DEVELOPMENT OF A COMPREHENSIVE FRAMEWORK TO ASSESS THE IMPACTS OF CLIMATE CHANGE ON STREAM HEALTH

By

Sean Alexander Woznicki

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ABSTRACT

DEVELOPMENT OF A COMPREHENSIVE FRAMEWORK TO ASSESS THE IMPACTS OF CLIMATE CHANGE ON STREAM HEALTH

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Freshwater streams are critical resources that provide benefits to humans and natural systems. As climate becomes more extreme, changes to the hydrologic cycle and surface air temperatures will affect the health of aquatic ecosystems, individual biota in the system, and their relationship to human uses of freshwater. Understanding of the vulnerability of stream ecosystems to climate change is critical to ensure their continued health and protection. Therefore, the goal of this study was to develop a modeling process to assess the impacts of climate change on fish and macroinvertebrate measures of stream health, as represented by four measures: the number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family Index of Biotic Integrity (FIBI), Hilsenhoff Biotic Index (HBI), and fish Index of Biotic Integrity (IBI). The research objectives were to: (1) identify sets of influential in-stream variables for stream health modeling, (2) develop widely applicable large-scale stream health models, but with reach-scale resolution appropriate for natural resources decision-making, and (3) identify vulnerable stream ecosystems at risk of declining stream heath due to climate change. The framework was developed for seven watersheds that encompass cold, cold transitional, cool, and warm stream thermal classes in Michigan. This process linked Soil and Water Assessment Tool (SWAT) hydrological models, selection of ecologically relevant in-stream variables, adaptive neuro-fuzzy inference systems (ANFIS) stream health models, and an ensemble of climate models and representative concentration pathways. A stream temperature model was also developed The Bayesian variable selection technique was identified as superior to Spearman's Rank Correlation and Principal Component Analysis as the best method for selecting influential in-stream variables. A few key flow regime variables, mostly related to timing and duration of major low and high flow events, played a significant role in dictating the health of streams in the studies area. Building ANFIS stream health models based on stream thermal class improved their performance. The best stream health models were suitable for performing large-scale impacts assessments at the individual reach level necessary for site-specific decision-making. Extending the stream health models into the future, the process was repeated with a climate model ensemble from the Coupled Model Intercomparison Project Phase 5 (CMIP5) to compare a control period of 1980-2000 to 2020-2040. The overall impacts of climate change on stream health across stream thermal regimes were low in terms of magnitude of stream health decline. However, at the reach level there were many streams with high probability of declining stream health coupled with large projected declines in stream health, revealing highly vulnerable aquatic communities. By combining the probability and magnitude of declining stream health, decision-makers can target stream ecosystems that are critically at-risk due to climate change.

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KEY TO ABBREVIATIONS

AGNPS: Agricultural Non-Point Source Pollution Model

AMLE: Adjusted Maximum Likelihood Estimation

ANFIS: adaptive neuro-fuzzy inference system

ANN: artificial neural network

ANSWERS: Areal Nonpoint Source Watershed Environmental Simulation

AREA: loge of the network catchment surface area

ARS: USDA Agricultural Research Service

AUSRIVAS: Australian River Assessment System

B-IBI: Benthic Index of Biotic Integrity

BRT: boosted regression tree

CART: classification and regression tree

CCA: canonical correspondence analysis

CCIAV: climate change impact, adaptation and vulnerability (assessments)

CDF: cumulative distribution function

CDL: Cropland Data Layer

CF: change factor

CMIP3: Coupled Model Intercomparison Project Phase 3

CMIP5: Coupled Model Intercomparison Project Phase 5

CO2: carbon dioxide (ppm)

DH11: annual maximum of 1-day moving average flows divided by the median for the entire record

DH14: flood duration, the 95th percentile of mean monthly flows divided by the mean of the monthly means

DH15: high flow pulse duration for flows above the 75th percentile flow for the flow record

DH18: duration of flow events greater than three times the median flow for the flow record

DH19: high flow duration above seven times the median flow for the entire flow record

DH20: high flow duration of flow events greater than the 75th percentile flow for the flow record

DH22: number of days between flood events with a recurrence interval greater than 1.67 years

DH24: flood free days, maximum number of days flow is below a flood recurrence of 1.67 years

DH6: variability of annual maximum daily flows

DL11: annual minimum flow divided by the median flow for the entire record

DL12: annual minimum of 7-day moving average flow divided by the median for the entire record

DL15: low exceedance flows, the 90% exceedance value divided by the median for the entire record

DL16: low flow pulse duration, the median of the average annual pulse durations for flow events below the 25th percentile value for the entire flow record

DL17: variability in low pulse duration

DL18: number of zero-flow days for the entire flow record

DL2: annual minimum of 3-day moving average flow

DL4: annual minimum of 30-day moving average flow

DL9: variability of annual minimum 30 day moving average flow

DO: dissolved oxygen (mg/L)

EPT: number of Ephemeroptera, Plecoptera, and Trichoptera taxa

FH10: flood frequency (average number of events) above median of the annual flow minima

FH2: variability in high pulse count for flow events greater than the 75th percentile value for the flow record

FH6: flood frequency (average number of events) above three times the median flow value for the entire record

FH7: flood frequency (average number of events) above seven times the median flow for the entire record

FIBI: Family Index of Biotic Integrity

FL1: low flood pulse count, number of flow events with flows below the 25th percentile of the entire flow record

FL2: variability in low pulse count

FL3: frequency of low pulse spells for flow events with flows below 5% of the mean flow value for the flow record

FOREST: percent forested land in the local catchment

GCM: global climate model

GHG: greenhouse gas

HBI: Hilsenhoff Biotic Index

HIT: Hydrologic Index Tool

HRU: hydrologic response unit

HSPF: Hydrologic Simulation Program-FORTRAN

HUC: hydrologic unit code

IBI: fish Index of Biotic Integrity

IFR: Michigan Institute of Fisheries Research

IPCC: Intergovernmental Panel on Climate Change

JULAIR: July mean air temperature

KINEROS: Kinematic Runoff and Erosion Model

LAD: Least Absolute Deviation

LMM-Smooth: linear mixed modeling using low-rank radial smoothing splines

LOADEST: USGS Load Estimator

MA1: mean of the daily flow values for the entire flow record

MA12: mean of January flows

MA16: mean of May flows

MA24: variability of January flows

MA25: variability of February flows

MA26: variability of March flows

MA27: variability of April flows

MA28: variability of May flows

MA3: mean of the coefficients of variation for each year

MA31: variability of August flows

MA32: variability of September flows

MA33: variability of October flows

MA34: variability of November flows

MA35: variability of December flows

MA37: variability across monthly flows

MA38: variability across monthly flows

MA39: variability across monthly flows

MA4: standard deviation of the percentiles of the logs of the entire flow record divided by the mean of percentiles of the logs.

MA40: skewness in monthly flows

MA43: variability across annual flows

MA44: variability across annual flows

MA45: skewness in annual flows

MACPACS: MACrophyte Prediction and Classification System

MAE: mean absolute error

MDEQ: Michigan Department of Environmental Quality

MF: membership function

MH10: mean of maximum October flows

MH12: mean of maximum December flows

MH13: variability across maximum monthly flow values

MH15: high flow discharge index (the 1% exceedance value divided by the median flow for the entire record)

MH18: variability across annual maximum flows

MH19: skewness in annual maximum flows

MH22: high flow volume, the average flow volume for flow events above three times the median flow for the entire record divided by the median flow for the entire record

MH24: high peak low for flow events greater than the median flow for the flow record

MH25: high peak flow for flow events above three times the median flow for the entire record

MH27: high peak flow for flow events greater than the 75th percentile flow for the flow record

MinPann: annual mineral phosphorus concentration

ML1: mean minimum flows for January

ML11: mean minimum flows

ML12: mean minimum December flows

ML13: variability across minimum monthly flows

ML14: mean of the ratios of minimum annual flows to the median flow for each year

ML2: mean minimum flows for February

ML20: base flow

ML4: mean minimum April flows

ML9: mean of minimum September flows

MLE: Maximum Likelihood Estimation

NASS: National Agricultural Statistics Service

NASS: USDA National Agricultural Statistics Service

NCDC: National Climatic Data Center

NED: National Elevation Dataset

NH4ann: annual average ammonium concentration

NH4djf: average ammonium concentration (December-January-February)

NH4mam: average ammonium concentration (March-April-May)

NH4son: average ammonium concentration (September-October-November)

NHDPlus: National Hydrography Dataset Plus

NO2mam: average nitrite concentration (March-April-May)

NO3djf: average nitrate concentration (December-January-February)

NO3jja: average nitrate concentration (June-July-August)

NO3mam: average nitrate concentration (March-April-May)

NO3son: average nitrate concentration (September-October-November)

NRCS: USDA Natural Resources Conservation Service (not in lit review)

NSE: Nash-Sutcliffe coefficient of efficiency

O/E: ratio of observed versus expected taxa

OrgNjja: average organic nitrogen concentration (June-July-August)

OrgPson: average organic phosphorus concentration (September-October-November)

PBIAS: percent bias

PCA: principal component analysis

PERM: mean network catchment soil permeability

PPCC: probability plot correlation coefficient

PRISM: Parameter-elevation Relationships on Independent Slopes Model

PRMS: Precipitation Runoff Modeling System

r: serial correlation of residuals

R^2: coefficient of determination

RA2: variability in rise rate

RA4: variability in fall rate

RA5: number of day rises, in which the flow is greater than the previous day

RA6: change of flow

RA7: median of change in log flow for days in which the change of flow is negative from the previous day

RA8: number of flow reversals

RA9: variability in flow reversals

RCM: regional climate model

RCP: representative concentration pathway

RIVPACS: River Invertebrate Prediction and Classification System

RMSE: root-mean-square error

RSR: root-mean-square error-observations standard deviation ratio

SCS: Soil Conservation Service

SEDjja: average sediment concentration (June-July-August)

SLOPE: mean network catchment slope

SRES: Special Report on Emissions Scenarios

SSURGO: Soil Survey Geographic Database

STATSGO2: Digital General Soil Map of the United States

SWAT: Soil and Water Assessment Tool

TA1: constancy (Colwell, 1974)

TA2: predictability (Colwell, 1974)

TH2: variability in Julian date of annual maxima

TH3: Seasonal predictability of non-flooding, flows below a 1.67 year recurrence interval

TL1: Julian date of annual minimum

TL2: variability in Julian date of annual minima

TL3: seasonal predictability of low flow

TL4: seasonal predictability of non-low flow

TMDL: Total Maximum Daily Load

TN: total nitrogen (mg/L or kg)

TP: total phosphorus (mg/L or kg)

USDA: United States Department of Agriculture

USEPA: United States Environmental Protection Agency

USGS: United States Geological Survey

WATER: percent water in the network catchment

ρ: Spearman's rank correlation coefficient

1 INTRODUCTION

Over 70% of the Earth surface is covered in water. While seemingly abundant, only 2.5% is freshwater, and of this only 1.2% is present as rivers and lakes (Shiklomanov, 1993). Freshwater provides innumerable services and benefits to humans and aquatic ecosystems worldwide. These important and scarce resources are under increasing pressure from emerging stressors, especially population growth and climate change. The Earth's population is expected to grow to 9.6 billion people by 2050 and 10.9 billion by 2100 (Gerland et al., 2014), placing increasing demand on supplies of freshwater (Vörösmarty et al., 2000). At the same time, anthropogenic greenhouse gas (GHG) emissions are changing the climate and hydrological cycle (IPCC, 2013). These stressors are already affecting both humans' and natural ecosystems' uses of freshwater, creating a need for smarter and more comprehensive water resources management.

Historically, water resources management has focused on human needs, whether it be for drinking, recreation, or agricultural and industrial uses, leading to extensive water pollution across the United States prior to the 1970s (Adler et al., 1993). To address growing public concern for controlling water pollution, several amendments were made to the Federal Water Pollution Control Act (1948) in 1972, in which the law became publicly known as the Clean Water Act (CWA).

The stated goal of the CWA is to "restore and maintain the chemical, physical, and biological integrity of the Nation's waterways". In the 40 years since the CWA was enacted, its focus has typically been on chemical criteria and water quality standards (Karr and Yoder, 2004). For example, the Total Maximum Daily Load (TMDL) program determines the maximum allowable amount of a pollutant that a waterbody can receive and still meet water quality standards. Under the law, there have been significant improvements in the condition of the nation's 3.5 million miles of rivers and streams (USEPA, 2011). However, 42% of streams are in poor biological condition (USEPA, 2011), and degradation of native aquatic species continues (Bryce et al., 2008).

Given the continuing problems affecting freshwater conditions in the United States, the EPA has begun a push to use biological assessment (or bioasessment) to support water quality management (USEPA, 2011), in addition to chemical criteria and water quality standards. Bioassessments are advantageous in water quality management because biological endpoints are considered to be the gold standard in water quality (Karr and Yoder, 2004). Biota are continual monitors of stream conditions, and their presence, absence, and community composition are indicators of biological integrity (USEPA, 2011). Fish and macroinvertebrates are commonly used as indicators because they represent local (macroinvertebrates) and broad (fish) habitat conditions, and short-term (macroinvertebrates) and long-term (fish) effects of changing stream conditions (Herman and Nejadhashemi, 2015).

Although the need for bioassessment has been recognized as critical to water resources management, these data are limited by sparse monitoring spatially and temporally (Einheuser et al., 2012) because extensive monitoring is costly, time-consuming and impractical for a regional study. Therefore, the use of ecological models is increasingly important to assess the health status of streams and rivers in unsampled locations. Models of stream health typically explore the relationship between landscape characteristics and stream biotic responses (Einheuser et al., 2012), such as relating percent agricultural landuse to a fish indicator of stream health. While these models are useful, they do not account for the conditions in which the biota live and do not have the potential to address new stressors to the system, such as the climate change. By constructing an assessment process that moves from landscape characteristics to in-stream conditions (e.g. flow regime and water quality) and biotic responses, more robust models can be built with the ability to account for emerging stressors such as climate change. As climate change becomes reality, it is imperative that the impacts it has on aquatic ecosystems are understood at large-scales to facilitate their continued protection.

This research is built upon the following gaps in knowledge:

(1) There are hundreds of landscape and in-stream variables that control aquatic ecosystem characteristics. Selecting variables that are important in ecological systems is difficult due to the complexity and nonlinearity of the systems and sheer number of available variables.

(2) Most aquatic ecosystem models are developed at large-scales to capture a wide range of conditions, but have limited local accuracy to be useful for stakeholders in development of natural resources management interventions.

(3) Climate change is an emerging stressor to aquatic ecosystems, and water resources management needs to account for these changes to protect both chemical and biological water quality.

Therefore, the goals of this research are to (1) identify a method of variable selection to identify important parameters in development of stream health models (2) develop large-scale stream health models that have individual reach scale management, thereby producing flexible models that are applicable for use in the decision-making process, and (3) extend these models to the future to by developing projections of future stream health based on potential climate change.

The outcome of this research is a framework that includes development of: variable selection methods that identify underlying relationships between in-stream conditions and stream health indicators, models that sufficiently characterize the complex and nonlinear relationships between these variables and the stream health indicators, and projections of how future climate change will impact stream health. This process was developed for Michigan and designed to be transferrable to other regions with different physiographic, biotic, and climate characteristics. Ultimately, the results developed in this study can be used by watershed and natural resources managers to guide the decision-making process in allocating limited resources for aquatic ecosystem protection and development of climate change adaptation measures.

2 LITERATURE REVIEW

2.1 OVERVIEW

This literature review describes climate change and its potential impacts on water resources and aquatic ecosystem health. The first section reviews projected climate change and methods of integrating climate data into climate impact, adaptation and vulnerability (CCIAV) assessments. This includes creation of an ensemble that includes selection of climate models, emissions scenarios, downscaling methods, and bias correction methods. Next, the potential impacts of climate change on water quantity and quality are discussed, followed by considerations when selecting hydrological models for simulating these changes. Stream health and integrity is discussed next, including details on the importance of flow regime, water quality and stream condition variables to stream health and different stream health indicators that are used to describe aquatic ecosystem conditions. Finally, various ecohydrological models for prediction of stream health indicators are discussed.

2.2 CLIMATE CHANGE

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) confirmed that "warming of the global climate system is unequivocal", as evidenced by increasing concentrations of greenhouse gases (GHGs), warming of the ocean and atmosphere, diminishing snow and ice, and rising sea levels (IPCC, 2013). Multiple lines of independent evidence indicate that the primary cause of these changes are emissions resulting from anthropogenic energy use as well as urbanization and land use change (Karl and Trenberth, 2003; Melillo et al., 2014). As GHGs accumulate in the atmosphere, they trap outgoing radiation from Earth, causing the planet to warm (Karl and Trenberth, 2003).

Radiative forcing quantifies the change in energy fluxes caused by natural and anthropogenic substances and processes (e.g. GHG emissions, albedo due to land use change, and changes in solar irradiance) that alter the global energy budget and drive climate change (IPCC, 2013). As radiative forcing increases, surface warming occurs, while when it is negative, surface cooling occurs (IPCC, 2013). Although there is uncertainty in estimates of radiative forcing, the estimates of radiative forcing since 1750 are positive (indicating surface warming), from 1.13 to 3.33 W/m^2 (IPCC, 2013). The biggest contributors to positive radiative forcing are well-mixed greenhouse gases (CO_2, methane, halocarbons, and nitrous oxide), while negative forcing stems from aerosols and albedo changes associated with changes in land use (IPCC, 2013). However, the negative forcing components generally have much greater uncertainties than the drivers of positive radiative forcing; the uncertainty associated with aerosols indicates that the forcing may also be positive (IPCC, 2013)

Understanding of the climate system is complicated by feedbacks that amplify or damp changes in climate (Karl and Trenberth, 2003). Increasing air temperatures result in a greater amount of water vapor in the atmosphere due to the subsequent increase in saturation vapor pressure (IPCC, 2013). This results in a net positive feedback; because water vapor is a GHG, this further increases radiative forcing (Karl and Trenberth 2003; IPCC, 2013). In addition, melting of snow and ice creates a positive feedback as the landscape's reflectivity decreases to absorb more solar radiation, which increases melting, a phenomena known as the ice-albedo feedback (Karl and Trenberth 2003; IPCC, 2013). While water vapor and ice-albedo feedbacks are fairly well defined, cloud feedbacks are still uncertain and not well quantified (IPCC, 2013).

The observed changes in the climate system have been demonstrated to be not entirely due to natural variability and consistent with the estimated responses of either physical or biological systems to a given regional climate change (Rosenzweig et al., 2008). This is evidenced by warming of 0.85 °C since 1880, while GHGs have likely contributed to surface warming in the range of 0.5-1.3 °C (offset by cooling effects of aerosols and natural internal variability) (IPCC, 2013). This correlates with anthropogenic radiative forcing of 2.29 W/m^2 since 1750, which has increased rapidly since 1970 (IPCC, 2013). As emissions of GHGs continue, global surface temperatures in 2100 are projected to be between 0.3-4.8 °C greater than today depending on radiative future forcing (IPCC, 2013). This warming will not be globally uniform, as the air will warm more rapidly over land than the ocean (IPCC, 2013). Changes in the water cycle will also vary regionally, although it is expected that wet and dry regions will generally become wetter and drier, respectively (IPCC, 2013).

2.3 Climate Modeling

To develop projections of future climate change, climate models are used. Climate models are mathematical computer models of the physical, chemical, and biological systems of the atmosphere, land surface, oceans, and cryosphere and their interactions with the sun and each other (Karl and Trenberth, 2003). These models vary in their complexity from simple, to intermediate, to comprehensive models of the climate system, to Earth System Models that include multiple biogeochemical cycles (IPCC, 2013). In the following sections, the process for using climate models to perform CCIAV assessments is described in detail. This includes selection of emissions scenarios and/or representative concentration pathways, climate model downscaling methods, and model bias correction. Each of these components requires careful consideration when developing an ensemble, or group of scenarios), for use in a CCIAV assessment.

The use of ensembles is encouraged to account for the range of uncertainty present in projections of future climate change. This uncertainty stems from several sources, including uncertainty in future GHG emissions (scenario uncertainty) and an incomplete understanding of climate processes (Winkler et al., 2011b). Our incomplete understanding of climate processes manifests itself in parametric (values of model parameters) and structural (model structure) uncertainty (IPCC, 2013). Ensembles allow for robust projections of future climate change impacts (Wiley et al., 2010). Model spread (the range of behavior represented by climate models) is often used as a measure of climate uncertainty, but this does not account for model quality or independence (IPCC, 2013).

Water resources CCIAV assessments typically use a small number of climate scenarios, although an increasing number have used larger ensembles of RCMs or GCMs (Jimenez Cisneros et al., 2014). Some of these studies develop probability distributions of future impacts through the combination of results from multiple climate projections within an ensemble (Jimenez Cisneros et al., 2014). The uncertainty in the range of climate scenarios is typically larger than hydrological parameter uncertainty (Steele-Dunne et al., 2008; Arnell et al., 2011), although structural uncertainty in hydrological models can still be significant (Schewe et al., 2013). Therefore, incorporating structural and parameter uncertainty of hydrological models in CCIAV assessments of water resources would further the range of projected future impacts (Jimenez Cisneros et al., 2014).

2.3.1 CCIAV Assessments

The cornerstone of CCIAV assessments is to guide decision-making in light of uncertainty (IPCC, 2007b). Primary orientations of CCIAV assessments are top-down and bottom-up, and forward-looking and backward-looking (Jones and Preston, 2011). Top-down approaches use scenarios and models to measure potential impacts, which includes downscaled climate projections, impact assessments, and strategy/option development (IPCC, 2014).

Conversely, bottom-up assessments begin locally, identify vulnerabilities and/or thresholds for sectors and communities, and develop adaptation options through stakeholder participation (IPCC, 2014). A forward-looking (or predictive) assessment is based on event risk using likelihood of occurrence, and is often, though not exclusively, associated with top-down approaches (Jones and Preston, 2011). Meanwhile, backward-looking (or diagnostic) assessments are related to bottom-up methodologies and are outcome or goal-oriented, where consequences are defined using risk of exceeding some standard (Jones and Preston, 2011).

Historically, most assessments have been top-down, but growing dissatisfaction with the scenario-driven approach has led to more local approaches using bottom-up methodologies (van Aalst et al., 2008). This dissatisfaction stems from climate scenarios simplifying the full array of variables (e.g. variability, extremes, seasonality, and rainfall distributions are simplified to means) and the lack of consideration for adaptive capacity (van Aalst et al., 2008). Bottom-up assessments address these issues by continual involvement of local stakeholders and examination of vulnerability to current climate and adaptation strategies that have been observed (van Aalst et al., 2008). Based on the existing knowledge of risk, new risks (i.e. from climate change) can be analyzed (van Aalst, 2008). However, both methodologies have advantages and it is unwise to adopt only one (Urwin and Jordan, 2008). Two way approaches that include components of both top-down assessments of climate change and bottom-up assessments can manage the trade-offs between methods (Jones and Preston, 2011). Ultimately, the CCIAV assessments delivering the most effective adaptation measures include top-down and bottom-up approaches that focus on local solutions to risks derived from global biophysical climate changes (IPCC, 2014).

2.3.2 Emissions Scenarios

Climate models require time-series data on emissions or concentrations of radiatively active constituents that extend to some future point (Moss et al., 2010). Known as emissions scenarios, these data describe potential future atmospheric discharges of substances GHGs and aerosols that affect Earth's radiation balance in the form of emissions scenarios (Moss et al., 2010). Emissions scenarios provide snapshots of potential alternative futures, but because of the complexity of the atmosphere, potential sources and causes of emissions (society, technology, etc.), accurate prediction of future GHG emissions is impossible (Nakicenovic and Swart, 2000). Therefore, they are not forecasts or predictions (Moss et al., 2000). Due to the substantial uncertainty surrounding future GHG emissions and atmospheric concentrations, emissions scenarios provide highly variable projections of the future. As a result, magnitudes of projected climate changes after the mid-21st century by GCMs are significantly impacted by the choice of emissions scenario (IPCC, 2013).

Special Report on Emissions Scenarios: The IPCC Special Report on Emissions Scenarios (Nakicenovic and Swart, 2000), also known as SRES scenarios, are a set of GHG emissions scenarios used to make future climate change projections. The SRES scenarios were used in models from phase three of the Coupled Model Intercomparison Project (CMIP3), and subsequently, in the IPCC's Third (TAR) and Fourth (AR4) assessment reports. SRES scenarios are based on alternative demographic, economic, and technological driving forces and their resulting GHG emissions through the end of the 21st century (IPCC, 2007a). Scenarios are grouped into families, or storylines (A1, A2, B1, and B2), that differ in their societal and GHG projections, as described in Table 1. The approximate CO_2-equivalent concentrations (ppm) of each scenario corresponding to computed radiative forcing are about 600 (B1), 700 (A1T), 800 (B2), 850 (A1B), 1250 (A2), 1550 (A1FI) (IPCC, 2007a).

Table 1. SRES Scenarios (Nakicenovic and Swart, 2000) adapted from IPCC (2007a)

Storyline	Details
A1	• Rapid economic growth and technological development • Global population peaks in the mid-21st century • Convergent world, increased cultural and social interaction • Varying technological emphasis: fossil-intensive (A1FI), non-fossil energy sources (A1T), and balanced energy (A1B)
A2	• Continuously increasing population • Regional economic development • Heterogeneous world with preservation of local identity • Fragmented and slower per capita economic growth and technological development
B1	• Global population peaks in the mid-21st century (same as A1) • Convergent world • Global solutions to economic, social, and environmental sustainability • Service and information based economy, clean energy use
B2	• Continuously increasing population, but at a slower rate than A2 • Local solutions to economic, social, and environmental sustainability • Intermediate economic development, less rapid and more diverse technological change than A1 and B1 • Local and regional environmental protection and social equity

Representative Concentration Pathways: For the IPCC Fifth Assessment Report (AR5) and CMIP5, Representative Concentration Pathways (RCPs) developed by Moss et al. (2010) replaced the SRES scenarios. The development process of RCPs differed from that of the SRES scenarios in that it began with identifying radiative forcing characteristics (rather than detailed socioeconomic scenarios) that supported climate modeling (Moss et al., 2010). In addition, the RCPs are defined by radiative forcing pathways (rather than socioeconomic scenarios and their GHG emissions) and the specific radiative forcing reached by 2100 (Moss et al., 2010). The four scenarios are RCP2.6, 4.5, 6.0, and 8.5, of which the numbers signify the target radiative forcing trajectory in W/m^2. Associated CO_2-equivalent GHG concentrations in ppm by 2100 are greater than 1370 (RCP8.5), about 850 (RCP6.0), about 650 (RCP4.5), and a peak of 490 that declines before 2100 (RCP2.6). Socioeconomic scenarios were developed in parallel of RCPs, some that are consistent to the radiative forcing characteristics of RCPs and those that explore different issues and futures (Moss et al., 2010).

2.3.3 Downscaling

GCMs are the most common tools used in CCIAV assessments. CCIAV assessments are typically performed at a local or regional scale, while GCMs generally operate on spatial scales between 100-250 km (Teutschbein and Seibert, 2010). These large-scale models cannot resolve many regional and local scale processes often required for CCIAV assessments (Diaz-Nieto and Wilby, 2005). Hence, downscaling is essential to achieve greater spatial and temporal resolutions than those available from GCM output. Downscaling GCM data attempts to bridge the gap between coarse resolution models and regional and local scale processes (Fowler et al., 2007). The ultimate objective of downscaling is to create local scale climate statistics that are consistent with the large-scale atmospheric state (von Storch et al., 1993).

There is still disagreement regarding which downscaling method is most effective. These methods fall into two or three categories. Traditionally, the two categories are ‘dynamical’ and ‘empirical’ (also known as ‘empirical-statistical’ or ‘statistical’), while the three category classification includes dynamical, empirical-dynamical, and disaggregation (Winkler et al., 2011a). Each downscaling method is discussed in detail in the following sections.

2.3.3.1 Dynamical Downscaling

Dynamical downscaling uses regional climate models (RCMs) over a limited-area domain with boundary conditions based on GCM simulations or reanalysis fields (Teutschbein and Seibert, 2010). Grid resolutions of RCMs are typically 25-50 km (Teutschbein and Seibert, 2010), which is much finer than the 100-250 km resolution of GCMs (Teutschbein and Seibert, 2012). The objective in using an RCM is to simulate small-scale climate processes absent from lower resolution GCMs (Di Luca et al., 2012). RCMs are particularly useful when a CCIAV requires a large suite of physically consistent variables (Winkler et al., 2011a). Unfortunately, the high-resolution of RCMs results in somewhat cumbersome computational times and resource requirements (Winkler et al., 2011a). Therefore, runs are limited to smaller timeslices; there are few high-resolution runs at long time scales (Stocker et al., 2013).

RCMs are often tested to determine whether they improve upon GCMs, or 'add value'. Added value is defined as whether or not the downscaled climate variables are closer to observations than the model (usually a GCM) from which the boundary conditions were obtained (Stocker et al., 2013). Many studies have demonstrated the added value of RCMs through improvement of meso-scale precipitation processes and representation of orographic forcing and rain-shadow effects (Fowler et al., 2007). However, RCMs do have model errors and uncertainties, in that they typically inherit GCM error (in addition to their own shortcomings) while simulating too many wet days with low-intensity precipitation (Teutschbein and Seibert et al., 2012). These issues are related to shortcomings in process parameterization, e.g. representation of clouds (Stocker et al., 2013). This necessitates the need for correction of biases following downscaling. Given the advantages of RCMs and advent of coordinated efforts to make dynamically downscaled data available to researchers (e.g. ENSEMBLES, PRUDENCE, NARCCAP, etc.), numerous water resources CCIAV assessments have used dynamically downscaled data.

2.3.3.2 Empirical-Dynamical Downscaling

Empirical-dynamical downscaling refers to any downscaling method that uses circulation and/or free atmosphere variables to estimate local or regional surface climate variables, usually precipitation or temperature (Winkler et al., 2011a). Ultimately, these observed relationships define statistical models that translate large-scale atmospheric anomalies into anomalies of local climate variables (Zorita and von Storch, 1999). There are multiple empirical-dynamical downscaling methods, including analogues (also known as weather typing) and empirical transfer functions. These methods assume that the relationships between large-scale predictors and local predictands are valid under future climate forcing (Diaz-Nieto and Wilby, 2005), which is not guaranteed (Zorita and von Storch, 1999).

Analogs. The analog method is simple to use and implement (Matulla et al., 2008; Winkler et al., 2011a), while it has been successfully used in weather forecasting and short-term climate prediction (Zorita and von Storch, 1999). It requires a library of coarse-resolution and corresponding high-resolution climate anomaly patterns (Maurer and Hidalgo, 2008). Relationships are built between historical observations between large-scale and fine-scale anomalies and then applied to large-scale GCM or reanalysis anomalies (Maurer et al., 2010). The skill of the analog method is a function of the similarity measure used (between large-scale and fine-scale anomalies) and the selection process of similar atmospheric states (Matulla et al., 2008). Because the analog method uses observed weather patterns, the spatial covariance of local weather information is preserved (Matulla et al., 2008). In addition, the method does not assume the form of downscaled variables' probability distributions, allowing for simple construction of variables that are non-normal, such as precipitation (Matulla et al., 2008). However, the analog method is unable to extrapolate beyond the range of observed values (Hanssen-Bauer et al., 2005). Analogs are often inadequate in extreme event simulation and require stationary relationships between large-scale and local predictors (Wilby et al., 2002). This method has been used in a limited number of water resources CCIAV assessments, such as in Barnett et al. (2008), Cayan et al. (2010), Maurer et al. (2010), and Gädeke et al. (2014).

Empirical transfer functions. This approach develops functions that create empirical relationships between local-scale predictands and regional-scale predictors (Wilby et al., 2002). The relationships are developed from observations of predictors and predictands and then applied to GCM output (Winkler et al., 2011a). There are several considerations when using this method, including choice of predictand and predictors, calibration and validation, and definition of the transfer function using statistical methods. Choice of predictor is crucial in capturing the signal of climate change in the GCM (Hewitson and Crane, 2006), while poor choice of predictor can lead to poor results (Hanssen-Bauer et al., 2005). Many unique transfer functions have been established to develop relationships between predictors and predictands, including linear regression, non-linear regression, artificial neural networks (ANNs), canonical correspondence analysis (CCA), principal component analysis (PCA), support vector machines, and hidden Markov models (Wilby et al., 2002; Winkler et al., 2011a). Choice of predictor and statistical method used to define the transfer function are of equal importance in empirical transfer function downscaling (Fowler et al., 2007). Advantages of these methods are ease of application and ability to use observable relationships, while disadvantages included limited ability to explain climate variability, difficulty downscaling extreme events, and assumption that relationships between predictor and predictand are valid in the future (Wilby et al., 2002). Given the extent of choices in predictor selection and transfer function construction, software tools such as the Statistical DownScaling Model (SDSM, Wilby et al. 2002) have been developed and are often used in water resources CCIAV assessments. A number of studies have used empirical transfer functions, mostly through the SDSM (e.g. Chung et al., 2011; Gosling et al., 2011; Jun et al., 2011; Liu et al., 2011; Teutschbein et al., 2011; Chen et al., 2012; Gädeke et al., 2014).

2.3.3.3 Disaggregation Downscaling

Disaggregation downscaling can be spatial or temporal in nature. Spatially, this method interpolates climate variables from low a low-resolution grid to a higher resolution grid or point location (Winkler et al., 2011a). Temporally, a finer time resolution is inferred from temporal averages of a specific climate variable (Winkler et al., 2011a). This is achieved through using monthly or seasonal averages or accumulations and interpolating them to daily resolution.

Spatial disaggregation. Spatial disaggregation uses large-scale simulated values from coarse resolution models (GCMs) as the predictors for downscaling to a fine-grid or point scale (Widmann et al., 2003; Salathé, 2005). This is accomplished through statistical methods such as linear regression (Winkler et al., 2011a), more complex methods that use other spatial characteristics such as topography and wind fields (Bindlish and Barros, 2000), or multiplicative random cascade models (Sharma et al., 2007). The bias-correction and spatial disaggregation (BCSD) method developed by Wood et al. (2002, 2004) is commonly used for disaggregation downscaling In the spatial disaggregation step of BCSD, additive and ratio anomaly fields for precipitation and temperature, respectively, are used. The BCSD method has been compared favorably to various statistical and dynamical downscaling techniques in hydrologic CCIAV assessments (Maurer and Hidalgo, 2008). Consequently it is often used these assessments (e.g. Barnett et al., 2008; Cherkauer and Sinha, 2010; Maurer et al., 2010; Nafaji et al., 2011; Jung et al., 2012; Ficklin et al, 2013; Qiao et al., 2014).

Temporal disaggregation. Temporal disaggregation creates daily or sub-daily data from monthly or seasonal aggregated GCM data (Winkler et al., 2011a). Stochastic weather generators such as WGEN (Wilks, 1999) and LARS-WG (Semenov and Barrow, 1997) are used to develop synthetic daily time-series precipitation and temperature data. Markov processes are used to estimate wet days, and from wet day occurrence, it estimates precipitation, temperature, and other variables (Winkler et al., 2011a). Advantages of weather generators include the ability to reproduce observed climate statistics and ability to develop a large ensemble of scenarios (Wilby et al., 2002). However, weather generators suffer from over-dispersion by underestimating interannual variability, especially with temperature (Qian et al., 2004). In addition, they are usually designed for use at a single site (station), and therefore producing spatially consistent datasets across multiple sites is difficult (Winkler et al., 2011a). Weather generators have been used with some success in water resources CCIAV assessments (e.g. Dibike and Coulibaly, 2005; Minville et al., 2008; Bae et al., 2011; Wilson and Weng, 2011; Chen et al., 2012).

2.3.4 Model Bias and Bias Correction

Due to errors and biases in GCM simulations, bias correction methods are usually employed prior to use in a CCIAV assessment. Model biases stemming from systematic errors are usually the result of misrepresentation of physical processes (Wang et al., 2014), which occurs because theoretical understanding of climate is still incomplete, and simplifications are made when building climate models (Reichler and Kim, 2008). Biases in GCMs and/or RCMs are identified through statistical comparison between historical observations and a model control run for the same period. The eventual bias correction method found from the relationship between observations and the model control assumes that the bias is unchanging (stationary) between control and future periods (Berg et al., 2012; Teutschbein and Seibert, 2012).

Reichler and Kim (2008) identified several issues with validation of climate model performance and bias correction, including (1) difficulty in identifying model errors because of complex and poorly understood climate process; (2) uncertainties in historical climate observations coupled with a lack of consistent and reliable observations; and (3) good model performance of present climate does not guarantee reliable future climate predictions.

Nonetheless, comparison between observations and model prediction of the current climate is the only way to assess model performance (Reichler and Kim, 2008). Two of the more common bias correction methods are presented in the following sections: change factors and distribution mapping.

2.3.4.1 Change Factors

Using change factor (CFs) methodology for bias correction is common in CCIAVs, especially in water resources studies, accomplished through developing monthly CFs between control and future climate periods for precipitation and temperature and applying the factors to observed station or gridded data. Precipitation CFs are developed using a ratio because it is zero-bounded, while temperature CFs are additive. The simplicity of this method allows for rapid application to several GCMs, producing a range of climate scenarios (Fowler et al., 2007).

There are several assumptions when using the CF method. It assumes that GCMs are better at simulating relative changes than absolute values; the bias is constant in time (Fowler et al., 2007). The scaled and "baseline" scenarios differ in their means, maxima, and minima, while range and variability of the data remain the same (Diaz-Nieto and Wilby, 2005). Therefore, the bias in distributions and frequencies of GCM simulated variables is ignored (Winkler et al., 2011b; Gädeke et al., 2014). Finally, the number of wet days remains constant, while changes in wet and dry spells may be important in climate change impact assessment studies (Fowler et al., 2007). The CF method is relatively common in water resources CCIAV assessments to bias correct both GCM (e.g. Abbaspour et al., 2009; Elsner et al., 2010; Prudhomme et al., 2010; Bae et al., 2011; Bastola et al., 2011; Chen et al., 2012) and RCM (e.g. Akhtar et al., 2009; Stoll et al., 2011; Fiseha et al., 2014; Gädeke et al., 2014) data.

2.3.4.2 Distribution Mapping

Distribution mapping (also known as probability mapping, quantile-quantile mapping, and histogram equalization) creates transfer functions to shift precipitation and temperature distributions, thereby correcting simulated climate values to agree with their observed counterparts (Teutschbein and Seibert, 2012). This has a notable advantage over the CF methodology in that it does not ignore bias in the distributions of GCM variables (Teutschbein et al., 2011), while it is still computationally efficient (Maurer and Hidalgo, 2008).

The distribution mapping process constructs control period cumulative distribution functions (CDFs) of monthly GCM precipitation and temperature and maps them to their corresponding observed variables (Maurer and Hidalgo, 2008). Then, the same mapping for the control period is applied to future GCM projections. Therefore, the statistical moments of the GCM and observations agree for the control period, while allowing variability of the GCM to evolve throughout the simulation (Maurer and Hidalgo, 2008). Distribution mapping is found in the BCSD method (Wood et al., 2004), where it is combined with spatial disaggregation downscaling. In the BCSD framework, quantile mapping has been commonly used in surveyed water resources CCIAV assessments (e.g. Barnett et al., 2008; Cherkauer and Sinha, 2010; Maurer et al., 2010; Nafaji et al., 2011; Jung et al., 2012; Ficklin et al, 2013; Qiao et al., 2014). Meanwhile, distribution mapping as a standalone bias correction method for GCMs and RCMs was found in numerous studies (e.g. Steele-Dunne et al., 2008; Franczyk and Chang, 2009; Hagemann et al., 2011; Teutschbein and Seibert et al., 2012; Koutroulis et al., 2013).

2.4 Impacts of Climate Change on Freshwater Resources

Due to the effects of climate change and anthropogenic influences, the global water cycle is expected to change throughout the 21st century (IPCC, 2014). As the planet warms, the atmosphere's water holding capacity will increase, resulting in changes to hydrologic drivers such as precipitation, precipitation extremes, evapotranspiration, and drought intensification (Prudhomme et al., 2014). Meanwhile, non-climatic drivers such as population growth, urbanization, land use change, and economic development also threaten water resources sustainability by increasing demand and/or decreasing supply (Jimenez Cisneros et al., 2014). Ultimately, the negative impacts of climate change on freshwater resources are expected to outweigh the benefits across the globe (Bates et al., 2008). Understanding how these changes affect a watershed's water balance is critical to successful river management and development of climate change adaptation strategies (Gädeke et al., 2014). Given the need to understand the impacts of climate change on water quantity and quality from a management perspective, several studies have explored these impacts at the watershed scale, as discussed in the following sections.

2.4.1 Impacts of Climate Change on Water Quantity

The primary climatic drivers affecting freshwater resources are precipitation and potential evaporation, while other drivers are air temperature, atmospheric CO_2, and black carbon and dust (Jimenez Cisneros et al., 2014). As temperature increases, the warmer air holds more water, affecting magnitudes of precipitation (Jimenez Cisneros et al., 2014). Increased precipitation intensity and frequency will likely increase flood and drought risks in many areas (Bates et al., 2008; Jimenez Cisneros et al., 2014). Potential evaporation is projected to increase because of the increased water holding capacity of the atmosphere and subsequent increases in vapor pressure deficit (Bates et al., 2008). Meanwhile, atmospheric CO_2 enrichment decreases plant stomatal conductance, reducing transpiration losses (Eckhardt and Ulbrich, 2003; Chaplot, 2007). At the same time, these higher CO_2 concentrations increase plant growth and the need for transpiration, resulting in competing effects of CO_2 on plant transpiration (Bates et al., 2008).

Although there is considerable uncertainty in quantitative projections of future precipitation at the watershed scale, it is very likely that hydrological characteristics will change (Bates et al., 2008). Future projections of climatic global water cycle drivers from CMIP5 model simulations are summarized by Jimenez Cisneros et al. (2014) as follows:

- Less precipitation falls as snow, with less snow cover and duration of cover.
- Wet regions and season become wetter and dry regions and seasons become drier.
- Global mean precipitation increases with temperature, but there are variations regionally. In addition, precipitation changes are statistically significant only after a 1.4°C temperature increase, while some precipitation projections are still in the range of 20th century variability.
- Changes in evaporation are consistent with those of precipitation, while soil moisture decreases are prevalent. Potential evapotranspiration is very likely to increase with warmer temperatures according to climate models, which will accelerate the hydrological cycle.

Future changes to watershed scale hydrological cycles are largely a function of a particular watershed's sensitivity to climatic characteristics and the regionally projected magnitudes and distributions of precipitation, temperature, and evaporation (Jimenez Cisneros et al., 2014). Precipitation is the key driver of projected changes in annual runoff and streamflow patterns (Adam et al., 2009). Therefore, decreasing summer precipitation coupled with increases in temperature and evapotranspiration leads to decreased summer low flows (Dibike and Coulibaliy, 2005; Cherkauer and Sinha, 2010; Ficklin et al., 2013). The summer precipitation and evapotranspiration trends also amplify soil moisture deficits, reducing runoff (Cayan et al., 2010).

Despite regional differences in projected changes to watershed scale hydrology, some trends are apparent across water resources CCIAV assessments, especially with regard to snow/rain ratios, snowmelt timing, spring runoff and peak flows. In most studies, warming results in less winter snow accumulation and spring snowmelt, and ultimately less warm-season runoff (Adam et al., 2009; Cayan et al., 2010; Chang and Jung, 2010; Driessen et al., 2010) and spring/summer soil moisture (Boé et al., 2009; Cayan et al., 2010; Elsner et al., 2010). In most cases, snowmelt begins earlier (Akhtar et al., 2008; Ficklin et al., 2013). The decrease in the ratio of snow to liquid precipitation in winter and spring result in greater winter streamflows but decreases in spring streamflows and timing of peak spring flows (Boyer et al., 2010; Elsner et al., 2010; Ficklin et al., 2013).

2.4.2 Impacts of Climate Change on Water Quality

The manner in which water quality is impacted by climate change will likely vary based on changes to a watershed's hydrological cycle. Agricultural and urban areas are likely to experience the greatest water quality degradation in this respect, as greater magnitude precipitation events lead to increases nonpoint source pollution in runoff (Abbaspour et al., 2009). Higher water temperatures and increases in extreme events such as floods and droughts are projected to increase loads and concentrations of sediments, nutrients, pesticides, and others (Bates et al., 2008). For example, more severe runoff events will result in more sediment erosion that eventually enters freshwater bodies; regions projected to increase in drought incidence will have smaller stream discharges, more concentrated pollutants, and longer residence times (Abbaspour et al., 2009). As winter flows increase, the risk of events that produce sediment transport occurring will increase (Boyer et al., 2010). Overall, sediment and nutrient loadings in surface waters are correlated to surface runoff, and their changes will depend on how climate affects watershed hydrology (Marshall and Randhir, 2008).

2.5 Hydrological/Water Quality Models

To determine the impacts of climate change on freshwater resources, hydrological/water quality (watershed) simulation models are used. Watershed models help with understanding and predicting watershed hydrology. There are several hydrologically significant and complex properties of watersheds that require consideration in the development and use of these models, including topography and structure of the drainage network, geomorphological and soil characteristics, climatic characteristics, vegetative cover and land use, and population density. Each property is complex in both space and time. The goal of the watershed model is to convert these spatially complex processes and patterns into simple, easy to understand output, such as a hydrograph (Wainwright and Mulligan, 2005). However, reliably simulating them is a continuous challenge for scientists and engineers (Borah and Bera, 2003).

There are numerous watershed models available, where each model approaches watershed hydrology uniquely, with associated assumptions and limitations. These considerations relate to time-step, handling of various physical processes, and integration of spatial and temporal data. The major approaches, assumptions, and limitations in development and use of watershed models are discussed in the following sections. Approaches are defined by how the model defines simulation type, algorithms that simulate landscape processes, and parameterizes variables, as well as their corresponding assumptions and limitations. Given these issues, the modeler should develop a strategy for model use.

2.5.1 Simulation Type

Watershed models generally fall into two categories related to their simulation:

continuous or event-based. Continuous simulation models (e.g. SWAT) analyze long-term watershed hydrology, such as the effects of management practices and climate change on streamflow. These models typically operate on a daily time-step. Conversely, single-event models (e.g. ANSWERS, KINEROS) focus on short-term simulation. The typical use for single-event models are analyzing design storms or severe storm events, and in designing structural stormwater control practices. Single-event models generally operate on a sub-daily time-step (e.g. minute or hour). Some models have continuous and single-event capabilities (e.g. MIKE SHE, PRMS). There are limitations to both simulation types: continuous models poorly simulate the necessary details in single storm events, while event-based models cannot simulate long-term impacts of land use and climate change on hydrology.

2.5.2 Mathematical Basis

Mathematical basis refers to how a model, whether continuous or single-event, simulates hydrology and related natural processes. From this perspective, models are classified as physically-based models that are established on physical understanding of watershed processes, empirical models that are based on patterns in observed data, and conceptual models that 'ignore' physics and represent a watershed as stores, sinks, and fluxes (Wainwright and Mulligan, 2005). Physically-based models may use dynamic wave equations, kinematic wave equations, and diffusive wave equations in one, two, or three dimensions for surface runoff and open channel flow. These partial differential equations require analytical or numerical methods for solving. Empirical models may use simpler methods like the SCS curve number approach, which uses empirical relations to compute peak runoff rates. Manning's equation is another example empirical models that often used with the continuity equation for simple storage routing and modeling of open channel flow. A conceptual model builds on empirical models by using several coupled with the user's understanding of a whole system process (Mulligan and Wainwright, 2005).

Many watershed models include both physically based and empirical equations because of the sheer number of processes required in simulate. With the advent of increased computing power, improved spatial datasets, more data availability, and geographic information systems, conceptual models are used less and less.

Algorithm selection and mathematical equations used in each model carry assumptions, simplifications, and limitations. Physically based models are the most sophisticated, but require voluminous data at the appropriate spatial scale (Wainwright and Mulligan, 2005). In addition, numerical uncertainty is a common problem in physically based models. Algorithm selection is also important for empirical equations. For example, SWAT provides the option to use the Penman-Monteith, Priestly-Taylor, and Hargreaves methods to estimate potential evapotranspiration (Neitsch et al., 2005).

Empirical and conceptual models tend to be better predictors, because incomplete understanding of physical processes generally leads to poor performance for the completely physically based models (Wainwright and Mulligan, 2005). In addition, these models (physically based or otherwise) all carry structural uncertainty due to our incomplete knowledge of the true physics of the watershed system.

2.5.3 Watershed Representation

Watershed models can be lumped or distributed. A lumped model (e.g. AGNPS) represents variables at the watershed scale, varying in time only. Distributed models (e.g. MIKE SHE) contain variables that change in time and space, where they are 'lumped' at a much smaller scale, usually the size of a raster grid (e.g. 30 m resolution). These models typically used physically based equations. The number of parameters in a distributed model is usually two to three orders of magnitude greater than in a lumped model (Refsgaard, 1997). Situated in between these are semi-distributed models such as SWAT. Here, a watershed is delineated into subwatersheds and further delineated into hydrologic response units (HRUs). HRUs vary in size and consist of homogeneous land use, soils, and topography. It is at this level that parameterization occurs. It is distributed in the sense that the subwatersheds have a spatial component, but they are lumped at the non-spatial HRU level and do not model their interactions (Mulligan and Wainwright, 2005).

Each watershed parameterization introduces unique assumptions, strengths, and limitations. Fully distributed models allow for modeling interactions between neighboring grid cells and give extremely detailed results. However, they are computationally intensive, usually require the use of numerical solvers, and carry instabilities inherent to these solvers (Borah and Bera, 2003). This is especially true when approaching a large number of grid cells, meaning their use is limited to relatively small watersheds or areas. Lumped models by nature are very limited in application area because they lack spatial variability (Mulligan and Wainwright, 2005). A lumped model will only output single values (spatially) in time for an entire watershed. However, their advantage is in simulation time and ease of use. Semi-distributed models allow for increased spatial parameterization while significantly reducing simulation time when compared to distributed models (El-Nasr et al., 2005). Despite these compromises, semi-distributed models still require many spatial and temporal datasets and considerable user experience to operate.

Both distributed and semi-distributed models approach over-parameterization (El-Nasr et al., 2005). In these models, several parameter sets give adequate results, which is the concept of equifinality (Beven and Binley, 1992). This makes it difficult to determine which parameter set is physically 'correct' (Beven and Binley, 1992). This requires an analysis of parameter uncertainty, because most exact parameter values in the watershed are unknown.

2.5.4 Utilization

There are several issues to consider when selecting a watershed model. Selecting the appropriate model structure is critical for robust simulation of hydrologic processes (Bai et al., 2009). The user needs to understand their problem to determine whether to use continuous vs. single-event models, physically based vs. empirical models, and distributed vs. lumped models. Each has its own data requirements, computational resource needs, experience requirements, assumptions, and limitations (Mulligan and Wainwright, 2005). There is no perfect model to address each individual problem, but considering these issues will allow the user to select the model most suited for their needs.

2.6 STREAM HEALTH/INTEGRITY

Rivers and streams provide many benefits to society, both economic and recreational. They supply water for irrigation, drinking, and power generation. They supply fish for commercial fishing operations. They provide recreational opportunities for sport fishers, swimmers, and boaters. However, humans have drastically altered rivers over the past century to meet their needs, and the concept of a 'healthy' stream has been narrowly focused on its designated or beneficial uses (Karr, 1999). For example, a stream is healthy to a sport fisher if there are enough trout, and that same stream is healthy to a drinking water utility if there is enough clean water to withdraw for human consumption. In some cases, stream health as assessed by some criteria is damaged because these beneficial uses conflict (Boulton, 1999).

