OPTIMIZATION OF ENVIRONMENTAL FLOW TO PRESERVE/IMPROVE ECOLOGICAL FUNCTION

By

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ABSTRACT

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Freshwater is vital for all life, and with the growth of the human population, the need for this limited resource has increased. However, human activities have significant impacts on freshwater ecosystems, leading to their degradation. In order to ensure that freshwater resources remain sustainable for future generations, it is critical to understand how to evaluate stream health and mitigate degradation. To address these issues, the following research objectives were developed: 1) assess current methods used to evaluate stream health, in particular macroinvertebrate and fish stream health indices and 2) introduces a new strategy to improve stream health to a desirable condition at the lowest cost by optimizing best management practice (BMP) implementation plan. Analysis of over 85 macroinvertebrate and fish stream health indices indicated that the most commonly used macroinvertebrate and fish indices are: Benthic Index of Biotic Integrity (B-IBI), *Ephemeroptera Plechoptera Trichoptera* (Index) index, Hilsenhoff Biotic Index (HBI), and Index of Biological Integrity (IBI). These indices are often modified to take into account local ecosystem characteristics. In order to address objective two, several hydrological models including Soil and Water Assessment Tool and Hydrologic Integrity Tool were integrated and the results were used to develop stream health predictor models. All of the models were guided by a genetic algorithm to design the watershed-scale management strategies. The coupled system successfully identified eight BMP implementation plans that were resulted in excellent stream health conditions according to the IBI score.

This thesis is dedicated to my family and friends for all the love and support they have given me.

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KEY TO ABBREVIATIONS

AMBI	AZTI Marine Biotic Index
ANFIS	Adaptive Neuro-fuzzy Inference Systems
BI	Biotic Index
B-IBI	Benthic Index of Biotic Integrity
BMPs	Best Management Practices
CCT	Cool-Cold Transition
CDL	Cropland Data Layer
CWA	Clean Water Act of 1972
CWT	Cool-Warm Transition
DHRAM	Dundee Hydrologic Regime Assessment Method
ElPT	*Elmidae*, *Plecoptera*, and *Trichoptera*
EPA	United States Environmental Protection Agency
EPT	*Ephemeroptera*, *Plecoptera*, and *Trichoptera*
EPTC	*Ephemeroptera*, *Plecoptera*, *Trichoptera* and *Coleoptera*
FBI	Fish Based Index
FBIL	Fish Based Index for Lakes

GA	Genetic Algorithms
GLUE	Generalized Likelihood Uncertainty Estimation
HBI	Hilsenhoff Biotic Index
HIP	Hydroecological Integrity Assessment Process
HIT	Hydrologic Integrity Tool
HUC	Hydrologic Unit Code
IBI	Index of Biological Integrity
IBI_i	Individual stream health scores
ICI	Invertebrate Community Index
IHA	Indicators of Hydrology Alterations
ISI	Invertebrate Species Index
L_i	Individual stream lengths
MA24	Variability of flow values in January
MCMC	Markov Chain Monte Carlo
MFs	Membership Functions
MH18	Variability across annual maximum flows
MH19	The skewness of the annual maximum flows
MNFI	Michigan Natural Features Inventory

NBI	Nutrient Biotic Index
NBI-N	Nitrogen Nutrient Biotic Index
NBI-P	Phosphorous Nutrient Biotic Index
NCDC	National Climatic Data Center
NED	National Elevation Data
NHDPlus	National Hydology Dataset plus
NRCS	Natural Resources Conservation Service
NSE	Nash-Sutcliffe model efficiency coefficient
ParaSol	Parameter Solution
PBIAS	Percent Bias
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
R^2	Coefficient of determination
RA5	The number of days where flow increased from the previous day
RA9	Variability in reversals
RMSE	Root-mean-square deviation
RSR	Root-mean-squared error-observations standard deviation ratio
R-SWAT-FME	R program language-Soil and Water Assessment Tool-Flexible Modeling Environment

SEMCOG	Southeast Michigan Council of Governments
SGI	Stressor Gradients Index
SHI	Stream Health Index
SOFM	Self-organizing feature map
SSURGO	Soil Survey Geographic Database
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Analysis
TIVI	Tolerance Indicator Values Index
TN	Total Nitrogen
TP	Total Phosphorous
TSS	Total Suspended Solids
USDA-ARS	United States Department of Agriculture - Agricultural Research Service
USDA-NASS	United States Department of Agriculture-National Agricultural Statistics Service
USGS	United States Geological Survey

1. INTRODUCTION

With the continued population growth, the demand for freshwater has also increased in order to sustain human needs including crop production and drinking water. However, anthropogenic activities have negatively impacted freshwater ecosystems, resulting in their degradation (Dos Santos et al., 2011; Pander and Geist, 2013; Walters et al., 2009: Young and Collier, 2009). Furthermore, changing climates are expected to add additional stress to these already strained systems (Meyer et al., 1999; Ridoutt and Pfister, 2010). To ensure that freshwater ecosystems will be available for future generations, evaluation of stream health condition has become vital (EPA, 2011). In the United States, the focus on protecting freshwater resources began with the passing of the Clean Water Act of 1972, with the goal of reducing point and non-point source pollution and improving water quality (EPA, 2012a). Originally, chemical indicators were used to evaluate stream conditions, leading to noticeable water quality improvements. However, recent evaluation of the biotic components of freshwater ecosystems revealed that they are still degraded, indicating that using only chemical indicators for stream health is not effective (EPA, 2011). This led to the introduction of a new type of evaluation called biological assessments or bioassessment (Jeong, et al., 2012). Bioassessment can be used to assess physical, chemical, and biological stressors within stream systems, which makes them ideal for evaluating stream conditions (Brazner, et al., 2007; Pelletier, et al., 2012).

In the first study, different stream health indices were reviewed to aid in the selection of the most appropriate index in different region, stressor, and species. For example, some indices are sensitive to specific stressors such as organic pollution (Hilsenhoff, 1987; Johnson et al., 2013) or nutrients (Smith et al., 2007; Hasse and Nolte, 2008). Other indices are developed for specific water systems, such as warm water (Lyons, 1992) or cold water (Kanno et al., 2010; Lyons, 2012); or regional areas (Wan et al., 2010; Esselman et al., 2013; Krause et al., 2013) All of this variability makes it challenging to determine which index should be used for different studies. The goal of this study is to provide a detailed analysis of the different indices to aid in index selection.

For the first study the overall goal is to provide a review of macroinvertebrate and fish based stream health indices that can be used for watershed management.

The specific objectives of this study are to:

- Assess current methods used to evaluate stream health, in particular macroinvertebrate and fish stream health indices.

After identifying degraded streams, the next logical step is to develop mitigation strategies. Best management practices (BMPs) are commonly used to control runoff and filter pollutants, sustaining water quantity and improving water quality. However, implementation of multiple BMP scenarios on the ground and monitor them over the years to identify the best option is not feasible due to the cost and time constraints. Therefore, models are inexpensive and fast alternative to monitoring and therefore widely used in water resources management (Giri, et al., 2012). Meanwhile, modeling presents its own set of challenges by producing large volume of data that is hard to interpret.

For the second study the overall goal is to develop a system that can be used to evaluate different BMP scenarios to find near-optimal solution(s) for a watershed in Michigan by maximizing stream health score and minimizing implementation cost. In addition, this study will explore the relationship between a fish-based stream health index (IBI) and hydroecological variables. This will be done in order to develop a stream health predictor model that can be applied to the entire study area allowing for evaluation of stream conditions.

The specific objectives of this study are to:

- Assess current methods used to evaluate stream health, in particular macroinvertebrate and fish stream health indices.
- Develop a Soil and Water Assessment Tool model that can model to estimate long-term streamflow data for all stream segments within the study area.
- Identify the most influential hydroecological parameters.
- Develop a stream health predictor model based on selected hydroecological parameters with the use of fuzzy logic techniques.
- Evaluate the impacts of different best management practice scenarios with the use of genetic algorithm to maximize stream health and minimize cost.

2. LITERATURE REVIEW

2.1 Stream Health/Function

As water resources become more scarce, the importance of riverine ecosystem and their condition has become more important to insure that there will be enough water for both human and natural needs for the future (USGS, 2013a). However, our knowledge about natural system needs, health, and its interrelations is limited.

Analysis of river systems is being performed to identify the status or health of the riverine ecosystem. Stream health can be defined as the combined analysis of alterations caused by anthropogenic activities in aquatic organisms, riparian vegetation, invertebrates, and channel properties (Jeong et al., 2012). Anthropogenic impacts, often referred to as stressors, are defined as an abiotic or biotic factors that are varied by human activities to the point where it has a negative impact on an organism or the environment (Magbanua, 2012). It is important to note that stressors often compound upon each other to create the environmental degradation (Magbanua, 2012). This makes it difficult to restore the ecosystem when the actual cause of the degradation cannot be easily identified. However, there is a solution, biological indicators are able to represent the complex nature of stream ecosystems and provide information about what is occurring within the stream system (Jeong et al., 2012).

2.1.1 Indicators

Indicators are aspects of the ecosystem that can be used to identify degradation in the system; they can include nutrient uptake and denitrification (Young and Collier, 2009); as well as biological indicators (Bunn et al., 2010), and hydrologic changes (Jeong et al., 2012). These indicators can describe different functions and interactions within the stream allowing them to be useful in determining what is impacting the stream or what the condition of the stream is.

However, biological indicators are often are used because they are able to represent multiple layers of interaction within the ecosystem (Jeong et al., 2012), as well as being easier to observe while still providing detailed information about the condition of the stream (Einheuser, 2011). In the following sections, more detailed information is provided on a variety of indicators that can be used to assess stream health.

2.1.1.1 Stream Health Index

The Stream Health Index (SHI) was developed to determine the degree of impairment of a river or watershed, which is found by observing the pollutant loads within the water (Carlson et al., 2012). This relatively simple method allows for determining degradation. However, it only considers the Total Suspended Solids (TSS), Total Nitrogen (TN), and Total Phosphorous (TP) levels (Carlson et al., 2012), and there are many other stressors that are not accounted for, such as water quantity. Nevertheless, the SHI model allows for easy comparison between locations and relates the results in a layman's perspective useful for communicating with the public about river and watershed degradation.

2.1.1.2 Dundee Hydrologic Regime Assessment Method and Indicators of Hydrology Alterations

The Dundee Hydrologic Regime Assessment Method (DHRAM) assesses changes to the hydrologic cycle and patterns caused by human activities (Jeong et al., 2012). It does this by using a set of characteristics called the Indicators of Hydrology Alterations (IHA). IHA is a very comprehensive method used to determine the alteration to the hydrology of the system; it uses a set of 67 indicators to determine the condition of the stream and uses statistics to display the results of the alterations (Jeong et al., 2012). At this point DHRAM is used to link the indicators, from IHA, to what risk they pose to the environment (Jeong et al., 2012). This is useful at identifying which river systems are most threatened, allowing policy makers and stokeholds to make decisions on how to improve the environment.

2.1.1.3 Fish

Fish are a common, easily observed indicator of stream health. Their long lifespans and migrations within the river systems (Karr, 1981) allow them to provide long term and large-scale results to impairment in the entire system. Also due to their distribution within the tropic levels (Karr, 1981), they can provide insight to the interactions that occur within the aquatic ecosystem. Another benefit to using fish is that they tend to have well documented life histories and are resistant to harsh environmental conditions (Karr, 1981) allowing for easy classification of disturbances occurring in the system. As a system is degraded, it is expected that more of the tolerant fish species will be found, and knowing what each species is tolerant to helps identify what is impacting the river system. A final benefit to using fish as indicators is that very little training is needed for identification (Karr, 1981), reducing the cost of monitoring them over an entire watershed.

2.1.1.3.1 Index of Biological Integrity

The Index of Biological Integrity (IBI) is an indicator that utilizes the fish community in river systems and is often used to monitor the health of the river and shed some light on the interactions within the system (Jeong et al., 2012). IBI is calculated by observing a variety of metrics; including species diversity, trophic composition, and abundance and condition (Einheuser, 2011). Each metric is observed and ranked given a score of 1, 3, or 5 which higher scores indicating better conditions. These scores can be summed for the calculation of a score for the river network and be compared to other sites to determine restoration project order. A benefit of this index is that it can be modified to match the species found in the region (Einheuser, 2011).

2.1.1.4 Macroinvertebrates

Along with fish, invertebrates are a major component to river ecosystems. Having species in all of the trophic levels and being able to easily identifiable, especially macroinvertebrates, makes them efficient indicators of stream health and function. However, unlike fish, invertebrates are not as well traveled and thus tend to show the health of a stream in a localized area (Einheuser, 2011). However, with the vast diversity of macroinvertebrates, several different indicator systems have been developed and are used to monitor stream health.

2.1.1.4.1 EPT

EPT is an indicator based on the observation of organisms of the *Ephemeroptera* (mayflies), *Plecoptera* (stoneflies), and *Trichoptera* (caddisflies) families (Goetz and Fiske, 2013). These species tend to be very sensitive to changes in the environment and thus make EPT as an ideal indictors for early detection of stream degradation (Johnson et al., 2013). However, since they have shorter lifespans than fish, EPT indicators are not as efficient at looking at large watershed level disturbances, but do excel at local degradation identification (Einheuser, 2011). Also like fish, it is relatively easy to identify the EPT species so it is easy to collect data for analysis; allowing EPT to be an efficient indicator for identifying local degradation before it becomes a larger problem to solve.

2.1.1.4.2 Benthic Index of Biological Integrity

The Benthic Index of Biotic Integrity (B-IBI) is a multi-metric index developed by Kerans and Karr (Kerans and Karr, 1994) and is based on the IBI. Like with the IBI, the B-IBI's metrics are divided into 3 categories: species diversity, trophic composition, and abundance and condition (Einheuser, 2011). However, the characteristics observed by the metrics are all characteristics of the invertebrate community in the river system. This allows for a detailed analysis of the system and its condition. Each metric is given a score based on the observations, just like in the IBI, and that score is used to evaluate the overall system as well as being used to compare between different sites (Kerans and Karr, 1994).

2.1.1.5 Biotic Index

The Biotic Index (BI) or HBI developed by Hilsenhoff in the 70's, was based on the tolerance of each taxa observed to organic pollutants (Goetz and Fiske, 2013). After recording all of the tolerances, the river system was ranked on a scale from 0 to 10, with 0 being the best (Goetz and Fiske, 2013); this value could then be compared to other sites to determine the degradations across the region.

2.1.1.6 Water Footprint

Another way to look at the health of a stream is to observe how much water is being removed from the system; this can be done with a water footprint calculation. Water footprints are similar to carbon footprints, where analysis is preformed to see how much water is being used by various practices (Ridoutt and Pfister, 2010). This allows for easy identification of the major hydrologic stressors to river systems and can be used to show how different methods of irrigation, farming, industry, etc… compared to each other. By showing the comparison between different practices makes individuals conscious of the water requirements needed to produce products, and how much can be saved by changing to a more efficient method of production. By finding the least withdrawing practices, improvements can be made to limit the damages caused by over taxing the river systems. Unfortunately, there is no one standard to calculating a water footprint, so depending on the calculation process different water footprints may be calculated

(Ridoutt and Pfister, 2010). Therefore, if a comparison between water footprints is planned it should be verified that all the water footprints being compared were calculated by the same method to allow for fair comparisons.

2.2 Environmental Flow

Environmental flow describes the patterns and quantity of water flow needed to support aquatic ecosystems as well as the needs of humans (King et al., 2009; Poff et al., 2010; Chen and Zhao, 2011). Originally, this idea led to a minimalist strategy, where only a static minimum amount of water was released so that the environment could survive (Alfredsen et al., 2012). This insured that we could alter the flow by storing and removing almost as much as we wanted, only the minimum had to remain to insure the environment did not die out. However, further studies showed that supplying the environment with just the minimum level of water needed was flawed because it was actually more damaging to the riverine ecosystems than originally thought (Poff et al., 2010). In recent years, environmental flow has undergone a change from supplying the minimum amount of flow to a river system to support the ecosystem to trying to replicate the natural flow cycles in both timing and volume, to better support aquatic ecosystems (King et al., 2009; Poff et al., 2010; Alcázar and Palau, 2010; Chen and Zhao, 2011;).

With the demand for fresh water growing so being able to sustain the use of freshwater systems is vital to insure long-termed benefits (Nel et al., 2011). Based on current research, it has been well documented that maintaining the flow regime is vital to sustaining ecological integrity of river systems (Belmar et al., 2001; Poff et al., 2010; Poff and Zimmerman, 2010; Nel et al., 2011; Pinieski et al., 2011). This means that environmental flow has become a key factor in the management plans for freshwater systems (McCartney et al., 2009).

The process of defining an environmental flow has several steps. First selection of riverine organisms for which the flow will be established is preformed and a team of specialists gathered to determine what the organisms need to survive (Piniewski et al., 2011). It makes sense for this selection to be a species that is more sensitive than others are so that the final environmental flow will support more than one organism. Next, the sections of a river in which the environmental flow will be defined must be selected (Piniewski et al., 2011). These sections are usually riffles, runs and pools. Next specialists need to define what flow characteristics the organism needs which leads to the final step, the definition of the environmental flow (Piniewski et al., 2011). After establishing the environmental flow criteria, monitoring should be put in place to observe whether the desired organism is able to establish, if it fails, the environmental flow should be revised to insure success of the project.

2.3 Anthropogenic Impacts on Stream Flow

As humans, we rely on the environment for everything, from raw resources to make houses and tools to food and water, which are needed for survival. And to obtain what we need to survive we take from the environment and leave behind what we cannot use along with any destruction or disturbances inflicted on the environment. This leads to degradation of the environment, loss of habitat, and the destruction of the resources we need for the future, for example deforestation (Coe et al., 2011), during which we destroy forests that provide lumber, clean air, and produce when left standing. But are cut down to make farmland which quickly loses its fertility and thus productivity. Even sometimes when we attempt to reduce the impacts we have on the environment, the environment is still negatively impacted. For example selective logging, which has been considered as a compromise between deforestation and preservation (Putz et al., 2012). However, the impacts of this method result in the loss of carbon from damaged plants for several decades and result in a century long re-growth process for the forest to return to its pre-logging state (Huang and Asner, 2010). And while these examples describe the impact on forests, similar outcomes can be seen in river systems. In this review, emphasis will be put on impacts to the health of streams in terms of water quantity. In general, the exchanges between humans, water, and the environment can be grouped into two categories, withdraws, and returns. Both of which have impacts that degrade the environment.

2.3.1 Urbanization

Urbanization is the conversion of land to urban regions to support the increasing human population (USGS, 2013b). As the population of humans on the earth continues to grow, more land is needed for homes and more water is need for drinking and cleaning. These new demands on the environment have several negative impacts on the aquatic environment. Nevertheless, being aware of sources that degrade the systems allows steps to be taken to reduce the observed degradation. For this review, urban lands include residential, commercial, and industrial.

2.3.1.1 Runoff

With the increased urbanization, negative impacts to the hydrologic cycle can be seen. In Goetz and Fiske's study (2013) the hydrologic impacts of urbanization included reduced infiltration, increased peak flows, and reduced time to peak discharge. These impacts result in rapid inflows to nearby river systems, which can cause degradation to the health of the river system as well as damage the structural stability of the riverbanks. Impervious areas reduce the amount of infiltration that can occur, and the water that can no longer filter into the ground has to drain elsewhere, causing stormwater runoff. And as more land is converted into impervious surfaces, more stormwater runoff can be observed. In one study, urbanization of a region was shown to cause approximately a 200% increase in average annual flows as well as an increase in the mean daily water flow (Jeong et al., 2012). The increased storm water that flows into the river system can cause flooding and erosion of the riverbank, destroying habitats and threatening infrastructure too close to the river.

2.3.1.2 Drinking water

As the population grows, so does the need for freshwater. Over the last century, the demand for fresh water has more than tripled (Olden and Naiman, 2010). To obtain freshwater, it has to be obtained from some source, whether that is an underground aquifer, lake, river or other body of water, it depletes the amount of available water in the ecosystem. And if too much is withdrawn from the environment, the water source may be reduced to a stream or run dry like the Colorado River (USGS, 2012). This causes severe destruction to the natural ecosystem because habitats will be destroyed and riverine organisms' population will shrink or even die off. Studying and implementing environmental flows will help reduce this impact, but a compromise must be found to allow the ecosystem to be sustainable while still providing us with the water that we need.

2.3.2 Agriculture

As the population of the earth grows there is an increasing demand on the need for food and fiber. In order to accommodate this, farmers try to increase their yields and provide as much food as possible to the ever-increasing demand by using more water and agrochemicals. Transport of sediment and agrochemicals increase the risk of stream health degradation.

2.3.2.1 Irrigation

To support a growing population, more nutrients and water are needed to allow higher crop yields. Nutrients are obtained through the applications of fertilizers that can be obtained from local or regional resources. However for the needed water either the region has to have sufficient rainfall to support the growth of the plants or other sources need to be sought out. The obvious choice is often irrigation, especially in the dryer regions of the United States like Idaho (USGS, 2013a). Studies have shown that in the United States the largest use of water is irrigation, being 65% of all the water use between 1950 to 2005 (USGS, 2013a). And while most of the water currently used for irrigation comes from groundwater, the reservoirs that supply the groundwater are quickly shrinking or vanishing completely (Scanlon et al., 2012). For example, it is well known than the Ogallala aquifer has been severely depleted due to more water being withdrawn than can go through the soil to recharge it (Sophocleous, 2012). This means that eventually farming will have to find new sources of water for irrigation, and the most obvious choice is the river systems. And while taking some water from the environment has little impact, withdrawing larger amounts leads to the sever degradation of the aquatic ecosystem. Like mentioned above, however, due to the greater water need of irrigation, one could suspect that the impact from irrigation would be much greater than drinking water if not kept in check and regulated.

2.3.2.2 Runoff

As crops grow and are harvested the soil is disturbed, tilled, and left bare to withstand the forces of nature. Most soil systems are held together by a vast root system that holds the soil in place and allows the runoff to slow, infiltrate, and be used by plants; reducing the environmental impacts. Farmland lacks this system for periods of the year when crops are not being grown. This causes greater amounts of runoff and erosion to occur. While not nearly as severe as stormwater in urban area, the runoff can still cause degradation in river systems, by rapidly altering the water levels and clogging the streams with sediment from erosion. The settling of this sediment downstream causes alteration of the flow patterns and can lead to habitat destruction and reduced stream function.

2.3.3 Dams

Dams have been used since ancient times. There are accounts as far back as the 3rd to 4th millennium BC at Jawa in ancient Jordan where the Jawa Dam was built to hold water for irrigation of crops (Fahlbusch, 2009). Today dams provide a variety of services, they continue to provide water for irrigation and drinking, but in addition, they also provide hydroelectric power, protection from floods, and zones for recreational activities. By blocking the river and controlling its flow, we are able to harness water for our needs.

While dams are very useful in harnessing resources from water, the alteration of the flow causes a variety of negative impacts on the river ecosystem. These impacts include disrupting aquatic organism migrations and habitats, altering water temperature, preventing the transfer of nutrients, and interrupting the natural flow cycle (International Rivers, 2014). By retaining water and releasing specific amounts, the structure and function of the river is altered both above and below the dam. Dams that severely limit the water discharges can rest the order of the river system, which reduces the usefulness of the river downstream. Above the dam, a pool of water accumulates; this pool tends to be deep and hold cooler water, and while this pooling may seem like an ideal place to introduce fish species and draw water from for irrigation and drinking, it interrupts the natural habitats resets the ecosystem downstream (International Rivers, 2014). The region downstream for a dam alters water temperatures (warmer or cooler based on the design of the dam) and reduces nutrient levels making it difficult for aquatic species to survive.

2.4 Conservation Practices/Best Management Practices (BMPs)

To reduce the degradation of anthropogenic activities a variety of conservation practices and best management practices (BMPs) have been introduced. The majority of these can be implemented on agricultural lands however; several can also be used in urban settings as well to improve water quantity in riverine ecosystems (SEMCOG, 2008).

2.4.1 Bioretention

Bioretention basins are shallow vegetated structures that can be used to control stormwater runoff in both urban and agricultural areas. Designed to temporarily hold water and promote infiltration by allowing the water to seep through the basin and into the groundwater (SEMCOG, 2008). They can be implemented on large as well as small plots of land, which makes them very versatile for urban applications where available land is a constraint and impervious surfaces have increased the amount of runoff present. Also, the use of native vegetation in the design helps create a sustainable system as well as provide an aesthetically appealing area (SEMCOG, 2008).

