

INTEGRATING KEY ECOLOGICAL HEALTH AND SOCIAL DIMENSIONS IN
SUSTAINABLE WATER RESOURCES MANAGEMENT

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ABSTRACT

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The dynamics of coupled natural and human systems are complex and vary across time, location, and organizational unit. So different social groups may be unequally affected by degraded environments, which in many cases do not randomly occur over space. Therefore, the concept of environmental justice was introduced to address this issue. One environmental resource that has been a focus point for environmental justice is freshwater, and stream health based environmental justice studies are the most recent approach used by researchers to describe these phenomena. However, many of the previous studies were only performed at the census tract level and no proper spatial level was defined for environmental justice studies with respect to stream health. On the other hand, due to computational limitations for stream health indices estimation, only a few water quantity and quality parameters were used to develop stream health predictive models. Therefore, the purpose of this study is to address the following knowledge gaps in the area of stream health based environmental justice by: 1) determining the role of spatial level of socioeconomic factors on stream health based environmental justice studies and 2) assessing the relative importance of parameter estimation in stream health based environmental justice modeling.

To address the first knowledge gap, three Bayesian Conditional Autoregressive (CAR) models (ordinary regression, weighted regression and spatial) were developed for four common stream health measures based on 17 socioeconomic and physiographical variables at three census levels of county, census tract, and block group in the Saginaw River Basin in Michigan. This watershed was an ideal place to perform this study since it was identified as an area of concern in

the Great Lakes region while having one of the most diverse populations in the state. For all stream health measures, spatial models had better performance compared to the two non-spatial models at the census tract and block group levels. In addition, multilevel Bayesian CAR models were also developed to understand the spatial dependency across three levels. Results showed that considering level interactions improved the predictive power of the environmental justice models. Residual plots also showed that models developed at the block group and census tract (in contrary to county level models) were able to capture spatial variations, which is an important aspect of environmental justice studies.

To address the second knowledge gap, first ecologically relevant streamflow and water quality indices were used to improve the performance of the stream health predictive models. The outputs (fish and macroinvertebrate indices) from newly developed stream predictive models were then used to develop similar CAR models. Results showed that incorporating the more accurate stream health indices improved the spatial dependencies at the census tract and block group levels compared to county level. In addition, the multilevel models had better performance than single level models. Finally, the modified stream health indices improved stream health based environmental justice models' performance by reducing redundancies in independent variables. This research finding provides a valuable tool to target vulnerable communities with respect to access to clean water, which enables water resources policymakers to allocate resources in a way that reduces environmental inequality.

Dedicated to my loving wife and son, Behin and Aydin,
and my amazing parents, Abdolreza and Fatemeh, for their endless support.

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KEY TO ABBREVIATIONS

ANFIS: Adaptive Neuro-Fuzzy Inference System

ANN: Artificial Neural Network

AQUATOX: Aquatic Ecosystem Simulation Model

ARM: Agricultural Runoff Management

ARS: Agricultural Research Service

AusRivAS: Australian River Assessment Scheme

BASINS: Better Assessment Science Integrating point and Nonpoint Source

B-IBI: Benthic Index of Biotic Integrity

BMPs: Best Management Practices

CAR: Conditional Autoregressive

CWA: Clean Water Act

DIC₄: Deviance Information Criterion

ELOHA: Ecological Limits of Hydrologic Alteration

EPA: Environmental Protection Agency

EPT: Ephemeroptera, Plecoptera, and Trichoptera

GHGs: Greenhouse Gases

HBI: Hilsenhoff Biotic Index

HEC-DSS: Hydrologic Engineering Center-Data Storage System

HEC-HMS: Hydrologic Engineering Center-Hydrologic Modeling System

HIT: Hydrological Index Tool

HLM: Hierarchical Linear Modeling

HRU: Hydrological Response Units

HSP: Hydrocomp Simulation Program

HSPF: Hydrologic Simulation Program-Fortran

HUC: Hydrologic Unit Code

IBI: Index of Biotic Integrity

IHD: International Hydrological Decade

IHP: International Hydrological Program

LA: Load Allocation

LID: Low Impact Development

MCMC: Markov chain Monte Carlo

MDEQ: Michigan Department of Environmental Quality

MHIT: MATLAB Hydrological Index Tool

MOS: Margin of Safety

NATHAT: National Hydrologic Assessment Tool

NAWQA: National Water Quality Assessment

NPDES: National Pollutant Discharge Elimination System

NPS: Non-Point Source

NSE: Nash-Sutcliffe efficiency

NWIS: National Water Information System

PBIAS: Percent bias

PHABSIM: Physical Habitat Simulation Model

PLSR: Partial Least Square Regression

R^2 : Coefficient of determination

RIVPACS: River Invertebrate Prediction and Classification System

RMSE: Root Mean Square Error

RSR: root mean square error-observations standard deviation ratio

SAR: Simultaneous Autoregressive

SEM: Structural Equation Modeling

SUSTAIN: System for Urban Stormwater Treatment and Analysis Integration

SWAT: Soil and Water Assessment Tool

SWMM: Storm Water Management Model

SWMM-CAT: Storm Water Management Model-Climate Adjustment Tool

TMDL: Total Maximum Daily Load

UNESCO: United Nations Educational, Scientific and Cultural Organization

UNICEF: United Nations Children's Fund

USCB: U.S. Census Bureau

USDA: U.S. Department of Agriculture

USDA-ARS: U.S. Department of Agriculture-Agricultural Research Service

USGS: U.S. Geological Survey

WHO: World Health Organization

WIN: Watershed Initiative Network

WLA: Waste Load Allocation

WMO: World Meteorological Organization

WUA: Weighted Usable Area

1. INTRODUCTION

Anthropogenic activities in many areas resulted in the degradation of natural ecosystems. Almost half of land surfaces are transformed and many natural resources are altered by human activities that turned the earth to a human-dominated planet (Vitousek et al., 1997). Meanwhile, natural and human ecosystems are interconnected and impaired natural ecosystems have negative impacts on human ecosystems. In order to address this complex system, the concept of coupled natural and human systems was developed to evaluate the mutual impacts of these systems. However, these mutual impacts are dynamic and vary across time, location, and administrative units. As a result, different communities are impacted in different ways. Therefore, the concept of environmental justice was introduced to provide equal access to healthy environment, and equal right of being involved in environmental policy making as a right for all human beings.

Due to the fact that freshwater is a limited natural resource that is vital for both natural and human ecosystems, environmental justice studies with respect to clean water have been an area of research for years. For this purpose, both socioeconomic and water resources assessments must be conducted. In terms of social dimensions, socioeconomic indicators representing sociological and economical aspects of the society are used for environmental justice studies. These indicators are developed on top of census data collected by the U.S. Census Bureau at different spatial levels. While most environmental justice studies used data collected at the census tract level, studies show that socioeconomic data collected at different levels may result in dissimilar conclusions. To the best of my knowledge, no proper spatial level has been defined for environmental justice studies with respect to stream health. Therefore, one of the goals of this study is to address this knowledge gap by assessing the role of spatial levels in environmental justice studies with respect to stream health.

In terms of evaluating the health of water resources, several techniques have been used that mainly rely on water quality to evaluate the health of waterbodies. However, the newly introduced method known as bioassessment is considered as a more comprehensive approach since it measures the final impact of physical, chemical, and biological activities on aquatic species. However, it is almost impossible to sample all waterbodies to perform comprehensive stream health assessments. Therefore, many studies used water quantity and water quality parameters to evaluate the biological integrity of streams beyond the monitoring points. However, due to the complexity of the natural systems, the predictability of stream health models is low in general. Therefore, the goal of the second study is to evaluate whether the incorporation of more reliable stream health measures (fish and macroinvertebrate indices) can improve the overall performance of stream health based environmental justice modeling.

In the next six chapters (2 to 7), we address the aforementioned goals and provide a roadmap for future studies. Chapter 2 synthesizes key aspects of water resources and socioeconomic assessment, followed by modeling techniques used for these assessments. In chapter 3, we provide a summary of the knowledge gaps that will be addressed in chapters 4 and 5. In chapter 4, spatial dependencies among socioeconomic indices and water quality measures are evaluated at three levels of county, census tract, and block group. Then the role of level change and nested effects on their spatial dependencies are evaluated. In chapter 5, the role of water quality measures prediction on spatial dependencies are assessed. For this purpose, more recent developments in ecosystem modeling are used to develop accurate biological measures and then these predictions are used to re-evaluate the objectives defined in study one. The overall conclusions of both studies are summarized in chapter 6, followed by recommendations for future research in chapter 7.

2. LITERATURE REVIEW

2.1. Coupled Natural and Human Systems

The dynamic of both natural and human systems are complex and interrelated. For this purpose, multidisciplinary researches that integrate biological, physiological and socioeconomic sciences are needed (Carpenter et al., 2009; Alberti et al., 2011). The concept of coupled natural and human systems was introduced to address these complex and reciprocal effects at the same time (Liu et al., 2007a, b). Assessing impacts of natural systems on human systems and vice versa are two key aspects of this concept and have been extensively studied (Ostrom and Nagendra, 2006; Liu et al., 2007a; Alberti et al., 2011; NSF, 2014; Chen, 2015).

2.1.1. Impact of Anthropogenic Activities on Natural Systems

Anthropogenic activities influenced natural ecosystem in many aspects. Population increase and high demand for using resources such as land and freshwater have drastically affected terrestrial and aquatic ecosystems and made the earth a human dominated planet (Vitousek et al., 1997; Tilman et al., 2001; Tilman and Lehman, 2001; Halpern et al., 2008). Meanwhile, agricultural practices and urbanization have transformed the land as humans continue to modify natural system (Sanderson et al., 2002; Foley et al., 2005). As a result, more than half of the Earth's landscapes have been changed (Vitousek et al., 1997). Land transformation for agricultural practices are predicted to increase by up to ten million square kilometers by 2050 (Tilman et al., 2001). All of these changes result in broader impacts beyond transformed lands (Dupouey et al., 2002; Lambin and Geist, 2008). These alterations include but are not limited to increase in greenhouse gasses (GHGs) emission and climate change (Smith and Conen, 2004; Falloon and Betts, 2010), urban heat island development (Peng et al., 2011), and deforestation (Henderson-Sellers and Gornits, 1984). These changes will negatively affect the integrity of natural ecosystems

in many ways such as change in abundance and diversity of birds (Jets et al., 2007) mammals (Murray and Dickman, 2000; Thuiller et al., 2006), and plants (Thuiller et al., 2008).

At the same time, increase in freshwater demand for drinking and agricultural uses have put water resources at risk (Peters and Meybeck, 2000; Viessman et al., 2009). Although more than 70% of Earth's surface is covered by water, only 2.5% of that is freshwater that can be used for drinking, agricultural, industrial and recreational purposes (USGS, 2016). However, up to 90% of freshwater are either in the forms of groundwater, ice, or glaciers; and only about 0.007% of global water is available in rivers and lakes in form of surface water (Gleick, 1993). Due to the high demand for water usage, most rivers and lakes have been regulated while only one-third of Earth's rivers were undisturbed by the end of the twentieth century (Abramovitz, 1996; Vitousek et al., 1997). These changes to riverine ecosystems not only affect water quantity and quality, but also alter aquatic ecosystems (Kingsford, 2000; Halpern et al., 2008; Wei et al., 2009). Halpern et al. (2008) reported that more than 40% of aquatic ecosystems are highly impacted by human activities. As an example, excess agricultural nutrients (such as nitrogen and phosphorus) released into waterbodies enhanced eutrophication and diminished dissolved oxygen (U.S. EPA, 2017a). These degradations resulted in severe environments for aquatic species. Studies showed that by 2050, most of the existing species might become extinct (Schaaf et al., 2006; Halpern et al., 2008). On the other hand, fisheries that mainly target specific types of aquatic species, have modified natural predator-prey cycles, ending up with change in abundance and distribution of aquatic species (Vitousek et al., 1997; Pauly et al., 2005).

2.1.2. Impact of Natural Systems Degradation on Human Systems

Excess use of natural resources and ecosystem degradation caused by anthropogenic activities have impacted human systems as well. Water shortages, air pollution, and excess of water

borne and respiratory diseases are just some examples of the impacts of natural systems degradation on human health (Stikker, 1998; Kampa and Castanas, 2008; U.S. EPA, 2017a).

Climate change impacts on water resources and high demand for limited freshwater have made water shortages and water crises some of the main concerns of the 21st century (Saeijs and Berkel, 1995; Stikker, 1998). Almost a billion people around the world do not have access to clean drinking water, and more than two billion do not have proper sanitation facilities (WHO/UNICEF, 2008). Besides that, surges in use of fertilizers and pesticides threaten human health by polluting freshwater resources (Novotny, 1999). Stomach cancer in adults and methemoglobinemia in infants are just two examples of health problems associated with polluted water from agricultural practices (Almasri and Kaluarachchi, 2004). Water contamination also leads to widespread water-borne diseases caused by pathogenic microorganisms that exist in polluted water (Grabow, 1996). Cholera, Diarrhea, Hepatitis, Malaria, and SARS are just some out of many water-borne diseases that can be spread by polluted water (Lenntech, 2017). According to the World Health Organization (WHO), water-borne diseases kill more than three million (mostly children) every year (WHO, 2017).

Human activities have polluted air as well as water. Excess use of fossil fuels increase GHGs that not only cause global warming but also are harmful for human health (Ramanathan and Feng, 2009). Carbon monoxide, sulfur dioxide, nitrogen oxides and ozone are just some of the air pollutants generated as byproducts of fossil fuels combustion that cause health issues such as respiratory irritation, respiratory infection, bronchitis, heart disease and lung cancer (Kampa and Castanas, 2008). According to the WHO report, air pollution is the cause of almost 7 million annual premature deaths in the world (WHO, 2017).

2.1.3. The Concept of Environmental Justice

The mutual interactions of human and natural systems are dynamic and vary spatially among different organizational units (Liu et al., 2007a). In other words, impacts of degraded environments are not proportionally distributed among different groups, while some communities such as low-income people, minorities and people of color are usually more affected than others, which is called environmental inequality (Downey and Liam, 2008). According to the U.S. Environmental Protection Agency (U.S. EPA) report, hazardous facilities and industrial wastes are mostly located near poor and minority neighborhoods (Massey, 2004). The concern of environmental inequality raised movements in 1980s that resulted in the Environmental Justice executive order signed by President Clinton in 1994. The U.S. EPA interpreted the Civil Rights Act of 1964 to extent to cover the concept of Environmental Justice, which means that fair treatment and significant participation of all people regardless of their race, ethnicity, income, or national origin with respect to the environmental law, regulations and policies (U.S. EPA, 2017b). In other words, it means all people must have equal access to healthy environment (e.g. clean air and clean water) and the right of being actively involved in environmental policy making.

2.2. Water Resources Assessment

The concept of water resources assessment that includes both water quantity and quality evaluates the impact of human activities and excess in freshwater consumption on waterbodies integrity (GWP, 2013). Population growth and excess demand for limited available water resources raised concerns about water resources management in the late twentieth century. Back in 1965, the United Nations Educational, Scientific and Cultural Organization (UNESCO) started a worldwide program called the International Hydrological Decade (IHD) in order to raise awareness on the importance of the hydrological cycle's study that enhanced the field of hydrology

as a professional research area (Miloradov and Marjanovic, 1998). By the end of IHD in 1975, UNESCO started a global educational program called the International Hydrological Program (IHP) to address problems associated with excess water resources consumption (Miloradov and Marjanovic, 1998). In 1977, the IHP objectives were targeted to address conservation of water resources, in which water resources assessment was defined in order to pursue water resources management (Miloradov and Marjanovic, 1998). Water resources must be assessed for many reasons including water demand analysis, environmental and social impacts, and risk analysis of sustainable water resources (SSWM, 2016). According to the International Glossary of Hydrology, water resources assessment is defined as the “*determination of the sources, extent, dependability and quality of water resources for their utilization and control*” (UNESCO/WMO, 2012). For this purpose, hydrological data including water quantity and water quality and physiographical data including topography, river network, land use and soil must be collected. Statistical analysis is required to cover missing or out dated data. These data must be transferred into information and assessed by decision makers for both short term and long-term water resources management and policy making (SSWM, 2016).

2.2.1. Water Quality Assessment

Three classes of physical, chemical, and biological characteristics are being used to assess waterbodies including rivers, lakes and groundwater (Chapman, 1996). Physical characteristics such as stream meandering, depth, and slope affect water movement, while chemical characteristics such as acidity, dissolved solids, oxygen and nutrient contents represent water pollution status. Finally, biological characteristics such as abundance and integrity of instream organisms are being used to evaluate the responses of aquatic ecosystems to water quality. Based on these three criteria, water quality assessment is defined as “*the overall process of evaluation of*

the physical, chemical and biological nature of water in relation to natural quality, human effects and intended uses, particularly uses which may affect human health and the health of the aquatic system itself” (Chapman, 1996). However, more attention was placed on chemical evaluation compared to the two other aspects of water quality assessment and early studies have mainly focused on chemical evaluation (U.S. EPA, 2006; Abbasi and Abbasi, 2012).

2.2.1.1. Clean Water Act

Due to public awareness and concerns raised for waterbodies pollution, the first water regulatory amendment called Clean Water Act (CWA) was established in 1972 in order to regulate pollution discharge to waterbodies (U.S. EPA, 2016). It is the first environmental law enforcement that authorized by the U.S. EPA to implement pollution control programs.

The National Pollutant Discharge Elimination System (NPDES) is part of the CWA that limits point source pollution discharge (such as pollution discharge from pipes or ditches) to the nation’s water (U.S. EPA, 2017c). There are ten regional offices established by U.S. EPA around the nation that work with local governments to enforce the NPDES program. Under the NPDES program, any point source pollutant discharge requires a NPDES permit that limits the amount and type of pollutant released and enforces follow up monitoring and reporting to make sure that discharged pollutants are not affecting water quality (U.S. EPA, 2017c).

Under the CWA, the U.S. EPA has also developed water quality standards for states, territories and tribes in order to define desired waterbody condition, required protection, and planning to reach desired conditions for each water body (U.S. EPA, 2014a). These standards empower the U.S. EPA to eliminate pollutant discharge from sources such as industrial sites, sewer systems, and water treatment plants to waterbodies, unless four major issues of 1) designated use,

2) criteria, 3) antidegradation requirements, and 4) general policies have been addressed (U.S. EPA, 2014a).

- 1) Designated use: Federal and state agencies should define the purpose and amount of water that must be allocated for designated uses such as drinking water supply, recreation, and fisheries and wildlife protection.
- 2) Criteria: Water quality criteria defined by states, territories, and tribes limit the amount of pollutant release to designated waterbodies and must be followed by agencies.
- 3) Antidegradation requirements: The framework provided by agencies to protect and maintain waterbodies by designated use and defined criteria.
- 4) General policies: States, territories and tribes can adopt policies in term of local water quality standards. These policies must be approved by the U.S. EPA before implementation.

2.2.1.2. Total Maximum Daily Load

Under the section 303(d) of the CWA, all states, tribes and territories must monitor waterbody status and provide a list of waterbodies that do not meet water quality standards (called impaired), or are at risk of being impaired in future (called threatened) (U.S. EPA, 2017d). Impaired and threatened waterbodies must be prioritized and the threshold for pollutant discharge to them should be defined by agencies. Therefore, the Total Maximum Daily Load (TMDL) is defined as the maximum allowed discharge amount of each pollutant to a waterbody on a daily basis, while meeting water quality standards with respect to that pollutant (U.S. EPA, 2015a). Figure 1 shows how TMDL will be incorporated to reach water quality standards.

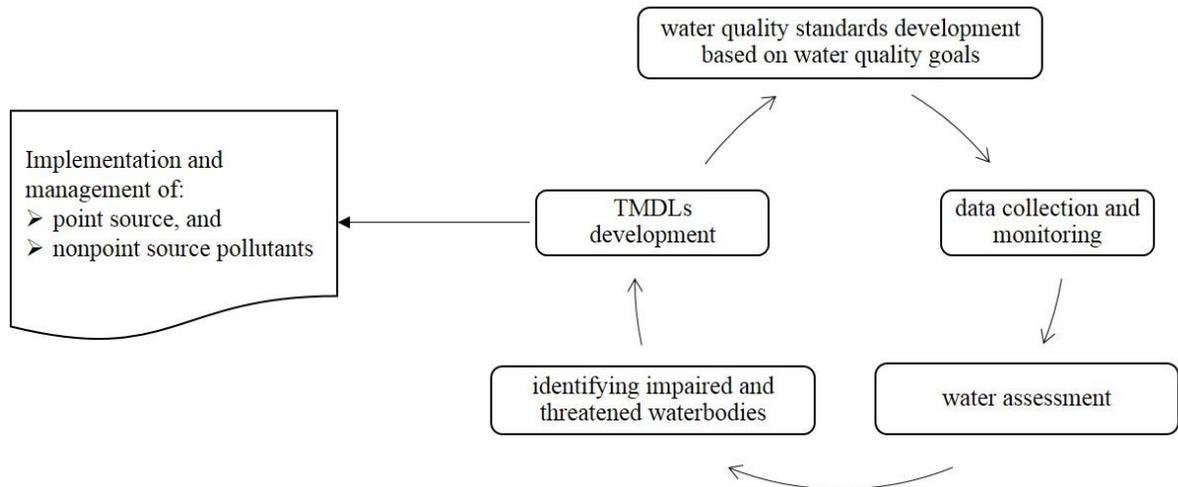


Figure 1. TMDL implication in the CWA (U.S. EPA, 2017d)

TMDLs are defined for each waterbody/pollutant combination as sums of waste load allocation from point sources (WLA), load allocation from natural background and other non-point sources (LA), and margin of safety (MOS) that considers uncertainty of prediction and will be calculated as follows (U.S. EPA, 2015a):

$$\text{TMDL} = \sum \text{WLA} + \sum \text{LA} + \text{MOS} \quad (1)$$

Defined TMDL by agencies must be approved by U.S. EPA before implementation. NPDES permits are required to address WLA, while voluntary or statewide projects funded by U.S. EPA aim to reduce LA from non-point sources (U.S. EPA, 2015a). The EPA also enforces states to monitor TMDL implementation and monitoring of impaired and threatened waterbodies status every two years until they reach desired water quality standards.

2.2.1.3. National Water Quality Assessment Program

In order to provide a reliable nationwide baseline for water quality assessment, in 1991 the U.S. Geological Survey (USGS) developed the National Water Quality Assessment (NAWQA) program. The four major objectives of this program were: 1) evaluating the current health status of waterbodies including streams, lakes, and groundwater around the U.S., 2) monitoring long-

term water quality variation 3) assessing the role of natural stressors and anthropogenic activities on waterbodies, and 4) finding the most vulnerable areas in terms of water quality (USGS, 2014). The NAWQA program requires durable and comprehensive data collection that can be used for initial assessments and further analysis. These data must represent the hydrology and chemistry of surface water and groundwater, stream ecology and land use changes over time (USGS, 2014). The first decade of the NAWQA program implementation (from 1991 to 2001) was focused on the first objective. For this purpose, water quality assessment was performed for 51 major river basins within the U.S. that resulted in baseline development for assessment of drinking water and aquatic ecosystem health, and resource management (Hamilton et al., 2008). The second decade of the NAWQA program implementation (from 2001 to 2012) was mostly focused on the second and third objectives that aimed to monitor the trend of water quality change over time and evaluate the response of waterbodies to natural and human stressors. Assessing responses of aquatic ecosystems to agrichemicals, nutrient enrichment and urbanization were some of the major concerns that were considered in this period (USGS, 2014). The NAWQA program is currently in the process for the third decade (from 2013 to 2023) that aims to maintain the program's integrity and meet stakeholders' demands while resources are facing degradation (National Research Council, 2012).

2.2.2. Modeling Approaches Used for Water Resources Assessment

Water resources assessment requires continuous data collection and data validation. For this purpose, widespread monitoring sites must be implemented and maintained for the long-term that is a costly and challenging endeavor. For instance, study units for NAWQA were reduced from 51 to 42 in the program's second decade (from 2001 to 2012) and one of the main concerns of the current program running for the third decade (from 2013 to 2023) is to maintain the program

while reducing associated costs (USGS, 2014). It is also impossible to perform monitoring for all waterbodies within the current and predict possible future scenarios, which is why modeling has been widely used to perform long term and wide-spread assessment of water resources, and to predict their response to possible upcoming conditions.

2.2.2.1. Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT) is a physically based and semi-distributed watershed model developed by U.S. Department of Agriculture (USDA) – Agricultural Research Service (ARS) (Gassman et al., 2007). SWAT uses topographic and river network data to divide the watershed into smaller sections called subwatersheds. Each subwatershed is then divided into unique Hydrological Response Units (HRUs) based on land use, soil, and slope variation within the subwatershed; each HRU will be considered as a homogenous cell for further analysis (Neitsch et al., 2011). Each subwatershed contains a single reach/stream segment that is connected to the tributary channel passing through the watershed and draining into the outlet (Arnold et al., 2012).

SWAT models are able to: 1) simulate water quantity and water quality parameters for each stream segment on a daily or sub-daily basis, 2) route it to the stream network, and 3) deliver it to the watershed outlet. SWAT is also able to assess long-term impacts of agricultural management practices on surface runoff, sediment, nutrients (nitrogen and phosphorus), pesticides, and bacteria yields at the watershed scale (Neitsch et al., 2011). The ArcGIS version of SWAT, called ArcSWAT, provides a graphical user interface for SWAT that made it user friendly. SWAT is one of the most widely used water resources assessment models and so far has been used in more than 2000 peer-reviewed articles (SWAT Literature Database, 2017).

2.2.2.2. System for Urban Stormwater Treatment and Analysis Integration

System for Urban Stormwater Treatment and Analysis Integration (SUSTAIN) is a decision support system developed by U.S. EPA to assess performance of Best Management Practices (BMPs) implementation on runoff and pollution regulation (Lee et al., 2012). SUSTAIN is able to assess 1) effectiveness of different BMPs for surface runoff and associated pollutants mitigation, 2) cost-effectiveness of proposed approaches to achieve desired water quantity and water quality standards, and 3) proper size and location of BMPs to meet these goals (U.S. EPA, 2014b).

SUSTAIN can simulate various types of BMPs implementation to control either point source or non-point source pollutants release that make it suitable for hydrology and water quality assessment of both urban and non-urban systems (U.S. EPA, 2014b). Considering both environmental and economic aspects of BMPs implementation scenarios, SUSTAIN provides a unique tool for water resources policy makers to meet water quality standards and maintain sustainable water resources (U.S. EPA, 2014b).

2.2.2.3. Hydrologic Simulation Program-Fortran

The Hydrologic Simulation Program-Fortran (HSPF) is an integrated hydrologic model developed by U.S. EPA for watershed scale water quantity and water quality assessment (U.S. EPA, 2015b). It has been developed on top of three former U.S. EPA models including Hydrocomp Simulation Program (HSP), Agricultural Runoff Management (ARM), and the Non-Point Source (NPS) pollutant loading that can simulate one-dimensional runoff as well as fate and transport of pollutants released from various land uses into streams, lakes, and well-mixed reservoirs (Duda et al., 2012). HSPF is able to provide continuous time series of simulated hydrologic cycle

components, temperature, sediment yield and removal, dissolved oxygen, nutrients cycle, and pesticide processes (Duda et al., 2012).

HSPF is a stand-alone program that can be integrated into the BASINS (Better Assessment Science Integrating point and Nonpoint Source) platform through a Windows interface called WinHSPF (Duda et al., 2001). Integrated HPSF and BASINS provides a unique tool for TMDL assessment and water quality criteria development at the watershed level (U.S. EPA, 2015b).

2.2.2.4. Storm Water Management Model

The Storm Water Management Model (SWMM) is a coupled hydrology-hydraulic water quality model developed by U.S. EPA to simulate stormwater runoff and its routing through urban drainage systems (U.S. EPA, 2014c). SWMM is able to simulate long-term continuous storm events and the quantity and quality of associated runoff. For this purpose, SWMM divides the region or catchment to smaller homogeneous regions called sub-catchments that produce surface runoff from precipitation falling within the sub-catchment. Surface runoff and associated pollutant loads will be routed through the urban sewage system that includes series of pipes, channels, storage and regulatory facilities (Rossman, 2015). SWMM generates time series of runoff quantity and quality passing through the drainage system that provides a useful tool for stormwater management design and planning (U.S. EPA, 2014c).

SWMM is able to assess the performance of some Low Impact Development (LID) controls such as rain gardens, vegetative swales, and green roofs on urban sewage system (Rossman, 2015). It enables water resources decision makers to design drainage systems that are suitable for flood control (U.S. EPA, 2014c). SWMM has also been equipped with Climate Adjustment Tool (SWMM-CAT) that enables it to simulate storm events under future climate scenarios (Rossman, 2014).

2.2.2.5. Hydrologic Engineering Center - Hydrologic Modeling System

The Hydrologic Modeling System developed by Hydrologic Engineering Center of the U.S. Army Corp of Engineers (HEC-HMS) is a hydrologic model that simulates precipitation-runoff process in dendritic watersheds (Scharffenberg, 2016). It is capable of using several alternative mathematical models for each part of hydrologic cycle that make it suitable for simulation in different topographic conditions ranging from large river basins to small urban watersheds (Scharffenberg, 2016). HEC-HMS is a comprehensive hydrologic model that can be used for optimization, forecasting, sediment transport and water quality studies (Hydrologic Engineering Center, 2016).

HEC-HMS uses an integrated system that includes database, computations, and reporting frameworks. Model outputs will be stored in Data Storage System (HEC-DSS) that make them accessible for being used with other software for further studies and comparisons (Hydrologic Engineering Center, 2016).

Table 1 summarizes the five models discussed for water resources management, and compares their applicability for different case studies as follows:

Table 1. Summary of common modeling tools used for water resources assessment

Modeling tool	Modeling type	Application	Major Outputs
SWAT	Physically based, and semi-distributed watershed model	Assessing long-term impacts of agricultural management practices on surface runoff, sediment, nutrients, pesticides, and bacteria yields at the watershed scale	Daily and sub-daily water quantity and water quality parameters
SUSTAIN	Coupled hydrology-hydraulic water quality model	Decision support system to assess performance of BMPs implementation on runoff and pollution regulation	Suitable places for BMPs implementation
HSPF	Integrated hydrological model	Assessing the impact of land-use change, point and nonpoint source treatments, and flow alteration on the water quantity and water quality at the watershed scale	Daily and sub-daily streamflow hydrographs and pollutographs
SWMM	Coupled hydrology-hydraulic water quality model	Evaluating performance of LID controls on urban sewage systems	Continuous water quantity and water quality of storm events runoff
HEC-HMS	Hydrologic model	Optimization, forecasting, sediment transport, and water quality simulation of dendritic watersheds	Precipitation-runoff process

2.3. Stream Health and Biological Integrity Assessment

A healthy stream is defined based on a combination of physical, chemical, and biological conditions, while chemical criteria is the most common approach for stream health assessment (Karr, 1981; Karr et al., 1986; Herman and Nejadhashemi, 2015). In order to assess the effectiveness of chemical criteria for stream health assessment, the U.S. EPA performed a nationwide evaluation of biological and recreational status of riverine ecosystems in summer 2008 to 2009. They performed assessments for almost two thousands streams with accumulative of more than a million miles to ensure covering all forms of riverine ecosystems (U.S. EPA, 2015c). They found that despite all regulations (such as CWA and TMDL) implemented, almost half of monitored streams are still in poor biological condition, while only twenty eight percent of streams

were in good condition and the rest were in fair condition (U.S. EPA, 2015c). In other words, implemented regulations have not addressed water quality concerns while all physical, chemical, and biological conditions must be evaluated in order to perform overall stream health assessment. So, the concept of biological integrity assessment was introduced in order to evaluate the final impact of the combination of physical, chemical, and biological activities on aquatic ecosystems (NSCEP, 2011; U.S. EPA, 2015c). It is also called the gold standard in water quality assessment since it measures the response of aquatic species as endpoints in riverine ecosystems to pollutants (Karr and Yoder, 2004; Woznicki, 2015).

2.3.1. Stream Health Indices and Metrics

Biological metrics are defined to quantify aquatic ecosystem conditions. These metrics enable stream ecologists to develop stream health indices that can be used for biological integrity assessment (Herman and Nejadhashemi, 2015). Biological metrics quantify 1) species abundance and condition, 2) species richness and composition, and 3) species trophic composition (Van Hoey et al., 2007; Herman and Nejadhashemi, 2015).

Species abundance and condition metrics are developed to quantify the number of collected species and their status, representing what percentage of collected species are healthy, damaged or have diseases (Karr et al., 1986). While species richness and composition metrics are qualitative measures of species diversity and distribution in a region (Karr et al., 1986). In general, streams with more diverse species have better stream health conditions than streams with limited species due to harsh environments that exist in those streams (Wan et al., 2010). The third group of metrics called species trophic composition, use the nutrients transfer among different functional feeding groups of riverine ecosystems for stream health assessment (Herman and Nejadhashemi, 2015). Nutrients level variation directly impacts the food chain of instream species; therefore, assessing

distribution of functional feeding groups represents the chemical status of aquatic ecosystem (Smith et al., 2007).

Stream health indices developed based on biological metrics are divided into two major groups of 1) biotic, and 2) multi-metric indices (Herman and Nejadhashemi, 2015). Biotic indices also called uni-metric indices, only measure one metric for stream health assessment. The major application of biotic indices is to evaluate the impact of organic pollutants on instream organisms (Hilsenhoff, 1987; Ollis et al., 2006). The calculation of these indices is simple which makes them suitable for local stream health assessment. The Hilsenhoff Biotic Index (HBI) is one of the popular biotic indices used to evaluate response of macroinvertebrate indices to organic pollutants (Hilsenhoff, 1987). However, biotic indices do not consider other forms of instream pollutants (such as sediment, nitrogen, and phosphorus). Therefore, multi-metric indices have been developed in order to provide more comprehensive assessment of complex riverine ecosystems (Herman and Nejadhashemi, 2015).

