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# Effects of Greenhouse Gas Mitigation on Drought Impacts in the United States

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## ABSTRACT

The authors present a method for analyzing the economic benefits to the United States resulting from changes in drought frequency and severity due to global greenhouse gas (GHG) mitigation. The method begins by constructing reduced-form models of the effect of drought on agriculture and reservoir recreation in the contiguous United States. These relationships are then applied to drought projections based on two climate stabilization scenarios and two twenty-first-century time periods. Drought indices are sector specific and include both the standardized precipitation index and the Palmer drought severity index. It is found that the modeled regional effects of drought on each sector are negative, almost always statistically significant, and often large in magnitude. These results confirm that drought has been an important driver of historical reductions in economic activity in these sectors. Comparing a reference climate scenario to two GHG mitigation scenarios in 2050 and 2100, the authors find that, for the agricultural sector, mitigation reduces both drought incidence and damages through its effects on temperature and precipitation, despite regional differences in the sign and magnitude of effects under certain model scenarios. The current annual damages of drought across all sectors have been estimated at \$6–\$8 billion (U.S. dollars), but this analysis shows that average annual benefits of GHG mitigation to the U.S. agricultural sector alone reach \$980 million by 2050 and upward of \$2.2 billion by 2100. Benefits to reservoir recreation depend on reservoir location and data availability. Economic benefits of GHG mitigation are highest in the southwestern United States, where drought frequency is projected to increase most dramatically in the absence of GHG mitigation policies.

## 1. Introduction

Droughts in the United States can have pronounced economic effects on a wide variety of water-dependent activities. Statewide costs to agriculture of the 2014 California drought have been estimated at \$2.2 billion

(U.S. dollars), with a loss of 17 000 seasonal and part-time jobs (Howitt et al. 2014). In the Colorado River basin, the longest drought in 100 years had left Lakes Mead and Powell at just over half their capacities as of 2007; and in the Klamath River basin on the Oregon–California border, a severe drought combined with environmental flow requirements caused a 96% reduction in total net agricultural revenues in 2001 (Boehlert and Jaeger 2010). The recent widespread drought in the Mississippi River system caused \$30 billion in impacts (NCDC 2013), including slowed barge traffic (Bjerga 2012) and crop and livestock losses that resulted in \$16 billion in crop insurance claims in 2012 (Washington

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*Post*, 22 March 2013). Although these recent regional events have gained broad attention, water shortages are a nationwide issue. Average annual damages of drought in the United States are \$6–\$8 billion, which is greater than the annual losses incurred from either flooding (\$5.9 billion) or hurricanes (\$5.1 billion; [NWS 2002](#)). In future years, water managers and policy makers will face increased drought planning challenges as demand for water rises and supplies fall ([Adams and Peck 2009](#)). Climate change could exacerbate these issues by altering the location, timing, frequency, and intensity of future droughts.

Based on a broad review of recent studies, the U.S. National Climate Assessment reports that, in most of the central and southern United States, droughts are projected to become more frequent under higher emissions scenarios ([Melillo et al. 2014](#)). Using hydrological model runs from downscaled general circulation models, [Cayan et al. \(2010\)](#) find that drought duration and severity, based on soil moisture depletion will increase in the southwestern United States. In a global study, [Burke et al. \(2006\)](#) project that, by 2100, droughts will affect 30% of worldwide land area, up from only 1% of land area at present. However, some research suggests, but does not conclusively show, that greenhouse gas (GHG) mitigation may offset some of these effects (e.g., [Strzepek et al. 2010](#)). [Strzepek et al. \(2010\)](#) characterize U.S. drought risk under a suite of 22 Intergovernmental Panel on Climate Change (IPCC) climate models and three Special Report on Emissions Scenarios (SRES) emissions scenarios. They find that drought frequencies are considerably lower under lower emissions scenarios.

In this paper, we present a method for analyzing economic benefits in the United States of changes in drought frequency and severity due to global GHG mitigation. Although many sectors of the U.S. economy are affected by drought, our analysis focuses on two large sectors that have sufficient data available to characterize these economic impacts: crop-based agriculture and reservoir recreation. The method follows several steps in order to estimate the future effects of drought on economic outcomes. We first estimate reduced-form relationships between fluctuations in historical drought frequency and severity and historical fluctuations in crop-based agricultural output and reservoir visitation.<sup>1</sup> We then project the effect of global GHG mitigation on drought frequency and severity in four future time

periods in the twenty-first century, based on the outputs of several climate scenarios. Last, we estimate the economic effect of GHG mitigation by coupling the statistical relationships between drought and economic outcomes in each sector with the effect of mitigation on drought frequency and severity.

## 2. Methods

We first describe the drought indicators used in our analysis, then provide the structure and statistical relationships from the reduced-form models, and finally describe how we use model results to predict the effects of climate change and GHG mitigation on the damages of drought in each economic sector included in the analysis.<sup>2</sup> The analysis of each of the two sectors considers two climate stabilization scenarios, along with a reference scenario, over four twenty-first-century time periods. For each sector, the chosen spatial unit and drought indicator vary depending on the sector's characteristics.

### a. Drought indicators

From the supply side, drought can be defined as persistent arid conditions that affect the hydrological cycle, for example by lowering streamflow, reducing reservoir levels, or depleting soil moisture ([Gonzalez and Valdes 2006](#); [Keyantash and Dracup 2002](#)). Drought can also be defined for specific sectors of the economy. Agricultural drought is defined as the difference between water supply and crop demand. For rainfed agriculture, a year of normal precipitation may actually result in water-stressed crops if the growing season is abnormally warm. On the other hand, irrigated crops facing a warmer/drier growing period may receive adequate supplies from a reservoir filled to capacity by an above-normal snowmelt from winter precipitation.

We focus on definitions of drought most relevant to the sectors analyzed in this study. For reservoir recreation, we rely on the standardized precipitation index (SPI), which is a statistically defined measure of drought based on precipitation alone.<sup>3</sup> For agriculture, we use

<sup>1</sup> Reduced-form models are simplified in that they identify relationships between variables directly, rather than building a model based on theories of the economy, as is the practice with a structural-form approach.

<sup>2</sup> Note that the drought index selection and processing methods presented here closely follows the approach of [Strzepek et al. \(2010\)](#) in their characterization of U.S. drought risk under a suite of 22 IPCC climate models. We also employ drought projections described by [Strzepek et al. \(2015\)](#).

<sup>3</sup> Note that while temperature can affect water available for recreation (i.e., by increasing reservoir evaporation and increasing downstream water demand), we do not estimate this effect directly in the drought projections. Also note that the second stage of the reservoir regression equation does incorporate temperature as an explanatory variable to account for the effect of temperature on reservoir visitation.

TABLE 1. Variables included in agriculture analysis. The dependent variable is percentage change in total crop output.

Variable name	Description	Variable type
$output_{it}$	Dependent variable; natural log of the value of 1960–2004 crop outputs in real terms, in year $t$ and state $i$	Continuous
$mildModDrought_{it}$	Indicator variable equal to 1 when state-level PDSI in the growing season in year $t$ is less than $-1$ and greater than $-3$	Binary
$sevExtDrought_{it}$	Indicator variable equal to 1 when state-level PDSI in the growing season in year $t$ is less than $-3$	Binary
$mxTemp_{it}$	Indicator variable equal to 1 when the state-level maximum monthly average temperature in the growing season in year $t$ is in the 15th percentile of the historical distribution	Binary
$state_i$	State-level fixed effect	Binary
$trend$	Time trend	Discrete
$\mathcal{E}_{it}$	Error term	—

the Palmer drought severity index (PDSI), which incorporates temperature effects and better reflects soil moisture conditions. We model the historical SPI and PDSI measures of drought frequency and severity, and these are then used as explanatory variables in reduced-form models of the agricultural and reservoir recreation sectors. For historical climate data, we use monthly temperature and precipitation from 1900 to 2009 across the contiguous 48 states at a spatial resolution of  $2.5 \text{ min} \times 2.5 \text{ min}$  (approximately  $4 \text{ km} \times 4 \text{ km}$ ; PRISM Climate Group 2012); these data are aggregated to the state and river basin levels for the agricultural and recreation analyses, respectively. The indices and their calculations are described below.

1) STANDARDIZED PRECIPITATION INDEX

The SPI is a probability index that measures the degree to which precipitation in a given time period and geographic area diverges from the historical median (McKee et al. 1993). An SPI of zero indicates rainfall is at the median value, where half of historical precipitation is above the value and half is below. A moderate drought’s SPI ranges from  $-0.75$  to  $-1.25$ ; a severe drought’s SPI ranges from  $-1.25$  to  $-1.55$ ; an extreme drought’s SPI ranges from  $-1.55$  to  $-2.0$ ; and an exceptional drought’s SPI is less than  $-2.0$  (Svoboda 2009).