Through these anthropogenic or designated uses, the conditions of rivers and streams have declined (Karr and Yoder, 2004). Transformation of the landscape through urbanization and agricultural intensification has led to the transport of excessive sediment, nutrients, pesticides, and heavy metals to streams (USEPA, 2011). Water withdrawal for irrigation and drinking has altered flow characteristics of streams (Kanno and Vokoun, 2010). Habitat structure and energy sources have been affected through riparian zone removal (Richardson et al., 2007; Skroblin and Legge, 2012).

Given these issues, the term 'stream health' can be ambiguous, with no clear consensus (Bunn et al., 1999; Norris and Hawkins, 2000). Health implies prosperity, vitality, and good condition (Karr, 1996; Norris and Hawkins, 2000). Meyer (1997) contended that a healthy stream is one that maintains its ecological structure and function while still meeting political and societal needs and expectations, because today streams exist within the realm of broader social institutions and human attitudes. Conversely, Karr and Dudley (1981) proposed the use of the term 'integrity', which they defined as a stream with "the capability of supporting and maintaining a balanced, integrated, adaptive community of organisms having a species composition, diversity, and functional organization comparable to that of the natural habitat of the region." This definition focuses on stream biota, as the ability to sustain a balanced biotic community is a good indicator of the potential for beneficial stream uses (Karr, 1981). Therefore, integrity is defined as a pristine condition or endpoint, unaffected by anthropogenic use, where the integrity of a stream should be judged based on similar reference sites with little human impact (Karr 1999). The distinction between stream health and integrity is that the health term considers anthropogenic use and values in ecosystem evaluation, while stream integrity is purely scientific without considering societal needs (Boulton 1999; Gessner and Chauvet, 2002).

Now that the relationship between stream health and integrity is clear, it is important to examine in detail how streams have diverged from their pristine state. Various factors have caused, and continue to cause, declines in stream integrity. These factors can be defined as four variables that, when altered through anthropogenic means, affect the long-term structural and functional integrity of stream biota: (1) flow regime, (2) energy source, (3) water quality, and (4) habitat structure (Karr and Dudley, 1981). These issues are discussed at length in the following sections.

2.6.1 Flow Regime Impacts on Stream Ecosystem Health

Flow regime is extremely important to stream ecosystems because it determinant of the structure and function of stream and riparian ecosystems (Poff et al., 1997; Poff et al., 2010). Streamflow drives physical habitat in streams, which is a major component in determining a stream's biotic composition (Bunn and Arthington, 2002). A natural, unaltered flow regime is critical to sustaining the ecological integrity of streams. There are five components (magnitude, frequency, duration, timing, and rate of change) of the natural flow regime that characterize stream hydrology and regulate ecological integrity directly and indirectly (Poff et al., 1997).

- *Magnitude*: amount of water moving past a fixed location per unit time.
- *Frequency*: how often a flow above a given magnitude occurs over a specified time interval.
- *Duration*: period defined by a particular flow condition (e.g. number of days of streamflow above a specified magnitude).
- *Timing* (also known as *predictability*): regularity at which flows of a certain magnitude occur. A predictable stream has high or low flows that occur at regular or consistent intervals over a long time.
- *Rate of change* (also known as flashiness): how quickly flow changes between

magnitudes. A flashy stream has quick rates of change in magnitude, while a stable stream experiences changes in magnitude more slowly.

Classification of flow regime plays an important role in understanding flow variability, exploring of streamflow impacts on biological communities and ecological processes, supporting hydrologic modeling, and prioritizing conservation efforts (Olden et al., 2012). Using the five components of the natural flow regime as a guide, Olden and Poff (2003) identified 171 hydrologic indices to characterize flow regime:

While the natural flow regime is extremely important to maintain ecosystem integrity, it has been altered by humans (Carlisle et al., 2010a). These anthropogenic alterations can greatly affect ecosystem structure and function (Carlisle et al., 2010b). Flow regime controls physical, chemical, and biological processes of the stream, leading to direct and indirect community responses to alteration (Carlisle et al., 2010b).

Streamflow is often modified or regulated to provide dependable services to society, such as water supply, hydropower generation, flood control, recreation, and navigation (Kennard et al., 2010). Regulation of streamflow with dams is one of the most significant drivers of alterations to the natural flow regime (Maheshwari et al., 1995; Gao et al., 2009). For example, there are more than 2.5 million water control structures in the United States, and less than 2% of rivers are in their natural condition (Lytle and Poff, 2004). In addition, land use changes such as urbanization and agricultural expansion have altered the natural flow regime by changing surface runoff, infiltration, and evapotranspiration. However, altering the natural landscape while regulating rivers and streams for human benefits often ignores the ecological uses of freshwater by native organisms.

Streamflow is a major determinant of stream physical habitat, which in turn affects aquatic plants, macroinvertebrates, and fish (Bunn and Arthington, 2002). In addition, flow regime can directly influence the life histories of these aquatic organisms (Bunn and Arthington, 2002). Alteration of natural flows can result in biodiversity loss and enable colonization by nonnative and invasive species, resulting in a loss of native species and an overall decline in biodiversity (Chang et al., 2011). Rather than just a defined minimum low flow, a naturally varying flow regime is now recognized to support healthy stream ecosystems (Bunn and Arthington, 2002). Due to these issues, the natural flow regime paradigm is now fundamental to the management of stream ecosystems (Lytle and Poff, 2004).

Aquatic vegetation composition is often determined by timing, frequency, magnitude, and predictability of flooding disturbance, shaping community structure (Pettit et al., 2001; Bunn and Arthington, 2002). Extended floods can affect emergent macrophyte growth and reproduction (Pettit et al., 2001). Regulated and/or modified streamflow has increased macrophyte abundance in streams worldwide (Bunn and Arthington, 2002). In turn, macrophyte beds can exert significant influence on stream velocity and structure, especially in warmer months (Champion and Tanner, 2000).

Several studies have demonstrated that macroinvertebrate communities are linked to hydrologic conditions such as changes in streamflow (Basaguren et al., 1996; Wills et al., 2006). Macroinvertebrate community composition is often determined by physical disturbances from floods and droughts because these species are vulnerable to quick changes in streamflow (Bunn and Arthington, 2002). Among these changes are increases in taxa with preferred low velocity (diminished streamflow conditions) and increases in taxa with preferred turbulent conditions (increased minimum flows and high flow conditions) (Carlisle et al., 2010b). Increasing occurrence of high flow disturbances has led to community shifts favoring species with short life cycles and high mobility (Poff et al., 2010). Declining streamflows have also been observed to change macroinvertebrate behavior as evidenced by altered drift densities (Poff and Ward, 1991).

Flow is an important component of fish life, as several life events are linked to flow regime, such as spawning behavior, reproduction, growth patterns, and recruitment (Bunn and Arthington, 2002). Collapses or changes in a stream's fish populations are usually the most obvious effect of stream regulation or alteration (Marchetti and Moyle, 2001). Altered flow regimes affect fish diversity and community structure because of the strong relationships between habitat structure, streamflow, and fish (Bunn and Arthington, 2002). Spatial differences in species richness, abundances and habitat relationships are often a function of streamflow predictability (Kennard et al., 2010). Increased flashiness favors fish that are generalist foragers, habitat generalists, or those species tolerant of prolonged low flow periods (Poff et al., 2010). Loss of predictable seasonal flooding (alterations from natural timing) can be beneficial to non-native fish species (Marchetti and Moyle, 2001). In addition, sustained low summer flows have been observed to support non-native fish species (Propst and Gido, 2004). The profound negative impacts of altered streamflow on fish communities is evidenced by Poff and Zimmerman (2010), as they were the only taxonomic group to consistently respond negatively to changes in streamflow magnitude. Therefore, fish can be considered sensitive indicators of flow alteration (Poff and Zimmerman, 2010).

2.6.2 Water Quality Impacts on Stream Ecosystem Health

2.6.2.1 Sediment

Although sediments are a natural and integral component of aquatic ecosystems (Kemp et al., 2011), elevated stream sediment concentrations and loads shift community assemblages and food chain structure (Wood and Armitage, 1997; Henley et al., 2000). The impact of sedimentation is apparent at all trophic levels, affecting growth, reproduction, and mortality rates of primary producers, macroinvertebrates, and top predators alike (Kemp et al., 2011).

The primary impact of suspended sediment on primary producers is related to reduction of light availability for photosynthesis (Davies-Colley and Smith, 2001). Increased turbidity decreases light penetration and photosynthesis, which results in lower primary production (Henley et al., 2000; Davies-Colley and Smith, 2001; Allan, 2004) by periphyton (Yamada and Nakamura, 2002; Liboriussen et al., 2005), phytoplankton (Cline et al., 1994), and macrophytes (Madsen et al., 2001). Disturbance intensity of periphyton also increases with increasing sediment transport (Biggs et al., 1999), usually related to the abrasiveness of sediment (Horner et al., 1990; Henley et al., 2000) or the suitability of substrate for colonization (Allan, 2004). Here, the physical composition of periphyton can change, adversely affecting its quality as an invertebrate food source (Graham, 1990). The decrease in primary production and quality of primary producers as autochthonous food sources cascades through all trophic levels (Henley et al., 2000).

Macroinvertebrate community composition is altered in response to increased turbidity and sedimentation because of decreased autochthonous food sources (Rice et al., 2001). Filling of benthic interstitial spaces by sediment can smother macroinvertebrates (Davies-Colley and Smith, 2001) and limit their oxygen supply (Wood and Armitage, 1997; Kemp et al., 2011). Macroinvertebrate drift can also increase, as these organisms will avoid turbid areas reducing their preferred habitat range (Wood and Armitage, 1997). Lower population density has also been reported in streams with high sediment loading (Wohl and Carline, 1996), while community composition changes with increased turbidity (Rice et al., 2001; Liboriussen et al., 2005). Additionally, relative abundance of species that feed on leaf litter can increase as the prevalence of autochthonous food sources decrease (Bojsen and Barriga, 2002)

Through changes in primary producer and macroinvertebrate community, fish are also indirectly affected by increased sedimentation and turbidity in the water column. Fish habitat is affected: filling of interstitial spaces harms gravel-spawning fishes, while deposition can lead to filling of stream pools and decreased pool species (Allan, 2004). Sediments suspended in the water column cause physical stress by irritating fish gills (Davies-Colley and Smith, 2001; Allan, 2004), causing more frequent gill flaring (Berg and Northcote, 1985), thickening the gill epithelium resulting in respiratory problems (Kemp et al., 2011), and clogging gill rakers and filaments (Wood and Armitage, 1997). These physical stressors reduce growth rates, delay hatching, increase mortality, and impede migration (Zimmerman et al., 2003). Predators' hunting effectiveness decreases with higher turbidity as they are unable to visualize prey easily (Berg et al., 1985; Cline et al., 1994). Planktivores will have an advantage in more turbid environments as their vulnerability to top predators will decrease (Wilber and Clarke, 2001; De Robertis et al., 2003). However, Sutherland et al. (2002) stated that sedimentation is major cause of decline in fish with benthic specializations. Changes in abundance and distribution of fish with increased sedimentation have been noted because of turbidity avoidance (Boubée et al., 1997; Henley et al., 2000; Kemp et al., 2011). Ultimately, sediment disrupts fishes' social organization, feeding habits, and physical health, resulting in energy expenditure that could have otherwise been spent on growth and (Berg et al., 1985).

2.6.2.2 Nutrients

Excessive nutrient (nitrogen and phosphorus) loadings in streams are a major threat to aquatic biodiversity (Woodward et al., 2012) and have significant impacts on aquatic ecosystem health (Wang et al., 2007). While these nutrients are essential to aquatic organisms, in excess they influence flora and fauna at the individual, community and ecosystem level. Aquatic fauna are primarily impacted by elevated levels of nitrogen and phosphorus compounds indirectly through changes in primary productivity (Richards et al., 1993; Allan, 2004) and autotroph assemblage composition (Allan, 2004).

Elevated nutrients generally increase algal biomass (Paul and Meyer, 2001), although algae and periphyton growth is stimulated more by increases in phosphorus and the combination of nitrogen and phosphorus rather than increases in nitrogen alone (Genito et al., 2002). Excess nutrients contribute to growth of plants and eutrophication. While eutrophication is a natural process, its acceleration due to anthropogenic sources of nitrogen and phosphorus causes extreme physical changes in habitat, decreases in dissolved oxygen, and growth of toxic algal species, especially in lakes (Cooper, 1993). In eutrophic and hyper-eutrophic systems, invertebrate and fish die-off are possible due to extreme declines in dissolved oxygen and presence of toxic algae (Camargo and Alonso, 2006). Hypoxic conditions caused by eutrophication are unlikely to occur in lotic systems, except in places with localized areas of slow-moving water (Allan, 2004). In less extreme cases, increases in litter breakdown rates and plant biomass decay, resulting in impaired, but survivable, dissolved oxygen levels. Under these conditions, more sensitive fish and macroinvertebrates give way to tolerant and non-native species (Lenat and Crawford, 1994; Allan, 2004; Weitjers et al., 2009) and resultant biodiversity decreases (Stevenson et al., 2012). Along nutrient gradients, invertebrates attain their highest densities in moderately enriched streams, possibly causing the greatest breakdown rates at these levels of enrichment (Woodward et al, 2012).

Impacts of nutrient additions to streams can be unpredictable in terms of effects on primary and secondary consumers (Miltner and Rankin, 1998). The response is more uncertain in the complex food webs of warmwater streams than in coldwater streams (Miltner and Rankin, 1998). Generally, increases in periphyton abundance affect the primary consumer level, where minnows (Lenat and Crawford, 1994) and certain macroinvertebrates (Delong and Bruvsen 1998) benefit from nutrient-rich waters and proliferated food sources. Changes in periphyton abundance have been observed to reduce macroinvertebrate drift and food quality (Miltner and Rankin, 1998), possibly influencing fish community assemblages (Wang et al., 2007).

Overall measures of diversity and stream integrity also respond to excessive nutrient pollution in streams. For example, Wang et al. (2007) found that index of biotic integrity, salmonids abundance, and percentage of carnivorous, intolerant, and omnivorous fishes were correlated with most in-stream nutrient measures. Macroinvertebrate indices also respond to nutrient pollution, where the Hilsenhoff Biotic Index (HBI) and percentages of Ephemeroptera, Plecoptera, and Trichoptera (EPT) individuals and taxa were strongly correlated to most nutrient measures (Wang et al., 2007). Similar results were found by Justus et al. (2010), where fish and macroinvertebrate biotic indices were both correlated with in-stream nutrients. In addition, Miltner and Rankin (1998) observed a negative correlation between nutrients and biotic integrity, especially with total phosphorus in low and mid-order streams.

2.6.2.3 Pesticides

Pesticides have a wide range of direct and indirect impacts on aquatic biota and their interactions at all trophic levels (Friberg et al., 2003; Schäfer et al., 2007). Exposure to pesticides is generally characterized by high-concentration spikes after agricultural spraying followed by a storm runoff event or chronic exposure due to continual spraying (Davies et al., 1994). Less than 2% of agriculturally applied pesticides enter streams and become stressors to aquatic biota (Battaglin and Fairchild, 2002). However, as of 2001, more than 90% of sampled streams in the

United States residing in agricultural, urban, or mixed-use watersheds contained pesticide compounds (Gilliom, 2007). In addition, persistent organochlorides (such as DDT) banned in the United States as of 1990 are still consistently found in fish and bed-sediment (Gilliom, 2007).

Herbicides entering streams produce major alterations to community structure by affecting primary producers. Some herbicides are toxic to phytoplankton and reduce primary productivity (Cooper, 1993). As primary producers die from herbicide exposure, their organic matter depletes available dissolved oxygen (Cooper, 1993). Habitat structure can also change when aquatic macrophyte communities are destroyed by herbicides (Cooper, 1993). In turn, macroinvertebrates and fish are affected by damages to primary producers.

Macroinvertebrate taxa presence, distribution, and density are influenced by pesticide concentration in streams (Berenzen et al., 2005). Pesticide contamination can trigger overall community loss (Castillo et al., 2006) and changes in community composition (Schäfer et al., 2007) and community dynamics (Schulz and Liess, 1999). These changes in community are due to sublethal effects of pesticides, such as reduced fecundity, delayed emergence, and the resulting competitive disadvantages (Fleeger et al., 2003). Diazinon and chloripyrifos presence correlates with decreases in taxonomic richness, number of Ephemeroptera taxa, and percentage of Chironomidae (Anderson et al., 2006). Macroinvertebrate drift can increase because of sublethal concentrations of pesticides, resulting in changes to community structure in streams (Schulz and Liess, 1999; Schulz and Dabrowski et al., 2001; Beketov and Liess, 2008). Although the drift is likely an active reaction to pesticide presence, it is possible that pesticide presence inhibits effective predator-avoidance related drift and results in macroinvertebrates becoming easy prey for insectivores (Schulz and Dabrowski et al., 2001).

Fish are indirectly affected by pesticide-related changes in macroinvertebrate community composition and dynamics because of their role as a food source (Pimentel, 2005). Meanwhile, pesticides directly influence fish health through behavioral changes at sublethal concentrations and mortality at lethal levels (Rao et al., 2005). Salmonid olfactory capacity, which mediates predator avoidance, juvenile homing, imprinting, and kin recognition, is compromised due to pesticide exposure (Scholz et al., 2000; Tierney et al., 2006). Consequently, these behavioral and life history deficits diminish the possibility of individuals' survival and reproductive success (Scholz et al., 2000). In addition to behavioral modifications, reduced egg production (Goodman et al., 1979), damages to fish organs such as the liver and kidneys (Capkin et al., 2006), and disruption of cell metabolic processes (Davies et al., 1994) have been observed following pesticide exposure.

2.6.3 Stream Condition Impacts on Stream Ecosystem Health

2.6.3.1 Stream Temperature

Stream temperature is widely recognized as a fundamental control on stream ecosystems (Webb and Walling, 1993; Olden and Naiman, 2010). Thermal regimes commonly dictate abundance and occurrence (Lyons et al., 2009) as well as distribution and physiology (Poole and Berman, 2001; Wehrly et al., 2003) of aquatic biota. Life history traits and productivity are also directly influenced by water temperature (Poole and Berman, 2001). Beyond direct influences, water temperatures also indirectly impact stream biota by affecting dissolved oxygen concentrations (Belsky et al., 1999) and nutrient cycling (Poole and Berman, 2001). Warmer water temperatures generally increase diversity, productivity, and support more species, but increases beyond suitable thresholds can be detrimental to stream biota.

The natural thermal regime is important to fish because it signals migration, spawning, and hatching while influencing egg survival and development (Olden and Naiman, 2010). Fish survival, growth, and reproduction are based on chronic and acute temperature thresholds (Vannote and Sweeney, 1980). Stream temperature regulates biological activity of fish, where higher summer temperatures increase metabolic activity (Beschta, 1997; Ebersole et al., 2001). As metabolic activity increase, higher quality or greater quantities of food are required to maintain growth and survival (Lessard and Hayes, 2003). Coldwater fish species such as salmonids are especially impacted by increasing summer stream temperature, where they will experience increases in stress and disease susceptibility while being less effective in competition with warmwater species (Beschta, 1997; Belsky et al., 1999). Temperature specific fish species can be eliminated from formerly suitable habitat (Bunn and Arthington, 2002) by limiting longitudinal distribution, restricting seasonal migration, and fragmenting populations that find isolated suitable habitats (Ebersole et al., 2001). For example, coldwater streams, temperature impairment pushes out coldwater species, but increases suitability for a wide range of warmwater species (Lyons et al., 1996). Conversely, when a warmwater temperature impairment eliminates sensitive warmwater species, leading in a net decline in species richness (Lyons et al., 1996). July temperatures in particular are useful predictors of fish assemblage structure, while northern latitude streams experience the most pronounced differences in temperature in July (Wehrly et al., 2003; Caissie, 2006; Wehrly et al., 2009).

Macroinvertebrates are similarly affected by stream temperatures. Increased metabolic rates lead to requirements of higher quantity or quality food (Lessard and Hayes, 2003). Modified thermal patterns in streams can disrupt macroinvertebrate emergence and reduce population success (Bunn and Arthington, 2002). Consistent increases in stream temperature above the norm have been shown to decrease density and increase growth rates and precocious breeding for some macroinvertebrates and smaller mature sizes in others (Hogg and Williams, 1996). Meanwhile, winter water temperature increases result in early macroinvertebrate emergence and consequent exposure to air temperatures too cold for survival (Nebeker, 1971).

2.6.3.2 Dissolved Oxygen

Dissolved oxygen (DO) in the water column is a critical resource for aquatic organisms. In fact, DO is generally more limiting for aquatic organisms than it is for terrestrial ones (Kramer, 1987). Acute deficiencies of DO can result in permanent effects to individual organisms and the aquatic ecosystem as a whole (Garvey et al., 2007). Consequently, it is an important determinant of community composition, distribution, and abundance of fish and macroinvertebrates (Wang et al., 2003; Connolly et al., 2004), and can be considered a benchmark for aquatic ecological health (Loperfido et al., 2009). Due to the effects of low DO on fish, the USEPA Total Maximum Daily Load (TMDL) program has set a standard lower limit of 5 mg/L in streams (USEPA, 1986). However, these limits were developed with limited knowledge of baseline conditions for a variety of organisms (Garvey et al., 2007). In several cases, DO concentrations below tolerable limits have caused fish mortality (Ostrand and Wilde, 2001; Cox, 2003). Other effects of declines in DO concentrations include reduced fish growth rates (Garvey et al., 2007), altered heart rates, changes in respiration (Seager et al., 2000), and metabolism changes (Diaz and Rosenberg, 1995). Meanwhile, macroinvertebrates have a wide array of respiratory adaptations that are behavioral and structural in nature, which indicates that oxygen requirements and tolerances vary between taxa (Connolly et al., 2004).

DO concentrations in aquatic ecosystems are influenced by many factors, including temperature, light, streamflow, aeration, channel morphology, and community composition of the resident biota (Garvey et al., 2007; Loperfido et al., 2008). Autotrophs produce DO by photosynthesis, but also deplete it in light-limited conditions (Wang et al., 2007; Loperfido et al., 2009). This occurs in a diurnal pattern, where DO concentrations decrease at night due to macrophyte and periphyton respiration, and reach a maximum at solar noon when photosynthesis is occurring (He et al., 2011). Abiotic factors (temperature, light, flow velocity, and nutrient concentrations) also affect abundance and composition of macrophyte and periphyton communities, indirectly influencing DO concentrations (He et al., 2011). For example, increasing stream temperatures reduce the ability of the water column to hold oxygen while increasing metabolic rate and oxygen demand of fish (Rottmann et al., 1992).

Stream impairment from anthropogenic activities also dictates DO concentrations. High biological productivity caused by spiking nutrient loads results in a severe oxygen depletion, known as hypoxia (Rabalais et al., 1994). The influx of nutrients results in an increase in autotrophs, but their nocturnal respiration results in extreme oxygen decreases, and their decomposition following death further reduces DO (Rabalais et al., 1994). Here, benthic macroinvertebrates are the first to experience the effects of oxygen decrease because hypoxia events typically begin in the benthos (Dauer et al., 1992). These conditions have periodically occurred in the Chesapeake Bay (Dauer et al., 1992) and Gulf of Mexico (Rabalais et al., 1994) due to intensive agricultural production and subsequent nutrient transport in streams (Rixen et al., 2010). Urban streams also experience low dissolved oxygen conditions due to effluent from wastewater treatment plants and combined sewer overflow discharges (Paul and Meyer et al., 2001).

2.6.3.3 Physical Habitat and Channel Morphology

The primary attributes that characterize a stream’s physical habitat structure are stream size and channel dimensions, channel gradient, channel substrate and type, habitat complexity, vegetative cover and structure in the riparian zone, and channel-riparian interaction (Kaufman et al., 1999). These factors usually vary longitudinally along the length of a stream, and affect many aspects of stream ecosystems in terms of community structure, species abundance, and others. Quality and quantity of physical habitat dictates structure and composition of biological communities in streams (Maddock, 1999).

Stream size and channel dimensions. Stream size is a key predictor of species richness and presence (Pont et al., 2009). Catchment area dictates potential habitat capacity (Pont et al., 2009). Zonation has been observed moving downstream, where fish community changes occur with addition of new species moving downstream (Rahel et al., 1991). Potential stream volume (Pont et al., 2009), catchment area (Brosse et al., 2003), stream width (Park et al., 2003; Gabriels et al., 2007; Mouton et al., 2010), cross-sectional area (Einheuser et al., 2012), and stream order (Park et al., 2003; Céréghino et al., 2003; Mouton et al., 2010) have been used as measures of stream size and predictors of fish and macroinvertebrate communities.

Channel gradient. Channel gradient influences the hydraulic characteristics of a stream, which in turn dictates flow regime. Streams with high gradients and rocky substrates were found to have superior habitat quality and biotic integrity than low-gradient sandy streams that have experienced agricultural expansion (Wang et al., 1997). Fish assemblages in Wisconsin were found to be more responsive to channel gradient than ecoregion-related landscape features (McCormick et al., 2001).

Channel substrate. In terms of channel substrate, diversity and abundance has been found to increase with substrate stability and presence of organic detritus (Allan, 1995). The physical nature of channel substrate is of great biological significance (Beschta and Platts, 1986). For example, salmonids use substrates as locations for food and cover as well as for spawning (Beschta and Platts, 1986). Substrate size is correlated with macroinvertebrate indicators

(Lammert and Allan, 1999) and species richness (Brosse et al., 2003). Therefore, it is commonly used in prediction of stream health (Aadland, 1993; Brosse et al., 2003; Lammert and Allan, 1999).

Habitat complexity. Species richness and habitat complexity are positively correlated (Diehl, 1992). For example, abundance and species richness has been observed to increase with increasing density of submerged macrophytes, but reduces forage efficiency of fish (Diehl, 1992). Meanwhile, woody debris influences quality of food and habitat for fish; changes in woody debris abundance can result in changes in fish communities (Angermeier and Karr, 1984). There is positive correlation between species richness and increased structural complexity of a habitat (O'Connor, 1991).

Riparian vegetation, bank condition, and riparian-channel interaction. Riparian zone vegetation is a primary source of leaf litter in headwater streams, which is a dominant food resource for many fish and macroinvertebrates (Richardson and Danehy, 2007). Riparian vegetation and channel bank condition are important for providing fish rearing habitat (Beschta and Platts, 1986). Shape and condition of channel banks are linked to quality of fish habitat; fish use edges and niches for rearing and cover (Beschta and Platts, 1986). Elimination of riparian vegetation causes a variety of changes to the stream such as widening, shallowing, warming, and decreased food supplies, all of which ultimately results in declines to fish populations (Beschta and Platts, 1986). Organic carbon production and fate in the aquatic food web is also influenced by changes in riparian conditions (Bunn et al., 1999). Interaction between the stream and riparian zone is also important because it determines the quantity and quality of organic matter contributed to the stream as well as input of woody debris (Gregory et al., 1991). Connectivity between the riparian zone and greater floodplain area is a driver of species composition and richness in the aquatic and terrestrial environments as a result nutrient, sediment, organic matter, and biotic exchanges (Leyer, 2006).

2.6.4 Stream Health Indicators

There are many methods to quantify biological stream health. Traditionally, measurement and assessment endpoints for water quality and biological stream health have been physical and chemical in nature (Karr, 1987). Assessment endpoints should be biological, rather than physical or chemical, because ecosystems in which organisms cannot survive cannot support human uses (Karr and Chu, 1997). Supporting these human uses is often the target of water quality improvement programs. Biological assessments (bioassessments) are an evaluation of a waterbody's condition using surveys of community structure and function of resident biota (USEPA, 2011), and is now a widely accepted tool for evaluating stream health and ecosystem response to human-induced stressors (Simon, 2000; Flinders et al., 2008). Effective biological assessment has many advantages over traditional water quality evaluation methods: the ability to detect low levels of pollutants, changes in physical habitat, and long-term ecosystem effects of disturbance events (Flinders et al., 2008). Biological assessments are also more accurate than pollutant-specific sampling in detecting and quantifying aquatic impairments (Karr and Yoder, 2004). Biological data, rather than chemical or toxicological, has consistently proven to be a better predictor of environmental impact (Simon, 2000). Karr (2006) contended that biological measures are more effective than chemical water quality standards at stream health diagnosis and defining the causes and proposing treatments of degradation. Consequently, the US Environmental Protection Agency (EPA) has stated that biological assessments should be integrated into state and tribal water quality programs and used together with chemical analysis to assess attainment of designated aquatic life uses in water quality standards (USEPA, 2011).

Several states have moved from relying on chemical and physical measures to using narrative or numerical biological criteria to understand stream conditions, identify further monitoring needs, and evaluate management strategies (Morley and Karr, 2002). Measures of biological integrity via biological assessment are now a priority in the USA (Barbour et al., 2000).

Biological assessment programs typically monitor/sample assemblages of a taxonomic group and translate biological attributes into a stream health rating/multimetric index, often called an indicator (Karr and Chu, 1997; Flinders et al., 2008). These indicators are a widely accepted technique to determine how aquatic communities respond to stressors (Flinders et al., 2008). Biological indicators are divided into three types: (1) diversity and similarity indexes, (2) pollution-tolerance indexes or "biotic indexes", and (3) multimetric indexes (Fore et al., 1996).

Diversity indices measure community structure, while similarity indices compare community structure between two sites or at the same site between two time periods (Danilov, and Ekelund, 1999; Lydy, et al., 2000). Two assumptions are inherent in diversity indices: (1) stable communities have high diversity and unstable communities have low diversity, and (2) stability (and diversity) is an index of environmental integrity (Ravera, 2001). Therefore, diversity is inversely related to environmental degradation. However, Hilsenhoff (1982) stated that they are unreliable in most situations and Fore et al. (1996) stated that "the response of these indexes to systematic changes in the assemblage are often erratic, inconsistent, dependent on initial conditions, and can give misleading interpretations of biological data". Examples of diversity and similarity indices include Simpson's D (Simpson, 1949) Shannon's diversity index (Shannon and Weaver, 1948), and Pinkham and Pearson's index (Pinkham and Pearson, 1976).

Pollution-tolerance indices assign a value of pollution tolerance to every taxon (Fore et al., 1996). These indices are calculated by multiplying the tolerance value by the number of individuals of that species found in the sample that correspond to the given value (Hilsenhoff, 1982). Values are then summed across taxa and divided by total number of individuals in the sample to get an average pollution tolerance (Hilsenhoff, 1982). Tolerance values are generally derived using expert opinion, and these indices are only as good as the system used to develop the values (Lenat, 1993). In addition, strong response by a few taxa to the stressor of interest can be overshadowed because assemblages are generally dominated by taxa that are neither sensitive nor insensitive to the stressor (Fore et al., 1996). The most commonly used pollution tolerance index is the HBI (Hilsenhoff, 1982; Hilsenhoff, 1987; Hilsenhoff, 1988).

Multimetric indices are the most common tools for bioassessment of fish and macroinvertebrates (Stoddard et al., 2008) and are used on six continents (Karr, 2006). Multimetric indices incorporate many unique attributes of an ecosystem to describe a stream's condition (Karr and Chu, 1997). Attributes that comprise a multimetric index are selected based on whether they reflect predictable responses of organisms to human activities and are sensitive to a broad range of anthropogenic stressors (Karr and Chu, 1997; Karr, 1999). Useful multimetric indices balance metrics that respond across different types and ranges of degradation (Fore et al., 1996). The most effective multimetric indices include many metrics of an assemblage, including taxa richness, indicator taxa (tolerant and intolerant groups), individual organism health, and food web organization (Karr and Chu, 1997; Karr, 1999). However, most multimetric indices are still developed using expert judgment despite the desirability of using rigorous statistical evaluation instead (Stoddard et al., 2008). Multimetric indices are commonly developed based on regions or watersheds and therefore are site-specific. Examples of multi-metric indices include the fish index of biotic integrity (fish IBI) (Karr, 1981) and the benthic index of biotic integrity (B-IBI) for macroinvertebrates (Kerans and Karr, 1994; Weisberg et al., 1997).

Selection of an indicator for a biological assessment is often based on personal bias, technical considerations, and knowledge constraints (Boulton, 1999). Biological assessments of streams commonly use fish and macroinvertebrate assemblages. Periphyton, macrophytes, and diatoms have also been used in some studies. A biological monitoring program should integrate several major taxa (Karr, 1981), but few studies have evaluated the response of multiple taxonomic groups to stressors even though different assemblages are often sensitive to different stressors (Flinders et al., 2008).

2.6.4.1 Fish Indices

Fish are particularly beneficial in bioassessment because they occupy many trophic levels (from piscivores to planktivores) and sit at the top of the food web in relation to macroinvertebrates and diatoms (Karr, 1981). They provide an integrative view of the stream ecosystem because of their dependence on the health of other taxonomic groups (Karr, 1981; Barbour et al., 1999). As they are longer-lived and mobile, they are good indicators of long-term effects and reflect conditions at broad spatial scales (Plafkin et al., 1989; Barbour et al., 1999). From a practical perspective, they are relatively easy to sample and identify (Karr, 1981, Barbour et al., 1999), while environmental requirements and life histories are well known for most species (Barbour et al., 1999). The fish IBI is a multi-metric index that detects divergence from biological integrity because of anthropogenic activities (Karr, 1999). Broadly based and ecologically sound, the fish IBI evaluates human effects on a stream by integrating many community measures of richness, composition, and abundance (Wang et al., 2007).

2.6.4.2 Macroinvertebrate Indices

Macroinvertebrates present a different set of benefits in their use as stream health indicators. They are generally sessile and limited in their migration, facilitating representation of localized/site-specific conditions (Barbour et al., 1999; Flinders et al., 2008). Small streams naturally support many macroinvertebrate taxa, while these streams contain a more limited number of fish (Plafkin et al., 1989; Barbour et al., 1999). Macroinvertebrates also have sensitive life stages in which they respond quickly to stressors (Barbour et al., 1999). They exhibit a broad range of pollution sensitivity, from those that are intolerant (stoneflies, caddisflies, and mayflies), to more tolerant species, such as midges. Unlike fish, there is little agreement on which macroinvertebrate measures to use in bioassessment (Lammert and Allan, 1999).

Some common macroinvertebrate indices are the number of EPT taxa, Family-level Index of Biotic Integrity (FIBI) (also known as B-IBI), and the HBI. EPT taxa is a count that quantifies the taxonomic richness of common pollutant-intolerant macroinvertebrate orders, and their presence/absence is widely used as an indicator of the level of stream disturbance or degradation (Sponseller et al., 2001). FIBI is a multi-metric index comprised of information on macroinvertebrate composition (e.g., percent shredders) and richness (e.g. total number of taxa) at a family-level taxonomic resolution. FIBI has a range of 0-45, with 45 being excellent stream health. HBI is an organic pollution-tolerance index for macroinvertebrate taxa based on taxon-specific tolerance values (Hilsenhoff, 1988). Ranging from 0-10, 0 indicates excellent health and 10 indicates very poor health.

2.7 Stream Health Assessment Methods

Several methods have been used to assess biological condition of aquatic ecosystems. These methods include sampling surveys that make inferences of a larger population of streams, models of observed versus expected (O/E) taxa and models that predict values of stream health indicators.

2.7.1 Sampling Surveys

Sampling is commonly used to assess the biological condition of streams. Probability (or random) sampling is a practical approach to sampling when it is difficult or cost prohibitive to survey every stream of interest in a census (Larsen, 1997). These sample surveys allow for inferences of biological condition within a defined area (Larsen, 1997). Probability-based sampling design gives every stream in the population a known probability of being selected for sampling, thereby ensuring that sampling results are representative of the full range of characteristics and variation in streams (USEPA, 2006). The USEPA Wadeable Streams Assessment (USEPA, 2006) used this methodology to collect macroinvertebrate samples and draw conclusions regarding biological condition at the ecoregion level. From these samples, the percentage of degraded stream kilometers can be determined based on the number of sites that exhibited degraded conditions (USEPA, 2006).

2.7.2 Observed Versus Expected Taxa Models

O/E measures the number of taxa that have been lost at a site, where the expected taxa are predicted from a model based on data collected from least-disturbed reference sites (USEPA, 2006). This method is utilized in the River Invertebrate Prediction and Classification System (RIVPACS) modeling approach that assess biological condition based on macroinvertebrate communities (Wright et al., 1998). The RIVPACS approach requires minimally impaired reference sites that represent a region's physical and biological variability (Clarke et al., 2003; Ostermiller and Hawkins, 2004). Discriminant analysis models are then developed using empirical relationships between probability of taxon capture and measured values of environmental characteristics at the reference sites (Clarke et al., 2003; Hargett et al., 2007). The model is extended to new test sites, where the same environmental characteristics are measured and the expected macroinvertebrate fauna at the site are predicted assuming the test site is unstressed (Clarke et al., 2003). The final step is sample collection at the test site and the O/E measure can be calculated (Clarke et al., 2003). However, it cannot be used as a dynamic model to predict the impact of environmental changes on biological condition (Clarke et al., 2003). Using this method, biological condition can only be assessed in locations where samples of interest (e.g. macroinvertebrates, fish, and macrophytes) have been collected. However, it has been used in several studies (e.g. Aguiar et al., 2011; Clarke et al., 2003; Hargett et al., 2007; Simpson and Norris, 2000; Wright, 1995; Wright et al., 1998).

2.7.3 Stream Health Indicator Models

Many studies have used samples of stream health indicators to develop models that predict biological condition in unsampled streams that represent an array of environmental gradients, including both least-disturbed and highly disturbed sites. These models can range for traditional linear models to newer prediction-tree approaches (Cao and Hawkins, 2011). Most are developed using relationships between stream health indicators and physical environmental variables (e.g. substrate type, channel width, channel bank height, channel bank slope, drainage area, land use, and riparian condition) (Cao et al., 2007; Lammert and Allan, 1999; Moore and Palmer, 2005; Pont et al., 2006). These models are able to predict stream health at unsampled reaches, but often do not account for streamflow and water quality conditions. More recently, models have addressed this shortcoming in predicting fish and macroinvertebrate indicators by focusing on in-stream flow and water quality variables generated from watershed models rather than direct landscape factors (Einheuser et al., 2012; Einheuser et al., 2013a; Einheuser et al., 2013b).

2.8 ECOHYDROLOGICAL MODELING TECHNIQUES

There are multiple methods for developing ecohydrological models, and several criteria for determining methods well suited for a given application. Each modeling method has its own requirements, advantages, and disadvantages. These issues define the criteria for determining which model to use. Criteria to determine model applicability for a given problem are defined by the project objectives, knowledge and physical understanding of the problem, variable selection needs, volume of available data (both dependent and independent variables), ability to deal with complex and nonlinear ecological relationships, and ease of interpretation. However, because there is a limited set of studies that have compared multiple modeling methods, it is difficult to determine in what situation a particular method should be used (Goethals et al., 2007). Each method has advantages and disadvantages, and it is likely that no single method will be perfect for any given application.

There are several methods used to study the complex relationships between human disturbances, landscape and in-stream variables, and stream health. These methods encompass linear, nonlinear, and soft computing approaches. Some commonly used methods for model development include artificial neural networks (ANNs), fuzzy logic-based methods, linear regression, decision/classification/regression tree analysis, and canonical correspondence analysis (CCA). Descriptions, strengths, and weaknesses of each method are detailed in the following sections.

2.8.1 Artificial Neural Networks

ANNs are nonlinear mapping structures useful in predictive modeling and classification (Goethals et al., 2007). This method is powerful in dealing with nonlinear ecological relationships in place of linear statistical models (Gevry et al., 2003). It is flexible and can uncover patterns in a dataset (Olden and Jackson, 2002). However, ANNs are a 'black box' because it is difficult to determine the individual contribution of input variables in predicting output values (Lek and Guégan, 1999; Olden and Jackson, 2002). Therefore, little understanding of the relationships between variables can be gained (Olden and Jackson, 2002). Selection of important variables for use in ANNs remains a critical challenge; introducing too many parameters increased network size, resulting in cumbersome data requirements and decreased computation speed (Goethals et al., 2007). In addition, there are no clear methods for determining model; trial and error seems to be the best method for this process (Goethals et al., 2007). Despite these drawbacks, ANNs have been consistent in their suitability for addressing nonlinear ecological problems. Examples of using ANN in addressing ecological problems include linking biological integrity to stream habitat and geomorphic conditions (Mathon et al., 2013), modeling macroinvertebrate assemblages (Park et al., 2003; Compin and Céréghino, 2007; Lencioni et al., 2007; Mouton et al., 2010), and modeling brown trout density (Lek et al., 1996).

2.8.2 Fuzzy Logic

Fuzzy logic uses linguistic fuzzy-based membership functions (MFs) defined by IF-THEN rules. There are several advantages to using fuzzy logic: it can adequately approximate nonlinear functions, it can be interpreted linguistically, and it can deal with imprecise values (Adriaenssens et al., 2004). In addition, models can be developed using only qualitative knowledge of a problem and its relationships (Van Broekhoven et al., 2006), while accounting for inherent uncertainty and complexity of ecological systems (Metternicht, 2001; Chen and Mynett, 2003). However, building MFs is a challenging, time-consuming task (Huang et al., 2010) that is subjective (Adriaenssens et al., 2004). To solve these issues, fuzzy logic has been combined with ANNs in artificial neuro-fuzzy inference systems (ANFIS), which finds relationships in the data to develop and tune MFs (Jang, 1993). Unfortunately, there are no commonly agreed upon methods for initial variable selection using ANFIS (Einheuser et al., 2012). In addition, the number of variables used in ANFIS and fuzzy logic is limited (Goethals et al., 2007), as increasing variables greatly increases model complexity in terms of rule sets (number of fuzzy rules and MFs), while in data-scarce situations the model can be easily over-fitted. Fuzzy rule-based models have been used extensively in development of ecological models because of their applicability in nonlinear problems (Marchini, 2011). Such applications include developing environmental condition indices (Lermontov et al., 2009; Marchini et al., 2009), modeling wetland conditions (Mah and Bustami, 2012), algal biomass (Chen and Mynett, 2003), macroinvertebrate taxa (Adriaenssens et al., 2006; Einheuser et al., 2012), biotic integrity of fish (Einheuser et al., 2013a), water quality (Ocampo-Duque et al., 2006), and predicting habitat suitability (Mouton et al., 2009; Van Broekhoven et al., 2006).

2.8.3 Regression

Multiple linear regression is used frequently in ecology (Gevry et al., 2003), and is reliable when there is limited data and knowledge of a problem (Van Sickle et al., 2004). The main advantage of linear regression lies in its simplicity and ease of use. However, in an ecological setting this method develops linear generalizations of nonlinear processes (Gevry et al., 2003). With limited sample size, regression models also suffer from inability to find significant effects of predictor variables (Carrascal et al., 2009). Some variants of linear regression are able to overcome specific deficiencies in the modeling method. For example, in stepwise linear regression methods variable selection is implicitly included in development of the model. Partial least squares regression is superior to simple linear regression because it handles interactions that are more complex and reduces redundancy among large variable sets (Carrascal et al., 2009). Nonlinear regression methods have been employed to address the complexity of ecological processes, such as piecewise regression (Maret et al., 2010). These methods have proven to be useful in modeling ecological processes, as Mouton et al. (2010) found multiple linear regression models were only slightly outperformed by ANNs in macroinvertebrate modeling. Linear regression has been used in multiple ecological settings, such as in predicting fish (Frimpong et al., 2005; Kennard et al., 2005; Kennard et al., 2006; Van Sickle et al., 2004) and macroinvertebrates (Einheuser et al., 2012; Mouton et al., 2010; Moya et al., 2011; Van Sickle et al., 2004).

2.8.4 Decision/Classification/Regression Trees

Decision/classification/regression tree (CART) analysis builds a predictive model using a hierarchical method that splits predictors based on most variance explained, resulting in a tree with end nodes that identify final response variable values derived from predictors (Goetz and Fiske, 2008). The general objective is to keep the tree small while partitioning the response into homogeneous groups (De'ath and Fabricius, 2000). Tree analyses make no assumptions about relationships between independent and dependent variables (Robertson et al., 2006). They are an alternative to traditional linear statistical methods because they handle nonlinear problems, are easy to construct and interpret, accept numerical and categorical data, and can handle missing response and explanatory variable values (De'ath and Fabricius, 2000; Kennard et al., 2010). Decision trees are white box models, meaning they allow interpretation of model parameters, unlike ANNs (Dreiseitl and Ohno-Machado, 2002). However, if trees become too large there is a danger of over-fitting. Tree-based methods have been used to predict coral taxa (De'ath and Fabricius, 2000), classify flow regime (Kennard et al., 2010), predict fish species richness

(Rathert et al., 1999), abundance (Steen et al., 2008), and biotic integrity (Wang et al., 2007; Weigel and Robertson, 2007) and identify headwater stream disappearance due to urbanization (Elmore and Kaushal, 2008).

Boosted regression trees (BRTs) are a subset of regression trees that improve upon their predecessors' shortcomings. BRT is different from traditional regression in that it does not produce a single best model, but uses boosting to combine several tree models adaptively to optimize predictive performance (Elith et al., 2008). Overall, BRT models are robust and require few assumptions compared to traditional regression techniques (May et al., 2015). They also outperform general linear models and general additive models in variable selection and predictive abilities while handling sharp discontinuities in a dataset (Waite et al., 2012; Waite et al., 2014). In addition, BRTs provide insight regarding relative importance of explanatory variables while accounting for nonlinear variables and variables that interact (Pilière et al., 2014; May et al., 2015). These models are relatively new in ecology, but have been used to predict observed vs. expected (O/E) taxa in a few studies (Waite et al., 2012; Waite, 2014; Waite et al., 2014; May et al., 2015).

2.8.5 Canonical correspondence analysis

As a special case of multivariate regression, CCA is able to test the effects of environmental variables on biological communities, even if the effects are hidden by large sources of variation (ter Braak and Verdonschot, 1995). It can determine how species respond to environmental variables using observational data (ter Braak and Verdonschot, 1995). Variable selection in CCA is accomplished using stepwise methods (Dodkins et al., 2005; Merritt and Cooper, 2000). The result of CCA is a linear combination of independent variables that allow their direct comparison with dependent variables (Merritt and Cooper, 2005). When a significant relationship between dependent and independent variables is found, an index of disturbance conditions is represented by the linear combination of predictors (Wang et al., 2008). CCA has been shown to have good performance under nonlinear relationships between environmental gradients and species (Palmer, 1993). However, CCA was developed for explanation and description rather than prediction (ter Braak and Verdonschot, 1995). Regardless, CCA has been used to assess condition of aquatic macrophytes (Dodkins et al., 2005), macroinvertebrate communities (Richards et al., 1993), fish communities (Wang et al., 2011), and modeling riparian vegetation (Merritt and Cooper, 2000).

3 INTRODUCTION TO METHODOLOGY AND RESULTS

This dissertation consists of three studies that develop a framework for assessing the impacts of climate change on stream health. The first study focuses on methods for selecting in-stream variables that are influential in dictating stream health. The second study builds upon the first study by developing large-scale stream health models with local-scale resolution, based upon commonly found stream thermal classes present in Michigan. The third study couples climate change data with the stream health models to develop projections of future stream health and identify streams potentially vulnerable to climate change.

The first study, titled "Ecohydrological Model Parameter Selection for Stream Health Evaluation" developed methods to identify and select in-stream variables for prediction of the number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family Index of Biotic Integrity (FIBI), Hilsenhoff Biotic Index (HBI), and fish Index of Biotic Integrity (IBI). Flow regime and water quality variables were simulated using a calibrated SWAT model for the River Raisin Watershed in Michigan. Ecologically relevant flow regime variables and water quality variables were included as candidates in the variable selection process. Streams of the watershed were divided into multiple groupings based on their characteristics using stream order (order 1-3 and order 4-6), *k*-means clustering with two clusters, and all streams. Variable selection was performed from the variables in all groupings using Bayesian variable selection, principal component analysis, and Spearman's Rank Correlation. Following selection of best variable sets, models were developed to predict each of the four stream health measures using ANFIS, a technique well suited to complex, nonlinear ecological problems. The suitability of the variable selection techniques were compared based on the stream health models' performance.

The second study, titled "Ecohydrological Modeling for Large-scale Environmental Impact Assessment", examines scale in development of stream health models. The goal was to develop large-scale stream health models with reach level accuracy. This would promote more effective impacts assessments and improved decision-making capabilities. SWAT was used to simulate streamflow and water quality and the Hydrologic Index Tool was used to calculate 171 ecologically relevant in-stream variables in seven Michigan watersheds (Au Sable, Boardman-Charlevoix, Cedar-Ford, Flint, Muskegon, Pere Marquette-White, and Raisin). Using the Bayesian variable selection method and ANFIS, stream health models (EPT, FIBI, HBI, and IBI) were developed based on four thermal classes (cold, cold-transitional, cool, and warm) of streams that broadly dictate the distribution of aquatic biota in Michigan. The models were tested to determine the impact of land use change on stream health by comparing pre-settlement conditions of the early 1800s to current conditions.

The final study, titled "Large-scale Climate Change Vulnerability Assessment of Stream Health" uses the modeling process established in the first two studies. Then it determines the risk of declining stream health due to future climate change and identifies potentially vulnerable streams throughout the seven watersheds selected in the second study. An ensemble of climate models from the Coupled Model Intercomparison Project Phase 5 (16 models and 3 RCPs) were used to drive the watershed models and stream health models to determine the impacts of climate on the stream health in 2020-2040 compared to the 1980-2000 control period. The risk of declining stream health was determined using cumulative distribution functions across all thermal regimes and at individual reaches. A regression model (linear mixed model with low-rank radial smoothing splines) of stream temperature was also developed to assess potential changes in stream thermal regime, which could cause shifts in composition of aquatic communities.

4 ECOHYDROLOGICAL MODEL PARAMETER SELECTION FOR STREAM HEALTH EVALUATION

4.1 INTRODUCTION

Rivers are an important resource for humans and natural systems alike. To humans, rivers provide water for consumption, economic and recreational opportunities, and innumerable ecosystem services. As a natural system, rivers are complex webs that support an array of flora and fauna. Although rivers are critical to humans and nature, they have degraded at an alarming rate. For example, the Environmental Protection Agency (EPA) has determined that 44% of surveyed streams and rivers in the United States are impaired for at least one designated use (USEPA, 2009). The primary causes of impairment are diverse, including pathogens, oxygen depletion, habitat alteration, nutrients, and sediment. Sources of impairment are mostly anthropogenic, including agriculture, hydromodification, habitat alteration, and municipal discharge. It is increasingly recognized that these activities are a primary threat to ecological integrity of freshwater systems because they affect water quality, biota, and habitat in many ways that are often complex (Allan, 2004).

By the 1970s, a majority of lakes, rivers, and coastal waters were deemed unsafe for fishing and swimming. Upon realizing the level of freshwater impairment due to unchecked pollution dumping in the United States, the Clean Water Act was enacted in 1972 with the goal "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters". Since the act's passage, major water quality improvements have been accomplished; however, the degradation of native aquatic communities continues (Bryce et al., 2008). As a result, there has been a push to consider biological criteria as in addition to chemical or physical criteria to achieve water quality goals, because biological integrity is the ultimate endpoint of concern (Karr and Yoder, 2004). Biological integrity describes an ecosystem comparable to a natural habitat in terms of species composition, diversity, and functional organization, while supporting a balanced, integrated, and adaptive community of organisms (Karr and Dudley, 1981). The strength in using biological assessment to measure biological integrity is that biota residing in a stream are continual monitors of environmental quality and stream conditions (USEPA, 2011).

