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ORIGINAL ARTICLE

Climate change impacts on freshwater recreational fishing in the United States

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Abstract We estimated the biological and economic impacts of climate change on freshwater fisheries in the United States (U.S.). Changes in stream temperatures, flows, and the spatial extent of suitable thermal habitats for fish guilds were modeled for the coterminous U.S. using a range of projected changes in temperature and precipitation caused by increased greenhouse gases (GHGs). Based on modeled shifts in available thermal habitat for fish

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guilds, we estimated potential economic impacts associated with changes in freshwater recreational fishing using a national-scale economic model of recreational fishing behavior. In general, the spatial distribution of coldwater fisheries is projected to contract, being replaced by warm/cool water and high-thermally tolerant, lower recreational priority (i.e., "rough") fisheries. Changes in thermal habitat suitability become more pronounced under higher emissions scenarios and at later time periods. Under the highest GHG emissions scenario, by year 2100 habitat for coldwater fisheries is projected to decline by roughly 50 % and be largely confined to mountainous areas in the western U.S. and very limited areas of New England and the Appalachians. The economic model projects a decline in coldwater fishing days ranging from 1.25 million in 2030 to 6.42 million by 2100 and that the total present value of national economic losses to freshwater recreational fishing from 2009 to 2100 could range from $81 million to $6.4 billion, depending on the emissions scenario and the choice of discount rate.

Keywords Climate change · Economic impacts · Fisheries · Hydrology · Physical impacts

1 Introduction

Global average air temperatures are expected to increase throughout the 21st century (Meehl et al. 2007). Furthermore, air temperatures in most areas over the coterminous United States (U.S.) are expected to increase more than the global average (Christensen et al. 2007). This increase in air temperatures will result in higher stream temperatures, potentially altering the thermal suitability of U.S. streams for freshwater fish (Christensen et al. 2007; Field et al. 2007).

These projected changes in temperature, along with changes in the timing and intensity of precipitation, are anticipated to alter the behavior of the hydrologic cycle, thus affecting many aspects of water resources systems. As described in the United Nations Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4; Solomon et al. 2007) and supporting documents (e.g., Bates et al. 2008), one broad manifestation of climate change is an intensification of the hydrologic cycle, characterized by increases in evapotranspiration, atmospheric water vapor, and precipitation. Induced changes in regional hydrology include alterations in patterns of stream discharge and groundwater recharge; changes in snowpack (which affects stream discharge); and increased evaporation from lakes, reservoirs, and other freshwater bodies. Taken collectively, these impacts are likely to alter future streamflow and fish habitat in the U.S. (Field et al. 2007).

Climate change impacts to fish habitats could adversely affect tourism and recreational fishing, commercial fish harvests, and other ecosystem services. We investigated *only one* component of these potential losses to fish habitats, specifically, a decline in the value of freshwater recreational fishing in streams and rivers. The impact of environmental factors on the value of recreational fishing, which was valued at $42 billion in 2006 (USFWS 2006), has been widely investigated in the natural resource economics literature (Morey et al. 1993; Train 1998; Herriges and Kling 1999). We rely on a model developed by Vaughan and Russell (1982a) to project the economic impacts of habitat changes on recreational fishing in the U.S. These economic estimates provide a policy-relevant context for the results of our fish habitat model.

Our objective was to integrate expert knowledge in the fields of climate, hydrologic, and economic modeling to project the national-scale physical and economic impacts of climate change on freshwater fisheries. In other words, given anticipated changes in global average temperatures and precipitation patterns, how might the spatial distribution of fisheries habitat change, and how might this change be quantified in economic terms.

Using a geographic information system (GIS), we developed a spatially explicit modeling framework of grid cells organized into 2,099 eight-digit hydrologic unit code (HUC-8) polygons for the coterminous U.S. (Fig. 1). Projected temperature and precipitation changes associated with climate change were obtained for three future greenhouse gas (GHG) emissions scenarios representing low, moderate, and high emissions in 2030, 2050, and 2100. We projected water temperatures using regional air/water temperature regressions. Habitat suitability was derived from the value of the lowest average monthly water temperature within a HUC-8 compared to a model-calibrated maximum water temperature tolerance of coldwater and warm/cool water fish guilds. The lowest value is used based on the conservative assumption that low temperature refugia within a larger geographic area can serve to shelter fish populations whose thermal thresholds may have been exceeded elsewhere in that HUC-8.

Changes in streamflow and habitat associated with climate change were estimated using the macro-scale water balance model Climate and Runoff (CLIRUN; Kaczmarek 1993). We then estimated the potential economic impacts of projected habitat changes on recreational fishing by updating a national-scale economic model developed by Vaughan and Russell (Russell and Vaughan 1982; Vaughan and Russell 1982b), which estimated losses in fishing days. Using per day economic values for recreational fishing for different fish guilds derived from the current economics literature, we estimated the total present value of national economic losses to freshwater recreational fishing from 2009 to 2100.

Because our overall objective was to evaluate potential effects of climate change at a national scale, our modeling approach lacked the precision that might be possible for studies performed at local or basin scales. However, by using spatially explicit regional climate projections, we were able to evaluate broad regional trends, thereby obtaining reasonably robust national-level estimates of potential impacts.

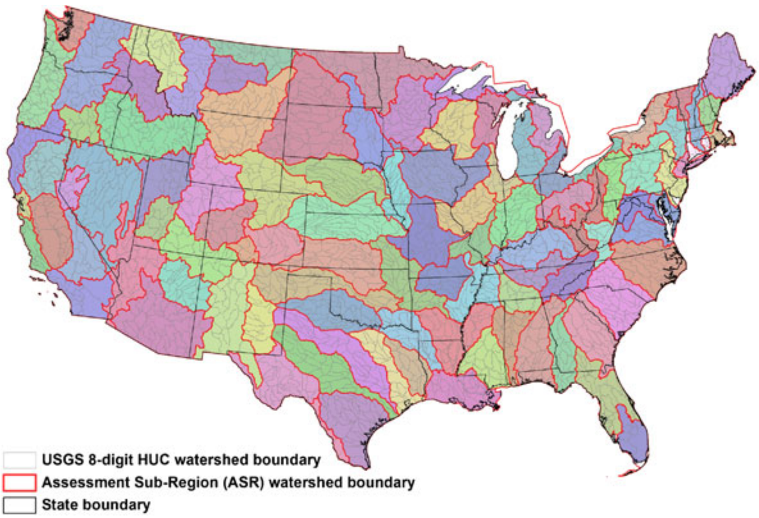

Fig. 1 ASR and USGS eight-digit HUC watershed boundaries of the U.S.

2 Methods

Because of the complexity of this study, we first summarize the methodology and then describe each step in detail in individual subsections below.

- *Projecting future climate conditions:* Obtain temperature and precipitation change projections for future climate scenarios for the continental U.S. using averaged output from general circulation models (GCMs) in a gridded format for three GHG emissions scenarios and three timeframes.
- *Establishing a baseline of historical climate:* Combine coarse-resolution GCM output for change in mean and maximum air temperature with higher-resolution baseline gridded data to derive a projected absolute temperature grid.
- *Developing an air/water temperature relationship*: Determine the relationship between air temperature and water temperature at U.S. Geological Survey (USGS) stream gauges along relatively "natural" streams using nonlinear regressions. Air/water temperatures at each gauge are used to develop nonlinear regressions specific to gauges grouped by ecoregion, climate scenario, and time period. The subsequent regressions are then applied to gridded air temperature data across the U.S. The model explicitly does not address atypical or anthropogenic factors (e.g., groundwater inflows, dams, or thermal discharge) that may affect water temperatures.
- *Modeling fish habitat thermal suitability*: Compare current and projected maximum water temperatures for each HUC-8 to thermal tolerances for cold, cool/warm water, and rough fish guilds to determine changes in fish distributions.
- *Calculating changes in streamflow:* Use projected precipitation and temperature data for each climate scenario and time period as inputs into a hydrologic flow model to calculate changes in streamflow for 99 watersheds across the U.S. The flow changes are then applied to the contributing watersheds of each HUC-8 to determine the final change in flow at each HUC-8.
- *Calculating stream habitat area*: Combine flow change for each climate scenario and time period with changes in fish guild to derive changes in acreages for the economic analysis, summed by states.
- *Performing economic modeling*: Input guild and acreage changes into a recreational fishing model to determine changes in fishing days and total valuation of recreational fisheries by guild for each climate scenario and time period.

2.1 Projecting future climate conditions

Similar to previous national-scale studies (EPA 1995; Eaton and Scheller 1996; O'Neal 2002; Mohseni et al. 2003), our future climate scenarios were based on GCM output. We used the Model for the Assessment of Greenhouse Gas–Induced Climate Change (MAGICC) and the Regional Climate Scenario Generator (SCENGEN; Wigley 2008) to project changes in temperature and precipitation for three 30-year periods, centered on years 2030, 2050, and 2100. MAGICC/SCENGEN (M/S) scales output from multiple GCMs to a common GIS-compatible grid scale of 2.5 arc-degrees (latitude and longitude; approximately 240 km on a side) and allows users to run a range of GHG emissions scenarios from the IPCC *Special Report on Emission Scenarios* (Nakićenović and Swart 2000).

To capture a wide range of potential GHG emissions throughout the 21st century, we used the B1 scenario as the low-end projection, A1FI as the high-end projection, and A1B as the mid-range projection. SCENGEN provides monthly precipitation and temperature fields for each grid over the coterminous United States under each emissions scenario and for each time period of interest.

Reported changes in monthly temperature and precipitation are averages of the values from 10 GCMs used in the IPCC AR4 (BCCRBCM2, CCSM-30, ECHO-G, GFDLCM20, GFDLCM21, MIROCMED, MPIECH-5, MRI-232A, UKHADCM3, and UKHADGEM) (Randall et al. 2007) and were selected as the most physically accurate at replicating recent climate patterns globally and over the coterminous U.S. (Wigley 2008). The advantage of using averages across multiple GCMs is that multi-model averages, also known as ensembles, are less spatially noisy and tend to be better than any one individual model at simulating present-day climate (Wigley 2008).

