Rev Fish Biol Fisheries (2017) 27:443–462
DOI 10.1007/s11160-017-9467-0

RESEARCH PAPER

Comparing stream-specific to generalized temperature models to guide salmonid management in a changing climate

Andrew K. Carlson · William W. Taylor · Kelsey M. Hartikainen · Dana M. Infante · T. Douglas Beard Jr. · Abigail J. Lynch

Received: 15 August 2016 / Accepted: 10 January 2017 / Published online: 7 February 2017

Abstract Global climate change is predicted to increase air and stream temperatures and alter thermal habitat suitability for growth and survival of coldwater fishes, including brook charr (*Salvelinus fontinalis*), brown trout (*Salmo trutta*), and rainbow trout (*Oncorhynchus mykiss*). In a changing climate, accurate stream temperature modeling is increasingly important for sustainable salmonid management throughout the world. However, finite resource availability (e.g. funding, personnel) drives a tradeoff between thermal model accuracy and efficiency (i.e. cost-effective applicability at management-relevant spatial extents). Using different projected climate change scenarios, we compared the accuracy and efficiency of stream-specific and generalized (i.e. region-specific) temperature models for coldwater salmonids within and outside the State of Michigan, USA, a region with long-term stream temperature data and productive coldwater fisheries. Projected stream temperature warming between 2016 and 2056 ranged from 0.1 to 3.8 °C in groundwater-dominated streams and 0.2–6.8 °C in surface-runoff dominated systems in the State of Michigan. Despite their generally lower accuracy in predicting exact stream temperatures, generalized models accurately projected salmonid thermal habitat suitability in 82% of groundwater-dominated streams, including those with brook charr (80% accuracy), brown trout (89% accuracy), and rainbow trout (75% accuracy). In contrast, generalized models predicted thermal habitat suitability in runoff-dominated streams with much lower accuracy (54%). These results suggest that, amidst climate change and constraints in resource availability, generalized models are appropriate to forecast thermal conditions in groundwater-dominated streams within and outside Michigan and inform regional-level salmonid management strategies that are practical for coldwater fisheries managers, policy makers, and the public. We recommend fisheries professionals reserve resource-intensive stream-specific models for runoff-dominated systems containing high-priority fisheries resources (e.g. trophy individuals, endangered species) that will be directly impacted by projected stream warming.

Keywords Brook charr · Brown trout · Climate change · Coldwater fisheries · Rainbow trout · Temperature

A. K. Carlson (✉) · W. W. Taylor · K. M. Hartikainen · D. M. Infante
Department of Fisheries and Wildlife, Center for Systems Integration and Sustainability, Michigan State University, 115 Manly Miles Building, 1405 S. Harrison Rd., East Lansing, MI 48824, USA
e-mail: carls422@msu.edu

T. D. Beard Jr. · A. J. Lynch
National Climate Change and Wildlife Science Center, United States Geological Survey, 12201 Sunrise Valley Drive, Reston, VA 20192, USA

Introduction

Streams and rivers cover 0.30–0.56% of the globe across a fluvial area of 485,000–682,000 km^2 (Downing et al.

2012). Climate change is projected to increase stream and river temperatures and alter their thermal habitat suitability for growth, reproduction, and survival of resident fishes (Pilgrim et al. 1998; Lyons et al. 2010; Carlson et al. 2016). In addition, warmer air temperatures are predicted to increase stream and river temperatures indirectly through more variable (and overall lower) precipitation (Stoner et al. 2013), increased evaporation (Compagnucci et al. 2001), and thus decreased groundwater discharge into these river systems. Salmonids such as brook charr (*Salvelinus fontinalis*), brown trout (*Salmo trutta*), and rainbow trout (*Oncorhynchus mykiss*) are coldwater fishes with laboratory temperature preferenda less than or equal to 20 °C and critical thermal maxima less than or equal to 31 °C (Raleigh 1982a, b; Raleigh et al. 1986; Lyons et al. 2009). These species support ecologically, socioeconomically, and culturally important fisheries in North America, South America, Europe, and parts of Asia and Australia (MacCrimmon 1971; Budy et al. 2013; Weber et al. 2015). As such, understanding the effects of climate change on these valuable species will have economic and social ramifications for the management of coldwater stream fisheries throughout the world.

Temperature regulates fish metabolism, growth, reproduction, and survival (Dodds and Whiles 2010; Isaak et al. 2012), all of which affect fish recruitment and fisheries productivity. Temperatures above species-specific thermal maxima cause mortality, whereas temperatures at or below maxima alter individual growth and reproduction (Magnuson et al. 1997). Predicted climate-driven increases in stream temperatures are likely to decrease the thermal habitat suitability of coldwater streams for growth and survival of brook charr, brown trout, and rainbow trout because these species have relatively low thermal tolerances to warm temperatures (Fry et al. 1946; Raleigh 1982a, b; Raleigh et al. 1986). Despite the importance of climate change-induced temperature increases of riverine ecosystems throughout the world (Kaushal et al. 2010; van Vliet et al. 2013), there is widespread scarcity in the availability of long-term stream temperature datasets throughout the world. This data deficiency impedes or prevents development of region- and stream-specific temperature models and inhibits the prediction and mitigation of the ecological and social effects of stream warming on salmonid fisheries (e.g. fragmented species distribution, reduced socioeconomic output). Collectively, the global distribution and importance of stream salmonids, the global scope of climate change, and the general dearth of long-term stream temperature data indicate the importance of developing accurate, efficient approaches for projecting effects of climate change on coldwater streams and designing data-limited strategies for sustainable salmonid management in a warming world.

Fisheries management is broadly defined as the process of using information (e.g. ecological, economic, social, political) to develop strategies for achieving goals established for fisheries resources (Kruger and Decker 1999). Decision-making is fundamental to fisheries management and necessitates informed choices regarding allocation of finite resources (e.g. funding, time, personnel) to achieve the goals set for specific fisheries systems. For example, to mitigate the effects of climate change on coldwater stream ecosystems, fisheries professionals must understand how stream temperature is regulated by ambient atmospheric conditions (e.g. air temperature) and also influenced by meteorological (e.g. solar radiation, wind, humidity) and hydrological (e.g. discharge, depth, groundwater input) conditions in stream watersheds (Gu et al. 1998; Pilgrim et al. 1998). With this knowledge, fisheries professionals can make informed temperature modeling decisions, including which models and variables to use, amidst constraints in resource availability and, ultimately, which thermal habitat management strategies to implement for mitigation purposes.

Heat budget models generally predict water temperatures with high accuracy (i.e. exactness of temperature projection) because they prioritize the relative influence of the various atmospheric, meteorological, and hydrological drivers of stream temperature (O'Driscoll and DeWalle 2006; Wehrly et al. 2009). However, these models generally require extensive and expensive data collection protocols for small spatial extents (e.g. stream reaches), limiting their applicability at the regional scales (e.g. watersheds) where fisheries management agencies typically operate (WDNR 2002; MNDNR 2015). As a result, alternative approaches such as air-stream temperature regression models are often less complex, more cost-effective (i.e. same accuracy at lower cost), and more spatially appropriate than heat budget models (Mohseni et al. 1998; Benyahya et al. 2007), making them more useful for fisheries management agencies when managing for most fish species of interest.

In lieu of heat budget models, fisheries professionals currently use two broad approaches to describe the relationship between air temperature and stream temperature: stream-specific models and generalized models. Stream-specific temperature models account for the unique combination of factors that influence each stream's thermal regime (e.g. air temperature, discharge, groundwater input), whereas generalized models are region-specific in representing the thermal regimes of all streams in a particular area. Stream-specific models treat each stream as a distinct system with a thermal regime influenced by discrete factors, whereas generalized models assume that regional patterns in air temperature, as opposed to system-specific characteristics, are the primary drivers of water temperature (Stefan and Preud'homme 1993; Krider et al. 2013). Each modeling approach has advantages and disadvantages. Generalized models may be less accurate than stream-specific models in predicting exact water temperatures, but their development requires significantly lower investments of funding, time, and personnel as streams do not have to be monitored individually. In contrast, stream-specific models are generally more accurate than generalized models but require significantly more resources to develop. In addition, fisheries management strategies (e.g. harvest regulations) implemented based on stream-specific models may be cumbersome to implement because they will likely be unique to—and thus variable among—individual streams reaches.

Many U.S. states (e.g. Michigan, Wisconsin, Minnesota; MDNR 2000; WDNR 2002; MNDNR 2015) already manage streams on a regional basis, aligning more closely with the generalized, rather than stream-specific, temperature modeling framework. However, the tradeoffs associated with stream-specific and generalized models are important to consider in evaluating the accuracy and efficiency (i.e. cost-effective applicability at management-relevant spatial extents) of each modeling approach to achieve specific management objectives for sustaining stream salmonid fisheries in a changing climate.

Comparing stream-specific and generalized temperature models necessitates the availability of long-term (i.e. $\geq$10 year) stream temperature data. Although long time-series stream temperature data sets are relatively uncommon, fisheries professionals in the State of Michigan, USA, have monitored temperatures in many trout streams for 10–20 years, making it an ideal study area in which to compare stream-specific and generalized models. Brook charr, brown trout, and rainbow trout are ecologically and socio-economically important fishes in Michigan (Godby et al. 2007), serving as keystone predators in coldwater streams and supporting valuable recreational fisheries in which more than 585,000 anglers spent 8.2 million angling days in 2011 (USFWS 2011). In Michigan, projected air temperature warming is predicted to increase summer temperatures in coldwater streams by 0.19–5.49 °C from 2016 to 2056 (Carlson et al. 2016) and decrease thermal habitat availability and salmonid growth in systems that exceed thermal optima during the warmest period of the year (i.e. July; Zorn et al. 2011). Although Carlson et al. (2016) used stream-specific models to project future water temperatures in Michigan streams, the present study expands upon previous work by explicitly comparing stream-specific and generalized models to inform stream salmonid management amidst climate change and limitations in the availability of funding, time, and personnel.

