Introduction

Quantifying the economic damages of climate change requires projecting future indicators of economic activity, such as gross domestic product (GDP), decades into the future; projecting numerous climate impacts at highly detailed spatial and temporal scales; determining how these climate impacts interact with human and natural systems; and monetizing those impacts. A number of multidisciplinary research projects are working to address these challenging tasks through the development of multisector climate impacts models. All of these projects use consistent greenhouse gas (GHG) emissions, socioeconomic, and climate scenarios across sectors, within their respective research scope, to drive a number of detailed sectoral models, which are then used to estimate climate impacts under future scenarios that have varying levels of GHG emissions. Although time and resource intensive, such consistent frameworks allow for more direct comparisons of results across sectors.

Climate damage functions can be a less resource-intensive approach to estimating the relationship between temperature change and the magnitude of sectoral damages (e.g., the economic value of land and structures that could be lost to coastal flooding) than reapplying the full
multidisciplinary research frameworks and their associated complex sectoral models. A climate damage function is a simplified expression of economic damages (which theoretically can encompass both positive and negative effects) as a function of climate inputs, such as changes in temperature. These functions are based on regression analyses that use only the damage output of more detailed and complex sectoral models. The more detailed models are designed to reflect complex structural, biological, physical, and economic relationships that define the pathways through which climate change affects economic impacts—their reflection of the processes through which economic impacts arise from changes in climate is one reason detailed models such as these are called “process-based.” For example, a process-based model of the economic impacts of changes in temperature on road surfaces should include an estimate of how extreme temperatures can soften road surfaces, which leads to increased costs to repair the road more often and/or costs in terms of damage to cars traveling on the road before it is repaired. It must also consider reductions in freeze–thaw damage to the road associated with warmer winter seasons. Thus the model must include a complex set of climate stressor–response relationships, estimate how road agencies will respond to the need to repair the road more often, and estimate how travelers may respond to impaired road conditions; moreover, it must be run at a detailed spatial scale (a 5–10 km grid nationwide) and temporal scale (daily). Climate damage functions can be a simpler alternative to the full process-based model if they can identify statistically robust patterns in the aggregate response across spatial and temporal scales.

While not a perfect substitute for the more detailed process-based models, these climate damage functions have the potential to estimate damages across multiple scenarios when it is not feasible to directly simulate impacts using complex physical and economic models. This “reduced form” approach—that is, developing a simplified expression for an otherwise complex modeling process—has been used in the past, primarily in global-scale climate impact analyses (e.g., Nordhaus and Boyer 2000; Fussel et al. 2003; Arnell et al. 2016). Climate damage functions are also the basis of the modeling (e.g., Nordhaus 2010; Anthoff and Tol 2013; Hope 2013) that supports estimates of the social cost of carbon (National Academies of Sciences, Engineering, and Medicine 2017).

This article demonstrates how damage functions can be developed from the results of detailed modeling studies and then used to estimate economic impacts in future years. The damage functions are estimated from the economic damage outputs and climate inputs of 15 more complex models of sectoral impacts in the United States that were run under a consistent set of future climate scenarios. These climate damage functions are then standardized to both temperature and time, thus providing a means for estimating future climate damages under new climate change scenarios, that is, beyond the scenarios used in the more complex economic impact models. The resulting system of multisectoral damage functions responds directly to calls to continuously update the scientific basis for estimating the marginal damages of climate changes (Marten et al. 2013; Pizer et al. 2014), to test the ability to estimate damages from temperature increases above 3°C (Newbold and Marten 2014; Stoerk et al. 2018), and most recently, to update estimates of damages as part of improvements in and updates to integrated assessment models (IAMs) (chapter 5 of National Academies of Sciences, Engineering, and Medicine 2017).  