Multimetric biological indicators (e.g. indices of biotic integrity for macroinvertebrates or fish) are commonly used to measure stream health. These indicators represent large array of aquatic species that are sensitive to a variety of stressors (Wang et al., 2008; USEPA, 2011). Measuring multiple indicators, rather than a single endpoint, provides a holistic view of ecological integrity (Clapcott et al., 2012). However, assessing biological integrity is usually limited to a small portion of a watershed where data about aquatic fauna communities is collected (Wang et al., 2008). Meanwhile, biota often respond to landscape factors and stressors in a complex and nonlinear manner (Wang et al., 2008; Johnson and Host, 2010; Waite et al., 2010; Einheuser et al., 2012). In light of these limitations, modeling can play a major role in characterizing biological integrity in large study areas such as watersheds. However, modeling approaches are not straightforward because of the challenges in connecting specific disturbances or variables with multimetric measures of integrity (Niemi and McDonald, 2004; Wang et al., 2008). In reality, these indicators represent the lumped effects of different stressors (USEPA, 2011). Given these challenges, how should models be parameterized and what type of models should be developed?

Model Parameterization: Selecting variables for use in ecological modeling is a common problem due to the complex, nonlinear, and uncertain relationships in these systems. Among hundreds of variables that influence stream health (e.g. landscape attributes, hydrologic indices, and water quality parameters), a limited number should be selected that are relevant to the problem and can be reliably obtained (Maier and Dandy, 2000). Selection of variables for assessment is subjective and it is impractical to monitor a large suite of variables (Pinto and Maheshwari, 2011). In addition, increased parameterization often leads to model over-fitting (Whittaker et al., 2010). Variable selection can be performed using expert knowledge or data-driven techniques (Adriaenssens et al., 2004). Using expert knowledge for selection of large number of variables is difficult, since the interactions between variables are often composite and confounding. Conversely, data-driven techniques for input variable selection such as artificial neural networks (ANNs) and Principal Component Analysis (PCA) do not require prior understanding of relationships between variables (Adriaenssens et al., 2004) and have been used extensively in characterizing stream health (Olden and Poff, 2003; Kennard et al., 2005; Fellows et al., 2006; Lencioni et al., 2007; Lücke and Johnson, 2009; Mondy and Usseglio-Polatera, 2014).

Model Selection: In ecological and environmental applications, model selection is especially important (Lek and Guegan, 1999; Metternicht, 2001; Chen and Mynett, 2003; Adriaenssens et al., 2004; Mathon et al., 2013). Multiple approaches have been used to develop predictive relationships between landscape factors or human disturbance stressors to stream health. Linear regression is widely used to analyze ecological data for prediction and explanation (Hawkins et al., 2000; Frimpong et al., 2005; Kennard et al., 2006; Pont et al., 2009; Maret et al., 2010; Moya et al., 2011). This approach implies linearity among variables, which is rare in ecology (Lek et al., 1996). The major drawback of multiple linear regression is its inability to account for nonlinearity between independent and dependent variables (Gevrey et al., 2003). Conversely, soft computing methods such as ANNs and fuzzy logic are well-suited to ecological and environmental applications because of the inherent uncertainty, complexity, ambiguity, and non-linearity of these systems and their data (Metternicht, 2001; Chen and Mynett, 2003; Adriaenssens et al., 2004). Developed by Zadeh (1965), fuzzy logic requires linguistic variables and rules rather than numerical values and Boolean logic (Marchini et al., 2011). Fuzzy logic is useful for prediction of multimetric indices because of its linguistic nature. For example, the fish index of biotic integrity (Karr, 1981), uses linguistic terms such as ‘poor’, ‘good’, and ‘excellent’. Several studies have demonstrated the utility of ANNs and fuzzy logic over linear regression methods in ecological settings (Lek et al., 1996; Einheuser et al., 2012; Einheuser et al., 2013a, Hamaamin et al., 2013). Fuzzy models have been used in development of environmental condition indices (Lermontov et al., 2009; Marchini et al., 2009), modeling wetland conditions (Mah and Bustami, 2012), and predicting habitat suitability (Mouton et al., 2009), algal biomass (Chen and Mynett, 2003), macroinvertebrate taxa (Adriaenssens et al., 2006; Einheuser et al., 2012), biotic integrity of fish (Einheuser et al., 2013a), baseflow (Hamaamin et al., 2013), and water quality (Ocampo-Duque et al., 2006). Similarly, ANNs have been used to link biological integrity to stream habitat and geomorphic conditions (Mathon et al., 2013), and model macroinvertebrate assemblages (Park et al., 2003a; Compin and Céréghino, 2007; Lencioni et al., 2007; Mouton et al., 2010) and brown trout density (Lek et al., 1996). Studies have been particularly successful in combining ANNs and fuzzy logic using adaptive-neuro fuzzy inference systems (ANFIS) to model biotic integrity of macroinvertebrates (Einheuser et al. 2012; Einheuser et al., 2013b) and fish (Einheuser et al., 2013a). Due to these recent successes, ANFIS was used to model stream health in this study. However, variable selection in ANFIS has no commonly agreed upon methods (Einheuser et al., 2012) and the number of variables needs to be controlled to limit noise.

Given the large array of variables and their numerous selection techniques available, there is a lack of guidance on how to proceed when developing stream health prediction models. Meanwhile, limiting the number of predictor variables used in ANFIS is critical to reduce the fuzzy logic rule set size and improve efficiency (Chen and Mynett, 2003), because the number of if-then rules in fuzzy logic is a function of the number of input variables and membership functions (MFs) (Mahabir et al., 2006). This study explores multiple model parameterization methods ranging from simple (Spearman's Rank Correlation) to complex (Bayesian variable selection), and then use those variables in model development for prediction of four stream health measures. The specific objectives of this study were to: (1) identify appropriate scales for stream health modeling, (2) select variable sets for further exploration in four stream health models, and (3) develop predictive models for stream health measures.

4.2 Materials and Methods

4.2.1 Study Area

The River Raisin watershed, hydrologic unit code 04100002, is located in southeastern Michigan and a small portion of northern Ohio (Figure 1). The watershed drains an area of 2,757 km^2 into Lake Erie. Historically, the River Raisin watershed was dominated by wetlands and hardwood forest (Roth et al., 1996). The watershed is now representative of many agricultural river systems in the Great Lakes region (Allan et al., 1997). Currently, land use/land cover in the watershed is distributed between agricultural row crops (53%), pasture (16%), forest (12%), urban/developed (11%), wetlands (7%), and open water (1%). Topography is hilly and rolling in the western and northwestern regions and comparatively flat in the southeast. Underlying soils in the watershed are dominated by sandy loams, loams, and clay loams with moderate/high infiltration rates in the northwest, while in the southeast soils are clay, clay loams, and silty clays with lower infiltration rates (Dodge, 1998). The River Raisin watershed is considered one of the most biologically rich watersheds in Michigan (Allan et al., 1997).

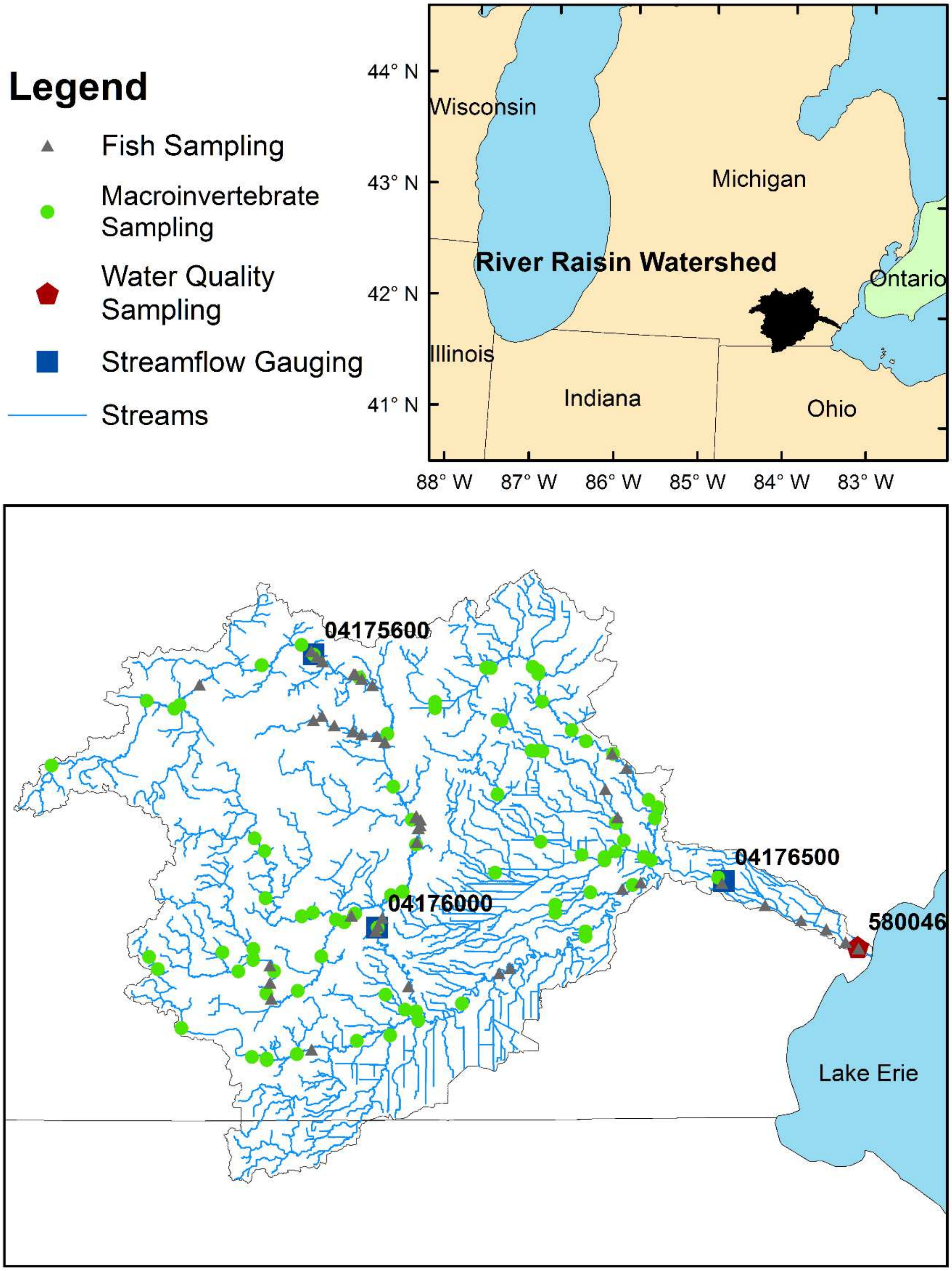

Figure 1. River Raisin watershed

4.2.2 Data Collection

4.2.2.1 Physiographic Data

Various spatial and temporal datasets were collected to characterize the physiographic features of the River Raisin watershed. Spatial datasets include topography, land use/land cover, and soils. Topography was obtained from the United States Geological Survey (USGS) in the form of the 30 m spatial resolution National Elevation Dataset (NED, 2014). Land use/land cover data was obtained from the United States Department of Agriculture (USDA) – National Agricultural Statistics Service (NASS) in the form of the 2012 Cropland Data Layer (CDL), which has a 30 m spatial resolution (NASS, 2012). Tabular and spatial soil data was obtained at the county level from the Natural Resources Conservation Service (NRCS) Soil Survey Geographic (SSURGO) Database (NRCS, 2014). Spatial information in SSURGO, which includes physical and chemical soil properties, was gathered at scales ranging from 1:12,000 to 1:63,360. Climate data was obtained from the National Climatic Data Center (NCDC). Continuous daily precipitation and temperature data were available at five and four locations, respectively from 1988-2009.

Predefined streams and subwatersheds layers were obtained from the Great Lakes Regional River Database Classification System prepared by the Michigan Institute for Fisheries Research (IFR). Both datasets are based on the 1:24,000 resolution National Hydrography Dataset Plus. The database divides the stream network into confluence-to-confluence stream reaches, where each subwatershed contains an individual stream reach representing a stretch of homogeneous physicochemical, geomorphological, and biological features (Einheuser et al., 2013). Using this database, the River Raisin watershed contains 1,235 individual stream segments and associated subwatersheds.

4.2.2.2 Biological Data

There are several advantages of using both macroinvertebrates and fish as indicators of stream health (Barbour et al., 1999). Macroinvertebrates are useful as stream health indicators because they react to localized impacts (sessile lifestyle or limited migration), assemblages are comprised of species that constitute a broad range of trophic levels and pollution tolerances, and they respond to short-term variations in environment (Barbour et al., 1999). Macroinvertebrate measures of stream health used in this study were number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family-level Index of Biotic Integrity (FIBI), and the Hilsenhoff Biotic Index (HBI). EPT taxa is a count that quantifies the taxonomic richness of common pollutant-intolerant macroinvertebrate orders, and their presence/absence is widely used as an indicator of the level of stream disturbance or degradation (Sponseller et al., 2001). FIBI is a multi-metric index comprised of information on macroinvertebrate composition (e.g., percent shredders) and richness (e.g. total number of taxa) at a family-level taxonomic resolution. FIBI has a range of 0-45, with 45 being excellent stream health. HBI is an organic pollution-tolerance index for macroinvertebrate taxa based on taxon-specific tolerance values (Hilsenhoff, 1988). Ranging from 0-10, 0 indicates excellent health and 10 indicates very poor health. Locations of macroinvertebrate sampling are presented in Figure 1, while histograms of each macroinvertebrate stream health measure within the study area are presented in Figure 2. Each measure was divided into five stream health classes (very poor, poor, fair, good, and excellent) by splitting the entire Michigan macroinvertebrate health measure dataset (2634 data points) into quintiles (Table 2).

Table 2. Stream health classes for EPT taxa, FIBI, HBI, and IBI

Measure	Very Poor	Poor	Fair	Good	Excellent
EPT taxa	0-2	3-5	6-7	8-10	>10
FIBI	0-8	9-14	15-20	21-23	24-45
HBI	5.5-10	5.1-5.4	4.7-5.0	4.4-4.6	0-4.3
IBI	0-19	20-29	30-49	50-64	65-100

Fish are useful as stream health indicators because they represent long term effects and broad habitat conditions (long-lived and mobile) and fish assemblages are comprised of species that represent many trophic levels (e.g. planktivores, herbivores, insectivores, piscivores) (Barbour et al., 1999). The Index of Biotic Integrity of fish (IBI) is a multi-metric index detects divergence from biological integrity that is attributable to human actions (Karr, 1999). Broadly based and ecologically sound, evaluates human effects on a stream by integrating many fish community measures of richness, composition, and abundance (Wang et al., 2007). IBI was developed based MDEQ (1997) methods for warmwater streams and ranges from 0-100, where 100 indicates excellent stream health. Locations of fish sampling are presented in Figure 1, while a histogram of the IBI samples within the study area are presented in Figure 2. Stream health classes for IBI are derived from Lyons (1992) and presented in Table 2.

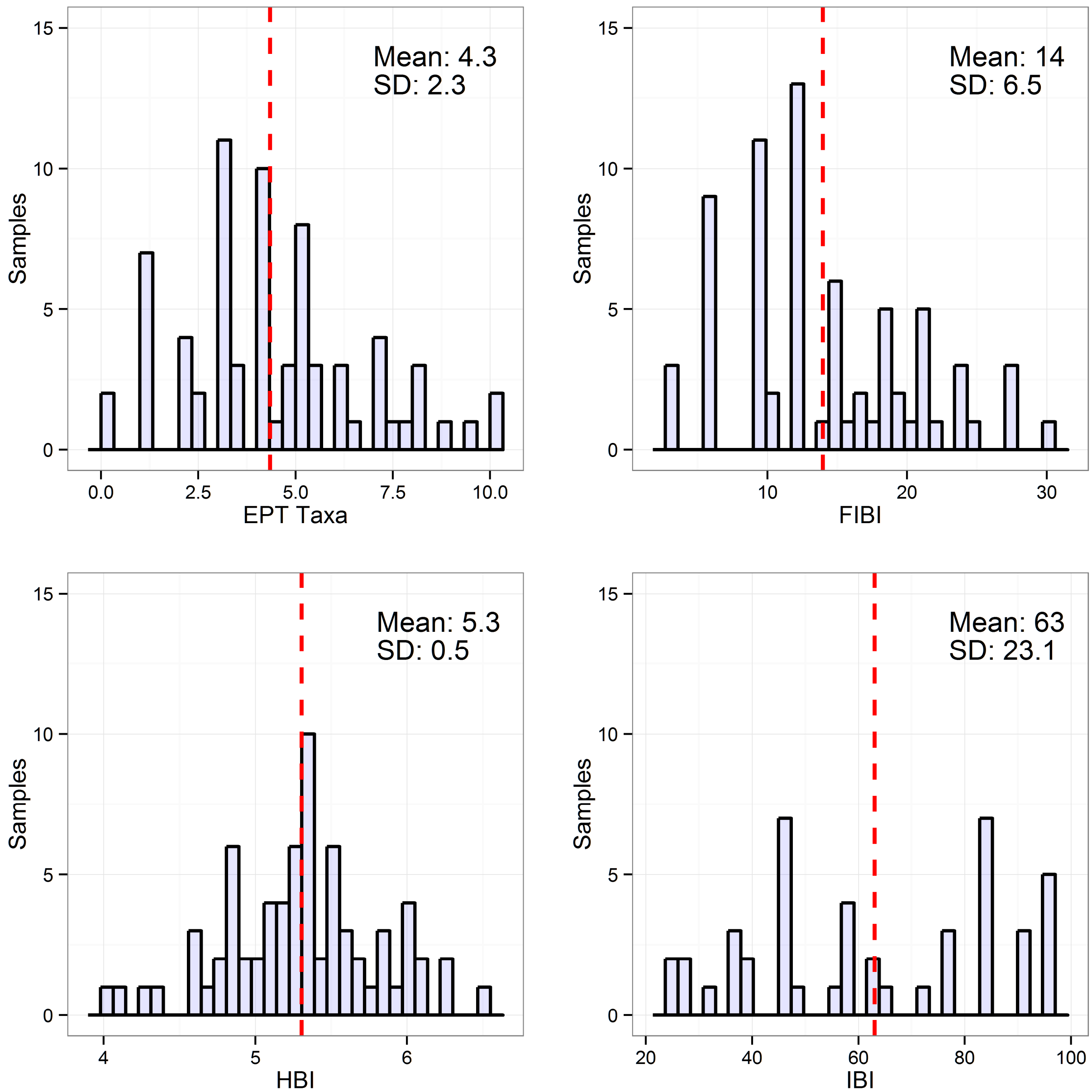

Figure 2. Data distribution of stream health samples

Biological data was obtained at 71 sites for benthic macroinvertebrates and 45 sites for fish in the River Raisin watershed (Figure 1). Macroinvertebrate sampling was performed by the Michigan Department of Environmental Quality from 1996-2003 in June through September (MDEQ, 1997). Stream sampling length was between 30 m and 100 m, where the goal was to collect approximately 300 ± 60 organisms over a minimum of 20 minutes per site (Einheuser et al., 2012). Fish data were obtained from the Michigan River Inventory database (Seelbach and

Wiley, 1997) and Michigan Department of Natural Resources monitoring program, where single-pass sampling occurred in wadeable streams along 80-960 m stretches and along lengths of 1,610 m in non-wadeable streams between 1982-2007 (Einheuser et al., 2013). The sampling data was used to develop three macroinvertebrate measures and one fish measure as described above for characterizing stream health.

4.2.3 Modeling Process

A multi-step modeling process was used to simulate the four stream health measures in the River Raisin watershed (Figure 3). First, we use Soil and Water Assessment Tool (SWAT) to generate daily time-series streamflow, sediment, and nutrient data for every stream in the watershed. The streamflow data was input into the Hydrologic Index Tool to calculate 171 hydrologically significant flow regime variables. Flow regime variables and sediment and nutrient concentration variables were grouped by three methods: all streams (no-grouping), *k*-means clustering, and by stream order. Variable selection was performed within each group using three methods (Bayesian variable selection, PCA, and Spearman's rank correlation) to produce best variable sets. Each variable set and grouping combination was used to build ANFIS models that predict stream health measures (EPT taxa, FIBI, HBI and IBI). Final best model selection (a combination of stream grouping method, variable selection method, and ANFIS model characteristics) for each stream health measure was based on multiple performance measures.

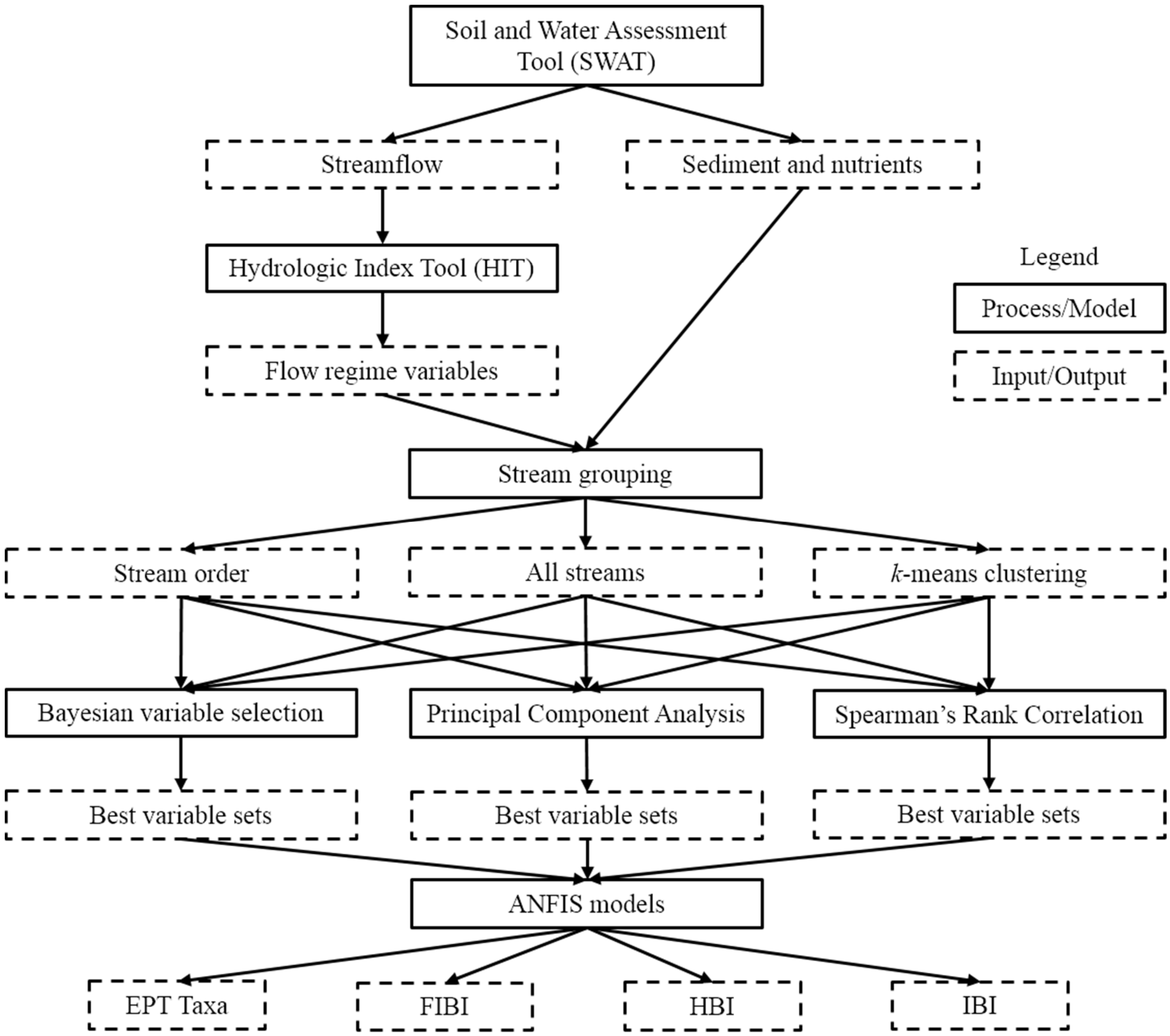

Figure 3. Stream health variable selection and modeling process

4.2.4 Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT version 2012) is a physically based, semi-distributed watershed/water quality model widely used for water resources planning and decision-making (Neitsch et al., 2005). Developed by the USDA – Agricultural Research Service, SWAT predicts the impact of management practices and climate change on hydrology and sediment, nutrient, pesticide, and bacteria yields on a daily time-step over long simulation periods (Arnold et al., 1998). SWAT simulates various processes of a watershed system, including surface runoff, soil erosion, evapotranspiration, nutrient cycling, crop growth, streamflow routing, sediment deposition and entrainment, bacterial growth and die-off, and pesticide transport (Gassman et al., 2007).

SWAT delineates a watershed into multiple subwatersheds based on topography and stream networks. Subwatersheds are further discretized into unique hydrologic response units (HRUs). An HRU is defined as an area of homogeneous land use, soil type, slope, and management operations. In this study, we used predefined Michigan IFR layers that divided the watershed into individual reaches and subwatersheds. Each subwatershed represents a stretch of homogeneous physicochemical, geomorphological, and biological features. Therefore, in each subwatershed, the dominant land use, soil type, and slope were selected for HRU definition in SWAT.

4.2.4.1 SWAT Model Calibration and Validation

Model calibration was performed by modifying input parameter values and comparing model output values (such as time-series stream discharge) with corresponding measured data (White and Chaubey, 2005). Calibration was satisfactory after meeting some statistical criteria, such as minimization of error or optimizing the Nash-Sutcliffe model efficiency coefficient (NSE). Model validation was performed by comparing the calibrated model output with measured data for a time-period independent of the calibration period (Moriasi et al., 2007).

Three statistical criteria were used to ensure the model was calibrated and validated: NSE, root-mean-square error-observations standard deviation ratio (RSR), and percent bias (PBIAS). Moriasi et al. (2007) developed model evaluation guidelines for each parameter with recommended performance ratings on a monthly time-step. Calibration is considered satisfactory for any parameter at NSE > 0.50 and RSR < 0.70. Acceptable PBIAS varies by parameter, where streamflow calibration is satisfactory at PBIAS < |25%|, sediment at PBIAS < |55%|, and nutrients at PBIAS < |70%|.

The River Raisin watershed SWAT model was calibrated and validated for streamflow, sediment load, nitrate (NO_3) load, nitrite (NO_2) load, and total phosphorus (TP) load on a daily time-step. Locations of streamflow gauging stations (USGS 04175600, 04176000, and 04176500) and sediment and nutrient sampling (580046) are presented in Figure 1.

4.2.5 Stream Characterization

Following calibration, SWAT was run from 1988-2009 on a daily time-step. The first two years (1988-1989) were used for the model initialization period. Based on the SWAT model output, daily streamflow, sediment, and nutrient concentrations were obtained for all 1,235 reaches in the study area. Flow regime was characterized using the USGS Hydrologic Index Tool (HIT version 1.48) (Henriksen et al., 2006). The HIT calculated 171 biologically relevant hydrologic indices using daily and peak flow data, where the indices were divided into the five major components of flow regime (magnitude, frequency, duration, timing, and rate of change). The hydrologic indices were partitioned into five categories (M, magnitude; F, frequency; D, duration; T, timing; and R, rate of change) and type of flow event (A, average; L, low; and H, high). Flow regime characterization required continuous daily streamflow data for each stream reach in the RRW from the beginning of the 1990 water year (October 1, 1989) through the end of the 2009 water year (September 30, 2009).

In addition to flow, seasonal and annual sediment and nutrient concentrations were also characterized for each reach. The specific nutrients were organic nitrogen (OrgN), nitrate (NO_3), nitrite (NO_2), ammonium (NH_4), organic phosphorus (OrgP), and mineral phosphorus (MinP). Seasons were defined as December-January-February (DJF), March-April-May (MAM), June-

July-August (JJA), and September-October-November (SON), and annual (ANN). The seven water quality components defined across five time periods (annually and four seasons) resulted in 35 concentration measures. Combining the 171 hydrologic indices and the 35 sediment and nutrient concentration measures, there were 206 variables from which to develop EPT taxa, FIBI, HBI, and IBI prediction models.

4.2.6 Stream Grouping

Stream size has been reported as a key predictor of species richness and presence (Pont et al., 2009). Due to large variability in flow regime characteristics and composition of the organisms in different sections of the stream network, streams were grouped to improve predictability of stream health measures. In this study, two methods were used to group stream networks within the study area. The first method partitions streams based on the stream order and the second method partitions streams into *k* clusters based on the nearest mean. The results were compared with a no grouping scenario (all streams) in which one predictive model is used for all stream segments within the watershed.

4.2.6.1 Stream Order

Stream order was calculated for all streams using the Strahler stream order (Strahler, 1957). Based on the River Continuum Concept developed by Vannote et al. (1980), streams were grouped into headwaters (orders 1-3) and medium-sized streams (orders 4-6). This grouping considers broad characteristics of lotic communities that vary according to stream size from headwaters to river mouths.

4.2.6.2 K-Means Clustering

As an alternative to the River Continuum Concept for grouping streams, a data-driven method known as *k*-means clustering was used. It was hypothesized that grouping streams based on their physicochemical characteristics may approximate ecological behavior as defined in the River Continuum Concept. The original data was standardized by computing each value's z score, and then PCA with the Euclidean distance metric was applied. This resulted in 206 new variables (principal components) computed from the correlation, and given by a linear combination of the original data. The data were then grouped into two clusters (C1 and C2) using *k*-means. This unsupervised learning technique was parameterized with two initial points and the Euclidean metric.

We define each of the measurements of a particular stream reach as its *d*-many features. Each reach, *X*, will then be represented in a *d*-dimensional Euclidean vector space as X = (x_i, $x_2,\ldots,x_d$) with the value of feature *i* as x_i. We do not impose any grouping on the reaches, rather we rely on the unsupervised clustering method of k-means discover the latent class labels. Given a set of these *n* *d*-dimensional points, *k*-means will partition the set into *k* distinct clusters, C = $\{c_1, c_2, \ldots c_k\}$ where the sum of the squared error between the mean of each c_i and its members is minimized (Equation 1).

$$Error(c_j) = \sum_{x_i \in c_j} \left\| x_i - \mu_j \right\|^2 \tag{1}$$

Where μ_j is the empirical mean of cluster c_j. The overall objective is to minimize the error over all clusters (Equation 2).

$$Error(C) = \sum_{j=1}^{k} \sum_{x_i \in c_j} \left\| x_i - \mu_j \right\|^2 \tag{2}$$

An optimal clustering solution via *k*-means is achieved when the sum of the squared error over the set of all possible clustering solutions, $\boldsymbol{C}$, is minimized. (Equation 3).

$$\min_{C \in \boldsymbol{C}} \sum_{j=1}^{k} \sum_{x_i \in c_j} \left\| x_i - \mu_j \right\|^2 \tag{3}$$

The number of clusters and the distance metric are user-defined parameters. In this study, two clusters were calculated with the standard Euclidean distance metric.

The computation of the minimum value is non-deterministic polynomial-time hard, so a computationally feasible implementation of an algorithm with this objective function will converge to a locally, but not necessarily globally, optimal solution. Implementation of *k*-means is greedy and computationally fast. This algorithm selects initial centroids, assigns all points to the nearest centroid, and updates the centroid as the mean of each cluster. The process stops when the centroids no longer change after a defined number of iterations. A description of the model implementation pseudocode is presented in Appendix A.

4.2.7 Variable Selection

Given the large number of variables characterizing the flow regime and water quality conditions in each reach, a variable selection procedure was required to eliminate redundant variables. The number of predictor variables used in ANFIS is limited by available stream health data, necessitating a maximum of three variables. Three methods were explored to select variables for use in the biological models to predict stream health: Spearman's Rank Correlation, PCA, and Bayesian variable selection. The first two methods are widely used in ecological settings but the application of Bayesian variable selection is new in this field.

4.2.7.1 Spearman's Rank Correlation

Spearman's rank correlation is a nonparametric measure of statistical dependence between two variables, and has been used for variable selection and redundancy reduction in multiple studies related to predicting stream health measures (Maret et al., 2010; Waite et al., 2010; Einheuser et al., 2012; Einheuser et al., 2013). Spearman's rank correlation coefficient (ρ) was calculated for all variable pairings. Predictor variables (flow regime and water quality variables) that exhibited significant correlation ($\rho < 0.05$) with each of the stream health indices (EPT taxa, FIBI, HBI, and IBI) were identified. Independent variables with the highest ρ were selected. Of selected predictor variables that had high correlations ($\rho > |0.7|$) with each other, the one with the weakest correlation with the stream health measure was removed from consideration (Wang et al., 2008; Waite et al., 2010).

4.2.7.2 Principal Component Analysis

Principal component analysis orthogonally transforms the dataset of predictor variables (in which the variables may be correlated) into a new set of values that are linearly uncorrelated (Pearson, 1901). These new values are known as principal components (PCs), where the number of PCs is equal to the number of variables in the original dataset. In the transformed dataset, the first PC (PC1) is defined such that it accounts for as much of the variability in the dataset possible, i.e. it has the largest variance (Jolliffe, 2005). The remaining components capture non-increasing amounts of variance, but have the highest variance possible given that they are orthogonal (uncorrelated) to the preceding components. Therefore, the dataset can be described with only the first few PCs that capture most of the dataset's variance.

Individual variable PC loadings are the correlation coefficients between the PC score and original variables; they indicate the importance of that variable in accounting for the PC's variability. Therefore, the individual variables can be extracted to interpret the PC and the dataset's variation. Variables with the greatest component loadings were extracted from the PC1 to develop one variable set. In addition, the variable with the greatest component loading from each of the top three principal components (PC1-PC3) was extracted to create a new set of three variables. Finally, the transformed coefficients of the first three PCs were used as variables in model development.

4.2.7.3 Bayesian Variable Selection

Bayesian variable selection was used to identify a subset of important variables from the independent variable set. The Bayesian framework assumes that the combinations and number of relevant variables that yields the most predictive power are random. Therefore, they can be sampled by combining the data evidence and uniform prior weights on all such possible combinations. Given $\boldsymbol{I}$ as a combination of q variables that have been selected, Equation 4 is defined as follows:

$$\boldsymbol{Y} = \boldsymbol{X_I} \beta_{\boldsymbol{I}} + \boldsymbol{\varepsilon} \quad (4)$$

Where $\boldsymbol{X_I}$ contains the subset of predictors under $\boldsymbol{I}$ and $\beta_{\boldsymbol{I}}$ is the corresponding regression coefficients. The error term $\boldsymbol{\varepsilon}$ is assumed to follow a normal distribution with mean zero and variance τ^2 that measures the unexplained information, which can be written as $\varepsilon_j \sim N(0,\tau^2)$ independently. We also assume $\beta_j \sim N(0,\lambda\tau^2)$ independently for each index j in $\boldsymbol{I}$, with the scale parameter λ that measures the overall detectability, or signal-to-noise ratio, for the important variables. Because the signal-to-noise ratio can be affected by the scale of the variables, the data is standardized before implementing the variable selection procedure. The intercept for capturing the grand mean of the dependent variable $\boldsymbol{Y}$ is also included.

For the Bayesian model implementation, the reversible jump Markov Chain Monte Carlo (MCMC) technique (Green, 1995) is used for drawing posterior samples of $\boldsymbol{I}$, which involves varying dimensionality, i.e., a different number of regression parameters $\beta_{\boldsymbol{I}}$. More specifically, with a randomly initialized $\boldsymbol{I}$, each time a new index set $\boldsymbol{I}^*$ is proposed by either adding another variable or excluding one existing variable, we compare the model likelihood suggested by the data to determine if we should either accept $\boldsymbol{I}^*$ or keep $\boldsymbol{I}$. We then update the corresponding parameters $\{\beta_{\boldsymbol{I}}, \tau^2, \lambda\}$ following the standard Gibbs sampler procedure that samples one set of parameters from the full conditional posterior density given the remaining parameters. The complete procedure is repeated many times until the convergence of multiple MCMC runs with distinct initializations is committed. For detailed model implementation, refer to Appendix B.

For each of the four dependent variables (EPT taxa, FIBI, HBI, and IBI), we proceed with five MCMC runs with distinct initial numbers of selected independent variables and hence distinct initial values for the remaining parameters. For each chain we run 150,000 iterations. The convergence is well commmitted after a burn-in period of the first 100,000 iterations. The remaining 50,000 samples per chain are stacked and a sample is drawn at every 10th iteration. Therefore, 25,000 posterior samples of $\{\boldsymbol{I}, \beta_{\boldsymbol{I}}, \tau^2, \lambda\}$ are obtained for inference. For example, one can obtain the posterior distribution of the number of variables q to measures its uncertainty and obtain the corresponding 95% credible set, which is typically lacking under traditional variable selection approaches.

The posterior samples provide estimates and uncertainties from a variable-wise summary. This is conditional on the k-th variable selected $k \in \boldsymbol{I}$, and the corresponding $\beta_{\boldsymbol{I}}$ (posterior mean, 95% credible set that is constructed using the 2.5% and 97.5% quantile of the posterior samples). The *selectivity*, as a measure of importance for the specific variable, is defined as the probability of being selected out of all posterior samples for the variable. Selectivity directly compares the importance of the variables. Variables with the greatest selectivity were chosen for further use for development of stream health predictive models.

4.2.8 ANFIS and Best Model Selection

Predictive models were created using fuzzy logic for each of the stream health indices. Input variables are defined using graphical MFs. An MF is a curve that determines an input value's degree of membership in a particular class. Here, a membership value of zero represents no membership and one represents full membership in a class.

Building MFs and inference rules is one of the most challenging tasks in modeling with fuzzy logic (Chen and Mynett, 2003; Huang et al., 2010) and is often subjective (Adriaenssens et al., 2004) and time consuming (Huang et al., 2010). Given these limitations, a hybrid approach called adaptive-neuro fuzzy inference system (ANFIS) was used to optimize MF development. ANFIS uses artificial neural networks (ANNs) to construct and tune MFs by minimizing output error for use in fuzzy logic (Jang, 1993).

The ANFIS models were built using the Fuzzy Logic Toolbox in MATLAB R2013b (MathWorks, 2013). Five MF shapes were tested and up to four MFs were created for each variable. Triangular and trapezoidal MFs are linear and are commonly used because of simplicity (Adrieanssens et al., 2004; Marchini, 2011). The remaining MFs, generalized bell (Bell), Gaussian and Gaussian composite (GaussC), are nonlinear and better suited to ecological data (Marchini, 2011). A limit of three variables was imposed on model creation. The numbers of variables and MFs per variable limits are based on the size of the macroinvertebrate and fish datasets, where the number of samples cannot exceed the number of modifiable parameters when building ANFIS MFs. The number of modifiable parameters in building an ANFIS model is a function of the number of variables, MFs per variable, and shape of the MF. All possible combinations of number of MFs (two to four) for two and three variable sets were developed under each MF type. A total of 180 ANFIS models for each stream health measure were created using these options. Following determination of number of variables, MF types and number of MFs per variable, the ANFIS models were trained and tested.

Cross-validation was used to train, test, and select the best ANFIS model. Specifically, k-fold cross-validation was used because it is effective in situations where more data cannot be collected, prevents over-fitting during model construction, and helps in best model selection (Mahmood and Khan, 2009). In k-fold cross-validation, the dataset is randomly split into k mutually exclusive subsets (folds) of approximately equal size (Kohavi, 1995). Here, ten folds were used, which is common practice in many fields (Mahmood and Khan, 2009). The ANFIS models (based on MF type and number of MFs per variable) were trained on nine folds (90% of the data) and tested on the remaining fold (10% of the data). This process was repeated ten times, with one fold being removed from model training and used for testing each time. Unique folds were created for each distinct MF type and number of MFs per variable combination. Two performance measures, coefficient of determination (R^2) and root-mean-square error (RMSE), were calculated for each testing dataset and averaged across the ten ANFIS models. The highest average R^2 and lowest average RMSE was used to select the best ANFIS model.

Following selection of the best general ANFIS model (MF type and number of MFs per variable), the best individual model from ten-fold cross validation was selected for each stream health measure and stream grouping. Final best model selection was accomplished by testing each model on all ten sets of test data (10% of the data) (Hamaamin et al., 2013). Once again, the highest average R^2 and lowest average RMSE was used to select the best ANFIS model from the best MF type and number of MFs per variable combination. When predicted values were beyond the minimum or maximum of the stream health measures they were adjusted to the minimum or maximum values.

4.3 Results and Discussion

4.3.1 SWAT Model Calibration and Validation

Streamflow was calibrated from 1996-2000 and validated from 2001-2005 at three USGS locations (streamflow gauging stations 04175600, 04176000, and 04176500), with a two year model initialization period (1994-1995). Based on grab sample data availability for sediment and nutrients, these parameters were calibrated from 2000-2002 and validated from 2003-2005 at one location (station 580046). Results of the calibration and validation are presented in Table 3. Time-series observed and simulated streamflows are presented in Figure 27 of Appendix C. Based on the criteria described by Moriasi et al. (2007), the model was successfully calibrated and validated for all parameters and locations.

Table 3. River Raisin watershed calibration and validation results

Parameter (station)	Calibration			Validation		
	NSE	RSR	PBIAS	NSE	RSR	PBIAS
Streamflow (04175600)	0.54	0.68	14.6%	0.47	0.73	1.6%
Streamflow (04176000)	0.64	0.60	14.5%	0.46	0.73	11.1%
Streamflow (04176500)	0.76	0.49	13.4%	0.61	0.62	5.7%
Sediment (580046)	0.57	0.65	24.1%	0.50	0.71	-18.7%
NO_3 (580046)	0.97	0.78	11.5%	0.58	0.64	31.5%
NO_2 (580046)	0.60	0.63	-36.1%	0.58	0.65	13.9%
TP (580046)	0.78	0.47	-0.9%	0.58	0.65	-31.5%

4.3.2 Stream Grouping

Streams were clustered into two groups using the River Continuum Concept (stream order 1-3 and order 4-6) and *k*-means clustering on the hydrologic indices and pollutant concentrations data. Stream order and cluster groupings are presented in Figure 4. The two clusters were expected to emulate the stream order grouping, where cluster 1 (C1) is similar to stream orders 1-3 and cluster 2 (C2) is similar to stream orders 4-6. Clustering was equivalent to stream order for 80% of the streams in the study area. Streams of order 1-3 were classified as C1 at a rate of 80%, while streams of order 4-6 were classified as C2 at a 75% rate. Therefore, there was a 20% difference between order 1-3 and C1, and a 25% difference between order 4-6 and C2.

The difference in clustering and stream order methods occurs in two key watershed locations. C2 extends further into the northwestern headwaters of the River Raisin watershed, classifying many order 1-3 streams as C2. This area is the headwaters of the River Raisin, the largest and longest river in the watershed. This also occurs for the watershed's other major river (the Saline River) in the northeastern headwaters. The clustering procedure identified the two major river systems in the watershed and grouped them based on their flow regime and water quality attributes. However, because most of the variables are streamflow-driven, the similarity within each cluster is primarily due to similarities in flow parameters rather than water quality parameters.

Using *k*-means clustering to designate headwaters (order 1-3) versus midreaches (order 4-6) could be a robust alternative to the River Continuum Concept, as it generally reproduces these traditional stream classifications. However, the River Continuum Concept does not take into account stream disturbances such as floods, (Junk et al., 1989) and hypothesizes an ideal ecological system (Statzner and Highler, 1985). By clustering streams based on their hydrologic and pollutant concentration characteristics, a more realistic grouping of similar streams may be produced for later use in variable selection and model development.

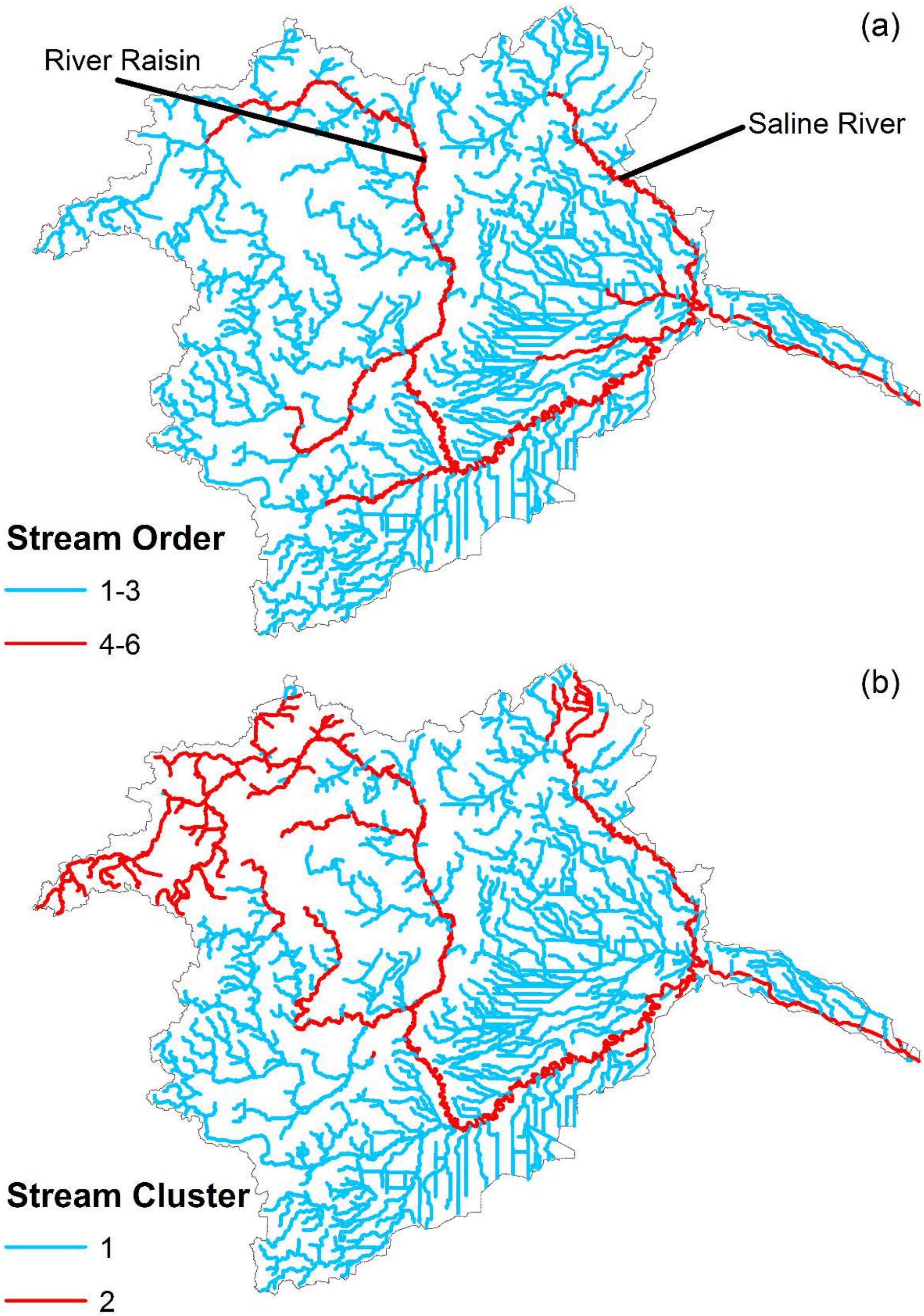

Figure 4. Stream order grouping (a) and stream cluster grouping (b)

4.3.3 Variable Selection

Variable selection was completed for each method (Spearman's rank correlation, Bayesian variable selection, and multiple PCA variable sets), stream health measure (EPT Taxa, FIBI, HBI, and IBI), and stream grouping (all streams, stream order 1-3, stream order 4-6, cluster 1, and cluster 2). The top three variables selected using these methods are presented in Table 4 for all streams. Variable selection for the remaining stream groupings are presented in Table 14 through Table 17 of Appendix C.

Table 4. Variable selection for all streams

Method		EPT Taxa	FIBI	HBI	IBI
Spearman (ρ)		MA4 (-0.67) OrgPson (-0.61) MA26 (-0.58)	MH24 (-0.64) ML2 (0.54) DL11 (0.51)	SEDjja (0.64) DH14 (0.57) RA5 (-0.50)	TA1 (0.82) MA34 (-0.81) NO_3djf (-0.72)
Bayesian (selectivity)		FH10 (0.49) MA35 (0.28) RA5 (0.20)	MA3 (0.12) MA35 (0.11) MA39 (0.11)	NO_3son (0.65) NO_3djf (0.16) RA8 (0.14)	DH22 (1.00) TL3 (0.99) RA9 (0.98)
PCA	PC1 (loading)	ML2 (0.75) MA45 (-0.53) ML1 (0.28)	ML2 (0.75) MA45 (-0.53) ML1 (0.28)	ML2 (0.75) MA45 (-0.53) ML1 (0.28)	ML2 (0.75) MA45 (-0.53) ML1 (0.28)
PCA	PC1 to PC3 (loading)	ML2 (0.75) MA28 (0.36) ML13 (-0.45)	ML2 (0.75) MA28 (0.36) ML13 (-0.45)	ML2 (0.75) MA28 (0.36) ML13 (-0.45)	ML2 (0.75) MA28 (0.36) ML13 (-0.45)
PCA	PC1 to PC3 (variation explained)	PC1 (30.0%) PC2 (17.5%) PC3 (10.9%)	PC1 (30.0%) PC2 (17.5%) PC3 (10.9%)	PC1 (30.0%) PC2 (17.5%) PC3 (10.9%)	PC1 (30.0%) PC2 (17.5%) PC3 (10.9%)

Variable selection by method: Unique variable sets were selected for each stream health measure using Spearman's rank correlation and Bayesian variable selection in all stream groups. Variable selection using PCA (PC1: top three variables from the first PC, and PC1 to PC3: top variable from each of the first three PCs) is the same regardless of stream health measure because PCA is a non-dependent procedure (a response variable is not specified). Individual variables extracted from PCA are presented with their loading scores, while the percentage of variation explained is presented for the top three principal components. Spearman's ρ (correlation with stream health measure) is presented for Spearman's rank correlation. All selected variables have a significant ρ at α=0.05. Selectivity (percentage of times variable was selected for model building) is presented for Bayesian variable selection. Component loading (correlation of each variable with its principal component) is presented for both PCA methods.

Diverse variable sets were identified for all variable selection methods (Table 4 and Table 14 through Table 17 in Appendix C). Spearman's rank correlation and Bayesian variable selection produced multiple unique variable classifications for each stream health index and grouping. For example, under all streams for HBI (Table 4), sediment concentration (SED), duration (DH), and rate of change (RA) variables were selected. Rate of change/flashiness variables are consistently of high importance across all stream groupings and stream heath indices for these two variable selection methods. Among this variable set, RA5 (number of days in which flow is greater than the previous day) and RA9 (variability in flow reversals) are the most common. Individual selectivity of variables in Bayesian variable selection is low in many cases, such as for FIBI (Table 4). Given the low selectivity of the most important variables, it is possible that the resultant ANFIS created from these variables will have low predictive power. However, for other stream health measures (IBI and HBI in Table 4) the highest ranked variables have high selectivity, which may lead to better predictions in the ANFIS models.

While resultant variable sets from Spearman's rank correlation and Bayesian variable selection were diverse, this was not the case for the PCA methods. Individual variables extracted from PCA consistently include related average (MA), low (ML), and high magnitude (MH) hydrologic indices (Table 4). This is not surprising when selecting the variables within PC1, because their high loading indicates high correlation with PC1 and with each other. Magnitude variables (MA, ML, and MH) also had highest loading in PC1-PC3, indicating that magnitude variables explain most of the dataset's variation. Of the principal components themselves, the sum of their explained variance is 58% for all streams, while it is lower for order 1-3 and C1 (54% and 55%, respectively) and higher for order 4-6 and C2 (84% and 74%, respectively). The lower percentage of explained variance for all streams, order 1-3, and C1 indicates that these variables (PC1, PC2, and PC3) may not adequately predict stream health because they do not capture enough of the dataset's variance.