The goal of this study was to evaluate the impact of warming water temperatures on salmonid growth and survival in coldwater streams in select areas of North America. Two modeling approaches were used to predict thermal habitat changes: stream-specific and generalized models. These models were chosen as they are spatially and temporally robust and thus can inform salmonid management approaches amidst a changing climate and resource limitations. As such, this study was intended to lay a conceptual foundation for future studies in other areas of the world with coldwater streams and fish populations susceptible to climate change. The specific objectives of this study were to: (1) measure the accuracy of stream-specific and generalized models in predicting water temperature and thermal habitat suitability for salmonid growth and survival in streams in the State of Michigan and the eastern USA that span latitudinal and hydrological gradients and support socioeconomically valuable salmonid populations; (2) forecast future water temperatures and thermal habitat suitability in these streams in select future years (i.e. 2036, 2056); and, (3) evaluate the accuracy and efficiency of stream-specific and generalized models to develop a model comparison approach that can be used for salmonid management programs within and outside Michigan.

Methods

Study area

Fifty-two coldwater salmonid streams were selected throughout Michigan based on latitudinal, hydrological, and recreational criteria (Fig. 1; Table 1). Streams spanned a latitudinal thermal gradient from north to south. Base flow, the component of streamflow attributable to groundwater, varied among streams such that they covered a gradient from surface-runoff to groundwater dominance (see "Baseflow measurements" below) over which brook charr, brown trout, and rainbow trout occur in Michigan. In addition, all streams were important from a fisheries management perspective as they support productive recreational fisheries for brook charr, brown trout, or rainbow trout. These species are widely distributed throughout Michigan (Zorn et al. 2011, 2012), making them effective indicator species for evaluating the impact of climate change on coldwater stream fishes adapted to groundwater-dominated and surface runoff-dominated streams. Overall, brook charr were found in 28 of the streams evaluated, brown trout in 26 streams, and rainbow trout in 21 streams. Seventeen of the streams studied supported more than one salmonid species, and six streams supported all three species (Table 1).

Baseflow measurements

A United States Geological Survey (USGS) report of base flow (Neff et al. 2005) was used to obtain each study stream's base flow index (BFI), a value that represents the mean rate of base flow (mm*year^{-1}) divided by the corresponding mean rate of total streamflow (mm*year^{-1}) and ranges from zero (i.e. no groundwater) to one (i.e. all groundwater; Wahl and Wahl 1988). All BFI calculations were made using a digital filter hydrograph separation technique (Arnold and Allen 1999; Kelleher et al. 2012) whereby daily streamflow records were partitioned into

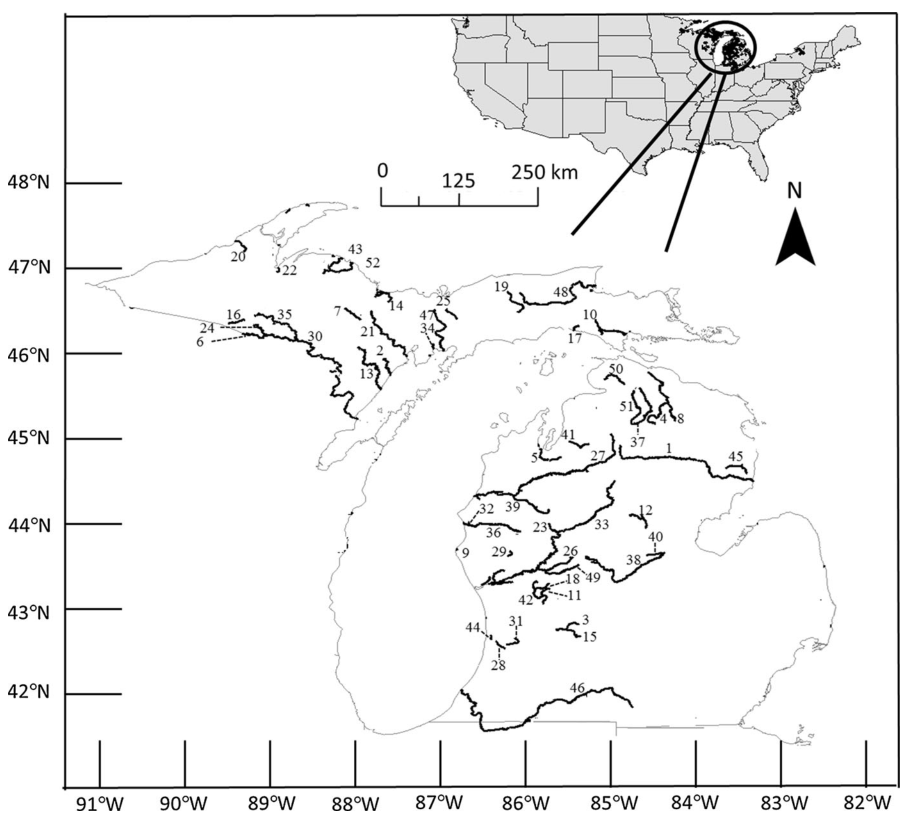

Fig. 1 Map of 52 brook charr, brown trout, and rainbow trout streams used for air–stream temperature modeling in Michigan. Streams and corresponding identification numbers are listed in Table 1. Modified from Carlson et al. (2016)

Table 1 Descriptive information about 52 salmonid streams used for temperature modeling in Michigan, USA

Stream	Map	Type	Species	BFI	Area	Elevation
Au Sable River	1	GD	BKC, BNT, RBT	0.72	5003.86	401.68
Bark River*	2	RD	BNT	0.60	114.74	238.14
Bear Creek*	3	GD	BNT	0.65	25.23	256.07
Black River*	4	RD	BKC	0.55	1180.62	368.47
Boardman River*	5	GD	BKC, BNT	0.63	626.78	319.63
Brule River	6	RD	BNT	0.52	2719.49	515.46
Bryan Creek*	7	RD	BKC	0.60	175.60	432.32
Canada Creek*	8	RD	BKC	0.55	472.24	284.20
Carlton Creek	9	GD	BKC	0.73	20.10	235.04
Carp River*	10	RD	BKC, BNT, RBT	0.60	675.99	260.19
Cedar Creek*	11	RD	BKC, BNT	0.50	48.17	267.04
Cedar River (SLP)*	12	RD	RBT	0.60	114.74	336.84
Cedar River (UP)	13	RD	BNT	0.60	735.56	306.49
Chocolay River*	14	RD	RBT	0.56	404.04	379.63
Coldwater River	15	RD	BNT	0.45	432.53	271.94
Cooks Run	16	RD	BKC, BNT	0.52	183.63	529.42
Davenport Creek*	17	RD	RBT	0.57	20.12	250.71
Duke Creek*	18	RD	BKC, BNT	0.50	85.73	276.93
East Branch Fox River*	19	GD	BKC, BNT	0.73	310.80	274.93
Elm River*	20	RD	RBT	0.45	31.34	424.23
Escanaba River*	21	RD	BKC, BNT	0.44	1012.69	424.08
Falls River	22	RD	BKC	0.52	118.62	377.38
Hersey River	23	GD	BNC	0.62	297.85	368.40
Iron River*	24	RD	BKC	0.52	181.04	488.86
Little Indian River*	25	GD	BKC	0.73	220.93	277.80
Little Muskegon River	26	GD	RBT	0.62	966.07	313.04
Manistee River*	27	GD	BKC, BNT, RBT	0.65	1916.59	406.05
Mann Creek	28	GD	BKC	0.65	44.29	202.39
Martin Creek	29	GD	BKC	0.61	52.84	259.35
Menominee River	30	RD	RBT	0.57	10,308.15	477.73
Miller Creek	31	GD	BKC	0.65	2.80	241.26
Mosquito Creek	32	GD	BKC	0.62	29.01	193.09
Muskegon River	33	GD	RBT	0.62	6604.47	359.73
Ogontz River	34	GD	RBT	0.74	53.16	214.53
Paint River	35	RD	BNT	0.52	1613.56	496.64
Pere Marquette River*	36	GD	BNT	0.61	1901.05	310.87
Pigeon River*	37	GD	BNT, RBT	0.65	944.50	380.18
Pine River (SLP)*	38	RD	BNT	0.49	1622.37	318.84
Pine River (NLP)*	39	GD	BKC, BNT, RBT	0.65	688.94	395.08
Prairie Creek*	40	RD	BNT	0.50	270.83	246.30
Rapid River	41	GD	BKC, BNT, RBT	0.63	212.64	355.73
Rogue River*	42	RD	BNT, RBT	0.50	678.58	278.19

Table 1 continued

Stream	Map	Type	Species	BFI	Area	Elevation
Salmon Trout River*	43	RD	BKC	0.45	104.12	442.89
Silver Creek	44	GD	BKC	0.65	8.00	224.22
South Branch Pine River	45	GD	RBT	0.72	114.34	273.14
St. Joseph River	46	GD	BKC, RBT	0.63	10,722.55	346.56
Sturgeon River	47	GD	BKC, RBT	0.74	505.05	276.66
Tahquamenon River*	48	RD	BNT	0.55	2027.96	285.95
Tamarack Creek	49	GD	BNT, RBT	0.62	375.55	302.21
West Branch Maple River	50	GD	BKC	0.65	598.29	282.57
West Branch Sturgeon River*	51	GD	BKC, BNT, RBT	0.65	473.97	394.90
Yellow Dog River*	52	RD	RBT	0.52	178.71	537.07

Map number refers to stream identifiers in Fig. 1. Type denotes hydrological influence: groundwater-dominated (GD) streams had base-flow index (BFI) values > 0.60, whereas surface-runoff dominated (RD) systems had BFI values ≤ 0.60. Species refers to salmonids present in each stream (i.e. brook charr [BKC], brown trout [BNT], rainbow trout [RBT]). Area is drainage area (km^2) and Elevation is mean catchment elevation (m). *Asterisks* indicate that streams had historical field-collected air and stream temperatures for development of stream-specific regression models. SLP, NLP, and UP refer to Michigan's Southern Lower Peninsula, Northern Lower Peninsula, and Upper Peninsula, respectively

groundwater and surface-runoff components to determine the relative contribution of each. A BFI of 0.60 was treated as a threshold for streams to be categorized as groundwater-dominated (GD; BFI > 0.60) or surface runoff-dominated (RD; BFI ≤ 0.60; McKergow et al. 2005; Dukić and Mihailović 2012).

