RISK-BASED REANALYSIS OF THE EFFECTS OF CLIMATE CHANGE ON U.S. COLD-WATER HABITAT

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Abstract. A probabilistic risk assessment was conducted for the effects of future climate change on U.S. cold-water habitat. Damage functions for the loss of current cold-water fish habitat in the United States and the Rocky Mountain region were integrated with probability distributions for U.S. June/July/August (JJA) temperature change using Monte Carlo techniques. Damage functions indicated temperature thresholds for incipient losses ($\geq$5%) of cold-water habitat in the United States and the Rocky Mountains of 0.6 and 0.4 °C, respectively. Median impacts associated with different temperature distributions suggested habitat loss in 2025, 2050, and 2100 of approximately 10, 20, and 30%, respectively, for the United States and 20, 35, and 50%, respectively, in the Rocky Mountains. However, 2100 losses in excess of 60% and 90% were possible for the United States and the Rocky Mountains, respectively, albeit at low probabilities. The implementation of constraints on greenhouse gas emissions conforming to the WRE750/550/350 stabilization scenarios had little effect on reducing habitat loss out to 2050, but median effects in 2100 were reduced by up to 20, 30, and 60%, respectively. Increased focus on probabilistic risk assessment may be a profitable mechanism for enhancing understanding and communication of climate change impacts and, subsequently, risk management.

1. Introduction

Ecological systems are sensitive to climatic variability and change due to constant exposure to the climate and the limited capacity of individuals within populations to adapt to climatic conditions via genetic, physiological, and behavioral mechanisms. A number of reviews have identified aquatic ecosystems within the United States as being particularly vulnerable to the effects of climate change (Meyer et al., 1999; IPCC, 2002; Poff et al., 2002), with cold-water species having a high sensitivity to thermal stress, relative to cool and warm-water fish guilds (Eaton and Scheller, 1996; Mohseni et al., 2003). In addition, over the past fifteen years, several studies have examined the potential effects of anthropogenic climate change on the distribution of cold-water species (Meisner et al., 1987; Magnuson et al., 1990; Matthews and Zimmerman, 1990; Meisner, 1990; Eaton and Scheller, 1996; Keleher and Rahel, 1996; Rahel et al., 1996; O'Neal, 2002; Mohseni et al., 2003). Therefore, this group of organisms may be an early responder to the effects of U.S. climate change, and those effects may have significant consequences at the economic and ecosystem level (U.S. EPA, 1995; Ahn, 2000).

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A fundamental shortcoming of current methods to quantify the potential impacts of climate change on both natural and societal systems is the use of climate scenarios in the projection of climatic changes in the absence of information regarding the absolute or even relative probabilities associated with different scenarios (Jones, 2000, 2001). For example, Eaton and Scheller (1996) and Mohseni et al. (2003) estimated the effects of future changes in U.S. mean temperature on cold-water fish habitat in response to the radiative forcing associated with a doubling of the pre-industrial atmospheric concentration of carbon dioxide (CO_2). Such scenario-driven impact assessment is invaluable in clarifying the sensitivity of a particular system to changes in climate conditions and constraining projections of possible effects. However, by themselves, such sensitivity analyses provide limited information regarding the likelihood that a particular consequence will occur. For example, criticisms have been leveled at the Intergovernmental Panel on Climate Change's (IPCC) projection of future mean global temperature increase of 1.4–5.8 °C (IPCC, 2001) for its failure to assign probabilities to this range (Reilly et al., 2001; Schneider, 2001), and currently there is ongoing debate regarding the utility of probabilistic information on climate change (Dessai and Hulme, 2003).

One approach for addressing such challenges is the application of risk-based methods in the analysis of climate change impacts (Jones, 2001; Jones and Mearns, 2005). Risk analysis is designed to integrate information regarding the response of systems to forcings of interest with information regarding a system's exposure to such forcings to yield a probabilistic estimate of system response. Its advantage in the analysis of climate change impacts is its ability to account for uncertainty and provide information regarding not only the sensitivity of systems to climatic changes, but also the likelihood that such changes will, in fact, occur. As such it may be a valuable tool for informing environmental management processes, because it allows one to evaluate the necessity and efficacy of alternative management strategies (Jones, 2001; Pittock et al., 2001; Schneider, 2001).

Probabilistic risk analysis for climate change impacts can be performed provided two components are available. First, information is needed on the sensitivity of a particular system to changes in climatic conditions (Jones and Mearns, 2005), be they temperature, precipitation, or some other variable. Such sensitivity can be expressed either as a discrete threshold (see O'Neill and Oppenheimer, 2002), a probability distribution (see Mastrandrea and Schneider, 2004), or a damage function (see Toth et al., 2000). Thresholds provide point estimates for the incipient level of exposure at which system responses become significant or excessive. Such thresholds may be an inherent property of the system (e.g., point of failure) or may be a subjective judgment by stakeholders through qualitative or quantitative analyses (Moss, 1995; Jones, 2001; Anand, 2002; Jones and Mearns, 2005). Probability distributions and damage functions are strictly quantitative estimates of the response of a system over a range of plausible exposure conditions. Such sensitivity analyses can be readily constructed from a number of sources, including historical data regarding system changes in response to climate variability or projected changes in response to an ensemble of climate scenarios.

The second component that is needed is information on the relative probabilities of future changes in climate conditions (Jones and Mearns, 2005). Although attempts to express climate uncertainty probabilistically date to at least the mid-1990s and the IPCC's Second Assessment Report (Titus and Narayanan, 1995, 1996; Visser et al., 2000), renewed interest in the probabilistic uncertainty of climatic changes has emerged in the wake of the IPCC's Third Assessment Report (Reilly et al., 2001; Wigley and Raper, 2001; Allen and Stainforth, 2002; Giorgi and Mearns, 2003; Webster et al., 2003). Different methods utilize different approaches and emphasize different sources of uncertainty such as climate sensitivity, model performance criteria, greenhouse gas (GHG) and aerosol emissions, the carbon cycle, or some combination thereof. The number of probability distributions generated to date remains limited, with most focusing on the aggregate global level (Reilly et al., 2001; Wigley and Raper, 2001; Knutti et al., 2002; Webster et al., 2003), although some regional analyses have been conducted as well (Giorgi and Mearns, 2003; Tebaldi et al., 2004).

The current study applies a risk-based approach to the analysis of data from previously published impact assessments regarding the effects of future climate change on current cold-water fish habitat in the United States. Cold-water fish species such as trout and salmon are valued for recreational and commercial fishing as well as for their contribution to U.S. freshwater biodiversity (U.S. DOI, 1997). The existence of multiple studies of cold-water habitat at the national level, utilizing different scenarios but similar assessment endpoints, makes this a useful resource for exploring applications of risk analysis methods. Here, previous impact assessments are expanded to develop damage functions that relate changes in national and regional cold-water fish habitat to future changes in ambient mean U.S. temperature, which are subsequently used to estimate thresholds for incipient loss of cold-water habitat. Damage functions are also compared with various probability distributions for future U.S. temperature change in 2025, 2050, and 2100 to assess the timing and likelihood of different magnitudes of habitat loss. Finally, the sensitivity of habitat impacts to potential GHG mitigation is assessed using various carbon dioxide atmospheric stabilization scenarios as constraints on future U.S. climate change.

2. Methods

2.1. DATA SOURCES

Data regarding the impacts of U.S. climate change on current cold-water fish habitat in the United States were derived from five previously published impact assessments (Eaton and Scheller, 1996; Keleher and Rahel, 1996; Rahel et al., 1996; O'Neal, 2002; Mohseni, et al., 2003). Three of these studies (Eaton and Scheller, 1996;

O'Neal, 2002; Mohseni, et al., 2003) reported changes in the distribution of current U.S. cold-water habitat by adding the projected summer temperature change generated for $5^\circ \times 5^\circ$ grid cells for one or more scenarios of future climate change from general circulation models (GCMs) to average air temperatures recorded at monitoring stations within each grid cell. Changes in local air temperature were scaled to changes in stream temperatures at USGS gauging stations, based upon various scaling algorithms (e.g., Stefan and Preud'homme, 1993; Mohseni et al., 1998). However, different studies used different models to estimate changes in stream temperatures from air temperatures. Eaton and Scheller (1996), for example, utilized a linear model whereas Mohseni (1998) and O'Neal (2002) utilized non-linear models that tend to produce more conservative estimates of stream temperature changes. Once calculated, stream temperatures were then compared with published thermal tolerances for cold-water fish species (e.g., Eaton and Scheller, 1996). Stations where stream temperatures exceeded species tolerances were assumed to no longer be suitable as habitat for a particular species. Such local data were aggregated over the nation to produce national estimates of the geographic extent of habitat loss relative to current distributions in response to U.S. average temperature change.

