Large-scale Climate Change Vulnerability Assessment of Stream Health

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ABSTRACT

Freshwater streams are critical resources that provide multiple benefits to humans and aquatic biota alike. As climate changes, it is projected that changes to the hydrological cycle and water temperatures will affect individual biota and aquatic ecosystems as a whole. The goal of this study was to determine the extent of climate change impacts on stream ecosystems as represented by four commonly used stream health indicators (Ephemeroptera, Plecoptera, and Trichoptera taxa (EPT), Family Index of Biotic Integrity (FIBI), Hilsenhoff Biotic Index (HBI), and fish Index of Biotic Integrity (IBI)). Seven watersheds in Michigan were selected based on stream thermal regimes. The Soil and Water Assessment Tool was used to simulate streamflow and pollutant loads. Important variables for each thermal class were selected using a Bayesian variable selection method and used as inputs to adaptive neuro-fuzzy inference systems models of EPT, FIBI, HBI, and IBI. Finally, an ensemble of climate models from the Coupled Model Intercomparison Project Phase 5 were used to determine the impacts of climate on the stream health in 2020-2040 compared to 1980-2000. The risk of declining stream health was determined using cumulative distribution functions. A stream temperature regression model was also developed to assess potential changes in stream thermal regimes, which could cause shifts in composition of aquatic communities. Several flow regime variables, including those related to flow variability, duration of extreme events, and timing were mainly affected by changing climate. At the watershed scale, most indicators were relatively insensitive to changing climate and the magnitude of stream health decline was low. However, at the reach scale, there are many instances of high risk and large magnitude of declines in the stream health indicators. At the

41 same time, several streams experienced changes in thermal class, mostly transitioning from cold-
42 transitional and cool streams to warm streams. This research demonstrated the applicability of
43 the stream health modeling process in performing a climate change impacts assessment.

44 ***Keywords:*** Stream Health; Biological Integrity; Fish; Macroinvertebrate; Fuzzy Logic; Stream
45 Temperature

46

47 **1 INTRODUCTION**

48   Since 1951, the Earth's surface has warmed by 0.72 °C, while the last three decades were
49 successively warmer than any ever recorded (IPCC, 2013). The Intergovernmental Panel on
50 Climate Change (IPCC) concluded that it is extremely likely that anthropogenic activities,
51 primarily greenhouse gas (GHG) emissions, caused more than half of these increases (IPCC,
52 2013). By the end of the 21st century, increases in global average surface temperatures
53 projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations are
54 projected to be between 0.3-4.8 °C depending on radiative forcing, although these increases will
55 vary regionally (IPCC, 2013). As the atmosphere warms, its water holding capacity will increase
56 and the hydrologic cycle will intensify, resulting in changes in frequency of precipitation
57 extremes and increased evaporation and dry periods (Liebowitz et al., 2014; Piani et al., 2010;
58 Praskievicz and Bartlein, 2014; Prudhomme et al., 2014). These changes in the hydrologic cycle
59 have potentially serious implications for water resources and freshwater ecosystems. Hydrologic
60 conditions such as floods and droughts have direct ecological effects (Lytle and Poff, 2004),
61 while water temperature is a controlling factor on species distribution and community
62 composition (Durance and Omerod, 2007; DeWeber and Wagner, 2014). Some locations have
63 already experienced shifts in aquatic community composition and structure towards selection of
64 species that tolerate increased temperature and lower flows (Chessman, 2009). The IPCC (2014)
65 has recognized that climate change is a significant threat to global biodiversity and ecosystem
66 function.

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

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

to a changing climate, establishing their continued utility in biological assessment. In addition, Lawrence et al. (2010) demonstrated that higher taxonomic resolutions (order and family) rather than genus and species were useful for detecting climate change.

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

2 MATERIALS AND METHODS

2.1 Study Watersheds

Seven 8-digit hydrologic unit code (HUC-8) watersheds in Michigan, USA were the subject of this study: the Au Sable (HUC 04070007), Boardman-Charlevoix (HUC 04060105), Cedar-Ford (HUC 04030109), Flint (04080204), Muskegon (04060102), Pere Marquette-White (04060101), and Raisin (04100002) (Figure 1). The watersheds were selected based on their availability of fish and macroinvertebrate sampling data, and diversity of physiographic characteristics including land use, soils, and stream thermal classes.

