).

1.3.2 Agriculture and Sediments

With variable flows, higher peak rates, and higher velocities, comes easier and increased transport of sediments. Sediments can be transported from either the channel itself or from the catchment through erosion (Wood and Armitage, 1997). Both of these are found to be amplified in agricultural regions. Rowe and others (2009) illustrated this connection between land-use and sediments when looking at fine substrates and different land covers. Row-crop agriculture showed a positive relationship with fine substrates. Easily erodible sediments from bare soil and cultivated lands contribute to these increases along with easier transport of sediments with increases in run-off (Zimmerman et al., 2003). Agricultural regions often have riparian areas with reduced vegetation (Bernot et al., 2006) and this can not only promote easier sediment transport with higher runoff velocities and reduced trapping efficiencies (Liu et al., 2008), but it can also lead to less stable banks (Lyons et al., 2000). This in turn leads to bank erosion and added sediments. Similar outcomes can be seen in areas of grazing. Wohl and others (1996) exhibited this when comparing un-grazed and grazed reaches. They found both increases in stream bank erosion and the amount of streambed composed of fine sediments. A Yankey and others (1991) study even estimated that grazed reaches, compared to croplands, can supply two to five times' greater amounts of sediments (Wohl and Carline, 1996).

1.3.3 Agriculture and Nutrients

Along with sedimentation, nutrients are also a significant factor originating from agriculture that contributes to the alterations within a watershed. Increases in nitrogen and phosphorus are well documented in their association with agricultural practices (Bernot et al., 2006), especially the use of fertilizers (Robertson and Vitousek, 2009; Gentry et al., 2007). Fertilizers, soil disturbances, and biological fixation from crops all contribute in making agriculture the leading source for nutrients in streams (Bernot et al., 2006). The transport of nutrients from agricultural lands to channels can be further driven by climatic factors, application timing, soil characteristics, and different flows (Heathwaite and Johnes, 1996). Groundwater, runoff, drainage, and irrigation all help to determine the loads and concentrations of nutrients (Domagalski et al., 2008). Irrigation using local water sources can result in lower loads than the use of imported water due to the possibility that local water withdrawals might break the connection between groundwater and a stream (Domagalski et al., 2008). Once nutrients reach a stream, the flow and biological conditions determined by agricultural practices can continue to direct impacts by affecting stream flow, with low discharges creating conditions for retention, while higher discharges process and transport nutrients downstream (Royer et al., 2006; Bernot et al., 2006).

Nitrogen can be in many forms and is often an abundant nutrient found in agricultural regions and the watersheds they influence. Johnson and others (1997) found that the highest nitrate and nitrite concentrations were in catchments that were dominated by row-crops agriculture. Along with nitrate and nitrite, other inorganic forms of nitrogen, including ammonium and ammonia, are of the more common forms of nitrogen that are introduced to fields through microbial activity, animal waste, and fertilizers (Robertson and Groffman, 2007). Manure can be an input of nitrogen where animals graze and where it is used as a fertilizer. In other areas, often intense cropping operations, synthetic fertilizer is another main nitrogen source (Robertson and Vitousek, 2009). The nitrogen from these sources can be transported both by runoff and subsurface flow (Domagalski et al., 2008), with subsurface flows often being a dominant means of transport (Heathwaite and Johnes, 1996).

Phosphorus is another main nutrient in streams that can reach degrading levels in areas of agriculture and like nitrogen, phosphorus in these regions have shown increase in many studies (Bernot et al., 2006). Fertilizers are a large contributor and source of inorganic phosphorus to a system (Heathwaite and Johnes, 1996). Phosphorous levels can be further raised with the input of organic phosphorus through animal wastes and manures. Phosphorus's tendency to be immobile and connect with soils, make overland transport through runoff and erosion the primary mode (Sims et al., 1998; Heathwaite and Johnes, 1996). This makes application timing, soils, precipitation, and flow driving forces behind its transport. Greater concentrations of phosphorus have been observed in areas where fertilizer was applied on frozen soils, right before a precipitation event (Gentry et al., 2007) and also in areas of heavily grazed grasslands (Heathwaite and Johnes, 1996). Sharpley and others (1999) further explain the significances of location and that P application near stream has more of an impact on a watershed than areas of application further from the channel. Besides runoff, Phosphorus, like nitrogen, can also reach a channel through leaching, subsurface runoff (Sims et al., 1998), and tile drainage (Royer et al., 2006).

1.3.4 Agriculture and Pesticides

Pesticides are commonly used in protecting crops and agricultural practices from insects (insecticides), unwanted vegetation (herbicides), bacteria (Antimicrobials), fungi (Fungicides), and other pests (USEPA, 2009b). Gillium (2007) showed that 97% of streams in agricultural areas had detectible pesticides. These pesticides can have significant negative impacts to streams. They can enter channels through transports similar to those of nutrients, including overland runoff, erosion, groundwater flow, and leaching. Wind and spray drift is another means of transport for pesticides within agricultural areas (USGS, 2000). Runoff, however, continues to be one of the most important routes (Schulz and Liess, 1999; Domagalski et al., 2008). Transport of pesticides can be affected by soil characteristics, field slope, climatic conditions, and application timing and amount (MSU Weed, 2010). Pesticides can accumulate in sediment and biota based on their solubility in water and their persistence in soils. Low solubility and longer soil half-lives can lead to more accumulation and affects, much like that of earlier used pesticides, including DDT (USGS, 2000). Herbicides are the most widely used pesticides with hundreds of kinds available for use (Helfrich et al., 2009). Some herbicides that are commonly used and detected include Atrazine, Deethylatrazine, Simazine, and Metolachlor, which show high yields in basins correlated with high use (Domagalski et al., 2008; Gillium, 2007). Additional herbicides that are commonly used include 2, 4-D, Glyphosate and Acetochlor, along with several others (MSU Weed, 2010). Other pesticides that have originated from agricultural uses and have been monitored in streams include insecticides like Diazinon, Chloropyrifos (Gillium, 2007), Fenvalerate, and Parathionethyl, which was observed in river channels through edge of field runoff by Schulz and Liess (1999).

1.3.5 Agriculture and Bacteria

Agricultural practices can continue to impact water quality by amplifying the amount of bacteria and pathogens found in streams and channels. Although this data is often unavailable and not within the scope of our project, we recognize that they can have significant impacts on our water resources. Animal and livestock grazing, along with manure applications in agricultural areas, can lead to these increases in bacteria (Mishra et al., 2008; USEPA, 2006a; Jamieson, 2002). With bacteria and pathogens living in the digestive system of humans and animals, fecal matter then continues to carry these organisms to the land. Two main bacteria, Fecal Coliform and Escherichia coli (E.coli), are often tested due to efficiency and their indication of other more harmful bacteria, pathogens, viruses, and protozoa (USEPA, 2006a; Mishra et al., 2008). The survival of these bacteria in agricultural areas and soils can be contributed to soil characteristics such as nutrients, moisture, and organic matter (Jamieson et al., 2002). Mishra and others (2008) showed that manure applications lead to higher edge of field concentrations of Fecal coliform and E. coli. Lyautey et al. (2010) and Vidon et al. (2007) further showed the influence of animals and animal waste on bacteria numbers by observing an increase in E. coli densities with proximity to livestock production and stream sections where cattle have access. Grazing practices and lack of vegetated riparian areas also have been observed to show increases in bacteria in streams (Roodsari et al., 2005; Jamieson et al., 2002; Sullivan et al., 2007). Transport of bacteria is often related to precipitation, soil characteristics, land cover, and bacteria survival. Precipitation has been shown to influence transport of bacteria through runoff, splash transport (Boyer, 2008), and leaching (Gagliardi and Karns, 2000). Once these bacteria have reached a stream, agricultural effects on other characteristics of the stream like sediments, temperature, and flow, further influence their survival and levels (Minnesota Pollution Control Agency, 2008).

1.3.6 Agriculture and Water Temperature

Water temperature is an additional characteristic of streams that can be manipulated by external factors from catchment and land-use. One factor that affects stream temperature is stream morphology (Poole and Berman, 2001). Agriculture can affect this morphology by increased bank erosion and increased sediments. This can further lead to channel widening and shallowing, which can also increase temperatures (Webb et al., 2008). Another factor influencing temperature is solar radiation and canopy cover from riparian zones (Wehrly et al., 2003; Poole and Berman, 2001; Caissie, 2006). As discussed previously, agricultural lands often have limited vegetated riparian area, meaning little shading. These conditions also lead to increase lateral inputs and overland flow, which can affect temperature. Wehrly and others (2003) showed that agricultural areas with surface runoff-dominated reaches that had little shading were found to be warmer then streams that were groundwater dominated and had forested landscapes. Vegetated cover, often lacking in agricultural areas, can also influence temperature by decreasing heat exchange through wind and air movement (Poole and Berman, 2001; Webb et al., 2008). In addition, irrigation and water withdrawals are another activity frequently tied to these areas, which can further manipulate temperatures (Poole and Berman, 2001; Cassie, 2006).

1.3.7 Agriculture and Dissolved Oxygen

Dissolved oxygen (DO) is used in both biotic and abiotic components of lotic systems and can, too, be affected by agricultural practices (Garvey et al., 2007). The relationship and responses of DO to agriculture however, is much more complex. This complexity is due to all the interactions involved, including temperature, nutrients, flow, and further biotic interactions (Garvey et al., 2007; Wang et al., 2002). The temperature of a stream, affects the amount of dissolved oxygen in it, with colder waters being able to hold more dissolved oxygen (USEPA, 2006b). Because agricultural regions affecting stream temperatures, as explained earlier, they too, indirectly affect DO. Additionally, this indirect relationship is seen with flow. Garvey and others (2007) explains how flow can affect oxygen levels through the interaction of water and the atmosphere, along with the effects of substrates and depth. Further agricultural effects on dissolved oxygen include factors that influence eutrophication. Due to light, dissolved oxygen in streams varies often from day to night, through photosynthesis and respiration from organisms within, including algae and periphyton. This lack of oxygen at night can reach extremes in impacted areas (Wang et al., 2002; Loperfido et al., 2009; Hill et al., 2009). Nutrients, sediments, light, temperature, and flow continue to influence abundance, respiration, production and decomposition of these organisms which alter and often limit dissolved oxygen within a system (Loperfido et al., 2009).

1.3.8 Agriculture, Physical Habitat and Stream Morphology

As shown, previously, agriculture can change both water quantity and quality characteristics. In addition to those, there are also more physical conditions that can be impacted by land use. Although majority of these variables are not included within the scope of our project, we do recognize their importance. Structure and debris within a stream is one of these conditions. The amount of woody debris and organic material that is found in a stream is influenced and primarily driven by the vegetation and forested composition within the riparian zone (Roth et al., 1996; Poole and Berman, 2001). Agricultural areas, having less forested riparian areas, have been shown to have lower numbers of large woody debris within a channel (Shields et al., 2006). Channelization, homogenous habitat, and decreases in stream sinuosity can also be conditions associated with agricultural areas, through the straightening of channels and increased drainage. This can lead to a decrease in bed stability, peak stream flow and power, and other further impacts (Sullivan et al., 2004; Rowe et al., 2009).

1.4 Stream Conditions and Aquatic Health

The above mentioned stream conditions and factors affected by agriculture can have a large influence on the aquatic biota and overall aquatic health of a system. These factors include flow, sediment, nutrients, pesticides, bacteria, water temperature, dissolved oxygen, and channel morphology.

1.4.1 Flow and Aquatic Health

Flow within a lotic system has a great deal of influence on ecological processes and fish assemblages. As earlier explained, flow can affect temperature, sediment, nutrient, and pesticide input, dissolved oxygen levels, and other stream conditions, which in turn affect aquatic organisms. Flow can also affect the biota in more direct ways, including habitat availability, wash out, and other stressors. Macrophytes and aquatic vegetation that are a resource for food, juvenile habitat and cover, among other things, can be impacted by altered flows (Poff et al., 1997; Bunn and Arthington, 2002). In addition, flow is tied to many important life events for some fish, including spawning and recruitment, and changes can have negative implications on these species behavior and survival (Bunn and Arthington, 2002). All of these impacts can be observed through five components of flow; including magnitude, frequency, timing, duration, and rate of change (Poff et al., 1997). With changes in flow, potential areas for habitat and or connections to areas of habitat can be created or reduced (Sparks, 1995).A common way of describing how flow can have an effect on fish and macroinvertebrates in this way is the IFIM, Instream Flow Incremental Methodology. This model shows the amount of available habitat with varying discharges based on water depth, velocity, and substrate (Poff et al., 1997). Within several studies, fish have consistently been shown to be negatively affected, including diversity of species, to changes in natural flow regimes. This is true for both decreases and increases in flows. Also, in their review of 165 papers, Poff and Zimmerman (2010) found that 92% of them showed negative responses of ecological metrics to alterations in flow. Lammert and Allan (1999) observed flow's effect on fish, revealing that IBI score variation was strongly associated with flow stability. Abundance and diversity of macroinvertebrates are also commonly reduced in studies with flow alterations (Poff and Zimmerman, 2010). These reductions can occur due to changes in substrate habitat from flow and, in a more direct affect, increased drift and downstream transport (Bunn and Arthington, 2002; Borchardt, 1993).

1.4.2 Sediments and Aquatic Health

Sediments can also impact the ecology of stream in several direct and indirect ways. Primary production within a stream can be affected due to sediments limiting light penetration, transporting nutrients, and covering substrate (Wood and Armitage, 1997). Izagirre et al. (2009) observed sediments impacting periphyton negatively soon after siltation. Although they saw a recovery, it was partially contributed to a shift in community structure. These influences on periphyton can be linked to and show indirect effects from sediments on fish and macroinvertebrates through habitat structure alteration, food availability, and dissolved oxygen levels (Griffith et al., 2009). Although sediments are shown to have negative effects toward larger aquatic organisms, it is also possible that they can improve habitats by limiting periphyton growth and eutrophication (Hill et al., 2009).

Sediments can further affect fish in other ways by degrading their habitat within a stream; with, increased turbidity, their feeding efficiency and abundance of food is obstructed (Wood and Armitage, 1997; Karr and Dudley, 1981). Sullivan et al. (2009) showed results that indicated that sediment loads and their duration affected certain feeding guilds more than others, with opportunistic feeders being the most resilient. Fish can also be hindered by sediments that cover and embed substrates, which impede on spawning, nesting, and juvenile habitat (Sullivan et al., 2009; Newcombe and Jensen, 1996). Sediments continue to affect fish in more direct ways like physiological stress when sediments clog gills (Wood and Armitage, 1997) and increase respiration rate (Zimmerman et al., 2003). All these stresses can further impact fish assemblages by reducing growth rates, causing delayed hatching, mortality, and natural fish migration (Zimmerman et al., 2003; Wood and Armitage, 1997). Overall community structure and diversity can be influenced by suspended sediments and sediment deposition. Rowe et al. (2009) observed significant declines in fish IBI's from sites where substrates were dominated by sediments. Along with loads and concentrations, effects of sediments have been observed to increase with particles size and have more of an affect to fish in warmer waters (Newcombe and Jensen, 1996).

Macroinvertebrates have been shown to be directly impacted from sediments as well. Their abundance, diversity, density, and community structure have been observed in studies to be affected, due to covered and modified substrate habitat, affecting their respiration, impairing feeding, and increasing drift (Wood and Armitage, 1997). Wohl and Carline (1996) observed lower densities in streams with higher sediment loads. Griffith et al. (2009) also continued to see effects of sediments on macroinvertebrates in direct ways, including increases in percent burrower taxa, as well as indirect means through interactions with periphyton as explained earlier.

1.4.3 Nutrients and Aquatic Health

Sediments often are accompanied by nutrients when they reach channels. These nutrients, although essential to organisms, can exceed levels that are needed and have considerable negative impacts on the individual, community, and the system as a whole. In some situations, where nutrients are low, supplied nutrients from agriculture can show positive effects on a lotic system and aquatic organisms. However, often this is not the case and there is an excess of nutrients in the system (Miltner, 2010). One of the main effects of nitrogen and phosphorus overload in a lotic system is the acceleration of eutrophication (Carpenter et al., 1998). Both nitrogen and phosphorus, predominantly in areas of adequate light (Hill et al., 2010); have been shown to increase algal, macrophyte, periphyton, and phytoplankton growth (Bernot et al., 2006; Carpenter et al., 1998). Shifts in algal community structure have also been observed, leading to more tolerant species like blue-green algae becoming dominant in streams with high nutrients (Minnesota pollution Control Agency, 2003). These alterations and increases can reach levels that create dangerous algal blooms and conditions, which lead to low dissolved oxygen levels and areas of hypoxia, which are unable to support other organisms (USEPA, 2009d; Robertson and Vitousek, 2009). Not only can these increases in periphyton and algae negatively affect dissolved oxygen levels, but they can continue to affect consumers and secondary consumers by influencing feeding and habitat structure (Griffith et al., 2009).

Some fish are more intolerant than others to high levels of nutrients, along with the conditions they create within the habitat. These increased levels of nitrogen and phosphorus have been observed many times to affect fish assemblages and communities. For example, Wang et al. (2006) showed that total phosphorus and total nitrogen contributed to most variation in fish variables, including negative relationships with IBI, number of carnivores, omnivores, and intolerant species. This negative relationship between these nutrients and IBI was also observed by the Minnesota Pollution Control Agency (2003) and Miltner (1998) as well.

In addition, these effects have been reflected in macroinvertebrate communities. Miltner and Rankin (1998) observed a decrease in ICI associated with NH_3. It was also shown that EPT taxa decreased, while some other taxa increased, with higher nutrient levels. Justus et al. (2010) observed that biotic indexes for both fish and macroinvertebrates were negatively correlated with nutrients and were found to be lowest where nutrient concentrations were at their highest.

1.4.4 Pesticides and Aquatic Health

Pesticides can be introduced to streams through agricultural practices and throughout the years have proven to be detrimental to aquatic systems. One of the most well-known and damaging pesticides was DDT (dichlorodiphenyl-trichloroethane). This, along with all other organochlorine insecticides, has now been banned from use in the United States due to harmful effects on the environment and biota (Helfrich et al., 2009). Other types of pesticides, however, are still commonly used and can affect aquatic organisms directly through absorption, respiration through the gills, and orally through feeding and drinking. Pesticides, although toxic to aquatic life in high doses and for long periods of time, seldom cause kills. This is due to pesticides being often short lived and strongly absorbent to sediments and mud. Insecticides are generally the most harmful to a lotic system, being highly toxic to macroinvertebrates and fish (Helfrich et al., 2009). Schulz and Liess (1999) observed several macroinvertebrate species disappearing and others' population densities showing significant reductions in streams affected by insecticides.

Schafer and others (2007) also showed negative relationships between pesticides and macroinvertebrate community structure. These eliminations and shifts in macroinvertebrates can affect food resources for specific fish and ultimately impact them as well (Pimentel, 2005). Herbicides, like Atrazine, Metolachlor, and Simazine, also can be detrimental to streams through their impacts on macrophytes and vegetation, which can affect habitat, food, and refuge for many aquatic organisms (Solomon et al., 2008).

1.4.5 Bacteria and Aquatic Health

Fecal bacteria that originate from manure and animal waste in agricultural areas can have impact on the ecological health of a stream. Along with the cloudiness and turbidity that it can create, the decomposition of the organic material can contribute to low dissolved oxygen concentrations as well. The bacteria, pathogens, viruses, and protozoan that are present can all present health risks within a lotic system, especially for humans (USEPA, 2006a). Geldreich and Clarke (1966) observed levels of fecal coliform in fish's intestinal tracts that were reflective of the pollution levels within the stream and indicated that these bacterial microorganisms could in fact survive and multiply in favorable temperatures. Similar results were obtained by Del Rio-Rodriguez and others (1997) who found that E.coli could be established in trout through feeding on infected feed in water at warmer temperatures. These pathogens cannot only be found in the digestive tract of fish, but also in their skin, organs, and muscles, making them a potential risk for human consumption (Fattal et al., 1992).

1.4.6 Water Temperature and Aquatic Health

Temperature and thermal regimes within streams is significant when it comes to aquatic biota and their distributions and physiologies (Wehrly et al., 2003; Poole and Berman, 2001). Not only can temperature affect aquatic organisms directly, but it can also affect them indirectly through its influence on oxygen levels, with colder waters are able to hold more dissolved oxygen (USEPA, 2006b; Garvey et al., 2007). Nutrient toxicity is also influenced, with many contaminates showing an increase in toxicity at higher temperatures (Caissie, 2006). Temperature has also influenced alterations in production and consumption (Loperfido et al., 2009). Additionally, there influence on the system affects rates of nutrient cycling and productivity (Poole and Berman, 2001). Although warmer waters are known to support more aquatic species and diversity (Karr, 1981; Lyons et al., 2009), warmer waters can also lead to detrimental conditions as well.

Fish, through community composition, variations in species richness, and amounts of standing stock, have shown that temperature is significant in determining their distribution and its use for classifying them and their habitats is very valuable in management (Wehrly et al., 2003; Lyons et al., 2009). Water temperature has been observed to have direct effects on fish, including warmer waters associated with increased metabolic rates (Pool and Berman, 2001; MDEQ, 1997) and increased growth rate (Hinz and Wiley, 1998; Caissie, 2006). With both increases in metabolic rates and lower levels of dissolved oxygen, these factors can sometimes lead to unfavorable and harmful conditions (Cassie, 2006). Increases in temperature have also been shown to exceed optimal levels for fish and in effect show declines in the above mentioned rates (Power et al., 1999). Many life events can be triggered by temperatures as well, including fish movement, spawning, and smolt runs (Caissie, 2006; Power et al., 1999). Along with this, habitat and food availability can be influenced by water temperature and its fluctuations. Groundwater supplies are often associated with colder waters with less fluctuation, allowing for refuge from extreme temperatures in both summer and winter (Poole and Berman, 2001; Power et al., 1999). When groundwater is the primary source of flow, creating constant colder thermal conditions, different fish, that are intolerant to warmer waters, are supported in that system (Chu et al., 2008; Lyons et al., 2009; Wehrly et al., 2003). This variation in distribution of fish at varying temperatures has systems commonly classified as cold water, cool water, or warm water streams, with cool water being the most common within Michigan and Wisconsin (Lyons et al., 2009).

Macroinvertebrates are also influenced by temperature in much of the same way as fish. It can affect their habitat around them and increases in temperature have shown increases in their metabolic rates (MDEQ, 1997; Poole and Berman, 2001) and growth rates (Caissie, 2006). Pockets of desired temperatures also create localized refuge for macroinvertebrates in extreme temperatures (Poole and Berman, 2001). Hinz and Wiley (1998) found that several temperature measures, including annual maximum and mean daily summer temperature, were positively correlated with macroinvertebrate biomass and standing stock.

1.4.7 Dissolved Oxygen and Aquatic Health

With oxygen often being a limiting substance for aquatic organisms, like fish (Garvey et al., 2007), dissolved oxygen can be a significant predictor of ecological conditions within a stream (Loperido et al., 2009). The dissolved oxygen within an aquatic system can be influenced by temperature, light, flow, channel morphology, and the organisms within (Loperfido et al., 2009; Garvey et al., 2007; Wang et al., 2002). Although densities of larger organisms seldom reach levels where they can deplete a system of dissolved oxygen, smaller organisms like zebra mussels, macrophytes, and periphyton can be significant in reducing DO levels (Caraco and Cole, 2002; Garvey et al., 2007). Although macrophytes, algae, and periphyton all contribute to creating dissolved oxygen through photosynthesis, they also deplete the system through respiration at times of limited light (Loperfido et al., 2009; Francis-Floyd, 1992). This is why aquatic systems see diurnal fluxes in dissolved oxygen levels, with low levels being reached at night (Francis-Floyd, 1992). During those times in which oxygen levels reach insufficient amounts, fish and macroinvertebrates, especially at earlier life stages, can be impacted, leading to migration or even lethal states of hypoxia (Francis-Floyd, 1992). Other, more specific effects on fish include growth declines (Garvey et al., 2007), altered heart rate, changes in circulation, changes in respiration, and increases in breathing rate (Seager et al., 2000).

Lethal impacts of low dissolved oxygen have been observed along with its correlation with fish IBI and macroinvertebrates (Minnesota Pollution Control Agency, 2003; Garvey et al., 2007).

1.4.8 Physical Habitat, Channel Morphology and Aquatic Health

Woody debris and substrate have also been connected to fish and macroinvertebrate assemblages. Woody debris can affect flows and heterogeneity of depth and habitat along with providing structure and cover for aquatic biota (Roth et al., 1996). Degerman and others (2004) showed that brown trout were more frequent and abundant in sites with more woody debris. Similar results were observed by Schneider and Winemiller (2008) who saw abundance and richness increase in areas with woody debris, as well as macroinvertebrate abundance and community structure.

A diversity of pools, riffles, runs, and bends allows for a diversity of species and organisms that need and rely on them (Rowe et al., 2009; Sullivan et al., 2004). This variation of habitat units supports life cycle stages and special requirements for species including spawning areas and juvenile habitat. These areas also provide refuge for organisms, whether it is for thermal conditions, dissolved oxygen needs, cover, feeding, flow patterns, or extreme conditions

(Caissie, 2006). Areas of channelization and little diverse habitats have been shown to support less diversity in fish assemblages (Sullivan et al., 2004).

1.4.9 Influences and Different Scales

Agriculture can influence streams and their ecological integrity from both the local and catchment scale, requiring a hierarchical approach of thinking when looking at its affects (Rowe et al., 2009; Roth et al., 1996). There have been several studies that have observed local riparian habitat to be a better predictor of biotic integrity, including Lammert and Allan (1999). Rowe and others (2009) also showed these results with a stronger relationship with physical habitat at a small scale. However, these and several other studies recognize the importance of the landscape and catchment area and its ultimate influence on the local area (Infante et al., 2008; Hutchens et al., 2009). Roth and others (1996) especially saw this influence and reported a higher correlation between IBI and the catchment scale with local riparian conditions being a secondary and often an ineffective predictor. These results have also been observed by others as well, including Lyons and others (2000), who observed fish communities to be more influenced by conditions at the larger scale. Although Wang and others (2006) observed local factors explaining fish communities better, these were in catchments of relatively low disturbance. As the local and catchment areas became more disturbed, the more local factors had less of an impact and influence on fish communities. The contradicting results, of the scale at which agriculture has more of a weight on fish, have additionally been seen with macroinvertebrates. Several studies have shown that macroinvertebrates are more commonly influenced by local riparian conditions, yet, some have shown that the watershed scale can also be a significant predictor as well (Flinders et al., 2008). It is apparent that factors at a variety of scales contribute to the conditions of aquatic biota communities within lotic systems and can be influential (Stewart et al., 2001;

Hutchens et al., 2009). For predictive modeling purposes, it is very common that the off stream environmental variables including the types and percentages of different land uses are included in development of a predictor for stream health indicators. However, using this variable in a watershed that mainly dominated with one landuse (e.g. agriculture) can lead to poor predictions (Heitke et al., 2006; Stauffer et al., 2000; Johnson and Host, 2010). In addition, the relationship built base on the percentages of different landuse is insensitive to climatological variables, which has an important influence on stream health. There continues to be a challenge in capturing the confounding interactions among landscape factors that help in forming aquatic ecosystems (Johnson and Host, 2010).

1.5 Methods Linking Environmental Stressors and Ecological Variables

Several approaches have been proposed to study the complex relationships between stream health and human disturbance. Efforts to link disturbances and stream variables to aquatic macroinvertebrates and fish have been made through numerous methods ranging from simple linear models to complex soft computing techniques such as fuzzy logic.

1.5.1 Linear Methods

Simple models such as regression models have been considered reliable where there is a lack of knowledge or limited data (Van Sickle et al., 2004). These models are relatively easy to develop and can help in understanding how changes in independent variables affect the dependent variable. There have been numerous studies demonstrating the use of linear regression models for ecological studies (Van Sickle et al., 2004; Maret et al., 2010). Waite and others (2010) used linear regression when looking at the relationship between environmental variables and macroinvertebrate metrics. Other studies employed multivariate and dimensional approaches like canonical correspondence analysis (CCA) (Pool et al., 2010; Wang et al., 2008) and nonmetric multidimensional scaling (NMS) (Sutela et al., 2010). In addition, other multivariate approaches such as partial least squares regression (PLSR) has advantages compared to general linear regression methods when dealing with ecological processes, due to their ability to handle complex interaction and redundancy among a large array of variables (Carrascal et al., 2009). PLSR is a multivariate method that linearly combines several predictor variables into latent factors that maximize the explained variance in the response variable or variables (Carrascal et al., 2009).

1.5.2 Non-Linear Methods

As it is often the case in ecological processes, relationships are complex and non-linear. To better understand and represent these relationships for purposes including modeling, Non-linear statistical methods can be used. These methods include piecewise linear regression, regression tree analysis (Wang et al., 2007; Weigel and Robertson, 2007), and kernel regression. Maret and others (2010) used piecewise regression to identify thresholds in biotic responses and nutrient concentrations. Wang and others (2007) employed regression tree analysis to analyze linkages between nutrients and aquatic organisms (fish and macroinvertebrates). Kernel regression is another non-linear technique that can be used to create a non-linear and flexible regression function (Hastie et al., 2009). Kernel methods are memory-based and use a localized weighting function along with different local smoothing techniques (Hastie et al., 2009).

1.5.3 Soft-Computing Methods

Other methods that can handle complex problems and are based on “inexact” computing techniques are known as soft computing (Huang et al., 2010). Methods, such as fuzzy logic (Adriaenssens et al., 2006) can provide robust solutions with tolerances to imprecision, uncertainty, and approximation (Huang et al., 2010) and has shown an increasing trend in ecological research (Marchini, 2011).

Fuzzy logic is a computing approach introduced in 1960's by Zadeh (1965) and is a method that deals with approximate reasoning (Huang et al., 2010), which can be data driven or executed through expert knowledge. Fuzzy logic approach can be especially effective when dealing with highly variable, complex, non-linear, and uncertain relationship of variables, commonly observed in ecological studies (Adriaenssens et al., 2004; Chen and Mynett, 2003). In addition, the fuzzy models constructed can often be easily interpreted based on their linguistic nature. Fuzzy logic techniques involve the creation and building of membership functions and inference rules, which can often be the most difficult part involved in fuzzy modeling (Chen and Mynett, 2003) and can often be subjective (Adriaenssens et al., 2004). This is especially true when working with fuzzy logic models based on Mamdani-Assilian methods (Mamdani, 1977). When building a Mamdani-Assilian type model, both the input and output variables are incorporated into membership functions. Whereas in the other approach, Takagi-Sugeno (Takagi and Sugeno, 1985), the input variables are expressed in membership functions, however, the output is expressed through as a linear relationship with the input variables. In addition, fusion of fuzzy logic with other soft computing methods, such as neural networks, can provide adaptive learning techniques that can be very useful when data is already available and a predetermined model structure is not (MathWorks, 2010). The adaptive neural-fuzzy inference system (ANFIS) is an example of the fusion technique.

Applying to environment and ecological processes, fuzzy logic has proven to be a valid method for developing predictive models and decision support tools (Adriaenssens et al., 2004). Fuzzy logic has been used for water quality assessment and classification, such as construction of an index model for surface water quality classification (Icaga, 2007) and the evaluation of watershed conditions and creation of a decision support system (Jensen et al., 2000). Fuzzy logic has also been used to develop predictive models for both abiotic and biotic processes. Using fuzzy logic for flow (Zhang et al., 2009) and flood forecasting (Nayak et al., 2005) have been shown to be reliable. Fuzzy logic techniques have been successfully used for modeling algae, macroinvertebrate, and fish communities. Chen and Mynett (2003) illustrated the use of fuzzy logic developed with the combination of data mining techniques and heuristic knowledge in predicting algal biomass and eutrophication for a lake system. Adriaenssens and others (2006) illustrated that fuzzy models were valuable and practical for predicting the abundance of macroinvertebrate taxa in a river basin based on conductivity, dissolved oxygen, water velocity, and stream width. Predictions of fish assemblages and their physical habitat have also been conducted using fuzzy logic approaches. For example, Mouton and others (2008) demonstrated fuzzy logic application in developing a physical habitat model for European grayling in a river system. Jorde and others (2000) used fuzzy logic to evaluate relationships among floodplain processes, in-stream habitat quality, and fish communities.

1.6 Conservation Practices

There are several conservation and best management practices that are implemented by land owners and organizations that aim to reduce the negative environmental consequences that come from agriculture procedures. These conservation actions, more specifically, help in reducing erosion and sedimentation, nutrient transport, water runoff and surface transport, and impacts to stream morphology and habitat (NRCS, 2006).

1.6.1 Filter Strips

Filter strips are a conservation practice that works similarly to herbaceous riparian buffers. Filter strips are strips of vegetation that is often placed adjacent to streams in the act of removing or reducing contaminates pesticides, and sediments from runoff produced by fields. These strips can also reduce the quantity of overland flow through infiltration and the potential benefits, like in riparian buffers, can increase with width and vegetation used (NRCS, 2006).

1.6.2 Terraces

When trying to reduce runoff, terraces are often used as well. This best management practice consists of a series of earth embankments or ridges that lay across a farmed hillside, which retain runoff and direct it to a desired location. They can hold runoff for moisture and also reduce erosion, which leads to less sediment transport to stream and channels (NRCS, 2006).

1.6.3 Grassed Waterways

Another conservation practice that works by directing water to favorable outlets is grassed waterways. These are vegetated channels through fields that direct runoff in low velocities to stable outlets, while reducing erosion and keeping contaminates and sediments from going directly into streams (NRCS, 2006). Not only can these waterways direct runoff and trap sediments efficiently, but they can also reduce velocities by prolonging infiltration time (Fiener and Auerswald, 2002).

