Climate change impacts and greenhouse gas mitigation effects on U.S. water quality*

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GLOBAL CHANGE

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Climate change impacts and greenhouse gas mitigation effects on U.S. water quality

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Key Points:
- Linked system models are critical to assess impacts of climate change on water quality
- Mitigation reduces water temperatures and increases DO levels considerably
- Economic impacts on water quality of mitigating climate change are considerable

Supporting Information:
- Supporting Information S1
- Supporting Information S2

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Abstract Climate change will have potentially significant effects on freshwater quality due to increases in river and lake temperatures, changes in the magnitude and seasonality of river runoff, and more frequent and severe extreme events. These physical impacts will in turn have economic consequences through effects on riparian development, river and reservoir recreation, water treatment, harmful aquatic blooms, and a range of other sectors. In this paper, we analyze the physical and economic effects of changes in freshwater quality across the contiguous U.S. in futures with and without global-scale greenhouse gas mitigation. Using a water allocation and quality model of 2119 river basins, we estimate the impacts of various projected emissions outcomes on several key water quality indicators, and monetize these impacts with a water quality index approach. Under mitigation, we find that water temperatures decrease considerably and that dissolved oxygen levels rise in response. We find that the annual economic impacts on water quality of a high emissions scenario rise from $1.4 billion in 2050 to $4 billion in 2100, leading to present value mitigation benefits, discounted at 3%, of approximately $17.5 billion over the 2015–2100 period.

1. Introduction

Climate change is likely to have far-reaching impacts on water quality in the United States due to projected increases in air and water temperatures, more intense precipitation and runoff, and intensified extreme events [*Georgakakos et al.*, 2014]. Water temperature has been increasing in many rivers [*Kaushal et al.*, 2010] and lakes [*Schneider and Hook*, 2010], and the length of time that lakes and reservoirs are thermally stratified has also increased [*Sahoo et al.*, 2012; *Sahoo and Schladow*, 2008]. Reduced mixing, elevated water temperatures, and biotic consumption of dissolved oxygen may lead to deteriorated water quality in lakes and ponds across the United States [*Sahoo et al.*, 2011]. Overall, the United States (U.S.) is likely to experience widespread water quality declines in lakes and rivers due to climate change and development, with changes in water quality parameters and micropollutant concentrations expected to negatively affect drinking water treatment and distribution systems [*Romero-Lankao and Smith*, 2014].

These physical impacts on water quality will also have potentially substantial economic impacts, since water quality is valued for a number of recreational and commercial activities including river and lake visits, boating, swimming, and fishing, among others. For example, *Van Houtven et al*. [2014] use a contingent valuation study to estimate that households in Virginia would combined pay $184 million per year (in 2010 dollars) to improve lake water quality through policy changes, while *Boyle et al*. [1998] found that a 1 m change in water clarity at three lakes in Maine led to total property value changes in surrounding communities of $16 to $22 million. Many studies have estimated the value of water quality changes at recreational sites, for example, *Bouwes and Schneider* [1979] estimated a potential loss of $85,700 per year in recreational benefits at Pike Lake in Wisconsin due to deteriorations in water quality.

Since unmitigated climate change is projected to have negative impacts on water quality in the U.S., consequently leading to negative economic effects, greenhouse gas (GHG) mitigation may avoid or reduce these adverse impacts. In this research, we present a methodology for analyzing the physical and economic effects of climate change on freshwater quality in the contiguous U.S. (CONUS). We use a coupled water system and water quality model of 2119 river basins to evaluate the effects of global-scale GHG mitigation

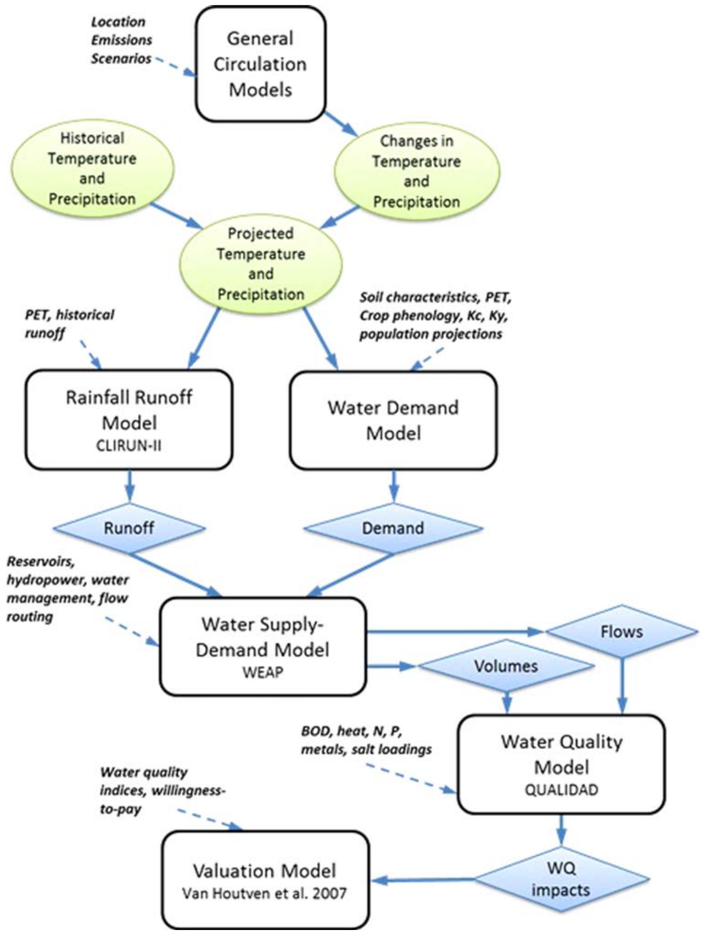

Figure 1. Model Framework.

under a range of GHG emission stabilization scenarios. To our knowledge, such a U.S.-wide nested modeling framework has never previously been developed at this level of detail to evaluate water quality impacts and mitigation benefits. The results provide a first approximation of the physical and economic benefits of global GHG mitigation to changes in U.S. water quality. This analysis is part of the Climate Change Impacts and Risk Analysis (CIRA) project [see *Waldhoff et al.*, 2014], an ongoing effort to quantify and monetize the multisector risks of inaction on climate change and the benefits of global GHG mitigation.