Figure 1.

Drainage areas of the watershed range 2639 km² for the Cedar-Ford to 7071 km² for the Muskegon. Land use characteristics of the watersheds vary, where the Au Sable, Boardman-

111 Charlevoix, and Cedar-Ford primarily consist of forests and wetlands, while the Flint, Raisin,
112 Muskegon, and Pere Marquette-White are a mix of agriculture, forests, urban areas, and
113 wetlands. Soils range from well-drained sandy soils for the Au Sable, Boardman-Charlevoix,
114 Muskegon, and Pere-Marquette White to more poorly drained soils in the Flint and Raisin
115 watersheds.

116 The Au Sable River watershed surface geology consists of coarse-textured sands and
117 gravels from glacial and ice-contact outwash (Zorn and Sendek, 2001). Over 90% of the
118 watershed consists of sand, loamy-sand, or wet-sandy-organic (Zorn and Sendek, 2001). The
119 sandy soils are poorly consolidated and susceptible to erosion. Soil and geologic conditions in
120 the watershed cause high groundwater inflows and very stable streamflow (Zorn and Sendek,
121 2001). Almost 90% of the stream length in the watershed is composed of headwater streams
122 (Strahler stream order 1-3), while the remaining is order 4-6, where order 6 makes up 6% of total
123 watershed stream length (152 km).

124 The Boardman-Charlevoix watershed consists of similar surficial geology and soils,
125 where glacial till and outwash dominate. Soils are primarily dry and sandy of the Kalkaska,
126 Grayling, and Rubicon series (Kalish and Tonello, 2014). However, the fruit-growing areas of
127 the watershed are characterized by poorly drained organic soils such as Tawas and Carbondale
128 (Kalish and Tonello, 2014). Flows in the Boardman watershed and tributaries are very stable due
129 the geology and soils. Hydrologic conditions in the Boardman-Charlevoix are similar to the Au
130 Sable, given their similar geology, soils, and geographic proximity. Over 90% of the watershed
131 is composed of headwater streams, while 5 is the highest stream order present.

The Cedar-Ford watershed surficial geology is primarily made of medium-textured glacial till. Alfisols and histosols are the dominant soil types, alternating between well drained and poorly drained conditions. Slopes in the watershed are moderate, averaging between 1-7%. Streamflow in the watershed is moderately stable. The Cedar-Ford watershed has the smallest stream orders of the study watersheds: 86% of the stream length is order 1-3, with the remaining 14% being 4th order streams.

The Flint River watershed geology and soils vary widely from the headwaters to the outlet. The headwaters are generally comprised of rolling hills with sandy loam glacial moraines, while the downstream reaches and main branch of the Flint River flatten out into a glacial lake plain with poorly drained clay and sandy soils (Leonardi and Gruhn, 2001). Alterations in the Flint River watershed (e.g. urbanization and agricultural expansion) have led to unstable daily flows that are highly responsive to storms and snowmelt. The Flint River is the only river in the study watersheds to reach order 7 (for 8 km of its length). Almost 90% of the total watershed stream length is comprised of headwater streams, while the remaining streams are generally of order 4-5.

The Muskegon River watershed is dominated by glacial landforms that support constant groundwater inputs (O'Neal, 1997). Soils in the watershed are primarily classified as moderately and highly permeable. Glacial aquifers composed of lacustrine sand, till, and outwash and glaciofluvial deposits underly the entire watershed (O'Neal, 1997). Daily streamflow for the Muskegon River and its tributaries are moderately stable with high levels of groundwater input (O'Neal, 1997). Stream orders in the Muskegon are 90% headwaters, and 10% mid-reaches. The Muskegon River itself is order 6 for 171 stream km.

The Pere Marquette-White watershed geology is primarily glacial drift, with both high moraines and low outwash plains (Balke et al., 2011). Overlying soils are sandy with moderate to excessive drainage. Some hydric soils are present (mucky sand and muck) and form wetland complexes in the headwaters of the watershed (Balke et al., 2011). Topography in the watershed is generally flat. Given the surface geology and soils, streams in the Pere Marquette-White watershed are generally groundwater fed and moderately stable (Balke et al., 2011). Stream orders in the Pere Marquette-White are 87% order 1-3 and 13% order 4-6, where over half of the total stream miles are 1st order streams.

