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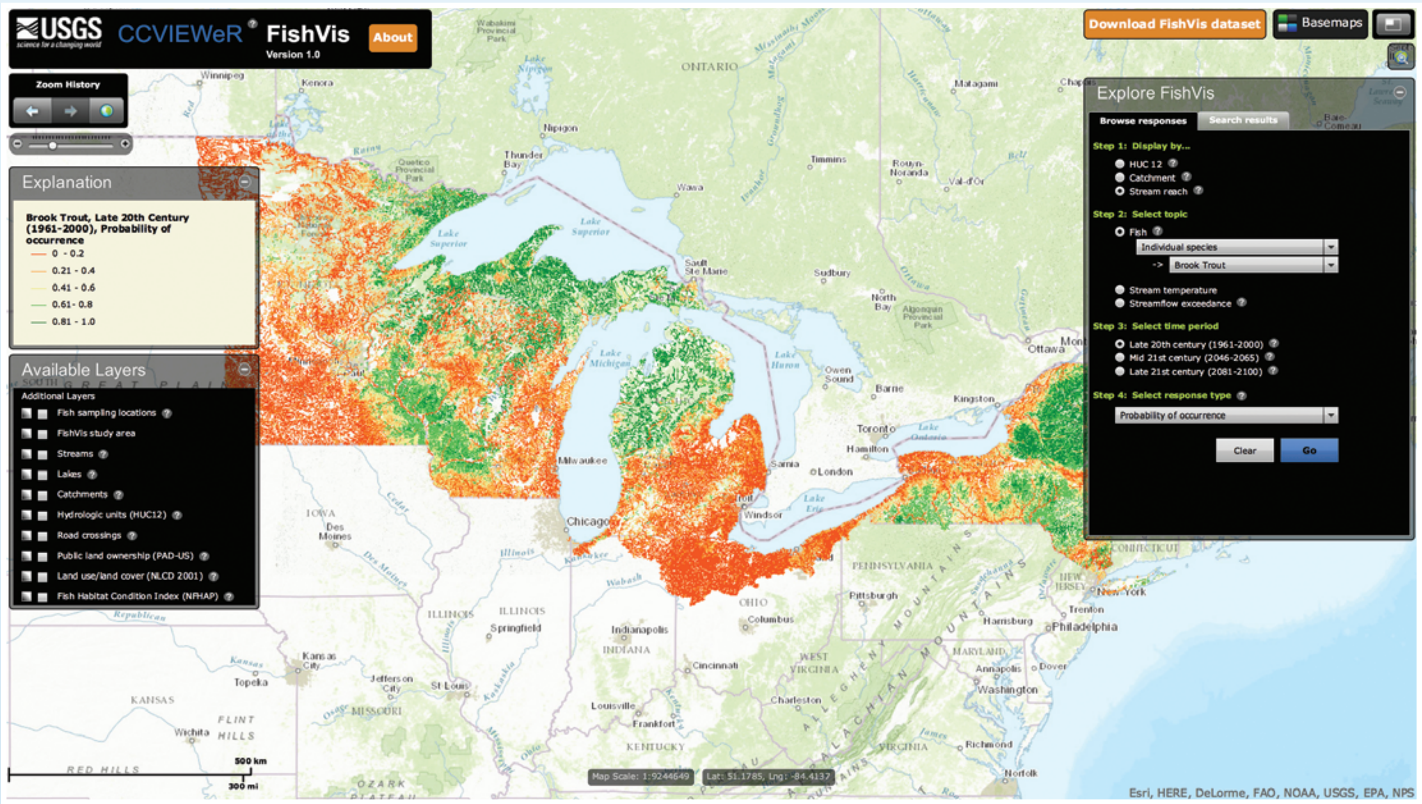
FishVis, A Regional Decision Support Tool for Identifying Vulnerabilities of Riverine Habitat and Fishes to Climate Change in the Great Lakes Region



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Cover. Figure 1 in this report.

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Conversion Factors

[International System of Units to U.S. customary units]

Multiply	By	To obtain
	Length	
centimeter (cm)	0.393701	inch (in.)
millimeter (mm)	0.03937	inch (in.)
meter (m)	3.281	foot (ft)
kilometer (km)	0.6214	mile (mi)
	Area	
hectare (ha)	2.47105	acre (ac)
square kilometer (km^2)	0.3861	square mile (mi^2)
	Flow rate	
cubic meter per second (m^3/s)	35.31	cubic foot per second (ft^3/s)
cubic meter per second per square kilometer [(m^3/s)/km^2]	91.49	cubic foot per second per square mile [(ft^3/s)/mi^2]

Abbreviations

ANN	Artificial neural network
DNR	Department of Natural Resources
FGDC	Federal Geographic and Data Committee
GAP	National Gap Analysis Program
GCM	General circulation model
GIS	Geographic information system
HUC12	12-digit hydrologic unit code subwatersheds
IFR	Institute of Fisheries Research
IPCC	Intergovernmental Panel on Climate Change
MDNR	Michigan Department of Natural Resources
NCCWSC	National Climate Change and Wildlife Science Center
NCDC	National Climatic Data Center
NFHP	National Fish Habitat Partnership
NHDPlusV1	National Hydrography Dataset version 1
PRISM	Parameter-elevation Relationships on Independent Slopes Model
Q10	10-percent exceedance discharge
Q50	50-percent exceedance discharge
Q90	90-percent exceedance discharge
R^2	Coefficient of determination

RF	Random Forests
RMSE	Root mean square error
USGS	U.S. Geological Survey
UMGL LCC	Upper Midwest and Great Lakes Landscape Conservation Cooperative
UWCCR	University of Wisconsin Center for Climatic Research
WBD	Watershed boundary dataset
WDNR	Wisconsin Department of Natural Resources
WICCI	Wisconsin Initiative on Climate Change Impacts

FishVis, A Regional Decision Support Tool for Identifying Vulnerabilities of Riverine Habitat and Fishes to Climate Change in the Great Lakes Region

By Jana S. Stewart,[1] S. Alex Covert,[1] Nick J. Estes,[1] Stephen M. Westenbroek,[1] Damon Krueger,[2] Daniel J. Wieferich,[1] Michael T. Slattery,[1] John D. Lyons,[3] James E. McKenna, Jr.,[1] Dana M. Infante,[2] and Jennifer L. Bruce[1]

Abstract

Climate change is expected to alter the distributions and community composition of stream fishes in the Great Lakes region in the 21st century, in part as a result of altered hydrological systems (stream temperature, streamflow, and habitat). Resource managers need information and tools to understand where fish species and stream habitats are expected to change under future conditions. Fish sample collections and environmental variables from multiple sources across the United States Great Lakes Basin were integrated and used to develop empirical models to predict fish species occurrence under present-day climate conditions. Random Forests models were used to predict the probability of occurrence of 13 lotic fish species within each stream reach in the study area. Downscaled climate data from general circulation models were integrated with the fish species occurrence models to project fish species occurrence under future climate conditions. The 13 fish species represented three ecological guilds associated with water temperature (cold, cool, and warm), and the species were distributed in streams across the Great Lakes region. Vulnerability (loss of species) and opportunity (gain of species) scores were calculated for all stream reaches by evaluating changes in fish species occurrence from present-day to future climate conditions. The 13 fish species included 4 cold-water species, 5 cool-water species, and 4 warm-water species. Presently, the 4 cold-water species occupy from 15 percent (55,000 kilometers [km]) to 35 percent (130,000 km) of the total stream length (369,215 km) across the study area; the 5 cool-water species, from 9 percent (33,000 km) to 58 percent (215,000 km); and the 4 warm-water species, from 9 percent (33,000 km) to 38 percent (141,000 km).