2. Methodological Approach

We use a series of linked models to evaluate the impacts of climate change on water quality in futures with and without global-scale GHG mitigation (Figure 1). Projections from General Circulation Models (GCMs) are at the beginning of the modeling chain. GCM projections of precipitation and temperature are inputs into: (a) a rainfall-runoff model (CLIRUN-II), which is used to simulate monthly runoff in each of the 2119 CONUS basins; and (b) a water demand model (WEAP), which projects the water requirements of the municipal and industrial (M&I) and agriculture sectors. With these runoff and demand projections, a water resources systems model produces a time series of reservoir storage, release, and allocation to the various demands in the system, which include M&I, agriculture, environmental flows, transboundary flows, hydropower, and others. We rely on the QUALIDAD water quality model [*Chapra*, 2014], which uses these managed flows and reservoir states to simulate a number of water quality constituents in rivers and reservoirs. Finally, concentrations of these water quality constituents are passed through a valuation model to estimate the total costs and/or benefits under each climate change stabilization scenario, which are subsequently compared to evaluate the economic benefits of global GHG mitigation.

2.1. Emission Scenarios and Climate Projections

Climate projections and future time periods (henceforth referred to as eras) allow us to estimate the benefits of GHG mitigation and how those benefits evolve in time. First, we develop a control scenario that represents present-day climate conditions but includes population projections. We then alter the control scenario input data by changes in future climate, and measure the resulting changes in output across the various scenarios. Detailed descriptions of the global GHG mitigation scenarios used in this analysis, along with a comparison to the representative concentration pathways (RCPs) and global climate projections, are provided in *Paltsev et al.* [2013] and *Waldhoff et al.* [2014]. In short, three emission scenarios are used: a reference (REF) or "business as usual," and two scenarios representing futures with policies that limit global

GHG emissions such that total radiative forcing levels in 2100 are stabilized at 4.5 W/m^2 (Policy 4.5) or 3.7 W/m^2 (Policy 3.7). The REF scenario has a total radiative forcing of 10.0 W/m^2 in 2100. Using the IPCC simplified equations, the REF has a total radiative forcing of 8.8 W/m^2, and is therefore similar to representative concentration pathway (RCP) 8.5. The base framework used to project future climate, the Community Atmospheric Model linked with the MIT Integrated Global Systems Model (IGSM-CAM), is presented in *Monier et al*. [2013, 2014], which also provide a summary of the simulations and details on the regional projections of climate change used in this study. The climate projections for each of the three GHG mitigation scenarios are split into two eras: 2050 and 2100. Each era is represented by daily climate variability (sourced from *Sheffield et al*. [2006]) with changes in climate applied. For precipitation, we use a simple ratio method where the change in precipitation is expressed as the future monthly mean precipitation divided by the historical monthly mean precipitation. For temperature, we use a simple "delta" method, where changes in temperature are expressed as differences between the mean monthly modeled historical temperature and projected future temperature. The primary climate projections in this analysis assume a climate sensitivity of 3°C; to evaluate the effect of higher climate sensitivity levels, two projections assume a sensitivity of 6°C.

2.2. Runoff Model

The climate projections for each emission scenario were used to develop monthly runoff estimates. Runoff modeling converts the climate changes into changes in surface water availability important for the water resource model. Surface water runoff was modeled with the rainfall-runoff model CLIRUN-II [see *Strzepek et al*., 2011, 2013], the latest available application in a family of hydrologic models developed specifically for the analysis of the impact of climate change on runoff, first proposed by *Kaczmarek* [1993]. CLIRUN-II models runoff with a lumped watershed defined by climate inputs and soil characteristics averaged over the entire watershed, simulating runoff at a gauged location at the mouth of the catchment on a monthly time step.

CLIRUN-II has adopted a two-layer approach following the framework of the SIXPAR hydrologic model [*Gupta and Sorooshian*, 1983, 1985]. A unique conditional calibration procedure was used to determine the coefficient values that characterize each of the 2119 catchments. This procedure optimizes via a pattern search algorithm developed by MATLAB minimizing the sum of square errors of the simulated and observed runoff. As no naturalized runoff data set for the eight-digit HUCs of CONUS is currently available, the observed runoff data used to calibrate CLIRUN-II were based on naturalized runoff data for 99 basins of CONUS from *U.S. Water Resources Council* [1978]. To calibrate each eight-digit HUC, the runoff within each of these 99 basins was allocated to the underlying eight-digit HUCs based on mean annual 1971–1980 precipitation that was spatially averaged from the 1/12° × 1/12° PRISM data set [*PRISM Climate Group*, 2014].

Although we have confidence in the calibration runoff data set at the resolution of the 99 basins, downscaling these data to the 2119 eight-digit HUC introduces uncertainties. An alternative to using a calibrated rainfall-runoff model would have been to rely on a routing model such as the Variable Infiltration Capacity (VIC) or Soil Water Assessment Tool (SWAT) that are capable of simulating runoff without calibration. The aggregated runoff outputs from these models could be validated and then "tuned" using the 99 basin outflows, but no assurances exist that the runoff at the eight-digit resolution will fit naturalized observations. Efforts at the U.S. Geological Survey (USGS) are currently underway to develop an improved naturalized runoff data set for the U.S. [e.g., *Farmer and Vogel*, 2012], although a CONUS-wide data set is far from complete.