The River Raisin watershed is comprised of undulating and hilly topography in the west and northwest leading into flat terrain in the southeast (Dodge, 1998). In the northwestern glacial moraines (headwaters) the geology and soils are permeable and semi-permeable, leading to relatively stable flows and more groundwater recharge (Dodge, 1998). In the flat southeast lake plain, the surficial geology and soils are less permeable with flashy streams (Dodge, 1998). In general, agricultural expansion and channel modification have made streamflow throughout the watershed flashier. The River Raisin watershed contains 85% 1-3 order streams and 15% order 4-6 streams.

Stream thermal class was used as a selection criteria because temperature dictates the abundance, occurrence, distribution, and physiology of aquatic biota (Lyons et al., 2009; Poole and Berman, 2001; Wehrly et al., 2003). Differences in water temperature among streams are most pronounced during peak summer temperatures in the northern hemisphere (Caissie et al., 2006; Wehrly et al., 2009). Therefore, July mean temperature is a commonly used predictor of fish assemblage structure (Steen et al., 2008; Werhly et al., 2003; Wehrly et al., 2009). Given the importance of temperature as a control of stream ecosystem function (Olden and Naiman, 2010),

Zorn et al. (2008) developed stream thermal classes (cold, cold-transitional, cool, and warm) for Michigan based on July mean water temperature and fish communities. Macroinvertebrates are also affected by stream temperature, as modified thermal regimes can disrupt emergence and reduce population success (Bunn and Arthington, 2002). However, because of the economic value of fisheries and its management need, stream thermal classes have only been developed based on fish in Michigan. Study watersheds and stream thermal classes are presented in Figure 1. The stream thermal classes and watersheds that have at least 10% of streams in a particular class are defined in Table 1.

Table 1.

2.2 Data Collection

2.2.1 Physiographic Data

Several physiographic datasets were used for watershed model development, including topography, land use, soils, stream networks, and climate. The topography dataset was the 30 m resolution United States Geological Survey (USGS) gridded National Elevation Dataset (NED, 2014). The land use dataset was the 30m United States Department of Agriculture (USDA) – National Agricultural Statistics Service (NASS) 2012 Cropland Data Layer (NASS, 2012). The soil dataset was the spatial and tabular USDA Soil Survey Geographic Database (SSURGO) with resolutions ranging from 1:12,000 to 1:63,600. Stream networks were obtained from the Great Lakes Regional River Database Classification System developed by the Michigan Institute of Fisheries Research (IFR), based on the 1:24,000 resolution National Hydrography Dataset Plus (NHDPlus). These streams and catchments are defined so each individual stream segment and subwatershed represents a homogeneous area of biological, physiological, and

geomorphological characteristics (Einheuser et al., 2013b). Daily precipitation and air temperature (maximum and minimum) were obtained for 1978-2005 from the National Climatic Data Center (NCDC, 2015). The NCDC dataset was comprised of 40 precipitation and 39 temperature stations selected for minimal missing data (less than 5% missing of the 1978-2005 record). Precipitation and temperature station locations are presented in Figure A1 of the Supplementary Materials.

2.2.2 Biological Data

Fish data were from the Michigan stream fish survey database managed by the Institute for Fisheries Research (Ann Arbor, Michigan). This database contains survey records where wadeable stream fish were collected using backpack and tow-barge electrofishing units from May to October between 1982 and 2008 (Wang et al. 2012). Macroinvertebrate data were from the Michigan Department of Environmental Quality. This database contains survey records that macroinvertebrates were sampled using dip-nets on multiple habitats from June to September in of 1996-2003 (MDEQ, 1997). From these data, we calculated three macroinvertebrate and one fish indicator: number of Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa, Family-level Index of Biotic Integrity (FIBI), the Hilsenhoff Biotic Index (HBI), and the fish Index of Biotic Integrity (IBI). Both fish and macroinvertebrate data were used because they respond differently to stressors, operate on dissimilar scales, and represent unique trophic levels (Barbour et al., 1999; Flinders et al., 2008). The total number of samples in each stream thermal class varied: 141 macroinvertebrate and 85 fish for cold, 51 macroinvertebrate and 38 fish for cold-transitional, 120 macroinvertebrate and 113 fish for cool and 123 macroinvertebrate and 59 fish for warm.