Fish models linked to projections from 13 downscaled climate models projected that in the mid to late 21st century (2046–65 and 2081–2100, respectively) habitats suitable for all 4 cold-water species and 4 of 5 cool-water species under present-day conditions will decline as much as 86 percent and as little as 33 percent, and habitats suitable for all 4 warm-water species will increase as much as 33 percent and as little as 7 percent. This report documents the approach and data used to predict and project fish species occurrence under present-day and future climate conditions for 13 lotic fish species in the United States Great Lakes Basin. A Web-based decision support mapping application termed “FishVis” was developed to provide a means to integrate, visualize, query, and download the results of these projected climate-driven responses and help inform conservation planning efforts within the region.

Introduction

The aquatic ecosystems in the Great Lakes region have both national and worldwide significance. The Great Lakes contain more than 20 percent of surface freshwater on Earth and 95 percent of North America’s surface freshwater, and support one-fifth of all freshwater fish species in North America (Herdendorf, 1982). Streams in the region are particularly vulnerable to climate change because of their gradients of cold-cool-warm aquatic thermal habitats and associated diverse biological communities (Lyons and others, 2009). The effects of climate change in this region are also poorly understood because of the natural climatic effects of the Great Lakes; global-scale or United States national-scale climate change models have been unable to provide projections at the scale needed for resource management. The output from global-scale models has been too coarse and too low in resolution to give a clear picture for specific regions. In addition, such models do not incorporate landscape features, water bodies, or other characteristics that may affect regional or local climate (Wisconsin Initiative on Climate Change Impacts [WICCI], 2011).

Early projections of climate change indicate warmer and wetter trends in the Great Lakes region, with the potential for altered hydrologic functions of surface-water and

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groundwater resources, including elevated water temperature, decreased minimum instream flow, and increased peak events (WICCI, 2011). Such changes will have profound effects on aquatic ecosystems by altering instream habitat that may, in turn, result in changes in fish distribution and community composition. For example, in some cases, cold-water species may be displaced by warm-water species, toxic algal blooms or lethal water temperatures may result in massive fish kills, survival rates during spawning may be reduced owing to low water levels during spring runoff, and species invasions and disease outbreaks may be more likely to occur (WICCI, 2011). Hence, there is an urgent need to integrate current fish habitat classifications and associated fish community data with regionally downscaled climate projections to identify vulnerabilities of riverine systems and to project potential changes in fish species distributions under future climate conditions. Stakeholders from national, state, local, university, and nongovernmental organizations have identified the need for an effective decision-support tool and access to supporting data and results to help them plan, develop, and consider management options and to implement adaptation strategies at a variety of landscape scales.

This study, conducted by the U.S. Geological Survey (USGS) in cooperation with Michigan State University, Michigan Department of Natural Resources Institute of Fisheries Research, and the Wisconsin Department of Natural Resources, is part of the Upper Midwest and Great Lakes Landscape Conservation Cooperative (UMGL LCC) funded project, A Regional Decision Support Tool for Identifying Vulnerabilities of Riverine Habitat and Fishes to Climate Change. Fish sample collections and environmental variables from multiple sources across the Great Lakes region were integrated and used to develop empirical models to predict fish species occurrence under current climate conditions, project fish species occurrence under future climate conditions, and identify fish species and stream reaches that are vulnerable to future climate change. Predictive models were developed for 13 lotic fish species distributed across the Great Lakes Basin that represent the range of thermal guilds, from cold to warm (Lyons and others, 2009) (table 1). Downscaled climate data from general circulation models (GCMs) were integrated with the fish species occurrence models to project fish species occurrence under future climate conditions (Notaro and others, 2011). Vulnerability and opportunity scores were calculated for all stream reaches by evaluating changes in fish species occurrence under current to future climate conditions. A Web-based decision support mapping application termed “FishVis” was developed to provide a means to integrate, visualize, query, and download the results of these projected climate-driven responses and inform conservation planning efforts within the region. These geospatial tools and data can be used to identify baseline conditions and guide strategic conservation investments and restoration efforts. Resource managers tasked with developing adaptation strategies to protect streams and fisheries can use these results to help identify streams that are potentially vulnerable to climate change, guide stream monitoring and thermal classifications, prioritize the allocation of limited financial resources, identify approaches for climate adaptation to best protect stream thermal habitat, and to help make quantitative assessments of environmental resources.

Purpose and Scope

The purpose of this report is to document models for prediction of fish species occurrence and the data assembled, modeled, and synthesized as part of the UMGL LCC funded project, A Regional Decision Support Tool for Identifying Vulnerabilities of Riverine Habitat and Fishes to Climate Change. The fish sample collections, environmental characteristics, fish species occurrence models, and fish climate vulnerability analyses are described and documented in this report. FishVis version 1.0, a companion Web-based decision support mapping application, is described. Results are presented in tables and can also be accessed via the companion interactive map of the Great Lakes region where results are displayed.

Description of Study Area

The study area (fig.1) (http://ccviewer.wim.usgs.gov/FishVis/) includes 369,215 kilometers (km) of streams in the Great Lakes region across parts of seven states in the United States (Indiana, Michigan, Minnesota, New York, Ohio, Pennsylvania, and Wisconsin) and overlaps with the UMGL LCC region. This area encompasses the entire United States Great Lakes Basin, part of the Upper Mississippi River Basin (Minnesota and Wisconsin) to the west, and part of the Mid-Atlantic Basin (New York) to the east. It extends from New York in the east to Minnesota in the west and rises from sea level to the high elevations of the mountains of upstate New York. Streams encompass a range of thermal conditions—cold-water, cool-water, and warm-water systems. Cold-water streams are common in the unglaciated (Driftless Area) and glaciated (Lake Superior Basin) parts of Minnesota and Wisconsin, the northern and eastern parts of Lower Michigan, throughout the Upper Peninsula of Michigan, and in the higher elevations of New York. Warm-water streams dominate the agricultural areas of the Great Lakes Basin in Indiana, Ohio, Pennsylvania, eastern Wisconsin, and parts of western Minnesota. Cool-water systems are interspersed throughout the remainder of Michigan, Minnesota, New York, Wisconsin, and the Great Lakes Basin in Pennsylvania.