2.4.2 Constructed Wetlands

Constructed wetlands are vegetated aquatic systems that provide flow regulation and habitats for aquatic and terrestrial organisms. Designed to mimic natural wetlands, constructed wetlands primarily improve the water quality however they also slow the flow of water through the system, reducing peak flows (SEMCOG, 2008). Similar to bioretention systems except where bioretention designs reach unsaturation a few after days after the storm event; constructed wetlands can be designed to treat a continuous flow and never become unsaturated. They can be implemented as a standalone treatment system connected to an outlet or can be installed in rivers and lakes to improve the water quality and flow regime. This allows for the restoration of natural ecosystems while providing improvement to the system.

2.4.3 Detention Basins

Detention basins are vegetated depressions that are used to temporally hold stormwater runoff. Designed to catch stormwater runoff, promote infiltration, and reduce peak flows and flooding (SEMCOG, 2008). They can be implemented in a variety of areas, including urban, residential, and agricultural regions. Due to their ability to hold stormwater runoff, they are very useful in urban areas were the increased impervious areas result in high peak flows. Here again the use of native vegetation provides the benefit of sustainability as well as aesthetic appeal (SEMCOG, 2008).

2.4.4 Filter Strips/Riparian buffer

Filter strips or riparian buffer zones are vegetated zones that reduce the quantity of runoff before it enters rivers and lakes. They can be used to efficiently reduce water quantity along bodies of water. Designed to restore or replicate natural systems found along water bodies, they use native vegetation to slow water flows, promote infiltration, and stimulate plant uptake (SEMCOG, 2008; Merritt et al., 2010); often implemented along rivers, lakes, and wetlands to prevent degradation of the natural ecosystem as well as to prevent flood damage. The vegetation in the BMP includes trees and shrubs as well as grasses and forbes (SEMCOG, 2008), which provides flow reduction, filtration, and habitat creation. Here again the use of native vegetation allows for the creation of a sustainable system, like in bioretention basins.

2.4.5 Vegetated Swale

Vegetated swales are shallow vegetated channels used to direct and control flows of water. Designed to reduce the flow velocities, promote infiltration, and control the flow direction (SEMCOG, 2008), by using the channel as a vegetated gutter. They can be implemented in a variety of locations however heavily urbanized regions often lack the available space needed to implement their design. Often used in agricultural lands where they slow and direct runoff from farm fields to nearby streams. Also like all BMPs that utilize vegetation the use of native species allows the design to be customized for the region allowing for a more efficient and sustainable system (SEMCOG, 2008).

2.4.6 Native Grasses

Native grasses are plots of land that are restored to natural prairies and grasslands to help control the flow of stormwater runoff. Designed to slow the flow of runoff and increase infiltration by filtering the water through the grasses and into the soil (SEMCOG, 2008), they utilize native vegetation to reduce maintenance costs and create a more sustainable system (SEMCOG, 2008). These systems function much like bioretention and vegetated filter strips, using plants and soil to control water flow, but in this case, the plant selection plays a bigger role since it is also used for restoration projects. Often their designs tend to take up more space than is available in heavily urbanized areas and are thus more common in areas where there is available plots of land.

2.5 Optimization/Modeling

For many applications in environmental sciences, it is expensive, inefficient, and time consuming to implement every possible solution and then monitor them to determine the best design to use for the project goal. Also, BMPs' effectiveness is dependent heavily on the location, type of pollutant, and pollution concentration so just because a BMP works in one area does not guarantee that it will work in another location. To solve these problems, modeling can be used because it is inexpensive, effective, and fast. Models allow us to gather information about how the entire system would respond to stressors as well as provide information on how BMPs will perform in the region (Giri et al., 2012). The following sections discuses a couple of the key models that are used to optimize and model the BMPs and the watershed.

2.5.1 SWAT

Soil and Water Assessment Tool (SWAT) is a commonly used watershed model that was developed by USDA Agricultural Research Service (USDA-ARS) and Texas A&M AgriLife Research (Texas A&M University System, 2013). It uses data like topography, water levels, pollution concentrations, and weather events and predicts the effects of different managements systems and BMPs on the environment (Texas A&M University System, 2013). Some of the processes that can be simulated by this model include runoff, erosion, and sediment transport. SWAT has been documented by a variety of studies which use it to predict outcomes in river systems (Cibin et al., 2010; Lam et al., 2010; Setegn et al., 2010). In Setegn et al. (2010) study of the Lake Tana Basin, SWAT was used to predict the stream flow based on the topography, land use, soil, and climate condition. They concluded that the predicted values were very similar to the observed values validating the use of the SWAT model in prediction of stream flow. The study done by Lam et al. (2010) reached a similar result of accuracy of the SWAT model but this time when applied to modeling point and non-point source pollution. However the study done by Cibin et al. (2010) noted that depending on the location, SWAT was not always as sensitive to paraemeters as desired. This can lead to the need to calibrate models to make them more accutate which leads to the next model SWAT-CUP.

2.5.2 SWAT-CUP

When dealing with models as comprehensive as SWAT, it is expected that some uncertainty would develop; the typical categories of uncertainty are conceptual uncertainty, input uncertainty, and parameter uncertainty (Abbaspour, 2007). There is a variety of causes for these uncertainties from the model being too simple to errors in the input data but instead of trying to locate these issues, it is easier to calculate the uncertainty of the results of the model. This provides insight to how accurate the model actually is. SWAT Calibration and Uncertainty Analysis (SWAT-CUP) is a model that does just that. SWAT-CUP is used to calibrate and then validate a SWAT model to insure it can predict known observations and then it preforms an uncertainty analysis on the model to determine how accurate the predicted values are and what range of error can be associated with them (Abbaspour, 2007). The uncertainty can be calculated by using one of the following five methods, Sequential Uncertainty Fitting (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), Mark Chain Monte Carlo (MCMC), and Particle Swarm Optimization (PSO) (Abbaspour, 2007). SWAT-CUP was used in a study of a Japanese river catchment and it was found that the calibration and validation of the model lead to accurate predictions with low uncertainty values (Luo et al., 2011).

2.5.3 R-SWAT-FME

R program language-Soil and Water Assessment Tool-Flexible Modeling Environment (R-SWAT-FME) is another method that can be used to calibrate SWAT models and analyze the uncertainty and sensitivity of the model. This model is still based on SWAT, so all of the calibration and testing is based on a premade SWAT project. However when the model is run, it is converted into a Fortran compatible version that can be run by RFortran (Wu and Liu, 2012); this allows it to run faster, which is beneficial to large watersheds that can be modeled in SWAT. The use of a Flexible Modeling Environment (FME) allows the SWAT model to undergo the uncertainty and sensitivity analysis, performed by SWAT-CUP. To test their new model Wu and

Liu (2012) ran a case study using R-SWAT-FME. While running the case study on the Cedar River in the Iowa River Basin, the model successfully converted the SWAT model to the RFortran platform and was able to perform the calibration, sensitivity, and uncertainty with satisfactory results (Wu and Liu, 2012).

2.6 Data Mining

When using models such as SWAT were there could be thousands of subbasins and data being calculated for each, analysis of the results becomes challenging. Without the use of new technology, the only way to evaluate this data would be to slowly go through the results looking at all the data points manually to find any patterns that may be present and draw conclusions about the results of the run. However, this method is a slow and tedious process, which would have to be repeated if some data was overlooked or misread. A more efficient method would be to use Data Mining. Data Mining is an approach that automatically analyzes the data and can be taught to find specific ranges or develop patterns seen among databases (Alcalá-Fdez et al., 2009). This is very useful and saves time during the process of running a project with lots of results to analyze. There are a variety of ways to preform Data Mining including artificial neural networks and genetic algorithms. Artificial neural networks are used to predict values given a known dataset; it does this by mapping the inputs and outputs of a system a developing a system that when given a new set of inputs with no outputs it can predict the missing values (Singh et al., 2009). This makes it useful for predicting water flows in a river system. The model can be calibrated with a known set of flow values and then applied to a range of years where flow data is unknown and it will be able to generate the flow data. On the other hand, genetic algorithms are mainly used for nonlinear and spatial optimization, by initiating a set of possibilities and finding the best solution from them and then re-calculating based on the results (Arabi et al., 2006). This is useful for identifying the optimal placement of BMPs within a watershed over several years, by insuring that the application of BMPs will provide maximum reduction of pollutants in the river system.

There are five phases through which the process of DM occurs. The first phase is called data understanding; during this phase, data collection occurs and the program identifies the data and begins the analysis of the data (Terzi, 2011). The second phase is known as data preparation; here the data is refined and cleaned to allow easier final analysis (Terzi, 2011). The next phase is called modeling; during this phase, multiple models are applied to the data to determine the optimal results that are desired (Terzi, 2011). The fourth phase is known as evaluation; in this step, the program preforms validation and confirms that the selected model is the most efficient (Terzi, 2011). For the final step know as knowledge; the results and statistics are displayed as the solution to the problem (Terzi, 2011).

Applications of Data Mining within the realm of stream heath are not well known, however there are several studies that discuss the use of Data Mining to help improve modeling and evaluation of stream health. One example of a study that incorporated Data Mining techniques into a modeling method was performed by Chen and Mynett (2003). In this study, a neural network technique known as a self-organizing feature map (SOFM), was added to the steps needed to behind create a fuzzy logic model which was designed to predict algal blooms in Taihu Lake in China (Chen and Mynett, 2003). The SOFM was used to make clusters of data that could then be combined with expert knowledge to create the membership functions and inference rules that are needed for the fuzzy logic model. The final model was tested on 2 sites and had R^2 values of 0.76 and 0.60 (Chen and Mynett, 2003). And Chen and Mynett noted that including a optimization step and sensitivity analysis would increase the R^2 value, the values they obtained indicated that the method developed to create the fuzzy logic model was capable of predicting the algal blooms. Another application of Data Mining in stream health studies was done by Beck et al. (2014). In this study, the statistical selection of metrics for stream health indicators was challenged. Primarily the selection of indicators is based on regressions between other metrics to insure the most informative metrics are kept (Beck et al., 2014). To improve on this Beck, et al. applied a feed-forward 3 layer neural network to a set on metrics, in the hope of selecting the best metrics that corresponded to anthropogenic and natural characteristics. It was found that the application of the neural networks was capable of determining the connection between the characteristics and the metrics, however it was only slightly better than other convention methods like linear regression and decision trees (Beck et al., 2014). The cause for this is that the neural network used needs to have adequate training data which was not possible in this study. Both of these applications show how Data Mining can be applied to stream health studies and so long as it is used correctly can improve the models and techniques currently being used.

2.7 Conclusion

Stream health is becoming an increasingly important aspect to monitor and regulate as the need for fresh water increases. To help with this, monitoring environmental flows are a useful way to regulate the use of water while still maintaining the sustainability of the aquatic ecosystem. However, to truly use environmental flows, detailed studies are needed to provide adequate analysis of the systems to determine optimal stream flows. However, running detailed simulations leads to challenging analysis. Yet with the use of data mining, detailed studies will become easier to analyze. Allowing for increased model resolution, which in turn increases the accuracy of the results obtained from them, opening new areas of research.

3. 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 “A Review of Macroinvertebrate and Fish Stream Health Indices”, discusses the current uses and developments of macroinvertebrate and fish indices. Macroinvertebrates and fish are among the most commonly used organisms for evaluating stream health. Hence, there are many different stream health indices that have been developed based on these organisms. The overall goal of this study is identify which indices should be used in the subsequent study. To do this, 85 macroinvertebrate and fish stream health indices were reviewed and commonly used/modified indices were identified and described. Furthermore, individual components, collection strategies, and applications of stream health indices were also discussed.

The second paper, entitled “Optimization of Conservation Practice Implementation Strategies in the Context of Stream Health”, utilizes one of the stream health indices identified in the first paper to develop a stream health model based on hydroecological variables. This model was then used to evaluate BMP scenarios in order to maximize the watershed-level stream health while minimizing the cost. To accomplish this, a biophysical model was built to estimate daily streamflows within the study region. This model was calibrated and validated using long term observed streamflows data from nine monitoring sites within the Saginaw Bay Watershed in Michigan. Daily streamflows data from biophysical model were used to calculate 171 hydroecological indices for each stream segment within the Honeyoey Creek-Pine Creek Watershed, which is a subbasin in the Saginaw Bay Watershed. Three dimensionality reduction techniques (Spearman’s Rank Coefficients, Principal Component Analysis, and Bayesian variable selection) were used to select a limited number of hydroecological indices that best represented stream health. Selected variables were then incorporated in adaptive neuro-fuzzy inference systems (ANFIS) to develop stream health predictor models. After the models were developed, they were coupled with a genetic algorithm that generated and analyzed BMP scenarios. This identified a near-optimum solution that maximized the stream health score while minimizing the BMP implementation cost.

4. A Review of Macroinvertebrate and Fish Stream Health Indices

4.1 Abstract

The focus of this review is to discuss the historical and current uses and developments of macroinvertebrate and fish indicators. Macroinvertebrates and fish are commonly used indicators of stream heath, due to their ability to represent degradation occurring at site specific or within the entire river system, respectively. A total of 85 macroinvertebrate and fish indices were reviewed, and the frequently used macroinvertebrate and fish indices are discussed in detail in the context of aquatic ecosystem health evaluation. This review also discusses several types of common components, or metrics, used in the creation of indices. Following this, the review will focus on the different methods used for macroinvertebrate and fish collection, in both wadeable and non-wadeable aquatic ecosystems. With the basics of macroinvertebrate and fish indices discussed, emphasis will be placed on the application of indices and the different regions for which they are developed. The final section will provide a brief summary of the benefits and limitations of macroinvertebrate and fish indices.

4.2 Introduction

As the human population continues to grow, it can be expected that anthropogenic activities will have impacts on the environment (Walters et al., 2009; Dos Santos et al., 2011; Pander and Geist, 2013). This in combination with changing climates will only cause greater impacts to the stream ecosystems (Meyer et al., 1999). To determine how climate change and anthropogenic activities impact aquatic ecosystems, it has been recognized that monitoring the health of streams is required to insure systems are able to function and will be able to provide ecosystem services for future generations (USGS, 2013c). Stream health can be defined as the combined analysis of impacts caused by anthropogenic activities on aquatic organisms, riparian vegetation, and channel properties (Jeong et al., 2012). This definition describes aspects of a very complex system, in which organisms interact with their surrounding and vice versa.

To evaluate stream health three components are often used, these three components are the chemical, physical, and biological integrity of the surface water (Butcher et al., 2003a). Traditionally of these three, chemical is the most commonly used to evaluate stream health; however, recently it has be recognized that the use of biological integrity can be lead to a better understanding of what is occurring in the ecosystem as well as identify the cause of degradations (EPA, 2011). And with the high diversity found within aquatic ecosystems (Pander and Geist, 2013), there are many organisms that can be included into the decision making process to evaluate the quality of the stream health. Another benefit to using biological indicators for evaluating stream health is that they are not only take into account biological factors but also the physical and chemical characteristics of the system (Brazner et al., 2007; Pelletier et al., 2012). This is because biological factors are influenced by the physical and chemical characteristics of the ecosystem. By using indicators to evaluate the biotic integrity, environmental resource managers are able to identify degradation areas and can allocate resources to restore the ecosystem's with the greatest needs (Butcher et al., 2003a; Walters et al., 2009; Einheuser et al., 2012; Pelletier et al., 2012), in the most cost-effective way (Neumann et al., 2003a). The overall goal of this study is to provide a comprehensive review of macroinvertebrate and fish based stream health indices. This will be done by first reviewing the individual components, collection strategies, and applications of stream health indices. And then by exploring the macroinvertebrate and fish based indices that have been developed as well as more detailed reviews of the major indices being used in the field.

4.3 Metrics

The complexity of stream systems makes it difficult to create an index that is applicable in multiple regions. To account for local characteristics when determining stream health an index is often developed or modified; this insures that the analysis of the system accurately describes what is occurring at the site. To create these personalized indices, individual characteristics of the ecosystem are measured (Butcher et al., 2003a). These different measurements are known as metrics. The information that metrics represent provide insight to the condition of the ecosystem; from identifying the species richness (Butcher et al., 2003a; Walters et al., 2009; Couceiro et al., 2012) to the number of trophic levels or functional groups present in the ecosystem (Butcher et al., 2003a; Monaghan and Soares 2010; Oliveira et al., 2011; Couceiro et al., 2012). The observations of each metric also allows for the calculation of the index value, which then allows for comparison within and among (when possible) streams.

As the desire for sustainable water resource management grows so has the amount of data collected from stream monitoring, this additional data has allowed for the creation of multi-metric indices. These indices are able to provide a better understanding of what is actually occurring in the environment since they have different level of sensitivity to different pollutants. To create a multi-metric index the first step is evaluating a variety of metrics and preforming statistical analysis to find unique responses to degradation (Butcher et al., 2003a). For example, Butcher et al. (2003a) study initially included 42 candidate metrics and ended with 10 metrics that were incorporated into their index for stream health. By using a three-step validation process, they were able to select the metrics that best described the system. The sections below describe some of the larger categories metrics can be split into: abundance, species richness, and functional groups.

4.3.1 Abundance

Metrics that fall under the category of abundance are used to describe the number of each species found in the rivers. This includes looking at the number of individual species collected, like the number of Ephemeroptera collected per sample (Butcher et al., 2003a), or determining the percentage of a species in a sample, like the percentage of *Oecetis* within a sample (Butcher et al., 2003a; Brazner et al., 2007). In many multi-metric indices, the use of abundance metrics is common (Houston et al., 2002; Boyle and Fraleigh, 2003; Butcher et al., 2003a; Couceiro et al., 2012). Often abundance indicators are used to evaluate key or sensitive macroinvertebrate and fish families, like in the EPT index, to provide information about the condition in the stream. In general, streams with more organisms that are sensitive to stressors are less impacted by anthropogenic degradation and vice versa (Johnson et al., 2013).

4.3.2 Species Richness

Metrics that fall under the category of species richness or number of taxa are used to describe the biodiversity found in the ecosystem. This not only gives an overview of what is found in the stream but it can also indicate the health condition of the stream. It has been shown that regions with high biodiversity are in better condition and show less degradation while the opposite condition, of low biodiversity, indicates a region with more degradation (Boyle and Fraleigh, 2003). These are calculated by recording the number of different taxa taken from a stream sample. In many multi-metric indices, including the Index of Biotic Integrity, the Benthic Community Index, and government indices like the Alabama Department of Environmental Management Index, include the use of species richness metrics (Houston et al., 2002; Boyle and Fraleigh, 2003; Butcher et al., 2003a; Couceiro et al., 2012).

4.3.3 Functional Feeding Groups

Metrics that fall under the functional feeding groups category are used to study the transfer of energy through the system. Benthic macroinvertebrates can be classified in one or more of the following functional groups collectors, scrapers, shredders, and predators (Couceiro et al., 2012). Meanwhile fish can be classified as omnivores, herbivores, insectivores, planktivores, and piscivores (Karr, 1981). Each functional group has a specific role in the ecosystem; collectors either filter or gather nutrients from the water, scrapers live on the rocks on the streambed and scrap off organic material to eat, shredders break down biomass like leaves, and predators actively hunt other organisms for a food supply. Similarly herbivores feed off plant life within the streams, insectivores feed off the macroinvertebrates, planktivores feed off microscopic organisms, and piscivores feed off other fish. Since macroinvertebrates and fish can be found in every functional level (Karr, 1981; Barbour et al., 1999), they can be used to develop an overall picture of the ecosystem. To use these metrics, the functional group of each organism taxa is determined and then the distribution of functional groups within the system is used to evaluate the status of the stream. Often changes in the functional feeding groups are driven by nutrient changes (Smith et al., 2007), which means that the use of these metrics can provide information about the chemical composition of the river system. Like with the species richness metrics, many multi-metric indices, including the Index of Biotic Integrity, Benthic Community Index, and government indices like the Florida Department of Environmental Protection Index, use function feeding group metrics (Karr, 1981; Houston et al., 2002; Boyle and Fraleigh, 2003; Butcher et al., 2003a; Couceiro et al., 2012).

4.4 Collection strategies

Since the majority of metrics used for indices are based on observations of macroinvertebrate and fish communities found in rivers, strategies needed to be developed to collect samples for analysis. And while individual strategies may change from study to study, like number of samples and equipment used for sampling, all require the use individuals, either volunteers or trained workers, to go out and take samples (Butcher et al., 2003a). Often times this includes taking samples at different times of the year to determine the general condition year round (Neumann et al., 2003b). However, the actual process of collecting the samples is not uniform across all regions; this brings up the issue of the river size and the availability of resources to take samples from larger bodies of water. To make a distinction about these differences, the monitoring sites have been categorized as either wadeable or non-wadeable.

4.4.1 Wadeable Waterways

Streams are classified wadeable by the Environmental Protection Agency (EPA) when they are shallow enough to take samples in without the use of a boat (EPA, 2006). It was determined by the EPA that the major focus of the analysis of US waterways would be these small wadeable streams since they represent about 90% of the perennial streams and river miles in the United States (EPA, 2006). For macroinvertebrate sampling of these sites, the most often used method is a collection net that is dragged along the bottom of the river to catch displaced macroinvertebrates as the upstream environment is disturbed by collectors (Butcher et al., 2003b; Couceiro et al., 2012). The organisms collected in the nets are then transferred to containers (Barbour et al., 1999), which are then sent to the labs for analysis and identification. Since this is easily preformed and the equipment is also relatively easy to obtain and use, the majority of macroinvertebrate studies are performed in regions that are deemed wadeable (Butcher et al., 2003a; Iliopoulou-Georgudaki et al., 2003; Justus et al., 2010; Couceiro et al., 2012; Li et al., 2012). As for sampling fish communities in wadeable streams, both nets and electrofishing are used (Terra et al., 2013). And while this is good for regions that have lots of lower order streams, 1st order through 5th order (EPA, 2006); regions with lowland rivers and lakes cannot benefit from the use of stream health indices if the only collection method was using wading nets.

4.4.2 Non-wadeable Waterways

All other sources of aquatic ecosystems that do not fall into the wadeable regions are classified as non-wadeable. These sites are too large for an individual to take samples without the use of a boat (EPA, 2006). Nevertheless, understanding all of the waterways is important to gain an understanding of the whole ecosystem, especially since larger rivers and lakes contain the combined flows from many smaller streams and rivers potentially causing an increase in the concentration of pollutants. Some effort has been put into creating indices that can be used on non-wadeable water bodies. These water bodies include coastal regions (Muxika et al., 2005), estuaries (Puente et al., 2008), large rivers (Angradi and Jicha, 2010), and lakes (Rossaro et al., 2007; Launois et al., 2011). The sampling methods for these types of studies often included the use of a boat sampling technique (Rossaro et al., 2007), and sometimes the use of a combination of both wading and boat sampling techniques (Couceiro et al., 2012). And while these studies provide insight to the impacts of anthropogenic activities on the health in these non-wadeable regions, there is still much that is unknown about how macroinvertebrates and fish respond to different anthropogenic stressors in these ecosystems (Rossaro et al., 2007), providing fields of research for future studies.

4.5 Application

Studies involving macroinvertebrate and fish communities often focus on either defining stream health in a region through the development of a new index (Butcher et al., 2003a) or use a previously created index (Butcher et al., 2003b), testing an index to see if it can identify a known stressor (Compin and Cereghino, 2003), comparing the results of different indices in one region (Justus et al., 2010), or testing to see if a previously created index can be applied to a new region (Muxika et al., 2005). The first type of study is preformed to provide an index that can be used for streams in the region; stakeholders and governments to implement projects to improve the regions that most require it can then use this. Testing already know indices is preformed to see if the current index can be extended to include more results about the ecosystem. If the results of the study are positive, this shows that the index can be applied to more regions and provide a more complete understanding of the environment (Compin and Cereghino, 2003). The comparison studies between different indices are very useful on several levels. First, it identifies the best index to use for stream health evaluation in the region; secondly, it allows generalizations to be drawn about indices and what they can determine. This was the case in the study by Justus et al. (2010), where macroinvertebrates were not as capable as algae at detecting low concentration changes in nutrients levels. However, the macroinvertebrates were able to respond to the low nutrient concentrations better than the fish community. The final type of study was to determine if an index can be applied to a new region. This is important because it can expand the use of new indices to provide information about the region without having to create a new index. This was found in the study of the AZTI Marine Biotic Index (AMBI) by Muxika et al. (2005). The AMBI was applied to 6 different costal sites throughout Europe with the goal of determining the suitability of the index for evaluating the health of the ecosystems found there. These sites ranged from the Baltic Sea to the Mediterranean. After evaluating the ABMI at all the sites with was decided that the AMBI was suitable for all European coastal ecosystems.   At the same time these studies have the chance of showing that the index in question cannot be applied to the region without modifications.

4.6 Materials and Methods

Indices are evaluation systems used to assess conditions within an aquatic ecosystem and rank them to allow comparison and identification of the regions of greatest degradation. They can be designed for individual streams (Hu, et al., 2007) or can be used to analyze entire ecoregions (Butcher, et al., 2003a). Below, we will discuss the frequently used macroinvertebrate and fish indices in the context of aquatic ecosystem health evaluation.