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

2.3 Modeling Process

The modeling process contains two primary procedures: development of stream health models and development of the stream temperature model (Figure 2). Both procedures began with baseline climate data and climate scenarios from climate models' future projections of temperature and precipitation. The stream health models began with development of Soil and Water Assessment Tool (SWAT) watershed models that simulate streamflow and water quality for each study stream. Ecologically relevant flow regime variables were calculated using the Hydrologic Index Tool (HIT) on SWAT streamflow output. Bayesian variable selection (Woznicki et al., 2015) identified best variable sets for use as predictors in stream health models of EPT taxa, FIBI, HBI, and IBI. These models were developed for each thermal class. Meanwhile, the statistical stream temperature model used climate and physiographic data to predict future stream temperatures and potential changes in thermal class.

Figure 2.

2.4 Development of Ecologically-Relevant In-Stream Variables

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

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

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

2.5 Stream Health Model

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

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

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

The MATLAB (R2013b) Fuzzy Logic Toolbox was used to build the ANFIS models. Five MF shapes were tested: triangular, trapezoidal, Gaussian, Gaussian composite, and generalized bell. A limit of three variables was placed on model development, because increasing the number of variables requires an increase in the number of fuzzy parameters, and subsequently more input data, which was scarce. To prevent over-fitting, the number of ANFIS parameters should not exceed the number of training input (Sanikhani and Kisi, 2012). For the same reason, a maximum of four MFs per variable was used. All possible combinations of MF shape, number of MFs, and variables (selected from the Bayesian method) were fit (over 500 epochs) using 10-fold cross validation. More details about the ANFIS model details can be found

in Woznicki (2015). Model performance ranged from R^2 equal to 0.49 (cold) to 0.68 (cold-transitional) for EPT, 0.44 (cool) to 0.74 (cold-transitional) for FIBI, 0.41 (cold) to 0.65 (cold-transitional) for HBI, and 0.37 (cool) to 0.90 (cold) for IBI. The most commonly selected MF shapes were nonlinear: Gaussian, Gaussian composite, and generalized bell. The selected variables for the final 16 stream health models are presented in Table 2.

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

Table 2.

2.6 Climate Change Data

The control period of 1980-2000 was compared with future climate change data that was obtained from World Climate Programme's CMIP5 (Taylor et al., 2011) multi-model ensemble for 2020-2040. The 2020-2040 period was selected for analysis because near-century changes are more applicable to decision-makers. Middle and end of century climate change is construed in terms that are more abstract by decision-makers (Weber, 2006). This will affect the perceived risk of declining stream health and damage the potential for development of adaptation strategies because it will require immediate costs and sacrifices to achieve distant and abstract goals (Weber, 2006).

The CMIP5 dataset used in this study included simulations from ten modeling groups (Table 3) comprised of sixteen general circulation model (GCMs) under three representative

concentration pathways (RCPs), for a total of 48 scenarios. The RCPs were developed by Moss et al. (2010) for the IPCC Fifth Assessment Report and are defined by radiative forcing pathways rather than the socioeconomic scenarios and GHG emissions as in the Special Report on Emissions Scenarios (Nakicenovic and Swart, 2000) of the IPCC Third and Fourth Assessment Reports. The three RCPs used were RCP4.5, RCP6.0, and RCP8.5, where each number represents the estimated trajectory of radiative forcing (W/m²) by 2100. Estimated CO₂-equivalent GHG emissions by 2100 of each RCP are approximately 650 ppm, 850 ppm, and greater than 1370 ppm for RCP4.5, RCP6.0, and RCP8.5, respectively. The CO₂ concentrations used in SWAT were selected for the middle of the simulation period (2030), characterized by atmospheric concentrations of 435 ppm, 428 ppm, and 448 ppm for RCP4.5, RCP6.0, and RCP8.5, respectively.

Table 3.

The change factor approach was used in this study to generate daily time series climate change projections. This method calculates monthly anomalies between the GCM simulated control (1980-2000) and future scenario runs (2020-2040) that are superimposed on the observed time series data (1980-2000) (Teutschbein and Seibert, 2012). Precipitation change factors are calculated using a ratio (because precipitation is zero-bounded), where a change factor of one indicates no change in precipitation. Temperature change factors are additive. Gridded GCM data was extracted at the nearest land grid point for each observation station (40 precipitation and 39 temperature) and monthly change factors were applied to the daily precipitation and daily maximum and minimum temperature. Change factors for precipitation and maximum and minimum temperature are presented in Figure 3 for one weather station central to the study

watersheds (USC00203429 at 43.2025°, -85.2422° in Figure A1 of the Supplementary Materials).