Eaton and Scheller (1996) and Mohseni et al. (2003) utilized only a single climate change scenario (equilibrium climate change associated with a CO_2 doubling) in their analyses. In comparison, O'Neal (2002) utilized eight different scenarios (based upon the output from three different GCMs and four different emissions scenarios) and reported results over three different time periods (2030, 2060, and 2090). As such, the current national analysis is dominated by the methodology and results of O'Neal (2002) due to the greater number of scenarios, and thus, data. However, data from Eaton and Scheller (1996) and Mohseni et al. (2003) contributed to capturing some of the range of uncertainty among different studies and were an important check on the consistency of results among different national studies and methodologies. Eaton and Scheller (1996), O'Neal (2002), and Mohseni et al. (2003) also reported results for eight individual cold-water species, enabling construction of species-specific damage functions.

Two studies (Keleher and Rahel, 1996; Rahel et al., 1996) reported changes in the distribution of cold-water fish habitat in the Rocky Mountain region by comparing current habitat climate envelopes for cold-water fish species (based upon summer air temperatures), with estimated changes in climate envelopes in response to five scenarios of increases in regional surface air temperatures. Keleher and Rahel (1996) divided their analysis into regional (i.e., Rocky Mountains) and local (Wyoming) components, both of which were included in the current study. Rahel et al. (1996) focused specifically on the North Platte River drainage of the Rocky Mountains. Collectively, these results enabled a region-specific risk analysis of climate change impacts to habitat in the Rocky Mountains.

Results from these five studies formed the basis for the calculation of habitat damage functions in response to U.S. temperature increases for both the coterminus United States as a whole, as well as specifically for the Rocky Mountain region.

2.2. DAMAGE FUNCTIONS FOR HABITAT LOSS

Calculation of damage functions for both the United States and the Rocky Mountains was achieved by first plotting the current habitat loss versus the temperature change in the associated scenario for each climate change scenario from each of the studies outlined above. A least-squares linear regression (with the regression line forced through the origin) was subsequently conducted on the U.S. and Rocky Mountain data to model the relationship between future average temperature change and cold-water habitat. Uncertainty around these regression models was estimated by calculating 99.9% confidence intervals for regression coefficients. Regression coefficients and confidence intervals were subsequently used to calculate probability distributions for regression coefficients using Analytica^{TM} 2.0. These probability distributions were subsequently used as parameters in stochastic risk modeling (see below). Probability distributions were calculated by assigning the regression coefficients cumulative probabilities of 0.5, and lower and upper 99.9% confidence limits for regression coefficients cumulative probabilities of 0 and 1, respectively. Using these damage functions, an effect threshold for incipient cold-water habitat loss was defined as a $\geq$5% reduction, assuming such a threshold protects 95% of habitat as suggested by international standards on effect levels in risk assessment and management (Emans et al., 1993; Okkerman et al., 1993). Threshold temperature changes associated with this level of effect were estimated from both the United States and Rocky Mountain damage functions.

Species-specific damage functions and temperature thresholds were also calculated, based upon those species common to Eaton and Scheller (1996), O'Neal (2002), and Mohseni et al. (2003), which included Brook trout, Cutthroat trout, Rainbow trout, Brown trout, Chum salmon, Pink salmon, Coho salmon, and Chinook salmon. In calculation of the species-specific damage functions, data from Eaton and Scheller (1996) and Mohseni et al. (2003) suggested higher habitat loss in response to warming. Data from Mohseni et al. (2003), though higher, were generally consistent with those of O'Neal (2002). However, data from Eaton and Scheller (1996) were outliers relative to O'Neal (2002) as well as Mohseni et al. (2003), which was likely a function of the aforementioned differences in the manner in which studies estimated stream temperatures. Although those studies focused on the Rocky Mountains also utilized common species, species-specific results were not presented, which prevented species-specific risk analysis for this region.

2.3. PROBABILITY DISTRIBUTIONS FOR FUTURE U.S. WARMING

The probabilistic uncertainty in future average U.S. June/July/August (JJA) temperature change was estimated from multiple climate simulation exercises using the publicly available Model for the Assessment of Greenhouse-Gas Induced Climate

Change (MAGICC; v.4.1) coupled with a regional climate change scenario generator (SCENGEN). The MAGICC model used was identical to that utilized by the IPCC (2001) for its projections of global mean temperature and sea-level rise changes. Global temperature changes in 2025, 2050, and 2100 relative to unperturbed baseline controls were simulated using MAGICC tuned to seven different Atmosphere/Ocean General Circulation Models (GCMs): CSIRO, CSM, HADCM2, HADCM3, ECHM4, GFDL, PCM. Default (mid-range) estimates were used for carbon cycle modeling, aerosol forcing, and ice melt parameters as well as variable thermohaline circulation and carbon cycle feedbacks. The output from different climate models was used to capture the range of uncertainty associated with climate sensitivity in addition to fundamental differences in model representation of the climate system. The range for climate sensitivity reported by the IPCC (2001) was 1.5–4.5 °C ($\sim$90% confidence interval), and the seven GCMs emulated by MAGICC cover the majority (1.7–4.2 °C) of this range, although other analyses have yielded significantly wider ranges for climate sensitivity (Forest et al., 2002; Murphy et al., 2004; Stainforth et al., 2005). To capture uncertainty associated with future global GHG emissions, simulations for each GCM were conducted using six of the Special Report on Emissions Scenarios (SRES) scenarios (A1B-AIM, A1T-MESSAGE, A1Fi-MiniCAM, A2-MESSAGE, B1-MESSAGE, and B2-MESSAGE) of the IPCC (2000). Previous analysis has indicated that CO_2 emissions in the IPCC SRES scenarios span much of the range of uncertainty in future global emissions, although the SRES scenarios tend to over-represent the low-end of this uncertainty range (Webster et al., 2002). Modeling the seven GCMs with the six emissions scenarios resulted in a total of 42 MAGICC simulations of global mean temperature change for each time period. Global mean temperature change in 2100 for these 42 simulations ranged from 1.5–5.4 °C, compared to the IPCC's corrected range of 1.4–5.6 °C (IPCC, 2001; Wigley and Raper, 2002). The disparity between the simulated 2100 global mean temperature range in the current study and that of the IPCC is a function of the current analysis' use of only six of the SRES scenarios and the use of default mid-range estimates for carbon cycle and aerosol forcing parameters to limit the number of model simulations.

Global mean temperature changes were scaled to the United States (25° to 50°N by 65° to 125°W) for each of the above GCMs and emissions scenarios using the SCENGEN regional modeling tool (with exponential/power law scaling), which downscales global average temperature changes to 5° × 5° grid cells using the scaling technique of Santer et al. (1990). This technique involves normalizing spatial patterns of climate change from AOGCMs to global mean temperature change, which enables regional projections to be generated from relatively simple climate models simply by varying the strength of the signal for global temperature change. Temperature changes for individual grid cells were subsequently averaged to yield a model estimate of mean U.S. JJA temperature change.

Data output from SCENGEN was used to calculate continuous cumulative probability distributions for U.S. JJA temperature change in 2025, 2050, and 2100.

Various methods can be used to estimate probability distributions from ensemble model results. The current study utilized six different approaches to partially account for the lack of standardized methods and to assess the sensitivity of different assumptions about the relative likelihood of different model configurations and/or emissions scenarios. The first method (referred to hear as EQUAL) assumed all models performed similarly with respect to simulating future U.S. climate conditions (i.e., results from different models for a particular emissions scenario were treated as equally likely). Thus, the probability of a particular model result was calculated using the following equation:

$$P_{S\Delta T} = P_{Sk} \times P_{m\Delta T,k} \tag{1}$$

where $P_{S\Delta T}$ is the probability of a projected temperature change for a particular model and emissions scenario, P_{Sk} is the probability of the k emissions scenario, and $P_{m\Delta T,k}$ is the probability of an individual model result for the k emissions scenario. For the EQUAL distribution, $P_{m\Delta T,k}$ among different models was treated as equally likely, which, given the seven models used, equaled 0.14. Meanwhile, P_{Sk} could be weighted based upon the probability of various emissions scenarios used with the climate models. For the EQUAL distribution, the six emissions scenarios were not weighted, and thus each carried a probability of 0.17 (Table I).