Methods

An approach was developed to predict fish species occurrence under current (present day) climate conditions and to assess the manner in which fish species occurrence may change in the future by using climate projections from regional downscaled general circulation models (GCMs). First, data

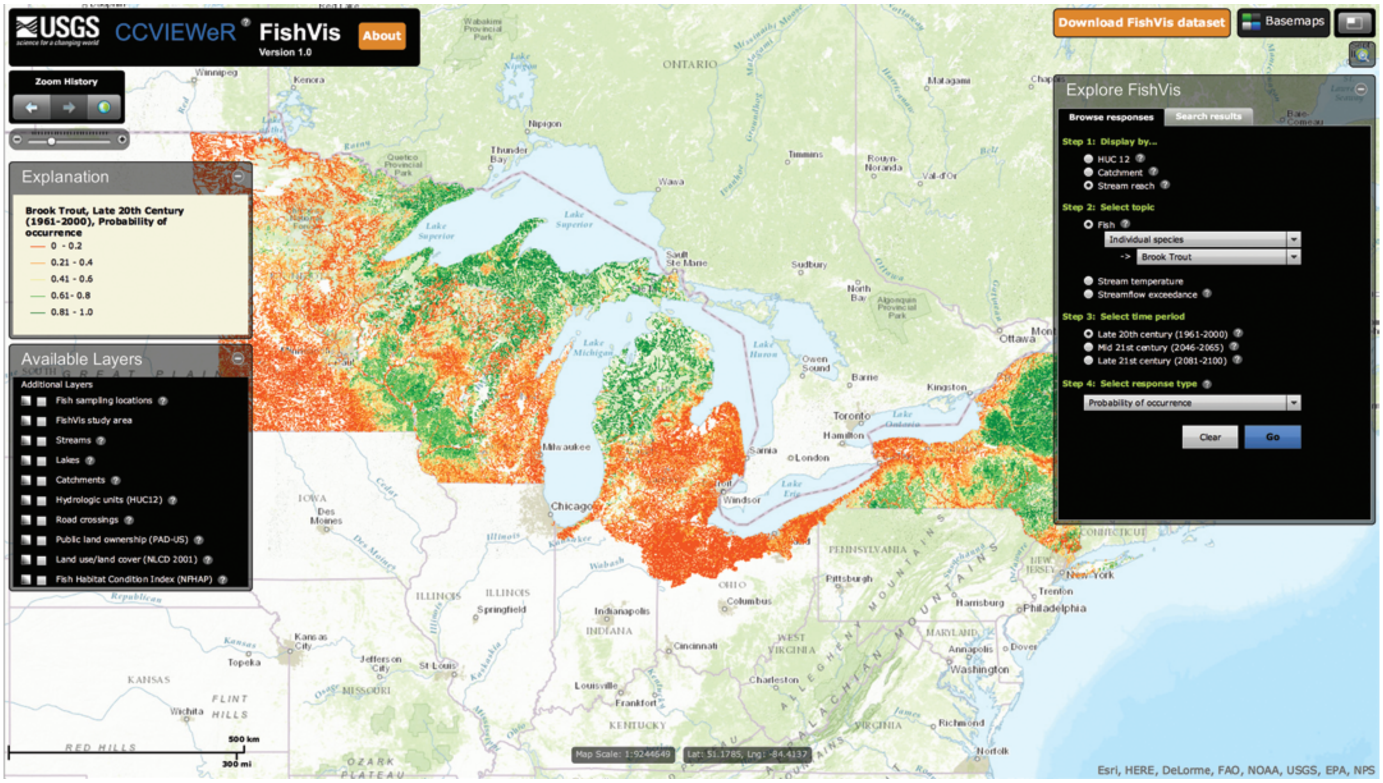

Figure 1. Screen capture of model results for brook trout probability occurrence for the late 20th century (1961–2000) displayed through the FishVis decision support mapping application.

on fishes and environmental characteristics were compiled for stream sites across the region and used to develop empirical models of species occurrence for 13 lotic fish species that represent the three ecological thermal guilds (cold, cool, and warm; table 1) (Lyons and others, 2009). Second, environmental characteristics were compiled for all stream reaches in the study area, and models and thermal thresholds were applied to predict present-day fish species occurrence for all reaches, most of which were unsampled (table 1, appendix 1). Modeling fish species occurrence under current climate conditions required fish sample collections from state natural resource agencies and environmental characteristics that were either modeled or derived from a geographic information system (GIS). Third, the models were rerun using climate projections from regional downscaled GCMs to project fish species occurrence under future climate conditions (table 2). Estimating the effects of future climate conditions on fish species occurrence required air temperature and precipitation projections from regional downscaled climate models.

The 1:100,000 scale National Hydrography Dataset Plus version 1 (NHDPlusV1) (USGS, 2010) served as the spatial framework to which all environmental and biological data were attributed. The following sections describe fish sample collections, environmental characteristics, fish species occurrence models, and their integration with downscaled climate data to project and evaluate fish species occurrence under current and future climate conditions.

Fish Sample Collections

Fish species occurrence models were developed using fish sample collections from sites across the region. Presence/absence data for 13 fish species were collected by state natural resource agencies and local organizations at 2,012 sites across the study area, including City of Elkhart, Indiana, and Indiana Department of Environmental Management (28 sites); Michigan Department of Natural Resources (DNR; 482 sites); Minnesota Pollution Control Agency (484 sites), New York State Department of Environmental Conservation (442 sites); Ohio Environmental Protection Agency (137 sites); Pennsylvania Fish and Boat Commission (7 sites); and Wisconsin DNR (432 sites). All source data originated from community fish sample collections that were greater than or equal to 100 meters in stream length, sampled from late April to late October from 1995 to 2011, using electroshocking gear. The 13 fish species were chosen to represent three ecological classifications for water temperature (Lyons and others, 2009) and ranged in distribution from *Notropis heterodon* (blackchin shiner) at 16 sites to the ubiquitous *Catostomus commersonii* (white sucker) at 1,405 sites (table 1).

In an effort to prevent density bias, the numbers of fish sampling sites were modified to approximately reflect each state's total stream miles (as calculated using the NHDPlusV1) and the proportion of streams in each stream-size category, small, medium, or large, as established by electroshocking

Table 1. Thermal guilds and Random Forests model performance statistics for 13 fish species at 5,627 sites, Great Lakes region.