Figure 3.

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

2.7 Stream Temperature Model

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

from 1990-2003 by the Michigan Department of Natural Resources (Wehrly et al., 2009). There were 422 samples, with multiple years of data from some sites.

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

Linear mixed modeling using low-rank radial smoothing splines (LMM-Smooth) was used to develop the stream temperature model. Wehrly et al. (2009) found that the LMM-Smooth method outperformed multiple linear regression, generalized additive modeling, and kriging in predicting July mean stream temperature for Michigan and Wisconsin. The landscape variables are fixed effects, while the random error is comprised of smooth-scale and micro-scale variation in stream temperature and white noise measurement error. Spatial autocorrelation in stream

temperature is considered by placing knots throughout the study area that are based on the distances between streams and knots (Wehrly et al., 2009). Because the method is low-rank, the number of knots is less than the number of observations (Schabenberger, 2005). The *kd*-tree method was used to determine optimal number and placement of knots (Schabenberger, 2005), produced a total of 47 knots throughout the study area. The LMM-Smooth model was fit using the SAS 9.3 GLIMMIX procedure (SAS, 2015).

The LMM-Smooth model fitting process used 10-fold cross validation and the root-mean-square error (RMSE) and mean absolute error (MAE) of each validation fold were used to assess model accuracy. Average RMSE and MAE across the ten validation folds were 2.07 °C and 1.59 °C, respectively, similar in performance to the Michigan (RMSE = 2.00 °C, MAE = 1.55 °C) and Wisconsin (RMSE = 2.32 °C, MAE = 1.83 °C) LMM-Smooth models fit by Wehrly et al. (2009). The standardized coefficients of the fixed effects for the LMM-Smooth model fit to the full dataset are presented in Table A2 of the Supplementary Materials. All variables were significant at $\alpha=0.01$ except FOREST, which also was the case for the Wisconsin model developed by Wehrly et al. (2009). Following model fitting, each of the 10-fold models were applied to all streams in the study area for each climate scenario to develop projections of changes in future stream temperatures based on the predictions of the ten models. The stream temperature projections were based on the change factors applied to the NCDC station data with results representing average July mean stream temperature for 2020-2040.

3 RESULTS AND DISCUSSION

3.1 Ecological-Relevant Variables and Stream Health

Scatterplots of stream health indicators versus percent changes under climate change scenarios for predictor variables used in the stream health models are presented in Figure 4 (cold) and Figure A2 (cold-transitional), Figure A3 (cool), and Figure A4 (warm) of the Supplementary Materials. Here, the stream health predictions and predictor variable values were calculated using the stream length-weighted average across all study streams. Each figure also presents the Spearman's rank correlation coefficient (ρ) between stream health measures and percent change in flow regime variable. These figures demonstrate potentially altered flow regimes in the future (comparing 2020-2040 to the baseline 1980-2000), and that these changes both positively and negatively affect stream health represented by EPT, FIBI, HBI, and IBI.

Several of the stream health indicators were correlated with changes in predictor variables, indicated by a larger r . For example, the projected changes in variability of monthly flow values MA31 (August flows) and MA27 (April flows) were highly correlated with EPT and HBI, respectively (Figure 4). This shows that when variability decreased, stream health improved in cold streams. Note that HBI was positively correlated with increasing variability; this indicates that stream health declined with increased flow variability because lower HBI represents better stream health. These correlations are likely due to relatively lower flashiness in cold streams (especially in the Boardman-Charlevoix and Au Sable) because they are primarily groundwater-fed rather than surface-fed (Zorn and Sendek, 2001). However, projected increases in timing variables TA1 (constancy) and TA2 (predictability) result in declining FIBI, although the increases in constancy and predictability and decrease FIBI were relatively minor.

Figure 4.