The second method for estimating a probably distribution for future temperature change (referred to here as SENS), was identical to EQUAL (Equation (1)) except that the probability of model results for a particular climate model ($P_{m\Delta T,k}$) were weighted based upon the normal deviation of model effective climate sensitivities

TABLE I

Probabilities associated with different emissions scenarios in the estimation of probability distributions for future U.S. temperature change. Weighted probabilities were assigned assuming net radiative forcing from greenhouse gases corresponded to a normal probability distribution based upon the scenario ensemble mean and standard deviation. Probabilities associated with individual scenarios were then normalized so that the probabilities of the six scenarios summed to unity

		Weighted		
Scenario	Unweighted	2025[1]	2050	2100
A1B	0.17	0.23	0.23	0.23
A1Fi	0.17	0.18	0.06	0.07
A1T	0.17	0.13	0.21	0.18
A2	0.17	0.10	0.17	0.18
B1	0.17	0.13	0.20	0.13
B2	0.17	0.24	0.14	0.21
Total pobability	1.0	1.0	1.0	1.0

TABLE II

Probabilities associated with different climate models under the SENS and SENS/Scenario distributions, based upon weighting of effective climate sensitivities. Weighted probabilities were assigned assuming climate sensitivities among the seven models simulated in the current study corresponded to a normal probability distribution with the highest sensitivity corresponding with the upper 90% confidence limit. Probabilities associated with individual models were then normalized so that the probabilities of the seven models summed to unity

Model	Effective climate sensitivity	Unweighted	Weighted
CSIRO	3.7	0.142	0.12
CSM	1.9	0.142	0.12
ECHM4	2.6	0.142	0.21
GFDL	4.2	0.142	0.05
HADCM2	2.5	0.142	0.20
HADCM3	3.0	0.142	0.21
PCM	1.7	0.142	0.09
Total pobability		1.0	1.0

from the ensemble mean. Probabilities were assigned by assuming that effective climate sensitivities for the seven climate models (ranging from 1.7–4.2) conformed to a normal distribution with the highest effective sensitivity representing the upper 90% confidence limit (see Morgan and Keith, 1995). This distribution was then used to assign probabilities to the output of each climate model, and these probabilities were then normalized so that they summed to unity (Table II). This weighting scheme effectively biased the resulting probability distribution toward the mean, reducing the likelihood of temperature projections based upon models with effective climate sensitivities that deviated significantly from the ensemble mean of 2.9 °C.

The third method for estimating a probability distribution for future temperature change (referred to here as REA), weighted the probability of model results based upon performance criteria following the reliability ensemble analysis (REA) methodology of Giorgi and Mearns (2002, 2003). The REA method weights the results from an ensemble of GCMs based upon two criteria: 1) the reliability with which an individual model reproduces historical climate changes and 2) the extent to which the projections of an individual model converge on the ensemble mean. Each model was assigned a reliability indicator (R_i) based upon its performance with respect to these two criteria using the following formula (Giorgi and Mearns, 2002):

$$R_i = \left\{ \left[\frac{\varepsilon_T}{\mathrm{abs}(B_{T,i})} \right]^m \left[\frac{\varepsilon_T}{\mathrm{abs}(D_{T,i})} \right]^n \right\}^{[1/(m \times n)]} \tag{2}$$

where ε_T represents historical climate variability based upon the difference in the minimum and maximum value for average U.S. temperatures from 30-year running means of (linear) detrended average annual U.S. temperature anomalies (1880–2003; Hansen et al., 2001; Giorgi and Mearns, 2002); $B_{T,I}$ represents the average model bias in reproducing the historical (1961–1990) baseline mean temperature climatology for the study area (CRU; New et al., 1999). Root-mean square errors among the seven models for the coterminus United States ranged from 1.2–3.2. $D_{T,I}$ represents the distance between an individual model's projection and the ensemble mean, and m and n represent weighting coefficients for the two R_i criteria (here both were assigned equal weights of 1). As noted in Giorgi and Mearns (2002), calculation of R_i is an iterative procedure. Here, values for R_i converged after four iterations. Using this formula, reliability indicators were assigned to each of the 42 model simulations for each time period. Reliability indicators for each simulation were then used to estimate probabilities for projected temperature changes using the following formula (Giorgi and Mearns, 2003):

$$P_{S\Delta T} = P_{Sk}\left[\frac{R_{i,k}}{\sum R_{j,k}}\right] \tag{3}$$

where $P_{S\Delta T}$ represents the probability of a projected temperature change; P_{Sk} is the probability associated with a particular emissions scenario; $R_{i,k}$ represents the reliability indicator for a particular model given the k emissions scenario; and $\Sigma R_{j,k}$ represents the sum of R_i among all climate models for the k emissions scenario.

The fourth, fifth, and sixth methods for generating a probability distribution (referred to here as EQUAL/Scenario, SENS/Scenario, REA/Scenario) were identical to the first three methods, but with an additional weighting scheme applied to the emissions scenarios (P_{Sk}). Weights for emissions scenarios were calculated based upon the normal deviation of an individual scenario's net radiative forcing from GHGs and sulfate aerosols for a particular time period from mean radiative forcing among all six scenarios. Probabilities for P_{Sk} were assigned by assuming that radiative forcing for the six SRES scenarios for each time period conformed to a normal distribution based upon the mean and standard deviation for the six scenarios. This distribution was then used to assign probabilities to each emissions scenario, and these probabilities were then normalized so that they summed to unity (Table I). This weighting scheme effectively biased the resulting probability distribution toward the mean, reducing the likelihood of temperature projections based upon emissions scenarios that deviated significantly from the emissions scenario ensemble mean. This also resulted in some counterintuitive weights for individual emissions scenarios. For example, the A1Fi emissions scenario, which generally represents a high emissions scenario, has relatively low net radiative forcing over the near-term due to high sulfate aerosol emissions. In addition, the probabilities associated with individual scenarios changed across time periods, which was an artifact of dispensing of the underlying storyline context for individual scenarios and using them simply as a means of bounding the uncertainty in emissions. It should be noted that there are various arguments for and against assigning probabilities to emissions scenarios (Schneider, 2001; Jones, 2004; Risbey, 2004), and that applying probabilities to the SRES scenarios specifically violates the underlying assumptions utilized in scenario development (IPCC, 2000).

The probabilities associated with simulated temperature changes using the various weighting schemes identified above were subsequently summed and expressed as cumulative probabilities. Temperature changes and their associated cumulative probabilities were then used to estimate continuous cumulative probability distributions via linear interpolation among data points using Analytica^{TM} 2.0.

2.4. MITIGATION SCENARIOS

To assess the sensitivity of cold-water habitat to global GHG emissions reductions, a series of climate model simulations were also conducted using three of the WRE emissions stabilization scenarios (WRE350/550/750) as upper constraints on future emissions in the MAGICC/SCENGEN ensemble modeling. The WRE emissions scenarios constrain future GHG emissions in order to achieve a stable atmospheric CO_2 concentration (Wigley et al., 1996), thus limiting, as a consequence, future radiative forcing and temperature change. However, some of the IPCC illustrative scenarios have lower emissions trajectories and radiative forcing over the 21st century than some of the WRE stabilization scenarios. Failure to account for this fact results in the counterintuitive result that in some ensemble simulations, minimum warming in response to mitigation is higher than minimum warming in a no mitigation case. Thus, modeling of GHG mitigation cases in MAGICC/SCENGEN was performed for 2025, 2050, and 2100 using each of the three WRE scenarios as well as other SRES scenarios that generated equal or less net radiative forcing for each time period as indicated by MAGICC output. As before, probability distributions for stabilization cases were calculated using different assumptions regarding the weighting of model outputs (here EQUAL-350/550/750 and SENS-350/550/750). However, due to the assumption of policy action in order to achieve a stabilization goal, all of the emissions scenarios were only considered with equal weights. Continuous cumulative probability distributions were estimated for the stabilization distributions in the same manner as above. Due to insufficient sample size for REA distributions under the WRE350 constraint, REA weighting was not utilized in the analysis of climate change in response to mitigation.