Compared to biotic indices, multi-metric indices are able to assess the response of aquatic ecosystems to several stressors at the same time; however, their calculation is more complex than biotic indices (Fierro et al., 2017). The Index of Biotic Integrity (IBI) and Benthic Index of Biotic Integrity (B-IBI) are two major multi-metric indices that are developed from several metrics to provide comprehensive assessment of fish and macroinvertebrates communities, respectively (Karr, 1981; Kerans and Karr, 1994). The Ephemeroptera, Plecoptera, and Trichoptera (EPT) index is another common multi-metric index that evaluates comprehensive responses of three macroinvertebrates including Ephemeroptera (mayflies), Plecoptera (stoneflies), and Trichoptera (caddisflies) to organic pollutants (Lenat, 1988).

There is another group of stream health measures called multivariate indices that unlike biotic and multi-metric indices, uses modeling approaches instead of metrics for stream health assessment. Multivariate indices use physical and chemical characteristic of waterbodies to develop predictive models for aquatic ecosystem status (Reynoldson et al., 1995). The Australian River Assessment Scheme (AusRivAS), and River Invertebrate Prediction and Classification System (RIVPACS) are two common multivariate models developed for stream health assessment (Reynoldson et al., 1997; Fierro et al., 2017). Multivariate indices development requires modeling processes and model calibration that make them more complicated than metric based indices; however, multivariate indices can be easily applied for large scale assessments since they are not limited to sampling stations (Herman and Nejadhashemi, 2015). Table 2 summarizes different types of stream health indices and their specifications.

Table 2. Comparison of stream health indices (Fierro et al., 2017)

	Stream health assessment indices		
	Biotic indices	Multi-metric indices	Multivariate indices
Advantages	easy calculation, good for local assessment	providing comprehensive assessment	good for large-scale assessment beyond monitoring sites
Disadvantages	limited to organic pollutants and cannot evaluate response to sediment and nutrients pollutants	requires several metrics for index development, limited by requirements of all used metrics	complicated model development and calibration processes, sensitive to model inputs
Commonly used	Hilsenhoff Biotic Index (HBI), Biological Monitoring Working Party Index (BMWP)	Index of Biotic Integrity (IBI), Benthic Index of Biotic Integrity (B-IBI)	Australian River Assessment Scheme (AusRivAS), River Invertebrate Prediction and Classification System (RIVPACS)

2.3.1.1. Fish Indices

Fish characteristics are representative of water quality status and are widely used for stream health assessment (Karr, 1981; Carlisle et al., 2013). Unlike many other instream species, fish

exists in many trophic levels (e.g. omnivores, and herbivores) and can be found in the most waterbodies (Karr, 1981). Besides that, fish are representative of a wide range of instream stressors since their wellbeing is connected to various aquatic species (Karr, 1981; Barbour et al., 1999). All these characteristics make fish a suitable representative of stream health status and fish indices development (Herman and Nejadhashemi, 2015).

Fish indices are commonly used for large scale and long-term assessments since fish can move through the entire waterbody and will be affected by both spatial and temporal aquatic stressors (Barbour et al., 1999; Herman and Nejadhashemi, 2015). Fish indices also represent the response of aquatic ecosystems to flow altering structures (e.g. dams) since fish are highly sensitive to flow variation (Navarro-Llácer et al., 2010). Several fish indices including biotic indices (e.g., fish species biotic index, and fish response curves), multi-metric indices (e.g. index of biotic integrity, fish community index, and similarity index), and multivariate indices (e.g. stressor gradients) are being used for stream health assessment (Karr, 1981; Paller et al., 1996; Jordan et al., 2010; Angradi et al., 2009; Navarro-Llácer et al., 2010; Zorn et al., 2012; Herman and Nejadhashemi, 2015). Among those, the IBI (Index of Biotic Integrity) that has been developed based on 12 metrics, is the most commonly used fish index for overall stream health assessment (Karr, 1981; Herman and Nejadhashemi, 2015). The IBI provides comprehensive fish assessment based on species richness, abundance, and trophic composition and reports overall stream health scores ranging from zero to 60 (Karr et al., 1981; Hu et al., 2007; Herman and Nejadhashemi, 2015). One of the most recent forms of IBI index implementation is the Fish-Based Index (FBI) that uses 15 metrics instead of 12 and is suitable for detecting degraded waterbodies (Launois et al., 2011). This new index ranges from zero to 100, where 100 represents excellent status (Herman and Nejadhashemi, 2015).

2.3.1.2. Macroinvertebrate Indices

Macroinvertebrates are another group of instream species that are used for stream health assessment and several indices have been developed that utilize their communities. Unlike fish, macroinvertebrates have limited mobility that make them suitable for local assessment (Kerans and Karr, 1994). Besides that, macroinvertebrates are highly sensitive to slight instream alterations that make them valuable indicators of early stage degradation of water quality (Compin and Céréghino, 2003). These unique characteristics require different indices to be developed for various stream types. So far, more than 40 macroinvertebrate indices have been developed. Among those, three indices including one biotic index (Hilsenhoff Biotic Index (HBI)), and two multi-metric indices (Benthic Index of Biotic Integrity (B-IBI), and Ephemeroptera, Plecoptera, Trichoptera (EPT) Index) are the most commonly used (Herman and Nejadhashemi, 2015). Table 3 summarizes these indices specifications and measurement criteria.

Table 3. Commonly used macroinvertebrate indices (Herman and Nejadhashemi, 2015)

Index name	Score range (min – max)	Measurement	Application
HBI	10 – 0	quantifies dissolved oxygen level	evaluates chemical degradation of stream with focus on organic pollutants
B-IBI	0 – 65	uses 13 metrics to quantify organism communities based on taxa richness, composition, and aquatic ecosystem	assesses industrial degradation to riverine ecosystem, measures response of aquatic ecosystem to watershed management scenarios
EPT	0 – maximum*	quantifies richness and abundance of mayflies, stoneflies, and caddisflies	early detection of locally impacted regions with organic pollutants. Applicable for wide range of streams

* Maximum EPT score is defined based on the study area

2.3.1.3. Sampling Survey

In-stream sampling of fish and macroinvertebrate species is required to develop metrics and indices. Depending on the stream size and type (e.g. headwater, or large rivers), different species exist and require different techniques and equipment for sampling (Vannote et al., 1980; Butcher et al., 2003). The U.S. EPA proposed a classification for aquatic species sampling, which divides waterbodies to two major groups: wadeable and non-wadeable (U.S. EPA, 2006).

Wadeable waterbodies are those that are shallow enough to be sampled by samplers walking through them (U.S. EPA, 2006). Almost 90% of nation's streams fall in this category; that makes them the main focus of the U.S. EPA oversight (U.S. EPA, 2006). Regarding macroinvertebrate sampling in wadeable waterbodies, methods such as: surbers, hesses, D-frame dip nets, rectangular dip nets, and kick nets are proposed that can collect instream species in depths less than one meter (Plakfin et al., 1989). Among those, kick nets are the most commonly used method. The standard recommended mesh size by the U.S. EPA for macroinvertebrates sampling is 500 μ ; however, it can vary depending on the sampling site location (U.S. EPA, 2012). The major drawback of this method is that it is only able to collect samples from the streambed at transects (Blocksom and Flotemersch, 2005). To overcome this issue, several samplings along the transects are recommended. Regarding fish, electrofishing is the most common approach in wadeable waterbodies (Terra et al., 2013). In this method, an electric current is used to stun fish that must be collected (Plakfin et al., 1989). A major limitation of this method is that it does not consider seasonal variations in fish populations (Roset et al., 2007). To address this issue, several samplings in different times of the year is recommended (Herman and Nejadhashemi, 2015).

Unlike wadeable waterbodies, non-wadeable waterbodies cannot be accessed by walking sampling and require the use of a boat (U.S. EPA, 2006). Large rivers, lakes, and coastal regions

fall in this category (Herman and Nejadhashemi, 2015). Regarding the macroinvertebrates, drift nets and multi-plate samplers are commonly used in deep regions, while wadeable methods will be used for the edges (Blocksom and Flotemersch, 2005). Regarding the fish, electrofishing conducted on boat is a common approach in deep rivers, while trawling nets is recommended for deep lakes and coastal regions (Esselman et al., 2013).

2.3.2. Modeling Used for Biological Integrity Assessment

It is impossible to exhaustively sample the biological integrity of the entire riverine ecosystem. One approach for performing overall assessment is using probability-based (or random) sampling in which a few streams will be surveyed in a way that represents the entire riverine ecosystem (Larsen, 1997; U.S. EPA, 2006). Modeling is another approach and ecohydrological models are developed in order to evaluate aquatic health beyond sampling stations (Woznicki et al., 2016a).

2.3.2.1. Physical Habitat Simulation Model

The Physical Habitat Simulation Model (PHABSIM) was developed by the USGS in order to assess the response of aquatic ecosystems to anthropogenic activities. For this purpose, PHABSIM simulates physical microhabitat changes as a function of streamflow variations (Milhous et al., 1984). It assumes that flow-dependent microhabitat structures are representative of the stream health and any alteration of physical microhabitats directly impacts health status of instream species such as fish and macroinvertebrates (Waddle, 2001).

PHABSIM only uses physical characteristics (e.g. velocity, depth, and bathymetry) and does not consider water quality components (e.g. temperature) and energy input (e.g. nutrients) (Milhous et al., 1984; Wu et al., 2006). One of the most common parameters calculated by PHABSIM is the Weighted Usable Area (WUA) that measures the density of microhabitats in a

defined length of stream. WUA is known as well representative of both quantity and quality of microhabitats and can be used for further aquatic ecosystems health assessment (Milhous et al., 1984).

2.3.2.2. *AQUATOX*

AQUATOX is a biophysical model developed by the U.S. EPA to assess the impact of nutrients and toxic organic chemicals on aquatic ecosystems and is one of the most comprehensive risk assessment models. It can simulate fate of up to twenty organic chemicals processes and their impacts on aquatic biota (Park et al., 2008).

AQUATOX is also able to provide uncertainty analysis and ranges of possible scenarios that make it suitable for ecological risk assessment of aquatic ecosystems (U.S. EPA, 2014d). Developed models are applicable for streams, lakes, ponds, and reservoirs. AQUATOX models can also be linked to SWAT and HSPF in order to perform aquatic risk assessment at the watershed level (Park et al., 2008).

2.3.2.3. *Ecological Limits of Hydrologic Alteration*

Anthropogenic activities have altered flow regimes that not only degraded aquatic ecosystems, but also impaired human wellbeing (Dyson et al., 2003). The concept of Environmental Flow is defined in order to describe the minimum threshold of water quantity and timing needed to sustain aquatic ecosystems and human wellbeing at the same time (O Keeffe et al., 2012). The traditional approach was assessment of each individual stream in order to meet the minimum flow requirement. However, a holistic approach is needed in order to develop large-scale water resources management and planning (Le Quesne et al., 2010). Ecological Limits of Hydrologic Alteration (ELOHA) is a comprehensive framework developed for environmental flow assessment at the watershed, and statewide scales (Le Quesne et al., 2010).

ELOHA uses existing hydrological and ecological data to develop empirical equations to assess aquatic ecosystems response to flow alteration in a defined region (Poff et al., 2010). For this purpose, hydrologic models must be developed to predict baseline and current flow patterns in each stream segment. Streams classification based on common features is the next step. Then flow alteration-ecological response curves will be developed for each stream class based on current and baseline flow patterns (Poff et al., 2010). These empirical curves not only provide a guideline for water policy makers to find ecologically vulnerable areas, but also aids to minimize the impact of future water development projects on aquatic ecosystems (Poff et al., 2010).

2.3.2.4. Hydrological Index Tool

The ecological integrity of riverine ecosystems highly relies on physiochemical characteristics of streams also called “master variables” (Poff et al., 1997). These characteristics are defined based on five major components of flow regime including 1) magnitude, 2) frequency, 3) duration, 4) timing, and 5) rate of change (Poff et al., 1997). 171 ecologically relevant hydrological indices are introduced in order to quantify these five major components for average, low, and high flow rates (Olden and Poff, 2003). The Hydrological Index Tool (HIT) was developed by the USGS in order to calculate these ecologically relevant hydrological indices based on daily and peak flow records (Henriksen et al., 2006).

HIT was originally designed to calculate ecologically relevant hydrological indices from data collected by the USGS National Water Information System (NWIS). However, this has been expanded beyond the USGS observation points including observed and simulated daily streamflow datasets (Henriksen et al., 2006).

2.3.2.5. National Hydrologic Assessment Tool

Similar to HIT, the National Hydrologic Assessment Tool (NATHAT) was also developed to assess ecologically relevant hydrological indices, but it uses ten hydrologic classifications defined by Poff (1996) based on data collected from 420 monitoring sites across the United States (Cade, 2006). NATHAT can be used for hydrologic baseline (reference time period) development, and assessing response of riverine ecosystems to current and proposed future hydrologic modifications (Cade, 2006). Both HIT and NATHAT are commonly used by federal, states, and nongovernmental agencies that aim to maintain ecological integrity of aquatic ecosystems (Henriksen et al., 2006).

2.4. Socioeconomic Assessment

Biophysical assessment is the common approach of evaluating the impact of anthropogenic activities on the environment including land, air, water, and wildlife (Slootweg et al., 2001). However, recent studies revealed the significance of socioeconomic assessment as well as biophysical assessment in order to maintain sustainable environment for both human and natural ecosystems (Environmentalist, 2014). Socioeconomic assessment is defined as evaluation of proposed developments on socioeconomic status of individuals and communities (MVEI, 2007). Socioeconomic status is defined based on combination of sociological and economic measures such as income, education and social reputation (APA, 2017). These measures are usually developed from census data. The U.S. Census Bureau (USCB) is the principal agency in the U.S. for collecting and producing sociological and economic data.

Census data are collected every ten years, while estimations and projections are used for years in between. Census data include population, economy, business, education, employment, health, housing, income and poverty information that can be used for decision making in resource

allocation to schools, hospitals, and transportation infrastructure development (U.S. Census Bureau, 2013). These data are collected at the census block level that is the finest level in the geographic hierarchy (Figure 2) and are tabulated and reported in coarser geographic levels ranging from block group to the national level (U.S. Census Bureau, 2015).

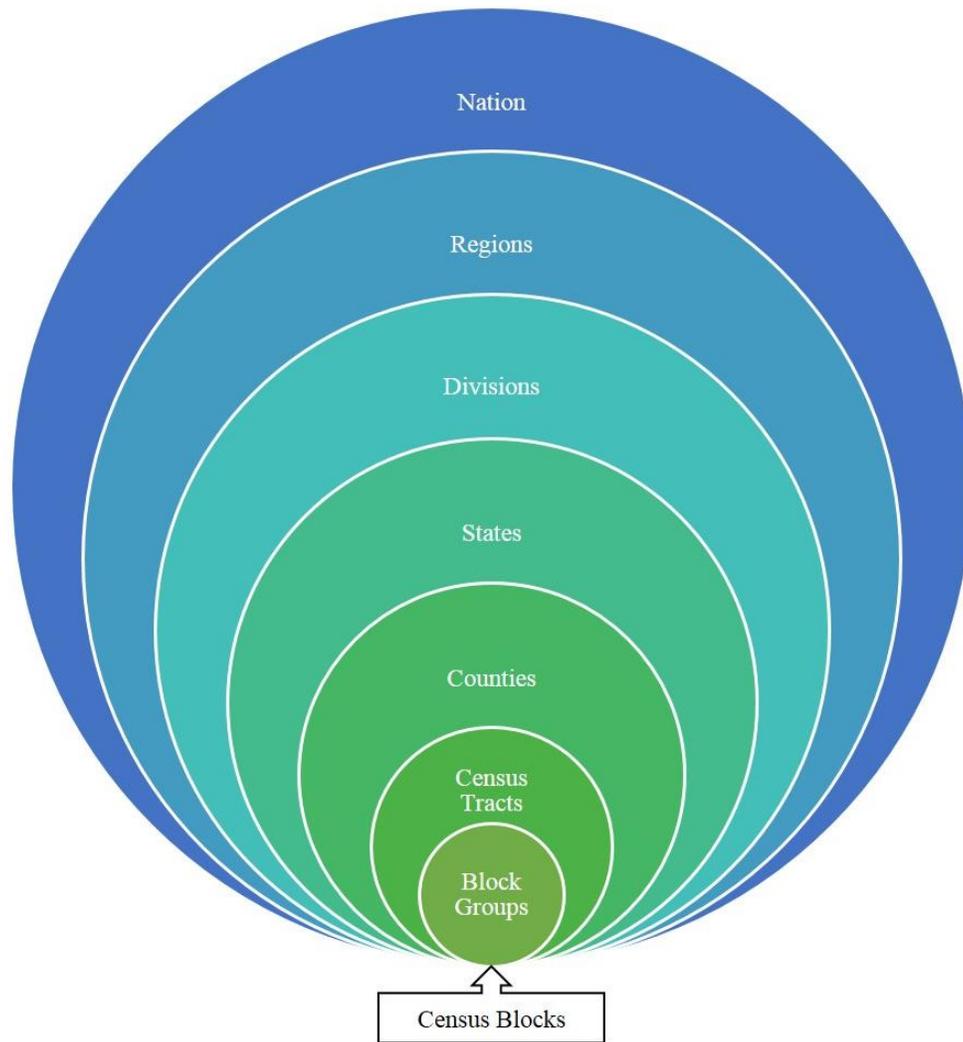


Figure 2. Geographic hierarchy of census data collection (U.S. Census Bureau, 2015)

The average block group contains 39 census blocks with a population range of 600 to 3,000 people. Aggregation of block groups result in census tract development with a population range of 1,200 to 8,000 people. County is the next level in the hierarchy; counties have varying numbers of census tracts. Based on the USCB report, 3,144 counties are defined within the 50 states and

territories around the nation (U.S. Census Bureau, 2017). Nine divisions are defined on top of the states, these divisions are grouped into four main regions of the nation including West, Midwest, South, and Northeast (U.S. Census Bureau, 2017).

2.4.1. Socioeconomic Aspects of Environmental Justice Assessment

Uneven socioeconomic status has been an area of concern as they are growing around the world (Boyce et al., 2007). Socioeconomic status is also known as the measure of social inequality since its variation represents unequal distribution of resources and power (Hasenfeld, 1987). Typically, three major socioeconomic levels are defined as 1) poor or lower class, 2) middle class, and 3) wealthy or upper class, while more detailed classifications are also provided that include up to twelve socioeconomic levels (Eichar, 1989; Beegle et al., 2007). However, these classifications do not provide useful information on social and environmental inequalities (Sampson et al., 2008). Further analysis of socioeconomic data is required in order to find socioeconomic aspects of these inequalities. In terms of Environmental Justice, socioeconomic indicators that represent distribution of age, race, housing, welfare, employment, and educational status of a society are commonly used as predictors (Sampson et al., 2008). These indices are obtained from census data collected at different spatial levels such as county, census tract, and block group.

2.4.2. Statistical Models for Socioeconomic Assessment

Socioeconomic data collected by the U.S. Census Bureau contains spatial information. Therefore, spatial statistical modeling is used to reveal spatial dependencies that may exist among collected data.

2.4.2.1. Structural Equation Modeling

Structural Equation Modeling (SEM) is a multivariate statistical method that combines factor analysis and multiple regression analysis to assess structural relationships (Schumacker and

Lomax, 2004). Factor analysis is a statistical approach to find unobserved potential variables called factors that can describe variability and correlation among observed data (Thompson, 2004), while regression analysis aims to find relationships among observed variables. That makes SEM a useful tool for researchers to consider multiple and interrelated dependencies simultaneously (Statistics Solutions, 2017).

SEM helps social science researchers to evaluate theoretical assumptions that are developed based on observed data and to assess how they might be affected by unmeasured variables (Schumacker and Lomax, 2004). Additionally, SEM is a useful tool for assessing the unreliability of conducted measurements by constructing latent variables that were not seen in data collection, and also data reduction (Chin, 1998).

2.4.2.2. Hierarchical Linear Modeling

Hierarchical Linear Modeling (HLM) is an extension of linear regression modeling that considers the hierarchy of nested data (Woltman et al., 2012). It can reveal the complexity of nested multilevel data with spatial, temporal, or organizational dependencies while providing a framework for data collected at each level (Snijders and Bosker, 2012).

HLM is useful for social science studies since socioeconomic data are nested in spatial and temporal levels (Stevens, 2012). HLM is defined by five groups of multilevel analysis including 1) one-way analysis of variance with random effects, 2) one-way analysis of covariance with random effects, 3) random coefficient regression model, 4) intercepts and slopes as outcome, and 5) means as outcome (Snijders and Bosker, 2012, Sanchez, 2014). HLM can be also used for either multilevel prediction or data reduction.

2.4.2.3. Conditional Autoregressive Models

The Conditional Autoregressive (CAR) models are regression models in which, spatial dependencies are taken into account for model development. For this purpose, CAR models estimate values conditioned based on neighboring values (de Smith, 2015), which requires implementation of a diagonal weighting matrix in regression analysis (Besag, 1974). This feature makes CAR models suitable for areal data analysis that are required in many fields such as demography, economy, epidemiology, and geography (Arab et al., 2008; Oliveira et al., 2012). CAR models can also reveal spatial dependencies among data, quantify spatial variation of parameters of interest, and detect hot spots (Oliveira et al., 2012). CAR models typically use Bayesian frameworks in which prior distributions of parameters will be used to predict posterior distributions (Lee, 2013; Banerjee et al., 2014).

2.4.2.4. Simultaneous Autoregressive Models

The Simultaneous Autoregressive (SAR) models are another type of autoregressive models developed for areal data analysis (Besag, 1974). While CAR models only consider neighbor's effects (first-order dependency), SAR models use information of neighbors of neighbors (second-order dependency) in model prediction as well. In other words, CAR models use defined study area for neighborhood matrix development that makes them suitable for local spatial analysis, while SAR models are more common for global spatial analysis (Baltagi et al., 2016). Depending on the data set and type of study, the proper model must be selected, however in some cases both SAR and CAR models may produce similar results (Lichstein et al., 2002; Wall, 2004). Finally, a summary of statistical models that are commonly used in socioeconomic assessment is presented in Table 4.

Table 4. Summary of common statistical models used for socioeconomic assessment

Model name	Statistical analysis	Major application
SEM	Factor analysis and multiple regression analysis	Assessing irregularity of existing measurements by constructing variables that are not covered in collected data
HLM	Extension of linear regression, with hierarchy effect of nested data	Conducting multilevel analysis of nested data with spatial, temporal, or organizational dependencies
CAR	Spatial auto-regression, with first-order neighbors' dependency	Suitable for local spatial analysis, while revealing areal dependencies among data
SAR	Spatial auto-regression, with second-order neighbors' dependency	Suitable for global spatial analysis, while revealing areal dependencies among data

3. INTRODUCTION TO METHODOLOGY AND RESULTS

This dissertation consists of two studies that improve the performance of stream health based environmental justice models. The first study focuses on the role of spatial levels on environmental justice analysis concerning stream health. The second study builds upon the first study by improving stream health prediction and evaluates the significance of the incorporation of more accurate stream health scores in environmental justice studies.

The first study, titled “Evaluating stream health based environmental justice model performance at different spatial scales”, focuses on the spatial dependencies among stream health, socioeconomic, and physiographic indices used for environmental justice studies. The Saginaw River Basin in Michigan is selected as the study area. Four biological indices that quantify the response of fish and macroinvertebrates to instream stressors are used for stream health assessment. However, these indices are monitored for only a few stations; therefore, stream health predictive models are used to evaluate these indices beyond the limited monitoring stations. Seventeen socioeconomic and physiographic indices representing concentrated disadvantages are used for the environmental justice assessment. These indices are collected at three census levels of county, census tract, and block group. For each level of study, the correlation of the indices are evaluated, and spatial data analysis are conducted to evaluate spatial dependencies among the stream health indices and independent socioeconomic and physiographic indices. Finally, multilevel models, in which the nested effect of data collected at different levels is also incorporated, are developed and their performances are compared with single level models.

The second study, titled “Assessing the Relative Importance of Parameter Estimation in Stream Health Based Environmental Justice Modeling”, uses the same datasets as are used in the first study, while focusing on improvement of stream health prediction impacts on environmental

justice studies. For this purpose, ecologically relevant streamflow and water quality parameters are used for the development of stream health predictive models, while in earlier studies, the role of these parameters was not considered. As a result, more reliable stream health indices are estimated within the study area. This information are then used in the development and evaluation of the new stream health based environmental justice models. Similar modeling practices as study one are adopted in study two in order to make the results of the two studies comparable.

4. EVALUATING STREAM HEALTH BASED ENVIRONMENTAL JUSTICE MODEL PERFORMANCE AT DIFFERENT SPATIAL SCALES

4.1. Introduction

Human and natural ecosystems are interconnected and affect one another. Studies show that human activities can substantially alter ecosystems, changing biological diversity, land surface, and other resources that often have long-term environmental effects (Skole and Tucker, 1993; Vitousek et al., 1997, Halpern et al., 2008, Einheuser et al., 2013a). Anthropogenic activities have changed more than one-third of land surfaces (Vitousek et al., 1997; Allan 2004). Halpern et al. (2008) reported that no marine ecosystem has been left untouched by human activities, while more than forty percent of these ecosystems have faced notable changes. Fresh water contamination is one of the more apparent impacts of human interventions, which also negatively affects human health (Smith et al., 1999; Pomati et al., 2006; Vairavamoorthy et al., 2007) through waterborne diseases such as diarrhea, cholera, SARS, and hepatitis (Levine et al., 1990; Wu et al., 1999; Ashbolt, 2004; Mieiro et al., 2009). Therefore, sustaining healthy streams can be beneficial to both human and natural systems.

A healthy stream is a stream that is sustainable and resilient, while maintaining both societal and ecological necessities (Meyer, 1997). In order to evaluate stream health conditions, biological indicators are used to quantify the ecological integrity of river systems (Cairns et al., 1993). In other words, biological indicators represent aquatic communities' response to human and natural disturbances (Barbour et al., 1999; Flinders et al., 2008). Fish and macroinvertebrates are commonly used for the development of biological indicators (Meyer, 1997; Hering et al., 2006; Wang et al., 2007; Walters et al., 2009; Holguin-Gonzalez et al., 2013; Muñoz-Mas et al., 2014). Macroinvertebrates are used for assessing local habitat conditions due to limited mobility, while

fish are often used for large-scale stream health assessment because of seasonal migrations within stream systems (Karr, 1981; Lenat, 1988; Plafkin et al., 1989; Lammert and Allan, 1999; Young et al., 2000; Herman and Nejadhashemi, 2015).

On the contrary, unhealthy streams negatively affect ecosystem services that ultimately influence human well-being, social health, and access to resources (Corvalan et al., 2005). However, the level of influences are different between racial or ethnic groups, in particular minorities and low-income communities are generally more affected (Pollock and Vittas, 1995; Helfand and Peyton, 1999). In order to address these issues, the concept of ‘Environmental Justice’ was introduced that deals with the fair distribution of resources to all people regardless of race, color, national origin or income (U.S. EPA, 2014e). Therefore, environmental justice by nature deals with different elements that vary across space, time and organizational units (Pickett et al., 2005; Liu et al., 2007a; An, 2012). However, using the wrong scale can lead to the wrong decision (Wilson et al., 1999; Silver, 2008; Maantay, 2007; Maantay and Maroko, 2009). For example, while the census tract is the most commonly used unit in environmental justice studies (Jerret et al., 2001; Corburn et al., 2006; Gilbert et al., 2011; Sanchez et al., 2014; Sanchez et al., 2015), socioeconomic data are also collected at county, block group, and census block scales (U.S. Census Bureau, 2010).

Zimmerman (1993) reported that using jurisdictional boundaries, such as counties, results in different environmental equity results compared to non-jurisdictional boundaries, such as census tract (Zimmerman, 1993). Fisher et al. (2006) studied air toxic pollution (point source) in the context of environmental justice and across various spatial levels (census tract, block group, and census block). They concluded that using census tract data is not a proper scale for a point source pollutants study, since it assumes uniform distribution of pollutant and population among census

tracts, regardless of their size or shape (Fisher et al., 2006). Zou et al. (2014) used socioeconomic data at three spatial levels (zip code, census tract and block group) in an environmental justice study in the context of sulfur dioxide exposure. Using whites as a reference for racial inequality analysis, they showed that not only pollutant source (e.g. industrial or vehicle) but also spatial scale (e.g. county or census tract) affect final outcomes. For example, less exposure to pollutants was reported at the block group level compared to the zip code and census tract levels in black populations. In general, more reliable results were obtained at the smallest spatial scale, which was block group (Maantay, 2007). Apart from that, Arcaya et al. (2012) showed that considering multilevel dependency between the U.S. life dataset of 1999 at different scales (county, state, and region) improved projection of the life expectancy pattern (Arcaya et al., 2012).

The goal of this study is to evaluate the effects of spatial data resolution on environmental justice analysis with respect to stream health integrity. We hypothesis that the environmental justice analysis using socioeconomic data at the block group level is the most reliable and will capture more spatial dependency between socioeconomic and environmental (stream health) parameters compare to census tract and county levels. We also hypothesis that considering multilevel dependency between socioeconomic data may improve the predictably of the environmental justice models. This study is unique since to the best of knowledge no study has considered both the effects of socioeconomic spatial resolutions and multilevel interactions in the context of stream health. The specific objectives are to: a) measure the degree of dependency between stream health indicators and control parameters across the three spatial scales (county, census tract, and block group); b) understand the spatial dependency at the three levels and among stream health indicators and control parameters using regression analysis; and c) evaluate the importance of multilevel analysis in improving the environmental justice model predictability.

4.2. Methodology

4.2.1. Study Area

The study area is the Saginaw River Basin, the largest six-digit hydrologic unit located in Michigan. Each hydrologic unit is identified by a unique hydrologic unit code (HUC). The HUC for the Saginaw River Basin is 040802. The study area contains six hydrologic units Tittabawassee (04080201), Pine (04080202), Shiawassee (04080203), Flint (04080204), Cass (04080205) and Saginaw (04080206), which drains to the Lake Huron (Figure 3). The size of study area is 16,120 square kilometers. Approximately, half of the study area is agricultural land, mostly covered by corn and soybean, 25% is forestlands, while developed areas, wetlands, rangeland, and surface water cover the rest.

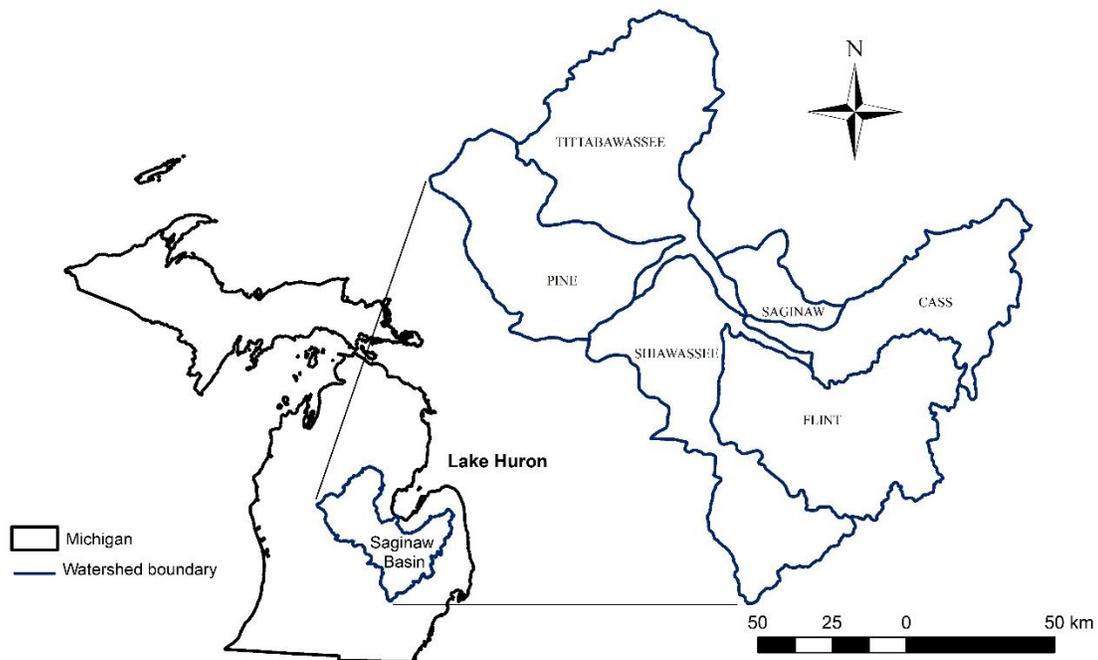


Figure 3. Saginaw River Basin

Increase in soil erosion, contaminated sediment, and nutrients, has degraded aquatic life and recreational values in the study area to the extent that the U.S. Environmental Protection

Agency (EPA) has identified the Saginaw River as an area of concern in the Great Lakes basin (U.S. EPA, 2015d).

4.2.2. Stream Health Indicators

In order to evaluate stream health, four biological indicators, which represent macroinvertebrates and fish abundance, were used in this study (Karr, 1981; Lenat, 1988; Hilsenhoff, 1987; Lyons 1992; Kerans and Karr, 1994; Sponseller et al., 2001; Infante et al., 2008; Einheuser et al., 2012; Einheuser et al., 2013b). The first indicator is the Index of Biotic Integrity (IBI); it describes a series of fish measures such as species richness and composition, trophic composition, abundance and condition that are evaluated by a numeric score that ranges from 0 to 100 (Karr, 1981; Kerans and Karr, 1994, Herman and Nejadhashemi, 2015). The lower scores represent high level of stream disturbance and vice versa. The Hilsenhoff Biotic Index (HBI) is a common macroinvertebrate indicator, which represents tolerance values of organic pollution within different species. It is varied from 0 to 10, where 10 suggests very poor water quality and 0 represents an excellent water quality in terms of organic pollution (Hilsenhoff, 1987). The next macroinvertebrate indicator is the Family-level Index of Biological Integrity (FIBI), which relates the composition of species in a family taxonomic resolution to pollution tolerance, ranging from 0 to 45 (Woznicki et al., 2015). For this index, higher values represent better stream health conditions. *Ephemeroptera* (mayflies), *Plecoptera* (stoneflies), and *Trichoptera* (caddisflies), also known as EPT taxa, are orders that are sensitive to degradation and commonly used in bioassessment. EPT scores below three will be considered as very poor stream health conditions and scores above 10 will be classified as excellent (Woznicki et al., 2015).