To estimate the SPI value for a given year, we follow the statistical approach outlined by Edwards and McKee (1997). We first create a gamma probability density function (PDF) based on the time series of annual precipitation (all years) in the baseline dataset, and for each spatial unit of interest. The gamma density function has been shown to be an appropriate model for rainfall (Thom 1951, 1966). Next, for each PDF, we develop a cumulative density function (CDF) based on nonzero precipitation values in the dataset (the gamma function is undefined at zero) and then shift the starting point of the CDF to account for the fraction of zeros in the

dataset. Last, the CDF is transformed to a standard normal distribution with mean zero and variance of one, which is the value of the SPI. This is an equiprobability transformation: the probability of being less than a particular value of the transformed standard normal variate is the same as the probability of being less than the corresponding value of the gamma variate (Edwards and McKee 1997). The SPI value for precipitation in a particular year in the baseline or projected period is then the position of that precipitation value on the transformed standard normal distribution. As our goal is evaluating the effect of climate change on drought frequency and occurrence, the standard normal distribution for a given spatial unit is fixed based on historical data. Consequently, if the occurrence and/or severity of extremely dry years systematically increases or decreases under climate change, these changes will be observed in the resulting SPI values.

The reservoir recreation sector relies on water storage accumulated over many months, so we employ a 12-month SPI to estimate the occurrence and severity of annual droughts for this sector. To account for the lag between precipitation and reservoir water levels, annual precipitation for a given year is defined as the sum of monthly precipitation between October of the previous year and September of the year in question. For example, the annual precipitation for 1974 would be the sum of monthly precipitation between October 1973 and September 1974.

2) PALMER DROUGHT SEVERITY INDEX

PDSI is a drought indicator that uses data on soil characteristics, precipitation, and potential evapotranspiration (based in part on temperature) to determine the water balance of a region (Palmer 1965, 1968). PDSI is generally calculated on a monthly time scale but considers both current meteorological conditions and those of past months, accounting for the cumulative nature of

TABLE 2. Agriculture regression model output. The dependent variable is the percentage change in total crop output (over the 1960–2004 period).

Variable	Coefficient	
	Eastern	Western
Mild-to-moderate drought	−0.017*	−0.049**
Severe-to-extreme drought	−0.044**	−0.12**
Max temperature	−0.096**	−0.09**
Trend	0.013**	0.021**
Constant	−12.37**	−29.39**
States included in region	AL, AR, CT, DE, FL, GA, IA, IL, IN, KY, LA, MA, ME, MD, MI, MO, MN, MS, NC, NH, NJ, NY, OH, OK, PA, RI, SC, TN, VA, VT, WI, WV	AZ, CA, CO, ID, KS, MT, ND, NE, NM, NV, OR, SD, TX, UT, WA, WY
$R^2$	0.57	0.81
Number of observations	1440 (32 states × 45 yr)	720 (16 states × 45 yr)

\* Significant at the  $p < 0.1$  level.

\*\* Significant at the  $p < 0.01$  level.

drought (NOAA 2010). A PDSI value of 0 is considered normal,  $-1$  is a mild drought,  $-2$  is a moderate drought,  $-3$  is a severe drought, and  $-4$  is an extreme drought. Positive PDSI numbers, on the other hand, reflect wetness in excess of normal conditions. Because of its focus on soil moisture as a primary indicator of drought, PDSI is particularly appropriate for agricultural droughts.<sup>4</sup> For further discussion of PDSI, see Alley (1984) and Karl and Knight (1985). To estimate PDSI values for future years, we first transform general circulation model (GCM) outputs into monthly potential evapotranspiration data using the modified Hargreaves method (Droogers and Allen 2002) and then generate monthly PDSI values, following procedures outlined by Palmer (1965, 1968).

### b. Reduced-form models

Our reduced-form sectoral models describe the statistical relationship between drought occurrence and economic impacts within each sector and will be used to estimate the benefits or damages of drought under different climate scenarios. In the agriculture model, economic output from the crop sector is the dependent variable. In the reservoir recreation model, reservoir visitation is the dependent variable. Below, we describe the models' formulations, their data sources, and the empirical relationships they generate.

<sup>4</sup> Like SPI, PDSI does not consider runoff, snowmelt, or water storage and therefore may not account for water supplies effectively, particularly west of the Continental Divide. See Quiring and Papakryiakou (2003) and Vicente-Serrano et al. (2012) for comparisons between drought indices.

## 1) AGRICULTURE MODEL

The appropriate model for measuring climate change impacts on agriculture is subject to debate within the economics literature. A Ricardian (or hedonic) model was first used to assess the economic impacts of climate change on agriculture (Mendelsohn et al. 1994). This model takes advantage of cross-sectional variation in climate to estimate the impact of climate change on either agricultural revenue or land value under the assumption that spatial variation in land values reflects underlying differences in climate, holding all else constant.

The Ricardian model is attractive in theory, but difficulties arise empirically. To obtain econometrically consistent estimates of the impact of climate on land values, the Ricardian model must be correctly specified; that is, it must account for all variables—both observed and unobserved—that impact agricultural land values or revenues and are correlated with climate. Note that, according to the Frisch–Waugh theorem, uncorrelated variables can be excluded from the model without biasing the estimated climate coefficients. Various studies have shown that observable variables like soil quality, water supply, and socioeconomic characteristics are correlated with temperature and precipitation (Schlenker et al. 2005; Deschenes and Greenstone 2007). It is therefore plausible that unobserved variables also vary with climate, subjecting the hedonic model to omitted variable bias.

In an effort to circumvent the issue of omitted variable bias, some economists have opted to use panel data with fixed effects to measure the impact of climate change on agriculture (e.g., Deschenes and Greenstone 2007; Schlenker and Roberts 2009). In general, these models relate annual agricultural revenues or profits to changes in weather variables over time, including fixed effects at

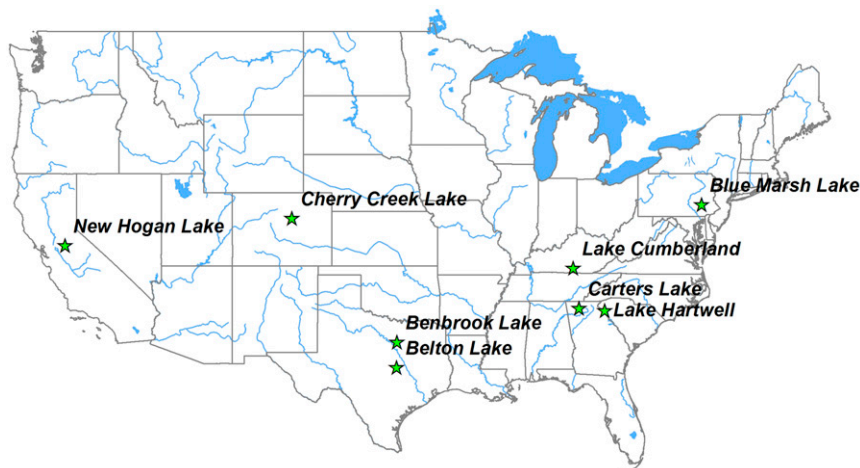


FIG. 1. Reservoir locations. Note that the following reservoirs are dropped from the economic analysis because of data and statistical modeling limitations: Cherry Creek Lake, Belton Lake, and Blue Marsh Lake.

the spatial and/or temporal level. By including fixed effects, these models account for any time-invariant characteristics that covary with weather. One drawback, however, is that the fixed effect captures differences in climate, so this model can only estimate the impact of weather on agriculture.

With these econometric challenges in mind, we use a state-level panel dataset from 1960 to 2004 to estimate the impacts of annual variation in drought on the total value of crop output, conditional on weather variables, state-level indicator variables, and a time trend. Data on state-level crop output were provided by the U.S. Department of Agriculture's (USDA) Economic Research Service (ERS; E. Ball 2013, personal communication; Ball et al. 2004, 2011, 2013).<sup>5</sup> Crop output reflects the sum of the value of the following categories: crops sold off the farm, additions to inventory, and quantities consumed as part of final demand, as well as the value of goods and services closely linked to agricultural production (e.g., processing and packaging agricultural products on the farm and machine services for hire). Ball et al. (2004, 2013) constructed this dataset in order to isolate changes in state-level agricultural productivity over time. In doing so, they divided the total value of outputs into two components: an aggregate price index that accounts for inflation and short-run price responses to change in crop supply, and an aggregate output measure that is valued using a temporally constant price (fixed at 1996 price

levels; we adjusted these to 2005 dollars) to place these estimates of changes in output in an economic context. This removes the effects of both inflation and short-run price responses to changes in crop supply so that variation in the aggregate output dataset is attributable to changes in productivity and shocks resulting from climatic variability and extreme events. Note that using this dataset, which allows us to statistically isolate the effects of drought on production, causes the resulting economic estimates to ignore price effects.

Drought occurrence is measured using the average growing season (March–September) PDSI over those agricultural counties that account for 80% of crop acreage within each state. We also include a maximum monthly temperature variable to account for implications of extreme heat on agriculture, which are not captured in the PDSI calculation.<sup>6</sup> State-level indicators capture time-invariant state-level characteristics that impact crop output. This accounts for agricultural inputs, such as the amount of land and labor in production (which vary little over time) and soil quality characteristics. A time trend accounts for explanatory variables that are not included in the model but have driven changes in crop outputs over time (e.g., technology). Note that if climate change has changed the frequency or severity of droughts between 1960 and 2004, there

<sup>5</sup> Data provided by the USDA ERS via e-mail correspondence on 6 February 2013. Further details on this dataset and its other applications is provided at the following USDA URL: <http://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us.aspx>.