4.6.1 Macroinvertebrate Indices

Since there are so many characteristics that can be observed in water bodies, from water quality to presence of species indices, several components are often used to access stream health or to understand how a certain stressor will impacts the ecosystem. One group of often-used organisms for determining stream health are macroinvertebrates. They are useful at determining local sources of degradation due their limited mobility with in the stream channel (Kerans and Karr, 1994). Also, macroinvertebrates are sensitive to low levels of pollutants allowing for early detection of stream degradation (Compin and Cereghino, 2003). Due to the frequent use of macroinvertebrates (Flinders et al., 2008; Sharma and Rawat, 2009; Pelletier et al., 2012), several indices have been developed and are used to monitor stream health. Table 1 presents 35 of the macroinvertebrate indices that were reviewed in this study. The first column indicates the name of the index followed by the reference. The 3rd column indicates the index that it was based on. The 4th column presents specifics about the index such as the number of metrics, score trends, or aspect that is evaluated. And the final column indicates changes or modifications made from the based index to create the new index. However, these indices are generally originated from three common indices, which include Benthic Index of Biotic Integrity (B-IBI), Hilsenhoff Biotic Index (HBI), and *Ephemeroptera Plecoptera Trichoptera* (EPT). These indices can be either multi-metric, looking at many aspects of the ecosystem like B-IBI, or focused on one particular characteristic of the environment like EPT. Out of the 35 macroinvertebrate indices listed in Table 1, 12 used EPT as their base index. This made EPT the most often used base index. Of the modifications made to the EPT index, the most common was the addition of metrics that evaluated other aspects of the streams, such as the presence of other organisms or other functional feeding groups; this allowed the new index to provide a better picture of the conditions within the stream as well as take into account local characteristics. The following sections describe the three main macroinvertebrate indices.

Table 4.1. List of macroinvertebrate based indices.

Index Name	Reference	Base Index	Specific Characteristics	Changes from Base Index
Nutrient Biotic Index	(Smith et. al., 2007)	Hilsenhoff Biotic Index	Used to determine nutrient tolerances of organisms for evaluation of nutrient loading in river systems	Uses nutrient tolerances instead of organic pollutant tolerances
Tolerance Indicator Values	(Meador et. al., 2008)	Hilsenhoff Biotic Index	Used organism tolerances of dissolved oxygen, nitrite plus nitrate (nitrate), total phosphorus, and water temperature to evaluate stream conditions	Uses dissolved oxygen, nitrite plus nitrate (nitrate), total phosphorus, and water temperature instead of organic pollutants Looked at both fish and macroinvertebrates
Multimetric Index for Castilla-La Mancha	(Navarro-Llácer et al., 2010)	Original	Uses 3 metrics to evaluate conditions within streams	No changes
Benthic Community Index	(Butcher et. al., 2003a)	Includes EPT and HBI	Uses 10 metrics, from 3 categories (Structural, Functional, Conditional) describing the Macroinvertebrate community to evaluate stream health	No changes
Benthic Quality Index Modified	(Rossaro et. al., 2007)	Benthic Quality Index	Scores organisms based on indicator values, and sums the scores of all present organisms to determine the water quality. Higher scores represent regions with lower nutrient loads.	Looks are more than just chironomids
Non-wadeable Macroinvertebrate Assemblage Condition Index	(Blocksom and Johnson, 2009)	Includes EPT	Uses 9 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	No changes

Table 4.1. (cont'd)

Macroinvertebrate Index of Biotic Integrity	(Griffith et. al., 2005)	B-IBI, HBI and EPT	Uses 9 metrics to determine the conditions within the stream, with higher scores indicating less degradation	Based on macroinvertebrate communities instead of fish
Macroinvertebrate Multimetric Index	(Couceiro et. al., 2012)	EPT	Uses 7 metrics to evaluate conditions within streams. Higher scores indicate less degradation	No changes
EPTC	(Compin and Céréghino, 2003)	EPT	Uses metrics describing *Ephemeroptera*, *Plecoptera*, *Trichoptera* and *Coleoptera* populations to determine stream health. Higher scores indicate healthier streams	Added the *Coleoptera* family
Ephemeroptera Plecoptera Trichoptera	(Walters et. al., 2009)	EPT	Uses metrics describing *Ephemeroptera*, *Plecoptera*, and *Trichoptera* populations to determine stream health. Higher scores indicate healthier streams.	
ICI	(Walters et. al., 2009)	B-IBI	ICI used 9 metrics to evaluate the conditions within the stream, Higher scores indicates less degradation	One metric of ICI was dropped due to the fact that it was not contributing to the analysis
Guapiacu-Macau Multimetric Index	(Oliveira et. al., 2011)	EPT	9 metrics used to evaluate the conditions within streams. Higher scores indicate healthier scores	No changes

Table 4.1. (cont'd)

Invertebrate Species Index	(Haase and Nolte, 2008)	HBI	Ranks macroinvertebrates on their tolerances to nutrient levels. Uses these scores to determine the conditions within streams. Higher scores indicate greater sensitivity and thus better stream conditions	Looks at nutrient tolerances instead of organic pollutant tolerances
AZTI Marine Biotic Index	(Muxika et. al., 2005)	Original	Ranks organisms based on sensitivy to pollutants and uses the composite scores of each site describe the conditions at the site	No changes
Abundance Biomass Comparison	(Monaghan and Soares, 2010)	Original	Looks at the distribution of individuals and biomass within the region to evaluate pollution-induced disturbances	No changes
Family-level Biotic Index (FBI/HBI)	(Hu et. al., 2007)	HBI	Ranks macroinvertebrates on their tolerances to organic pollutants. Uses these scores to determine the conditions within streams. Higher scores indicate greater sensitivity and thus better stream conditions	No changes
Chesapeake Bay IBI	(Weisberg et. al., 1997; Pelletier et. al., 2012)	B-IBI	Uses 15 metrics ranked 1, 3, or 5 and then summed to determine the condition of the system. Higher values indicate better conditions	Used to evaluate the Chesapeake Bay region instead of the Tennessee Valley Used 15 metrics instead of 11

Table 4.1. (cont'd)

SIGNAL	(Besley and Chessman, 2008)	Based on rapid biological assessment sampling	Uses sensitivity values assigned to organisms found in the stream to evaluate stream health	No changes
Benthic Index of Biotic Integrity	(Kerans and Karr, 1994)	IBI	Uses 13 metrics to evaluate the condition of the system. Higher values indicate better conditions.	Based on Macroinvertebrate communities instead of fish communities
Alabama Department of Environmental Management Index of Stream Health	(Houston et. al., 2002)	Original	Uses 7 metrics to evaluate the condition of the system. Higher values indicate better conditions, includes EPT.	No changes
Florida Department of Environmental Protection Index of Stream Health	(Houston et. al., 2002)	Original	Uses 7 metrics to evaluate the condition of the system. Higher values indicate better conditions, includes EPT.	No changes
Mississippi Department of Environmental Quality Index of Stream Health	(Houston et. al., 2002)	Original	Uses 8 metrics to evaluate the condition of the system. Higher values indicate better conditions, includes EPT.	No changes
North Carolina Division of Water Quality Index of Stream Health	(Houston et. al., 2002)	Original	Uses 3 metrics to evaluate the condition of the system. Higher values indicate better conditions, includes EPT.	No changes
South Carolina Department of Health and Environmental Control Index of Stream Health	(Houston et. al., 2002)	Original	Uses 2 metrics to evaluate the condition of the system. Higher values indicate better conditions, includes EPT.	No changes

Table 4.1. (cont'd)

B-IBI modified	(Roy et. al., 2003)	B-IBI	Uses 11 metrics to evaluate the condition of the stream. Higher values indicate better conditions	Metrics used modified to fit conditions in Georgia.
ICI modified	(Roy et. al., 2003)	B-IBI	Uses 10 metrics to evaluate the condition of the stream. Higher values indicate better conditions	Metrics used modified to fit conditions in Georgia.
NFAM	(Sanchez-Montoya et. al., 2010)	Original	Uses the total number of families to evaluate stream health	No changes
Yungas Biotic Index based on 4 taxa	(Dos Santos et al., 2011)	Original	Uses 4 metrics to evaluate the condition of the stream. Higher scores indicate better conditions	No changes
ElPT	(Dos Santos et al., 2011)	EPT	Uses metrics describing *Elmidae, Plecoptera*, and *Trichoptera* populations to determine stream health. Higher scores indicate healthier streams.	Looks at *Elmidae* taxa instead of *Ephemeroptera* taxa

4.6.1.1 Benthic Index of Biotic Integrity

The Benthic Index of Biotic Integrity (B-IBI) is a multi-metric index developed by Kerans and Karr (1994) and is based on the Index of Biotic Integrity (IBI) developed by Karr in 1981, which looked at the fish communities found in streams to determine the overall system health (Karr, 1981). The B-IBI functions just like the IBI by the fact that is looks at organism communities to evaluate stream health; however, the major change is that the B-IBI considers macroinvertebrates instead of fish. The metrics used in the B-IBI are divided into three categories taxa richness, taxa composition, and biological processes of the invertebrate community in the aquatic ecosystem (Kerans and Karr, 1994). This allows for a detailed analysis of the system and its condition. The thirteen metrics included in this index are 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. Each metric is given a score from 1 to 5 based on the observations of the stream region in comparison to a reference site that had no ecosystem degradation (Kerans and Karr, 1994). A higher score indicates that the metric is closer to the reference site conditions. All of the metric scores are then summed to provide the overall B-IBI score for that region, which can then be used to evaluate the impacts of watershed management scenarios. Based on this analysis, sites that are given lower scores exhibit greater degradation and thus can be selected for restoration projects. For example, the original metric score ranged from 0 to 65 with a score of 65 representing a non-impacted ecosystem and a score of 0 representing a heavily degraded ecosystem (Kerans and Karr, 1994). Kerans and Karr (1994) showed that this index is effective of detecting industrial degradations by taking samples above and below the industrial effluents. However, a universal

B-IBI does not exist and the B-IBI components need to be adjusted for different regions to better describe the ecosystem. This was done in the study by Roy et al. (2003), where the B-IBI was modified to better represent the local condition using 11 metrics instead of original 13 metrics. Table A1 presents the metrics used in the B-IBI as well as what was added or removed in other indices that are originated from the B-IBI. Of the indices listed, the most commonly removed metrics were % Grazers and intolerant snail and mussel species richness; however, no commonly metric were added. Overall, these changes were made to better represent the local conditions and the ecosystem.

4.6.1.2 Hilsenhoff Biotic Index

The HBI is a commonly used (Butcher et al., 2003a) index developed by Hilsenhoff in the 70's (Hilsenhoff, 1987). It was based on the tolerances to organic pollutants of each observed taxa in the river system (Goetz and Fiske, 2013). Therefore, HBI is used as an indicator for chemical degradation within the river system. To use this index, samples are taken from the river and used to determine the average tolerance value for the system (Hilsenhoff, 1987). After recording all of the tolerances the river system was ranked on a scaled from 0 to 10, with 0 being the best (Goetz and Fiske, 2013). This value could then be compared to other sites to determine the degradations across the region. To allow for a faster analysis of the system Hilsenhoff provided a table describing the HBI values and their corresponding stream health classification. The scores were grouped into water quality categories of Excellent, Very Good, Good, Fair, Fairly Poor, Poor, and Very Poor. Each water quality score represented a different level of organic pollution, for example an Excellent water quality category corresponds to no apparent organic pollution and a score range of 0.00-3.50, while a Very Poor water quality category corresponds to severe organic pollution and a score range of 8.51-10.00. Continued use of the HBI has also led to the discovery that this index can also be used to identify regions with low dissolved oxygen as well as other pollutants (Butcher et al., 2003a). This has become a very useful measurement of stream heath to the point where is has been included as a metric in other multi-metric indices (Butcher et al., 2003a) to provide information about the condition of the stream with respect to organic pollutants.

Other studies have taken the concept used for the HBI and applied it to other stressors to make new indices. One example of a new index that is based on the HBI, is the Nutrient Biotic Index (NBI), which instead of considering the impacts of organic pollutants, it was developed to assess the tolerances of organisms to nutrient loading within aquatic ecosystems and in particular wadeable streams (Smith et al., 2007). To do this, two different indices were created, one for nitrogen (NBI-N) and one of phosphorous (NBI-P). To calculate these indices, samples were taken from the streams and used to determine average nitrogen and phosphorous tolerance scores (Smith et al., 2007). These values were then used to compare between different streams and locate the optimal concentration of each nutrient for the organisms (Smith et al., 2007). Smith, et. al.(2007) identified the tolerances of the 164 collected taxa and ranked them from a 0 to 10 scale where 10 indicated high tolerance and 0 low tolerance (Smith et al., 2007). This allowed for comparisons between different streams and evaluation of the nutrient loading in the study region. Using the concept of HBI to evaluate nutrient loading was also used in Haase and Nolte (2008). The Invertebrate Species Index (ISI) was developed to determine stream health and in particular the impacts of eutrophication in Queensland, Australia (Haase and Nolte, 2008). They scaled the sensitivity of macroinvertebrate species from 1 to 10, where a score of 10 means the species is very sensitive to pollution and a score of 1 means the species is very hardy (Haase and Nolte, 2008), just like the HBI and NBI. Once all the sensitivity scores were determined an average score is calculated to represent the conditions within the stream (Haase and Nolte, 2008). In Haase and Nolte (2008), the ISI were calculated for 203 species of macroinvertebrates, which were used for comparison and evaluation of the upland streams in southeast Queensland, Australia. However, they were noted that ISI species related scores that were calculated for the stream classifications may not be accurate in other regions (Hasse and Nolte, 2008). This is because certain species that were never present in a stream should not be included in the calculation for the sensitivity score for that stream (Haase and Nolte, 2008). But if reference conditions are rescored, this index would be useful for identifying nutrient based degradations within stream systems. In addition to NBI and ISI, other stressors were developed for calculating nutrient tolerances. A study by Meador et al. (2008) looked at organism tolerances to dissolved oxygen, nitrite plus nitrate, total phosphorus, and water temperature. This shows how versatile the concept of organism tolerances is, and the need for studies to explore tolerances of organisms to other stressors. Table A2 presents the metrics used in HBI as well as what was added or removed in other indices that are either based on or use HBI for analysis. Of the indices listed in Table A2, the most common adjustment to the HBI was to change the stressor being evaluated. The HBI looks at organism tolerances of organic pollutants, while the indices based on the HBI look at organism tolerances to other stressors like nutrients or temperature.

4.6.1.3 Ephemeroptera Plecoptera Trichoptera

EPT is an indicator based on the observation of organisms of the *Ephemeroptera* (mayflies), *Plecoptera* (stoneflies), and *Trichoptera* (caddisflies) families (Goetz and Fiske, 2013). These families are used because they are particularly sensitive to pollution levels within the ecosystem (Compin and Cereghino, 2003); they have been used to identify local regions impacted by pollution (Compin and Cereghino, 2003) and low dissolved oxygen (Butcher et al., 2003a) as well as to provide an overall view of the conditions in a stream (Butcher et al., 2003a). Their sensitivity to pollutants allows for early indication of problems in the ecosystem and subsequent actions to be taken to repair the ecosystem before more degradation can occur (Johnson et al., 2013). To use this index, the EPT richness and percent abundance is calculated for each sample taken from the waterbody (Couceiro et al., 2012), and the overall conclusion about the condition of the river can be made based on the results from all samples. In Couceiro et al. (2012) study, the use of the EPT index was initially considered and preformed as expected with higher scores representing less degraded sites. However, the range of scores obtained from the sites was only 0 to 8, this was considered too small to be useful and was eliminated for further analysis (Couceiro et al., 2012). In contrast, Oliveira et al. used EPT as one of the final 9 metrics for their multi-metric index with a range from 0.27 to 65.90 (Oliveira et al., 2011). EPT was also part of the final list of metrics for the benthic community index developed by Butcher, et al. (2003a). EPT can also be used as a standalone index. However, in the last two examples EPT was used in multi-metric framework, which can then lead to a better understanding of the system and what is affecting it (Butcher et al., 2003a; Oliveira et al., 2011;). In addition, the EPT index has been modified by including invertebrates from the *Coleoptera* family, which is known as EPTC (Compin and Cereghino, 2003). By adding an additional species to the index, the sensitivity of the index to pollution is increased, and helps provide a better view of what is happening in the ecosystem. EPTC index were used to evaluate both streams and large rivers conditions (Compin and Cereghino, 2003). The scores from the index we grouped into 5 different classes, Excellent, Good, Good-fair, Fair, and Poor. The score ranges for each class depended on the type of ecosystem evaluate; for example the 50 or more scores were considered as “Excellent” for streams while for the large rivers, the scores more than 35 considered as

“Excellent”. Meanwhile, EPTC score less than 24 considers as a poor stream condition while EPTC score less than 2 is poor for the large rivers. Distinction between streams and large rivers in the EPTC method makes it more realistic because the ecosystems found in each are generally quite different. However, EPTC is more recommended for evaluation of small bodies of water like streams than large bodies of water like rivers.

Overall, it can be concluded that while EPT has been successfully used to evaluate stream health conditions, it can be site specific and may not always be applicable to every system. Table A3 C presents the metrics used in EPT as well as what was added or removed in other indices that are either based on or use EPT for analysis. Of the indices listed, the most common change to the EPT was the removal of the % abundance metric. In the cases when EPT % abundance was removed additional organisms were added such as *Diptera* taxa richness, % *Coleoptera* taxa, and % *Oligochaete* and leech taxa (Blocksom and Johnson, 2009). Another common addition to the EPT index was functional feeding group metrics, like % Collector-filterer individuals, Predator taxa richness, # Scrapers/# gatherers, # Shredders/total # collected, and Filterers* (%) (Houston, et. al., 2002; Blocksom and Johnson, 2009).   The addition of these metrics increases the index’s ability to determine what is occurring within the ecosystem. For example the addition of the functional feeding group metrics helps determine energy and nutrient flows while the abundance EPT metrics identify pollution levels within the stream.

4.6.2 Fish Indices

Another group of organisms that is often used to evaluate stream heath are fish (Mack 2007; Zhu and Chang 2008; Krause et al., 2013). Karr (1981) listed seven advantages for using fish for evaluating the stream conditions, which included (1) well known life-history, (2) species found in many trophic levels (omnivores, herbivores, insectivores planktivores, and piscivores),

(3) easy identification, (4) understood by general public, (5) can be used to identify a variety stresses, (6) are present in most water bodies, (7) can be easily connected with regulations. Points 1, 2, 5, and 6 show the usefulness of fish as indicators to determine what is occurring within the ecosystem; while points 3, 4, and 7 show that data collection and presentation is relatively easy when compared to other types of organisms. Also unlike macroinvertebrates, fish move throughout entire river systems, which allows for representation of the conditions within an entire water system over a longer period of time (Karr, 1981). Another benefit to fish is that they are impacted by changes in flow regime (Navarro-Llácer et al., 2010), which means that they can be used to evaluate the impacts of flow altering structures, like dams, on the ecosystem. All of these factors make fish based indices very useful for stream health monitoring. Nevertheless, the system is not without flaws. Using fish communities for indices has its fair share of limitations as well. Limitations include sampling selectivity, fish seasonal migrations, and the cost of sampling. Table 2 shows 28 of the fish indices reviewed in this study. The first column indicates the name of the index used in the study followed by the reference. The 3rd column indicates the index that it was based on. he 4th column presents specifics about the index like the number of metrics, score trends, or aspect that is evaluated. And the final column indicates changes or modifications made from the based index to create the new index. Out of the 28 fish indices listed in Table 2, 23 were based on the Index of Biological Integrity (IBI). This made IBI by far the most often used base index as well as the most commonly modified. Of the modifications made to the IBI index, the most common was the addition or subtraction of metrics to provide a better picture of the ecosystems by taking into account local characteristics. An example of this is the Fish Based Index for Lakes (FBIL) developed by Launois et al. (2011). To take into account the differences for evaluating a lake in France; 3 metrics were added,

number of planktivore species, total biomass of strict lithophilic individuals, % total biomass of tolerant individuals, and 10 of the 12 original metrics used in the IBI were removed (Launois et al. 2011). By doing this the FBIL was able to identify urban and local pressures, like as the most prominent sources of degradation for the French lakes. Of the indices listed in Table 2 few are not based on the IBI, included in this category is the Tolerance Indicator Values Index (TIVI) and the Stressor Gradients Index (SGI). The TIVI was developed by Meador et al. (2008) and functions just like the HBI. However, instead of just looking at organic pollutant tolerances, it looks at the organism tolerances to dissolved oxygen, nitrite plus nitrate, total phosphorus, and water temperature (Meador et al., 2008). The scores from each river can be used to compare between different rivers as well as indicate the levels of each component identifying where there is too much or too little of each. The SGI was used by Angradi et al. (2009) and was used to correlate stressor gradients, like total nitrogen, sediment toxicity, and water temperature, to stream health. This was unique in the fact that the stressor gradients were correlated to biological metrics to determine the conditions within the stream. The use of the SGI was able to identify the anthropogenic impacts on the river systems of the Upper Mississippi River basin.

Table 4.2. List of fish based indices.

Index Name	**Reference**	**Base Index**	**Specific Characteristics**	**Changes from Base Index**
Tolerance Indicator Values	(Meador et. al., 2008)	HBI	Used organism tolerances of dissolved oxygen, nitrite plus nitrate, total phosphorus, and water temperature to evaluate stream conditions	Uses dissolved oxygen, nitrite plus nitrate (nitrate), total phosphorus, and water temperature instead of organic pollutants Looked at both fish and macroinvertebrates
Mebane IBI	(Mebane, et. al., 2003; Pelletier, et. al., 2012)	IBI	Uses 10 metrics to evaluate the condition of the system. Higher values indicate better conditions	Some metrics changed to match
Northern Glaciated Plains Index of Biotic Integrity	(Krause et., al., 2013)	IBI	Uses 6 metrics to evaluate the condition of the system. Higher values indicate better conditions	Metrics used were changed to match the conditions in the Northern Glaciated Plains Ecoregion
Yangtze River Index of Biotic Integrity	(Zhu and Chang, 2008)	IBI	Uses 12 metrics to evaluate the condition of the system. Higher values indicate better conditions	Metrics used were changed to match the conditions in the Yangtze River
Multi-metric Index for Atlantic Rain Forest Streams	(Terra et. al., 2013)	IBI	Uses 6 metrics to evaluate the condition of the system. Higher values indicate better conditions	Metrics used were changed to match the conditions in the Atlantic Rain Forest Streams
Cool–cold transition IBI	(Lyons, 2012)	IBI	Uses 5 metrics to evaluate the condition of the system. Higher values indicate better conditions	Modified to represent the communities in cool-cold rivers
Similarity Indices	(Navarro-Llácer et al., 2010)	Original	Uses 4 metrics to evaluate the condition of the system.	No changes
Cool–warm transition IBI	(Lyons, 2012)	IBI	Uses 5 metrics to evaluate the condition of the system. Higher values indicate better conditions	Modified to represent the communities in cool-warm rivers

Table 4.2. (cont'd)

Fish Based Index for Lakes	(Launois et. al., 2011)	IBI	Uses 6 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified for use in lakes instead of streams
Fish Based Index for Reservoirs	(Launois et. al., 2011)	IBI	Uses 9 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified for use in reservoirs instead of streams
Esturine Multi-metric Fish Index	(Harrison and Kelly, 2013)	Original	Uses 14 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	No changes
Stressor Gradients	(Angradi et al., 2009)	Original	Uses relationship between abiotic condition stressor gradients and biological indicators to determine conditions within the streams	No changes
European Fish Index	(Musil et. al., 2012)	IBI	Uses 10 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in European streams

Table 4.2. (cont'd)

Czech Multi-metric Index	(Musil et. al., 2012)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in Czech Republic streams
Minnesota fish index of biotic integrity	(Wan et. al., 2010)	IBI	Uses 9 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in Minnesota streams
Index of Biotic Integrity	(Karr, 1981)	Original	Uses 12 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	No changes
Fish Community Index	(Jordan et. al., 2010)	Original	Uses 3 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	No changes
Multi-metric Index for the Coastal Plain Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Coastal Plain Ecoregion

Table 4.2. (cont'd)

Multi-metric Index for the Northern Appalachians Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Northern Appalachians Ecoregion
Multi-metric Index for the Northern Plains Ecoregion	(Esselman et al., 2013)	IBI	Uses 5 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Northern Plains Ecoregion
Multi-metric Index for the Southern Appalachians Ecoregion	(Esselman et al., 2013)	IBI	Uses 3 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Southern Appalachians Ecoregion
Multi-metric Index for the Southern Plains Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Southern Plains Ecoregion
Multi-metric Index for the Temperate Plains Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Temperate Plains Ecoregion

Table 4.2. (cont'd)

Multi-metric Index for the Upper Midwest Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Upper Midwest Ecoregion
Multi-metric Index for the Western Mountain Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Western Mountain Ecoregion
Multi-metric Index for the Xeric West Ecoregion	(Esselman et al., 2013)	IBI	Uses 4 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in the Xeric West Ecoregion
Coldwater Multi-metric Index	(Kanno et. al., 2010)	IBI	Uses 5 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in Coldwater streams
Mixed-water Multi-metric Index	(Kanno et. al., 2010)	IBI	Uses 7 metrics to evaluate the conditions within the stream. Scores obtained from the sum of the metrics allow for comparison, higher scores indicate less degradation	Modified to fit the conditions in Mixed-water streams

4.6.2.1 Index of Biological Integrity (IBI)

The Index of Biotic Integrity (IBI) is a multi-metric index introduced by Karr in 1981. It is based on fish communities and widely used to determine the overall stream health (Karr, 1981). Karr listed three assumptions that are needed for the use of this index; (1) the fish sample is a balanced representation of the community at the site, (2) the chosen site is representative of the region in which the IBI is being applied, and (3) the personal charged with analysis of the collected data are trained (Karr, 1981). If any of these assumptions is violated, the results of this index can be misleading. Originally, the IBI was composed of 12 metrics, which can be grouped in one of the three following classifications; (1) species richness and composition, (2) tropic composition, and (3) fish abundance and condition (Hu, et al., 2007). Each of these metrics is given a score of 1, 3, or 5 based on undisturbed reference sites where a score of 5 is the best. After all the scoring the metrics, the individual scores are summed to provide the IBI score for each site. The IBI score ranged from 0 to 60 and were grouped into 9 stream classes, Excellent, Excellent-Good, Good, Good-Fair, Fair, Fair-Poor, Poor, Poor-Very Poor, and Very Poor. Under this class system, and stream scoring a 23 or less would be classified as Very Poor while scores of 57-60 would be considered Excellent. Even though, the 9 stream classes are applicable in different regions, caution should be taken when correlating the IBI score from different regions. This is because the IBI is a region specific index, and the values presented here or in other studies may not accurately represent different regions. In order to address this issue, Karr (1981) also provided description of what may be found in the streams for different scoring system. This helps IBI technique to be more transferable for multiregional studies of stream health evaluation. The IBI has been applied and modified in a variety of studies (Zhu and Chang, 2008; Smith and Sklarew, 2012; Krause et al., 2013). In Europe, a commonly used index of stream health is the

Fish-Based Index (FBI) (Launois et al., 2011). With 15 metrics and scores ranging from 0 to 100 with 100 being the best, the FBI was successful to identify degraded water bodies, but lacked the ability to detect the cause, which was believed to be agricultural related activities and stressors (Launois et al., 2011),. This shows that the selection of metrics for FBI is vital to ensure that the regional characteristics and stresses are taken into account.