2IAMs are global in scale and combine information on the costs and marginal benefits of reducing GHG emissions to estimate an optimal pathway through time for GHG reduction policies. Our work here is
Although we specifically seek to address these challenges, our approach has several limitations. First, we consider only one region of the world (the contiguous United States), and do not comprehensively address all sectors that are impacted by climate change. Second, because some of the sectoral models are estimated based on historical data, the damage functions may not accurately reflect the magnitude of either future climate shocks or future adaptation. Finally, the underlying sectoral models, and therefore our damage functions, do not completely account for the economic and social context in which the biophysical and economic damages from climate changes are expected to occur. For example, a policy to limit warming to 2°C over the course of the twenty-first century could also reduce demand for electricity, thus limiting impacts in the electric energy sector. In addition, we do not consider interactions between sectors (e.g., changes to hydrology might also reduce the availability of cooling water for thermal power plants, which could constrain the deployment of these plants to meet electric energy demand).

The remainder of the article is organized as follows. First, we present our approach to estimating damage functions from more complex sectoral models. Then we present the results of the reduced-form damage function estimation, including a discussion of the uncertainty of these results. Finally, we identify key next steps for developing rigorous damage functions.

**Approach**

In this section we review the detailed sectoral models from which we estimate damage functions, explain our rationale for using temperature change as the primary driver of damages in our functions, and describe the process of estimating damage functions.

**Overview of the Sectoral Modeling Framework**

The set of 15 sectoral models we rely on to estimate U.S. sectoral damage functions were developed as part of the second phase of the Climate Change Impacts and Risk Analysis (CIRA2.0) project, a modeling effort designed to inform the U.S. Fourth National Climate Assessment (U.S. Environmental Protection Agency 2017a). The CIRA2.0 project assesses climate damages for 22 economic sectors over four 20-year periods in the twenty-first century, using a consistent set of climate projections, population projections, and GDP projections. Fifteen of these models provide sufficient information to estimate a damage function.

The climate projections for CIRA2.0, and for which the detailed sectoral models were run, were based on guidance from the U.S. Global Change Research Program (USGCRP) Scenarios and Interpretive Science Coordinating Group for use in the Fourth National Climate Assessment. As noted in National Academies of Sciences, Engineering, and Medicine (2017) and Pizer et al. (2014), the basis for damage functions in some IAMs is quite dated, with some sources from the 1990s and early 2000s. These models are described in more detail in Martinich and Crimmins (2019) and U.S. Environmental Protection Agency (2017a). See also tables SM-1 and SM-2 in the online supplementary materials.

Details concerning the climate (US Bureau of Reclamation et al. 2016), population (Bierwagen et al. 2010; U.S. Environmental Protection Agency 2017b), and GDP projections (Chen et al. 2015) and the CIRA2.0 models are presented in the online supplementary materials. Additional details concerning the design and structure of the CIRA2.0 modeling framework can be found in U.S. Environmental Protection Agency (2017a).

See Table SM-2 in the online supplementary materials for a summary of these sectoral impact analyses.
Climate Assessment (US Global Change Research Program 2015), using the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathway (RCP) 8.5 and RCP4.5 as higher and lower greenhouse gas concentration scenarios, respectively. CIRA2.0 focused on a subset of five general circulation models (GCMs) from among more than 60 possibilities. These GCMs, which are complex global models of future climate change based on GHG emissions inputs, met criteria established in U.S. Environmental Protection Agency (2017a), including independence and quality, and were chosen to ensure that, as a group, they provide a broad range of temperature and precipitation outcomes over the contiguous United States. Twenty-year periods of aggregation were used to reduce the effects of climate variability on the results. CIRA2.0 uses a 20-year reference period—1986–2005—and four projection periods identified by the central year in the 20-year period: 2030 (for 2020–2039), 2050 (for 2040–2059), 2070 (for 2060–2079), and 2090 (for 2080–2099).

The geographic scope for our analysis is the contiguous United States, which is divided into the seven multistate regions used in the latest National Climate Assessment. We divide the 15 sectors modeled in CIRA2.0 and used in our analysis into three broad megasectors: health effects, infrastructure and electricity impacts, and natural or managed ecosystem-mediated effects. Together, these modeled sectors represent 87 percent of the total damages modeled in the U.S. Environmental Protection Agency (2017a) analysis.