Stream-specific regression models

Historical air and water temperatures were used to develop stream-specific temperature regression models (Table 2). Daily air temperatures measured in July from 1990 to 2010 were obtained using the United States Department of Energy Historical Climate Network (CDIAC 2016). Air temperature measurements were reported from the gauging station closest to each stream's headwaters, where MDNR gauges recorded daily stream temperatures in July from 1990 to 2010. July temperatures were used because this month is typically the warmest and most thermally stressful for salmonids in Michigan (Zorn et al. 2011) and likely to be the time period that will first impact salmonid thermal habitat quality and quantity in a changing climate. In July, temperatures are typically more suitable (i.e. cooler) for salmonids that live in GD, heavily forested headwater reaches of Michigan streams (Drake and Taylor 1996; Hayes et al. 1998), so emphasis was placed on these reaches with the understanding that if they become warmer, temperatures in downstream reaches will also generally increase. The National Hydrography Dataset Plus Version 1 (NHDPlusV1) and the Watershed Boundary Dataset (USEPA USEPA 2005) were used to identify each stream's sub-basin (8-digit Hydrologic Unit Code [HUC8]) and sub-watershed (HUC 12). In addition, NHDPlusV1 and the USGS StreamStats interactive map application (USGS 2015) were used to measure drainage area (km^2) and mean elevation (m) for each stream. Stream-specific regression models were developed by pairing mean July air and water temperatures from recent years (i.e. 2002–2010) for the 28 streams for which historical stream temperatures were available (Tables 1, 2). To predict future stream temperatures, the product of air temperature regression coefficients and air temperature projections (described below) was calculated and added to model intercepts (i.e. stream temperature = air temperature coefficient*projected future air temperature + intercept). Air temperature coefficients represented indices of stream thermal sensitivity (i.e. relative susceptibility to temperature change) because larger positive coefficients produced warmer stream temperatures (Kelleher et al. 2012).

Generalized regression models

Stream temperatures were also predicted by converting sub-basin air temperature projections to water

Table 2 Stream-specific temperature regressions with standard errors (SE), *F* values, *P* values, and R^2 values

Stream	Model	SE	*F*	*P*	R^2
Runoff-dominated					
Bark River	Water = 12.98 + 0.32*air	0.05	49.41	<0.01	0.86
Bryan Creek	Water = 7.69 + 0.42*air	0.08	28.86	<0.01	0.78
Carp River	Water = 12.06 + 0.28*air	0.04	41.63	<0.01	0.84
Cedar Creek	Water = 6.32 + 0.56*air	0.09	39.10	<0.01	0.83
Cedar River (SLP)	Water = 11.42 + 0.25*air	0.03	97.82	<0.01	0.92
Elm River	Water = 2.11 + 0.82*air	0.06	193.20	<0.01	0.96
Escanaba River	Water = 3.03 + 0.88*air	0.14	39.26	<0.01	0.83
Pine River (SLP)	Water = 9.23 + 0.40*air	0.04	119.15	<0.01	0.94
Prairie Creek	Water = 0.95 + 0.74*air	0.07	106.03	<0.01	0.93
Salmon Trout River	Water = 8.23 + 0.29*air	0.05	33.60	<0.01	0.80
Tahquamenon River	Water = 12.29 + 0.50*air	0.05	115.88	<0.01	0.93
Groundwater-dominated					
Bear Creek	Water = 11.61 + 0.23*air	0.03	46.74	<0.01	0.85
Black River	Water = 8.74 + 0.29*air	0.04	57.04	<0.01	0.88
Boardman River	Water = 11.99 + 0.14*air	0.02	72.85	<0.01	0.90
Canada Creek	Water = 6.91 + 0.60*air	0.08	61.72	<0.01	0.88
Chocolay River	Water = 10.29 + 0.23*air	0.03	77.99	<0.01	0.91
Davenport Creek	Water = 8.97 + 0.13*air	0.01	99.55	<0.01	0.92
Duke Creek	Water = 4.45 + 0.48*air	0.08	37.27	<0.01	0.82
East Branch Fox River	Water = 7.73 + 0.33*air	0.04	86.45	<0.01	0.91
Iron River	Water = 12.76 + 0.30*air	0.04	52.58	<0.01	0.87
Little Indian River	Water = 14.86 + 0.06*air	0.01	83.65	<0.01	0.91
Manistee River	Water = 10.67 + 0.13*air	0.02	57.70	<0.01	0.88
Pere Marquette River	Water = 12.50 + 0.18*air	0.02	51.89	<0.01	0.86
Pigeon River	Water = 11.93 + 0.11*air	0.01	60.49	<0.01	0.88
Pine River (NLP)	Water = 10.89 + 0.22*air	0.03	73.41	<0.01	0.90
Rogue River	Water = 13.17 + 0.23*air	0.04	27.46	<0.01	0.77
West Branch Sturgeon River	Water = 11.93 + 0.06*air	0.01	67.49	<0.01	0.89
Yellow Dog River	Water = 9.90 + 0.38*air	0.06	45.58	<0.01	0.85

SLP and *NLP* refer to Michigan's Southern Lower Peninsula and Northern Lower Peninsula, respectively

temperatures using two generalized regression equations. The Stefan and Preud'homme (1993, hereafter referred to as SP) model, developed specifically for RD streams, estimates weekly stream temperature by:

$$T_w = 2.9 + 0.86T_a,$$

where T_w is water temperature (°C) and T_a is air temperature (°C). The standard deviation (SD) of the model is 2.16 °C.

The Krider et al. (2013, hereafter referred to as K) model, developed specifically for GD streams, estimates weekly stream temperature by:

$$T_w = 6.63 + 0.38\ T_a,$$

where T_w is water temperature (°C) and T_a is air temperature (°C). The model SD is 4.80 °C.

The K model was used to project GD stream temperatures, whereas the SP model was used to predict RD stream temperatures, as these models were developed specifically for those corresponding streams types. Although both models were developed for weekly temperatures, daily and monthly air and water temperatures have been reported to be associated through a nearly 1:1 relationship (Ozaki et al. 2003), suggesting a strong positive weekly-to-monthly relationship and validating use of monthly average air temperatures to project stream temperatures.

Air temperature projections

Mean July air temperatures were forecasted in future years (2036 and 2056) for each sub-basin evaluated. Air temperatures were projected using three coupled climate models: the Third Generation Coupled Global Climate Model (CGCM3, Canadian Centre for Climate Modelling and Analysis), the CM2 Global Coupled Climate Model (CM2, Geophysical Fluid Dynamics Laboratory at the National Oceanic and Atmospheric Administration), and the Hadley Centre Coupled Model version 3 (HadCM3, Met Office, United Kingdom's National Weather Service). All models were based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset and had variable thermal input parameters (e.g. solar radiation, volcanic activity, trace gases, sulfate aerosols). Spatial downscaling was performed using the Bias-Correction Spatial Disaggregation (BCSD) approach to adjust the resolution of the climate model ($\sim$200 km $\times$ 200 km) to a scale appropriate for Michigan streams (12 km $\times$ 12 km; Maurer et al. 2007). Mean July air temperatures were obtained for Michigan sub-basins containing salmonid streams from the United States Forest Service's (USFS) Eastern Forest Environmental Threat Assessment Center (EFETAC) in North Carolina. Temperatures were projected using the Special Report of Emission Scenarios A2 and B1 climate forcing scenarios and the CGCM3, CM2, and HadCM3 models using area-weighted means for all years. The A2 scenario (hereafter "high emissions") predicts atmospheric CO_2 concentrations to be 820 ppm in 2100 in a world characterized by rapid economic growth and efficient energy technologies (IPCC 2007). In contrast, the B1 scenario (hereafter "low emissions") projects atmospheric CO_2 concentrations to be 550 ppm in 2100 in a convergent world with a service and information economy and reduced material consumption (IPCC 2007).

Stream temperature and thermal habitat suitability projections

Stream-specific and generalized models were used to backcast July stream temperatures in 2006 and 2012 and forecast July temperatures in 2036 and 2056 based on air temperature predictions in these years. Backcasting was performed to evaluate the accuracy of stream-specific and generalized models by comparing predicted and actual temperatures in years with pre-existing stream temperature metrics. Mean air temperatures were calculated from the three CCMs to account for each model's uncertainty, unique temperature drivers (e.g. forest canopy density, atmospheric pressure, soil layering), and range of predicted air temperatures. Species-specific thermal habitat suitability statuses were assigned for each stream based on temperature thresholds for growth and survival associated with projected July temperatures. Status 1 streams had maximum July average temperatures that were optimal for growth of brook charr (11.0–16.5 °C; Raleigh 1982a), brown trout (12.0–17.0 °C; Raleigh et al. 1986; Hay et al. 2006), and rainbow trout (12.0–16.4 °C; Wurtsbaugh and Davis 1977; Raleigh 1982b). Temperatures of status 2 streams resulted in reduced growth of brook charr (16.5–20.5 °C; Raleigh 1982a), brown trout (17.0–20.0 °C; Elliott and Hurley 2000), and rainbow trout (16.4–22.5 °C; Wurtsbaugh and Davis 1977). Status 3 streams had temperatures that were too warm for growth to occur: 20.5–25.3 °C for brook charr (Baldwin 1957; Raleigh 1982a), 20.0–26.2 °C for brown trout (Hay et al. 2006), and 22.5–25.0 °C for rainbow trout (Wurtsbaugh and Davis 1977; Raleigh 1982b). Finally, status 4 streams had thermal conditions that create high mortality risk for brook charr (>25.3 °C; Fry et al. 1946; Raleigh 1982a), brown trout (>26.2 °C; Hay et al. 2006), and rainbow trout (>25.0 °C; Wurtsbaugh and Davis 1977; Raleigh 1982b).