Recently, Lyons (2012) modified the IBI for use in perennial coolwater streams in Wisconsin. This required the creation of two different IBIs the Cool-Cold Transition (CCT) IBI and the Cool-Warm Transition (CWT) IBI. Each index uses five metrics to represent the ecosystems (Lyons, 2012). Then the metric was given a score of 0, 10, or 20 based on the analysis of the sample. Next, the metric scores are summed to calculate the IBI score giving a range of scores from 0 to 100 with 100 being the best just like the FBI (Lyons, 2012). Overall, the results showed that while both indices identified disturbed areas with low scores; the CWT index performed better than the CCT index. However, due to the wide variation in scores for similar stream sites, it was recommended to use multiple samples and then a mean or median score to classify the systems instead of a single (Lyons, 2012).

A different study that utilized the IBI found that rare taxa had major impacts on the results of IBI scores (Wan et al., 2010). In Wan et al. (2010), the sensitivity of the IBI was tested and it found that the presence/removal of rare taxa, often considered an indicator of lower degradation, can lower the IBI score by 38 points. While this was a concern, this result of the study still shows that the IBI is sensitive to the conditions within the stream, and as long as the metrics are weighted correctly, the results of the index can provide accurate information about stream degradation. Table A4 presents the metrics used in IBI as well as what was added or removed in other indices that are either based on or use IBI for analysis. Of the indices listed in the table, the most common change to the IBI was the removal of most of the original metrics like the species richness and composition of darters, suckers, and sunfish (except green sunfish), and the proportion of green sunfish (Karr, 1981). This was done in combination with the addition of other metrics to represented local characteristics. For example, number of coolwater species, percentage tolerant species, % invertivore/piscivore individuals, and % native large river taxa (Kanno et al., 2010; Esselman et al., 2013). By modifying the IBI to such an extent allows for better understanding of what is occurring within the ecosystems by taking into account local characteristics.

4.7 Conclusions

Throughout this review a variety of macroinvertebrate and fish indices were discussed, each had benefits and limitations. In macroinvertebrate indices the B-IBI was capable of identifying industrial and chemical degradation (Kerans and Karr, 1994) as well as changes brought about by land use change like urbanization (Roy et al., 2003). However, these indices are site specific (Kerans and Karr, 1994), which means that to insure accurate evaluation of stream health the metrics needs to be fitted to the conditions of the site. The HBI, NBI, and ISI were all able to determine organism tolerances to pollutants whether organic (HBI) (Goetz and Fiske, 2013) or nutrient (NBI, ISI) (Smith et al., 2007; Haase and Nolte, 2008). The HBI also has the benefit that it can be used as a metric of other multi-metric indices (Butcher et al., 2003a), allowing for better understanding of the ecosystems Yet again these indices may not be applicable to other regions (Haase and Nolte, 2008) because the tolerances of species may change based on the natural conditions within different habitats. The EPT index is capable of detecting low levels of degradation due to the sensitivity of the *Ephemeroptera* (mayflies), *Plecoptera* (stoneflies), and *Trichoptera* (caddisflies) families (Goetz and Fiske, 2013). And like the HBI, the EPT index can all be included in other multi-metric indices (Butcher et al., 2003a). However if these families do not appear frequently in a river system the index is not very useful in evaluating stream health (Couceiro et al., 2012). In terms of fish indices, the most commonly used and modified index is the IBI. This index allows for the evaluation of entire regions (Karr, 1981) while at the same time being easily modified to take into account different climates (Lyons, 2012). However, the selection of the metrics used in this index is vital for interpretation of the results (Wan et al., 2010; Launois et al., 2011).

4.7.1 Benefits

There are many reasons that a macroinvertebrate or fish index would be applied to a river system; whether it is to indicate to presence of pollutants (Karr, 1981; Johnson et al., 2013) or to determine the optimal nutrient load for the system (Smith et al., 2007), or to compare levels of degradation between streams (Karr, 1981; Kerans and Karr, 1994). Meanwhile, macroinvertebrates are sensitive to very low levels of degradation at local levels; therefore they can used by stakeholders to detect and correct problems before more serious damage occurs (Barbour et al., 1999; Flinders et al., 2008). On the other hand, fish indices can be used to evaluate the conditions on a regional scale, due to their mobility and lifespans (Karr, 1981). This makes them useful for watershed managers, since they can be used to identify problems found throughout the entire watershed. Another benefit to using macroinvertebrate and fish indicators are also sensitive to the development of storage structures like dams (Navarro-Llácer et al., 2010; Marzin et al., 2012) and can be used to monitor the impact of anthropogenic changes to the flow levels in the rivers. Besides being able to be used for a variety of different stream health indices, macroinvertebrates and fish can also be used to identify the stressors causing the degradation of a site, based on the number of sensitive taxa present. And the wide distribution of macroinvertebrates and fish over the trophic levels allows for a better understanding of what is actually happening within the system and what changes are occurring due to anthropogenic impacts. When all of this is taken into account, macroinvertebrates and fish can be seen as a very versatile indicator of stream health and the impacts humans have on the aquatic ecosystems in which they reside.

4.7.2 Limitations

While macroinvertebrates and fish are useful indicators of stream health (Karr, 1981; Iliopoulou-Georgudaki et al., 2003) there are still limitations to their application as well as regions, like lakes and large rivers, that require further research so that actions can be taken to reduce the levels of degradation found in freshwater ecosystems.. Often indices will be used to compare streams within regions, and while some regions like the Northern Lakes and Forest Ecoregion in the United States are relatively uniform (Butcher et al., 2003b) majority of regions are not. So if indices are applied outside the region the results may be very inaccurate. This means that streams indices should always be modified to fit the characteristics of the region of study.

Thorough out this review, different aspects and applications of macroinvertebrate and fish indices have been discussed. However, majority of these works were performed in wadeable streams, describing how the ecosystem responds to different stressors. However, non-wadeable streams are not nearly as studied. Therefore, future studies should be focus on these waterbodies to better understand how anthropogenic activities impact the overall aquatic ecosystems at the local and regional levels.

5. Optimization of Conservation Practice Implementation Strategies in the Context of Stream Health

5.1 Abstract

Sustainability of freshwater ecosystems is vital to insuring their continued use. This study introduces a new strategy to improve stream health to a desirable condition at the lowest cost by optimizing the best management practice (BMP) implementation plan. To accomplish this, several hydrological models including the Soil and Water Assessment Tool (SWAT) and Hydrologic Integrity Tool (HIT) were integrated and the results were used to develop stream health predictor models. All of the models were guided by a genetic algorithm to design the watershed-scale management strategies. Five BMPs were considered for use on agricultural land within the study area: cover crop, forest, native grass, no tillage, and residue management. Results from the hundreds of simulation identified eight unique BMP implementation scenarios that resulted in overall excellent stream health scores for the Honeyoey Creek-Pine Creek Watershed in Michigan. From these scenarios it was found that the most often implemented BMP was no tillage (20.43%) followed by residue management (17.26%) and forest (15.88%). Finally, one scenario was selected at the end for having maximized stream health score while minimizing the implementation cost. The technique introduced here can be successfully adapted in different regions and used by stakeholders and decision makers to identify the optimal solution from both environmental and economic points of view.

5.2 Introduction

With the continued growth of the human population, the need for freshwater has significantly increased. This increase in freshwater demand is mainly attributed to agricultural production, which accounts for 70% of freshwater consumption worldwide (Worldometers, 2014). However, the impacts of anthropogenic activities is not only limited to water quantity but also quality due to point and non-point source discharges (Walters, et al., 2009; Dos Santos, et al., 2011; Giri et al., 2014 Pander and Geist, 2013). For example, water withdrawals and dams alter the flow regime of river systems (International Rivers, 2014), while agricultural production increases nutrient and sediment loads within these systems (USGS, 2013a). These activities degrade river systems, which in turn impact the humans that use freshwater resources for drinking or recreation. To protect the surface water resources in the United States, the Clean Water Act was passed (CWA, 1972), with the goal of restoring the chemical, physical, and biological integrity of the Nation's waterways. In the framework of the CWA, chemical water quality has greatly improved and point source discharges have largely been eliminated (EPA, 2012b). Despite all of these improvement, recent assessment has revealed that degradation of aquatic ecosystems continue and even accelerated since the program was started (EPA, 2011). EPA (2011) report concluded that a central focus on chemical water quality is not enough to achieve healthy streams due to river system complexity and the effect of compounding stressors (Magbanua, 2012). This shortcoming led to the introduction of bioassessment in river monitoring (Jeong, et al., 2012). Bioassessment is the use of a stream's biological components to evaluate the conditions within the stream (Barbour et al., 1999). The hope is that bioassessment, with chemical and physical assessments, provide a more comprehensive view of stream health, allowing watershed managers to accurately address water quality issues.

Stream health can be defined as the combined quality of chemical, physical, and biological components of a stream (USGS, 2011). In order to describe and measure stream health, the concept of biological integrity was introduced (Karr and Dudley, 1981). Biological integrity describes the ability of an ecosystem to support and maintain a balanced, integrated, adaptive community of diverse organisms in its original stage and before disturbance due to human intervention (Karr and Dudley, 1981). Bioassessments use indices of biological integrity (biological indicators) to evaluate the quality of a system by monitoring the organisms living in a stream (Pander and Geist, 2013). Biological indicators take into account not only the biological characteristics of the system but the physical and chemical conditions as well (Brazner, et al., 2007; Pelletier, et al., 2012).

Environmental flow is another element of bioassessment that is critical to monitor conditions within river systems. Environmental flows describe the patterns and quantity of water needed to support both the environment and human needs (King, et al., 2009; Poff, et al., 2010; Chen and Zhao, 2011). Environmental flows initially focused on maintaining the minimum levels of water needed to sustain the ecosystem (Alfredsen, et al., 2012). However, the scope of environmental flows were further expanded to replicate the natural flow cycles in both timing and volume (King, et al., 2009; Alcázar and Palau, 2010; Poff, et al., 2010; Chen and Zhao, 2011;).

By incorporating both biological indicators and environmental flows, watershed managers are able to identify degraded streams and can work on implementation plans to restore the ecosystem (Butcher, et al., 2003a; Neumann, et al., 2003a; Walters, et al., 2009; Pelletier, et al., 2012). However, there are several challenges with implementation of bioassessment techniques in large and diverse watersheds. First, it is expensive and impractical to perform monitoring in every stream segment to evaluate stream health condition. Second, it is not possible to examine every possible management scenario to effectively improve overall stream health condition.

Modeling provides an inexpensive and effective way to explore stream health conditions beyond the monitoring sites or examining the impacts of management practices to improve water quality (Arabi et al., 2006; Einheuser et al., 2012; Giri et al., 2012; and Einheuser et al., 2013b). However, to the best of our knowledge no work has been done to optimize best management practice implementation plan in the context of stream health, which is the goal of this study. The specific objectives of this study were to: (1) predict stream health conditions beyond the monitoring points based on a biological indicator, (2) develop series of management practice scenarios that maximize stream health conditions while minimizing the cost in a watershed.

5.3 Materials and Methodology

5.3.1 Study Area

The region used for this study was the Honeyoey Creek-Pine Creek Watershed (Figure 5.1), located in the central eastern region of the Lower Peninsula of Michigan. This is a 10-digit hydrologic unit code (HUC 0408020203) watershed the Honeyoey Creek-Pine Creek watershed is part of the Pine 8-digit HUC watershed and flows into the Tittabawassee and Saginaw 8-digit HUC watersheds. The final outlet for the region discharges into Lake Huron at the mouth of the Saginaw River. With a total area of 106,131 ha, the region is dominated by agricultural land (52%), followed by forest and wetland (both 20%), and finally pasture (8%). With such a large percentage of agricultural land, water flow throughout this region is in high risk to be altered by water withdrawal for irrigation or degraded by agrochemical nonpoint source pollution.

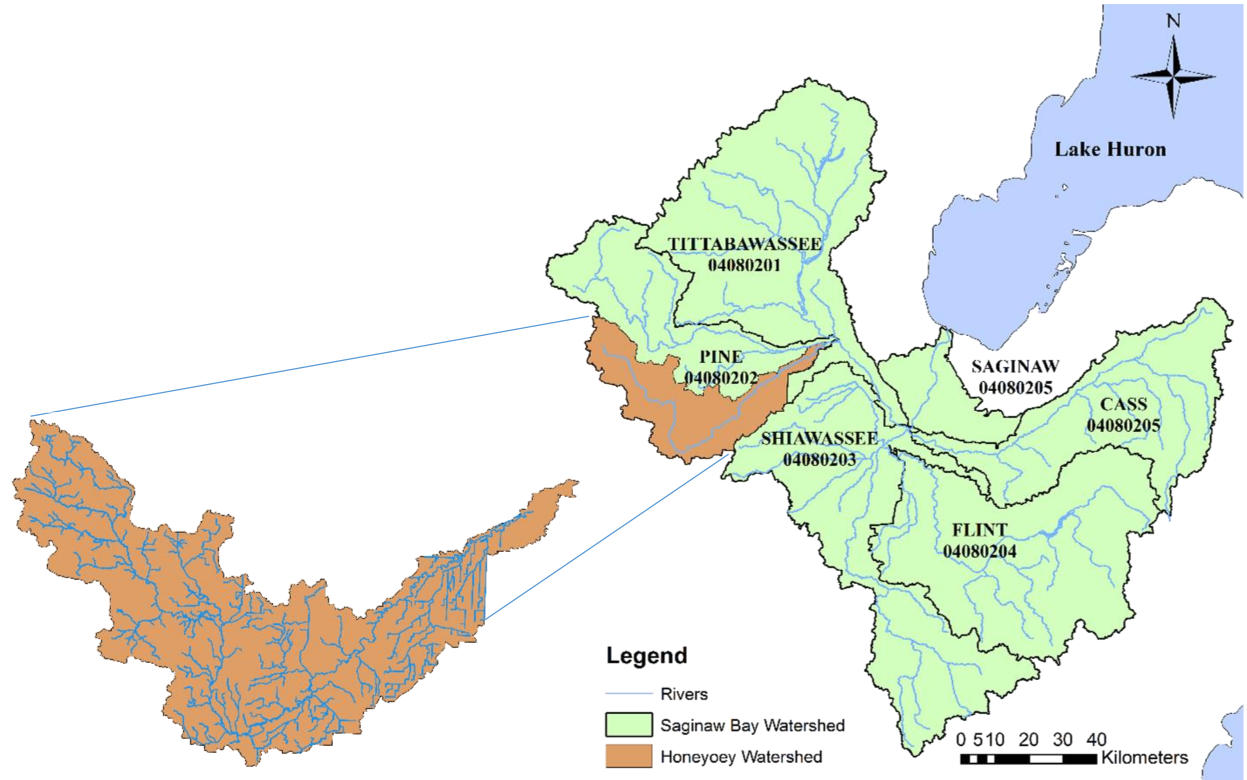

Figure 5.1. Saginaw Bay Watershed (HUC 040802) and the Honeyoey Creek-Pine Creek Watershed (HUC 0408020203).

5.3.2 Data Collection

5.3.2.1 Physiographic Data

Several spatial and temporal dataset were used to characterize the physiographic features of the study area for model developments. These datasets included topography, land use, soil characteristics, climate data, and management practices. The 30 m spatial resolution National Elevation Data set from the US Geological Survey (USGS) was used to represent the topography of the region (NED, 2014). The 30 m spatial resolution 2012 Cropland Data Layer (CDL) from the United States Department of Agriculture-National Agricultural Statistics Service (USDA-

NASS) was used to represent the land use for the region (NASS, 2012). Pre-settlement vegetation circa1800 maps were obtained from the Michigan Natural Features Inventory (MNFI) and were used to represent the pre-settlement land use from the mid-1800s (MNFI, 2014). Soil characteristics data was obtained from the Natural Resources Conservation Service (NRCS) Soil Survey Geographic (SSURGO) Database at a scale of 1:250,000 (NRCS, 2014a). Climate data (precipitation and temperature) were obtained from the National Climatic Data Center (NCDC). Within the Saginaw Bay watershed, 16 precipitation and 13 temperature stations were used to supply daily climatological information. These datasets spanned from 1990 to 2012. Other climate data such as relative humidity, solar radiation, and wind speed were obtained by using the SWAT weather generator (Neitsch et al., 2011). The stream network and subbasins were created from a 1:24,000 National Hydology Dataset plus (NHDPlus) and obtained from the Michigan Institute for Fisheries Research. Each of the 553 subbasins from this dataset contains an individual stream and is considered to be physicochemical, geomorphological, and biological unique (Einheuser et al., 2013a). Management operations, schedules, and crop rotations were modified from SWAT default values, as presented by Love and Nejadhashemi (2011) for the study area.

5.3.2.2 Biological data

Fish are commonly used for stream health assessment. This is due to their wide distribution and easy identification as well as their sensitivity to a variety of stressors (Karr, 1981; Mack, 2007; Zhu and Chang, 2008; Navarro-Llácer et al., 2010; Krause et al., 2013). Furthermore, they provide regional evaluation of stream conditions due to their seasonal migrations (Karr, 1981).

For this study, the Index of Biotic Integrity (IBI) was used to evaluate stream health conditions. The IBI, first introduced by Karr (1981), is a multi-metric index that looks at the species diversity, trophic composition, and abundance of the fish community to evaluate stream health. Each metric used in the index is given a score of 1, 3, or 5, with 5 representing non-disturbed conditions within the stream (Karr, 1981; Lyons, 1992). All the metrics scores are summed to provide the IBI score for the stream, ranging from 0 to 100, which can then be used to compare between different streams. IBI scores were divided into five stream health classes (very poor, poor, fair, good, and excellent) based on Lyons' warmwater stream IBI (1992), the ranges for each steam health class are presented in Table 5.1.

Table 5.1. IBI stream heath class ranges (adapted from Lyons, 1992).

Stream Health Class	IBI Score Range
Very Poor	0 – 19
Poor	20 – 29
Fair	30 – 49
Good	50 – 64
Excellent	65 – 100

Data for this index was obtained from the Michigan Department of Natural Resources Fish Collection System and the Michigan River Inventory dataset (Seelbach et al., 1997). Samples for these indices were collected from June to September from 1996 to 2003. Due to limited number of biological sampling points within the Honeyoey Creek-Pine Creek Watershed (18 sites), all sampling locations (193 sites) throughout the Saginaw Bay Watershed was used to develop stream health predictor models based on the IBI scores (Figure S1).

5.3.3 Modeling Process

In order to accomplish the goal of this study, two phases were established, the development phase that was performed in the Saginaw Bay Watershed and the scenario phase that was performed in the Honeyoey Creek-Pine Creek Watershed (Figure 5.2). Within the development phase, steps are taken to develop a stream health model. These include the calibration/validation of a biophysical Soil and Water Assessment Tool (SWAT) model to obtain daily flow rates for all stream segments within the Saginaw Bay Watershed; and calculation of 171 hydrological indices based on long-term daily flow rate for all streams using the Hydrological Index Tool (HIT). Given the large number of variables (171) three dimensionality reduction techniques were explored to identify the best variables for the stream health models. Once the models were developed, they were then used in the scenario phase where different management practices were applied to agricultural lands. The scenario phase utilizes the evolutionary algorithm technique known as Genetic Algorithms (GA) to find a near optimum solution by maximizing the stream heath index and minimizing the implementation cost. The steps in this phase include, estimating long stream flow rate using SWAT, using HIT to calculate flow variables selected in the development phase for the stream health models, using ANFIS to estimate IBI scores for each stream segment, calculating the weighted average value for the study area, sing the GA for selection and placement of best management practices (BMPs) on agricultural land, and examining the stream health scores and cost. This process is repeated until the near optimum solution is achieved.

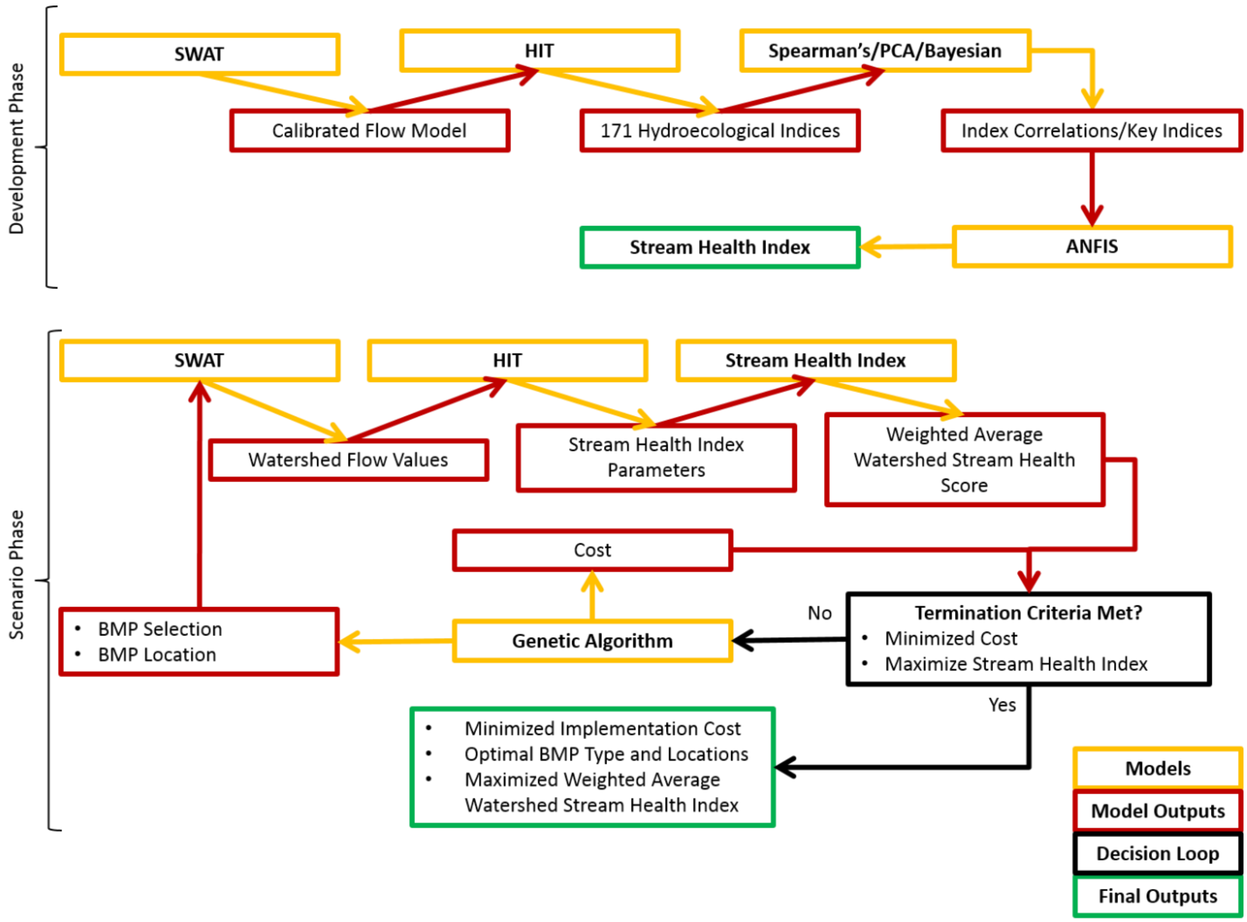

Figure 5.2. Flow diagram of the development and scenario phases.