[Thermal guilds based on water temperature preferences are from Lyons and others, 2009]

Fish species (Common name)	Fish species (Scientific name)	Number of sites	Thermal guild	Overall accuracy (percent)	Omission error (percent)	Commission error (percent)
Blackchin shiner	*Notropis heterodon*	16	Cool	79.9	0.5	19.6
Brook stickleback	*Culaea inconstans*	353	Cool	76.2	3.5	20.3
Brook trout	*Salvelinus fontinalis*	314	Cold	82.7	1.9	15.4
Brown trout	*Salmo trutta*	394	Cold	82.1	2.2	15.7
Common carp	*Cyprinus carpio*	480	Warm	82.5	4.1	13.4
Green sunfish	*Lepomis cyanellus*	510	Warm	76.9	4.1	19.0
Mottled sculpin	*Cottus bairdii*	393	Cold	77.3	3.5	19.2
Northern hog sucker	*Hypentelium nigricans*	425	Cool	78.6	3.7	17.8
Northern pike	*Esox lucius*	414	Cool	75.3	4.9	19.8
Rainbow trout	*Oncorhynchus mykiss*	151	Cold	77.6	1.5	20.8
Smallmouth bass	*Micropterus dolomieu*	592	Warm	82.8	5.0	12.2
Stonecat	*Noturus flavus*	180	Warm	78.4	1.7	19.8
White sucker	*Catostomus commersonii*	1,405	Cool	69.3	21.1	9.6

Table 2. List of 13 general circulation models used to project the occurrence of fish species, Great Lakes region.

[Modified from Notaro and others, 2011; CSIRO, Commonwealth Scientific and Industrial Research; KMA, Korea Meteorological Administration; LASG, State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics; NOAA, National Oceanic and Atmospheric Administration; USA; United States of America; NASA, National Aeronautics and Space Administration; JAMSTEC, Japan Agency for Marine-Earth Science and Technology]

Originating group(s)	Country	Model identification	Model code	Emissions scenario
Canadian Centre for Climate Modelling & Analysis	Canada	CGCM3.1(T47)	ccc	A1B
Canadian Centre for Climate Modelling & Analysis	Canada	CGCM3.1(T63)	t63	A1B
Météo-France/Centre National de Recherches Météorologiques	France	CNRM-CM3	cnr	A1B
CSIRO Atmospheric Research	Australia	CSIRO-Mk3.0	c30	A1B
CSIRO Atmospheric Research	Australia	CSIRO-Mk3.5	c35	A1B
Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM	mpi	A1B
Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group	Germany/ Korea	ECHO-G	miu	A1B
LASG/Institute of Atmospheric Physics	China	FGOALS-g1.0	iap	A1B
U.S. Department of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.0	gfd	A1B
NASA/Goddard Institute for Space Studies	USA	GISS-AOM	aom	A1B
NASA/Goddard Institute for Space Studies	USA	GISS-ER	ger	A1B
Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)	Japan	MIROC3.2 (hires)	mir	A1B
Meteorological Research Institute	Japan	MRI-CGCM2.3.2	mri	A1B

gear type used (for example, backpack = small streams, barge = medium streams, boat = large streams) or length of stream sampled. Criteria for determining stream size were determined by the project team using the original fish sample collection source data from each agency.

After calculating the appropriate numbers of fish sampling sites for each state, the sites were randomly selected from the pool of available data collection sites within each state. Maps were produced that showed the distributions of the fish sampling sites selected for model development and were reviewed by experts on the project team who were familiar with lotic fish species distribution across the region. Sampling sites were excluded if fish sample collections were not identified to the species level or if the environmental characteristics were missing for the related NHDPlus reaches or catchments.

Climate Projections from General Circulation Models

This study used statistically downscaled air temperature and precipitation projections from the University of Wisconsin Center for Climate Research (UWCCR) for 13 GCMs (table 2) (Notaro and others, 2011). Statistical downscaling of daily air temperature and precipitation was acquired for three periods—a historical hindcast, late 20th century, baseline (1961–2000); mid 21st century (2046–65); and late 21st century (2081–2100)—for the A1B scenario (moderate to high emissions) (Intergovernmental Panel on Climate Change (IPCC), 2007). The three periods are treated as stationary periods, even though greenhouse gas emissions are continuing to change through each time span, as described in Notaro and others (2011).

Climate data variables included maximum and minimum daily air temperature and total daily precipitation. Both air temperature and precipitation were summarized as annual averages for each of the three periods for each of the 13 GCMs and attributed to the NHDPlus stream reaches. Bias correction factors were calculated and applied to future projections of air temperature and precipitation in order to align the GCM-based 20th century baseline (1961–2000) values with actual climate observations for the late 20th century. The actual climate observations for the late 20th century for use in the fish species occurrence models were based on the Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset attributed to NHDPlus for the time period 1961–2000 (USGS, 2010; Wang and others, 2011).

Environmental Characteristics

Environmental characteristics were acquired from a hierarchical spatial framework and database that was developed for the National Fish Habitat Partnership (NFHP) National Inland Assessment of Streams (Esselman and others, 2011; Wang and others, 2011; Daniel and others, 2015). This framework uses interconfluence stream reaches and their local and network catchments as fundamental spatial stream units and include measures of watershed size, land cover, topography, canopy cover, soils, impervious surfaces, groundwater delivery, and climate. The stream reaches are the finest spatial unit in the framework and are defined from a tributary confluence or lake or impoundment outlet (or the stream's source) downstream to the next tributary confluence or lake or impoundment inlet (or the stream's mouth). The other two spatial scales are the local and network catchment scales. The local catchment scale encompasses attributes of the land that drains directly to the stream reach, and the network catchment describes aspects of the entire upstream drainage area that drain to the stream reach, including its local catchment.

The 369,215 km of streams in the study area were divided into 172,766 stream reaches; some stream reaches in the NHDPlusV1 dataset were not included in the analysis owing to one or more of the following reasons: catchments were not defined in NHDPlusV1, flow lines were either coastline or pipeline, flow lines were artificial connectors through waterbodies such as lakes, or flow lines had missing attributes. Forty environmental landscape variables were selected from the database that were thought to affect fish species occurrence and distribution in riverine systems of the Great Lakes region, based on previous studies (Zorn and others, 2002; McKenna, 2005; Steen and others, 2008; Lyons and others, 2010), and were used in subsequent modeling of suitable habitat for 13 fish species (appendix 1).

Eight additional variables describing flow and water temperature were estimated for each stream reach from existing statistical models for a total of 48 environmental variables used to model fish species occurrence (appendix 1). Five of the eight variables characterized streamflow exceedance for several seasons and flows (April 10-percent exceedance flow [Q10], a measure of spring high flows; August 90-percent exceedance flow [Q90] and yield, a measure of summer low flows; and Annual 50-percent exceedance flow [Q50] and yield, a measure of average annual flow) and were based on regression analyses of land cover, geology, topography, and climate variables with daily flow data collected at USGS streamgages over the time period 1980–2010 (Brenden and others, 2006; Seelbach and others, 2011; Damon Krueger, Michigan State University, written commun., 2012; and McKenna and others, 2014). These estimates were calculated as part of three other projects, the USGS Great Lakes Aquatic Gap project (Brenden and others, 2006; Steen and others, 2008; Lyons and others, 2010; McKenna and others, 2014), Ecological Classification of Rivers for Environmental Assessment project (Seelbach and others, 2011), and the Projected Climate and Land Use Change Impacts on Aquatic Habitats in the Midwestern United States project (Damon Krueger, Michigan State University, written commun., 2012). The three exceedance flows were expressed directly as discharge measured in cubic feet per second (ft^3/s); the annual and August flows were also expressed as yield (flow in ft^3/s per unit catchment area) for a total of five flow variables. The regression models explained a high degree of observed variation in exceedance discharges with adjusted R^2 ranging from 0.91 to 0.98 for Annual Q50 models, from 0.86 to 0.97 for April Q10 models, and from 0.73 to 0.94 for August Q90 models. Estimates of future streamflow exceedances were calculated for individual stream reaches by replacing precipitation values in the regression equations with bias-corrected precipitation projections from 13 GCMs for two future periods (2046–65 and 2081–2100).