1.6.4 Constructed Wetlands

Sometimes grassed waterways can lead to outlets like constructed wetlands. These low lying ecosystems with hydrophytic vegetation are an additional best management practice used to improve water quality (NRCS, 2006). These wetlands can not only help in improving water quality and regulate flow, but they can also supply important wildlife habitat (USEPA, 2000).

1.6.5 Conservation Tillage

Conservation Tillage is another conservation practice that is known to reduce erosion, improve soil matter content, increase plant available moisture, and reduce soil particulate emissions. This is the practice of managing of plant residue on the soil surface, while limiting disturbances to the soils when applying nutrients and planting crops (NRCS, 2006). There are several types of conservation tillage, including strip till, ridge till, and no till, all being beneficial to lessening the impact on water quality in nearby aquatic systems (USEPA, 2009e).

1.6.6 Rotational Grazing

The managing of grazing animals and their harvest of vegetation is a conservation practice that can improve plant species composition, riparian and watershed function, subsurface and surface water quality and quantity, and soil condition, all while reducing soil erosion (NRCS, 2006). There have been several studies where areas of intense grazing have led to increased sediments and runoff (Wohl and Carline, 1996).

1.6.7 Contour Farming

Contour farming is the practice of using farming operations, tillage ridges, and plantings to alter the transport of runoff from going directly downhill. This technique can reduce sediment and contaminate transport, along with increasing infiltration as well. This practice is especially efficient on sloped land with increased residue cover and roughness, achieved through vegetation (NRCS, 2006).

1.6.8 Strip Cropping

Strip cropping is the act of growing rotational crops in an arrangement of strips across a field in effort to reduce soil erosion from both wind and overland flow. Strips should alternate between erosion-resistant crops and crops that are subject to erosion. Several factors determine the efficiency of this practice including, number of strips, alignment, width, and orientation (NRCS, 2006).

1.6.9 Conservation Reserve Program (Native Grasses)

The Conservation Reserve Program is a voluntary program that contracts and pays farmers to designate, usually cropped land, to be planted with tree, shrubs, grasses, and native prairie species. These actions can reduce erosion, sediments inputs into streams, and improve other water quality conditions (NRCS, 2006).

1.6.10 Conservation Effects Assessment Project (CEAP)

Following the 2002 farm bill and the boost of conservation program funding, the USDA Natural Resources Conservation Service (NRCS) and other USDA agencies established the Conservation Effects Assessment Project (CEAP) in an effort to show the environmental benefits of conservation practices at the national, regional, and watershed level (Maresch et al., 2008; Duriancik et al., 2008; Mausbach and Dedrick, 2004). With the U.S. Federal government spending about 4 billion annually in agricultural conservation programs (Shields et al., 2006), being able to quantify and support these programs is critical. Outcomes of this project are intended to continue to provide insight, understanding, and recommendations for conservation decisions to everyone in the conservation community, from policy makers to the farmers themselves (Duriancik et al., 2008; NRCS, 2010; Maresch et al., 2008). Educating farmers and others on conservation options and effectiveness, has proven to be influential in practice adoption and the move toward more conservation actions. CEAP also can provide other insights into human dimensions of conservation practices and the factors influencing adoption (Maresch et al., 2008). Several programs and conservation techniques are assessed and covered by CEAP, including the Conservation Reserve Program (CRP), Wildlife Habitat Incentives Program (WHIP), Conservation buffers, nutrient management, pest management, and tillage management (Duriancik et al., 2008). There are three main components of CEAP, one being bibliographies, literature reviews, and a scientific workshop. This component was initiated to distinguish what is known about the impacts of conservation practices and what still needs further research and data collection. This includes not only the effects, but also, methods that are used to assess the effects (Duriancik et al., 2008). The second component is watershed assessment studies, which is aimed at providing the effects of conservation practices on water and soil quality at the local level. This can allow for more efficient management and implementation of conservation methods within a watershed (Dureiancik, 2008). Earlier research focused in on environmental impacts at the individual farm or field level, however CEAP recognizes and looks at the off-site effects through the watershed, which are regularly unseen by the people who apply the conservation practice (Maresch et al., 2008). The third component in CEAP is national and regional assessments. Much like the second component, this too looks at the benefits and impacts of conservation practices, but on a larger scale (Duriancik et al., 2008). It can also help in applying or designing new conservation programs for more efficiency at reaching desired outcomes (Maresch et al., 2008; NRCS, 2010). Within the national assessment, CEAP focuses on the effects of conservation practices on four elements including croplands, wetlands, grazing lands, and wildlife. Due to diversity of fish and wildlife resources, agricultural landscapes, and conservation activities from region to region, the wildlife component is split up into four regions, including the Midwest, Southeastern, Northeastern, and Western (Duriancik et al., 2008). Because fish and wildlife are connected to landscapes and the conservation practices, the wildlife element is linked and influenced by the other three elements (NRCS, 2010). Because of this connection and the complexity of biological outcomes, the impacts on fish and wildlife are often difficult to understand and measure. After the compiling of literature reviews, Duriancik and others (2008) identified areas with a lack of research pertaining to and understanding the effects on fish and wildlife from conservation practices. The research that was available often used habitat quality and suitability, which is seen as a reliable predictor of the impacts.

1.7 Modeling

Other environmental effects, from conservation practices in agricultural regions, have been assessed within CEAP through model development and application (Mausbach and Dedrick, 2004). These include AnnGNPS, a watershed model; CONCEPTS, a channel evolution model; REMM, a riparian ecosystem management model; and SWAT, a watershed model (Shields et al., 2006). Although these models can be used to see water quality and quantity effects, limited connection to ecological effects has been shown (Shields et al., 2006). The development of models is often very complex, which has led to gaps in research. The improvement of application and uncertainty of models is a strong focus for CEAP (Maresch et al., 2008). Shields and others (2006) look at the possibilities of using current models and adapting their use for assessing fish or macroinvertebrate habitats. Simulated flow, water quality, channel morphology, and other outcomes, which are all valuable habitat characteristics, could, with further processes, be applied to modeling habitat and ecological conditions.

1.7.1.1 SWAT

The Soil and Water Assessment Tool (SWAT) is a commonly used watershed scale model that can simulate runoff, soil erosion, chemical and sediment transport, along with several other hydrologic processes, in an aim to predict effects from land use and agricultural watersheds. This GIS based and spatially explicit model, developed by the USDA-ARS temple Texas, uses input data, including but not limited to weather, topography, soil, and vegetation. Simulation, along with calibration and validation, then provides outputs for sub-watersheds and reaches on different time scales (Casper et al., 2011; Neitsch et al., 2009; Shields et al., 2006). Several studies have shown the use of SWAT in evaluating hydrologic condition in agriculture areas and its possible impacts on aquatic health. For example, Rossi and others (2008) looked at SWAT's ability to simulate hydrology, pollution discharge from point sources, runoff, and average stream flow, and found it to be an effective tool. The SWAT model's prediction of stream flow was also demonstrated to be more efficient than that of other models in uncalibrated conditions (Heathman et al., 2008). Other studies have shown SWAT's ability to evaluate best management practices and nutrient loading (Sood and Ritter, 2010), sediments, and bacteria (Parajuli et al., 2008). Casper and others (2011) used the SWAT model in efforts to simulate hydrograph data for streams that did not have monitored or gauged data. They found that predicted model outputs such as hydrographs, although significantly sensitive to resolution, could be a viable option in linking to the habitat model, PHABSIM.

1.7.1.2 AnnAGNPS

Another watershed scale model developed by the USDA, used for simulating the long term allocation and load of pollutants is the Annualized Agricultural Non-point Source Model (ANNAGNPS) (Bingner and Locke, 2009). This model, much like SWAT, can simulate runoff, sediment and chemical yields, in-channel transport, and the effects agricultural practices have on them (Shields et al., 2006). Some differences between the two models include; AnnAGNPS uses various sized designated cells, while SWAT uses HRUs; AnnAGNPS has less components and capabilities, like pathogen transport and crop growth; and there are different methods and simulators within the model (Parajuli et al., 2009). Although SWAT is often found to be a more appropriate and efficient model for watersheds (Heathman et al., 2008), Parajuli and others (2009) observed that AnnAGNPS can be used in simulating surface runoff and sediment yield in 'impaired waters' within a CEAP watershed in Kansas. Other studies have observed similar results with AnnAGNPS and it has been used to show how conservation practices can reduce sediment load, including Yuan and others (2008) who observed a 77% and 64% reduction of sediment load when converting crop land to no-till soybeans and no-till cotton respectively.

1.7.1.3 APEX

When trying to simulate environmental and hydrologic impacts from agricultural practices on a whole farm or smaller watershed scale, the Agricultural Policy/Environmental eXtender model, APEX, is a viable option (Williams et al., 2008; Harman et al., 2004). APEX was developed from the EPIC model and can evaluate erosion, economics, water quantity and quality, soil quality, plant competition, weather, and pests, along with routing water, sediments, nutrients, and pesticides (Williams et al., 2008). The outputs from APEX can then be put into SWAT and be further evaluated (Duriancik, 2008). Harmon and others (2004) used APEX to look at Atrazine loss related to different conservation practices on a crop farm and found several practices, including filter strips and constructed wetlands, which reduced the amount lost. Both runoff and sediment yield have also been shown to be reduced through different tillage systems, using a validated and calibrated APEX model (Wang et al., 2008).

1.7.1.4 CONCEPTS

The Conservation Channel Evolution and Pollutant Transport System (CONCEPTS) is a model developed for simulating channel hydraulics, morphology, and sediment transport (Langendoen, 2000; Shields et al., 2006). This model can predict in-channel processes along with riparian processes, including simulating streamside riparian vegetation's effects on stream morphology and pollutant loading (Bingner and Locke, 2009), along with stream bank erosion and channel widening. Outputs from this model can be used within CEAP to see the effects of varying riparian area and stream bank activities. Shield and others (2006) used CONCEPTS to show the effects of deforestation on bed sediment gradation and percent gravel/cobble content. Other studies used CONCEPTS with AnnAGNPS to identify sediment sources and flows through different management and climatic scenarios (Kuhnle et al., 2005).

1.7.1.5 REMM

The earlier mentioned models have all been used and integrated with the Riparian Ecosystem Management Model (REMM) in looking at riparian buffers and there efficiency at reducing sediments and nutrients (Liu et al., 2007; Yuan et al., 2007; Langendoen et al., 2009). REMM, developed by USDA, helps to simulate riparian buffers based on three zones and their effects on, surface and subsurface hydrology; sediment and nutrient transport, removal, and cycling; and buffer conditions, like vegetation type, size, slope, and harvesting (Lowrance et al., 2000; Shields et al., 2006). Yuan and others (2007) used REMM to simulate water and sediment movement and reduction along a riparian buffer, given inputs of sediment and water loading from AnnAGNPS model outputs. REMM was also used with CONCEPTS to show reduction of bank erosion rates with woody vegetation and coarse rooting systems (Langendoen et al., 2009). Other significant uses that can apply to CEAP include large woody debris and leaf litter inputs, which are important habitat components for fish and macroinvertebrates. These too can be obtained with the help of REMM modeling (Shields et al., 2006).

1.7.1.6 PHABSIM

The Physical Simulation Model (PHABSIM) is also a hydraulic model. However, PHABSIM relates changes in stream flow, including surface elevation and velocities, to quantities of physical habitat, based on weighted useable area (WUA). Although PHABSIM cannot relate hydrology directly to biota measures, like abundance or diversity, it can be predictor of available physical habitat through defined hydraulic parameters and habitat suitability criteria (Casper et al., 2011; USGS, 2010). This model uses the same approach as IFIM, Instream Flow Incremental Methodology, using a curve of WUA over discharge, and can be used in developing standards for withdrawals. Applications of PHABSIM have also been used in urban rivers to look at modifications to the stream channel and effluent discharges (Booker and Dunbar, 2004). However, some studies have shown little relations between WUA and population parameters of fish (Nuhfer and Baker, 2004) and that PHABSIM carries a great deal of uncertainty (Williams, 2010).

1.7.1.7 AQUATOX

Although there is little modeling available to predict all the ecological processes within a system, because of the complexity, the U.S. EPA’s AQUATOX model is one of the few that comes close. AQUATOX is a simulation of aquatic systems, including the processes, direct and indirect effects, and relationships between pollutants, nutrients, sediments, dissolved oxygen, periphyton, macroinvertebrates, fish, and many other components. This is done with the use of 450 equations within the model, system linkages with SWAT and EPA-BASINS, and uncertainty analysis (Park et al., 2008). Carleton and others (2009) used AQUATOX to develop nutrient and sediment criteria and thresholds of impairment to lotic systems, using biological indexes. Food web modeling, bio-magnification of PCBs, and the recovery for specific species have also been characterized and simulated through AQUATOX (Rashleigh et al., 2008). The Dominant pathway for PCB’s was also observed in this study showing its course from detritus to daphnia to shad to largemouth bass. Other known AQUATOX applications include the assessments of pesticides, dissolved oxygen, nutrients, sediments, periphyton biomass, and fish dynamics (Park et al., 2008).

INTRODUCTION TO METHODOLOGY AND RESULTS

This thesis is in the form of two research papers that have been submitted to scientific journals. The first paper, entitled "Exploring Relationships between In-Stream Conditions and Ecological Health while Assessing Land-use and Climate Scenarios", aims to employ watershed model results to obtain in-stream flow and water quality data and fill a critical gap in data collection. This data was then used to describe and estimate fish index of biological integrity (IBI) and the percent of intolerant fish individuals through series of models representing ecological health at un-sampled stream reaches within the Saginaw River watershed in Michigan. The ecological health models were then used to predict historical reference conditions for streams under pre-settlement landuse and climate scenarios. The process started by setting up a Soil and Water Assessment tool (SWAT) model to generate high-resolution flow and water quality data for all reaches within the study area. The model was calibrated and validated for stream flow, sediment concentrations, total nitrogen concentrations, nitrate concentrations, and total phosphorus concentrations. Relationships between estimated flow and water quality variables obtained from the watershed model and stream health measures were described using statistical methods and fuzzy logic techniques based on 10-fold cross validation. The best performing model to predict the Index of Biological Integrity (IBI) and percent intolerant individuals was then used to forecast the ecological health measures under pre-settlement conditions. Next, pre-settlement and current scenarios were compared to evaluate the potential impacts that landuse and climate change may have on IBI and the percent of intolerant individuals, as well as demonstrate the applications of linking ecological health to a watershed model.

The second paper, entitled “Study and Model the Effects of Conservation Practices on Stream Health”, aims to complement the first paper by estimating additional ecological health measures using in-stream flow and water quality variables and ultimately study the impacts of agricultural conservation practices on overall stream health measures. This paper, specifically, focuses on connecting in-stream variables to macroinvertebrate measures (Family index of biological integrity, Hilsenhoff Biotic Index, and number of Ephemeroptera, Plecoptera, and Trichoptera taxa). Model setup, calibration, and validation were performed in the same matter as the first paper. Relationships between model outputs and macroinvertebrate measures were described using statistical methods and adaptive neural fuzzy inference system. The best performing model was selected based on the 10-fold cross validation for each macroinvertebrate measure and then used to forecast the potential impacts of agricultural best management practice (BMP) implementation in a large-scale watershed. Three BMPs (no-tillage, residue management, and native grass) were physically represented within the SWAT model. The BMP scenarios were compared through statistical significant analysis and spatial representation of stream segment degradation or improvement in regards to current land use scenario.

EXPLORING RELATIONSHIPS BETWEEN IN-STREAM CONDITIONS AND ECOLOGICAL HEALTH WHILE ASSESSING LAND-USE AND CLIMATE SCENARIOS

Matt Einheuser, A. Pouyan Nejadhashemia, Lizhu Wang, Scott Sowa

1.8 ABSTRACT

Land use and other human disturbances have significant impacts on physicochemical and biological conditions of stream systems. A good understanding of the relationships among those factors will help aquatic resource managers to make wise decisions in protecting un-impacted systems and rehabilitate degraded systems. The objectives of this study were to employ watershed model results to obtain in-stream flow and water quality data and fill a critical gap in data collection. This data was then used to describe and estimate fish index of biological integrity (IBI) and the percent of intolerant fish individuals representing ecological health at un-sampled stream reaches within the Saginaw River watershed. Three methods were used in connecting in-stream variables to fish measures including stepwise linear regression, partial least squares regression, and fuzzy logic. The model developed using fuzzy logic showed the best performance based on the highest R^2 for IBI (R^2 = 0.48) and for percent intolerant fish individuals (R^2 = 0.21) and the lowest mean square error for IBI (MSE=268) and for percent intolerant fish (MSE=275). Overall, average annual flow rate had the strongest correlation with IBI, whereas nutrient concentration showed the largest influence on the percentage of intolerant individuals. Based on the best model identified from the previous section, predictions were made for pre-settlement landuse and climate conditions. Results showed overall significantly higher

IBI and percent intolerant individuals under pre-settlement landuse scenario. This implies that landuse change from pre-settlement to current has profound negative impacts on stream health. Results also showed that including pre-settlement climate factors have strong influences on stream flow and water quality measures that interactively affect stream health as indicated by fish measures. These results suggest that efforts to model historic baseline habitat conditions and to provide context for stream health assessments should include both pre-settlement land use and climate conditions.

1.9 INTRODUCTION

Land use and other anthropogenic activities have profound effects on water resources through complex interactions among specific land practices and lotic systems' structure, process, and function. Agriculture and urbanization have especially strong influence on water quality and quantity of streams and rivers (Dale and Polasky, 2007; Zimmerman et al., 2003; Webb et al., 2008; USGS, 2011). Several of the reported impacts include altered flow (Dale and Polasky, 2007; Shields et al., 2006; Rowe et al., 2009), temperatures (Poole and Berman, 2001; Caissie, 2006; Webb, 2008), and channel morphology. Additionally, those land uses have shown increases in sediment loading (Rowe et al., 2009; Dale and Polasky, 2007; Zimmerman et al., 2003), nutrients levels (Bernot et al., 2006), and pesticide concentrations (Gillium, 2007). Consequently, those influences may impact biological communities, such as fish and macroinvertebrate assemblages, and hence aquatic system health.

A healthy stream can be described in several ways. In general it refers to the condition of the stream when it is flourishing, resilient, sustainable, and maintains its ecological and societal values (Meyer, 1997). Numerous biological monitoring methods measure the ecological condition of a stream and quantify its health. Biological indicators is a commonly accepted technique for assessing how different communities respond to water quality issues and can often be efficient when physical habitat (Flinders et al., 2008) and low levels of pollutants may be otherwise hard to detect (Barbour et al., 1999; Flinders et al., 2008). The most common and widely used biotic indicators in aquatic systems are fish and macroinvertebrate assemblages (MDEQ, 1997; Flinders et al., 2008; Barbour et al., 1999; Infante et al., 2008; Karr, 1991; Wang et al., 2007; Sutela et al., 2010). Fish and macroinvertebrates can react differently, vary in sensitivity to different stressors, and mirror conditions at different scales (Griffith et al., 2009; Lammert and Allan, 1999; Infante et al., 2008; Flinders et al., 2008; Karr, 1981). Fish have several strengths for biological monitoring and being used as indicators. Karr (1981) explained that fish cover many trophic levels, including piscivores, herbivores, omnivores, and insectivores, which allows them to be a good representation of aquatic systems and its interactions. Fishes' long lives and mobility allow for observation of long-term effects at broad scales (Karr, 1981; Babour et al., 1999). Often, when using fish as indicators, there is an aim to capture the biological integrity of the system. Biological integrity, as defined by Karr and Dudley (1981) is the ability of a system to support "a balanced, integrated, adaptive community of organisms having a species composition, diversity, and functional organization comparable to that of natural habitat of the region" (Karr, 1991). Biological integrity involves three main principles; temporal and spatial scales, elements of biodiversity and processes, and that biotic species are important components in a dynamic evolutionary and biogeographic context (Karr, 1999). In addition to biological integrity, ecological integrity also includes biochemical and physical integrities, which refer to the condition of the physical and chemical environment (Karr, 1996).

In this research, we used the index of biological integrity (IBI) of fish as an indicator of stream health, which is widely recognized and used (Lammert and Allan, 1999; Van Sickle et al., 2004; Wang et al., 2008; Weigel and Robertson, 2007). IBI scores are calculated by summarizing multiple metrics. The original 12 fish metrics, developed for the Midwest United States, are broken up into three main components including species richness and composition, trophic composition, and abundance and condition. Within species richness and composition, six metrics focus on quantifying native, benthic, water-column, long-lived, intolerant, and tolerant species. With the trophic composition component, three metrics look at percentages of omnivores, insectivores, and piscivores. The last three metrics, within fish abundance and condition component, quantify number of individuals, hybrids, and those with diseases or abnormalities (Karr, 1991). However, over the years, some modifications to the IBI have been made to properly assess stream conditions for specific regions (Lyons, 1992; Lyons et al., 1996; Roth et al., 1996; MDEQ, 1997; Lammert and Allan, 1999; Wang et al., 2008).

Flow, sediments, and nutrients are among the many factors influencing biotic composition and overall stream health. Numerous studies have linked environment variables of both in-channel and landscape of different scales to fish biological integrity. Van Sickle et al. (2004) used regression model to evaluate interaction among land use and flow variables and fish metrics, and a coefficient of determination of 0.37 was obtained for predicting IBI. They further employed their models to predict IBI values based on future alternative land-use scenarios. Wang et al. (2008) developed a disturbance index for all stream reaches in Michigan based on environmental factors and their relationship with fish measures, including IBI. Relationships among nutrient concentrations and stream fish and macroinvertebrate measures have also been used for the development of nutrient criteria for water resource management (Wang et al., 2007; Weigel and Robertson, 2007; Sutela et al., 2010).

Stream flow regime has strong influence on ecological processes and fish assemblages. Not only can flow be a reflection of stream size (Lyons, 1992), but flow is a driving force that affects temperature, sediment, nutrient, pesticide, dissolved oxygen, and other stream conditions, which in turn affect aquatic organisms (Poff et al., 1997). Flow also affects biota in more direct ways such as habitat availability, wash out, and diluting stressors. In addition, flow is tied to many important life events for some fish, including spawning and recruitment, and flow regime changes can have negative implications on these species behavior and survival (Bunn and Arthington, 2002). For example, changes in flow can directly impact habitat areas and river network connections (Sparks, 1995). In the review of 165 studies, Poff and Zimmerman (2010) reported that 92% studies showed negative responses of ecological metrics to flow alterations. Lammert and Allan (1999) also showed that variation in IBI scores was strongly associated with flow stability.

Sediments impact the function and process of stream systems in several direct and indirect ways. Primary production within a stream can be affected due to sediments limiting light penetration, transporting nutrients, and covering substrate (Wood and Armitage, 1997). Izagirre et al. (2009) observed sediment negative impacts on periphyton soon after siltation. Such an indirect influence of sediments through periphyton can be realized by alteration of habitat structure, reduction of food availability, and changes in dissolved oxygen levels (Griffith et al., 2009). In addition, sediments can directly affect fish through physiological stress, such as sediments clogging gills (Wood and Armitage, 1997) and increasing respiration rate (Zimmerman et al., 2003). All these stresses can further impact fish assemblages by reducing growth rates, causing delayed hatching, increasing in mortality, and affecting natural fish migration (Zimmerman et al., 2003; Wood and Armitage, 1997). Overall community structure and diversity can be influenced by suspended sediments and sediment deposition. Rowe et al. (2009) observed significant declines in fish IBI scores from sites where substrates were dominated by sediments. Meanwhile, effects of sediments have been observed to have more impact on fish in warmer waters (Newcombe and Jensen, 1996).

Sediments often are accompanied by nutrients when they reach the channel. These nutrients, although essential to organisms, can exceed levels that are needed and have negative impacts on the individual, community, and the entire system. In fact, an excess amount of nutrients is one of the top ranked causes for the degradation of US waters during the past decade (USEPA, 2011b). In some situations, where nutrients are low, supplied nutrients from agriculture can have positive effects on aquatic organisms. However, often this is not the case and there is an excess of nutrients in the system (Miltner, 2010). One of the main effects of nitrogen and phosphorus overload in a lotic system is the acceleration of eutrophication (Carpenter et al., 1998). Not only can these increases in periphyton negatively affect dissolved oxygen levels, but also they can affect primary and secondary consumers by influencing food sources and habitat structure (Griffith et al. 2009). High levels of nitrogen and phosphorus have been observed to affect fish assemblages. For example, Wang et al. (2006) showed that total phosphorus and total nitrogen contributed to most of the variation in their observed fish variables, including negative relationships with IBI, number of carnivores, omnivores, and intolerant species. This negative relationship between nutrients and IBI was also reported by the Minnesota Pollution Control Agency (2003) and Miltner (1998).

Along with the above mentioned variables, there are several other variables that have large influences on fish communities and ecological health. These variables include stream morphology, temperature, physical habitat variables, etc. Although these variables are recognized as being very important, considering all of these variables are beyond the scope of this research.

1.9.1 Ecological Modeling

Several approaches have been proposed to study the complex relationships between stream health and human disturbance or environmental stresses. Simple models such as general regression models have been considered reliable where there is a lack of knowledge or limited data (Van Sickle et al., 2004). These models are relatively easy to develop and can help in understanding how changes in independent variables affect the dependent variable. There have been numerous studies demonstrating the use of linear regression models for ecological studies (Van Sickle et al., 2004; Maret et al., 2010; Waite et al., 2010). Other studies have employed multivariate and dimensional approaches like canonical correspondence analysis (Pool et al., 2010; Wang et al., 2008) and nonmetric multidimensional scaling (Sutela et al. 2010). In addition, the use of methods addressing the non-linear nature of the relationships have also been increasing, including the use of regression tree analysis (Weigel and Robertson, 2007), regression neural networks (Sutela et al., 2010), and other non-linear models like piecewise regression (Maret et al., 2010).

One non-linear approach that is particularly suitable for modeling and exploring the relationship of ecological processes is fuzzy logic (Marchini, 2011). Fuzzy logic is a computing approach introduced in 1960’s by Zadeh (1965) and is a method that deals with approximate reasoning (Huang et al., 2010), which can be data driven or executed through expert knowledge.

Fuzzy logic approach can be especially effective when dealing with highly variable, complex, non-linear, and uncertain relationship of variables (Adriaenssens et al., 2004). In addition, the fuzzy models constructed can often be easily interpreted based on their linguistic nature. Applying to environment and ecological processes, fuzzy logic has proven to be a valid method for developing predictive models and decision support tools (Adriaenssens et al., 2004). Fuzzy logic has been used for water quality assessment and classification, such as construction of an index model for surface water quality classification (Icaga, 2007) and the evaluation of watershed conditions and creation of a decision support system (Jensen et al. 2000). Fuzzy logic has also been used to develop predictive models for both abiotic and biotic processes. Using fuzzy logic for flow (Zhang et al., 2009) and flood forecasting (Nayak et al., 2005) have been shown to be reliable. Fuzzy logic techniques have been successfully used for modeling algae, macroinvertebrate, and fish communities. Chen and Mynett (2003) illustrated the use of fuzzy logic developed with the combination of data mining techniques and heuristic knowledge in predicting algal biomass and eutrophication for a lake system. Adriaenssens et al. (2006) illustrated that fuzzy models were valuable and practical for predicting the abundance of macroinvertebrate taxa in a river basin based on conductivity, dissolved oxygen, water velocity, and stream width. Predictions of fish assemblages and their physical habitat have also been conducted using fuzzy logic approaches. For example, Mouton et al. (2008) demonstrated fuzzy logic application in developing a physical habitat model for European grayling in a river system. Jorde et al. (2000) used fuzzy logic to evaluate relationships among floodplain processes, in-stream habitat quality, and fish communities.

1.9.2 Motivation and Objectives

Linking anthropogenic disturbances in watersheds with in-stream physicochemical and biological conditions is challenged by the lacking of high resolution and complete landscape datasets and the selection of modeling techniques that can adequately deal with the complex and non-linear relationships of model components (Wang et al., 2008; Sutela et al., 2010). The Great Lakes regional river database and classification system (GLRRDACS), including all streams and rivers in Michigan, meets such high resolution and complete landscape database needs. This database divides stream networks into confluence-to-confluence stream reaches, with each reach having delineated local and network catchments (Brenden et al., 2008). The local and network catchments provide the basis for attributing landscape-scale information to the streams, which is essential for comprehensive evaluation of watershed conditions affecting biotic or habitat conditions of a reach.

Quantifying linkages among watershed anthropogenic factors and in-stream stressors and biological assemblages to provide management information is focus of many studies. However, most such studies are either simply linked coarse-scale watershed condition measures (e.g., % watershed land use) directly with stream reach-scale biological indicators or modeled fine-scale watershed condition measures (e.g., land use in 30x30 m cells) for only river mouth. Our study incorporated a highly detailed SWAT model (13,831 stream reach watersheds) and connects environmental and ecological variables at an individual homogenous reach scale.

The objectives of this research were to (1) employ the Soil and Water Assessment Tool (SWAT) to generate high resolution flow and water quality data for all reaches within a large watershed so that the SWAT outputs could be estimated for all un-sampled stream reaches; (2) link stream reach scale SWAT estimates to fish measures to identify how much those estimates could explain in overall stream health; (3) describe the relationships among stream health, flow, and water quality using statistical methods and fuzzy logic techniques, and (4) show the applications of SWAT to model beyond sampled locations and forecast conditions by predicting historical reference conditions for streams in the Saginaw River watershed using pre-settlement land-use and climate data.

1.10 METHODOLOGY

1.10.1 Study Area

The Saginaw River watershed, hydrologic unit code (HUC) 040802, is located in the central eastern portion of the lower peninsula of Michigan (Figure 1). This 6-digit HUC Watershed is approximately 1,612,266 ha and is made up of six 8-digit HUC watersheds including the Tittabawassee (04080201), Pine (04080202), Shiawassee (04080203), Flint (04080204), Cass (04080205), and Saginaw (04080206) watersheds that discharge into Lake Huron. The Saginaw River watershed is the largest watershed within Michigan. This watershed has a large amount agricultural land use along with the America's largest contiguous freshwater coastal wetland system (USEPA, 2011c). The basin’s land cover is made up of 42.9% agriculture, 3.7% Rangeland, 24% forest, 14.1% developed, 14.1% wetland, and 1.2% water. Agricultural production within the region in mainly composed of corn, soybean, and pasturelands. The study area is dominated by warm water streams that belong to three Level-3 Ecoregions (USEPA, 2011d): 21% within Northern Lakes and Forests Ecoregion (NLF), 39% within Southern Michigan/Northern Indiana Drift Plains Ecoregion (SMNIDP), and 40% within Huron/Erie Lake Plains Ecoregion (HELP). Segments of the Saginaw River within the Saginaw River watershed, along with its outlet, have been designated as an area of concern with degraded fisheries, fish consumption advisories, loss of recreational values, and contaminated sediments (USEPA, 2011c).

Figure 1. Saginaw River watershed

1.10.2 Biophysical Model

Although field sampled data for quantifying the relationships between in-stream water quality and biotic assemblages is regularly measured, this approach is expensive and cannot be performed for a large-scale study area for a long period due to budget and logistical constraints.

Biophysical models play an important role to estimate water quality where it may otherwise be missing or impractical to collect. For example, Wang et al. (2008) used nutrient estimates from spatially referenced regressions on watershed attributes (SPARROW) model to assess stream health. Casper et al. (2011) used the Soil and Water Assessment tool (SWAT) to simulate flows and then predict fish habitat using Physical Habitat Simulation (PHABSIM) model. In this present study, the SWAT model (ArcSWAT v.2.3.4) developed by the USDA-ARS Temple Texas, was used. SWAT is a spatially explicit watershed scale model that can simulate several hydrologic processes and is commonly used in water resources management (Neitsch et al., 2005). The model can be used to simulate runoff, soil erosion, chemical components, and sediment transport, along with hydrologic processes, in an aim to predict effects of land use in watersheds. Input data to the model include, but are not limited to, weather, topography, soil, and vegetation (Arnold et al., 1998). In addition, both scheduled fertilizer applications and management operations can be included in the SWAT modeling process to allow for detailed simulations of real world processes and conditions along a continuous time scale.

Within SWAT, the watershed being modeled is delineated into subbasins that contain one stream reach and at least one hydrologic response unit (HRU). An HRU is a unit area with unique combination of land use, soil, and slope conditions based on thresholds designated by the user (Neitsch et al., 2005). Once hydrologic balance, sediment loads, and nutrient losses are calculated for each HRU, each variable is then accumulated within subbasins and routed through the stream network. The hydrologic balance is achieved within SWAT by simulating canopy interception, evapotranspiration, precipitation partitioning, snowmelt, surface runoff, lateral subsurface flow, infiltration, redistribution of water through soil profile, and return flow from aquifers (Gassman et al., 2007). A complete and detailed description of the processes within

SWAT can be found in Neitsch et al. (2005). However, here we briefly describe the sediment and nutrient components.

1.10.3 Water Quality Elements of SWAT

In this study, we used SWAT to calculate erosion and sediment yield using the Modified Universal Soil Loss Equation (MUSLE). MUSLE generates erosive energy through precipitation data, as well as simulating yields through surface runoff. In addition to these factors, runoff volume, peak runoff rates, subbasin area, soil surface characteristics, slope characteristics, land cover, and management conditions were also contributed to the calculations (Neitsch et al., 2005). Once these sediments reach the channel for routing, they are controlled and transported through the processes of deposition and degradation (Neitsch et al., 2005).