A Focus on Temperature-Denominated Damage Functions

As noted earlier, this article seeks to address a number of recent calls for improving U.S. climate damage estimates. We will focus here on temperature-denominated damage functions (i.e., functions that estimate damages per unit of temperature change) for two key reasons. First, Yohe (2017) illustrates how damage estimates, including those for the United States only, can be applied in a climate policy framework that focuses on specific temperature thresholds. Second, the literature on “reasons for concern” about climate change risks that has emerged from successive IPCC assessment rounds is also denominated in terms of temperature, primarily because it is closely correlated with other climate stressors (e.g., changes in precipitation and extreme events), albeit with important variation by climate model.

Our focus on temperature-denominated damage functions does not prevent us from including other climate stressors (e.g., precipitation) in the estimation of a damage function. Although we use temperature as the primary driver in the damage functions, we also include a
mean precipitation ratio that effectively estimates precipitation as a function of temperature, region, and time period.\textsuperscript{10}

**Approach to Estimating Damage Functions**

We estimate a set of damage functions through ordinary least squares regression, using the economic damage results from the CIRA2.0 project by sector and across the seven U.S. multistate regions. We used a linear functional form for most sectors, although in a few cases a log-linear form is a better fit for the nonlinearities in the relationship between temperature and economic impacts. The primary explanatory variables are spatially averaged surface air temperature and annual precipitation for 10 climate scenarios (the five GCMs discussed earlier, for each of the two GHG emissions scenarios, RCP8.5 and RCP4.5). Because precipitation is also likely to be an important determinant of damages for some infrastructure and water-dependent sectors, including roads, municipal and industrial water supply, freshwater fishing, and harmful algal blooms, it is included in the estimation of those damage functions.\textsuperscript{11} To account for variation in damages over time, controls for each of the 20-year periods within the 2015–2100 simulation range are included as explanatory variables in all of the damage functions. In addition, because differences in regional damages are important in all sectors, we account for this variation by adding control (fixed effects dummy) variables for each region in the damage function estimations.

The damage function estimation technique can be considered to be reasonable if we observe systematic relationships between the economic damage results and the key explanatory variable—temperature—when examining the underlying CIRA2.0 data. Moreover, we can have confidence that the damage functions will be applicable across a wide range of future temperature change scenarios if the underlying set of functions reflects a broad range of future temperatures.

Figure 1, which presents scatterplots of the relevant CIRA2.0 economic damage results for two sectors (labor and rail), provides support for both a clear temperature–damage relationship and the broad variation in temperature we seek from the dataset. The data for the labor sector, in panel A, reveals a clear positive temperature–damage relationship, as indicated by the general pattern of results, which are aligned from the lower left to the upper right. While the data as a whole indicate wide variation in this relationship, the data for each region (indicated by symbols in the legend) line up much more tightly along a series of upward sloping lines. The same pattern is clear for the rail sector (see figure 1, panel B). Although not shown in the figure, the temperature–damage relationship can also vary by projection period; this variation can be important to consider in order to estimate the model properly. Finally, the horizontal axis in both panels of figure 1 indicates wide variation in temperature across regions, up to almost 8\textdegree C, with the largest temperature ranges seen in the Northeast, Midwest, and Northern Plains regions.\textsuperscript{12}

\textsuperscript{10}The precipitation ratio is defined as the absolute level of land-based precipitation in the period of interest divided by the absolute level of precipitation in the baseline period. Thus it is a unitless scalar meant to reflect cross-climate model precipitation ranges.

\textsuperscript{11}For the coastal property sector, the reduced form modeling uses the sea level rise trajectory, which is the most direct stressor and the one that provides the best fit to the damage data.

\textsuperscript{12}Additional sector-specific scatterplots are presented in the online supplementary materials.
Results of Damage Function Estimation

In this section we discuss the results of the damage function estimation and present an application of the estimated sectoral damage functions to identify economic impacts of future temperature changes in the United States. We conclude the section by presenting estimates of the uncertainty in the projected economic impacts; we consider the uncertainty concerning the underlying relationship between GHG emissions and temperature as well as the estimation uncertainty in our projections of future economic impacts based on temperature.