<sup>6</sup> Numerous other climate variables that may affect yields include minimum temperature (i.e., effect of frosts), hail, or strong winds. These were excluded for two reasons: 1) these other variables are unlikely to cause the widespread damage caused by extreme heat events; and 2) hail and wind data are not available at an appropriate scale from climate models.



TABLE 3. Characteristics of reservoirs.

Reservoir	Location	Management and activities	Proximity to substitute sites and municipalities	Source
New Hogan Lake	Valley Springs, CA	The recreational area is managed by the U.S. Army Corps of Engineers and offers many activities including boating, fishing, and swimming. The lake covers 4400 acres and encompasses 50 miles of shoreline when full.	Valley Springs is set in the foothills of the Sierra Nevadas, about 30 miles east of Stockton, CA. Camanche Reservoir and Pardee Reservoir, which offer fishing, watersports, and boating, among other activities, are located within a 30-min drive to the northeast and north, respectively.	<a href="http://www.lakecamancheresort.com/">http://www.lakecamancheresort.com/</a> <a href="http://www.pardeelakerecreation.com/">http://www.pardeelakerecreation.com/</a> <a href="http://www.spk.usace.army.mil/Locations/SacramentoDistrictParks/NewHoganLake.aspx">http://www.spk.usace.army.mil/Locations/SacramentoDistrictParks/NewHoganLake.aspx</a>
Cherry Creek Lake	Aurora, CO	The recreational area is managed by the U.S. Army Corps of Engineers and its partners, including Colorado State Parks and the cities of Denver, Greenwood Village, and Aurora. As part of the Colorado State Park system it offers fishing, swimming, a marina, ice fishing, and several other activities.	Cherry Creek Lake lies on the southeast edge of Denver, CO, in Aurora, CO. Nearby Chatfield State Park, located on the southern edge of Denver, CO, also offers boating, fishing, jet skiing, ice fishing, water skiing, and swimming.	<a href="http://cpw.state.co.us/placestogo/Parks/cherrycreek">http://cpw.state.co.us/placestogo/Parks/cherrycreek</a> <a href="http://www.nwo.usace.army.mil/Missions/DamandLakeProjects/TrILakesProjects/CherryCreekDam.aspx">http://www.nwo.usace.army.mil/Missions/DamandLakeProjects/TrILakesProjects/CherryCreekDam.aspx</a>
Benbrook Lake	Fort Worth, TX	The lake is managed by the Fort Worth District of the U.S. Army Corps of Engineers and offers several recreational opportunities, including swimming, fishing, and boating.	Benbrook Lake lies about 15 miles from downtown Fort Worth, TX. Eagle Mountain Lake, Arlington Lake, and Lake Worth lie within an hour drive of Benbrook Lake, and offer similar recreational activities.	<a href="https://tpwd.texas.gov/">https://tpwd.texas.gov/</a> ; <a href="http://www.swf-wc.usace.army.mil/benbrook/">http://www.swf-wc.usace.army.mil/benbrook/</a>
Belton Lake	Belton, TX	The lake is managed by the Fort Worth District of the U.S. Army Corps of Engineers and offers several recreational activities, including fishing, boating, and swimming.	Located in Belton, TX, the lake is about eight miles west of major city Temple, TX. Nearby Stillhouse Hollow Lake, also managed by the U.S. Army Corps of Engineers, Fort Worth District, offers similar recreational opportunities on a smaller scale. Another Corps-managed lake, Lake Waco, is about 50 miles to the northeast and also offers recreational water activities.	<a href="https://tpwd.texas.gov/">https://tpwd.texas.gov/</a> ; <a href="http://www.swf-wc.usace.army.mil/belton/">http://www.swf-wc.usace.army.mil/belton/</a>
Lake Cumberland	Clinton, Laurel, McCreary, Pulaski, Russell, and Wayne counties in KY	This lake, boasting the largest volume of any lake east of the Mississippi, is managed by the U.S. Army Corps of Engineers and offers fishing, boating, and swimming, as well as, most famously, houseboating.	Lake Cumberland lies about 100 miles from major cities Lexington, KY, Bowling Green, KY, and Louisville, KY. Dale Hollow Lake, located about 40 miles to the southwest in Tennessee, offers similar recreational activities on a smaller scale and without the emphasis on houseboating.	<a href="http://www.lakecumberland.com/">http://www.lakecumberland.com/</a> <a href="http://www.dalehollow.com">http://www.dalehollow.com</a> <a href="http://www.irm.usace.army.mil/Locations/Lakes/LakeCumberland.aspx">http://www.irm.usace.army.mil/Locations/Lakes/LakeCumberland.aspx</a>
Carters Lake	Chatsworth, GA	Managed by the U.S. Army Corps of Engineers, this lake offers swimming beaches, fishing, boating, and a variety of lakeside amenities.	Located 20 miles south of Chatsworth, GA, this lake is the only of its kind, in terms of recreational opportunities, for a fifty mile radius. The closest offerings are Lake Lanier and Allatoona Lake.	<a href="http://www.carterslake.com/">http://www.carterslake.com/</a> <a href="http://www.sam.usace.army.mil/Missions/CivilWorks/Recreation/CartersLake.aspx">http://www.sam.usace.army.mil/Missions/CivilWorks/Recreation/CartersLake.aspx</a>

TABLE 3. (Continued)

Reservoir	Location	Management and activities	Proximity to substitute sites and municipalities	Source
Lake Hartwell	Border of GA and SC	Managed by the U.S. Army Corps of Engineers, Savannah District, this lake offers several outdoor recreational opportunities, including boating, beaches, and fishing.	The lake is located about 1 h from Greenville, SC, and 2 h from Atlanta, GA. This lake and water bodies connected to the region by the Savannah River offer the best recreational opportunities of their kind for a 50-mile radius, with Lake Lanier lying about 80 miles to the southwest.	<a href="http://www.sas.usace.army.mil/About/DivisionsandOffices/OperationsDivision/HartwellDamandLake.aspx">http://www.sas.usace.army.mil/About/DivisionsandOffices/OperationsDivision/HartwellDamandLake.aspx</a>
Blue Marsh Lake	Berks County, PA	Managed by the U.S. Army Corps of Engineers, recreational opportunities include boat launches, swimming beaches, and more.	Located only 10 miles outside of Reading, PA, this reservoir is situated within 20 miles of Ontelaunee Lake, and the smaller Middle Creek reservoir, which offer similar amenities on a smaller scale.	<a href="http://www.nap.usace.army.mil/Missions/CivilWorks/BlueMarshLake.aspx">http://www.nap.usace.army.mil/Missions/CivilWorks/BlueMarshLake.aspx</a>

would be a correlation between drought occurrence and the trend. The correlation between the year variable with the mild-to-moderate and severe-to-extreme drought variables is  $-0.04$  and  $-0.10$ , respectively, suggesting minimal covariance. On a related note, as climate has changed, so too has the portfolio of crops and water infrastructure in each state. As these characteristics change, so too does the sensitivity of agriculture to drought. We tested the effect of including an interaction term between drought occurrence/severity and the time trend and of including one trend for 1960–79 and another for 1980–2004, but we found that neither structure improved model performance.

The impact of weather on agricultural output is fundamentally different for irrigated and rainfed crops (Schlenker et al. 2006). To account for this difference, we run separate models for states east and west of the 100th meridian, an approximation of the rainfall line in the United States.<sup>7</sup> To the east of the 100th meridian, rainfall generally exceeds  $20 \text{ in. yr}^{-1}$ ; to the west, precipitation is generally less. As such, farming west of the 100th meridian is typically possible only with use of irrigation (Schlenker et al. 2006).<sup>8</sup>

Equation (1) below shows the basic model form. Correlations between explanatory variables are low, ranging from  $-0.18$  to  $0.14$ . A description of variables and data sources is provided in Table 1. We employ a log-linear specification so we can interpret the inverse logs of the coefficients on drought variables as percentage change in the total value of crop output when mild/moderate or severe/extreme drought occurs.<sup>9</sup>

$$\log(\text{output}_{it}) = \beta_0 + \beta_1 \text{mildModDrought}_{it} + \beta_2 \text{sevExtDrought}_{it} + \beta_3 \text{mxTemp}_{it} + \beta_4 \text{state}_i + \beta_5 \text{trend} + \varepsilon_{it} \quad (1)$$

<sup>7</sup> Note that another alternative would be including the percentage of irrigation in each state as an explanatory variable, but such a variable is likely to have high correlation with the state fixed-effects variable. This fixed-effects variable provides a constant term for each state in the analysis, which allows us to capture many unobservable state-level differences and thus develop a much more parsimonious model.

<sup>8</sup> Although drought in the east would influence demand for agricultural goods grown in the west and vice versa, this would primarily cause changes in the distribution of crops and in total agricultural revenues rather than in per hectare crop productivity, which is our dependent variable.