2.2.1. Water Demands

Water demands are the other side of the water system, and are developed using 2005 data from USGS on annual water withdrawals and consumptive use in a range of sectors including irrigation, municipal, and industrial (M&I) use, mining, thermal cooling, and several other sectors [*Kenny et al*., 2009]. These data are available at the 3109 counties of CONUS, which were spatially averaged to the eight-digit HUC resolution using the same approach taken by the U.S. Forest Service in their development of the Water Supply Stress Index (WaSSI) [*U.S. Forest Service*, 2014]. For all sectors but irrigation, we assumed that withdrawals were constant each day of the year, such that monthly withdrawals are apportioned from yearly values based on the number of days in each month.

Base monthly 2005 irrigation withdrawals were developed by allocating the total annual withdrawals (from USGS) according to the total irrigation water requirements (IWRs) of the irrigated crop mix in each HUC. IWRs were based on the meteorological data set described above [*Sheffield et al*., 2006], irrigated crop area estimates from the 2008 Farm and Ranch Irrigation Survey [*U.S. Department of Agriculture*, 2010], and estimates of irrigation water depth requirements for each crop using methods developed by the U.N. Food and Agriculture Organization (FAO) [*Allen et al*., 1998]. The FAO method requires estimates of potential evapotranspiration (PET), which were calculated using the Modified Hargreaves approach [*Droogers and Allen*, 2002]. This procedure generated a base time series of 29 years (1980–2008) of irrigation water requirements that vary on a monthly basis, with the 2005 annual totals summing to USGS data for each eight-digit HUC. Water requirements for each of the future eras and under each emission and climate scenario were driven by the FAO method, which vary based on both PET and precipitation under each scenario. As a result, total CONUS irrigation withdrawals in each era-scenario combination vary from 2005 levels.

2.3. Water Resources Planning Model

We then simulate reservoir management and routing using a water resources systems model, where the simulated runoff—used as surface water supply—and projected water demands are used to optimize water allocation based on a prescribed set of priorities. This model is an adaptation of the Water Evaluation and Planning (WEAP) model [*Sieber and Purkey*, 2007], a well-established river basin system modeling software. This version was rewritten in the MATLAB language for computation speed and automation, but remains consistent with the WEAP model methodologically, all described in detail in the WEAP documentation.

The WEAP model simulates the sequence of existing and planned reservoir activity and demand nodes along the system. Three demand types, or nodes, are modeled throughout the system, which are in competition for water dependent on the sequence (upstream/downstream). The node types are municipal and industrial (M&I) water use, hydropower generation, and irrigation withdrawal. The hydrologic boundaries used to define the basins are the 2119 eight-digit HUCs of CONUS. The structure of each basin is generic, prescribed with input characteristics that are unique to each HUC. Reservoir data, such as locations, hydropower capabilities, and the information needed to calculate surface area and volume are all retrieved from the Army Corps of Engineers [*U.S. Army Corps of Engineers*, 2013]. Hydropower production is calculated and calibrated to the National Renewable Energy Laboratory (NREL) Regional Energy Deployment System (ReEDS) model [*Short et al*., 2011]. For each of the basins, the priorities of the various water users are assumed to be in the following order: (1) minimum flows driven by environmental and transboundary concerns, (2) M&I water demands (including mining and thermal cooling), (3) irrigation demands, and (4) hydropower production.

2.4. Water Quality Model Description

Using the managed flows from the water planning model and climate parameters, we use the QUALIDAD model [*Chapra*, 2014] to track several water quality constituents for each eight-digit HUC, including temperature, dissolved oxygen (DO), three nitrogen species, two phosphorus species, a generic metal, and salt. All variables in this model have a daily time step except temperature, which is hourly. To track water quality constituents within the CONUS framework, each eight-digit HUC is divided into a number of segments based on the Enhanced River Reach File (ERF1) from USGS [*U.S. Geological Survey*, 1999], which is the U.S. Environmental Protection Agency's (EPA) digital record of over 60,000 river reaches in the U.S., intended for national water-quality modeling. For each river segment, the data set contains corresponding parameters such as flow, velocity, segment length, and the sequence of segments. Based on these parameters, the main river channel is found within each eight-digit HUC, and then separated into segments at the points where rivers join. The river segments are on average 16 km long, and each HUC contains approximately 30 river segments, though only six or seven river segments form the main river that spans each HUC, the rest are side branches feeding into the main segment. We assume that each riverbed is parabolic, following *Leopold and Maddock* [1953], which helps to derive a relationship of flow with surface area and velocity. Each constituent is modeled separately in each segment, and upstream to downstream mass transfer is governed using numerical methods documented by *Chapra* [2007] and *Chapra and Canale* [2006].

QUALIDAD is a parsimonious water quality model that is designed to model daily water quality dynamics at the basin scale. The state variables governing the DO, nitrogen, and phosphorus dynamics within the model are shown in Table 1. A general mass balance for a constituent in an element is written as

$$\frac{dc_i}{dt} = \pm(\text{transport}) + \frac{W_i}{V_i} + S_i$$

where c_i = concentration of element i (mg/L or μg/L), t = time (days), W_i = the external loading of the constituent to element i (g/d or mg/d), V_i = element volume (m^3), and S_i = sources and sinks of the constituent

Table 1. Model State Variables

Variable	Symbol	Units[a]
Particulate organic carbon[b]	c_p	mg C/L
Dissolved organic carbon	c_d	mg C/L
Organic nitrogen[b]	n_o	μg N/L
Ammonia nitrogen	n_a	μg N/L
Nitrate nitrogen	n_n	μg N/L
Organic phosphorus[b]	p_o	μg P/L
Inorganic phosphorus	p_i	μg P/L
Phytoplankton	a	μg A/L
Dissolved oxygen	o	mg O_2/L

[a]mg/L = g/m^3 and μg/L = mg/m^3; in addition, the terms C, N, P, and A refer to carbon, nitrogen, phosphorus, and chlorophyll *a*, respectively.
[b]Excludes phytoplankton.

due to reactions and mass transfer mechanisms (g/m^3/d or mg/m^3/d). The sources and sinks for the state variables are depicted in Figure 2. The mathematical representations of these processes are presented by *Chapra* [2014] and *Chapra et al*. [2014], and a set of explanatory graphics showing relationships between loadings in a representative basin and resulting constituent concentrations at the basin outlet are presented in supporting information Supplement 2 of this article.