Fish monitoring was performed in 193 monitoring sites from 1982 to 2007, while macroinvertebrate were monitored between 1996 to 2003 for 262 sites within the study area

(MDEQ 1997; Seelbach and Wiley, 1997). Electrofishing techniques such as backpack, tow-barge and boom units were used for fish sampling in the field (Seelbach and Wiley, 1997). While sampling methods such as hand picking and dip nets were used to obtain about 300±60 organism within the minimum 20 min for each site for macroinvertebrates (Einheuser et al., 2012). The ranges of the four indices recorded within the study area are summarized in Table 5.

Table 5. Summary of stream health measures in Saginaw River Basin

Variable	Min	Max
IBI	0	100
HBI	3.61	7.89
FIBI	0	36
EPT	0	17

Using the Soil and Water Assessment Tool (SWAT) and Adaptive Neuro Fuzzy Inference System (ANFIS) a predictive model was developed to calculate stream health indicators throughout the study area (Einheuser et al., 2012; Einheuser et al., 2013a). The current stream health conditions based on the four biological indicators for the 13,831 stream segments are presented in Figure 4.

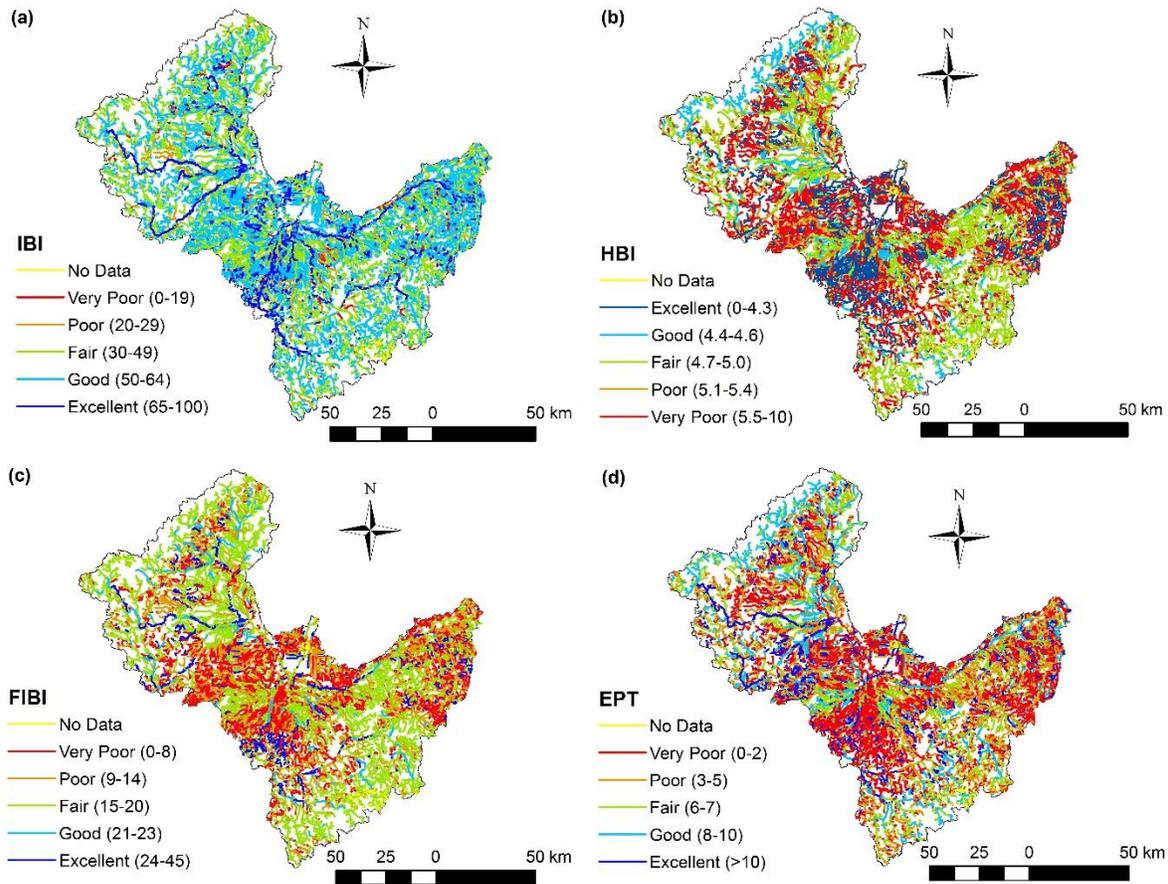


Figure 4. Stream health condition across Saginaw River Basin: (a) IBI, (b) HBI, (c) FIBI, and (d) EPT (adapted from Einheuser et al., 2012; 2013a).

4.2.3. Socioeconomic and Physiographic Indicators

From numerous reported socioeconomic measures, 16 indicators were selected in this study (Table 6). These indicators were selected since they have been widely used in many environmental justice researches and represent concentrated disadvantage (Bowen et al., 1995; Bowen, 2002, Taquino et al., 2002, Brulle and Pellow, 2006, Bullard et al., 2008, Sampson et. al. 2008; Lin and Morefield, 2011, Malley et al., 2012). Selected indicators represent population (S2 and S3), household composition (S4, S5, S8, S9), racial composition of household (S6), female-headed households (S7), housing (S10, S11), educational disadvantage (S12), economic disadvantage (poverty) (S13, S14, S15), welfare receipt (S16) and unemployment (S17). These indicators were

obtained from the U.S. Census Bureau for three census levels of county, census tract, and block groups (U.S. Census Bureau, 2010).

Table 6. List of the socioeconomic/physiographic indicators (Census bureau, 2010)

ID	Socioeconomic/physiographic indicators
S1	Drainage density
S2	Population density (per sq. mile)
S3	Percentage of land area
S4	Percentage of population under 18 years
S5	Percentage of population age 65 and over
S6	Percentage of black or African American population:
S7	Percentage of family households: Female householder, no husband present
S8	Percentage of households: Nonfamily households: Householder living alone
S9	Average household size
S10	Housing units
S11	Percentage of occupied housing units
S12	Percentage of population 25 years and over: Less than high school education level
S13	Percentage of families: Income in 2010 below poverty level
S14	Average household income (In 2010 inflation adjusted dollars)
S15	Aggregate household income (In 2010 inflation adjusted dollars)
S16	Percentage of households: With public assistance income
S17	Percentage of unemployed civilian population 16 years and over

The Saginaw River Basin was covered by 21 counties (Figure 5a), 393 census tracts (Figure 5b), and 1,076 block groups (Figure 5c). According to U.S. Census Bureau (2010), more than 1.5 million people are living in the study area. 71.6% of the population are living in urban and 28.6% in rural area. The race distribution is: 83.1% white, 10.6% black or African American, 2.8% Asian and 3.5% others.

In addition to socioeconomic indicators, a watershed physiographical indicator called drainage density was used to account for the accessibility of people to water bodies. In this study, the drainage density was defined as the ratio of the total length of all rivers divided by the socioeconomic area of interest (counties boundary, census tract, and block group). Scale adjustment was also performed to match socioeconomic and stream health measures, because stream health was calculated in much finer resolution (13,831 stream segments) than the

socioeconomic data. This was accomplished by calculating the weighted average of stream health scores by length for the different census levels.

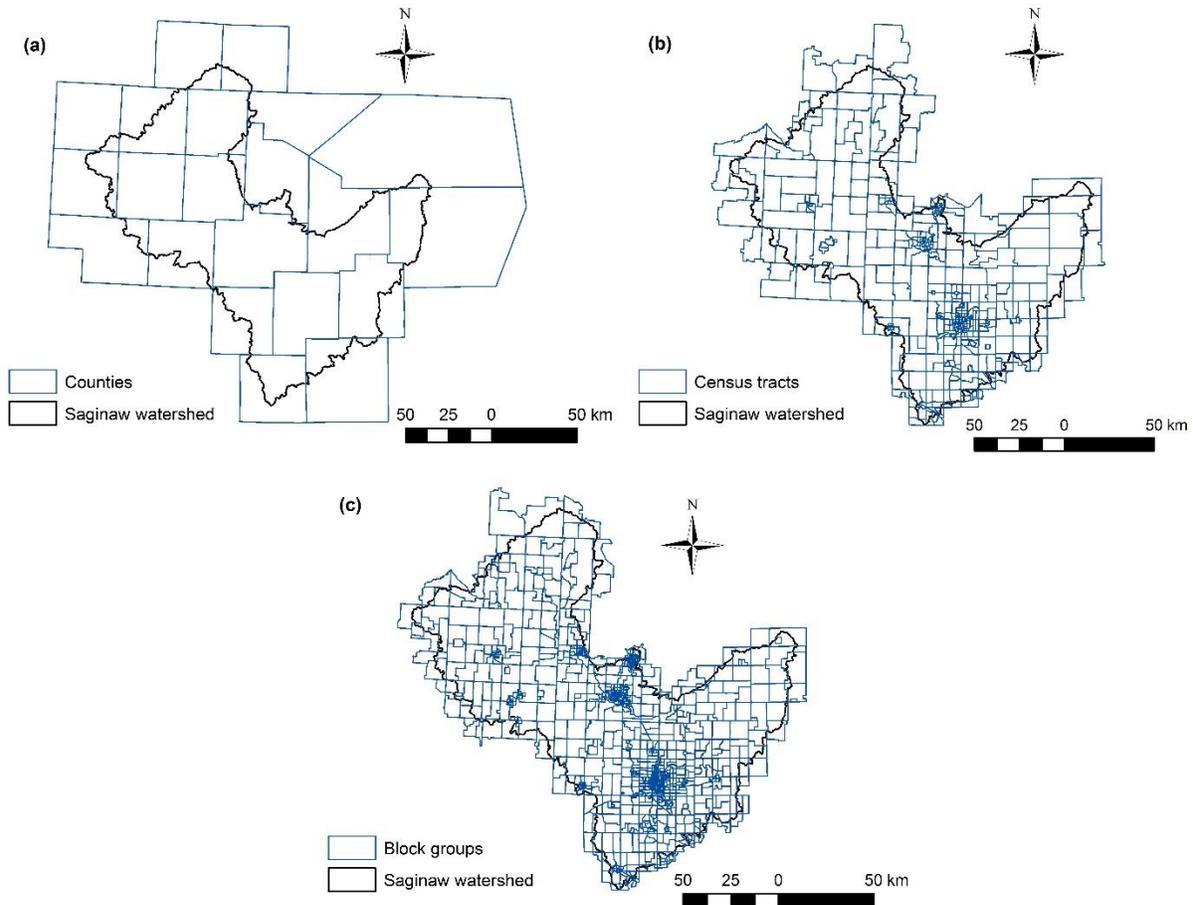


Figure 5. Boundary maps: (a) counties, (b) census tracts, and (c) block groups across Saginaw River Basin.

4.2.4. Data Analysis and Modeling

Scatterplot matrices including histograms of each individual variable distribution (the four stream health indicators, drainage density, and sixteen socioeconomic indicators) and pairwise correlation coefficients at three census levels were calculated based on the Spearman's rank correlation coefficient, a non-parametric measure of statistical dependence between two variables (Lehmann and D'Abrera 1998). However, to better understand the spatial dependency

among control parameters and stream health indicators, regression analysis was performed using spatial Conditional Autoregressive (CAR) models (Banerjee et al., 2014).

First, assume counties are represented by $i = 1, 2, \dots, I$, census tracts are represented by $j = 1, 2, \dots, J$, and block groups are represented by $k = 1, 2, \dots, K$. Since the three levels are nested, $K = \sum_{j=1}^J K_j$ where K_j is the number of block groups in the j th census tract, and $J = \sum_{i=1}^I J_i$ where J_i is the number of census tracts in the i th county. Therefore, the total observation for each block group at the finest resolution is $K = \sum_{j=1}^J K_j = \sum_{i=1}^I \sum_{j=1}^{J_i} K_j$.

For each resolution level of data presentation, the spatial CAR model is presented as follows:

- a) County level data: Assume Y_i represents the stream health indicator, X_i includes the corresponding p socioeconomic indicators plus an intercept to account for the mean level of the response, i.e. $X_i = (1, S_{i1}, \dots, S_{ip})$ for the i th sample. We consider:

- 1) Spatial CAR model (Model [1]):

$$Y_i = X_i \beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 (M_I - \gamma_I W_I)^{-1}) \quad (2)$$

where, W_I denotes the spatial neighborhood matrix for the I counties and M_I represents the diagonal matrix with the number of total neighbors as the diagonal entries. In this model, τ_I^2 measures the variation and γ_I measures the spatial dependence. The vector $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ includes the regression coefficients, hence $X_i \beta = \beta_0 + \sum_{t=1}^p S_{it} \beta_t$ in (1).

To evaluate the importance of modeling spatial dependence, two partial implementations were considered:

- i) the weighted regression model (Model [2]):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 M_I^{-1}), \quad i = 1, 2, \dots, I \quad (3)$$

where, $\gamma_I = 0$ is fixed, i.e., no spatial dependence but the residual variance is weighted by the number of neighbors; and

ii) the ordinary regression model (Model [3]):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 I_I), \quad i = 1, 2, \dots, I \quad (4)$$

where, $M_I = I_I$ the identity matrix. In this model, no spatial information is included; therefore, it becomes the ordinary regression model.

In the following context whenever a CAR structure is incorporated, the full and the two partial implementations (weighted least squares and ordinary least squares) were considered.

b) Census tract level data:

2) Spatial CAR model with no random effect (single level):

$$Y_j = X_j\beta + \varepsilon_j, \quad \varepsilon \sim N(0, \tau_j^2 D_j(\gamma_j)), \quad j = 1, 2, \dots, J \quad (5)$$

with a total of three submodels and double index for [county, census tract], $D_j(\gamma_j) = (M_j - \gamma_j W_j)^{-1}$ as full implementation (Model [0.1]) that accounts for the spatial dependence, and two partial implementations $D_j(\gamma_j) = M_j^{-1}$ (Model [0.2]) that considers spatial heterogeneity using the number of surrounding regions as weights, and $D_j(\gamma_j) = I_j$ (Model [0.3]) that is just simple multiple regression without considering any spatial information.

3) Spatial CAR model with random effect on county (multilevel):

$$Y_{ij} = X_{ij}\beta + u_i + \varepsilon_{ij}, \quad \varepsilon \sim N(0, \tau_j^2 D(\gamma_j)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)) \quad (6)$$

$$j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

with a total of $3 \times 3 = 9$ submodels while considering the full implementation and two partial implementations on both levels, indexed from Model [1.1] to Model [3.3].

c) Block group level data:

4) Spatial CAR model with no random effect (single level)

$$Y_k = X_k \beta + \varepsilon_k, \quad \varepsilon \sim N(0, \tau_K^2 D_K(\gamma_K)), \quad k = 1, 2, \dots, K \quad (7)$$

with a total of three submodels and triple index for [county, census tract, block group],

$D_K(\gamma_K) = (M_K - \gamma_K W_K)^{-1}$ as full implementation (Model [0.0.1]), and two partial implementations $D_K(\gamma_K) = M_K^{-1}$ (Model [0.0.2]) and $D_K(\gamma_K) = I_K$ (Model [0.0.3]).

5) Spatial CAR model with nested random effects on county and census tract

(multilevel):

$$Y_{ijk} = X_{ijk} \beta + u_i + v_{ij} + \varepsilon_{ijk}, \quad (8)$$

$$\varepsilon \sim N(0, \tau_K^2 D(\gamma_K)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)), \quad \mathbf{v} \sim N(0, \tau_J^2 D(\gamma_J))$$

$$k = 1, 2, \dots, K_j, \quad j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

with the total of $3 \times 4 \times 4 - 3 = 45$ submodels by considering the full implementation and two partial implementations on all three levels, and with either \mathbf{u} or \mathbf{v} fixed at 0 (but not both), indexed from Model [0.1.1] to Model [3.3.3] with the triple index for [county, census tract, block group].

In total, 63 models (3 + 12 + 48) were fitted to the data at different resolution level and by considering the interactions between levels and spatial dependence structure. The model fit is carried out by running six Markov chain Monte Carlo (MCMC) per model with distinct starting values and a total of 6,000 iterations. After convergence, the last 1,000 samples for each chain is stacked as posterior samples for inference.

4.2.5. Markov Chain Monte Carlo Implementation Details

Equation 7 is considered as the full spatial CAR model with nested random effects on county and census tract for the block group data. Other models are either nested or reduced at simpler levels but having similar format. Equation (7) can be rewritten in format of the mixed-effect model as follows:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + Z_u\mathbf{u} + Z_v\mathbf{v} + \boldsymbol{\varepsilon} \quad (9)$$

$$\boldsymbol{\varepsilon} \sim N(0, \tau_K^2 D(\gamma_K)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)), \quad \mathbf{v} \sim N(0, \tau_J^2 D(\gamma_J))$$

The associated model parameters were estimated through the full Bayesian framework by eliciting prior assumptions. A flat prior on the regression coefficient $\boldsymbol{\beta}$ but a conjugate prior for the variation parameters τ_I^2 , τ_J^2 , and τ_K^2 were assumed. This is an inverse-gamma distribution with shape a and scale b . One option is to assume $a = 2$ and $b = 0.01$ that yields a rather dispersed prior distribution when there is a lack of strong prior knowledge. In addition, uniform prior distributions were considered on γ_I, γ_J and γ_K over their required ranges to guarantee the corresponding matrices $D(\gamma_I)$, $D(\gamma_J)$ and $D(\gamma_K)$ would be valid covariance matrices for CAR model. In the next step, posterior samples of the parameters were drawn by combining the selected diffused prior distributions and data likelihood via the MCMC technique. More specifically, the Gibbs sampler was used, which involves updating a set of parameters given the data and the remaining parameters, from their full conditional densities at each iteration of the MCMC runs. Due to the conjugate prior choice, the full conditional distribution of $\boldsymbol{\beta}$ is $N(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}_\beta)$ was adopted where;

$$\begin{cases} \boldsymbol{\Sigma}_\beta = \tau_K^2 (\mathbf{X}'(M_K - \gamma_K W_K)\mathbf{X})^{-1} \\ \boldsymbol{\mu}_\beta = \boldsymbol{\Sigma}_\beta \mathbf{X}'(M_K - \gamma_K W_K)(\mathbf{Y} - Z_u\mathbf{u} - Z_v\mathbf{v}) \end{cases} \quad (10)$$

and at each Gibbs circle a sample of β from the full conditional distribution above was first simulated. Similarly, the full conditional distribution of county random effect \mathbf{u} is $N(\mu_u, \Sigma_u)$ where;

$$\begin{cases} \Sigma_u = \tau_K^2 \left(Z_u' (M_K - \gamma_K W_K) Z_u + (M_I - \gamma_I W_I) \frac{\tau_K^2}{\tau_I^2} \right)^{-1} \\ \mu_u = \Sigma_u Z_u' (M_K - \gamma_K W_K) (\mathbf{Y} - \mathbf{X}\beta - Z_v \mathbf{v}) / \tau_K^2 \end{cases} \quad (11)$$

The full conditional distribution of census tract random effect \mathbf{v} is $N(\mu_v, \Sigma_v)$ where;

$$\begin{cases} \Sigma_v = \tau_K^2 \left(Z_v' (M_K - \gamma_K W_K) Z_v + (M_J - \gamma_J W_J) \frac{\tau_K^2}{\tau_J^2} \right)^{-1} \\ \mu_v = \Sigma_v Z_v' (M_K - \gamma_K W_K) (\mathbf{Y} - \mathbf{X}\beta - Z_u \mathbf{u}) / \tau_K^2 \end{cases} \quad (12)$$

The full conditional distribution of τ_I^2 is inverse-gamma with shape a_I and scale b_I , where;

$$\begin{cases} a_I = a + I/2 \\ b_I = b + \mathbf{u}' (M_I - \gamma_I W_I) \mathbf{u} / 2 \end{cases} \quad (13)$$

The full conditional distribution of τ_J^2 is inverse-gamma with shape a_J and scale b_J , where;

$$\begin{cases} a_J = a + J/2 \\ b_J = b + \mathbf{v}' (M_J - \gamma_J W_J) \mathbf{v} / 2 \end{cases} \quad (14)$$

The full conditional distribution of τ_K^2 is inverse-gamma with shape a_K and scale b_K , where;

$$\begin{cases} a_K = a + K/2 \\ b_K = b + \frac{\mathbf{e}' (M_K - \gamma_K W_K) \mathbf{e}}{2} \\ \text{with } \mathbf{e} = \mathbf{Y} - \mathbf{X}\beta - Z_u \mathbf{u} - Z_v \mathbf{v} \end{cases} \quad (15)$$

γ_I was also sampled from its full conditional distribution with density proportional to

$$|M_I - \gamma_I W_I|^{1/2} \exp\{\gamma_I \mathbf{u}' W_I \mathbf{u} / (2\tau_I^2)\} \quad (16)$$

Similar sampling was performed for γ_J and γ_K . Updating all parameters completes one Gibbs circle, and this procedure is repeated over a large number of iterations in order to obtain posterior samples for inferential stage after convergence of multiple MCMC runs. Finally, Deviance Information Criterion (DIC₄) was used for mixed-effect model evaluation (Celeux et al 2006).

4.3. Results and Discussions

4.3.1. Variables Distribution and Pairwise Correlations

Figures 6, A1, and A2 show the correlation matrixes for the three census levels of county, census tract, and block group, respectively. Histograms of each individual variable distribution are shown on the diagonal of each matrix. The upper and lower parts of the matrices are spearman rank correlation coefficients and scatter plots of each pair of variables, respectively.

4.3.1.1. Variables Distribution

Understanding the variable distribution is important for selecting appropriate analysis techniques or examining the underlying assumption about a set of variables. Among the four stream health indicators at the three levels (county, census tract, and block group), the HBI and IBI had the most bell-shaped histograms, especially at the census tract and block group levels, while a little skewness to the right can be seen in both indices at the county level. This shows that the level of study has an effect on variable distribution as the aforementioned indices have normal distributions at the census tract and block group levels but skewed at the county level. Besides that, these two indices are less sensitive to aggregation at the county level compared to the FIBI and EPT. The FIBI and EPT were right-skewed at the census tract and block group level meaning that most of the units (census tracts or block groups) have low scores, which is consistent with low stream health scores reported at the reach level (Figure 4 (c) and (d)).

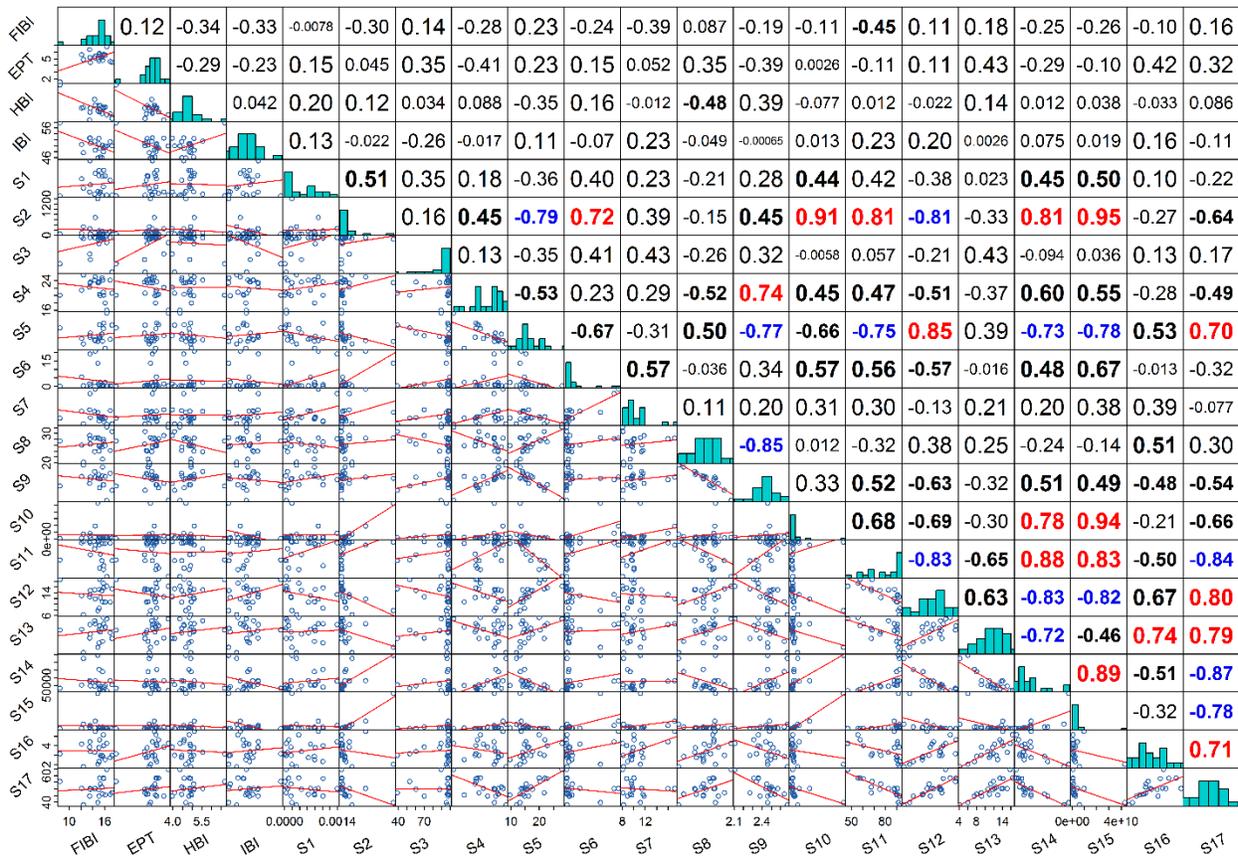


Figure 6. Spearman rank correlation matrix between dependent and independent variables at the county level. **Boldfaced** value indicates significance at the 0.05 level and correlation less than 0.7, **Boldfaced** value in red indicates significance at the 0.05 level and strongly positive correlation equal or above 0.7, and value in blue indicates significance at the 0.05 level and strongly negative correlation equal or below -0.7

However, their distributions were the opposite at the county level and showed left-skewness, meaning that most of units have high FIBI and EPT scores. These results show how using coarse census resolutions can be misleading in stream health data analysis, especially for FIBI and EPT, which were more sensitive to the level change. Considering stream health scores at the reach level (Figure 4) also suggests that census tract and block group levels can better represent stream health data distribution compared to the county level.

Regarding the socioeconomic data, most of them had consistent distributions at the census tract and block group levels, and in general, were less affected at the county level than the stream

health measures. This means that these indices are less sensitive to aggregation than the stream health measures. Among the 16 socioeconomic parameters, only S17 (percentage of unemployed population of 16 years old and above) had normal distributions at all three levels. The S3 (percentage of land area), S9 (average house size) and S11 (percentage of housing units occupied) parameters were left-skewed. The left skewness of S3 means that the majority of census units (at each level) have few water bodies and are mostly covered by land. While the distributions for S9 and S11 show that the majority of house units in the study area are larger than average and most of them are occupied. The rest of the parameters were right-skewed. The right skewness of S2 and S10 showed that many of the census units have low population densities (S2) and few housing units (S10), which correlates with the house size (S9) distribution mentioned above. The same pattern was seen for S6 (percentage of black or African American population), meaning that only a few census units have the majority of the population as black or African American. The S7 (percentage of households with female householder) and S8 (percentage of householders living alone) distributions, also showed that few units of study have a high percentage of households with a female householder or householders living alone. Poverty and welfare receipt indicators also showed that only a few census units are dominated by people with low incomes (S14 and S15), incomes below poverty level (S13), or receive public assistance (S16). These distributions can help decision makers to select areas, which have higher priorities for environmental justice practices.

4.3.1.2. Stream Health Indicators Correlations at Three Levels

Considering the census tract and block group levels, the IBI, FIBI and EPT were positively correlated with each other and all were negatively correlated with HBI, which is consistent with their definitions where high values for the IBI, FIBI and EPT indicate better stream health conditions, while for the HBI lower values indicate better stream health conditions. However, this

consistency is lost at the county level, where the IBI had a reversed correlation with macroinvertebrate indices. This means that streams, which had better conditions for macroinvertebrates (having high FIB, high EPT and low HBI scores), had worse conditions for fish (low IBI scores). Furthermore, significant correlations between the IBI and FIBI and EPT indices at the census tract and block group levels were also lost at the county level. Overall, correlations among stream health measures show how sensitive they are to census data resolution and how their aggregation at the county level can be misleading conclusions compared to the census tract and block group levels. These changes in data interpretation among different census levels also matches with their histograms comparison.

4.3.1.3. Socioeconomic/Physiographic Indicators Correlations at Three Levels

Almost all of the socioeconomic/physiographic indicators had significant correlations with each other at the county level with thirty-one absolute correlation coefficients above 0.7 (shown in red) and three correlation coefficients above 0.9 among S2 (population density) and S10 (housing units), S2 and S15 (aggregate household income). However, moving from county to census tract level, these correlation values drastically dropped with only three absolute values above 0.7 among S8 (householders living alone) and S9 (average household size), S12 (population above 25 years old and education less than high school) and S14 (average household income), and S13 (families with income below poverty level) and S14. However, none of them were significant. Like the census tract level, only three absolute correlation values were above 0.7, for S8 and S9, S13 and S14, and S14 and S15 at the block group level. Overall, correlation values were even less at block group level. For example, correlation coefficients between S13 and S14 dropped from -0.83 to -0.71 at the block group compared to the census tract level. In addition, the correlation coefficients of S12 and S14 dropped from -0.75 at the census tract to -0.58 at the block group,

while correlation coefficients for S14 and S15 increased from 0.65 to 0.73 when the block group level is compared to the census tract level. These examples show how correlations found between different indicators can vary among census levels and can lead to different interpretations. In general, socioeconomic/physiographic data showed high correlations among each other at course resolutions (e.g. county level) while these correlations were lost at finer census levels (e.g. census tract and block groups), which are more detailed and can better represent spatial distribution.

4.3.1.4. Interaction of Stream Health Measures and Socioeconomic/Physiographic Indicators at Three Levels

Like the interactions of the socioeconomic/physiographic indicators with each other, the highest correlation coefficients with the four stream health measures were also found at the county level, followed by the census tract and block group levels. In addition, more variables are significantly correlated at the county level. However, the values reported for these correlations were much lower than the numbers found among the socioeconomic/physiographic indicators. For example, the highest correlation of EPT with a socioeconomic/physiographic indicator at the county level was 0.43 with S13 (families with income below poverty level), which is much smaller than the correlations reported in the previous section (e.g. three correlation coefficients were above 0.9). Furthermore, significantly correlated socioeconomic/physiographic indicators for each stream health measure vary across the census levels. For example, at the county level the HBI had significant correlations with three household composition indicators (S5, S8, and S9). However, of these three only S8 continued to be significant at the census tract level. S9 was replaced with another household indicator (S7: Female-headed households). Besides that, a racial composition indicator (S6) and one population indicator (S3: percentage of land area) became significant at this

level. While at the block group level, one more population indicator (S2: population density) was also added to this list.

In general, all stream health measures had higher correlation coefficients at the county level, compared to the census tract and block group levels. Furthermore, the significant socioeconomic/physiographic indicators were not the same at all three levels, which again shows the role of census level resolution in data interpretation for each stream health measure.

4.3.2. Understand the Spatial Dependency Between Stream Health Indicators and Control Parameters Using Regression Analysis

In this stage, regression analysis was developed using spatial CAR models to discover spatial dependency among control parameters and stream health indicators with and without random effect as follows:

4.3.2.1. Spatial CAR Models with No Random Effect (Single Level)

Considering each stream health indicator, three models (spatial, weighted regression, and ordinary regression) were developed. These models were applied for each census level, so 36 models (4 response variables, 3 levels, and 3 models) were developed at this stage (Tables 7-10 and A1 to A8). In these tables, DIC, which is a measure of relative quality of a statistical model, was used to identify the best model at each level. However, this value should not be used to compare the models' performances from multiple levels (e.g. county versus census tract) due to differences in sample sizes. In addition to DIC, γ was reported to present spatial dependence in which 0 means no spatial effect while 1 mean full spatially dependency. Finally, each dependent parameter that its regression coefficient (β_1 - β_{17}) that does not contain zero in the range of their upper and lower bands can be considered as a significant parameter and are bolded for each model.