The temperature and precipitation values for any individual SCENGEN grid cell are calculated as the average of the given grid cell and the eight surrounding cells (Hewitson 2003). Although there will be small-scale, site-specific changes in actual temperature and precipitation, the current resolution of GCMs is not able to capture such high-resolution information. Consequently, individual grid box values are not expected to be fully representative of the site-specific changes.

Note that projections of future water temperatures were produced using version 5.0b of M/S whereas an updated version (5.3) was used to obtain temperature and precipitation projections for use in flow modeling. Eight of the 10 GCMs used by the different versions of SCENGEN were the same for both components of the study. The remaining two GCMs differed in how the pattern correlation was scored by SCENGEN (Wigley 2008) in version 5.0b and 5.3. To evaluate whether these differences in the GCM ensemble preclude combining the results of these two studies for the economic analysis, we evaluated the differences between future projections using the two GCM ensembles. The overall differences in the 10-model average projected changes between the two versions are very small. For annual temperature, the difference between the projections was less than 1 °C in all locations and years, and much less than 1 °C in most locations and years. For annual precipitation, the maximum difference in projected future precipitation over the 99 assessment subregions (ASRs) between the two model ensembles was 10 % and the mean was 2.8 %. Assuming that precipitation changes can be directly related to streamflow and stream width, precipitation is projected to have <2 % difference in the estimated fishable acres throughout most of the U.S., with a maximum difference of 5 %.

2.2 Establishing a baseline of historical climate

To model changes in fish habitat suitability in response to projected climate changes, we developed a GIS-based modeling framework that combined temperature and precipitation outputs from M/S with current spatial climate data in a grid format. The projected changes in temperature and precipitation for each 2.5° cell, emissions scenario, and time period output from M/S were overlaid on higher-resolution observed baseline climate data from PRISM (Parameter-elevation Regressions on Independent Slopes Model; PRISM Climate Group 2007) in order to generate absolute values for future climate. We calculated the average monthly maximum air temperatures over the past 30 years (1971–2000) for each of the 2,099 eight-digit HUCs in the GIS by spatially averaging monthly gridded temperature data from the PRISM Group at a resolution of 900-m cells.

2.3 Developing an air/water temperature relationship

We determined changes in stream temperature by developing a model that relates changes in stream temperature to changes in ambient air temperature. Stefan and Preud'homme (1993) proposed a linear relationship of the form:

$$T_W = \alpha + \beta \cdot T_A, \tag{1}$$

where T_W refers to stream temperature, T_A refers to air temperature (both typically in °C), and α and β values are estimated by linear regression. Mohseni and Stefan (1999), however, presented a physical argument that an upper limit to increases in water temperature is imposed by evaporative cooling and a lower limit is imposed by the freezing of freshwater. This yields a temperature response curve, instead of a linear relationship, taking the form:

$$T_W = \mu + \frac{(\alpha - \mu)}{1 + \exp(\gamma \cdot \{\beta - T_A\})}, \tag{2}$$

where T_W and T_A are water and air temperatures, respectively; μ is the lower bound of T_W (assumed to be 0 °C) and α the theoretical maximum of T_W; β is the value of T_A at the point of inflection; and γ is defined as:

$$\gamma = \frac{4 \tan \theta}{\alpha - \mu}, \tag{3}$$

where θ is the slope of the function at the point of inflection. This stream temperature model was estimated in three-parameter form, with the lower asymptote (μ in the four-parameter equation) set to zero to reflect the temperature (°C) at which freshwater freezes.

Two water temperature datasets were used in this analysis: (1) a subset of USGS Hydro-Climatic Data Network (HCDN; USGS 1992) and (2) a composite dataset provided by Omid Mohseni (Mohseni and Stefan 1999). The HCDN subset includes 123 HCDN gauges for which daily measurements of T_W are available out of 1,659 gauges with reasonably long, continuous records free of the influence of non-climatic factors likely to influence flow (Landwehr and Slack 1992). Daily records obtained from the USGS National Water Information Service database were aggregated to monthly averages. The water temperature data provided by Mohseni and Stefan (1999) contained weekly average water temperatures for 994 gauges. Weekly T_W data were aggregated to monthly averages weighted by the number of days per week. Only monthly records containing a minimum of four weeks or partial weeks were retained to eliminate systematic bias from incomplete records.

The air temperature data used to develop T_A - T_W relationships were the historical monthly average temperatures provided by the PRISM group in a gridded output at a resolution of 4 km over the continental U.S. Monthly temperature data, associated with the PRISM pixel containing each stream gauge, were used as predictors of stream water temperature. Only gauges containing at least 30 consecutive, monthly, paired T_W and T_A records were used to develop T_A - T_W relationships. We conducted preliminary estimation at the level of individual gauges in order to (1) screen gauges on the basis of model fit and (2) qualitatively evaluate regional patterns in the estimated model parameters. Because many natural and anthropogenic factors influence this relationship, including groundwater contribution, proximity to snowmelt, shading of streams, the presence of dams, thermal cooling water discharge, and urban runoff, we retained only those paired T_A - T_W observations that provided evidence of systematic relationships defined by the Nash-Sutcliffe Efficiency (NSE) described below. Although such influences clearly impact the thermal regimes of many of the nation's waters, our objective was to model quantitatively the T_A - T_W relationship to support a national-scale analysis.

Parameters were estimated by nonlinear least squares in the MATrixLABoratory software (MathWorks 2009). In addition to model parameters, several other summary statistics were abstracted from the estimation. These include minimum, mean, and maximum values of T_W and T_A and their respective standard deviations and the *NSE*. *NSE* describes the quality of the model fit with respect to the data, with $NSE=0$ indicating no fit and $NSE=1$ indicating perfect fit.

We used a minimum *NSE* of 0.85, as suggested in Mohseni et al. (2003) to eliminate gauge data that evidenced a non-systematic relationship (i.e., those affected by atypical environmental or anthropogenic factors). A total of 786 gauge records met the minimum fit criterion. The mean "slope" of the estimated models was obtained by taking the inverse tangent of ($\alpha\gamma/4$) for purposes of comparison with other studies employing a linear model. The mean of 786 pseudo-slope estimates was found to be approximately 0.8, which is consistent with O'Neal (2002).

To extrapolate these point location T_A - T_W relationships to the rest of the U.S. landscape, we grouped areas of the country with similar topographic, geologic, and ecological features under the assumption that these areas would have similar relationships between T_A and T_W. We used World Wildlife Fund (WWF) ecoregions (ESRI 2002) to group gauges into regions with similar environmental characteristics. These regions were generalized by combining adjacent regions with similar characteristics to ensure that each ecoregion contained at least one stream gauge. This enabled us to establish different T_A - T_W relationships for different regions (e.g., a river in upstate New York and a river in the desert southwest). Although many factors introduce variability in the T_A - T_W relationship within a specific stream, a qualitative review of T_A - T_W relationships developed for each ecoregion suggests that these groupings were reasonably assigned (i.e., T_A - T_W relationships were similar within ecoregions compared to gauges in other ecoregions). Figure 2 shows the ecoregions and gauges used in our analysis.

Recognizing the potential for difficulties in estimating and interpreting pooled regional models, a regional estimation approach was developed based on the concept of Enveloping Standard Deviates (ESDs), as described by Mohseni et al. (2002). The frequency-based

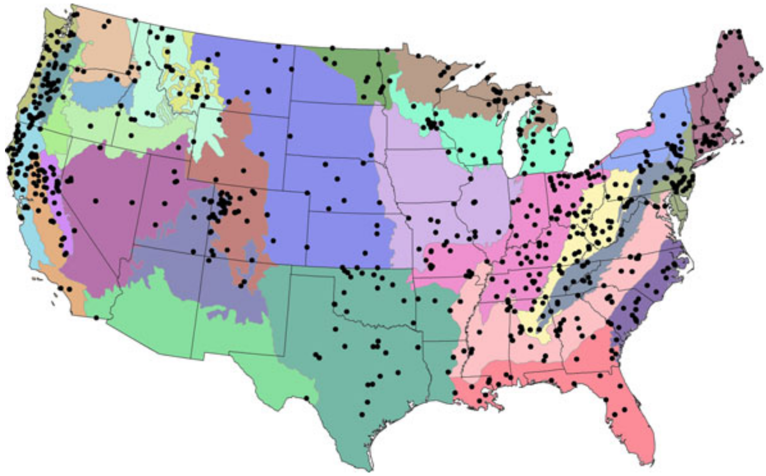

Fig. 2 Stream gauges and ecoregions (based on modification of WWF ecoregions) used in the analysis

statistical ESD approach provides an estimate of the maximum water temperature (T_{WMAX}) applicable to a given region, which can be compared with, and used to constrain, the asymptotic value (parameter α) in the Mohseni and Stefan (1999) three-parameter model.

Mohseni et al. (2002) developed their ESD estimate on the basis of weekly T_W data. Thus, we performed additional analyses to generate comparable estimates for monthly data. Gauge records were selected to have a minimum of 60 consecutive monthly observations and a minimum NSE of 0.85 in the test of at-site model fit. This was required to establish a systematic relationship between T_A - T_W at each site.