Figure 1  Temperature and damage estimates for the Labor and Rail sectors, by region
Source: Authors’ analysis.
Estimated Relationship between Temperature and Damages

Overall, the regression results indicate a very strong relationship between the regionally averaged temperature variable and regional damages, with statistically significant temperature coefficients and a high level of explanatory value for most models. For all of the sectoral damage functions, the temperature-dependent impact functions yield relationships between economic outcome and the change in temperature that are statistically significant at the 5 percent level or higher, and most show much stronger statistical relationships. Moreover, the estimation for all sectors reflects a good fit for the models, with the best models explaining up to 90 percent of the variation in damage results and, with only a few exceptions, the models explaining two-thirds or more of the variation in damage results (as expressed by the adjusted $R^2$ metric).

All results are standardized by either population or the appropriate infrastructure unit (i.e., damages are expressed as economic impact per unit population or unit of infrastructure) to allow for easier comparisons of impact across regions and time periods. For infrastructure sectors, damages are standardized by units of physical vulnerability that are meaningful, readily measured, and yield a good model fit (e.g., network mileage for road and rail, bridge count for bridges, metropolitan area for urban drainage, and baseline property value for coastal property). The population standardization is used for the remaining sectors. For example, the damage results for the health megasector, which includes extreme temperature mortality, labor, aeroallergens, harmful algal blooms, and West Nile virus, are standardized using the exposed population, which means the impact is effectively a per capita mortality or morbidity rate. The water and ecosystem megasector results are also standardized using population because the impacts are dominated by human welfare impacts, either for recreation (in the case of the winter recreation, water quality, and freshwater fish sectors) or water shortages (in the case of the municipal and industrial water supply sector). Overall, the ecosystem effects depend more than other sectors on changes in the hydrology associated with climate change (as proxied by temperature change). The time period dummy variables are often significant across all megasectors and most likely capture changes in GDP over time that are not included in the models.

Application of Sectoral Damage Functions

A key objective of the development of climate damage functions across multiple sectors is to apply the results of these sectoral functions to temperature and precipitation projections. To illustrate the economic impact results using the reduced-form models, we first estimated...
damages at the regional level and then aggregated them to the national level for four temperature changes. The temperature changes ranged from 1.5°C to 4°C in 2050 and were applied in each region (i.e., we applied a uniform 1.5°C to 4°C change to each regional base temperature).\textsuperscript{17}

Estimated sectoral damages

The estimated annual sectoral damages for these changes in temperature (aggregated for the seven regions) are presented in figure 2.\textsuperscript{18} The results reflect the expected pattern, with

\textsuperscript{17}We examine the results for a 1.5°C change (rather than for a 1°C change) because of the small number of observations in 2050 that are below 1.5°C, which increases the uncertainty of the estimates and indicates a low likelihood of the temperature change being below 1.5°C in 2050 in our lower emissions scenario.

\textsuperscript{18}These results use an indicator of the mean precipitation ratio across GCMs at the specified change in temperature. The 2050 population forecasts (or other scalars) are also now applied to rescale the per capita/per infrastructure unit damages that are estimated by the damage function.
impacts increasing with larger increases in temperature. The coastal property, labor, and extreme temperature mortality categories account for the largest share of overall impacts, increasing to more than $100 billion annually for coastal and $75 billion annually for labor and extreme temperature mortality for a 4°C increase. It is interesting to note that figure 2 also indicates some negative values for damages (i.e., benefits of climate change). In particular, winter recreation shows small negative damages (less than $1 billion) at temperature changes of 1.5°C and 2°C, municipal and industrial water supply damages are negative but even smaller at 1.5°C, and although not shown in figure 2, roads and harmful algal blooms have negative damages for a 1°C change. In these cases, the results are expected because of the climate–stressor response relationships in the underlying CIRA2.0 study. For example, for roads, one of the components of climate impact is damage from freeze–thaw cycles, which is reduced for a moderate change in temperature and thus leads to negative damages at low temperature changes. For larger temperature changes (i.e., greater than 2°C), the negative damage freeze–thaw result is overwhelmed by the much larger temperature-driven rutting of paved roads and precipitation-driven effects on unpaved roads. In the case of harmful algal blooms, the temperature effect is strictly increasing for damages, but the effect is partially offset by higher precipitation, which dilutes the pathogen concentration; nonetheless, with larger changes in temperature (i.e., greater than 2°C), the temperature damage effect overwhelms the precipitation benefit. For winter recreation, the length of the ski season is driven by both temperature and precipitation; at low levels of warming (i.e., 1.5°C) the positive effect of increased precipitation can outweigh the negative effect of higher temperatures, thus leading to negative damages. However, beyond a 2°C change in temperature, the warming effect dominates and damages are positive.