In general, different forms of nitrogen (N) and phosphorus (P) are simulated as a function of nutrient cycles with losses occurring through crop/plant uptake, surface runoff in their solution phases and by erodible sediments, percolation, lateral subsurface, degradation, and volatilization (Gassman et al., 2007). The supply and demand approach is used in determining plant use of nitrogen and phosphorus as explained by Williams et al. (1984) and Santhi et al. (2006). Both nutrients can be added to soils through fertilization, manure, or residue applications.

More specifically, Nitrogen can be found in three major form including organic, mineral form held by soils, and mineral form in solution. Nitrate (NO3) can be transported through surface runoff, lateral flow, and percolation, as a function of the runoff volume and nitrates concentration in the soil. Organic N, on the other hand, is more connected with sediment particles and is a function of sediment loading. Once the different forms of nitrogen have entered the stream reach, channel routing and transformations are simulated through routines developed for QUAL2E stream water quality model, with organic forms susceptible to settling (Neitsch et al., 2005; Gassman et al. 2007).

Phosphorus is modeled in three major forms, including organic, insoluble mineral and plant-available forms. Dissimilar to nitrogen, phosphorus' mobility is often limited and diffusion acts as its mode for movement through soils. Both organic and mineral forms attach to soil particles and are calculated based on sediment loadings (Neitsch et al., 2005). Once in-stream, phosphorus is routed and transformed through the routines based on QUAL2E, also having organic forms being lost to settling.

1.10.4 Model Setup

SWAT requires many input datasets, including topography, land use, soils type, and climate. For topography data, a 30m resolution USGS National Elevation Dataset (NED) was obtained from the Better Assessment Science Integrating point and Nonpoint Sources (BASINS) software, version 4.0 (BASINS, 2007).

Both current and pre-settlement land-use layers were used for this research. The current condition SWAT model scenario (Current) was built based on the 2009 Cropland Data Layer (CDL) map at 56 m resolution. This was obtained from the National Agriculture Statistics Service within the U.S. Department of Agriculture (USDA) (Johnson and Mueller, 2010). The CDL has crop-specific land cover classifications making it ideal for the study area, which is dominated by agricultural lands. The second SWAT model was developed using pre-settlement land-use data, which was acquired from the Michigan Natural Features Inventory (MNFI) and represents mid-1800's land cover. The land uses and their percentages of total area within the watershed our shown in Table 1.

Table 1. Current and pre-settlement landuse distributions

Landuse	Current % of Area	Pre-settlement % of Area
Water	1.2	0.8
Agriculture	42.9	0
Forest	24	82
Urban	14.1	0
Rangeland	3.7	1.5
Wetland	14.1	15.7

Soil data were obtained from the USDA State Soil Geographic dataset (STATSGO), which are primarily designed for planning, management and monitoring in areas such as river basins. The STATSGO map, at a scale of 1:250,000, is linked to both physical and chemical properties of the soil that are relevant to hydrologic modeling (USDA, 1995).

High resolution stream network data were obtained from the 1:24k National Hydrography Dataset plus (NHDPlus) that was acquired by Michigan Institute for Fisheries Research. In total, the Saginaw River watershed was delineated into 13,831 individual subbasins, each containing individual stream reaches that represented spatial units having homogenous physicochemical, geomorphological, and biological features. Both the stream network and subbasins were predefined layers added to the SWAT model. It is important to point out that this is one of the most comprehensive SWAT models built and is the first to include such detailed subbasins and reaches.

Climatic data for the period of 1990-2008 were obtained from the National Climatic Data Center (NCDC). A total of 21 stations provided precipitation data while 16 stations provided temperature data within and near the watershed. Supplementary meteorological data was generated by SWAT weather generator (Neitsch et al., 2005).

A third SWAT model scenario (Presettle2) was built based on both climate and landuse data from mid-1800s. Climate data used for the pre-settlement scenario was obtained from the Intergovernmental Panel of the Climate Change (IPCC) 20C3M scenario, representing historic conditions (1870-1889). The dataset is available in a GIS format by the Community Climate System Model (CCSM) project (www.ccsm.ucar.edu) and the National Center for Atmospheric Research (NCAR) GIS Initiative. The precipitation and temperature data were downscaled by NCAR to a 4.5 km scale for higher resolution (Hoar and Nychka, 2008). Conversion of observed precipitation and temperature data to historic values was performed based off of the delta method (Fowler et al., 2007; Woznicki et al., 2011) at each weather station. Monthly 20C3M precipitation averages are compared with observed monthly precipitation averages and delta ratios are calculated and applied to daily observed precipitation to obtain daily pre-settlement values. This can be seen in equation 1 below:

$$P_{daily,20C3M} = P_{daily,obs} * \left(\frac{P_{monthly,20C3M}}{P_{monthly,obs}}\right) \quad (1)$$

where, is the daily precipitation for 20C3M, is the daily precipitation of the current observed, is the monthly average precipitation for 20C3M (1870-1889), and is the monthly average precipitation of the current observed (1990- 2008). To calculate daily pre-settlement (20C3M) temperatures, monthly 20C3M temperature averages were compared with observed monthly temperature averages and additive deltas were calculated. These deltas were applied to daily observed maximum and minimum temperature values. This is presented in Equation 2:

$$T_{daily,20C3M} = T_{daily,obs} + \left(T_{monthly,20C3M} - T_{monthly,obs}\right) \quad (2)$$

where,   is the daily temperature for 20C3M,   is the daily temperature of the current observed,   is the monthly average temperature for 20C3M (1870-1889), and   is the monthly average temperature of the current observed (1990- 2008). Mean monthly temperature and precipitation over all the years from all sites representing current and pre-settlement conditions can be seen in the Figure 2.

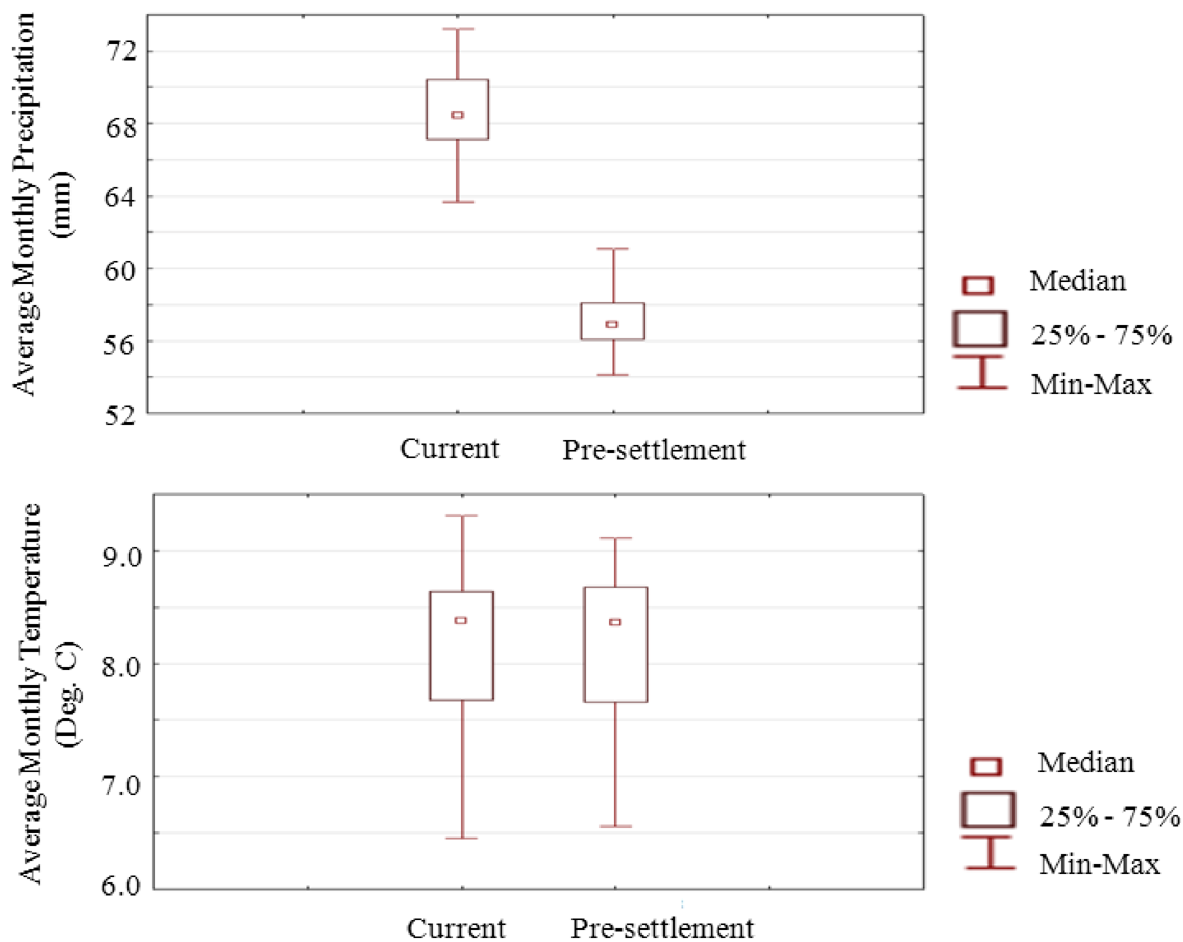

Figure 2. Average monthly (a) precipitation and (b) temperature

Once data were obtained, the model was set up for the Saginaw River watershed and HRUs were defined based on dominant landuse, soil, and slope class (0 to 2%, 2 to 5%, 5 to 10%, >10%) within each subbasin. In addition, localized management operations and crop rotations were applied to the model in replacement of SWATs default values. Further detail on the operations and rotations can be found in Love and Nejadhashemi (2011).

1.10.5 Sensitivity Analysis, Calibration, and Validation

Sensitivity Analysis was performed on the model to identify which input parameters had the most influence on the models output. A Latin Hypercube One-factor-At-a Time (LH-OAT) method, embedded in SWAT, was executed to perform the sensitivity analysis (Van Griensven et al., 2006). The analysis was completed for flow, sediment, nitrogen, and phosphorus, providing a rank of parameters to be explored during the calibration process.

The calibration and validation was performed, using observed flow, sediment, and nutrient data for current conditions. Calibration is the process of adjusting parameters to achieve predictions or outputs that are within the common acceptable range when compared against actual observed data, while reducing uncertainty. The validation is performed next, using the determined parameters from calibration in order to measure model accuracy and credibility (Moriasi et al., 2007). Parameters that were chosen to be involved in the calibration process were identified during sensitivity analysis and also from knowledge of the study area. The model was run from 2000 through 2005 with a two-year-warm-up (2000 - 2001). This period was selected since it coincides with stream water quality observations. The calibration was performed near the outlet (Figure 3) of the watershed with monthly observed data (24 monthly flow samples) from 2002 through 2003. First, flow was calibrated, using observed data from USGS site 04157000. Next, water quality outputs were calibrated individually, including sediments (SED), total phosphorus (TP), nitrate (NO3), and total nitrogen (TN). Observed data for sediment and nutrient calibration was obtained from EPA STORET (090177). The same sites were used to gather data for validation period that covers years 2004 through 2005. The calibration parameters used to calibrate the first SWAT model scenarios were then used for the rest of the scenarios.

Both calibration and validation was evaluated using three statistical measures; Nash-Sutcliffe efficiency (NSE), Percent bias (PBIAS), and coefficient of determination (R^2), to minimize the influence of biased single measures on performance. To determine if calibration and validation was satisfactory or better, we used guidelines proposed by Moriasi et al. (2007).

The NSE statistic determines the goodness-of-fit of the model output by comparing residual variance compared to the observed data variance (Moriasi et al., 2007). The NSE shows how well observed data versus simulated data fits the 1:1 line. NSE can range from - ∞ to 1.0, with 1.0 being a perfect fit and can be calculated based on equation 3, below:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{obs\,mean}\right)^2}\right] \quad (3)$$

where, is the observation for the constituent, is the simulated value for the constituent, is the mean of observed data for the constituent, and n is the total number of observations.

PBIAS is a measure of the average tendency of the simulated data to be larger or smaller than the observed data and has an optimum value of 0.0. Positive and negative values either represent an underestimating or overestimating model, respectively (Gupta et al., 1999; Moriasi et al., 2007). PBIAS can be computed through equation 4:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) * (100)}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)}\right] \quad (4)$$

where, is the observation for the constituent, is the simulated value for the constituent, and n is the total number of observations..

Another measure for goodness-of-fit is R^2, which determines collinearity between simulated and measured data. The coefficient of determination can range from 0 to 1, with higher values indicating a better fit. R^2 is a commonly used statistic; however, drawbacks include its sensitivity to extreme outliers and its absence in addressing whether the model is over predicting or under predicting (Moriasi et al., 2007; Love and Nejadhashemi, 2011). R^2 can be calculated with equation 5:

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y^{obs\,mean}\right) * \left(Y_i^{sim} - Y^{sim\,mean}\right)}{\sqrt{\sum_{i=1}^{n} \left(Y_i^{obs} - Y^{obs\,mean}\right)^2} * \sqrt{\sum_{i=1}^{n} \left(Y_i^{sim} - Y^{sim\,mean}\right)^2}} \right)^2 \quad (5)$$

where is the observation for the constituent, is the simulated value for the constituent, is the mean of observed data for the constituent, is the mean of the simulated data for the constituent, and n is the total number of observations.

1.10.6 Fish Data

Fish data (IBI and percent intolerant fish individuals) were used for 193 sites (Figure 3 and Table 2); including both wadeable and non-wadeable reaches, within the Saginaw River watershed. The data were obtained from the Michigan DNR Fish Collection System and Michigan River Inventory databases (Seelbach and Wiley, 1997). IBI was a main focus, because of its representation of the overall biological health. The percent of intolerant individuals was of interest because of its direct linkage to stressors within the reach, including water quality.

Wadeable sites were sampled along 80 to 960 m stretches, while sample lengths of non-wadeable sites were 1610 m. Fish sampling for these sites was performed between 1982 and 2007 and was collected through electrofishing methods including backpack, tow-barge, and boom units depending on stream size. Sampling was performed by single-pass methods and all measurements were taken in the field. Data were then summarized into indicator variables giving insight into species thermal, feeding, habitat preferences; reproductive strategies; tolerances to stressors; and taxonomic summaries. IBI scores were calculated depending on the temperature of the reach and the size of the rivers. A modified procedure developed by the MDEQ (1997) was used to determine IBI scores for wadeable warmwater streams. Wadable coldwater sites' IBI were calculated based on procedures described by Lyons et al. (1996). For transitional or cool water sites, IBI scores were calculated based on both methods and the higher of the two was obtained. Non-wadeable river IBI scores were calculated based on (Lyons et al., 2001).

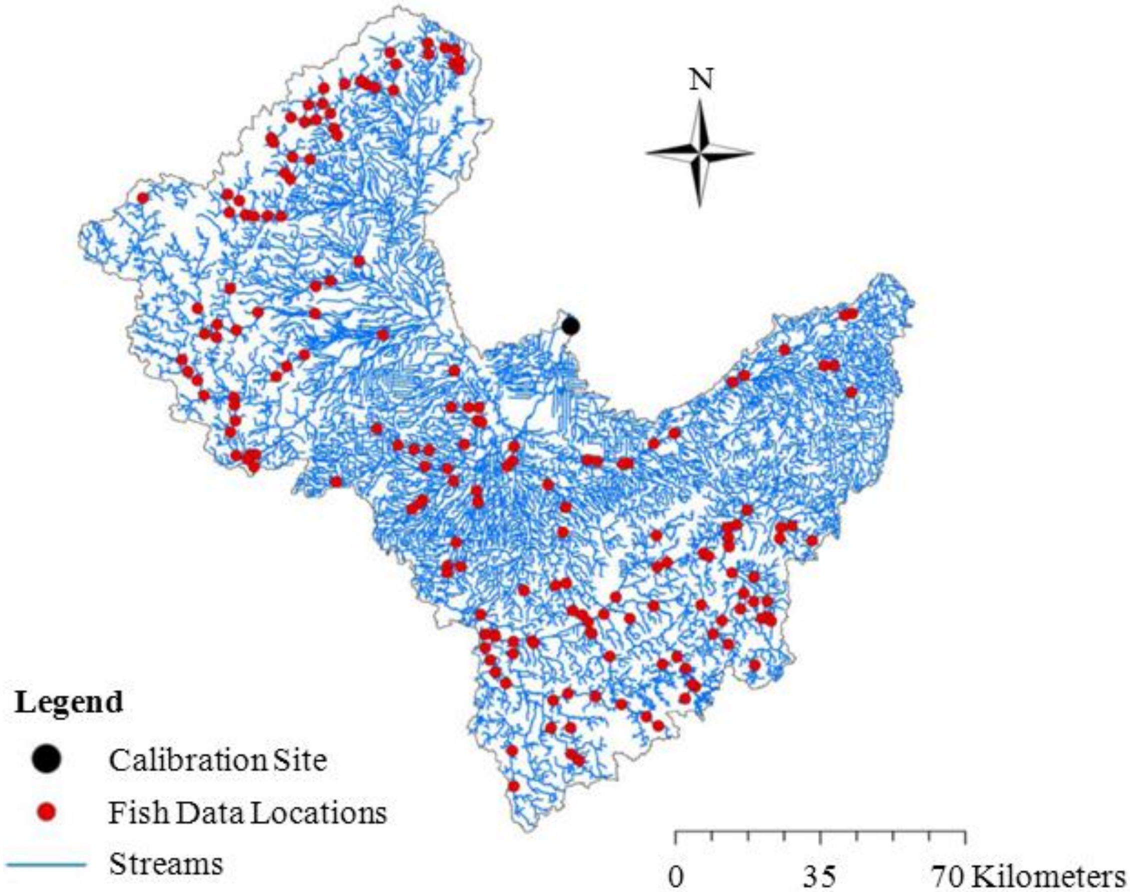

Figure 3. Location of fish data and calibration site. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis

Table 2. Summary of the fish and SWAT output data at the 193 sites

Variable	Description	Min	Max	Mean	Median	SD	Transform
Fish Measures							
IBI	Fish Index of Biotic Integrity	10.0000	54.00000	53.33641	100.0000	22.38380	None
%INTOL	% of intolerant fish individual	0.00000	11.76471	16.68774	95.06173	17.64305	BoxCox
In-stream Variables							
StreamGrad	Stream segment gradient (m/m)	0.00000	0.00130	0.00250	0.06120	0.00490	BoxCox
SFLOW	Average seasonal flow (cms)	0.00165	0.32700	1.71600	24.30000	3.66366	BoxCox
SPercBase	% Average seasonal water yield contributed by groundwater (%)	0.00000	0.05183	0.13089	0.61609	0.15216	BoxCox
SSED	Average seasonal sediment concentration (mg/L)	0.00581	30.70000	36.43494	667.00000	53.05459	BoxCox
SOrgN	Average seasonal organic nitrogen concentration (mg/L)	0.00057	0.18224	0.59930	19.14941	1.59855	BoxCox
SOrgP	Average seasonal organic phosphorus concentration (mg/L)	0.00049	0.04050	0.11592	4.42445	0.34060	BoxCox
SNo3	Average seasonal nitrate concentration (mg/L)	0.00523	0.54439	0.84929	6.73634	1.00706	BoxCox
SNH4	Average seasonal ammonium concentration (mg/L)	0.00081	0.07111	0.30408	16.59655	1.23761	BoxCox
SNo2	Average seasonal nitrite concentration (mg/L)	0.00000	0.03725	0.13397	5.20531	0.41631	BoxCox
SMinP	Average seasonal mineral phosphorus concentration (mg/L)	0.00007	0.06399	0.11104	2.14759	0.19370	BoxCox
SCHLA	Average seasonal Algal biomass (chl - a) concentration (mg/L)	0.00000	0.00028	0.00381	0.13178	0.01436	BoxCox
SCBOD	Average seasonal carbonaceous biochemical oxygen demand concentration (mg/L)	0.00000	0.01094	4.36289	340.83949	26.42415	BoxCox

Table 2 (cont'd)

SDO	Average seasonal dissolved oxygen concentration (mg/L)	16.4736	190.8016	192.8333	424.32580	93.41015	None
STN	Average seasonal total nitrogen concentration (mg/L)	0.05681	1.10778	1.88664	41.74690	3.38894	BoxCox
STP	Average seasonal total phosphorus concentration (mg/L)	0.00141	0.11848	0.22696	6.57204	0.51208	BoxCox
AFLOW	Average annual flow (cms)	0.00280	0.55110	2.34492	28.67000	4.44611	BoxCox
APercBase	% Average annual water yield contributed by groundwater (%)	0.00000	0.33706	0.38045	0.91104	0.32031	BoxCox
ASED	Average annual sediment concentration (mg/L)	0.04302	38.75000	43.78935	805.80000	63.73573	BoxCox
AOrgN	Average annual organic nitrogen concentration (mg/L)	0.00618	0.21370	0.86339	11.42676	1.69843	BoxCox
AOrgP	Average annual organic phosphorus concentration (mg/L)	0.00179	0.04138	0.14052	1.88790	0.26776	BoxCox
ANo3	Average annual nitrate concentration (mg/L)	0.05866	0.66349	1.09702	4.89171	0.98626	BoxCox
ANH4	Average annual ammonium concentration (mg/L)	0.00103	0.12063	0.40243	5.25043	0.71551	BoxCox
ANo2	Average annual nitrite concentration (mg/L)	0.00000	0.04004	0.12701	1.48670	0.23073	BoxCox
AMinP	Average annual mineral phosphorus concentration (mg/L)	0.00024	0.04952	0.10536	0.84138	0.13093	BoxCox
ACHLA	Average annual Algal biomass (chl - a) concentration (mg/L)	0.00000	0.00187	0.01258	0.61265	0.05069	BoxCox
ACBOD	Average annual carbonaceous biochemical oxygen demand concentration (mg/L)	0.00000	0.01513	5.94347	413.85163	34.10963	BoxCox
ADO	Average annual dissolved oxygen concentration (mg/L)	5.65440	188.4474	193.4237	432.68067	103.4019	None

Table 2 (cont'd)

ATN	Average annual total nitrogen concentration (mg/L)	0.14780	1.44068	2.48985	17.03094	2.95091	BoxCox
ATP	Average annual total phosphorus concentration (mg/L)	0.00476	0.11615	0.24588	2.36214	0.36750	BoxCox

1.10.7 Data Analysis

With instream conditions beings the focus of this research, water quality and water quantity outputs for each 13,831 individual reaches were generated from the model. These outputs include flows, sediment loads, nutrient loads, and other water quality measurements (Table 2). Flow data collected from SWAT comprised of flow in cubic meters per second (cms), percent of flow contributed by groundwater (PercBase), along with the stream gradient (StreamGrad) of each segment in meters per meter (m/m). Sediment and nutrient loads simulated were converted to concentrations (mg/L) and included organic nitrogen (OrgN), nitrate (NO3), nitrite (NO2), ammonium (NH4), organic phosphorus (OrgP), and mineral phosphorus (MinP). Total nitrogen (TN) and total phosphorus (TP) was also calculated by summing all their respective forms. Along with nutrients, other water quality outputs included dissolved oxygen (DO), carbonaceous biochemical demand (CBOD), and algal biomass based on chlorophyll A (CHLA). An annual average over the five years (2002-2006) was calculated for all variables. Seasonal averages were also attained to represent conditions during the time of collection of fish data and covered a three month time period of June through August. Once SWAT variables were gathered, data from 193 reaches were extracted to link with fish community data at those specific stretches where it was available.

Three methods were evaluated and compared in this study in order to identify the best model that can be used to predict ecological condition of a stream (IBI and percent intolerant fish individuals) using water quality and quantity measures. These methods include stepwise linear regression, partial least squares regression (PLSR), and fuzzy logic. To address some of the assumptions for two of the methods (stepwise and PLSR), normality was tested among all the variables with the Shapiro-Wilk and Kolmogorov-Smirnov tests. In several cases, normality was not achieved and transformations were made to best address this through the Box-Cox transformation technique (Box and Cox, 1964). Box-Cox transformation can be used to find potential nonlinear transformation based on a log-likelihood function (SAS/STAT, 2010).

Ten-fold cross validation was performed to validate the models, compare methods, prevent over fitting, and select the best model (Mahmood and Khan, 2009). To do so, we divided the 193 stream reaches with fish data into 10 approximately equal size mutually exclusive subsets. This was performed through random sampling within R statistical software v. 2.12.1. Once subsets were created, models can be trained based on 9 subsets and validated with the other subset. This is performed 10 times, with each subset being used for validation once. Following all analysis, the procedure for choosing the best method was conducted by comparing the mean square error (MSE) and R^2 based on validations. For each analysis method (Stepwise, PLSR, Fuzzy), the MSE and R^2 of the test data is averaged among the 10 models. These measurements are compared among methods and the method with the lowest average MSE and highest average R^2 was identified as the best model. All models within each method will be tested against validation datasets to identify the best model within each method using the criteria described above.

1.10.7.1 Stepwise linear regression

Stepwise linear regression was first performed within SAS 9.2 to identify and model the SWAT output variables that have significant influence on the two fish measures. Simple models such as regression models have been considered reliable where there is a lack of knowledge or limited data (Van Sickle et al., 2004). At the same the time, linear stepwise regression is an easy approach. In this modified forward-selection process, variables are added one by one, depending on the significance of the F statistic. After a variable has been added, the stepwise process goes back and looks at the significances of the other variables already in the model and may remove them (SAS/STAT, 2010). Once variables were selected, a test to detect collinearity among variables was performed. We used a conservative variance inflation factor threshold of two (VIF<2) (Maret et al., 2010) to identify whether or not to further investigate. This further investigation was based on eigenvalues approaching zero (Morris et al., 1986) and condition index values with high proportions of variation. If collinearity exists, the variable would be removed and stepwise would be rerun. Furthermore, residuals were checked for normality to satisfy the assumption of a normal distribution of the error.

1.10.7.2 Partial Least Squares Regression

Partial Least squares regression (PLSR) was also performed to identify significant variables that have strong influence on fish measures using STATISTICA (STATSoft, 2011). PLSR was performed because of advantages compared to general linear regression when dealing with ecological processes, including its ability to deal with large array of variables and to handle the complex interaction and redundancy among them (Carrascal et al., 2009). PLSR is a multivariate method that linearly combines several predictor variables into latent factors that maximize the explained variance in the response variable or variables (Carrascal et al., 2009). Because it is an extension of multiple linear regression, similar assumptions with stepwise were made and the transformed data were used in this analysis. Although, it is an option with PLSR to look at how a set of predictor variables affect a set of response variables, within this study we looked at each response variable independently. This was done so that comparison among the methods could be made, due to the fact that the other methods could only handle one response variable at a time.

1.10.7.3 Fuzzy Logic

Fuzzy logic was performed within MATLAB R2009A with Fuzzy Logic Toolbox and was choose as an alternative method that could deal with complexity, non-linearity, and uncertainty of the data that is commonly encountered in ecological studies (Chen and Mynett, 2003). When building the fuzzy logic models, the first step was to determine what variables to be included in the model. This can often be a common problem in ecological modeling and can be achieved through data-driven approaches or expert knowledge (Adriaenssens et al., 2004). In order to better describe the complexity/non-linear relationships among the variables, Spearman’s Rho correlations were performed within STATISTICA (STATSoft, 2011). Spearman's Rho rank correlation is a nonparametric approach for correlating two sets of measurements by their rank and is not limited by the assumption of a normal distribution, like when computing Pearson product-moment correlation. Based on this results, all variables showing a significant correlation ($p<0.05$) to IBI and percent intolerant individuals were considered to be incorporated in the fuzzy logic analysis. In the next step, pairs of variables that exhibited a high correlation coefficient ($r >0.7$) (Waite et al., 2010) were identified and the one with the weakest correlation with the fish measure were removed (Wang et al., 2008). Following construction of the ranked variables from the strongest correlated to fish measures to the weakest, a cutoff value $r>0.18$ was assigned. This value allowed for inclusion of multiple variables, yet still kept the number of variables to be included in the fuzzy logic model at a manageable size. This can be an issue in fuzzy logic analysis, because rule sets can exponentially increase with the addition of input variables (Chen and Mynett, 2003).

The creation and building of membership functions and inference rules can often be the most difficult part involved in fuzzy modeling (Chen and Mynett, 2003) and can often be subjective (Adriaenssens et al., 2004). This is especially true when working with fuzzy logic models based on Mamdani-Assilian methods (Mamdani, 1977). When building a Mamdani-Assilian type model, both the input and output variables are incorporated into membership functions. The membership construction approach in this study was driven by scatter plots of input and output variables, which had already been classified based on expert knowledge. For example, IBI was broke into membership functions based on IBI score ratings (Karr et al., 1986; Lyons, 1992). Natural breaks and clusters within the data lead to a starting point for the range and shape of the membership functions. Next, adjustments were made based on trial-and-error methods in order to optimize the model, which are often the only possible way (Adriaenssens et al., 2004). In addition, fuzzy inference rules were also based on both the data and heuristic knowledge. Once values were transformed (fuzzification) into linguistic terms, combinations were identified along with their respective outputs. The most observed combinations for each outcome helped in determining if-then rules.

1.10.8 Predictions

After selection of the best model for predictions of IBI and percent intolerant fish individuals, the models were then used with the outputs from the different scenarios within the SWAT model. Two pre-settlement scenarios were investigated; 1) with pre-settlement landuse and 2) with pre-settlement landuse and pre-settlement climate. Predictions from all three scenarios (current, pre-settlement landuse, pre-settlement landuse and climate) were then compared through paired-t test and further investigation.

1.11 RESULTS

1.11.1 Calibration and Validation

The SWAT model was calibrated and validated for flow, sediments, total phosphorus, nitrate, and total nitrogen. All components were successfully calibrated and validated based on NSE of 0.50 or greater recommended by Moriasi et al. (2007). PBIAS also showed a satisfactory or better performance with values within the range of ±25 for flow, ±55 for sediment, and ±70 for nutrients. In addition, $R^2 \geq 0.5$ has been used in other studies such as Nejadhashemi et al. (2008) and Chinkuyu et al. (2004) as one of the criteria to evaluate a satisfactory model performance. Model performances along with calibration and validation results are presented in Table 3.

Table 3. Calibration and validation results

Parameter	Performance measure	Calibration Period	Validation Period	Combined
Flow	NSE	0.72	0.85	0.81
	PBIAS(%)	6.02	-1.75	1.48
	R^2	0.74	0.85	0.82
Sediment	NSE	0.71	0.81	0.8
	PBIAS(%)	-10.27	0.86	-3.02
	R^2	0.71	0.92	0.88
Total Phosphorus	NSE	0.64	0.67	0.67
	PBIAS(%)	18.08	-22.68	-6.87
	R^2	0.68	0.71	0.7
Nitrate	NSE	0.76	0.82	0.8
	PBIAS(%)	22.7	12.87	17.01
	R^2	0.86	0.83	0.83
Total Nitrogen	NSE	0.5	0.67	0.62
	PBIAS(%)	47.34	38.73	42.4
	R^2	0.87	0.84	0.84

1.11.2 Model Results

Once the SWAT model was calibrated and outputs were generated, all three methods of analyses, including stepwise linear regression, partial least squares regression, and fuzzy logic were used to explore the relationships among variables and to find the best overall predictive models for IBI and percent intolerant percent intolerant fish individuals.

1.11.2.1 Stepwise linear regression

When performing stepwise linear regression, AFLOW (average annual flow), ANO2 (average annual nitrite concentration), ANO3 (average annual nitrate concentration), ANH4 (average annual ammonium concentration), SFLOW (average seasonal flow for months of June through August) were identified as significant predictors for all 10 models for IBI (Table 8). Among these variables, flow was the most influential, by consistently provided the highest partial R^2. Half of the models chose AFLOW, while the other half chose SFLOW as a predictor of IBI. Since collecting flow data for long periods is costly, we decided to examine the replacement of seasonal flow instead of annual flow. Therefore, as a test, annual flow was manually removed from the dataset before performing the stepwise regression. When compared, they performed very similarly based on MSE and R^2. All other variables that were identified by stepwise were average annual concentrations of nitrogen, including NO3, NO2, and NH4. Overall, through stepwise linear regression models, in-stream variables from SWAT explained on average 32% of the variation in IBI.

Majority of models created to predict the percent intolerant individuals by stepwise (Table 9) identified average annual total phosphorus concentration as the most influential variable, with the largest partial R^2 in 7 out of the 10 models. As for other variables identified, this differed based on the 10-fold datasets and included; ANH4 (average annual ammonium concentration), ASED (average annual sediment concentration), ANO3 (average annual nitrate concentrations), SNO2 (average seasonal nitrite concentrations), SFLOW (average seasonal flow). Four models identified seasonal flows, three identified average annual sediment concentration, and three identified annual nitrate concentrations as significant parameters. Overall, only 12% of variation in percent intolerant individuals was explained using stepwise regression method.

1.11.2.2 Partial Least Squares Regression

By using stepwise linear regression, many variables were removed to reduce or eliminate the collinearity and therefore, the interaction among certain variables may have not been captured. To address this, PLSR was performed. In all models, no more than two significant principal components were identified (Table 10). Within these components, seasonal and annual flows were the most important variables recognized through PLSR. Behind flow, all other water quality variables showed fairly equal importance, with none largely standing out. This shows the high collinearity and redundancy among the variables. Although variables were similar in importance, annual organic forms of nitrogen and phosphorus were found to be the next most important variables. Overall, the average R^2 for PLSR models built for IBI was nearly the same as stepwise, at 0.32. Similarly, PLSR models created for percent intolerant fish individuals (Table 11) identified important variables similar to those selected in stepwise procedure. Although, all variables were comparable in importance, average annual total phosphorus and average annual organic phosphorus concentrations were the most important. On average PLSR model explained 14% of the proportion of variation in percent intolerant individuals when validated, being slightly higher than that of stepwise.