The selection process yielded 611 gauge records meeting both criteria. For each station-year, maximum monthly values of T_W $(T_{WMAX,t})$ were identified and a quadratic regression equation specified, with maximum T_{WMAX} as the dependent variable and mean $T_{WMAX,}$ and its squared value as predictors. The approach used is as follows: (1) for each gauging site record, take the largest monthly T_W value from each year of record; (2) within this distribution, identify the highest single value (this will be the highest recorded value in the entire gauge record) and estimate the mean and standard deviation of the annual maxima series, but exclude the highest value; (3) determine the number of standard deviations this observation lies from the mean; and (4) repeat this for as many gauges as are available and assemble the distribution of values, expressed as standard (t) scores to standardize over differences in respective gauge means. The upper tail of this distribution suggests the maximum, or enveloping, value of the standard deviate, which describes the likely maximum value that monthly stream temperatures can take within a given region and climate. The regression equation for the quadratic model is:

$$T_{WMAX,max,pred} = -0.0446\left(T_{WMAX,mean}\right)^2 + 2.273\left(T_{WMAX,mean}\right) + 3.049, \tag{4}$$

The estimated regression model was then used to generate estimates of change in the maximum monthly T_W. This was then interpreted as the asymptotic value α in the regional T_A - T_W curve, using:

$$a = T_{WMAX,\max,pred} + ESD \times SE, \tag{5}$$

where ESD and SE are parameters of 3.52 and 1.75, respectively, derived from the estimated regression model, and $T_{WMAX,\ max,\ pred}$ is the predicted maximum temperature for the ecoregion, climate scenario, and time period. Using this method, an α value was obtained for each ecoregion based on projected air temperatures from each climate scenario; temperatures ranged from 24 °C to 37 °C for the baseline climate.

2.4 Modeling fish habitat thermal suitability

In addition to determining T_W from T_A, we needed to correlate T_W to habitat suitability. We did this by defining thermal tolerances for fish guilds. Note that this method does not indicate the actual presence of a fish guild in a stream but rather the assumed thermal conditions associated with each fish guild. By examining the thermal impacts to fish guilds, as opposed to an individual species, we were able to examine the trade-offs between fishing types and thereby assess the economic impact to recreational fishing at a national scale. The thermal tolerance limits that we used in this study are based on the maximum weekly average temperature (MWAT) approach developed by Eaton et al. (1995) and Eaton and Scheller (1996). MWATs are derived from a database containing observations of the presence of fish, by species, together with the maximum weekly average stream temperature at the stream gauge closest to the site of each observation (Eaton et al. 1995). Thermal tolerance limits are based on the 95th percentile of MWATs for each species (Eaton and Scheller 1996).

Maximum thermal thresholds for each fish guild were based on the temperature tolerance for the most tolerant species in each guild. This is, in effect, a conservative assumption that underestimates the total impacts on all species within a given guild, while still preserving the linkage between economic effects and recreational fishing that are expressed at the guild level. When we applied these temperature thresholds to current climatic conditions, our distribution of coldwater fish was more restricted than the observed native distribution of fish. To calibrate our model, we applied 10 % higher thermal thresholds (Table 1) to produce a distribution of coldwater fisheries more consistent with the literature describing native distributions of the coldwater fish guild. For example, we compared our estimated current coldwater fish distribution to maps of native and introduced coldwater fish derived by Behnke (2002) and found agreement over 75 % of the continental United States (see Fig. 3). We believe that this level of correspondence for thermal suitability mapping is reasonable since it is based only on our T_A - T_w relationships. In contrast, Behnke's observed fish distributions account for the many other site-specific environmental factors which are not feasibly addressed in a national-scale analysis. We used the 10 % calibration factor from the coldwater guild for all other fish guilds because spatially explicit data for other fish guilds are not available.

We generated a grid of estimated water temperatures by applying the regression equation (with α, β, and γ values specific to each climate change/timeframe scenario and ecoregion) to each of the corresponding average monthly maximum air temperature PRISM grid cells (900-m resolution) on a cell-by-cell basis. The grid cell within each HUC-8 that had the lowest maximum average monthly water temperature was then compared to the fish guild thermal tolerances. The rationale for using the lowest maximum temperature cell value within the HUC-8 was based on an assumption that the presence of habitat within a HUC-8 with suitable temperatures could serve as refugia for that fish guild. As with the 10 % adjustment of the MWAT data described above, we calibrated the use of this minimum-cell approach against the current distribution of fish.

The minimum mapping unit in this analysis was the eight-digit HUC, which subdivided the United States into 2,099 areas (Fig. 1). All streams within each HUC-8 were deemed either suitable or unsuitable for coldwater, cool/warmwater, or rough fish guilds. Thermal tolerance thresholds for cool and warmwater fishes were indistinguishable because thermal thresholds for individual species overlapped in these two guilds. To simplify the presentation in this paper, we refer to both the cool and warmwater guilds as "warmwater." The designation of "cold" for a stream indicates that, according to our analysis, the habitat is

Table 1 Fish guild temperature tolerances

Fish guild	Most tolerant high-fishing-value species[a]	Maximum weekly temperature threshold (°C)[b]	Maximum +10 %
Rough	Channel catfish (*Ictalurus punctatus*)	31.6	34.8
Cool/warmwater	Smallmouth bass (*Micropterus dolomieu*)	29.5	32.5
Cold	Brown trout (*Salmo trutta*)	24.1	26.5

[a] Based on upper temperature tolerance threshold

[b] Fish Temperature Database Matching System 95th percentile upper temperature threshold, as a MWAT, from Eaton and Scheller (1996) and Eaton et al. (1995)

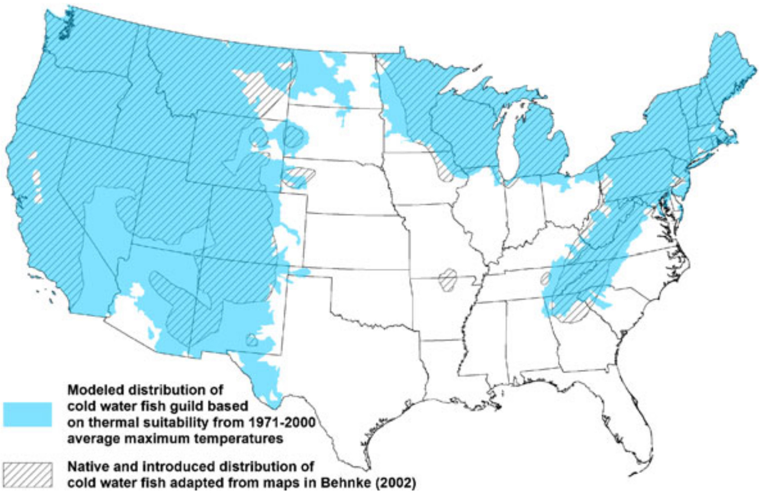

Fig. 3 Comparison between the distribution of native and introduced coldwater fisheries adapted from Behnke (2002) and modeled results of current coldwater fish guild based on thermal suitability

suitable for coldwater fish. However, some areas designated as "cold" may also support cool/warmwater fish or rough fish. On the other hand, a designation of "cool/warmwater" indicates that a stream could also support rough fish but is not suitable for coldwater fish.

2.5 Calculating changes in streamflow

The impacts of projected climate change on streamflow in the continental U.S. were estimated using the CLIRUN lumped integral water balance model (Kaczmarek 1993). This model simulates changes in monthly runoff corresponding to the changes in monthly temperature and precipitation associated with each climate change projection. CLIRUN simulates the most important lumped hydrologic processes, including soil moisture storage, evapotranspiration, surface runoff, subsurface runoff, and base flow. CLIRUN and the closely related model WatBal (Yates 1994) were developed and designed to simulate the impacts of climate change on the water balance of medium- to large-scale catchments (100–30,000 km^2) using a relatively restricted number of parameters (Kaczmarek 1993).

We calibrated CLIRUN over the U.S. using estimates of natural discharges from the Water Resource Council's (WRC's) 1978 Second National Water Assessment (WRC 1978) and historical data from the gridded Climatic Research Unit (CRU) 0.5° dataset. The CLIRUN grid cells associated with each hydrologic unit are calibrated as an ensemble using an automated parameter optimization routine. Our water balance analysis was guided in many ways by a study by Frederick and Schwarz (1999), who conducted much of the underlying analysis at the spatial unit of the ASRs, as defined by the WRC. We conducted our analysis using HUC-8 s rather than ASRs; each ASR is equivalent to a combination of several HUC-8s (Fig. 1).

The data tables from the 1978 WRC study required several corrections to provide a better estimate of naturalized flow prior to use in calibrating CLIRUN. First, the WRC streamflow values were adjusted to remove net imports into the basin and to add reservoir and pond evaporation losses. Second, flow from upstream basins had to be removed from the WRC streamflow values for use in CLIRUN, which assumes that streamflow represents the flow that would be generated only within each ASR.

In addition to the naturalized streamflow estimates, historical climate data are required for calibration of the CLIRUN model. For this study, we obtained historical climate data over the coterminous U.S. from the CRU TS 2.1 dataset (CRU 2009). This dataset, documented in Mitchell and Jones (2005), has monthly time series data from 1901 to 2002 at 0.5° spatial resolution. It should be noted that we used the CRU data for our historic climate conditions rather than PRISM as the PRISM data did not include many of the climate variables needed for the model. We overlaid the CRU data on the ASR boundaries to obtain the time series of monthly spatial average values for precipitation, maximum and minimum mean monthly temperatures, vapor pressure, and cloud cover for each ASR. Wind speed, which is also required for the calculation of potential evapotranspiration using the Penman-Monteith method (Monteith 1965), is not available in time series from the CRU. Monthly wind speed data were obtained for roughly 300 U.S. locations from the National Oceanic and Atmospheric Administration National Climatic Data Center (NCDC 1998). These station-level data, applicable for the 1930–1996 period, were used to develop mean wind speed estimates for each month at the ASR level using GIS interpolation techniques. For this study, the period 1961–2002 was used to characterize “current” climate, and specific years (e.g., 2002) were used in the preliminary analysis when it was necessary to match climatic conditions with years of agricultural and water use surveys. Median 1961–2002 values were used in model baseline simulations.

To estimate reference evapotranspiration (ET0), we relied on the United Nations Food and Agriculture Organization (FAO) Penman-Monteith formula (Allen et al. 1998). A recent assessment by the American Society of Civil Engineers (Itenfisu et al. 2003) concludes that this formula generates the most accurate estimates of ET0 over a wide range of climatic conditions. The monthly time series of ET0 values (1961–2002), in millimeters per day, was calculated for each ASR using this formula. The latitude corresponding to the ASR centroid and the mean ASR altitude were used in these calculations. Although ASRs are relatively large spatial units with considerable internal climatic variability, the potential error introduced through the use of ASR mean values is likely to be small relative to the regional uncertainty inherent in GCM outputs.