2.5. RISK ANALYSIS

Estimates of the probabilistic uncertainty associated with 2025, 2050, and 2100 habitat loss were generated by comparing habitat damage functions with the various probability distributions for future JJA temperature change. For each time period and probability distribution for JJA temperature change, a series of 1,000 Monte Carlo simulations was conducted using Analytica™ 2.0. Samples of future U.S. temperatures were taken from the different probability distributions and used as input in the damage functions for National (aggregate and species-specific) or Rocky Mountain habitat loss, while simultaneously sampling among probability distributions for damage function regression coefficients. This analysis resulted in continuous probability distributions for future cold-water habitat loss accounting for uncertainty in climate and habitat response.

3. Results

3.1. NATIONAL AND ROCKY MOUNTAIN DAMAGE FUNCTIONS

Although different climate models project different localized patterns of warming, linear damage functions based upon diverse climate models were well-constrained with high r^2 values and narrow confidence intervals (Table III). As such, average U.S. temperature changes were a useful indicator of the aggregate effects of U.S. climate change on cold-water habitat at smaller spatial scales. Damage functions indicated an incipient (≥5%) national temperature threshold for loss of cold-water habitat of 0.6 °C, with habitat decreasing by 8.3% for every 1 °C increase in average U.S. JJA temperature (Table III, Figure 1). The Rocky Mountain region was more sensitive to the effects of climate change than the nation as a whole. The incipient

TABLE III

Damage function statistics for cold-water habitat based upon least-squares linear regression. Aggregate damage functions among multiple species were calculated for the U.S. as a whole as well as the Rocky Mountain region. Species-specific damage functions are based upon national assessments. Thresholds were defined as the temperature change associated with a ≥5% reduction in current habitat.

Cold-water habitat	Habitat loss/°C (99.9% confidence limits)	r^2	p	Threshold (°C)
National	8.3 (6.9–9.7)	0.95	<0.0001	0.6
Rocky Mountains	13.8 (11.6–16.1)	0.98	<0.0001	0.4
Brook trout	8.8 (7.2–10.4)	0.94	<0.0001	0.6
Cutthroat trout	7.9 (6.5-9.2)	0.95	<0.0001	0.6
Rainbow trout	7.8 (6.3–9.2)	0.94	<0.0001	0.6
Brown trout	8.2 (6.7–9.6)	0.95	<0.0001	0.6
Chum salmon	8.2 (6.6–9.7)	0.94	<0.0001	0.6
Pink salmon	9.5 (7.7–11.2)	0.94	<0.0001	0.5
Coho salmon	8.6 (7.0–10.1)	0.95	<0.0001	0.6
Chinook salmon	7.9 (6.3–9.4)	0.94	<0.0001	0.6

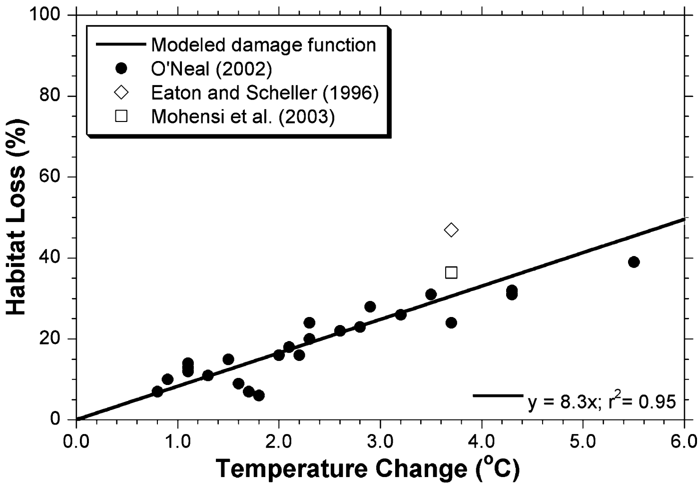

Figure 1. Response of U.S. of cold-water habitat to June/July/August temperature change. Individual data points are based upon published responses of cold-water habitat to various climate change scenarios. The modeled damage function was calculated by least-squares linear regression (Table III).

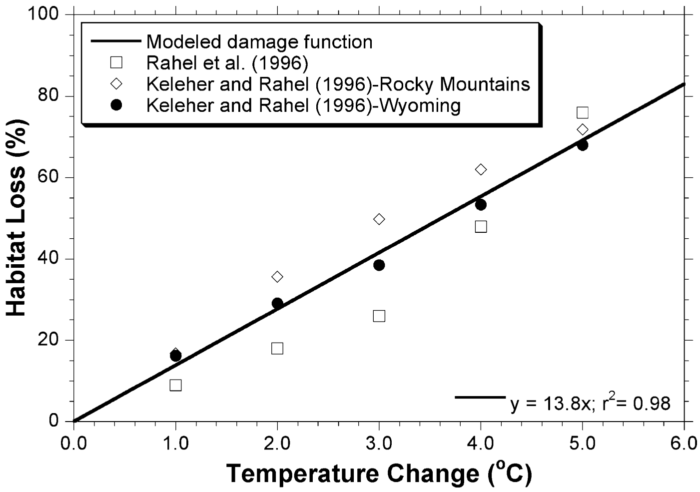

Figure 2. Response of Rocky Mountain region cold-water habitat to June/July/August temperature. Individual data points are based upon published responses of cold-water habitat to various climate change scenarios. The modeled damage function was calculated by least-squares linear regression (Table III).

threshold for loss of cold-water habitat in the Rocky Mountains was 0.4 °C, with habitat decreasing by 13.8% for every 1 °C increase in average U.S. JJA temperature (Table III, Figure 2).

Species-specific damage functions indicated nearly identical incipient national temperature thresholds for habitat loss among species. Incipient thresholds ranged

TABLE IV

Probability distributions for future June/July/August temperature change in the United States using different weighting techniques. The EQUAL and EQUAL/Scenario distributions apply equal weighting to model results. The SENS and SENS/Scenario distributions are weighted based upon model effective climate sensitivities (Table II). The REA and REA/Scenario distributions are weighted based upon model performance (Giorgi and Mearns, 2002, 2003). The EQUAL/Scenario, SENS/Scenario and REA/Scenario distributions also have weights applied to the emissions scenarios (Table I).

	Projected ΔT		
Distribution	2025 Median (95% confidence limits)	2050 Median (95% confidence limits)	2100 Median (95% confidence limits)
EQUAL	1.5 (0.9–2.1)	2.6 (1.6–4.0)	3.6 (1.4–7.8)
EQUAL/Scenario	1.4 (0.9–2.1)	2.6 (1.6–3.9)	3.6 (1.4–7.4)
SENS	1.5 (0.9–2.1)	2.6 (1.6–4.1)	3.7 (1.4–8.0)
SENS/Scenario	1.5 (0.9–2.1)	2.6 (1.6–3.9)	3.6 (1.5–7.5)
REA	1.4 (1.4–1.6)	2.6 (2.4–3.2)	3.5 (2.2–5.9)
REA/Scenario	1.5 (1.4–1.6)	2.5 (2.4–3.2)	3.5 (2.2–5.8)

from 0.5 to 0.6 °C, with median habitat decreases of 7.8–9.5% for every 1 °C increase in average U.S. JJA temperature (Table III). Rainbow trout was the least sensitive species and Pink salmon was the most sensitive.

3.2. PROBABILITY DISTRIBUTIONS FOR FUTURE U.S. WARMING

The probability distributions for future warming in 2025, 2050, and 2100 reflect the temporal influence on climate change uncertainty (Table IV). The distributions for 2025 were relatively well constrained, with the 95% confidence interval spanning approximately 1 °C for the EQUAL and SENS distributions and 0.2 °C or less for the REA distribution. However, by 2100, disparities among different emissions scenarios and model climate sensitivities contributed to a much greater degree of uncertainty, with the range associated with 95% confidence limits increasing to approximately 6.0 °C for the EQUAL and SENS distributions and 4.0 °C for the REA distribution. One important artifact of the use of the SRES scenarios to represent the uncertainty in future emissions, is the counterintuitive result that the lower 95% confidence limit for U.S. temperature change is higher in 2050 than in 2100.