The initial conditions for water temperature are approximated using the *Stefan and Preud'homme* [1993] method, defined by three regionally specific constants, α_s, β_s, and γ_s (henceforth referred to as the Stefan-Preud'homme constants), as well as the mean air temperature of the previous 7 days, ($\overline{T_a}$), as follows.

$$T_1 = \frac{\alpha}{1+e^{\gamma(\beta+\overline{T_a})}}$$

Temperature is tracked within QUALIDAD using a heat budget model approach [*Chapra*, 1997], that simulates the surface heat exchange of a body of water as well as water sources/sinks through inflows from upstream basins, outflows downstream, small tributaries, and groundwater. The equation in its simplest form is as follows

$$V\rho C_p \frac{dT}{dt} = A_s J + Q_{in}\rho C_p T_{in} - Q_{out}\rho C_p T$$

Where, V is volume, ρ is water density, C_p is specific heat, T is temperature, t is time, A_s is surface area of the water body, J is the total heat exchange through the air-water interface, Q_{in} and Q_{out} are the flows into and out of the system, respectively, and T_{in} is the temperature of Q_{in}. Q_{in} includes both upstream flow into the reach as well as additional runoff from surface and base flow. We assume that the runoff temperature is flowing into the reach at the temperature calculated using the Stefan-Preud'homme constants, same as the initial condition temperature. We model this differential equation using a predictor corrector approach

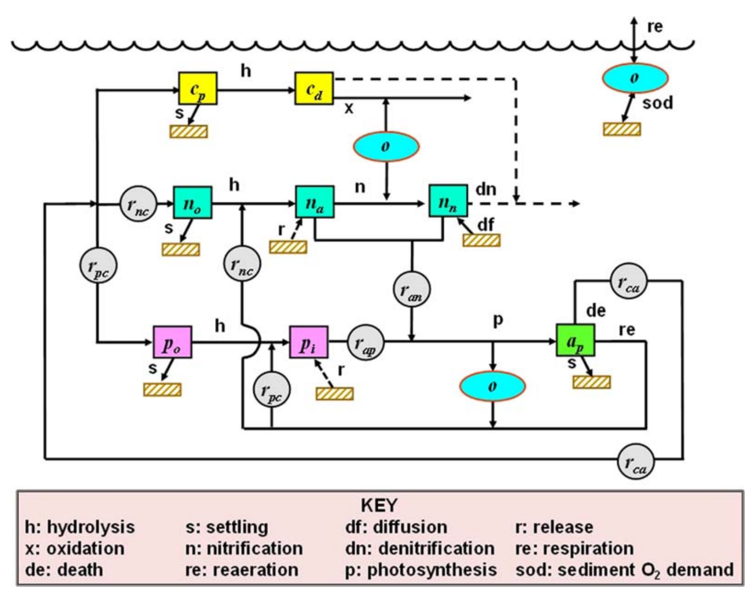

Figure 2. Model kinetics and mass transfer processes. The state variables are defined in Table 1; italicized *r* elements denote reactions between states.

outlined in *MacCormack* [1969], which has the advantage of stability and is not plagued by numerical dispersion.

In the summer, as temperature warms and solar radiation increases, stratification in temperate reservoirs occurs. Temperature during the season of stratification is modeled differently for reservoirs, where a two-layer model is used, representing both the epilimnion (top) and the hypolimnion (bottom) layers. For example, if the reservoir is bottom releasing (i.e., outflow is occurring in the hypolimnion), then the following is used to model the reservoir temperature [*Chapra*, 1997].

$$V_e \rho C_p \frac{dT_e}{dt} = A_s J + Q_{in} \rho C_p T_{in} + v_t A_t \rho C_p (T_h - T_e)$$

$$V_h \rho C_p \frac{dT_h}{dt} = -Q_{out} \rho C_p T_e + v_t A_t \rho C_p (T_e - T_h)$$

Where the subscripts e and h represent the epilimnion and hypolimnion, respectively, v_t is the thermocline heat transfer coefficient, and A_t is the thermocline area. v_t is estimated using the relationship developed by *Snodgrass* [1974].

2.4.1. Water Quality Input Data

Loadings enter the system as point and nonpoint sources. Agricultural nonpoint source loadings were developed using data available from the Spatially Referenced Regressions on Watershed Attributes (SPARROW) model [see *Schwarz et al*., 2006]. These included total annual nitrogen and phosphorus from fertilizer application, as well as biological oxygen demand (BOD) outputs from livestock. Monthly loadings were developed from these annual nonpoint source data based on crop evapotranspiration requirements in each eight-digit HUC. Municipal contributions for each constituent were assumed to be point sources and are based on per capita export coefficients [from *Chapra*, 1997]. These annual per capita loadings were scaled to kilograms based on U.S. population projections developed using the Integrated Climate and Land Use Scenarios (ICLUS) [*Bierwagen et al*., 2010] model. Internally consistent with the population projections of the GHG emission scenarios, ICLUS was applied to generate county-level population projections at 5 year time steps between 2000 and 2100, which were then spatially averaged to the eight-digit HUCs. These point source loadings rose proportionately to projected population through 2100. For illustration, Figure 3 displays average annual nitrogen and BOD loadings for 2005 at the HUC-4 level.

2.5. Valuation of Water Quality

Most studies that value water quality improvements use three main approaches: travel cost, hedonic pricing, and contingent valuation [*Birol et al*., 2006]. Travel cost methodologies place a value on freshwater quality changes by comparing observed consumption in similar markets (e.g., travel expenditures associated with trips to different freshwater bodies), while studies utilizing hedonic models have also demonstrated the value of water quality through investigations of how changes in water quality impact lake-front property values. Contingent valuation studies rely on surveys through which participants directly state their willingness-to-pay for water quality.