One outstanding issue to be addressed is the fact that climate change projections specific to a HUC-8 may not sufficiently account for more pronounced climate changes in upstream areas of the watershed (e.g., warm temperatures leading to snowmelt in the source water for a given watershed). However, to account for the different spatial footprints of the estimated flow changes and contributing watersheds of each HUC-8, we assigned the flow ratio in each ASR to its corresponding location within the contributing watershed of the eight-digit HUC. This in essence represents an area-weighted assignment of the ratios to the HUC-8’s contributing watershed. We derived the contributing area above the pour point (outfall) for each eight-digit HUC using the ArcInfo GRID “watershed” function (ESRI 2006), with flow accumulation and flow direction grids acquired from the North American HYDRO1k dataset (USGS 1996). The input datasets are derived products generated from the hydrologically correct, 1-km cell size, GTOPO30-regional digital elevation model. As an example, Fig. 4 shows the contributing area of a HUC-8 in Georgia, U.S. Once the ASR ratios were assigned, we calculated the total percentage change in flow over the contributing watershed to the HUC-8 compared to baseline.

2.6 Calculating stream habitat area

Because the economic model (Russell and Vaughan 1982; Vaughan and Russell 1982b) requires stream area to determine recreational fishing values, estimates must be made of

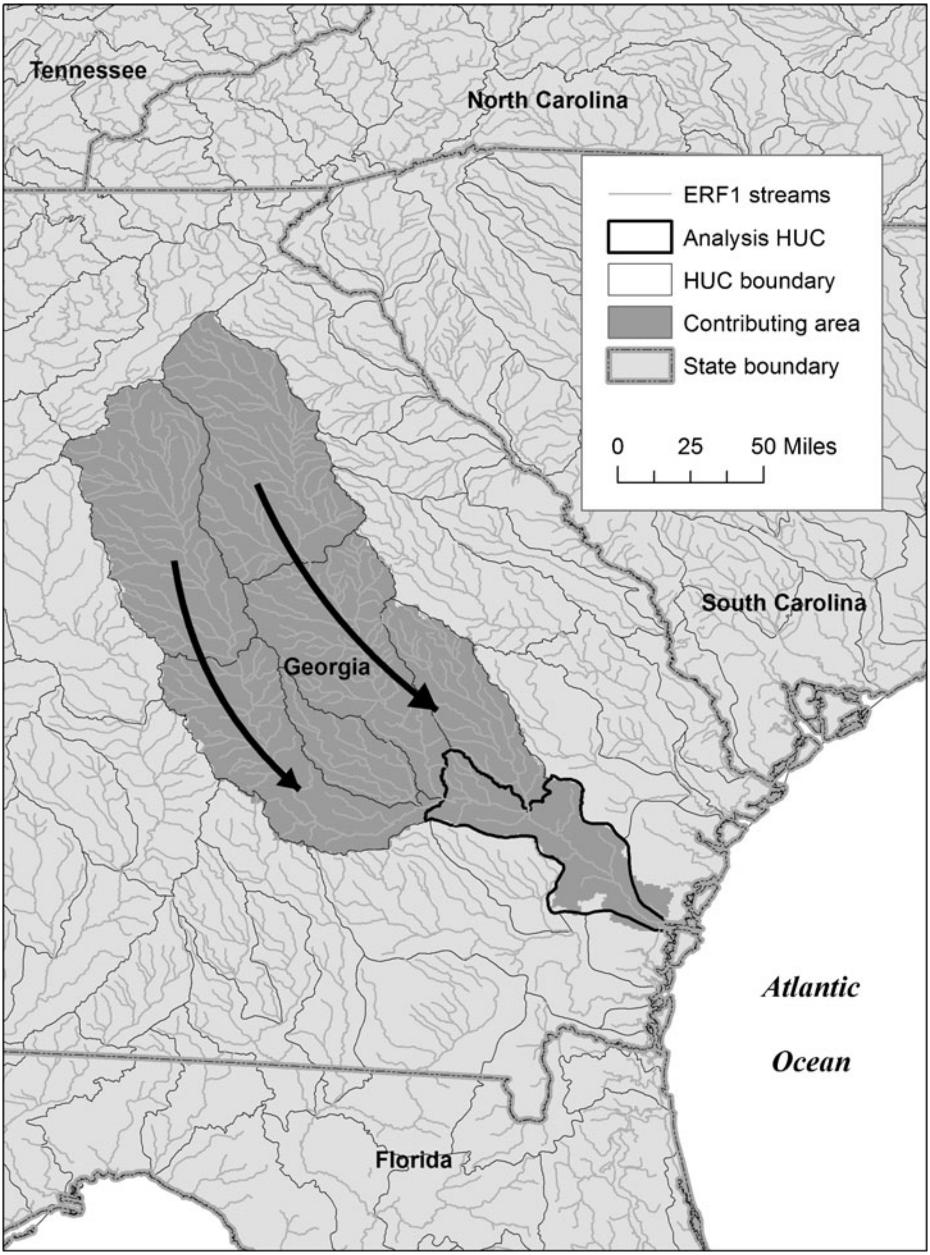

Fig. 4 Area of a watershed contributing to a HUC-8 in Georgia, U.S.

stream width and reach across the entire coterminous United States. The length of each reach was determined from Enhanced River Reach File (v. 1.2; ERF1) data (Alexander et al. 1999). The average width of the river was then estimated and multiplied by the reach length to calculate the surface area of each stream reach in the HUC-8.

The average width was determined from the average discharge of the river. River width, W, can be related to river discharge, Q, using the following regression equation (Dunne and Leopold 1978):

$$W = aQ^b. \tag{6}$$

Using data for 674 stream gauging stations from watersheds throughout the U.S., Allen et al. (1994) determined best-fit coefficients for this equation of $a=1.22$ and $b=0.557$, where Q was discharge at either bank-full conditions or the 2-year or 2.33-year return frequency. This relationship was developed using data from gauging stations that encompass a wide variety of channel geometries.

In our study, the regression equation developed by Allen et al. (1994) was used to estimate the average width of the streams in each HUC-8 from the average discharge reported in the ERF1 data. Because the regression equation was developed for bank-full discharge rather than average discharge, the average discharge and width may not correlate well for certain channel geometries. However, we consider this equation to be reasonably predictive of stream width on a nationwide scale and adequate for the purpose of estimating the surface area of streams for use in our economic analysis.

Because the economic model requires additional area estimates by state, we overlaid the stream data with state boundaries using Environmental Systems Research Institute, Inc.'s detailed state dataset (ESRI 2002). We then calculated the acres on each stream reach, by HUC-8 and state, and summed the acreages for each HUC-8/state combination. Because each HUC-8 was assigned to a fish guild due to estimated water temperatures for each climate/year scenario, we summed the total acres by fish guild and state for use in the economic model.

Our model provided estimates of changes in potentially suitable habitat area from thermal and/or flow projections associated with climate change. For each climate change scenario and time period, we applied the projected thermal suitability or flow changes to the estimates of mean annual flow provided in the ERF1 streams for each reach. In our economic analysis, we considered only decreases in flow based on our belief that flow reductions would exacerbate the effects of temperature more than increases in flow would alleviate them. We then used the revised thermal suitability for different guilds in conjunction with the estimated stream width to recalculate the acreages of suitable habitat by fish guild.

2.7 Performing economic modeling

We relied on an economic model developed by Vaughan and Russell that estimated a relationship between the number of recreational fishing days by state and key independent variables, including the availability of fishing habitat, average catch rates, and average demographic variables by state (Russell and Vaughan 1982; Vaughan and Russell 1982b). The model included three stages. The first stage predicted the likelihood that an individual is an angler. The second stage predicted the likelihood that an individual, conditional on being an angler, fishes for cold, cool/warmwater, or rough species. The third stage predicted the number of fishing days taken by an angler who engages in each type of fishing.

We updated the Vaughan and Russell model to include recent demographic variables following procedures outlined by U.S. Environmental Protection Agency (EPA) (1995). Despite revisions to the data, we found that the first stage of the Vaughan and Russell model overestimated the current number of anglers in the U.S. population by a factor of 4 when compared to recent estimates of the number of anglers available from the 2006 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation (DOI et al. 2007). We therefore calibrated predictions from the first-stage model downward. Under current climate conditions, the calibrated first-stage model reproduces current data on participation in fishing drawn from the 2006 U.S. Department of the Interior (DOI) survey (DOI et al. 2007). For future climate change scenarios, the first stage of the model predicts a decline in the number of participants in fishing when total fish habitat declines and an increase in participation when total fish habitat increases.

The second stage of the model predicts the proportion of anglers participating in coldwater, cool/warmwater, and rough fishing based on the proportion of fishing habitat suitable for each type of fishing. This portion of the model includes demographic variables for the angler population, which were updated using data obtained from the DOI national survey (DOI et al. 2007). In all climate change scenarios and all time periods, the proportion of coldwater habitat declines and the proportion of rough habitat increases.

The stage-three portion of the model predicts the number of fishing days taken annually by each type of angler based on per capita acreage of each type of habitat. Following EPA (1995), we included socioeconomic characteristics in the stage-three model using input values from the original Vaughan and Russell analysis because current data on variables such as gender and age are not available for groups of anglers broken out by those participating in each type of fishing.

To develop values for fishing days, we updated calculations reported in EPA (1995). The U.S. Environmental Protection Agency (EPA) study relied on Walsh et al. (1992) to determine the value of coldwater and cool/warmwater fishing trips, then used adjustments from Charbonneau and Hay (1978) to estimate a rough fishing value in proportion to the cool/warmwater value. To update the values, we conducted a literature search to identify relevant valuation studies conducted since 1988, the last year included in the Walsh et al. (1992) study. We identified five new studies of coldwater fishing and no new studies specifically associated with cool/warmwater or rough fishing. We combined the new coldwater studies with the Walsh et al. coldwater values in proportion to the number of individual value estimates available. Specifically, the five new sources included 20 coldwater value estimates, which were combined with 48 coldwater values included in Walsh et al. (1992). The inclusion of the new values resulted in a 6 % increase in the estimated per day value of coldwater fishing. Value estimates for all three types of fishing were updated to 2009 dollars using the Consumer Price Index (CPI). For our analysis, the estimated value of a coldwater fishing day was $65.20, the estimated CPI value of a coldwater fishing day was $42.91, and the estimated value of a rough fishing day was $33.88.