The application of different weights to model results had a varying influence on the resulting probability distributions for future U.S. JJA temperature change (Table IV). The SENS distribution was nearly identical to the EQUAL distribution, across all time periods. However, the REA distribution was consistently narrower than either the EQUAL or SENS distributions as indicated by higher lower 95% confidence limits and lower upper 95% confidence limits. Ranges for median warming projected among different probability distributions in 2025, 2050, and 2100 were 1.4–1.5 °C, 2.5–2.6 °C, and 3.5–3.7 °C, respectively, indicating a high degree of similarity in median warming among different weighting approaches. The weighting of emissions scenarios had negligible influence on resulting probability distributions, as the EQUAL/Scenario, SENS/Scenario, and REA/Scenario distributions were nearly identical to those of EQUAL, SENS, and REA, respectively. The exceptions being the EQUAL/Scenario and SENS/Scenario distributions in 2100, for which projected temperature changes at the upper 95% confidence limits were reduced by approximately 0.5 °C compared to the EQUAL and SENS distributions.

Probability distributions for the WRE scenarios indicated that mitigation efforts would have modest benefits with respect to reducing future temperature change over the 50–100 year time frame, but no direct benefits over the next 25 years (Table V). Probability distributions for the 2025 EQUAL-350/550/750 and SENS-350/550/750 distributions were less than 0.3 °C cooler at the 2.5, 50, and 97.5th percentiles than their corresponding distributions in the absence of mitigation. Median warming in 2050 for the stabilization distributions was also only moderately reduced under the WRE constraints, with median and 97.5th percentile warming dropping by up to 0.6 °C and 1.2 °C, respectively, for the WRE350 constraint. By 2100, however, even under the WRE750 constraint, median and 97.5th percentile warming was reduced by approximately 0.4 °C and 2.6 °C, respectively. Median

TABLE V

Sensitivity of probability distributions for future June/July/August temperature change in the United States to different mitigation scenarios. The EQUAL and SENS distributions are identical to those in Table IV. The EQUAL-350/550/750 and SENS-350/550/750 distributions represent projected temperature change under CO_2 mitigation cases, where future radiative forcing was capped based upon radiative forcing associated with the WRE350/550/750 emissions pathways. The REA distribution is not included due to insufficient sample size under some of the mitigation scenarios. No weighting was applied to emissions scenarios.

	Projected ΔT		
Distribution	2025 Median (95% confidence limits)	2050 Median (95% confidence limits)	2100 Median (95% confidence limits)
EQUAL	1.5 (0.9–2.1)	2.6 (1.6–4.0)	3.6 (1.4–7.8)
EQUAL-750	1.5 (0.9–2.0)	2.4 (1.0–3.6)	3.2 (1.3–5.4)
EQUAL-550	1.4 (0.9–2.0)	2.6 (1.4–3.5)	2.6 (1.3–4.6)
EQUAL-350	1.3 (0.8–1.8)	2.1 (1.0–2.9)	1.7 (0.9–2.5)
SENS	1.5 (0.9–2.1)	2.6 (1.6–4.1)	3.7 (1.4–8.0)
SENS-750	1.5 (0.9–2.0)	2.4 (1.1–3.7)	3.3 (1.4–5.4)
SENS-550	1.4 (0.9–2.0)	2.4 (1.4–3.5)	2.7(1.3–4.6)
SENS-350	1.3 (0.8–1.8)	2.0 (1.1–2.9)	1.8 (0.9–2.5)

warming under the WRE550 constraint was approximately 1 °C less than that associated with the no mitigation distributions (Table V), consistent with other studies (Dai et al., 2001), and 97.5th percentile warming was reduced by approximately 3.5 °C. For the WRE350 constraint, median temperature change was reduced by approximately 2 °C (50%), and the projected warming associated with the 97.5th percentile was approximately 5.5 °C lower than in the no mitigation distributions.

3.3. RISK ANALYSIS

Median impacts projected for current U.S. cold-water habitat were quite comparable among different probability distributions for U.S. JJA temperature change (Figure 3). Median effect levels for 2025 were approximately 12% across distributions. By 2050 and 2100, median impacts were projected of 21% and 29–31%, respectively. However, confidence intervals indicated that habitat loss well below and above median effect levels is possible. For example, 2100 habitat loss at the upper 95% confidence interval for the EQUAL and SENS distributions was approximately twice median effect levels. Despite the consistency in results for median effect levels, the probability of different magnitudes of habitat loss did vary among

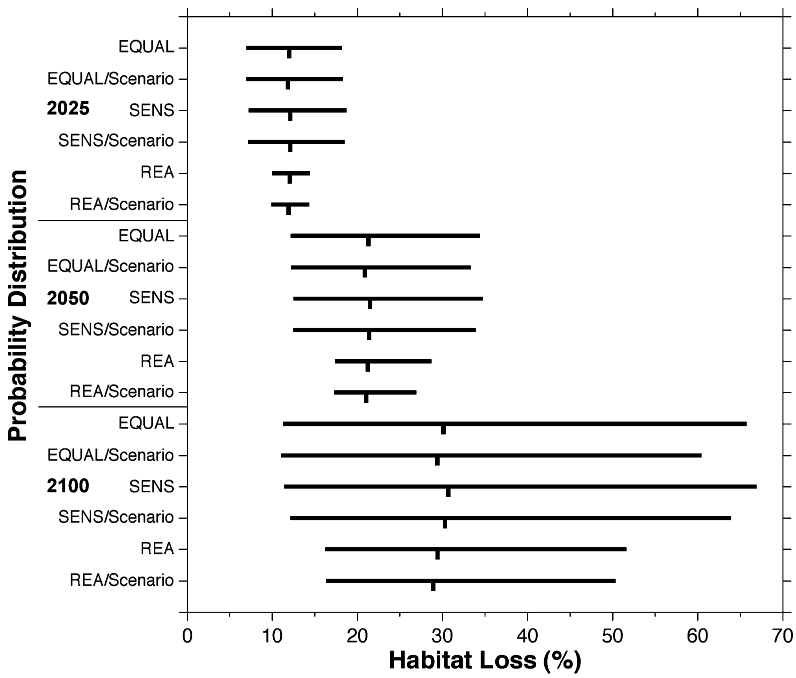

Figure 3. Median and 95% confidence limits for the effects of future climate change on current U.S. cold-water habitat in 2025, 2050, and 2100 for various probability distributions for June/July/August temperature change (Table 4).

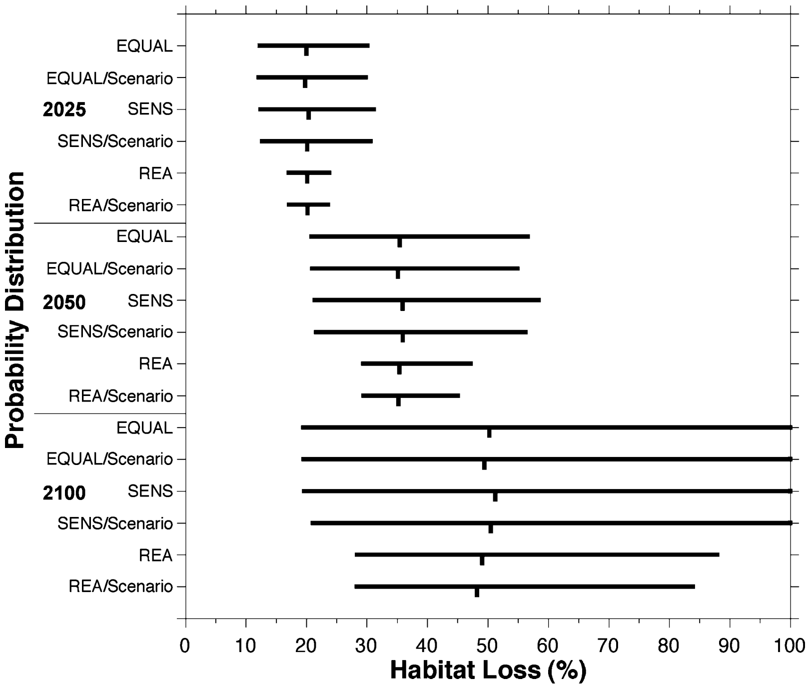

Figure 4. Median and 95% confidence limits for the effects of future climate change on current Rocky Mountain cold-water habitat in 2025, 2050, and 2100 for various probability distributions for June/July/August temperature change (Table IV).

different probability distributions for temperature change (Figure 3). The range of uncertainty associated with projected habitat loss was consistently greater for the EQUAL, EQUAL/Scenario, SENS, and SENS/Scenario distributions relative to the REA and REA/Scenario distributions, as were the upper 95% confidence intervals for habitat loss.