The three remaining variables characterized stream water temperature (June–August mean, July mean, and maximum daily mean) and were estimated from artificial neural network (ANN) models that predicted daily summertime water temperature from measured water temperature coupled with static landscape characteristics and dynamic climate time series data (McKenna and others, 2010; Damon Krueger, Michigan State University, written commun., 2012; McKenna and others, 2014; Stewart and others, 2006; Stewart and others, 2015). The June–August mean was based on the average of daily water temperature from June 1st to August 31st for all years in the stream temperature model time periods; the July mean, the average of daily water temperature for July for all years for stream temperature model time periods; and the maximum daily mean, the average of the maximum daily mean water temperature for each year in the stream temperature model time periods (table 2) (Lyons and others, 2010; Stewart and others, 2015). The landscape characteristics were acquired from the Great Lakes Aquatic GAP project, as described by Brenden and others (2006), and the NFHP National Inland Assessment of Streams (Wang and others, 2011; Esselman and others, 2011; Daniel and others, 2015). The climate data consisted of air temperature time series from observation stations (National Oceanic and Atmospheric Administration, 2011) for the current time period and projections of future air temperature from downscaled regional climate models (Notaro and others, 2011), both of which are described in the preceding sections of this report. These models used continuous water temperature measurements for the summer (June–August) acquired from the USGS, Michigan Department of Natural Resources (DNR), Minnesota DNR, Minnesota Pollution Control Agency, Wisconsin DNR, and New York Department of Environmental Conservation for 1990–2012. The three water temperature variables (June–August mean, July mean, and maximum daily mean) have been shown to be important for explaining fish distribution patterns in streams across the region (Wehrly and others, 2006; Lyons and others, 2010); July mean stream temperature was used to classify stream reaches into thermal classes on the basis of Lyons and others (2009).

Separate stream temperature models were developed for Michigan, Minnesota, Wisconsin, and New York because of the diversity of the landscape across the region; the New York model included the streams in the Great Lakes Basin of Indiana, Ohio, and Pennsylvania, in addition to New York. For Wisconsin, the ANN stream temperature model was developed as part of the USGS Great Lakes Aquatic Gap project and in cooperation with the Wisconsin Department of Natural Resources (WDNR; Brenden and others, 2006; Lyons and others, 2010; McKenna and others, 2014; Stewart and others, 2015); for Michigan and Minnesota, as part of the Projected Climate and Land Use Change Impacts on Aquatic Habitats in the Midwestern United States project (Damon Krueger, Michigan State University, written commun., 2012); and for New York and the Great Lakes Basin of Indiana, Ohio, and Pennsylvania, as part of USGS Great Lakes Aquatic Gap project (Brenden and others, 2006; McKenna and others, 2010) and this project. The approach used for developing all four ANN models is described in more detail in Stewart and others (2015); the variables used for model calibration are listed in appendix 2, and model performance statistics are summarized in appendix 3. Output from all of the ANN stream temperature models explained at least 70 percent of the variation (R^2=0.70) in daily summer stream temperature. Model performance ranged from 0.71 to 0.75 for model training sites and from 0.72 to 0.76 for model validation sites.

The individual stream-temperature models were applied to all stream reaches statewide (Michigan, Minnesota, and Wisconsin) and regionally (New York and the Great Lakes Basin parts of Ohio and Indiana) to predict daily summer stream temperatures under current climate conditions and project stream temperatures under future climate scenarios. Estimates of future stream temperatures were determined for individual stream reaches and the 13 GCMs for both future periods (2046–2065 and 2081–2100) by replacing the current time series data with the future bias-corrected time series data. An average July mean stream temperature for the 13 GCMs also was calculated for each stream reach and for both periods for use in estimating the effects of projected future climate scenarios on stream temperature. The results of stream temperature models were attributed and mapped to both NHDPlusV1 reaches and catchments.

Fish Species Occurrence Models

Random Forests (RF) models (Breiman, 2001) were used to predict the probability of the occurrence of the 13 fish species within each stream reach in the study area. Species-specific RF models were constructed from the observed presence/absence data for the 2,012 fish sampling sites, coupled with the 48 environmental variables for those sites. Each RF model was based on a summary of 500 independent classification trees. Each classification tree split the sites into presence and absence groups for the species using a statistical algorithm that selected the single predictor variable and value that maximized within-group homogeneity (that is, as high a proportion as possible of either sites where the species was present or sites where the species was absent) while also maximizing the difference between the two groups (that is, one group maximizing sites where the species was present, the other where it was absent). The first split represented the single best division of the sites into presence and absence groups. Each of these two groups were then subsequently further split into smaller presence/absence groups on the basis of the same or different predictor variables and values, with splitting continuing until a stopping rule, which balanced model complexity against relative gain in group homogeneity, was reached. Each tree in the RF model was developed from a random subset of the 2,012 sites and a random subset of the 48 environmental variables; the accuracy of each tree was assessed on the basis of how well its prediction of occurrence compared with observed presence at the sampling sites. The final RF model for a given species was a weighted average of the results from the 500 trees, with the weighting based on the accuracy of each tree for predicting observed fish occurrence. An analytics and data mining platform, Salford Predictive Modeler® 6.6 Pro Random Forests, was used to develop the models (Salford Systems, 2013).

The RF model for each species was applied to all of the stream reaches within the study area to yield a probability of occurrence for that species for each reach, which was the fraction of the 500 classification trees that classified the species as present, adjusted for the accuracy of each tree. Where predicted probability of occurrence was greater than or equal to (≥)50 percent, species were classified as being present; otherwise, species were classified as being absent.