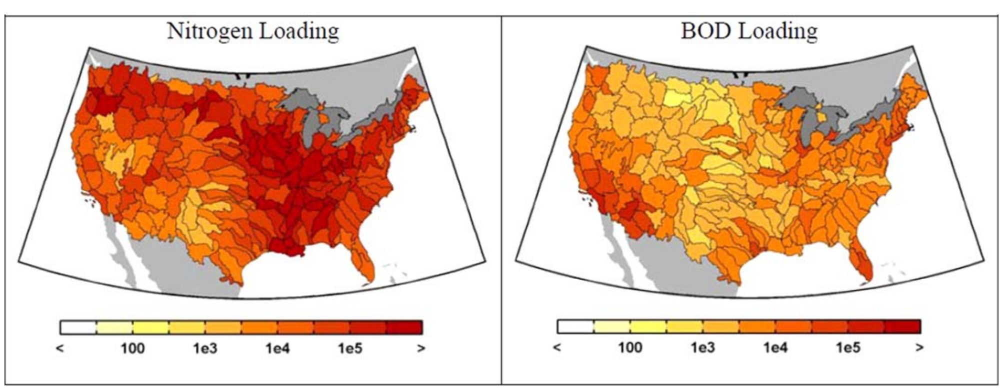

Figure 3. Average annual (left) nitrogen and (right) BOD loadings in kg/d in the baseline period.

Other efforts have used meta-analyses of multiple contingent valuation studies to create valuation models for water quality improvements. For example, *Van Houtven et al*. [2007] use 131 willingness-to-pay estimates from 18 studies to construct a meta-regression analysis, while *Johnston et al*. [2005] conduct a similar meta-analysis using 81 observations from 34 studies. More recently, *Ge et al*. [2013] use such a valuation model to estimate that a typical household in Iowa has a willingness-to-pay of $138 for a water quality increase from 40 to 50 (out of 100) at a 2.6 km^2 aquatic site. By linking these valuation models to water quality indices, the economic benefits (or costs) of changes in water quality can be estimated across a wide range of scenarios and locations.

In this study, the economic impacts of changes in water quality measures are estimated using a valuation of changes in the 10-point Water Quality Index (WQI_{10}).The WQI was first developed and applied by the National Sanitation Foundation (NSF) and explained in detail in *McClelland* [1974]. We develop WQI following a similar approach outlined by the *U.S. Environmental Protection Agency* [2009], which follows three steps: (1) obtain measurements on water quality constituents, obtained directly from the water quality model previously described, (2) convert each measurement into a subindex using water quality curves, and (3) aggregate the subindex values into the WQI. *McClelland* [1974] provides water quality curves (step 2) and aggregation weights (step 3) for nine water quality parameters. Four of these parameters coincide with output developed by the water quality model used in this study—namely, DO, Nitrates, Phosphates, and Temperature. Although quality curves can vary by location, we use the arithmetic mean for all basins. We also use the multiplicative form of the WQI aggregation, as suggested by *McClelland* [1974], redistributing the weights of these five parameters to equal 1.

In order to model the relationship between changes in WQI and changes in Willingness-to-Pay (WTP)—used here as an indicator of economic costs and/or benefits—we use the reported values from the full linear meta-regression transfer function from *Van Houtven et al*. [2007] to develop a piecewise linear function for both users and nonusers. We use state-level data from the *U.S. Census Bureau* [2014] on persons per household to convert WTP per household to WTP per person and use the population projections used to estimate municipal and industrial water demands to develop a national WTP across scenarios and eras. *Van Houtven et al*. [2007] also distinguish costs by users and nonusers. We use state-level boating survey data [U.S. Coast Guard, 2012] to weight each eight-digit HUC by fraction of users and nonusers. The constituent values in each segment are averaged, weighting by segment surface area. Consequently, we are assuming that each unit area is of equal importance.

3. Results

In the following section, we present the resulting constituent values for the control scenario as well as the changes from the control to the three GHG emission scenarios. Then, the valuation results are presented in terms of the differences between the REF and the Policy 3.7 and Policy 4.5 scenarios, which represent the benefits of global GHG mitigation. The results presented are based on the year between 1980 and 2009 with median level of mean annual runoff, selected for each hydrologically independent U.S. basin.

3.1. Baseline Water Quality

Figure 4 shows the baseline annual average of four constituents output by the water quality model: temperature, total nitrogen, total phosphorus, and DO. Water temperatures for the baseline range from about 3°C to 23°C, with warmer temperatures in the southern HUCs and colder temperatures in north and around the mountainous west. Total nitrogen and total phosphorus concentrations vary across the country governed mostly by a ratio of loading over streamflow, with higher concentrations in drier western U.S. DO levels are generally higher in the West, and lower DO around the midwest and the coastal southwest.

3.2. Effect of Mitigation on Water Quality

We next evaluate the effects of global GHG mitigation on water quality by comparing changes projected under the REF scenario to changes under the mitigation scenarios. Figure 5 shows the difference in temperature change between the REF and both the Policy 3.7 and Policy 4.5 scenario in 2100, where negative values indicate that the specified Policy results in lower river temperatures than the REF scenario. Changes in water body temperature under the Policy 3.7 scenario compared to the REF range from a reduction of approximately 2°C in the majority of the country, to more than 4°C in the inland west. In the Policy 4.5 case,