3 Results

3.1 Thermal suitability of waters

Figures 5, 6 and 7 show the distribution of estimated suitable habitat generated through our analysis for coldwater, cool/warmwater, and rough fisheries for the three emissions scenarios (A1FI, A1B, and B1) and three timeframes (2030, 2050, and 2100). In general, the spatial distribution of coldwater fisheries diminishes, being replaced by cool/warmwater and rough fisheries. Many cool/warmwater fisheries habitats are replaced by waters suitable for only rough fisheries. The change in coldwater fisheries to cool/warmwater and rough fisheries is more pronounced in 2100 than in 2030 and in high-emissions scenarios than in low-emissions scenarios. Similarly, the area affected by an anticipated change from cool/warmwater to rough fisheries increases with time and emissions scenario. Under the highest GHG

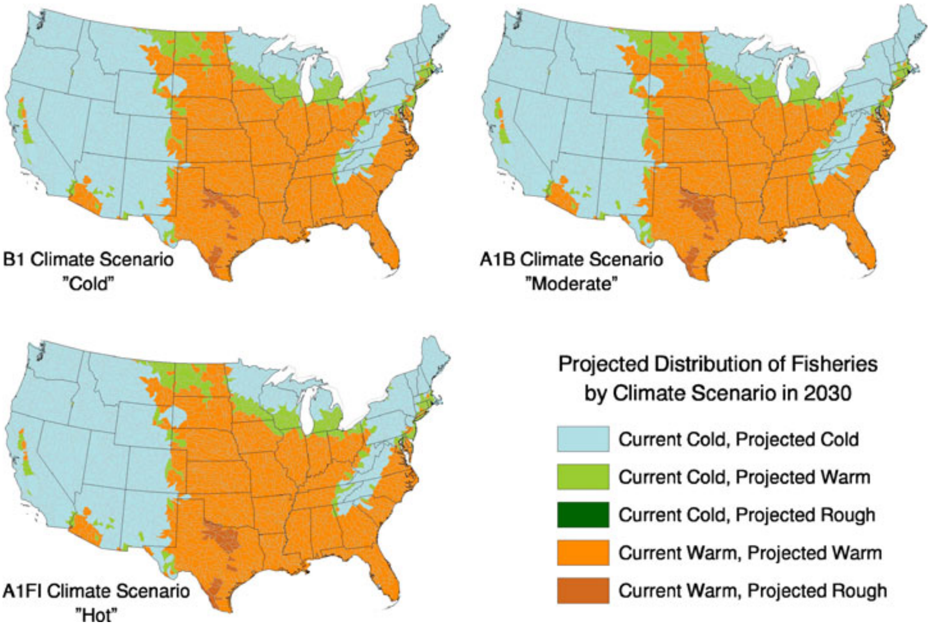

Fig. 5 Projected change in distribution of coldwater, cool/warmwater, and rough fish guilds by 2030 for B1, A1B, and A1FI climate scenarios. Guild shown is the guild with the lowest thermal threshold. "Cold" indicates that the water is thermally suitable for coldwater fisheries but does not exclude cool/warmwater or rough fish. "Warm" indicates that the water is unsuitable for coldwater fisheries but does not exclude rough fish. "Rough" indicates that the water is unsuitable for either cold or cool/warmwater fisheries

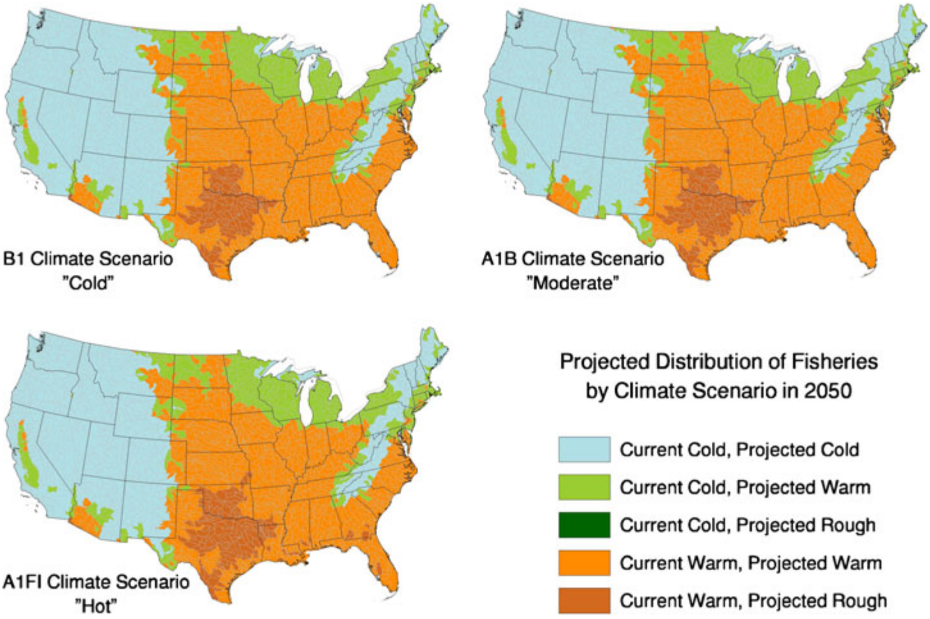

Fig. 6 Projected change in distribution of coldwater, cool/warmwater, and rough fish guilds by 2050 for B1, A1B, and A1FI climate scenarios

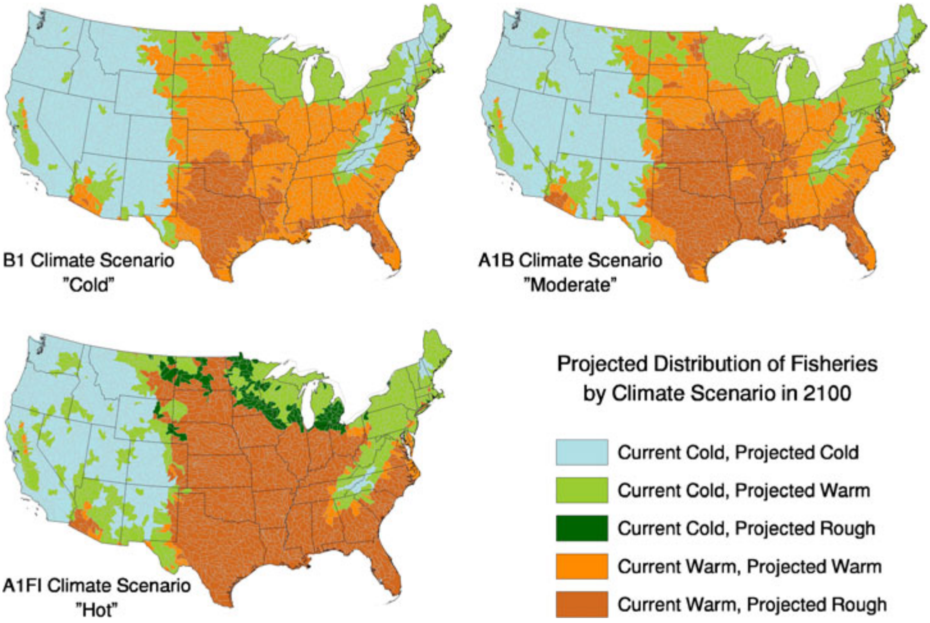

Fig. 7 Projected change in distribution of coldwater, cool/warmwater, and rough fish guilds by 2100 for B1, A1B, and A1FI climate scenarios

emissions scenario (A1FI by 2100), habitat for coldwater fisheries is expected to decline by roughly 54 % and to be limited to mountainous areas in the western U.S. and very limited areas of New England and the Appalachians.

3.2 Changes in flow

The projected percentage change in flow over the contributing area for each HUC-8 is shown in Figs. 8, 9 and 10 for each emissions scenario and time period. The spatial pattern of changes in streamflow is quite variable among emissions scenarios and time periods. The variability of streamflow response is dynamically influenced by the hydrogeologic factors used in the CLIRUN water balance model (e.g., temperature, evapotranspiration, groundwater flow). This variability may also be influenced by the integration of aerosols and scaled temperature and precipitation patterns from M/S. Nevertheless, under all emissions scenarios, streamflow is estimated to increase in New England by 2030, and this increase is shown to extend south to the mid-Atlantic by 2050 and 2100. In contrast, streamflows over watersheds in the western U.S., the Plains, and southern Florida are projected to decrease. The most dramatic changes, both in increases and decreases in streamflow, are anticipated for the high-emissions A1FI scenario; these changes are expected to become more pronounced over time. However, in the lower A1B and B1 emissions scenarios, the trend is quite different. With the exception of the Northeast, there is a pronounced reduction in streamflow in 2030. However, the trend lessens (A1B) or is even reversed (B1) by 2050, with many watersheds showing increased flows. The trend is then reversed again by 2100, with a significant reduction in flows over the entire western portion of the United States and Florida. These patterns of streamflow likely are due in part to the complex interactions of evapotranspiration and changes in precipitation timing and intensity.