In addition to the inclusion of three water temperature variables as part of the 48 variables used for the Random Forests models, model predictions were constrained by applying a water temperature threshold to the model output in order to provide a balance between modeling ecological realism and statistical performance. Sometimes the best predictive species models lacked an upper limit for the water temperature variables, resulting in predictions that increasing water temperature would have no effect on species occurrences. Yet it is well established that all fish species have upper lethal water thermal limits, which are based on physiological constraints. Because of the objectives of this study, it was essential that relevant water temperature effects were taken into account during the prediction of fish species distributions. To make assessment of climate change effects more accurate and realistic, physiologically based upper thermal limits can be used to constrain predictions from fish species models (Lyons and others, 2010; Lyons and Stewart, 2014). Consequently, if a species was predicted to occur in a reach where modeled water temperature was clearly unsuitable, based on previous studies, then those reaches were changed from present to absent. Reaches in which average maximum daily mean water temperatures were greater than 24.6 degrees Celsius (°C) were considered unsuitable for cold-water species; greater than 27.1 °C were considered unsuitable for cool-water species; and greater than 31.7 °C were considered unsuitable for warm-water species (Lyons and others, 2009, 2010). Temperature estimates that define the upper thermal limits for the 13 fish species in this study were based on the thermal preferences and tolerances given in Lyons and others (2009) along with data from Wehrly and others (2007), although relevant information to support the temperature limits for the warm-water species is scarce. By applying these constraints, unrealistic predictions of occurrence were eliminated in an objective and justifiable fashion. Undoubtedly there is variation in temperature limits within each thermal class, but the data are generally insufficient to assign precise species-specific temperatures. The limits used in this study are conservative and represent temperatures where it is almost certain that the species would be unable to survive.

To estimate fish species occurrence under future climate conditions, models were rerun using downscaled projections of air temperature and precipitation (corrected for bias) from the UWCCR for 13 GCMS and two future time periods, mid 21st century (2046–65) and late 21st century (2081–2100). Twelve of the 48 habitat variables used to predict fish distributions were replaced with new values to represent future conditions—conditions that have the potential to alter species distributions and suitable habitat. These 12 climate-change variables include measures of flow, stream temperature, air temperature, and precipitation (appendix 1). Using new estimates for the climate-change variables, the RF models were rerun to generate future projections of fish species occurrence for all stream reaches. As with the current fish distributions, water-temperature thresholds were applied to the future fish distributions. The output for the fish species occurrence models consisted of probability of occurrence for every stream reach for 13 fish species, 13 GCMs, and the mid 21st century (2046–65) and late 21st century (2081–2100). Where probability of occurrence was ≥50 percent, the species was considered to be "present." The results of fish species occurrence under current and future climate conditions were attributed to NHDPlusV1 reach and catchment scales, and species distribution maps were prepared and reviewed by fish experts on the project team.

Fish Species Climate Change Vulnerability Analyses

Vulnerability of fish species to climate change was evaluated by comparing predicted species occurrence under current climate conditions to projected fish species occurrence under future conditions for the 13 GCMs and two periods for all 13 fish species and individual stream reaches. Three key climate change questions were identified that managers may face when assessing the potential effects of future climate conditions on fish species occurrence in streams. (1) Which species and streams will have declines? (2) Which species and streams will have gains? (3) What are the magnitudes of these changes? Three concepts were defined for assessing climate change effects. The terms "vulnerability," "opportunity," and "sensitivity" were adopted to describe loss of species, gain of species, and loss or gain (that is, change) of species for individual stream reaches, respectively, and values for the three concepts were calculated for individual species and for species thermal guilds.

Vulnerability, or loss of species, was calculated as the percentage of GCMs where species occurrence was predicted to change from "present" (probability of occurrence ≥50 percent) under current climate conditions to "absent" under future climate conditions. For example, if brook trout were predicted to be present under current climate conditions in a given stream reach, but under future climate conditions, brook trout were projected to be present for only 11 of 13 GCMs and absent for 2 of 13 GCMs, then vulnerability would be calculated as the percentage of GCMs for which species occurrence changed from present to absent (2 of 13 GCMs or 15.4 percent). Similarly, opportunity, or gain of species, was calculated as the percentage of GCMs for which species occurrence was predicted to change from absent under current climate conditions to present under future climate projections.

Lastly, sensitivity, or the loss or gain of species, was calculated as the percentage of GCMs for which species occurrence was projected to change from absent to present or from present to absent. In an example for the cool thermal guild, sensitivity was essentially the sum of vulnerability and opportunity for the 5 cool-water species as a percentage of all 5 species–13 GCM combinations.

In addition to vulnerability, opportunity, and sensitivity, the probability of occurrence was calculated for individual species. The probability of occurrence for a given species was estimated for the two future periods and all GCMs. In addition, an average probability of occurrence for each species was calculated using all 13 GCMs. The average change in probability of occurrence from current to future was also calculated for mid 21st century (2046–65) and late 21st century (2081–2100). For the fish thermal guilds (cold, cool, and warm) the number of species lost, number of species gained, number of species lost or gained, percentage of species lost, and percentage of species gained were also calculated. These results were attributed to the spatial framework for both the NHDPlusV1 reach and catchment scales.

Results for fish species and stream temperature response under current and future climate conditions were summarized at the National Watershed Boundary Dataset (WBD) 12-digit hydrologic unit code (HUC12) subwatershed scale. For each HUC12, summary metrics for fish response were calculated for individual species and included stream length-weighted probability of occurrence, absolute miles of fish species occurrence, and percentage of miles of species occurrence under current and future climate conditions. Additional metrics were calculated to represent change from current to future conditions, including change in length-weighted probability of occurrence, number of miles of stream where species occurrence was lost (that is, change from present [probability of occurrence ≥50 percent] to absent [probability of occurrence < 50 percent]); number of miles gained, lost or gained, and unchanged; and percentage of miles of stream where species occurrence was lost, gained, lost or gained, and unchanged.

The stream length-weighted probability of occurrence for individual species was determined by (1) calculating the percentage of total stream length within a HUC12 for each stream reach, then (2) multiplying the probability of occurrence for an individual species for that reach by the percentage total stream length to get the length-weighted probability of occurrence for each species for each reach, and (3) lastly, summing the length-weighted probabilities for all of the reaches within a HUC12 for each species to get the length-weighted probability of occurrence at the HUC12 scale.

Similarly, HUC12 summary metrics were calculated for stream temperature, including length-weighted July mean stream temperature and length-weighted change in July mean stream temperature from current to future climate conditions. The length-weighted July mean stream temperature was determined by (1) calculating the percentage of total stream length within a HUC12 for each stream reach, then (2) multiplying the July mean stream temperature for each reach by the percentage of total stream length to get the length-weighted July mean stream temperature for each reach, and (3) lastly, summing the length-weighted July mean stream temperature for all of the reaches within a HUC12 to get the length-weighted July mean stream temperature at the HUC12 scale. Similar calculations were done to determine the length-weighted change in July mean stream temperature for both future climate periods. The length-weighted July mean stream temperatures and change in July mean stream temperature were also converted to stream thermal class on the basis of Lyons and others (2009) for the purpose of displaying the results on the FishVis decision support mapper.