Table 7. Regression models for FIBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	14.68	14.15	15.22	14.69	14.29	15.09	14.64	14.18	15.09
β_1	0.09	-0.63	0.78	0.08	-0.63	0.84	0.05	-0.82	0.90
β_2	-18.32	-26.10	-10.70	-18.39	-26.17	-10.72	-18.26	-27.05	-9.66
β_3	2.18	0.87	3.54	2.21	0.78	3.54	2.26	0.77	3.72
β_4	-0.79	-2.38	0.77	-0.82	-2.35	0.75	-0.78	-2.63	1.018
β_5	1.81	-0.36	4.03	1.83	-0.45	4.06	1.79	-1.11	4.65
β_6	-3.25	-5.45	-1.03	-3.22	-5.39	-1.00	-3.10	-5.54	-0.72
β_7	0.98	-1.10	3.11	0.96	-1.23	3.09	0.82	-1.53	3.26
β_8	-0.38	-4.88	4.17	-0.36	-5.04	4.27	-0.57	-5.73	4.68
β_9	-0.51	-6.18	5.13	-0.47	-6.40	5.23	-0.77	-7.21	5.84
β_{10}	47.36	29.04	66.21	47.39	28.51	66.04	47.69	27.80	67.81
β_{11}	-0.38	-2.07	1.36	-0.37	-2.16	1.42	-0.20	-2.25	1.81
β_{12}	-0.98	-3.47	1.62	-0.94	-3.67	1.58	-0.88	-3.77	1.98
β_{13}	-1.33	-3.20	0.57	-1.35	-3.25	0.58	-1.26	-3.12	0.66
β_{14}	-1.41	-4.44	1.61	-1.40	-4.51	1.50	-1.52	-4.86	1.72
β_{15}	-28.88	-41.66	-16.28	-28.89	-41.93	-15.89	-29.28	-43.40	-15.06
β_{16}	0.06	-1.36	1.39	0.07	-1.33	1.52	-0.02	-1.74	1.69
β_{17}	-3.91	-6.15	-1.54	-3.94	-6.33	-1.58	-4.03	-6.70	-1.28
τ^2	3.2	1.0	8.5	3.5	1.1	10.34	1.1	0.3	3.4
γ	-0.12	-0.97	0.93	0	0	0	0	0	0
DIC		71.55			71.47			75.60	

At the county level (Tables 7 to 10) none of the models (spatial, weighted regression, and ordinary regression) had significant spatial dependency (all four γ ranges had zero). For each stream health measure, the exact same significant parameters were highlighted among the three developed models. Besides that, the comparison of the three DICs showed only slight differences meaning that there is no major difference between spatial, weighted regression, and ordinary regression models at the county level and all of them have the same patterns. Regarding the lowest DIC, a weighted regression model for EPT, and ordinary regression models for FIBI, HBI and IBI were identified to be the best predictive models.

Table 8. Regression models for EPT at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.16	4.86	5.46	5.16	4.94	5.37	5.15	4.95	5.35
β_1	-0.42	-0.81	-0.02	-0.42	-0.81	-0.03	-0.44	-0.83	-0.07
β_2	-3.03	-7.20	1.05	-3.03	-7.01	0.96	-3.03	-7.26	0.86
β_3	1.56	0.81	2.28	1.56	0.83	2.29	1.50	0.85	2.13
β_4	-0.79	-1.62	0.01	-0.79	-1.61	0.02	-0.76	-1.57	0.04
β_5	1.63	0.42	2.81	1.61	0.41	2.79	1.56	0.28	2.82
β_6	-0.56	-1.69	0.61	-0.54	-1.69	0.64	-0.51	-1.58	0.58
β_7	-0.56	-1.69	0.61	-0.59	-1.69	0.49	-0.63	-1.76	0.51
β_8	3.19	0.74	5.63	3.23	0.77	5.84	3.28	0.72	5.55
β_9	3.37	0.28	6.37	3.40	0.39	6.54	3.47	0.42	6.26
β_{10}	8.96	-1.01	18.87	8.94	-0.75	18.89	8.73	-0.30	18.09
β_{11}	0.86	-0.08	1.79	0.87	-0.04	1.81	0.85	-0.07	1.75
β_{12}	0.28	-1.13	1.63	0.29	-1.02	1.68	0.19	-1.07	1.38
β_{13}	-0.30	-1.31	0.71	-0.30	-1.36	0.70	-0.25	-1.13	0.61
β_{14}	0.69	-0.96	2.25	0.70	-0.92	2.35	0.75	-0.78	2.29
β_{15}	-6.94	-13.89	-0.06	-6.94	-13.95	-0.21	-6.75	-13.35	-0.38
β_{16}	0.30	-0.44	1.06	0.31	-0.46	1.04	0.33	-0.41	1.11
β_{17}	-0.82	-2.06	0.41	-0.80	-2.05	0.46	-0.71	-1.89	0.51
τ^2	1.0	0.3	2.8	1.0	0.3	3.1	0.2	0.1	0.6
γ	-0.04	-0.96	0.93	0	0	0	0	0	0
DIC		44.79			43.89			42.80	

However, within in census tract level (Tables A1 to A4), more variations were seen among spatial, weighted regression and ordinary regression models. In contrast to the county level, significant parameters for all three models and for all four stream health measures were not the same. In general, spatial models gave better prediction (lower DICs), meaning that the use of the census tract level can capture more spatial patterns, while these variations were lost at the low detailed county level. Besides that, fewer dependent parameters showed significant correlations with each of the stream health measures at the census tract compared to the county level. For example, the IBI at the county level had significant correlations with nine out of seventeen indicators including one physiographic (S1), one population (S3), one household (S7), one housing (S11), one educational disadvantages (S12), three poverty/welfare receipt (S13, S14, S16), and one unemployment (S17). However, at the census tract level, only one welfare receipt

Table 9. Regression models for HBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	4.85	4.70	5.01	4.85	4.75	4.95	4.85	4.76	4.95
β_1	0.14	-0.04	0.32	0.14	-0.05	0.32	0.13	-0.06	0.31
β_2	3.44	1.60	5.32	3.47	1.62	5.28	3.27	1.39	5.16
β_3	-0.67	-1.01	-0.35	-0.67	-1.01	-0.33	-0.66	-0.98	-0.32
β_4	0.35	-0.01	0.72	0.35	-0.03	0.73	0.32	-0.07	0.72
β_5	-1.00	-1.54	-0.46	-1.00	-1.53	-0.46	-1.01	-1.62	-0.39
β_6	0.43	-0.09	0.96	0.43	-0.11	0.96	0.38	-0.14	0.89
β_7	-0.46	-0.97	0.06	-0.45	-0.95	0.06	-0.38	-0.92	0.15
β_8	-0.62	-1.75	0.52	-0.61	-1.78	0.53	-0.66	-1.83	0.53
β_9	-0.66	-2.01	0.72	-0.65	-2.10	0.76	-0.70	-2.19	0.76
β_{10}	-6.15	-10.67	-1.60	-6.21	-10.72	-1.67	-5.88	-10.45	-1.43
β_{11}	0.13	-0.30	0.54	0.13	-0.31	0.55	0.13	-0.33	0.58
β_{12}	0.31	-0.31	0.93	0.32	-0.30	0.93	0.35	-0.26	0.96
β_{13}	0.56	0.10	1.0	0.57	0.11	1.04	0.56	0.11	0.99
β_{14}	0.36	-0.37	1.11	0.37	-0.40	1.13	0.41	-0.32	1.14
β_{15}	3.12	-0.06	6.24	3.14	-0.03	6.28	3.01	-0.18	6.28
β_{16}	-0.30	-0.64	0.04	-0.31	-0.65	0.03	-0.29	-0.66	0.07
β_{17}	1.38	0.82	1.93	1.38	0.83	1.94	1.32	0.73	1.92
τ^2	0.19	0.06	0.54	0.21	0.07	0.62	0.05	0.02	0.15
γ	0.06	-0.94	0.96	0	0	0	0	0	0
DIC		12.82			11.68			12.50	

indicator (S16) showed significant correlation with the IBI index. Other stream health measures also had fewer significant correlations with socioeconomic/physiographic indicators at the census tract level, compared to the county level. This indicates that using more detailed census data reveals more distinctions among dependent variables and as a result reduces the number of parameters required to predict stream health measures; while, some of these variables became correlated at the county level due to the aggregation at this course level. Similar reductions in the number of significant parameters were seen in the comparison of pairwise correlations at the two levels (Figures 6 and A1) for all other stream health measures.

At the block group level, spatial models showed even better performance (lower DICs) compared to weighted regressions and ordinary regression models (Tables A5 to A8). However, comparison of γ values between spatial census tract (Tables A1 to A4) and block group models

Table 10. Regression models for IBI at county level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	50.02	49.56	50.47	50.02	49.70	50.34	50.04	49.73	50.35
β_1	0.61	0.01	1.17	0.61	0.01	1.22	0.69	0.07	1.30
β_2	4.16	-1.78	10.19	4.11	-1.78	10.12	4.50	-1.56	10.67
β_3	-2.34	-3.41	-1.23	-2.36	-3.52	-1.28	-2.34	-3.39	-1.29
β_4	-0.21	-1.43	1.02	-0.21	-1.37	1.01	-0.20	-1.49	1.11
β_5	-0.44	-2.17	1.30	-0.45	-2.25	1.33	-0.29	-2.30	1.67
β_6	-1.61	-3.34	0.13	-1.63	-3.31	0.12	-1.65	-3.36	0.05
β_7	2.20	0.57	3.85	2.21	0.48	3.95	2.24	0.59	3.95
β_8	-1.97	-5.72	1.71	-2.01	-5.52	1.63	-1.89	-5.68	1.87
β_9	-2.88	-7.36	1.45	-2.93	-7.44	1.47	-2.74	-7.55	2.12
β_{10}	-9.62	-24.83	5.43	-9.45	-24.09	4.84	-10.20	-24.81	4.04
β_{11}	3.27	1.91	4.63	3.29	1.89	4.70	3.19	1.72	4.59
β_{12}	2.42	0.37	4.42	2.40	0.33	4.51	2.38	0.34	4.42
β_{13}	2.88	1.35	4.34	2.87	1.40	4.41	2.79	1.40	4.12
β_{14}	3.98	1.56	6.31	3.99	1.66	6.42	3.87	1.41	6.32
β_{15}	4.95	-5.75	15.45	4.85	-5.05	15.04	5.28	-4.96	15.74
β_{16}	-1.43	-2.52	-0.28	-1.42	-2.50	-0.28	-1.45	-2.68	-0.26
β_{17}	2.23	0.34	4.06	2.25	0.43	4.22	2.25	0.37	4.15
τ^2	2.03	0.62	6.09	2.24	0.68	6.95	0.53	0.17	1.55
γ	-0.03	-0.96	0.95	0	0	0	0	0	0
DIC		61.34			61.13			62.56	

(Tables A5 to A8) showed that higher spatial dependency exists for the three macroinvertebrates models at the block group level than at the census tract (higher γ values and/or narrower range of γ variations). While for the IBI, higher spatial dependency was seen at the census tract level than at the block group level. This can be explained, since macroinvertebrates are better representatives of local habitat conditions, while fish are representative of large-level stream health due to their mobility. Therefore, at the block group level, which is the finest level, macroinvertebrate indices have more spatial dependency on socioeconomic/physiographic parameters, while the IBI has higher spatial dependency at the census tract, which is a larger scale than the block group.

Like the census tract level models, significant parameters were not the same for the spatial, weighted regression, and ordinary regression models, which again shows that, unlike the county level, these models differ from each other at the block group level. In addition, the significant

parameters were also different for each stream health measure at different census levels. For IBI spatial models for example, only S16 (percentage of households receiving public assistance) was highlighted as significant parameter at the census tract level, while at the block group level, S2 (population density) and S7 (percentage of households with female householder) were also found to be significant.

4.3.2.2. Spatial CAR Models with Random Effects (Multilevel)

Using three (spatial, weighted regression and ordinary regression) models for each census level interacting with its courser resolutions (random effects) resulted in 63 models for each stream health measure. Table 11 presents the DICs for all of these models. The best models at each census level (lowest DIC) are bolded for each stream health measure. It is important to note that the single-level models in subsection 4.3.2.1 can be viewed as special cases of the multi-level modeling where we fix some of the random effects on other levels to be exactly 0.

The county level is the coarsest resolution with no higher-level interactions (no random effect), so the first three rows in Table 11, represent the spatial, weighted regression, and ordinary regression models the exist at this level. Like the single level (no random effect) results (Tables 7 to 10), all three models have very close DICs meaning that their performances are likely to be the same. Here also the weighted regression and ordinary regression models had slightly lower DICs compared to spatial models.

Table 11. DICs for multilevel models with random effects (**boldfaced** values represent best models at each census level)*

Model Level	FIBI	EPT	HBI	IBI	County	Census Tract	Block Group
County	72.06	43.93	12.74	61.42	S	-	-
	70.02	43.44	12.28	61.67	WR	-	-
	76.23	41.38	12.16	61.14	OR	-	-
Census Tract	1943.57	1606.15	1062.99	2146.48	-	S	-
	2011.43	1743.71	1124.47	2216.50	-	WR	-
	2030.39	1774.0	1150.45	2246.78	-	OR	-
	1866.06	1531.67	989.11	2071.61	S	S	-
	1938.10	1717.27	1096.36	2141.15	S	WR	-
	1956.05	1800.30	1123.93	2174.01	S	OR	-
	1867.88	1531.13	985.37	2070.07	WR	S	-
	1939.19	1736.73	1096.97	2139.39	WR	WR	-
	1957.50	1765.388	1124.67	2173.79	WR	OR	-
	1897.97	1558.115	1016.58	2100.25	OR	S	-
	1974.39	1758.908	1093.39	2179.20	OR	WR	-
1986.60	1795.37	1121.14	2208.49	OR	OR	-	
Block Group	4369.31	3505.23	2305.20	5120.27	-	-	S
	3175.85	2292.42	968.30	3885	-	S	S
	3166.25	2173.78	1228.27	3793.52	-	WR	S
	3614.55	2845.55	1615.11	4367.52	-	OR	S
	4297.06	3428.30	2228.81	5046.62	S	-	S
	3044.48	2224.19	928.11	3730.10	S	S	S
	3072.51	2127.33	822.83	3740.65	S	WR	S
	3506.49	2777.09	1413.94	4298.93	S	OR	S
	4296.65	3431.07	2228.07	5044.30	WR	-	S
	3154.50	2145.78	1011.15	3757.87	WR	S	S
	2988.34	2145.87	876.93	3860.37	WR	WR	S
	3602.88	2780.58	1442.18	4531.91	WR	OR	S
	4322.78	3458.86	2258.74	5072.66	OR	-	S
	3155.93	2374.83	959.11	3915.40	OR	S	S
	2981.18	2117.40	980.45	3778.31	OR	WR	S
	3531.47	2716.33	1508.92	4326.08	OR	OR	S
	4622.22	3843.96	2528.03	5215.88	-	-	WR
	5782.70	4656.31	2804.94	4928.61	-	S	WR
	5172.72	4140.10	3002.87	4124.09	-	WR	WR
	5970.25	4894.86	2981.39	5341.34	-	OR	WR
	4640.88	3770.08	2484.65	5143.59	S	-	WR
	4902.58	4579.76	2724.49	5771.39	S	S	WR
	5043.04	4078.78	2914.90	3865.1	S	WR	WR
	5894.27	4857.45	2551.23	6696.03	S	OR	WR
	4640.55	3769.05	2483.71	5140.31	WR	-	WR
	5701.90	4582.33	2726.72	4867.69	WR	S	WR
	3350.02	4844.90	2915.35	3899.55	WR	WR	WR
	5923.63	4821.54	2869.64	5153.44	WR	OR	WR
4636.55	3846.81	2479.80	5208.41	OR	-	WR	

Table 11. (cont'd)

5736.15	4609.32	2752.76	4850.89	OR	S	WR
4229.44	2653.88	2910.95	3888.06	OR	WR	WR
5969.41	4896.13	2843.53	4471.86	OR	OR	WR
4744.05	3956.18	2651.11	5275.56	-	-	OR
5114.78	4770.84	2966.77	4863.84	-	S	OR
4364.45	4264.09	3157.07	5061.88	-	WR	OR
6137.42	5076.35	3178.44	6144.27	-	OR	OR
4756.91	3967.19	2608.60	5276.87	S	-	OR
5046.17	4696.45	2889.99	3924.74	S	S	OR
5194.36	4199.25	3097.25	4035.92	S	WR	OR
6075.38	5069.57	3119.79	6843.7	S	OR	OR
4756.48	3966.91	2608.91	5197.52	WR	-	OR
5083.31	4692.98	2888.83	3978.51	WR	S	OR
5254.76	4966.44	3098.74	3879.62	WR	WR	OR
6124.29	5070.39	3119.43	6065.81	WR	OR	OR
4751.88	3963.71	2605.37	5298.28	OR	-	OR
5075.60	4719.87	2917.87	4002.86	OR	S	OR
5221.79	5039.66	3094.77	5040.38	OR	WR	OR
6135.05	5063.93	3113.07	6086.95	OR	OR	OR

* S: spatial, WR: weighted regression, OR: ordinary regression, -: no random effect

Regarding the census tract level, interactions with the county level (random effects) were also considered, so twelve models (rows 4 to 15) were developed at this level. Like tables A1 to A4, the spatial models had lower DICs compared to the weighted regression and ordinary regression models. Adding county level data improved model predictions; however, it is important to note that adding county level random effect had a lower impact on the overall DIC than the models used at the census level. This is also in agreement with Tables 7 to 10, which showed that the three models had very close values at the county level. Considering the interactions of the two levels (random effects), the FIBI combined spatial models at both the census tract and county levels resulting in a lower DIC; while for EPT, HBI and IBI, coupled spatial models at the census tract and weighted regression models at the county level had lower DICs, indicating better predictions.

The next 48 rows in Table 11 belong to models developed for the block group level interacting with the census tract and county levels (nested random effects). In general, models that

considered the spatial effect for the block groups had lower DICs compared to non-spatial ones. Compared to single level (no random effect) models, inputting census tract and county levels also had a positive impact on the models' predictions. The lowest DIC for the IBI was achieved through the combination of spatial models at all three (county, census tract and block group) levels. While for the three macroinvertebrate stream health indicators, the combination of spatial models at the block group level, weighted regression models at the census tract level, and spatial (for HBI) and ordinary regression (for FIBI and EPT) models at county levels produced the lowest DICs. Since the IBI is based on fish, the selection of all spatial models resulting in the lowest DIC makes sense due to the large mobility of fish throughout a river network (Allan et al. 1997; Flinders et al. 2008). Spatial models selected for macroinvertebrates at the block group level is also in agreement with tables A5 to A8. However, considering the interactions of data at the census tract and block group levels (nested random effects) suggests that weighted regression models work better with census tract data. That can be due to the macroinvertebrate behavior of limited movement within the river systems. Meanwhile, for county level data used in the block group level study (nested random effect) ordinary regression models worked better for the FIBI and EPT, while weighted regression models worked better for HBI. These variations among models is also in agreement with previous results that all three (spatial, weighted regression and ordinary regression) models performances were very close at county level and each of them can be selected as the best.

Overall, spatial models at the finest levels (in this case, block group) have better performance than the two non-spatial forms. Meanwhile combining the nested effect of data collected in upper levels improves their predictive power.

Table 12 presents the dependent parameters that were significant in the best models at each level. Except for ETP taxa at the block group level, all stream health indicators at each level (both

for single level or no random effect models and models across different levels having random effects) have the same significant parameters. In other words, while DIC values can differ and the model performances can be improved with the addition of interactions among the different levels (random effects), the significant parameters are not affected. However, these significant parameters may be lost by changing the resolution level and some new parameters may show significant effects, revealing potentially misleading results that arise from selecting an inaccurate level or scale.

Table 12. Significant parameters among all selected best models

Levels	FIBI	EPT	HBI	IBI
Block group multilevel model (with nested random effects)	S2, S5, S6, S7	S17	S1, S16	S2, S7, S16
Block group single level model (no nested random effects)	S2, S5, S6, S7	-	S1, S16	S2, S7, S16
Census tract multilevel model (with random effects)	S2, S10	S4, S5, S7, S9	S3	S16
Census tract single level model(no random effects)	S2, S10	S4, S5, S7, S9	S3	S16
County level	S2, S3, S6, S10, S15, S17	S1, S3, S5, S8, S9, S15	S2, S3, S5, S10, S13, S17	S1, S3, S7, S11, S12, S13, S14, S16, S17

4.3.2.3. Residual Plots

Figures 5 and A3 through A6 show the residual plots for the selected models at both multilevel (with random effects) and single level (no random effect) cases (Tables 7 to 11 and A1 to A8). As mentioned before, county level data is not likely to be a good predictor and may cause misinterpretations. This is further reinforced by Figure 5, which shows that the models developed at this level have little to no variation across the study area. This lack in variation shows that these models are unable to uncover the complexities of relations among the variables. As an important

contrast, for the more detailed levels (census tract and block group), shown in Figures A3 through A6, more variations are captured.

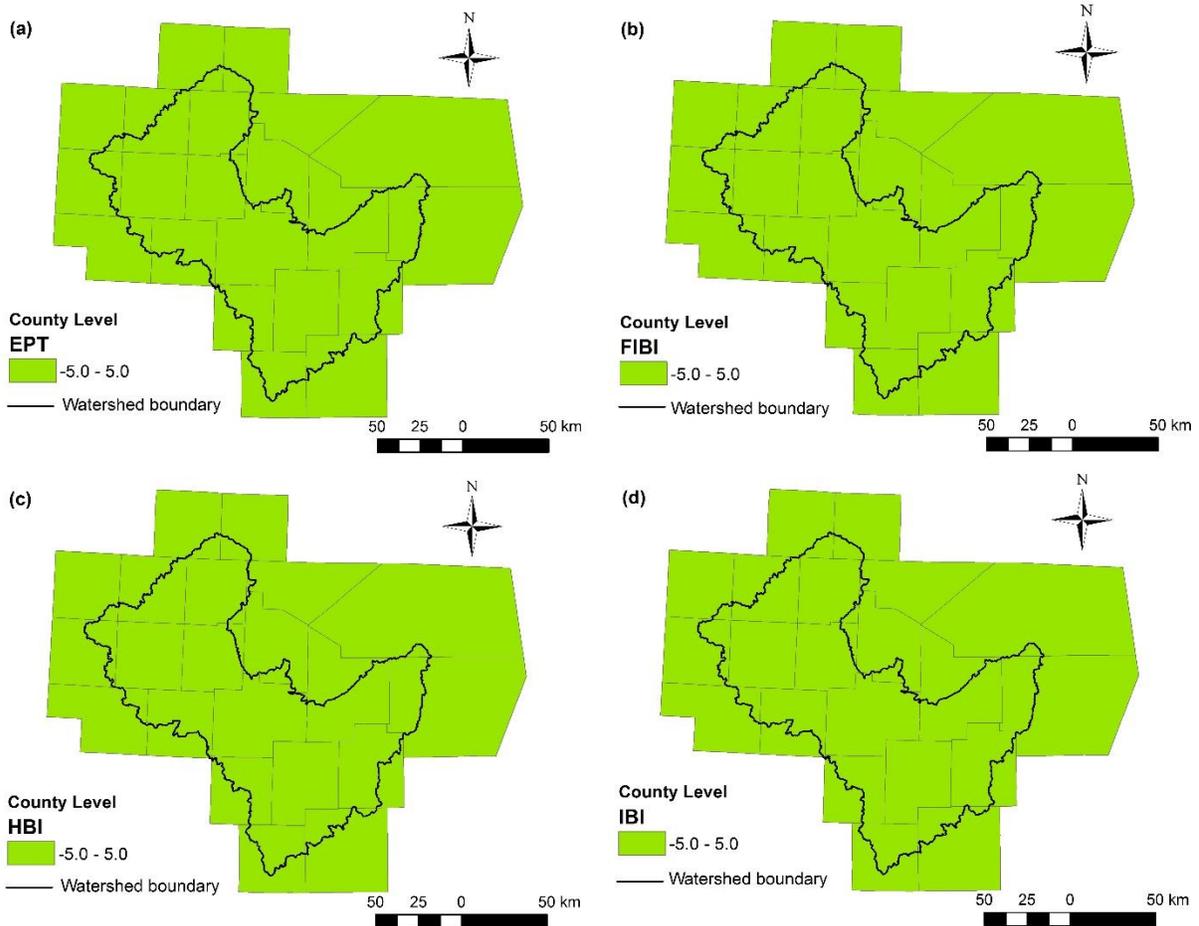


Figure 7. model prediction residuals at county level for a) EPT, b) FIBI, c) HBI, d) IBI

EPT and HBI show very low residuals in the study area and values ranging from -5 to +5 are reported for the majority of the study area in both census tract and block group models developed for these indices (Figures A3 and A4). It means that developed models for these two stream health measures have acceptable performances in this region. In contrast, the FIBI and IBI have some significant residuals in the study area (Figures A5 and A6). Most of the high residual areas are located in highly populated areas and close to the watershed outlet, which means model

predictions for the FIBI and IBI at the given areas have less accuracy, compared to the rest of the study area.

4.4. Conclusions

The goal of this study was to evaluate the effects of spatial data resolution on environmental justice analysis with respect to stream health integrity. Seventeen socioeconomic/physiographic indicators representing population, household composition, racial composition of household, female headed households, housing, educational disadvantage, economic disadvantage, welfare receipt, and unemployment in addition to four stream health measures (including one fish and three macroinvertebrate indices) were used.

Data distributions and pairwise correlations at all three levels showed that stream health data is highly sensitive to census level resolution. In addition, some variables had opposite skewness and/or even correlation sign at the county level compared to two finer resolutions (census tract and block group levels). Meanwhile, socioeconomic/physiographic data distributions were less sensitive to census level change and most of them had similar distributions among all three levels. Many significant correlation coefficients were found at the county level, while moving to the census tract and block group levels, the number of significant correlations and correlation coefficients drastically dropped. This showed that the use of the county level data can be misleading due to aggregation.

For each stream health measure, three regression models including spatial, weighted regression and ordinary regression were developed at each level. County level models for each stream health measure had similar significant parameters. Besides that, each set of three models had similar predictions with no spatial dependency. However, at the census tract and block group

levels, spatial models had better predictions with fewer number of significant parameters, meaning that the census tract and block group levels were able to capture spatial variations, which were aggregated in county level. Furthermore, using multilevel models (with random effects) also improved model prediction compared to single level models (with no random effects); however, did not affect significant parameters. The difference between spatial models and weighted regression and ordinary regression models was even more pronounced at the block group level, compared to the census tract level. The IBI had higher spatial dependency at the census tract level, while the three macroinvertebrate indices had higher spatial dependency on dependent variables at the block group level. This matched the movement patterns of fish and macroinvertebrates within river systems.

Residual plots also proved that the county level models are not able to capture spatial patterns while the census tract and block group levels do. This confirmed that the block group level models performed better than both the county and census level models. Residual plots also showed that for the best developed IBI and FIBI models prediction in densely populated areas and close to the watershed outlet was less accurate compared to other places, while the best models for EPT and HBI worked well for the whole region.

To better understand the interactions between socioeconomic variable and stream health, it is recommended that additional studies will be performed in larger regions and different timeframes. This provides additional information to examine the importance of spatial and temporal variations in the context of environmental justices.

5. ASSESSING THE RELATIVE IMPORTANCE OF PARAMETER ESTIMATION IN STREAM HEALTH BASED ENVIRONMENTAL JUSTICE MODELING

5.1. Introduction

Anthropogenic activities have degraded natural resources which in turn also threatens human ecosystems due to the interwoven nature of natural and human system interactions (Liu et al., 2007a; Carpenter et al., 2009; Alberti et al., 2011). However, degraded environments do not equally affect various groups in society and some communities such as low income and people of color are more vulnerable to environmental hazards than other groups (Massey, 2004; Downey and Liam, 2008). Therefore, the concept of Environmental Justice was introduced to provide fair treatment and involvement of all social groups in implementation and enforcement of environmental laws and regulations (U.S. EPA, 2014e). In other words, the aim of environmental justice is providing equal access to healthy environments as right for all people.

Water is one of the environmental resources that is considered in the environmental justice studies. In the U.S., the traditional approach for water resources assessment was mainly focused on water quality and physical characteristics of the water bodies. However, a nationwide assessment of riverine ecosystems that was performed by the U.S. Environmental Protection Agency found that despite all implemented water quality regulations, still more than 40% of nation's streams were in poor biological condition (U.S. EPA, 2015c). Therefore, a new criterion called Biological Integrity Assessment was introduced in which the physical, chemical, and biological characteristics of streams should be simultaneously considered to improve the overall assessment of water resources (NSCEP, 2011; U.S. EPA, 2015c; Woznicki, 2015). In order to consider biological characteristic in to overall water resources assessment, stream health indices

were introduced, which quantify the response of aquatic species to instream stressors (Herman and Nejadhashemi, 2015; Van Metre et al., 2017).

Regarding the stream health indices, predictive models have been developed to evaluate these indices beyond limited monitoring sites (Wozniski et al., 2016a). The general inputs to these models are landscape features and in instream water quantity and water quality parameters (Miserendino et al., 2011; Einheuser et al., 2012). Traditionally, linear regression (Frimpong et al., 2005; Pont et al., 2009; Moya et al., 2011), and multivariate techniques (Simpson and Norris, 2009; Aguiar, 2011) were used for stream health model development. While recent studies showed that nonlinear techniques such as Fuzzy Logic (Adriaenssens et al., 2006; Marchini et al., 2009), Artificial Neural Network (ANN) (Lencioni et al., 2007; Mathon et al., 2013), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Einheuser et al., 2012; 2013a) provide more reliable prediction of complex ecological systems than linear techniques. Poff and Zimmerman (2010) reported that ecological response is very dependent to flow alteration. In particular, the magnitude, frequency, duration, timing, and rate of change of flow are master variables that affect aquatic species (Poff et al., 1997; Olden and Poff, 2003; Poff and Zimmerman, 2010). Therefore, several tools such as Hydrological Index Tool (HIT) (USGS, 2017), EflowStats (EflowStats, 2015), MATLAB Hydrological Index Tool (MHIT) (Abouali et al., 2016a) were developed to assess ecologically relevant hydrological parameters. Studies showed that incorporating these parameters significantly improved the accuracy of stream health predictive models (Herman et al., 2015; Herman et al., 2016; Wozniski et al., 2016b). However, due to the complexity of natural systems, the predictive power of stream health models are moderate. For example, a recent study by Wozniski et al. (2015) using both HIT tool and the ANFIS technique resulted in development of twenty stream health models in which the range of models' performance (R^2) varies between 0.41

to 0.74 for macroinvertebrate indices while for a fish index, the R^2 can be as low as 0.37 to as high as 0.99 for different stream size and temperature (Woznicki et al, 2015).

These new stream health models have recently been introduced in environmental justice studies in which fish and macroinvertebrate indices were used. Sanchez et al. (2014) used spatial regression models and bivariate mapping to find vulnerable social communities. They used four common stream health indices (for fish and macroinvertebrates), and nine socioeconomic indices (representing education, housing, income, population, and race) collected at the census tract level. The results were promising and showed high correlations between regions with the lowest stream health status and vulnerable social communities (Sanchez et al., 2014). Sanchez et al. (2015) also found that spatial clustering improved spatial regression models prediction. Daneshvar et al. (2016) evaluated the role of spatial level in stream health based environmental justice models' performance. They used sixteen commonly used socioeconomic parameters for environmental justice studies, collected at three census levels of county, census tract, and block group, and the same four stream health indices used by Sanchez et al. (2014; 2015) to identify significant parameters for stream health based environmental justice models at each level (Daneshvar et al., 2016). They also reported that more spatial dependencies were found at the block group level compared to other levels, and that the nested effect of data collected in upper levels improved model's prediction (Daneshvar et al., 2016).

As described earlier, the variability in the stream health model performance can introduce a large level of errors on stream health based environmental justice models. However, new developments in stream health modeling, such a two-phase approach (Abouali et al., 2016b), has resulted in significant improvement in the overall predictability for both fish and macroinvertebrate based stream health models. Therefore, the goal of this study is to assess the

relative importance of parameter estimation in stream health based environmental justice models by comparing the results against previous studies. Our hypothesis was that more accurate stream health predictions would result in the development of more robust environmental justice models in which spatial dependencies among biological and socioeconomic characteristics at different spatial levels would be revealed.

5.2. Materials and Methods

5.2.1. Study Area

The Saginaw River Basin, which is located in the state of Michigan, U.S.A. was selected as the study area (Figure 8). With the total drainage area of more than 16,000 km², it is the largest watershed in Michigan and drains to the Lake Huron. Agricultural lands are the dominant landuse (36.2%), followed by forest (24.8%), wetland/lake (14.3%), pasture (12.4%) and urban (12.3%) lands. The U.S. Environmental Protection Agency identified the Saginaw River and Bay as an area of concern due to degraded fisheries, sediment pollution, and loss of recreational values (U.S. EPA, 2015d). Agricultural and urban runoff, industrial discharges, and sewer overflows are some major sources of pollution in this region (U.S. EPA, 2015d). With more than 7,000 miles of streams, the Saginaw River Basin provides a wide range of habitats for fish and other species (WIN, 2017). It also addresses the needs for drinking water, electrical power generation, and industrial consumption in this region (WIN, 2017). According to the U.S. Census Bureau (2010), the Saginaw River Basin is home of almost 1.5 million people, where 49% are men and 51% are women. The majority of residents are young and more than 52% of them are in the range of 25 to 65 years old, 34% are under 25 years old, while only 14% are senior (above 65 years old). More than 85% of population is white, followed by African American (10%), while other races are less than 5%. The Saginaw River is also a key shipping transit in Mid-Michigan that connects two

cities, Saginaw and Bay City. Flint is another big city in this region that has faced water contamination problems (U.S. EPA, 2013).