1.11.2.3 Fuzzy Logic

Although, the above methods provided insightful results that were consistent with other studies, it is recognized that the assumption of linear relationships may not be the most accurate. To explore this, fuzzy logic models were built based on variables identified through spearman rank correlations (Table 14, Table 12). The variables identified and used in fuzzy logic for explaining IBI, from most correlated to least correlated, were AFLOW (average annual flow), AOrgP (average annual organic phosphorus, SNO2 (average seasonal nitrite), SNO3 (average seasonal nitrate), and StreamGrad (stream gradient). Models that were built, assuming non-linear relationships, on average had an R^2 of 0.44 when validated, which explained an additional 12% of the variation in IBI than that of stepwise linear regression and PLSR methods. Fuzzy logic also improved MSE values, which were 17% and 15% lower than stepwise and PLSR, respectively. The same improvement of model performance was observed when building fuzzy logic models for the percent intolerant fish (Table 13). The variables identified and used for the models, from the highest correlated to the lowest, included, AOrgP (average annual organic phosphorus), ANO2 (average annual nitrite), AFLOW (average annual flow), and ACHLA (average annual chlorophyll-a). On average fuzzy logic models improved R^2 to 0.25, which is almost 78% improvement than other methods. In addition, MSE was also found to be lower in fuzzy logic than the other models (Table 4).

1.11.3 Model Interpretations and Selection

Overall, all the methods described above consistently revealed significant relations between average annual flow and both measures of stream health. Average annual flow was positively correlated with IBI. This positive relation could result from the fact that, reaches with smaller average annual flows are more sensitive to extreme weather conditions and the resulting fluctuations in habitat have been shown to be negatively related to fish community metrics and IBI (Poff and Zimmerman, 2010; Lammert and Allan, 1999). However, this positive relation could also be explained by the significant correlation of average annual flow and stream size and in turn how species richness has been shown to increase with stream size (Lyons, 1992). Given that so many instream habitat variables change predictably with stream size (Vannote et al., 1980) it is impossible to determine with our set of predictor variables, which interpretation is correct. Adding a measure of stream size and instream physical habitat variables along with other measures of watershed physiographic characteristics would likely provide the necessary context to reveal the relative residual effects of flow and water quality on IBI. However, these variables were not included in the scope of our project, but are being investigated in a current study building upon our research.

IBI was negatively associated with nitrogen and phosphorus concentrations. This result is consistent with several other studies including Wang et al. (2006) who showed total nitrogen and total phosphorus explaining a high amount of variation in fish measures, including a negative correlation with IBI. In addition, all three methods identified phosphorus concentrations as being significant and of great influence on percent intolerant individuals. This negative correlation among total phosphorus and intolerant fishes is consistent with the fact that a species is classified as intolerant based on its sensitivity to environmental degradation and poor water quality (Lyons, 1992). Once again, similar results were observed by Wang et al. (2006) between total phosphorus and percent intolerant species.

Based on the results (Table 4), fuzzy logic models showed greater explanatory and predictive performance, for both IBI and percent intolerant fishes. The final fuzzy logic model chose for predicting IBI (from the 10 fuzzy logic model developed for the cross validation) had an average R^2 among all validation subsets of 0.48 and a MSE of 268. The final fuzzy logic model performance for the prediction of percent intolerant had an average R^2 of 0.21 and a MSE of 275 among all validation subsets. The best models for all methods and the variables associated with those models are presented in Table 5.

Table 4. Average MSE and R^2 amongst models from 10-fold cross validation

Method	IBI		% Intolerant	
	Average Test MSE	Average Test R^2	Average Test MSE	Average Test R^2
Stepwise Linear Regression	363.9	0.32	334.2	0.12
PLS Regression	358.4	0.32	331.7	0.14
Fuzzy Logic	303.2	0.44	261.3	0.25

Table 5. Best performing models for all methods

Method	Response Variable	Predictor Variables	R^2	MSE
Stepwise	IBI	TSFlow LANo2	0.36	326.8
PLSR	IBI	Component 1 Component 2	.34	335.0
Fuzzy Logic	IBI	AFlow AOrgP SNo2 SNo3 StreamGrad	.48	268
Stepwise	%INTOL	TATP TASED LSNo2	.20	299.8
PLSR	%INTOL	Component 1 Component 2	.16	311.7
Fuzzy Logic	%INTOL	AOrgP ANo2 Aflow ACHLA	.21	274.6

1.11.4 Evaluation of Landuse and Climate Changes Impacts on Stream Health

1.11.4.1 Impacts on IBI and percent intolerant individuals classes

The best fuzzy logic models choose in the previous section were used to predict the IBI and percent intolerant fishes of each stream reach within the Saginaw River watershed under different climate and landuse scenarios. As it was described earlier, the current condition scenario evaluates basin-wide stream health under 2009 CDL landuse information. The second scenario (Presettle1) consists of mid-1800 pre-settlement landuse data, while current climate information was used. This scenario allows evaluation of landuse change effects to stream health without considering climate variability. In addition, the last scenario (Presettle2) considered both climate and landuse information from mid-1800. To further analyze and graphically present the results, IBI scores were divided into five classes as very poor (0-19), poor (20-29), fair (30-49), good (50-64), and excellent (65-100) (Lyons, 1992). Because the percent intolerant fish variable does not have a rating system in connection to stream health, we used the classes adopted from the fuzzy logic model (class I ($x=0$), class II ($0<x\leq10$), class III ($10<x\leq20$), class IV ($20<x\leq40$), and class V ($40<x\leq100$). We evaluated the impacts of landuse and climate changes on fish metrics for stream reaches with fish data(Figures 4-5) and those without fish data, basin-wide (Figures 8-9).

Total reach lengths within different IBI score and rating classes is presented in Figure 4 for the 193 fish sampling locations. As shown in Figure 4 for the current IBI conditions, 40% of the total stream length was classified as good, 28% as fair, 22% as excellent, 8% as poor, and 1% as very poor. For the Presettle1, 44% of the total stream length was classified as good, 36% as fair, 19% as excellent, 1% as poor, and 0% as very poor. For the Presettle2, 48% stream length was classified as good, 33% as fair, 13% as excellent, 6% as poor, and 0% as very poor. Although the distributions for each scenario are very similar, the pre-settlement scenarios showed decreases in lengths of less poor, very poor, and excellent classes and increases in fair and good classes. The result of pre-settlement conditions falling into poor and fair categories is surprising in that we expect these sites to be in undisturbed and good conditions. This is a reflection of the limitation of the model and how flows large influence within the model can lead to possible misinterpretation. In addition, further examination of reaches that had unclear trend between current and pre-settlement conditions showed that the land uses had been converted from forestlands to wetlands during the two study periods. This likely contributed to the higher

IBI scores observed. Total reach lengths within different percent intolerant fish classes is presented in Figure 5 for the 193 fish sampling locations. As shown in Figure 5, the model did not predict any reach in either class I ($x=0$) or class V ($40<x\leq100$). However, the percentages of total stream length within class IV ($20<x\leq40$) increased by 25% for Presettle1 and 15% for Presettle2 from Current conditions. It is apparent that incorporating pre-settlement climate data into the model mitigates the changes from Current scenario when compared to Presettle1.

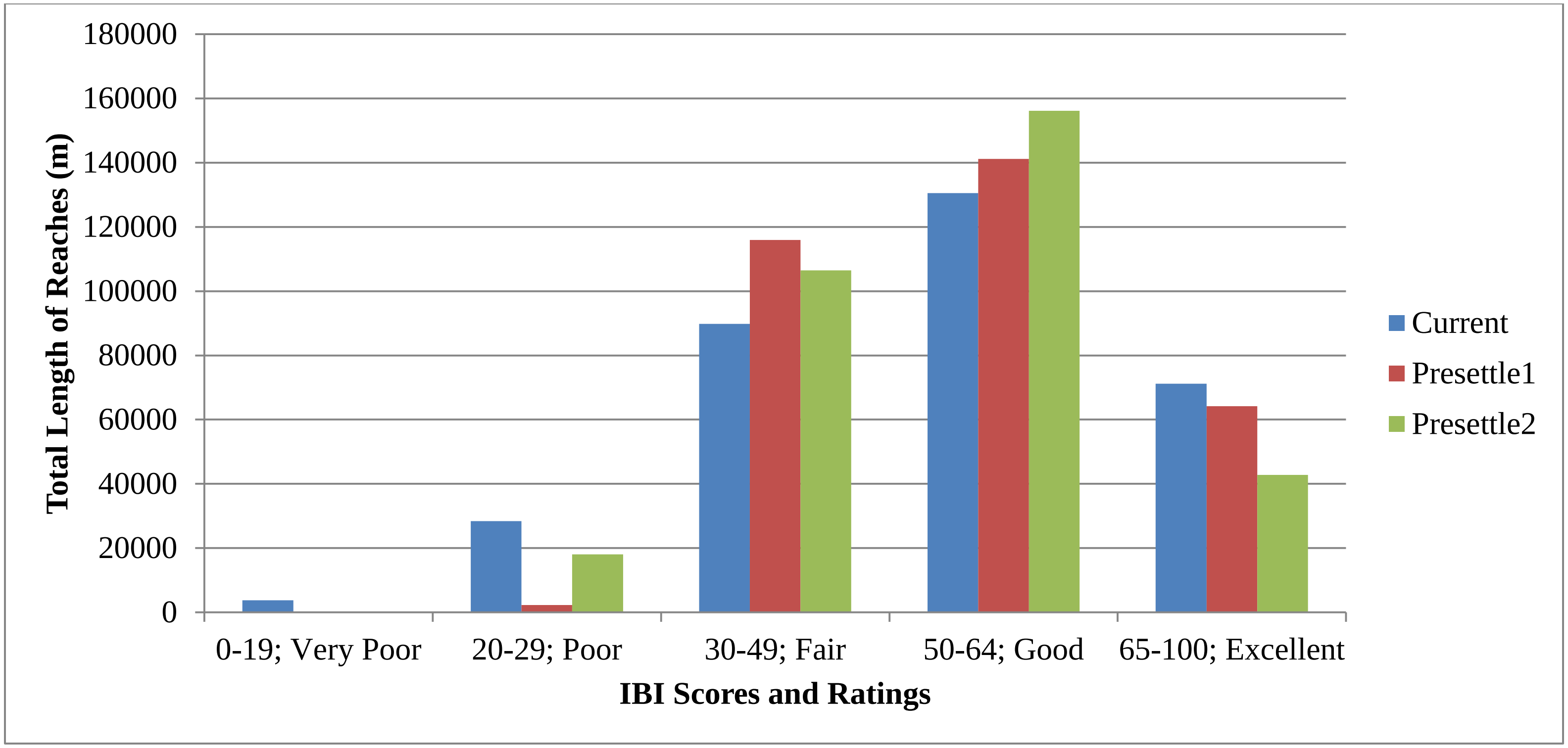

Figure 4. IBI scores and total reach lengths among 193 fish locations

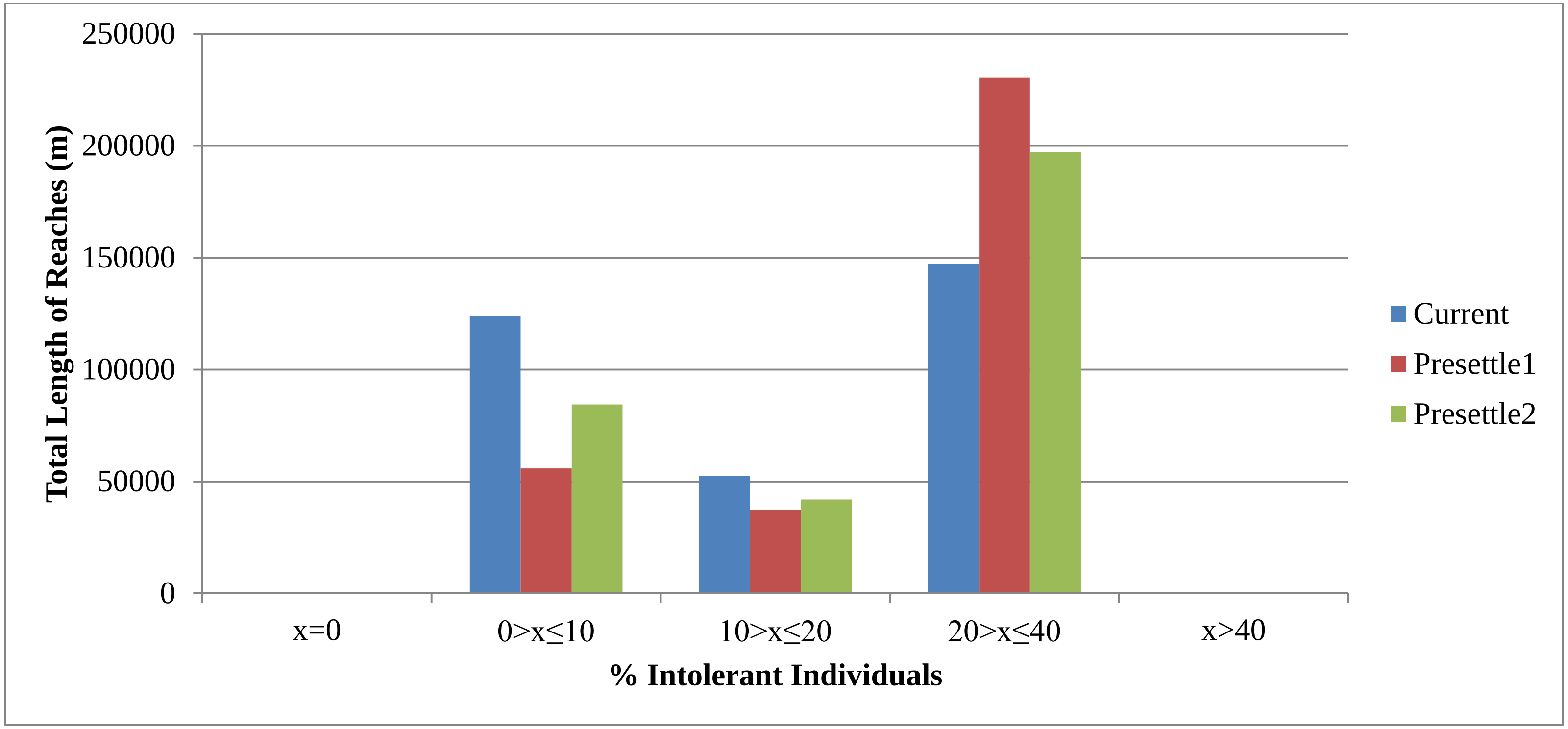

Figure 5. Percent intolerant individuals and total reach lengths among 193 fish locations

Total reach lengths within different IBI score and rating classes are presented in Figure 6 for the entire basin (watershed). Overall, at the basin scale, a similar trend was observed to the 193 fish sampling sites with the exception of the “good” class when incorporating historic climate data (Presettle2). Results indicated a reduction of the total reach length classified as good by 4% when compared to Presettle1. Meanwhile, total reach lengths within different percent intolerant individuals classes is presented in Figure 7 for the entire watershed. Once again, similar trends were observed to the 193 fish sampling sites with the exception of the class V under Current scenario. As it was previously discussed, the majority of the areas classified as V are currently covered by wetlands. The conversion from forested lands (pre-settlement) to wetlands (current) could explain the models prediction of expansion to class V under the current conditions. This provides insight into the potential benefits of wetlands and their ability to reduce nutrients that provide better conditions to fish and overall stream health. The full impact of this particular landuse change however cannot be fully interpreted from the models based on the numerous other factors that would be altered as well that were not included within this study.

Overall, the results showed increases in IBI and percent intolerant individuals under pre-settlement conditions. This can be expected since pre-settlement scenarios represent less human disturbance. Results also support the importance of including historic precipitation and temperatures data in in evaluating land-use change impacts on aquatic communities.

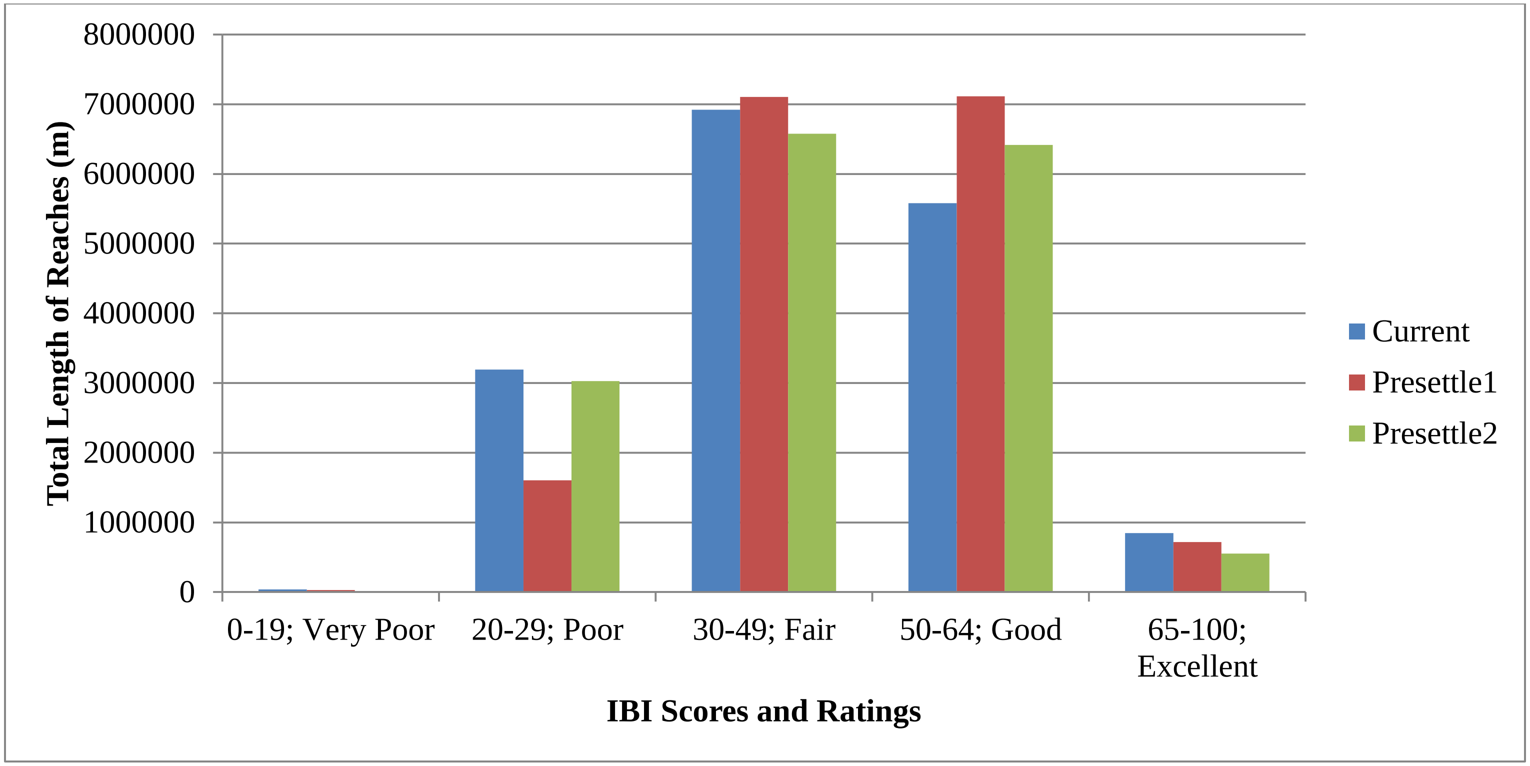

Figure 6. IBI scores and total reach lengths within Saginaw River watershed

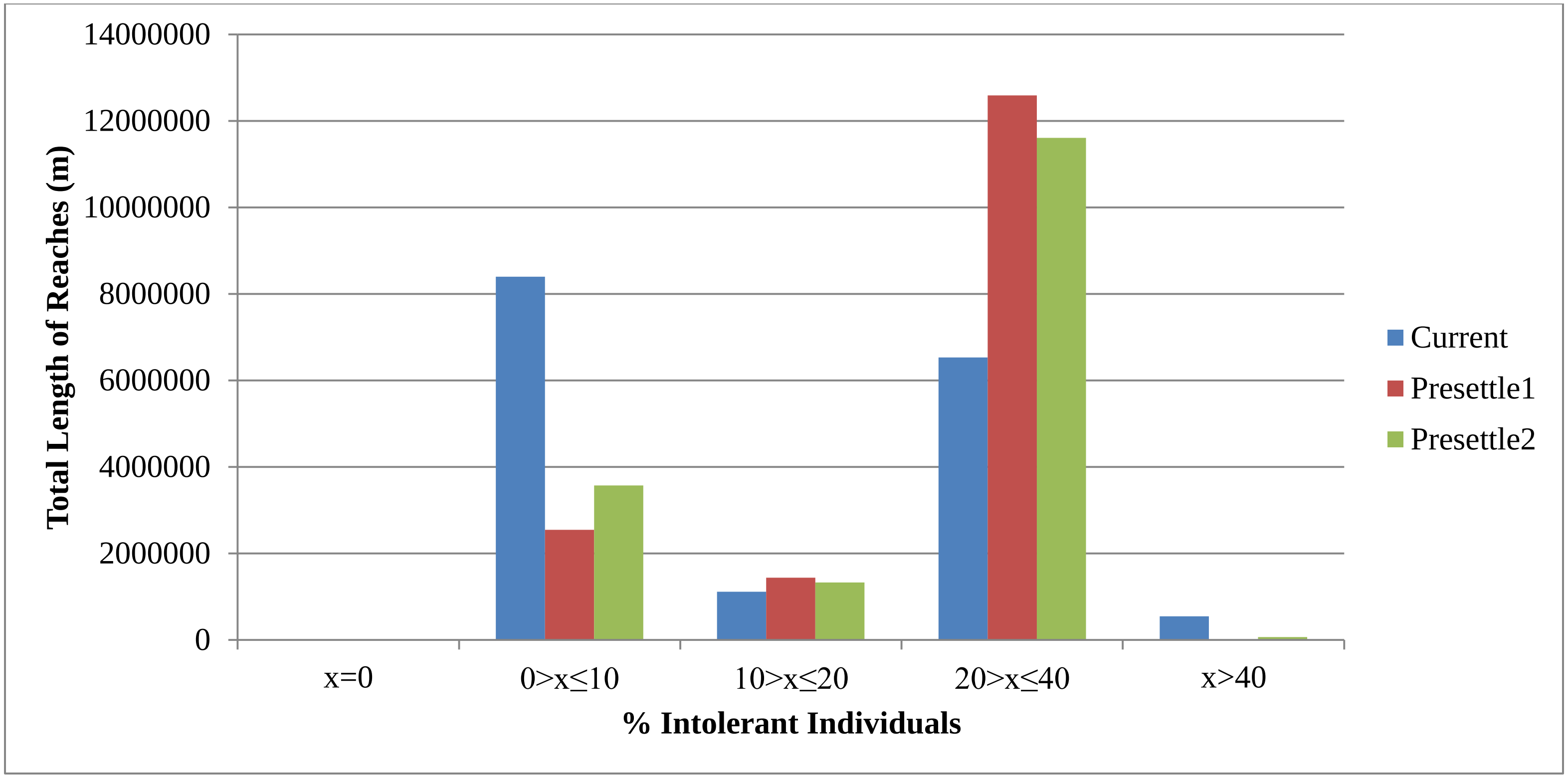

Figure 7. Percent intolerant individuals and total reach lengths within Saginaw River watershed

1.11.4.2 Statistical significance analysis

Paired t-tests were performed to evaluate if and how landuse and climate factors affected current predictor variables and ultimately IBI and percent intolerant at the basin-scale. Before starting the analysis, it is important to provide some evidences about the fuzzy logic models performance under Current condition. This was done by comparing our predicted fish measures versus the actual observed values. The predicted IBI did not show a significant difference (p-value = 0.034) from actual IBI observations at 1% level of significance. In addition, the percent of intolerant individuals predicted from the fuzzy logic model did not a show a significant difference (p-value = 0.69) from actual percentages observed values. This gives further insight into the reliability of the fuzzy logic models' predictions.

Next, the impacts of landuse and climate changes on 193 fish data sampling locations were evaluated. Results showed no significant changes in index of biological integrity from either of the pre-settlement conditions to current conditions. These insignificant changes could be because all water quality variables within the model changed in a manner that predicts decreases in IBI. Meanwhile, flow, the most influential variable within the IBI model, showed significant increases with a corresponding predicted increase in IBI, which may counteract the predicted decline from the water quality variables. However, a significant change ($p < .01$) was observed in IBI when comparing the two pre-settlement scenarios, implying the effects of climate change (Presettle1 to Presettle2). This resulted in a 4% decrease in the overall average IBI with the addition of pre-settlement climate. The significant changes between these scenarios resulted from the significant reduction in flow (due to precipitation reduction-Figure 2) while mixed changes in water quality variables were observed. Once again, here we see a limitation of the model where reduction in flow leads to a reduction in IBI. When the model was built, flows inclusion was more than likely based on its reflection of stream size, with lower values correlating with lower IBI scores. With flow reductions occurring between scenarios, IBI predictions based on the models show reductions as well. Further inclusion of other variables, such as stream size, can mitigate this limitation in the model.

Percent intolerant individuals on the other hand showed significant decreases from pre-settlement scenarios (Presettle1 and Presettle2) to the current scenario, with no significant change between the two pre-settlement scenarios. As it was discussed earlier, AOrgP and ANO2 were found to be the most influential variables for predicting percent intolerant individuals. Therefore, the significant reduction to percent intolerant individuals resulted from the SWAT model predicted increases in AOrgP and ANO2 (between 65 to 73 and 74 to 82 percent in average concentration, respectively). For the last scenario (Presettle1 and Presettle2), AOrgP and ANO2 were significantly increased (average values were raised less than 50%). Meanwhile, ACHLA (the fourth ranked variable for percent intolerant individuals) was significantly increased while the average value was raised by 350%. The counteracting nature of these variables may explain the insignificant change in percent intolerant individuals between the two pre-settlement scenarios.

In order to predict the impacts of land-use and climate changes for stream reaches having no fish observations, the above analysis were replicated for the entire basin (13,831 reaches). Table 7 presents the results of paired t-tests and average changes between land-use and climate scenarios. Overall, significant differences were observed in all predictor variables along with IBI. In general, IBI significantly decreased from pre-settlement to current conditions. The basin-wide average of IBI values decreased by 7% from Presettle1 to the Current scenario. This predicted decrease in biotic integrity can be attributed to the significant increase in nutrients and other water quality measures that are often negatively associated with agricultural and urban land uses (Table 1). When climate factors were considered, the basin-wide average IBI decreased 2% from Presettle1 to Current conditions as a result of AFLOW increasing. This result underscores the importance of incorporating climate information when assessing temporal changes in stream health conditions. This result is not consistent with conventional knowledge of likely changes in biological integrity of streams since European settlement (Trautman, 1981; Harding et al., 1998), which underscores the need for further investigation into mechanisms behind the relations within our models and in particular the relations of predictors, like AFLOW, with other important contextual variables like drainage area and stream size.

For the percent intolerant fishes, all predictor variables showed significant changes. The only exception is that the average ANO2 concentration increased 4% from Presettle2 to Current conditions. This is a result of climate change in combination of land-use changes. In addition, significant increase (576%) in ANO2 was observed for Presettle1 to Presettle2 scenarios. For the percent intolerant fish models, although ANO2 did not show significant changes from Presettle2 to Current conditions, the overall percent intolerant fishes significantly decreased from pre-settlement to current conditions. The basin wide average of percent intolerant fish values decreased 35% from Presettle1 to Current conditions, which can be attributed to the significant increases in nutrients and other water quality measures. When climate condition was incorporated, the predicted basin-wide average percent intolerant fishes increased 32% between Presettle2 and Current conditions, which can be attributed to less increases in AOrgP and the fact that flow is not as influential to fish for stream reaches having on poor environmental conditions. Such water quality change is combination of several factors, including basin-wide average concentration changes in AOrgP (33%), ACHLA (221%), and ANO2 (576%).

Table 6. Paired t-test and changes among scenarios based on 193 fish sampling locations

Variables	Presettle1 to Current		Presettle 2 to Current		Presettle1 to Presettle2	
	% change	p-value	% change	p-value	% change	p-value
IBI	-2	0.093	2	0.111	-4	**<.01**
PCINTONB	-24	**<.01**	-23	**<.01**	-1	0.764
AFLOW	6	**<.01**	23	**<.01**	-18	**<.01**
AOrgP	73	**<.01**	65	**<.01**	32	**<.01**
ANO_2	82	**<.01**	74	**<.01**	46	**<.01**
ACHLA	86	**<.01**	36	0.169	354	**<.01**
SNO_3	13	**<.01**	14	**<.01**	-4	**<.01**
SNO_2	84	**<.01**	92	**<.01**	-49	**<.01**

Table 7. Paired t-test and changes among scenarios considering all reaches within the Saginaw River watershed

Variables	Presettle1 to Current		Presettle2 to Current		Presettle1 to Presettle2	
	% change	p-value	% change	p-value	% change	p-value
IBI	-7	**<.01**	-2	**<.01**	-5	**<.01**
PCINTONB	-35	**<.01**	-32	**<.01**	-2	**<.01**
AFLOW	8	**<.01**	24	**<.01**	-17	**<.01**
AOrgP	77	**<.01**	70	**<.01**	33	**<.01**
ANO_2	86	**<.01**	4	0.777	576	**<.01**
ACHLA	80	**<.01**	37	**<.01**	221	**<.01**
SNO_3	70	**<.01**	91	**<.01**	-69	**<.01**
SNO_2	85	**<.01**	95	**<.01**	-67	**<.01**

1.11.4.3 Overall stream health changes among reaches

In this section, overall stream health for individual reaches at the basin level will be evaluated. Figures 8-10 show whether any changes were predicted for fish measures within individual reaches. In these figures, improvement was defined as any increase in the IBI scores or percent intolerant individuals, while decline was defined as any decrease in the aforementioned scores.

As land use changed from the Presettle1 to Current conditions (Figure 8a), the IBI scores for the majority of stream reaches (59%) in the study region decreased, while 39% of reaches increased, and 2% reaches had no change. When changes in IBI class is considered, 30% of the reaches declined by one class or more, 17% improved in one or more classes, and 53% did not change. This result highlights that although IBI scores in majority of reaches changed; many are still classified as the same and may not experience substantial biological assemblage changes. However, it is expected that under pre-settlement conditions, substantial biological changes would occur compared to current conditions. This once again shows limitations of the models and possible misinterpretations that may be made without considering other variables (stream size, components of flow, physical habitat). The percentages of intolerant fishes decreased for 66%, increased for 31%, and unchanged for 3% stream reaches from pre-settlement to current land use conditions (Figure 8b). Such changes are presumably attributed to the conversion of forest to agricultural and urban land uses (Table 1), which could have led to increased nutrients that had strong influence on percent intolerant fishes.

When pre-settlement climate condition was incorporated, the percentages of stream reaches having negative (52%) and positive (47%) IBI scores changes were similar from Presettle2 to Current conditions (Figure 9a). In contrast, the IBI classes were unchanged for the majority of the stream reaches (50%), while IBI classes declined for 26% and increased for 24% stream reaches. For the study region, both precipitation and anthropogenic land use increased from pre-settlement to current conditions. The predicted changes in biological conditions are a result of integrated influences of precipitation and land-use changes on the variables incorporated in our models. These combined impacts of landuse and climate changes on percent intolerant individuals were stronger than IBI with 70% stream reaches showing a decrease and 29% showing an increase between presettle2 and Current conditions (Figure 9b).

The stream health changes when evaluated Presettle1 and Presettle2 models differed substantially (Figures 10a and 10b), emphasizing the importance of incorporation of climate information. Overall, the addition of historic climate data resulted in 63% reaches declining and 36% reaches increasing in IBI scores. However, when considering changes in IBI class, only 22% of the reaches declined while 10% showing improvement to a higher class. Unlike IBI, 59% of reaches increased and 41% reaches decreased in percent intolerant fishes (Figure 10b), which was largely due to the changes in the predictor variables (AOrgP, ANO2, AFLOW, and ACHLA).