<sup>9</sup> Note that past research (e.g., Attavanich and McCarl 2014) has found that crop yields may respond nonlinearly to technological progress and climate variables. We tested a quadratic trend term, but model performance did not improve.



As documented in Table 2, under this regression specification, mild-to-moderate droughts do not have statistically significant impacts on the total value of crop output in the east but do in the west. Severe-to-extreme droughts and the remaining explanatory variables are all significant in both regions of the contiguous United States. The western states are more sensitive to drought, with a 12% reduction in the total value of crop output under severe drought conditions, compared to a 4.4% reduction in the east.

## 2) RESERVOIR RECREATION MODEL

The relationship between droughts and reservoir recreation is indirect; droughts influence reservoir levels, which, in turn, affects visitation by restricting access to docks, beaches, and other amenities.<sup>10</sup> Several prior studies examine the relationship between either reservoir elevations or river flow and water-based recreation. For example, Cameron et al. (1996) performed a case study on federal reservoirs and rivers in the Columbia River basin to examine the relationship between recreation demand and reservoir elevations. Ward (1987) used a travel cost model to estimate the potential recreational demand on Rio Chama in New Mexico. Although this study focuses on river flows rather than reservoir elevations, the authors showed a potential return of \$900–\$1100 per acre foot of water released from reservoirs to increase instream flows, demonstrating the potentially high value of water for recreational activity.

We construct a two-stage statistical model to estimate the impact of drought on reservoir visitation. We follow a case-study approach because data on reservoir visitation are not available for the entire contiguous United States. Specifically, we look at historical drought occurrence, reservoir levels, and visitation at reservoirs that historically experience high levels of fluctuation as a result of regional drought events. Locations of the reservoirs included in our analysis, which were selected based on data availability, are shown in Fig. 1. Note that, although eight reservoirs are shown in the figure, three of the reservoirs—Belton, Blue Marsh, and Cherry Creek Lakes—were omitted from results presentation for reasons discussed below. Information on these

reservoirs, including location, managing agency, available recreation activities, and nearby municipalities and substitute sites is provided in Table 3.

In the first-stage regression, we model historical average annual water level (elevation) at each reservoir as a function of long-term drought, represented by the average 12-month SPI within each reservoir drainage basin. The U.S. Army Corps of Engineers (USACE) provided data on lake elevation (J. Custer 2013, personal communication).<sup>11</sup> We lag the 12-month SPI variable 3 months behind the reservoir water level so that the effects of cumulative drought have time to sufficiently influence reservoir management, which in turn may affect lake levels. Accordingly, the first-stage regression for each reservoir is given by Eq. (2). Correlation between moderate drought and severe-to-exceptional drought is  $-0.14$ . A description of the variables is provided in Table 4.

$$\text{level}_t = \beta_0 + \beta_1 \text{ModDrought}_t + \beta_2 \text{sevExcDrought}_t + \varepsilon_t \quad (2)$$

Although only multimonth droughts affect the management of large reservoirs, reservoir water level affects recreational activity on a monthly, weekly, or even daily time step. Consequently, the second stage of the model focuses on the relationship between monthly visitation (provided by USACE) and monthly water levels at each reservoir, along with other explanatory variables. Monthly water levels are categorized according to resource impact levels (ILs) defined by the Corps. The ILs for each reservoir correspond to unique water levels that reflect tipping points where recreational opportunities fall sharply as lake levels decline. These ILs include points at which large numbers of boat docks, boat launches, and beaches become unusable. For modeling purposes, we assume that a change in lake level only affects visitation when it crosses an IL. The three ILs defined by the Corps include the initial impact level (IIL), wherein some boat launching ramps are unusable and most beaches are unusable; the recreation impact level (RIL), wherein more ramps are not usable and all beaches are unusable; and the water access limited (WAL), wherein all or most boat ramps are out of service and all beaches are unusable.

The second-stage regression model includes binary variables for each of the three impact levels, which take a value of one if the lake level (from the first-stage regression) falls within the impact level range for that

<sup>10</sup>Note that drought, if correlated with air temperature, could also increase demand for reservoir recreation. Correlation between air temperature and moderate drought occurrence over the reservoir catchments is 0.17, and correlation between air temperature and severe/extreme drought occurrence over the catchments is 0.25. This suggests there may be a mild positive relationship between drought and visitation that is not captured in this analysis.

<sup>11</sup>Data provided by the USACE Recreation Program via e-mail correspondence on 14 March 2013 and 22 March 2013.

TABLE 4. Variables included in first-stage regression for reservoir recreation analysis. The dependent variable is the historical average annual water level (elevation) at each reservoir as a function of long-term drought, represented by the average 12-month SPI within each reservoir drainage basin.

Variable name	Description	Variable type	Units
level <sub><i>t</i></sub>	Dependent variable; average annual water level of the reservoir in year <i>t</i>	Continuous	ft MSL
ModDrought <sub><i>t</i></sub>	Indicator variable equal to 1 when 12-month SPI in year <i>t</i> is less than -0.75 and greater than -1.25	Binary	—
severeExcDrought <sub><i>t</i></sub>	Indicator variable equal to 1 when 12-month SPI in year <i>t</i> is less than -1.25	Binary	—
ε <sub><i>t</i></sub>	Error term	—	—

month and zero otherwise. This stage is restricted to include data for only the months of May through September, which reflects the peak recreation season in many reservoir systems. Under alternative regressions that included data for a wider range of months, visitation was much less sensitive to changes in lake levels. Henceforth, when we refer to visitation changes and corresponding economic effects, these impacts are only referring to this peak recreation season.

The log-log model form was used to conduct the regression analysis. With this model specification, the regression coefficients on all continuous variables can be interpreted as elasticities: that is, the percentage change in visitation that would occur with a percentage change in the level of each explanatory variable, holding all other explanatory variables constant. The inverse logs of the coefficients for binned impact level variables represent the percentage change in peak season visitation that would occur when moving from the no-impact level into IIL, RIL, or WAL. Accordingly, the second-stage regression is given by Eq. (3). Correlations between all explanatory variables are between -0.16 and 0.16, except for the relationship between local municipal population and average temperature, which is 0.34. A description of the variables included is presented in Table 5.<sup>12</sup>

$$\begin{aligned} \log(\text{Visits}) = & \beta_0 + \beta_1 \text{IIL} + \beta_2 \text{RIL} + \beta_3 \text{WAL} \\ & + \beta_4 \log(\text{Pop}) + \beta_5 \log(P) + \beta_6 \log(T) \\ & + \beta_7 \log(\text{Days}) + \varepsilon \end{aligned} \tag{3}$$

As documented in Table 6, under first-stage regression, the relationship of reservoir elevation to both moderate droughts and severe-to-exceptional droughts

tends to be negative and statistically significant, with the exception of Blue Marsh Lake, which also has an exceptionally poor overall *R*<sup>2</sup> value. Historical Blue Marsh elevations never exceed the impact levels in more than 99% of observations, so the regression specification is unable to identify adequately the relationship between visitation and elevation.

The second-stage regression (Table 7) generally shows significant reductions in reservoir visitation when reservoir elevation declines across impact levels, with larger reductions associated with higher impact levels. Note that for two of the reservoirs, Belton and Cherry Creek, we find a positive relationship between transitions into the initial impact level and visitation. This counterintuitive finding is partly the result of too few lake level observations that were below the IIL levels but may also suggest an omitted variable that is positively correlated with both visitation and lower reservoir elevations.

Visitation forecasts can be translated into dollar amounts (i.e., recreational use value), then compared across climate scenarios to assess impacts to visitors' economic welfare. Using a benefit transfer approach, we reviewed the recreation valuation literature for studies with sound approaches and relevant geographic foci to the reservoirs evaluated in this study (e.g., Eiswerth et al. 2000; Fadali and Shaw 1998; Jakus et al. 2000).<sup>13</sup> The outcome was a set of per trip unit values reported in consumer surplus terms. Note that, because this approach is focused on the consumer surplus implications of changes in visitation, any effects on regional producers from decreases or increases in visitor expenditures will not be captured.

<sup>12</sup> Note that price (or distance traveled) is not included as an explanatory variable in this formulation, which may lead to omitted variable bias. The effect on the results of omitting this variable is uncertain.

<sup>13</sup> The economics literature is mixed on how well benefit transfer performs compared to values developed in primary studies. For example, Parsons and Kealy (1994) compared the results of several hypothetical benefit transfers to those of a random utility model (RUM) and found that the benefit transfers methodologies on average deviated less than 10% from the RUM values. On the other hand, Kirchhoff et al. (1997) and others have found that applying benefit transfer can result in large errors, even for similar amenities.

TABLE 5. Variables included in second-stage regression for reservoir recreation analysis. The dependent variable is visitation at the reservoir.