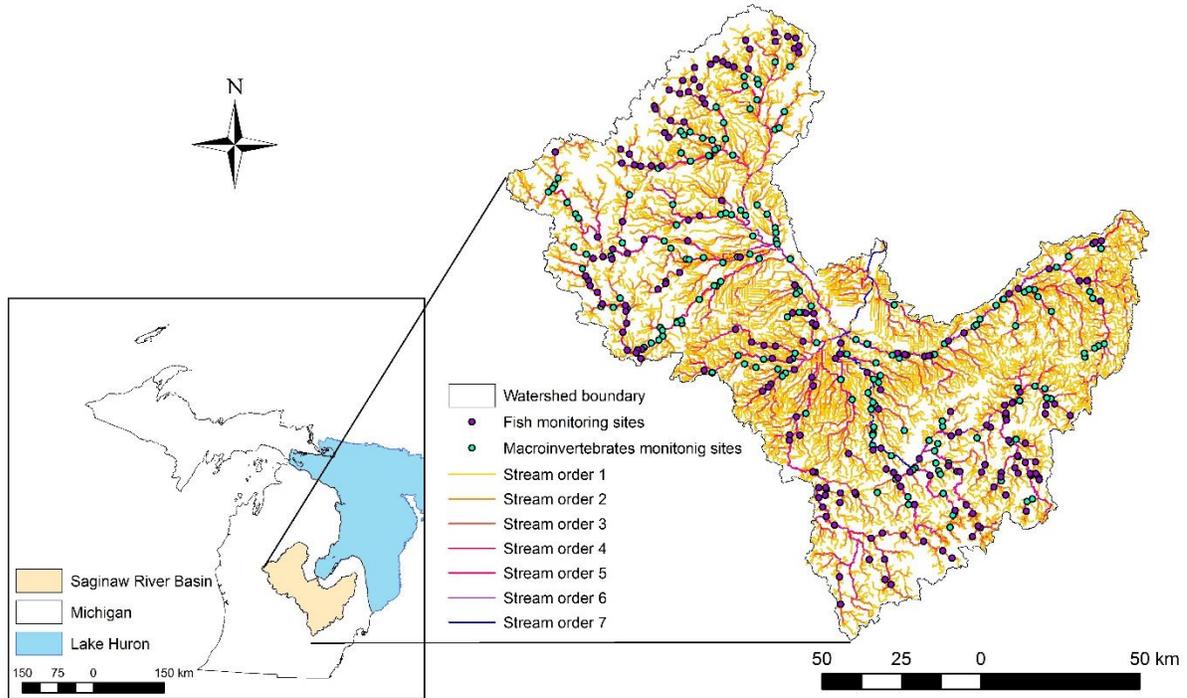


Figure 8. The locations of biological monitoring sites at the Saginaw River Basin

5.2.2. Stream Health Indices

Four common stream health indices including: (1) the Index of Biotic Integrity (IBI) for fish, and (2) the Hilsenhoff Biotic Index (HBI), (3) Family Index of Biotic Integrity (FIBI), and (4) Ephemeroptera, Plecoptera, Trichoptera (EPT) index for macroinvertebrates were used in order to assess the biological integrity of riverine ecosystems. The IBI evaluates the species richness, abundance and trophic composition of fish communities and ranges from zero (lowest score) to 100 (highest score) (Karr, 1981; Kerans and Karr, 1994; Herman and Nejadhashemi, 2015). Meanwhile, the HBI quantifies the response of macroinvertebrates species to organic pollutants and ranges from zero to 10, where higher values mean more degradation by organic pollutants (Hilsenhoff, 1987). The FIBI is the third index used in this study and measures the response of

macroinvertebrates communities to industrial pollutants by quantifying species' composition in family taxonomic groups with scores ranging from zero (lowest score) to 45 (highest score) (Woznicki et al., 2015). The sensitivity of the three macroinvertebrate orders of Ephemeroptera (mayflies), Plecoptera (stoneflies), and Trichoptera (caddisflies), known as EPT taxa, to local instream degradations are evaluated by positive EPT scores where zero scores represent the highest degradation (Lenat, 1988; Woznicki et al., 2015).

The Michigan Department of Environmental Quality (MDEQ) has quantified the fish index (IBI) and the three macroinvertebrate indices (HBI, FIBI, and EPT) for 193 and 262 monitoring sites within the Saginaw River Basin, respectively (MDEQ, 1997; Seelbach and Wiley, 1997). These monitoring sites are shown in Figure 8. However, since there are 13,831 stream segments in the Basin, stream health models need to be developed for both fish and macroinvertebrate indices to estimate the overall biological conditions of streams beyond the monitoring sites.

5.2.3. Socioeconomic/Physiographic Indices

Socioeconomic indices representing concentrated disadvantages are commonly used for environmental justice assessments (Sampson et al., 2008). In this study, sixteen frequently used indices for population, age, race, housing, education, and income disadvantages assessment are taken into account and are listed in Table 13 (Brulle and Pelow, 2006; Bullard et al., 2008; Sampson et al., 2008; Lin and Morefield; 2011).

Table 13. Socioeconomic/Physiographic indices

ID	Category	Type of aggregation	Indicator description	Average values		
				County	Census tract	Block group
S1	Water access	Ratio	Drainage density (m^{-1})	4.76×10^{-4}	8.257×10^{-4}	9.85×10^{-4}
S2	Population	Ratio	Population density (people/ mi^2)	75.31	368.57	350.57
S3		Percentage	Land area (%)	88.93	97.12	97.07
S4	Age	Percentage	Population under 18 years old (%)	22.16	23.65	23.46
S5		Percentage	Population of or over 65 years old (%)	16.76	14.36	14.98
S6	Race	Percentage	African American population (%)	3.56	8.62	6.88
S7	Household	Percentage	Households with female householder (no husband present) (%)	10.48	12.65	11.79
S8		Percentage	Households with living alone householder (%)	26.53	25.25	24.93
S9	Household	Average	Household size (people/household)	2.44	2.51	2.52
S10		Count	Household units (No.)	61.77×10^3	1632.00	592.44
S11	Education	Percentage	Occupied housing units (%)	78.98	87.612	88.52
S12		Percentage	Population of or over 25 years old with less than high school education (%)	13.35	12.01	11.57
S13	Income	Percentage	Families with income below poverty level (%)	11.50	12.30	11.53
S14		Average	Household income (\$ adjusted with 2010 inflation)	55.06×10^3	59.52×10^3	60.02×10^3
S15	Income	Aggregate	Household income (\$ adjusted with 2010 inflation)	38.23×10^8	86.10×10^6	31.78×10^6
S16		Percentage	Households with public assistance income (%)	3.46	3.88	3.55
S17	Income	Percentage	Unemployed population of and over 16 years old (%)	50.08	48.36	47.77

These indices are obtained from the U.S. Census Bureau for three census levels of county, census tract and block group (U.S. Census Bureau, 2010). The Saginaw River Basin overlaps with 21, 393, and 1076 census units of counties (Figure 9 (a)), census tracts (Figure 9(b)), and block groups (Figure 9(c)) respectively. In addition to sixteen socioeconomic indices, one physiographic index called drainage density was also used to quantify the relative distance of population under

study to waterbodies. Drainage density was calculated as the ratio of the total length of streams in a census unit (of county, census tract, or block group) to the unit area.

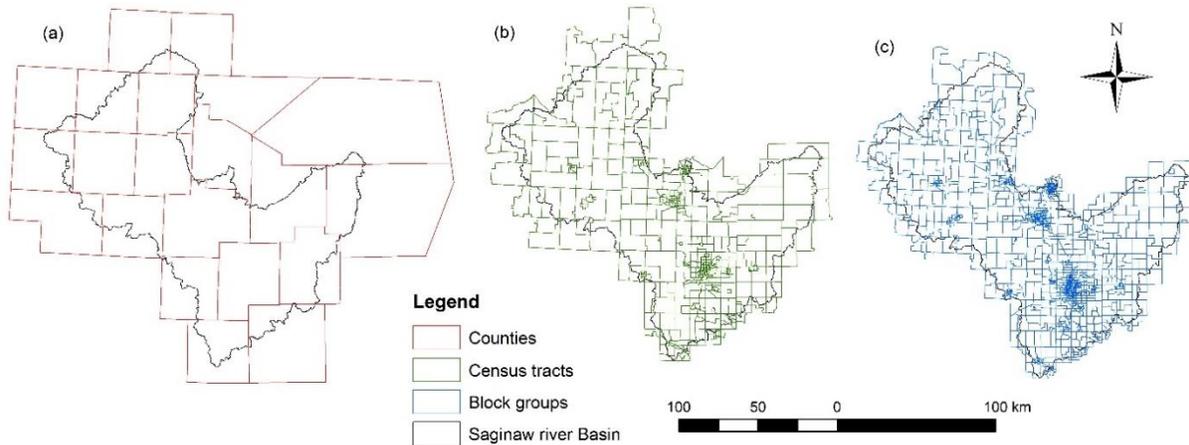


Figure 9. Census units of (a) counties, (b) census tracts, and (c) block groups overlapping with the Saginaw River Basin

5.2.4. Modeling Process

Figure 10 illustrates the modeling process used to predict the stream health indices beyond the monitoring sites and the analysis conducted for the stream health based environmental justice assessments. A hydrologic/water quality model was initially setup, calibrated, and validated for the study area to estimate streamflow and water quality parameters (including sediment, total nitrogen, and total phosphorus loads) for each stream segment on a daily time- step. The estimated flow and water quality parameters were used as inputs to the MATLAB Hydrological Index Tool (MHIT) that calculates ecologically relevant water quality and water quantity parameters (Abouali et al., 2016a). These parameters quantify the magnitude, frequency, duration, timing, and rate of change in flow and water quality parameters that can affect aquatic ecosystems (Poff et al., 1997; Henriksen et al., 2006). MHIT outputs were then used to develop stream health predictive models. For this purpose, a two-phase approach (Abouali et al., 2016b) was implemented, in which (1) Partial Least Square Regression (PLSR) was used to predict the initial stream health indices and

their associated errors, and then (2) a fuzzy logic approach (e.g. ANFIS) was used to estimate the modified stream health indices based on the initial estimations and associated errors. Having the four predicted stream health measures along with 17 socioeconomic and physiographic indices at three census levels of county, census tract and block group, the individual correlations among indices were evaluated and the stream health based environmental justice models were developed. Since these two datasets are in different spatial units (one at the stream level, and one at the census levels), scale adjustment was conducted first, in which weighted average scores based on stream lengths falling in each census unit were used as their associated stream health scores.

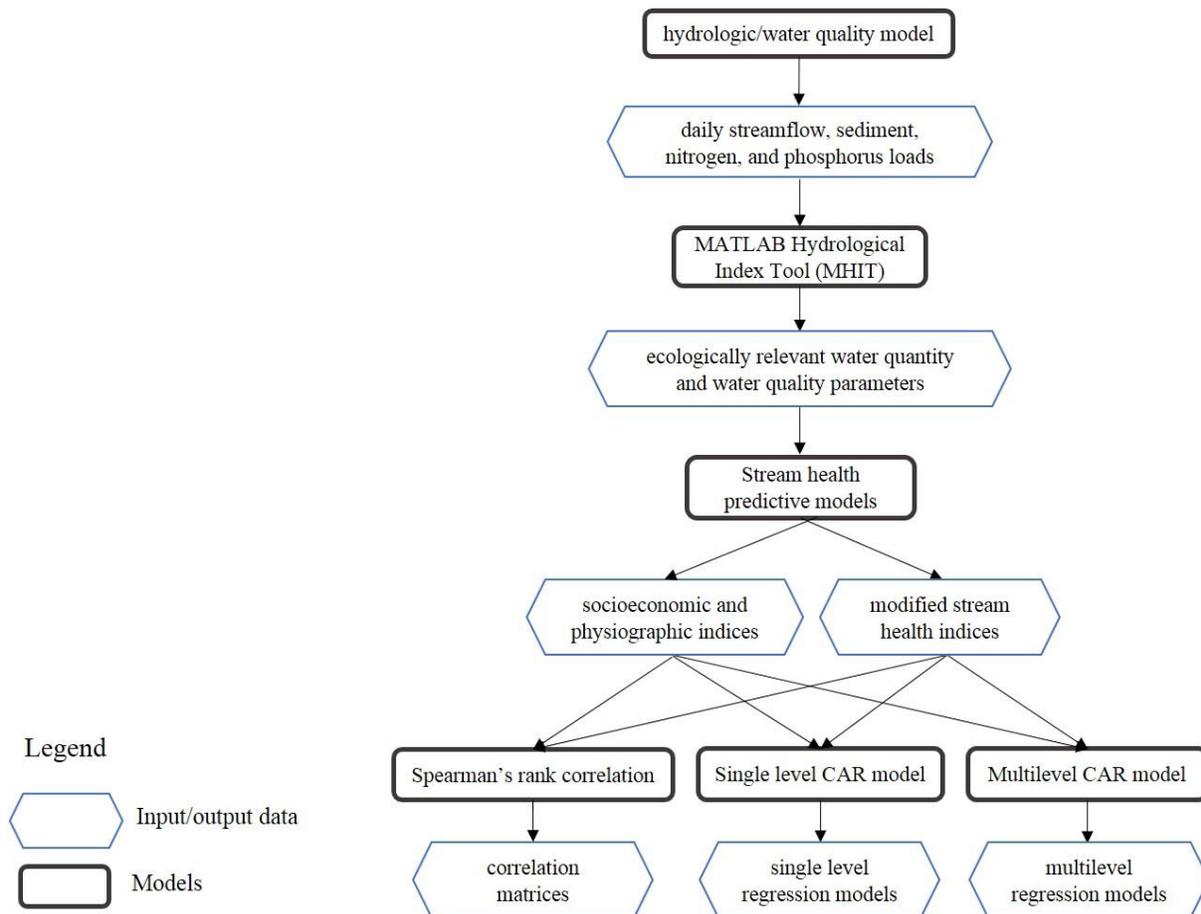


Figure 10. The overall modeling processes

5.2.4.1. Hydrological/Water Quality Modeling

The Soil and Water Assessment Tool (SWAT) was used to develop a hydrologic/water quality model for the study area. SWAT is a physically based and semi-distributed watershed and water quality model developed by U.S. Department of Agriculture-Agricultural Research Service (USDA-ARS) in order to evaluate the impact of land management practices on water quantity and water quality (Arnold et al., 1998). SWAT delineates a watershed into subwatersheds with unique stream segments passing through them, while each subwatershed can be divided into several Hydrologic Response Units (HRUs) based on similarity in landuse, soil, and slope variations within the region (Neitsch et al., 2011). In this study, a pre-delineated watershed developed by Michigan Institute of Fisheries Research was used in which the study area was divided into 13,831 subwatersheds with unique HRUs. The developed SWAT model was then calibrated based on three statistical criteria including 1) Nash-Sutcliffe efficiency (NSE), 2) Percent bias (PBIAS), and 3) root mean square error-observations standard deviation ratio (RSR) (Moriasi et al., 2007). NSE ranges from one (optimum value) to minus infinity, PBIAS ranges from minus infinity to infinity (with optimum value of zero), and RSR ranges from zero (optimum value) to infinity (Moriasi et al., 2007). For both streamflow and water quality components, NSE above 0.5, and RSR below 0.7 are called satisfactory. While satisfactory range of PBIAS varies based on variable, where absolute PBIASs below 25, 55, and 70 are called satisfactory for streamflow, sediment, and nutrients respectively (Moriasi et al., 2007). Streamflow was calibrated and validated based on daily streamflow data collected by the U.S. Geological Survey (USGS) for nine monitoring stations within the region, while water quality (including sediment, total nitrogen, and total phosphorus) loads were calibrated and validated based on monthly observations provided by the U.S. EPA (Daneshvar et al., 2017). All three statistical criteria were met for streamflow (NSEs

ranging from 0.54 to 0.80, PBIASs ranging from 16.34 to -1.53, and RSRs ranging from 0.68 to 0.45) and water quality (NSEs ranging from 0.57 to 0.75, PBIASs ranging from 35.52 to 10.00, and RSRs ranging from 0.65 to 0.50), components calibration and validation (Daneshvar et al., 2017). The calibrated SWAT model was then used to evaluate streamflow, sediment, total nitrogen, and total phosphorus loads for all stream segments on a daily basis.

5.2.4.2. Stream Health Model Development

5.2.4.2.1. One-Phase Approach

Fuzzy Logic and ANFIS models developed by Einheuser et al. (2012; 2013a) were used in former stream health based environmental justice studies by Sanchez et al. (2014; 2015), and Daneshvar et al. (2016). These techniques are commonly used for ecological modeling (Woznicki et al., 2016a), however their inputs are limited due to computational resources and finite ecological observations (Hamaamin et al., 2013). Therefore, parameter selection must be conducted first to limit models' inputs (Woznicki et al., 2015). Einheuser et al. (2012; 2013a) used Spearman's rank correlation to find the most significant water quantity and water quality parameters with respect to stream health measures, which reduced the number of inputs to four for each macroinvertebrates index (Einheuser et al., 2012), and five for the fish index (Einheuser et al., 2013a). Selected input parameters for this approach are listed in Table B1.

5.2.4.2.2. Two-Phase Approach

To address the drawback of limited input parameters, a two-phase approach (Abouali et al., 2016b) was used in this study, where during the first phase, all input parameters will be used to estimate the stream health index and associated error, while during the second phase, ANFIS will use these two predictions as inputs to estimate the final stream health score.

PLSR was used for the first phase to project both the inputs and outputs into a mutually orthogonal coordinate system. PLSR is able to use all input parameters and unlike regular linear regressions, it is not affected by multicollinearity that may exist among input parameters. Therefore, all 171 ecologically relevant hydrologically indices introduced by Poff et al. (1997) in addition to the 78 water quality parameters representing annual and seasonal averages and coefficients of variations were used as input parameters for the first phase. These PLSR predictions of stream health indices and their associated errors were used as inputs for the ANFIS models in the second phase. Table B1 summarizes the two-phase input parameters.

During the second phase, two different sets of stream health predictive models were developed, one set for all streams and then another set for different stream groups. Based on the river continuum concept (Vannote et al., 1980), instream species characteristics vary across different stream sizes that can be classified into three major groups of headwater (stream orders 1-3), medium (stream orders 4-7), and large (stream orders 7-10) streams. The maximum stream order within the Saginaw River Basin is 7 (Figure 8), therefore two stream groups of headwater streams (orders 1-3), and medium and large streams (orders 4-7) were defined and different stream health predictive models were developed for each group. Then the set of stream health predictive models with a better performance was used to calculate the four stream health measures for all 13,831 stream segments.

5.2.5. Data Analysis

Scatter plot matrices were developed for each census level in which histograms, pairwise distributions, and pairwise correlation coefficients were evaluated for all indices including the four stream health measures and the seventeen socioeconomic/physiographic indicators. Spearman's ranking was used for pairwise correlation coefficients evaluation (Lehmann and D'Abrera, 1998).

Bivariate maps were also developed to identify area of high priority concerning environmental justice. In the case of stream health, the area was divided into three classes of high, medium, and low quality using the four biological factors. However, for the socioeconomic indicators, the Jenks natural break method (Jenks, 1967) was used first and then summed to identify the overall area of concern. These two maps were overlapped to identify communities that are vulnerable regarding the environmental justice issue.

To evaluate spatial dependencies among stream health measures and socioeconomic/physiographic indices, the spatial Conditional Autoregressive (CAR) technique (Banerjee et al., 2014) was used to develop stream health based environmental justice models. Equation (17) represent the general form of CAR model used in this study

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2(M_I - \gamma_I W_I)^{-1}) \quad ; \quad i = 1, 2, \dots, I \text{ census units} \quad (17)$$

in which, Y_i and X_i represent the stream health measure and the corresponding p covariates vector for the i th census unit (e.g. county, census tract, or block group). Spatial neighborhood dependencies for the I census units are represented by W_I , and the number of neighbors are listed as diagonal entries of the M_I matrix. Variation and spatial dependency are also measured by τ_I^2 and γ_I respectively.

In order to assess the significance of spatial dependency, two simplified forms of the spatial CAR model were also developed as follows:

- (i) Assuming $\gamma_I = 0$, means no spatial dependence while the residual variance is weighted by the number of neighbors. This simplifies the spatial model to a weighted regression model as shown in Equation (18):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 M_I^{-1}) \quad ; \quad i = 1, 2, \dots, I \text{ census units} \quad (18)$$

- (ii) While setting $\gamma_I = 0$ and $M_I = I_I$, the identity matrix, means no spatial information is implemented and the spatial model will be simplified to an ordinary regression model as shown in Equation (19):

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 I_I) \quad ; \quad i = 1, 2, \dots, I \text{ census units} \quad (19)$$

These three forms of spatial, weighted regression, and ordinary regression were used to develop single level (with no random effect) and multilevel (with random effect) models at three census levels of county, census tract, and block group.

5.2.5.1. Single Level (With no Random Effect) Models

Assuming $i = 1, 2, \dots, I$, $j = 1, 2, \dots, J$, and $k = 1, 2, \dots, K$ represents the number of counties, census tracts, and block groups respectively. The single level (with no random effect) CAR models at the three census levels are presented as follow:

$$Y_i = X_i\beta + \varepsilon_i, \quad \varepsilon \sim N(0, \tau_I^2 D_I(\gamma_I)), \quad i = 1, 2, \dots, I \quad (20-1)$$

$$Y_j = X_j\beta + \varepsilon_j, \quad \varepsilon \sim N(0, \tau_j^2 D_j(\gamma_j)), \quad j = 1, 2, \dots, J \quad (20-2)$$

$$Y_k = X_k\beta + \varepsilon_k, \quad \varepsilon \sim N(0, \tau_K^2 D_K(\gamma_K)), \quad k = 1, 2, \dots, K \quad (20-3)$$

Where using full forms of $D_I(\gamma_I) = (M_I - \gamma_I W_I)^{-1}$, $D_j(\gamma_j) = (M_j - \gamma_j W_j)^{-1}$, and $D_K(\gamma_K) = (M_K - \gamma_K W_K)^{-1}$ resulted in spatial models development while $D_I(\gamma_I) = M_I^{-1}$, $D_j(\gamma_j) = M_j^{-1}$, and $D_K(\gamma_K) = M_K^{-1}$ implementations resulted in weighted regression models at three census levels of county, census tract, and block group respectively. Ordinary regression models are also developed by setting $D_I(\gamma_I) = I_I$, $D_j(\gamma_j) = I_j$, and $D_K(\gamma_K) = I_K$ for the three levels of county, census tract, and block group respectively.

5.2.5.2. Multilevel (With Random Effect) Models

Since the three census levels of county, census tract, and block group are nested, the total number of census tracts is $J = \sum_{i=1}^I J_i$ where J_i is the number of census tracts in the i th county, and

the total number of block groups is $K = \sum_{j=1}^J K_j = \sum_{i=1}^I \sum_{j=1}^{J_i} K_j$ where, K_j is the number of block groups in the j th census tract. To assess the nested effect of aggregated data at different spatial levels, multilevel (with random effect) models were also developed for the census tract and block group levels as follows:

(1) Multilevel (with random effect) models at the census tract level

Implementation of the random effects of data collected at the census tract and county levels resulted in the following form of the spatial CAR model at the census tract level:

$$Y_{ij} = X_{ij}\beta + u_i + \varepsilon_{ij}, \quad \varepsilon \sim N(0, \tau_j^2 D(\gamma_j)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)) \quad (21)$$

$$j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

where, u and ε represent the residual terms at two levels of county and census tract, respectively. $D(\gamma_I)$ and $D(\gamma_j)$ can be either be in spatial, weighted regression, or ordinary regression form and their combination will result in $3 \times 3 = 9$ different multilevel (with random effect) models.

(2) Multilevel (with random effect) models at the block group level

Implementation of the random effects of data collected at the block group, census tract, and county levels resulted in the development of the following form of the spatial CAR model at the block group level:

$$Y_{ijk} = X_{ijk}\beta + u_i + v_{ij} + \varepsilon_{ijk}, \quad (22)$$

$$\varepsilon \sim N(0, \tau_K^2 D(\gamma_K)), \quad \mathbf{v} \sim N(0, \tau_j^2 D(\gamma_j)), \quad \mathbf{u} \sim N(0, \tau_I^2 D(\gamma_I)),$$

$$k = 1, 2, \dots, K_j, \quad j = 1, 2, \dots, J_i, \quad i = 1, 2, \dots, I$$

where, u , v , and ε represent the residual terms at the three levels of county, census tract, and block group, respectively. Combinations of the three forms of spatial, weighted regression, and ordinary regression implementation of $D(\gamma_I)$, $D(\gamma_j)$, and $D(\gamma_K)$ will result in the development

of $3 \times 4 \times 4 - 3 = 45$ multilevel (with random effect) models, while only one of $D(\gamma_I)$ or $D(\gamma_J)$ can be zero (not both) at the same time.

For both the single level (with no random effect) and multilevel (with random effect) analysis, Markov chain Monte Carlo (MCMC) was used to estimate parameters. Six chains with different initial values were used for each model and were run for 6,000 iterations. The last 1,000 samples after convergence for each chain were then used as posterior samples. Deviance Information Criterion (DIC_4) was used for model comparison (Celeux et al., 2006), which measures both model simplicity and model fit at the same time and models with lower DICs are preferred.

5.3. Results and Discussion

5.3.1. Stream Health Indices

Tables 14 and B2 present the coefficient of determination (R^2) and root-mean-square error ($RMSE$) of current (two-phase approach) and former (one-phase approach) developed stream health predictive models. Comparison of the stream health model performances when all streams were used for development of the predictive model reveals that the two-phase approach, used in this study, has outperformed the former predictive models for all four stream health measures within all streams. The Fish index (IBI) has the highest improvement compared to previous approach where a R^2 of 0.89 and $RMSE$ of 7.56 are achieved compared to the former R^2 of 0.48 and $RMSE$ of 16.37. This shows that incorporating larger sets of ecologically relevant water quantity and water quality parameters (249), and combining the two methods of PLSR and ANFIS resulted in more accurate predictions of stream health measures rather than just using the one-phase fuzzy logic model with a few water quantity and water quality parameters (4 to 5), especially

for fish that are highly sensitive to ecologically relevant flow parameters (Poff and Zimmerman, 2010).

The next two columns of Tables 14 and B2 summarize the performance of the stream health predictive models developed for two stream classes of “Headwater streams” and “Medium and large streams”. Results show that for all stream health indices, models developed for the two classes have better performances (with R^2 values ranging from 0.90 to 0.97) than models developed for all streams combined (with R^2 values ranging from 0.70 to 0.89). For instance, R^2 values of 0.97 and 0.91 were achieved for the EPT predictive models for the two stream classes instead of the 0.72 obtained for the EPT predictive model for all streams combined. This is due to the fact that species are often found in specific stream classes and have different responses to stressors (McManamay et al., 2014; Herman et al., 2015). So distinct models for different stream classes are preferred to models that are developed for all streams especially for macroinvertebrate indices (HBI, FIBI, and EPT) that are more sensitive to local impairment than fish (Kerans and Karr, 1994).

Table 14. Comparison of coefficient of determination of developed stream health predictive models

Stream health measures	One-phase approach	Two-phase approach		
	All streams	All streams	Headwater streams	Medium and large streams
IBI	0.48*	0.89****	0.90****	0.96****
HBI	0.57**	0.83***	0.91***	0.97***
FIBI	0.50**	0.70***	0.94***	0.94***
EPT	0.54**	0.72***	0.97***	0.91***

* This data was obtained from Einheuser et al. (2013a)

** This data was obtained from Einheuser et al. (2012)

*** This data was obtained from Daneshvar et al. (2017)

**** Results obtained from this study

The new developed stream health predictive models for two stream classes were then used to simulate the four stream health indices beyond the sampling points (Figure B1) and their predictions are compared with the one-phase approach by calculating the absolute percent of

change in prediction (Nejadhashemi et al., 2011) as shown in Table 15. Results show that HBI scores have the lowest deviation from the results obtained in the one-phase approach where 71.2% of headwater streams and 91.1% of medium and large streams have less than a 25% change in scores. Meanwhile, the highest changes are found in the IBI prediction for headwater streams where 38.8% of streams in this class have more than a 75% change in score prediction. High changes in the IBI scores prediction reveals the high dependency of the fish index on ecologically relevant water quantity and water quality parameters (Poff and Zimmerman, 2010). While the HBI is less sensitive to these parameters due to the fact that it measures the response of aquatic species to organic pollutants (Hilsenhoff, 1987).

Table 15. Absolute percent of change in the stream health measures prediction between one- and two-phase approaches

Stream health measure	Stream classes	Absolute percent of change			
		< 25%	25% - 50%	50% - 75%	> 75%
IBI	Headwater streams	31.3%	17.0%	12.9%	38.8%
	Medium and large streams	58.0%	24.0%	6.7%	11.2%
HBI	Headwater streams	71.2%	22.6%	4.4%	1.8%
	Medium and large streams	91.1%	7.8%	0.6%	0.5%
FIBI	Headwater streams	42.4%	18.9%	14.5%	24.2%
	Medium and large streams	54.6%	19.3%	12.4%	13.6%
EPT	Headwater streams	44.5%	12.3%	11.0%	32.2%
	Medium and large streams	40.7%	27.1%	15.8%	16.4%

5.3.2. Variables Distribution and Pairwise Correlations

Figures 11, B2, and B3 present the correlation matrices for all indices including the four stream health measures (IBI, HBI, FIBI, and EPT), and the seventeen socioeconomic and physiographic variables (S1 to S17) at three levels of county, census tract, and block group respectively. The diagonals of the matrices represent the indices distribution, while upper and lower parts represent pairwise correlation coefficients and scatterplots respectively. Modified stream health indices prediction has changed their distribution, correlation with each other and correlation with independent variables (S1 to S17).

11, B2, and B3). This means that the new developed stream health scores are less sensitive to stream health score aggregation and more consistent at the different census levels.

The same consistency among the three levels exists in pairwise correlations, where correlation coefficients have the same sign at all three levels, while in the previous study correlation coefficients at the county level showed opposite correlations compared to the census tract and block group levels (Tables 16-18). For the new developed stream health scores, HBI had negative correlations with IBI, FIBI, and EPT at all three levels, while these three had positive correlations with each other. This is also in agreement with their definitions, where higher values of IBI, FIBI, and EPT represent better stream health condition, while for HBI it is reversed (Woznicki et al., 2016b). Besides that, pairwise correlation coefficients for each pair are almost the same at all three census levels, which again reveals that the new developed stream health scores are not as sensitive to aggregation at different spatial levels.

Table 16. Comparison of pairwise correlations among stream health indices at the county level. (Blue upper right values represent correlations among the new developed stream health indices using a two-phase approach, while red lower left values are correlations reported by Daneshvar et al. (2016) using a one-phase approach)

IBI	-0.69	0.46	0.59
0.042	HBI	-0.28	-0.36
-0.33	-0.34	FIBI	0.78
-0.23	-0.29	0.12	EPT

Table 17. Comparison of pairwise correlations among stream health indices at the census tract level. (Blue upper right values represent correlations among the new developed stream health indices using a two-phase approach, while red lower left values are correlations reported by Daneshvar et al. (2016) using a one-phase approach)

IBI	-0.40	0.27	0.48
-0.31	HBI	-0.42	-0.50
0.21	-0.40	FIBI	0.38
0.32	-0.29	0.24	EPT

Table 18. Comparison of pairwise correlations among stream health indices at the block group level. (Blue upper right values represent correlations among the new developed stream health indices using a two-phase approach, while red lower left values are correlations reported by Daneshvar et al. (2016) using a one-phase approach)

IBI	-0.37	0.30	0.41
-0.23	HBI	-0.40	-0.45
0.16	-0.40	FIBI	0.40
0.20	-0.18	0.14	EPT

5.3.3. Identifying High Priority Area

Figure 12 shows the area of concern for stream health and socioeconomic aspects using bivariate maps at three census levels of county, census tract, and block group. Overall, the highest spatial variations are found at the block group (Figure 12-c), while aggregations in upper levels (census and county) smoothed these variations, especially at the county level (Figure 12-a). Considering spatial variations at the block group level, northern regions of the watershed that are mainly dominated by forests and less affected by human activities have the best conditions for both stream health and socioeconomic indicators. Moving to the watershed outlet, both stream health, and socioeconomic measures are declined. In general, the central region has been identified as the most vulnerable area. This highly populated area (Bay city and Flint) suffers from low water quality condition and dense concentration of vulnerable communities. Such analysis for other regions enables policymakers to identify areas that have higher priority for resources allocation.

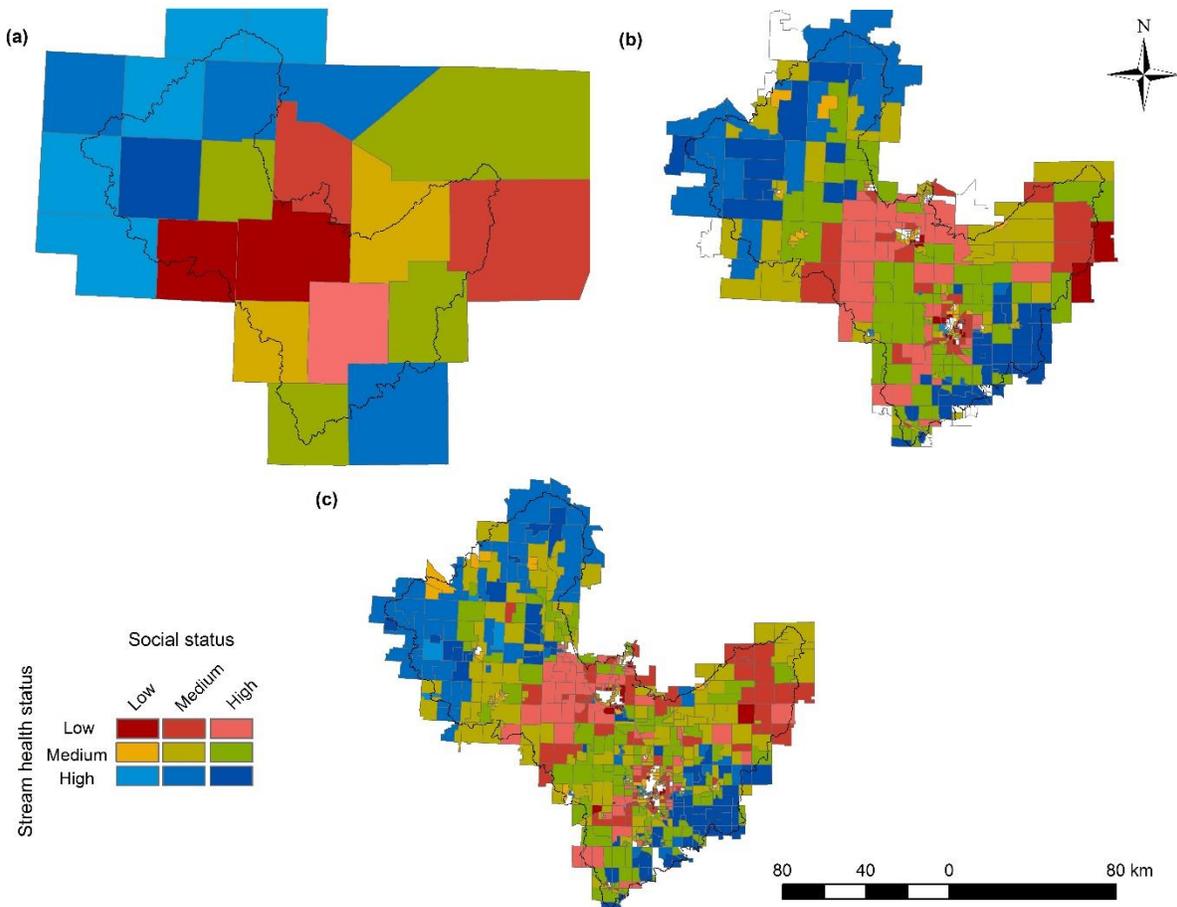


Figure 12. Bivariate map of overall stream measures and their predictors across Saginaw River Basin at (a) county, (b) census tract, and (c) block group levels

5.3.4. Single Level (with No Random Effect) Stream Health Based Environmental Justice Regression Models

Tables B3 to B14 summarize the outputs of the three single level (with no random effect) regression models (including spatial, weighted regression, and ordinary regression) developed for the four stream health measures of IBI, HBI, FIBI, and EPT at three levels of county, census tract and block group. DICs of the developed models are also shown in Table 19 and lower DICs (representing better performances) for each of the four stream health measures at all three census levels are boldfaced.