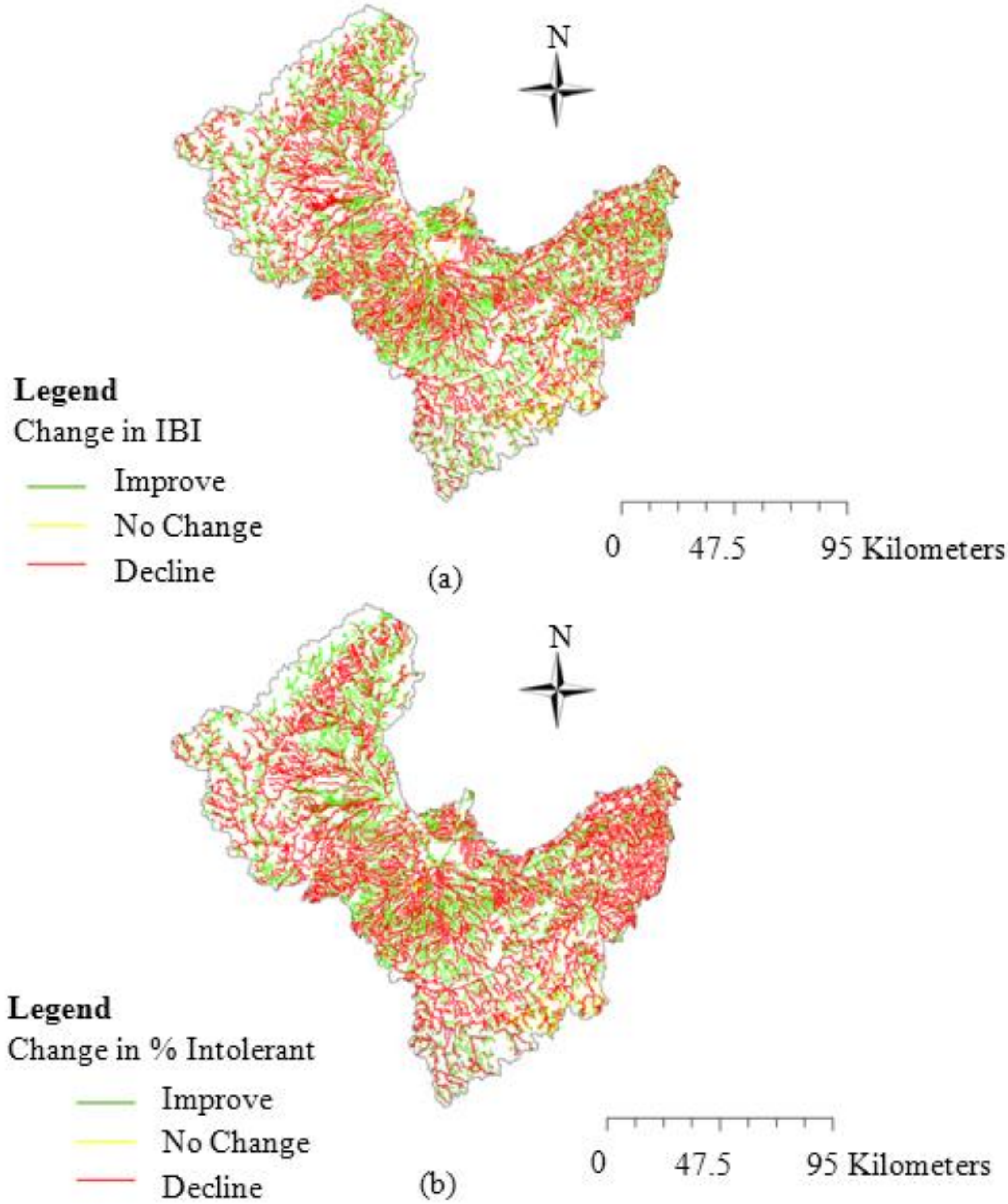

Figure 8. Improvements and declines in IBI (a) and percent intolerant individuals (b) from Presettle1 to Current.

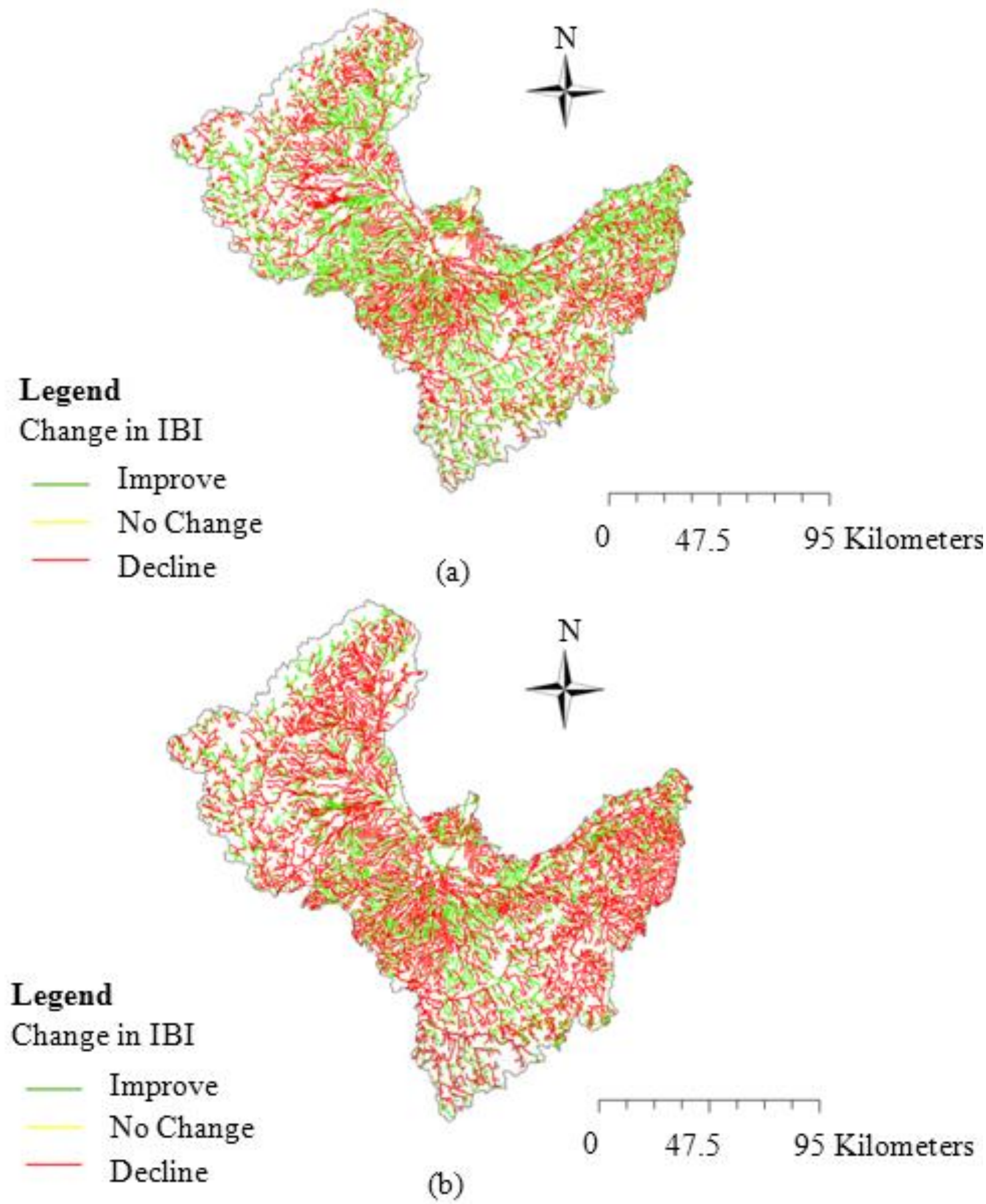

Figure 9. Improvements and declines in IBI (a) and percent intolerant individuals (b) from Presettle2 to Current

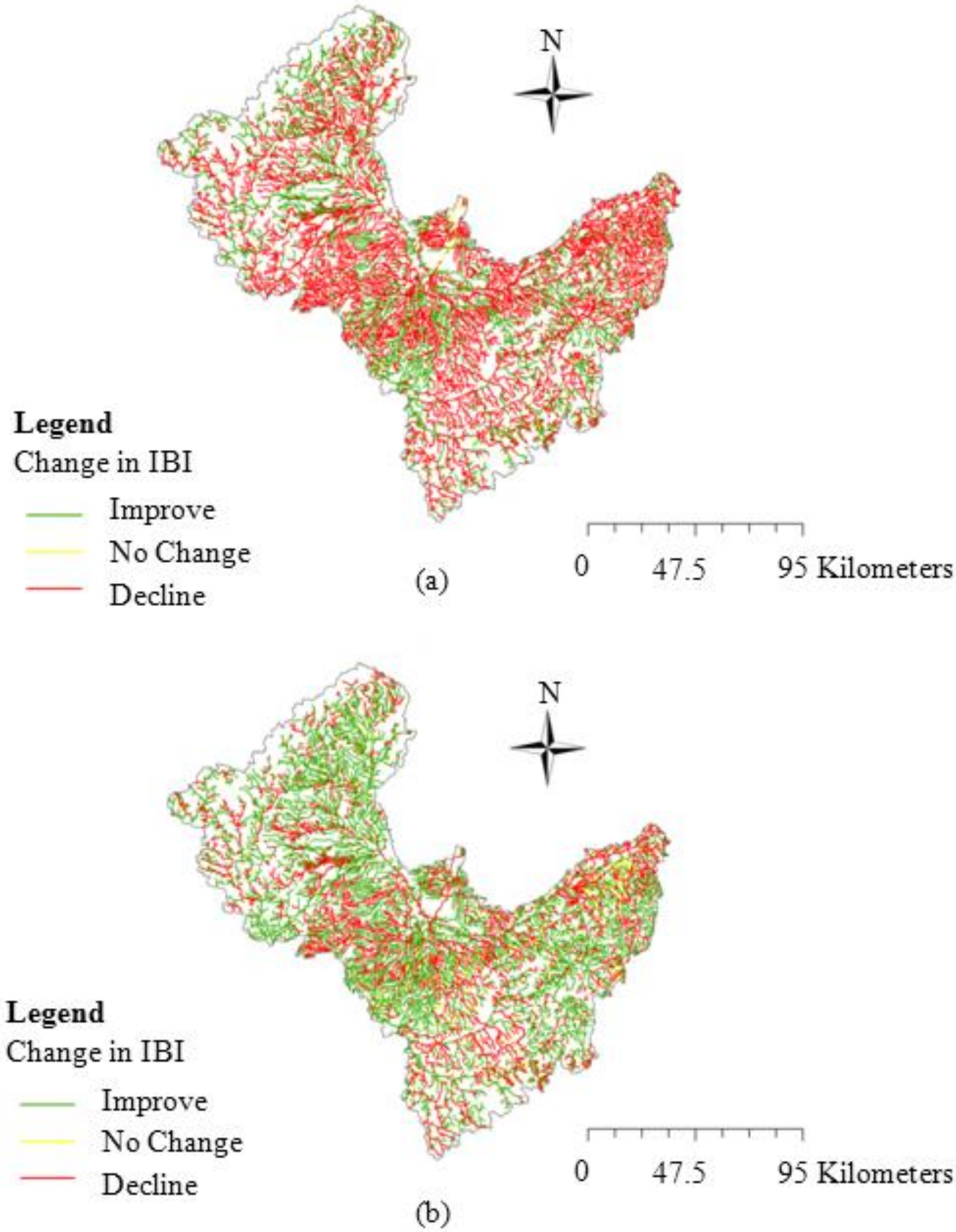

Figure 10. Improvements and declines in IBI (a) and percent intolerant individuals (b) from Presettle1 to Presettle2

1.12 CONCLUSION

Anthropogenic activities could have profound impacts on the health of aquatic ecosystems. To rehabilitate or prevent these impacts, there is a need to fill critical gaps where data is not available, to enhance our understanding of the complex relationships between biotic communities and in-stream conditions, and to explore alternative methods of for predicting the consequences.

This study employed a highly detailed and calibrated SWAT model for the Saginaw River basin. SWAT successfully provided information to fill a knowledge gap in un-sampled locations by supplying high-resolution in-stream predictions, such as flow, sediment, nutrient concentrations, which may directly or indirectly determine the health of a stream. Overall, water quality and quantity variables obtained from SWAT explained 48% of the variation in IBI and 21% of the variation in percent intolerant individuals. Since the goal of our study is to identify the roles of in-stream water quality stressors in influencing fish indicators, the limited variations in fish measures explained by the SWAT model outputs are expected. This is because many other natural and human induced factors within the watershed and stream also influence the fish indicators. Therefore, in order to have more comprehensive predictions and explanation of ecological measures, additional variables such as physical, chemical, and natural factors should be considered. However, this is not always possible and it is impractical to collect this data for every reach within a watershed. Both linear (stepwise linear regression, partial least squares regression) and non-linear (fuzzy logic) methods were employed to describe the relationship between in-stream variables and fish measures (IBI and the percent of intolerant individuals). The best model was selected through 10-fold cross validation analysis for the development of a baseline evaluation of stream health using pre-settlement landuse and historical climate data.

In general, similar predictors of biological condition were identified and selected to develop stepwise linear regression, partial least squares regression, and fuzzy logic models. Average annual flow consistently revealed the strongest relation to IBI; with annual flows generally positively related to this measure of stream health. Due to the significant positive correlation between average annual flow and drainage area, the ecological significance of AFLOW to fish communities in the Saginaw River watershed is difficult to decipher. Land uses that increase run-off, like agriculture and urbanization, can lead to increases in average annual flows yet also alter other significant components of flow (e.g., reduced base flows and increased peak flows) which have been consistently shown to reduce biological integrity (Poff and Zimmerman, 2010). More detailed studies of these relations are currently underway to evaluate and better understand the relative influence of watershed and instream variables on fish community metrics. On the other hand, the percent of intolerant individuals was more influenced by nutrient concentrations and average annual chlorophyll-a. This is the fact that those species are identified by their inability to inhabit waters that experience poor water quality and environmental degradation.

Among the methods considered above, non-linear fuzzy logic method performed the best. This reemphasizes the fact that non-linear models should be used when dealing with complex and no-linear relations such as among water quality, water quantity, and stream health. The best models were then employed to show the applicability of using SWAT as a means of collecting essential data for predicting fish communities. Our results imply that human activities in our study area have largely impacted overall stream health as measured by IBI and percent intolerant fish individuals. Such impacts are largely resulted from increases in nutrient concentrations from the conversion of forest to agricultural or urban lands (Table 1). The inclusion of climate data is critical for this type of analysis because climate variables have direct influences on biological communities through water quantity and indirect influences through its effects on nutrient, sediment, and physical habitat. In contrast to the above mentioned improvements of pre-settlement landuse, some improvements were observed under Current conditions, which were linked to the change from forests (pre-settlement) to wetlands (current). In addition, these conflicting results may be attributed to the above mentioned limitations of the inputs to the model (AFLOW) without considering highly correlated natural driving variables (stream size, drainage area) that were not within scope of this project. Although the results of this study provide insight into possible consequences of different landuse and climate scenarios, it is important to acknowledge the uncertainty in the process of data collection, model input, model structure, model parameter, and model output.

This research not only identified water quality variables and stream characteristics that can be linked to stream health indicated by fish communities, but also demonstrated the possibilities of working with a watershed model such as SWAT, as well as alternative, non-parametric modeling methods. With such complex interactions and relationships involved in aquatic species and their environments, there is a need to continue to explore alternative methods for capturing and modeling these processes. Furthermore, understanding the relationship between fish community metrics and variables obtained from watershed models, like SWAT, provides an effective tool to more directly study how different landuse management and human disturbances alter biological endpoints of aquatic ecosystems.

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STUDY AND MODEL THE EFFECTS OF CONSERVATION PRACTICES ON STREAM HEALTH

Matthew D. Einheuser, A. Pouyan Nejadhashemi, Scott Sowa, Lizhu Wang, Yaseen Hamaamin

1.13 ABSTRACT

Anthropogenic activities such as agricultural practices can have large effects on the ecological components and overall health of stream ecosystems. Therefore, having a better understanding of those effects and relationships allows for better design of mitigating strategies. Our study began with the development of a high-resolution watershed model for the Saginaw River basin in Michigan for generating in-stream water quality and quantity data at stream reaches with biological sampling data. These in-stream data was then used to explain macroinvertebrate measures of stream health including family index of biological integrity (Family IBI), Hilsenhoff biotic index (HBI), and the number of Ephemeroptera, Plecoptera , and Trichoptera taxa (EPT taxa). Three methods (stepwise linear regression, kernel regression, and adaptive neuro-fuzzy inference systems (ANFIS)) were evaluated for developing predictive models for macroinvertebrate measures. The ANFIS method performed the best on average and the final models displayed the most favorable R^2 and mean squared error (MSE) for Family IBI (R^2 =0.50, MSE=29.80), HBI (R^2 = 0.57, MSE=0.20), and EPT taxa (R^2 =0.54, MSE=6.60). Results suggest that nutrient concentrations have the strongest influence on all three macroinvertebrate measures. Consistently, average annual organic nitrogen showed the most significant association with EPT taxa and HBI. Meanwhile, the best model for Family IBI

included average annual ammonium and average seasonal organic phosphorus. The ANFIS models were then used in conjunction with the Soil and Water Assessment Tool to forecast and assess the potential effects of different best management practices (no-till, residual management, and native grass) on stream health. Based on the model predictions, native grass resulted in the largest improvement for all macroinvertebrate measures.

1.14 INTRODUCTION

A healthy stream can be described as one that is resilient, sustainable, and maintains its ecological and societal values (Meyer, 1997). Often associated with the term stream health is the term integrity, which refers to a quality or condition that is compared to an original, undisturbed, condition (Karr, 1996). A common and accepted technique to quantify ecological health is the use of biological indicators for measuring how communities react to disturbances. This can be especially efficient when pollutants and physical habitat are otherwise impractical or hard to quantify (Flinders et al., 2008; Barbour et al., 1999). Among biological indicators, macroinvertebrate assemblages are one of the most widely used (Infante et al., 2008; Wang et al., 2007; Flinders et al., 2008; Barbour et al., 1999). Due to their smaller migration habits and sessile lifestyle, macroinvertebrates can accurately reflect localized site conditions (Barbour et al., 1999; Flinders et al., 2008; USEPA, 2009). In addition, they often respond quickly to stressors due to sensitive life stages, complex life cycles, and varying pollution intolerances. Macroinvertebrates represent a range of trophic levels and being that they are an important food source for fish (Barbour et al., 1999); they act as a link in the food web connecting multiple organisms (USEPA, 2009). Over the years, numerous indices and metrics have been developed and used for identifying and measuring stream conditions and integrity using macroinvertebrates as indicators. There are two main informative types: multi-metric indexes, that measure specific attributes of the assemblage; and pollution-tolerance indexes, which are based on taxon-specific tolerance values (Fore et al., 1996). An example of a multi-metric index is the Family IBI which is made up of metrics at a family taxonomic resolution. The Hilsenhoff biotic index (HBI; Hilsenhoff, 1987) is an example of a pollution-tolerance index based on the tolerance values of organic pollution for species and genera (Hilsenhoff, 1988; Barbour et al., 1999). Often, metrics within indices include information on certain taxonomic orders of macroinvertebrates that are highly intolerant to pollutants and can represent environmental conditions quite well. The three common orders often looked at in rapid bioassessments are Ephemeroptera (mayflies), Plecoptera (stoneflies), and Trichoptera (caddisflies), also known at EPT. These three orders of macroinvertebrates are very sensitive to degradation and their occurrence in streams can be a great indication of the water quality and overall health of the stream (Michigan DEQ, 1997).

Anthropogenic disturbances, such as agricultural production, can affect the ecological processes and biota within lotic systems by altering flows, introducing point and non-point source pollutants, modifying geomorphology, and influencing other components of aquatic habitats (Wang et al., 2008; Dale and Polasky, 2007; Rowe et al., 2009). Such alteration can have large impacts on macroinvertebrate communities and stream health in general (Bedoya et al., 2011).

Flow is a primary characteristic of lotic systems and can be altered by different land uses. In an indirect manner, flow can affect other characteristics including temperature, sediment, nutrient and pesticide input, and dissolved oxygen levels. These conditions in turn affect aquatic organisms. Flow can also affect the biota more directly, including habitat availability and downstream drift (Bunn and Arthington, 2002; Borchardt, 1993). Abundance and diversity of macroinvertebrates were found to be commonly reduced in studies with flow alterations (Poff and Zimmerman, 2010).

With variable flows, higher peak rates, and higher velocities, often an increase in the transport of sediments to a channel occurs. Bare soil and cultivated lands can contribute most of this sediment to the channel (Zimmerman et al., 2003). These increases in sediments can impact the ecology of stream in several direct and indirect ways. Sediments can affect macroinvertebrates indirectly by affecting primary production (Wood and Armitage, 1997). These influences on primary production can be linked to habitat structure alteration, food availability, and dissolved oxygen levels (Griffith et al., 2009). Studies have also shown that sediment impacts macroinvertebrate abundance, diversity, density, and community structure due to covered and modified substrates, affecting their respiration, impairing feeding, and increasing drift (Wood and Armitage, 1997).

Often bound to sediments, nutrients are also a significant factor originating from agriculture activities within a watershed. Increases in nitrogen and phosphorus are well documented in their association with agricultural practices (Bernot et al., 2006), especially the use of fertilizers (Robertson and Vitousek, 2009; Gentry et al., 2007). These nutrients, although essential to organisms, can exceed needed levels and have considerable negative impacts on the biological communities and overall health of stream systems, commonly through eutrophication (Carpenter et al., 1998). Macroinvertebrates have shown negative responses to nutrients as demonstrated by Miltner and Rankin (1998), who observed a decrease in the Invertebrate Community Index (ICI) score associated with NH_3. It was also shown that EPT taxa decreased, while some other taxa increased, with higher nutrient levels.

Several other factors can shape macroinvertebrate communities, including water quality parameters such as dissolved oxygen (DO) and physical habitats such as substrate and cover (Bedoya et al., 2011).

1.14.1 Approaches to Linking Environmental Variables and Biota

Efforts to link disturbances and stream variables to aquatic macroinvertebrates have been made through multiple approaches. These range from simple linear models to complex soft computing techniques such as fuzzy logic and artificial neural networks. Simple linear models, such as stepwise regression are commonly used and are considered to be reliable when there is lack of knowledge of the relationships or processes being examined (Van Sickle et al., 2004). Waite and others (2010) used linear regression when looking at the relationship between environmental variables and macroinvertebrate metrics as well as Maret et al. (2010) and Van Sickle et al. (2004) who also employed standard regression models. Other authors such as Cheimonopoulou et al. (2011) have used multidimensional approaches like Canonical Correspondence Analysis (CCA) and Principle Component Analysis (PCA) to study the relationships between macroinvertebrate communities and stressors. Meanwhile increasing attention has been brought to addressing these relationships in a non-linear fashion. These methods include piecewise linear regression (Maret et al., 2010), regression tree analysis (Wang et al., 2007), and soft computing techniques such as artificial neural networks (Dedecker et al., 2004).

Fuzzy logic is another soft computing method based on approximate reasoning that has been increasingly used in ecological studies (Marchini, 2011). Fuzzy logic, introduced by Zadeh (1965), is an effective approach for developing models used for prediction or decision support (Adriaenssens et al., 2004). Fuzzy techniques can be interpreted easily because of its linguistic nature and it efficiently deals with highly variable, complex, and uncertain data and processes (Adriaenssens et al., 2004). Both data driven and expert knowledge techniques have been used and several fuzzy methods exist. Fuzzy logic have been shown to be reliable for modeling several aquatic biota related to stream health including algae (Chen and Mynett, 2003), fish (Mouton et al., 2008; Jorde et al., 2000), and macroinvertebrates (Adriaenssens et al., 2006; Van Broekhoven et al., 2006).

1.14.2 Challenges and Objectives

The first challenge when linking disturbances and in-stream water quality and quantity conditions to ecological health is the lack of field data. There is not only a lack of high resolution data, but it is often impractical and impossible to have complete and long term datasets for streams networks, especially in a large basin as in this study. However, biophysical models can play an important role in successfully filling this knowledge gap as well as forecasting hypothetical conditions. Some studies have partially incorporated such models to help fill this role including Wang et al. (2008) who used nitrogen and phosphorus estimates from a spatially referenced regressions on watershed attributes (SPARROW) model to link with ecological measures. It is very common for investigators to use the types and percentages of different land uses in the watershed as predictor variables for biological measures of stream health. However, using these variables in a region where watersheds are mainly dominated with one land-use type (e.g. agriculture) can lead to poor predictions (Heitke et al., 2006; Stauffer et al., 2000; Johnson and Host, 2010). In addition, relations base on the percentages of different land uses is insensitive to climatological variables, which has an important influence on stream health. In order to solve these problems, instead of using percentages of different land use or cover, the geospatial information about land cover was incorporated in the Soil and Water Assessment Tool

(SWAT) model to determine local and regional stream conditions that are essential in development of biological model. This also addressed the challenge of capturing the confounding interactions among landscape factors that help in forming aquatic ecosystems (Johnson and Host, 2010). Another challenge is finding a suitable modeling technique or method that can capture the complex and non-linear relationships that exist between stream conditions and ecological components (Wang et al., 2008; Sutela et al., 2010). Alternative soft computing methods, such as fuzzy logic, may provide a possible answer for this challenge (Marchini, 2011). Overall, the relationships between variables such as nutrients and macroinvertebrates need to be further investigated and have not yet been well documented (Wang et al., 2007). Currently, there are efforts through the Conservation Effects Assessment Project (CEAP) to quantify the ecological benefits of best management practices (BMPs) and conservation practices through modeling applications and tools (Maresch et al., 2008; Shields et al., 2006).

The objectives of this study were to: (1) bridge the gap between hydrologic models and ecological conditions using the (SWAT) as a means of quantifying high resolution flow and water quality elements; (2) identify the influential variables in explaining macroinvertebrate indices and metrics, ultimately indicating overall stream health; (3) describe the relationships between aquatic macroinvertebrates and local in-stream conditions (SWAT outputs) through models built using statistical methods and adaptive neuro-fuzzy inference systems (ANFIS) technique; and (4) show the applicability of SWAT coupled with the predictive macroinvertebrate models to forecast and assess the effects of numerous agricultural BMPs on stream health within the Saginaw River watershed.

1.15 METHODOLOGY

1.15.1 Study Area

The Saginaw River watershed (or basin) is Michigan's largest 6-digit HUC (hydrologic unit code 040802) basin with a size of 612,266 ha (Figure 11). Located in the central eastern portion of the Lower Peninsula, this watershed consists of six 8-digit HUC watersheds, the Tittabawassee (04080201), Pine (04080202), Shiawassee (04080203), Flint (04080204), Cass (04080205), and Saginaw (04080206). The outlet of the Saginaw River basin discharges into Lake Huron. Streams and rivers within the basin range in size and order; however, majority of the basin is dominated by warm water streams. The basin lies within three Level-3 Ecoregions, the Northern Lakes and Forests Ecoregion, the Southern Michigan/Northern Indiana Drift Plains Ecoregion, and the Huron/Erie Lake Plains Ecoregion (USEPA, 2011b). The Saginaw River watershed consists of approximately 43% of agricultural lands that are mainly comprised of corn, soybean, and pasture fields. The remaining lands are 24% forest, 14% developed, 14% wetland, 4% rangeland, and 1% water. With a large percentage of its drainage area being agriculture and developed, segments of river as well as the outlet of the basin have been impaired due to nutrient loading, soil erosion, and contaminated sediments. Because of this, it has been identified as an area of concern by the US EPA. These concerns are in regards to degraded fisheries, fish consumption advisories, and loss of recreational values (USEPA, 2011a).

Figure 11. Saginaw River watershed (040802)

1.15.2 Soil and Water Assessment Tool

To obtain much needed water quality and quantity data at a large scale, an inexpensive and informative approach is the use of models. The Soil and Water Assessment Tool (SWAT) is one such model that is commonly used for watershed scale predictions that may be used by decision makers and managers for dealing with water resource issues (Neitsch et al., 2005). SWAT (ArcSWAT v.2.3.4) was a spatially explicit model developed by the USDA-ARS Temple Texas. This physically based model was developed to simulate runoff, stream flow, soil erosion, along with nutrient, pesticide, and sediment loadings and transportation based on input data including landuse, weather, topography, soils, and scheduled management operations (Gassman et al., 2007).

The SWAT model and watershed being simulated, at its basic unit, is made up of hydrologic response units (HRUs) that represent areas with unique land use, soil, and landscape slope (Neitsch et al., 2005). For each HRU, a hydrologic balance, sediment loads, and nutrient losses are calculated and then accumulated within subbasins that have been delineated throughout the watershed. At this time, routing of each variable occurs through the stream network within the model.

1.15.2.1 Model Setup

In order to build an accurate and reliable model within SWAT, the use of accurate and reliable input data is a must. As mentioned earlier, this input data includes, but is not limited to landuse, topography, soils, and climate. For land-use data, the 2009 Cropland Data Layer (CDL) map at 56-m resolution, acquired from the National Agriculture Statistics Service within the U.S. Department of Agriculture (USDA) (Johnson and Mueller, 2010) was used. Classifications within this layer are of a high resolution and are crop specific making it ideal for this dominated agricultural watershed.

For topography data, the USGS National Elevation Dataset (NED) at 30-m resolution was obtained through the Better Assessment Science Integrating point and Nonpoint Sources (BASINS version 4.0) software (BASINS, 2007).

For soil data, the USDA State Soil Geographic dataset (STATSGO) at a scale of 1:250,000 was used. This data includes both physical and chemical properties for hydrologic modeling, which is commonly used for management in large areas such as watersheds and basins (USDA, 1995).

Precipitation and temperature data was obtained from the National Climatic Data Center (NCDC). Within and around the basin, 21 stations and 16 stations provided precipitation and temperature data, respectively. The acquired climate data spanned from 1990 to 2008. Additional climatic data, including wind speed and relative humidity, was obtained by SWAT weather generator (Neitsch et al., 2005).

Typically, watershed boundaries and stream networks are delineated and defined based on the topography data. However, for this study, both the stream network and subbasins were predefined layers inputted into the SWAT model. These layers were created using stream network data from a 1:24k National Hydrography Dataset plus (NHDPlus), acquired by the Michigan Institute for Fisheries Research. The 13,831 predefined subbasins and individual stream reaches are presumably homogenous in physicochemical, geomorphological, and biological characteristics.

Further setup of the model included defining HRUs based on dominant land use, soil, and slope class (0 to 2%, 2 to 5%, 5 to 10%, >10%) within each subbasin. Additionally, management operations, schedules, and crop rotations were modified from SWAT default values, as presented by Love and Nejadhashemi (2011) for the study area.

1.15.2.2 Sensitivity Analysis, Calibration, and Validation

Following the model setup, sensitivity analysis and calibration was performed. Sensitivity analysis was used to first identify input parameters within the SWAT model that had the most influence on model outputs. This was done for model outputs including flow, sediments, nitrogen, and phosphorus. SWAT employs a Latin Hypercube One-factor-At-a Time (LH-OAT) method when performing sensitivity analysis (Van Griensven et al., 2006).

Calibration was then performed using parameters identified through sensitivity analysis as well as parameters known to be sensitive based on knowledge of the study area. Calibration was executed by adjusting those parameters in efforts to obtain outputs that meet an acceptable accuracy when compared to actual data, while reducing the uncertainty. In addition, validation was performed by using the adjusted parameters from calibration to determine model accuracy and reliability (Moriasi et al., 2007). Both calibration and validation was performed at the basin outlet (Figure 12) for flow, sediments, and nutrients. The model was run from 2000 through 2005 with the first two years being warm up years. This time frame was chosen according to availability of measured streams and habitats data. In addition, the time frame includes both wet and dry precipitation periods. Calibration and validations were performed on monthly basis. Calibration period was 2002-2003 while the validation period was 2004-2005. Flow was calibrated and validate against data from USGS (site # 04157000). In addition, the model was calibrated and validated for water quality elements including total phosphorus, nitrate, and total nitrogen based on observed data acquired from EPA STORET (site # 090177).

Evaluations of both calibration and validation were done using Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and coefficient of determination (R^2). The evaluations and the performance of the model were based on guidelines outlined in Moriasi et al. (2007). Multiple measures were used to minimize biased results that might arise from using only one performance measure. NSE is a commonly used performance measure in hydrologic models and reflects how well simulated data versus observed data fit a 1:1 line. PBIAS on the other hand helps in showing if the model is over-predicting and under-predicting. Meanwhile R^2 is a commonly used statistic that measures the goodness of fit between simulated and observed data. R^2 however, can be over sensitive to outliers and does not help in addressing over or under predicting of the model (Moriasi et al., 2007; Love and Nejadhashemi, 2011). Further information and details on the measures and evaluation guidelines used in this study can be found in Moriasi et al. (2007).

1.15.2.3 BMP Scenarios

Multiple best management practices (BMP) ,1) no tillage (NT),2) residue management (RM 1000) (1000 kg/ha), and 3) native grass (NG) were simulated using SWAT model (applied to all agricultural lands) to forecast the potential effects of these scenarios on the three macroinvertebrate measures of stream health.

The no-tillage BMP refers to practice of keeping soils untilled and undisturbed until agricultural planting. This not only reduces erosion of soils, but it also can increase soil moisture.(USDA, 2010). To represent this in the SWAT model, custom operation schedules were made to halt tillage operations.

Residue management refers to the practice of keeping a certain amount of crop residue on the soil surface within an agricultural field. This can reduce both sheet and rill erosion, while improving soil conditions (USDA, 2010). To model this within SWAT, no-till operations were incorporated as well as modifying parameters including average moisture condition curve number (CN2 (-2)), universal soil loss equation support practice factor (USLE_P (0.39)), and Manning's n value for overland flow (OV_N (0.2)) (Arabi et al. 2007). The modified values are based on the amount of residue to be left, which was 1000 kg/ha for this study.

Native grass was the third BMP incorporated into the model and refers to the practice of replacing agricultural row crops with native grasses (e.g. big bluestem) as done in programs such as Conservation Reserve Program. This conservation practice can reduce sediment and nutrient transport within watersheds. To represent this in the SWAT model, a custom operation was used where row crops were converted to rangeland (Woznicki et al., 2011) and mowing was done every 5 years according to the information obtained from the NRCS field office.