Variable name	Model variable name	Variable type	Units
Visitation at reservoir	Visits	Continuous	Count of people
Initial impact level	IIL	Binary	—
Recreation impact level	RIL	Binary	—
Water access limited	WAL	Binary	—
Nearest municipal population	Pop	Continuous	Count of people
Monthly precipitation	$P$	Continuous	mm
Monthly average temperature	$T$	Continuous	°C
No. of weekend days	Days	Continuous	Count of days per month
Error term	$\varepsilon$	Continuous	—

### c. Projecting the effects of GHG mitigation on drought frequency and severity

To translate the above relationships into projections of the economic effects of global GHG mitigation, we project the frequency and severity of future drought under a range of climate scenarios, apply the reduced-form relationships to these projections, and then evaluate the differences in economic outcomes under mitigation and reference emission scenarios. We apply a set of climate scenarios that include alternative emission policies to evaluate the benefits of mitigation. Specifically, we employ climate projections developed using the National Center for Atmospheric Research (NCAR) Community Atmospheric Model (CAM), which is built into the Integrated Global System Modeling (IGSM) framework (Monier et al. 2015). The IGSM-CAM projections provide the primary projections for this paper. However, since the IGSM-CAM represents a single GCM pattern, simplified representations of other GCM patterns were employed to analyze the structural uncertainties associated with GCM selection in the contiguous United States. Two additional GCM patterns were used to produce a range of temperature and precipitation futures: MIROC3.2 (medres) and CCSM3. Compared to other GCMs for the contiguous United States, these two GCM patterns project hotter/drier and less-hot/wetter patterns, respectively.<sup>14</sup> Monier et al. (2015) describes the details of this IGSM pattern-scaling methodology, as well as how projections compare to an ensemble mean and the IGSM-CAM simulations. These two additional GCM patterns are run under the same set of climate scenarios (described below) as the IGSM-CAM.

<sup>14</sup>Note that by “less hot,” we mean that the CCSM pattern projects less warming than many of the other GCM signatures; it still projects warming relative to the historical baseline.

Characteristics of the three emissions scenarios employed in this analysis are presented in Table 8.<sup>15</sup> GHG emissions from human activities, and the resulting climate change impacts and damages depend on future socioeconomic development (e.g., population growth, economic development, energy sources, and technological change). Emissions scenarios provide scientifically credible starting points for examining questions about an uncertain future and are illustrations of how the release of different amounts of climate-altering gases and particles into the atmosphere will produce different climate conditions in the United States and around the globe. Table 8 provides information on the characteristics of each emissions scenario in 2100. Similar to the representative concentration pathways (RCPs) used by IPCC in its Fifth Assessment Report, the Climate Change Impacts and Risk Analysis (CIRA) project scenarios are based on different GHG emissions and different trajectories of radiative forcing—a metric of the additional heat added to Earth’s climate system caused by anthropogenic and natural emissions. These three scenarios include a business-as-usual future, in which GHG emissions continue to increase unchecked to  $10 \text{ W m}^{-2}$  of radiative forcing [referred to as the reference scenario (REF)], a stabilization scenario in which total radiative forcing levels are at  $4.5 \text{ W m}^{-2}$  by 2100 (POL4.5), and a more stringent stabilization scenario with forcing levels at  $3.7 \text{ W m}^{-2}$  by 2100 (POL3.7).<sup>16</sup>

<sup>15</sup>These GHG emission scenarios and climate projections were developed for and applied in the CIRA project, a multisector analysis of the damages of inaction and benefits of global GHG mitigation (see Waldhoff et al. 2015).

<sup>16</sup>These scenarios were developed using the Emissions Predictions and Policy Analysis (EPPA) model, which is the human systems component within IGSM. EPPA provides projections of world economic development and emissions, including analysis of proposed emissions control measures, such as limiting emissions from major emitting sectors like electricity production and transportation [see Paltsev et al. (2015) for more details].

TABLE 6. Results from the first-stage recreation regression. The dependent variable is the reservoir elevation (over the 2000–10 period).

Variable	Coefficient							
	Belton Lake (TX)	Benbrook Lake (TX)	Blue Marsh Lake (PA)	Carters Lake (GA)	Cherry Creek Lake (CO)	Lake Cumberland (KY)	Lake Hartwell (GA and SC)	New Hogan Lake (CA)
Moderate drought	-2.71	-2.43 <sup>a</sup>	0.27	-3.24 <sup>b</sup>	-0.40	-2.91	-4.27 <sup>a</sup>	-23.06 <sup>b</sup>
Severe-to-exceptional drought	-4.90 <sup>b</sup>	-6.20 <sup>a</sup>	-0.04	-3.74 <sup>a</sup>	-1.52 <sup>c</sup>	-15.84 <sup>a</sup>	-6.84 <sup>a</sup>	-40.38 <sup>b</sup>
Constant	595.33 <sup>a</sup>	693.28 <sup>a</sup>	287.52 <sup>a</sup>	1071.96 <sup>a</sup>	5550.01 <sup>a</sup>	710.01 <sup>a</sup>	658.66 <sup>a</sup>	663.33 <sup>a</sup>
<i>R</i> <sup>2</sup>	0.20	0.55	0.02	0.32	0.19	0.40	0.61	0.41
No. of observations	30	29	22	35	40	30	40	30

<sup>a</sup> Significant at the  $p < 0.01$  level.

<sup>b</sup> Significant at the  $p < 0.05$  level.

<sup>c</sup> Significant at the  $p < 0.1$  level.

To convert the raw IGSM-CAM and MIROC and CCSM pattern-scaled outputs to inputs suitable for the SPI and PDSI calculations, we evaluated the changes in temperature and precipitation projected by the GCM, combined these changes with a baseline dataset from the PRISM Climate Group at Oregon State University (PRISM Climate Group 2012), and then aggregated these projections to the state and river basin levels.<sup>17</sup> We used these temperature and precipitation time series to estimate future PDSI and SPI drought projections for each emissions scenario and for each of four 30-yr periods centered on 2025, 2050, 2075, and 2100. The impact of GHG mitigation on drought projections is equal to the difference between the number of droughts in each severity category under the policy case (POL3.7 or POL4.5) and the REF case.

While the northeastern United States is projected to experience reductions in 12-month SPI drought frequency under the IGSM-CAM REF scenario because of rising precipitation, the southwestern United States could experience pronounced increases in drought frequency by the 2050 and 2100 periods. Changes in seasonal PDSI drought frequency were similar to those of SPI; however, the magnitude and pattern of changes differ somewhat, because PDSI is cumulative and considers temperature in calculating the index value. As with SPI, the largest increases in drought frequency under the IGSM-CAM REF are in the southwestern United States. Following these patterns, for both SPI and PDSI, GHG mitigation, as estimated in the POL3.7 and POL4.5 scenarios, substantially decreases drought frequency in the southwestern United States and moderately increases drought

frequency in parts of the eastern United States.<sup>18</sup> Figures 2 and 3 provide an overview of the effect of global GHG mitigation on the total number of severe and extreme (i.e., the sum of these two severity categories) SPI and PDSI droughts that occur over a 40-yr period across the contiguous United States under the IGSM-CAM policy and reference scenarios. Again, these positive U.S.-wide effects represent the net outcome of positive effects in western states offset partially by negative effects in eastern states.

Figures 4 and 5 illustrate the effect of mitigation on SPI and PDSI droughts under the MIROC (hotter/drier pattern) and CCSM (less-hot/wetter pattern) simulations. Under MIROC, GHG mitigation substantially reduces SPI drought occurrence in the states west of the Mississippi and south of Idaho; as with the IGSM-CAM signal, mitigation increases drought occurrence under MIROC over the northeastern United States. Under CCSM, on the other hand, GHG mitigation causes moderate increases in SPI drought frequency over the majority of the United States, with the largest increases occurring over a broad band of the central and southeastern United States. The spatial patterns are similar for the effect of GHG mitigation on PDSI occurrence. However, PDSI incorporates temperature, and because temperature is consistently lower under mitigation scenarios, PDSI droughts are projected to fall more

<sup>17</sup> PRISM is a high-resolution gridded (2.5 × 2.5 min) dataset of monthly precipitation and temperature variables over the contiguous United States.

<sup>18</sup> Importantly, note that this finding pertains only to drought occurrence rather than the overall effects of mitigation. If mitigation has the effect of dampening large projected increases in precipitation in the eastern United States, this will increase drought frequency relative to a wetter future with unmitigated climate change, but it may also reduce flood occurrence and other consequences of a wetter future, such as water logging of root zones. As a result, the net effects of mitigation in the eastern United States, particularly on agriculture, may very well be positive.

TABLE 7. Results from the second-stage recreation regression. An em-dash indicates that reservoir elevations in the observed record did not decline to or beyond these impact levels. The dependent variable is reservoir visitation (over the 2000–10 period).