Several input variables were correlated with stream health indices used in the cold-transitional models (Figure A2 in the Supplementary Materials). As with cold streams, lower flashiness and improved predictability resulted in improved stream health measures. Increases in TH3 (seasonal predictability of non-flooding) improved EPT, demonstrating the importance of predictability in the timing of flood free periods for macroinvertebrates; with the potential for increases in future flooding and variability in flood timing due to climate change, sensitive EPT taxa will decline. Decreases in skewness of monthly flows (MA40) resulted in lower FIBI, while increasing RA9 (variability in number of days where the change in flow from one day to another changes direction), caused falling FIBI. The changes in variability as represented by MA40 and RA9 demonstrate the importance of consistent flows (less flashiness) for cold-transitional streams. Finally, fish IBI decreased with greater RA7 (negative changes in flow from previous day's flow) magnitudes, where the greater the average decrease in flow from the previous day resulted in worse stream health.

Predictor variables for cool streams (Figure A3 in the Supplementary Materials) experienced trends as with cold and cold-transitional streams. As climate change increased variation in February flows (MA25), both EPT and FIBI decrease; a similar relationship was found in the colder thermal classes. In addition, TH3 (seasonal predictability of non-flooding) was positively correlated with FIBI, as in cold and cold-transitional streams. Changes in low (DL) and high (DH) duration variables with respect to HBI also exhibited clear trends. When climate changes projected increases in DL15 (magnitude of 90% exceedance flows), stream health improved, while greater high flow durations (DH18) negatively affected stream health. This demonstrates the balance between the benefits of greater low flows but highlights potential

impacts on stream health as duration of flooding events increases. No obvious trends were present with IBI variables, although decreases in constancy (TA1) and predictability (TA2) resulted in slight IBI declines. Due to the overall small decreases in IBI coupled with small changes in TA1 and TA2, overall cool IBI can be considered insensitive to climate change.

Warm stream predictor variables' characteristics were similar to some of those found in cool streams (Figure A4 in the Supplementary Materials). For example, DH22 (number of days between flood events with recurrence interval of 1.67 years) increased in most climate scenarios, resulting in improved fish IBI. This demonstrates that more frequent flooding as projected in some climate scenarios will be detrimental to stream health. However, many of the variables experienced slight increases in flow variability due to climate change (DL9, FH2, DL17, and MH19). Most warm streams in the study area are located in watersheds that contain flow regimes driven by surface runoff (due to relatively poorly drained soils and extensive agricultural operations). Increases in DL9 (variability annual minimum of 30-day moving average flow), FH2 (variability in high pulse count), DL17 (variability in low pulse duration), and MH19 (skewness in annual maximum flows) improved stream health overall. Because the increases in variability are not extreme under climate change, they maintain the existing flow regime of surface runoff-driven streams, and their increases are beneficial to macroinvertebrate and fish communities in warm streams.

Overall, climate change affects flow regime of streams in all thermal classes. However, these changes were projected to have both positive and negative effects on stream health. The changes in EPT, FIBI, and HBI with respect to changes in the predictor variables were relatively low, indicating that coldwater macroinvertebrates are somewhat insensitive to changing climate. Changes in cold fish IBI were much greater. The resulting impacts on macroinvertebrate and fish

communities demonstrate the contrast between stream thermal classes and their biotic response to climate change. Healthy biotic communities in cold and cold-transitional streams will be contingent upon continued predictability and low flashiness of representative streams, while warm streams showed the importance of maintaining a surface runoff-driven flow regime to stream biota. Meanwhile, the transitional nature of cool streams was a bridge between the effects of climate change on cold streams and warm streams by exhibiting similarities to both thermal classes.

3.2 Climate Change Impacts on Stream Temperature

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

Changes in stream temperature were projected to be smaller than the projected changes in air temperature. Mean increases were consistent across thermal classes (with minimum and maximum in brackets): +0.81°C [0.21 – 1.62°C] for cold streams, +0.82°C [0.26 – 1.63°C] for

cold-transitional streams, +0.82°C [0.26 – 1.64°C] for cool streams, and +0.82°C [0.29 – 1.67°C] for warm streams.

These changes translated into some shifts in thermal classes, where a colder class converted to a warmer class. Figure 5 presents the number of stream kilometers across the study area in each class change. Warm streams do not experience any change in stream class because there were no climate scenarios that project cooler July mean air temperatures. The greatest changes occur in the “transitional” streams, cold-transitional and cool. This was expected because they are defined by relatively narrow stream temperature ranges (Table 1) and are occupied by varying biota that prefer cold and cool waters. Of greatest concern was the warming of cold streams due to their temperature sensitive biota. Across all climate scenarios, an average of 20% of the cold streams (based on length) became cold-transitional, while no streams increased by more than one thermal class. Projected changes in stream thermal class across all climate scenarios are presented in Figure 6 for the Pere Marquette-White watershed. This figure confirms the overall minimal changes in thermal class. Due to only a limited number of changes occurring (which were shifts to cold-transitional streams), cold streams will still be able to support coldwater species and negative effects would likely only be experienced by the most sensitive coldwater species. This is because cold-transitional streams still support primarily coldwater species (Zorn et al., 2008).