5.3.3.1 Development Phase

5.3.3.1.1 Soil Water Assessment Tool

Daily stream flow data was modeled throughout the Saginaw Bay Watershed using the physically based Soil Water Assessment Tool. SWAT was developed by the USDA Agricultural Research Service (USDA-ARS) and Texas A&M AgriLife Research (Texas A&M University System, 2013). In addition to streamflow, the model is capable of estimating sediment, nutrient, and pesticide loadings using physiographical and climatological characteristics of the study area including land use, river network, topography, soils, agricultural rotations and scheduled management operations, precipitation, and temperature (Gassman et al., 2007; Neitsch et al., 2011).

The model was calibrated and validated against daily stream flow data from nine USGS gauging stations (Figure S2) from 2001 to 2010. Calibration was preformed from 2001 to 2005 while validation was preformed from 2006 to 2010. Calibration and validation were considered successful when the following criteria were met: a) Nash-Sutcliffe model efficiency coefficient (NSE) is larger than 0.5, b) root-mean-squared error-observations standard deviation ratio (RSR) is smaller than 0.7, c) and percent bias (PBIAS) < +/- 25. After calibration and validation, the SWAT models were run from 1996 to 2003 to provide the stream flow values needed for the development step.

5.3.3.1.2 Hydrological Index Tool

Flow has been called the "master variable" (Power et al, 1995) and the most influential factors affecting stream health index concerning fish (Einheuser et al., 2013a). The Hydrological Index Tool (HIT) was developed by the USGS as part of the Hydroecological Integrity Assessment Process (HIP) (EPA, 2006). It is used to calculate 171 biologically relevant stream flow indices or hydroecological indices originally introduced by Olden and Poff (2003). These indices can be divided into five main categories: magnitude, frequency, duration, timing, and rate of change (Henriksen et al., 2006). Magnitude refers to the availability of water within the system. This availability is used to describe habitat suitability (Richter et al., 1996). Frequency refers to how often certain events, such as droughts and floods, occur. These events can have major impacts on stream organism populations allowing these indices to describe population dynamics (Gupta, 1995). Duration refers to the length of certain events, such as droughts and floods. This can be used to indicate the impacts of these events on the system or they can be used to monitor organism growth stages (Poff et al., 1997). Timing refers to when certain events, such as seasonal flooding, occur within the year. These indices can be used to monitor organism growth or the impacts severe water events (droughts and floods) have on populations (Richter et al., 1996). Rate of change refers to the speed at which stream conditions change. These indices can be related to organism access to adequate water as well as impacts on population caused by extreme water events (Poff et al., 1997).

For this study, HIT indices were calculated for 193 stream segments with biological monitoring sites. The sites were further divided into two additional sets according to the river continuum concept. The river continuum concept describes the predictable physical and biological patterns seen in different regions of rivers (EPA, 2014). Based on the river continuum concept, three physically based categories are used to describe the ecological regions of a river system; headwaters (stream orders 1-3), medium-sized streams (stream orders 4-6), and large rivers (stream orders > 6) (Vannote et al., 1980). However, because not enough monitoring sites available for stream order 7 (two sites), the Saginaw Bay watershed were divided into two classes (stream orders 1 – 3 and 4 – 7) for further model development.

5.3.3.1.3 Variable Selection

To eliminate redundant variables in the final stream health models, three dimensionality reduction techniques (Spearman's Rank Coefficients, Principal Component Analysis, and Bayesian variable selection) were used. These techniques were used for three stream grouping (all, orders 1 – 3, and orders 4 – 7). Up to six variables were selected from each dimensionality reduction/stream grouping scenarios and used to develop stream health model using ANFIS.

Spearman's rank correlation (ρ) is a nonparametric technique that is used to identify the correlation between two sets of variables. This is a useful technique for selecting the most highly correlated variables from a larger set (Einheuser et al., 2013a; Einheuser et al., 2013b). For this study, spearman's rank correlations were calculated between all predicator variables (171 stream flow indices obtained from the HIT model) and the response variable IBI. Variables that were significantly correlated ($\rho < 0.05$) to the stream heath indices (IBI) were selected. Selected variables were analyzed to insure they were not highly correlated ($\rho < 0.7$) to other selected variables to reduce variable redundancy (Waite et al., 2010).

Principle component analysis is a multivariate statistical technique that is used to orthogonally convert observation sets of possibly correlated observations into sets of linearly uncorrelated variables or principal components (PCs) (Pearson, 1901). The order of PCs is so that the first PC (PC1) accounts for the most variability within the original dataset (Schölkopf et al., 1998). All PCs after that (PC2, PC3…) account for nonincreasing levels of variability within the original dataset. This means that the original dataset can be described by the first few PCs (Schölkopf et al., 1998). This was used to find which HIT indices best described the stream heath scores from the IBI. All of the final variables were selected from PC1.

Bayesian variable selection is a technique that utilizes reversible jump Markov Chain Monte Carlo (MCMC) methods to sample all possible combinations of variables to find the best fitting model (Carlin and Chib, 1995). This is done by selecting different samples sets of the variables (MCMC chains) and randomly adding or removing variables and comparing the previous sets model likelihood to the modified sets model likelihoods. The model with the better likelihood is kept and then modified again. This process continues until all variable sets converge to a model likelihood, at which point the best variables were determined. Five MCMC chains, with different initial variable sets, were used to insure that the best variables were selected.

5.3.3.1.4 Stream Health Model

The final step in the model development phase is creation of stream health predictor models capable of estimating IBI score for each stream segment. The artificial neural network technique known as ANFIS or adaptive neuro-fuzzy inference system was used for development of stream health models. ANFIS is a multi-layer network that utilizes artificial neural networks and fuzzy logic to create membership functions (MFs) while minimizing the output errors (Jang, 1993). MFs describe the degree of belonging for each element in a set from full exclusion (0) to full inclusion (1) (Hamaamin, 2014). In this study, ANFIS was used because is well-suited to capture uncertainty and complexity of ecological and environmental systems and their data (Metternicht, 2001; Chen and Mynett, 2003; Adriaenssens et al., 2004; Einheuser et al., 2013a).

The variables selected by Spearman's rank coefficient, PCA, and Bayesian variable selection techniques were used for ANFIS model developments. This was done using the Fuzzy Logic Toolbox in MATLAB R2013b (MathWorks, 2014). Five MFs (triangular, trapezoidal, generalized bell, Gaussian, and Gaussian composite) were used to represent the variable sets. All possible combinations of MFs, and stream grouping were evaluated to determine the best model. At this point, the different variables obtained from three variable selection techniques sets were used to develop ANFIS models. The criteria for selecting the best variable set were the highest coefficient of determination (R^2) and the lowest root-mean-square deviation (RMSE) values.

After determining which variable selection method provided the best models for each stream grouping, 10-fold cross-validation was used to train, test, and select the best ANFIS model. In the10-fold cross validation technique, the models are trained on 90% of the data (9 folds) and tested on the remaining 10% (1 fold). This was repeated 10 times for each model a different fold being used for testing each time (Hamaamin et al., 2013). Similar results for R^2 and RMSE were used to determine the final best model.

5.3.3.2 Scenario Phase

5.3.3.2.1 Develop the Reference Condition

Stream reference condition is a benchmark condition in which the environmental impacts of anthropogenic activities can be measured (Stoddard et al., 2006). In order to develop a reference condition for the Honeyoey Creek-Pine Creek Watershed a new SWAT project was created that used pre-settlement landuse. Vegetation circa1800 maps were obtained from the Michigan Natural Features Inventory (MNFI). These maps were based on detailed fields notes taken from a General Land Office survey of the state from 1816 to 1856 (MNFI, 2014).

To identify which stream order experienced the most change between the pre-settlement and current conditions a Wilcoxon Signed-Ranks statistical test was performed. The Wilcoxon Signed-Ranks test is a non-parametric technique that calculates the difference between two sets of observations by ranking the differences between paired values (Pratt, 1959). Due to the presence of ties and zeros in the differences between paired values, the method presented by Pratt (1959) was used to calculate the p-values for the variables within each set of stream orders. Furthermore, percent changes were also calculated between all data sets.

5.3.3.2.2 Best Management Practices

To reduce the degradation within the stream systems a variety of best management practices were applied to agricultural land throughout the region based on Natural Resources Conservation Service recommendations. These included cover crop, forest, native grass, no tillage, and residue management.

Cover crops are primarily used to reduce sediment erosion during the times when the field would normally be barren (post-harvest till planting) (Arabi et al., 2007). However they can help control the flow of water during this time as well by slowing run off and reducing peak flow. Winter wheat was chosen as the cover crop due to its popularity in the study area. Use of no tillage or conservation tillage reduces the amount of soil disturbances that occur on the field from agricultural practices (Tuppad and Srinivasan, 2008). This increases the amount of residue on the field that can also reduce runoff from the field. Application of residue management reduces the amount of tillage applied to a field post-harvest. This leaves behind crop residue that helps protect the soil and controls the flow of water on the site during the time between the harvest and planting. A residue management of 1000 kg/ha was chosen for use in this study. Returning the agricultural land to forest has been successfully used to improve stream flow conditions within the region of application (Qui, et al., 2011). In addition, the pre-settlement conditions for the majority of the agricultural land in the Honeyoey Creek-Pine Creek Watershed was forest. Therefore this BMP attempts to return the region to its original pristine condition, by improving both water quality and quantity of the region. Converting the agricultural land to native grass, is an attempt to restore the land to a more natural condition by cultivating native grasses on the land (Einheuser et al., 2013b). This reduces the amount of runoff from the site and can significantly lower the peak flow discharge.

In addition to environmental flow benefits of BMP implementation, associate cost is an important factor to consider in order to develop practical solution. This cost includes the implementation and maintenance costs for each BMP per unit area (Table 5.2). BMP costs were obtained from the NRCS Typical Statewide Average Practice Costs for 2014 (NRCS, 2014b).

Table 5.2. BMP costs per unit area (NRCS, 2014b).

BMP	Cost/ha
Cover Crop	$167.29
No Tillage	$42.01
Residue Management	$29.65
Forest	$355.19
Native Grass	$160.62

SWAT BMP implementation procedures were adopted from other studies (Arabi et al., 2007; Tuppad et al., 2010; Woznicki and Nejadhashemi, 2012; Giri et al., 2014). However, for the forest BMP, land use condition from pre-settlement map was used to replace current agricultural land.

5.3.3.2.3 Optimizing BMP Placement

In order to evaluate the overall stream health condition and identify near optimal locations in which to apply Best Management Practices while minimizing implementation cost a GA technique was proposed. This is because the intractable size of the solution space. Given six scenarios (five control practices and one no-BMP) and 185 target agricultural land parcels, there are $6^{185} \approx 10^{144}$ possible implementation options. To accelerate the process, first we maximized the overall stream health score and next calculated the implementation cost in post-processing. The overall stream health scores were calculated for every stream in the subbasin (m = 553 stream segments) and then used to calculate a weighted average stream health score for the entire region. Equation 1 was used to calculate the weighted average stream health score:

$$Stream\ Health\ Score = \frac{\sum_{i=1}^{m} IBI_i \times L_i}{\sum_{i=1}^{m} L_i} \tag{1}$$

Where IBI_i is the individual stream health scores, L_i is the individual stream lengths, and m is the number of subbasins in the region.

The fitness is the quality of a solution under a defined metric, in our case this is stream health. So given an assignment of practices to all target reaches, P_i, from the set of all possible assignments, $\mathcal{P}$, the fitness is optimized at:

$$\max_{P \in \mathcal{P}} health(P) \tag{2}$$

We do not require the cost to be constrained during the application of the algorithm, but we do save the cost value for distinguishing the feasibility of results with similar health scores.

The actual algorithm can be described as an evolutionary DNA encoding process. The data are similar to a DNA strand where the array of control practices, ranging from zero to five (corresponding to the possible control practices), represent a string of nucleotides. Each candidate solution then gives an assignment of actions which can be quantified in terms of fitness. With such an arrangement we need information on the river reaches, the control practices, and the cost per practice to derive the watershed's overall health and the total cost of any applied actions.

The candidates are initialized by providing a pseudo-random assignment of control practices to each targeted reach. There are n such candidates produced and the top m solutions are chosen for the initial set. No fitness control is applied during generation, but the highest m members will survive to the evolutionary stages. Both m and n are user-selectable values which we choose to be $m = 20$ and $n = 100$. Through a series of generations new candidates are created from the most fitted candidates of the previous generation. In each step a crossover with mutation is performed to create offspring instances capturing the desirable traits of the parent candidates.

Each generation is pruned to contain only the 20 members with the highest stream health score, these candidates will become the parents of the new generation. This combination of the high performing parents into a child candidate is called crossover. This process exploits the good genetic traits of the parents while approaching a locally maximum solution. Crossover occurs for the control practices by first selecting two candidates from the group of parents. Next a random point is chosen to break the genes in half. The left of the break point is copied from the first parent's chromosome's genes (list of control practices) and the right similarly with the second parent's chromosome's genes. Similarly create another child by swapping in parent one's genes on the right and parent two's on the left. Note that if the split point is chosen on one of the endpoints no crossover will occur.

With only crossover applied a local solution will be reached, but this may be a poor solution. To combat this, a random selection of control practices of a selected candidate are changed randomly to inject diversity into the population of candidate solutions. This effect is called mutation. Mutation allows for new solutions to be explored by increasing diversity and lowers the chance remaining fixed on a local maximum solution. The probability of mutation is done randomly on a gene by gene basis at a rate of 5%. Rarely, due to its probabilistic nature, mutation may not occur on a chromosome.

After the new set of children are created from crossover and mutation, the old generation is discarded and the set of children become the new potential parents to again be pruned into the 20 fittest candidates. There are several possible termination conditions. The simplest is to terminate after a fixed number generations have been evaluated and selecting the most fit member of this generation. Because we were interested in finding many solutions of high stream health we terminated after sufficiently many candidates had IBI scored of over 65, which represent an excellent stream health condition according to Lyons' (1992) warmwater stream IBI classification.

5.4. Results and Discussion

5.4.1 SWAT Model Calibration and Validation

The SWAT model evaluation criteria (NSE, RSR, and PBIAS) for the calibration and validation periods are reported in Table 5.3. As can be seen in Table 5.3 all NSE values are above 0.5 with a range from 0.534 to 0.776 for calibration and 0.518 to 0.788 for validation, all RSR values are under 0.7 with a range of 0.474 to 0.682 for calibration and 0.46 to 0.694 for validation period, and all PBIAS values are within a range of +/- 25 with a maximum value of 23.167 for calibration and -24.267 for validation. This indicates that the developed SWAT models met the satisfactory evaluation criteria and can be used to estimate daily streamflow data.

Table 5.3. Statistical criteria for the calibrated SWAT model at different USGS gauging stations (Figure S2).

USGS Station Number	NSE Calibration	RSR Calibration	PBIAS Calibration	NSE Validation	RSR Validation	PBIAS Validation
04144500	0.625	0.612	21.300	0.601	0.632	9.421
04148500	0.699	0.548	23.167	0.751	0.499	8.276
04148140	0.534	0.682	10.389	0.539	0.679	-24.267
04147500	0.631	0.608	8.508	0.647	0.594	-10.969
04151500	0.586	0.643	15.144	0.679	0.566	12.624
04157000	0.776	0.474	16.215	0.788	0.460	11.746
04155500	0.632	0.607	19.483	0.580	0.648	0.953
04156000	0.734	0.516	6.479	0.733	0.517	9.850
04154000	0.577	0.650	6.324	0.518	0.694	13.792

5.4.2 Variable Selection for the Best Stream Health Model

ANFIS was used to determine which dimensionality reduction technique (Spearman's Rank Coefficient, PCA, and Bayesian Variable Selection) and variables should be used for development of stream health predictor model. This was done by evaluating all combinations of variables and number of MFs (two, three, and four). Table 5.4 reports the R^2 and RMSE for all selected sets of variables. For stream grouping, all, 1 – 3, 4 – 7, the Bayesian Variable Selection had the highest overall R^2 values; 0.571, 0.514, and 0.699, respectively. This indicates that the variables selected by this method represented the region most accurately when compared to all sets of selected variables. This led to the selection of variables from Bayesian technique for the 1–3 and 4–7 stream grouping for the final stream health model. The second best technique is Spearman's Rank Coefficient based on average R^2 value. In addition, this technique produced the lowest average RMSE, which is a robust performance. For the PCA, the performance was poor for stream order 1-3 (the lowest R^2 value); however, perform better than Spearman's Rank Coefficient for stream order 4-7 based on higher R^2 and the lowest RMSE between all techniques and stream grouping.

Table 5.4. Coefficients of determination for each variable selection technique.

Variable Selection Technique	Number of Variables	Stream Orders	RMSE	R^2
Spearman's Rank Coefficient	3	All	15.869	0.447
Spearman's Rank Coefficient	2	1 – 3	14.371	0.481
Spearman's Rank Coefficient	2	4 – 7	16.507	0.547
Principal Component Analysis	3	All	18.695	0.569
Principal Component Analysis	2	1 – 3	18.329	0.228
Principal Component Analysis	3	4 – 7	13.082	0.634
Bayesian Variable Selection	4	All	14.703	0.571
Bayesian Variable Selection	3	1 – 3	19.895	0.514
Bayesian Variable Selection	2	4 – 7	13.313	0.699

The final stream health ANFIS model for stream orders 1 – 3 is a linear model with three variables as follow: variability of flow values in January (MA24), variability across annual maximum flows (MH18), and variability in reversals (RA9). All variables had two Gaussian MFs. The RMSE and R^2 for this model are 19.895 and 0.514, respectively. For stream orders 4 – 7, a linear model with two variables was selected, these variables were: the number of days where flow increased from the previous day (RA5) and the skewness of the annual maximum flows (MH19). RA5 had four Gaussian MFs, while MH19 had 3 Gaussian MFs. The RMSE and R^2 for the model are 13.313 and 0.699, respectively.

5.4.3 The Reference versus Current Conditions

A comparison was done between the pre-settlement (reference) and current conditions in order to identify the impacts of human activates on local and regional stream health. The streams were classified according to Lyons' (1992) stream IBI classification method (Table 5.1 and Figure 5.3),

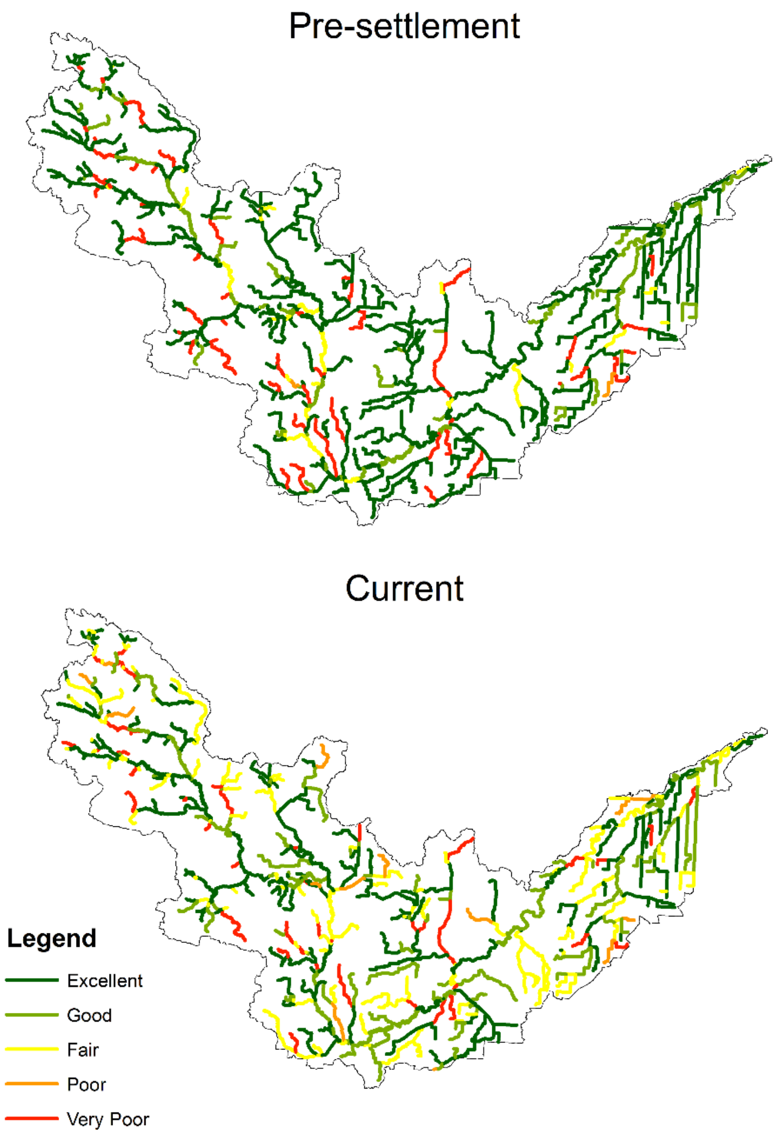

Figure 5.3. Pre-settlement and current stream health classes.

Overall the stream health score for the Honeyoey Creek-Pine Creek Watershed was reduced from 73.1 for the pre-settlement to 59.3 for the current condition. To determine the differences between the pre-settlement and current stream health scores the percentage of the total stream length for the study area was calculated (Table 5.5). Excellent and Good health scores were combined together as Satisfactory, and Poor and Very Poor health scores were combined together as Unsatisfactory. Based on these percentages, the pre-settlement conditions have more stream length within the *Satisfactory* stream health group, with 80% of the total stream length compared to the current conditions value of 66%. However the greatest difference between the two conditions is the percentage of stream length that falls within the *Fair* stream health group. This means that 14% (80%-60%) of the stream with the *Satisfactory* conditions were downgraded to *Fair* condition while only 4% (14%-10%) of the streams were upgraded to *Fair* condition from *Unsatisfactory*. As the land use changed from the pre-settlement to the current conditions, the stream health score for 58 % of the streams decreased. While 26 % of the streams showed improvement and 16 % showed no change (S3). Therefore, as it was expected, the overall stream health pattern shown degradation in the majority of the watershed.

Table 5.5. Comparison of pre-settlement and current conditions based on the length of stream for each health class.

Stream Health Class	Pre-settlement	Current	Overall Condition	Pre-settlement	Current
Excellent	69.36%	44.70%	Satisfactory	80.49%	65.76%
Good	11.13%	21.06%			
Fair	5.69%	23.92%	Fair	5.69%	23.92%
Poor	1.49%	1.66%	Unsatisfactory	13.82%	10.32%
Very Poor	12.33%	8.66%			

The Wilcoxon Signed-Ranks statistical test was performed to evaluate the significant differences between reference and current conditions for different stream orders. p-values and percent changes are presented in Tables 6 and 7. The maximum stream order in the Honeyoey Creek-Pine Creek Watershed was five.

Table 5.6. Wilcoxon Signed-Ranks test and percent changes between the pre-settlement and current conditions for stream orders 1 through 3.

Variables	Stream Order 1		Stream Order 2		Stream Order 3	
	% change	p-value	% change	p-value	% change	p-value
Stream Health Score	-22	<0.01	-22	<0.01	-23	<0.01
MA24	120	<0.01	122	<0.01	135	<0.01
MH18	-70	<0.01	46	<0.01	-38	<0.01
RA9	1	<0.01	0	0.075	-1	0.053
RA5	3	<0.01	2	<0.01	4	<0.01
MH19	-30	<0.01	-28	<0.01	-35	<0.01

*Bold values indicate significance probability at the 0.01 level

Table 5.7. Wilcoxon Signed-Ranks test and percent changes between the pre-settlement and current conditions for stream orders 4 through 5 and for all streams.