Variable	Coefficient							
	Belton Lake (TX)	Benbrook Lake (TX)	Blue Marsh Lake (PA)	Carters Lake (GA)	Cherry Creek Lake (CO)	Lake Cumberland (KY)	Lake Hartwell (GA and SC)	New Hogan Lake (CA)
Initial impact level	0.20 <sup>a</sup>	−0.07	−0.27 <sup>a</sup>	−0.21	0.07	−0.26 <sup>b</sup>	−0.02	−0.24 <sup>b</sup>
Recreation impact level	−0.009	−0.26 <sup>b</sup>	−0.51 <sup>b</sup>	−0.35 <sup>b</sup>	—	−0.40 <sup>b</sup>	−0.19 <sup>b</sup>	−0.30
Water access limited	—	−0.24	—	−0.53 <sup>b</sup>	—	—	−0.27 <sup>b</sup>	—
ln(population)	−3.17 <sup>b</sup>	−1.05	8.65 <sup>b</sup>	−0.28	0.94	1.19	1.21	−0.11
ln(precipitation)	−0.009	0.027	0.10 <sup>c</sup>	−0.07	0.07 <sup>c</sup>	0.05 <sup>a</sup>	−0.001	−0.02
ln(temperature)	−0.04	0.01	0.38 <sup>b</sup>	0.01	0.01	1.12 <sup>b</sup>	0.59 <sup>b</sup>	1.36 <sup>b</sup>
ln(weekenddays)	0.15	0.18	−0.11	0.37	−0.12	0.20	−0.11	−0.13
Constant	54.22 <sup>b</sup>	26.07	−110.10 <sup>b</sup>	14.04	−0.48	−3.69	−2.83	7.93
R <sup>2</sup>	0.27	0.23	0.66	0.17	0.16	0.79	0.68	0.73
No. of observations	39	41	75	49	53	44	111	79
Months included in regression	May–Sep	May–Sep	Jan–Dec	May–Sep	May–Sep	May–Sep	Jan–Dec	Jan–Dec

<sup>a</sup> Significant at the  $p < 0.05$  level.

<sup>b</sup> Significant at the  $p < 0.01$  level.

<sup>c</sup> Significant at the  $p < 0.1$  level.

consistently across the contiguous United States than SPI droughts.

#### d. Projecting the economic effects of GHG mitigation

Using the statistical relationships described in section 2b, we estimate the economic effect of unmitigated climate change by imposing the associated drought projections on the historical relationship between drought and each sector's dependent variable. Although drought frequency/severity, estimated from the climate projections, vary over time, most of the remaining variables are fixed at their average historical values, with the exceptions noted below. We update agricultural output figures from 1982 levels (the average in the ERS dataset) to 2004 levels (the last year in the dataset) by estimating and applying linear trends to eastern and western U.S. agricultural output over the 1960–2004 ERS dataset period.<sup>19</sup> In the case of recreation, we scale recreational activity at each reservoir using county-level population projections from 2015 to 2100 and, operating along the assumption that population is evenly distributed over the county, spatially average from the counties to the drainage basin of each reservoir.<sup>20</sup> To estimate

the benefits of mitigation, we then evaluate the difference between the two emissions stabilization scenarios and the reference scenario for each set of model runs.

### 3. Results

In this section, we present a summary of the economic effects of global GHG mitigation in the agricultural sector and for five of the recreational reservoirs. Economic effects are presented in average real annual terms for the 2050 and 2100 eras (i.e., 2036–65 and 2086–2115), and in present-value terms for the 2015–2100 period.<sup>21</sup> In terms of effect on the crop-based agricultural sector, GHG mitigation has a strong positive effect in the western United States and a mild negative effect in the eastern United States, for an overall positive U.S.-wide effect. On the other hand, results of the recreation analysis depend largely on the assumed GCM pattern (IGSM-CAM, MIROC, or CCSM) and mitigation scenario (POL3.7 or POL4.5), as well as the location of each reservoir, because of the widely variable effects of GHG mitigation on SPI drought occurrence (Figs. 2 and 4).

<sup>19</sup> As this analysis identifies changes in average output, this procedure essentially updates the average agricultural output in the dataset from 1982 to 2004 so that we are measuring impacts to 2004 output rather than 1982 output.

<sup>20</sup> Using the U.S. population projections described in Paltsev et al. (2015), the Integrated Climate and Land Use Scenarios (ICLUS; Bierwagen et al. 2010) model was applied to generate county-level population projections at 5-yr time steps between 2000 and 2100.

<sup>21</sup> Present values are constructed by building a piecewise linear time series of average annual effects in 2005 dollars, discounting that series at 3% (2005\$), and then summing the result. The piecewise linear series assumes zero effect starting in 2015 and then linearly interpolates to the average annual effects in 2025, 2050, 2075, and 2100.



TABLE 8. Emission mitigation scenarios.

Scenario name	Forcing stabilization level	Atmospheric concentration in 2100 (CO <sub>2</sub> equivalent, IPCC gases)
POL3.7 (strongest mitigation)	3.7 W m <sup>-2</sup>	500 ppm
POL4.5 (weakest mitigation)	4.5 W m <sup>-2</sup>	600 ppm
REF (no mitigation)	Business-as-usual reference case (10 W m <sup>-2</sup> )	1750 ppm

*a. Agriculture results*

GHG mitigation benefits agriculture in western states, and the United States overall, in 2050 and 2100 under all GCM patterns and both the POL3.7 and POL4.5 scenarios. However, the effect of mitigation on agriculture in the eastern states is varied (Table 9).<sup>22</sup> The stronger GHG mitigation policy (POL3.7) offers additional benefits compared to the POL4.5 (Tables 9 and 10; Fig. 3). Average annual GHG mitigation benefits for the contiguous United States, in real 2005 dollars, are \$390 million (POL4.5) and \$980 million (POL3.7) in 2050, and they rise to over \$2.1 billion (POL4.5) and \$2.2 billion (POL3.7) by 2100. In present-value terms, mitigation benefits for the contiguous United States are \$4.3 billion (POL4.5) and \$7.8 billion (POL3.7) under the IGSM-CAM pattern between 2015 and 2100, which are 0.18% and 0.10% of total present value of projected reference agricultural outputs. These seemingly modest benefits are the result of combining smaller near-term 2025 effects with larger, yet more discounted, 2100 effects.

GHG mitigation also benefits the agricultural sector under both the MIROC pattern and the CCSM pattern (Table 10). In present-value terms over the 2015 to 2100 period, total benefits in present-value terms over the 2015–2100 period range from \$1.3 to \$28.6 billion across these four pattern/emissions combinations (e.g., MIROC/POL3.7), with the latter figure (from MIROC/POL 3.7 in Table 10) representing 0.67% of total U.S. agricultural output. Again, keep in mind that these positive U.S.-wide effects represent the net outcome of positive effects in western states offset partially by negative effects in eastern states.

<sup>22</sup> Although we would expect that the relationship between degree of mitigation (i.e., increasing from POL4.5 to POL3.7) and changes in extreme precipitation in a given time period to be monotonic at the global or very large regional (e.g., continents) scale, shifts in spatial patterns of precipitation under the different mitigation scenarios mean that we may not observe this monotonicity over a narrower spatial extent, such as the eastern United States or state-level results presented in Figs. 2–5. For example, in the eastern states (2050 era in Table 9), we see damage from mitigation under POL4.5 but a benefit under POL3.7.

*b. Reservoir recreation results*

The effect of GHG mitigation on reservoir recreation benefits vary depending on which GCM pattern and mitigation scenario are assumed, as well as the responsiveness of reservoir visitation to drought events within a drainage basin and whether mitigation has a positive or negative effect on drought occurrence and severity. We present results for the five recreational reservoirs with sufficient variation in their explanatory variables to formulate statistical relationships between drought occurrence and visitation (for reasons discussed above, Belton, Blue Marsh, and Cherry were dropped from this portion of the analysis). Overall, for the very limited sample of reservoirs evaluated, the effect of mitigation on reservoir recreation is negative for the IGSM-CAM and CCSM patterns and positive for the MIROC pattern (Tables 11 and 12). For illustration of how drought effects translate to economic effects at Cumberland Lake, drought lowers average lake levels, and visitation responds negatively when impact levels are reached. GHG mitigation is expected to increase the number of droughts there (POL4.5) or have little effect on the number of droughts (POL3.7); therefore, mitigation is expected to reduce visitation to this lake.

Under the IGSM-CAM climate projections, only one (New Hogan, in California) of these five reservoirs experiences increased recreational benefits from mitigation and four experience decreases (Table 11). Cumberland, Hartwell, and Carters are located in the southeastern United States (Fig. 1) where mitigation is projected to increase SPI droughts under the IGSM-CAM pattern. Benbrook Lake, in Texas, is also projected to experience increased SPI droughts, even though GHG mitigation under the IGSM-CAM projections generally decreases the occurrence of droughts within Texas. Under the IGSM-CAM pattern, the present value of benefits of GHG mitigation (from 2015 until 2100) range from –\$5.9 million at Hartwell in South Carolina to \$0.33 million at New Hogan in California.