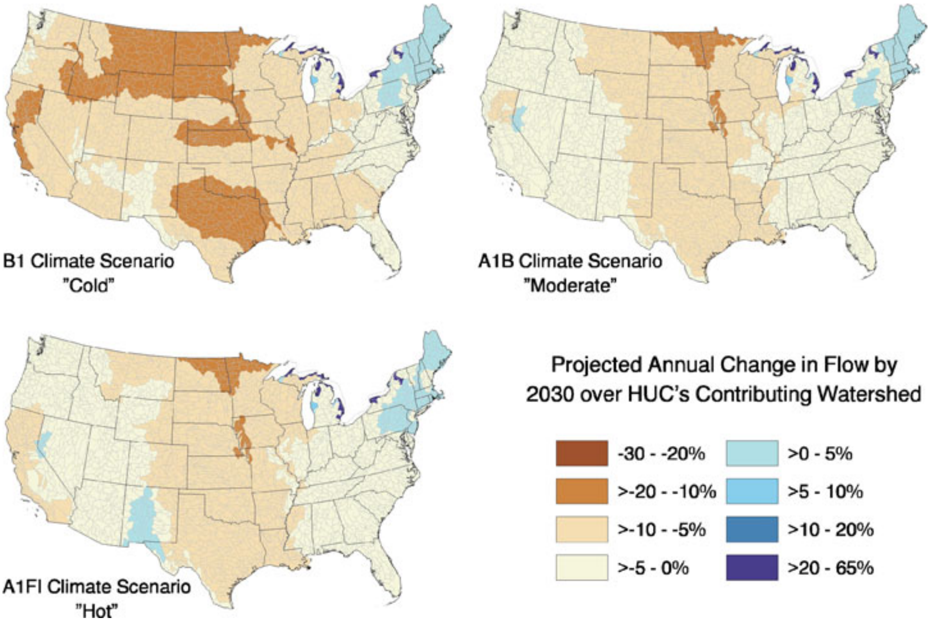

Fig. 8 Projected annual change in flow over HUC-8's contributing watershed by 2030 for B1, A1B, and A1FI climate scenarios

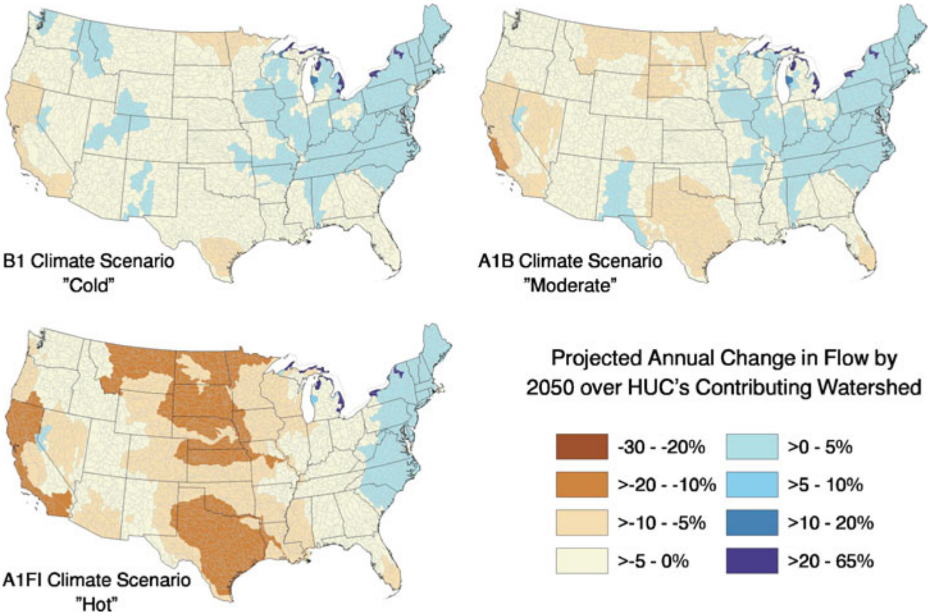

Fig. 9 Projected annual change in flow over HUC-8's contributing watershed by 2050 for B1, A1B, and A1FI climate scenarios

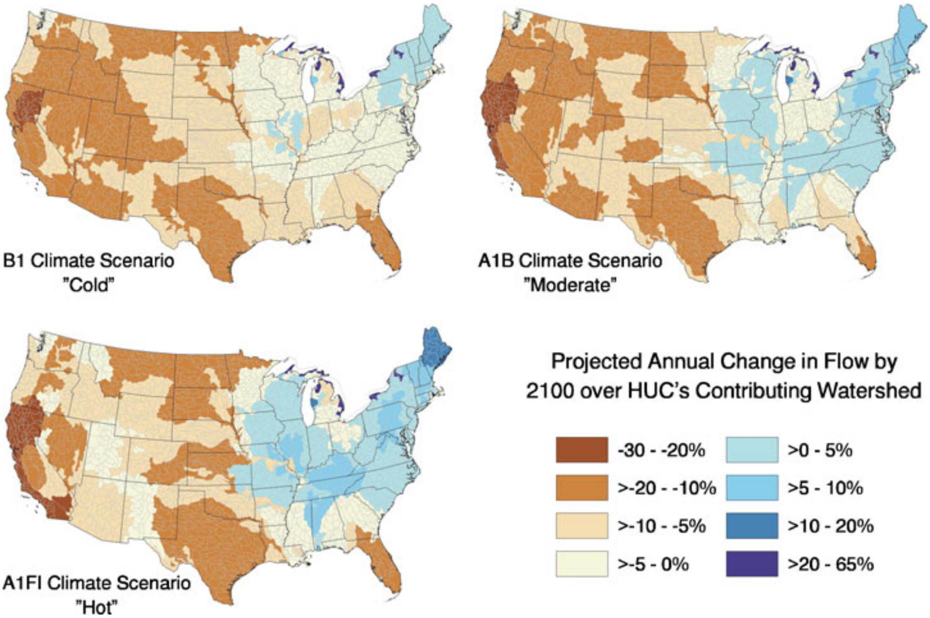

Fig. 10 Projected annual change in flow over HUC-8's contributing watershed by 2100 for B1, A1B, and A1FI climate scenarios

3.3 Combined effect of temperature and flow on habitat suitability

We also evaluated the potential for flow effects to either exacerbate or ameliorate anticipated thermal stress. At a conceptual level, we hypothesized that areas expected to be under threat of thermal modification will be more vulnerable to such change if flows are decreased and vice versa. To undertake this vulnerability analysis, we demarcated those areas projected to have either greater than 10 % change in streamflow or be within 1 °C of the thermal threshold for that fish guild. Areas with a projected 10 %+increase in flow are assumed to be less prone to thermal disruption. Areas with a projected 10 %+decrease in flow are assumed to be more prone to thermal disruption. Those locations with a projected 10 % decrease in flow *and* an anticipated shift in fish guilds are deemed areas most likely to experience impacts to fisheries.

Figures 11, 12 and 13 show the results of these modeling overlays for the years 2030, 2050, and 2100, respectively. By 2030, habitat for coldwater species in the upper Midwest/ Great Lakes region and parts of southern New England and the mid-Atlantic shore begin to be constrained under all three emissions scenarios. Further, flow reductions may impose additional vulnerabilities on both cool/warmwater and coldwater species in the northern Midwest and Missouri River drainage, along with a few HUC-8s in Oregon, Washington, and the Central Valley of California. The A1B and A1FI scenarios show much less vulnerability to flow reductions through 2030, with impacted HUC-8s restricted to a few areas along the Missouri River and in North Dakota and Minnesota. In all three scenarios, there are a few HUC-8s along the shore of Lake Michigan where flow increases will alleviate potential thermal impacts.

By 2050, the thermal pattern expands – again, for all three emissions scenarios – with large-scale reductions in viable coldwater fish habitat in the northern Midwest/Great Lakes

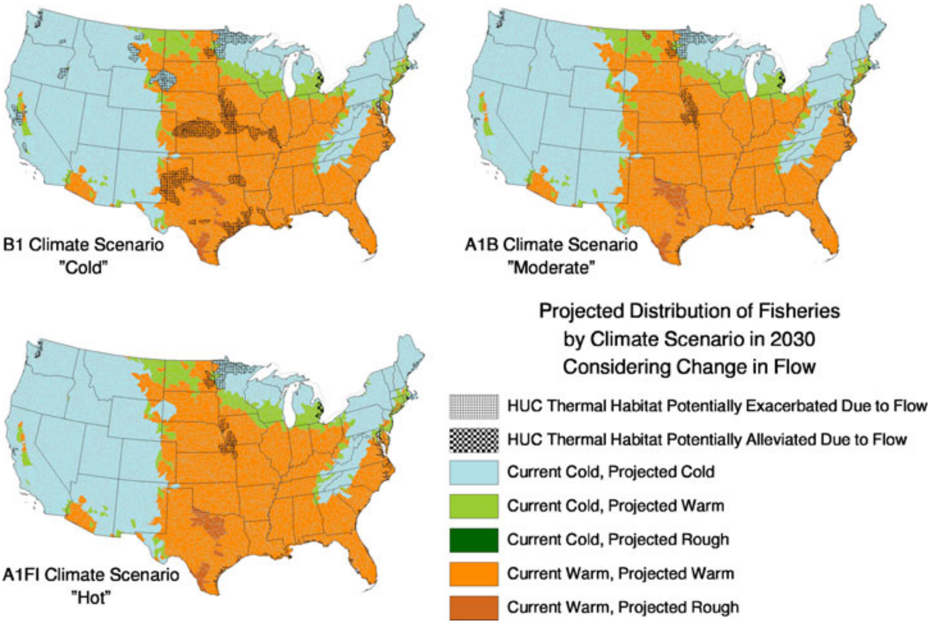

Fig. 11 Projected change in distribution of fisheries over HUC-8's contributing watershed by 2030 for B1, A1B, and A1FI climate scenarios considering change in flow

states, large portions of New England and the mid-Atlantic, the mountain regions of southern Arizona and New Mexico, and the Central Valley in California. Moreover, large