Variables	Stream Order 4		Stream Order 5		All Stream Orders	
	% change	p-value	% change	p-value	% change	p-value
Stream Health Score	-20	<0.01	18	0.373	-21	<0.01
MA24	133	<0.01	83	<0.01	123	<0.01
MH18	-114	<0.01	-48	0.011	-83	<0.01
RA9	-1	0.960	1	0.343	0	<0.01
RA5	3	<0.01	5	0.048	3	<0.01
MH19	-34	<0.01	-37	<0.01	-31	<0.01

*Bold values indicate significance probability at the 0.01 level

Of all streams within the region, 5th order streams were the least affected by the land use changes; with three variables (MH18, RA9 and RA5) as well as the stream health scores showing no significant change ($p > 0.01$) between the two scenarios (Table 5.7). In contrast, 1st order streams were the most impacted with all variables and the stream health scores showing significant change ($p < 0.01$) between the two scenarios (Table 5.6). This significance was mirrored by the evaluation of all streams. But this is expected since the region it predominantly 1st order streams.

Of all the variables evaluated, the largest positive percent change was seen in the MA24 variable (variability of flow values in January), with an average increase of 123 % between all stream orders (Table 5.7) and a maximum change of 135 % for 3rd order streams (Table 5.6). This shows that there is more variability of flow values within the month of January in the current condition compared to the pre-settlement condition. The largest negative percent change was seen in the MH18 variable (variability across annual maximum flows), with and average decrease of 83 % between all stream orders (Table 5.7) and a maximum decrease of 114 % for 4th order streams (Table 5.7). This shows that the variability of annual maximum flows has decreased in the current condition when compared to the pre-settlement condition. The variable with the least percent change was the RA9 variable (variability in reversals), with an average change of 0 % between all streams orders (Table 5.7). This variable also was the variable that showed the least significant change between the two conditions. For the stream health score overall, there was an average decrease of 21 % for all stream orders (Table 5.7) with a maximum decrease of 23 % for 3rd order streams (Table 5.6). This indicates that on average the health streams within the region has decreased by 21%.

5.4.4 Optimizing BMP Placement

After the development of the stream health model, the Genetic Algorithm was used to create different BMP scenarios. Without the guide, the selection and placement of the BMPs can be random; however, the genetic algorithm was used to improve the overall stream health score by optimizing the type and placement of various BMPs. After one hundred and eighty two iterations, the maximum stream health score reached a plateau at a value of 71.036. Because IBI scores of 65 and above present the excellent stream health condition, it was decided that only scenarios with the scores ≥ 65 would be further analyzed to identify the best scenario. From these one hundred and eighty two scenarios, eight unique scenarios satisfied the aforementioned criteria even though they had different BMP compositions. Table 5.8 shows the percentage of the total agricultural area allocated to BMP implementation.

Table 5.8. Percentage of allocated area to BMP implementation within the agricultural lands in scenarios that overall IBI score is greater than 65.

BMP Scenario	**BMP Practices**					
	No BMP	**Cover Crop**	**Forest**	**Native Grass**	**No Tillage**	**Residue Management**
1	14.98%	16.11%	11.99%	14.13%	20.47%	**22.32%**
2	**24.63%**	21.31%	7.76%	15.95%	14.62%	15.73%
3	19.70%	13.90%	13.58%	14.01%	**24.93%**	13.88%
4	13.89%	19.92%	12.53%	13.44%	**20.31%**	19.91%
5	18.48%	11.30%	14.70%	12.31%	20.03%	**23.18%**
6	10.94%	16.97%	21.57%	13.97%	**22.92%**	13.63%
7	11.35%	13.71%	**24.84%**	13.04%	22.78%	14.29%
8	11.38%	17.18%	**20.08%**	18.84%	17.39%	15.13%

*** Bold values indicate dominant BMP(s) per scenario**

Based on Table 5.8, no tillage was the dominant BMP for three of the eight scenarios (Scenarios 3, 4, and 6) and had an average implementation of 20.43%. This indicates that no tillage was the most often implemented BMP. After no tillage, both residue management and forest were the dominant BMP for two of the eight scenarios (Scenarios 1 and 5 and Scenarios 7 and 8 respectively). Even though both residue management and forest were dominant for two scenarios, residue management was applied on more area than forest (17.26% and 15.88% respectively). Another interesting observation is the dominant BMP for Scenario 2. No BMP was the most often implemented BMP for this scenario, covering 25% of all agricultural land (Table 5.8). This is interesting, because it shows that we still can achieve excellent stream health condition (IBI $\geq$ 65) in the study area while not implementing BMPs on all agricultural lands.

For the eight BMP implementation scenarios with the overall IBI scores above 65, the individual stream health scores are different. Figure 5.4 shows the distribution of the individual stream health scores for all scenarios. To better represent this data, scores were categorized by stream order.

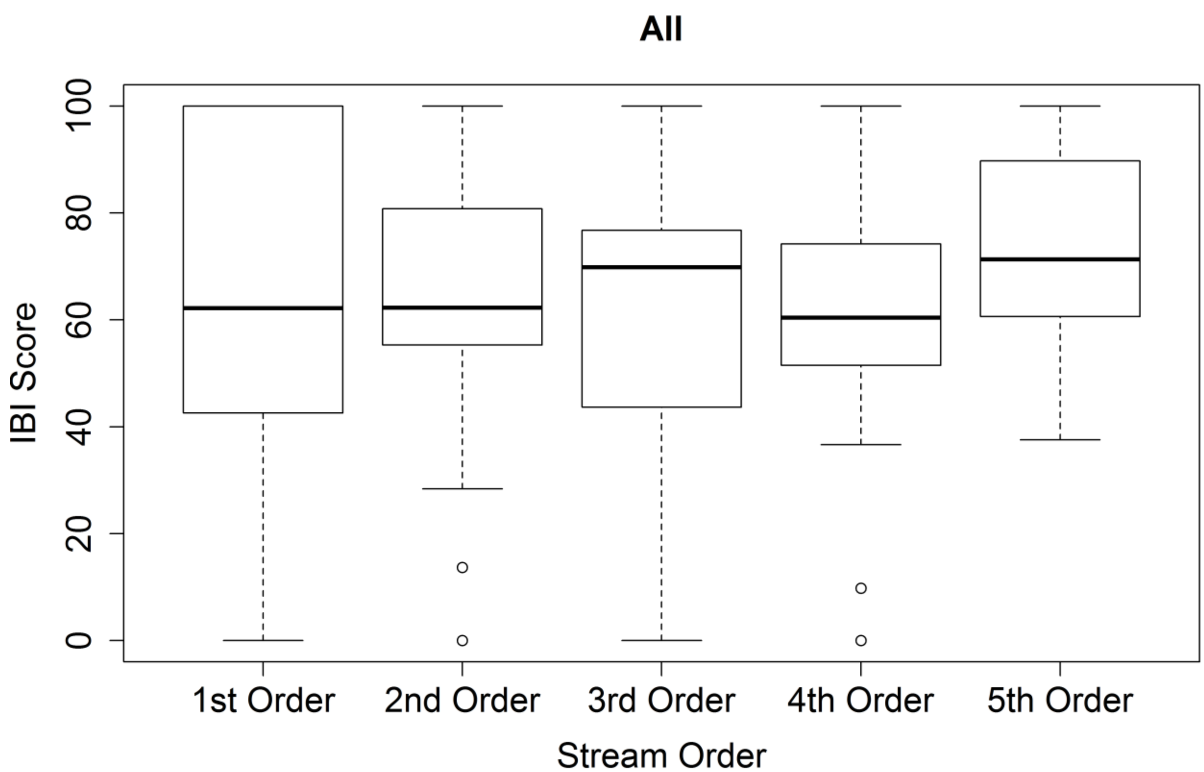

Figure 5.4. Distributions of individual stream health scores for all BMP scenarios.

As can be seen in Figure 5.4, all stream orders had maximum stream health scores of 100 and a median stream health score between 60 and 80. However, 1st and 3rd order streams were the only stream orders that spanned the entire stream health range (0 to 100). While 2nd and 4th order stream had outliers within the lower ranges of the stream health scores. In contrast, 5th order streams never dropped below a stream health score of 35. This shows that 5th order streams had the smallest range of scores. Individual scenario stream health score distributions can be found in Figures S4 through S11 in the Appendix.

To better examine the upper ranges of the individual stream health scores. The percentage of stream health scores greater than 65 for each scenario were calculated and presented in Table 5.9. While this is not indicative of the overall steam health score, it does show which scenario was able to reach the excellent stream health class for more of the total stream length. As can be seen in Table 5.9, Scenarios 4, 6, and 7 had the largest amount stream length within the excellent stream health class, with a percentage of 61%. While Scenarios 3 and 8 had the least amount of stream length within the excellent stream health class, with a percentage of 41%. Therefore if decision makers wanted to improve individual stream health scores, Scenarios 4, 6, or 7 are the logical choice. However, if improving the overall stream health score is the focus any of the scenarios can be used

Table 5.9. Percentage of individual streams with a stream health score greater than 65 for all BMP scenarios.

BMP Scenario	**Percentage of Individual Steams within the Excellent Stream Health Class**
1	46%
2	46%
3	41%
4	61%
5	46%
6	61%
7	61%
8	41%

5.4.5 Associated cost of BMP Implementation Scenarios

Finally, the costs of the eight acceptable scenarios were calculated. This was the final criteria for selecting a near optimum solution that account for both stream health and associated implementation cost. Furthermore since the overall stream health scores for all scenarios was identical, it became the key factor for identifying the best scenario. Table 5.10 displays each scenario's overall steam health scores and total cost of implementation.

Table 5.10. All unique BMP scenarios with an overall stream health score above 65.

BMP Scenario	Stream Health Score	Cost
1	71.036	$1,964,889
2	71.036	$1,822,138
3	71.036	$1,985,994
4	71.036	$2,081,966
5	71.036	$1,941,840
6	71.036	$2,580,815
7	71.036	$2,668,190
8	71.036	$2,599,286

* Bold values indicate scenario with the lowest cost.

As can be seen in Table 5.10, Scenario 2 had the lowest cost among all scenarios with a stream health score greater than 65. This made it the best of all the scenarios because it was able to achieve the maximum stream health score (71.036) while costing the least to implement ($1,822,138). This result matches the BMP selection percentages presented in Table 5.8 in which no BMP was selected for the majority of agricultural areas, and a solution with fewer implemented BMPs will cost less.

Figure 5.5 displays the locations of the BMP implementations within the study area as well as the individual stream health class for Scenario 2. A final comparison between Scenario 2 and the current condition was preformed to evaluate the impacts made by implementing Scenario 2. Any increase of stream health scores was considered as improvement while any decrease of stream health score was considered as decline. These changes are presented in Figure 5.6.

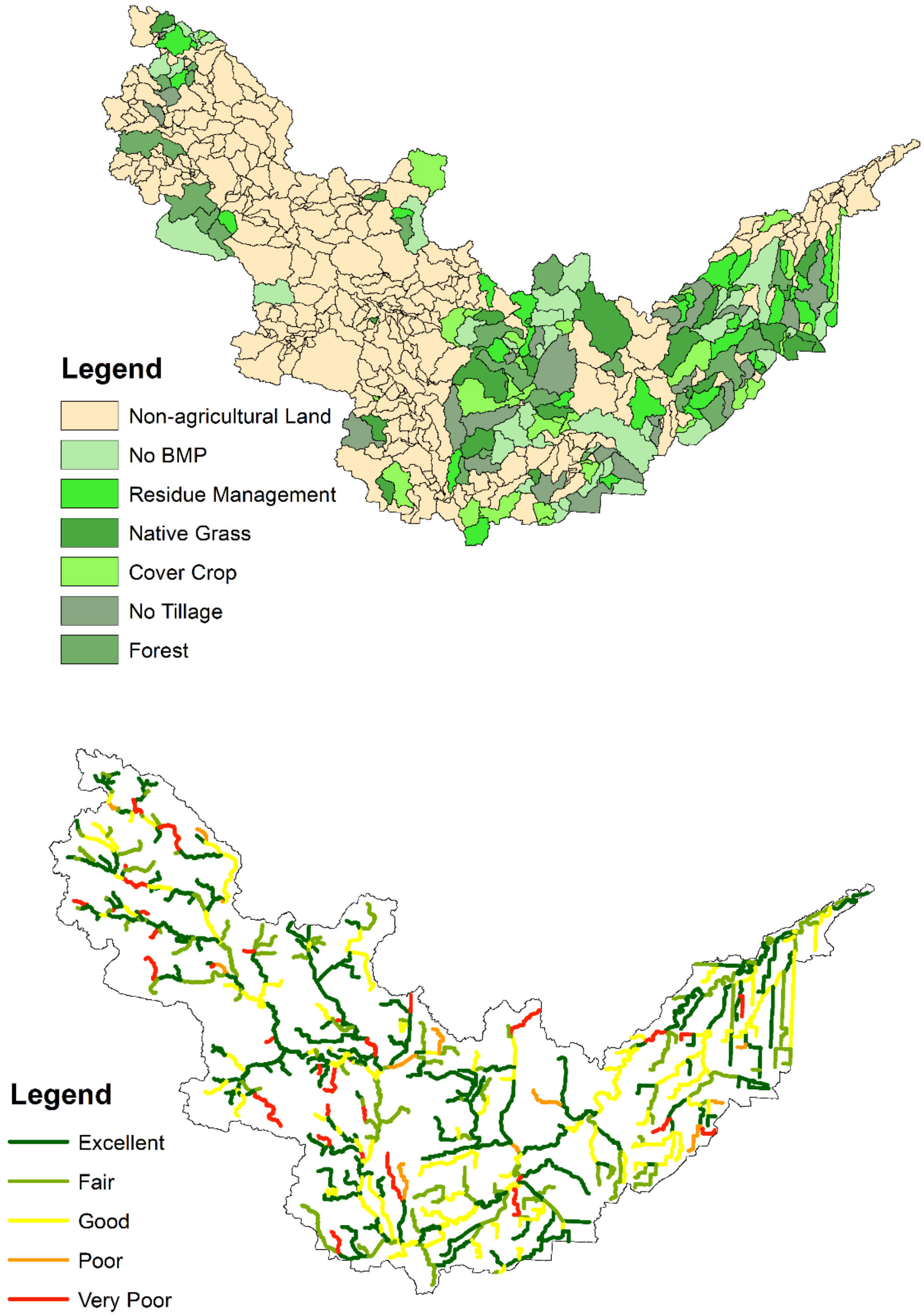

Figure 5.5. BMP placement and individual stream health scores for Scenario 2.

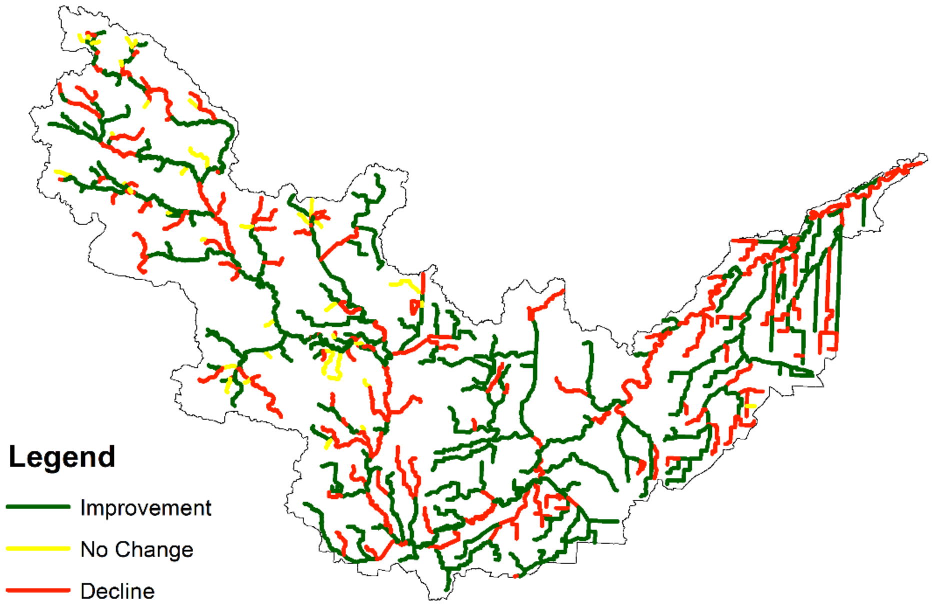

Figure 5.6. Improvements and declines in stream health scores between the pre-settlement and current conditions.

As can be seen in Figure 5.6 the implementation of Scenario 2 resulted in the increase in stream health score for 52 % of the streams. While 11 % of the streams showed no change and 36 % showed decline. This shows that the majority of streams improved with the implementation of Scenario 2.

5.5 Conclusion

In order to optimize best management practice implementation plan in the context of stream health, a series of models including SWAT, HIT, Stream Health Predictor (ANFIS), and Genetic Algorithm were coupled. Daily stream flow data were incorporated in the HIT model to estimate 171 biologically relevant stream flow indices. Three dimensionality reduction techniques including Spearman's Rank Correlation, PCA, and Bayesian variable selection were used to reduce number of variables that were incorporated in development of stream health predictor models using ANFIS. The stream health predictor models were used to estimate individual stream IBI scores and overall stream health scores for the watershed. The genetic algorithm was used to guide BMP selection and placement in the study area to achieve the highest overall stream score at the lowest price.

The Bayesian variable selection was selected as the best approach to reduce the number of variables and eliminate redundancy in the stream health predictor model. Two ANFIS models were selected to evaluate stream health conditions within the region; one for stream orders 1 – 3 and one for stream orders 4 – 7. For stream orders 1 – 3, the final stream health model included three variables (MA24, MH18, and RA9). RA represents rate of change for an average event while MA and MH prefix represent magnitude of average and high flow events, respectively. For the stream orders 4 – 7 two variables (RA5, and MH19) were selected. The main deference between these two models is that the model for the stream orders 4 – 7 is not as sensitive as the model for stream orders 1 – 3 to average flow magnitude. These models were used to evaluate the stream health scores for all stream segments within the region.

Analysis was done to identify the changes in stream health due to the alteration of land use from pre-settlement to current conditions. It was found that in the current conditions 58% of streams had a decrease in stream health, 26% showed improvement, and 16% showed no change. In term of overall stream health score 21% decline was observed. Furthermore, analysis indicated that 5th order streams were the least affected by this change, while 1st order streams were the most impacted.

The implementation of different BMP scenarios was preformed to find a near optimum solution that maximized the stream health score and minimized the cost. Eight unique BMP scenarios with different BMP compositions were identified that had a maximum stream health score of 71.036. The most commonly implemented BMP was no tillage. Scenarios 4, 6, and 7 had the highest percentage of individual streams with health scores greater than 65. However, cost analysis of the scenarios, identified Scenario 2 as the lowest costing option, thus matching the criteria set for this study. Comparison of the stream health scores from Scenario 2 to the Current condition yielded an increase of stream health scores for 52 % of the streams, no change for 11% of streams, and a decrease of stream health for 36 % of streams.

In order to improve the predictability and reliability of the stream health predictor models, future studies should include wide range of water quality and quantity variables along with both fish and macroinvertebrates biological indicators. Studies like the one perform here can provide valuable information to decision makers, allowing them to develop a watershed level BMP implementation scenarios that will improve the stream health conditions at the lowest cost.

5.6 Acknowledgments

This work is supported by the USDA National Institute of Food and Agriculture, Hatch project MICL02212. We also would like to thank the Michigan Institute for Fisheries Research for providing stream and catchment data.

6. CONCLUSIONS

This research evaluated the application of a genetic algorithm in combination with a stream health model to find a near-optimum solution that maximizes stream health while minimizing BMP implementation cost. In the first study, a review of currently existing macroinvertebrate and fish stream health indices was used to identify the most appropriate biological index that can represent stream health conditions in a large and diverse watershed. The Index of Biological Integrity (IBI) was selected because the study area is comprised of warm water streams (Lyons, 1992) and degradation of fisheries in the region has be identified as a major issue (EPA, 2013). Then, the relationship between IBI score, stream health condition, and hydroecological variables was explored to develop a new stream health predictor models. Finally, a genetic algorithm was used to identify a near-optimal solution of BMP implementation. The following can be concluded from the results of both studies:

- The most commonly used and modified macroinvertebrate and fish indices were the Benthic Index of Biotic Integrity (B-IBI), *Ephemeroptera*/ *Plechoptera*/ *Trichoptera* (Index) index, Hilsenhoff Biotic Index (HBI), and Index of Biological Integrity (IBI).
- The IBI was the most commonly used and modified fish index.
- Macroinvertebrate indices can be used to describe local degradation, while fish indices can be used to describe regional degradation.
- Stream health indices often need to be modified to take into account local stream conditions and biological communities.
- Watershed models built using the Soil and Water Assessment Tool were able to satisfactorily represented observed streamflow conditions.

- Bayesian variable selection and ANFIS techniques were able to develop stream health models using hydroecological variables and IBI scores. These models were applicable for all stream segments within the study area.
- Comparison of the pre-settlement land use (reference conditions) and current conditions indicated that la nude change in the study area has had significant negative impacts on stream health.
- The Genetic Algorithm identified no tillage, residue management, and forest as the most appropriate BMPs to be implemented in the study area.
- The coupled models and genetic algorithm were identified a near-optimum solution that maximized stream health condition while minimizing BMP implementation cost.

7. FUTURE RESEARCH RECOMMENDATIONS

This research provides valuable insight into using genetic algorithms with stream health predictor models to explore BMP implementation. However, additional research should be perform on applicability of the developed technique in different regions and to improve our understanding of the relationships between hydroecological variables and biological indices. The following are few suggestions for future research:

- Apply this technique to a larger watershed allows for better understanding of the link between BMP selection and placement, streamflow, and stream health.
- Examine the uncertainty of the collected data and model components. Quantifying uncertainty will aid water resource managers and stakeholders in the decision making process.
- Explore the impacts of climate change on stream health and BMP selection. To ensure freshwater resource sustainability, future impacts need to be taken into account.
- Evaluation of additional BMPs. For this study, five different BMPs were evaluated. However, there are many more BMPs that may have a greater impact on stream health.
- Explore the use of other stream health indices as the basis for more comprehensive stream health predictor models. Only the IBI was addressed in this study, where macroinvertebrate indices or a combination of macroinvertebrate and fish indices should be used to determine if a more accurate stream health model can be developed.
- Explore the addition of social aspects, such as stakeholder and decision maker preferences, to the decision making and genetic algorithm framework developed in this study.

APPENDIX

Table A1. Comparisons between B-IBI and other indices that either used or modified it for application elsewhere.

Index	**Metrics included**	
B-IBI	Total taxa richness Intolerant snail and mussel species richness Mayfly richness Caddisfly richness Stonefly richness Relative abundance of Corbicula % Oligochaetes % Omnivores % Filterers % Grazers % Predators Proportion of individuals in two most abundant taxa Total abundance.	
Index	**Metrics Added to B-IBI**	**Metrics Removed from B-IBI**
Macroinvertebrate Index of Biotic Integrity	Relitive Abundance Crustacea and Mollusca Chironomidae genera richness Relative Abundance five most dominant genera Macroinvertebrate density Relitive Abundance EPT Orthocladiinae/Chironomidae ratio Tanytarsini/Chironomidae ratio Hilsenhoff's biotic index	Total taxa richness Intolerant snail and mussel species richness Relative abundance of Corbicula % Oligochaetes % Omnivores % Filterers % Grazers % Predators Proportion of individuals in two most abundant taxa Total abundance.
Invertebrate Community Index	Number of Dipteran taxa % Mayfly composition % Caddisfly composition % Tribe Tanytarsini Midge composition % other Dipteran and non-insect composition % tolerant organisms Number of qualitative EPT taxa	Intolerant snail and mussel species richness Stonefly richness Relative abundance of Corbicula % Oligochaetes % Omnivores % Filterers % Grazers % Predators Proportion of individuals in two most abundant taxa Total abundance.
Chesapeake Bay IBI	Shannon-Weiner diversity Biomass	Total taxa richness Intolerant snail and mussel species richness

	% of abundance as pollution-indicative taxa % of biomass as pollution-indicative taxa % of abundance as pollution-sensitive taxa % of biomass as pollution-sensitive taxa % of abundance as carnivores and omnivores % of abundance as deep deposit feeders % of biomass deeper than 5 cm % of taxa deeper than 5 cm	Mayfly richness Caddisfly richness Stonefly richness Relative abundance of Corbicula % Oligochaetes % Filterers % Grazers % Predators Proportion of individuals in two most abundant taxa
Modified B-IBI	Proportion of Scrapers	% Grazers Intolerant snail and mussel species richness
Modified ICI	Number Dipteran taxa % Mayfly composition§ % Caddisfly composition‡ % predatory Chironomidae composition§ % other dipteran and non-insects§ % tolerant organisms§ Number EPT taxa	Intolerant snail and mussel species richness Stonefly richness Relative abundance of Corbicula % Oligochaetes % Omnivores % Filterers % Grazers % Predators Proportion of individuals in two most abundant taxa Total abundance.