Again, under the MIROC and CCSM patterns, results are varied. Under the MIROC pattern (i.e., hotter/drier), GHG mitigation generates either positive or zero recreational benefits through 2100 for four



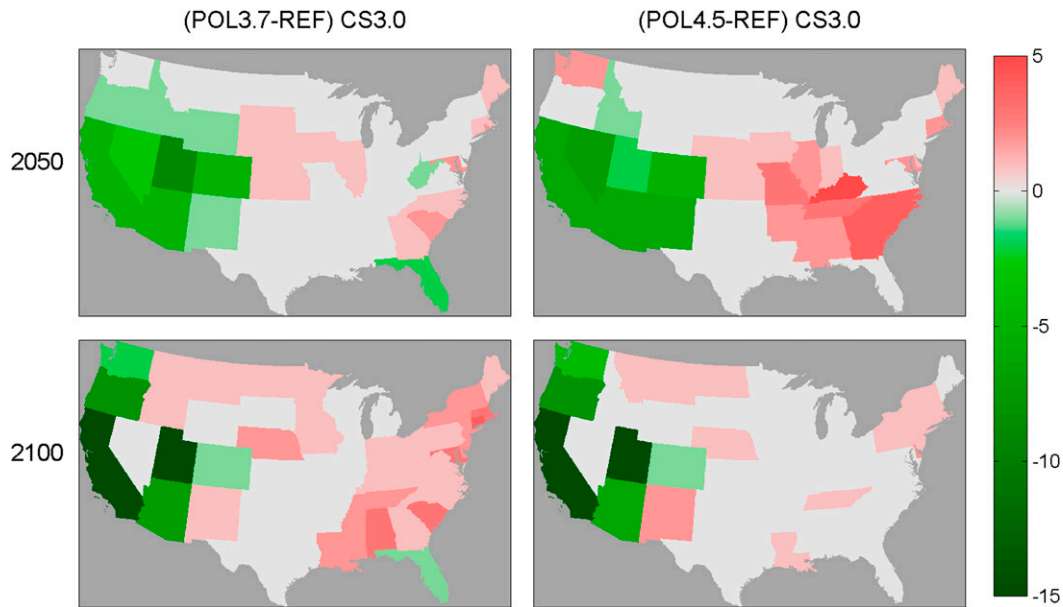


FIG. 2. Projected change in number of severe plus extreme 12-month SPI droughts in a 40-yr period due to GHG mitigation (i.e., policy minus reference), 2050 and 2100, under the IGSM-CAM pattern.

of the five reservoirs. Under the CCSM pattern (i.e., less-hot/wetter), GHG mitigation generates damages for three of the five reservoirs (Table 12). The inconsistent sign and magnitude of recreation benefits across GCM patterns and mitigation levels highlights the importance of structural uncertainties across GCMs. For example, at Benbrook, the positive present-value

(PV) results under MIROC/POL4.5 (+1.04%) oppose the negative PV results under IGSM-CAM/POL4.5 (−0.85%). Overall, the 2015–2100 present-value benefits range from −\$3.7 million at Hartwell in South Carolina (CCSM/POL3.7) to \$6.6 million at Benbrook in Texas (MIROC/POL3.7). Benbrook could instead experience zero or negative benefits if future climate

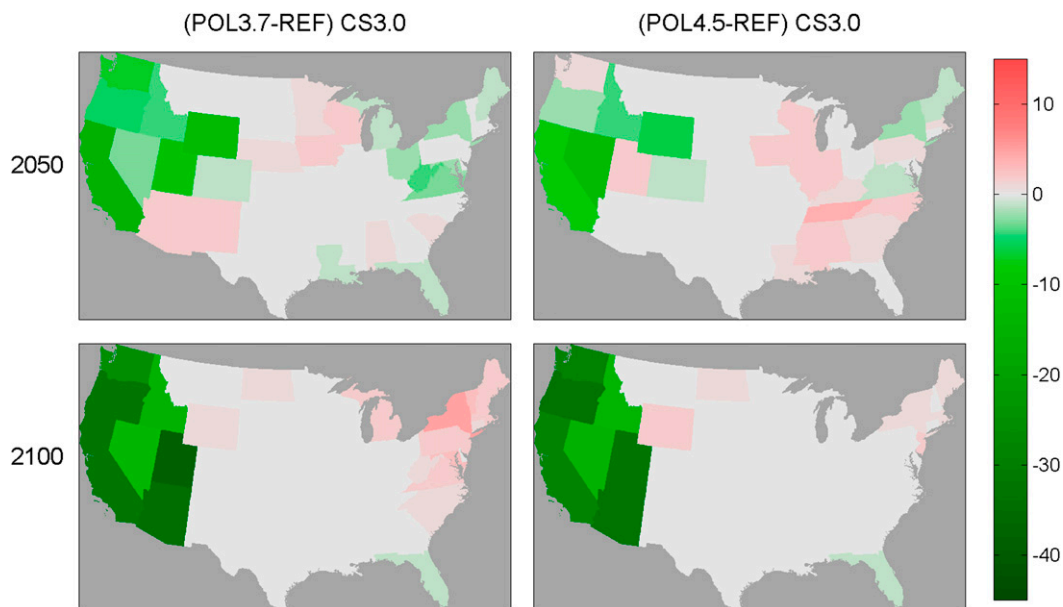


FIG. 3. Projected change in number of severe and extreme seasonal PDSI droughts in a 40-yr period due to GHG mitigation (i.e., policy minus reference), 2050 and 2100, under the IGSM-CAM pattern.

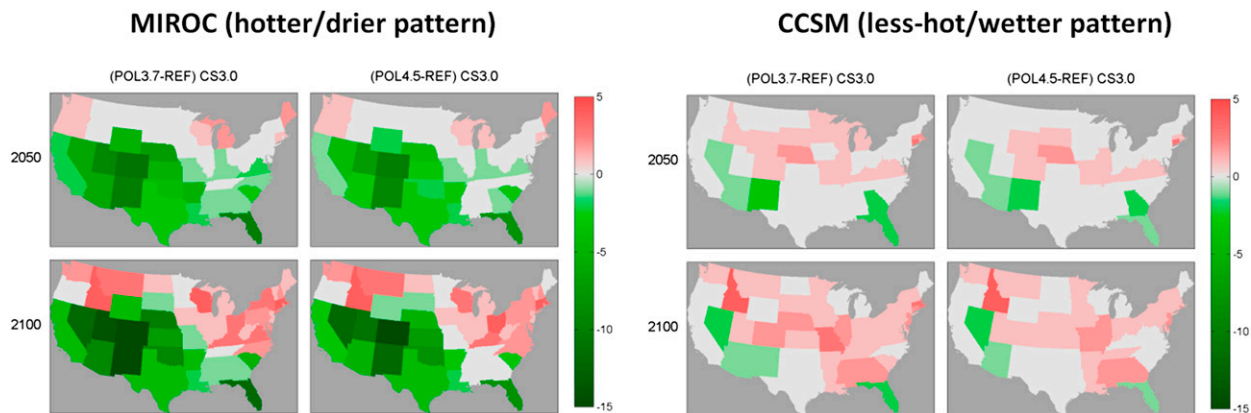


FIG. 4. Projected change in number of severe and extreme 12-month SPI droughts in a 40-yr period due to GHG mitigation (i.e., policy minus reference), 2050 and 2100, under the MIROC and CCSM pattern-scaled runs.

change resembles the IGSM-CAM pattern instead of MIROC or CCSM.

#### 4. Discussion and further research

The modeled regional effects of drought on crop-based agriculture sectors are generally negative and almost always statistically significant. This finding aligns with prior research showing that drought has been an important driver of historical reductions in economic activity in these sectors (Howitt et al. 2014; NCDC 2013; Boehlert and Jaeger 2010; NWS 2002). The spatial pattern of drought projections shows increases in occurrence in the western United States and decreases in the east under the IGSM-CAM pattern, matching results in prior research (e.g., Strzepek et al. 2010). Finally, at a national scale, we find that GHG mitigation reduces both drought incidence and damages for the agricultural sector, despite regional differences in the sign and

magnitude of effects under certain model scenarios. Between 2015 and 2100, the present value of benefits of GHG mitigation in the agricultural sector reaches \$7.8 billion (IGSM-CAM/POL 3.7) in 2005 dollars (at a 3% discount rate). This outcome comprises \$7.9 billion in positive benefits to western states and \$0.25 billion in damages to eastern states.

More frequent and severe droughts reduce reservoir visitation. Consequently, GHG mitigation tends to benefit regions in which higher GHG emissions would otherwise cause more frequent drought occurrence and increased severity. However, given the prevalence of negative benefits within our reservoir recreation results, this intuitive conclusion should be tested on a larger set of reservoirs. It was infeasible to evaluate the economic effects of droughts on each recreational reservoir in the United States. Further refinement of the statistical analyses and addition of more reservoirs would allow a more robust and U.S.-wide analysis.