The magnitude of impacts to Rocky Mountain cold-water habitat projected in response to U.S. climate change were considerably larger than those projected for the nation as a whole, although this may have been due to methodological differences rather than greater inherent sensitivity of the Rocky Mountain habitat to temperature change. Median effect levels for 2025 were 20–21% across temperature distributions (Figure 4). By 2050 and 2100, median effect levels increased to 32–36% and 48–51%, respectively. Again, however, the probability of different magnitudes of habitat loss varied among different probability distributions for temperature change (Figure 4). The EQUAL, EQUAL/Scenario, SENS, and SENS/Scenario distributions indicated that habitat loss as high as 55–60% is possible by 2050, whereas 97.5th percentile losses for REA and REA/Scenario were 44–48%. By 2100, all distributions indicated the potential for considerable habitat loss of 85–100% in the Rocky Mountain region.

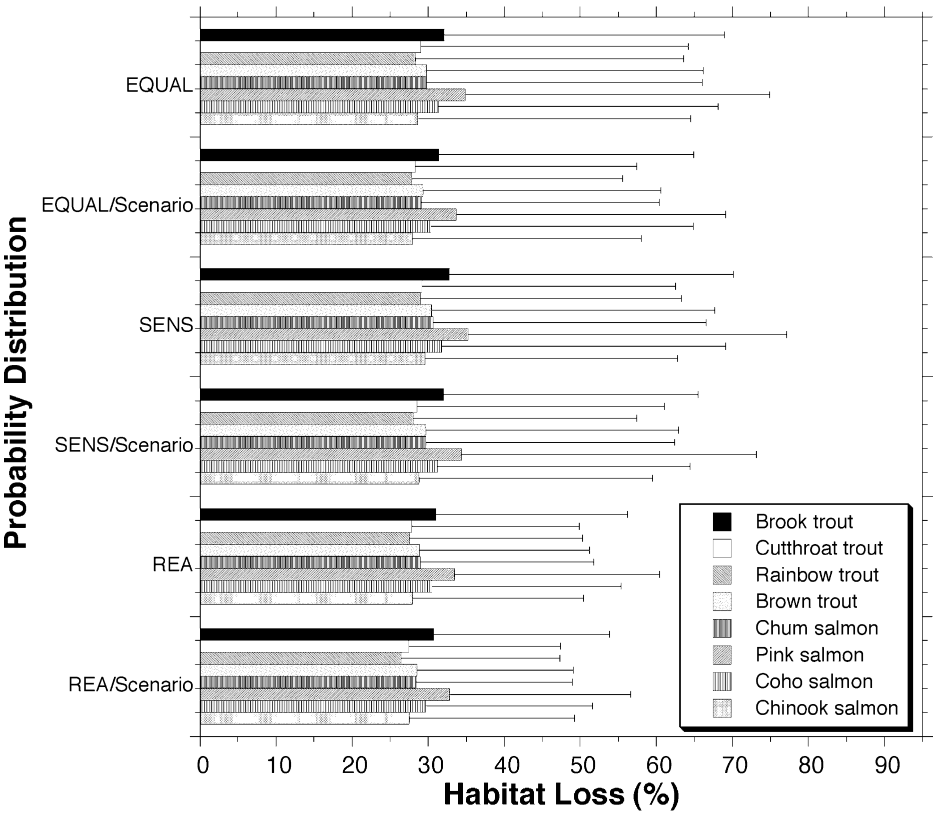

Figure 5. Effects of future climate change on species-specific cold-water habitat in 2100 for various probability distributions for June/July/August temperature change (Table IV). Horizontal columns represent median effects and error bars represent upper 95% confidence limits.

Results for the eight individual species for which damage functions were constructed indicated that the magnitudes of habitat loss for specific species were quite comparable to aggregate national risks. Median effect levels in 2025 ranged from 10–14% among species, and median effects for individual species in 2025 were identical regardless of the temperature distribution used to estimate risk. Median effect levels increased to 27–35% by 2100 (Figure 5), and median effects associated with the REA and REA/Scenario distributions for 2100 were 1–2 percentage points lower than for the other distributions. However, as with the national aggregate results, higher magnitudes of habitat loss were possible at lower probabilities (Figure 5). Pink salmon demonstrated the largest potential for habitat loss among the eight species evaluated, with Rainbow trout and Chinook salmon having the lowest potential, consistent with species-specific damage functions (Table III).

Due to the sensitivity of current-cold-water habitat to U.S. temperature change, the effects of mitigation scenarios over the 21st century on reducing the risk

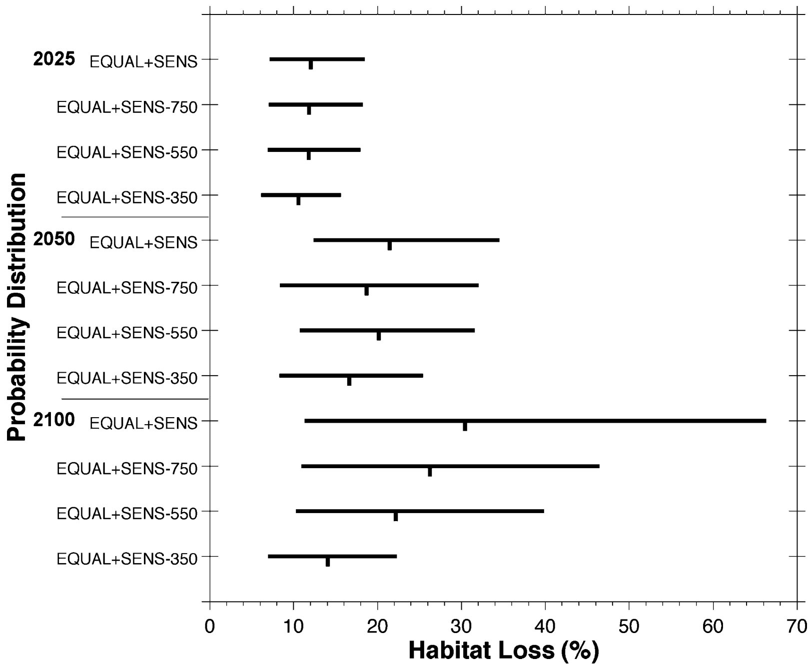

Figure 6. Median and 95% confidence limits for the effects of future climate change on current U.S. cold-water habitat in 2025, 2050, and 2100 under no mitigation and WRE mitigation scenarios using the EQUAL and SENS weighting schemes (Table V). Due to the similarities between EQUAL and SENS probability distributions for June/July/August temperature change, results are presented as the mean habitat loss for the two distributions.

associated with climate change were modest. Analysis of the sensitivity of cold-water habitat to mitigation scenarios indicated that the benefits of mitigation were highly time dependent. Out to 2025, the projected median habitat loss was reduced by only a few percentage points in response to the WRE scenarios, and the WRE350 scenario was equally as effective at reducing habitat loss as WRE750 (Figure 6). By 2050, however, the relative benefits under different mitigation scenarios became more apparent, with WRE350 reducing habitat loss by 30%, relative to 20% for WRE550/750. By 2100, WRE350/550/750 reduced habitat loss by 50%, 25%, and 15%, respectively. Reductions were even greater at the upper 95% confidence limit, with reductions in habitat loss of approximately 65%, 40%, and 30%, respectively. Comparable reductions in risk were obtained for the Rocky Mountain region and for specific species at the national level.

Perhaps more important than the impact distributions, however, was the probability of exceeding various magnitudes of effect. For example, the results of Monte Carlo simulations indicated that it is virtually certain that the incipient thresholds ($\geq$5%) for U.S. and Rocky Mountain cold-water habitat loss will be exceeded as early as 2025 (Table VI). In fact, results indicate that in the absence of mitigation,

TABLE VI

Probabilities (as a percent) of exceeding the incipient ($\geq$5%) as well as a series of other arbitrary thresholds for cold-water habitat loss assuming no mitigation or CO_2 mitigation cases, where future radiative forcing was capped based upon the radiative forcing associated with the WRE350/550/750 emissions pathways. Probabilities represent mean results for the EQUAL and SENS distributions. The REA distribution is not included due to insufficient sample size under some of the mitigation scenarios. No weighting was applied to emissions scenarios.