Table A2. Comparisons between HBI and other indices that either used or modified it for application elsewhere.

Index	**Metrics included**	
Hilsenhoff's Biotic Index	Organism tolerance to organic pollutants	
Index	**Metrics Added to HBI**	**Metrics Subtracted from HBI**
Nutrient Biotic Index	Organism tolerance to nitrogen Organism tolerance to phosphorous	Organism tolerance to organic pollutants
Tolerance Indicator Values	Organism tolerance to dissolved oxygen Organism tolerance to nitrite plus nitrate (nitrate) Organism tolerance to total phosphorus Organism tolerance to water temperature	Organism tolerance to organic pollutants
Invertebrate Species Index	Organism tolerance to nutrient loading	Organism tolerance to organic pollutants
Family-level Biotic Index	No changes made	
Macroinvertebrate Index of Biotic Integrity	Relative Abundance Crustacea and Mollusca Chironomidae genera richness Relative Abundance (five most dominant genera) Macroinvertebrate density Orthocladiinae/Chironomidae ratio Tanytarsini/Chironomidae ratio EPT richness EPT % abundance	
Benthic Community Index	# Ephemeroptera # Diptera Richness Shannon–Wiener Diversity % Trichoptera % Crustacea and Mollusca # Filterers # Scrapers EPT richness EPT % abundance	

Table A3. Comparisons between EPT and other indices that either used or modified it for application elsewhere.

Index	Metrics included	
EPT	EPT richness EPT % abundance	
Index	**Metrics Added to EPT**	**Metrics Subtracted from EPT**
Benthic Community Index	# Ephemeroptera # Diptera Richness Shannon–Wiener Diversity % Trichoptera % Crustacea and Mollusca # Filterers # Scrapers Hilsenhoff's biotic index	
Non-wadeable Macroinvertebrate Assemblage Condition Index	Diptera taxa richness % Coleoptera taxa % Oligochaete and leech taxa % Collector-filterer individuals Predator taxa richness % Burrower taxa Tolerant taxa richness % Facultative individuals	EPT % abundance
Macroinvertebrate Index of Biotic Integrity	Relative Abundance Crustacea and Mollusca Chironomidae genera richness Relative Abundance (five most dominant genera) Macroinvertebrate density Orthocladiinae/Chironomidae ratio Tanytarsini/Chironomidae ratio Hilsenhoff's biotic index	
Macroinvertebrate Multimetric Index	#Family Sensitive taxa EPT/Chironomidae %Gathering-collector %Shredder	
EPTC	Coleoptera richness	EPT % abundance
Guapiacu-Macau Multimetric Index	% Plecoptera % Shredders Family richness Trichoptera richness (families)	EPT richness

	Shannon diversity (families) % Mollusca and Diptera Hydropsychidae/Trichoptera Chironomidae/Diptera	
Alabama Department of Environmental Management Index of Stream Health	Total # taxa # Chironomidae taxa NCBI Dominant taxon* (%) Chironomidae (%) Filterers* (%)	EPT % abundance
Florida Department of Environmental Protection Index of Stream Health	Total # taxa # Chironomidae taxa Florida Index Dominant taxon* (%) Chironomidae (%) Filterers* (%)	EPT % abundance
Mississippi Department of Environmental Quality Index of Stream Health	Total # taxa NCBI Dominant taxon* (%) # Scrapers/# gatherers # Shredders/total # collected # EPT/# Chironomidae Community loss Index	EPT % abundance
North Carolina Division of Water Quality Index of Stream Health	Total # taxa NCBI	EPT % abundance
South Carolina Department of Health and Environmental Control Index of Stream Health	NCBI	EPT % abundance
EIPT	Elmidae richness Elmidae % abundance	Ephemeroptera richness Ephemeroptera % abundance

Table A4. Comparisons between IBI and other indices that either used or modified it for application elsewhere.

Index	Metrics included
IBI	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies

Index	Metrics Added to IBI	Metrics Subtracted from IBI
B-IBI	Intolerant snail and mussel species richness Mayfly richness Caddisfly richness Stonefly richness Relative abundance of Corbicula % Oligochaetes % Filterers % Grazers Proportion of individuals in two most abundant taxa Total abundance.	Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Insectivorous Cyprinids Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Mebane IBI	Native coldwater species, number Coldwater individuals, percent Alien species, number Sensitive native individuals, percent Tolerant individuals, percent	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers

	Common carp Cyprinus carpio individuals, percent Sculpin age-classes, number Sculpin individuals, percent Salmonid age-classes, minus mountain whitefish Prosopium williamsoni, number	Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores
Northern Glaciated Plains Index of Biotic Integrity	Centrarchidae species richness plus Micropterus salmoides Tolerant species richness % Lithophilic spawners % Alien fish % Native coolwater species	Number of Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Yangtze River Index of Biotic Integrity	% Number of species in the family Cyprinidae % Number of species in Bagridae catfishes % Number of species in the family Cobitidae Percent of tolerance individuals Number of families in fishery catches Individual condition Percent of non-native fish species	Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Cyprinids
Multi-metric Index for Atlantic Rain Forest Streams	% Characiform individuals	Number of Species

	% Water column native individuals % Tolerant species % Detritivorous individuals	Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Cool–cold transition IBI	Number of madtom and sculpin species Number of coolwater species Percentage tolerant species Percentage generalist feeders	Number of Species Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Cool–warm transition IBI	Number of native minnow species Percentage tolerants Percentage omnivores	Number of Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish)

		Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Fish Based Index for Lakes	Number of planktivore species Total Biomass of strict lithophilic individuals % Total biomass of tolerant individuals	Number of Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Fish Based Index for Reservoirs	Number of strict lithophilic species % strict lithophilic species % Species Piscivores Number of Herbivores Total biomass of tolerant species Total biomass of Planktovores % Total biomass of lithophilic species	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Proportion of Insectivorous Cyprinids Proportion of Top Carnivores

		Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
European Fish Index	Density of omnivorous species Density of phytophilic species Relative abundance of lithophilic species Number of benthic species Number of rheophilic species Relative number of tolerant species Number of species migrating over long distances Number of potamodromous species	Number of Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Czech Multi-metric Index	Ecological-quality ratio of the typical species presence Ecological-quality ratio of the overall abundance Ecological-quality ratio of the relative abundance of rheophilic species Ecological-quality ratio of the relative abundance of eurytopic species	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies

Minnesota fish index of biotic integrity	The number of taxa designated as darter, sclupin, and madtoms taxa The number of insectivore taxa minus the number of tolerant taxa The number of headwater taxa minus the number of tolerant taxa The number of minnow taxa minus the number of tolerant taxa The number of piscivore taxa The number of wetland taxa minus the number of tolerant taxa The abundance of fish per 100m minus that of tolerant taxa The percentage of total abundance of the two most dominant taxa The percentage of total abundance of the piscivore taxa The percentage of total abundance of the lithophilic taxa The percentage of total abundance of the tolerant taxa	Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Cyprinids Proportion of Top Carnivores
Multi-metric Index for the Coastal Plain Ecoregion	% native lotic taxa	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Top Carnivores

		Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Northern Appalachians Ecoregion	% native large river taxa % native egg hider taxa % invertivore/piscivore individuals	Number of Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Southern Appalachians Ecoregion	% native large river taxa % native egg hider individuals Herbivore richness % threatened and endangered individuals	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies

Multi-metric Index for the Southern Plains Ecoregion	% native lotic individuals Native large river species richness	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Temperate Plains Ecoregion	% native large river taxa % native rheophilic individuals % lithophilic spawner taxa	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Upper Midwest Ecoregion	Threatened and endangered species richness % native large river taxa % lithophilic spawner individuals	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers

		Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Western Mountain Ecoregion	% native egg hider individuals % piscivore individuals % native large river individuals	Number of Species of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Multi-metric Index for the Xeric West Ecoregion	% lithophilic spawner taxa % native water column individuals Threatened and endangered species richness Herbivore richness	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish

		Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Coldwater Multi-metric Index	# Brook trout individuals per $100m^2$ % Fluvial dependent individuals # Warmwater species (stream-size-corrected) % Warmwater individuals % Brook trout individuals	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals Number of Individuals in Sample Proportion of Omnivores (Individuals) Proportion of Insectivorous Cyprinids Proportion of Top Carnivores Proportion with Disease, Tumors, Fin Damage, and Other Anomalies
Mixed-water Multi-metric Index	% White sucker individuals % Fluvial-specialist individuals, except blacknose dace % Non-tolerant general feeder individuals % Native warmwater individuals % Intolerant individuals # Fluvial specialist species	Number of Species Presence of Intolerant Species Species Richness and Composition of Darters Species Richness and Composition of Suckers Species Richness and Composition of Sunfish (except Green Sunfish) Proportion of Green Sunfish Proportion of Hybrid Individuals

Number of Individuals in Sample
Proportion of Omnivores (Individuals)
Proportion of Insectivorous
Proportion of Top Carnivores
Proportion with Disease, Tumors, Fin Damage, and Other Anomalies

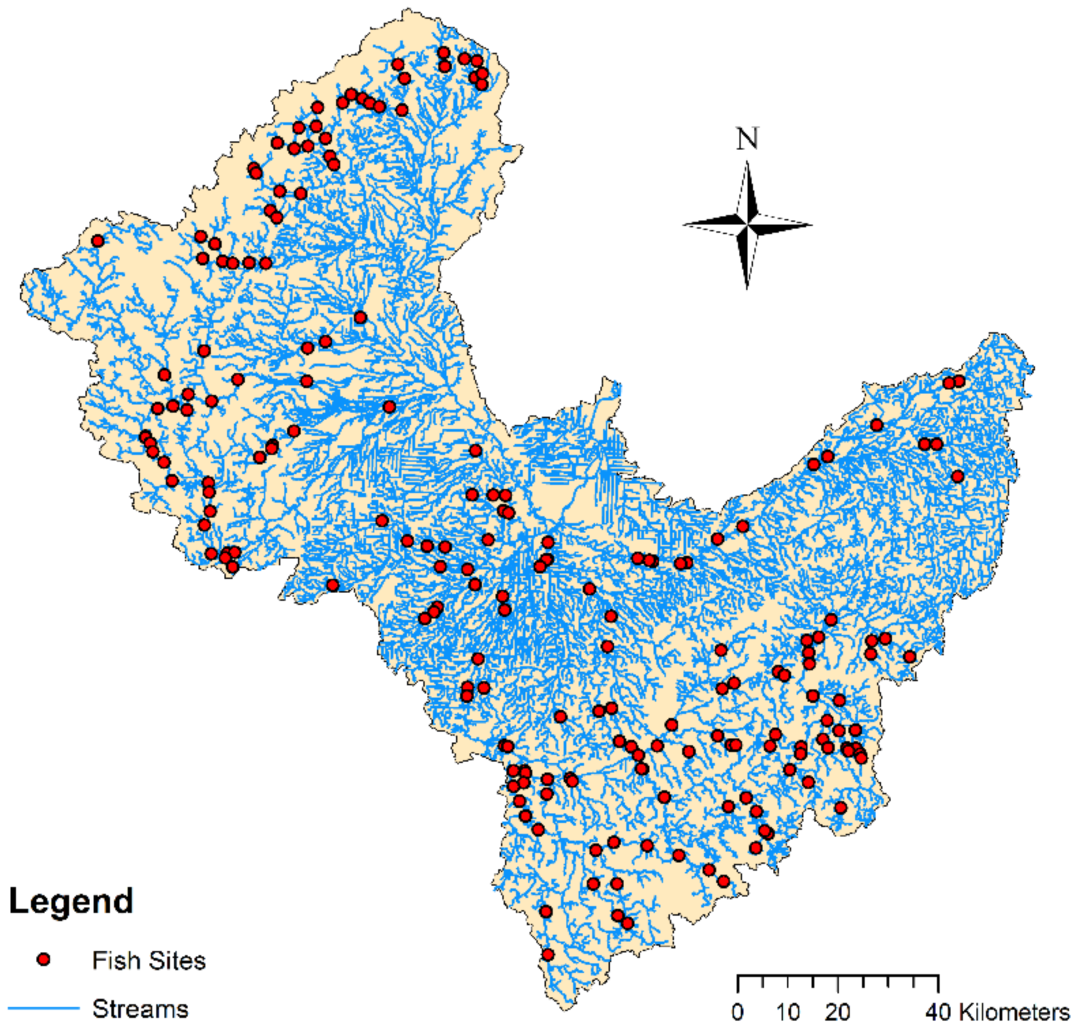

Figure S1. IBI monitoring stations in the Saginaw Bay Watershed.

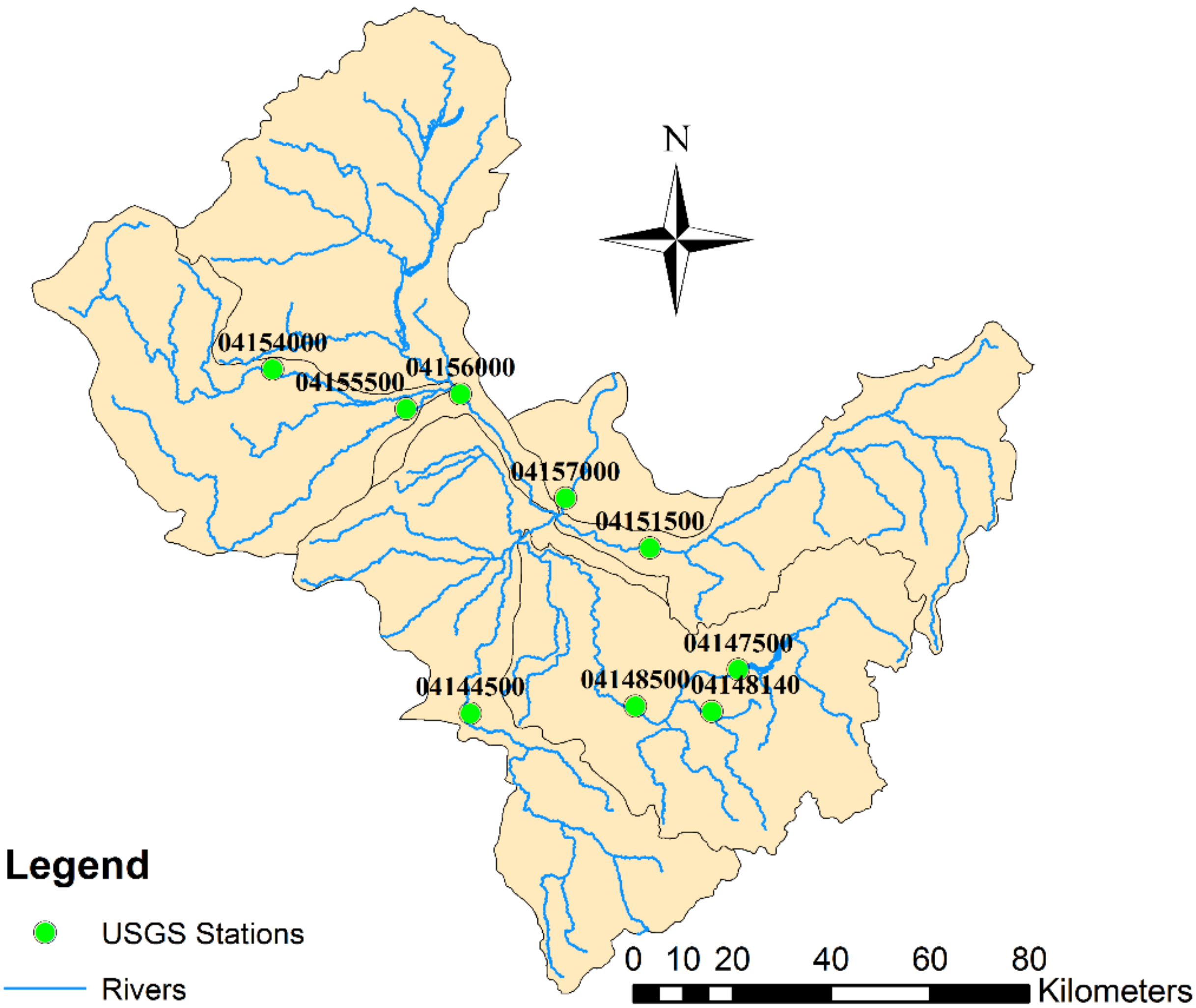

Figure S2. USGS streamflow gauging stations.

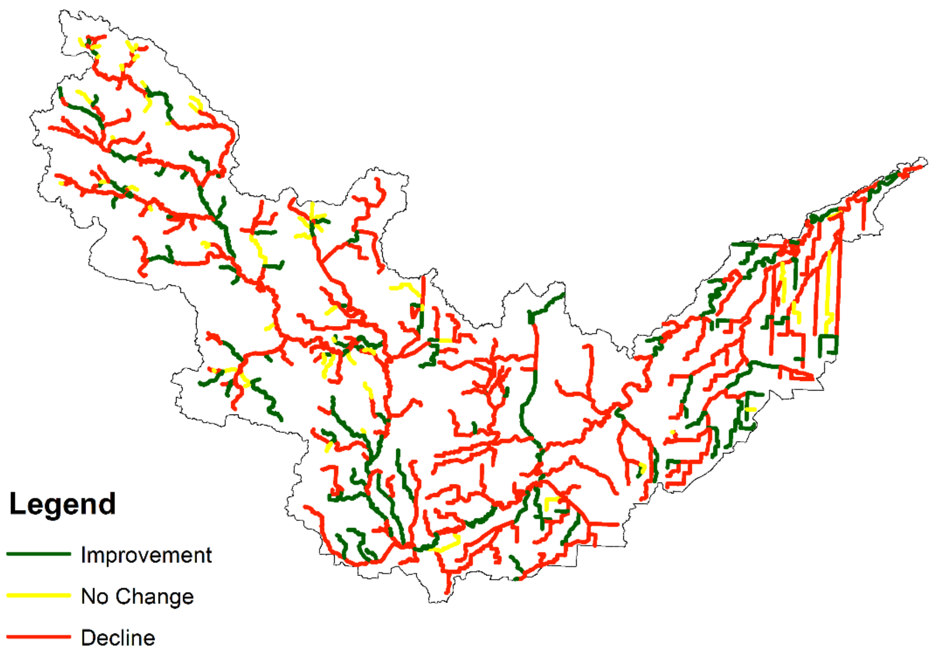

Figure S3. Improvements and declines in stream health scores between the pre-settlement and current conditions.

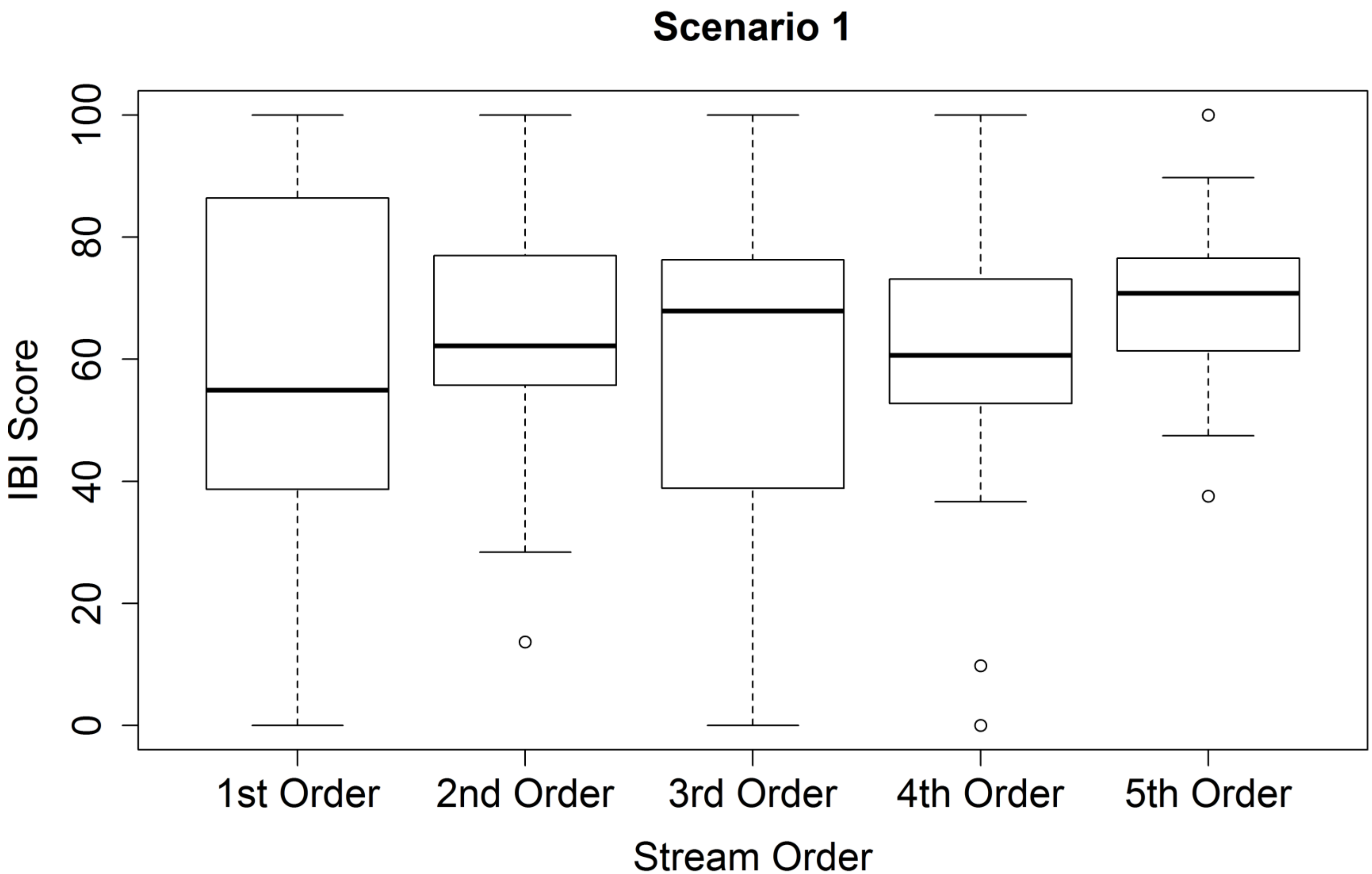

Figure S4. Distributions of individual stream health scores against stream order (scenarios 1).

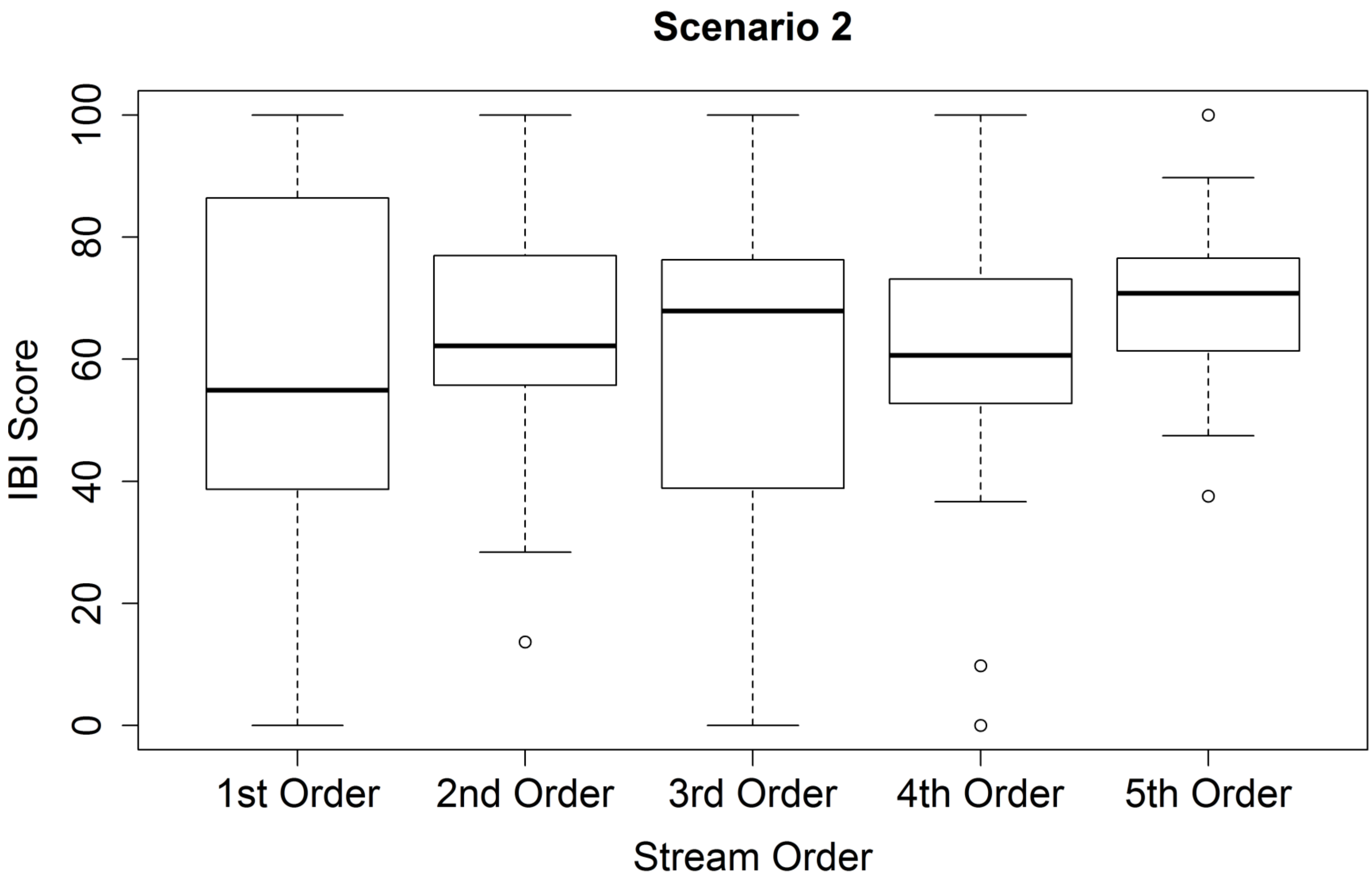

Figure S5. Distributions of individual stream health scores against stream order (scenarios 2).