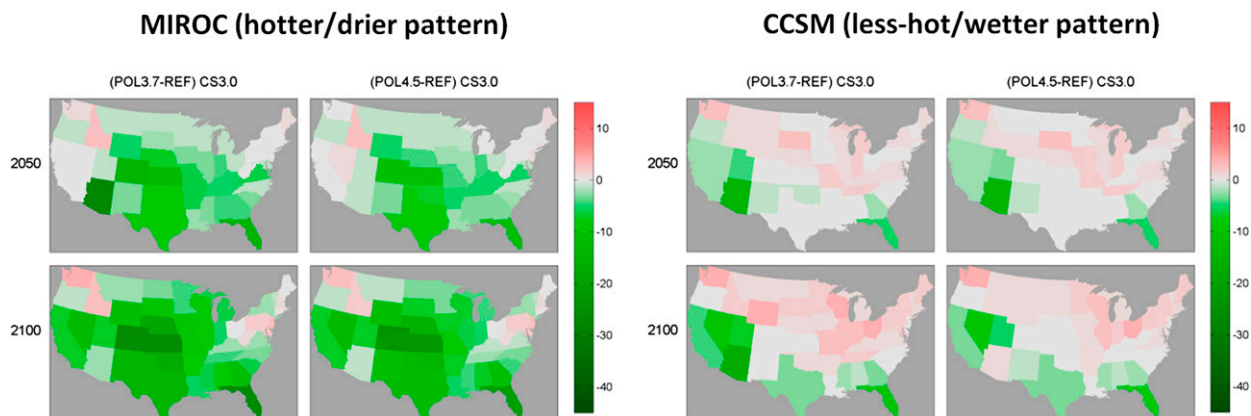


FIG. 5. Projected change in number of severe and extreme seasonal PDSI droughts in a 40-yr period due to GHG mitigation (i.e., policy minus reference), 2050 and 2100, under the MIROC and CCSM pattern-scaled runs.

TABLE 9. Effect on total value of crop output of changes in drought frequency and severity due to GHG mitigation: 2050 and 2100 annual values and 2015–2100 present-value IGSM-CAM results. Annual values and present values for the REF scenario are shown in billions of real 2005 U.S. dollars (2005\$ BIL). Positive percentages indicate mitigation benefits; negative percentages indicate mitigation damages. Present values are generated by discounting at 3% to 2015 (2005\$ BIL); the time series used to estimate present values is generated by linearly interpolating between 2015 (zero) and the mitigation results from the 2025, 2050, 2075, and 2100 eras. Because results from 2025 and 2075 are included in this calculation, the magnitude and possibly sign of this result can differ from the 2050 and 2100 values.

Scenario		Eastern states	Western states	U.S.-wide
2050 annual	REF	\$93	\$70	\$163
	POL3.7	0.02%	1.38%	0.60%
	POL4.5	-0.18%	0.80%	0.24%
2100 annual	REF	\$93	\$69	\$162
	POL3.7	-0.15%	3.40%	1.37%
	POL4.5	-0.05%	3.15%	1.32%
PV (2015–2100)	REF	\$2462	\$1882	\$4344
	POL3.7	-0.01%	0.42%	0.18%
	POL4.5	-0.17%	0.45%	0.10%

Because the IGSM-CAM pattern projects more widespread increases in precipitation in the United States than many other GCMs, we also simulated a drier future climate scenario using the MIROC pattern. We find that the present value of GHG mitigation benefits to agriculture may be as large as \$28.6 billion (MIROC/POL 3.7). These benefits are highest in the southwestern United States, where, in the absence of GHG mitigation, drought frequency is projected to increase most dramatically.

This analysis presents a method for analyzing the economic effects of changes in drought frequency and severity due to GHG mitigation. We apply the methods

TABLE 10. Effect on crop output of changes in drought frequency and severity due to GHG mitigation: 2050 and 2100 annual values and 2015–2100 present-value MIROC and CCSM pattern-scaled results. Annual values and present values for REF scenario are shown in billions of real 2005 U.S. dollars (2005\$ BIL). Positive percentages indicate mitigation benefit; negative percentages indicate mitigation damages. Present values are generated by discounting at 3% to 2015 (2005\$ BIL); the time series used to estimate present values is generated by linearly interpolating between 2015 (zero) and the mitigation results from the 2025, 2050, 2075, and 2100 eras. Because results from 2025 and 2075 are included in this calculation, the magnitude and possibly sign of this result can differ from the 2050 and 2100 values.

Scenario		NCAR CCSM (less-hot/wetter model)	MIROC (medres) (hotter/drier model)
2050 annual	REF	\$164	\$161
	POL3.7	0.06%	0.74%
	POL4.5	0.05%	0.54%
2100 annual	REF	\$164	\$159
	POL3.7	0.19%	1.65%
	POL4.5	0.15%	1.39%
PV (2015–2100)	REF	\$4349	\$4288
	POL3.7	0.05%	0.67%
	POL4.5	0.03%	0.53%

to just two sectors of the U.S. economy using three different GCM patterns (IGSM-CAM, MIROC, and CCSM) and two different GHG mitigation levels (POL3.7 and POL4.5). There are several notable limitations of the work. First, the analysis focuses only on the effects of GHG mitigation on drought; mitigation will also affect the risk of flooding and other relevant weather events, such as hail, wind storms, frost events, and growing degree days. In regions such as the northeastern United States, where GCMs project increases in precipitation, the flood-reduction benefits of GHG

TABLE 11. Effect on recreational benefits of changes in drought frequency and severity due to GHG mitigation: 2050 and 2100 annual values and 2015–2100 present-value IGSM-CAM results. Annual values and present values for REF scenarios are shown in millions of real 2005 U.S. dollars (2005\$ MIL). Positive values indicate mitigation benefit; negative values indicate mitigation damages. Note that because of data and statistical modeling limitations, Belton, Blue Marsh, and Cherry were dropped from this portion of the analysis. Present values are generated by discounting at 3% to 2015 (2005\$ MIL); the time series used to estimate present values is generated by linearly interpolating between 2015 (zero) and the mitigation results from the 2025, 2050, 2075, and 2100 eras. Because results from 2025 and 2075 are included in this calculation, the magnitude and possibly sign of this result can differ from the 2050 and 2100 values.

Scenario		Benbrook (TX)	Carters (CO)	Cumberland (KY)	Hartwell (GA and SC)	New Hogan (CA)
2050 annual	REF	\$23.6	\$18.9	\$16.4	\$145.7	\$3.6
	POL3.7	0%	0%	-0.85%	0%	0.67%
	POL4.5	-0.14%	0%	-1.79%	-0.02%	0.05%
2100 annual	REF	\$32.6	\$33.4	\$6.2	\$137.5	\$1.9
	POL3.7	0%	-0.75%	-1.10%	-1.07%	7.89%
	POL4.5	0%	-0.75%	-0.42%	-1.07%	7.76%
PV (2015–2100)	REF	\$582	\$468.1	\$477	\$3,701	\$93.3
	POL3.7	-0.05%	-0.19%	-0.76%	-0.15%	-0.18%
	POL4.5	-0.85%	-0.19%	-0.89%	-0.16%	0.35%

TABLE 12. Effect on recreational benefits of changes in drought frequency and severity due to mitigation: 2015–2100 present-value MIROC and CCSM pattern-scaled results. Present values for REF scenarios are shown in millions of real 2005 U.S. dollars (2005\$ MIL). Positive percentages indicate mitigation benefit; negative percentages indicate mitigation losses. Note that because of data and statistical modeling limitations, Belton, Blue Marsh, and Cherry were dropped from this portion of the analysis. Present values are generated by discounting at 3% to 2015 (2005\$ MIL); the time series used to estimate present values is generated by linearly interpolating between 2015 (zero) and the mitigation results from the 2025, 2050, 2075, and 2100 eras. Because results from 2025 and 2075 are included in this calculation, the magnitude and possibly sign of this result can differ from the 2050 and 2100 values.

Scenario		Benbrook (TX)	Carters (CO)	Cumberland (KY)	Hartwell (GA and SC)	New Hogan (CA)
MIROC (PV 2015–2100)	REF	\$549	\$466	\$472	\$3691	\$93.8
	POL3.7	1.21%	0.12%	0.17%	0%	0.01%
	POL4.5	1.04%	0%	–0.02%	0%	0.01%
CCSM (PV 2015–2100)	REF	\$569	\$467	\$482	\$3698	\$93.8
	POL3.7	0.21%	–0.01%	–0.05%	–0.07%	0%
	POL4.5	0.21%	–0.01%	–0.05%	–0.07%	0%

mitigation may more than offset the damages due to higher drought incidence. Second, by using historical data to inform the regressions, the analysis assumes that agricultural producers and reservoir managers will continue to use the same management tools and practices under future climate change as they have historically. In reality, future climate conditions might require producers to drastically change crop mixes (e.g., note the dramatic fallowing taking place in California right now), adopt irrigation on previous dryland acreage, change irrigation technologies or practices, tap into new water sources, such as deep aquifers, or switch to dryland cropping because aquifers have gone dry. Government policies and incentives could also change dramatically in the future, disrupting the relative value of agricultural output in different states.

We recommend two areas for future research. First, the benefits of GHG mitigation can be estimated for a wider variety of economic activities that are also affected by drought, including hydropower, municipal and industrial use, water-based navigation, ecosystem services, other water-dependent recreational activities, and various economic activities that depend on surface water quality, which declines during low flows. Second, we recommend developing drought indices based on runoff and reservoir yield, which may be more relevant for understanding and projecting the economic impacts of drought and GHG mitigation on hydropower, reservoir recreation, and commercial navigation.

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