EPT taxa variable selection: Variables selected for EPT taxa models were diverse, although magnitude and rate of change variables were commonly included in most stream groupings for Spearman's rank correlation and Bayesian variable selection. Pollution concentrations selected through Spearman's rank correlation exhibit negative correlation with EPT taxa: higher concentrations result in reduced presence of sensitive macroinvertebrates, as exhibited for all streams (Table 4), order 4-6 (Table 15 of Appendix C), and C2 (Table 17 of Appendix C). A single frequency variable was also commonly identified using Bayesian variable selection (FH10: number of flows above the median of the annual minima) and was positively correlated with EPT taxa, demonstrating that consistent flows above annual minimums are beneficial to sensitive macroinvertebrates.

FIBI variable selection: Variables important to FIBI often characterize magnitude and nitrogen concentrations. Magnitude variables are important for all streams (Table 4), order 1-3 (Table 14 of Appendix C), and C1 (Table 16 of Appendix C). In the grouping of larger streams such as those in order 4-6 seasonal nitrogen variables are commonly selected (Table 14 of Appendix C). As expected, higher nutrient concentrations decreased macroinvertebrate integrity. Low flow duration (DL) was deemed important for FIBI in order 1-3 (Table 14 of Appendix C) and C1 (Table 16 of Appendix C) through Spearman's rank correlation. Here, there is a positive correlation between magnitude of low flow duration (DL2 and DL4) and FIBI; longer periods of extremely low magnitude flow are detrimental to macroinvertebrates. Meanwhile, in streams of order 4-6 (Table 15 of Appendix C), flood frequency (FH7 – average number of flow events above seven times the median flow) is highly negatively correlated with FIBI, indicating that increased frequency of extreme floods affects macroinvertebrate integrity. In a predominantly agricultural watershed with limited floodplain connectivity, as observed in the study area, these events are expected to occur with greater frequency because water is not able to dissipate onto a floodplain. A river's connection to a floodplain during high flow conditions maintains productivity and diversity (Poff et al., 1997), but this is inhibited by land use modification in the watershed and may result in lower FIBI.

HBI variable selection: Variables selected for HBI models prominently include sediment and nutrient concentrations, which is unsurprising given that the index is a measure of macroinvertebrate pollution tolerance. Of the pollution concentration variables related to HBI, seasonal nitrogen concentrations are the most common. The Spearman ρ values reveal that as pollution concentrations increase, HBI increases and stream health declines. Rate of change variables are also prevalent in most stream groupings for Spearman's rank correlation and Bayesian variable selection. For example, RA5 (number of days when flow is greater than the previous day) is negatively correlated (ρ=-0.50, Table 4). When streamflow magnitude increases regularly, pollution concentrations decrease and HBI improves. Meanwhile, the negative correlation between IBI and RA9 in stream order 4-6 (Table 17 of Appendix C) demonstrates that increased variability in streamflow is detrimental to fish communities. This is consistent with the concept of flow variability as a determinant of physical habitat, which itself is a determinant of biotic composition (Naiman et al., 2008). Streams with higher streamflow variability generally have comparatively worse biotic integrity in the study area.

IBI variable selection: Variables important for IBI were the most diverse of all stream health measures. For example, magnitude, duration, timing, rate of change, and seasonal nitrate concentration variables are all selected as important for all streams (Table 4), higher order streams (Table 15 of Appendix C), and C2 (Table 17 of Appendix C). Meanwhile, in order 1-3 (Table 14 of Appendix C) and C1 (Table 16 of Appendix C), average magnitude variables are the most commonly selected. DH22 (number of days between floods with a recurrence interval of 1.67 years) is selected by the Bayesian method in multiple instances (all streams, orders 4-6, and C2). Variability in average spring and autumn flow magnitudes are particularly important for smaller streams (order 1-3 and C1). More variability correlates with improved stream health, as these variables have large positive Spearman's ρ values. The importance of stream magnitude variability is unsurprising as it often dictates ecosystem function and biodiversity (Poff et al., 1997). Meanwhile, the prevalence of rate of change variables in each unique stream grouping demonstrates that variability in streamflow is plays a role in fish community health. This is consistent with the concept of flow variability as a determinant of physical habitat, which itself is a determinant of biotic composition (Naiman et al., 2008). Streams with higher streamflow variability as observed through RA variables generally have comparatively worse biotic integrity in the study area.

4.3.4 Best Model Selection

Best models for each variable selection method: Best ANFIS models for each stream health measure and variable selection method are presented in Table 5 for all streams. The best models for other stream groupings are presented in Table 18 through Table 21 of Appendix C.

Within each table, the individual best variable selection method/MF characteristics are highlighted for each stream health measure. Best models were determined by the lowest average RMSE and highest average R^2 across ten check datasets. ANFIS models are denoted by the MF type, number of variables, and number of MFs per variable. For example, the best Bayesian variable selection ANFIS model for HBI in Table 5 is GaussC (2/3), which indicates the Gaussian MF type with two variables, where the first variable has two MFs and the second variable has three MFs. This corresponds to the variables NO_3son and NO_3djf in Table 4 for HBI Bayesian variable selection. ANFIS models were not built for IBI under C1 and order 1-3 because the fish sampling dataset was not large enough to build ANFIS models or perform model checking. In these cases, there were nine IBI observations, where the number of modifiable parameters for all possible ANFIS models was always greater than this.

Table 5. ANFIS model average performance across 10-folds, no stream grouping, for best model (MF type and number of variables) under each variable selection method

Health Measure	Method	MF Type	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	Spearman	Trapezoid	2 (2/2)	1.234	0.695	1.493	0.633
	Bayesian	Triangle	2 (2/2)	1.332	0.655	1.438	0.622
	PCA	Triangle	2 (2/2)	1.409	0.625	1.494	0.534
	PCA PC1	Triangle	2 (2/2)	1.528	0.534	1.596	0.473
	PCA PC1-3	GaussC*	2 (2/2)	1.304	0.662	1.428	0.644
FIBI	Spearman	Triangle	3 (2/2/2)	3.794	0.617	5.161	0.452
	Bayesian	Triangle	2 (2/2)	4.655	0.461	5.017	0.452
	PCA	Triangle	2 (2/2)	4.579	0.479	5.235	0.356
	PCA PC1	Bell**	2 (4/3)	3.859	0.584	4.945	0.463
	PCA PC1-3	Gaussian	2 (2/3)	3.797	0.630	5.390	0.451
HBI	Spearman	Gaussian	2 (2/2)	0.338	0.521	0.380	0.467
	Bayesian	Gaussian	2 (2/3)	0.294	0.628	0.412	0.374
	PCA	Bell**	2 (2/3)	0.378	0.242	0.408	0.447
	PCA PC1	Triangle	2 (2/2)	0.396	0.346	0.440	0.335
	PCA PC1-3	Triangle	2 (2/3)	0.365	0.454	0.437	0.369
IBI	Spearman	Gaussian	2 (3/3)	4.131	0.945	7.094	0.839
	Bayesian	GaussC*	2 (2/2)	10.612	0.742	12.41	0.621
	PCA	Gaussian	2 (3/3)	3.082	0.764	3.470	0.938
	PCA PC1	Gaussian	2 (2/4)	1.763	0.984	3.926	0.939
	PCA PC1-3	GaussC*	2 (2/3)	5.045	0.936	6.917	0.857

*GaussC: composite Gaussian MF

** Bell: generalized bell MF

Each variable selection method produced a best ANFIS model that varied among stream grouping and health measures. Models created using Bayesian variable selection and Spearman's rank correlation were often the best. However, all three PCA methods also produced best models, as in the case of IBI in Table 5. Best variable selection methods also differed between stream health measures. For example, PCA selection methods always produced the best method for IBI. Therefore, when developing IBI prediction models with ANFIS, PCA should be used as the variable selection method. Bayesian variable selection and Spearman's rank correlation were more successful for the macroinvertebrate measures. However, the success of Spearman's rank correlation coupled with the method's simplicity suggests it can be used as an alternative to more complex methods such as Bayesian variable selection.

MF type selection for best models was generally diverse. All five MF types were selected at least once under each variable selection method and stream health measure. Most MF shapes were triangular for the macroinvertebrate measures across all stream groupings, while the shapes for fish IBI were either Gaussian or Gaussian composite (GaussC). The triangular MF was selected for over half of the models across all stream groupings/variable selection methods for FIBI and HBI. Number of EPT taxa was the only stream health measure where linear (triangular and trapezoidal) and nonlinear (generalized bell, Gaussian, and Gaussian composite) MF types were equally selected as the best across variable selection methods.

In terms of number of variables used, the two variable models overwhelmingly outperformed those with three variables. Further, these models generally used two MFs per variable, resulting in relatively simplistic (less parameterized) models. This was true for the four stream health measures.

Overall best variable selection methods and models: Table 6 lists the final best ANFIS models for each stream grouping method. Most of the best models were built with Gaussian-type MFs, supporting the findings of Marchini (2011) that nonlinear MFs are more suitable for ecological problems. Stream health prediction was generally better when splitting the watershed into distinct groups. The best models in stream order 1-3 performed better than the comparable C1 (lower RMSE and higher R^2), while model performance in C2 was generally superior to stream order 4-6. Model performance under the all-stream set was typically worse than the clustering methods. This indicates the benefit of splitting streams into groups based on their characteristics prior to ANFIS model development. However, because models performed well for all grouping approaches, it is difficult to select one method over another (*k*-means clustering versus stream order) for grouping streams.

Table 6. Final best models for each stream health measure and stream grouping

Health Measure	Group	Method	MF Type	Vbls (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	All	PC 1-3	GaussC*	2 (2/2)	1.327	0.678	1.266	0.673
	C1	Bayesian	GaussC*	2 (2/2)	0.990	0.660	0.959	0.677
	C2	PC 1	Triangle	2 (2/2)	0.905	0.810	0.765	0.921
	Order 1-3	Spearman	Gaussian	2 (3/2)	0.877	0.850	0.760	0.824
	Order 4-6	Bayesian	Triangle	2 (2/3)	0.836	0.836	0.776	0.697
FIBI	All	Bayesian	Triangle	2 (2/2)	4.699	0.474	4.529	0.485
	C1	Bayesian	Gaussian	2 (2/4)	2.539	0.720	2.423	0.728
	C2	PC 1-3	Gaussian	2 (2/2)	3.204	0.719	2.781	0.854
	Order 1-3	Bayesian	Triangle	2 (2/2)	4.125	0.520	3.616	0.654
	Order 4-6	PCA PC1	Gaussian	2 (2/3)	3.322	0.694	2.838	0.798
HBI	All	Spearman	Gaussian	2 (2/2)	0.342	0.543	0.327	0.563
	C1	Spearman	Gaussian	2 (2/2)	0.317	0.492	0.298	0.601
	C2	Bayesian	Triangle	2 (2/2)	0.245	0.702	0.228	0.751
	Order 1-3	Bayesian	Triangle	2 (2/2)	0.321	0.655	0.304	0.620
	Order 4-6	Bayesian	Gaussian	2 (2/2)	0.271	0.601	0.235	0.598
IBI	All	PC 1	Gaussian	2 (2/4)	1.477	0.996	1.209	0.996
	C2	PCA	Gaussian	2 (3/2)	1.676	0.994	1.579	0.993
	Order 4-6	PC 1	GaussC*	2 (2/2)	1.912	0.993	1.834	0.995

Combined stream grouping model performance: Best model predictions of all stream health measures are presented in Figure 5 (all streams), Figure 6 (C1 and C2), and Figure 7 (order 1-3 and order 4-6). The result of combining the best performing clustering models and stream order models is a discrete modeling system comprised of two models. Each model in the system uses unique variables, MF shape, and number of MFs, and is applicable for different streams (based on stream order or cluster) in the watershed.

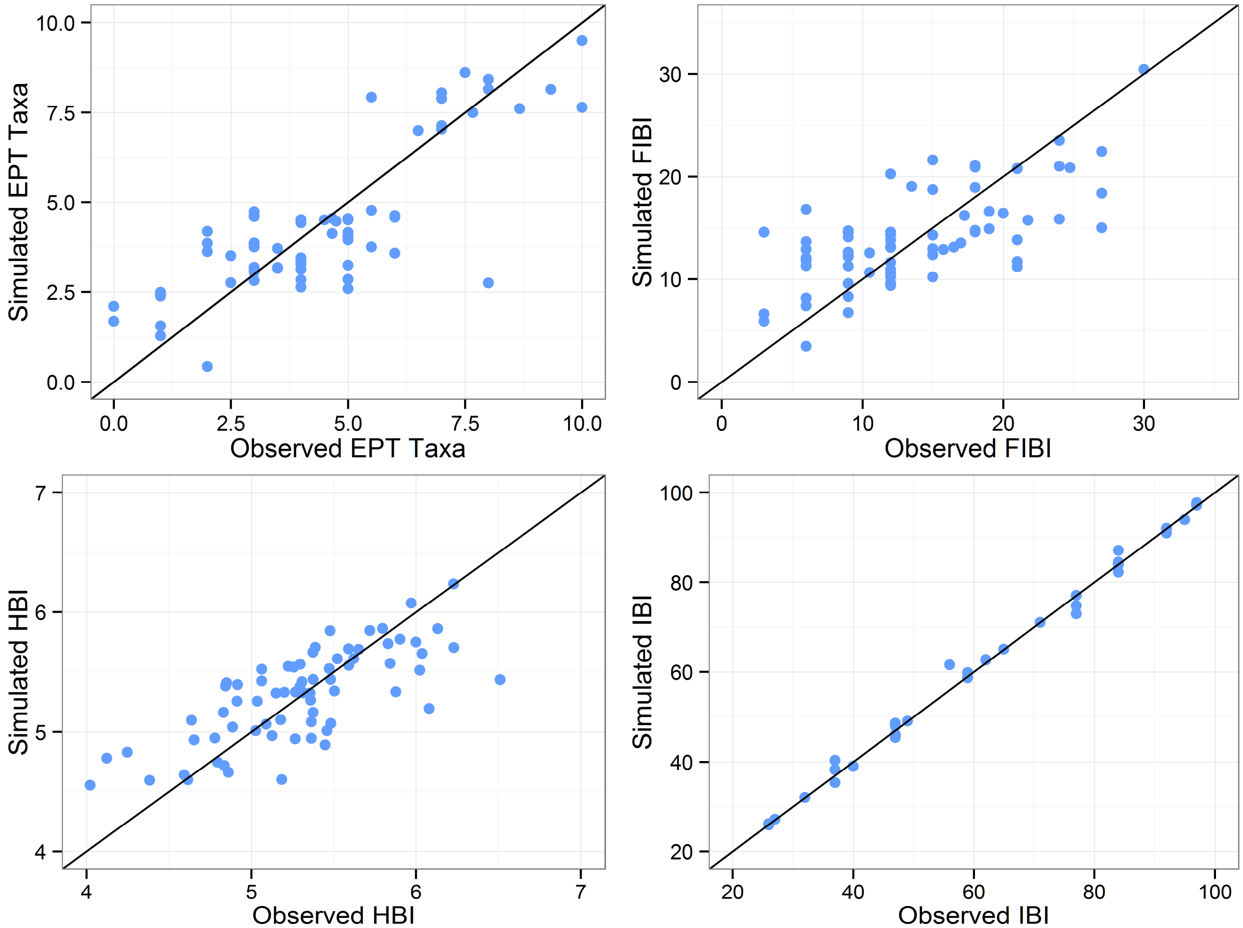

Figure 5. Best model performance for each stream health measure without stream grouping

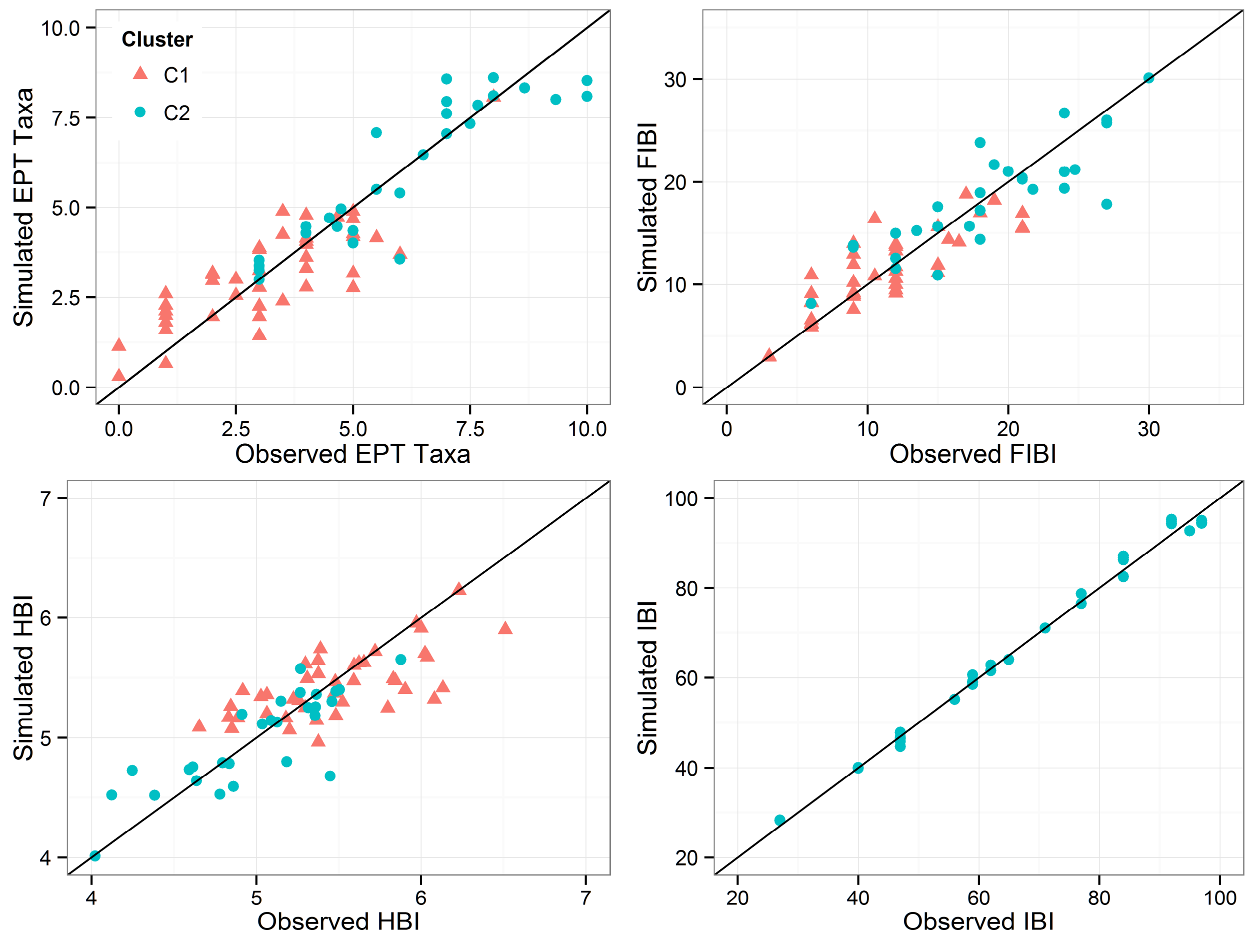

Figure 6. Best model performance for each stream health measure with *k*-means clustering

The stream grouping methods reveal distinct differences in the prediction models. For example, models built on clusters C1 and C2 separately for EPT taxa, FIBI, and HBI are generally distinct in stream health. Here, C1 corresponds to relatively worse stream health (lower EPT taxa and FIBI, higher HBI). This association is also present in the stream order models for macroinvertebrate measures, although it is not as pronounced. Given that the *k*-means clustered stream model performances are satisfactory in all cases, C1 models are good predictors of poorer stream health and C2 models generally correspond to better stream health.

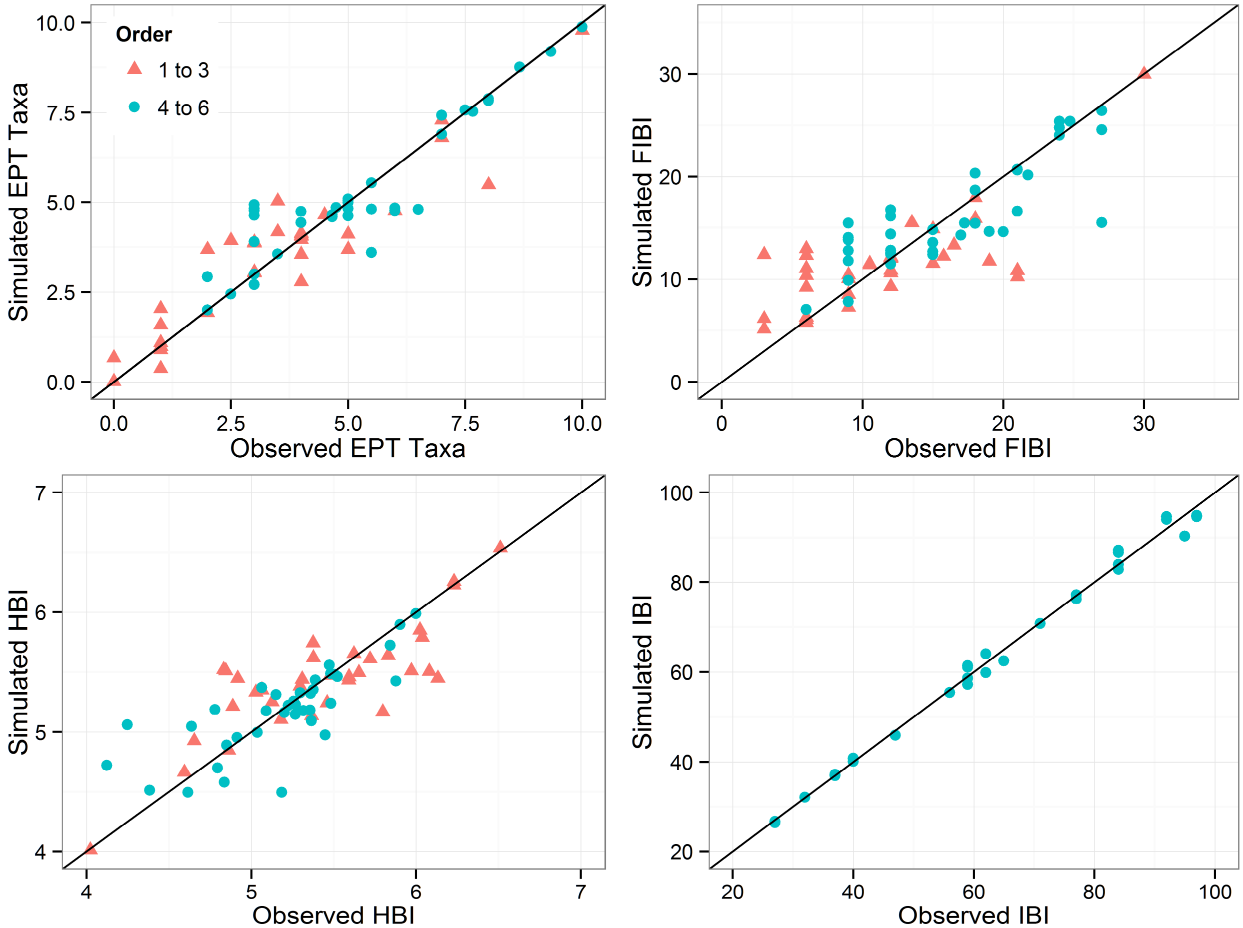

Figure 7. Best model performance for each stream health measure by stream order

Although IBI models were only built on the larger stream groups and for all streams, each model performed exceptionally well, with validation R^2 values reaching 0.99. Overall, the models built on all streams generally displayed more dispersion from the 1:1 prediction line than models built on stream order or *k*-means clustering.

Statistical differences: Wilcoxon signed-rank tests showed that there were no statistically significant differences (α=0.05) between observed datasets and any of the stream health measure/stream grouping combinations Therefore, the ability to correctly predict stream health class was used to determine which stream grouping method was superior. Stream health classes are defined as excellent, good, fair, poor, and very poor (Table 2).

Stream health class prediction: Correct prediction of stream health class is important for effective modeling of stream health because these qualitative descriptors are often used to communicate with watershed stakeholders and natural resources managers. The number of correct stream health class predictions and total number of incorrect class predictions is presented for each macroinvertebrate measure and stream grouping in Figure 8. EPT taxa models had the lowest number of incorrect class predictions. In contrast, the non-grouped models of FIBI, HBI, and HBI incorrectly predicted the stream health class for about 40% of the observed data, which corresponds with the relatively worse RMSE and R^2 of these models (Table 6). Both grouping methods correctly predicted class more frequently than the models built without stream grouping. Based on the number of incorrect classifications, stream order grouping models should be selected for EPT taxa and HBI modeling. Stream order and *k*-means clustering classify the same number of data point incorrectly, but the clustered models have superior performance measures. Therefore, clustering models were selected to predict FIBI for all streams in the study area.

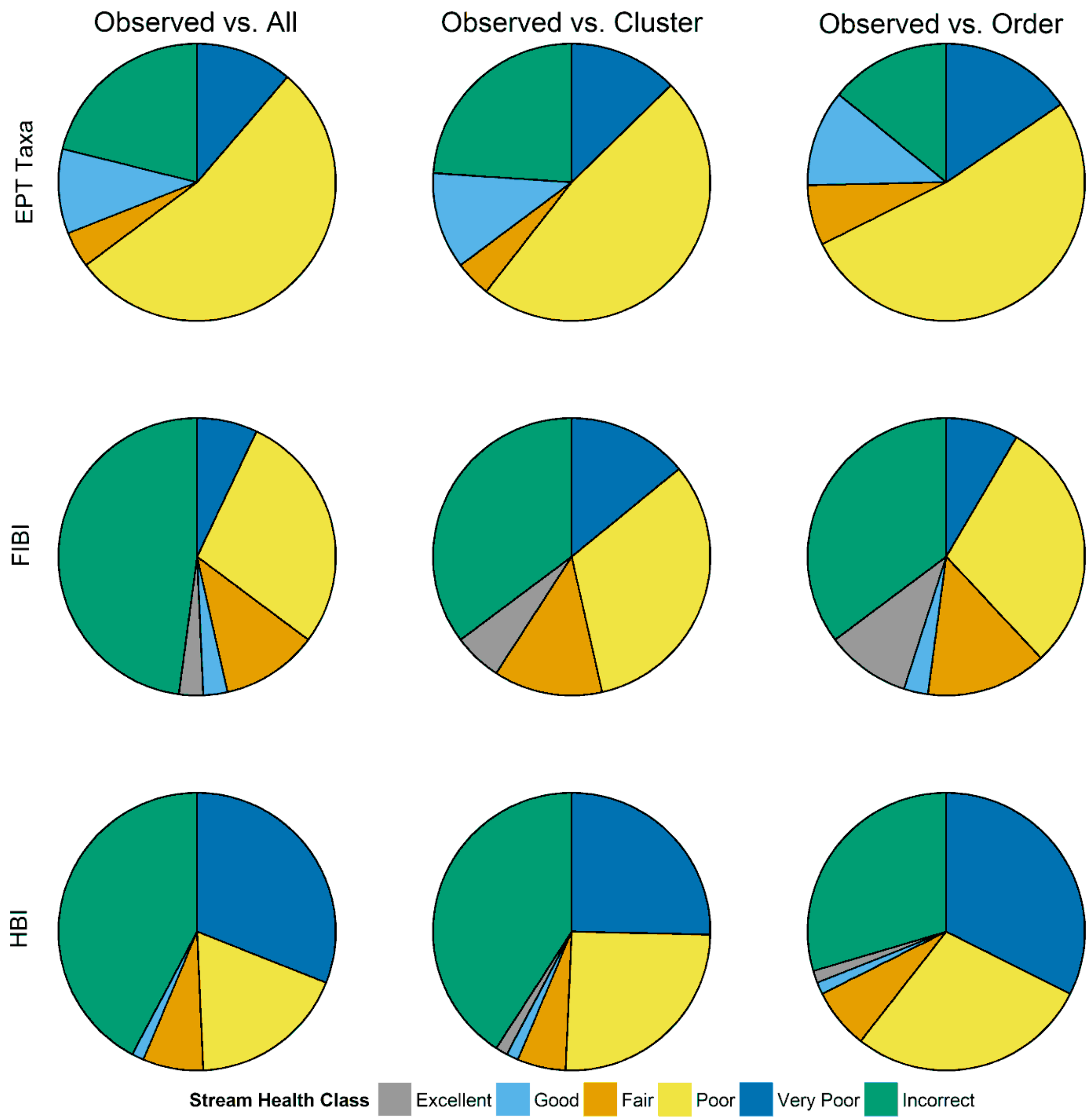

Figure 8. Model predictions compared with observed data. Each pie chart indicates the proportion of model predictions that correctly predict the stream health class. Rows represent macroinvertebrate measures and columns represent stream groupings

4.3.5 Watershed Stream Health

Using the best models for EPT taxa, FIBI, HBI, and IBI, health class was predicted for all streams in the River Raisin watershed (Figure 9). Percentages of each stream health class are presented in Figure 28 of Appendix C. The macroinvertebrate measures indicate that a majority of the watershed has “poor” or “very poor” stream health, especially in the southeastern part of the watershed where most land has been converted to agriculture. This is apparent in the organic pollution-sensitive HBI where most of the watershed is classified as “very poor”, due to nitrogen and phosphorus sourced from agriculture. The outlet of the River Raisin extending to Lake Erie is an EPA Area of Concern with nonpoint source pollution issues, so these conditions are expected. Most occurrences of “fair” to “excellent” stream health are in the northern headwaters of the study area, where much of the land is still forested.

Conversely, much of the watershed is classified as “excellent” to “fair” when examined using fish IBI. The variables select through PCA for developing the IBI model without stream grouping were based on flow magnitude. Although land use change has altered the flow regime in the past 150 years, the predictability of the streamflow still supports good biotic integrity in terms of fish communities.

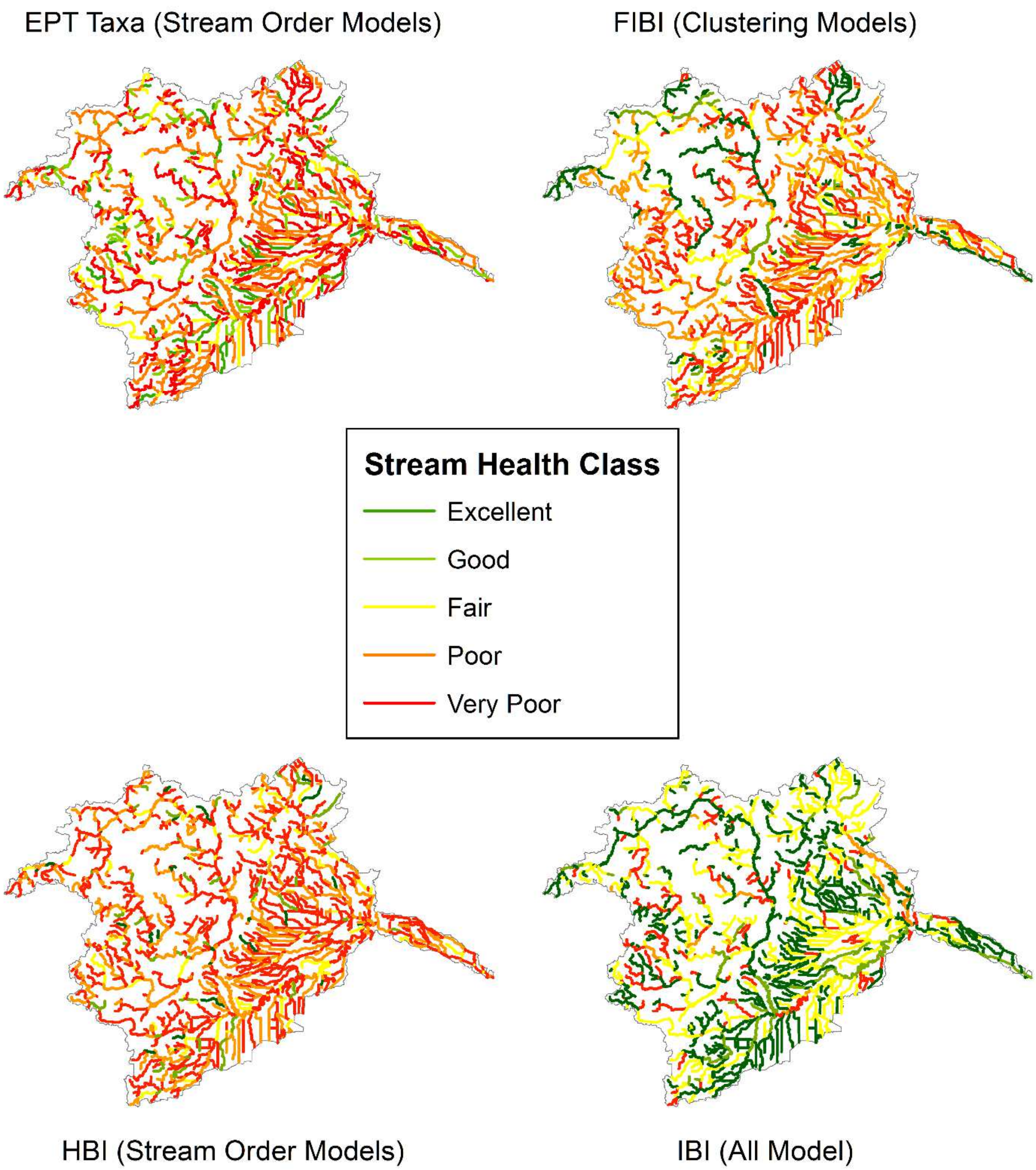

Figure 9. River Raisin watershed stream health classes for each measure and best model

4.4 CONCLUSIONS

Variable selection for development of stream health models is often challenging. Hundreds of in-stream and landscape variables can be used to predict stream health measures. Therefore, the goal of this research was to test multiple selection techniques (ranging from simple to complex) to identify influential variables for use in the development of stream health models for three macroinvertebrate measures and one fish measure. These stream health models developed using scarce monitoring data can be extended to all streams in a watershed to create a comprehensive view of biotic integrity.

Here, more than two hundred variables that characterize flow regime and water quality were considered in the variable selection process. The variables were obtained for all reaches in the River Raisin watershed using a calibrated hydrological/water quality model. Spearman's rank correlation, Bayesian variable selection, and multiple PCA variants were used to identify the most influential variables for each of the four stream health measures. Each method resulted in a unique variable set from which stream health models were developed using ANFIS. Streams were grouped in an attempt to improve ANFIS model performance by classifying streams into groups using two methods: the ecologically based stream order concept and data-driven *k*-means clustering. The grouping methods produced similar stream classifications.

Variables identified for model development were often diverse and differed between variable selection methods, stream health measures, and stream groupings. The best variable selection method based on ANFIS model performance was often Bayesian variable selection, although Spearman's rank correlation and PCA methods yielded best models for some stream health measures and stream groupings.

The best stream health prediction models were often based on Gaussian-shaped MFs. This demonstrates that nonlinear shapes more adequately represent ecological data. Grouping streams and creating unique variable sets and models for each group proved to be superior to the general watershed-wide stream health models. Finally, the stream order grouping method was able to better predict linguistic stream health classes (excellent, good, fair, poor, and very poor), although this will likely vary geographically, particularly if a watershed's stream network is a poor representative of the River Continuum Concept as contested in Statzner and Higler (1985). However, the *k*-means clustering method commonly used in data mining is recommended because it forms stream groups based on the data characteristics of each stream while reproducing general stream order trends.

This research lays the foundation for using data-driven methods to select influential in-stream variables for stream health models. In addition, it was found that grouping streams based on similar characteristics in the variable selection and model development process is useful to improve prediction of stream health measures. Predicting stream health conditions beyond existing monitoring points allows watershed managers and stakeholder to identify areas with critical biotic health issues and prepare successful mitigation plans.

5 ECOHYDROLOGICAL MODELING FOR LARGE-SCALE ENVIRONMENTAL IMPACT ASSESSMENT

5.1 INTRODUCTION

Aquatic ecosystem health is increasingly recognized as crucial to the economic viability and social wellbeing of society (Nichols and Dyer, 2013). Poor aquatic ecosystem health endangers the services they provide, including potable water and water for agricultural, industrial, and recreational uses (Nichols and Dyer, 2013). The importance placed on ecological status of freshwater resources is now apparent in legislation worldwide, including the United States Clean Water Act (1972), the National River Health Program and the Monitoring River Health Initiative in Australia (Davies, 1994), the European Union Water Framework Directive (European Union, 2000), and the Michigan Water Withdrawal Assessment Process (Herbert and Seelbach, 2009). These pieces of legislation promote the use of various biota to monitor aquatic ecosystem integrity. Integrity refers to a system that supports a “balanced, integrated, and adaptive” biotic community with attributes comparable to that region’s natural ecosystems (Karr and Dudley, 1981). Despite the push to maintain and restore biological integrity of aquatic ecosystems, it continues to decline (Kuemmerlen et al., 2014; Lammert and Allan, 1999). For example, in its first national stream condition survey, the United States Environmental Protection Agency (USEPA) found that 42% of US river miles were in poor biological condition (USEPA, 2006), 30 years after passage of the Clean Water Act.

To protect and restore freshwater ecosystems, assessments of their physical and biological condition are critical (Ogren and Huckins, 2014). This can be accomplished through bioassessments that measure the condition of resident biota in a waterbody (USEPA, 2011). Indicators that are used in bioassessment can be single metrics (e.g. taxonomic richness of a species or group of species), multi-metric indices (e.g. the index of biotic integrity – IBI), or taxonomic completeness (ratio of taxa observed vs. expected – O/E) (May et al., 2015). However, obtaining these indicators in large and diverse watersheds is difficult due to the associated cost (Einheuser et al., 2012). Therefore, ecohydrological models are used as an alternative approach to identify the effects of stressors on biological metrics in unsampled locations, while controlling for confounding environmental variables (Garey and Smock, 2015). Meanwhile, they provide a framework for hypothesis testing and identifying direct and indirect linkages between environmental factors/stressors and biota (Waite et al., 2012).

Several ecohydrological models of varying complexity have been developed for use in bioassessment. Linear regression is widely used to explain the relationships between landscape factors and biological conditions (Einheuser et al., 2012; Frimpong et al., 2005; Moya et al., 2011; Pont et al., 2009). Multivariate techniques are also common in bioassessment modeling. The River Invertebrate Prediction and Classification System (RIVPACS) (Wright, 1995; Wright et al., 1998), the Australian River Assessment System (AUSRIVAS) (Simpson and Norris, 2000), and the MACrophyte Prediction and Classification System (MACPACS) (Aguiar et al., 2011) are all examples of multivariate techniques that use reference conditions to predict O/E ratios of aquatic biota. To overcome nonlinearity issues in the modeling of complex ecological systems, recently methods such as artificial neural networks (Compin and Céréghino, 2007; Lencioni et al., 2007; Mathon et al., 2013), fuzzy logic (Adriaenssens et al., 2006; Lermontov et al., 2009; Marchini et al., 2009), adaptive neuro-fuzzy inference systems (ANFIS) (Einheuser et al., 2012; Einheuser et al., 2013a, Woznicki et al., 2015a), and boosted regression trees (Brown et al., 2012; May et al., 2015; Waite et al., 2012; Waite et al., 2014) have been used.

Paramount to model development is consideration of appropriate spatial scale. Stream ecosystem disturbances are complex in time and space, as different disturbances act on different scales (Allan, 2004; Mykrä et al., 2007). Regional models (e.g. watershed or ecoregion) are usually more effective in identifying and characterizing disturbance-related processes. However, many regional models have limited applicability at larger-scales (Waite et al., 2010). However, large-scale models (e.g. statewide, country, or continent) are often more useful to decision-makers in development of broad land management strategies (Marchant et al., 1999; May et al., 2015; Waite et al., 2014). Several studies have developed regional and large-scale models. Turak et al. (1999) used RIVPACS regional model to predict macroinvertebrates and hypothesized that regional specific models would improve predictions, but require large sampling data. Heino et al. (2003) recommended regional stratification for development of more robust models than those developed at larger scales. Strayer et al. (2003) found that local riparian scales (sub-regional) were more useful than large-scales in estimating macroinvertebrate species richness, although fish were insensitive to scale. Feio et al. (2009) developed large-scale (national) and regional AUSRIVAS models of Portuguese macroinvertebrate communities, where the regional models exhibited better performance, although the large-scale model was also acceptable. Large-scale geographic trends and sub-regional (local) environmental conditions were both found to be important in predicting macroinvertebrate assemblages in Finland (Mykrä et al., 2007). As spatial extent decreased, the importance of local environmental gradients increased. May et al. (2015) determined that regional boosted regression tree models were better suited for O/E prediction in California than a large-scale model. However, Waite et al. (2014) found that a large-scale model predicted macroinvertebrate structure almost as well as region specific models, although they recommended development of sub-regional models when more specificity is needed.

In order to select the best model to address land and stream management strategies, the trade-offs between large-scale and regional models are important to consider. Large-scale models generally use predictors easily obtained using geographic information systems, such as landuse, geography, topography, and climate variables. They are less costly than regional models developed for that same area because regional models require additional physical, chemical, and biological sampling (May et al., 2015). However, regional models are generally more accurate than their large-scale counterparts (May et al., 2015). Therefore, the objective of this study is to develop a large-scale model that includes the detail that is often desired from regional models. Here, we use high-resolution in-stream variables (flow regime and water quality) across several watersheds in Michigan, USA, to develop a large-scale model for prediction of fish and macroinvertebrate measures of stream health.

5.2 Materials and Methods

5.2.1 Study Watersheds

Seven 8-digit hydrologic unit code (HUC-8) watersheds in Michigan, USA were the subject of this study (Figure 10): Au Sable (HUC 04070007), Boardman-Charlevoix (HUC 04060105), Cedar-Ford (HUC 04030109), Flint (04080204), Muskegon (04060102), Pere Marquette-White (04060101), and Raisin (04100002). The watersheds range in drainage area from 2639 km^2 (Cedar-Ford) to 7071 km^2 (Muskegon). Predominant land uses in the watersheds vary from combinations of forest-grassland-wetlands (Au Sable and Boardman-Charlevoix), forested wetlands and forest (Cedar-Ford), agriculture-forest-urban (Flint and Raisin), and forest-agriculture-wetland (Muskegon and Pere Marquette-White). Soils across the watersheds also vary; Au Sable, Boardman-Charlevoix, Pere Marquette-White, and Muskegon have well-drained sandy soils, Flint contains sandy loams and loams with varying organic matter, and the Raisin is dominated by poorly drained clay soils.

The watersheds were selected for their unique physiographic characteristics, availability of water quality, fish, and macroinvertebrate samples and composition of stream thermal classes (cold, cold-transitional, cool, and warm). The stream thermal classes were used as the basis for development of a large-scale model because stream temperature is a fundamental control of aquatic ecosystems (Olden and Naiman, 2010), while thermal regimes dictate abundance and occurrence of aquatic biota (Lyons et al., 2009). In Michigan, stream thermal classes based on July mean water temperature were derived from Zorn et al. (2008). Cold streams are defined by temperatures ≤ 17.5 °C and primarily coldwater fish communities. Cold-transitional temperatures range between 17.5 °C and 19.5 °C with fish communities that are mostly comprised of coldwater fishes with some warmwater fishes. Cool (or warm-transitional) temperature range between 19.5 °C and 21.0 °C with mostly warmwater fishes but contain some coldwater fishes. Finally, warmwater stream temperatures are greater than 21.0 °C, and the fish community contains warmwater fishes. Each watershed was broadly classified by the thermal classes of its streams: Boardman-Charlevoix is primarily cold, Cedar-Ford is primarily cool, Flint and Raisin are warm, Au Sable is a mixture of cold and cold-transitional, and Muskegon and Pere Marquette-White contain a mixture of cold, cold-transitional, and cool streams.

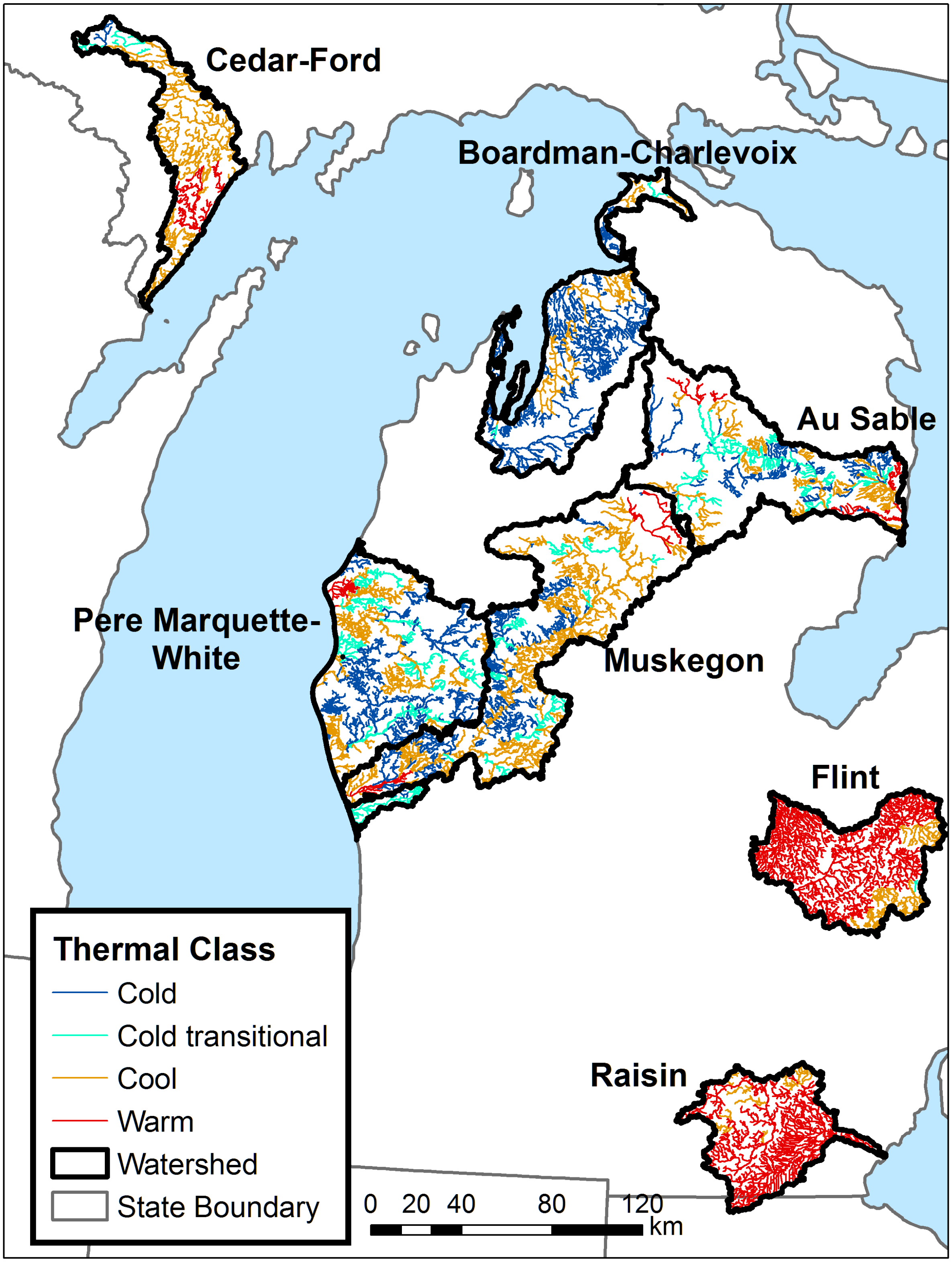

Figure 10. Study watersheds and thermal classes

5.2.2 Data Collection

5.2.2.1 Physiographic Data

Physiographic datasets included topography, land use/land cover, soils, and climate. Gridded topography data (30 m resolution) was obtained from the United States Geological Survey (USGS) National Elevation Dataset (NED, 2014). The 2012 Cropland Data Layer (NASS, 2012) 30 m resolution land use/land cover dataset was obtained from the United States Department of Agriculture (USDA) – National Agricultural Statistics Service. To supplement the landuse/land cover data, agricultural management operations were obtained from Sommerlot et al. (2013). The USDA Soil Survey Geographic Database (SSURGO) with resolutions ranging from 1:12,000 to 1:63,600, was used for spatial and tabular soil chemical and physical properties (NRCS, 2014). Daily precipitation and temperature data from 1978-2005 was obtained from the National Climatic Data Center (NCDC, 2015). A total of 40 precipitation stations and 39 temperature stations were selected for use across the seven watersheds.

Stream networks were delineated using a predefined subwatershed and stream dataset from the Great Lakes Regional River Database Classification System developed by the Michigan Institute of Fisheries Research (IFR). Based on the National Hydrography Dataset Plus (1:24,000 resolution), the stream network is comprised of confluence-to-confluence reaches. Each subwatershed contains a single stream reach and represents a stretch of consistent physiographical, geomorphological, and biological features (Einheuser et al., 2013b). There were over 26,000 reaches in this study, while the number of reaches in the watersheds ranged from 979 (Cedar-Ford) to 7,730 (Pere Marquette-White).

5.2.2.2 Biological Data

Fish and macroinvertebrate data are commonly used as stream health indicators (Herman and Nejadhashemi, 2015). This is because they vary in sensitivity and react differently to stressors while operating at contrasting scales (Flinders et al., 2008; Lammert and Allan, 1999). Macroinvertebrates are more localized due their sessile lifestyle, occupy multiple trophic levels, and respond to short term environmental changes (Barbour et al., 1999). Conversely, fish respond to long-term environmental changes and broad spatial habitat conditions because of their mobility, while they represent multiple trophic levels (Barbour et al., 1999). Three macroinvertebrate indicators were used: number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family-level Index of Biotic Integrity (FIBI), and the Hilsenhoff Biotic Index (HBI). The fish Index of Biotic Integrity (IBI) was also used.

EPT taxa is a count of pollutant-intolerant species present, where lower taxonomic richness indicates degradation (Sponseller et al., 2001). FIBI is a multi-metric index that includes composition and richness measures, ranging from 0-45 where 45 indicates excellent stream health. HBI is based on organic pollution tolerance and ranges from 0-10, where 0 indicates excellent stream health (Hilsenhoff et al., 1988). Fish IBI evaluates effects of stressors on a stream by integrating many fish community measures of richness, composition, and abundance (Wang et al., 2007). Scores range from 0-100, with 0 and 100 indicating very poor and excellent health, respectively. In this study, stream health measures were split into five classes: 'very poor', 'poor', 'fair', 'good', and 'excellent' for all indicators. Macroinvertebrate classes were developed by calculating quintiles of the complete Michigan dataset (2634 data points), while fish IBI classes were derived from Lyons (1992). The stream health classes are presented in Table 2.

Macroinvertebrate sampling occurred from 1996-2003 during the months of June through September (MDEQ, 1997). Approximately 300 ± 60 organisms were collected along 30-100 m stretches during a minimum of 20 minutes sampling duration (Einheuser et al., 2012). Single-pass fish sampling was performed in wadeable streams along 80-960 m stretches and in non-wadeable streams along 1,610 m stretches using backpack and tow-barge electrofishing units from May to October between 1982 and 2008 (Wang et al. 2012). This data was obtained from the Michigan stream fish survey database managed by the Institute for Fisheries Research (Ann Arbor, Michigan). Macroinvertebrate and fish sampling locations are presented in Figure 29 and Figure 30 of Appendix D. The total number of macroinvertebrate and fish samples across the seven study watersheds was 435 and 295, respectively. Across thermal classes, there were 141/85 (macroinvertebrate/fish) cold samples, 51/38 cold-transitional samples, 120/113 cool samples, and 123/59 warm samples.