Table 19. DICs of single level (with no random effect) regression models (**Boldfaced** values indicate best selected models with lower DICs)

Stream health index	County			Census tract			Block group		
	S	WR	OR	S	WR	OR	S	WR	OR
IBI	156.50	158.74	156.65	2623.42	2786.37	2767.44	5964.52	6454.62	6403.28
HBI	22.47	22.08	21.72	452.75	577.96	567.20	1139.18	1488.91	1463.87
FIBI	102.85	105.09	102.42	1984.03	2090.95	2081.21	4491.20	4865.83	4836.51
EPT	91.50	94.33	91.56	1378.87	1501.52	1503.99	3301.39	3602.18	3589.46

S: Spatial; WR: Weighted Regression; OR: Ordinary regression

Similar to the previous study using one-phase approach (Daneshvar et al., 2016), spatial models had better performances (with lower DICs) than the two non-spatial models at the census tract and block group levels, while at the county level, the DICs of the three models are close and in some cases (e.g. HBI), non-spatial models had slightly lower DICs than the spatial model. In other words, spatial models are preferred at the census tract and block group levels, while at the county level there is no major preference.

Comparison of significant parameters selected for each model also resulted in the same conclusion. For each regression model (Tables B3 to B14), significant parameters, meaning that their range does not cover zero, are boldfaced. Table 20 summarizes all significant parameters for the three regression models developed for each of the four stream health measures.

Like the previous study (Table B15), all three models of spatial, weighted regression, and ordinary regression had similar significant parameters at the county level, while moving to census tract and block group, fewer and different parameters were identified as significant for the spatial models than the two non-spatial models. For instance, three independent variables of S2 (population density), S16 (households with public assistance income), and S17 (unemployed population over 16 years old), were significant for EPT prediction by all three regression models at the county level. Meanwhile, at the census tract, S1 (drainage density) and S11 (percentage of

occupied housing units), and at the block group only S1 were significant for spatial models. Meanwhile for the two non-spatial models, significant parameters were S6 (percentage of African American population) and S11 at the census tract, and S1, S5 (percentage of population of or over 65 years old), S6, and S11 at the block group levels. This is also in agreement with the former study (Daneshvar et al., 2016), showing that spatial dependencies are lost at the county level, while census tract and block group levels can capture spatial dependencies among variables. In summary, three models of spatial, weighted regression, and ordinary regression had similar performance at the county level. While spatial models are preferred to the two non-spatial forms at the census tract and block group levels with fewer number of significant parameters.

Table 20. Significant parameters of new developed single level (with no random effect) regression models

Index	Census level	Spatial	Weighted regression	Ordinary regression
IBI	County	S1, S3	S1, S3	S1, S3
	Census tract	S5, S9, S11	S1, S3, S5, S11	S1, S3, S5, S11
	Block group	S6, S8, S10, S17	S2, S3, S5, S6, S11, S12	S1, S3, S5, S6, S11, S12
HBI	County	S1	S1	S1
	Census tract	-	S1, S6, S11, S13	S6, S11, S13
	Block group	-	S2, S8, S10, S11	S2, S4, S6, S10, S11
FIBI	County	S2, S7, S16, S17	S2, S7, S16, S17	S2, S7, S16, S17
	Census tract	S1, S11, S16	S1, S3, S5, S11, S12	S1, S3, S5, S11, S12
	Block group	S1, S2, S6	S1, S2, S3, S5, S6, S11	S1, S2, S3, S5, S6, S11
EPT	County	S2, S16, S17	S2, S16, S17	S2, S16, S17
	Census tract	S1, S11	S6, S11	S6, S11
	Block group	S1	S1, S5, S6, S11	S1, S5, S6, S11

However, comparison of current significant parameters (Table 20) with those from the previous study (Table B15) reveals that modified stream health scores used the two-phase approach resulted in much fewer and somehow different significant parameters for the same

regression model. Overall, 115 significant parameters are identified for all regression models (Tables B3 to B14), while this number was 171 in the former study (Daneshvar et al., 2016). Especially at the county level, the number of significant parameters have drastically dropped compared to the previous study. For instance, nine independent parameters (S1, S3, S7, S11, S12, S13, S14, S16, and S17) identified by all regression models developed for the IBI at the county level has reduced to only two parameters (S1, S3). This shows that using the two-phase approach modified the regression models and removed redundancies that existed before, especially at the county level. This is also in agreement with the pairwise correlation results that showed that the new developed stream health scores improved the correlations at the county level while in the former study using the one-phase approach, aggregated stream health scores at the county level showed opposite correlations compared to the census tract and block group levels.

5.3.5. Multilevel (with Random Effect) Stream Health Based Environmental Justice Regression Models

The combination of the three residual forms of spatial, weighted regression, and ordinary regression for data collected at the three census levels (county, census tract, and block group) resulted in 48 multilevel (with random effect) models among the three levels. Table B16 summarizes the DICs of these models and the lowest DICs are boldfaced. The county level is the coarsest level used in this study with no nested upper level, so only three regression models (spatial, weighted regression, and ordinary regression) are developed for each stream health measure at this level. Similar to the single level analysis, there is no major preference among the three models developed for each stream health measure at the county level, and the three DICs are very close (<2%). Meanwhile, at the census tract and block group levels considering the nested effect of data collected at upper levels, the models' predictability outperformed the single level

analysis. For both census tract and block group analysis, combinations of spatial models at the finest resolution and a mix of spatial and non-spatial models for nested upper levels resulted in lower DICs compared to the single level models.

Table 21 summarizes the DICs of best selected single level and multilevel models developed for the four stream health based environmental justice analysis. Multilevel models have much lower DICs compared to the single level models at the same level, especially in the block group level where much lower DICs are achieved for the multilevel models compared to the single level models (ranging from 23% to 120% decrease in DICs). This is also in agreement with Daneshvar et al (2016) results showing that multilevel models had better performance than single level models.

Table 21. DICs of the best selected regression models for the census tract and block group levels

Stream health index	Census tract		Block group	
	Single level	Multilevel	Single level	Multilevel
IBI	2623.42	2545.98	5964.52	4575.22
HBI	452.75	374.58	1139.18	-232.51
FIBI	1984.03	1907.28	4491.20	3012.60
EPT	1378.87	1302.31	3301.39	1951.01

Meanwhile, the significant parameters of the best selected models are different from the former study using a single-phase approach. Table 22 summarizes the significant parameters of the best selected models for each of the four stream health measures at all three census levels.

Similar to the previous study, both single level and multilevel models had the same significant parameters. This shows that considering the nested effect of data collected in upper levels does not change the significant parameters, while at the same time considering the nested effect of aggregated data at different levels will improve the model prediction. However, a totally different trend in significant parameters selected was observed in this study. Table 22 shows that for the fish index (IBI), only two significant parameters (S1, and S3) are selected at the county

level, while moving to the census tract and block group levels resulted in a change in significant parameters selected as well as an increase in the total number of parameters selected to three (S5, S9, and S11), and four (S6, S8, S10, and S17) for the census tract and block group levels respectively. However, the trend is the opposite for the other three other macroinvertebrate indices (HBI, FIBI, and EPT). For instance, three significant parameters (S2, S16, and S17) are selected at the county level, while moving to the census tract and block group levels resulted in a change in significant parameters selected as well as a decrease in the total number of parameters selected to only two (S1, and S11), one (S1) for the census tract and block group levels respectively.

Table 22. Significant parameters (in black) for the best-selected stream health based environmental justice models (Boldfaced values indicate repeated indices from Daneshvar et al. (2016), while red indices are those from Daneshvar et al. (2016) that are eliminated with the new approach)

Census level	Model type	IBI	HBI	FIBI	EPT
County	Single level	S1, S3, S7, S11, S12, S13, S14, S16, S17	S1, S2, S3, S5, S10, S13, S17	S2, S3, S6, S7, S10, S15, S16, S17	S1, S2, S3, S5, S8, S9, S15, S16, S17
Census tract	Single level	S5, S9, S11, S16	S3	S1, S2, S10, S11, S16	S1, S4, S5, S7, S9, S11
	Multilevel	S5, S9, S11, S16	S3	S1, S2, S10, S11, S16	S1, S4, S5, S7, S9, S11
Block group	Single level	S2, S6, S7, S8, S10, S16, S17	S1, S16	S1, S2, S5, S6, S7	S1
	Multilevel	S2, S6, S7, S8, S10, S16, S17	S1, S16	S1, S2, S5, S6, S7	S1, S17

The same trend of reduction in significant parameters is observed for the HBI and FIBI when moving from county, to census tract and block group levels, respectively. This dissimilarity in the trend of significant parameters among fish and macroinvertebrate indices can be explained by the fact that fish indices measure large scale impacts, while macroinvertebrates are responding to local stressors (Flinders et al., 2008; Paller et al., 2014; Herman and Nejadhashemi, 2015). Therefore, for the IBI (fish index) less significant parameters are selected at the county level

compared to the two detailed spatial levels of census tract and block group. Meanwhile for macroinvertebrate indices that are sensitive to local stressors, more parameters are selected as significant at the coarser resolution compared to finer census levels. This trend was not observed in the former study by Daneshvar et al. (2016). For instance, six significant parameters (S2, S3, S6, S10, S15, and S17) were reported for the FIBI at the county level, while at the census tract level the number of significant parameters was reduced to two (S2, and S10), and again increased to four (S2, S5, S6, and S7) at the block group level (Daneshvar et al., 2016). Therefore, the modified stream health scores using the two-phase approach improved model performances not only in terms of DICs, but also with regard to the type and number of significant parameters required for stream health based environmental justice models development. This is especially true for the county level where the number of significant parameters was drastically reduced from 9, 6, 6, and 6, to 2, 1, 4, and 3 for IBI, HBI, FIBI, and EPT, respectively. Therefore, using more accurate stream health indicators when developing the environmental justice models can help with mitigating redundancy among predictors while revealing more meaningful relationships.

5.4. Conclusion

The goal of this study was to assess the relative importance of parameter estimation in stream health based environmental justice model development. The results showed that incorporating ecologically relevant water quantity and water quality parameters and using a two-phase approach will provide more reliable and consistent stream health predictions that are less sensitive to aggregation at different census levels. Besides that, comparison of significant parameters selected for the development of stream health based environmental justice models for one- and two-phase approaches revealed that the modified stream health indices improve stream

health based environmental justice models' performance by reducing redundancies especially at the county level.

In addition, more meaningful spatial dependencies were observed among fish and macroinvertebrate indices and socioeconomic/physiographic components using the improved stream health models, where more significant parameters were selected at the finest level (block group) compared to the coarsest level (county) for fish index, while the trend was opposite for macroinvertebrate indices. Finally, in order to better evaluate the robustness of the developed techniques in this study, it is recommended that future studies will be implemented in other regions with different socioeconomic and physiographic characteristics.

6. CONCLUSIONS

This research study enhanced the existing framework for environmental justice studies with respect to stream health. Four stream health indices evaluating response of fish and macroinvertebrates to instream stressors were used for stream health assessment. Meanwhile, in order to capture the socioeconomic indices representing concentrated disadvantages of a community, sixteen common indices from the U.S. Census Bureau in addition to one physiographic index were used to assess the environmental justice conditions within the study area. In this study, the role of spatial levels in stream health based environmental justice studies was evaluated. In addition, the significance of parameters estimation on the newly developed stream health based environmental justice models was assessed. The following conclusions were made based on the two conducted research studies:

- Pairwise correlation was highly sensitive to level of aggregation, especially for social parameters, where more than 30 significant correlations with absolute correlation coefficient above 0.7 were found at the county level. Whereas at the census tract and block group levels, this number drastically reduced to three.
- Single level analysis of stream health based environmental justice models revealed that in general county level models are not able to capture spatial dependencies among stream health measures and their predictors. Meanwhile, spatial dependencies were seen at the census tract and block group levels.
- Three developed forms of spatial, weighted regression, and ordinary regression models had quite similar performances at the county level, while at the census tract and block group levels, spatial models were preferred (with lower DICs).

- The highest spatial dependencies were found at the block group level, where spatial models had the lowest DICs compared to two non-spatial models.
- In general, multilevel models that incorporate the nested effect of data collected at upper levels had lower DICs than single level models. Significant parameters required for both single level and multilevel models were almost the same. That revealed that multilevel models perform better than the single level models.
- *Summary of study 1:* Incorporation of the spatial level of socioeconomic factors will improve the predictability of the stream health based environmental justice studies.
- Incorporating ecologically relevant water quantity and water quality parameters, using the two-phase modeling approach, and stream order grouping enhanced the predictability of the stream health models. Using the new two-phase approach resulted in coefficient of determinations above 0.9 for all stream health measures. In contrast, the highest coefficient of determination for the one-phase approach was 0.57.
- Comparison of one- and two-phase approaches of stream health modeling showed an improvement of model predictability of stream health scores by 25% for almost half of the streams in the study area. However, improvement for the HBI predictor model was minimum compared to other indices. This is because the HBI evaluates the response of aquatic ecosystems to organic pollutants; and therefore it is less sensitive to ecologically relevant hydrologic and water quality parameters than other macroinvertebrates and fish indices.
- In the two-phase stream health modeling approach and similar to the one-phase approach, the most special dependencies among the stream health and the socioeconomic indices exist at the block group level, while these dependencies are lost at the county level.

- Using the two-phase approach and for all four stream health indices, spatial models had better performances than non-spatial ones at the census tract and block group levels. However at the county level, both spatial and non-spatial models had similar performances.
- Evaluation of spatial correlations between stream health measures and their predictors at three census levels showed block group data are able to capture vulnerable communities with both low social and stream health status. However, aggregation of data in upper levels smoothed these spatial variations especially at the county level.
- *Summary of study 2:* improvement in the accuracy of biological indices predictions will improve the overall performance of the stream health based environmental justice models.
- Overall, using more accurate stream health predictive models provide robust and reliable stream health predictions while improving the performance of environmental justice models. We also observed more consistent responses at all three levels of study when more accurate biological measures were used in study 2.
- Studies such as this can help policy makers to better understand the complex socioeconomic and environmental relationships. Also, using bivariate maps can help with identification of vulnerable communities.

7. FUTURE RESEARCH RECOMMENDATIONS

The ultimate goal of this research is to identify the environmental inequality among different social groups. This will help water resources managers to find the most suitable places to implement conservation practices to expand environmental justice. This study improved our understanding regarding the relationship between aquatic species and socioeconomic factors that are key in detecting and modeling environmental justice concerning the health of streams. However, additional works are needed including:

- This study was conducted in the Saginaw River Basin in Michigan. In order to evaluate the reliability of the proposed methods, regional and national scale analysis of these types of models are recommended. As a result, different and wider ranges of socioeconomic and biological characteristics can be examined. The next step is extending analysis for the entire Michigan. So far, hydrological datasets and models were created for all watersheds in Michigan. Then all models will be calibrated and validated using flow and water quality data at monitoring points. Once all hydrologic models are calibrated, their outputs are going to be used to predict statewide stream health measures. These indices along with existing socioeconomic/physiographic indices will be used to develop a statewide environmental justice model.
- In this study, one fish and three macroinvertebrate indices were used to examine the overall health condition of the riverine systems. These indices were commonly used in the Great Lakes region to evaluate stream health. However, different biological indices are used in different regions of United States and around the world. Therefore, it is recommended to establish similar types of relationships between other biological and

socioeconomic indices to assure the applicability of the proposed work at larger scales and for different regions.

- Socioeconomic indices that were used here are typically employed to perform environmental justice studies. However, many of these indices can lose their predictive ability when aggregated to large scales. Future research should identify and recommend appropriate scales of use for different socioeconomic indices.
- In this study, CAR models were used to evaluate the spatial dependencies among stream health measures and socioeconomic indices. Future study should examine the applicability of other techniques, such as spatial autoregressive models, to improve the reliability and accuracy of the stream health based environmental justice models.

APPENDICES

APPENDIX A: Study One

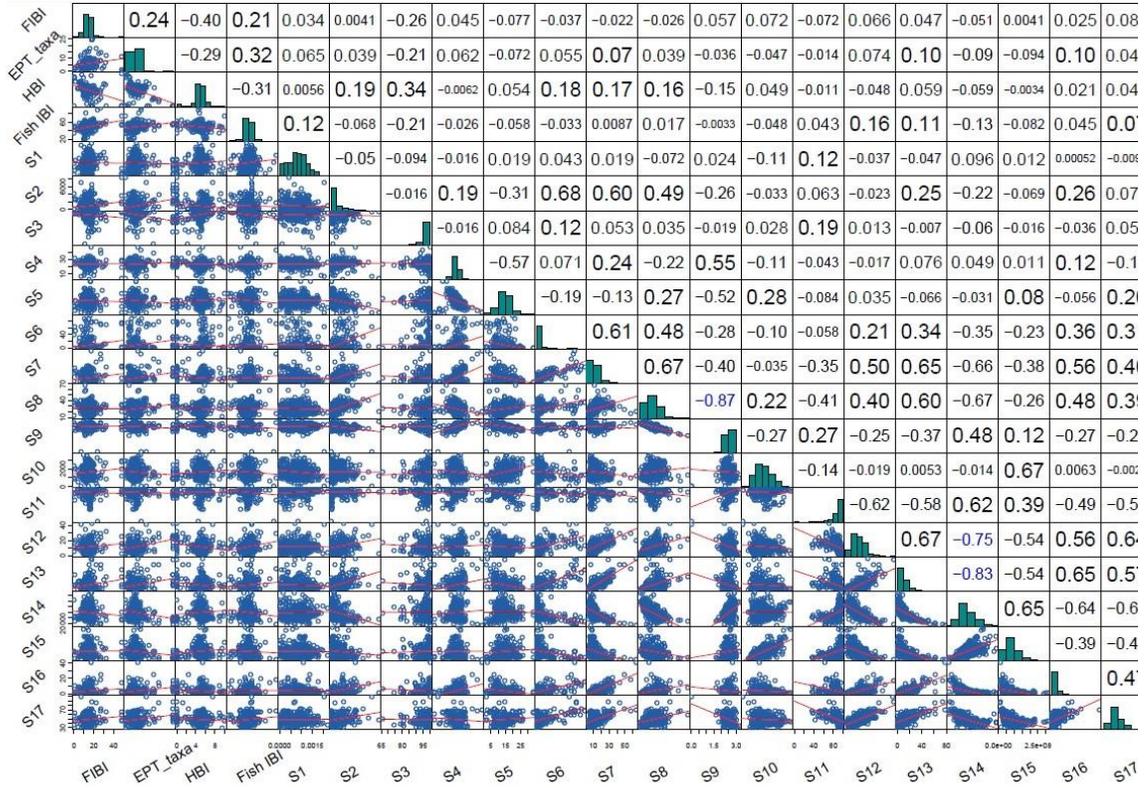


Figure A1. Spearman ranks correlation matrix between dependent and independent variables at the census tract level. **Boldfaced** value indicates significance at the 0.05 level and correlation less than 0.7, **Boldfaced** value in red indicates significance at the 0.05 level and strongly positive correlation equal or above 0.7, value in blue indicates significance at the 0.05 level and strongly negative correlation equal or below -0.7

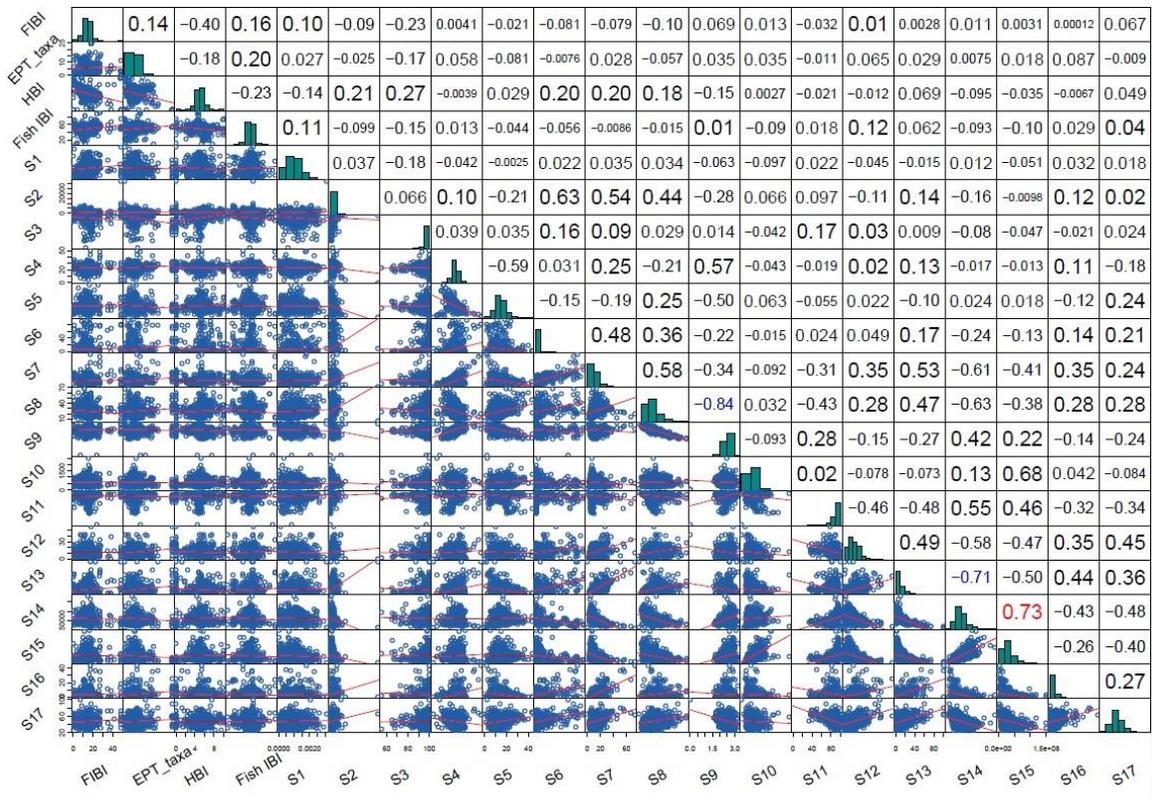


Figure A2. Spearman rank correlation matrix between dependent and independent variables at the block group level. **Boldfaced** value indicates significance at the 0.05 level and correlation less than 0.7, **Boldfaced** value in red indicates significance at the 0.05 level and strongly positive correlation equal or above 0.7, value in blue indicates significance at the 0.05 level and strongly negative correlation equal or below -0.7

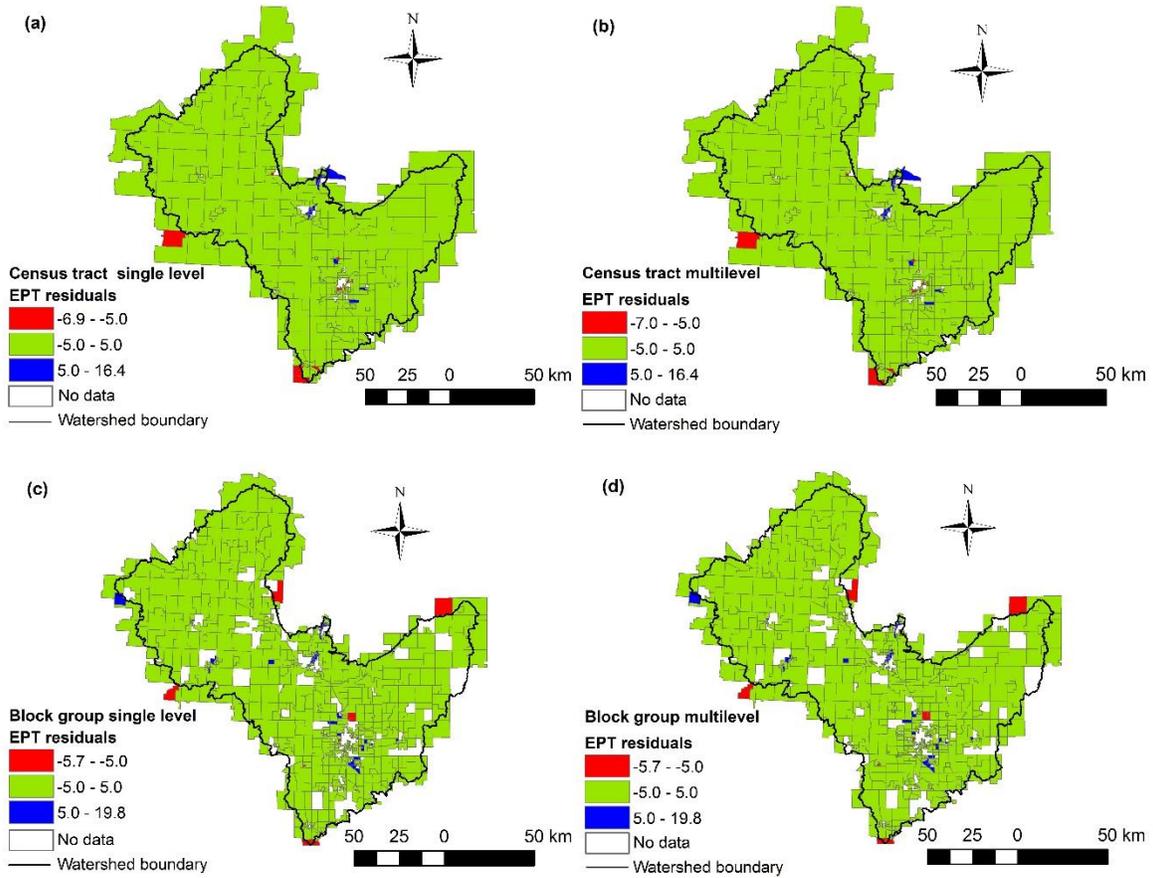


Figure A3. EPT model residuals at: a) census tract single level (no random effect), b) census tract level with multilevel (random) effect, c) block group single level (no random effect), d) block group level with multilevel (nested random) effect

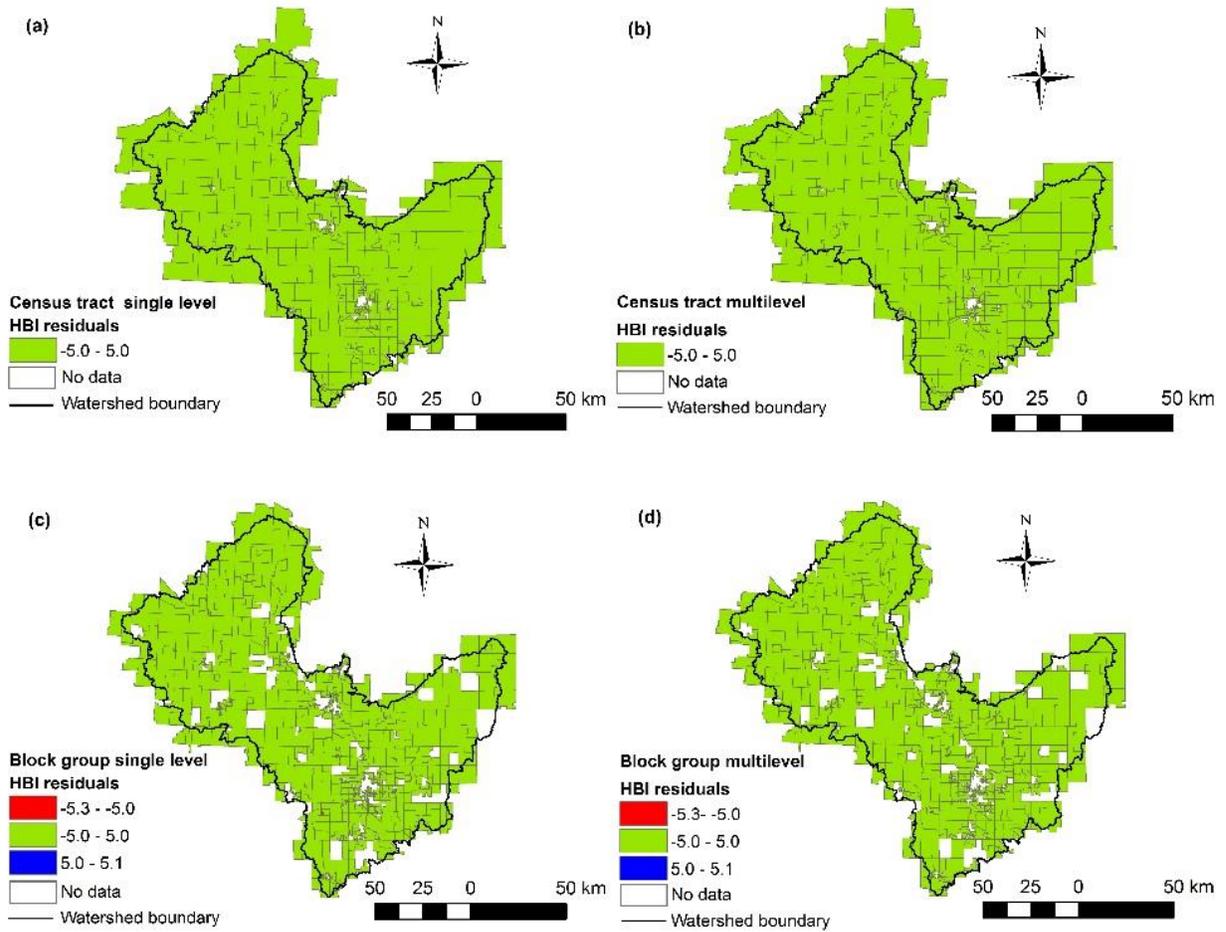


Figure A4. HBI model residuals at: a) census tract single level (no random effect), b) census tract level with multilevel (random) effect, c) block group single level (no random effect), d) block group level with multilevel (nested random) effect

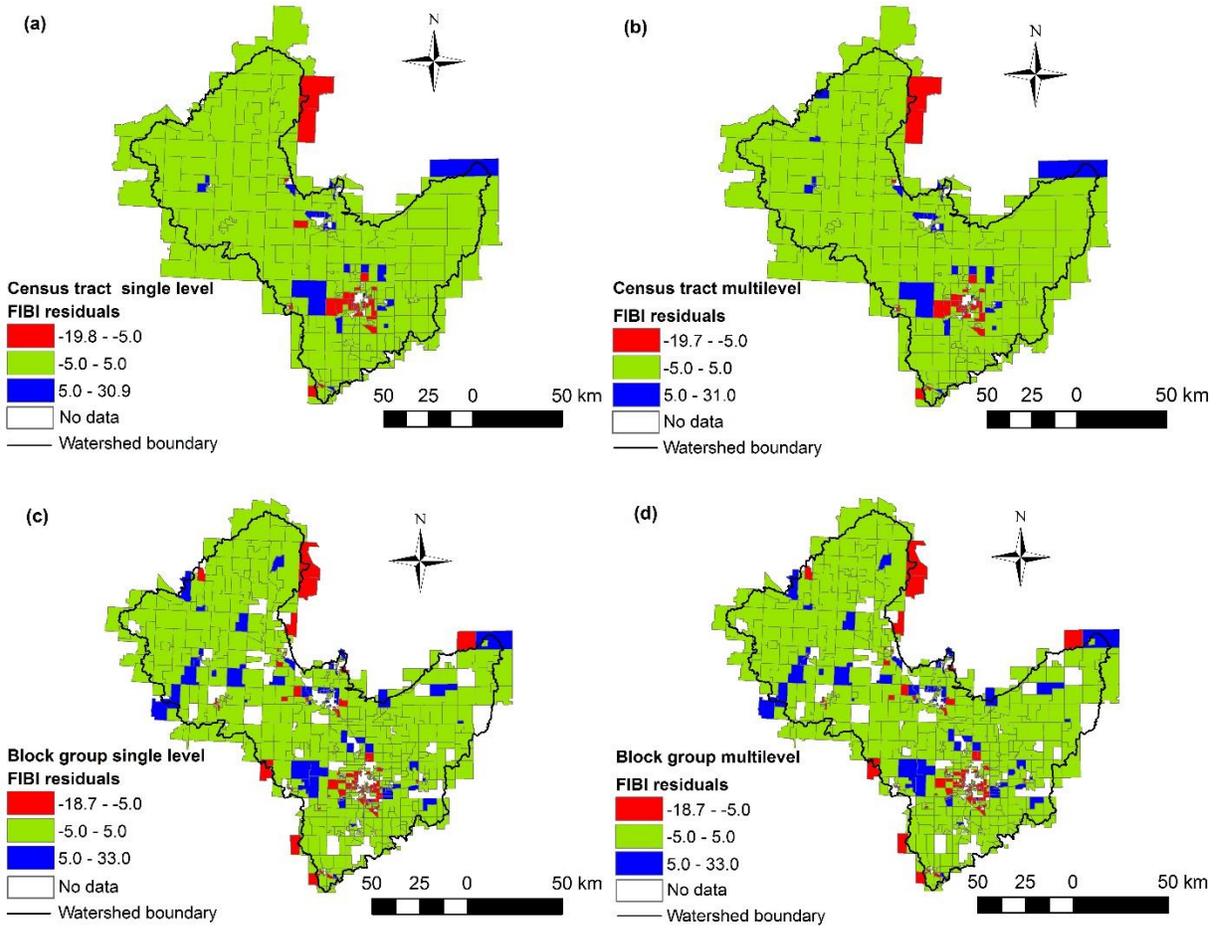


Figure A5. FIBI model residuals at: a) census tract single level (no random effect), b) census tract level with multilevel (random) effect, c) block group single level (no random effect), d) block group level with multilevel (nested random) effect