1.15.3 Macroinvertebrate Data

Macroinvertebrate data, including HBI, family IBI, and total EPT taxa, were obtained from 262 sites (Figure 12 and Table 15) within the Saginaw River watershed. Both Family IBI and HBI are indices of the overall stream health of the system while the total number of EPT taxa reflects stream health based on those macroinvertebrates' intolerance to degraded water. All the macroinvertebrate data was obtained from the Michigan Department of Environmental Quality (DEQ) and collected through standard DEQ procedures (Michigan DEQ, 1997). Sampling was performed in all habitat types and in both high velocity and low velocity areas. Methods of sampling included hand picking and dip nets, meanwhile samples were identified to the family taxonomic level. Metrics were then calculated and index scores were obtained. Metric measurements included taxa richness, numbers of taxa in the orders of Ephemeroptera, Trichoptera, and Plecoptera, percent Ephemeroptera composition, percent Trichoptera composition, percent contribution of the dominant taxon, percent isopods, snails, and leeches, and percent surface dependent macroinvertebrates. Ephemeroptera taxa are pollution sensitive and are often the first groups to disappear at impacted sites, Trichoptera taxa are often a predominant component within the community and few species are tolerant to pollution, and Plecoptera are sensitive to environmental quality (Michigan DEQ, 1997).

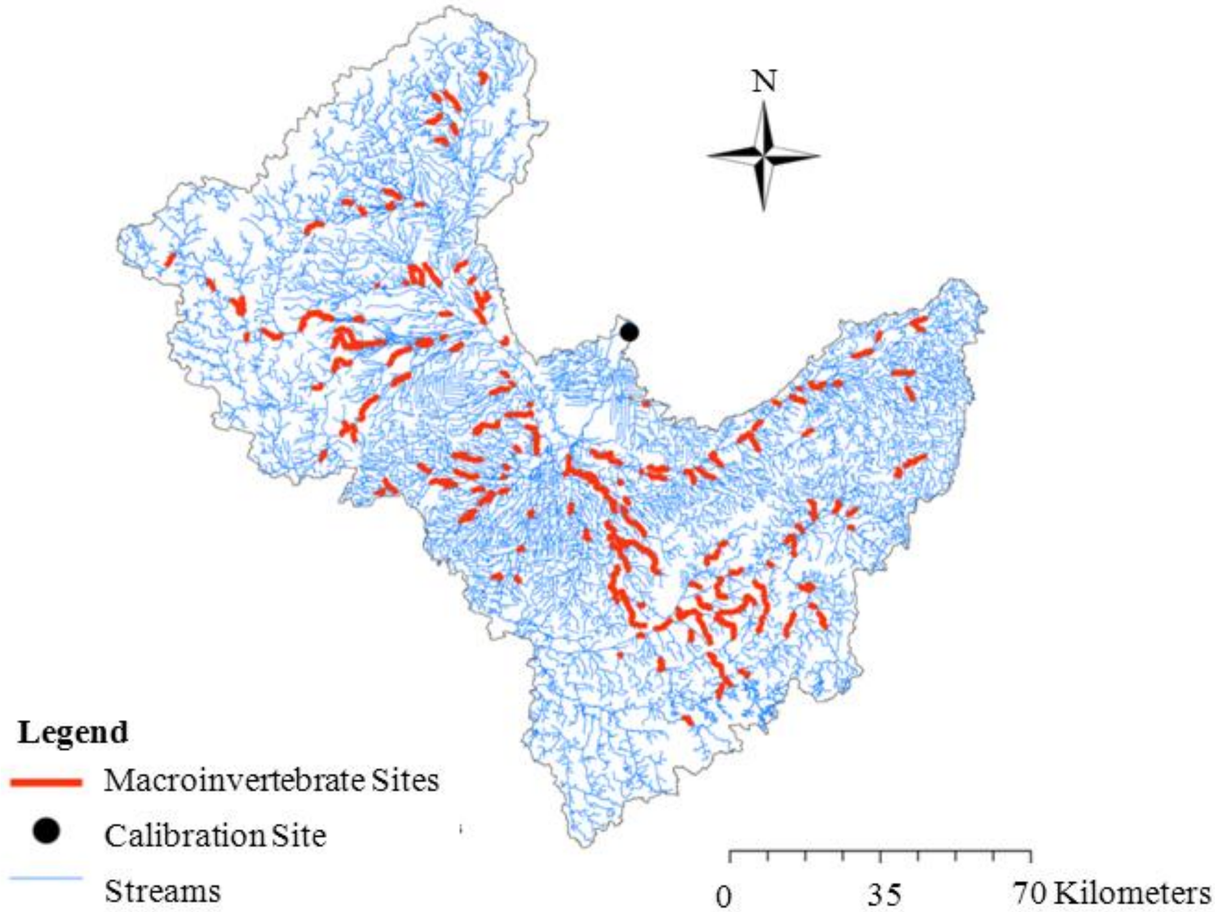

Figure 12. Location of macroinvertebrate data and calibration site

1.15.4 Data Analysis

Analysis of the data began with gathering and calculating in-stream concentrations and conditions, both water quality and quantity variables, from the output of the watershed SWAT model. The in-stream variables (flow, sediment loads, nutrient loads, etc.) generated from the model was obtained for each of the 13, 831 individual reaches within the basin. The annual and seasonal (June through August) averages were calculated over the five years when the model was run (2002 to 2006). In addition, the bankfull cross sectional area of the reach as a trapezoidal shape was attained based on bankfull depths and widths calculated through SWAT for each stream segment. Flow related measurements included discharge (m^3/second, flow), the percentage of flow that is driven by groundwater (PercBase), and stream gradient (StreamGrad) of the reach (m/m). Sediment and nutrient concentrations (mg/L) were then calculated based on the loads and discharge within each reach. Nutrient forms and values that were obtained from SWAT included organic nitrogen (OrgN), nitrate (NO3), nitrite (NO2), ammonium (NH4), organic phosphorus (OrgP), mineral phosphorus (MinP), total nitrogen (TN), and total phosphorus (TP). In addition, dissolved oxygen (DO), carbonaceous biochemical demand (CBOD), and algal biomass based on chlorophyll A (CHLA) concentrations were acquired from the model. These water quality and quantity variables along with the natural variable of stream cross-sectional area were then specifically extracted for 262 reaches where the macroinvertebrate data was available (Table 15). At these sites, the relationship between the above mentioned variables and the macroinvertebrate measures were then investigated. Finally, three methods were evaluated to explain these relationships.

Table 8. Summary of macroinvertebrate and SWAT output data at 262 sites

Variable	Description	Min	Max	Mean	Median	SD	Transform
Macroinvertebrate Measures							
HBI	Macroinvertebrate Biotic Index	3.60541	7.89024	5.10950	5.02465	0.68171	BoxCox
FamilyIBI	Family Index of Biotic integrity	0.00000	36.00000	16.07634	15.0000	7.80202	None
EPTtaxa	Total number EPT taxa	0.00000	17.00000	6.13691	6.00000	3.82337	None
In-stream Variables							
CrossArea	Cross-sectional area of reach (m^2)	0.02100	573.0581	51.79563	14.0755	100.438	BoxCox
StreamGrad	Stream segment gradient (m/m)	0.00000	0.03140	0.00179	0.00120	0.00267	BoxCox
SFLOW	Average seasonal flow (cms)	0.00066	25.00000	1.87672	0.39700	4.04417	BoxCox
SPercBase	% Average seasonal water yield contributed by groundwater (%)	0.00000	0.58796	0.09320	0.04437	0.11958	BoxCox
SSED	Average seasonal sediment concentration (mg/L)	0.08670	518.0000	41.41481	34.5000	44.5916	BoxCox
SOrgN	Average seasonal organic nitrogen concentration (mg/L)	0.00294	15.42615	0.84168	0.29599	1.52020	BoxCox
SOrgP	Average seasonal organic phosphorus concentration (mg/L)	0.00114	2.75150	0.16056	0.05695	0.28803	BoxCox
SNo3	Average seasonal nitrate concentration (mg/L)	0.00079	10.76602	1.11424	0.72740	1.32166	BoxCox
SNH4	Average seasonal ammonium concentration (mg/L)	0.00073	4.77614	0.35343	0.11764	0.61962	BoxCox
SNo2	Average seasonal nitrite concentration (mg/L)	0.00000	2.21420	0.15899	0.05961	0.24940	BoxCox
SMinP	Average seasonal mineral phosphorus concentration (mg/L)	0.00003	1.23628	0.13475	0.08921	0.15353	BoxCox
SCHLA	Average seasonal Algal biomass (chl - a) concentration (mg/L)	0.00000	1.04482	0.01192	0.00065	0.08284	BoxCox

Table 8 (cont'd)

SCBOD	Average seasonal carbonaceous biochemical oxygen demand concentration (mg/L)	0.00000	299.6894	5.45341	0.01764	26.8655	BoxCox
SDO	Average seasonal dissolved oxygen concentration (mg/L)	13.3485	424.3258	187.8763	179.877	84.4387	None
STN	Average seasonal total nitrogen concentration (mg/L)	0.28433	23.05467	2.46834	1.67509	2.86633	BoxCox
STP	Average seasonal total phosphorus concentration (mg/L)	0.00428	3.26787	0.29532	0.16339	0.38360	BoxCox
AFLOW	Average annual flow (cms)	0.00133	29.53000	2.58448	0.70005	4.94849	BoxCox
APercBase	% Average annual water yield contributed by groundwater (%)	0.00000	0.91104	0.31717	0.33018	0.28845	BoxCox
ASED	Average annual sediment concentration (mg/L)	0.21060	660.7000	49.35930	42.5650	55.0759	BoxCox
AOrgN	Average annual organic nitrogen concentration (mg/L)	0.00618	8.74909	1.17311	0.34997	1.77460	BoxCox
AOrgP	Average annual organic phosphorus concentration (mg/L)	0.00179	1.27287	0.18353	0.06978	0.25342	BoxCox
ANo3	Average annual nitrate concentration (mg/L)	0.04488	6.32230	1.37998	1.25396	1.02889	BoxCox
ANH4	Average annual ammonium concentration (mg/L)	0.00122	3.13374	0.51953	0.23141	0.62542	BoxCox
ANo2	Average annual nitrite concentration (mg/L)	0.00000	0.98350	0.15704	0.07660	0.19189	BoxCox
AMinP	Average annual mineral phosphorus concentration (mg/L)	0.00017	0.52431	0.13105	0.09111	0.11607	BoxCox
ACHLA	Average annual Algal biomass (chl - a) concentration (mg/L)	0.00000	0.61265	0.01836	0.00331	0.05920	BoxCox

Table 8 (cont'd)

ACBOD	Average annual carbonaceous biochemical oxygen demand concentration (mg/L)	0.00000	468.7425	8.71597	0.01659	43.9080	BoxCox
ADO	Average annual dissolved oxygen concentration (mg/L)	5.93453	432.6806	182.3555	175.107	97.8748	None
ATN	Average annual total nitrogen concentration (mg/L)	0.24720	12.05519	3.22965	2.31450	2.69881	BoxCox
ATP	Average annual total phosphorus concentration (mg/L)	0.01120	1.48351	0.31458	0.17047	0.32449	BoxCox

These methods included stepwise linear regression, kernel regression, and adaptive neural-fuzzy inference system (ANFIS). Ten-fold cross validation was performed among all methods. This allows the comparison among methods, facilitates in model validation, prevents over-fitting, and helps with selection of the overall best predictive model for each of the response variables (Mahmood and Khan, 2009). Random sampling was performed with R statistical software v. 2.12.1 to divide the data for the 263 reaches into 10 approximately equally size subsets. Models and relationships were built and trained based on 9 of the subsets and validated with the remaining subset. This is done until each subset has been used for validation, resulting in 10 models. Performance measures including mean square error (MSE) and coefficient of determination (R^2) were then calculated for the test or validation datasets and averaged across the 10 models. This average performance based on validation is then compared among the three methods (stepwise, kernel, and ANFIS) and the method with the lowest MSE and highest R^2 was recognized as the best method. Finally, models within the best method were tested against each of the 10 folds or subsets and their average performance dictated the best model, which was later used for predictions.

1.15.4.1 Stepwise Linear Regression

Stepwise linear regression models were developed using SAS 9.2 for each of the macroinvertebrate response variables (HBI, family IBI, and EPT taxa) based on the significant in-stream variables obtained from SWAT. Although linear models are a simple approach, they are thought to be reliable and effective in cases where knowledge or data is limited (Van Sickle et al., 2004). Variable normalties were evaluated using Shapiro-Wilk and Kolmogorov-Smirnov tests. Box-Cox transformations (Box and Cox, 1964), which applies non-linear transformations based on log-likelihood functions (SAS/STAT, 2010), were performed for those variables that did not satisfy the normal assumption. In this stepwise procedure, a modified forward-selection process was performed and variables were added based on significance of the F statistic. Following the addition of a variable, the process goes back to check if other variables need to be removed in the model based on their significances (SAS/STAT, 2010). Additionally, the collinearity among predictive variables was addressed by looking at the variance inflation factor (VIF), eigenvalues, and condition index. If a variable had a VIF of greater than two (Maret et al., 2010) and either an eigenvalue approaching zero (Morris et al., 1986) or condition index value with a high proportions of variation, then that variable was removed and stepwise would be rerun.

1.15.4.2 Kernel Regression

Kernel regression was performed through R statistical software v. 2.12.1 in efforts to explain and model macroinvertebrate measures with a non-linear and more flexible regression function (Hastie et al., 2009). Kernel methods are memory-based and use a localized weighting function. The specific analysis for this study uses a local linear regression technique due to computational time and it’s un-biasness at boundaries of the domain, which is unlike some other kernel methods. Three different kernels were considered (Tri-cube, Epanechnikov, and Gaussian) to look at different local smoothing techniques. Within each kernel, leave-one out cross validation was performed to define the best width of the local neighborhood (Hastie et al., 2009). Environmental variables used within the kernel regression were selected with the same methods as the ANFIS method based on Spearman’s Rho correlations. However, for kernel method, there is no limit of the number of variables used in the models; therefore all variables identified in the process were used.

1.15.4.3 Adaptive Neural-Fuzzy Inference Systems (ANFIS)

ANFIS is a fuzzy logic approach that uses adaptive learning techniques similar to that of neural networks and was performed in MATLAB R2009A with Fuzzy Logic Toolbox (MathWorks, 2010). This fusion technique is suitable for very suitable when data is already available and when a predetermined model structure is unknown. Fuzzy logic is an alternative soft computing method that can be used when dealing with non-linear and complex interactions (Chen and Mynett, 2003). To determine the variables to be included in the ANFIS model, Spearman's Rho correlations were performed within STATISTICA (STATSoft, 2011) among all variables. This non-parametric approach identified variables that were significantly correlated ($p<0.05$) with either HBI, family IBI, or EPT taxa for further consideration. Meanwhile, where pairs of variables had a high correlation coefficient ($r >0.7$) (Waite et al., 2010) amongst each other, the one with the weakest correlation with the macroinvertebrate measure was removed (Wang et al., 2008). The top three variables were then selected to be incorporated in the model for each macroinvertebrate measure. In addition, stream size (cross-sectional area) was also incorporated into each model to represent the natural longitudinal variation in stream morphology, substrate, shading, and flow regime. Cross-sectional area was forced into the models for the methods where it was possible (kernel and ANFIS). This was in attempt to model the residual effects of flow, which is highly correlated with cross-sectional area, on macroinvertebrate and ultimately stream health. This is another benefit to the fuzzy approach compared to other methods in that variables can be included where otherwise they may be rejected. The limit of four variables was used based on number of samples, which limits the building of membership functions without exceeding the number of modified parameters. At this point, ANFIS builds initial fuzzy inference system parameters based on grid partitioning and continues to shape membership functions and rules with training data. Meanwhile, test data and error of the model was tracked throughout the process to prevent over-fitting. Multiple membership function shapes were tested as well as optimization options within the program while building models. The output's membership function could either be linear or constant. An example of a linear membership function may be if the inputs are in specific membership functions, then the output is a specific linear equation. The ending model was identified based on minimizing error of both training and test datasets. Further information and a detailed explanation of the ANFIS function can be found in the Fuzzy Logic Toolbox 2, User's Guide (MathWorks, 2010).

1.16 RESULTS

1.16.1 Calibration and Validation

Calibration and validation was performed within the SWAT model for water quantity and quality components in the following order; flow, sediments, total phosphorus, nitrate, and total nitrogen. Based on criteria explained in Moriasi et al. (2007), all variables were successfully calibrated and validated based on NSE (>0.50) and PBIAS (within ±25 for flow, ±55 for sediment, and ±70 for nutrients) (Table 16).

Table 9. SWAT model calibration and validation summary

Parameter	Performance measure	Calibration Period	Validation Period	Combined
Flow	NSE	0.72	0.85	0.81
	PBIAS(%)	6.02	-1.75	1.48
	R^2	0.74	0.85	0.82
Sediment	NSE	0.71	0.81	0.8
	PBIAS(%)	-10.27	0.86	-3.02
	R^2	0.71	0.92	0.88
Total Phosphorus	NSE	0.64	0.67	0.67
	PBIAS(%)	18.08	-22.68	-6.87
	R^2	0.68	0.71	0.7
Nitrate	NSE	0.76	0.82	0.8
	PBIAS(%)	22.7	12.87	17.01
	R^2	0.86	0.83	0.83
Total Nitrogen	NSE	0.5	0.67	0.62
	PBIAS(%)	47.34	38.73	42.4
	R^2	0.87	0.84	0.84

1.16.2 Model Results

Calibrated and validated outputs from the watershed model were obtained at sites where macroinvertebrate data were available. The three methods of analyses (stepwise linear regression, ANFIS, and kernel regression) were than performed to explore and identify in-stream variables that can be used to explain and predict macroinvertebrate measures (HBI, FamilyIBI, and EPTtaxa).

1.16.2.1 Stepwise Linear Regression

Average annual organic nitrogen concentration (AOrgN) was consistently identified as the most influential variable for HBI in the Stepwise linear regression analysis. . Throughout the ten-fold process, AOrgN had the highest partial R^2 in explaining the variation of HBI for all models. Throughout the stepwise technique and based on correlations, organic phosphorus also exhibited high correlations with HBI, but it was removed because of its collinearity with AOrgN. Additionally, all models identified average annual sediment as a significantly influential variable for HBI. All other variables that were incorporated in the models were some forms of nitrogen concentrations. However, one of the models built did identify dissolved oxygen as a significant addition to the regression equation. Because HBI is based on macroinvertebrate pollution tolerance scores, the selection of nutrient and sediment concentrations as predictors is consistent. When applying the linear regression models to test datasets, on average in-stream water quality variables (SWAT outputs) explained 25% of the variation in HBI (table 18).

Stepwise regression performed for FamilyIBI also recognized nitrogen concentrations as a highly influential variable. Based on 9 out of the 10 models created during the 10-fold cross validation, average annual total nitrogen concentration (ATN) was found to have the highest partial R^2. Average annual flow was also identified consistently as a significant variable. Flow, unlike ATN however, showed a positive correlation with FamilyIBI and explained an additional four to eight percent of the variation. In majority of the models, no other variables significantly increased the R^2 or reduced MSE. Much like, HBI, the tolerances of macroinvertebrates to nutrients is reflected in the FamilyIBI. However, this index also takes into consideration other metrics not just based on tolerances, which may explain the selection of flow as an influential variable, which may be a reflection of natural longitudinal variation within the watershed. Based on stepwise linear regression techniques, on average, in-stream variables from SWAT explained 27% of the variation in FamilyIBI (Table 18).

For EPTtaxa, average annual nitrogen concentration (ATN) was also consistently incorporated into the models. Similar to FamilyIBI average annual flow was also identified in majorities of the models. The reason these two variables were selected in both FamilyIBI and EPTtaxa is likely due to the fact that EPTtaxa is related to several of the metrics in FamilyIBI. In addition to the above mentioned variables, average seasonal nitrite (SNO2) was also included in majority of the models, explaining only an additional one to two percent of the variation in EPTtaxa. Some models built based on certain folds of data, included other forms of nitrogen (e.g. average annual nitrate and average seasonal ammonium) as well as the concentration of chlorophyll *a*. The identification of nutrient values as being predictors of EPT taxa is consistent based on the fact that EPT taxa are known to be sensitive to water quality. Overall, through the stepwise process, water quantity and quality variables explained 34% of the variation in EPTtaxa (table 18).

1.16.2.2 Kernel Regression

The first step of performing the kernel regression for HBI was identifying what parameters should be used in the models. Unlike stepwise, this analysis does not have a set selection process. The predictors identified by our spearman rank correlation analysis in the order of importance include average annual organic nitrogen concentration (AOrgN), average annual nitrite (ANO2), average seasonal total nitrogen (STN), average annual and seasonal flows, average annual water yield contributed by groundwater (APercBase), average annual carbonaceous biochemical oxygen demand concentration (ACBOD), average annual algal biomass (chl - a) concentration (ACHLA), and average seasonal sediment concentrations (SSED). Within the 10-fold process, no specific type of kernel for local smoothing consistently outperformed the others and all three methods (Tri-cube, Epanechnikov, and Gaussian) were used depending on the dataset. When applying these “black-box” models built through kernel regression to test data, those predictors explained an average of 19% of the variation in HBI (table 18). This low predictability was unexpected because it does not assume linear relationships and performed worse than linear regression. This result could be contributed to how the variables were selected and the fact that the kernel method used different variables than stepwise.

Kernel regression models for FamilyIBI used similar variables that were chosen for HBI. Once again, concentrations of different nitrogen forms were included in every model such as organic nitrogen, total nitrogen, nitrite, and nitrate. Also ACHLA, ACBOD, ASED, and APerceBase were included in the kernel models. In addition to the common variables that have been involved in majority analysis, average seasonal dissolved oxygen concentration (SDO) was also an input variable in five of the ten models. One of the models based off of a specific dataset within the 10-fold process used average seasonal ammonium (SNH4) and average seasonal organic phosphorus (SOrgP) as inputs, replacing AOrgP and ANO2. The kernel regression process for FamilyIBI consistently used a tri-cube kernel for local smoothing, which outperformed the other kernels in every model. Kernel regression models explained on average 18% of the variation in FamilyIBI (table 18). Similar to HBI, once again kernel regression did not show favorable results.

Similar variables were used for the kernel analysis of EPTtaxa. The highly correlated variables were comparable to that of FamilyIBI. This likeness may be due to the fact that highly related measures to EPTtaxa, are used to calculate FamilyIBI. However, some notable differences were apparent in EPTtaxa model inputs and spearman rank correlations. Average seasonal dissolved oxygen concentrations (SDO) were included in all models built based on the 10-fold datasets. Also, stream gradient was included in several of the models. Tri-cube kernels, once again outperformed other local smoothing methods for EPTtaxa; however, Epanechnikov kernel was also used for some of the models. On average, when applied to test data, the kernel method explained 24% of the variation in EPTtaxa (table 18).

1.16.2.3 ANFIS

Average annual organic nitrogen concentration (AOrgN) was once again found to have a strong association with HBI when variables were identified based on spearman rank and modeled through the ANFIS approach. Meanwhile, concentrations of other forms of nitrogen also were included in the models consistently, including average seasonal total nitrogen (100% of the models) and average annual nitrite (50% of the models). Average annual flow was the other variable that was incorporated into the ANFIS for some of the folds. Cross-sectional area was selected for five of the models by spearman rank correlations, but was forced into all the models. ANFIS model structures varied depending on the training dataset used throughout the 10-fold validation analysis. Variables were either broken down to two or three membership functions and HBI's membership function was also linear or constant, depending on the dataset. Gaussian curve, triangular-shaped and generalized bell-shaped membership functions were the common membership function structures identified within the HBI models. Based on test data within 10-fold validation, ANFIS models on average explained 36% of the variation in HBI, which is 11% more than linear regression and 17% more than kernel methods. MSEs were also more favorable for ANFIS models, when compared to the other methods (table 18).

ANFIS models for FamilyIBI also included nitrogen concentrations in different forms as highly influential inputs. In five out of the ten models built, average annual total nitrogen (ATN) was included as a variable. Within the specific datasets used to build those models, ATN was found to have the highest spearman correlation with FamilyIBI. Other models however, included AOrgN (4 out of 10) and ANH_4. Specifically, the model built that identified NH4, also included average seasonal organic phosphorus (SOrgP) and was one of the better performing models. Also, consistent among the data folds, average annual flow was selected and included into the models. Cross-sectional area was forced into the models as a natural variable, although it was correlated with flow in most of the models. The input variables were once again made up of two or three membership functions and varied in shape. The common membership function shapes that built the best models based on training datasets, included Gaussian (4 out of the 10 models), triangular (2 out of the 10 models), and trapezoidal (2 out of the ten models). On average, ANFIS models explained 28% of variation in FamilyIBI, similar to that of stepwise. MSEs based on test data were also slightly more favorable for the ANFIS method (table 18). However, R^2 values obtained from training sets explain 12% more variation then stepwise methods (table 17).

For EPT taxa, ANFIS and spearman rank correlations selected AOrgN to be included in all models throughout the 10-fold process. Average annual nitrite concentrations (ANo2) were also selected for every model. Five out of the ten models included average annual flow, whereas the other five included average seasonal flow. Cross-sectional area was forced into the model to represent the natural variations, although it was selected for five of the models by spearman rank correlation. The structure of the membership functions for all variables differed among models depending on the training data. EPTtaxa membership function was found to be linear, instead of constant, in nine of the ten models. Similar to the models built for HBI and FamilyIBI, input variables for EPTtaxa were made up of two to three membership functions. The most common shape used to build the membership functions within the EPTtaxa models was triangular. On average, based on test data, the ANFIS models explained 39% of the variation in EPTtaxa (table 18).

1.16.3 Model Selection and Interpretation

Based on all the methods of analysis and model development, the effects of nutrients on stream health were apparent. Nitrogen concentration, especially organic nitrogen, was consistently identified as an influential variable for all of the macroinvertebrate measures. At the same time, other variables such as nitrite, total nitrogen, and ammonium were also identified having an effect on macroinvertebrate health. In most cases based on spearman rank correlations, phosphorus measures were highly correlated with nitrogen concentrations and therefore removed during the variable selection process. However, in some situations phosphorus, such as organic phosphorus, showed strong correlations with macroinvertebrate measures. In fact, the best model chosen for FamilyIBI included seasonal organic phosphorus concentration. Flow also was identified as an influential factor for FamilyIBI and EPTtaxa. Although flow was used in the models, a high correlation was revealed with cross-sectional area. Flow is likely to be selected based on its correlation with this natural variation that captures several other factors. Flow, however, was not found to be as influential in HBI, which is strictly based of pollutant tolerance values. Both seasonal and annual outputs were highly correlated. In several situations, for the same macroinvertebrate measure, both average seasonal and average annual nitrogen concentrations and flows were selected to be in the model depending on the 10-fold dataset. On average, EPTtaxa was explained the most by the in-stream variables for all three methods (stepwise, kernel, and ANFIS). This could be a result where indices, like HBI and FamilyIBI may be less sensitive because they are based off several metrics that may respond differently to different stressors.

Overall, ANFIS displayed better performance (MSE and R^2) for explaining and predicting all three macroinvertebrate measures. ANFIS outperformed other methods for both model training dataset (table 17) and model testing dataset (table 18). This highlights the importance of recognizing the non-linear relationships that are involved in ecological processes. At the time, it also displays the complexity and further variation that exists due to other variables and interactions that are unknown or were not considered in the scope of this study. The inclusion of these factors would lead to more reliable predictive models and may reduce uncertainty and misinterpretation of results. Based on the average MSE and R^2 from the test dataset, the ANFIS method was chosen to further identify the best model for prediction. The best model for each biological indicator was selected based on average MSE and R^2 among all validation subsets within the 10-fold validation process. The final predictive ANFIS model identified for predicting HBI had a R^2 of 0.57 and MSE of 0.20. The final model selected for FamilyIBI had a R^2 of 0.50 and MSE of 29.80. The final predictive model for EPTtaxa performed with an average R^2 of 0.54 and MSE of 6.60 (Table 19).

Table 10. Average R^2 and MSE obtained from 10-fold cross validation based on training data

Response Variable	**Stepwise Regression**		**Kernel Regression**		**ANFIS**	
	Avg. Training MSE	Avg. Training R^2	Avg. Training MSE	Avg. Training R^2	Avg. Training MSE	Avg. Training R^2
HBI	0.357	0.27	0.364	0.21	0.236	0.49
FamilyIBI	43.836	0.28	47.570	0.22	36.270	0.40
EPTtaxa	9.006	0.35	10.113	0.31	7.519	0.48

Table 11. Average R2 and MSE obtained from 10-fold cross validation based on test data

Response Variable	Stepwise Regression		Kernel Regression		ANFIS	
	Avg. Test MSE	Avg. Test R^2	Avg. Test MSE	Avg. Test R^2	Avg. Test MSE	Avg. Test R^2
HBI	0.387	0.25	0.410	0.19	0.321	0.36
FamilyIBI	46.275	0.27	53.293	0.18	45.712	0.28
EPTtaxa	9.872	0.34	12.232	0.24	9.229	0.39

Table 12. Predictor variables used for the best performing macroinvertebrate model

Method	Response Variable	Predictor Variables	Overall MSE	Overall R^2
ANFIS	HBI	crossArea AOrgN STN ANo2	0.20	0.57
ANFIS	FamilyIBI	crossArea ANH4 AFLOW SOrgP	29.80	0.50
ANFIS	EPTtaxa	crossArea AOrgN SFLOW ANo2	6.60	0.54

1.16.4 Evaluations of Best Management Practices' Effectiveness on Stream Health

1.16.4.1 Significant Changes with Implementation

The best models selected in the above sections were used to assess the potential effects of the implementation of three best management practices (BMPs) on stream health (macroinvertebrate measures) within the Saginaw River watershed. This was not only to evaluate the potential ecological impacts of conservation practices, but also to demonstrate the flexibility and opportunities when using predictive models and connecting data with SWAT model outputs. As mentioned earlier, the inclusion of other factors would provide more reliable predictions as well as allow for more meaningful interpretations of the results obtained. A Wilcoxon rank signed rank test, which is a non-parametric test used to compare populations based on the medians, was performed for all variables to see if HBI, FamilyIBI, and EPTtaxa significantly differed across the basin when applying the BMP scenarios. To begin, the current scenario predictions, representing land-use conditions with no BMPs was compared with observed data from the 262 sites within the basin. The predicted HBI scores across those sites showed no significant difference from the observed population of scores (p-value = 0.7213). The FamilyIBI scores from the predicted population also showed no significant difference from the scores observed (p-value = 0.4093). In addition, the number of EPTtaxa did not significantly differ from observed numbers across the sites (p-value = 0.2593). This provides further insight into the reliability of the ANFIS model's predictions.

For the 262 sites from which the predictive models were built and represented (Table 20),both HBI and EPTtaxa showed no significant change between no-tillage BMP and the current conditions (p-values > 0.01). However, FamilyIBI did show a significant decrease in the median value and increase in the mean with the addition of no-till operations. All water quality variables showed significant small decreases with the implementation of no-till, except seasonal organic phosphorus concentration (SOrgP), which increased. Increases in organic phosphorus has been shown in other studies (Giri et al., 2011), and is likely due to an increase in organic matter on fields from no-tillage. In addition, flow measures also showed small significant increases between no till and the current condition. This could be resulted from reduced infiltration and/or increased runoff, which can be a consequence of no-tillage operations (Jones et al., 1994). The significant change in FamilyIBI, as opposed to EPTtaxa and HBI, could be due to the inclusion and interaction of seasonal organic phosphorus concentrations with other variables in the predictive model. When observing the effects of residue management at the 262 sites, significant differences from current conditions were displayed. HBI values significantly decreased, while EPTtaxa and FamilyIBI showed a significant increase, all indicating that stream health improved. Both annual and seasonal flows along with nutrient concentrations showed significant decreases with the implementation of residue management. However, SOrgP showed a significant increase. As assumed, all significant changes were amplified when compared to the effects of no-tillage. This was expected because residue management includes no-tillage operations plus a decrease in runoff. This trend continues when exploring the effects of implementing conservation practices like the Conservation Reserve Program and converting lands to native grass. Significant increases were predicted for both FamilyIBI and EPTtaxa. At the same time, HBI scores showed a significant improvement. Significant decreases in nutrient concentrations (greater than 25% change in mean and median values) were observed and likely the biggest contribution to significant changes in macroinvertebrate measures. Both annual and seasonal flow measures showed a significant reduction when comparing the native grass scenario to current conditions.

The same analysis was performed to evaluate the BMP effects throughout the basin (13,831 reaches), including un-sampled sites where no observed data are available (Table 21). Similar results are observed when looking at the difference among the whole basin compared to the differences at the 262 sites. No-Till practices did not seem to make a significant difference for HBI and EPTtaxa throughout the basin (p-values > 0.01). However, FamilyIBI did show a significant increase. Although small, significant changes were observed among all water quality and quantity variables. When focusing on the effects of residue management, all three macroinvertebrate measures significantly improved. HBI showed a significant decrease and both

EPT taxa and Family IBI increased. All water quality and quantity variables across the basin responded in a similar fashion to the 262 sampled sites. When comparing native grass to current conditions, significant improvement were detected for all three macroinvertebrate measures. It is important to note that the results from the Wilcoxon rank test are primarily used to evaluate the statistical significant effects of BMPs' implementation on the three ecological health measures on the study area as a whole. The percent changes, however, can be misleading because they are based on the mean and medians, which in some cases contradict each other (e.g. No-Till effects on HBI and FamilyIBI).