Figure 5.

Figure 6.

3.3 Climate Change Vulnerability Assessment of Stream Health

Cumulative distribution functions (CDFs) were developed based on the stream length-weighted average of EPT, FIBI, HBI, and IBI for each thermal class (Figure 7). In this figure, stream thermal classes are defined by row and stream health indicators are defined by column (e.g. top-left is EPT Taxa for cold streams and bottom-right is IBI for warm streams). The CDFs represent stream health values under climate change projections (2020-2040) compared to the baseline stream health (1980-2000). Each CDF indicates the relative risk of declining stream health for each thermal class. The location of the baseline stream health on the CDF identifies the probability declining stream health under projected future climate. In addition, the slopes of the CDFs indicate the climate change sensitivity of each thermal class and stream health indicator. A greater CDF slope represents lower sensitivity of the stream health indicator to changing climate.

Figure 7.

The risk of declining in average stream health and the indicators' sensitivity to climate change varied greatly across stream indicators and thermal classes (Figure 7). For EPT, the risk of decline is relatively low (less than 50% for all thermal classes). The sensitivity of EPT to climate change is also low because there is little variation in EPT across climate scenarios. FIBI demonstrated a greater risk of decline, where all but cold-transitional streams are projected to experience greater than 50% risk of FIBI degradation. Cold-transitional and cool streams also are the most sensitive with respect to FIBI. HBI is likely to improve overall (decreasing HBI represents better stream health, left of the current health), especially in the warmer thermal classes. Cool and warm streams' HBI was projected to improve under all climate scenarios.

Finally, IBI sensitivity to climate change varied greatly across thermal class. Cold streams were highly sensitive to climate change and all climate scenarios projected declines of up to 20 points. Meanwhile, IBI in cold-transitional and cool streams was projected to decline, but the magnitude of the decline was much less than for cold streams.

Climate sensitivity of each stream health indicator and thermal class combination is largely a function of the ANFIS stream health models and the predictor variables. We can link the relationship between how climate change altered the predictor variables in section 4.1 to the CDFs. For example, the average timing variables TA1 (constancy) and TA2 (predictability) do not experience extreme changes (Figure 4), and therefore cold-EPT is somewhat insensitive to climate change (Figure 7). Meanwhile, cold-IBI is greatly declines under changing climate (Figure 7), likely because of the climate sensitivity of the timing variables that were used in the ANFIS stream health models. Here, variables TL1 (Julian date of annual minimum flow) and TL2 (variability in Julian date of annual minima) are highly sensitive to changing climate, and these timing changes have extensive negative impacts on cold IBI.

For climate change adaptation measures and targeting of critically vulnerable streams, analysis at the local scale is critical to stream protection. A probability map of declining stream health indicators is presented for the Pere Marquette-White watershed in Figure 8, which demonstrates the reach scale variability in probability of decline. The same figure for the complete study area (IBI) is presented in Figure A5 of the Supplementary Materials. For example, Figure 8a (EPT) demonstrates the overall agreement between the CDFs in Figure 7 and the individual reaches, in that risk of declining EPT is relatively low across the watershed. However, several individual reaches are highly likely to experience declines in stream health.

A map that describes the average magnitude of stream health decline (Figure 9) can be multiplied by the probability map (Figure 8). This combination identifies locations that have a large risk of declining stream health coupled with a large magnitude of decline. In locations where these conditions are met, individual streams should be classified as critically threatened by climate change. The ‘unacceptable’ levels of risk and magnitude of stream health degradation could be defined by watershed stakeholders and natural resource managers to determine locations to target adaptation and stream protection measures. This process was completed in Figure 10 using the Jenks natural breaks method to define low, medium, and high vulnerability streams for the Pere Marquette-White watershed. There are few locations that are highly vulnerable in the watershed, as most of the streams were experienced to project low or no vulnerability. The magnitude of declining IBI and risk of declining IBI are presented in Figure A6 and Figure A7 of the Supplementary Materials, respectively.