Fish Species Occurrence Under Current and Future Climate Conditions

The 13 fish species RF models varied in terms of the order of importance of environmental predictor variables, but the 10 most important variables were common among the 13 fish species RF models. The RF model computes a variable importance list and indicates which among the 48 habitat variables (appendix 1) are most driving the performance of the models. Of the 10 most important variables, the mean annual 50-percent exceedance flows, mean April 10-percent exceedance flows, all three stream temperature metrics (July daily mean, June–August daily mean, and summer maximum daily mean), and the watershed catchment area were the most common among models, occurring in at least 9 of the 13 fish species models (appendix 4). The mean April 10-percent exceedance flow occurred most frequently in the top 10 important variables, occurring in 11 of the 13 fish species models. July daily mean, June–August daily mean, and watershed catchment drainage area were similar in importance, occurring in the top 10 most important variables for 10 of the 13 fish species models. Twenty-seven of the 48 environmental variables occurred in the top 10 important variables; all variable categories were represented in the top 10 with the exception of surficial lithology (appendix 4). Note that all 12 of the environmental variables that are associated with climate change and that were replaced with new estimates (appendix 4) from downscaled climate projections to predict future scenarios and distributions were found at varying degrees in the top 10 important variables.

The accuracy of fish species occurrence (presence/absence) models using RF models for 13 individual species ranged from 69.3 (white sucker) to 82.8 percent (*Micropterus dolomieu,* smallmouth bass) with an overall mean of 78.4 percent. Most species had greater errors of commission (predicted present, actually absent) than omission (predicted absent, actually present), which likely is a product of the project's goal to predict "potential distributions" on the basis of physical habitat environmental variables (table 1).

The distribution of the 13 fish species under current climate conditions varied greatly, ranging from a low of 32,603 km, representing 8.8 percent of total stream length in the study area for *Hypentelium nigricans* (northern hog sucker), to a high of 215,465 km, representing 58.4 percent of total stream length for *Culaea inconstans* (brook stickleback). Only one species (brook stickleback) was estimated to be present in greater than 50 percent of the total stream length in the study area, and two species (northern hog sucker and smallmouth bass) were estimated to be present in less than 10 percent of the total stream length in the study area.

Projected responses to future climate conditions varied dramatically among the 13 species. Overall, 8 of the 13 species declined in distribution, and 5 increased in distribution for both future periods. Responses varied among the three thermal guilds of fishes. All cold-water species declined, and 4 of 5 cool-water species declined. All warm-water species increased, and 1 of the 5 cool-water species increased in distribution (table 3). In the late 21st century, decreases were greater for the 8 cold- and cool-water species, and increases were greater for the 4 warm-water species, when compared to the mid 21st century period. Increases were greater in the mid 21st century for one cool-water species (northern hog sucker) than in the late 21st century. The results of these projected climate-driven responses are available for viewing, query, and download through a Web-based decision support mapping application termed "FishVis."

Table 3. Predictions from 13 fish species occurrence models for stream length and percentage of total stream length in the Great Lakes region that would be suitable for 13 fish species under current climate conditions, projected lengths of suitable stream habitat under future climate conditions, and percent change from current climate conditions.

[Total stream length is 369,215 kilometers (km)]

Fish species (common name)	Thermal guild	Current baseline period (1961–2000)		Future (2046–65)		Future (2081–2100)	
		Stream length (km)	Length (percent of total)	Stream length (km)	Stream length (percent change from current)	Stream length (km)	Stream length (percent change from current)
Blackchin shiner	Cool	40,334	10.9	19,765	-51.0	14,740	-63.5
Brook stickleback	Cool	215,465	58.4	76,487	-64.5	42,669	-80.2
Brook trout	Cold	120,740	32.7	59,012	-51.1	49,077	-59.4
Brown trout	Cold	67,851	18.4	45,591	-32.8	41,887	-38.3
Common carp	Warm	55,493	15.0	59,288	6.8	60,233	8.5
Green sunfish	Warm	141,015	38.2	182,952	29.7	187,877	33.2
Mottled sculpin	Cold	130,114	35.2	78,274	-39.8	65,361	-49.8
Northern hog sucker	Cool	32,603	8.8	36,850	13.0	34,655	6.3
Northern pike	Cool	55,162	14.9	12,371	-77.6	7,513	-86.4
Rainbow trout	Cold	54,814	14.8	29,134	-46.8	23,168	-57.7
Smallmouth bass	Warm	32,888	8.9	39,741	20.8	42,573	29.4
Stonecat	Warm	38,071	10.3	47,629	25.1	49,392	29.7
White sucker	Cool	109,826	29.7	66,804	-39.2	55,894	-49.1

FishVis, A Web-Based Decision Support Mapping Application

A Web-based decision support mapping application termed “FishVis” was developed to display the results of this study and was designed to aid decision makers and managers in identifying where fish species and stream habitats are expected to change under future climate conditions (fig. 1). FishVis is currently accessible by following the publicly available Web link http://ccviewer.wim.usgs.gov/FishVis/.

FishVis is built using ArcGIS Server and web services and allows users to view and query results across the study region by selecting a hydrologic spatial display unit, fish species or habitat response, and time period. Results can be viewed spatially as maps or in tabular format as pop-up tables for three spatial scales—stream reach, catchment, or HUC12—or results can be downloaded for use in other applications or in conjunction with other datasets and analyses. Users can access FishVis to browse current and future distributions of the 13 fish species and examine current and future thermal and flow characteristics of stream habitats; download supporting data and results; or search and export customized results for stream reaches that meet specific criteria (that is, fish species presence, stream thermal class, stream size, percent land cover, land stewardship, and human disturbance) for current and future periods. FishVis may help users answer questions of specific interest, such as which stream habitats may support brook trout under future climate conditions. FishVis incorporates ancillary datasets that can be toggled on or off as background layers and can aid managers in decision making associated with types of land cover in stream catchments, locations of protected lands, and stream habitat condition scores developed as part of the 2010 NFHP national inland assessment of fish habitats (Esselman and others, 2011; Wang and others, 2011). Underlying base maps of imagery, topography, roads, protected areas, existing land use, road stream crossings, and an index of watershed environmental disturbances are also available as background layers to provide additional spatial context for FishVis results.

To explore FishVis results, the user begins by first selecting “Browse responses” or “Search results.” On the Browse tab, the first step is to select the spatial display unit (HUC12, catchment, or stream reach). Second, select the topic or theme to be mapped (individual fish species or thermal guild, stream temperature, or streamflow exceedance). Third, select the time period (current climate—late 20th century; future climate—mid 21st century or late 21st century), and last, select the type of response (for example, predicted occurrence (fish); thermal class (stream temperature); annual Q90 yield (90-percent streamflow exceedance). The results for the selected response will be displayed on the map for all stream reaches, catchments, or HUC12s that are included in the study area. The user can zoom to an area of interest, click on an individual spatial unit (for example, stream reach), and view all results for that particular location in pop-up tables. The pop-up tables are static tables of results for that given location (that is, stream reach, catchment, or HUC12) that appear above the FishVis map display. There are separate pop-up tables for fish, stream temperature, and streamflow exceedance responses that display all results for a given location; in addition, pop-up tables include links to information about the GCMs used in this study. Help tips are portrayed with a question mark (?) and provide the user with additional information about each radio button selection, when the user hovers the cursor above a given help tip.