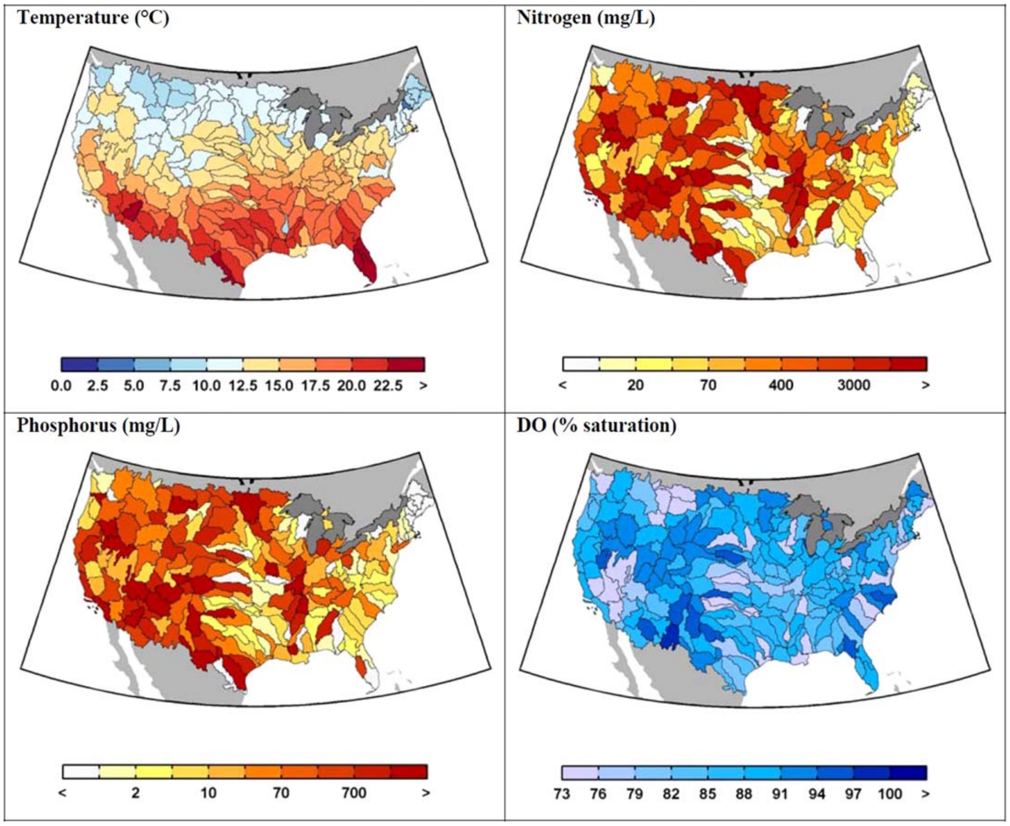

Figure 4. Four maps of constituents over the baseline period: (top left) temperature, (top right) total nitrates, (bottom left) phosphates, and (bottom right) dissolved oxygen.

changes in water body temperatures are lower in absolute value, especially in the inland west where we see the greatest benefit of the more stringent mitigation policy.

Similarly, Figure 6 shows the relative change, as a percent of the baseline, between the total 2100 nitrogen concentrations in REF and the two policy scenarios. Again, a negative value means that the specified policy reduces total nitrate concentrations. As shown, mitigation generally results in lower total nitrogen concentrations compared to REF, especially in the midwest and eastern regions of the U.S. We see a very similar pattern for changes in total phosphorus concentration. Figure 7 shows the same results for the effect of mitigation on DO concentrations, which show clear improvements under GHG mitigation, especially in the west, owing largely to the effect of lower temperatures on oxygen saturation levels.

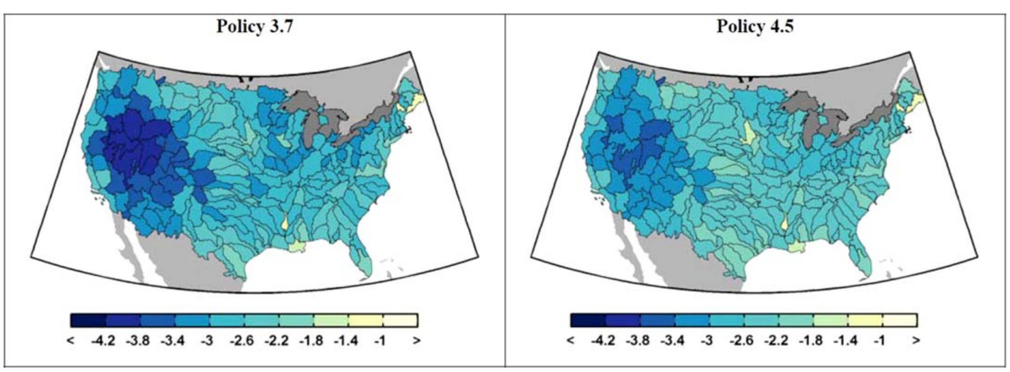

Figure 5. Change in temperature (°C), where REF temperature change is subtracted from the (left) Policy 3.7 and (right) Policy 4.5 temperature change in 2100 for the four seasons.

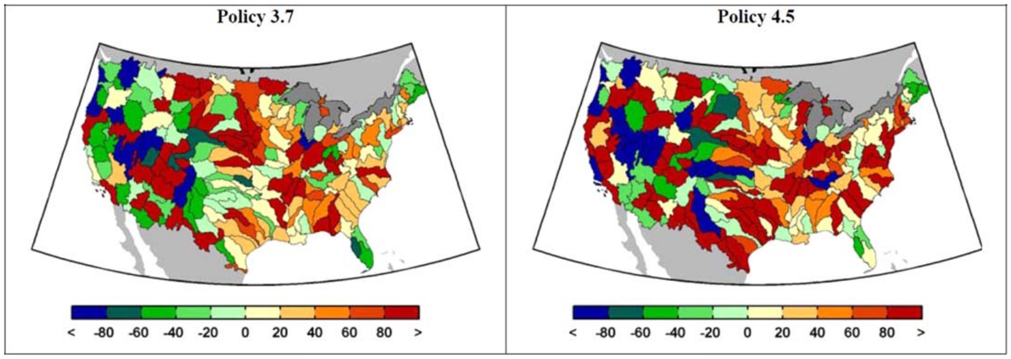

Figure 6. Percent change in Total Nitrogen from REF for (left) Policy 3.7 and (right) Policy 4.5 in 2100.