Figure 8.

Figure 9.

Figure 10.

4 CONCLUSIONS

The primary objective of this study was to determine the impacts of projected climate changes on stream health. Initially, watershed models were developed for seven watersheds in Michigan (Woznicki, 2015) encompassing four stream thermal classes (cold, cold-transitional, cool, and warm). Bayesian variable selection (Woznicki et al., 2015) was used to select

589 influential flow regime and water quality variables for development of ANFIS stream health
590 models for EPT, FIBI, HBI, and IBI. The watershed and stream health models were then driven
591 by climate scenarios from the multi-model CMIP5 ensemble to develop projections of stream
592 health in 2020-2040 as compared to the baseline 1980-2000. A stream temperature regression
593 model was also developed to identify shifts in stream thermal classes as defined by July mean
594 stream temperature.

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

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

607   Changes in stream health were depicted using CDFs to identify indicators and thermal
608 classes that were at risk of declining health under future climate change. In addition, the CDFs
609 characterized the overall sensitivity of a stream health indicator to climate change. The average
610 response of stream health indicators was generally insensitive to changing climate. However,

when analyzing risk and magnitude of declining stream health on a localized reach-level basis, the impacts of climate change were more pronounced. This demonstrates the importance of vulnerability assessment in development of potential adaptation measures.

There are limitations related to use of the change factor method in development of the climate change ensemble. Future studies will benefit from including multiple sources of climate data and multiple downscaling and bias correction methods, including those that do not adhere to the stationarity assumption. However, the assessment framework presented in this study is robust in that any climate data and downscaling and bias correction methods could be easily incorporated here.

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

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Figure Captions:

Figure 1. Stream thermal classes for (a) Au Sable, (b) Boardman-Charlevoix, (c) Cedar-Ford, (d) Flint, (e) Muskegon, (f) Pere-Marquette-White, and (g) Raisin; (h) watershed locations in Michigan

Figure 2. Modeling process

Figure 3. Monthly change factors across all climate models and RCPs for (a) precipitation, (b) maximum temperature, and (c) minimum temperature

Figure 4. Stream health for cold streams as a function of percent change in flow regime variable under future climate scenarios. Spearman's ρ values are presented in the top right of each figure, and red dots indicate baseline stream health. Variable definitions are provided in the supplementary materials

Figure 5. Percent change in stream thermal classes

Figure 6. Probability of shifted thermal class due to climate change for the Pere Marquette-White watershed

Figure 7. Average stream health CDFs of each thermal class and stream health indicator, where the black line is comprised of the climate scenarios (2020-2040) and the red dot is the baseline stream health (1980-2000)

Figure 8. Probability of declining (a) EPT, (b) FIBI, (c) HBI, and d (IBI) under projected climate change for the Pere Marquette-White watershed

Figure 9. Average magnitude of change in (a) EPT, (b) FIBI, (c) HBI, and d (IBI) under projected climate change. Symbology is reversed for HBI because lower values are better

Figure 10. Map combining risk of declining stream health with average magnitude of declining stream health across all climate scenarios for (a) EPT, (b) FIBI, (c) HBI, and d (IBI). This represents the vulnerability of degraded stream health in 2020-2040

Figure 1

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Table 1. Characteristics of Michigan stream thermal classes

Thermal Class	Temperature	Biotic community	Study Watersheds
Cold	$\leq 17.5\text{ }^{\circ}\text{C}$	Coldwater	Boardman-Charlevoix; Au Sable; Muskegon; Pere Marquette-White
Cold-transitional	$17.5 - 19.5\text{ }^{\circ}\text{C}$	Coldwater, some warmwater	Au Sable; Pere Marquette-White
Cool	$19.5 - 21.0\text{ }^{\circ}\text{C}$	Warmwater, some coldwater	Boardman-Charlevoix; Cedar-Ford; Flint; Muskegon; Pere Marquette-White; Raisin
Warm	$> 21\text{ }^{\circ}\text{C}$	Warmwater	Cedar-Ford; Flint; Raisin

Table 2. Variable selection results for each stream health model and temperature class, adapted from Woznicki (2015)

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

*See abbreviations section for complete variable definitions

Table 3. CMIP5 multi-model ensemble dataset

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