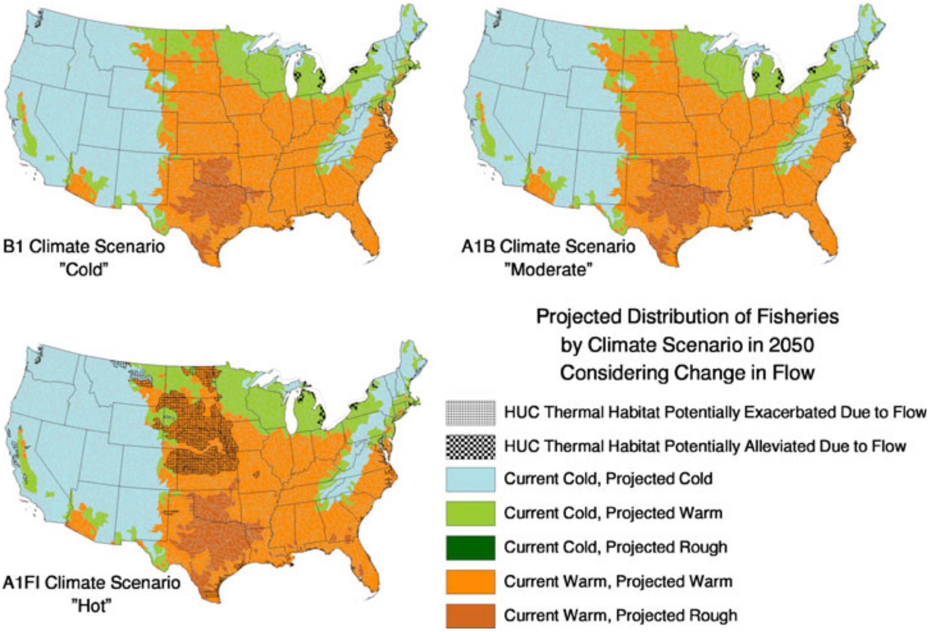

Fig. 12 Projected change in distribution of fisheries over HUC-8's contributing watershed by 2050 for B1, A1B, and A1FI climate scenarios considering change in flow

portions of Texas and Oklahoma may become increasingly less viable for cool/warmwater species, resulting in shifts to rough fish. Somewhat counterintuitively, by 2050 the B1 and A1B scenarios have no HUC-8s where flow reductions are estimated to exacerbate the thermal habitat. In addition, there are a few additional HUC-8s along the Great Lakes coastline of Michigan and New York where increases in flow are estimated to alleviate the thermal stresses. However, under the A1FI scenario, there are large areas in the northern and central Midwest, as well as a small number of HUC-8s in California, where reductions in flow could exacerbate the thermal stresses. Lastly, the A1FI shows a spatial pattern similar to the other scenarios where flow increases could reduce thermal stresses.

By 2100, the pattern of change expands to the point that coldwater fish guilds may be largely eliminated outside of the states west of the Plains (excluding Arizona), including the Rocky Mountains, the Pacific Northwest, and some areas in northern New England and Appalachia. By the end of the century, all three scenarios show an increase in the spatial extent of HUC-8s that are more vulnerable to shifts in thermal regime from flow reductions. The B1 and A1B scenarios show large areas of Montana and North Dakota and sporadic HUC-8s in the West with a high thermal vulnerability to decreases in flow. The A1FI shows extensive areas in California and Nevada that are potentially vulnerable, as well as smaller areas in Montana, along the Colorado/South Dakota border, and in New Mexico and Texas. It should be noted that the large areas in the northern and central Midwest that are potentially impacted by flow reductions by 2050 are not shown to be vulnerable by 2100. This is because the fish guilds are already expected to have shifted to the "rough" category by this time. All three scenarios continue to show sporadic HUC-8s along the coastline of the Great Lakes where flow increases may reduce the stress to fish guilds from thermal increases.

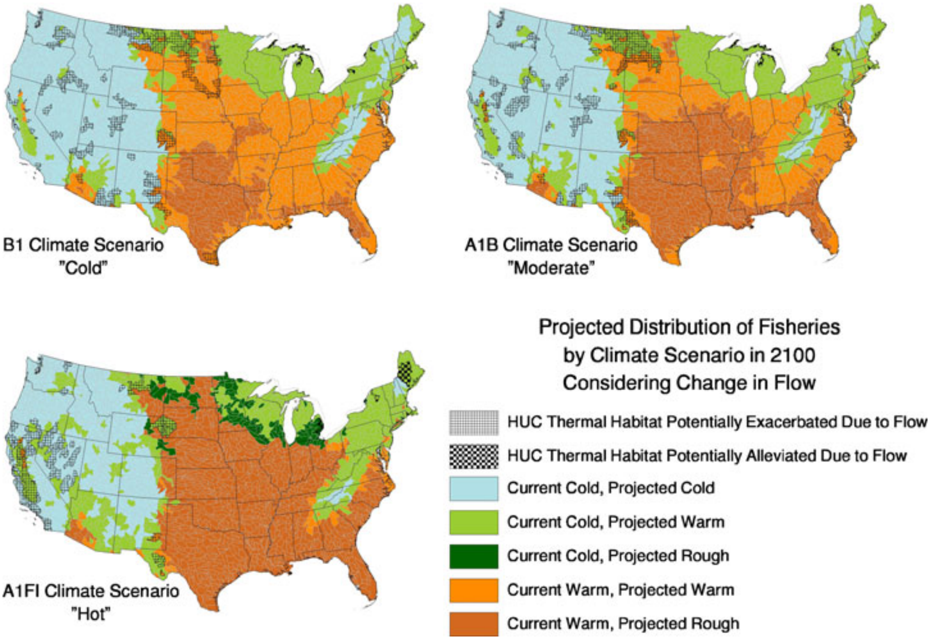

Fig. 13 Projected change in distribution of fisheries over HUC-8's contributing watershed by 2100 for B1, A1B, and A1FI climate scenarios considering change in flow

Lastly, the A1FI scenario is unique in showing an extensive area in Maine where this effect is estimated to occur.

3.4 Economic valuation

Based on habitat changes estimated by the other models, the economic model projects a decline in coldwater fishing days for all climate change scenarios. The decline in annual coldwater fishing days ranges from 1.25 million by 2030 for climate scenarios A1B and A1FI to 6.42 million by 2100 for scenario A1FI. Cool/warmwater fishing days increase in all scenarios, as people switch from coldwater to warmwater fishing in response to the decline in coldwater habitat. An increase in habitat suitable for rough fishing increases rough fishing days in some scenarios. However, scenarios A1B and A1FI suggest that a large decline in both coldwater and cool/warmwater habitats can cause a large number of people to stop fishing altogether, leading to a decline in rough fishing days despite an increase in habitat suitable for rough species. This decline in fishing days represents a long-term adjustment to changes in habitat since the model was estimated based on differences in habitat availability and fishing across states, and historically fishing availability in any given state has remained relatively constant over the long term. Table 2 presents the impact of alternative climate change scenarios on the estimated number of coldwater, cool/warmwater, and rough fishing days in 2030, 2050, and 2100. For comparison to the numbers in Table 2, the most recent DOI et al. fishing survey (DOI et al. 2007) estimates current annual activity of 136 million fishing days in U.S. rivers and streams.

The results of the valuation analysis are presented in Table 3. The total value of recreational fishing declines under all scenarios, attributable to a decline in the number of coldwater fishing days. In the economic valuation model, a complete change from coldwater habitat to warmwater habitat would lead to an increase in fishing value, because warmwater habitat is associated with more fishing days than coldwater habitat. In all the scenarios in Table 3, the increase in warmwater habitat is smaller than the decline in coldwater habitat, so the increase in warmwater fishing only partly offsets the loss in the value of coldwater fishing. The difference between the decrease in coldwater habitat and the increase in warmwater habitat is partly explained by a shift from warmwater to rough-fishing habitat and partly explained by a decline in the total area of freshwater stream habitat attributable to reductions in precipitation.

Table 2 Change in annual fishings (million days) in the U.S.

Climate change scenario	Type of fishing	Year		
		2030	2050	2100
B1	Coldwater	−1.29	−2.24	−3.46
	Cool/warmwater	1.38	2.45	3.17
	Rough	0.68	1.03	1.06
A1B	Coldwater	−1.25	−2.35	−4.42
	Cool/warmwater	1.38	2.57	2.37
	Rough	0.65	1.08	−0.77
A1FI	Coldwater	−1.25	−2.63	−6.42
	Cool/warmwater	1.38	2.71	1.08
	Rough	0.66	1.12	−3.69

Table 3 Present value of losses (2009–2100) at selected discount rates (millions of dollars)

Climate change scenario	Discount rate, %		
	1	3	5
B1	$823	$235	$81
A1B	$2,737	$694	$196
A1FI	$6,437	$1,633	$460

All scenarios in Table 3 reflect losses from 2009 through 2100, with annual losses assumed to be zero through 2030, then increasing linearly for each time period from 2030 to 2050 and from 2050 to 2100. For example, for the A1B scenario, the loss in value in 2030 is estimated to be $0.3 million per year; the loss in 2050 is $6.4 million per year; and the loss in 2100 is $212.4 million per year. Losses in intermediate years were estimated by interpolating linearly between the three points in time evaluated in the stream habitat model. To estimate the total loss through 2100, economic discounting procedures were applied. Discounting allows losses across time to be summed and expressed as a single present value, comparable to current dollar amounts. We show results using discount rates from 1, 3, and 5 %, where a lower discount rate places a higher present value on future years (i.e., lower discount rates are therefore associated with larger losses). The total present value of estimated losses from 2009 to 2100 ranges from $81 million to $6.4 billion.

4 Discussion

The results of this national-scale analysis for the coterminous U.S. point to several trends. At a national level, increased water temperatures are very likely to result from increased air temperatures. These increased temperatures are likely to be sufficient to render some fish habitat unsuitable for current resident species. Coldwater fish species are more prone to this thermal habitat disruption because their temperature tolerance is narrower than that of cool/warmwater species. Because coldwater species such as trout are associated with higher recreational values than cool/warmwater species, a loss of coldwater fish habitat could generate considerable economic losses.