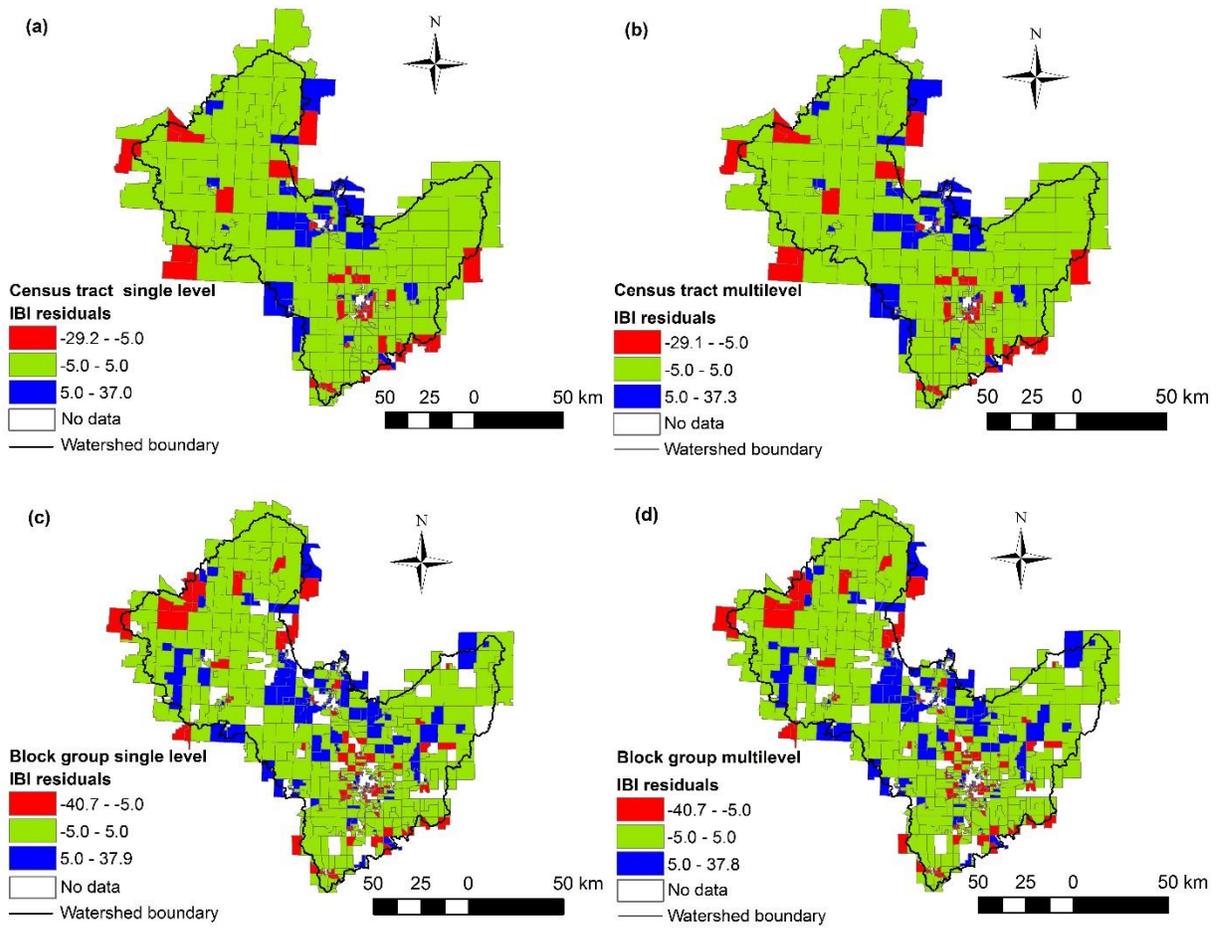


Figure A6. IBI model residuals at: a) census tract single level (no random effect), b) census tract level with multilevel (random) effect, c) block group single level (no random effect), d) block group level with multilevel (nested random) effect

Table A1. Regression models for FIBI at census tract level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	14.76	12.54	16.94	14.68	14.13	15.22	14.82	14.25	15.38
β_1	-0.05	-0.63	0.55	0.07	-0.53	0.65	0.23	-0.37	0.83
β_2	1.19	0.31	2.09	0.72	-0.24	1.69	1.028	0.10	1.95
β_3	-0.26	-0.86	0.36	-0.98	-1.57	-0.38	-0.82	-1.39	-0.24
β_4	-0.80	-1.89	0.30	-1.44	-2.60	-0.31	-1.61	-2.77	-0.45
β_5	0.70	-0.16	1.57	0.80	-0.14	1.73	0.93	-0.07	1.92
β_6	0.71	-0.41	1.79	-0.18	-1.35	0.98	-0.22	-1.33	0.89
β_7	1.65	-0.05	3.35	1.55	-0.31	3.44	1.78	-0.09	3.66
β_8	0.25	-1.62	2.23	-0.13	-2.27	1.98	-0.02	-2.18	2.20
β_9	1.65	-0.43	3.79	2.34	0.10	4.64	2.44	0.13	4.78
β_{10}	1.83	0.33	3.30	2.44	0.79	4.09	2.41	0.74	4.05
β_{11}	0.46	-0.54	1.47	0.91	0.01	1.79	0.83	-0.08	1.72
β_{12}	-0.14	-1.03	0.74	0.13	-0.82	1.08	0.17	-0.80	1.15
β_{13}	0.35	-0.82	1.53	1.67	0.35	2.30	1.57	0.210	2.94
β_{14}	1.40	-0.03	2.86	1.07	-0.51	2.65	1.24	-0.45	2.89
β_{15}	-1.51	-3.32	0.28	-1.68	-3.69	0.30	-1.68	-3.73	0.42
β_{16}	-0.65	-1.62	0.32	-0.97	-2.14	0.22	-0.99	-2.12	0.10
β_{17}	0.30	-0.59	1.22	0.39	-0.66	1.38	0.23	-0.85	1.30
τ^2	96.5	81.8	114.0	137.4	117.4	160.1	27.3	23.3	31.8
γ	0.93	0.83	0.99	0	0	0	0	0	0
DIC	1943.58			2011.64			2030.37		

Table A2. Regression models for EPT at census tract level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.86	3.22	8.33	5.98	5.61	6.34	5.94	5.57	6.32
β_1	-0.11	-0.46	0.25	-0.35	-0.74	0.04	-0.29	-0.68	0.10
β_2	0.46	-0.07	0.99	0.75	0.11	1.39	0.96	0.33	1.58
β_3	-0.04	-0.42	0.31	-0.98	-1.38	-0.59	-1.10	-1.50	-0.70
β_4	1.16	0.48	1.82	0.83	0.04	1.60	0.86	0.070	1.65
β_5	-0.63	-1.15	-0.10	-0.14	-0.79	0.49	-0.14	-0.79	0.49
β_6	0.14	-0.50	0.76	-0.56	-1.34	0.19	-0.66	-1.43	0.13
β_7	-1.36	-2.36	-0.33	-0.59	-1.82	0.62	-0.53	-1.78	0.73
β_8	-0.84	-1.95	0.26	-0.27	-1.71	1.16	-0.31	-1.75	1.15
β_9	-1.65	-2.87	-0.41	-0.73	-2.25	0.79	-0.76	-2.31	0.78
β_{10}	-0.73	-1.59	0.12	-1.24	-2.32	-0.18	-1.18	-2.28	-0.05
β_{11}	-0.04	-0.66	0.57	0.30	-0.30	0.88	0.36	-0.25	0.95
β_{12}	0.24	-0.29	0.77	0.77	0.12	1.40	1.05	0.39	1.71
β_{13}	0.31	-0.41	0.10	0.71	-0.22	1.61	0.51	-0.43	1.39
β_{14}	-0.42	-1.28	0.44	-0.76	-1.79	0.28	-0.67	-1.78	0.45
β_{15}	0.45	-0.62	1.51	1.31	0.02	2.65	1.19	-0.21	2.58
β_{16}	0.08	-0.47	0.64	-0.41	-1.15	0.37	-0.43	-1.18	0.33
β_{17}	0.39	-0.15	0.92	0.56	-0.14	1.24	0.70	0.01	1.43
τ^2	33.4	28.3	39.1	60.6	51.8	70.4	12.4	10.6	14.5
γ	0.98	0.94	0.998	0	0	0	0	0	0
DIC	1606.74			1743.92			1773.60		

Table A3. Regression models for HBI at census tract level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	4.82	4.26	5.36	4.82	4.68	4.95	4.83	4.69	4.97
β_1	0.12	-0.03	0.27	0.15	-0.01	0.30	0.14	-0.02	0.29
β_2	-0.15	-0.38	0.09	-0.16	-0.40	0.09	-0.26	-0.50	-0.01
β_3	0.18	0.02	0.34	0.50	0.35	0.65	0.49	0.34	0.65
β_4	0.09	-0.20	0.38	0.19	-0.10	0.50	0.20	-0.10	0.51
β_5	-0.01	-0.23	0.22	-0.18	-0.42	0.06	-0.19	-0.44	0.07
β_6	-0.22	-0.50	0.07	0.06	-0.23	0.36	0.09	-0.20	0.38
β_7	0.12	-0.32	0.56	0.10	-0.38	0.59	0.05	-0.44	0.54
β_8	-0.32	-0.81	0.17	-0.29	-0.85	0.26	-0.30	-0.88	0.27
β_9	-0.47	-1.02	0.07	-0.65	-1.23	-0.06	-0.67	-1.28	-0.07
β_{10}	-0.01	-0.37	0.38	0.01	-0.41	0.45	0.03	-0.38	0.46
β_{11}	-0.13	-0.40	0.13	-0.28	-0.50	-0.04	-0.25	-0.48	-0.02
β_{12}	-0.09	-0.32	0.14	-0.34	-0.60	-0.10	-0.40	-0.66	-0.15
β_{13}	0.18	-0.13	0.49	-0.17	-0.51	0.18	-0.08	-0.44	0.28
β_{14}	0.04	-0.33	0.41	0.01	-0.40	0.42	-0.03	-0.46	0.40
β_{15}	0.08	-0.38	0.55	-0.02	-0.54	0.49	0.01	-0.53	0.53
β_{16}	-0.05	-0.29	0.20	0.04	-0.25	0.34	0.05	-0.24	0.34
β_{17}	-0.15	-0.39	0.09	-0.08	-0.35	0.17	-0.10	-0.38	0.17
τ^2	6.5	5.6	7.7	9.1	7.8	10.6	1.9	1.6	2.2
γ	0.93	0.83	0.99	0	0	0	0	0	0
DIC	1062.41			1124.94			1151.03		

Table A4. Regression models for IBI at census tract level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	49.25	46.55	52.09	49.27	48.51	50.03	49.30	48.53	50.07
β_1	0.28	-0.52	1.07	0.45	-0.35	1.26	0.46	-0.36	1.27
β_2	-0.85	-2.02	0.41	-0.74	-2.12	0.59	-0.48	-1.76	0.78
β_3	0.02	-0.84	0.88	-1.07	-1.90	-0.26	-1.15	-1.98	-0.31
β_4	0.58	-0.93	2.11	0.12	-1.46	1.72	0.36	-1.27	1.98
β_5	-0.77	-2.00	0.41	-0.97	-2.26	0.32	-1.14	-2.48	0.23
β_6	-0.12	-1.60	1.38	-1.03	-2.65	0.56	-0.76	-2.41	0.82
β_7	1.54	-0.77	3.85	1.18	-1.38	3.71	0.55	-2.13	3.15
β_8	-1.51	-4.13	1.09	-1.39	-4.37	1.56	-1.54	-4.61	1.57
β_9	-1.21	-4.07	1.56	-0.83	-3.96	2.33	-1.22	-4.41	1.97
β_{10}	-1.98	-3.96	0.01	-2.17	-4.36	0.02	-1.96	-4.20	0.32
β_{11}	-0.89	-2.25	0.47	-0.09	-1.30	1.14	0.10	-1.13	1.30
β_{12}	0.73	-0.53	1.94	1.38	0.08	2.71	1.50	0.14	2.85
β_{13}	0.19	-1.44	1.81	1.01	-0.86	2.87	0.32	-1.58	2.18
β_{14}	-1.25	-3.21	0.76	-2.34	-4.48	-0.15	-2.47	-4.74	-0.11
β_{15}	2.28	-0.21	4.63	3.34	0.59	6.04	3.11	0.31	5.92
β_{16}	-2.21	-3.50	-0.89	-2.32	-3.92	-0.71	-1.77	-3.35	-0.16
β_{17}	0.73	-0.51	1.96	0.81	-0.59	2.19	1.11	-0.37	2.63
τ^2	180.7	153.2	212.9	257.6	219.7	301.7	52.9	45.2	61.9
γ	0.92	0.82	0.99	0	0	0	0	0	0
DIC	2146.73			2217.03			2247.36		

Table A5. Regression models for FIBI at block group level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	14.55	12.44	16.62	14.43	14.03	14.82	14.57	14.14	14.99
β_1	0.301	-0.07	0.67	0.59	0.17	1.01	0.53	0.08	0.99
β_2	0.98	0.50	1.47	0.82	0.29	1.36	0.86	0.31	1.41
β_3	-0.09	-0.50	0.30	-0.44	-0.85	-0.03	-0.57	-1.03	-0.11
β_4	-0.06	-0.70	0.58	-0.75	-1.51	-0.02	-1.30	-2.13	-0.49
β_5	0.51	0.001	1.00	0.37	-0.22	0.95	0.75	0.10	1.39
β_6	0.72	0.08	1.40	-0.35	-1.02	0.31	-0.17	-0.86	0.49
β_7	0.98	0.16	1.78	0.61	-0.31	1.55	0.96	-0.04	2.00
β_8	-0.42	-1.37	0.52	-1.39	-2.54	-0.24	-1.09	-2.31	0.15
β_9	0.46	-0.65	1.52	0.41	-0.94	1.72	1.17	-0.27	2.65
β_{10}	-0.01	-0.65	0.61	0.37	-0.42	1.17	0.42	-0.46	1.28
β_{11}	-0.33	-0.91	0.24	0.13	-0.39	0.66	0.30	-0.26	0.86
β_{12}	0.14	-0.28	0.56	0.07	-0.43	0.58	-0.14	-0.69	0.43
β_{13}	-0.31	-0.83	0.22	0.80	0.11	1.47	0.60	-0.12	1.33
β_{14}	0.17	-0.55	0.90	-0.16	-1.04	0.71	-0.51	-1.49	0.51
β_{15}	0.10	-0.72	0.92	-0.05	-1.11	1.02	0.08	-1.09	1.28
β_{16}	-0.06	-0.52	0.40	-0.13	-0.71	0.45	-0.08	-0.69	0.52
β_{17}	0.11	-0.33	0.56	0.30	-0.24	0.84	0.18	-0.43	0.79
τ^2	95.55	86.16	106.9	158.7	143.3	175.5	34.9	31.53	38.77
γ	0.97	0.93	0.99	0	0	0	0	0	0
DIC	4370.06			4622.94			4744.49		

Table A6. Regression models for EPT at block group level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.51	4.03	6.97	5.59	5.362	5.82	5.63	5.37	5.88
β_1	-0.12	-0.33	0.08	-0.25	-0.50	-0.01	-0.27	-0.54	-0.01
β_2	-0.02	-0.29	0.24	-0.17	-0.49	0.16	-0.13	-0.45	0.19
β_3	0.02	-0.20	0.25	-0.72	-0.97	-0.48	-1.08	-1.35	-0.82
β_4	0.13	-0.22	0.48	0.23	-0.20	0.66	0.39	-0.13	0.80
β_5	-0.12	-0.40	0.16	-0.19	-0.54	0.14	-0.21	-0.60	0.17
β_6	0.08	-0.26	0.45	0.12	-0.27	0.50	0.11	-0.28	0.52
β_7	-0.19	-0.64	0.26	0.05	-0.51	0.61	-0.11	-0.71	0.49
β_8	-0.05	-0.56	0.47	0.29	-0.39	0.97	0.38	-0.36	1.14
β_9	-0.16	-0.74	0.44	0.11	-0.69	0.91	0.06	-0.80	0.96
β_{10}	0.15	-0.19	0.50	0.19	-0.27	0.65	0.14	-0.36	0.63
β_{11}	-0.09	-0.42	0.23	0.10	-0.22	0.41	0.23	-0.11	0.58
β_{12}	0.16	-0.07	0.40	0.23	-0.08	0.54	0.32	-0.02	0.67
β_{13}	0.05	-0.26	0.35	0.18	-0.22	0.57	0.15	-0.28	0.57
β_{14}	0.27	-0.13	0.69	0.27	-0.26	0.77	0.18	-0.39	0.75
β_{15}	-0.30	-0.76	0.15	-0.34	-0.93	0.29	-0.34	-1.04	0.36
β_{16}	0.22	-0.03	0.47	0.16	-0.18	0.50	0.20	-0.16	0.57
β_{17}	-0.24	-0.48	0.01	-0.01	-0.32	0.31	0.09	-0.26	0.44
τ^2	29.30	26.37	32.61	55.32	49.86	61.25	12.03	10.86	13.32
γ	0.98	0.95	0.996	0	0	0	0	0	0
DIC	3505.78			3844.15			3956.94		

Table A7. Regression models for HBI at block group level (boldfaced values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.01	4.60	5.38	5.015	4.92	5.10	4.99	4.89	5.09
β_1	-0.11	-0.20	-0.02	-0.07	-0.18	0.03	-0.07	-0.18	0.04
β_2	-0.07	-0.19	0.05	0.01	-0.12	0.14	0.02	-0.11	0.15
β_3	0.04	-0.06	0.14	0.34	0.24	0.44	0.43	0.33	0.54
β_4	0.09	-0.06	0.25	0.20	0.02	0.38	0.24	0.045	0.44
β_5	-0.01	-0.13	0.12	-0.06	-0.20	0.08	-0.10	-0.25	0.06
β_6	-0.01	-0.16	0.15	0.08	-0.08	0.24	0.04	-0.12	0.21
β_7	0.05	-0.16	0.25	0.10	-0.13	0.33	0.11	-0.14	0.36
β_8	-0.04	-0.28	0.18	-0.13	-0.40	0.15	-0.29	-0.59	0.02
β_9	-0.22	-0.49	0.04	-0.50	-0.82	-0.18	-0.71	-1.06	-0.36
β_{10}	0.08	-0.07	0.24	0.05	-0.15	0.24	0.03	-0.18	0.23
β_{11}	0.05	-0.09	0.20	-0.01	-0.14	0.12	-0.04	-0.17	0.10
β_{12}	-0.01	-0.12	0.09	-0.03	-0.16	0.10	-0.06	-0.20	0.07
β_{13}	0.04	-0.09	0.18	-0.10	-0.26	0.05	-0.13	-0.30	0.05
β_{14}	0.12	-0.06	0.30	0.13	-0.08	0.34	0.15	-0.08	0.38
β_{15}	-0.13	-0.34	0.07	-0.07	-0.32	0.19	-0.05	-0.33	0.23
β_{16}	-0.12	-0.24	-0.01	-0.17	-0.31	-0.03	-0.14	-0.28	0.01
β_{17}	-0.01	-0.12	0.09	-0.01	-0.15	0.12	0.03	-0.13	0.18
τ^2	5.90	5.31	6.58	9.33	8.42	10.35	2.06	1.85	2.28
γ	0.95	0.91	0.99	0	0	0	0	0	0
DIC	2305.94			2528.70			2651.31		

Table A8. Regression models for IBI at block group level (**boldfaced** values indicates a significant parameter at the 0.05 level)

Parameters	Spatial			Ordinary regression			Weighted regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	49.14	47.79	50.47	48.98	48.4	49.56	48.99	48.4	49.6
β_1	0.34	-0.29	0.96	0.81	0.19	1.43	0.59	-0.05	1.21
β_2	-0.9	-1.75	-0.08	-1.7	-2.51	-0.85	-1.71	-2.51	-0.92
β_3	-0.57	-1.26	0.08	-0.94	-1.55	-0.34	-1.14	-1.77	-0.5
β_4	-0.69	-1.75	0.36	-0.77	-1.87	0.34	-0.97	-2.17	0.21
β_5	-0.29	-1.13	0.57	-0.48	-1.37	0.36	-0.41	-1.36	0.52
β_6	-0.42	-1.45	0.67	-0.64	-1.6	0.38	-0.65	-1.66	0.33
β_7	1.74	0.38	3.11	1.00	-0.38	2.43	0.86	-0.60	2.35
β_8	-0.56	-2.16	1.07	-1.19	-2.98	0.52	-1.09	-2.92	0.70
β_9	0.39	-1.42	2.197	0.09	-1.94	2.06	0.17	-1.95	2.24
β_{10}	-0.38	-1.48	0.69	-0.59	-1.81	0.59	-0.76	-2.00	0.51
β_{11}	-0.37	-1.27	0.50	0.17	-0.62	0.95	0.36	-0.46	1.18
β_{12}	0.07	-0.66	0.83	0.38	-0.41	1.20	0.23	-0.56	1.04
β_{13}	0.5	-0.42	1.43	1.35	0.35	2.38	1.43	0.40	2.45
β_{14}	-0.93	-2.15	0.32	-1.44	-2.77	-0.15	-1.74	-3.14	-0.32
β_{15}	1.01	-0.38	2.45	1.09	-0.48	2.69	1.24	-0.47	2.96
β_{16}	-0.92	-1.71	-0.13	-1.22	-2.09	-0.35	-1.26	-2.11	-0.42
β_{17}	0.15	-0.60	0.89	0.14	-0.66	0.94	0.24	-0.63	1.11
τ^2	281.2	252.8	313.7	354.2	319.4	393.2	71.6	64.7	79.3
γ	0.84	0.74	0.93	0	0	0	0	0	0
DIC		5120.12			5216.79			5275.78	

APPENDIX B: Study Two

Table B1. Input parameters used for stream health predictive models

Modeling approach	Stream health measure	Water quantity	Water quality
One-phase	IBI*	2 indices including: 1 annual average of flow, and 1 stream segment gradient	3 indices including: 1 annual average of phosphorus, and 2 seasonal averages of nitrogen concentrations
	HBI**	1 index of cross-sectional area	3 indices including: 2 annual averages of nitrogen, and 1 seasonal average of nitrogen concentrations
	FIBI**	2 indices including: 1 annual average of flow, and 1 cross-sectional area	2 indices including: 1 annual average of nitrogen, and 1 annual average of phosphorus concentrations
	EPT**	2 indices including: 1 seasonal average of flow, and 1 cross-sectional area	2 annual average indices of nitrogen concentration
Two-phase	All	171 indices introduced by Poff et al. (1997), including: 94 indices of magnitude, 14 indices of frequency, 44 indices of duration, 10 indices of timing, and 9 indices of rate of change in flow.	78 indices, including: 1 annual average, 1 annual average of coefficient of variation, 12 seasonal averages, and 12 seasonal averages of coefficient of variations for sediment, total nitrogen, and total phosphorus loads.

* This data was obtained from Einheuser et al. (2013a)

** This data was obtained from Einheuser et al. (2012)

Table B2. Comparison of root-mean-square error of developed stream health predictive models

Stream health measures	One-phase approach	Two-phase approach		
	All streams	All streams	Headwater streams	Medium and large streams
IBI	16.37*	7.56****	6.24****	4.96****
HBI	0.45**	0.27***	0.21***	0.11***
FIBI	5.46**	4.14***	1.71***	2.01***
EPT	2.57**	2.04***	0.73***	1.10***

* This data was obtained from Einheuser et al. (2013a)

** This data was obtained from Einheuser et al. (2012)

*** This data was obtained from Daneshvar et al. (2017)

**** Results obtained from this study

Table B3. Regression models for IBI at county level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	45.15	41.25	49.14	45.04	41.74	48.34	45.20	42.20	48.26
β_1	-10.21	-15.65	-4.89	-10.44	-16.77	-4.32	-10.14	-15.55	-4.39
β_2	-28.10	-88.45	29.65	-33.09	-96.69	29.10	-28.48	-87.58	29.80
β_3	13.04	2.99	23.50	14.07	3.34	24.65	13.41	2.54	23.50
β_4	-4.29	-15.89	7.20	-5.03	-18.38	8.02	-4.24	-15.88	7.68
β_5	-6.13	-22.34	10.23	-6.59	-27.57	14.07	-6.30	-23.61	10.68
β_6	5.22	-11.74	21.78	4.30	-13.43	21.47	5.27	-11.23	22.16
β_7	-7.79	-23.15	8.03	-6.71	-23.73	10.91	-7.91	-24.59	8.25
β_8	11.02	-23.49	45.46	9.27	-28.02	47.25	11.14	-24.40	46.32
β_9	9.46	-33.63	52.51	6.92	-39.72	54.71	9.29	-35.75	52.58
β_{10}	81.90	-58.65	228.29	94.54	-49.31	240.04	82.46	-61.00	224.19
β_{11}	0.42	-12.59	13.63	1.24	-13.55	15.83	0.31	-13.22	13.93
β_{12}	14.69	-4.23	34.34	16.67	-4.22	37.40	14.99	-5.71	34.22
β_{13}	-3.24	-18.23	11.55	-3.57	-17.06	10.34	-3.73	-18.16	10.94
β_{14}	10.70	-12.15	33.85	11.06	-13.09	34.49	10.39	-13.25	32.44
β_{15}	-63.48	-163.35	33.08	-71.27	-173.41	31.56	-63.70	-162.81	35.06
β_{16}	-6.27	-17.01	3.78	-6.36	-18.83	6.02	-6.12	-16.76	4.93
β_{17}	1.53	-15.43	19.23	-0.75	-20.03	19.15	1.20	-16.95	19.20
τ^2	181.19	56.99	493.82	56.25	16.03	175.95	202.35	63.39	599.48
γ	-0.14	-0.97	0.93	0.00	0.00	0.00	0.00	0.00	0.00
DIC		156.50			158.74			156.65	

Table B4. Regression models for HBI at county level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	4.96	4.76	5.17	4.95	4.83	5.07	4.95	4.83	5.08
β_1	0.28	0.04	0.51	0.28	0.04	0.51	0.27	0.05	0.50
β_2	1.77	-0.67	4.15	1.98	-0.62	4.37	1.73	-0.63	4.08
β_3	-0.06	-0.50	0.37	-0.07	-0.47	0.31	-0.06	-0.49	0.37
β_4	0.19	-0.30	0.66	0.23	-0.26	0.73	0.19	-0.30	0.67
β_5	0.12	-0.59	0.80	0.12	-0.67	0.90	0.10	-0.60	0.80
β_6	-0.29	-0.95	0.39	-0.21	-0.86	0.47	-0.28	-0.95	0.42
β_7	0.38	-0.28	1.05	0.28	-0.42	0.98	0.36	-0.29	0.99
β_8	0.60	-0.84	2.03	0.64	-0.94	2.03	0.61	-0.84	2.16
β_9	0.65	-1.17	2.39	0.69	-1.19	2.40	0.66	-1.12	2.52
β_{10}	-4.60	-10.47	1.26	-4.96	-10.52	0.79	-4.48	-10.20	1.40
β_{11}	-0.06	-0.62	0.48	-0.06	-0.62	0.50	-0.06	-0.60	0.50
β_{12}	-0.12	-0.94	0.68	-0.17	-0.95	0.56	-0.11	-0.89	0.71
β_{13}	-0.22	-0.82	0.37	-0.21	-0.75	0.32	-0.23	-0.85	0.37
β_{14}	-0.50	-1.47	0.41	-0.56	-1.50	0.39	-0.49	-1.46	0.48
β_{15}	3.08	-1.01	7.09	3.25	-0.80	7.17	2.99	-1.15	6.97
β_{16}	0.02	-0.41	0.47	0.01	-0.45	0.48	0.03	-0.43	0.46
β_{17}	0.09	-0.63	0.81	0.15	-0.58	0.90	0.10	-0.64	0.84
τ^2	0.32	0.10	0.96	0.08	0.02	0.23	0.34	0.11	1.07
γ	0.09	-0.95	0.96	0.00	0.00	0.00	0.00	0.00	0.00
DIC		22.47			22.08			21.72	

Table B5. Regression models for FIBI at county level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	14.88	13.64	16.14	14.80	13.93	15.68	14.89	14.00	15.73
β_1	0.88	-0.64	2.46	0.70	-0.98	2.32	0.87	-0.75	2.44
β_2	23.30	7.03	39.78	22.64	5.90	39.48	23.32	7.26	38.89
β_3	-0.49	-3.30	2.30	-0.40	-3.26	2.58	-0.38	-3.30	2.55
β_4	0.61	-2.47	3.89	0.58	-2.88	4.12	0.58	-2.75	3.90
β_5	-3.31	-8.05	1.34	-3.63	-9.13	1.84	-3.36	-7.97	1.25
β_6	3.69	-0.88	8.25	3.94	-0.77	8.48	3.71	-0.95	8.24
β_7	-5.04	-9.59	-0.57	-5.23	-10.04	-0.49	-5.07	-9.39	-0.62
β_8	4.12	-5.60	13.87	3.79	-6.66	14.43	4.39	-5.67	14.26
β_9	6.30	-5.36	18.41	5.75	-7.49	18.78	6.54	-5.96	18.74
β_{10}	-29.89	-69.31	10.77	-28.71	-69.45	10.96	-29.96	-68.95	9.27
β_{11}	-0.72	-4.44	2.83	-0.49	-4.60	3.56	-0.81	-4.60	2.87
β_{12}	3.93	-1.43	9.19	4.06	-1.37	9.46	4.03	-1.35	9.36
β_{13}	0.67	-3.30	4.71	0.89	-3.13	4.72	0.67	-3.26	4.77
β_{14}	-0.40	-6.86	6.14	-0.35	-6.82	6.21	-0.31	-6.99	6.28
β_{15}	9.12	-18.98	36.11	8.41	-19.97	37.58	9.02	-18.43	36.10
β_{16}	-4.28	-7.16	-1.30	-4.30	-7.58	-1.06	-4.35	-7.29	-1.42
β_{17}	7.45	2.44	12.25	7.19	1.92	12.53	7.42	2.66	12.25
τ^2	14.21	4.38	40.10	4.04	1.23	11.68	15.47	4.99	46.06
γ	-0.06	-0.97	0.96	0.00	0.00	0.00	0.00	0.00	0.00
DIC		102.85			105.09			102.42	

Table B6. Regression models for EPT at county level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	7.44	6.56	8.31	7.35	6.70	8.01	7.43	6.77	8.09
β_1	0.79	-0.42	1.95	0.73	-0.57	2.05	0.78	-0.46	2.02
β_2	16.01	3.54	28.37	16.37	3.46	29.49	15.91	3.76	28.30
β_3	-0.99	-3.25	1.29	-0.89	-3.14	1.33	-0.94	-3.34	1.29
β_4	0.95	-1.57	3.52	1.02	-1.73	3.81	0.94	-1.46	3.44
β_5	-3.24	-6.88	0.37	-3.25	-7.52	0.93	-3.26	-6.98	0.42
β_6	0.18	-3.34	3.78	0.59	-3.06	4.21	0.24	-3.23	3.85
β_7	0.21	-3.12	3.71	-0.18	-3.70	3.45	0.17	-3.40	3.76
β_8	0.19	-7.55	7.55	-0.02	-8.09	7.99	0.28	-6.96	7.79
β_9	-0.69	-10.00	8.19	-1.01	-11.25	9.34	-0.63	-9.95	8.45
β_{10}	-28.93	-58.44	1.72	-29.22	-60.29	1.09	-29.02	-59.22	0.48
β_{11}	-1.55	-4.32	1.27	-1.31	-4.42	1.67	-1.57	-4.46	1.34
β_{12}	1.11	-3.14	5.21	1.16	-3.19	5.50	1.11	-3.17	5.47
β_{13}	0.29	-2.82	3.34	0.42	-2.54	3.26	0.28	-2.75	3.47
β_{14}	-0.34	-5.28	4.50	-0.59	-5.84	4.61	-0.30	-5.11	4.72
β_{15}	14.95	-6.99	36.04	14.88	-6.91	37.13	15.03	-5.39	36.06
β_{16}	-2.88	-5.14	-0.54	-2.98	-5.60	-0.46	-2.88	-5.12	-0.53
β_{17}	5.18	1.34	9.01	5.03	1.03	9.07	5.16	1.40	9.23
τ^2	8.58	2.63	25.85	2.39	0.76	7.02	9.53	2.91	29.57
γ	-0.10	-0.96	0.94	0.00	0.00	0.00	0.00	0.00	0.00
DIC		91.50			94.33			91.56	