Analyses

The accuracy of stream-specific regression models was evaluated by calculating the deviation between projected and actual stream temperatures and salmonid thermal habitat suitability statuses in 2006. Similarly, the accuracy of generalized regression models was assessed by calculating differences between projected and actual stream temperatures and salmonid thermal habitat suitability statuses. In comparing generalized K and SP models, temperature projections were considered inaccurate if they were lower (i.e. under-prediction) or higher (i.e. over-prediction) than actual temperatures by an amount greater than the standard deviation of the model with the lowest standard deviation (i.e. SP, SD = 2.16 °C). The relative accuracy of stream-specific and generalized models was evaluated by comparing each model's deviation between projected and actual temperatures and salmonid thermal habitat suitability statuses with those of the corresponding model (i.e. generalized or stream-specific) in each of the 28 streams with historical water temperatures (Table 1). Stream-specific models could not be developed for the 24 streams (17 GD, 7 RD) for which historical water temperatures were not available. However, it was deemed appropriate to project stream temperatures and habitat suitability statuses using either the generalized K model (for the additional 17 GD streams) or the SP model (for the additional 7 RD streams) if the accuracy of these models in predicting habitat suitability in their respective streams was greater than 80%. Temperature deviations (i.e. between actual temperatures and model projections and between stream-specific and generalized model predictions) were considered biologically significant if they produced changes in thermal habitat suitability statuses. Such changes were necessary for biological significance as defined in this manuscript, so temperature deviations rather than absolute temperatures were the appropriate measurement and were required for defining management-relevant categories for growth and survival.

To investigate the applicability of stream-specific and generalized models in regions outside Michigan, temperatures and thermal habitat suitability projections from the two model types were compared with historical (i.e. 2006) temperatures and habitat suitability statuses in five reported high-quality brook charr and brown trout streams located in the States of Connecticut, Maine, North Carolina, and Wisconsin, USA (Schlee 2014). Historical data for these streams were obtained from the USGS National Water Information System (USGS 2016).

Results

Temperature projections

Stream-specific models projected historical water temperatures more accurately than generalized models in all 28 streams that had historical water temperatures available. In GD streams, the mean deviation of stream-specific model projections from actual temperatures in 2006 was −0.30 °C (SD = 0.35, range = −0.71–0.79) under the high CO_2 emission scenario and −0.38 °C (SD = 0.41, range = −1.04–0.79) under the low emission scenario. Compared to stream-specific model predictions, the mean deviation of generalized K model projections in GD streams was larger under high emissions (−1.21 °C, SD = 2.10, range = −5.40–2.60) and low emissions (−1.36 °C, SD = 2.13, range = −5.60–2.30). Similarly, the mean deviation of stream-specific model projections from actual temperatures in RD streams was −0.70 °C (high emissions, SD = 0.77, range = −1.78–1.14) and −0.88 °C (low emissions; SD = 0.75, range = −1.70–0.84), compared to 2.57 °C (high emissions, SD = 1.92, range = −0.70–5.30) and 2.10 °C (low emissions, SD = 2.11, range = −1.50–4.60) for the generalized SP model. For streams in the State of Michigan, stream-specific models predicted that stream temperatures will increase by an average of 1.5 °C (GD streams) and 3.1 °C (RD streams) under high emissions and 1.2 °C (GD streams) and 3.1 °C (RD streams) under low emissions from 2016 to 2056. Throughout Michigan, generalized models projected stream temperatures will increase by an average of 0.6 °C (GD streams) and 1.5 °C (RD streams) under high emissions and 0.8 °C (GD streams) and 1.9 °C (RD streams) under low emissions from 2016 to 2056.

Thermal habitat suitability projections

Although stream-specific models predicted temperatures of GD and RD streams more accurately than generalized models, both model types projected accurate salmonid thermal habitat suitability statuses in GD streams (Fig. 2). Under high and low CO_2 emissions, stream-specific models projected thermal habitat suitability with 100% accuracy in GD streams with brook charr, brown trout, and rainbow trout (Table 3). Deviations between actual temperatures and stream-specific model projections were not biologically significant as they produced the same thermal habitat suitability statuses. In comparison, the overall accuracy of the generalized K model in projecting thermal habitat suitability was 82% in GD streams for brook charr (80% accuracy), brown trout (89% accuracy), and rainbow trout (75% accuracy; Table 3) under both emissions scenarios.

In contrast to GD streams, differences in temperature predictions between stream-specific and

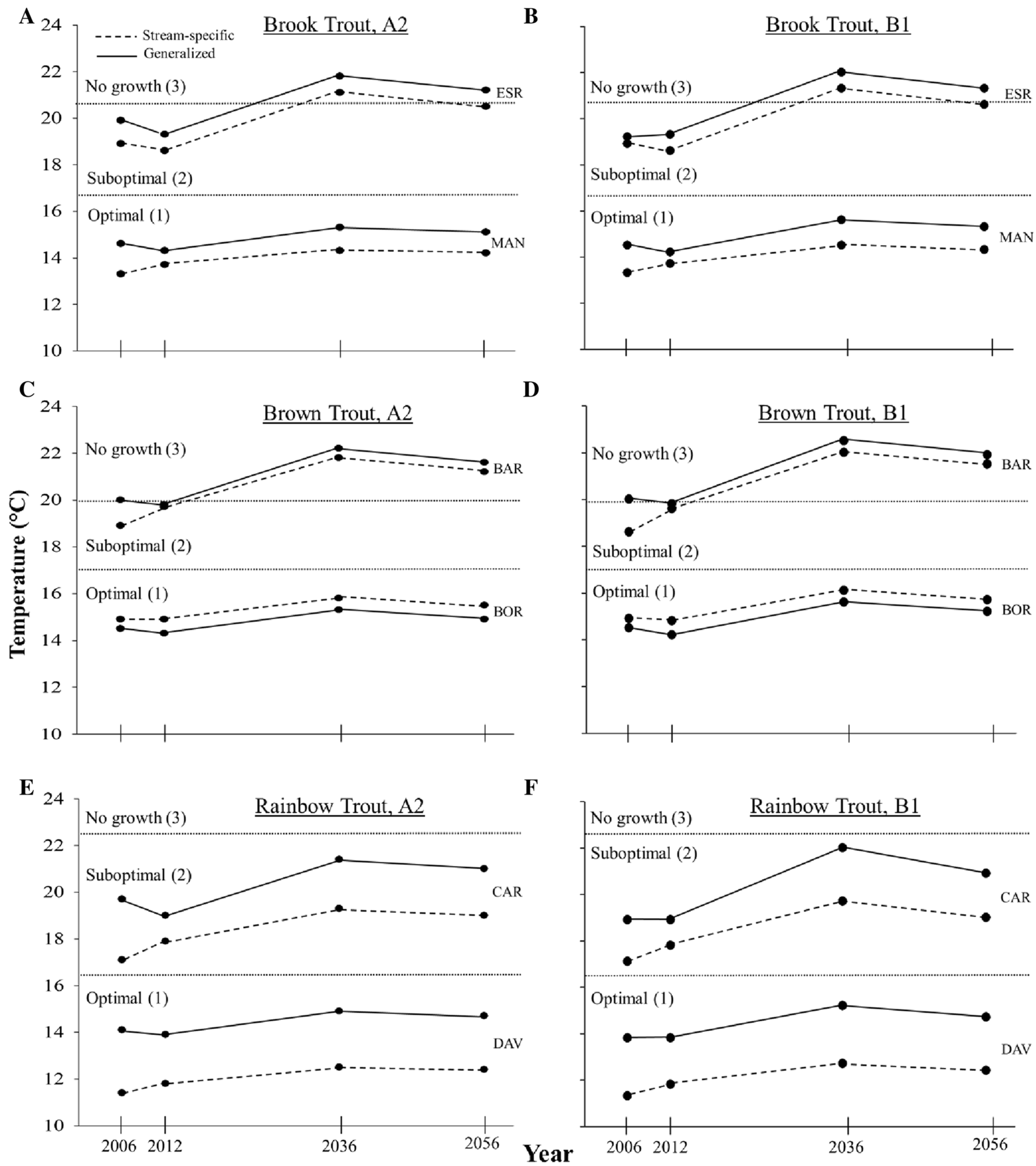

Fig. 2 Temperature predictions in representative Michigan streams in 2006, 2012, 2036, and 2056 using stream-specific (*lines*) and generalized (*solid lines*) temperature models. Plots are organized by species and emissions scenario: **a** Brook Charr, A2 Scenario; **b** Brook Charr, B1 Scenario; **c** Brown Trout, A2 Scenario; **d** Brown Trout, B1 Scenario; **e** Rainbow Trout, A2 Scenario; **f** Rainbow Trout, B1 Scenario. In each plot, the upper stream is surface runoff-dominated, and the lower stream is groundwater-dominated. *Dotted lines* represent transitions between thermal habitat suitability statuses (*1* optimal, *2* suboptimal, *3* no growth, *4* high mortality risk). Stream abbreviations are as follows: *BAR* Bark River, *BOR* Boardman River, *CAR* Carp River, *DAV* Davenport Creek, *ESR* Escanaba River, *MAN* Manistee River

Table 3 Projected and actual temperatures (°C) and associated thermal habitat suitability (THS) statuses for growth and survival of brook charr (BKC), brown trout (BNT), rainbow trout (RBT), and all three species (All) in groundwater-dominated streams (1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk)