Table 13. Wilcoxon rank sum test and percent changes variables before and after BMP implementation scenarios for 262 sampling locations

Variables	**Current to No Till**			**Current to Residue Mgt.**			**Current to Native Grass**		
	% change			% change			% change		
	Mean	median	pvalue	Mean	Median	pvalue	Mean	Median	pvalue
HBI	0.46%	-0.14%	**0.3961**	-2.5%	-0.79%	<0.01	-4.59%	-1.48%	<0.01
FamilyIBI	0.90%	-1.93%	<0.01	1.86%	-0.32%	<0.01	4.94%	3.63%	<0.01
EPTtaxa	-3.0%	-1.18%	**0.041**	4.90%	0.28%	<0.01	17.24%	10.49%	<0.01
AFLOW	0.34%	0.66%	<0.01	-2.4%	-1.46%	<0.01	-5.03%	-5.95%	<0.01
SFLOW	0.71%	0.22%	<0.01	-3.9%	-2.07%	<0.01	-12.3%	-7.73%	<0.01
AOrgN	-6.9%	-5.89%	<0.01	-9.6%	-14.8%	<0.01	-41.5%	-35.6%	<0.01
ANo2	-7.6%	-4.53%	<0.01	-13%	-16.2%	<0.01	-48.1%	-45.7%	<0.01
ANH4	-8.1%	-7.15%	<0.01	-15%	-15.3%	<0.01	-46.6%	-42.9%	<0.01
SOrgP	1.48%	5.50%	<0.01	7.51%	2.44%	<0.01	-33.9%	-25.3%	<0.01
STN	-7.4%	-8.11%	<0.01	-1.8%	-12.3%	<0.01	-42.8%	-39.8%	<0.01

Table 14. Wilcoxon rank sum test and percent changes variables before and after BMP implementation scenarios for the entire basin

Variables	Current to No Till			Current to Residue Mgt.			Current to Native Grass		
	% change			% change			% change		
	Mean	median	pvalue	Mean	Median	pvalue	Mean	Median	pvalue
HBI	0.62%	0.12%	**0.1169**	-1.86%	-0.33%	<0.01	-1.1%	-0.22%	<0.01
FamilyIBI	1.47%	0.33%	<0.01	1.46%	1.07%	<0.01	7.11%	7.99%	<0.01
EPTtaxa	-0.5%	0.07%	**0.0344**	4.31%	4.52%	<0.01	1.67%	2.54%	<0.01
AFLOW	0.32%	0.31%	<0.01	-2.49%	-3.32%	<0.01	-7.0%	-7.83%	<0.01
SFLOW	0.76%	0.95%	<0.01	-4.11%	-5.47%	<0.01	-9.5%	-14.6%	<0.01
AOrgN	-4.5%	-0.33%	<0.01	-4.29%	-3.71%	<0.01	-44%	-24.3%	<0.01
ANo2	-7.9%	0.01%	<0.01	-16.9%	-1.58%	<0.01	-51%	-39.6%	<0.01
ANH4	-8.2%	-1.34%	<0.01	-19.0%	-9.15%	<0.01	-56%	-66.4%	<0.01
SOrgP	0.01%	4.72%	<0.01	12.01%	-0.64%	<0.01	-31%	-28.3%	<0.01
STN	-6.7%	-1.87%	<0.01	-0.10%	-7.25%	<0.01	-39%	-39.4%	<0.01

1.16.4.2 Stream Health for Individual Reaches

In this section, the predicted effects of BMP implementation for individual reaches throughout the basin are evaluated. Overall, the practice of no-tillage increased FamilyIBI in 27% of the reaches within the basin. Meanwhile 18% showed a decline in FamilyIBI and the remaining 55% showed no change at all (Figure 13, Table 22). Of the reaches that showed no impact, only 5% of them were within a subbasin that had a BMP. Within the reaches that showed increases in Family IBI, roughly 50% were located within subbasins that implemented no-tillage. However, of the reaches that showed decreases, roughly 50% also were in subbasins that implemented BMPs. The water quality and quantity variables that were included in predicting FamilyIBI also changed similar among improved and declined reaches. This could be a result of the non-linearity responses that are captured in the ANFIS models and indicates the importance of interactions among variables. It also may be a limitation of the models that were built off of data that was affected by a large amount of other factors that are not captured in the scope of this study. The number of EPTtaxa was increased by no-till operations in 20% of the subbasins, while 62% showed no change, and the remaining 18% showed a decline (Figure 14, table 22). Of the reaches that showed no change, most were in subbasins that were classified as pasture, forest, and wetlands. Only 13% of them were in subbasins where no-tillage was implemented. Of the reaches that showed a decline in EPTtaxa, 45% of them were found in subbasins where no-tillage was practiced. Meanwhile, 52% of the reaches that showed increases were found in subbasins where no-tillage was present. A distinction that was made between the reaches that increased and decreased in EPTtaxa was that degraded reaches on average showed an increase in ANo2 concentration, whereas improved reaches showed a decrease in ANO2. In addition, higher percentage (40%) of the reaches with declined EPTtaxa showed an increase in AOrgN concentrations) compared to reaches with increased EPTtaxa (15% of the reaches increased in AOrgN). When focusing on no-tillage's effects to HBI, 21% of the reaches in the basin showed an improvement, 62% showed no change, and 17% showed a negative change (Figure 15, Table 22). The majority (86%) of the reaches that did not respond in HBI were those with no-BMP. Of those reaches with improved HBI scores, 66% reaches showed a decrease in all three nitrogen concentration variables (STN, AOrgN, and ANo2). For reaches with declined HBI scores, 93% showed an increase in at least one nitrogen measure.

The residue management BMP implementation in the subbasin also resulted mixed results. About 31% of the reaches showed an increase in FamilyIBI, 54% showed no change, and 15% showed a decrease (Figure 16, Table 22). For reaches that showed no change, 97% had no row-crop lands applicable for residue management. However, the majority (60%) of subbasins that had residue management implementation had increased FamilyIBI value. Reaches that had decreased FamilyIBI values showed an average increase in SOrgP. The EPTtaxa also showed more of an increase with residue management. About 26% of the reaches showed an increase in

EPTtaxa, 59% showed no change, and 15% showed decreases (Figure 17, Table 22). Of the reaches that showed no change, majority (57%) were in subbasins dominated by forest or forested wetland, and only 10% were in subbasins with residue management. A major difference between reaches that improved and declined was reflected on how AOrgN responded. For reaches where EPTtaxa declined, on average the AOrgN showed an increase, while for reaches that EPTtaxa improved, AOrgN showed a decrease on average. In addition, a larger percentage of reaches decreased in AOrgN for the improved reaches when compared to the degraded ones. For HBI, about 25% of the reaches improved, 58% did not respond, and 17% responded negatively to the Residue Management (Figure 18, Table 22). Of the reaches that did not respond, 93% of them were located in subbasins that were not disturbed through residue management operations. For reaches with degraded HBI condition, more than half of the reaches showed an increase in at least one nitrogen measure (STN, AOrgN, or ANo2). In addition, the proportion of reaches that had increased STN, AOrgN, and ANO2 for the degraded sites was higher than the proportion in the improved sites. This could potentially explain why some sites actually degraded from residue management.

In the case where native grass was applied to the agricultural lands, 50% of reaches increased in FamilyIBI score, 22% had no change, and 28% decreased (Figure 19, Table 22). Of the reaches that showed no change, only 1% was within subbasins that received the native grass conversion and the subbasins of those reaches were largely forests, wetlands, and pastures that were not altered between two scenarios. Reaches with increased FamilyIBI had a smaller proportion (16%) of reaches with increased ANH4. For EPTtaxa, about 46% of the reaches increased, 24% had no change, and 30% declined by native grass BMP (Figure 20, Table 22). Of the reaches that showed no change in EPTtaxa, 92% were in subbasins that had no BMP implementation and very little differences in water quality and quantity variables between scenarios. The reaches improved by native grass BMP had larger average decrease in AOrgN (-2.57 mg/L) than reaches degraded by native grass had (-0.85 mg/L). Native grass's effect on HBI benefitted for 44% of the reaches within the basin, had no effect for 25% of the reaches, and had negative for 31% of the reaches (Figure 21, Table 22). Among the reaches that had declined condition, 60% showed an increase in at least one of the three nutrient measures.

Table 15. The impact of BMP implementation scenarios at watershed scale based on macroinvertebrate measures

BMP	Family IBI % total reaches			EPT taxa % total reaches			HBI % total reaches		
	Improve	Decline	No Change	Improve	Decline	No Change	Improve	Decline	No Change
No-Till	27%	18%	55%	20%	18%	62%	21%	17%	62%
Residue Mgt.	31%	15%	54%	26%	15%	59%	25%	17%	58%
Native Grass	50%	28%	22%	46%	30%	24%	44%	31%	25%

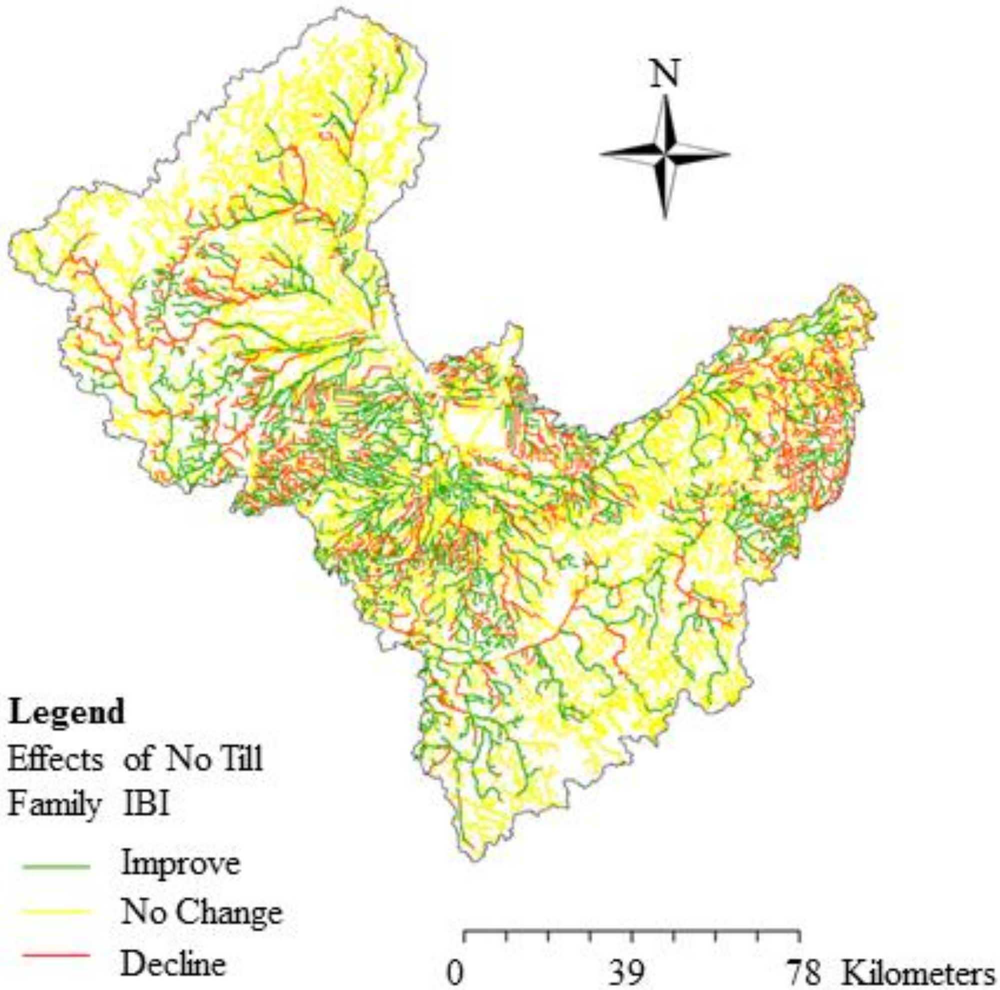

Figure 13. Improvements and declines in Family IBI from current scenario after no-till implementation

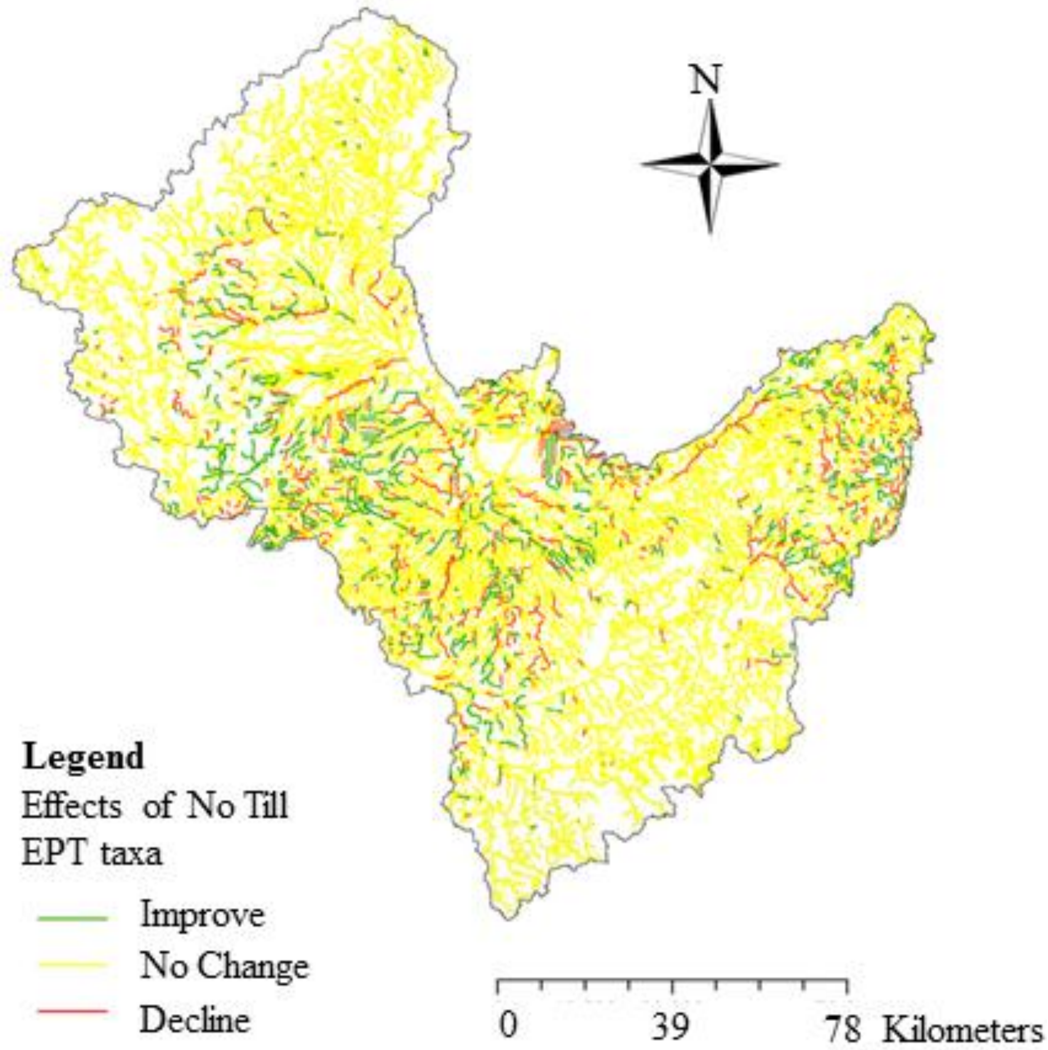

Figure 14. Improvements and declines in EPT taxa from current scenario after no-till implementation

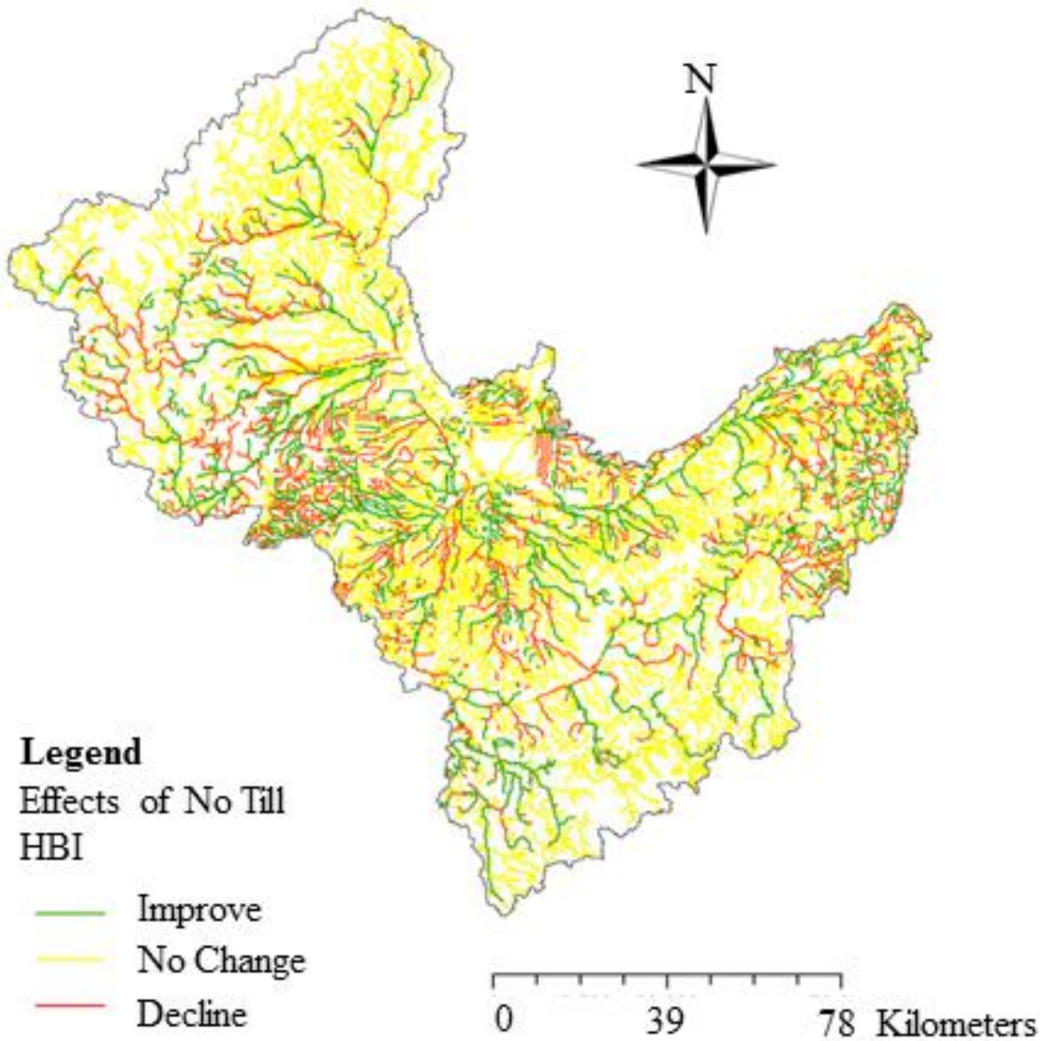

Figure 15. Improvements and declines in HBI from current scenario after no-till implementation

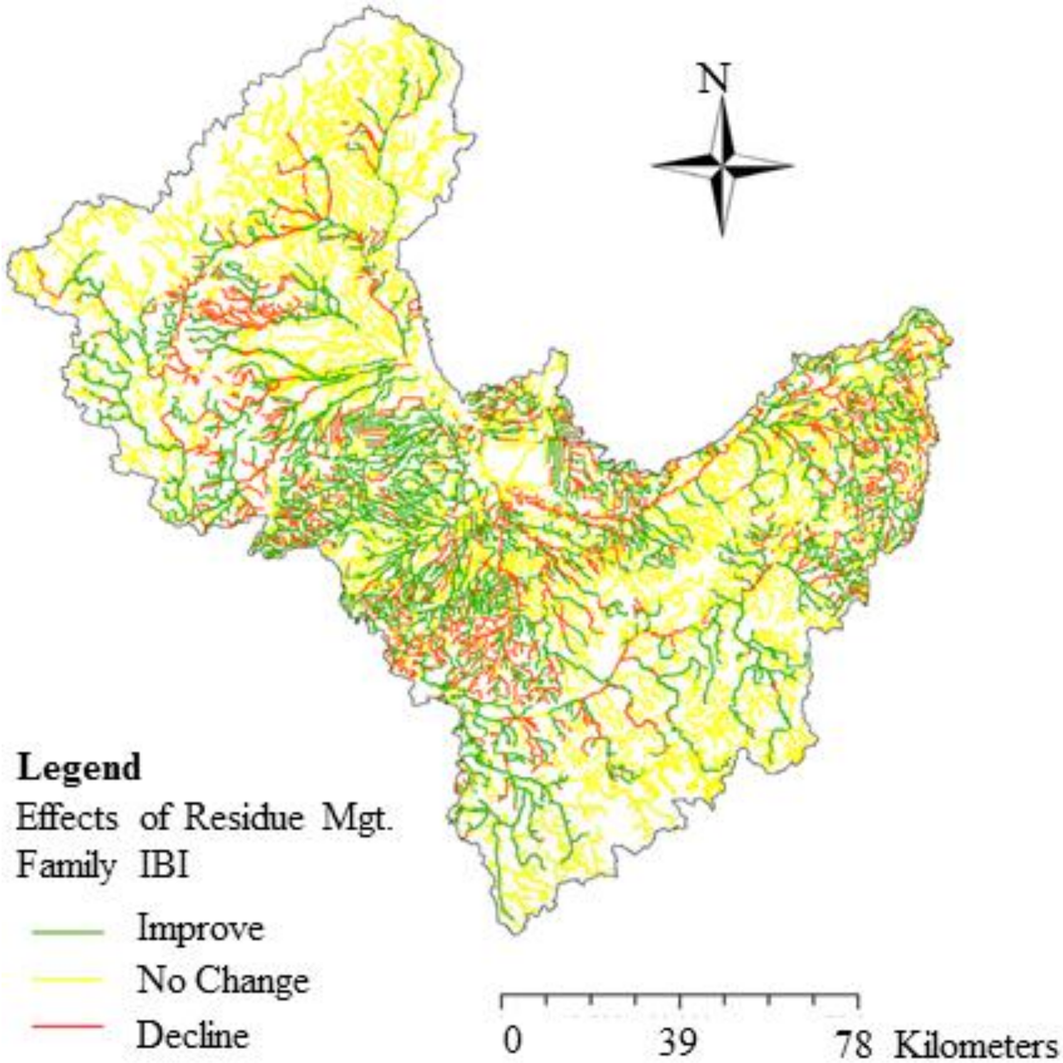

Figure 16. Improvements and declines in Family IBI from current scenario after residue management implementation

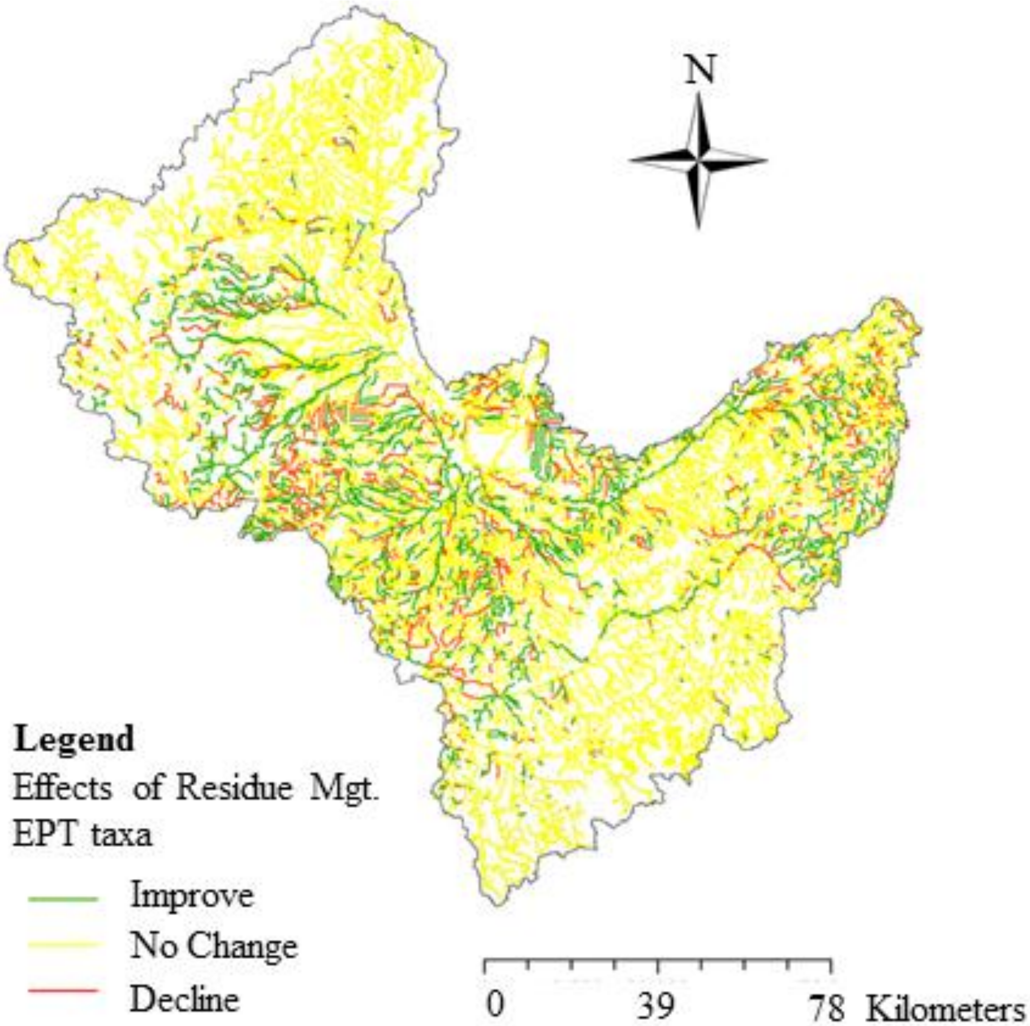

Figure 17. Improvements and declines in EPT taxa from current scenario after residue management implementation

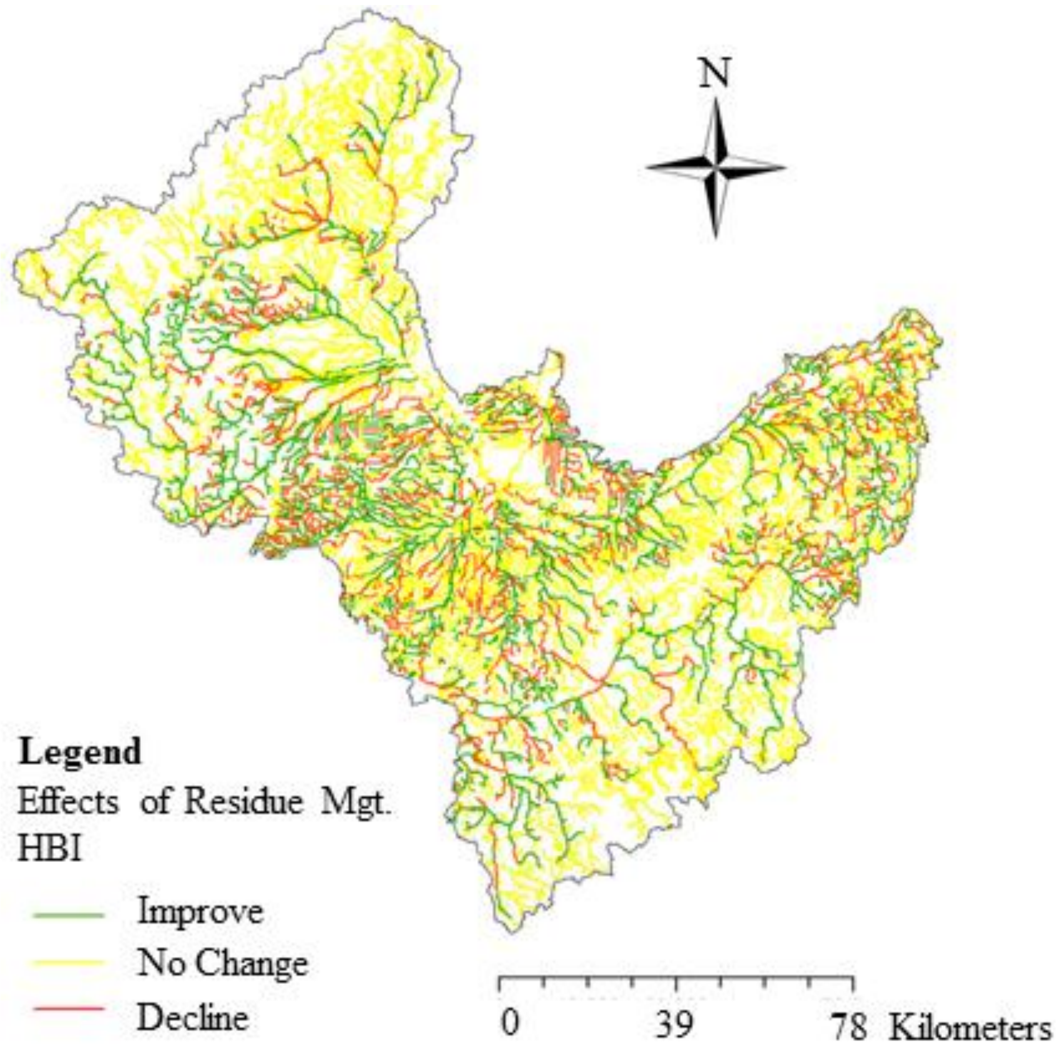

Figure 18. Improvements and declines in HBI from current scenario after residue management implementation

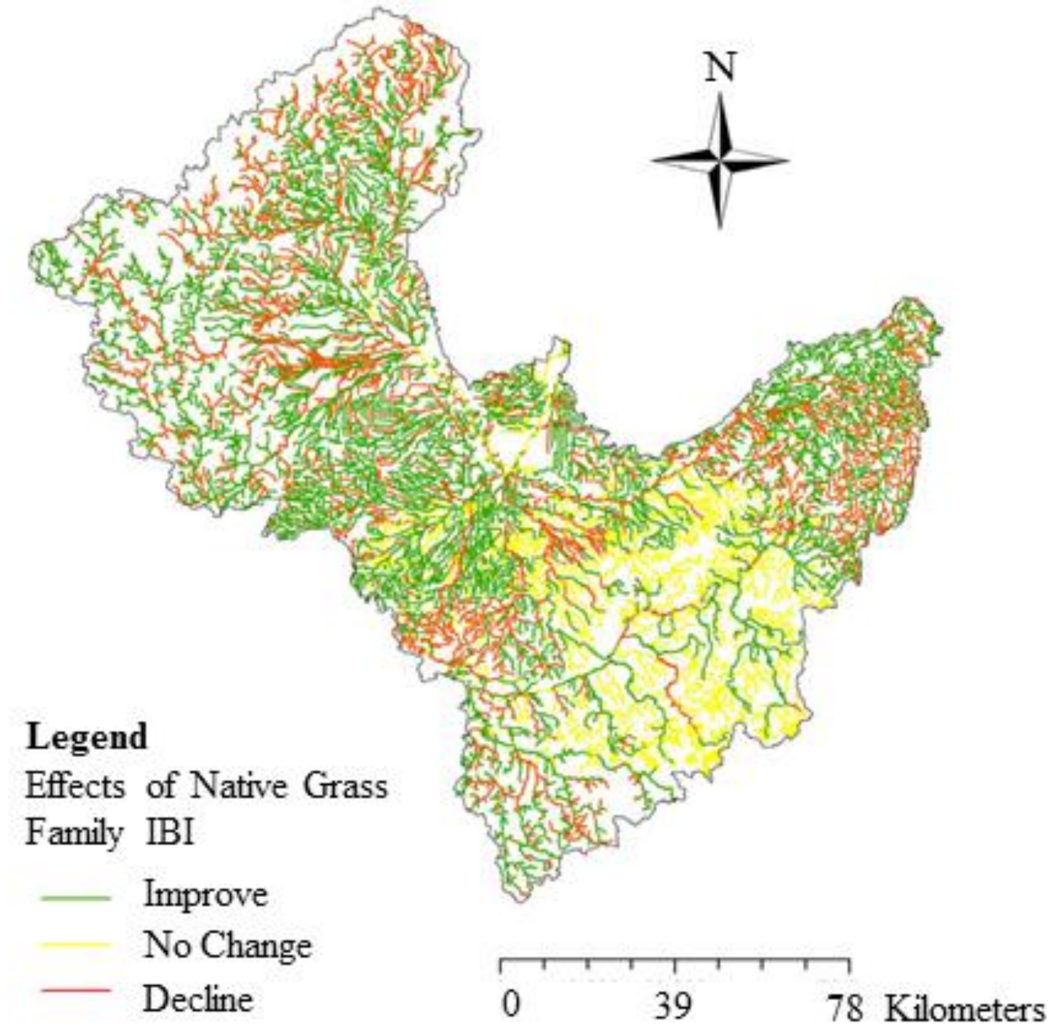

Figure 19. Improvements and declines in Family IBI from current scenario after native grass implementation