Our approach to quantifying and valuing freshwater fish impacts due to climate change offers substantial advantages compared to prior efforts, including: (1) development and use of region-specific nonlinear regressions to model the relationship between air and water temperatures; (2) in addition to analyzing thermal effects, application of a water balance model to quantify how projected changes in precipitation will affect naturalized flow and habitat for freshwater fisheries at a national scale; (3) use of the IPCC's most recently published emissions scenarios, and ensemble averaging across 10 GCMs to project future changes in temperature and precipitation; (4) use of a GIS-based approach to map results and visualize alternative futures; and (5) the ability to provide results at a higher degree of resolution. In addition, our analysis satisfies a critical limitation identified by Preston (2006) by quantifying net habitat changes across multiple fish guilds in order to identify where species ranges will contract and expand, instead of solely expressing climate change effects relative to current habitat.

Comparisons with other studies estimating the total change in habitat as the result of climate change are difficult for a variety of reasons, including: differences in emissions scenarios, differences in time periods considered, climate variables analyzed (i.e., temperature- and precipitation-driven flow), species considered, geographic extents examined, and methods used. In addition, other studies considered total area (e.g., Keleher and Rahel 1996), as opposed to stream habitat or additional variables such as biotic interactions (Wenger et al. 2011). However, we feel that it is instructive to at least provide gross comparisons to other studies. For example, Wenger et al. (2011) found habitat declines in the interior western U.S. of 16 % by 2040 and 48 % by 2080 for brown trout under the A1B scenario. This compares well to our study where we found a decline of 15.7 % by 2030 and 45 % by 2100 for the coldwater guild for the same emissions scenario, although our estimate was a national estimate. However, although Wenger et al. considered the combined impact from several factors, including flow regime, temperature, and biotic interactions, they found that the predominant factor influencing the decline of trout species was increasing temperature.

O'Neal's (2002) findings, compared with ours, are as follows. For the B1 emissions scenario, we showed a decline of approximately 17 % by 2030, 28 % by 2050, and 40 % by 2100, nationally. The O'Neal study showed declines of 20 % by 2030, 31 % by 2060, and 34 % by 2090. For the highest emissions scenarios, we showed declines of 15.4 % for 2030, 31.6 % for 2050, and 56 % for 2100 under the A1FI emissions scenario. O'Neal's estimates under their highest emissions scenario, A2 (which has a slightly different trajectory and lower final carbon dioxide (CO_2) concentration by 2100), by comparison showed declines up to 17 % by 2030, 35 % by 2060, and 42 % by 2090.

Keleher and Rahel's (1996) study in the U.S. Rocky Mountain region found a 50 % reduction in geographic range for salmonids with a 3 °C increase in mean July air temperature. This corresponds roughly to our B1 scenario by 2100, where we found a 16 % reduction for the same region. For a 5 °C increase, they found a 72 % reduction in range. This far exceeds our losses, even under the A1FI scenario with increases of 5 °C–7 °C, where we found a reduction of 33 %. It should be noted that Keleher and Rahel used a multiple regression analysis that related latitude and elevation with mean July air temperatures and a thermal threshold of 22 °C (mean air temperature), whereas our analysis considered water temperatures derived from air temperatures. Their study also examined changes in total geographic area rather than changes by river reach, as was conducted in our analysis. Lastly, our study compares well with the Eaton and Scheller (1996) study, which showed an average reduction in coldwater fish suitability across stream sites of 47 % under a doubling of CO_2. This roughly compares to our A1B scenario by 2100 where we found a 45 % reduction in thermal suitability for coldwater fishes.

4.1 Key limitations and sources of uncertainty

As a consequence of our assumption that all thermally modified habitats will be fully occupied by replacement fish guilds, our national-scale analysis may represent what is effectively a best-case scenario (therefore generating conservative estimates from a biological perspective) because we assume the existence of a recruitment source for new fish guilds and habitat compatibility across all fish guilds. It may be even more likely that those areas we have demarcated as being vulnerable to thermal stress (or combined thermal/flow stresses) will be subjected to large-scale reductions in fish populations. Such changes, were they to occur, could be associated with even larger-scale ecological perturbations because of food-chain disruptions and alterations in nutrient flows.

Although this analysis updates previous freshwater fishery thermal suitability analyses, a number of lingering uncertainties or limitations of this analysis could be exploited to further refine this national-scale climate change physical and economic impact analysis.

Omission of lakes and reservoirs We focused on rivers and streams to assess the potential loss of suitable fish habitat in terms of fishable acres. A comprehensive estimate of both currently suitable acreage and potential losses of suitable habitat would also include an assessment of lakes and reservoirs. However, this would pose modeling challenges at a national-scale if thermal stratification were to be modeled.

Aggregating at-site gauge data This study does not account for many site-specific factors that may affect the T_A - T_W relationship, such as elevation, aspect, proximity to snowmelt, riparian shading, extent of groundwater contribution to streamflow; as well as anthropogenic factors such as dams and municipal/power plant outfalls. We addressed this by eliminating gauges that exhibited non-systematic T_A - T_W relationships as well as by estimating parameters independently for each ecoregion. However, the availability of gauge data on naturally flowing streams was quite limited and not spatially uniform (see Fig. 1). Consequently, some T_A - T_W relationships are based on more data than others.

Uncertainty in thermal thresholds for fish Projecting thermal thresholds for fish guilds includes a number of uncertainties. Use of the guild-based analysis ignores possible species-level variability in both physiological temperature tolerances and ecological and behavioral differences (e.g., timing of spawning and rearing, feeding behaviors, migratory requirements). At an individual level, thermal effects also can be modulated through acclimation, reduced nighttime temperatures, or activity level. The use of generalized thermal tolerance data ignores site-specific factors that can mitigate against adverse effects (e.g., use of cooler groundwater inputs as thermal refugia, influence of stream morphology or overhanging vegetation on local temperatures, alterations of local temperature regimes because of water management). As a consequence of these sources of variability, local impacts to individual fish (or guilds) could differ from the national-level projections. Nonetheless, the national projections provide a reasonable estimate of the direction and magnitude of shifts in freshwater fisheries.

Availability of nationwide data on fish distributions We were not able to identify a definitive and comprehensive nationwide dataset showing the current distribution of the fish guilds. Furthermore, this study focuses on thermal suitability of natural waters and does not take into account anthropogenic and other factors that may influence the current observed distribution of fish. Consequently, a direct comparison to observed fish distributions is potentially unreliable. However, where possible, we compared our projected distributions to published information about nationwide fish distributions (e.g., Behnke 2002), professional judgment, and modeled distributions from other studies of the impacts of climate change on U.S. fisheries to inform our assessment. Because the primary purpose of this analysis is to show the potential relative change in distribution and the economic valuation under projected climate change over time, the nationwide fish distribution maps should be viewed in relative terms and the focus should not be on the presence or absence of a particular fish guild in any particular HUC-8.

Study does not evaluate local impacts on fisheries other than climate change Some streams might not support fish because they are too intermittent, polluted, ecologically depleted, or thermally unsuitable for reasons other than climate change impacts (e.g., dams, discharges from wastewater treatment plants and power plants). This study only evaluated changes in thermal suitability from climate change; other factors were not considered. Other stressors on habitat suitability and fish well-being (e.g., riparian vegetation; channel structure and morphological alterations associated with changes in runoff patterns; nutrients; pathogens; non-native, invasive species; impoundments) and how these stressors themselves may be affected by climate change were not considered. The assessment literature, however, suggests that many of these stressors will be exacerbated with increasing temperatures and precipitation variability (Field et al. 2007). We recognize that accurate determinations of habitat suitability at local to regional scales need to account for the impacts of these other stressors, which, in some places, could render streams unsuitable for fish populations before climate change effects occur.

Limitations of the economic model The economic model used to estimate the value of changes in recreational fishing does not account for the effect of habitat changes on anglers' value for fishing. For example, it is possible that the value of a fishing day for coldwater fisheries will increase as the habitat available for coldwater fishing decreases, rather than remaining the same as assumed in the model. This could also affect participation in coldwater fishing as anglers may be inclined to travel greater distances to fish in coldwater areas rather than switching to warm or rough species. Another limitation in the economic model is use of a functional structure that estimates a simple relationship between the extent of fish habitat and the number of fishing days, without any attempt to characterize individual preferences. Most models developed more recently than the Vaughan and Russell model would express the relationship between habitat extent and the amount of fishing as a tradeoff between the value of high-quality fishing and the additional distance anglers must travel to reach high-quality habitat. As noted earlier, the data required for this more detailed approach would be expensive to collect and is not currently available. Furthermore, our damage estimates do not capture non-market values, such as the worth that non-anglers place on the existence of freshwater fish. Proper accounting of these values will help to advance our understanding of how significant these climate change risks are.

5 Conclusion

The quantitative results of this study are consistent with those found in the literature noting that U.S. coldwater fisheries are highly vulnerable to climate change through the loss of suitable habitat. Over the course of this century, the impact of these changes to recreational fishing could represent economic damages in the billions of dollars. Furthermore, it is important to note that climate change effects on freshwater fish populations in the U.S. will likely have economic impacts far greater than what we have estimated here because of the conservative assumptions and limited scope of this analysis.

We believe that our approach and results are policy relevant across multiple disciplines, and we expand upon two of them here. First, our analysis shows that estimated losses of suitable habitat for coldwater fish by 2100 are substantial under all emissions scenarios. However, a comparison of projections for the low- and high – emissions scenario in 2100 indicates that ~18 % less coldwater fish habitat would be lost under the lower emissions trajectory. As described in the results section, the difference in emissions pathway also has large implications for the spatial distribution of suitable habitat for coldwater species across the coterminous U.S. Except in very limited locations, coldwater fish habitat under the high-emissions scenario could disappear from most of New England, the Appalachians, and the upper Midwest by 2100. Second, our approach and results can be useful for conservation planning. In addition to considering how other stressors will affect fish populations, fishery managers and conservation planners may need to analyze how climate change will drive changes in the suitability of habitat across the country. National wildlife and fishery groups (Wildlife Management Institute and the Theodore Roosevelt Conservation Partnership 2009) and the U.S. government (USFWS 2010) have both recognized the need to identify fishery habitat that will be least affected by climate change, so that these areas can be targeted and prioritized for watershed conservation and restoration efforts. Our analytical framework can serve as a screening tool for this purpose.

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