	Threshold habitat loss				
	5%	10%	25%	50%	75%
National					
No mitigation	100	100	69	12	1
750 ppmv	100	99	56	1	0
550 ppmv	100	98	40	0	0
350 ppmv	100	73	0	0	0
Rocky mountains					
No mitigation	100	100	93	52	20
750 ppmv	100	100	89	35	4
550 ppmv	100	100	83	16	0
350 ppmv	100	100	40	0	0

losses of 10% are certain at both the national and regional level. Probabilities of higher magnitudes of habitat loss generally increased as the threshold level increased. Losses of 25% were more likely than not at both the national and regional level. The likelihood of losses of 50% was relatively low ($\sim$10%) at the national level, while losses of 75% or more had a probability of 1% or less. In contrast, for the Rocky Mountain region, there was even chance of losses of 50% or more, and losses of 75% or more, though only approximately 20%, were certainly not negligible, particularly relative to the consequence.

Risk management in the form of different GHG stabilization pathways had a marked effect on the risk of exceeding various thresholds, although that effect was highly dependent on the stringency of the threshold under consideration. For example, even under a 350 ppmv stabilization case, the likelihood of remaining below the $\geq$5% incipient threshold was effectively zero at both the national and regional level. At more moderate thresholds, such as a 25% loss of habitat, mitigation was quite effective at the national level, effectively eliminating risk altogether for a 350 ppmv stabilization scenario. Although risk reduction of this magnitude was not observed for the Rocky Mountain region, a 350 ppmv stabilization scenario was sufficient to reduce the risk of exceeding a 25% threshold to less than 50%. The likelihood of exceeding higher thresholds such as 50–75% habitat loss, were moderate to low even in the absence of mitigation at both the national and regional level, and thus relatively modest stabilization scenarios (i.e., 550–750 ppmv) were sufficient to reduce the risk of exceeding these thresholds to low levels.

4. Discussion

A number of impact assessments of the effects of climate change on cold-water fish habitat in the United States have previously demonstrated that such habitat is potentially highly sensitive to climatic change, and thus future changes in climate pose a hazard to fish populations dependent upon such habitat, and, subsequently, U.S. biodiversity in general (Eaton and Scheller, 1996; Keleher and Rahel, 1996; Rahel et al., 1996; O'Neal, 2002; Poff et al., 2002; Mohseni et al., 2003). However, the risk associated with these hazards has remained undefined with respect to the likelihood that adverse effects would occur, the timing associated with those effects, and their magnitude. All of these are important quantifications if one is to develop an understanding of the consequences of climate change and, subsequently, design environmental management strategies that are robust with respect to risk. Acquiring this information, however, necessitates risk based-approaches to impact assessment that can incorporate uncertainty in relevant variables and yield probabilistic estimates of the effects of climatic change.

Here, multiple studies were used to construct damage functions for cold-water habitat in the United States and the Rocky Mountains. Such damage functions enable one to ask "what if" questions regarding the response of resources to hypothetical changes in climate. They are also useful for estimating threshold climate changes for adverse effects, also sometimes referred to as "critical levels" (Swart and Vellinga, 1994). For example, damage functions in the current study suggested threshold ($\geq$5%) effect levels for incipient U.S. and Rocky Mountain cold-water habitat occur for warming as low as 0.6 °C and 0.4 °C, respectively. This suggests that preventing adverse effects of climate change on current cold-water habitat loss would necessitate limiting future warming in the United States to levels comparable to those observed over the 20th century ($\sim$0.6 °C; NAST, 2000). This is an unlikely proposition, even with aggressive efforts to reduce GHG emissions (Wigley, 2005).

A number of authors have previously expressed uncertainty in future changes in climate, including precipitation as well as temperature, on global and regional bases, using probability distributions (Wigley and Raper, 2001; Giorgi and Mearns, 2003; Webster et al., 2003; Mastrandrea and Schneider, 2004). The principle drivers of uncertainty in these efforts have been climate sensitivity and future GHG emissions, although a range of other uncertainties including carbon cycle and aerosol effects also exist and may have a significant influence as well (Wigley and Raper, 2001). Estimates for 95% confidence intervals for future global temperature change range from approximately 1.0–4.9 °C (Webster et al., 2003) to 1.5–5.3 (Wigley and Raper, 2001), with median warming ranging from 2.4–3.1 °C. The current study utilized an ensemble of climate models to generate probabilistic estimates of future climate change in the United States, which is projected to experience higher mean warming than the global average (Wigley, 1999). The extent to which the probability distributions in the current study represent the full range of uncertainty in future temperature change is limited to the ability of the climate models in the ensemble to span the full range of climate sensitivity and GHG emissions. The range of climate sensitivities of the seven climate models used in the current study represents approximately 90% confidence intervals for climate sensitivity, based upon IPCC's estimated range (Morgan and Keith, 1995; IPCC, 2001). More recent studies have suggested this may be an underestimate of the actual uncertainty (Forest et al., 2002; Murphy et al., 2004; Stainforth et al., 2005). Similarly Webster et al. (2002) previously reported that the SRES scenarios represent most, but not all, of the actual uncertainty in future emissions. As a result, the extremes of both climate sensitivity and GHG emissions are likely underrepresented in the current probability distributions, although median temperature changes are relatively robust and agree well with other analyses.

Probabilities were assigned to ensemble model results using either raw, unweighted model results or model results weighted based upon model effective climate sensitivities or using the REA methodology, whereby model probability is a function of how well a particular model reproduces historical climate conditions and converges upon an ensemble average for future climate. Using the REA method, Giorgi and Mearns (2003) generated a probability distribution for 2100 JJA temperature change for the western and central United States ranging from approximately 2.5–8.5 °C, with a median of just under 5.0 °C. This is generally consistent (albeit with a higher median) with the EQUAL distribution (1.4–7.8 °C) generated in the current study, but Giorgi and Mearns (2003) utilized a larger number of climate models and only two emissions scenarios (SRES, A2 and B2), making the results difficult to compare. In any case, model ensembles may be a convenient method to estimate probability distributions for future climate conditions, given the availability of simple climate models and climate model data.

In the current study, the implications of different approaches for generating probability distributions for JJA U.S. temperature change varied depending upon the time period under consideration. Out to at least 2025, the range of uncertainty associated with future temperature change was relatively small. This suggests that temperature change, and downstream impacts, over short time-scales can be known to a relatively small degree of uncertainty. Beyond 2025, the uncertainty in temperature change expanded considerably, indicating the difficulty in drawing conclusions about climate change impacts far in advance. Estimated uncertainty was consistently much reduced using the REA weighting methodology, as indicated by the narrower 95% confidence interval for JJA temperature change. Both the upper and lower tails of the REA and REA/Scenario distributions were constrained, resulting in reduced warming at the upper 95% confidence limits as well as increased warming at the lower 95% confidence limits relative to the EQUAL and EQUAL/Scenario distributions.

Due to the narrower confidence intervals, REA may be a useful tool for reducing uncertainty in the analysis of model ensembles by filtering improbable results from models with high margins of error. These constrained confidence intervals are a function of REA's strong bias in favor of model results that demonstrate low error relative to historical observations and/or are consistent with other models. This latter criterion tends to result in a strong bias in favor of median model results. Further, because there is no way to validate the success with which the model reliability criteria used in the REA approach reflect the relative ability of models to faithfully project future climate conditions, the REA methodology may simply be masking rather than reducing uncertainty, which would be a detriment rather than a benefit to impact assessment and risk management. Weighting of models based upon effective climate sensitivities had negligible effects, despite a close correlation (>0.8) between projected temperature change and climate sensitivity among the seven climate models. The effects of weighting emissions scenarios had a limited effect on future JJA temperatures, although the upper 95% confidence interval 2100 JJA temperature change in the EQUAL/Scenario and SENS/Scenario distributions were approximately 0.5 °C lower than in the EQUAL and SENS distributions, primarily due to a bias against the A1Fi scenario (Table I). Overall, the use of different weighting schemes indicates that the risk assessment was generally robust to a range of a priori assumptions about the relative likelihood of different model parameterizations.

The integration of habitat damage functions with probability distributions for future climate change in the current study indicated that the probability that declines in the current distribution of cold-water habitat, and the species they contain, is virtually certain as early as 2025. Furthermore, the magnitude of current cold-water habitat that is likely to be lost from its current geographic range over the next century is substantial. Median effect levels for 2025, 2050, and 2100 suggest habitat loss in the United States on the order of 10, 20, and 30%, respectively. Even greater effects are projected for the Rocky Mountain region, with median effect levels of approximately 20, 30, and 50%, respectively.