For search results, the user can filter the results to be displayed by specifying user-defined search criteria. The first step is to select the spatial display unit and a state (option). Then, the user can limit the query by selecting any number of criteria within the three time periods, such as fish species occurrence, stream thermal class, stream size, or land cover percentages. Users can define criteria for multiple time periods within a single search, allowing them to query the dataset over multiple periods (For example, Where are the cold and cold-transition reaches, where agricultural land cover is less than 50 percent for the local catchment and where brook trout are predicted to be present in the late 20th century and projected to be present in the mid 21st century? These may be areas to consider for protection). Only those stream reaches that meet the criteria will be displayed on the map and can be exported to a comma-separated value (CSV) text file for download.

A geodatabase containing the full dataset of results that are being mapped in FishVis can be downloaded from the FishVis mapping application at http://ccviewer.wim.usgs.gov/FishVis/ or through USGS ScienceBase as a Data Release (Stewart and others, 2016). All of the results are tied to either the NHDPlusV1 hydrography or the National WBD hydrologic unit framework. Federal Geographic Data Committee (FGDC) compliant metadata were created for each spatial data layer and associated tabular data in the geodatabase, and are available with the geodatabase on USGS ScienceBase. Metadata are descriptive information about a spatial data layer or table and typically include how the spatial data layer or table was created, its geographic setting, and its projected coordinate system. Other metadata components include title, abstract, publication date, and sourcing information. The metadata also describe the fields in the layer, called attributes, and their potential range of values or domain. A detailed listing of the standard metadata contents can be found at http://www.fgdc.gov/metadata (Federal Geographic Data Committee, 2012).

Summary

Climate change is expected to alter hydrological systems in the Great Lakes region through changes in instream flow, stream temperature, and habitat. These changes in turn can have a profound effect on aquatic systems resulting in changes in fish distribution and community composition. Streams in the region are particularly vulnerable to climate change because of their gradients of cold-cool-warm aquatic thermal habitats and associated diverse biological communities. Fish responses to climate change may also be complex and vary across species, geographies, and stream types. Resource managers need information and tools to understand where fish species and stream habitats are expected to change under future climate conditions.

Predictive models were developed to estimate the occurrence for 13 lotic fish species distributed across the Great Lakes Basin and that represent the range of thermal guilds from cold to warm. Species-specific Random Forests (RF) models were constructed from fish sample collections coupled with 48 environmental variables for those sites. To estimate fish species occurrence under future climate conditions, RF models were rerun using downscaled projections of air temperature and precipitation for 13 general circulation models and two future time periods, mid 21st century (2046–65) and late 21st century (2081–2100) for the A1B emission scenario. Vulnerability of fish species to climate change was evaluated by comparing predicted species occurrence under current climate conditions to projected fish species occurrence under future conditions for the 13 general circulation models and two periods for all 13 fish species at individual stream reaches.

The 13 fish species RF models varied in terms of the order of importance of environmental predictor variables, but the 10 most important variables were common among the 13 fish species RF models. Of the 10 most important variables, two flow metrics (mean annual 50-percent exceedance flows and mean April 10-percent exceedance flows), all three stream temperature metrics (July daily mean, June–August daily mean, and summer maximum daily mean), and the watershed catchment area were the most common among models. All of the environmental variables associated with climate change and that were replaced with new estimates from downscaled climate projections to predict future scenarios and distributions were found at varying degrees in the top 10 important variables. These included 2 air temperature, 2 precipitation, 5 streamflow, and 4 water temperature variables.

The accuracy of fish species occurrence (presence/absence) models using RF models for 13 individual species ranged from 69.3 (*Catostomus commersonii*, white sucker) to 82.8 percent (*Micropterus dolomieu,* smallmouth bass) with an overall mean of 78.4 percent. Most species had greater errors of commission (predicted present, actually absent) than omission (predicted absent, actually present), which likely is a product of the project’s goal to predict “potential distributions” on the basis of physical habitat environmental variables.

Presently, cold-water species occupy between 55,000 kilometers (km; 15 percent) and 130,000 km (35 percent); cool-water, between 33,000 km (9 percent) and 215,000 km (58 percent); and warm-water species between 33,000 km (9 percent) and 141,000 km (38 percent) of streams across the region. Projected responses to future climate conditions varied dramatically among the 13 species. Overall, 8 of the 13 species declined in distribution, and 5 increased in distribution for both future periods. Responses varied among the three thermal guilds of fishes. Habitats suitable for all 4 cold-water species and 4 of 5 cool-water species under present-day conditions will decline as much as 86 percent and as little as 33 percent, and habitats suitable for all 4 warm-water species will increase as much as 33 percent and as little as 7 percent. In the late 21st century, decreases were greater for the 8 cold- and cool-water species, and increases were greater for the 4 warm-water species, when compared to the mid 21st century periods. Increases were greater in the mid 21st century for one cool-water species (*Hypentelium nigricans,* northern hog sucker) than in the late 21st century.

A Web-based decision support mapping application termed “FishVis” was developed to provide a means to integrate, visualize, query, and download the results of these projected climate-driven responses and inform conservation planning efforts within the region. FishVis allows users to interact by selecting a species or habitat response and time period to display results at regional or reach scales. Popups display results for individual stream reaches when queried. Underlying basemaps of imagery, topography, roads, protected areas, and existing land use, and an index of watershed environmental disturbance are available to aid in the identification of stream reaches which warrant specific management responses to projected climate-change impacts. These geospatial tools and data can be used to identify baseline conditions and guide strategic conservation investments and restoration efforts. Resource managers tasked with developing adaptation strategies to protect streams and fisheries can use these results and the FishVis decision support mapping application to help identify streams that are potentially vulnerable to climate change, guide stream monitoring and thermal classifications, prioritize the allocation of limited financial resources, identify approaches for climate adaptation to best protect stream thermal habitat, and help make quantitative assessments of environmental resources. A geodatabase containing the full dataset of results that are being mapped in FishVis can be downloaded from the FishVis mapping application at http://ccviewer.wim.usgs.gov/FishVis/ or through USGS ScienceBase as a Data Release (Stewart and others, 2016).

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Appendixes 1–4

These Microsoft Excel® (.xlsx) data files are included with the U.S. Geologlocial Survey Scientific Investigations Report 2016–5124 and are availabe for download at http://dx.doi.org/10.3133/sir20165124.

Appendix 1. Forty-eight habitat variables used as model predictors of fish species occurrence in Random Forests models.

Appendix 2. Landscape variables used as model predictors of stream temperature in Wisconsin, Minnesota, Michigan, and New York artificial neural network stream temperature models.

Appendix 3. Summary of performance statistics for the artificial neural network models used to estimate stream temperature in Wisconsin, Minnesota, Michigan, and New York.

Appendix 4. Importance ranking of the top 10 environmental variables for Random Forests models for each of 13 fish species in the Great Lakes region, as calculated by Salford Predictive Modeler®.

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