5.2.3 Modeling Process

An overview of the complete modeling process is presented in Figure 11. First, Soil and Water Assessment Tool (SWAT) models were calibrated and validated for each study watershed. SWAT generated daily streamflow discharge for each reach that fed into the Hydrologic Index Tool (HIT) to characterize ecologically relevant flow regime parameters. Bayesian variable selection technique was used to select important water quantity (obtained from the HIT) and quality (obtained from SWAT) variables for development of stream health models. Finally, stream health models were created for each stream health index (EPT taxa, FIBI, HBI, and IBI) and thermal class (cold, cold-transitional, cool, and warm).

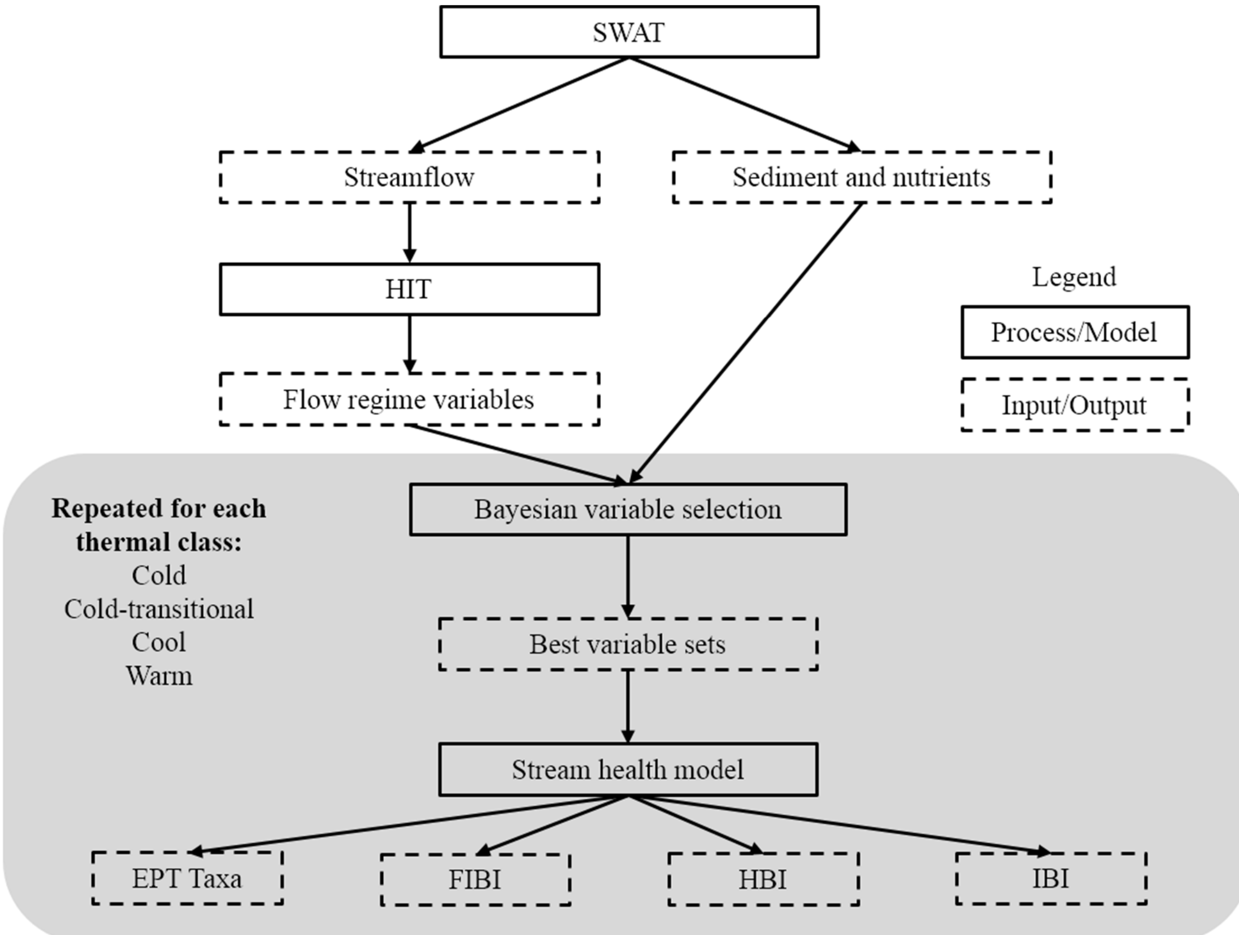

Figure 11. Modeling process flowchart

5.2.4 Soil and Water Assessment Tool

Developed by Arnold et al. (1998) for the USDA – Agricultural Research Service, SWAT (version 2012) is a physically based watershed/water quality model (Neitsch et al., 2005). SWAT is process-based, semi-distributed, and continuous-time with the objective of predicting the impact of land management practices in large watersheds over long time periods (Neitsch et al., 2005). Simulation components in SWAT include hydrology (land phase and in-stream routing phase), plant growth, evapotranspiration, sediment routing, and nutrient cycling (Arnold et al., 2012).

SWAT delineates a watershed into several subwatersheds based on a digital elevation model and stream network. Delineated subwatersheds are further segmented into non-spatial hydrologic response units (HRUs), which are areas of homogeneous topography, land use, soils, and management practices. Subwatersheds and streams were predefined using the Michigan IFR dataset. Because each subwatershed in this dataset represents homogeneous physiographical and geomorphological landscape features, one HRU per subwatershed was used.

5.2.4.1 SWAT Calibration and Validation

The SWAT models were calibrated and validated in order to ensure their accuracy. The goal of calibration is to reduce prediction uncertainty by adjusting values for model parameters and comparing subsequent model predictions with observed data for a specific time-period (Arnold et al., 2012). Model validation ensures model accuracy by comparing the calibrated model's performance against an observed dataset with a time-period that differs from the calibration period (Moriasi et al., 2007).

Three statistical measures were used to evaluate model performance. The Nash-Sutcliffe coefficient of efficiency (NSE) ranges from $-\infty$ to 1, where 1 indicates a perfect fit between observed and model simulated values. Values greater than 0 indicate that the model is a better predictor of observed data than the observed mean. According to Moriasi et al. (2007), a satisfactorily calibrated model will have NSE > 0.5 on a monthly time step. Percent bias (PBIAS) measures the model's tendency to over- or under-predict versus the observed dataset. Low magnitude PBIAS values are desirable, while acceptable values vary based on the constituent being modeled: $< \pm 25$ for streamflow, $< \pm 55$ for sediment, and $< \pm 70$ for nutrients simulated on a monthly time step (Moriasi et al., 2007). Finally, the root-mean-square error-observations standard deviation ratio (RSR) ranges from 0 (optimal) to large positive values. Satisfactorily calibrated models have an RSR < 0.7 on a monthly time step.

Each watershed was calibrated for daily streamflow and monthly sediment, total nitrogen

(TN) and total phosphorus (TP) loads. Time series streamflow data was obtained from United States Geological Survey gauging stations. Grab sampling of sediment and nutrients was obtained from the Michigan Department of Environmental Quality (MDEQ) (except for the Cedar-Ford, which was obtained from the USGS). Due to limited grab sample of water quality data, the USGS Load Estimator (LOADEST) was used to estimate monthly sediment, TN, and TP loads from grab sample data using regression with observed streamflow data. LOADEST develops regression models for estimation of constituent loads using functions of streamflow and decimal time (Runkel et al., 2004). There are three statistical estimation methods, where Adjusted Maximum Likelihood Estimation (AMLE) and Maximum Likelihood Estimation were used when residuals are normally distributed, while Least Absolute Deviation (LAD) was used when residuals are not normally distributed (Runkel et al., 2004). LOADEST results are presented in Table 22 of Appendix D.

Time periods of calibrations varied between watersheds based on availability of observed data. All watersheds were calibrated from 1996-2000 and validated from 2001-2005 for streamflow. However, the Cedar-Ford watershed calibration period was 1982-1985 and the validation period was 1986-1989. Sediment, TN, and TP were calibrated and validated for a combined period of 4 to 8 years (1998-2005) depending on data availability. However, the Au Sable watershed was not calibrated for sediment because all samples were less than the sampling quantification limit (<4 mg/L) and therefore were not defined. Locations of streamflow gauging stations and water quality sampling locations are presented in Figure 29 and Figure 30 of Appendix D.

5.2.5 In-Stream Variables

A natural flow regime is critical to sustain a stream's biological integrity and is a 'master variable' in dictating abundance and distribution of aquatic biota (Poff et al., 1997). Given the importance of flow regime, its component pieces (in-stream variables) were used in development of stream health models. Flow regime for each stream was characterized using the USGS HIT (Henriksen et al., 2006), which calculates 171 ecologically relevant variables that encompass the five components of the natural flow regime (Olden and Poff, 2003). The five components of the natural flow regime are magnitude (M), frequency (F), duration (D), timing (T), and rate of change (R); each component is further characterized by high (H), average (A), or low (L) flow events. The HIT requires at least 20 years of continuous daily streamflow data for a stream reach. Flow regime was characterized from 1980-2000 for each stream reach in the study based on output from the calibrated/validated SWAT watershed models. Annual and monthly sediment, TN, and TP loads were also calculated for each stream reach, for 39 variables. Finally, drainage area was also included because of its relationship with stream size, which is a key predictor of species richness and presence (Pont et al., 2009).

5.2.6 Bayesian Variable Selection

Bayesian variable selection was used to identify a subset of important variables from the independent dataset containing 211 variables. This method was found to be superior to principal component analysis and Spearman's Rank Correlation for development of stream health models using fuzzy logic (Woznicki et al., 2015a).

We used the Bayesian variable selection procedure to sample $\boldsymbol{I}$, the probable index set referring to q specific variables. The Bayesian paradigm treats both $\boldsymbol{I}$ and q as random components with diffused prior assumptions, and draws posterior samples given the data using the reversible jump Markov Chain Monte Carlo (MCMC) algorithm (Green, 1995). Specifically, at each MCMC iteration, a new index set $\boldsymbol{I}^*$ is proposed by either adding an extra variable or excluding one existing variable, and the data likelihood is compared under each regression model to determine either accepting $\boldsymbol{I}^*$ or preserving $\boldsymbol{I}$. Detailed model implementation is presented in Woznicki et al. (2015a).

For each of the dependent variables (EPT, FIBI, HBI, and IBI), we ran the Bayesian variable selection procedure to obtain a total of 25,000 posterior samples of probable combinations of important variables $\boldsymbol{I}$, and corresponding parameters including regression coefficients $\beta_{\boldsymbol{I}}$ for variables selected in $\boldsymbol{I}$. Note that the posterior samples of $\boldsymbol{I}$'s automatically provide inference about the plausible range of q, the number of important variables, which is a merit of this method by treating $\boldsymbol{I}$ and q random. We also monitored the *selectivity*, defined as the probability of being selected out of all posterior samples, as a measure of importance for each variable. Based on the most probable q, variables with the greatest selectivity were selected for further use in building the ANFIS models.

5.2.7 Stream Health Model Development

Several methods have been used in development of stream health models. In general, nonlinear methods such as fuzzy logic are preferable to linear methods in modeling ecological processes because they address the inherent uncertainty and nonlinearity in these systems (Adriaenssens et al., 2004; Chen and Mynett, 2003). Fuzzy logic uses graphical membership functions (MFs) that describe a value's degree of membership to a fuzzy set, where 0 and 1 represent non-membership and full membership, respectively. Membership is determined through development of if-then inference rules. This technique is robust when modeling complex and non-linear ecological systems (Chen and Mynett, 2003). However, building MFs is difficult due to its intensive and time-consuming nature (Adriaenssens et al., 2004; Chen and Mynett, 2003; Huang et al., 2010). To address these issues with building MFs and inference rules, a fusion method known as adaptive neuro-fuzzy inference systems (ANFIS) can be used. ANFIS uses artificial neural networks (ANNs) to build and optimize fuzzy logic MFs by minimizing predictive error (Jang, 1993).

ANFIS models were constructed using the MATLAB (R2013b) Fuzzy Logic Toolbox. For each output (EPT taxa, FIBI, HBI, and IBI), five MF shapes and two to four MFs were tested. Both linear and nonlinear MF shapes were tested. Triangular and trapezoidal shapes are linear, while Gaussian (Gauss), Gaussian composite (GaussC), and generalized bell (bell) are nonlinear. Linear MFs are commonly used due to their simplicity, while nonlinear MFs are well suited to ecological problems (Marchini, 2011). Finally, two output MF types were tested (constant and linear).

The in-stream variables with the highest selectivity following the Bayesian variable selection were used as input variables for the predictive EPT taxa, FIBI, HBI, and IBI models. The number of input variables used in the ANFIS models was limited by the sample size of fish and macroinvertebrate datasets. This is because the number of modifiable parameters in the ANFIS model (a function of the number variables, MFs per variable, MF shape, and output MF type) should not exceed the number of samples used in training to prevent over-fitting (Sanikhani and Kisi, 2012). All possible combinations of number of variables, MFs per variable, and MF shapes were calibrated (trained) and validated (checked) for each stream health measure and thermal class. Therefore, models were built for each combination of EPT taxa, FIBI, HBI, IBI and cold, cold-transitional, cool, and warm streams, for 2,880 models. Each model was trained for 500 epochs. To determine if individual model for each thermal class improved predictability, additional models were built using the complete dataset without considering thermal class.

K-fold cross validation was used for training and testing of ANFIS models. The data was split into ten mutually exclusive subsets, where the models were trained on 90% of the data (nine folds) and tested on the remaining 10% (one fold) and repeated ten times for each fold. The coefficient of determination (R^2) and root-mean-square error (RMSE) were averaged for the ten testing sets and the highest average R^2 and lowest average RMSE were used to select the best ANFIS model.

5.2.8 Impacts of Land use Change on Stream Health

Developing stream health predictions using pre-settlement vegetation data allows for understanding of stream reference conditions as they were prior to widespread European settlement and subsequent agricultural and urban expansion in Michigan. The Vegetation of Michigan *circa* 1800 digital map (Comer et al., 1995) was used to develop predictions of pre-settlement stream health conditions. This map was developed by biologists from the Michigan Natural Features Inventory using data from the United States General Land Office, who surveyed Michigan between 1816 and 1856 (Comer et al., 1995). The primary land cover types in this dataset are wetlands (forested and non-forested), uplands (non-forested, forested, and sparsely vegetated), and lakes and rivers. Within each land cover type, there are further divisions that describe detailed information on the types of vegetation present. Land use/land cover changes from pre-settlement to 2013 (CDL) are presented in Table 23 of Appendix D. The pre-settlement vegetation map was used as an input to develop SWAT models *circa* 1800 and parameters from the previously calibrated SWAT models were applied following Nejadhashemi et al. (2012). Streamflow was characterized using the HIT on the pre-settlement SWAT model streamflow predictions. Finally, the ANFIS stream health models were run to estimate the four biological indicators.

To determine differences in stream health between current and the pre-settlement environment, a non-parametric paired difference test (Wilcoxon signed-rank test) was performed (Sprent and Smeeton, 2000). The Wilcoxon signed-rank test was used because the populations (stream health measures) were not normal.

5.3 RESULTS AND DISCUSSION

5.3.1 SWAT Model Calibration and Validation

The SWAT model calibration and validation results for streamflow, sediment, TN, and TP are presented in Table 7 (NSE) and Table 24 (PBIAS) and Table 25 (RSR) of Appendix D. Model performances were generally satisfactory for all watersheds according to guidelines from Moriasi et al. (2007). However, results of the water quality calibration were not satisfactory for all watersheds. In some cases (e.g. Au Sable), this is due to the presence of dams just upstream of the water quality sampling location. In other cases the unsatisfactory calibration results are likely due to limited water quality sampling data from which to develop monthly LOADEST predictions (e.g. Boardman-Charlevoix). Less than satisfactory performance has been reported in SWAT simulation of streamflow and more commonly sediment and nutrients. Calibration and validation results data compiled by Gassman et al. (2007) and Douglas-Mankin et al. (2010) reported that 31% of 107 watershed calibrations and 44% of 86 validations were unsatisfactory based on the Moriasi et al. (2007) model performance evaluation guidelines. Although some constituents were not satisfactorily calibrated, they were improved from their initial uncalibrated states.

Table 7. SWAT model calibration and validation (NSE)

Watershed	Flow and water quality stations[a]	Time Period	Flow	Sediment	TN	TP
Au Sable	USGS 04137500 MDEQ 350061	Calibration	0.53	-	0.05	-3.83
		Validation	0.40	-	0.00	-4.86
		Combined	0.47	-	0.03	-4.37
Boardman-Charlevoix	USGS 04126970 MDEQ 280014	Calibration	0.51	0.69	-0.07	0.68
		Validation	0.69	0.66	-0.43	0.59
		Combined	0.61	0.68	-0.21	0.65
Cedar-Ford	USGS 04059500 USGS 04059500[b]	Calibration	0.63	0.67	0.71	0.46
		Validation	0.75	0.80	0.75	0.52
		Combined	0.70	0.76	0.74	0.51
Flint	USGS 04148500 MDEQ 730285	Calibration	0.59	0.67	0.61	0.78
		Validation	0.60	0.72	0.42	0.48
		Combined	0.59	0.69	0.49	0.59
Muskegon	USGS 04121500 MDEQ 510088	Calibration	0.50	0.38	0.66	0.62
		Validation	0.58	0.27	0.78	0.54
		Combined	0.55	0.30	0.73	0.57
Pere Marquette-White	USGS 04122500 MDEQ 530027	Calibration	0.61	0.28	0.54	0.45
		Validation	0.59	0.18	0.63	0.31
		Combined	0.61	0.23	0.60	0.38
Raisin	USGS 04176500 MDEQ 580046	Calibration	0.72	0.56	0.59	0.56
		Validation	0.59	0.55	0.39	0.41
		Combined	0.65	0.58	0.50	0.51

[a]USGS: United States Geological Survey streamflow gauging station; MDEQ: Michigan Department of Environmental Quality water quality sampling site; [b]Water quality sampling was performed at the USGS gauging station for the Cedar-Ford watershed.

5.3.2 Variable Selection and Model Development

5.3.2.1 Variable Selection

The best variable sets from Bayesian variable selection for each stream health measure and thermal class are presented in Table 8. This includes the selectivity measure, where a greater magnitude indicates a greater importance in the Bayesian variable selection process. Several variables are consistently ranked as important across both stream health measures and thermal classes. Although some variables were ranked most important for a stream health measure/thermal class combination, their selectivity values were still relatively low. This indicates that there were no specific variables consistently important in the Bayesian variable selection process. Several variables had selectivity values of a similar magnitude. This was expected since no single variable can describe a complex aquatic ecosystem in its entirety. Regardless, there were several trends apparent in the variable selection process, most of which were more apparent across thermal classes than stream health measures. Overall, magnitude (M) and timing (T) variables were selected the most, at a rate of 31% and 35% respectively, while frequency (F) and rate of change (R) were uncommon (Table 8).

Table 8. Best variable sets and selectivity measures*

Measure	Cold	Cold-Transitional	Cool	Warm	All
EPT	TA2 (0.515)	TH3 (0.510)	MA25 (0.666)	FH2 (0.497)	DL9 (0.835)
	TA1 (0.478)	MH18 (0.472)	DL16 (0.143)	MH19 (0.452)	MA25 (0.827)
	MA31 (0.256)	DH20 (0.208)	TA1 (0.139)	MA37 (0.330)	DL15 (0.787)
FIBI	TA1 (0.486)	TH3 (0.310)	MA25 (0.411)	RA5 (0.680)	TA1 (0.561)
	TA2 (0.336)	RA9 (0.283)	TA2 (0.133)	DL17 (0.302)	MA34 (0.548)
	RA8 (0.176)	MA40 (0.213)	TH3 (0.124)	DL9 (0.293)	FL3 (0.506)
HBI	FL3 (0.461)	TH3 (0.295)	DH18 (0.588)	MA37 (0.494)	DH15 (0.800)
	MA27 (0.226)	MH15 (0.165)	DL15 (0.579)	FH2 (0.436)	MA35 (0.765)
	MH24 (0.093)	MA4 (0.164)	MA25 (0.549)	DH22 (0.394)	DL15 (0.632)
IBI	TL1 (0.845)	RA7 (0.143)	TA2 (0.198)	TA1 (0.490)	DH6 (0.707)
	TL3 (0.814)	MH27 (0.087)	TA1 (0.122)	TA2 (0.355)	TA2 (0.629)
	TL2 (0.626)	ML20 (0.086)	DH6 (0.079)	DH22 (0.326)	MA44 (0.498)

*For detailed variable definitions, please see the abbreviations section.

In cold streams, timing of average and low flow event variables were consistently the most important in predicting stream health. These variables represent the constancy (TA1) and predictability (TA2) of streamflow; in addition, representing the timing of high (TH) and low flow (TL) events. Their importance is likely because cold streams in Michigan are highly stable; they are primarily groundwater-fed due to the prominence of sandy glacial drift soils and forested land cover, especially in the Boardman-Charlevoix and Au Sable watersheds (Zorn and Sendek, 2001; Kalish and Tonello, 2014) . In addition, cold streams are generally found in forested watersheds that have not experienced much agricultural expansion or urbanization, which makes them less vulnerable to flashy runoff events. We expect that these streams will be consistent and predictable in the timing of high and low flow events, and hence there is a correlation between timing-related indices and stream health measures for cold streams.

Cold-transitional variables were highlighted by the high selectivity of the TH3 variable (seasonal predictability of non-flooding, flows below a 1.67-year recurrence interval) for all macroinvertebrate measures. Due to the similarity between cold and cold-transitional, it is not surprising that a timing variable was consistently important. Here, increasing predictability of non-flooding signaled improved stream health measures for EPT, FIBI, and HBI. This is supported by organisms generally responding to long-term average dynamics of flow regime (sufficiently predictable annual floods and droughts) rather than having life-history strategies that respond to individual extreme events (Lytle and Poff, 2004). As with cold streams, cold-transitional streams had better stream health with increased predictability of streamflow. Meanwhile, high magnitude events were also important, likely related to the timing of those events.

As was the case for cold and cold-transitional, timing variables are influential in cool streams. In addition, variability of February flows (MA25) had high selectivity for all macroinvertebrate indices, while low and high duration variables (DL and DH) were important. For example, greater variability in February flows and longer duration of low flows (DL16) resulted in lower EPT counts. In general, cool streams seem to bridge the gap between cold/cold-transitional and warm streams by having both influential timing variables (cold/cold-transitional) and duration and magnitude variables (warm).

Influential variables for warm streams were more diverse than the other thermal classes. Timing variables were not identified as important to the extent of the other classes, but duration (DH22, DL9, and DL17) and magnitude (MA37 and MH19) variables were commonly influential. These variables were typically related to high or low flows, demonstrating the importance of extreme events in warm streams. Flow variability is important in warm streams because they are fed by surface runoff rather than groundwater, which is the case for the Flint and Raisin watersheds. In addition, the flow regimes of warm streams in Michigan have typically become flashier due to more runoff and less infiltration and recharge caused by agricultural expansion and urbanization. This is demonstrated with inclusion of important variables such as variability in high pulse count (FH2) and skewness in annual maximum flows (MH19) for EPT and number of days between flood events (DH22) for HBI and IBI.

Variables selected without considering thermal class followed similar trends as those selected by thermal class. Timing variables were still important for FIBI (TA1 – constancy) and IBI (TA2 – predictability). High and low flow duration variables were also commonly selected across health indices as was the case for the stream thermal classes.

There were also trends in variable selection across the stream health indicators. Most apparent was the presence of timing variables in almost all fish IBI models (they were not present in the cold-transitional model). Meanwhile, it was surprising that not a single pollution index was selected for any measure or thermal class. This was especially true for HBI (the organic pollution tolerance index for macroinvertebrates), where it was expected that some water quality parameters would be important.

5.3.2.2 Stream Health Model Development

Using the influential variables from the Bayesian variable selection process, stream health models were developed using ANFIS for each stream health measure and thermal class. The best models with their characteristics and training/checking statistics are presented in Table 9. This table includes the selected MF shape, number of variables, and number of MFs per variable, which corresponds to the variables listed in Table 8. For example, the best EPT cold model was a Gaussian composite (GaussC) with three variables, where the number of MFs per variable was four (TA2), three (TA1), and two (MA31). Performance statistics were generally acceptable and consistent, while the models based on thermal class performed better than the general models built using the complete dataset. This demonstrates the importance of thermal regimes in controlling abundance and occurrence of aquatic biota (Lyons et al., 2009).

Table 9. Best ANFIS models for each stream health measure and thermal class

Measure	Thermal Class	Shape	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
	Cold	GaussC[a]	3 (4/3/2)	2.564	0.487	2.504	0.485
	Cold-T	GaussC[a]	3 (2/3/2)	2.567	0.500	2.248	0.675
EPT	Cool	Gauss	2 (4/2)	2.463	0.466	2.413	0.511
	Warm	Bell[b]	3 (3/3/2)	2.106	0.555	2.050	0.581
	All	GaussC[a]	4 (2/3/2/2)	2.656	0.507	2.627	0.506
	Cold	GaussC[a]	3 (4/3/3)	5.002	0.487	4.909	0.508
	Cold-T	Bell[b]	3 (2/2/3)	4.473	0.658	4.161	0.735
FIBI	Cool	Triangle	3 (2/2/2)	6.157	0.341	6.077	0.436
	Warm	GaussC[a]	3 (4/3/2)	4.741	0.543	4.659	0.513
	All	GaussC[a]	2 (4/4)	6.231	0.339	6.185	0.345
	Cold	Gauss	3 (2/3/4)	0.409	0.416	0.400	0.409
	Cold-T	Gauss	2 (4/3)	0.323	0.657	0.304	0.650
HBI	Cool	GaussC[a]	2 (4/4)	0.420	0.548	0.392	0.606
	Warm	GaussC[a]	2 (3/4)	0.398	0.493	0.392	0.551
	All	Triangle	4 (4/2/4/2)	0.448	0.538	0.445	0.543
	Cold	Gauss[c]	3 (3/2/2)	17.534	0.483	9.187	0.897
	Cold-T	Triangle	2 (2/3)	22.875	0.264	21.725	0.548
IBI	Cool	GaussC[a]	3 (2/3/2)	19.991	0.274	19.409	0.371
	Warm	Bell[b]	3 (2/2/2)	18.034	0.369	16.269	0.549
	All	Gauss	4 (2/2/2/2)	20.566	0.286	20.390	0.291

[a] GaussC: Gaussian composite MF
[b] Bell: generalized bell MF
[c] All output MFs were constant except for the cold IBI model, which was linear

Among the best models, nonlinear MF types were consistently present. This supports the conclusions by Marchini (2011) and confirms the results of Woznicki et al. (2015a), where nonlinear MFs (Bell, Gauss, and GaussC) were determined to be better suited for modeling ecological processes than their linear counterparts. Including three variables (rather than two) in the model building generally improved model performance. Finally, only one model performed better with a linear output MF (cold IBI); the remaining 15 models used constant output MFs.

Following model development, predictions were made across each thermal class and stream health measure (Figure 12), where the average stream health value was calculated using a stream length-based average (stream health score times the length of the stream divided by the total stream length in a correspondence thermal class). Each measure is defined by a unique scale (Table 2), but comparing each on the same figure is useful to relate stream health between thermal classes. The warmer stream classes are in poorer health for macroinvertebrates, as evidenced by lower EPT and FIBI and greater HBI for cool and warm streams. This is likely related to the variables selected in each model, where cold streams have greater constancy and predictability due to their reliance on groundwater and minimal land use changes. Meanwhile, warmer streams are flashier, runoff-driven and present in watersheds with extensive agricultural and urban expansion. Fish IBI is best in cold streams, but there is a sharp decrease in cold-transitional health, which is consistent with the range of biological observations on which the models were developed.

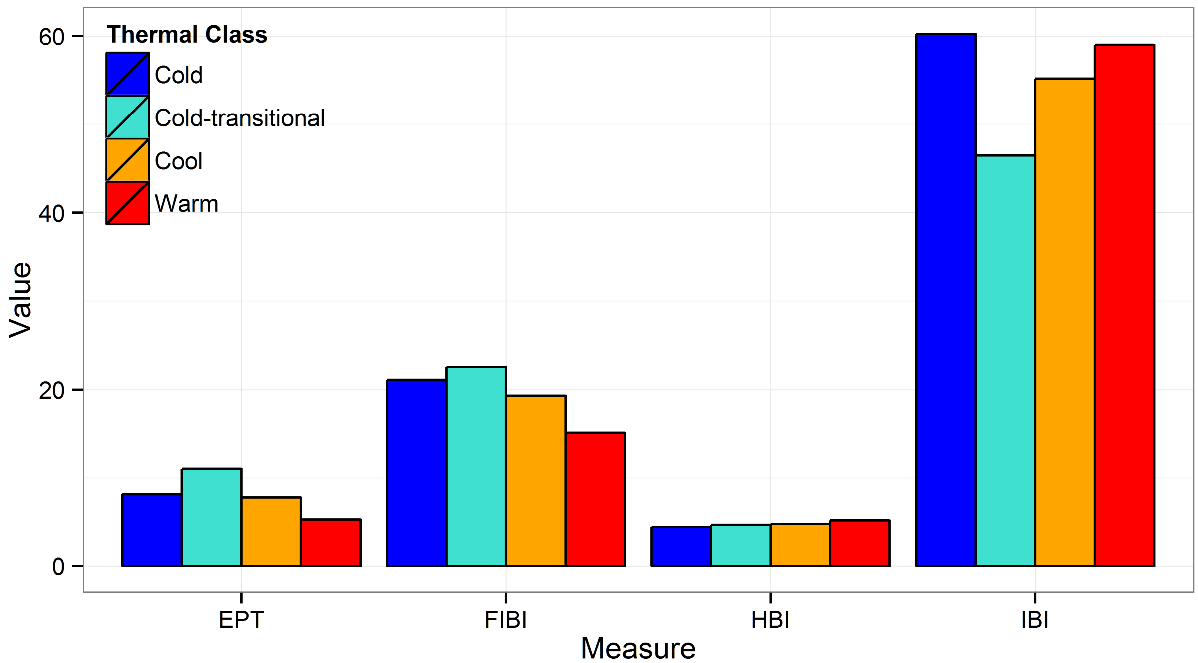

Figure 12. Length-based average stream health values for each measure and thermal class. Note that each measure is defined by a unique scale.

5.3.3 Impacts of Land use Change on Stream Health

Following development of stream health models, they can be implemented to study the impacts of stressors such as land use changes on stream health. In this study, the ANFIS models used outputs from the SWAT models created with pre-settlement land use maps to develop baseline 1800s predictions of stream health. Based on the changes in land use from pre-settlement to current, we hypothesized that stream health declines. This is due to clearing of forests and draining wetlands for agricultural and urban expansion leading to changes in the hydrologic cycle and ultimately degradation of stream conditions. This trend is apparent across most of the study watersheds, although the Au Sable and Cedar-Ford watersheds have experienced relatively less agricultural expansion and urban development since the 1800s (Table 23 of Appendix D).

Changes in stream health for the Pere Marquette-White watershed are presented in Figure

13 (EPT and fish IBI) and Figure 14 (FIBI and HBI). The Pere-Marquette-White watershed was selected for analysis because it contains a relatively even distribution of stream thermal classes and experienced moderate land use change over the past 150 years. These changes were conversion of forests and wetlands to agriculture, rangelands, and urban areas by 16%, 10%, and 9%, respectively (Table 23 of Appendix D). The result of these changes was a slight decline in stream health scores across all measures when moving from pre-settlement to current land use. A majority of streams in the watershed (60%) experienced at least a small decline in stream health, while only about 24% of streams in the watershed moved into a worse stream health class (e.g. from fair to poor). Considering 'excellent' and 'good' stream health as 'acceptable' and 'poor' and 'very poor' as unacceptable stream health, there is a decline in streams with acceptable health following land use change (the 'fair' class remains the same). For example, 8% (EPT) and 11% (HBI) of the total stream length moves from acceptable to unacceptable health. Meanwhile, there is no change in the length of acceptable streams for FIBI and IBI, but they experience a 2% and 4% decline from fair to unacceptable, respectively. The results of the paired difference Wilcoxon signed-rank test confirmed that there were statistically significant differences (declines) in stream health moving from pre-settlement to current land use conditions.

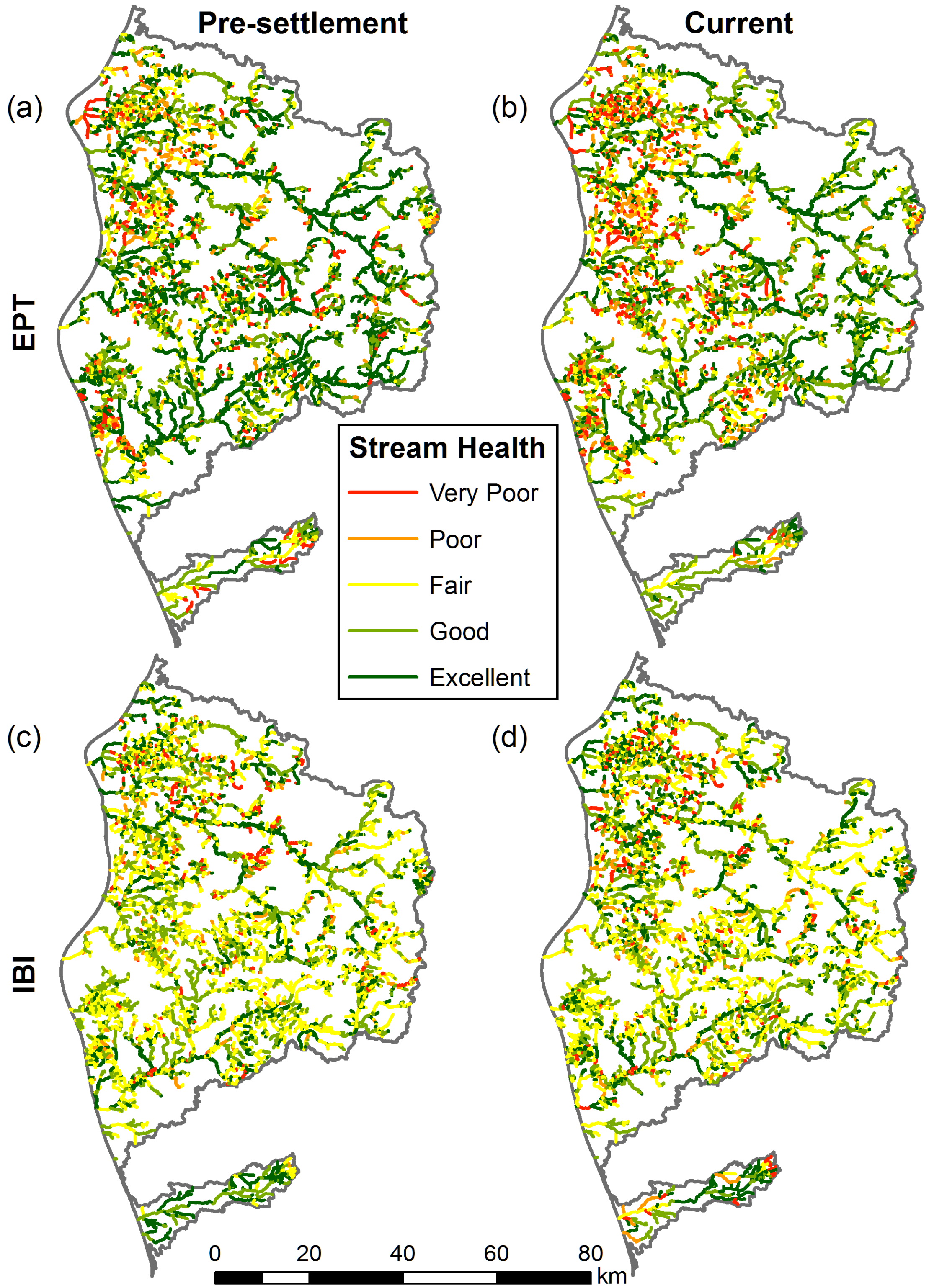

Figure 13. Pere Marquette-White stream health for (a) EPT pre-settlement, (b) EPT current, (c) IBI pre-settlement, and (d) IBI current

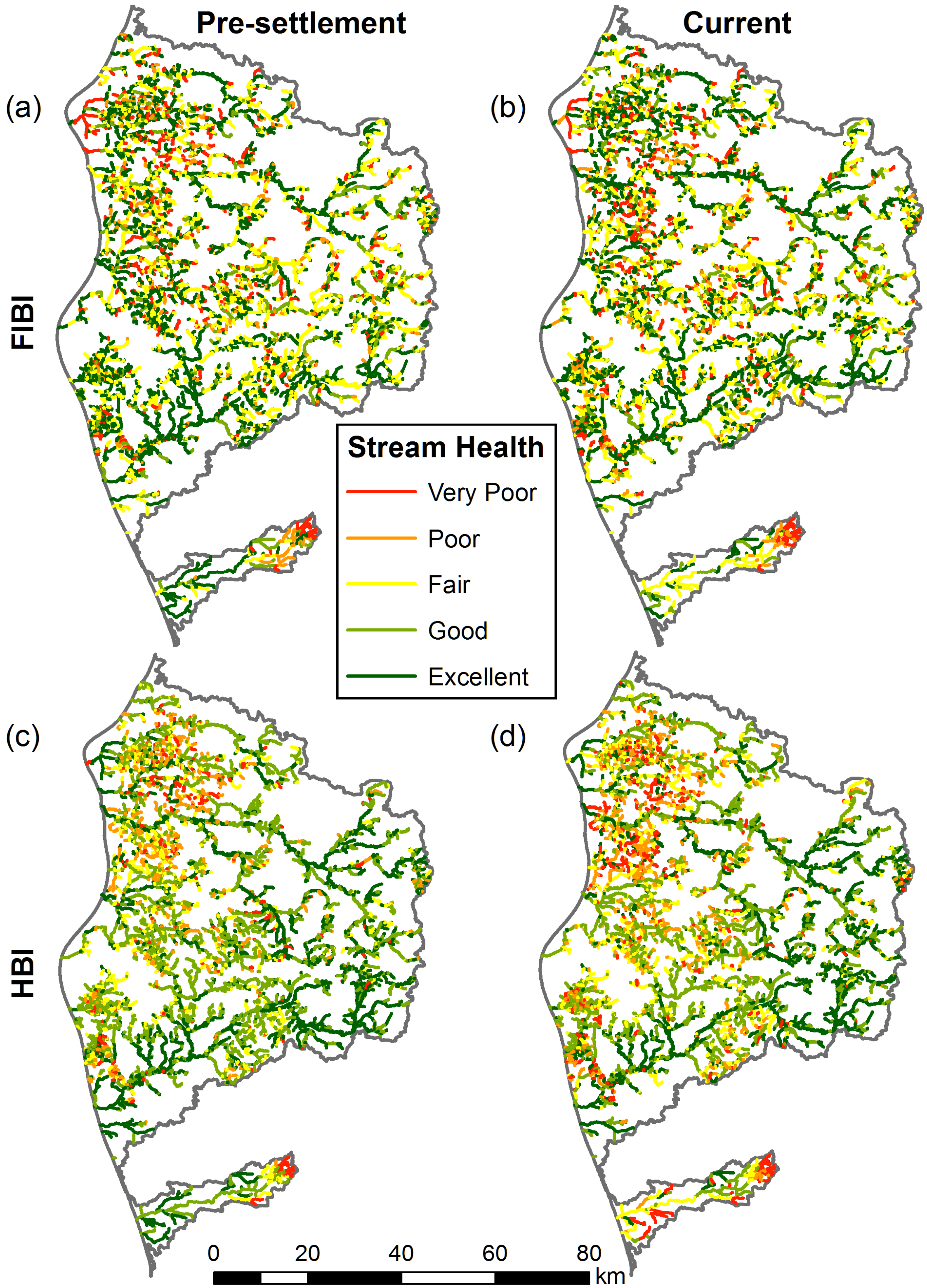

Figure 14. Pere Marquette-White stream health for (a) FIBI pre-settlement, (b) FIBI current, (c) HBI pre-settlement, and (d) HBI current

Land use change for the Pere Marquette-White watershed is presented in Figure 15 with streams identified as improving or declining in stream health class when comparing pre-settlement and current land use. Overall, most streams did not change health class: 58% (IBI), 63% (FIBI), 65% (HBI), and 62% (IBI) remained in the same stream health class. Most of the agricultural expansion and urbanization in the watershed occurred in the downstream reaches, while headwater streams are still generally surrounded by forests and wetlands. Consequently, most of the declines in stream health have occurred in downstream reaches. This is most evident in the case of EPT and HBI, where 32% and 27% of streams moved to a worse stream health class, respectively (e.g. good to fair). For FIBI and IBI, there were fewer changes in stream health class, though the majority of declining streams were located where land use change was the most prominent. For streams that improved in health over the last 150 years, it was in locations that generally experienced little to no land use change.

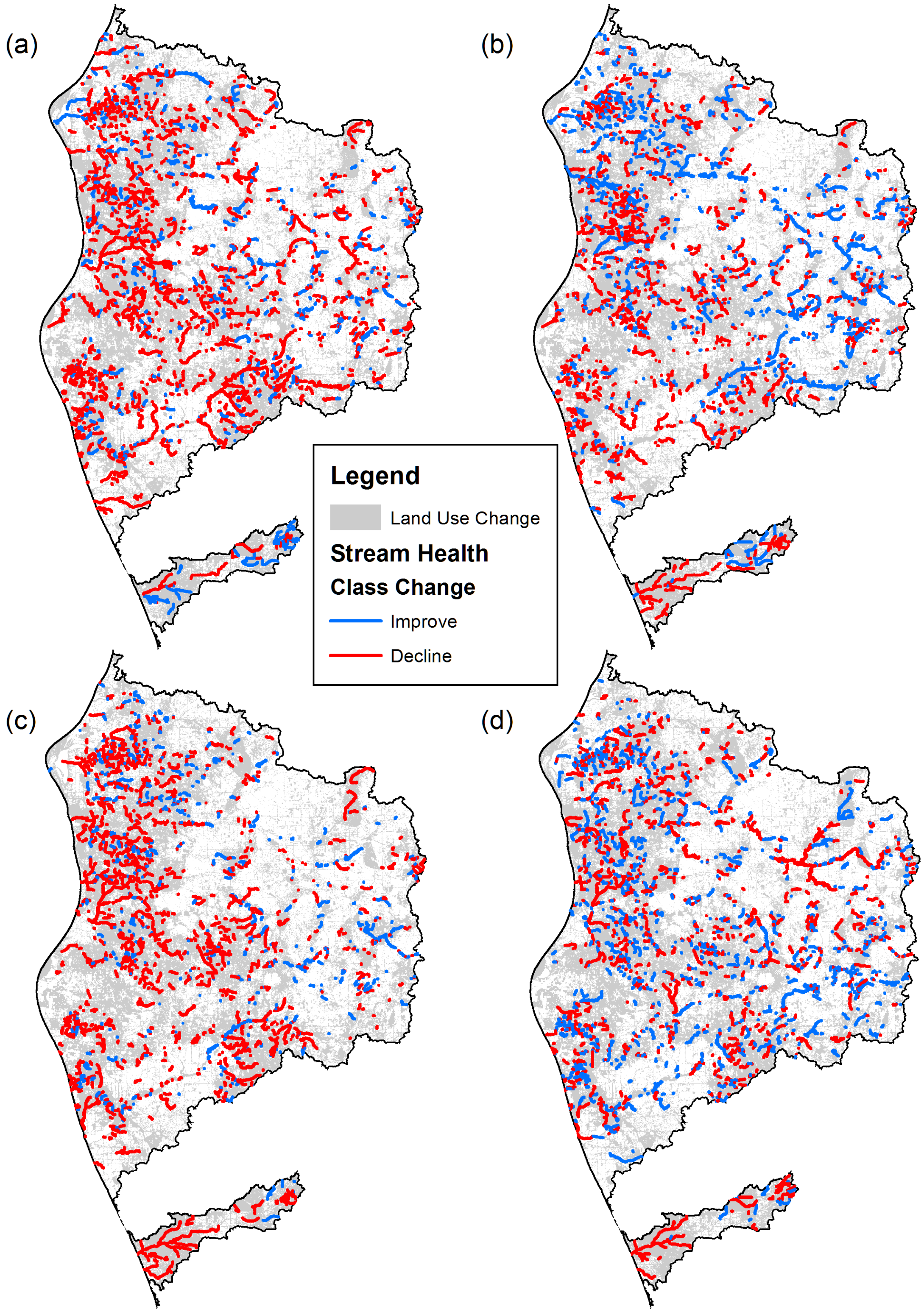

Figure 15. Land use change and change in stream health class from pre-settlement to current for (a) EPT, (b) FIBI, (c) HBI, and (d) IBI

Stream health was also examined across stream thermal classes with respect to changes from pre-settlement to current land use. Changes in stream km for each stream health measure, stream health class, and thermal class are presented in Figure 16. In general, all thermal classes experienced a decline in streams classified as being in good condition (good and excellent) and an increase in poor and very poor streams. This is most apparent in cool and warm streams, which is likely correlated with the extensive agricultural expansion that has occurred in watersheds that contain these streams (primarily Flint and Raisin). Cold and cold-transitional streams were less impacted because watershed such as the Au Sable and Boardman-Charlevoix still have large areas of forest and wetlands that have not changed since the 1800s.

The stream health measures also exhibited varying sensitivity to changes in health class. Changes in fish IBI were less pronounced than changes in macroinvertebrate taxa. This indicates more versatility in fish populations than the invertebrate populations. Small changes in land use had a pronounced impact on the macroinvertebrates, while fish IBI was not affected to the same extent.

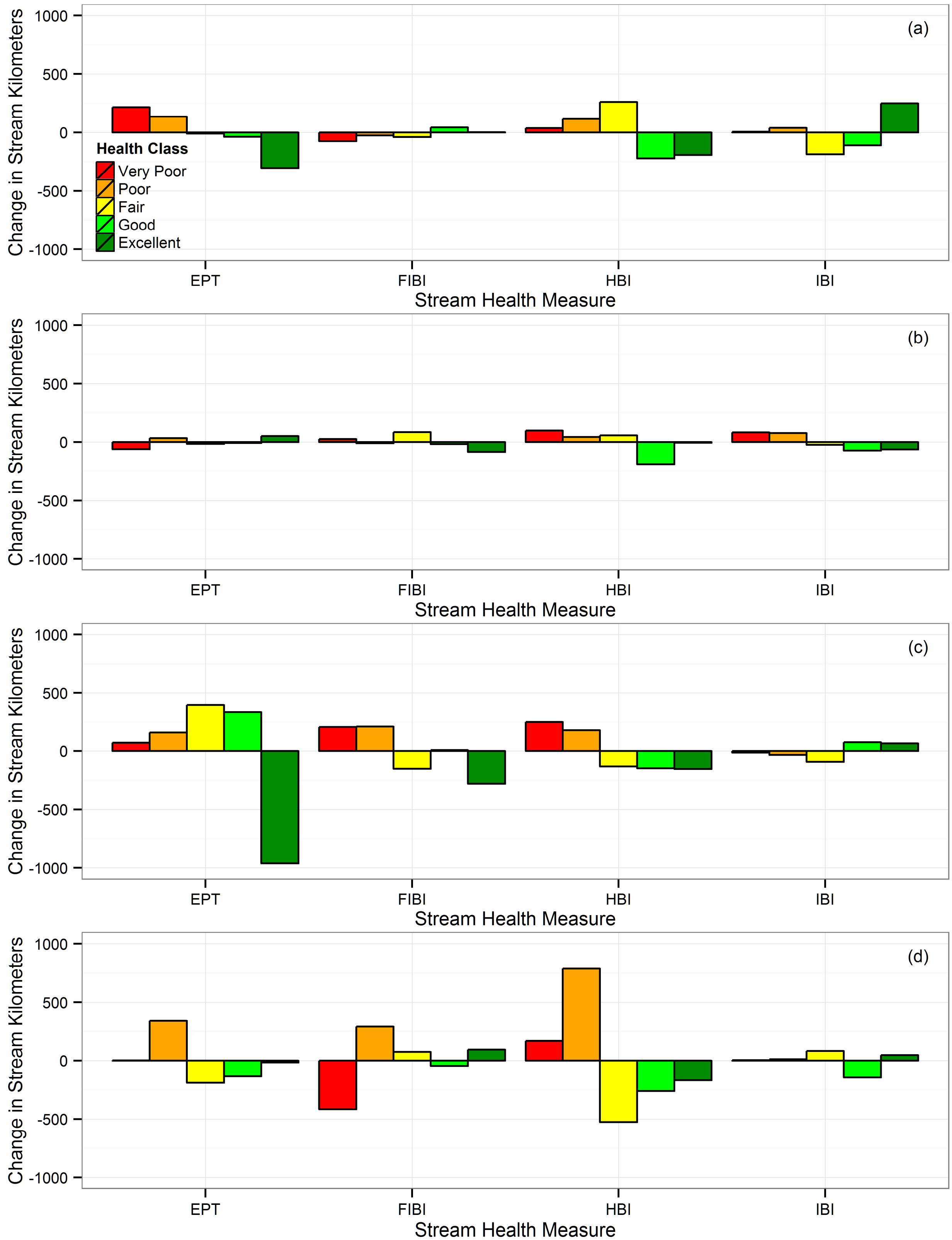

Figure 16. Changes in stream health class from pre-settlement to current for (a) cold, (b) cold-transitional, (c) cool, and (d) warm streams

5.4 CONCLUSIONS

The goal of this study was to develop detailed large-scale stream health models that are applicable in Michigan, which was accomplished by developing stream thermal class-based (cold, cold-transitional, cool, and warm) models, rather than watershed-specific models. Using a data-driven Bayesian variable selection method, influential in-stream flow regime and water quality variables were selected to build ANFIS stream health models of EPT, FIBI, HBI, and IBI. Finally, the utility of the models were tested through evaluating the impacts of land use change on stream health.

The consistent selection of several variables within the stream thermal classes across stream health measures indicates that a few key flow regime variables play a significant role in dictating the health of cold, cold-transitional, cool, and warm streams. These key variables were mostly related to timing and duration of major low and high flow events, indicating they exert control on Michigan stream ecosystems. The similarities and differences in variable sets across thermal classes demonstrated the relationship between flow regime, stream temperature, and stream health.

Thermal class was also found to be importance from a model performance perspective. Building ANFIS models based on stream thermal class generally improved their predictability. This demonstrates that the Bayesian variable selection procedure was able to select important variables better when considering thermal class. Regardless of thermal class, consistent trends in model characteristics were found in development of ANFIS models. Nonlinear MFs were consistently superior in performance to their linear counterparts, further confirming their utility in modeling nonlinear ecological systems.

The final stream health models were used to predict pre-settlement (early 1800s) and current stream health for seven Michigan watersheds. Model predictions were consistent with the hypothesis that declines in stream health were associated with locations that experienced by agricultural expansion and urbanization. Cool and warm streams generally experienced greater declines in stream health because watersheds containing these streams have undergone the most change since the early 1800s.

The applicability of these models in exploring the impact of landscape changes on stream health implies that they would be useful in exploring other watershed-scale environmental alterations, such as best management practice implementation and changing climate. This study has demonstrated the development stream health models that are applicable on both large and regional-scales. This process could be transferred to other regions to develop large-scale models of stream health that can be used for broad climate and land use change impact assessments and detailed site-level decision-making in natural resources management.