Stream	Species	Year	Projected Temperature	THS	Actual Temperature	THS
Bear Creek	BNT	2006	16.5, 15.4	1, 1	15.8	1
		2012	16.7, 15.1	1, 1		
		2036	17.8, 16.0	2, 1		
		2056	18.2, 16.2	2, 1		
Black River	BKC	2006	14.5, 14.6	1, 1	15.1	1
		2012	15.1, 14.3	1, 1		
		2036	16.3, 15.3	1, 1		
		2056	16.0, 15.0	1, 1		
Boardman River	BKC, BNT	2006	14.9, 14.5	1, 1	15	1
		2012	14.9, 14.3	1, 1		
		2036	15.8, 15.3	1, 1		
		2056	15.5, 14.9	1, 1		
Canada Creek	BKC	2006	19.4, 14.6	2, 1	20	2
		2012	19.5, 14.3	2, 1		
		2036	22.9, 15.3	3, 1		
		2056	21.9, 15.0	3, 1		
Duke Creek	BKC, BNT	2006	14.7, 15.3	1, 1	15.3	1
		2012	15.8, 14.9	1, 1		
		2036	18.5, 15.9	2, 1		
		2056	19.1, 16.0	2, 1		
East Branch Fox River	BKC, BNT	2006	13.8, 14.0	1, 1	14.2	1
		2012	14.1, 13.8	1, 1		
		2036	15.6, 14.8	1, 1		
		2056	15.3, 14.6	1, 1		
Iron River	BKC	2006	18.5, 14.1	2, 1	18.6	2
		2012	17.8, 13.8	2, 1		
		2036	19.7, 15.0	2, 1		
		2056	19.2, 14.7	2, 1		
Little Indian River	BKC	2006	16.1, 14.0	1, 1	16.2	1
		2012	16.1, 13.8	1, 1		
		2036	16.5, 14.8	2, 1		
		2056	16.4, 14.6	1, 1		
Manistee River	All	2006	13.3, 14.6	1, 1	13.6	1
		2012	13.7, 14.3	1, 1		
		2036	14.3, 15.3	1, 1		
		2056	14.2, 15.1	1, 1		
Pigeon River	BNT, RBT	2006	14.1, 14.4	1, 1	14.5	1
		2012	14.2, 14.2	1, 1		
		2036	14.8, 15.1	1, 1		
		2056	14.6, 14.8	1, 1		
Pine River (NLP)	All	2006	15.3, 14.6	1, 1	16	1
		2012	15.9, 14.3	1, 1		
		2036	17.1, 15.3	2, 1		

Table 3 continued

Stream	Species	Year	Projected Temperature	THS	Actual Temperature	THS
		2056	16.9, 15.1	2, 1		
Rogue River	BNT, RBT	2006	18.0, 15.3	2, 1	18.4	2
		2012	17.9, 14.9	2, 1		
		2036	19.0, 15.9	2, 1		
		2056	19.2, 16.0	2, 1		
W. Branch Sturgeon River	All	2006	13.1, 14.4	1, 1	13.3	1
		2012	13.2, 14.2	1, 1		
		2036	13.5, 15.1	1, 1		
		2056	13.4, 14.8	1, 1		
Yellow Dog River	RBT	2006	17.3, 14.1	2, 1	18	2
		2012	19.7, 13.9	2, 1		
		2036	21.8, 15.0	2, 1		
		2056	21.3, 14.8	2, 1		

Predictions are derived from stream-specific and generalized models (separated by commas) under the A2 carbon dioxide emissions scenario and are similar to those from the B1 scenario (not included here). NLP denotes the Northern Lower Peninsula of Michigan

generalized models in RD systems were more often biologically significant (Fig. 2). Stream-specific models were more accurate than generalized models in predicting salmonid thermal habitat suitability statuses in RD streams. Compared to 100% accuracy in GD systems, stream-specific models predicted thermal habitat suitability with 80% accuracy in RD streams for brook charr (80% accuracy), brown trout (75% accuracy), and rainbow trout (100% accuracy; Table 4) under high CO_2 emissions. Under low emissions, stream-specific models predicted thermal habitat suitability with 93% accuracy in GD streams for brook charr (80% accuracy), brown trout (100% accuracy), and rainbow trout (100% accuracy; Table 4). In comparison, under high emissions, the overall accuracy of the generalized SP model was 47% in RD streams for brook charr (60% accuracy), brown trout (25% accuracy), and rainbow trout (100% accuracy; Table 4). Under low emissions, the overall accuracy of the generalized SP model was 60% in RD streams for brook charr (60% accuracy), brown trout (50% accuracy), and rainbow trout (100% accuracy; Table 4).

Generalized K versus SP models

The generalized K model predicted stream temperatures more accurately than the generalized SP model. The generalized K model predicted historical GD stream temperatures with 75% accuracy under high and low CO_2 emissions (Table 3), whereas the generalized SP model backcasted temperatures with only 36% accuracy under high and low CO_2 emissions (Table 4). The generalized SP model over-predicted temperatures by 2.4–5.3 °C (average 3.8 °C) in seven RD streams (i.e. Bryan Creek, Cedar Creek, Cedar River, Elm River, Pine River, Prairie Creek, Salmon Trout River) under high emissions and by 2.5–4.6 °C (average 3.7 °C) in six RD streams (i.e. Bryan Creek, Cedar Creek, Cedar River, Pine River, Prairie Creek, Salmon Trout River) under low emissions (Table 4). The generalized SP model predicted thermal habitat suitability in RD streams with 35% lower accuracy (high emissions) and 22% lower accuracy (low emissions) than the generalized K model in GD systems. Therefore, generalized models are best suited for use in GD streams.

Data-limited streams

Because the generalized K model projected historical thermal habitat suitability statuses in GD streams with relatively high accuracy (>80%), the K model was used to predict temperature and habitat suitability in the 17 GD systems for which historical water temperatures were unavailable. Under both high and low CO_2 emissions, all of these streams were projected to maintain optimal growing conditions in July for brook

Table 4 Projected and actual temperatures (°C) and associated thermal habitat suitability (THS) statuses for growth and survival of brook charr (BKC), brown trout (BNT), rainbow trout (RBT), and all three species (All) in surface runoff-dominated streams (1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk)

Stream	Species	Year	Projected Temperature	THS	Actual Temperature	THS
Bark River	BNT	2006	18.9, 20.4	2, 3	19.9	2
		2012	19.7, 19.8	2, 2		
		2036	21.8, 22.2	3, 3		
		2056	21.2, 21.6	3, 3		
Bryan Creek	BKC	2006	15.3, 19.9	1, 2	16.7	2
		2012	17.2, 19.3	2, 2		
		2036	19.9, 21.8	2, 3		
		2056	19.4, 21.2	2, 3		
Carp River	All	2006	17.1, 19.7	2, 2	17.6	2
		2012	17.9, 19.0	2, 2		
		2036	19.3, 21.4	2, 3		
		2056	19.0, 21.0	2, 3		
Cedar Creek	BKC, BNT	2006	18.3, 22.5	2, 3	18.3	2
		2012	18.7, 21.7	2, 3		
		2036	19.9, 23.8	2, 3		
		2056	20.1, 24.2	2, 3		
Cedar River (SLP)	BNT	2006	16.6, 20.4	1, 3	17.1	2
		2012	16.0, 19.8	1, 2		
		2036	17.3, 22.2	2, 3		
		2056	16.9, 21.6	1, 3		
Escanaba River	BKC, BNT	2006	18.9, 19.9	2, 2	19.9	2
		2012	18.6, 19.3	2, 2		
		2036	21.1, 21.8	3, 3		
		2056	20.5, 21.2	3, 3		
Elm River	RBT	2006	17.0, 19.9	2, 2	17.5	2
		2012	20.7, 19.4	2, 2		
		2036	25.4, 22.2	4, 2		
		2056	24.3, 21.5	3, 2		
Pine River (SLP)	BNT	2006	17.5, 22.2	2, 3	18.4	2
		2012	18.5, 21.4	2, 3		
		2036	20.5, 23.6	3, 3		
		2056	20.7, 23.8	3, 3		
Prairie Creek	BNT	2006	16.6, 22.5	1, 3	18.3	2
		2012	17.9, 21.7	2, 3		
		2036	21.4, 23.8	3, 3		
		2056	22.0, 24.2	3, 3		
Salmon Trout River	BKC	2006	13.5, 19.9	1, 2	14.6	1
		2012	15.9, 19.4	1, 2		
		2036	17.8, 22.2	2, 3		
		2056	17.3, 21.5	2, 3		
Tahquamenon River	BNT	2006	21.2, 19.3	3, 2	20	3
		2012	21.6, 18.7	3, 2		
		2036	24.0, 21.1	3, 3		
		2056	23.6, 20.7	3, 3		

Predictions are derived from stream-specific and generalized models (separated by commas) under the A2 carbon dioxide emissions scenario and are similar to those from the B1 scenario (not included here). SLP denotes the Southern Lower Peninsula of Michigan

Table 5 List of groundwater-dominated streams without actual (i.e. field-measured) 2006 stream temperatures for which generalized models were used to predict temperatures and associated thermal habitat suitability (THS) statuses in 2006, 2012, 2036, and 2056 under A2 and B1 emissions (separated by commas). (1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk)