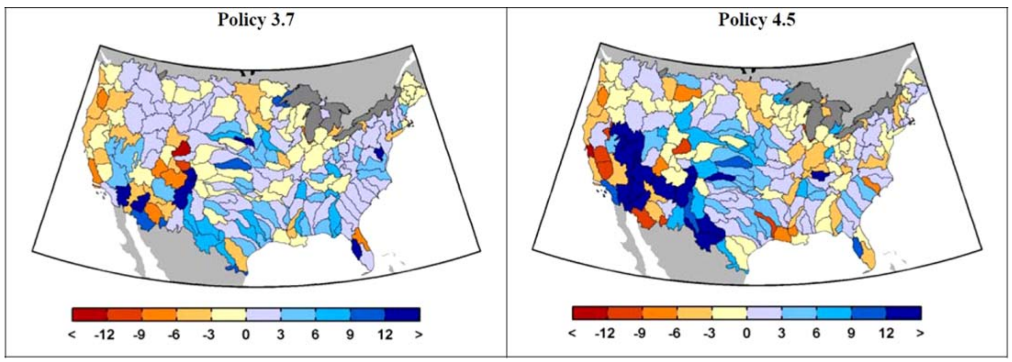

Figure 7. Percent change in Dissolved Oxygen from REF for (left) Policy 3.7 and (right) Policy 4.5 in 2100.

It is important to note that given the complex nature of this nested modeling system, interactions across space, time, and within and between modeling components can produces a sometimes-counterintuitive patchwork of basin and scenario-specific water quality and mitigation results, such as those observed in Figure 7. For example, mitigation generally produces lower air temperatures, and yet there are many basins in Figure 7 where mitigation causes DO to decrease. Similarly, the sign of the effect of mitigation on DO often differs between the Policy 3.7 and Policy 4.5 scenarios (e.g., in southern Florida, mid-Atlantic, Maine), although they are both mitigation scenarios from a common GCM. In these instances, the effects of mitigation on DO are driven by a combination of changes in air temperature, basin-specific changes in river flows, resulting adjustments in reservoir management, and changes in concentrations of BOD. Unlike the uniformly positive effect on air temperatures, the effect of climate change on precipitation and runoff patterns

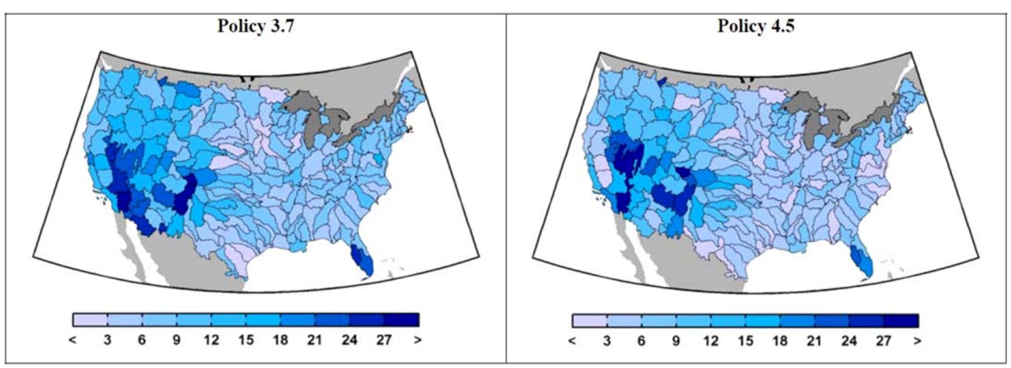

Figure 8. Percent change in WQI from REF for (left) Policy 3.7 and (right) Policy 4.5.

Table 2. National Average of the Annual Costs (i.e., Decreases in WTP) in 2050 and 2100 for Each Scenario

		Control	CS3-REF	CS3-pol3.7	CS3-pol4.5	CS6-REF	CS6-pol3.7
Mil 2005 USD	2050	$563	$1436	$841	$1202	$2060	$1276
	2100	$928	$4060	$1506	$1953	$5522	$2224
USD/Person	2050	$1.10	$2.80	$1.64	$2.34	$4.02	$2.49
	2100	$1.53	$6.67	$2.47	$3.21	$9.07	$3.65

is highly variable across both space and emissions scenario. Reduced river runoff will cause increased water temperatures, higher concentrations of BOD given constant upstream loadings, and warmer upstream reservoir temperatures. Thus, the positive effects of the lower air temperatures are often offset by the negative effects of increased BOD concentrations and lower river flows. Similar basin and scenario-specific patterns of change can be observed in the percent change in total nitrogen presented in Figure 6.

3.3. Valuation

In this section, we apply the valuation scheme presented previously to the output of each water quality constituent to obtain a WTP value in 2005 USD. Figure 8 shows the annual benefit of GHG mitigation for both policies as a percent change in the WQI. As the WQI was used to aggregate four water quality measures shown previously into a unitless index, this map shows the overall change in the WQI across the four-digit HUCs of CONUS. The reduced emissions under the Policy scenarios increases WQI from between 3% and 30% compared to REF. The larger changes in WQI are mostly in the west where drier and hotter conditions are projected, and the largest effects of the more stringent mitigation policy, Policy 3.7, are in the southwest.