6 LARGE-SCALE CLIMATE CHANGE VULNERABILITY ASSESSMENT OF STREAM HEALTH

6.1 INTRODUCTION

Since 1951, the Earth's surface has warmed by 0.72 °C, while each of the last three decades has been successively warmer than any ever recorded (IPCC, 2013). The Intergovernmental Panel on Climate Change (IPCC) concluded that it is extremely likely that anthropogenic activities, primarily GHG emissions, caused more than half of these increases (IPCC, 2013). By the end of the 21st century, increases in global average surface temperatures projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations are projected to be between 0.3-4.8 °C depending on radiative forcing, although these increases will vary regionally (IPCC, 2013). As the atmosphere warms, its water holding capacity will increase and the hydrologic cycle will intensify, resulting in changes in frequency of precipitation extremes and increased evaporation and dry periods (Liebowitz et al., 2014; Piani et al., 2010; Praskievicz and Bartlein, 2014; Prudhomme et al., 2014). These changes in the hydrologic cycle have potentially serious implications for water resources and freshwater ecosystems. Hydrologic conditions such as floods and droughts have direct ecological effects (Lytle and Poff, 2004), while water temperature is a controlling factor on species distribution and community composition (Durance and Omerod, 2007; DeWeber and Wagner, 2014). Some locations have already experienced shifts in aquatic community composition and structure towards selection of species that tolerate increased temperature and lower flows (Chessman, 2009). The IPCC (2014) has recognized that climate change is a significant threat to global biodiversity and ecosystem function.

Biological assessments are a commonly used tool to assess the health of freshwater ecosystems. Biological assessments are used to measure an aquatic ecosystem's biological integrity and the effects of stressors on that ecosystem's biota (USEPA, 2011). Here, the biological integrity of an ecosystem is based on its ability to "support and maintain a balanced, integrated, and adaptive community of organisms with a species composition, diversity, and functional organization" that is similar to that region's natural habitat (Karr, 1987). Multimetric biological indices or biotic indicators are a commonly accepted method for measuring ecosystem health and response to stressors (Einheuser et al., 2012). They measure ecosystem quality by communicating severity and extent of impairment through establishing a gradient of biological condition (Karr and Yoder, 2004). For example, the Index of Biotic Integrity (IBI) consists of metrics that describe structure, composition, and functional organization of a fish community (Lyons et al., 1996). In addition to fish, macroinvertebrates are prominently used in biological assessments because they respond quickly to a multitude of stressors at local scales (Flinders et al., 2008; Herman and Nejadhashemi, 2015). Using several biotic indicators is beneficial because it provides a holistic assessment of ecosystem health (Clapcott et al., 2012).

Community-level biological assessment is critical in light of potential climate change (Woodward et al., 2010). Most studies linking climate change and aquatic ecosystems have focused on individual species and taxonomic groups rather than communities (Lawrence et al., 2010; Woodward et al., 2010) such as individual macroinvertebrates (Domisch et al., 2011) and salmonids (Rahel et al., 1996; McDaniels et al., 2010; Isaak et al., 2012). Meanwhile, there are concerns that existing biotic indices ignore the potential effects of a changing climate and may become obsolete (Woodward et al., 2010). However, studies in Europe (Leunda et al., 2009) and North America (Larwrence et al., 2010) determined that biotic indicators were robust in response to a changing climate, establishing their continued utility in biological assessment. In addition, Lawrence et al. (2010) demonstrated that higher taxonomic resolutions (order and family) rather than genus and species were useful for detecting climate change.

Climate change impacts assessments that focus on individual species responses are invaluable, but natural resources managers are often interested in the broader system view that biological assessments provide. At the same time, our knowledge of ecological conditions at large-scales is limited by incomplete monitoring data (Wang et al., 2008; Einheuser et al., 2012). Therefore, the goal of this research is to focus on the impacts of climate change on broader ecosystems health. By developing biotic indicator models of fish and macroinvertebrates, we can establish a system-level outlook of potential changes in stream health.

6.2 MATERIALS AND METHODS

6.2.1 Study Watersheds

Seven 8-digit hydrologic unit code (HUC-8) watersheds in Michigan, USA were the subject of this study: the Au Sable (HUC 04070007), Boardman-Charlevoix (HUC 04060105), Cedar-Ford (HUC 04030109), Flint (04080204), Muskegon (04060102), Pere Marquette-White (04060101), and Raisin (04100002) (Figure 17). The watersheds were selected based on their availability of fish and macroinvertebrate sampling data, and diversity of physiographic characteristics including land use, soils, and stream thermal classes.

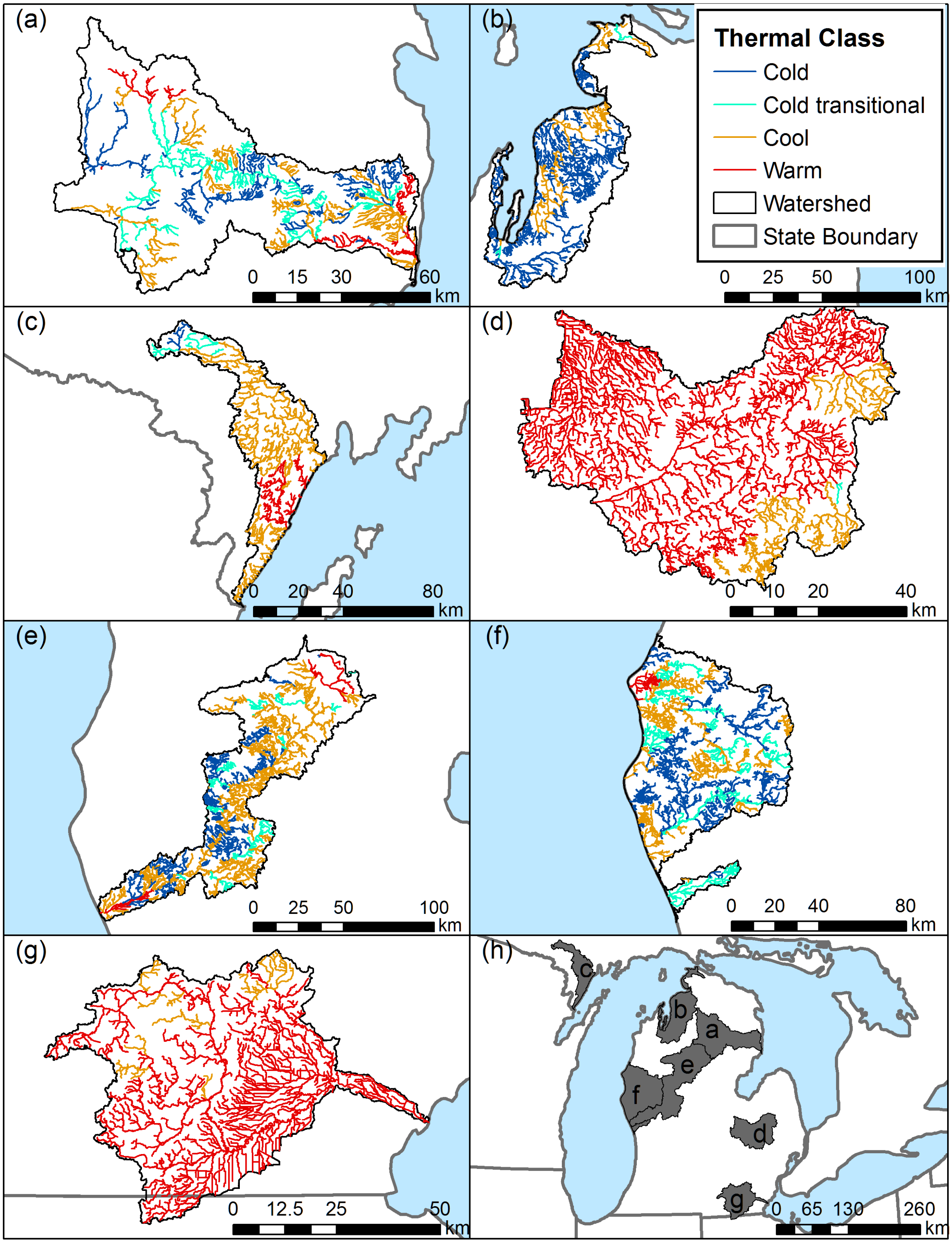

Figure 17. Stream thermal classes for (a) Au Sable, (b) Boardman-Charlevoix, (c) Cedar-Ford, (d) Flint, (e) Muskegon, (f) Pere-Marquette-White, and (g) Raisin; (h) watershed locations in Michigan

Drainage areas of the watershed range 2639 km^2 for the Cedar-Ford to 7071 km^2 for the Muskegon. Land use characteristics of the watersheds vary, where the Au Sable, Boardman-Charlevoix, and Cedar-Ford primarily consist of forests and wetlands, while the Flint, Raisin, Muskegon, and Pere Marquette-White are a mix of agriculture, forests, urban areas, and wetlands. Soils range from well-drained sandy soils (Au Sable, Boardman-Charlevoix, Muskegon, and Pere-Marquette White), while the Flint and Raisin have more poorly drained soils.

Stream thermal class was used as a selection criteria because temperature dictates the abundance, occurrence, distribution, and physiology of aquatic biota (Lyons et al., 2009; Poole and Berman, 2001; Wehrly et al., 2003). Differences in water temperature among streams are most pronounced during peak summer temperatures in the northern hemisphere (Caissie et al., 2006; Wehrly et al., 2009). Therefore, July mean temperature is a commonly used predictor of fish assemblage structure (Steen et al., 2008; Werhly et al., 2003; Wehrly et al., 2009). Given the importance of temperature as a control of stream ecosystem function (Olden and Naiman, 2010), Zorn et al. (2008) developed stream thermal classes (cold, cold-transitional, cool, and warm) for Michigan based on July mean water temperature and fish communities. Macroinvertebrates are also affected by stream temperature, as modified thermal regimes can disrupt emergence and reduce population success (Bunn and Arthington, 2002). However, fish are more sensitive to temperature, which is why the thermal classes have only been developed for fish in Michigan. Study watersheds and stream thermal classes are presented in Figure 17. The stream thermal classes and watersheds that have at least 10% of streams in a particular class are defined in Table 10.

Table 10. Characteristics of Michigan stream thermal classes

Thermal Class	Temperature	Biotic community	Study Watersheds
Cold	≤ 17.5 °C	Coldwater	Boardman-Charlevoix; Au Sable; Muskegon; Pere Marquette-White
Cold-transitional	17.5 – 19.5 °C	Coldwater, some warmwater	Au Sable; Pere Marquette-White
Cool	19.5 – 21.0 °C	Warmwater, some coldwater	Boardman-Charlevoix; Cedar-Ford; Flint; Muskegon; Pere Marquette-White; Raisin
Warm	> 21 °C	Warmwater	Cedar-Ford; Flint; Raisin

6.2.2 Data Collection

6.2.2.1 Physiographic Data

Several physiographic datasets were collected for watershed model development, including topography, land use, soils, stream networks, and climate. The topography dataset was the 30 m resolution United States Geological Survey gridded National Elevation Dataset (NED, 2014). The land use dataset was the 30m United States Department of Agriculture (USDA) – National Agricultural Statistics Service (NASS) 2012 Cropland Data Layer (NASS, 2012). The soil dataset was the spatial and tabular USDA Soil Survey Geographic Database (SSURGO) with resolutions ranging from 1:12,000 to 1:63,600. Stream networks were obtained from the Great Lakes Regional River Database Classification System developed by the Michigan Institute of Fisheries Research (IFR), based on the National Hydrography Dataset Plus (1:24,000 resolution). These streams and catchments are defined so each individual stream segment and subwatershed represents a homogeneous area of biological, physiographical, and geomorphological characteristics (Einheuser et al., 2013b). Daily precipitation and temperature (maximum and minimum) were obtained for 1978-2005 from the National Climatic Data Center (NCDC, 2015). The NCDC dataset was comprised of 40 precipitation and 39 temperature stations selected for minimal missing data (less than 5% missing of the 1978-2005 record). Precipitation and temperature station locations are presented in Figure 31 of Appendix E.

6.2.2.2 Biological Data

Fish and macroinvertebrate data was obtained from the Michigan River Inventory database (Seelbach and Wiley, 1997) and the Michigan Department of Natural Resources. This data included three macroinvertebrate and one fish indicator: number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family-level Index of Biotic Integrity (FIBI), the Hilsenhoff Biotic Index (HBI), and the fish Index of Biotic Integrity (IBI). Macroinvertebrate sampling occurred in June through September of 1996-2003 (MDEQ, 1997). Fish were collected on wadeable streams from 1982-2007 (Einheuser et al., 2012). Both fish and macroinvertebrate data were used because they respond differently to stressors, operate on dissimilar scales, and represent unique trophic levels (Barbour et al., 1999; Flinders et al., 2008). The total number of samples in each stream thermal class varied: 141 macroinvertebrate and 85 fish for cold, 51 macroinvertebrate and 38 fish for cold-transitional, 120 macroinvertebrate and 113 fish for cool, and 123 macroinvertebrate and 59 fish for warm.

The EPT taxa is a presence count of pollutant-intolerant macroinvertebrate species, where lower counts indicate potential aquatic community degradation. The FIBI is a multi-metric index comprised of macroinvertebrate community composition and richness metrics, with a score ranging from 0-45 (45 is excellent). The HBI (Hilsenhoff, 1988) is an organic pollution tolerance index for macroinvertebrates that ranges from 0-10 (0 is excellent). The fish IBI is a multi-metric index composed of community measures of richness, composition, and abundance (Wang et al., 2007); it ranges from 0 (very poor) to 100 (excellent).

6.2.3 Modeling Process

The modeling process contains two primary procedures: development of stream health models and development of the stream temperature model (Figure 18). Both procedures begin with baseline climate data and climate scenarios from climate models' future projections of temperature and precipitation. The stream health models began with development of Soil and Water Assessment Tool (SWAT) watershed models that simulate streamflow and water quality for each study stream. Ecologically relevant flow regime variables were calculated using the Hydrologic Index Tool (HIT) on SWAT streamflow output. Bayesian variable selection (Woznicki et al., 2015a) identified best variable sets for use as predictors in stream health models of EPT taxa, FIBI, HBI, and IBI. These models were developed for each thermal class. Meanwhile, the statistical stream temperature model used climate and physiographic data to develop projections of future stream temperatures and potential changes in thermal class.

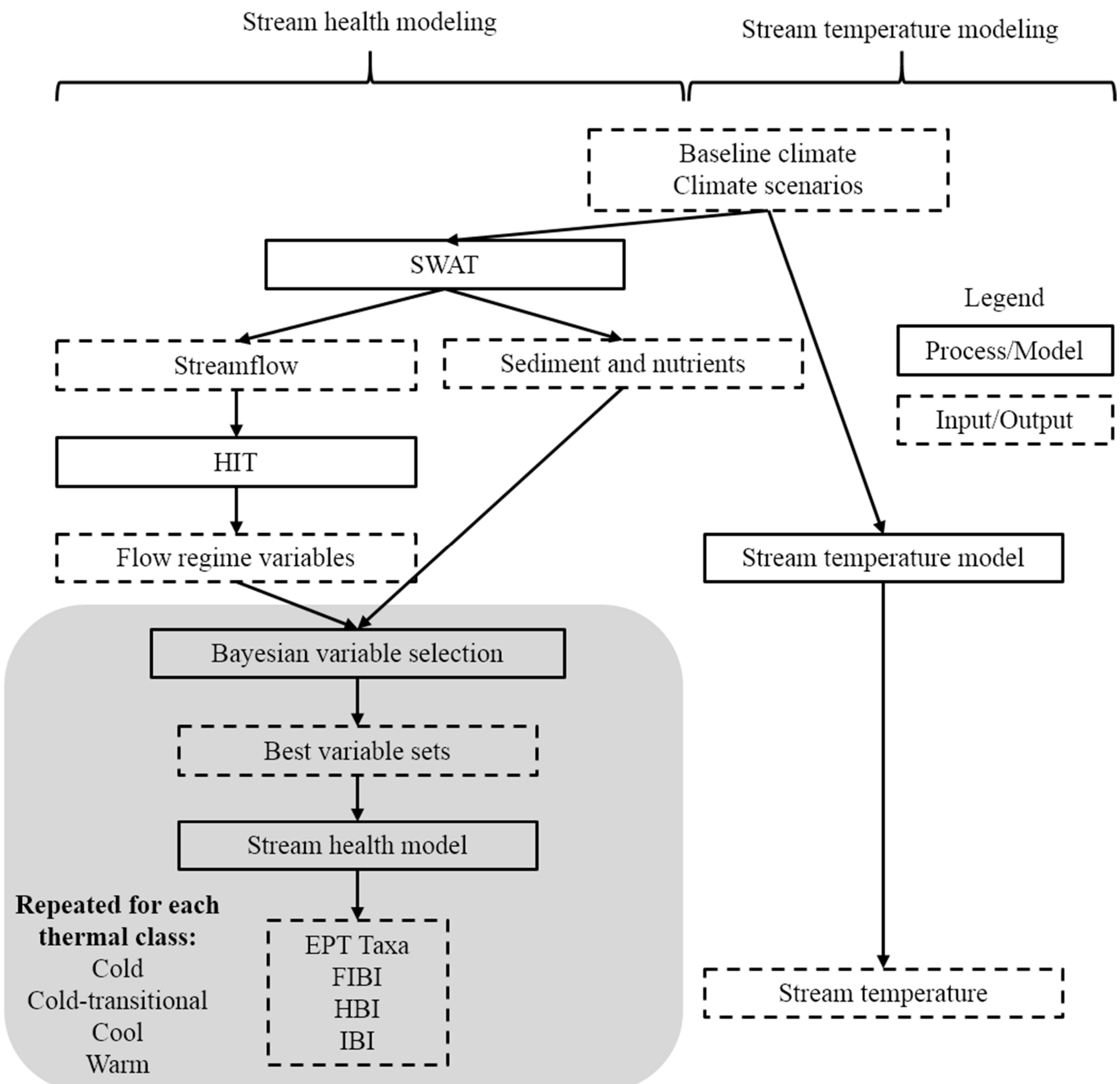

Figure 18. Modeling process

6.2.4 Development of Ecologically-Relevant In-Stream Variables

Development of ecologically relevant in-stream variables consists of two components: the watershed model (SWAT) and the flow regime characterization using the HIT. SWAT (Arnold et al., 1998) was developed for the USDA – Agricultural Research Service to predict the impact of land management practices on water, sediment, and chemical yields in large watersheds (Neitsch et al., 2005). The model is physically based, semi-distributed, and allows for simulation over long time periods (Neitsch et al., 2005). SWAT simulates hydrology, plant growth, evapotranspiration, sediment routing, and nutrient cycling. SWAT is semi-distributed, where a watershed is delineated into spatially oriented subwatersheds that are further delineated into non-spatial hydrologic response units (HRUs). Each individual HRU consists of a homogeneous land use, soil type, slope, and land management practice. In this study, each subwatershed contained only one HRU due to the characteristics of the IFR streams and subwatersheds.

Each watershed model was calibrated and validated for streamflow, sediment, total nitrogen (TN), and total phosphorus (TP). Continuous daily streamflow data was obtained from USGS gauging stations and grab samples of sediment and nutrients were obtained from the Michigan Department of Environmental Quality (MDEQ). SWAT Streamflow calibration and validation were performed from 1998-2001 and 2002-2005, respectively. Sediment and nutrient monthly load calibration and validation was performed for varying periods from 1998-2005, depending on availability of monitoring data. Details on model calibration and validation are presented in Woznicki et al. (2015b).

The calibrated daily streamflow data obtained from SWAT was input into the HIT (Henriksen et al., 2006) to characterize 171 ecologically-relevant flow regime indices over 1980-2000. The flow regime indices are comprised of the five components of the natural flow regime: magnitude (M), frequency (F), duration (D), timing (T), and rate of change (R). Each index is also characterized by flow event type: low (L), average (A), and high (H). These indices, along with annual and monthly sediment, TN, and TP loads simulated by SWAT were considered as potential variables (39 total) for the stream health models. In addition, drainage area and July mean stream temperature were included in the process. Drainage area was included because watershed size is a key predictor of aquatic biota distribution (Pont et al., 2009). This resulted in 212 total variables for each stream in the study watersheds.

6.2.5 Stream Health Model

The stream health modeling process consisted of variable selection and model development. Variable selection was performed using Bayesian variable selection and the stream health models were developed using adaptive neuro-fuzzy inference systems (ANFIS).

The variable selection process was performed using the Bayesian variable selection method presented in Woznicki et al. (2015a), where it was concluded that this method is superior to other selection methods such as principal component analysis and Spearman's Rank Correlation. In the Bayesian variable selection method the final outcome is a *selectivity* measure that describes the probability of a variable being selected out of all posterior samples. Selectivity was used to identify the top three variables to be used in development of the stream health models. Full selectivity results are presented in Woznicki et al. (2015b).

Several approaches have been used to model ecological systems, but fuzzy logic is often used due to its ability to model these complex, nonlinear problems (Chen and Mynett, 2003; Adriaenssens et al., 2004; Marchini et al., 2009; Einheuser et al., 2013). Adaptive neuro fuzzy inference system (ANFIS) (Jang, 1993), a fusion of artificial neural networks (ANNs) and fuzzy logic, was used to develop the stream health models for each combination of stream health indicator (EPT, FIBI, HBI, and IBI) and stream thermal class (cold, cold-transitional, cool, and warm). Fuzzy logic is a soft-computing technique that maps the degree of membership of a value to a fuzzy set, where 0 indicates no membership and 1 indicates full membership. These are defined by graphical membership functions (MFs) defined by particular shapes. If-then inference rules determine a value's membership to each specific function. While fuzzy logic is proficient in modeling ecological systems (Chen and Mynett, 2003), development of MFs and if-then statements is time consuming, intensive, and subjective (Adriaenssens et al., 2004). ANFIS is useful in this respect, because it uses ANNs to build and optimize MFs through minimizing predictive error in a validation dataset (Jang, 1993).

The MATLAB (R2013b) Fuzzy Logic Toolbox was used to build the ANFIS models. Five MF shapes were tested: triangular, trapezoidal, Gaussian, Gaussian composite and generalized bell. A limit of three variables was placed on model development, because increasing the number of variables requires an increase in the number of fuzzy parameters, and subsequently more input data, which was scarce. To prevent over-fitting, the number of ANFIS parameters should not exceed the number of training input (Sanikhani and Kisi, 2012). For the same reason, a maximum of four MFs per variable was used. All possible combinations of MF shape, number of MFs, and variables (selected from the Bayesian method) were fit (over 500 epochs) using 10-fold cross validation. More details about the ANFIS model details can be found in Woznicki et al. (2015b). Model performance ranged from R^2 equal to 0.49 (cold) to 0.68 (cold-transitional) for EPT, 0.44 (cool) to 0.74 (cold-transitional) for FIBI, 0.41 (cold) to 0.65 (cold-transitional) for HBI, and 0.37 (cool) to 0.90 (cold) for IBI. The most commonly selected MF shapes were nonlinear: Gaussian, Gaussian composite, and generalized bell. The selected variables for the final 16 stream health models are presented in Table 11.

Stream health scores were analyzed at the reach level and the stream thermal class level. Overall stream health scores at the thermal class level were calculated using length-weighted averages. Here, the stream health score for each individual reach was multiplied by its length. These values were summed for each thermal class and divided by the total reach length in each thermal class.

Table 11. Variable selection results for each stream health model and temperature class

	EPT				FIBI				HBI				IBI			
Variable	Cold	Cold-transitional	Cool	Warm	Cold	Cold-transitional	Cool	Warm	Cold	Cold-transitional	Cool	Warm	Cold	Cold-transitional	Cool	Warm
DH6															X	
DH15									X							
DH18											X					
DH20		X														
DH22																X
DL9								X								
DL15											X					
DL16			X													
DL17								X								
FH2				X								X				
MA25			X				X									
MA27									X							
MA31	X															
MA37				X								X				
MA40						X										
MH15										X						
MH18		X														
MH19				X												
MH24									X							
MH27														X		
RA5								X								
RA7														X		
RA8					X											
RA9						X										
TA1	X				X										X	X
TA2	X				X		X								X	X
TH3		X				X	X			X						
TL1													X			
TL2													X			
TL3													X			

6.2.6 Climate Change Data

Climate change data was obtained from World Climate Programme's CMIP5 (Taylor et al., 2011) multi-model ensemble for 2020-2040 (compared to a control period of 1980-2000).

Climate change data was obtained from World Climate Programme's CMIP5 (Taylor et al., 2011) multi-model ensemble for 2020-2040 (compared to a control period of 1980-2000). Although this period was selected as a control, it is important to note that this time slice contains non-stationarity in its climate conditions, such as increasing total annual precipitation, frequency of wet days, and frequency of heavy precipitation events (Andresen et al., 2012). The 2020-2040 period was selected for analysis because near-century changes are more applicable to decision-makers. Middle and end of century climate change is construed in terms that are more abstract by decision-makers (Weber, 2006). This will affect the perceived risk of declining stream health and damage the potential for development of adaptation strategies because it will require immediate costs and sacrifices to achieve distant and abstract goals (Weber, 2006). However, the 2020-2040 timeslice contains a greater effect of natural variability because the anthropogenic forcing signal is weaker in the early 21st century than later in the century (Knutti et al., 2008; IPCC, 2013).

The CMIP5 dataset used in this study included simulations from ten modeling groups (Table 12) comprised of sixteen GCMs under three RCPs for 47 scenarios. The RCPs were developed by Moss et al. (2010) for the IPCC Fifth Assessment Report and are defined by radiative forcing pathways rather than the socioeconomic scenarios and greenhouse gas (GHG) emissions as in the Special Report on Emissions Scenarios (Nakicenovic and Swart, 2000) of the IPCC Third and Fourth Assessment Reports. The three RCPs used were RCP4.5, RCP6.0, and RCP8.5, where each number represents the estimated trajectory of radiative forcing (W/m^2) by 2100. Estimated CO_2-equivalent GHG emissions by 2100 of each RCP are approximately 650 ppm, 850 ppm, and greater than 1370 ppm for RCP4.5, RCP6.0, and RCP8.5, respectively. The CO_2 concentrations used in SWAT were selected for the middle of the simulation period (2030), characterized by atmospheric concentrations of 435 ppm, 428 ppm, and 448 ppm for RCP4.5, RCP6.0, and RCP8.5, respectively.

Table 12. CMIP5 multi-model ensemble dataset

Modeling Center (or Group)	**Institution**	**Model(s)**
FIO	The First Institute of Oceanography, SOA, China	FIO-ESM
IPSL	Institut Pierre-Simon Laplace	IPSL-CM5A-LR IPSL-CM5A-MR
MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM MIROC-ESM-CHEM
MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5
MOHC	Met Office Hadley Centre	HadGEM2-AO HadGEM2-ES
MRI	Meteorological Research Institute	MRI-CGCM3
NASA GISS	NASA Goddard Institute for Space Studies	GISS-E2-H GISS-E2-R
NCAR	National Center for Atmospheric Research	CCSM4
NOAA GFDL	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3 GFDL-ESM2G GFDL-ESM2M
NSF-DOE-NCAR	Community Earth System Model Contributors: National Science Foundation, Department of Energy, National Center for Atmospheric Research	CESM1-CAM5

The change factor approach was used in this study to generate daily time series climate change data. This method calculates monthly anomalies between the GCM simulated control and scenario runs that are superimposed on the observed time series data (Teutschbein and Seibert, 2012). Precipitation change factors are calculated using a ratio (because precipitation is zero-bounded), while temperature change factors are additive. Gridded GCM data was extracted for each observed climate station (40 precipitation and 39 temperature) and monthly change factors were applied to the daily precipitation and daily maximum and minimum temperature. Change factors for precipitation and maximum and minimum temperature are presented in Figure 19 for one weather station central to the study watersheds (USC00203429 at 43.2025°, -85.2422° in Figure 31 of Appendix E).

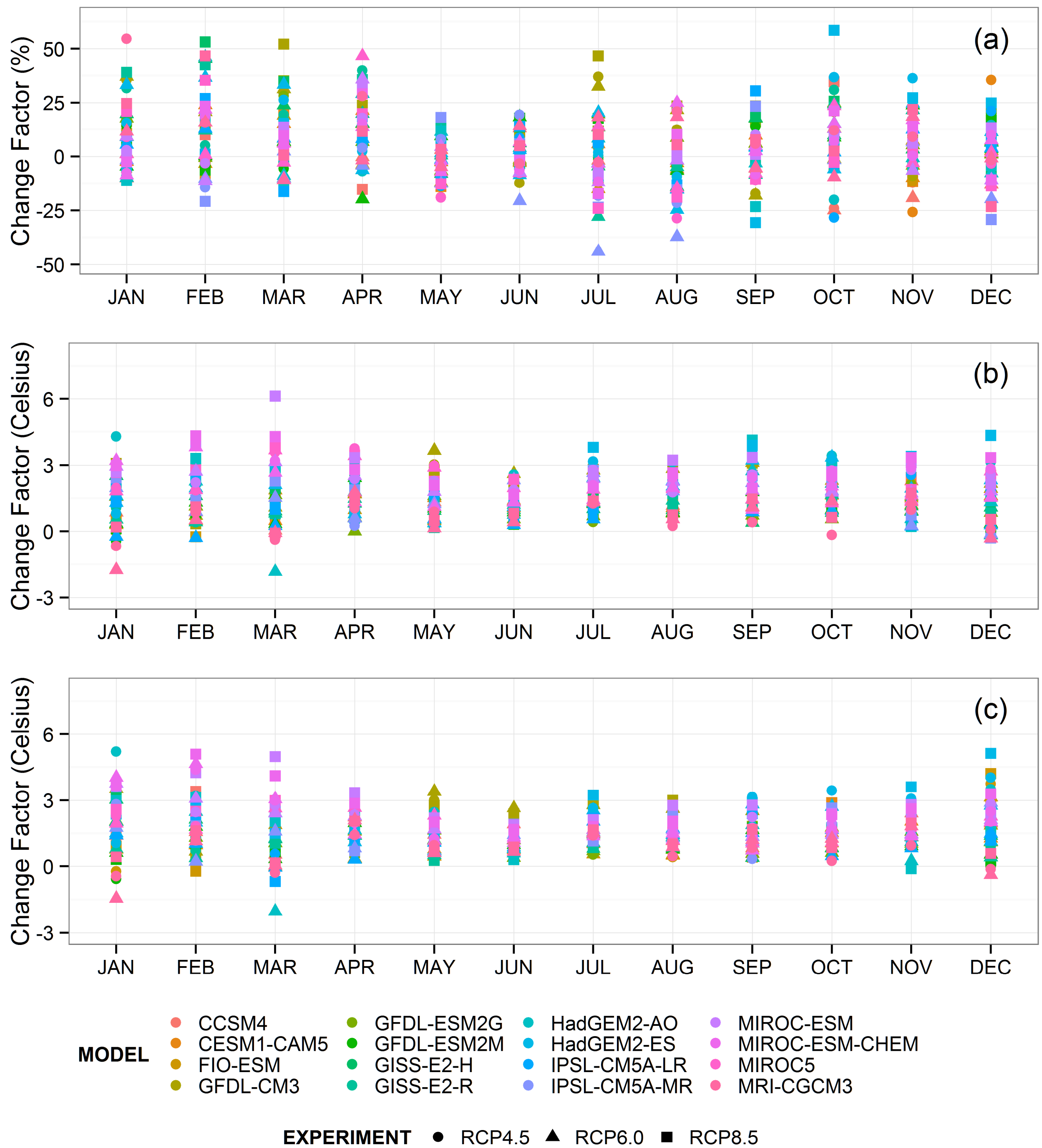

Figure 19. Monthly change factors across all climate models and RCPs for (a) precipitation, (b) maximum temperature, and (c) minimum temperature

The assumptions of the change factor method include: (1) GCMs are better at simulating relative changes rather than absolute values (Fowler et al., 2007), (2) GCM biases are similar in the control and future simulation periods (Boyer et al., 2010), and (3) the variability between the current and future climate remains the same, where bias in distribution and frequencies of simulated variables is ignored (Winkler et al., 2011; Gädeke et al., 2014). However, the change factor methodology is advantageous because it is stable and robust, widely used in hydrology (Abbaspour et al., 2009; Boyer et al., 2010; Elsner et al., 2010; Prudhomme et al., 2010; Bae et al., 2011; Bastola et al., 2011; Chen et al., 2012; Fiseha et al., 2014; Gädeke et al., 2014), and can be used to rapidly develop a large ensemble of GCMs and emissions scenarios or RCPs (Boyer et al., 2010). In addition, it assesses the uncertainty in mean GCM projected climate change, which is larger than that of the selected downscaling method (Boé et al., 2009; Chiew et al., 2009).

Stationarity is important to acknowledge when using the change factor method. The assumption that variability of natural systems is unchanging is compromised by anthropogenic climate change (McCarl et al., 2008; Milly et al., 2008). As previously stated, the change factor method does not account for changes in variability (e.g. number of wet days) and shifts in the distribution of precipitation and temperature (Gädeke et al., 2014). For example, many climate models suggest that the Midwest United States will experience an intensification of the hydrologic cycle: a decrease in summer wet days while also projecting intensification of heavy precipitation events (Winkler et al., 2014). These effects are not captured by the change factor method and influence projections of future flow events' frequency, timing, and duration. Changes in precipitation variability are expected to decrease low flows and increase peak flows (Lofgren and Gronewold, 2014).

In addition, the change factor method does not consider changes in net solar radiation. Solar radiation is a principal factor in dictating evapotranspiration (Allen et al., 1998). Excluding projected net solar radiation increases results in conservative estimates of changes in the hydrologic cycle. In this study, changes in potential evapotranspiration are not considered and subsequent projections of summer streamflow are higher than if net solar radiation increases were accounted for.

Despite the caveats associated with the change factor method, its strength is in its ability to develop a large ensemble of GCMs and RCPs while allowing for a broad analysis of the impacts of mean changes in precipitation and temperature on stream health. This provides a base reference case in which variability is held constant.

6.2.7 Stream Temperature Model

A stream temperature model was developed to determine if climate change would result in altered thermal classes, such as moving from a cold stream to a cold-transitional or cool stream. This would lead to changes in community composition and assemblage structure. When streams change thermal class, their stream health will likely be minimized because they will no longer be able to support their natural aquatic communities. The methods used were based on the July mean stream temperature models developed by Wehrly et al. (2009). A total of 332 summer stream temperature measurement sites throughout Michigan were included in the study, collected from 1990-2003 by the Michigan Department of Natural Resources (Wehrly et al., 2009). There were 422 samples, with multiple years of data collected at some sites.

Variables were defined by either local catchment (subwatershed) or network catchment. A local catchment drains directly to its corresponding stream, while a network catchment includes all upstream areas that drain to the stream by land or through a waterway. The six variables identified for model development by Wehrly et al. (2009) were AREA ($\log_e$ of the network catchment surface area), FOREST (percent forested land in the local catchment), JULAIR (July mean air temperature), PERM (mean network catchment soil permeability), SLOPE (mean network catchment slope), and WATER (percent water in the network catchment). Streams and catchments (AREA) were obtained from the National Hydrography Dataset Plus (NHDPlus, 2015). Land use (FOREST and WATER) and topography (SLOPE) data were obtained from the 2012 CDL and the NED, respectively. Soil data used to identify catchment permeability (PERM) was obtained from the NRCS Digital General Soil Map of the United States, STATSGO2 (NRCS, 2015) at a 1:250,000 resolution. Gridded July mean air temperature (JULAIR) at a 4km resolution was obtained from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) Climate Group (PRISM, 2015).

Linear mixed modeling using low-rank radial smoothing splines (LMM-Smooth) was used to develop the stream temperature model. Wehrly et al. (2009) found that the LMM-Smooth method outperformed multiple linear regression, generalized additive modeling, and kriging in predicting July mean stream temperature for Michigan and Wisconsin. The landscape variables are fixed effects, while the random error is comprised of smooth-scale and micro-scale variation in stream temperature and white noise measurement error. Spatial autocorrelation in stream temperature is considered by placing knots throughout the study area that are based on the distances between streams and knots (Wehrly et al., 2009). Because the method is low-rank, the number of knots is less than the number of observations (Schabenberger, 2005). The *kd*-tree method was used to determine optimal number and placement of knots (Schabenberger, 2005), produced a total of 47 knots throughout the study area. The LMM-Smooth model was fit using the SAS 9.3 GLIMMIX procedure (SAS, 2015).

The LMM-Smooth model fitting process used 10-fold cross validation and the RMSE and mean absolute error (MAE) of each validation fold were used to assess model accuracy. Average RMSE and MAE across the ten validation folds were 2.07 °C and 1.59 °C, respectively, similar in performance to the Michigan (RMSE = 2.00 °C, MAE = 1.55 °C) and Wisconsin (RMSE = 2.32 °C, MAE = 1.83 °C) LMM-Smooth models fit by Wehrly et al. (2009). The standardized coefficients of the fixed effects for the LMM-Smooth model fit to the full temperature dataset are presented in Table 13. All variables were significant at α=0.01 except FOREST, which also was the case for the Wisconsin model developed by Wehrly et al. (2009). Following model fitting, each of the 10-fold models were applied to all streams in the study area for every climate scenario to develop projections of changes in future stream temperatures based on the predictions of the ten models. The stream temperature projections were based on the change factors applied to the NCDC station data; with the results representing average July mean stream temperature for 2020-2040.

Table 13. Standardized coefficients and standard errors for LMM-Smooth model (Bold coefficients significantly different from zero at α=0.01).

Variable* (unit)	Catchment Scale	Coefficient estimate	Standard error
AREA ($\log_e$ km^2)	Network	**20.8617**	2.3881
FOREST (% area)	Local	-3.9630	2.4193
JULAIR (°C)	Local	**18.7481**	2.1789
PERM (cm/100 h)	Network	**-17.7958**	2.1393
SLOPE (%)	Network	**-6.9746**	2.3290
WATER (% area)	Network	**8.8070**	2.3097

*AREA: network catchment area; FOREST: local catchment percent forested land use; JULAIR: local catchment July mean air temperature; PERM: network catchment average soil permeability; SLOPE: network catchment average slope; WATER: network catchment percent water land use.

6.3 RESULTS AND DISCUSSION

6.3.1 Ecological-Relevant Variables and Stream Health

Scatterplots of stream health indicators versus percent changes under climate change scenarios for predictor variables used in the stream health models are presented in Figure 20 (cold) and Figure 32 (cold-transitional), Figure 33 (cool), and Figure 34 (warm) of Appendix E. Here, the stream health predictions and predictor variable values were calculated using the stream length-weighted average across all study streams. Each figure also presents the

Spearman's rank correlation coefficient (ρ) between stream health measures and percent change in flow regime variable. These figures demonstrate potentially altered flow regimes in the future (comparing 2020-2040 to the baseline 1980-2000), and that these changes both positively and negatively affect stream health represented by EPT, FIBI, HBI, and IBI. Note that projections of altered flow regimes are limited by use of the change factor method because historical and future time slices may not be stationary. This will affect simulation of flow regime components, specifically timing, duration and frequency of flow events. However, the directional response of both the flow regime variables and stream health indicators is expected to remain the same.

Several of the stream health indicators were linearly correlated with changes in predictor variables, indicated by a larger *r*. For example, the projected changes in variability of monthly flow values MA31 (August flows) and MA27 (April flows) were highly correlated with EPT and HBI, respectively (Figure 20). This shows that when variability decreased, stream health improved in cold streams. Note that HBI was positively correlated with increasing variability; this indicates that stream health declined with increased flow variability because lower HBI represents better stream health. These correlations are likely due to relatively lower flashiness in cold streams (especially in the Boardman-Charlevoix and Au Sable) because they are primarily groundwater-fed rather than surface-fed (Zorn and Sendek, 2001). However, projected increases in timing variables TA1 (constancy) and TA2 (predictability) result in declining FIBI, although the increases in constancy and predictability and decrease FIBI were relatively minor.

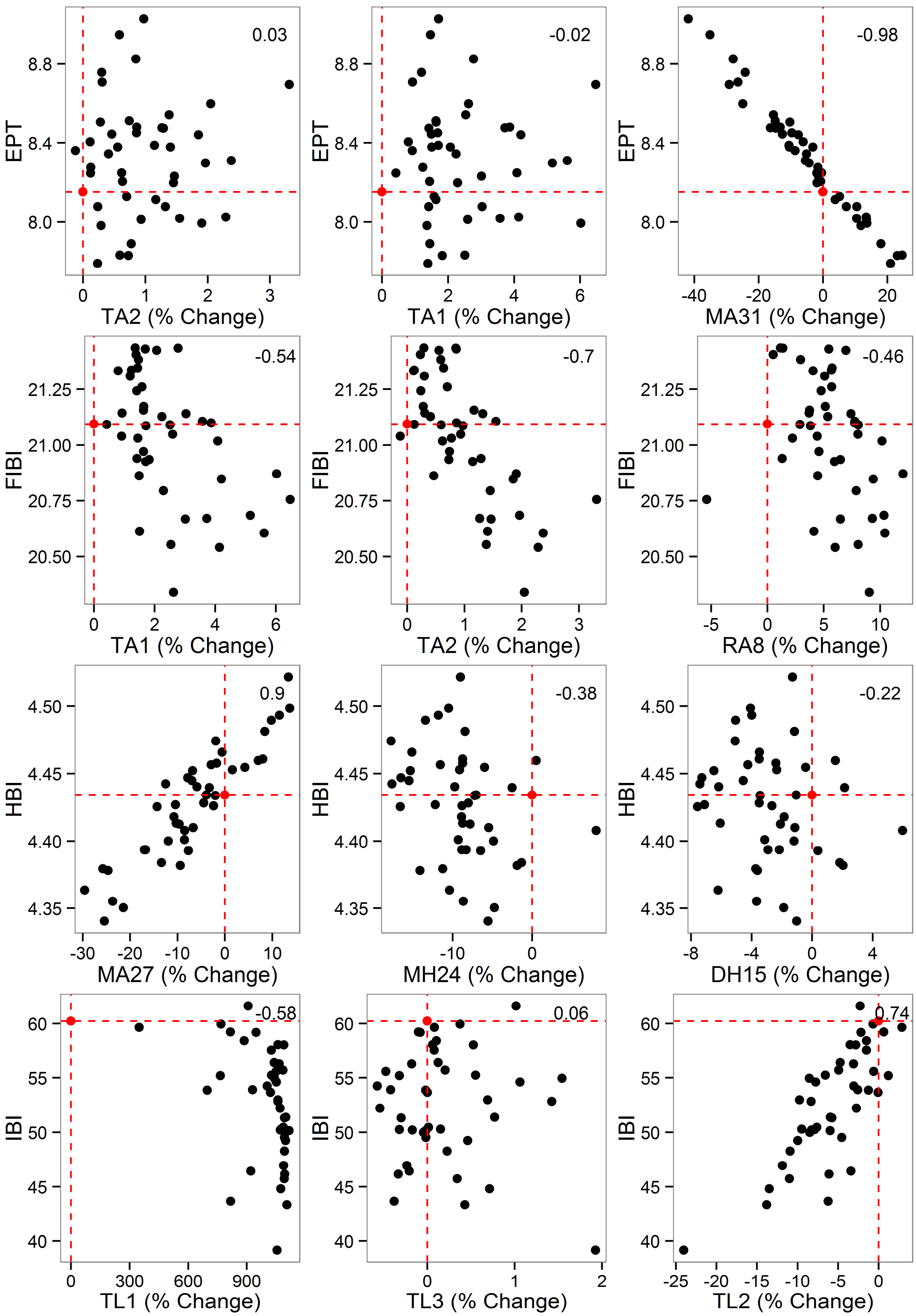

Figure 20. Stream health for cold streams as a function of percent change in flow regime variable under future climate scenarios. Spearman's ρ values are presented in the top right of each figure, and red dots indicate baseline stream health.

Several input variables were correlated with stream health indices used in the cold-transitional models (Figure 32 in Appendix E). As with cold streams, lower flashiness and improved predictability resulted in improved stream health measures. Increases in TH3 (seasonal predictability of non-flooding) improved EPT, demonstrating the importance of predictability in the timing of flood free periods for macroinvertebrates; with the potential for increases in future flooding and variability in flood timing due to climate change, sensitive EPT taxa will decline. Decreases in skewness of monthly flows (MA40) resulted in lower FIBI, while increasing RA9 (variability in number of days where the change in flow from one day to another changes direction), caused falling FIBI. The changes in variability as represented by MA40 and RA9 demonstrate the importance of consistent flows (less flashiness) for cold-transitional streams. Finally, fish IBI decreased with greater RA7 (negative changes in flow from previous day's flow) magnitudes, where the greater the average decrease in flow from the previous day resulted in worse stream health.

Predictor variables for cool streams (Figure 33 of Appendix E) experienced trends as with cold and cold-transitional streams. As climate change increased variation in February flows (MA25), both EPT and FIBI decrease; a similar relationship was found in the colder thermal classes. In addition, TH3 (seasonal predictability of non-flooding) was positively correlated with FIBI, as in cold and cold-transitional streams. Changes in low (DL) and high (DH) duration variables with respect to HBI also exhibited clear trends. When climate changes projected increases in DL15 (magnitude of 90% exceedance flows) stream health improved, while greater high flow durations (DH18) negatively affected stream health. This demonstrates the balance between the benefits of greater low flows but highlights potential impacts on stream health as duration of flooding events increases. No obvious trends were present with IBI variables, although decreases in constancy (TA1) and predictability (TA2) resulted in slight IBI declines. Due to the overall small decreases in IBI coupled with small changes in TA1 and TA2, overall cool IBI can be considered insensitive to climate change.

Warm stream predictor variables' characteristics were similar to some of those found in cool streams (Figure 34 in Appendix E). For example, DH22 (number of days between flood events with recurrence interval of 1.67 years) increased in most climate scenarios, resulting in improved fish IBI. This demonstrates that more frequent flooding as projected in some climate scenarios will be detrimental to stream health. However, many of the variables experienced slight increases in flow variability due to climate change (DL9, FH2, DL17, and MH19). Most warm streams in the study area are located in watersheds that contain flow regimes driven by surface runoff (due to relatively poorly-drained soils and extensive agricultural operations). Increases in DL9 (variability annual minimum of 30-day moving average flow), FH2 (variability in high pulse count), DL17 (variability in low pulse duration), and MH19 (skewness in annual maximum flows) improved stream health overall. Because the increases in variability are not extreme under climate change, they maintain the existing flow regime of surface runoff-driven streams, and their increases are beneficial to macroinvertebrate and fish communities in warm streams.

Overall, climate change affects flow regime of streams in all thermal classes. However, these changes were projected to have both positive and negative effects on stream health. The changes in EPT, FIBI, and HBI with respect to changes in the predictor variables were relatively low, indicating that coldwater macroinvertebrates are somewhat insensitive to changing climate. Changes in cold fish IBI were much greater. The resulting impacts on macroinvertebrate and fish communities demonstrate the contrast between stream thermal classes and how their biota will respond to climate change. Healthy biotic communities in cold and cold-transitional streams will be contingent upon continued predictability and low flashiness of representative streams, while warm streams showed the importance of maintaining a surface runoff-driven flow regime to stream biota. Meanwhile, the transitional nature of cool streams was a bridge between the effects of climate change on cold streams and warm streams by exhibiting similarities to both thermal classes.

6.3.2 Climate Change Impacts on Stream Temperature

Understanding potential alterations in stream thermal class under climate change is also critical for development of adaptation strategies. Where the thermal characteristics of a stream are projected to change under warming (e.g. cold streams transitioning to cool or warm), there is the potential for shifts in the characteristics of fish and macroinvertebrate communities. The stream temperature model was used to develop projections of changes in future stream temperature in 2020-2040 compared to the baseline 1980-2000. The goal was to identify streams that are at risk of changing their thermal class based on July mean stream temperature as defined by Zorn et al. (2008). If a stream thermal class is projected to change, the composition of the biota residing in that stream are at risk, and the stream habitat may become more suitable for species that do not normally reside in that environment.