The analysis of risk in response to GHG mitigation efforts in the form of constraining future emissions below the WRE stabilization pathways over the 21st century indicated that such an effort would have little influence on ameliorating the risk of cold-water habitat loss, particularly over the short-term. Out to at least 2050, the risks associated with the mitigation pathways were comparable to no mitigation cases, reflecting the fact that future global temperature changes are relatively insensitive to mitigation efforts over the next several decades (Stott and Kettleborough, 2002). By 2050, substantive reductions in median effects levels were only observed under the WRE350 constraint. By 2100, median national risks were reduced by 20, 30, and 60% in response to the WRE350/550/750 constraints, respectively. However, median habitat loss remained above 10% even under the WRE350 constraint.

The challenge for risk management, however, is the interpretation of impacts and risk away from the median. For example, the current study indicates that the incipient effect threshold of $\geq 5\%$ loss of habitat is virtually certain in the near future with or without mitigation efforts. This is a function of the warming, and thus impacts, to which the global climate system is already committed. Even assuming no future change in atmospheric composition, the projected warming over the 21st century is comparable to the temperature threshold for incipient habitat loss (Wigley, 2005). However, it is arguable whether such incipient effects are ecologically or economically relevant, or even detectable in natural systems. Thus, stakeholders may be much more interested in thresholds of greater relevance to management goals. For example, habitat losses of 25% are sufficient to have detectable ecological or economic consequences, and in a no mitigation future, such losses have a high probability of occurrence. Yet, risk analysis using stabilization scenarios suggests that mitigation can significantly reduce the risk of such losses (Table VI). Perhaps of greatest importance from a management perspective is the ability of mitigation to effectively eliminate the low, but non-negligible risk associated with truly high magnitudes of habitat loss (i.e., $>50\%$). Even a stabilization level of 750 ppmv, which is well above recent estimates of dangerous climate change or GHG levels (O'Neill and Oppenheimer, 2002; Hansen, 2005), is an effective hedge against such high magnitudes of habitat loss. Reaching consensus, however, on what levels of impact are to be avoided, the associated risk that stakeholders are willing to accept, and the willingness to pay to manage climate change and natural resources to address residual risk, is a fundamental challenge in the climate change debate. Nevertheless, the examination of the effects of different risk management strategies is an important, but often neglected, consideration in impact assessment (Arnell et al., 2002; Swart et al., 2002). Few attempts have been made to quantitatively assess the potential for mitigation to reduce the likelihood of exceeding a particular impact threshold, and no studies have assessed the role of adaptation in this regard (Jones, 2004).

The disparity in results between the Rocky Mountain region and the United States may reflect the influence of geographic scale, but may also simply be an artifact of differences in the methods of those studies used to generate damage functions. National estimates of resource sensitivity or risk to climate change provide a first-order approximation of the potential effects of climate change, but such analyses may not be representative of effects at smaller spatial scales, where the consequences as well as the implementation of management strategies are more critical. The current results suggest that the high-elevation, cold-water habitat of the Rocky Mountain region will be disproportionately affected by climate change. Yet this is not a robust conclusion because the damage functions for the Rocky Mountain region were based upon studies utilizing a linear stream temperature model whereas the majority of data points for the aggregate U.S. damage function were based upon a non-linear model. Mohseni et al. (1998) found that non-linear models are a better fit to the air/stream temperature relationship, and that linear models tend to overestimate stream temperature changes, particularly for higher air temperatures. As a consequence, the results from the Rocky Mountain region are not directly comparable to those of the United States as a whole.

An interesting question raised by the use of probability distributions for U.S. temperature change in the current study is the extent to which they increase the information associated with impact assessment beyond what can be obtained using scenarios alone. For example, median effects by 2025, 2050, and 2100 of 12–13, 21, and 29–30%, respectively, corresponded quite closely with average habitat loss in 2030, 2060, and 2090 reported by O'Neal (2002) of 10, 19, and 28%, respectively. This suggests that ensemble averaging may be an effective methodology for estimating likely effects associated with different magnitudes of temperature change. Scenarios, however, are not necessarily capable of estimating the probability of a particular magnitude of effect, such as that which might be identified as of concern to stakeholders. Similarly, scenarios cannot identify the risk associated with "low probability/high consequence" or "low probability/no consequence" events important to risk management decisions. For example, Eaton and Scheller (1996) projected cold-water habitat loss of approximately 50% in response to an equilibrium doubling of atmospheric CO_2. The current study enables one to place these estimates in context, and indicates that losses of this magnitude (or even greater) are indeed possible over the 21st century, but at relatively low probabilities ($\sim$10% chance regardless of the weighting scheme used). Nevertheless, given a range of scenarios generated by diverse climate models driven by diverse emissions scenarios, scenarios can likely generate credible estimates of at least the central tendency of climate change effects.

A critical limitation of existing studies on climate change effects on fish habitat is their tendency to express climate change effects relative to current habitat, as opposed to quantifying net habitat changes. Particularly for cold-water habitat, current methods identify areas where species ranges contract, but are less thorough in identifying potential areas of species' range expansion. Invariably, changes in climate conditions will decrease the suitability of some areas, but others should become more suitable. In addition, given the availability of thermal-tolerant genotypes, long-term physiological adaptation of fish populations may ameliorate the net effects of climate change (Etterson and Shaw, 2001; Stillman, 2003). Mohseni et al. (2003) also examined changes in warm-water habitat in the United States, and projected average increases of 31.4% relative to current habitat, comparable to habitat loss for cold-water species. Such results demonstrate the variability of species responses to climate change and the existence of ecological winners and losers. However, although warmer temperatures may offer a competitive advantage to some species with higher thermal tolerances, the loss of available cold-water habitat is indicative of reduced aquatic biodiversity in the future.

In addition, a number of authors have commented that other anthropogenic alterations of the environment, such as land-use change, development, and damning of streams and rivers, limit dispersion options for existing populations, making migratory adaptation to climate change more difficult, while simultaneously introducing other stressors to aquatic ecosystems (IPCC, 2002; Poff et al., 2002). Impact assessments limited to the future effects of climate change are not necessarily suitable for projecting the future status of ecological resources, as a broad range of drivers may interact to directly and indirectly affect species populations. Although analyses such as the current one indicate that temperature changes are likely to be a major driver of fish habitat changes at large geographic scales, at the more local level, other drivers such as habitat fragmentation, changes in water use and management, and invasive species may be more dominant drivers or may interact additively or synergistically with climate change (Sala et al., 2000; Novacek and Cleland, 2001; Kolar and Lodge, 2002; Thomas et al., 2004). Also, future changes in precipitation patterns will likely affect the distribution and abundance of aquatic species, yet the majority of studies to date have focused exclusively on the quantification of temperature effects. As a consequence, it remains difficult to project the net effects of climate change on species distributions and biodiversity or the future status of those species.

Despite such limitations, the current study demonstrates the utility of using probabilistic metrics of climate change impacts, particular with respect to its ability to assign likelihood to consequence. Given wider recognition of the potential value of risk-based methods for impact assessment, more focused attempts to express the results of impact assessments as sensitivity or damage functions, and more focus on methods for expressing climate uncertainty in probabilistic terms, risk analysis may become a routine analysis tool. A number of authors have already commented on the value of methodologies for creating damage functions and identifying thresholds for climate change (Swart and Vellinga, 1994; Parry et al., 1996; Toth et al., 2000; Jones, 2001), although these have largely been in the context of defining the concept of "dangerous interference" within Article II of the United Nations' Framework Convention on Climate Change (UNFCCC, 1992). In addition, proposals for risk-based frameworks for impact assessment have emerged (Jones, 2001; Willows and Connell, 2003; Jones and Mearns, 2005). Such efforts represent important attempts to develop an approach to impact assessment that can not only identify potential hazards associated with climate change, but also aid in development of strategies for risk management. However, considerable work remains in the development of tools for probabilistic exposure analysis that can be utilized by ecologists and resource managers. In the absence of probabilistic information on the consequences of climate change, attempts to quantify the consequences of climate change can be ambiguous. Such ambiguity can lead to erroneous conclusions regarding risk and consequence, and ultimately paralyze decision-making due to the absence of a context in which different management options can be weighed.

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