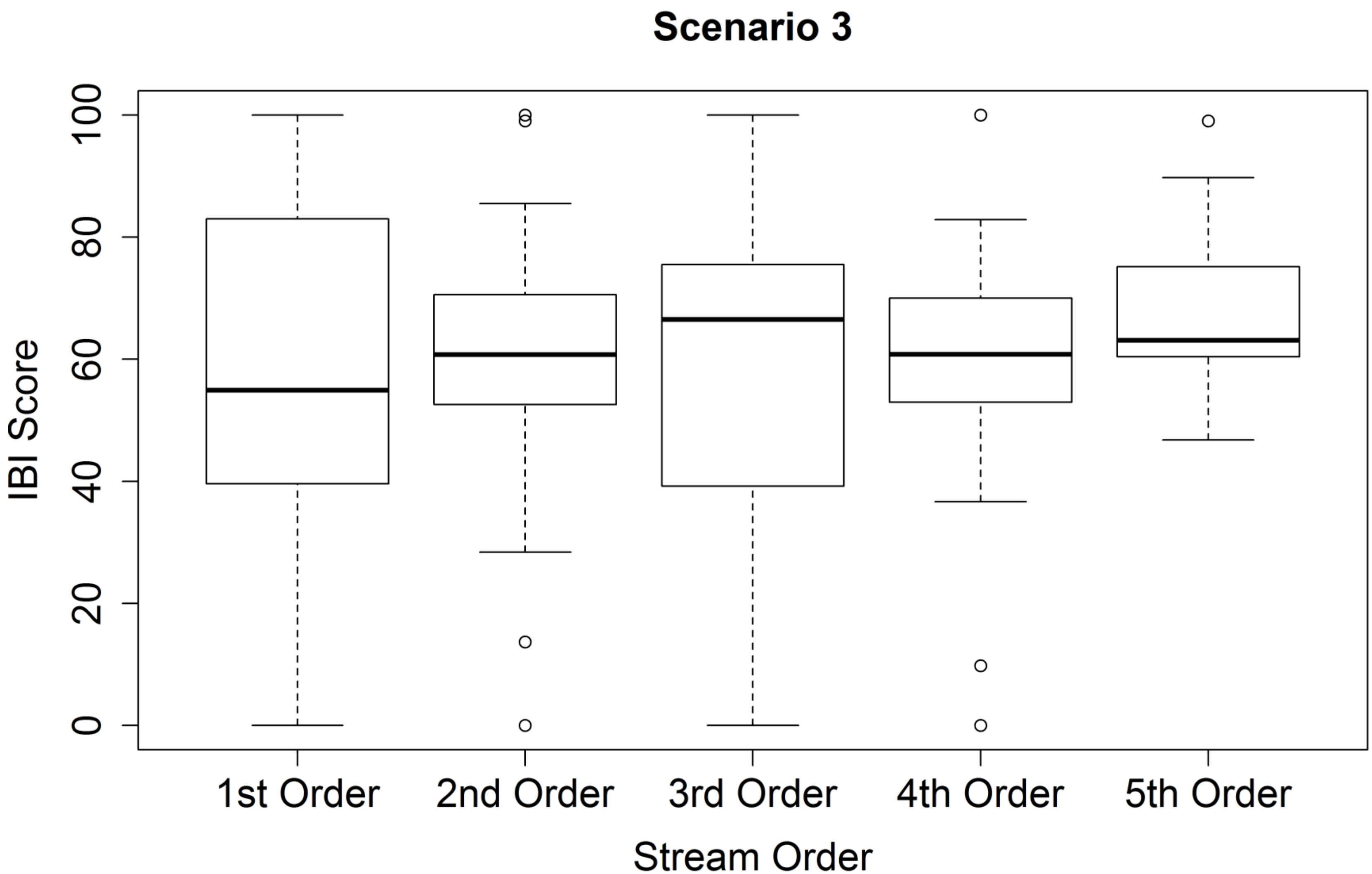

Figure S6. Distributions of individual stream health scores against stream order (scenarios 3).

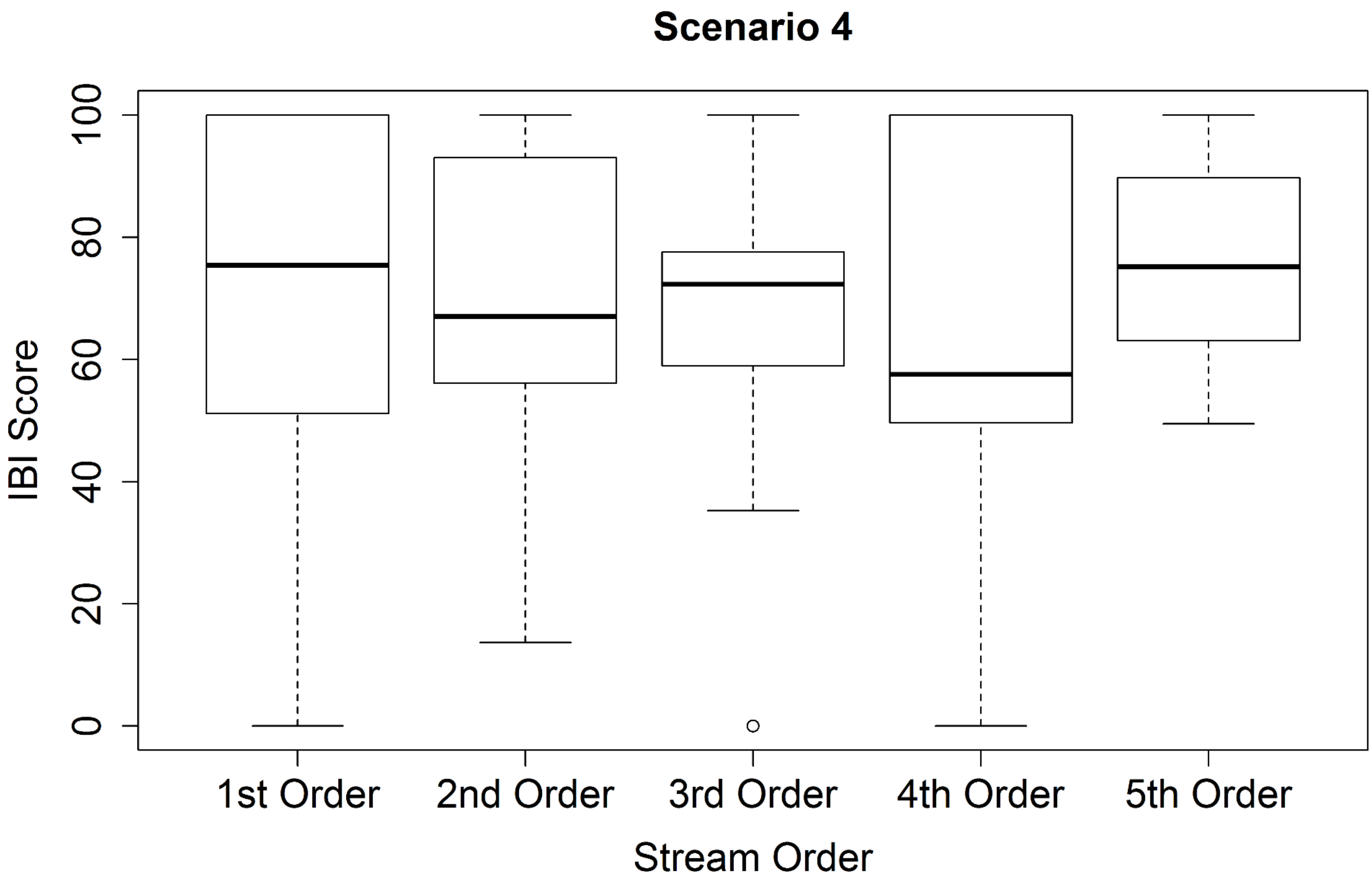

Figure S7. Distributions of individual stream health scores against stream order (scenarios 4).

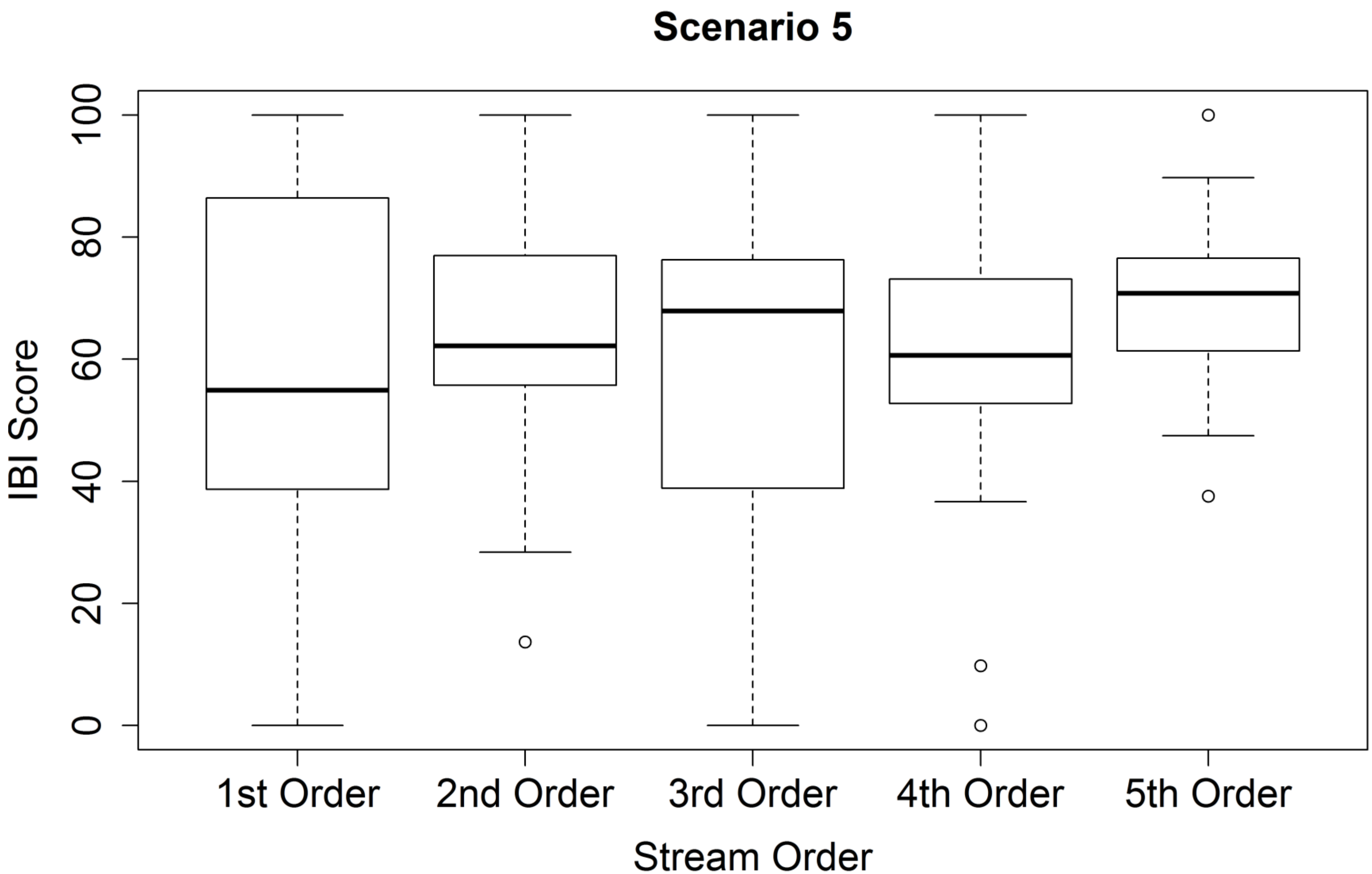

Figure S8. Distributions of individual stream health scores against stream order (scenarios 5).

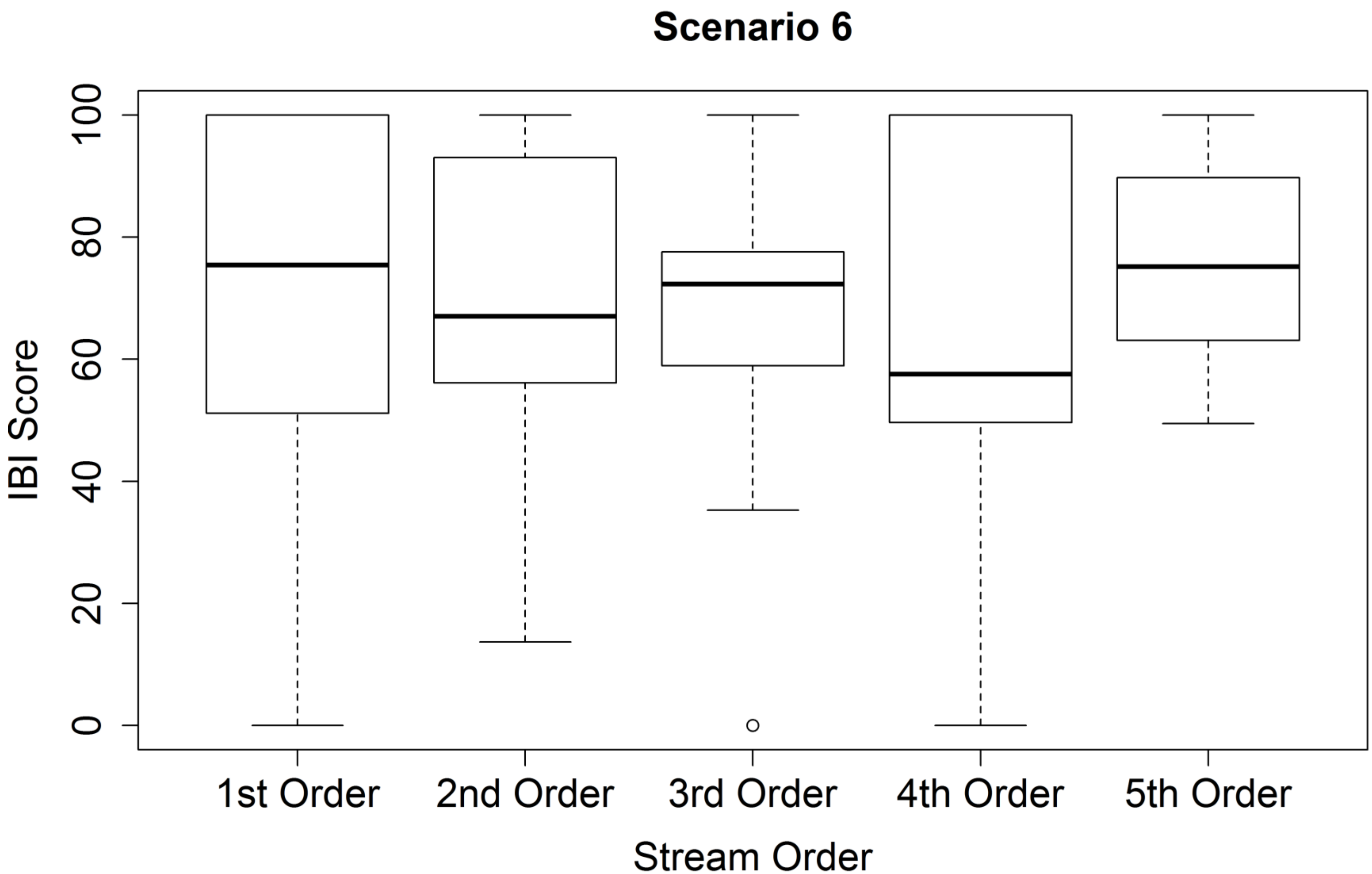

Figure S9. Distributions of individual stream health scores against stream order (scenarios 6).

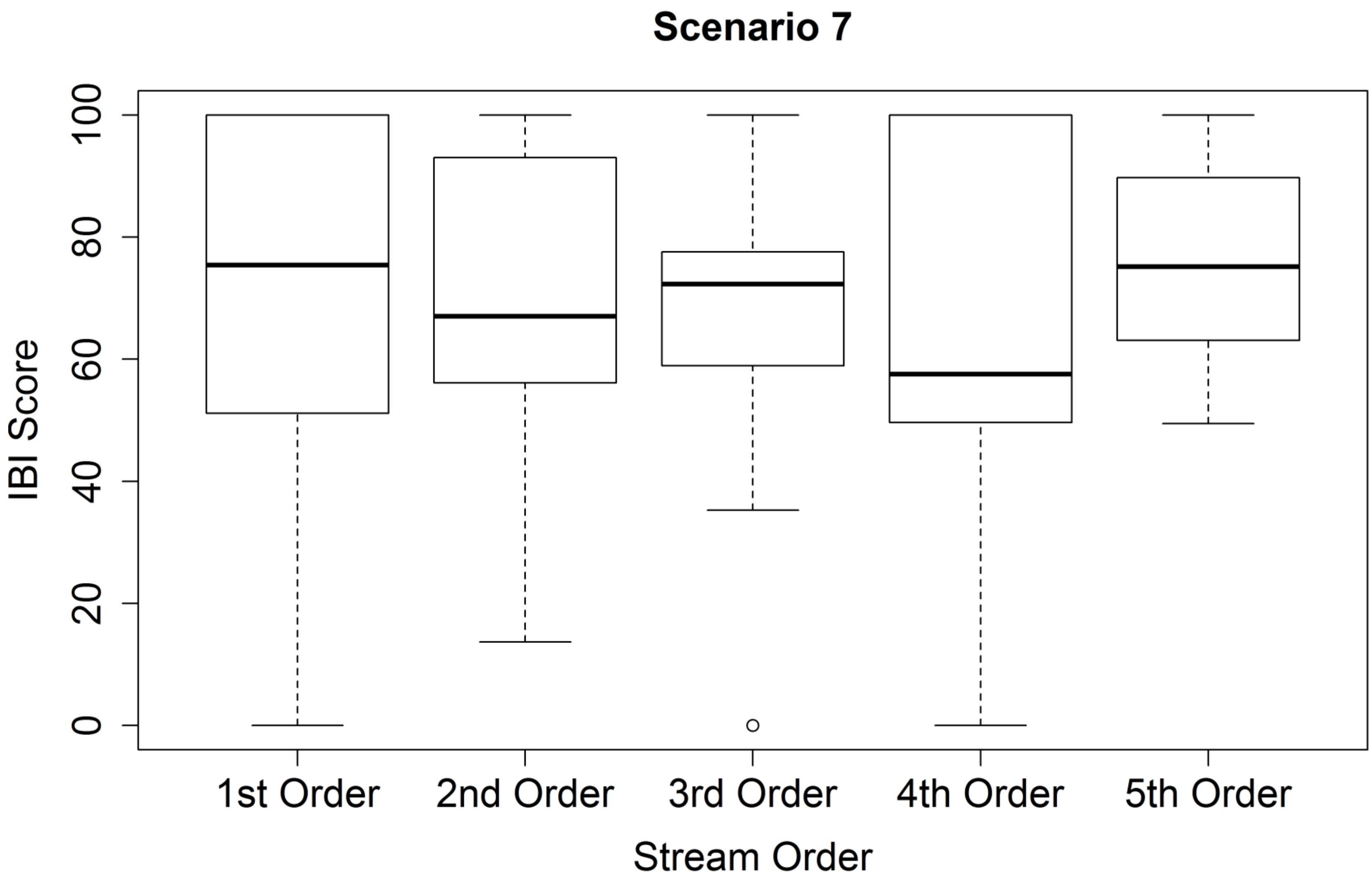

Figure S10. Distributions of individual stream health scores against stream order (scenarios 7).

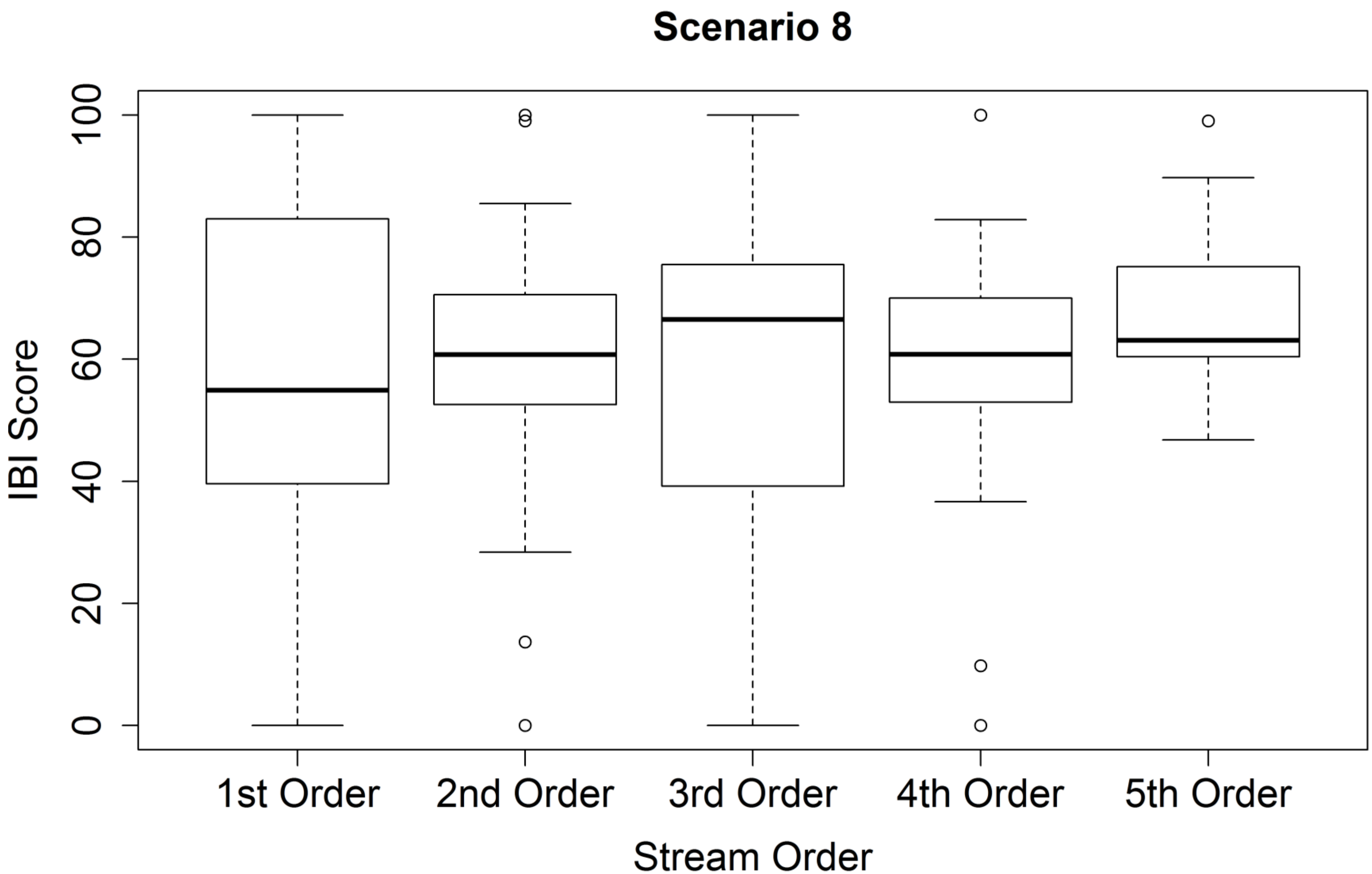

Figure S11. Distributions of individual stream health scores against stream order (scenarios 8).

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