Stream	2006 Pr	THS	2012 Pr	THS	2036 Pr	THS	2056 Pr	THS
Au Sable River	14.6, 14.4	ALL: 1, 1	14.2, 14.1	ALL: 1, 1	15.2, 15.5	ALL: 1, 1	14.9, 15.1	ALL: 1, 1
Carlton Creek	14.0, 13.7	BKC: 1, 1	13.8, 13.8	BKC: 1, 1	14.8, 15.1	BKC: 1, 1	14.6, 14.6	BKC: 1, 1
Hersey River	14.7, 14.7	BNT: 1, 1	14.4, 14.4	BNT: 1, 1	15.3, 15.7	BNT: 1, 1	15.3, 15.3	BNT: 1, 1
Little Muskegon River	14.7, 14.7	RBT: 1, 1	14.4, 14.4	RBT: 1, 1	15.3, 15.7	RBT: 1, 1	15.3, 15.4	RBT: 1, 1
Mann Creek	15.4, 15.4	BKC: 1, 1	15.1, 15.1	BKC: 1, 1	16.0, 16.3	BKC: 1, 1	16.2, 16.2	BKC: 1, 1
Martin Creek	14.9, 14.9	BKC: 1, 1	14.6, 14.6	BKC: 1, 1	15.5, 15.8	BKC: 1, 1	15.5, 15.6	BKC: 1, 1
Miller Creek	15.4, 15.4	BKC: 1, 1	15.1, 15.1	BKC: 1, 1	16.0, 16.3	BKC: 1, 1	16.2, 16.2	BKC: 1, 1
Mosquito Creek	14.7, 14.7	BKC: 1, 1	14.4, 14.4	BKC: 1, 1	15.3, 15.7	BKC: 1, 1	15.3, 15.4	BKC: 1, 1
Muskegon River	14.7, 14.7	RBT: 1, 1	14.4, 14.4	RBT: 1, 1	15.3, 15.7	RBT: 1, 1	15.3, 15.4	RBT: 1, 1
Ogontz River	14.1, 13.9	RBT: 1, 1	13.9, 13.9	RBT: 1, 1	14.9, 15.2	RBT: 1, 1	14.7, 14.7	RBT: 1, 1
Rapid River	14.5, 14.5	ALL: 1, 1	14.3, 14.2	ALL: 1, 1	15.3, 15.6	ALL: 1, 1	14.9, 15.2	ALL: 1, 1
S. Branch Pine River	14.6, 14.4	RBT: 1, 1	14.2, 14.1	RBT: 1, 1	15.2, 15.5	RBT: 1, 1	14.9, 15.1	RBT: 1, 1
Silver Creek	15.4, 15.4	BKC: 1, 1	15.1, 15.1	BKC: 1, 1	16.0, 16.3	BKC: 1, 1	16.2, 16.2	BKC: 1, 1
St. Joseph River	15.6, 15.5	BKC: 1, 1	15.2, 15.2	BKC: 1, 1	16.0, 16.4	BKC: 1, 1	16.4, 16.5	BKC: 1, 2
		RBT: 1, 1		RBT: 1, 1		RBT: 1, 1		RBT: 2, 2
Sturgeon River	14.1, 13.9	BKC, RBT: 1, 1	13.9, 13.9	BKC, RBT: 1, 1	14.9, 15.2	BKC, RBT: 1, 1	14.7, 14.7	BKC, RBT: 1, 1
Tamarack Creek	14.7, 14.7	BNT, RBT: 1, 1	14.4, 14.4	BNT, RBT: 1, 1	15.3, 15.7	BNT, RBT: 1, 1	15.3, 15.4	BNT, RBT: 1, 1
W. Branch Maple River	14.4, 14.3	BKC: 1, 1	14.2, 14.0	BKC: 1, 1	15.1, 15.5	BKC: 1, 1	14.8, 15.1	BKC: 1, 1

Species abbreviations are as follows: *ALL* brook charr, brown trout, and rainbow trout, *BKC* brook charr, *BNT* brown trout, *RBT* rainbow trout

charr, brown trout, and rainbow trout until the year 2056 (Table 5).

Model applicability to streams outside Michigan

Thermal habitat suitability projections from stream-specific and generalized models were compared with historical habitat suitability statuses in five streams outside the State of Michigan to gauge the applicability of the two model types in different regions of the USA. For these streams, generalized models predicted salmonid thermal habitat suitability with comparable accuracy to stream-specific models. In five brook charr streams, 67% of generalized model predictions were accurate, compared to 0% of stream-specific model predictions (Table 6). Thermal habitat suitability projections were consistent between generalized and stream-specific models in three of the five brook charr streams. In five brown trout streams outside Michigan, 67% of generalized and stream-specific model predictions were accurate, and thermal habitat suitability projections were consistent between model types in all five streams (Table 6). The accuracy of generalized model thermal habitat suitability predictions was similar in streams outside and inside Michigan. At least two-thirds of predictions were accurate in brook charr streams (outside Michigan: 67% accuracy; inside Michigan: 73% accuracy) and brown trout streams (outside Michigan: 67% accuracy; inside Michigan: 71% accuracy). The relatively high accuracy of generalized models in predicting thermal habitat suitability in streams within and outside Michigan indicates their applicability in coldwater fisheries management programs in the eastern and north central United States of America.

Table 6 List of brook charr (BKC) and brown trout (BNT) streams located outside Michigan with actual 2006 temperatures (Actual) and associated thermal habitat suitability (THS) statuses (2 = suboptimal, 3 = no growth, 4 = high mortality risk)

Stream	Actual	BKT THS	BNT THS	SS	Gen	BKT THS	BNT THS
Broad Swamp Brook, CT	–	–		24.9	21.8	3, 3	3, 3
Meduxnekeag River, ME	19.6	2	2	19.8	18.4	2, 2	2, 2
Deep Creek, NC	26.1	4	3	24.1	23.6	3, 3	3, 3
Embarrass River, WI	19.7	2	2	21.3	20.2	3, 2	3, 3
Red River, WI	–	–		21.1	20.2	3, 2	3, 3

The table also includes projected temperatures (stream-specific [SS] model, generalized [Gen] model) and associated THS statuses in 2006. State abbreviations are as follows: *CT* Connecticut, *ME* Maine, *NC* North Carolina, *WI* Wisconsin

Discussion

Salmonids are ecologically, socioeconomically, and culturally important throughout the world. However, their comparatively low thermal optima (Raleigh 1982a, b; Raleigh et al. 1986) combined with global climate warming and widespread scarcity in long-term stream temperature data indicate a pressing need for reliable, cost-effective methods for projecting stream temperatures with limited data to manage thermal habitats. Although heat budget models represent a highly accurate method for predicting stream temperatures, they are expensive, data-intensive, and require physical, hydrological, and meteorological measurements at small spatial extents (e.g. stream reaches; Mohseni et al. 1998; Benyahya et al. 2007), which most fisheries management agencies do not have the resources to collect or analyze. As a result, fisheries management agencies need efficient, cost-effective alternatives to accurately project future thermal habitat conditions.

This study demonstrates the utility of stream-specific and generalized temperature models for salmonid management amidst global climate change and resource limitations. This study shows that stream-specific models, reflecting the unique influence of thermal drivers in each system (e.g. air temperature, solar radiation, riparian shading, groundwater input, discharge, precipitation, evaporation; Bartholow 1989; Gu et al. 1998), predict temperatures more accurately than generalized, region-specific models. However, developing temperature profiles for stream-specific models requires considerable investments of funding, time, and personnel (e.g. purchase, installation, and monitoring of temperature gauges for each stream). Despite the higher accuracy of stream-specific models for prediction of stream temperatures in this study, generalized models were comparably accurate in projecting thermal habitat suitability for salmonid growth and survival in GD streams. Consequently, generalized models can be useful for fisheries professionals seeking to optimize the expenditure of finite resources on research and management efforts necessary to conserve coldwater stream fisheries with climate change.

The magnitude of stream warming projected in this study is similar to previous investigations conducted in and near the study area in Michigan. Water temperatures were predicted to increase by 0.1–3.8 °C in GD streams and 0.2–6.8 °C in RD streams in Michigan due to projected climate change from 2016 to 2056. These results corroborate projected stream temperature warming in other Upper Midwestern states (0.3–6.9 °C in the State of Minnesota, USA: Pilgrim et al. 1998; 0.8–4.0 °C in the State of Wisconsin, USA: Lyons et al. 2010). Previous research in Michigan indicates that GD streams are more thermally resilient than RD streams due to groundwater-driven thermal buffering and flow stability, which causes coldwater fishes to be more susceptible to summer growth reductions in RD systems (Zorn et al. 2012). The present study supports this finding as the magnitude of temperature warming was projected to be greater in RD streams than GD systems with thermal buffering.

Generalized temperature models accurately projected stream thermal dynamics in GD streams within and outside Michigan, indicating their broad utility for salmonid management in other regions of the world with coldwater streams vulnerable to climate-induced warming. Generalized models projected thermal habitat suitability with 82% accuracy in GD Michigan streams and were as accurate as stream-specific models in predicting thermal habitat suitability in systems outside Michigan. This indicates that generalized models are useful for forecasting temperature ranges for salmonid growth and survival in broad regions of the eastern and north central USA and suggests that generalized models are widely applicable in other regions that contain stream salmonid populations.

These findings are important for stream salmonid management because by using generalized models, fisheries professionals can invest fewer resources (e.g. funding, time, personnel) to achieve a comparable level of accuracy in projecting thermal conditions for salmonid growth and survival and may then invest more in implementing programs that enhance the thermal resilience of streams that are likely to be impacted by a warming environment. In addition, generalized models applied on regional scales would promote salmonid management strategies (e.g. harvest regulations) that, by virtue of their regional scale, would be more practical for fisheries stakeholders compared to the complex assortment of site-specific regulations that would result from using stream-specific models. Moreover, fisheries professionals can use generalized models as simple tools to inform anglers and other stakeholders about probable effects of climate change on coldwater stream fish communities, including reduced salmonid abundance and increased abundance of warmwater fishes (e.g. centrarchids; Pease and Paukert 2014). Compared to stream-specific models, generalized models could be efficiently incorporated into existing regional-level stream salmonid management programs in the States of Michigan (MDNR 2000), Wisconsin (WDNR 2002), Minnesota (MNDNR 2015), and elsewhere throughout the world (e.g. Spain; Antunes et al. 1999). Facing cost-benefit tradeoffs, fisheries professionals may willingly exchange the lower accuracy of generalized models in predicting temperature for their cost-effectiveness and efficiency, particularly their ability to project thermal habitat suitability with comparable accuracy and lower resource expenditure relative to stream-specific models.

Results from this study have other important implications for stream salmonid management throughout the world. As climate change increases air temperatures and decreases stream thermal habitat suitability for salmonid growth, reproduction, and survival (Lyons et al. 2010; Isaak et al. 2012), managing streams and their salmonid populations for thermal resilience will become an ever important task for fisheries professionals. This study indicates that by using generalized models, fisheries professionals can reduce costs associated with temperature modeling in GD streams and may then be able to allocate more resources toward thermal habitat management. Potential management actions include protecting riparian vegetation that provides shading (Blann et al. 2002), preserving grasslands and other land cover types that promote groundwater recharge (Siitari et al. 2011), and maintaining longitudinal stream connectivity that allows salmonids to move to cooler habitats (e.g. headwater reaches; Waco and Taylor 2010) during the warm summer months.