Changes in stream temperature were projected to be smaller than the projected changes in air temperature. Mean increases were consistent across thermal classes (with minimum and maximum in brackets): +0.81°C [0.21 – 1.62°C] for cold streams, +0.82°C [0.26 – 1.63°C] for cold-transitional streams, +0.82°C [0.26 – 1.64°C] for cool streams, and +0.82°C [0.29 – 1.67°C] for warm streams. These changes translated into some shifts in thermal classes, where a colder class in converted to a warmer class, where Figure 21 presents the number of stream kilometers across the study area in each class change. Warm streams do not experience any change in stream class because there were no climate scenarios that project cooler July mean air temperatures. The greatest changes occur in the "transitional" streams, cold-transitional and cool. This was expected because they are defined by relatively narrow stream temperature ranges (Table 10) and are occupied by varying biota that prefer cold and warm waters. Of greatest concern was the warming of cold streams due to their temperature sensitive biota. Across all climate scenarios, an average of 20% of the cold streams (based on length) became cold-transitional, while no streams increased by more than one thermal class. Projected changes in stream thermal class across all climate scenarios are presented in Figure 22 for the Pere Marquette-White watershed. This figure confirms the overall limited changes in thermal class. Due to only a limited number of changes occurring (which were shifts to cold-transitional streams), cold streams will still be able to support coldwater species and negative effects would likely only be experienced by the most sensitive coldwater species. This is because cold-transitional streams still support primarily coldwater species (Zorn et al., 2008)

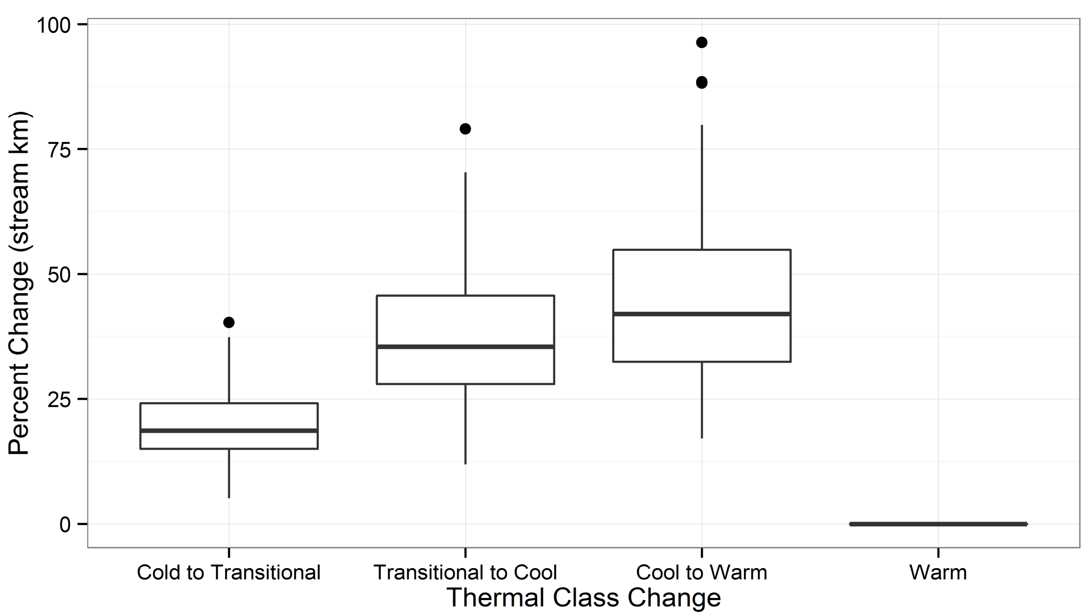

Figure 21. Percent change in stream thermal classes

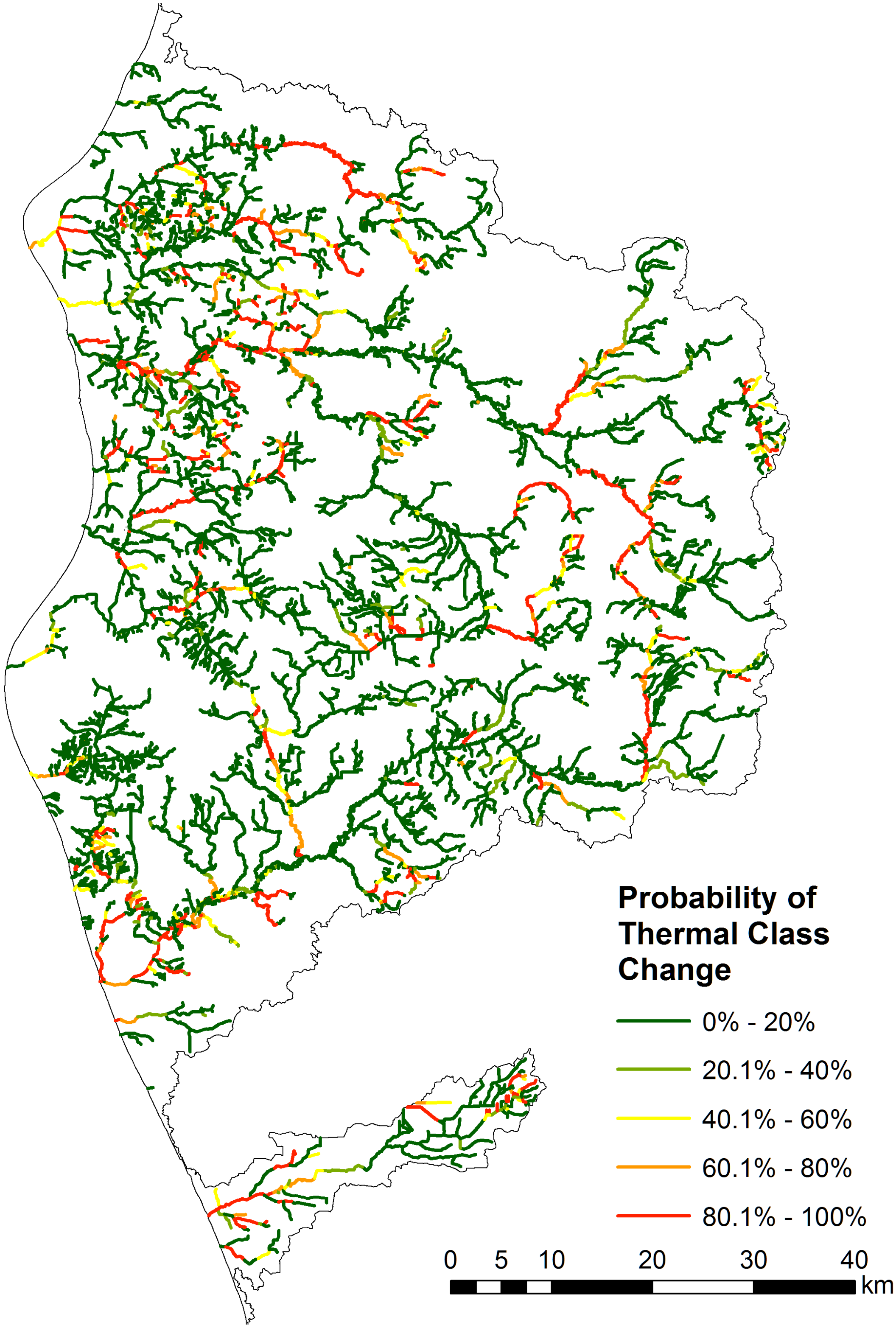

Figure 22. Probability of shifted thermal class due to climate change for the Pere Marquette-White watershed

6.3.3 Climate Change Vulnerability Assessment of Stream Health

Cumulative distribution functions (CDFs) were developed based on the stream length-weighted average of EPT, FIBI, HBI, and IBI for each thermal class (Figure 23). In this figure, stream thermal classes are defined by row and stream health indicators are defined by column (e.g. top-left is EPT Taxa for cold streams and bottom-right is IBI for warm streams). The CDFs represent stream health indicators under climate change projections (2020-2040) compared to the baseline stream health (1980-2000). Each CDF indicates the relative risk of declining stream health for each thermal class. The location of the baseline stream health on the CDF identifies the probability declining stream health under projected future climate. In addition, the CDF slopes represent the climate change sensitivity of each thermal class and stream health indicator combination. A greater CDF slope represents lower sensitivity of the stream health indicator to changing climate.

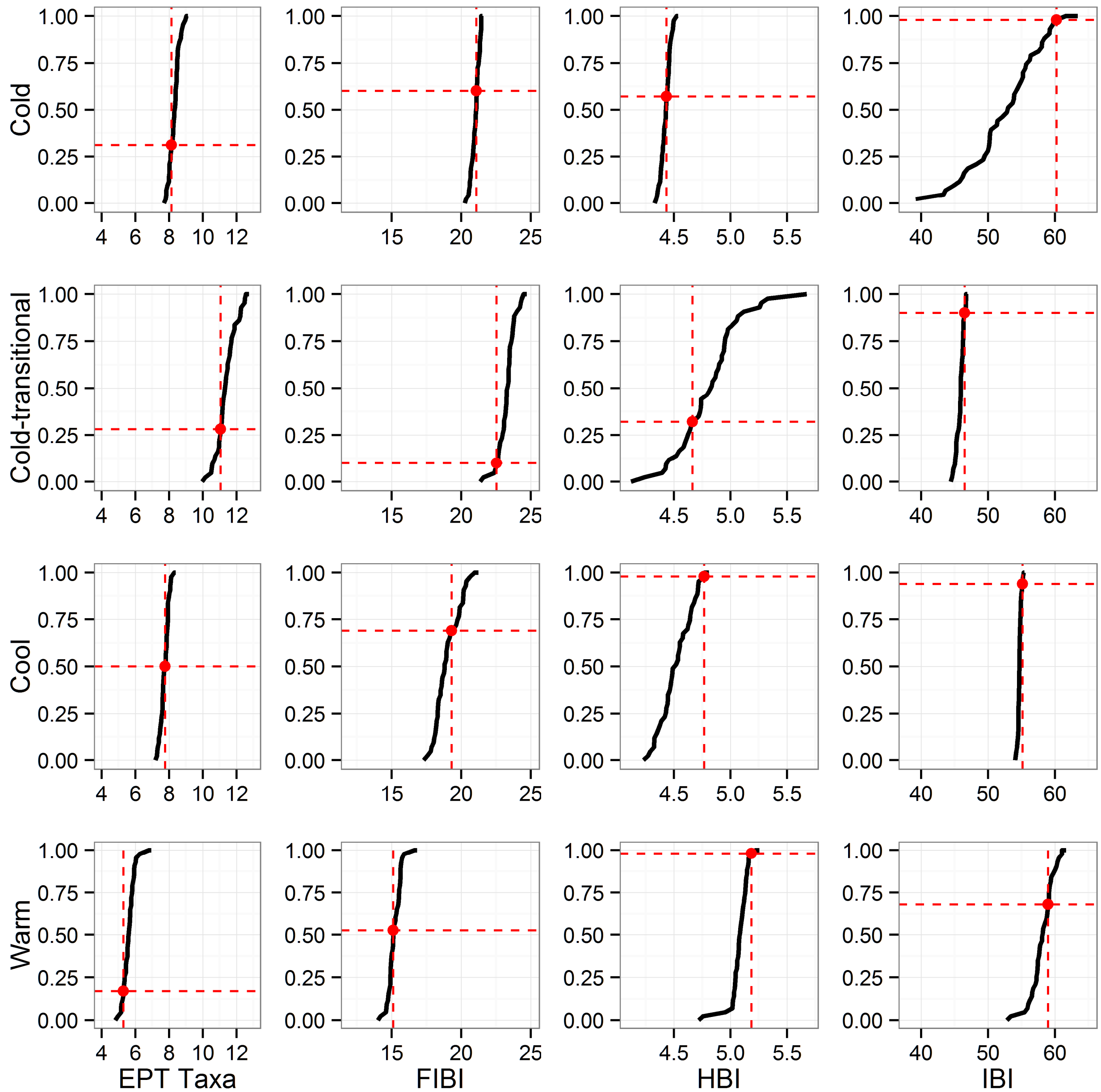

Figure 23. Average stream health CDFs of each thermal class and stream health indicator, where the black line is comprised of the climate scenarios (2020-2040) and the red dot is the baseline stream health (1980-2000).

The risk of declining average stream health and the indicators' sensitivity to climate change varied greatly across stream health indicators and thermal classes (Figure 23). For EPT, the risk of decline is relatively low (less than 50% for all thermal classes). The sensitivity of EPT to climate change is also low because there is little variation in EPT across climate scenarios. FIBI demonstrated a greater risk of decline, where all but cold-transitional streams are projected to experience greater than 50% risk of FIBI degradation. Cold-transitional and cool streams also are the most sensitive with respect to FIBI. HBI is likely to improve overall (decreasing HBI represents better stream health), especially in the warmer thermal classes. Cool and warm streams' HBI was projected to improve under all climate scenarios. Finally, IBI sensitivity to climate change varied greatly across thermal class. Cold streams were highly sensitive to climate change and all climate scenarios projected declines of up to 20 points. Meanwhile, IBI in cold-transitional and cool streams was projected to decline, but the magnitude of the decline was much less than for cold streams.

Climate sensitivity of each stream health indicator and thermal class combination is largely a function of the ANFIS stream health models and the predictor variables. We can link the relationship between how climate change altered the predictor variables in section 4.1 to the CDFs. For example, for EPT and cold streams, the average timing variables TA1 (constancy) and TA2 (predictability) do not experience extreme changes (Figure 4), and therefore cold-EPT is somewhat insensitive to climate change (Figure 23). Meanwhile, cold-IBI is greatly declines under changing climate (Figure 23), likely because of the climate sensitivity of the timing variables that were used in the ANFIS stream health models. Here, variables TL1 (Julian date of annual minimum flow) and TL2 (variability in Julian date of annual minima) are highly sensitive to changing climate, and these timing changes have extensive negative impacts on cold IBI.

For climate change adaptation measures and targeting of critically vulnerable streams, analysis at the local scale is critical to for stream protection. A probability map of declining stream health indicators is presented for the Pere Marquette-White watershed in Figure 24, which demonstrates the reach scale variability in probability of decline. The same figure for the complete study area (IBI) is presented in Figure 35 of Appendix E. For example, Figure 24a

(EPT) demonstrates the overall agreement between the CDFs in Figure 23 and the individual reaches, in that risk of declining EPT is relatively low across the watershed. However, several individual reaches are highly likely to experience declines in stream health.

A map that describes the average magnitude of stream health decline Figure 25) can be multiplied by the probability map (Figure 24). This combination identifies locations that have a large risk of declining stream health coupled with a large magnitude of decline. In locations where these conditions are met, individual streams should be classified as critically threatened by climate change. The 'unacceptable' levels of risk and magnitude of stream health degradation could be defined by watershed stakeholders and natural resource managers to determine locations to target adaptation and stream protection measures. This process was completed in Figure 26 using the Jenks natural breaks method to define low, medium, and high vulnerability streams for the Pere Marquette-White watershed. There are few locations that are highly vulnerable in the watershed, as most of the streams were experienced to project low or no vulnerability. The magnitude of declining IBI and risk of declining IBI are presented in Figure 36 and Figure 37 of Appendix E, respectively

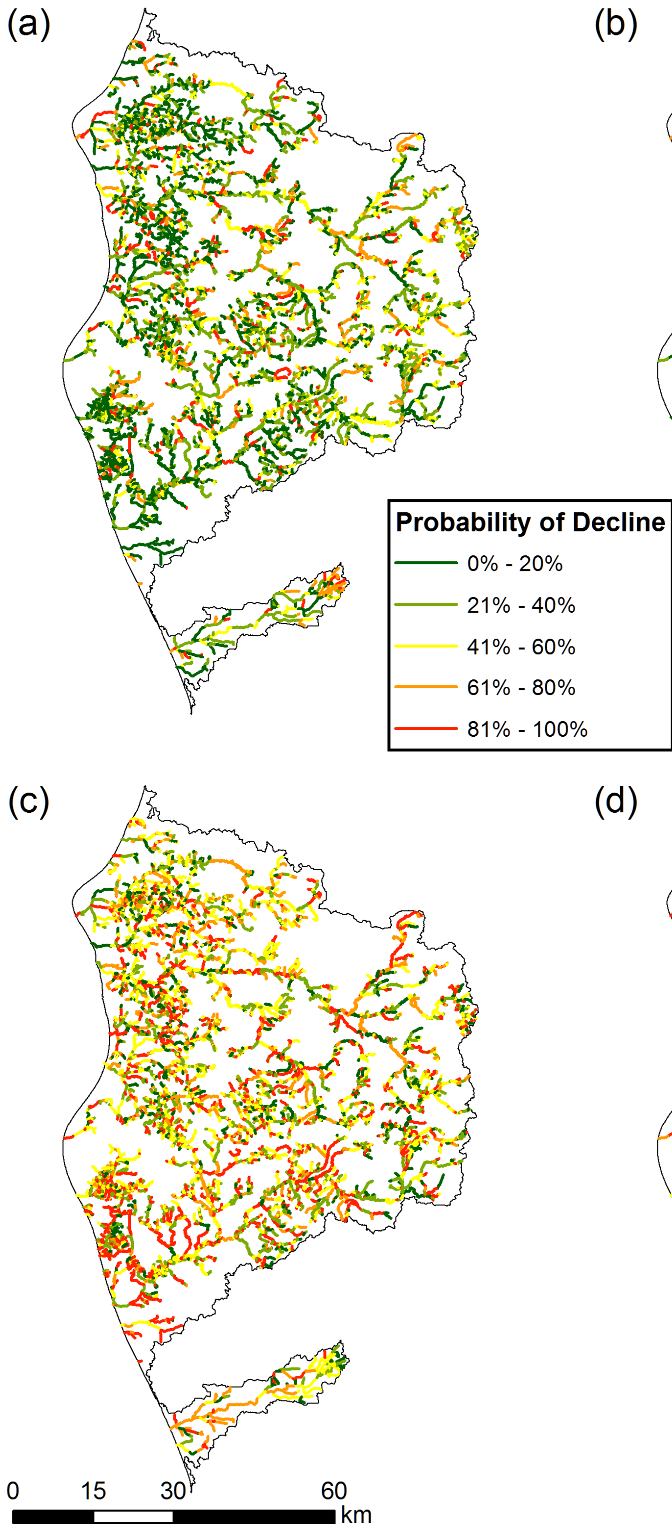

Figure 24. Probability of declining (a) EPT, (b) FIBI, (c) HBI, and d (IBI) under projected climate change for the Pere Marquette-White watershed

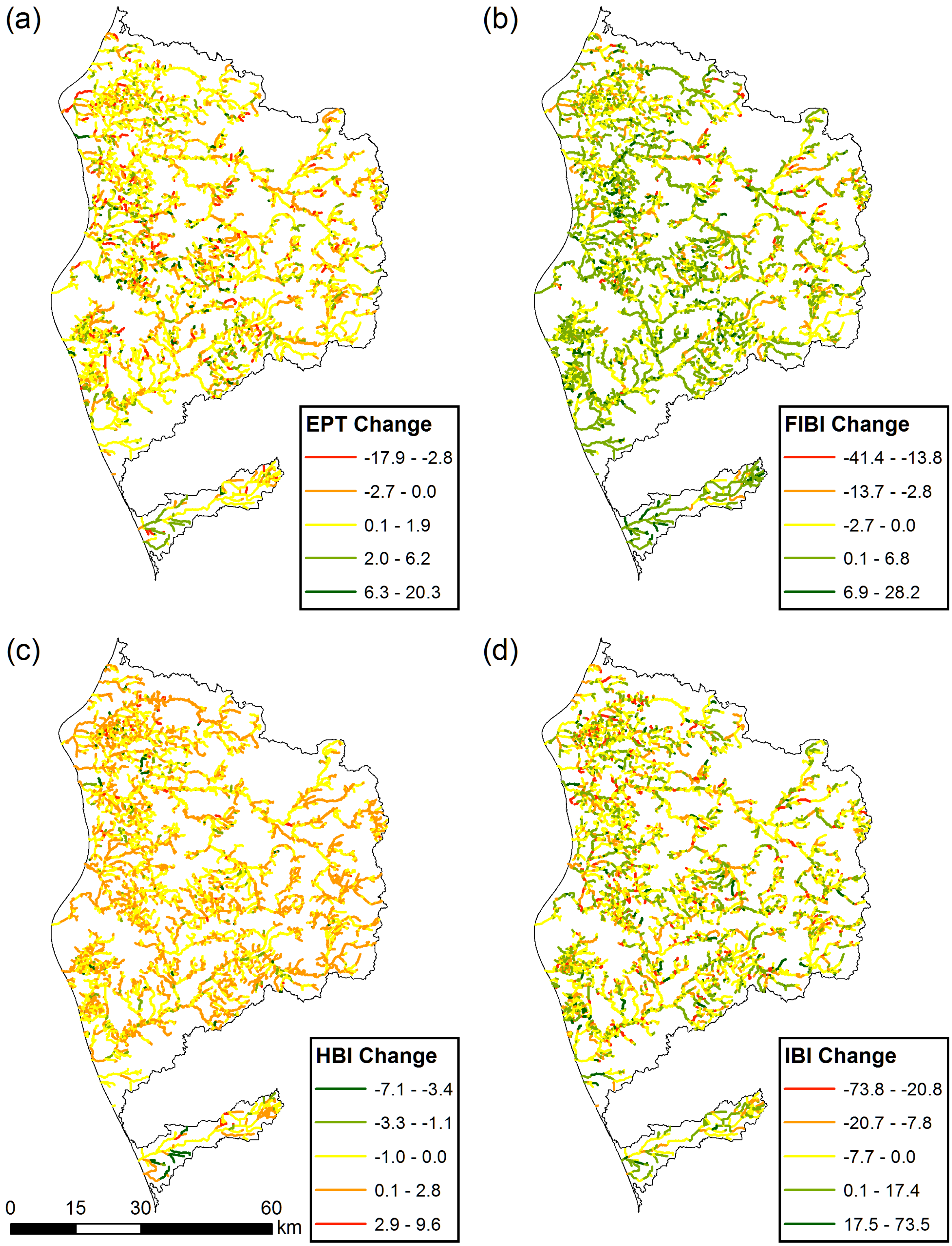

Figure 25. Average magnitude of change in (a) EPT, (b) FIBI, (c) HBI, and d (IBI) under projected climate change. Symbology is reversed for HBI because lower values are better.

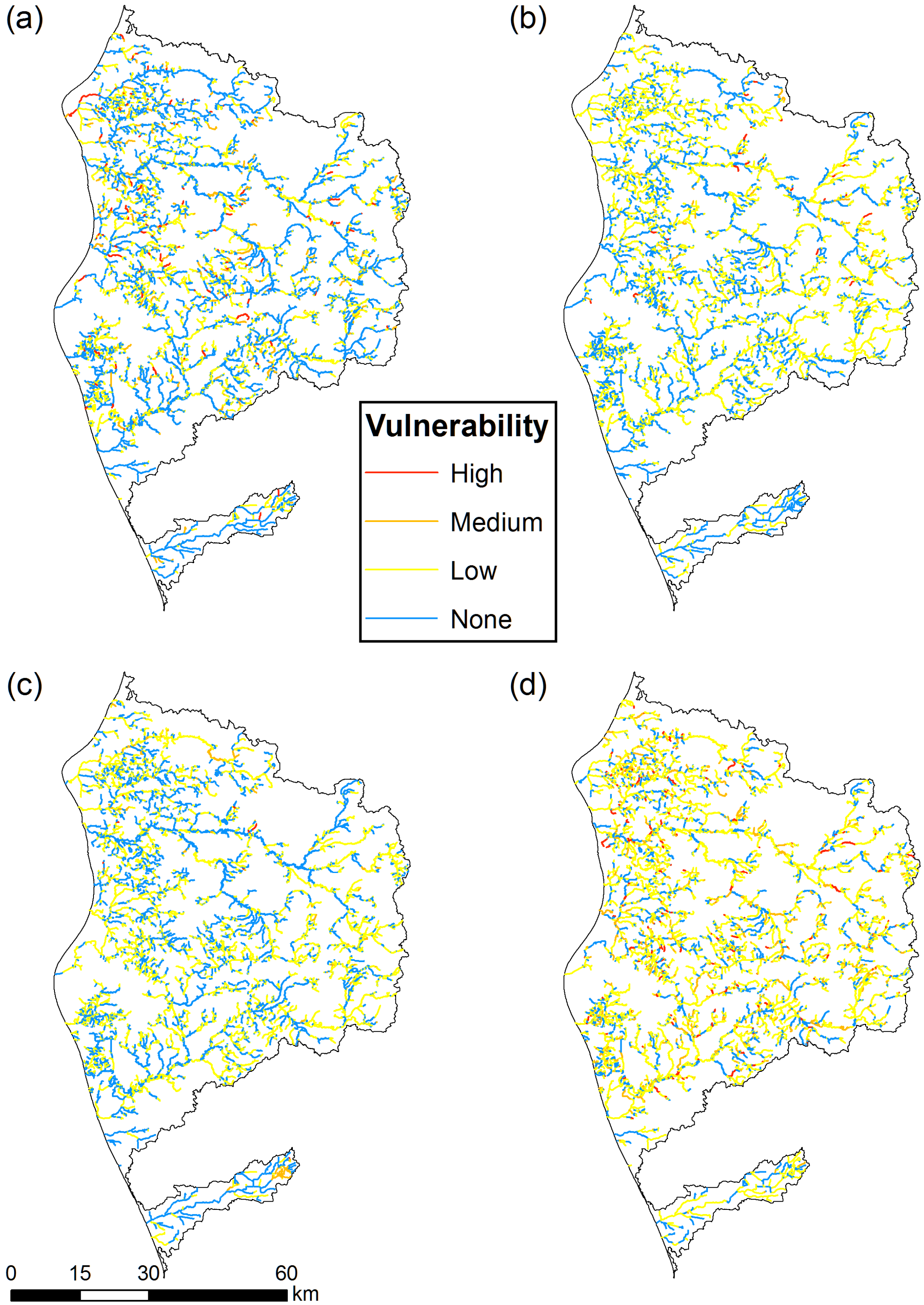

Figure 26. Map combining risk of declining stream health with average magnitude of declining stream health across all climate scenarios for (a) EPT, (b) FIBI, (c) HBI, and d (IBI). This represents the vulnerability of degraded stream health in 2020-2040

6.4 CONCLUSIONS

The primary objective of this study was determine the impacts of projected climate changes on stream health. Initially, watershed models were developed for seven watersheds in Michigan (Woznicki et al., 2015b) encompassing four thermal classes (cold, cold-transitional, cool, and warm). Bayesian variable selection (Woznicki et al., 2015a) was used to select influential flow regime and water quality variables for development of ANFIS stream health models for EPT, FIBI, HBI, and IBI. The watershed and stream health models were then driven by climate scenarios from the multi-model CMIP5 ensemble to develop projections of stream health in 2020-2040 as compared to the baseline 1980-2000. A stream temperature regression model was also developed to identify shifts in stream thermal classes as defined by July mean stream temperature.

Several flow regime variables exhibited sensitivity to changing precipitation and temperature. Flow variability, timing of flooding and low flow events, and duration of low and high flow events were affected by climate change and resulted in changes to stream health indicators across thermal regimes. Reduced flow variability was critical to maintaining the health of stable groundwater-fed cold streams. Meanwhile, slight increases in flow variability proved to be important to the health of more flashy runoff-driven warm streams.

Changes in thermal class due to stream temperature increases were also examined, because these shifts may affect the community composition of a stream. These shifts in thermal class were determined to occur mostly in the transitional thermal regimes (cold-transitional to cool and cool to warm). The greatest concern was extreme shifts from streams classified as cold to cool or warm because of the temperature sensitivity of many coldwater species, but the stream temperature increases were never large enough for this to occur.

Changes in stream health were depicted using CDFs to identify indicators and thermal classes that were at risk of declining health under future climate change. In addition, the CDFs characterized the overall sensitivity of a stream health indicator to climate change. The average response of stream health indicators was generally insensitive to changing climate. However, when analyzing risk and magnitude of declining stream health on a localized reach-level basis, the impacts of climate change were more pronounced. This demonstrates the importance of vulnerability assessment in development of potential adaptation measures.

There are limitations related to use of the change factor method in development of the climate change ensemble. The stationarity assumption may not be valid as evidenced by projections of future climate change. For example, this method does not account for changes in the number of wet days, which could mask changes to timing, duration, and frequency of low and high flow events. In addition, exclusion of changes in solar radiation resulted in conservative estimates of changes to the hydrologic cycle, especially regarding low flows and the water balance in summer months. Future studies will benefit from including multiple sources of climate data and multiple downscaling and bias correction methods, including those that do not adhere to the stationarity assumption. However, the assessment framework presented in this study is robust in that any climate data and downscaling and bias correction methods could be easily incorporated here.

The results of this study demonstrate the potential impacts of climate change on stream health and the applicability of the model development process to characterize these changes. Projected future risks of declining stream health and magnitude of decline varied considerably at the reach scale, and less so when examined at larger scales. Therefore, in guiding natural resource managers and watershed stakeholders in protecting stream ecosystems and developing adaptation plans to combat projected climate change, decision-making at the reach level will likely lead to greater success. The CCIAV process presented here is transferrable to other watersheds and can be extended to explore the potential benefits of adopting adaptation measures at both large and localized scales.

6.5 ACKNOWLEDGEMENTS

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7 CONCLUSIONS

This research developed a framework for assessing the impacts of climate change on stream health. Here, a unique modeling process was used to extend macroinvertebrate and fish measures of stream health beyond scarce monitoring points. Using the stream thermal classes of Michigan (cold, cold-transitional, cool, and warm) as the basis for modeling development, the projected impacts of climate change on stream health as represented by four indices of biotic integrity (the number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family Index of Biotic Integrity (FIBI), Hilsenhoff Biotic Index (HBI), and fish Index of Biotic Integrity (IBI)) was determined. This process consisted of watershed modeling, flow regime characterization, variable selection, stream health model development, and a climate change impact assessment. The following can be concluded from this research:

- Bayesian variable selection was consistently superior to Spearman's Rank Correlation and PCA based on the performance of ANFIS stream health models built upon these methods.
- In ANFIS model development, nonlinear membership functions were consistently linked to improved stream health predictions. This agrees with several studies, confirming the effectiveness of nonlinear membership functions in modeling ecological systems.
- Developing models based on stream thermal class generally improved their performance over a "global" model that ignored stream thermal class. The superior performance of the stream thermal class models indicates that "one size fits all" approaches for stream health modeling in diverse landscapes such as Michigan are ineffective.
- Several flow regime variables were consistently selected as important, usually related to timing and duration of major low and high flow events, as well as the variability

associated with these events. The differences in these variables across thermal classes demonstrated the interrelationships between flow regime, stream temperature, and stream health. These variables were also sensitive to changing climate. Reduced flow variability was critical to cold stream health. Slight increases in flow variability improved health in runoff-driven warm streams.

- Comparing stream health in pre-settlement (early 1800s) versus current conditions, declines were associated with landuse changes especially in agricultural and urban dominated regions. This most often occurred in warm and cool streams.
- Projected climate changes in 2020-2040 likely include a relatively large effect of natural variability because in the early 21st century the anthropogenic forcing signal is relatively weak (Knutti et al., 2008). However, early 21st century impacts are important for use in the stakeholder decision-making process, where later century impacts are often more abstract.
- There are some caveats in use of the change factor method to generate an ensemble of climate change projections. First, the assumption of stationarity is likely invalid under future climate change. Because changes in variability were not accounted for (e.g. less wet days in summer) in this method, the projected changes in flow regime (primarily frequency, duration, and timing components) are not captured well. In addition, exclusion of net solar radiation changes resulted in conservative estimates of potential evapotranspiration increases and overestimation of summer low flows.
- Despite its limitations, the change factor method was useful in developing a large ensemble of GCMs and RCPs to assess risk of declining stream health and identification of vulnerable streams. The structure of framework is such that the models included are

relatively interchangeable, especially regarding use of desired climate change data and methods (e.g. GCMs, downscaling methods, bias correction methods, and emissions scenarios/RCPs). This ultimately supports the goal of this research in development of a framework for climate change impacts assessment on stream health.

- Average July mean steam temperature increases were less than projected increases in air temperature (1.7 °C), with an average stream temperature increase of about 0.8 °C.
- Potential shifts in thermal class were examined, because it could result in altered aquatic community composition (e.g. moving from conditions preferable for coldwater species to those preferable for warmwater species). However, shifts were most common in the "transitional" classes (cold-transitional and cool). These streams are characterized by containing both coldwater and warmwater species. Sensitive coldwater streams never transitioned to the warmer classes (cool and warm streams).
- Cumulative distribution functions characterized probability of declining stream health and sensitivity of stream health indicators to climate change. At the thermal class scale, the indicators were generally insensitive to climate change. However, reach level impacts of climate change were more pronounced, demonstrating the importance of local scale analysis in assessing vulnerable streams.

8 FUTURE RESEARCH

This research provides a framework for assessing the impacts of climate change on stream health, including watershed modeling, variable selection, stream health modeling, and climate change impacts assessment. Here, the projected impacts of climate change on stream health were quantified. The result is information that can guide decision makers in identifying stream ecosystems that are vulnerable to projected climate changes, and use this information to target locations for implementation of adaptation measures. However, more research still needs to be done in light of the needs of decision-makers, and can build upon the work completed here. The following are potential areas to expand upon in future research:

- *Extend the modeling process spatially and temporally*. This research focuses on the thermal classes of Michigan streams and addresses the impacts of near-future climate change (2020-2040). An extended research area including all of Michigan would likely improve the stream health modeling process with inclusion of a bigger fish and macroinvertebrate dataset. Meanwhile, the 2020-2040 timeslice contains a larger proportion of natural variability because the anthropogenic forcing on precipitation and temperature is weaker in the early 21st century. To address this, mid- and late-century timeslices (e.g. 2040-2060 and 2080-2100) should also be included. Understanding the changes in vulnerability of stream ecosystems over time throughout the 21st century as climate change becomes more significant would be beneficial to decision makers in developing more long-term adaptation strategies.
- *Combine future landuse and climate change impacts*. Along with climate change, land use change will affect stream ecosystems. A warming climate will influence land use change, as areas further north in Michigan become more suitable for agriculture. These

land use changes will also create feedbacks to the climate system and hydrologic cycle. For example, changing surface reflectivity of solar radiation and changes in potential evapotranspiration. Because they are not mutually exclusive, combining these two potential stressors will provide an improved view of future stream health.

- *Test alternative climate change adaptation measures*. This research provides information on what impacts climate change will have on stream health, but does not include information on how to adapt. The next step in this research is to provide additional information to decision-makers in the form of projections of the potential successes and failures of adaptation measures. These adaptation measures could vary from agricultural and urban best management practices (e.g. filter strips, cover crops, reduced tillage schemes, nutrient management, and wetland restoration) that reduce nonpoint source pollution and surface runoff to riparian and in-stream interventions (e.g. establishing riparian shading, restoring pool-riffle sequences and floodplain connectivity, and stabilizing streambanks) that provide better habitat to native fish and macroinvertebrates.
- *Quantify uncertainty throughout the modeling process*. Uncertainty is an important consideration in modeling. Accounting for uncertainty at several stages of the process (input data, hydrological modeling, stream health modeling, and climate change modeling), and how it is inherited in each subsequent step, will ultimately improve future projections of stream health by allowing decision-makers to measure our understanding of each process in the framework.
- *Include additional climate modeling downscaling and bias correction methods*. While this research included a large ensemble of climate models and representative concentration pathways, there are no comprehensive rules regarding selection of

downscaling and bias-correction methods in hydrological studies. Including multiple downscaling and bias-correction methodologies in the climate change impacts assessment would account for the uncertainty in these necessary steps of the process. Of particular importance is including methods that account for changes in the variability/distribution of precipitation and temperature, such as capturing projected decrease in wet days and increases in higher magnitude precipitation events. Inclusion of projected increases in net solar radiation is also critical for less conservative estimates of declining summer streamflows.

- *Explore other stream health modeling methods*. Stream ecosystems are complex, with aquatic biota interacting with and responding to stressors and the environment in diverse ways. There is a need to continue to develop new methods that can model these processes, such as other soft computing methods and newly developed methods such as boosted regression trees. There are several capable modeling techniques, and a multi-model ensemble of stream health modeling methods may better capture the uncertainty and complexity of these systems.
- *Construct a decision-making tool.* The data developed in this process could be integrated into a web-based decision tool. Here, watershed and natural resources managers could interactively examine how their management decisions will hold up in the face of projected climate change for their areas and timelines of interest.

APPENDICES

APPENDIX A: K-MEANS CLUSTERING MODEL IMPLEMENTATION

Pseudocode of the *k*-means clustering implementation is given below.

Data: *n* points of dimension *d*, *k* number of desired clusters
Result: At most *k* partitions of the original data
for *i* = 1 to *k* **do**
    Select a random point as a cluster centroid
end
while *Cluster centroids are not unchanged* **do**
    Partition all points to the nearest centroid;
    Compute the new cluster centroids as the mean of each partition;
    Update centroids;
end

APPENDIX B: BAYESIAN VARIABLE SELECTION MODEL IMPLEMENTATION

For prior specification, we assume the Inverse-Gamma density prior on the noise level τ^2 with shape a_τ and scale b_τ, and the signal-to-noise ratio λ with shape parameter a_λ and scale parameter b_λ. The hyperparameters a_τ, b_τ, a_λ, and b_λ, are selected to yield rather dispersed prior distributions and make the posterior estimates more data-driven. For example, we choose $a_\lambda = a_\tau = 2$ and $b_\lambda = b_\tau = 0.01$. We also assume the equal prior probability on the number of selected variables q, and all combinations $\boldsymbol{I}$'s with q variables (including an intercept) receive equal prior weight, i.e., $1/\binom{p-1}{q-1}$.

We then proceed with the reversible jump Markov Chains Monte Carlo (Green, 1995) algorithm embedded in the Gibbs sampler for the parameters $\{\boldsymbol{I}, \beta_{\boldsymbol{I}}, \tau^2, \lambda\}$. The following steps update each set of parameters from their full conditional distributions given the data and the remaining parameters at one iteration, where each step is repeated many times until convergence is committed.

Step 1: update the index set $\boldsymbol{I}$: Conditional on the current $\boldsymbol{I}$, we propose a new state $\boldsymbol{I}^*$ from density function g. We specify g to be either a "birth" move (include one more variable that is not in $\boldsymbol{I}$) or a "death" move (exclude one existing variable in $\boldsymbol{I}$), with equal chance, that is, we toss a coin to determine if $q \to q+1$ or $q \to q-1$. We also propose the new τ^{2*} and $\beta_{\boldsymbol{I}^*}$ under $\boldsymbol{I}^*$ from certain proposal density h. Consequently, the probability of accepting the proposal $(\boldsymbol{I}^*, \tau^{2*}, \beta_{\boldsymbol{I}^*})$ is calculated as Equation 5.

$$min\left\{1,\ \frac{g(\boldsymbol{I}|\boldsymbol{I}^*)}{g(\boldsymbol{I}^*|\boldsymbol{I})} \times \frac{\pi\left(\boldsymbol{I}^*, \tau^{2*}, \beta_{\boldsymbol{I}^*}\middle|\boldsymbol{Y}\right)}{\pi\left(\boldsymbol{I}, \tau^2, \beta_{\boldsymbol{I}}\middle|\boldsymbol{Y}\right)} \times \frac{h\left(\tau^2, \beta_{\boldsymbol{I}}\middle|\boldsymbol{I}^*, \tau^{2*}, \beta_{\boldsymbol{I}^*}, \boldsymbol{I}\right)}{h\left(\tau^{2*}, \beta_{\boldsymbol{I}^*}\middle|\boldsymbol{I}, \tau^2, \beta_{\boldsymbol{I}}, \boldsymbol{I}^*\right)} \times 1\right\} \tag{5}$$

under the choice of $h(\tau^{2*}, \beta_{\boldsymbol{I}^*}|\boldsymbol{I}, \tau^2, \beta_{\boldsymbol{I}}, \boldsymbol{I}^*) = \pi(\tau^{2*}|\boldsymbol{I}, \boldsymbol{Y}) \times \pi(\beta_{\boldsymbol{I}^*}|\boldsymbol{I}, \boldsymbol{Y}, \tau^{2*})$ the posterior densities. More specifically, let $\Lambda = I/\lambda$ with I the identity matrix, we first propose τ^{2*} from its posterior density that marginalizes $\beta_{\boldsymbol{I}}$, Equation 6.

$$\pi(\tau^{2*}|\boldsymbol{I},\theta,\Lambda,\boldsymbol{Y}) \propto \pi(\tau^{2*}) \int \pi(\boldsymbol{Y}|\boldsymbol{I},\tau^{2*},\beta_{\boldsymbol{I}}) \times \pi(\beta_{\boldsymbol{I}}|\boldsymbol{I},\tau^{2*},\Lambda)d\beta_{\boldsymbol{I}} \qquad (6)$$

which is recognized as an Inverse-Gamma density with shape $a_\tau + N/2$ and scale $b_\tau + \boldsymbol{Y}'V(\lambda)\boldsymbol{Y}/2$, with $V(\lambda) = I - X(X'X + \Lambda^{-1})^{-1}X'$. Note the term $\boldsymbol{Y}'V(\lambda)\boldsymbol{Y}$ can be viewed as the sum of the squared spaitally weighted Least-Square error. Next we generate $\beta_{\boldsymbol{I}^*}$ from its posterior density $\pi(\beta_{\boldsymbol{I}}|\boldsymbol{I},\tau^{2*},\Lambda,\boldsymbol{Y})$ which is $N(\mu_\beta,\ \Sigma_\beta)$ with $\Sigma_\beta = \tau^{2*}(X'X)^{-1}$ and $\mu_\beta = (X'X + \Lambda^{-1})^{-1}X'\boldsymbol{Y}$. Consequently the probability of acceptance reduces to a simpler form (Equation 7).

$$min\left\{1,\ \frac{\pi(\boldsymbol{I}^*)}{\pi(\boldsymbol{I})} \times \frac{g(\boldsymbol{I}|\boldsymbol{I}^*)}{g(\boldsymbol{I}^*|\boldsymbol{I})} \times \frac{\pi(\boldsymbol{Y}|\boldsymbol{I}^*)}{\pi(\boldsymbol{Y}|\boldsymbol{I})}\right\} \qquad (7)$$

which is mainly determined by the marginal likelihood ratio $\pi(\boldsymbol{Y}|\boldsymbol{I}^*)/\pi(\boldsymbol{Y}|\boldsymbol{I})$ under our non-informative choice of prior and proposal density of $\boldsymbol{I}$. The marginal likelihood given variable set $\boldsymbol{I}$ is well-known to be a centered multivariate student's T-distribution with the log density determined by $-\frac{1}{2}\log|I + \lambda X'X| - (a_\tau + N/2)\log(1 + \boldsymbol{Y}'V(\lambda)\boldsymbol{Y}/(2b_\tau))$.

Step 2: update the noise level and fixed-effects ($\tau^2,\ \beta_{\boldsymbol{I}}$): Although this pair of parameters can be updated when proposing a new $\boldsymbol{I}^*$, we further update them separately in the Gibbs sampler to improve the mixing because the newly proposed $\boldsymbol{I}^*$ can be rejected. Sampling $\beta_{\boldsymbol{I}}$ is again from $N(\mu_\beta,\ \Sigma_\beta)$, which has the same form. However sampling τ^2 will also be conditional on $\beta_{\boldsymbol{I}}$, which is an Inverse-Gamma density with shape $a_\tau + (N + q)/2$ and scale $b_\tau + ((\boldsymbol{Y} - \boldsymbol{X}_{\boldsymbol{I}}\beta_{\boldsymbol{I}})'(\boldsymbol{Y} - \boldsymbol{X}_{\boldsymbol{I}}\beta_{\boldsymbol{I}}) +\ \beta_{\boldsymbol{I}}'\Lambda^{-\boldsymbol{1}}\beta_{\boldsymbol{I}})/2$.

Step 3: update the signal-to-noise ratio and dependency λ: We draw a sample of λ from the Inverse-Gamma density with shape $a_\lambda + q/2$ and scale $b_\tau +\ \beta_{\boldsymbol{I}}'\beta_{\boldsymbol{I}}/(2\tau^2)$.

APPENDIX C: STUDY ONE RESULTS

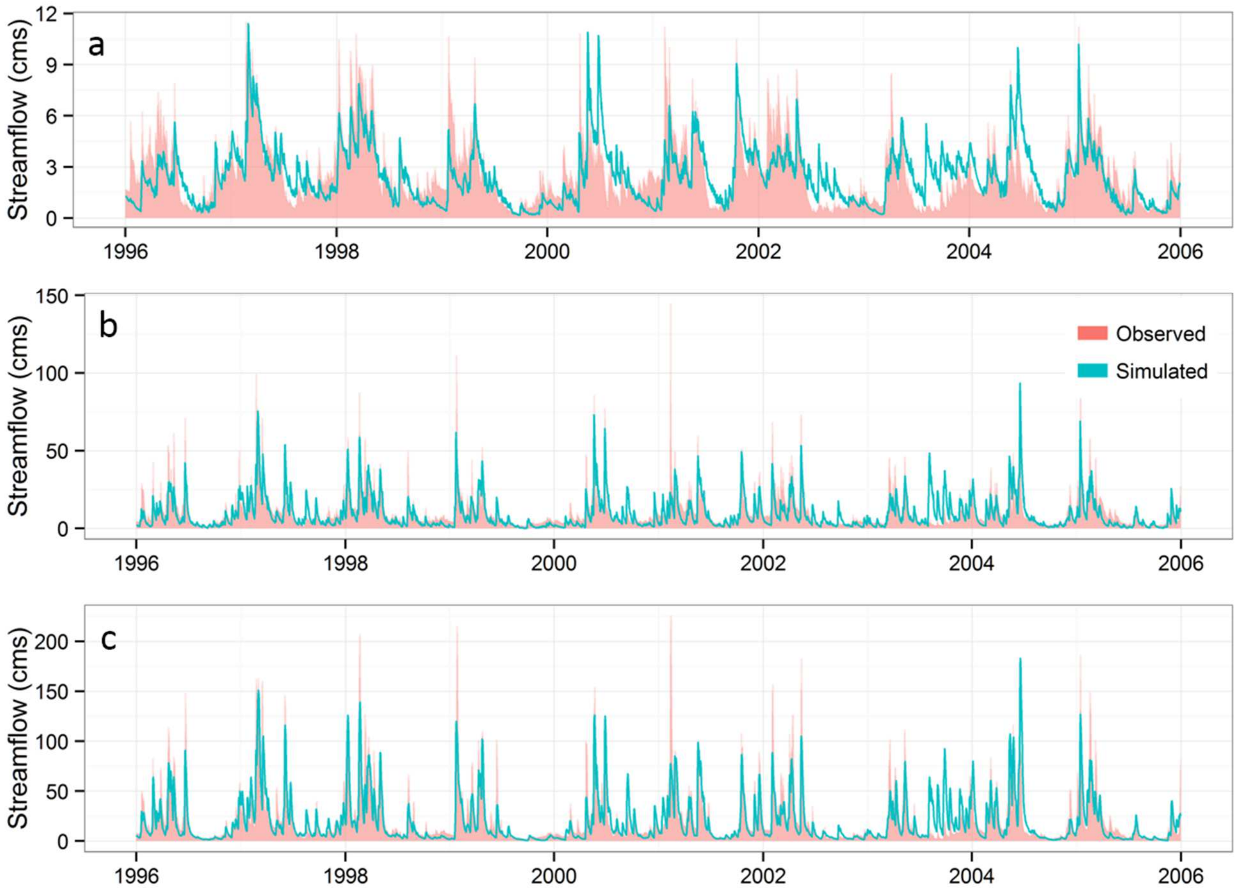

Figure 27. Time-series streamflow calibration: (a) USGS 04175600, (b) USGS 04176000, and (c) USGS 04176500

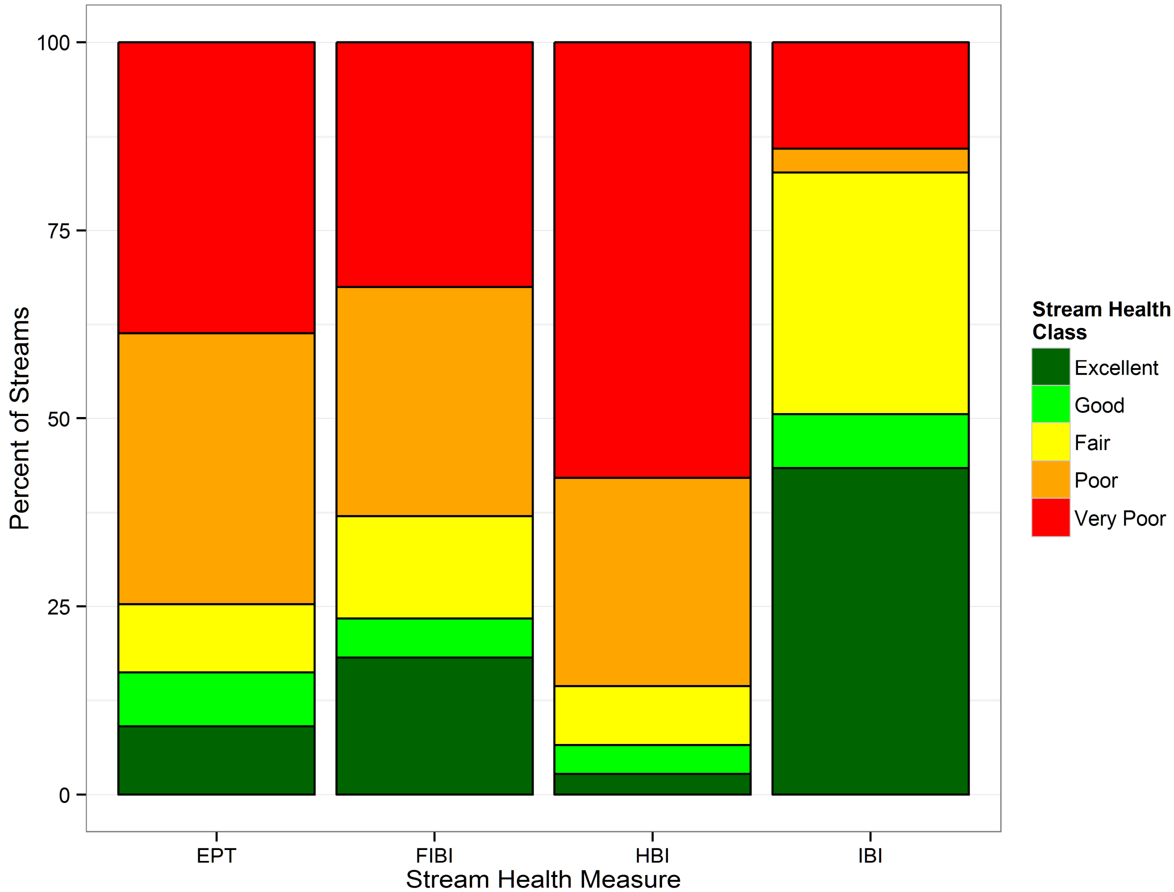

Figure 28. Percentage of streams in each stream health class, classified by best model for each stream health measure

Table 14. Variable selection for data in stream orders 1-3

Method		EPT Taxa	FIBI	HBI	IBI
Spearman (ρ)		RA5 (0.56) RA4 (-0.53) ML9 (0.53)	DL2 (0.54) RA4 (-0.52) MA27 (-0.47)	SEDjja (0.62) MA38 (0.47) RA8 (-0.47)	MA26 (0.91) MA32 (0.90) DL18 (0.72)
Bayesian (selectivity)		MA35 (0.27) RA5 (0.25) FH10 (0.20)	RA4 (0.29) MA35 (0.13) TA2 (0.11)	NO_3son (0.40) NO_3djf (0.16) DH24 (0.15)	RA6 (0.28) MA32 (0.23) MA26 (0.18)
PCA	PC1 (loading)	MH27 (-0.54) FL1 (-0.43) MH25 (-0.35)	MH27 (-0.54) FL1 (-0.43) MH25 (-0.35)	MH27 (-0.54) FL1 (-0.43) MH25 (-0.35)	MH27 (-0.54) FL1 (-0.43) MH25 (-0.35)
PCA	PC1to PC3 (loading)	MH27 (-0.54) MA32 (0.33) MA45 (0.39)	MH27 (-0.54) MA32 (0.33) MA45 (0.39)	MH27 (-0.54) MA32 (0.33) MA45 (0.39)	MH27 (-0.54) MA32 (0.33) MA45 (0.39)
PCA	PC1 to PC3 (variation explained)	PC1 (27.5%) PC2 (16.4%) PC3 (11.1%)	PC1 (27.5%) PC2 (16.4%) PC3 (11.1%)	PC1 (27.5%) PC2 (16.4%) PC3 (11.1%)	PC1 (27.5%) PC2 (16.4%) PC3 (11.1%)

Table 15. Variable selection for data in stream orders 4-6

Method		EPT Taxa	FIBI	HBI	IBI
Spearman (ρ)		SEDjja (-0.75) RA5 (0.68) NO_3jja (-0.64)	FH7 (-0.71) NO_3mam (-0.60) DH19 (-0.54)	NH_4ann (0.66) RA9 (0.56) NO_2mam (0.55)	RA4 (-0.93) RA9 (-0.73) MA32 (-0.65)
Bayesian (selectivity)		RA8 (0.21) FH10 (0.18) TH2 (0.14)	NH_4djf (0.12) RA9 (0.09) NH_4mam (0.08)	NH_4ann (0.13) NH_4son (0.10) RA9 (0.09)	DH22 (0.97) RA9 (0.93) TL3 (0.80)
PCA	PC1 (loading)	MA16 (0.39) MA34 (-0.29) MA33 (0.28)	MA16 (0.39) MA34 (-0.29) MA33 (0.28)	MA16 (0.39) MA34 (-0.29) MA33 (0.28)	MA16 (0.39) MA34 (-0.29) MA33 (0.28)
PCA	PC1to PC3 (loading)	MA16 (0.39) ML11 (0.30) MA38 (0.27)	MA16 (0.39) ML11 (0.30) MA38 (0.27)	MA16 (0.39) ML11 (0.30) MA38 (0.27)	MA16 (0.39) ML11 (0.30) MA38 (0.27)
PCA	PC1 to PC3 (variation explained)	PC1 (48.9%) PC2 (25.7%) PC3 (9.7%)	PC1 (48.9%) PC2 (25.7%) PC3 (9.7%)	PC1 (48.9%) PC2 (25.7%) PC3 (9.7%)	PC1 (48.9%) PC2 (25.7%) PC3 (9.7%)