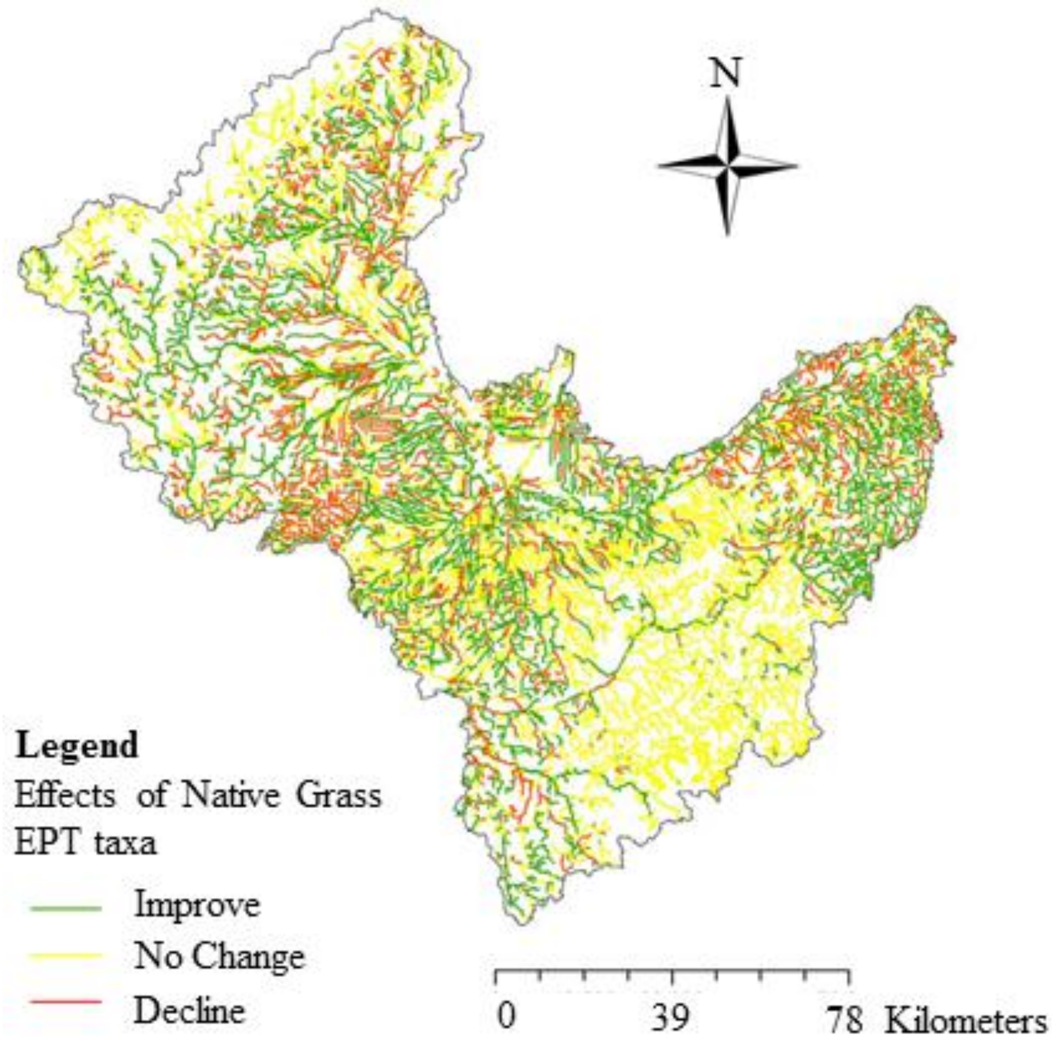

Figure 20. Improvements and declines in EPT taxa from current scenario after native grass implementation

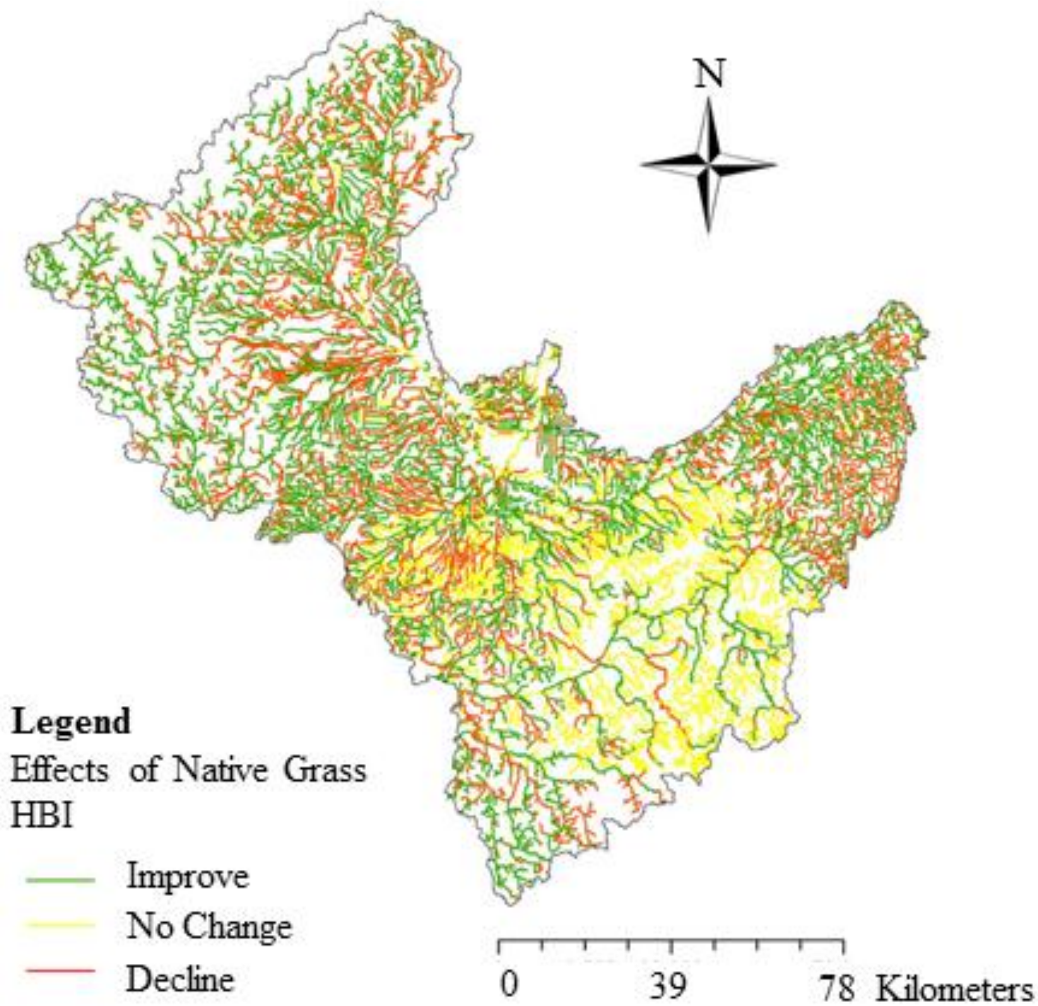

Figure 21. Improvements and declines in HBI from current scenario after native grass implementation

1.17 CONCLUSION

As demands for agricultural production and landscape conversion into urban environment continue, there is a need to assess the effects of these activities for developing possible mitigating strategies to protect the health of water resources. To effectively do so, there is a need to continue to explore alternative methods in predicting and understanding the complex relationships involved. The objectives of this study included linking hydrologic models and ecological conditions using the Soil and Water Assessment Tool (SWAT as a means of building and collecting high resolution flow and water quality elements. The study then identifies the influential variables for explaining macroinvertebrate indices. The relationships between aquatic macroinvertebrates and local in-stream conditions (SWAT outputs) are explored through models built using statistical and alternative methods. Those models were then used to forecast and assess the effects of numerous agricultural BMPs on stream health.

Within this study, a high resolution and detailed SWAT model was built and calibrated for the Saginaw River watershed to provide data and predictions of in-stream conditions, where they otherwise would not be available. Outputs obtained from the SWAT model included in-stream variables such as sediment and nutrient loads that often originate from anthropogenic activities. In addition, stream size was included in efforts to capture the natural longitudinal variation from headwaters to downstream rivers. The variables were then linked with three macroinvertebrate measures (HBI, FamilyIBI, and EPTtaxa), which were used as indicators of overall stream health.

Overall, in-stream variables obtained through the SWAT model explained 54% of the variation in EPTtaxa, 57% of the variation in HBI, and 50% of the variation in FamilyIBI. The limited variance explained by the in-stream water quality and quantity variables within this study exhibits the influence of other factors, which are not available for every reach or within the scope of this study. Linear (stepwise linear regression) and non-linear (ANFIS and kernel regression) methods were explored to describe the linkage between in-stream variables and macroinvertebrate measures. The best model was identified through 10-fold cross validation analysis for the prediction of stream health under current conditions and under scenarios involving the implementation of agricultural conservation practices. Among the methods, the non-linear ANFIS method performed the best for all three stream health measures. This highlights the non-linear and complex relationships between environmental and ecological components.

Throughout all three methods, similar in-stream variables were consistently identified as having a large association with the macroinvertebrate measures. Average annual organic nitrogen had the highest partial R^2 and highest spearman correlation with HBI; with lower concentrations generally associated with better stream health. This relationship was expected due to the fact that HBI is calculated based on pollution tolerance values. The best model for predicting HBI also included average seasonal total nitrogen and annual nitrite. EPTtaxa was also consistently explained through nitrogen concentrations, with AOrgN being included in the best model along with nitrite, average seasonal flow, and cross-sectional area. FamilyIBI was also commonly explained through nutrient concentrations more than any other variables. The best model for Family IBI included average annual ammonium and average seasonal organic phosphorus in addition to average annual flow and cross-sectional area.

The predicative models were then used in connection with outputs from SWAT models for forecasting the effects of BMP implementation within the Saginaw River watershed. The three best management practices looked at represented three different efficiencies when it comes to reducing the effects to our water quality and quantity, with no-tillage being minimal, residue management being medium, and native grass being the maximum. This was partially mirrored in the predicted effects on stream health (HBI, FamilyIBI, and EPTtaxa). Significant changes were observed with all three practices from current conditions with the exception of HBI and EPTtaxa under no-tillage scenario. The improvements observed from the implementation of the BMPs were highly caused by their reduction of nutrient concentrations, especially within subbasins where they were implemented. Meanwhile, there were a smaller percentage of reaches that showed declines in stream health with the implementation of BMPs. This was often connected with increases in one or more nutrient concentrations. In addition, these results could be misinterpretations because of limitations in the models and variables included. While the results help enhance the understanding of the potential benefits from large scale BMP implementation, uncertainty in the data collection and model components still exists, which should be explored in future studies. This study employed a SWAT model that was calibrated at a single location, and future studies using a more spatially extensive calibration may reduce this uncertainty. In addition, the use of more biological data, both spatially and temporally, may also improve understanding.

This study identified in-stream variables and conditions that have significant relations with macroinvertebrate communities and ultimately stream health. At the same time, it made these connections through a hydrologic model and the use of non-linear alternative methods. The benefit of linking watershed models, such as SWAT, to stream health is that it allows us to forecast the effects of different management practices and anthropogenic activities.

Acknowledgements

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CONCLUSIONS

The research presented here evaluated the potential for a Soil and Water Assessment Tool (SWAT) model to provide influential in-stream variables to explain fish and macroinvertebrate measures beyond the biological sampling points within the Saginaw River watershed, located in Michigan. The high resolution SWAT model was built that includes detailed information at spatial units having homogenous physicochemical, geomorphological, and biological features for all stream segments within the study area. The in-stream variables provided by the model included flow, sediment, nutrient concentrations, which may directly or indirectly influence the health of a stream. Relationships between in-stream variables (SWAT outputs) and fish (Index of Biological Integrity (IBI) and Percent Intolerant Individuals) and macroinvertebrate (Family index of Biological Integrity (Family IBI), Hilsenhoff Biotic Index (HBI), and Number of EPT taxa) measures were explored and predictive models were built using statistical methods and alternative soft computing techniques. Scenarios representing landuse conversion, climate change, and management practices were then presented within the SWAT model and their potential effects on stream health were estimated. The first section of this research focused on the connection between in-stream conditions and fish measures. In addition, historical reference conditions for streams in the Saginaw River watershed were predicted under pre-settlement land-use and climate data. The second study explored the relationships between in-stream conditions and macroinvertebrate measures and assessed different agricultural best management practices' (BMPs) performances on improving ecological health measures. The following can be concluded from the results of both studies:

- The Soil and Water Assessment Tool can be an effective tool to provide influential in-stream data where it otherwise would not exist

- In-stream variables obtained from SWAT explained 48% of the variation in IBI, 21% of the variation in the percent of intolerant individuals, 50% of the variation in Family IBI, 57% of the variation in HBI, and 54% of the variation in the number of EPT taxa.
- Fuzzy logic and adaptive neural-fuzzy inference system techniques outperformed other statistical methods (stepwise linear regression, partial least squares regression, and kernel regression) and provide a valuable and practical approach to connecting environmental and water quality conditions to ecological health measures.
- Average annual flow rate had the strongest correlation with IBI, whereas nutrient concentrations (e.g. organic phosphorus, organic nitrogen) showed the largest influence on the percentage of intolerant individuals and all three macroinvertebrate measures. However, adding a measure of stream size and in-stream physical habitat variables along with other measures of watershed physiographic characteristics would likely improve the accuracy of model predictions.
- Results showed overall significantly higher IBI and percent intolerant individuals under the pre-settlement landuse scenario. This implies that landuse change from pre-settlement to current has profound negative impacts on stream health.
- Pre-settlement climate factors had a strong influence on stream flow and water quality measures that interactively affect stream health as indicated by fish measures. These results suggest that efforts to model historic baseline habitat conditions and to provide context for stream health assessments should include both pre-settlement land use and climate conditions.

- Among the studied best management practices, native grass resulted in the most improvement in stream health as indicated by macroinvertebrate measures, followed by residue management and no-tillage operations.

RECOMMENDATIONS FOR FUTURE RESEARCH

This research provides results and valuable insight into the efforts of linking watershed models and in-stream variables with ecological health. In addition the information looks at alternative methods in capturing these relationships and building predictive models that can act as effective tools for decision makers in quantifying the impacts of landuse and climate change, along with management strategies. However, continuing research must be done that builds upon these studies and addresses issues outside the scope of this project. The following are suggestions for future research:

- There is a great deal of uncertainty in the data collection and model components that exists. This uncertainty should be explored and quantified to better aid managers and decision makers.
- In order to have more comprehensive predictions and explanation of ecological measures, additional variables such as physical, chemical, and natural factors should be considered. Adding measures, such as stream size and instream physical habitat variables would likely provide more robust predictions and the necessary context to reveal the relative residual effects of flow and water quality on aquatic communities.
- With such complex interactions and relationships involved in aquatic species and their environments, there is a need to continue to explore alternative methods for capturing and modeling these processes. This may include continuing research employing different fuzzy logic techniques or fusion-methods.
- Ideally, both fish and macroinvertebrates should be measured together because they can react differently, vary in sensitivity to different stressors, and mirror conditions at different scales. Assessing multiple indices of stream health and doing so through

methods such as analytic hierarchy processes may provide more comprehensive insight into the impacts of landuse and climate change.

- There are a number of potential best management practices that may be implemented within agricultural regions and at different scales, which go beyond the scope of this project. Additional studies addressing these scenarios will provide a more comprehensive assessment of BMP implementation within the Saginaw River watershed.
- Potential future changes in climate and landuse (e.g. biofuel crop expansion) and their impacts on ecological health need to be addressed. Future research, applying similar strategies as this study, can be performed to assess the potential associated risk involved.
- Relationships and measures studied in this project were within a highly agricultural and warm-water dominated watershed. Additional studies in different climatological and physiographical regions will likely provide diverse results and are needed to better understand the interactions involved and implications of landuse and climate change across a larger scale.

APPENDIX

APPENDIX

Table 16. Stepwise linear regression models for IBI

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	IBI	*1,*2	303.07	0.39	662.05	0.02	333.69	0.33
2	IBI	*1,*3,*4	336.94	0.35	301.67	0.19	326.48	0.34
3	IBI	*1,*2	323.89	0.35	399.22	0.29	326.27	0.34
4	IBI	*1,*2,*3	335.53	0.33	332.12	0.34	328.24	0.34
5	IBI	*1,*2,*3	321.30	0.35	452.56	0.31	327.57	0.34
6	IBI	*1,*2	345.94	0.35	251.83	0.32	331.30	0.33
7	IBI	*5,*2	333.05	0.32	314.53	0.50	326.05	0.34
8	IBI	*5,*4	326.71	0.37	399.29	0.08	329.15	0.34
9	IBI	*5,*2	338.90	0.31	270.62	0.63	326.55	0.34
10	IBI	*5,*2	340.19	0.32	255.86	0.49	326.16	0.34

* All Variables after transformation

*1 AFLOW; *2 ANO_2; *3 ANO_3; *4 ANH_4; *5 SFLOW

Table 17. Stepwise linear regression models for percent intolerant individuals

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	%INTOL	$*_1, *_2$	280.37	0.14	580.81	0.03	309.95	0.12
2	%INTOL	$*_3, *_4$	320.11	0.11	272.30	0.02	315.40	0.10
3	%INTOL	$*_1, *_4$	328.93	0.10	236.20	0.01	319.80	0.09
4	%INTOL	$*_3, *_2, *_5$	304.54	0.18	270.68	0.00	301.21	0.13
5	%INTOL	$*_3, *_4$	332.19	0.10	105.14	0.19	309.84	0.10
6	%INTOL	$*_3, *_6$	297.22	0.10	528.69	0.18	320.01	0.10
7	%INTOL	$*_3, *_6$	336.18	0.09	107.66	0.33	313.68	0.10
8	%INTOL	$*_3, *_6$	326.03	0.11	227.89	0.05	315.86	0.10
9	%INTOL	$*_3, *_6$	309.13	0.07	445.93	0.39	323.31	0.10
10	%INTOL	$*_1, *_2$	284.93	0.15	566.83	0.01	314.14	0.12

* All Variables after transformation

*1 ANH_4; *2 ASED; *3 ATP; *4 ANO_3; *5 SNO_2; *6 SFLOW

Table 18. PLSR models for IBI

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	IBI	PC1, PC2	313.39	0.35	606.05	0.04	342.20	0.31
2	IBI	PC1, PC2	343.04	0.33	320.04	0.16	340.77	0.31
3	IBI	PC1, PC2	331.88	0.32	374.17	0.31	336.04	0.32
4	IBI	PC1, PC2	345.17	0.30	290.32	0.42	339.77	0.31
5	IBI	PC1, PC2	325.90	0.32	472.06	0.29	340.29	0.31
6	IBI	PC1, PC2	347.33	0.32	246.22	0.27	337.37	0.32
7	IBI	PC1, PC2	342.41	0.29	294.15	0.56	337.66	0.32
8	IBI	PC1, PC2	335.04	0.34	403.52	0.07	342.14	0.31
9	IBI	PC1, PC2	342.54	0.29	308.11	0.56	338.97	0.31
10	IBI	PC1, PC2	342.12	0.31	269.80	0.46	334.63	0.32

Table 19. PLSR models for percent intolerant individuals

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	%INTOL	PC1, PC2	288.58	0.11	669.48	0.00	326.08	0.08
2	%INTOL	PC1, PC2	326.99	0.09	238.87	0.12	318.31	0.09
3	%INTOL	PC1, PC2	328.14	0.10	221.78	0.02	317.67	0.09
4	%INTOL	PC1, PC2	328.53	0.10	193.01	0.11	315.19	0.10
5	%INTOL	PC1, PC2	336.69	0.09	95.61	0.28	312.95	0.09
6	%INTOL	PC1, PC2	298.75	0.09	536.97	0.10	322.20	0.09
7	%INTOL	PC1, PC2	341.22	0.08	100.49	0.38	317.52	0.09
8	%INTOL	PC1, PC2	331.41	0.09	230.69	0.06	320.97	0.09
9	%INTOL	PC1, PC2	312.05	0.07	449.42	0.37	326.28	0.09
10	%INTOL	PC1, PC2	291.16	0.13	581.00	0.00	321.19	0.09

Table 20. Fuzzy logic models for IBI

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	IBI	*1,*2,*3, *4,*5	295.31	0.41	494.5	0.20	314.92	0.37
2	IBI	*1,*2,*3, *4,*5	319.65	0.40	240.6	0.47	274.90	0.40
3	IBI	*1,*2,*3, *4,*5	288.05	0.43	350.0	0.39	271.59	0.43
4	IBI	*1,*2,*3, *4,*5	341.08	0.37	237.4	0.56	330.88	0.39
5	IBI	*1,*2,*3, *4,*5	295.88	0.43	438.5	0.42	276.86	0.42
6	IBI	*1,*2,*3, *4,*5	283.89	0.47	219.8	0.31	250.64	0.46
7	IBI	*1,*2,*3, *4,*5	329.69	0.37	262.0	0.56	323.03	0.39
8	IBI	*1,*2,*3, *4,*5	280.83	0.49	387.7	0.25	263.11	0.46
9	IBI	*1,*2,*3, *4,*5	274.37	0.45	205.1	0.68	243.17	0.48
10	IBI	*1,*2,*3, *4,*5	298.17	0.41	196.2	0.61	287.62	0.43

*1 AFLOW; *2 AOrgP; *3 SNO_2; *4 SNO_3; *5 StreamGrad

Table 21. Fuzzy logic models for percent intolerant individuals

10 Fold Set	Response Variable	Predictor Variables	Training MSE	Training R^2	Test MSE	Test R^2	Overall MSE	Overall R^2
1	%INTOL	*1,*2,*3, *4	250.40	0.16	537.6	0.03	278.68	0.14
2	%INTOL	*1,*2,*3, *4	286.30	0.13	172.1	0.38	275.07	0.14
3	%INTOL	*1,*2,*3, *4	300.58	0.11	148.2	0.34	285.59	0.12
4	%INTOL	*1,*2,*3, *4	292.57	0.12	178.2	0.12	281.32	0.12
5	%INTOL	*1,*2,*3, *4	317.79	0.11	92.63	0.30	295.62	0.11
6	%INTOL	*1,*2,*3, *4	266.98	0.12	380.9	0.29	278.20	0.13
7	%INTOL	*1,*2,*3, *4	298.36	0.12	92.17	0.41	278.06	0.14
8	%INTOL	*1,*2,*3, *4	304.37	0.12	196.7	0.12	293.22	0.12
9	%INTOL	*1,*2,*3, *4	273.57	0.10	320.8	0.53	278.47	0.13
10	%INTOL	*1,*2,*3, *4	250.01	0.17	493.8	0.01	275.27	0.14

*1 AOrgP; *2 ANO_2; *3 AFLOW; *4 ACHLA

Table 22. Spearman rank correlations with red indicating significance

	IBI	%INTOL	StreamGrad	SFLOW	SSED	SOrgN	SOrgP	SNo3	SNH4	SNo2	SMinP
%INTOL	0.67	1.00	0.01	0.23	-0.08	-0.35	-0.36	0.05	-0.32	-0.30	-0.12
StreamGrad	-0.18	0.01	1.00	-0.52	-0.34	0.12	0.12	-0.48	0.01	-0.13	-0.41
SFLOW	0.43	0.23	-0.52	1.00	0.42	-0.43	-0.41	0.66	-0.18	0.09	0.51
SSED	0.02	-0.08	-0.34	0.42	1.00	0.30	0.30	0.74	0.51	0.59	0.84
SOrgN	-0.38	-0.35	0.12	-0.43	0.30	1.00	0.99	-0.06	0.83	0.60	0.23
SOrgP	-0.40	-0.36	0.12	-0.41	0.30	0.99	1.00	-0.03	0.85	0.63	0.26
SNo3	0.20	0.05	-0.48	0.66	0.74	-0.06	-0.03	1.00	0.25	0.44	0.88
SNH4	-0.35	-0.32	0.01	-0.18	0.51	0.83	0.85	0.25	1.00	0.84	0.53
SNo2	-0.29	-0.30	-0.13	0.09	0.59	0.60	0.63	0.44	0.84	1.00	0.63
SMinP	0.04	-0.12	-0.41	0.51	0.84	0.23	0.26	0.88	0.53	0.63	1.00
SCHLA	-0.02	-0.10	-0.63	0.49	0.65	0.23	0.24	0.63	0.35	0.43	0.67
SCBOD	-0.15	-0.14	0.07	-0.27	0.26	0.63	0.58	-0.05	0.39	0.22	0.12
SDO	0.13	0.08	-0.18	0.35	0.21	-0.24	-0.23	0.26	-0.08	0.02	0.21
STN	-0.04	-0.17	-0.31	0.26	0.78	0.50	0.52	0.77	0.66	0.65	0.89
STP	-0.13	-0.25	-0.22	0.13	0.74	0.65	0.67	0.59	0.73	0.67	0.81
SPercBase	0.03	0.10	-0.07	-0.08	-0.39	-0.50	-0.49	-0.16	-0.35	-0.31	-0.28
AFLOW	0.47	0.27	-0.49	0.98	0.35	-0.52	-0.49	0.61	-0.26	0.02	0.44
ASED	0.03	-0.05	-0.29	0.33	0.95	0.34	0.34	0.69	0.54	0.59	0.78
AOrgN	-0.41	-0.38	0.03	-0.44	0.41	0.88	0.87	0.08	0.81	0.61	0.32
AOrgP	-0.43	-0.40	0.06	-0.45	0.39	0.89	0.88	0.07	0.81	0.62	0.32
ANo3	0.08	-0.04	-0.40	0.34	0.74	0.12	0.14	0.83	0.35	0.45	0.77
ANH4	-0.30	-0.34	-0.13	-0.05	0.71	0.67	0.68	0.46	0.86	0.81	0.67
ANo2	-0.26	-0.32	-0.20	0.13	0.73	0.52	0.53	0.55	0.75	0.90	0.72
AMinP	-0.09	-0.21	-0.34	0.35	0.88	0.32	0.33	0.77	0.57	0.65	0.90
ACHLA	-0.15	-0.25	-0.61	0.33	0.59	0.34	0.34	0.53	0.44	0.53	0.61
ACBOD	-0.17	-0.15	0.16	-0.37	0.16	0.56	0.50	-0.12	0.35	0.16	0.03
ADO	0.09	0.12	-0.14	0.21	0.13	-0.19	-0.18	0.14	-0.11	-0.03	0.10
ATN	-0.17	-0.26	-0.27	0.05	0.74	0.50	0.50	0.65	0.63	0.60	0.75
ATP	-0.24	-0.34	-0.21	-0.01	0.71	0.62	0.62	0.51	0.70	0.63	0.71
APercBase	0.05	0.15	-0.06	-0.05	-0.36	-0.48	-0.45	-0.13	-0.28	-0.23	-0.24

Table 22. (cont'd)

	SCHLA	SCBOD	SDO	STN	STP	SPercBase	AFLOW	ASED	AOrgN	AOrgP
%INTOL	-0.10	-0.14	0.08	-0.17	-0.25	0.10	0.27	-0.05	-0.38	-0.40
StreamGrad	-0.63	0.07	-0.18	-0.31	-0.22	-0.07	-0.49	-0.29	0.03	0.06
SFLOW	0.49	-0.27	0.35	0.26	0.13	-0.08	0.98	0.33	-0.44	-0.45
SSED	0.65	0.26	0.21	0.78	0.74	-0.39	0.35	0.95	0.41	0.39
SOrgN	0.23	0.63	-0.24	0.50	0.65	-0.50	-0.52	0.34	0.88	0.89
SOrgP	0.24	0.58	-0.23	0.52	0.67	-0.49	-0.49	0.34	0.87	0.88
SNo3	0.63	-0.05	0.26	0.77	0.59	-0.16	0.61	0.69	0.08	0.07
SNH4	0.35	0.39	-0.08	0.66	0.73	-0.35	-0.26	0.54	0.81	0.81
SNo2	0.43	0.22	0.02	0.65	0.67	-0.31	0.02	0.59	0.61	0.62
SMinP	0.67	0.12	0.21	0.89	0.81	-0.28	0.44	0.78	0.32	0.32
SCHLA	1.00	0.24	0.17	0.62	0.57	-0.32	0.43	0.63	0.28	0.28
SCBOD	0.24	1.00	-0.23	0.32	0.41	-0.58	-0.32	0.30	0.60	0.58
SDO	0.17	-0.23	1.00	0.06	0.00	0.04	0.36	0.15	-0.25	-0.25
STN	0.62	0.32	0.06	1.00	0.94	-0.41	0.17	0.74	0.56	0.55
STP	0.57	0.41	0.00	0.94	1.00	-0.51	0.05	0.70	0.65	0.65
SPercBase	-0.32	-0.58	0.04	-0.41	-0.51	1.00	-0.01	-0.40	-0.43	-0.44
AFLOW	0.43	-0.32	0.36	0.17	0.05	-0.01	1.00	0.27	-0.53	-0.54
ASED	0.63	0.30	0.15	0.74	0.70	-0.40	0.27	1.00	0.48	0.45
AOrgN	0.28	0.60	-0.25	0.56	0.65	-0.43	-0.53	0.48	1.00	0.99
AOrgP	0.28	0.58	-0.25	0.55	0.65	-0.44	-0.54	0.45	0.99	1.00
ANo3	0.55	0.10	0.11	0.76	0.62	-0.16	0.30	0.74	0.34	0.31
ANH4	0.45	0.38	-0.02	0.75	0.77	-0.37	-0.14	0.75	0.83	0.83
ANo2	0.48	0.25	0.06	0.71	0.71	-0.32	0.06	0.74	0.66	0.66
AMinP	0.65	0.21	0.16	0.83	0.78	-0.32	0.28	0.86	0.49	0.49
ACHLA	0.86	0.32	0.14	0.57	0.54	-0.31	0.29	0.59	0.42	0.41
ACBOD	0.14	0.95	-0.26	0.23	0.30	-0.44	-0.40	0.22	0.56	0.54
ADO	0.11	-0.16	0.85	-0.02	-0.06	0.05	0.22	0.08	-0.20	-0.19
ATN	0.55	0.35	-0.02	0.87	0.80	-0.30	-0.03	0.76	0.71	0.69
ATP	0.54	0.43	-0.05	0.82	0.84	-0.42	-0.10	0.72	0.81	0.81
APercBase	-0.35	-0.69	0.04	-0.39	-0.48	0.87	0.00	-0.37	-0.41	-0.41

Table 22. (cont'd)

	ANo3	ANH4	ANo2	AMinP	ACHLA	ACBOD	ADO	ATN	ATP	APercBase
%INTOL	-0.04	-0.34	-0.32	-0.21	-0.25	-0.15	0.12	-0.26	-0.34	0.15
StreamGrad	-0.40	-0.13	-0.20	-0.34	-0.61	0.16	-0.14	-0.27	-0.21	-0.06
SFLOW	0.34	-0.05	0.13	0.35	0.33	-0.37	0.21	0.05	-0.01	-0.05
SSED	0.74	0.71	0.73	0.88	0.59	0.16	0.13	0.74	0.71	-0.36
SOrgN	0.12	0.67	0.52	0.32	0.34	0.56	-0.19	0.50	0.62	-0.48
SOrgP	0.14	0.68	0.53	0.33	0.34	0.50	-0.18	0.50	0.62	-0.45
SNo3	0.83	0.46	0.55	0.77	0.53	-0.12	0.14	0.65	0.51	-0.13
SNH4	0.35	0.86	0.75	0.57	0.44	0.35	-0.11	0.63	0.70	-0.28
SNo2	0.45	0.81	0.90	0.65	0.53	0.16	-0.03	0.60	0.63	-0.23
SMinP	0.77	0.67	0.72	0.90	0.61	0.03	0.10	0.75	0.71	-0.24
SCHLA	0.55	0.45	0.48	0.65	0.86	0.14	0.11	0.55	0.54	-0.35
SCBOD	0.10	0.38	0.25	0.21	0.32	0.95	-0.16	0.35	0.43	-0.69
SDO	0.11	-0.02	0.06	0.16	0.14	-0.26	0.85	-0.02	-0.05	0.04
STN	0.76	0.75	0.71	0.83	0.57	0.23	-0.02	0.87	0.82	-0.39
STP	0.62	0.77	0.71	0.78	0.54	0.30	-0.06	0.80	0.84	-0.48
SPercBase	-0.16	-0.37	-0.32	-0.32	-0.31	-0.44	0.05	-0.30	-0.42	0.87
AFLOW	0.30	-0.14	0.06	0.28	0.29	-0.40	0.22	-0.03	-0.10	0.00
ASED	0.74	0.75	0.74	0.86	0.59	0.22	0.08	0.76	0.72	-0.37
AOrgN	0.34	0.83	0.66	0.49	0.42	0.56	-0.20	0.71	0.81	-0.41
AOrgP	0.31	0.83	0.66	0.49	0.41	0.54	-0.19	0.69	0.81	-0.41
ANo3	1.00	0.62	0.61	0.82	0.53	0.03	0.07	0.85	0.68	-0.13
ANH4	0.62	1.00	0.92	0.83	0.56	0.33	-0.05	0.84	0.89	-0.32
ANo2	0.61	0.92	1.00	0.84	0.59	0.19	-0.01	0.76	0.79	-0.26
AMinP	0.82	0.83	0.84	1.00	0.67	0.13	0.07	0.86	0.85	-0.29
ACHLA	0.53	0.56	0.59	0.67	1.00	0.23	0.08	0.58	0.60	-0.35
ACBOD	0.03	0.33	0.19	0.13	0.23	1.00	-0.19	0.29	0.36	-0.59
ADO	0.07	-0.05	-0.01	0.07	0.08	-0.19	1.00	-0.04	-0.07	0.06
ATN	0.85	0.84	0.76	0.86	0.58	0.29	-0.04	1.00	0.93	-0.29
ATP	0.68	0.89	0.79	0.85	0.60	0.36	-0.07	0.93	1.00	-0.40
APercBase	-0.13	-0.32	-0.26	-0.29	-0.35	-0.59	0.06	-0.29	-0.40	1.00

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