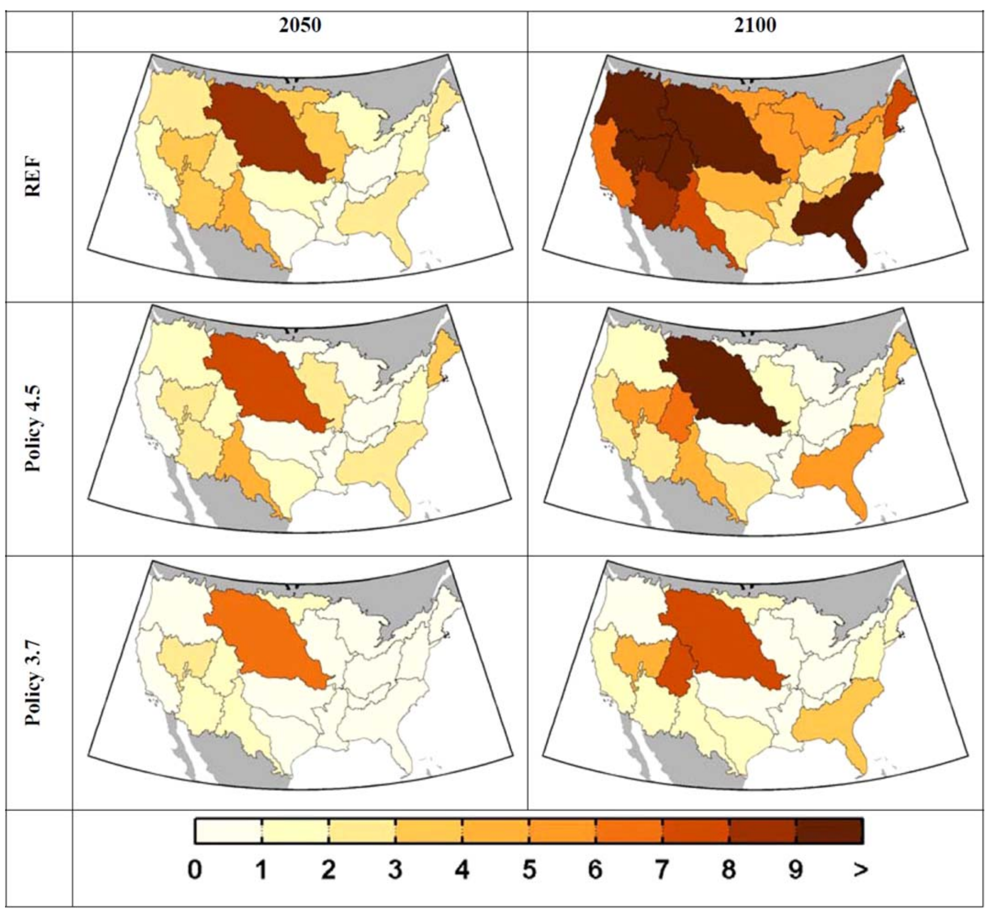

Figure 9. Costs (decreases in WTP) of each era and scenario in USD/person/year.

Table 2 shows the national average annual costs for the control scenario (future population with historical climate conditions), CS3 REF, Policy 3.7 and Policy 4.5, as well as CS6 REF and Policy 3.7 in both 2050 and 2100. Figure 9 shows maps of these values over the 18 two-digit HUCs. The difference between the GHG mitigation scenarios and the REF scenario is much higher in 2100, where WTP differences are about $2.5 billion for Policy 3.7 and about $2 billion for Policy 4.5, resulting in a total present value benefit of approximately $17.5 billion and $10.7 billion, respectively, using a 3% discount rate. As present value calculations require a time series of annual values, this calculation assumes a linear increase in GHG mitigation benefits from $0 in 2015 to the 2050 annual estimate between 2015 and 2050, and then another linear increase from the 2050 to 2100 value. In the map, we find that the larger costs in the REF are in the West, where hotter and drier conditions are projected, as compared to the East where increases in runoff often offset decreases in water quality. The southeast also shows large costs under the REF, which is partly driven by the larger percentage of the population involved in recreational boating.

4. Conclusions and Further Research

In this study, we have linked a network of models to assess the benefits of global-scale GHG mitigation on water quality in the contiguous U.S. The analysis runs changes in climate through a water resources systems model, which drives a water quality model that ultimately estimates changes in temperature and constituent concentrations of water bodies. Finally, valuation is used to aggregate four water quality constituents into a single metric, WQI, which is then used to estimate a benefit of GHG mitigation associated with WTP for recreational water use. To our knowledge, such a U.S.-wide nested modeling framework has never previously been developed at this level of detail to evaluate the full analytical chain of effects leading from climate change projections, to supply/demand effects, to water quality implications, to the economic benefits of GHG mitigation. Not surprisingly, we find that water temperatures increase substantially by 2100 in REF, but much less so under the Policy 4.5 and Policy 3.7. DO levels are mostly lower in the REF than Policy 3.7, although this varies across the country. The valuation results show that the overall benefit of GHG mitigation is substantial, at a present value of $17.5 billion for Policy 3.7, discounted at 3%.

Like all current studies on climate change impacts, we are limited by the resolution and confidence levels of simulated climate data from GCMs. In this regard, using projections from only one GCM, the IGSM-CAM does not address uncertainties caused by assumptions inherent in GCM model structure. Also, note that the IGSM-CAM model projects a relatively "wet" future, i.e., precipitation and runoff increases are large over CONUS as compared to other GCMs [see *Strzepek et al*., 2014]. Lower relative runoff in the future would lead to higher concentrations of contaminants (i.e., less dilution), and therefore more potential for mitigation benefit, suggesting that the results of this study are most likely conservative. It is also important to acknowledge the cascading errors that occur when employing nested models. The modeling framework employed in this study relies on a climate model, rainfall-runoff and water demand models, a water systems model, a water quality model, and a valuation model. To appropriately capture the uncertainty in such a framework would require a Monte-Carlo simulation or another technique that samples from assumed input probability distributions to develop a distribution of possible outputs.

Further research would evaluate a broader range of models and emissions scenarios to better capture the range of effects projected under climate change, providing a more appropriate risk portfolio for policy decisions. We are also limited by the accuracy of the WQI index used to aggregate the overall effect on water quality, including the WTP estimates. While WQI is widely used, the quality curves used to translate model output values into a common index are the same for all CONUS regions, whereas these relationships will likely vary across the country. Similarly, we use a constant relationship between WTP and changes WQI. Future research would disaggregate these relationships to include differences in public opinion on the importance of water purity as well as household income, both of which impact the resulting WTP estimates. These modeled WTP estimates could also be compared to observed site-specific values for water quality improvements.

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