Table 16. Variable selection for data in Cluster 1

Method		EPT Taxa	FIBI	HBI	IBI
Spearman (ρ)		RA5 (0.54)	DL4 (0.47)	OrgNjja (0.54)	MA24 (0.98)
		MA1 (0.50)	TA2 (-0.43)	NO_3djf (0.48)	OrgNjja (-0.73)
		TA2 (-0.45)	MA35 (-0.41)	MA33 (-0.38)	FH6 (0.70)
Bayesian (selectivity)		RA5 (0.29)	MA35 (0.13)	NO_3son (0.38)	MA24 (0.20)
		FH10 (0.15)	RA4 (0.09)	NO_3djf (0.15)	RA5 (0.18)
		MA35 (0.14)	MH18 (0.08)	FL3 (0.13)	MA35 (0.16)
PCA	PC1 (loading)	MH12 (0.84)	MH12 (0.84)	MH12 (0.84)	MH12 (0.84)
		MH10 (-0.23)	MH10 (-0.23)	MH10 (-0.23)	MH10 (-0.23)
		MH15 (-0.22)	MH15 (-0.22)	MH15 (-0.22)	MH15 (-0.22)
	PC1to PC3 (loading)	MH12 (0.84)	MH12 (0.84)	MH12 (0.84)	MH12 (0.84)
		ML4 (-0.31)	ML4 (-0.31)	ML4 (-0.31)	ML4 (-0.31)
		ML14 (-0.61)	ML14 (-0.61)	ML14 (-0.61)	ML14 (-0.61)
	PC1 to PC3 (variation explained)	PC1 (29.7%)	PC1 (29.7%)	PC1 (29.7%)	PC1 (29.7%)
		PC2 (13.8%)	PC2 (13.8%)	PC2 (13.8%)	PC2 (13.8%)
		PC3 (10.9%)	PC3 (10.9%)	PC3 (10.9%)	PC3 (10.9%)

Table 17. Variable selection for data in Cluster 2

Method		EPT Taxa	FIBI	HBI	IBI
Spearman (ρ)		NO_2mam (-0.77)	MH22 (-0.52)	NO_2mam (0.72)	DH11 (-0.87)
		DL12 (0.70)	MH13 (-0.48)	TH2 (-0.52)	MH13 (-0.70)
		TH2 (0.68)	DL16 (-0.36)	DL15 (-0.50)	TA2 (0.69)
Bayesian (selectivity)		FH10 (0.17)	DL16 (0.12)	RA9 (0.11)	DH22 (0.95)
		TL4 (0.13)	RA2 (0.12)	FH2 (0.09)	RA9 (0.69)
		RA8 (0.09)	NO_2mam (0.11)	DH22 (0.07)	FL2 (0.54)
PCA	PC1 (loading)	MA12 (-0.95)	MA12 (-0.95)	MA12 (-0.95)	MA12 (-0.95)
		MinPann (0.09)	MinPann (0.09)	MinPann (0.09)	MinPann (0.09)
		MA39 (0.08)	MA39 (0.08)	MA39 (0.08)	MA39 (0.08)
	PC1to PC3 (loading)	MA12 (-0.95)	MA12 (-0.95)	MA12 (-0.95)	MA12 (-0.95)
		MA43 (-0.34)	MA43 (-0.34)	MA43 (-0.34)	MA43 (-0.34)
		ML12 (0.48)	ML12 (0.48)	ML12 (0.48)	ML12 (0.48)
	PC1 to PC3 (variation explained)	PC1 (43.4%)	PC1 (43.4%)	PC1 (43.4%)	PC1 (43.4%)
		PC2 (19.0%)	PC2 (19.0%)	PC2 (19.0%)	PC2 (19.0%)
		PC3 (11.2%)	PC3 (11.2%)	PC3 (11.2%)	PC3 (11.2%)

Table 18. ANFIS model average performance across 10-folds, order 1-3, for best model (MF type and number of variables) under each variable selection method

Health Measure	Method	MF Type	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	Spearman	Gaussian	2 (3/2)	0.831	0.802	1.213	0.704
	Bayesian	Gaussian	2 (2/2)	1.078	0.698	1.237	0.639
	PCA	Bell*	2 (2/2)	1.353	0.560	2.871	0.437
	PCA PC1	Gaussian	2 (2/2)	1.273	0.646	2.526	0.507
	PCA PC1-3	Triangle	2 (2/2)	1.589	0.486	1.988	0.438
FIBI	Spearman	Trapezoid	2 (2/2)	4.071	0.505	8.840	0.421
	Bayesian	Triangle	2 (2/2)	4.029	0.536	4.702	0.555
	PCA	Triangle	2 (2/2)	4.686	0.294	7.694	0.560
	PCA PC1	Triangle	2 (2/2)	4.712	0.341	6.657	0.440
	PCA PC1-3	Triangle	2 (2/2)	4.385	0.432	5.070	0.507
HBI	Spearman	Triangle	2 (2/2)	0.370	0.504	0.472	0.334
	Bayesian	Triangle	2 (2/2)	0.314	0.574	0.437	0.556
	PCA	Triangle	2 (2/2)	0.444	0.270	0.679	0.462
	PCA PC1	Bell*	2 (2/2)	0.336	0.567	0.629	0.643
	PCA PC1-3	Triangle	2 (2/2)	0.406	0.437	0.676	0.507

* Bell: generalized bell MF

Table 19. ANFIS model average performance across 10-folds, order 4-6, for best model (MF type and number of variables) under each variable selection method

Health Measure	Method	MF Type	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	Spearman	GaussC*	2 (2/2)	1.061	0.695	1.355	0.750
	Bayesian	Triangle	2 (2/3)	0.815	0.792	1.181	0.634
	PCA	Triangle	2 (2/2)	1.086	0.697	1.397	0.524
	PCA PC1	Triangle	2 (2/2)	1.084	0.691	1.446	0.658
	PCA PC1-3	Trapezoid	2 (2/2)	0.961	0.776	1.460	0.682
FIBI	Spearman	Triangle	2 (2/2)	4.147	0.489	4.792	0.514
	Bayesian	Triangle	2 (2/2)	3.819	0.576	4.324	0.578
	PCA	Triangle	2 (2/2)	4.069	0.502	5.033	0.557
	PCA PC1	Gaussian	2 (2/3)	3.098	0.692	4.339	0.646
	PCA PC1-3	Bell**	2 (2/2)	3.563	0.624	4.108	0.565
HBI	Spearman	Triangle	2 (3/2)	0.229	0.661	0.371	0.449
	Bayesian	Gaussian	2 (2/2)	0.248	0.633	0.350	0.350
	PCA	Triangle	2 (2/2)	0.285	0.523	0.368	0.450
	PCA PC1	Triangle	2 (2/2)	0.286	0.496	0.440	0.408
	PCA PC1-3	Trapezoid	2 (2/2)	0.242	0.674	0.413	0.480
IBI	Spearman	Triangle	2 (2/2)	6.342	0.905	9.558	0.892
	Bayesian	Gaussian	2 (2/2)	3.099	0.974	7.227	0.942
	PCA	Gaussian	2 (2/3)	3.018	0.924	4.871	0.917
	PCA PC1	GaussC*	2 (2/2)	1.926	0.989	2.998	0.941
	PCA PC1-3	GaussC*	2 (2/2)	2.126	0.989	3.288	0.970

* GaussC: composite Gaussian MF
** Bell: generalized bell MF

Table 20. ANFIS model average performance across 10-folds, Cluster 1, for best model (MF type and number of variables) under each variable selection method

Health Measure	Method	MF Type	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	Spearman	Gaussian	2 (4/2)	0.743	0.628	1.173	0.642
	Bayesian	GaussC*	2 (2/2)	0.941	0.607	1.128	0.643
	PCA	Bell**	2 (2/2)	1.140	0.468	1.671	0.419
	PCA PC1	Gaussian	2 (2/2)	1.339	0.362	1.613	0.379
	PCA PC1-3	Bell**	2 (2/2)	1.299	0.370	1.517	0.454
FIBI	Spearman	Triangle	2 (2/2)	3.455	0.337	4.901	0.403
	Bayesian	Gaussian	2 (2/4)	2.393	0.647	3.531	0.598
	PCA	Bell**	2 (2/2)	3.162	0.494	4.835	0.411
	PCA PC1	Bell**	2 (3/2)	3.075	0.543	4.074	0.437
	PCA PC1-3	Triangle	2 (2/3)	3.779	0.330	5.121	0.335
HBI	Spearman	Gaussian	2 (2/2)	0.295	0.495	0.368	0.440
	Bayesian	Triangle	2 (2/2)	0.294	0.495	0.392	0.386
	PCA	Bell**	2 (2/2)	0.331	0.377	0.521	0.314
	PCA PC1	GaussC*	2 (2/2)	0.335	0.328	0.438	0.273
	PCA PC1-3	Triangle	2 (2/2)	0.392	0.134	0.470	0.159

* GaussC: composite Gaussian MF
** Bell: generalized bell MF

Table 21. ANFIS model average performance across 10-folds, Cluster 2, for best model (MF type and number of variables) under each variable selection method

Health Measure	Method	MF Type	Variables (MFs)	RMSE (train)	R^2 (train)	RMSE (check)	R^2 (check)
EPT Taxa	Spearman	Triangle	2 (2/2)	0.983	0.677	1.214	0.559
	Bayesian	Gaussian	2 (2/2)	0.888	0.750	1.249	0.869
	PCA	Gaussian	2 (2/2)	1.035	0.488	2.045	0.618
	PCA PC1	Triangle	2 (2/2)	0.842	0.790	1.088	0.808
	PCA PC1-3	Gaussian	2 (2/2)	0.759	0.843	1.172	0.824
FIBI	Spearman	Triangle	2 (2/2)	4.540	0.398	6.070	0.663
	Bayesian	Bell*	2 (2/2)	3.331	0.559	6.112	0.391
	PCA	Triangle	2 (2/2)	4.521	0.359	6.567	0.703
	PCA PC1	Gaussian	2 (2/2)	3.193	0.517	4.021	0.715
	PCA PC1-3	Gaussian	2 (2/2)	3.054	0.656	4.407	0.817
HBI	Spearman	Triangle	2 (2/2)	0.275	0.558	0.431	0.765
	Bayesian	Triangle	2 (2/2)	0.237	0.679	0.371	0.542
	PCA	Triangle	2 (2/2)	0.296	0.483	0.476	0.608
	PCA PC1	Gaussian	2 (2/2)	0.246	0.582	0.395	0.706
	PCA PC1-3	Triangle	2 (2/2)	0.249	0.598	0.412	0.695
IBI	Spearman	Gaussian	2 (2/3)	1.658	0.982	4.299	0.975
	Bayesian	Bell*	2 (2/2)	3.457	0.967	8.855	0.785
	PCA	Gaussian	2 (3/2)	1.569	0.930	1.863	0.986
	PCA PC1	Gaussian	2 (3/2)	0.943	0.994	2.087	0.978
	PCA PC1-3	Gaussian	2 (2/2)	2.082	0.986	2.272	0.984

** Bell: generalized bell MF

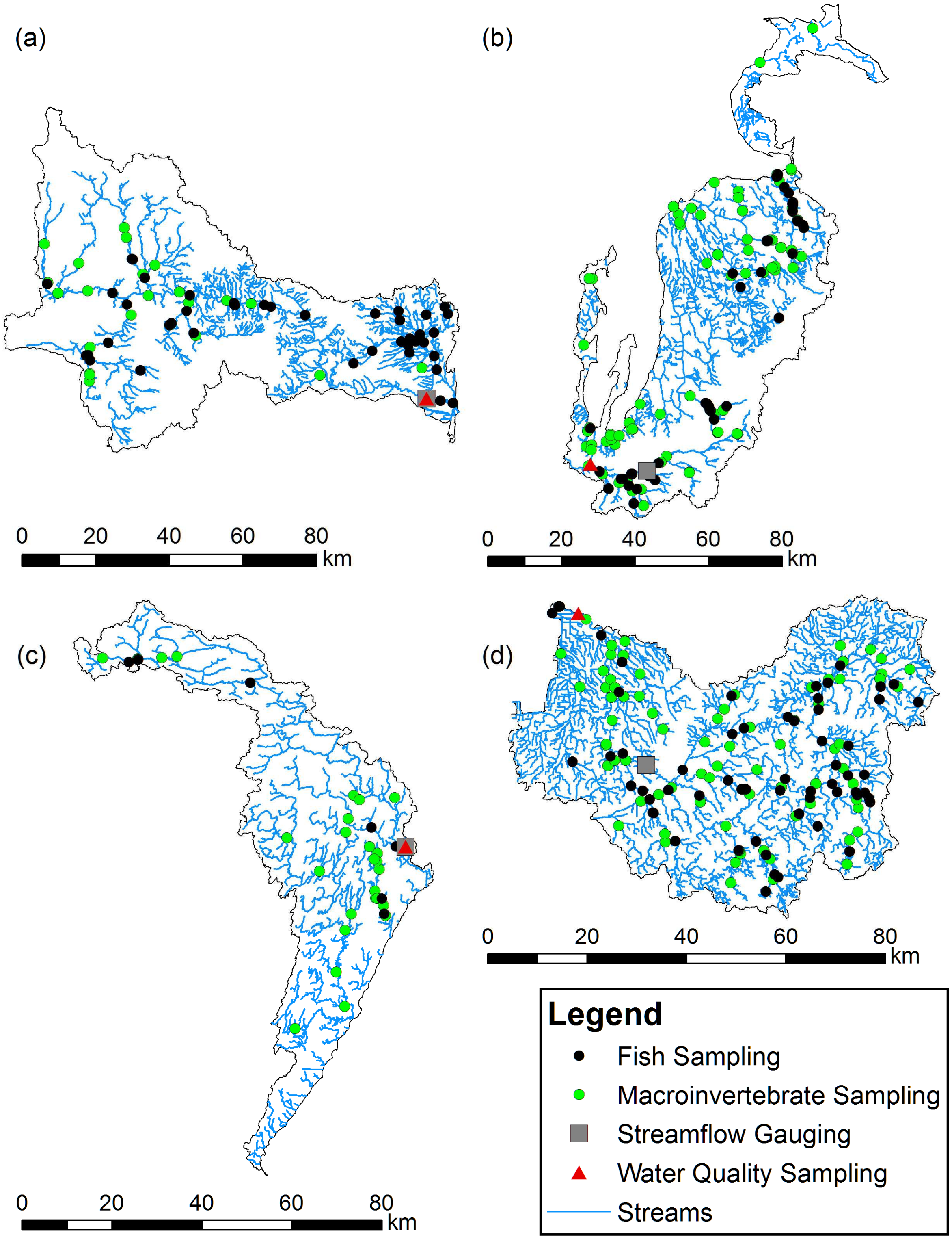

Figure 29. Sampling locations for (a) Au Sable, (b) Boardman-Charlevoix, (c) Cedar-Ford, and (d) Flint

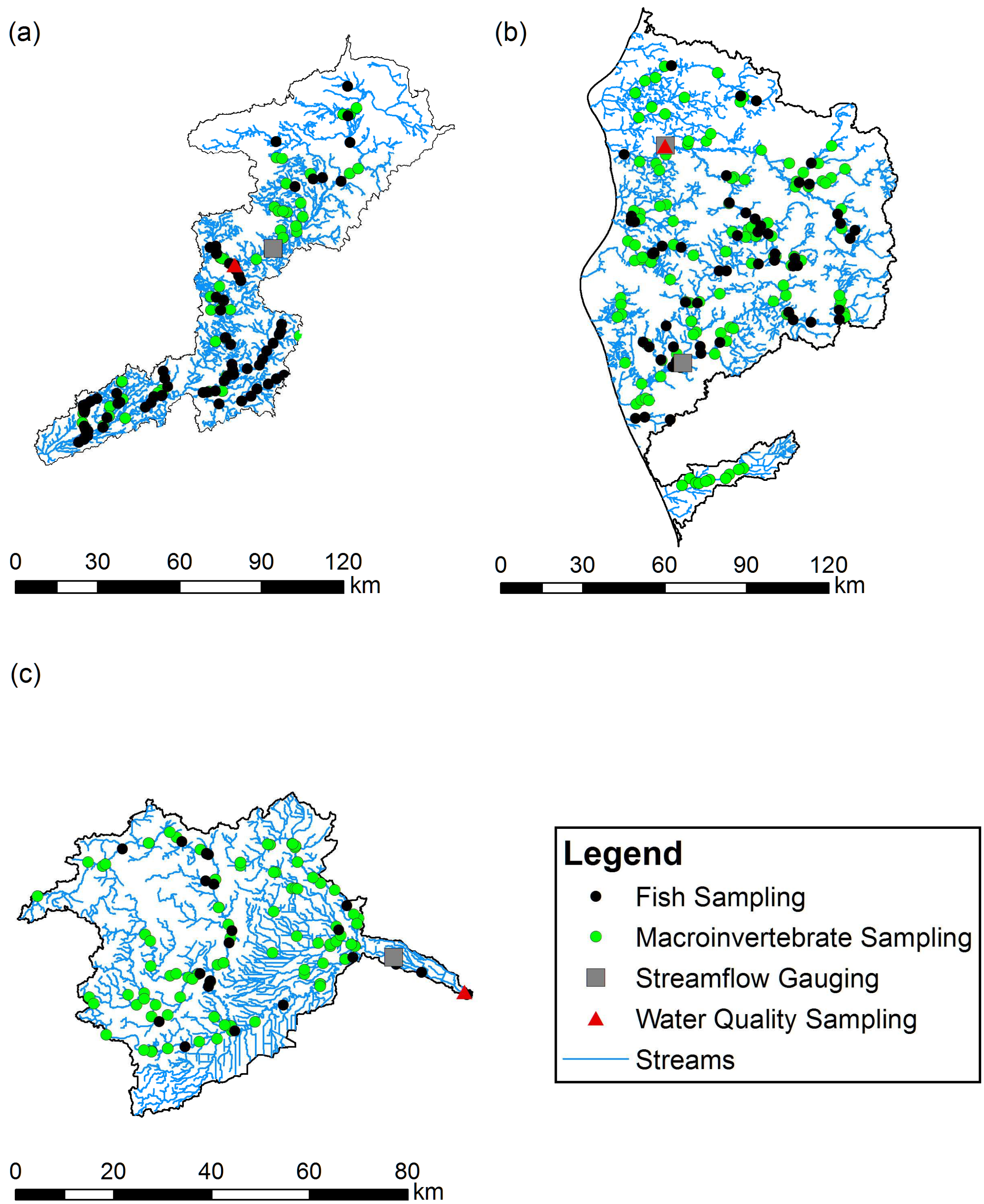

Figure 30. Sampling locations for (a) Muskegon, (b) Pere Marquette-White, and (c) Raisin

Table 22. LOADEST output statistics

Watershed	Constituent	n	AMLE Regression Statistics			Load Bias Diagnostics		
			R^2	r	PPCC	PBIAS	NSE	Model
Au Sable	Sediment	-	-	-	-	-	-	-
	TN	70	0.85	0.18	0.992	-0.37	0.81	AMLE
	TP	76	0.54	-0.13	0.990	-0.05	0.55	AMLE
Boardman-Charlevoix	Sediment	28	0.68	-0.09	0.969	0.24	0.84	AMLE
	TN	28	0.94	-0.16	0.965	0.19	0.97	AMLE
	TP	28	0.77	-0.20	0.942	-0.35	0.91	LAD
Cedar-Ford	Sediment	204	0.83	0.36	0.986	7.89	0.79	LAD
	TN	126	0.88	0.41	0.953	2.65	0.76	LAD
	TP	194	0.86	0.32	0.927	3.59	0.42	LAD
Flint	Sediment	24	0.69	-0.33	0.982	-20.9	0.34	AMLE
	TN	24	0.89	-0.04	0.957	-1.62	0.73	AMLE
	TP	24	0.83	-0.24	0.913	-17.45	0.33	LAD
Muskegon	Sediment	32	0.82	0.08	0.988	-8.45	0.45	AMLE
	TN	32	0.97	0.14	0.981	-1.04	0.91	AMLE
	TP	32	0.93	0.05	0.975	-5.36	0.68	AMLE
Pere Marquette-White	Sediment	47	0.62	-0.11	0.980	-0.81	0.30	AMLE
	TN	47	0.93	0.14	0.997	-0.04	0.91	AMLE
	TP	47	0.87	0.22	0.977	-0.74	0.76	AMLE
Raisin	Sediment	43	0.95	-0.39	0.989	10.56	0.42	AMLE
	TN	43	0.95	0.17	0.960	4.98	0.83	LAD
	TP	43	0.98	-0.14	0.988	5.35	0.88	AMLE

*n=number of observations; r = serial correlation of residuals, PPCC = probability plot correlation coefficient; AMLE = adjusted maximum likelihood estimation; LAD = least absolute deviation

Table 23. Land use change from pre-settlement (1800) to current (percentages may not add up to 100% due to rounding and exclusion of water)

Watershed	Period	Agriculture	Forest	Range	Urban	Wetland
Au Sable	1800	-	85.1%	0.5%	-	12.9%
	Current	3.2%	60.9%	13.3%	8.6%	12.2%
Boardman-Charlevoix	1800	-	79.5%	-	-	14.0%
	Current	11.9%	44.8%	14.0%	9.7%	13.2%
Cedar-Ford	1800	-	51.8%	-	-	47.7%
	Current	8.8%	26.1%	1.1%	4.3%	59.5%
Flint	1800	-	85.3%	-	-	14.0%
	Current	46.5%	25.3%	0.4%	19.5%	7.0%
Muskegon	1800	-	79.4%	0.3%	-	16.5%
	Current	19.2%	43.3%	8.5%	8.6%	16.5%
Pere Marquette-White	1800	-	84.6%	-	-	13.0%
	Current	16.3%	52.9%	9.8%	8.5%	10.5%
Raisin	1800	-	74.8%	-	-	24.0%
	Current	68.5%	11.9%	0.2%	10.8%	7.2%

Table 24. SWAT model calibration and validation (PBIAS)

Watershed	Flow and water quality stations*	Time Period	Flow	Sediment	TN	TP
Au Sable	USGS 04137500 MDEQ 350061	Calibration	4.69	-	18.54	28.96
		Validation	-2.36	-	15.71	26.06
		Combined	0.78	-	17.10	27.49
Boardman-Charlevoix	USGS 04126970 MDEQ 280014	Calibration	2.84	-10.00	15.32	0.73
		Validation	-0.04	5.26	24.68	9.73
		Combined	0.31	-3.44	19.07	4.53
Cedar-Ford	USGS 04059500 USGS 04059500	Calibration	4.10	-37.92	28.56	30.56
		Validation	-12.86	-33.27	26.57	14.54
		Combined	-2.47	-35.83	27.77	24.28
Flint	USGS 04148500 MDEQ 730285	Calibration	10.68	24.65	-5.23	18.76
		Validation	16.06	-25.13	33.58	24.89
		Combined	13.55	0.53	18.17	22.39
Muskegon	USGS 04121500 MDEQ 510088	Calibration	2.08	-19.29	17.24	1.48
		Validation	-9.04	-15.88	22.36	3.62
		Combined	-3.69	-17.53	19.85	2.57
Pere Marquette-White	USGS 04122500 MDEQ 530027	Calibration	5.41	18.39	21.60	13.77
		Validation	1.60	8.67	21.04	3.73
		Combined	3.29	14.06	21.36	9.40
Raisin	USGS 04176500 MDEQ 580046	Calibration	10.89	28.25	40.70	50.73
		Validation	-3.82	-23.61	41.99	19.10
		Combined	4.24	9.06	41.37	37.85

*USGS: United States Geological Survey streamflow gauging station; MDEQ: Michigan Department of Environmental Quality water quality sampling site

Table 25. SWAT model calibration and validation (RSR)

Watershed	Flow and water quality stations*	Time Period	Flow	Sediment	TN	TP
Au Sable	USGS 04137500 MDEQ 350061	Calibration	0.69	-	0.98	2.20
		Validation	0.78	-	1.00	2.42
		Combined	0.73	-	0.99	2.32
Boardman-Charlevoix	USGS 04126970 MDEQ 280014	Calibration	0.70	0.55	1.03	0.56
		Validation	0.56	0.58	1.19	0.64
		Combined	0.63	0.56	1.10	0.59
Cedar-Ford	USGS 04059500 USGS 04059500	Calibration	0.61	0.59	0.54	0.73
		Validation	0.50	0.45	0.50	0.70
		Combined	0.55	0.49	0.51	0.70
Flint	USGS 04148500 MDEQ 730285	Calibration	0.64	0.58	0.62	0.47
		Validation	0.64	0.53	0.76	0.72
		Combined	0.64	0.55	0.71	0.64
Muskegon	USGS 04121500 MDEQ 510088	Calibration	0.71	0.79	0.59	0.62
		Validation	0.65	0.86	0.47	0.68
		Combined	0.67	0.84	0.52	0.66
Pere Marquette-White	USGS 04122500 MDEQ 530027	Calibration	0.63	0.85	0.68	0.74
		Validation	0.64	0.91	0.61	0.83
		Combined	0.62	0.88	0.64	0.79
Raisin	USGS 04176500 MDEQ 580046	Calibration	0.53	0.66	0.64	0.66
		Validation	0.67	0.67	0.78	0.77
		Combined	0.59	0.65	0.71	0.70

*USGS: United States Geological Survey streamflow gauging station; MDEQ: Michigan Department of environmental Quality water quality sampling site

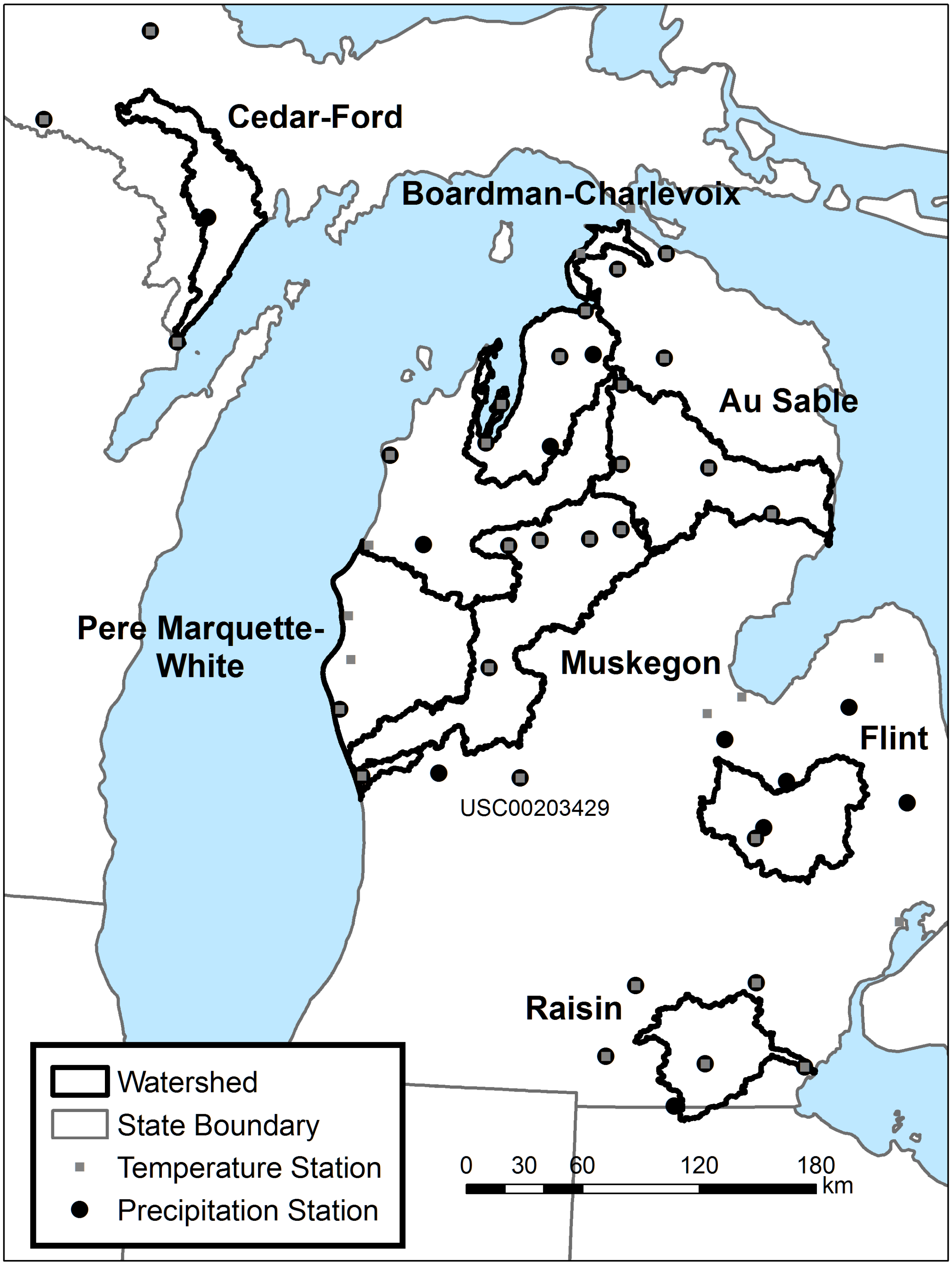

Figure 31. Precipitation and temperature gauge locations for all study watersheds.

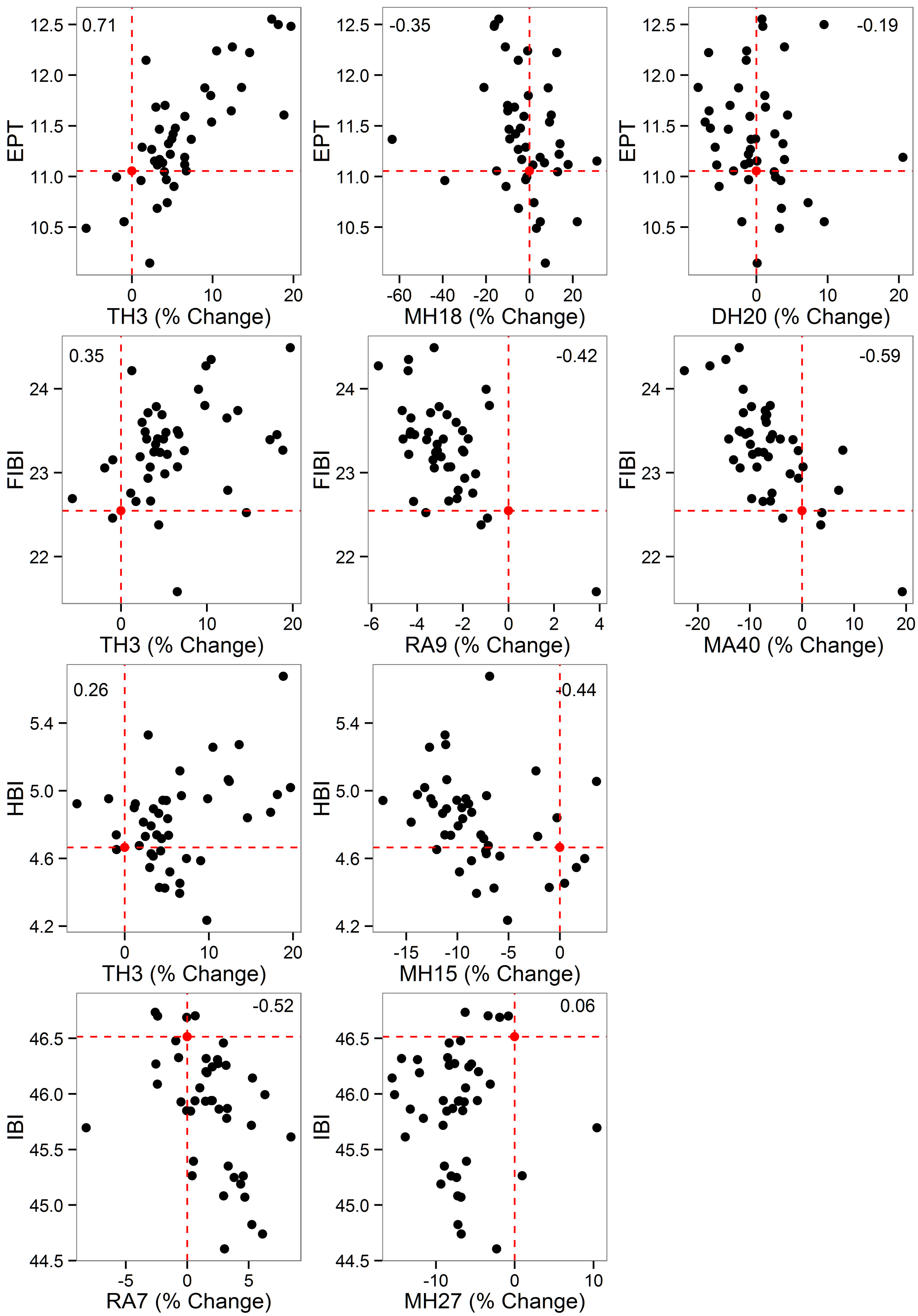

Figure 32. Stream health for cold-transitional streams as a function of percent change in flow regime variable under future climate scenarios. Spearman's ρ values are presented in the top right of each figure, and red dots indicate baseline stream health.

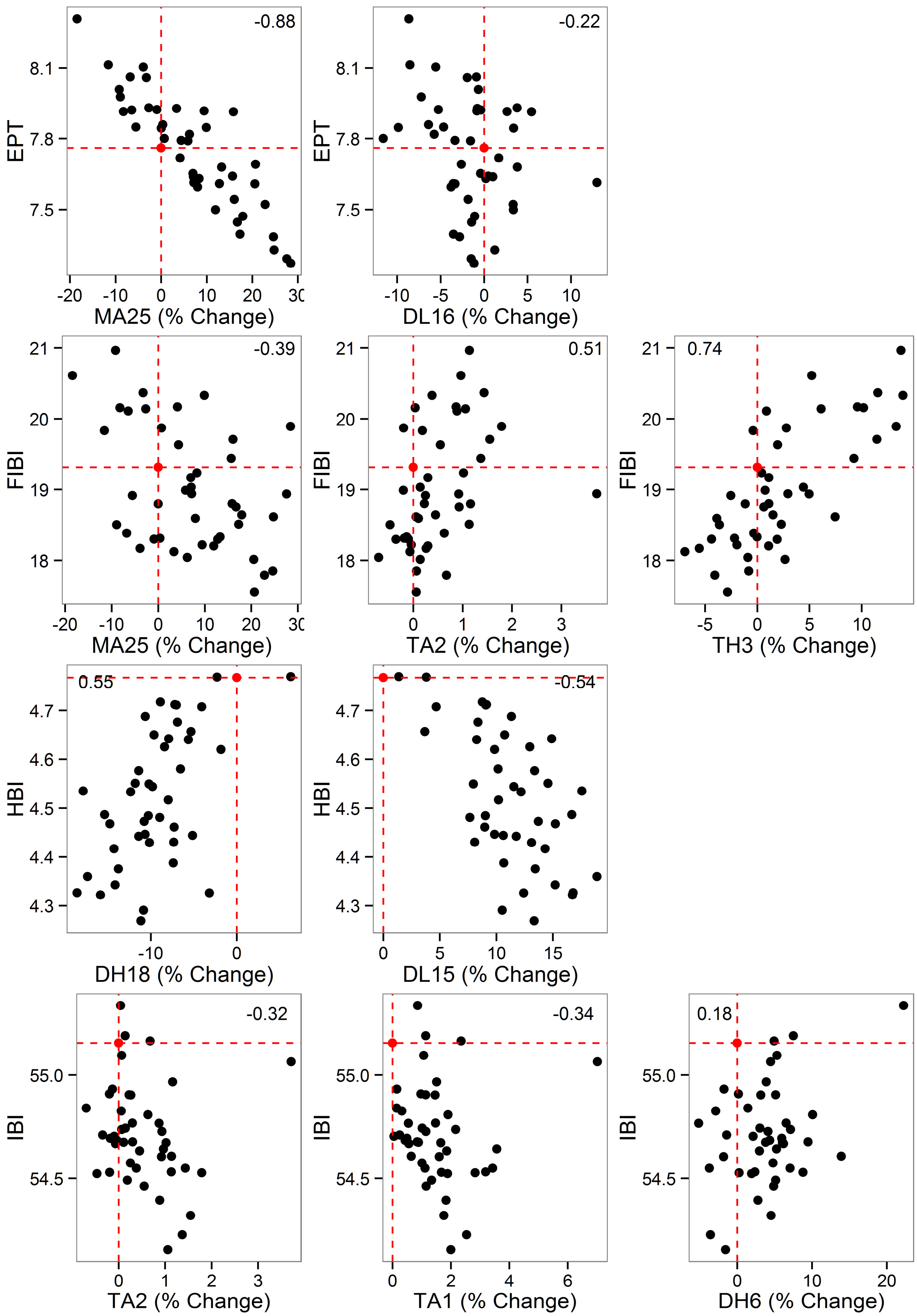

Figure 33. Stream health for cool streams as a function of percent change in flow regime variable under future climate scenarios. Spearman's ρ values are presented in the top right of each figure, and red dots indicate baseline stream health.

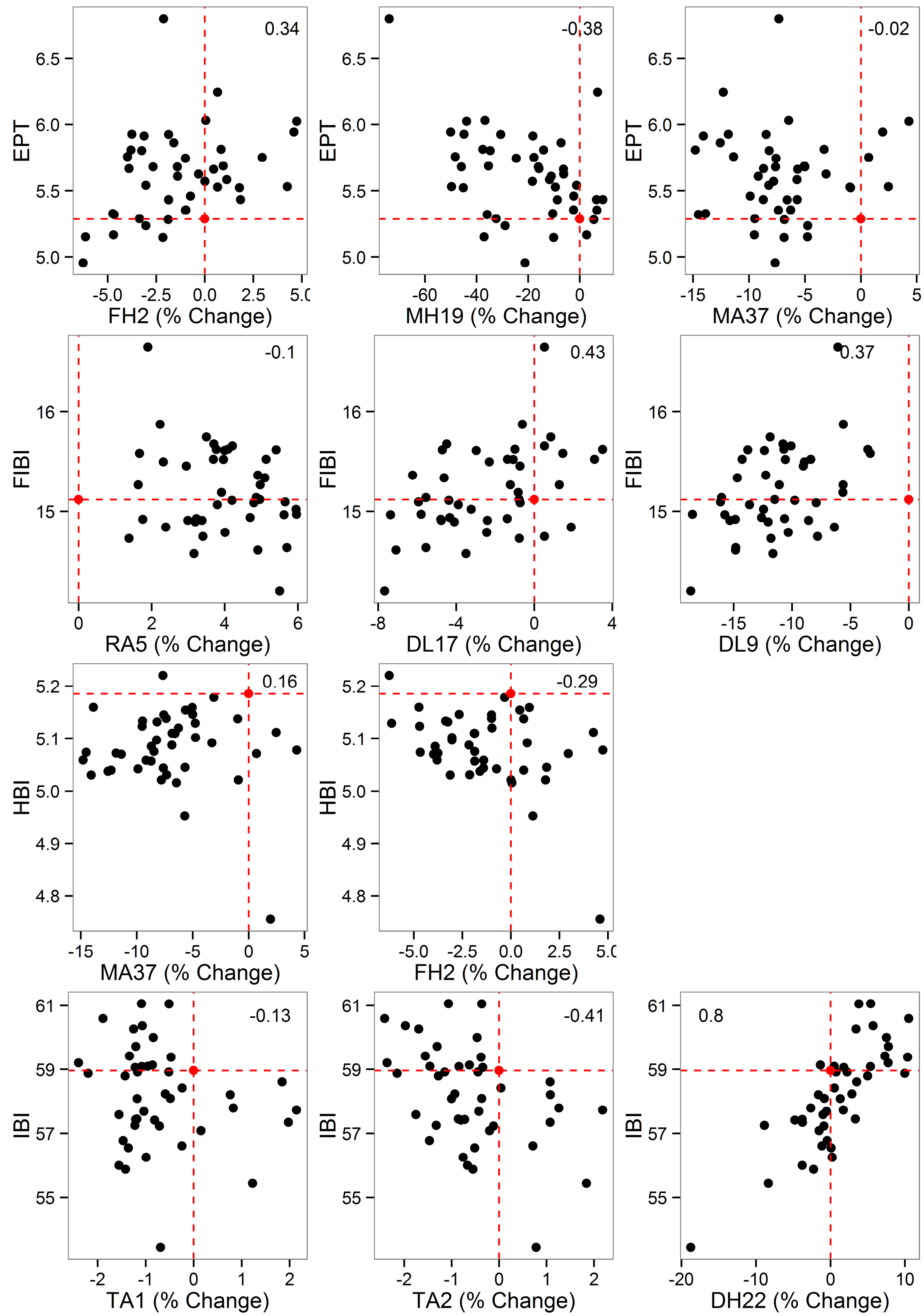

Figure 34. Stream health for warm streams as a function of percent change in flow regime variable under future climate scenarios. Spearman's ρ values are presented in the top right of each figure, and red dots indicate baseline stream health.

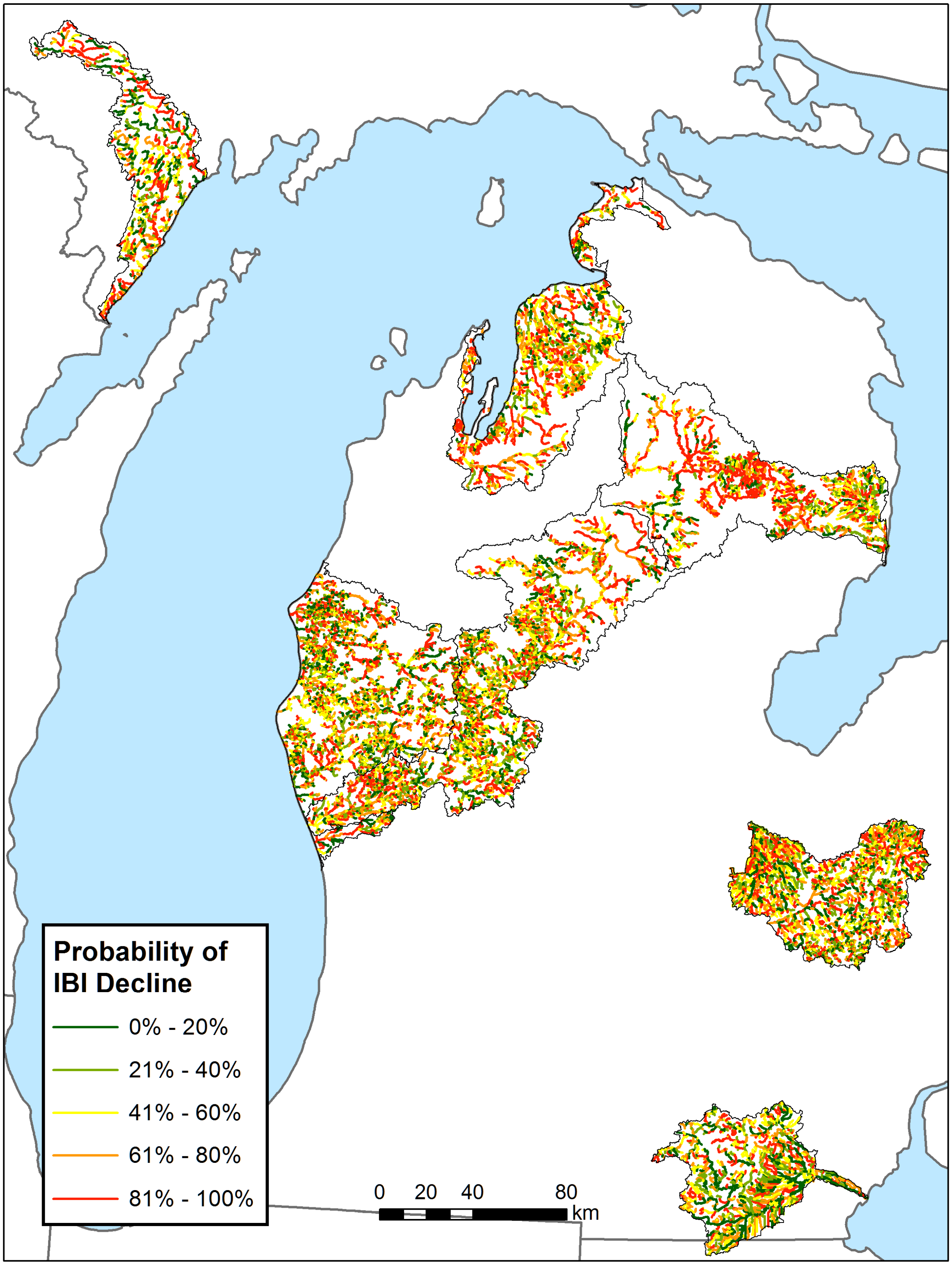

Figure 35. Probability of declining IBI under projected climate change

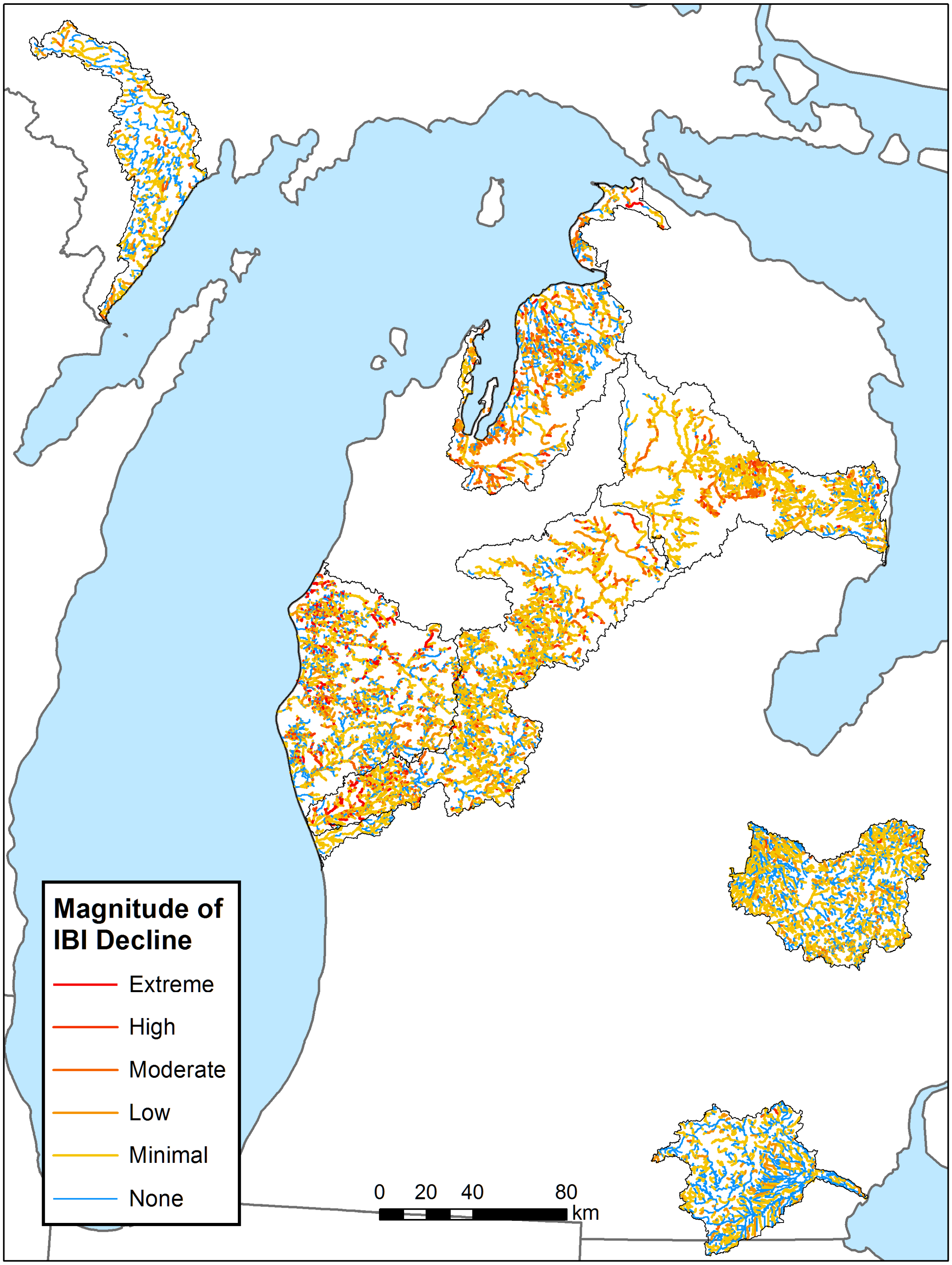

Figure 36. Average magnitude of declining IBI under projected climate change

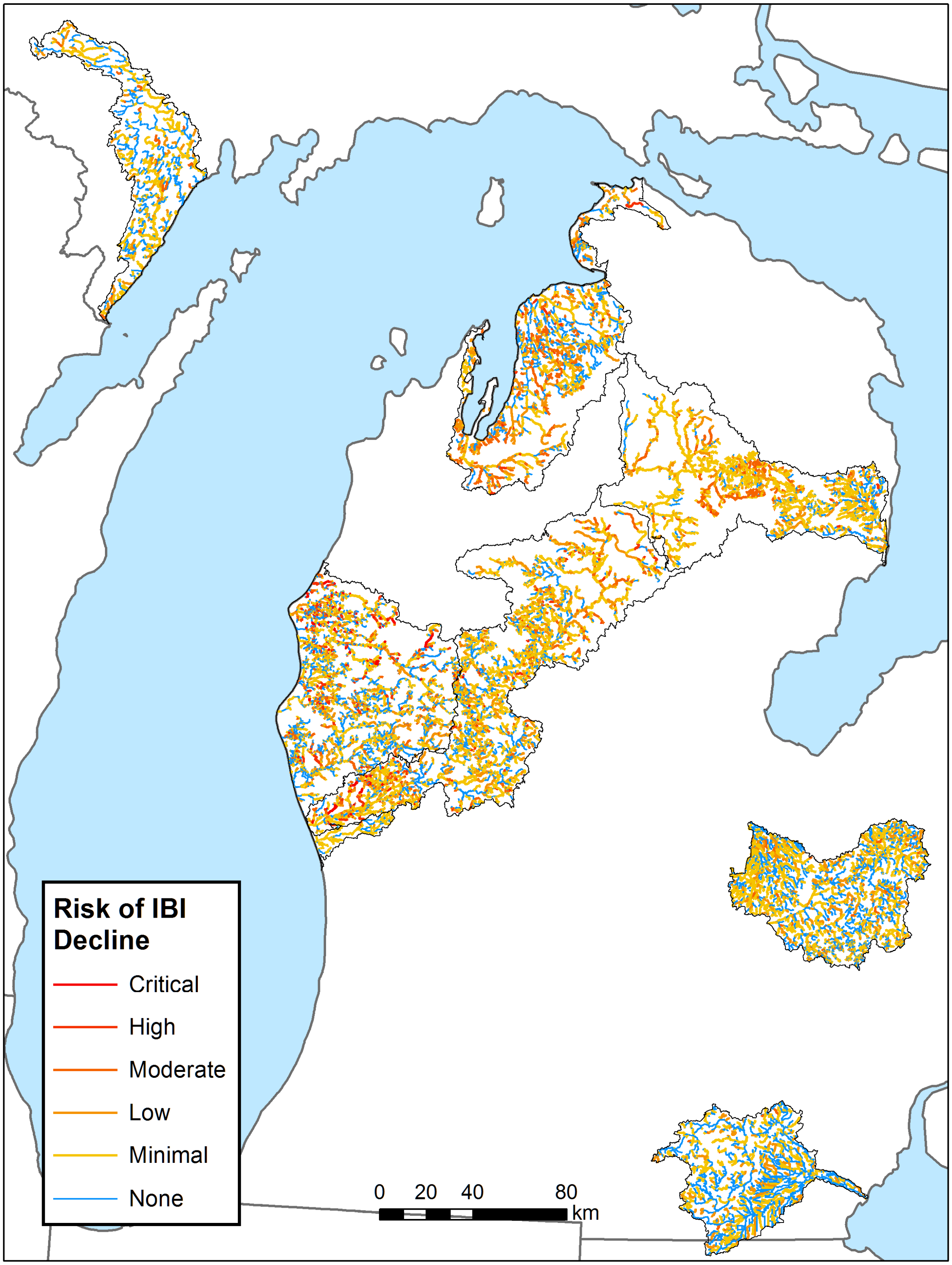

Figure 37. Vulnerability of streams to declining IBI under projected climate change

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