Table B7. Regression models for IBI at census tract level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	40.25	28.58	51.49	40.87	39.06	42.64	40.46	38.72	42.18
β_1	-0.15	-1.82	1.56	-1.95	-3.84	-0.03	-2.02	-3.92	-0.16
β_2	0.13	-2.37	2.64	0.14	-2.81	3.08	-0.02	-3.07	3.06
β_3	-0.97	-2.65	0.77	-2.02	-3.85	-0.21	-2.11	-3.98	-0.21
β_4	2.37	-0.73	5.50	2.80	-0.90	6.47	3.04	-0.63	6.63
β_5	-4.68	-7.14	-2.22	-6.00	-9.17	-2.85	-6.07	-9.09	-3.11
β_6	-0.34	-3.43	2.65	-3.00	-6.54	0.51	-1.71	-5.44	1.97
β_7	0.76	-4.02	5.53	-0.22	-6.18	5.74	-1.49	-7.41	4.52
β_8	-1.39	-6.61	4.12	-0.30	-7.15	6.75	-1.66	-8.47	5.02
β_9	-6.03	-11.87	-0.05	-4.69	-12.03	2.73	-5.60	-12.70	1.73
β_{10}	-2.06	-6.23	2.05	0.29	-5.00	5.51	0.49	-4.75	5.72
β_{11}	-3.33	-6.20	-0.38	-5.89	-8.80	-3.06	-5.90	-8.77	-3.10
β_{12}	-0.87	-3.37	1.64	-2.46	-5.55	0.66	-2.13	-5.14	0.90
β_{13}	-2.56	-5.81	0.72	0.80	-3.52	5.13	1.51	-2.71	5.72
β_{14}	1.38	-2.66	5.42	3.21	-2.18	8.44	2.46	-2.57	7.47
β_{15}	-0.87	-5.94	4.14	-2.86	-9.38	3.79	-3.01	-9.37	3.29
β_{16}	-0.77	-3.44	1.94	-3.06	-6.64	0.43	-3.27	-6.97	0.50
β_{17}	1.35	-1.15	3.87	0.64	-2.79	4.05	-0.05	-3.41	3.10
τ^2	748.36	635.32	880.81	275.47	234.80	320.85	1385.93	1184.42	1614.95
γ	0.98	0.93	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		2623.42			2786.37			2767.44	

Table B8. Regression models for HBI at census tract level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.23	4.83	5.61	5.22	5.16	5.28	5.23	5.17	5.29
β_1	0.00	-0.06	0.07	0.07	0.00	0.13	0.06	0.00	0.13
β_2	-0.02	-0.11	0.08	0.04	-0.06	0.14	0.05	-0.05	0.16
β_3	0.02	-0.04	0.08	-0.03	-0.09	0.04	-0.02	-0.09	0.05
β_4	0.04	-0.08	0.15	0.03	-0.09	0.16	0.03	-0.10	0.16
β_5	-0.01	-0.10	0.08	0.05	-0.06	0.15	0.05	-0.06	0.15
β_6	0.08	-0.03	0.18	0.13	0.01	0.26	0.13	0.01	0.26
β_7	-0.04	-0.22	0.13	0.03	-0.17	0.23	-0.01	-0.21	0.19
β_8	0.03	-0.16	0.22	0.01	-0.23	0.24	0.00	-0.24	0.24
β_9	-0.02	-0.23	0.20	-0.08	-0.33	0.17	-0.08	-0.33	0.17
β_{10}	0.12	-0.03	0.27	0.03	-0.14	0.21	0.02	-0.16	0.19
β_{11}	0.03	-0.08	0.13	0.18	0.09	0.28	0.21	0.11	0.31
β_{12}	0.00	-0.09	0.09	0.06	-0.05	0.17	0.05	-0.06	0.16
β_{13}	-0.08	-0.20	0.04	-0.18	-0.33	-0.04	-0.21	-0.37	-0.06
β_{14}	-0.01	-0.15	0.14	-0.08	-0.25	0.10	-0.09	-0.26	0.08
β_{15}	-0.15	-0.33	0.04	-0.06	-0.29	0.16	-0.05	-0.26	0.17
β_{16}	0.03	-0.06	0.13	0.06	-0.07	0.18	0.10	-0.02	0.23
β_{17}	0.00	-0.09	0.09	0.06	-0.05	0.18	0.09	-0.03	0.20
τ^2	0.98	0.83	1.15	0.32	0.27	0.37	1.66	1.42	1.93
γ	0.97	0.93	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		452.75			577.96			567.20	

Table B9. Regression models for FIBI at census tract level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	12.81	9.90	15.63	12.76	12.15	13.37	12.71	12.11	13.30
β_1	0.88	0.25	1.49	0.98	0.33	1.64	0.98	0.32	1.64
β_2	-0.11	-1.09	0.86	-1.04	-2.06	0.01	-0.86	-1.92	0.21
β_3	0.52	-0.11	1.16	1.29	0.65	1.94	1.25	0.58	1.90
β_4	-0.37	-1.56	0.84	-0.27	-1.53	1.03	-0.39	-1.67	0.93
β_5	-0.54	-1.47	0.38	-1.40	-2.46	-0.31	-1.26	-2.30	-0.24
β_6	-0.90	-2.07	0.26	-1.18	-2.44	0.05	-0.88	-2.15	0.39
β_7	1.62	-0.20	3.41	1.25	-0.81	3.30	1.23	-0.84	3.37
β_8	-1.79	-3.80	0.22	-1.16	-3.60	1.27	-1.67	-4.09	0.71
β_9	-1.63	-3.88	0.59	-1.10	-3.64	1.44	-1.33	-3.86	1.23
β_{10}	-1.33	-2.87	0.25	-0.42	-2.16	1.39	-0.53	-2.38	1.34
β_{11}	-1.28	-2.37	-0.18	-2.03	-2.99	-1.05	-2.22	-3.21	-1.22
β_{12}	-0.47	-1.42	0.47	-1.51	-2.63	-0.45	-1.26	-2.34	-0.19
β_{13}	0.48	-0.75	1.72	-0.21	-1.72	1.31	-0.13	-1.62	1.37
β_{14}	0.55	-0.98	2.06	0.23	-1.58	2.05	0.30	-1.47	2.05
β_{15}	1.10	-0.77	3.03	-0.03	-2.29	2.15	0.21	-2.02	2.43
β_{16}	-1.32	-2.32	-0.31	-0.93	-2.15	0.29	-1.14	-2.39	0.15
β_{17}	0.51	-0.48	1.47	0.67	-0.51	1.80	0.58	-0.57	1.69
τ^2	107.96	92.13	126.42	32.81	27.99	38.47	170.00	145.41	197.76
γ	0.95	0.88	0.99	0.00	0.00	0.00	0.00	0.00	0.00
DIC		1984.03			2090.95			2081.21	

Table B10. Regression models for EPT at census tract level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.80	4.08	7.58	5.91	5.67	6.16	5.83	5.57	6.08
β_1	0.38	0.13	0.63	0.16	-0.10	0.42	0.10	-0.17	0.37
β_2	0.22	-0.13	0.60	0.25	-0.16	0.66	0.15	-0.31	0.60
β_3	0.20	-0.06	0.46	-0.01	-0.27	0.26	-0.01	-0.29	0.26
β_4	-0.32	-0.78	0.15	-0.34	-0.87	0.17	-0.34	-0.87	0.20
β_5	-0.21	-0.59	0.15	-0.29	-0.72	0.15	-0.29	-0.72	0.15
β_6	-0.06	-0.52	0.40	-0.68	-1.20	-0.17	-0.62	-1.16	-0.09
β_7	0.18	-0.52	0.89	0.00	-0.86	0.83	-0.10	-0.96	0.75
β_8	-0.05	-0.85	0.75	-0.06	-1.04	0.93	-0.21	-1.21	0.78
β_9	0.00	-0.86	0.85	0.29	-0.73	1.31	0.19	-0.86	1.26
β_{10}	-0.13	-0.74	0.47	0.07	-0.64	0.80	0.06	-0.68	0.80
β_{11}	-0.51	-0.93	-0.08	-1.05	-1.44	-0.66	-1.05	-1.46	-0.64
β_{12}	0.01	-0.38	0.38	0.10	-0.33	0.53	0.08	-0.36	0.53
β_{13}	-0.02	-0.52	0.47	0.44	-0.17	1.04	0.49	-0.14	1.11
β_{14}	0.04	-0.57	0.65	0.31	-0.42	1.06	0.13	-0.59	0.87
β_{15}	0.18	-0.58	0.90	0.11	-0.78	1.01	0.21	-0.71	1.12
β_{16}	-0.19	-0.59	0.21	-0.50	-1.01	0.01	-0.44	-0.98	0.11
β_{17}	0.06	-0.32	0.44	0.02	-0.45	0.51	0.01	-0.46	0.47
τ^2	16.64	14.19	19.55	5.41	4.62	6.33	29.10	24.82	34.08
γ	0.98	0.93	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		1378.87			1501.52			1503.99	

Table B11. Regression models for IBI at block group level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameter s	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	39.00	27.53	49.97	39.39	38.01	40.73	39.31	38.00	40.61
β_1	0.79	-0.30	1.88	-1.43	-2.87	0.04	-1.63	-3.03	-0.21
β_2	-1.18	-2.60	0.24	-2.07	-3.81	-0.30	-1.72	-3.51	0.08
β_3	-0.63	-1.81	0.53	-2.97	-4.42	-1.50	-2.70	-4.08	-1.34
β_4	0.36	-1.48	2.23	0.96	-1.68	3.53	1.90	-0.63	4.34
β_5	-0.98	-2.48	0.44	-3.25	-5.34	-1.21	-2.82	-4.79	-0.89
β_6	-3.86	-5.74	-1.90	-4.30	-6.49	-2.19	-3.97	-6.22	-1.76
β_7	1.77	-0.61	4.14	0.30	-2.91	3.59	-0.30	-3.38	2.83
β_8	2.89	0.13	5.61	2.59	-1.30	6.53	2.03	-1.82	5.85
β_9	0.68	-2.55	3.78	0.27	-4.31	5.00	-0.47	-4.96	3.91
β_{10}	-2.14	-4.00	-0.31	-1.60	-4.37	1.15	-1.46	-4.10	1.21
β_{11}	-0.79	-2.52	0.90	-4.19	-5.94	-2.39	-3.81	-5.55	-2.05
β_{12}	-1.02	-2.25	0.21	-2.52	-4.29	-0.72	-2.18	-3.85	-0.45
β_{13}	-0.50	-2.01	1.03	0.18	-2.11	2.50	0.41	-1.87	2.65
β_{14}	-0.46	-2.57	1.67	-0.73	-3.87	2.51	-0.58	-3.51	2.34
β_{15}	1.82	-0.57	4.20	1.03	-2.70	4.83	0.68	-2.85	4.25
β_{16}	0.88	-0.47	2.21	-0.31	-2.24	1.61	0.13	-1.79	2.10
β_{17}	1.54	0.24	2.83	1.42	-0.53	3.37	1.23	-0.59	3.04
τ^2			901.9	353.4	318.9	392.2	1765.4	1593.5	1952.2
	810.55	731.39	7	6	7	1	5	3	8
γ	0.99	0.97	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		5964.52			6454.62			6403.28	

Table B12. Regression models for HBI at block group level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.23	4.94	5.52	5.23	5.18	5.27	5.23	5.18	5.28
β_1	-0.03	-0.07	0.01	0.01	-0.04	0.06	0.02	-0.03	0.07
β_2	-0.04	-0.10	0.01	-0.10	-0.16	-0.03	-0.10	-0.17	-0.04
β_3	-0.01	-0.05	0.04	-0.02	-0.07	0.03	-0.01	-0.06	0.04
β_4	-0.02	-0.09	0.05	-0.08	-0.17	0.01	-0.10	-0.19	-0.01
β_5	-0.01	-0.07	0.04	0.03	-0.04	0.10	0.01	-0.06	0.08
β_6	0.03	-0.04	0.10	0.07	-0.01	0.15	0.08	0.01	0.16
β_7	-0.02	-0.11	0.07	0.07	-0.04	0.19	0.06	-0.05	0.17
β_8	0.05	-0.06	0.15	0.14	0.00	0.28	0.11	-0.03	0.24
β_9	0.01	-0.10	0.13	0.05	-0.12	0.22	0.03	-0.13	0.19
β_{10}	-0.02	-0.09	0.05	-0.10	-0.19	-0.01	-0.09	-0.19	0.00
β_{11}	-0.01	-0.08	0.06	0.10	0.04	0.17	0.11	0.04	0.17
β_{12}	-0.03	-0.08	0.02	-0.02	-0.08	0.05	-0.03	-0.09	0.03
β_{13}	0.05	-0.01	0.11	0.01	-0.07	0.09	0.02	-0.06	0.09
β_{14}	0.03	-0.05	0.11	-0.05	-0.16	0.05	-0.05	-0.15	0.05
β_{15}	-0.01	-0.10	0.08	0.07	-0.06	0.20	0.07	-0.05	0.19
β_{16}	0.00	-0.05	0.05	0.01	-0.06	0.08	0.02	-0.05	0.09
β_{17}	0.01	-0.04	0.05	0.02	-0.05	0.09	0.03	-0.03	0.09
τ^2	1.19	1.07	1.33	0.43	0.38	0.47	2.21	1.99	2.45
γ	0.98	0.95	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		1139.18			1488.91			1463.87	

Table B13. Regression models for FIBI at block group level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	12.95	10.09	15.63	12.74	12.27	13.20	12.88	12.44	13.31
β_1	0.76	0.36	1.14	1.02	0.55	1.50	0.77	0.27	1.25
β_2	-0.55	-1.07	-0.02	-0.72	-1.31	-0.15	-0.68	-1.30	-0.03
β_3	-0.01	-0.44	0.43	0.69	0.21	1.18	0.51	0.03	1.00
β_4	0.16	-0.52	0.86	0.02	-0.86	0.90	0.25	-0.63	1.09
β_5	-0.52	-1.07	0.00	-0.96	-1.66	-0.28	-0.76	-1.42	-0.09
β_6	-0.74	-1.44	-0.05	-1.11	-1.87	-0.38	-1.13	-1.90	-0.36
β_7	0.15	-0.71	1.06	-0.30	-1.40	0.81	-0.21	-1.30	0.87
β_8	-0.94	-1.97	0.06	-0.89	-2.24	0.48	-1.07	-2.38	0.24
β_9	-0.79	-1.97	0.36	-0.36	-1.92	1.22	-0.36	-1.90	1.16
β_{10}	-0.25	-0.93	0.43	0.15	-0.77	1.04	0.23	-0.69	1.14
β_{11}	-0.16	-0.82	0.48	-1.42	-2.02	-0.79	-1.22	-1.82	-0.59
β_{12}	0.23	-0.23	0.69	-0.43	-1.04	0.18	-0.33	-0.94	0.29
β_{13}	0.10	-0.46	0.69	-0.20	-0.98	0.58	-0.18	-0.94	0.59
β_{14}	-0.28	-1.05	0.51	-0.08	-1.15	0.95	-0.15	-1.15	0.87
β_{15}	0.52	-0.39	1.41	-0.16	-1.42	1.12	-0.17	-1.38	1.06
β_{16}	0.04	-0.46	0.54	-0.04	-0.69	0.60	-0.11	-0.77	0.56
β_{17}	0.04	-0.43	0.52	0.37	-0.32	1.05	0.43	-0.20	1.05
τ^2	111.26	100.11	123.76	41.16	37.09	45.62	211.86	191.23	235.16
γ	0.98	0.95	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		4491.20			4865.83			4836.51	

Table B14. Regression models for EPT at block group level (**Boldfaced** values indicate significant parameters at the 0.05 level)

Parameters	spatial			Weighted regression			Ordinary regression		
	mean	lower	upper	mean	lower	upper	mean	lower	upper
β_0	5.85	4.70	7.01	5.87	5.68	6.07	5.82	5.63	6.01
β_1	0.32	0.14	0.49	0.27	0.06	0.47	0.22	0.02	0.43
β_2	0.09	-0.15	0.33	0.14	-0.12	0.39	0.10	-0.17	0.38
β_3	-0.03	-0.23	0.16	-0.18	-0.39	0.02	-0.11	-0.32	0.09
β_4	0.04	-0.27	0.34	-0.05	-0.43	0.33	0.04	-0.33	0.41
β_5	-0.14	-0.38	0.11	-0.33	-0.64	-0.03	-0.29	-0.58	-0.01
β_6	-0.17	-0.48	0.15	-0.44	-0.77	-0.13	-0.52	-0.85	-0.19
β_7	-0.15	-0.54	0.24	-0.43	-0.90	0.05	-0.44	-0.90	0.04
β_8	0.02	-0.43	0.49	-0.33	-0.92	0.25	-0.32	-0.91	0.25
β_9	0.01	-0.51	0.52	0.03	-0.66	0.69	0.01	-0.67	0.66
β_{10}	-0.07	-0.38	0.24	0.31	-0.09	0.72	0.27	-0.14	0.67
β_{11}	-0.16	-0.44	0.11	-0.69	-0.96	-0.43	-0.75	-1.01	-0.49
β_{12}	0.15	-0.06	0.36	0.14	-0.12	0.40	0.10	-0.16	0.37
β_{13}	-0.05	-0.31	0.21	0.13	-0.20	0.46	0.20	-0.13	0.55
β_{14}	-0.08	-0.43	0.28	0.16	-0.29	0.62	0.08	-0.36	0.51
β_{15}	0.11	-0.28	0.52	-0.31	-0.86	0.25	-0.23	-0.76	0.30
β_{16}	0.02	-0.20	0.24	-0.17	-0.45	0.10	-0.17	-0.46	0.12
β_{17}	0.07	-0.14	0.28	0.23	-0.06	0.51	0.19	-0.08	0.45
τ^2	22.32	20.13	24.85	7.44	6.72	8.24	39.16	35.32	43.48
γ	0.98	0.95	1.00	0.00	0.00	0.00	0.00	0.00	0.00
DIC		3301.39			3602.18			3589.46	

Table B15. Significant parameters of former developed single level (with no random effect) regression models (adapted from Daneshvar et al. (2016))

Index	Census level	Spatial	Weighted regression	Ordinary regression
IBI	County	S1, S3, S7, S11, S12, S13, S14, S16, S17	S1, S3, S7, S11, S12, S13, S14, S16, S17	S1, S3, S7, S11, S12, S13, S14, S16, S17
	Census tract	S16	S3, S12, S14, S15, S16	S3, S12, S14, S15, S16
	Block group	S2, S7, S16	S2, S3, S13, S14, S16	S1, S2, S3, S13, S14, S16
HBI	County	S2, S3, S5, S10, S13, S17	S2, S3, S5, S10, S13, S17	S2, S3, S5, S10, S13, S17
	Census tract	S3	S2, S3, S9, S11, S12	S3, S9, S11, S12
	Block group	S1, S16	S3, S9	S3, S9, S16
FIBI	County	S2, S3, S6, S10, S15, S17	S2, S3, S6, S10, S15, S17	S2, S3, S6, S10, S15, S17
	Census tract	S2, S10	S3, S4, S9, S10, S13	S3, S4, S9, S10, S11, S13
	Block group	S2, S5, S6, S7	S1, S2, S3, S4, S5	S1, S2, S3, S4, S8, S13
EPT	County	S1, S3, S5, S8, S9, S15	S1, S3, S5, S8, S9, S15	S1, S3, S5, S8, S9, S15
	Census tract	S4, S5, S7, S9	S2, S3, S4, S10, S12, S17	S2, S3, S4, S10, S12, S15
	Block group	-	S1, S3	S1, S3

Table B16. DICs of multilevel models with random effect (**boldfaced** values represent best models at each census level)

Census level	IBI	HBI	FIBI	EPT	County	Census tract	Block group
County	157.05	21.66	102.72	91.66	S	-	-
	155.21	21.26	103.02	92.10	WR	-	-
	159.36	20.66	104.73	92.91	OR	-	-
Census tract	2623.40	452.17	1984.62	1378.67	-	S	-
	2767.23	566.99	2080.73	1503.45	-	WR	-
	2786.39	578.36	2090.36	1500.95	-	OR	-
	2545.98	374.99	1911.28	1303.82	S	S	-
	2693.09	519.87	2051.87	1494.41	S	WR	-
	2758.83	532.41	2127.92	1492.62	S	OR	-
	2547.84	374.58	1907.28	1302.31	WR	S	-
	2738.06	518.64	2120.23	1496.95	WR	WR	-
	2711.38	531.05	2128.32	1495.14	WR	OR	-
	2577.94	398.04	1939.60	1332.71	OR	S	-
	2797.10	520.75	2117.31	1495.01	OR	WR	-
	2778.78	533.68	2124.73	1494.39	OR	OR	-
Block group	5963.90	1138.60	4490.49	3301.54	-	-	S
	4771.02	-14.54	3157.34	2728.20	-	S	S
	4760.74	-147.77	3477.51	2179.16	-	WR	S
	5209.03	424.34	5199.75	3085.80	-	OR	S
	5891.49	1059.42	4414.88	3227.68	S	-	S
	4638.39	-58.75	3995.43	2549.41	S	S	S
	4668.49	-178.71	3012.60	2567.20	S	WR	S
	5101.30	331.39	5664.51	3286.72	S	OR	S
	5891.27	1061.49	4414.31	3225.52	WR	-	S
	4748.95	-168.91	4891.46	1951.01	WR	S	S
	4582.47	-185.82	3067.69	2218.64	WR	WR	S
	5196.39	326.04	5669.20	3677.82	WR	OR	S
	5917.26	1085.44	4448.66	3253.57	OR	-	S
	4750.03	27.82	3156.61	3936.86	OR	S	S
	4575.22	-232.51	3178.86	1976.94	OR	WR	S
	5124.94	335.07	5707.52	3457.36	OR	OR	S
	6402.57	1463.68	4835.85	3588.55	-	-	WR
	6310.63	1154.37	5978.36	4228.37	-	S	WR
	5278.24	1384.96	5248.37	4448.53	-	WR	WR
	5647.59	1367.25	6153.98	4427.92	-	OR	WR
6349.00	1367.86	4820.98	3515.08	S	-	WR	
4981.45	1074.26	5076.34	4147.85	S	S	WR	
5215.06	1282.79	5250.74	4368.86	S	WR	WR	

Table B16. (cont'd)

6552.89	1269.07	6148.93	4346.66	S	OR	WR
6352.81	1368.25	4822.64	3522.26	WR	-	WR
8141.82	1075.42	5901.44	4150.88	WR	S	WR
5110.65	1284.42	4404.15	4379.42	WR	WR	WR
5649.36	1269.91	6150.23	4358.68	WR	OR	WR
6403.09	1365.45	4819.88	3520.87	OR	-	WR
5244.83	1099.75	5930.90	4181.62	OR	S	WR
5096.33	1281.20	4384.33	4374.62	OR	WR	WR
5561.06	1266.87	6149.38	4354.36	OR	OR	WR
6454.18	1488.14	4865.62	3601.96	-	-	OR
5255.03	1211.91	5999.84	4264.16	-	S	OR
5174.01	1431.45	4433.10	4483.43	-	WR	OR
6617.13	1436.20	6192.67	4481.22	-	OR	OR
6451.08	1396.14	4837.30	3530.47	S	-	OR
5058.44	1134.36	5205.39	4194.31	S	S	OR
5132.75	1331.21	5295.58	4402.44	S	WR	OR
6613.27	1337.35	6178.11	4401.13	S	OR	OR
6405.06	1397.41	4839.72	3537.43	WR	-	OR
5204.89	1132.23	5923.58	4192.28	WR	S	OR
5287.24	1333.95	4448.26	4410.71	WR	WR	OR
6788.09	1340.97	6180.55	4408.32	WR	OR	OR
6456.93	1393.59	4837.34	3536.58	OR	-	OR
5170.98	1154.58	5953.40	4223.69	OR	S	OR
6308.15	1330.46	5317.24	4408.29	OR	WR	OR
6652.80	1335.65	6175.45	4407.38	OR	OR	OR

S: Spatial; WR: Weighted Regression; OR: Ordinary regression

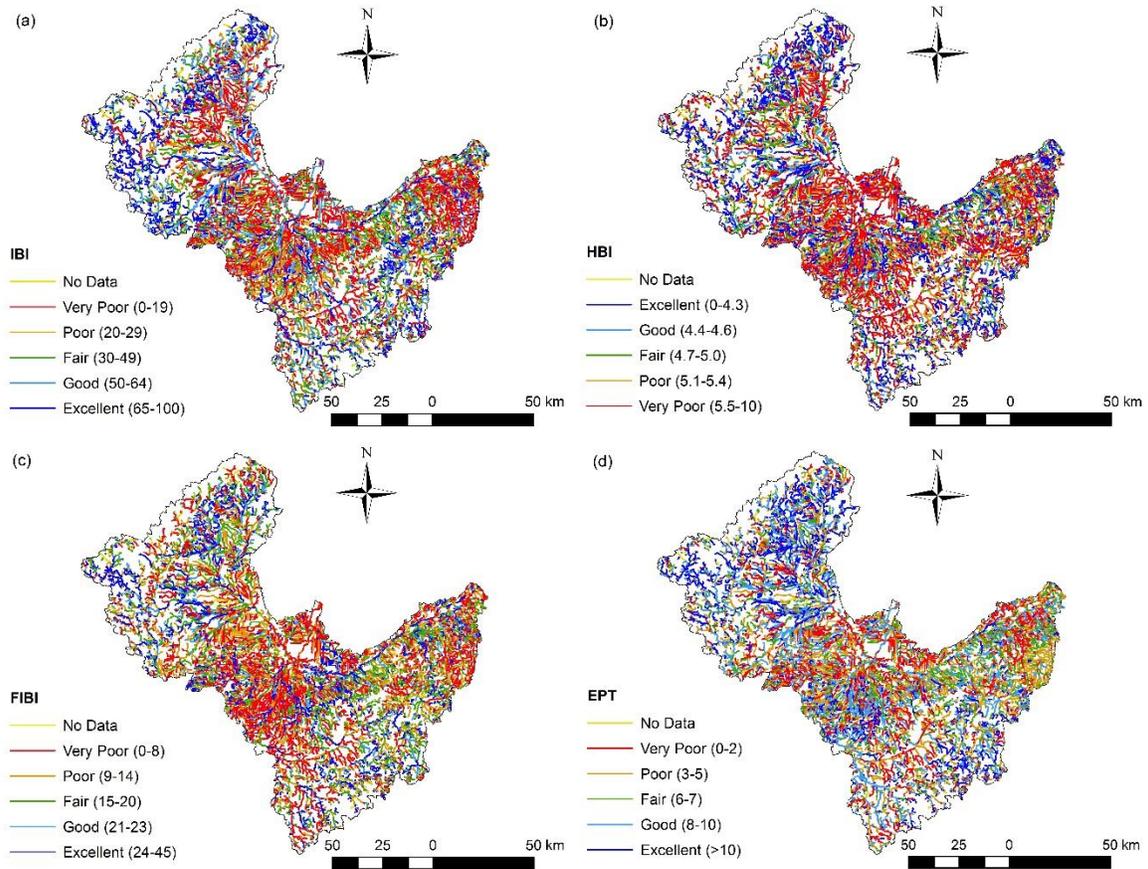


Figure B1. Predicted stream health indices for Saginaw River Basin: (a) IBI, (b) HBI, (c) FIBI, (d) EPT using the two-phased approach (data for sections b, c, and d are adapted from Daneshvar et al. (2017))

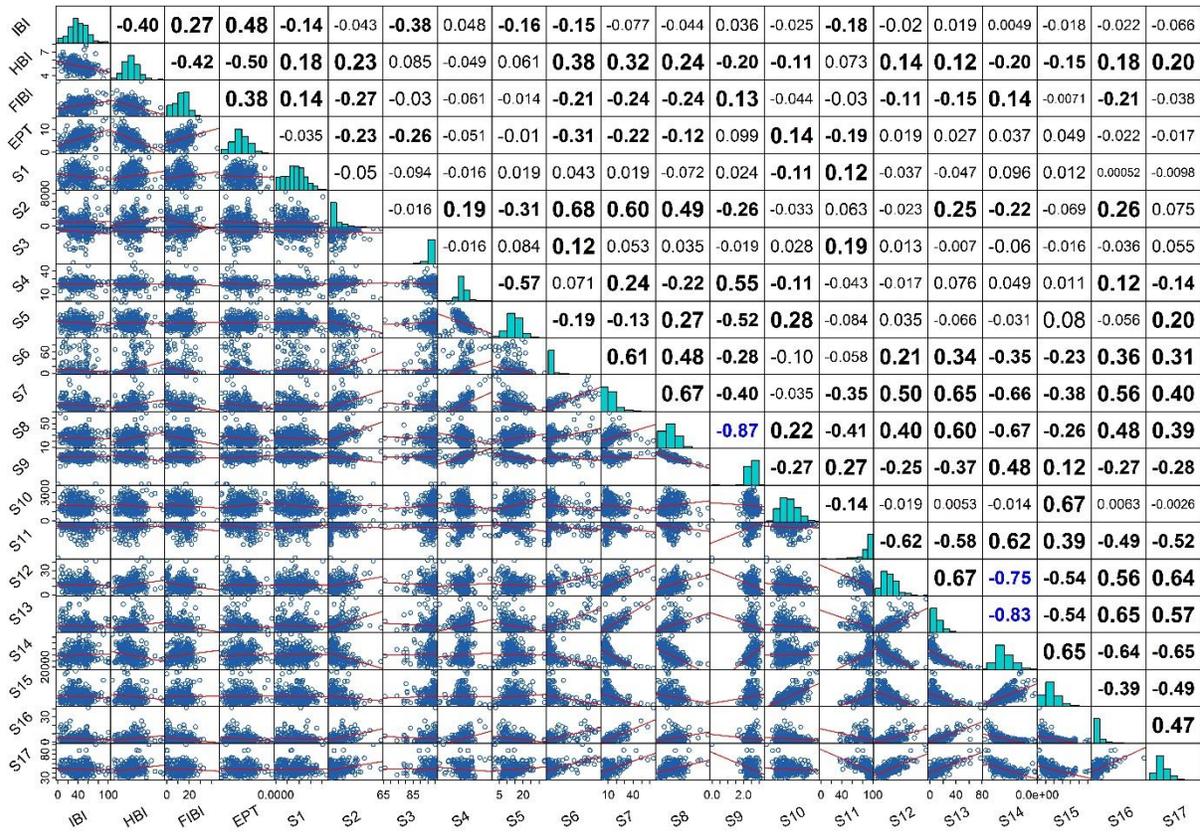


Figure B2. Correlation matrix of indices at the census tract level. The diagonal represents the scatterplots, while lower level and upper levels represent pairwise distributions and correlation coefficients, respectively. Boldfaced numbers represent significant correlation coefficients at the 0.05 level. Red and blue values represent positive and negative significant correlation coefficients with absolute value above 0.7 at 0.05 level

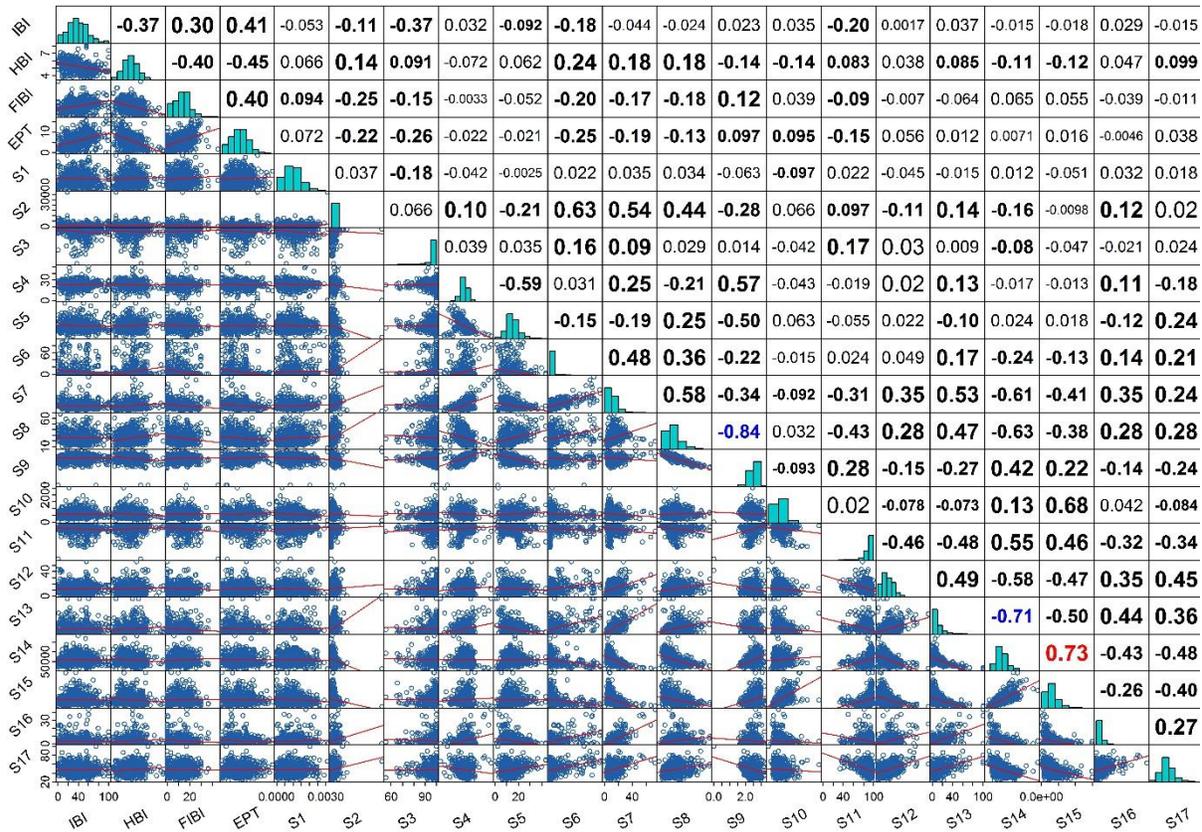


Figure B3. Correlation matrix of indices at the block group level. The diagonal represents the scatterplots, while lower level and upper levels represent pairwise distributions and correlation coefficients, respectively. Boldfaced numbers represent significant correlation coefficients at the 0.05 level. Red and blue values represent positive and negative significant correlation coefficients with absolute value above 0.7 at 0.05 level

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