Generalized models are advantageous for watershed-level salmonid management as they enable relatively accurate, cost-effective stream temperature forecasting at regional scales. Fisheries professionals can use results from generalized models to develop climate vulnerability maps that facilitate prioritization of streams for thermal habitat management in a changing climate. In addition, fisheries professionals can integrate generalized model temperature projections with socioeconomic information (e.g. angler values and behaviors, stream-specific resource availability) to design decision-support tools (DSTs) that streamline decision-making for stream salmonid management. As the applications of DSTs continue to be discovered (Azadivar et al. 2009; Bitunjac et al. 2016), they have proven to be important for ecologically, sociologically informed fisheries management in a changing climate (Lynch et al. 2015, 2016). Accurate, readily interpretable generalized models can enable fisheries professionals to collaborate with policy makers to ensure that stream temperature modeling is used to inform the development of policies that sustain stream salmonid populations amidst predicted changes in the world's climate.

This study provides a foundation for future coldwater fisheries research throughout the world regarding the effects of increased air and water temperatures on stream salmonid populations and approaches to mitigate—and adapt to—the impacts of global climate change. Although this study focused on relatively data-rich streams in Michigan, Wisconsin, and the eastern United States, it employed methods for developing and comparing stream-specific and generalized stream temperature models that are widely applicable in other regions of the world. Stream temperature data spanning multiple years are necessary for using the methods described herein, thus we encourage fisheries professionals to expand the spatial and temporal coverage of air and stream temperature monitoring networks and thereby enhance their utility for fisheries management. Increased temperature data collection and installation of air and stream temperature gauging stations will enable comparisons between the present study and research conducted in the western United States, Canada, Europe, and other regions of the world where stream salmonids are abundant yet stream-specific and generalized temperature models have not been juxtaposed. In addition to stream temperature modeling and thermal habitat management, further research is needed to assess other potential tools for sustaining stream salmonid populations and other species amidst climate change. For instance, the effects of management actions to restore stream habitat connectivity (e.g. dam removal, fish ladder installation at roadside crossings and culverts) on salmonid populations need to be more comprehensively assessed. Further research is needed to determine whether maintaining a diversity of salmonid genetic stocks, size classes, and prey species that tolerate temperatures projected under climate change (Hansen et al. 2015) is a useful strategy to increase the resilience of stream salmonid populations.

The goal of this study was to construct and compare stream-specific and generalized temperature models for Michigan streams to project future thermal habitat conditions (i.e. suitability statuses) for salmonid growth and survival, develop a model comparison approach that is spatially and temporally robust and broadly applicable within and beyond Michigan, and thereby inform salmonid management throughout the world amidst climate change and resource limitations. Our purpose was not to assess model performance in terms of absolute temperatures. Fisheries managers in Michigan and other regions with coldwater salmonid streams are primarily concerned with maintaining and/or improving thermal habitat conditions for salmonid growth and survival rather than evaluating model performance in terms of absolute temperatures. In these management systems, models assessing and comparing thermal habitat suitability statuses for growth and survival are more useful than those looking at absolute temperature. We structured the present manuscript correspondingly and believe a thermal habitat suitability approach is most appropriate for communicating with fisheries managers and other decision-makers who are principally concerned with thermal habitat conditions. These individuals are not temperature modelers per se but rather decision-makers who require information on current and future thermal habitat conditions. However, we acknowledge that other fisheries management systems throughout the world operate differently and may require distinct thermal modeling approaches, including absolute temperature assessment, that reflect unique research goals and objectives.

In summary, this study demonstrates the efficacy of generalized temperature models for stream salmonid management in a changing climate, particularly in GD streams. In RD systems, the lower accuracy of generalized models than stream-specific models in predicting water temperature was often biologically significant, leading to differences in projected thermal habitat suitability statuses between model types. This suggests that fisheries professionals can reserve stream-specific models for systems in which the accuracy of temperature prediction is especially important, including streams that support trophy fishing opportunities, threatened/endangered species, or other ecologically or socioeconomically valuable resources. In these streams, the added costs of using stream-specific models and installing additional air and stream temperature monitoring stations may be justifiable for fisheries management agencies, given that these systems are especially valuable. In regions that contain both GD and RD streams, integrating generalized and stream-specific models will be an effective strategy for balancing model accuracy and efficiency. Overall, this study illustrates how fisheries professionals throughout the world can use different temperature modeling frameworks to optimize the expenditure of finite resources as they project future stream thermal conditions and develop more effective strategies for coldwater fisheries management amidst global climate change.

Acknowledgements We thank T. Kwak (North Carolina State University) for comments that improved the quality of this manuscript. We thank K. Herreman and W. Daniel (Michigan State University); T. Zorn, T. Kolb, and T. Wills (Michigan Department of Natural Resources); and H. Quinlan (United

States Fish and Wildlife Service) for providing trout population and environmental data critical for development of this study. We thank J. Myers (USFS EFETAC) and S. Nelson and E. Hain (North Carolina State University) for assistance with data acquisition and air temperature projections. We acknowledge the Programme for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling for assisting in procurement of the WCRP CMIP3 multimodel data set. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

References

Antunes A, Apostolidis A, Berrebi P, Duguid A, Ferguson A, García-Marín JL, Guyomard R, Hansen MM, Hindar K, Koljonen ML, Laikre L, Largiader C, Martínez P, Nielsen EE, Palm S, Ruzzante D, Ryman N, Triantaphyllidis C (1999). Conservation genetic management of brown trout (*Salmo trutta*) in Europe. Report by the Concerted Action on Identification, Management and Exploitation of Genetic Resources in the Brown trout (*Salmo trutta*)

Arnold JG, Allen PM (1999) Validation of automated methods for estimating base flow and ground water recharge from streamflow records. J Am Water Resour Assoc 35(2): 411–424. doi:10.1111/j.1752-1688.1999.tb03599.x

Azadivar F, Truong T, Jiao Y (2009) A decision support system for fisheries management using operations research and systems science approach. Expert Syst Appl 36(2):2971–2978. doi:10.1016/j.eswa.2008.01.080

Baldwin NS (1957) Food consumption and growth of brook trout at different temperatures. Trans Am Fish Soc 86(1): 323–328. doi:10.1577/1548-8659(1956)86[323:FCAGOB]2.0.CO;2

Bartholow JM (1989) Stream temperature investigations: field and analytic methods. Instream flow information paper number 13. U.S. Fish and Wildlife Service, Biological Report Number 89, Washington, DC

Benyahya L, Caissie D, St-Hilaire A, Ouarda TBMJ, Bobée B (2007) A review of statistical water temperature models. Can Water Resour J 32(3):179–192. doi:10.4296/cwrj3203179

Bitunjac I, Jajac N, Katavic I (2016) Decision support to sustainable management of bottom trawl fleet. Sustainability 8(3):1–23. doi:10.3390/su8030204

Blann K, Nerbonne JF, Vondracek B (2002) Relationship of riparian buffer type to water temperature in the driftless area ecoregion of Minnesota. N Am J Fish Manage 22(2): 441–451. doi:10.1577/1548-8675(2002)022<0441:RORBTT>2.0.CO;2

Budy P, Thiede GP, Lobón-Cerviá J, Fernandez GG, McHugh P, McIntosh A, Vøllestad LA, Becares E, Jellyman P (2013) Limitation and facilitation of one of the world's most invasive fish: an intercontinental comparison. Ecology 94:356–367. doi:10.1890/12-0628.1

Carlson AK, Taylor WW, Schlee KM, Zorn TG, Infante DM (2016) Projected impacts of climate change on stream salmonids with implications for resilience-based management. Ecol Freshw Fish. doi:10.1111/eff.12267

CDIAC (Carbon Dioxide Information Analysis Center) (2016) Carbon dioxide information analysis center. United States Department of Energy, Oak Ridge National Laboratory. http://cdiac.ornl.gov/. Accessed 6 June 2016

Compagnucci R, da Cunha L, Hanaki K, Howe C, Mailu G, Shiklomanov I, Stakhiv E (2001) Hydrology and water resources. In: McCarthy JJ, Canziani OF, Leary NA, Dokken DJ, White KS (eds) Climate change 2001: impacts, adaptation, and vulnerability. International Panel on Climate Change Third Assessment Report, pp 191–233

Dodds WK, Whiles MR (2010) Freshwater ecology: concepts and environmental applications of limnology, 2nd edn. Academic Press, Burlington

Downing JA, Cole JJ, Duarte CM, Middelburg JJ, Melack JM, Prairie YT, Kortelainen P, Striegl RG, McDowell WH, Tranvik LJ (2012) Global abundance and size distribution of streams and rivers. Inland Waters 2:229–236. doi:10.5268/IW-2.4.502

Drake MT, Taylor WW (1996) Influence of spring and summer water temperature on brook charr, *Salvelinus fontinalis*, growth and age structure in the Ford River, Michigan. Environ Biol Fish 45(1):41–51. doi:10.1007/BF00000626

Dukić V, Mihailović V (2012) Analysis of groundwater regime on the basis of streamflow hydrograph. Facta Univ 10(3):301–314. doi:10.2298/FUACE1203301D

Elliott JM, Hurley MA (2000) Daily energy intake and growth of piscivorous brown trout, *Salmo trutta*. Freshwater Biol 44(2):237–245. doi:10.1046/j.1365-2427.2000.00560.x

Fry FEJ, Hart JS, Walker KF (1946) Lethal temperature relations for a sample of young speckled trout, *Salvelinus fontinalis*, vol 54. The University of Toronto Press, Toronto

Godby NA Jr, Rutherford ES, Mason DM (2007) Diet, feeding rate, growth, mortality, and production of juvenile steelhead in a Lake Michigan tributary. N Am J Fish Manage 27(2):578–592. doi:10.1577/M06-077.1

Gu R, Montgomery S, Austin TA (1998) Quantifying the effects of stream discharge on summer river temperature. Hydrol Sci J 43(6):885–904. doi:10.1080/02626669809492185

Hansen GJA, Gaeta JW, Hansen JW, Carpenter SR (2015) Learning to manage and managing to learn: sustaining freshwater recreational fisheries in a changing environment. Fisheries 40(2):56–64. doi:10.1080/03632415.2014.996804

Hay J, Hayes J, Young R (2006) Water quality guidelines to protect trout fishery values. Prepared for Horizons Regional Council. Cawthorn Report Number 1025

Hayes DB, Taylor WW, Drake M, Marod S, Whelan G (1998) The value of headwaters to brook trout (*Salvelinus fontinalis*) in the Ford River, Michigan, USA. In: Haigh MJ, Krecek J, Rajwar GS, Kilmartin MP (eds) Headwaters: water resources and soil conservation. Oxford and IBH Publishing Co., New Delhi, pp 75–185

IPCC (Intergovernmental Panel on Climate Change) (2007) Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland

Isaak DJ, Muhlfeld CC, Todd AS, Al-Chokhachy R, Roberts J, Kershner JL, Fausch KD, Hostetler SW (2012) The past as prelude to the future for understanding 21st-century

climate effects on Rocky Mountain trout. Fisheries 37(12):542–556. doi:10.1080/03632415.2012.742808
Kaushal SS, Likens GE, Jaworski NA, Pace ML, Sides AM, Seekell D, Belt KT, Secor DH, Wingate RL (2010) Rising stream and river temperatures in the United States. Front Ecol Environ 8(9):461–466
Kelleher C, Wagener T, Gooseff M, McGlynn B, McGuire K, Marshall L (2012) Investigating controls on the thermal sensitivity of Pennsylvania streams. Hydrol Process 26(5): 771–785. doi:10.1002/hyp.8186
Krider LA, Magner JA, Perry J, Vondracek B, Ferrington LC Jr (2013) Air-water temperature relationships in the trout streams of southeastern Minnesota's carbonate-sandstone landscape. J Am Water Resour Assoc 49(4):896–907. doi:10.1111/jawr.12046
Kruger CC, Decker DJ (1999) The process of fisheries management. In: Kohler CC, Hubert WA (eds) Inland Fisheries Management in North America, 2nd edn. American Fisheries Society, Bethesda, pp 31–59
Lynch AJ, Varela-Acevedo E, Taylor WW (2015) The need for decision-support tools for a changing climate: application to inland fisheries management. Fish Manage Ecol 22(1): 14–24. doi:10.1111/fme.12013
Lynch AJ, Myers BJE, Chu C, Eby LA, Falke JA, Kovach RP, Krabbenhoft TJ, Kwak TJ, Lyons J, Paukert CP, Whitney JE (2016) Climate change effects on North American inland fish populations and assemblages. Fisheries 41(7): 346–361. doi:10.1080/03632415.2016.1186016
Lyons J, Zorn T, Stewart J, Seelbach P, Wehrly K, Wang L (2009) Defining and characterizing coolwater streams and their fish assemblages in Michigan and Wisconsin, USA. N Am J Fish Manage 29(4):1130–1151. doi:10.1577/M08-118.1
Lyons J, Stewart JS, Mitro M (2010) Predicted effects of climate warming on the distribution of 50 stream fishes in Wisconsin, USA. J Fish Biol 77(8):1867–1898. doi:10.1111/j.1095-8649.2010.02763.x
MacCrimmon HR (1971) World distribution of rainbow trout (*Salmo gairdneri*): further observations. J Fish Res Board Can 29(12):1778–1791. doi:10.1139/f72-287
Magnuson JJ, Webster KE, Assel RA, Bowser CJ, Dillon PJ, Eaton JG, Evans HE, Fee EJ, Hall RI, Mortsch LR, Schindler DW, Quinn FH (1997) Potential effects of climate change on aquatic systems: laurentian Great Lakes and Precambrian Shield Region. Hydrol Process 11:825–871
Maurer EP, Brekke L, Pruitt T, Duffy PB (2007) Fine-resolution climate projections enhance regional climate change impact studies. EOS Trans Am Geophys Union 88(47):504
McKergow L, Parkyn S, Collins R, Pattinson P (2005) Small headwater streams of the Auckland Region. Volume 2: Hydrology and water quality. Auckland Regional Council Technical Publication No. 312. pp 1–67
MDNR (Michigan Department of Natural Resources) (2000) Michigan stream classification: 1967 system. In: Schneider JC (ed) Manual of fisheries survey methods II: with periodic updates. Michigan Department of Natural Resources, Fisheries Special Report 25, Ann Arbor
MNDNR (Minnesota Department of Natural Resources) (2015) Fisheries long-range plan for trout stream resource management in southeast Minnesota 2010–2015 and progress report. Minnesota Department of Natural Resources, St. Paul, Minnesota, p 50
Mohseni O, Stefan HG, Erickson TR (1998) A nonlinear regression model for weekly stream temperatures. Water Resour Res 34(10):2685–2692
Neff BD, Day SM, Piggott AR, Fuller LM (2005) Base flow in the Great Lakes basin. U.S. Geological Survey Scientific Investigations Report 2005–5217
O'Driscoll MA, DeWalle DR (2006) Stream-air temperature relations to classify stream-ground water interactions in a karst setting, central Pennsylvania, USA. J Hydrol 329:140–153
Ozaki N, Fukushima T, Harasawa H, Kojiri T, Kawashima K, Ono M (2003) Statistical analyses on the effects of air temperature fluctuations on river water qualities. Hydrol Process 17:2837–2853
Pease AA, Paukert CP (2014) Potential impacts of climate change on growth and prey consumption of stream-dwelling smallmouth bass in the central United States. Ecol Freshw Fish 23:336–346
Pilgrim JM, Fang X, Stefan HG (1998) Stream temperature correlations with air temperatures in Minnesota: implications for climate warming. J Am Water Resour Assoc 34:1109–1121
Raleigh RF (1982a) Habitat suitability index models: brook trout. Washington, D.C.: U.S. Fish and Wildlife Service, Biological Report Number 82
Raleigh RF (1982b) Habitat suitability index models: rainbow trout. Washington, D.C.: U.S. Fish and Wildlife Service, Biological Report Number 82
Raleigh RF, Zuckerman LD, Nelson PC (1986) Habitat suitability index models and instream flow suitability curves: brown trout. Washington, DC: U.S. Fish and Wildlife Service, Biological Report Number 82
Schlee KM (2014) The impact of climate change on brook trout (*Salvelinus fontinalis*) thermal habitat in their native range in the United States. MSc Thesis, Michigan State University, East Lansing
Siitari KJ, Taylor WW, Nelson SAC, Weaver KE (2011) The influence of land cover composition and groundwater on thermal habitat availability for brook charr (*Salvelinus fontinalis*) populations in the United States of America. Ecol Freshw Fish 20:431–437
Stefan HG, Preud'homme EB (1993) Stream temperature estimation from air temperature. Water Res Bul Am Water Res Assoc 29:27–45
Stoner AMK, Hayhoe K, Yang XH, Wuebbles DJ (2013) An asynchronous regional regression model for statistical downscaling of daily climate variables. Int J Climat 33:2473–2494
USEPA (United States Environmental Protection Agency) (2005) National Hydrography Dataset Plus–NHDPlus. http://www.horizon-systems.com/nhdplus/Accessed 6 June 2016
USFWS (United States Fish and Wildlife Service) (2011) 2011 National survey of fishing, hunting, and wildlife-associated recreation. Washington, DC: U.S. Department of the Interior, U.S. Fish and Wildlife Service, and U.S. Department of Commerce, U.S. Census Bureau
USGS (2016) National Water Information System. http://waterdata.usgs.gov/nwis. Accessed 6 June 2016

USGS (United States Geological Survey) (2015) StreamStats. http://water.usgs.gov/osw/streamstats/. Accessed 19 Dec 2016

van Vliet MTH, Franssen WHP, Yearsley JR, Ludwig F, Haddeland I, Lettenmaier DP, Kabat P (2013) Global river discharge and water temperature under climate change. Glob Environ Chang 23(2):450–464

Waco KE, Taylor WW (2010) The influence of groundwater withdrawal and land use changes on brook charr (*Salvelinus fontinalis*) thermal habitat in two coldwater tributaries in Michigan, USA. Hydrobiologia 650:101–116

Wahl KL, Wahl TL (1988) Effects of regional ground water declines on streamflows in the Oklahoma Panhandle. In: Waterstone M, Burt RJ (eds) Proceedings of the symposium on water-use data for water resources management. Tucson: American Water Resources Association, pp 239–249

WDNR (Wisconsin Department of Natural Resources) (2002) *Wisconsin trout streams*. Madison, Wisconsin: Wisconsin Department of Natural Resources, Report PUB-FH-806

Weber GM, Hostuttler MA, Semmens KJ, Beers BA (2015) Induction and viability of tetraploids in brook trout (*Salvelinus fontinalis*). Can J Fish Aquat Sci 72(10): 1443–1449. doi:10.1139/cjfas-2014-0536

Wehrly KE, Brenden TO, Wang L (2009) A comparison of statistical approaches for predicting stream temperatures across heterogeneous landscapes. J Am Water Resour Assoc 45(4):986–997

Wurtsbaugh WA, Davis GE (1977) Effects of fish size and ration level on the growth and food conversion efficiency of rainbow trout, *Salmo gairdneri* Richardson. J Fish Biol 11:99–104

Zorn TJ, Seelbach PW, Wiley MJ (2011) Developing user-friendly habitat suitability tools from regional stream fish survey data. North Am J Fish Manage 31:41–45

Zorn TJ, Seelbach PW, Rutherford ES (2012) A regional-scale habitat suitability model to assess the effects of flow reduction on fish assemblages in Michigan streams. J Am Water Resour Assoc 48:871–895