Economic impacts as a function of marginal changes in temperature

It is also important to understand the implications of marginal changes in temperature, specifically the importance of a 1°C change. Figure 3 presents the national damages (i.e., an aggregation of regional model predictions) associated with an increase in temperature from 2°C to 3°C in 2050. In contrast to the results in figure 2, the magnitude of the changes in marginal damages does not necessarily align with the total damages by sector. Although coastal properties is the sector with the largest total damages in 2050 (more than $100 billion for a 4°C change; see figure 2), the marginal damages of temperature change are less than the marginal damages for labor and extreme temperature mortality. This is because sea levels, and in turn coastal property damages, are more affected by long-term temperature trajectories than marginal changes. This suggests that policies aimed at reducing the temperature change from 3°C to 2°C in 2050 will reduce the damages in the coastal property sector, but by less than for other sectors, even though the total damages are highest in the coastal property sector.

Role of adaptation

In addition to estimates of damages with no adaptation, we also modeled the marginal damages of temperature changes under full adaptation for three sectors (coastal property, roads, and rail; the lower tier of circles in figure 3). We find that adaptation reduces damages (net of adaptation costs) considerably in all three sectors. More specifically, with adaptation,
marginal damages to coastal properties are reduced by about $14 billion on an annual basis by 2050. In the roads sector, adaptation results in a net benefit of about $1 billion, which is the result of highly cost-effective adaptations for rutting caused by temperature coupled with the positive freeze–thaw effect noted earlier. For rail, adaptation reduces damages from about $800 million to about $400 million per year. As we will discuss later, the potentially large differences between damage estimates with and without adaptation suggests some areas for future research. We did not include a “with adaptation” variant for all of the sectoral models because the underlying CIRA2.0 sectoral study does not yet include an adaptation scenario. Fully capturing adaption in these other sectoral models likely requires not only recognizing a cost-effective path forward, but also overcoming barriers to financing and local acceptance of adaptive measures.19

**Regional variation of marginal damage estimates**

Only 9 of the 97 regional/sectoral combinations have estimated damages that exceed $1 billion; however, with the exception of Northeast/urban drainage, all region/sector combinations have positive estimated damages.20 In some sectors there is significant regional}

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19 See Chambwera et al. (2014) for a summary of the economics of adaptation and barriers to fully cost-effective adaptation.

20 See figure SM-3 in the on-line supplementary materials for the marginal damage estimates by region for each sector for a 1°C temperature change in 2050.
variation, particularly in the coastal property sector, where marginal damages are slightly less than $14 billion in the Southeast and slightly less than $2 billion in the Northeast. The difference in regional results for the coastal property sector is likely due to both the much higher property value exposure and the higher risk of storm surge exposure in the Southeast. The human health sector with the largest damage is labor. However, regional damages vary widely, from about $6 billion per 1°C in the Midwest to less than $500 million per 1°C in the Northwest and Southeast. These types of regional differences are important for understanding which groups stand to gain or lose the most from future climate changes and may provide insights concerning individual incentives to migrate away from the worst manifestations of climate damage and toward less sensitive regions.

Uncertainty of Estimates

There are three main types of uncertainty in estimates of the economic impact of climate change: uncertainty underlying the validity of the detailed sectoral model, uncertainty about the emissions–temperature relationship, and uncertainty associated with estimating a damage function that is based on the sectoral model. We do not address the first type of uncertainty because we have chosen to adopt the CIRA2.0 sectoral models—other sectoral models could also be valid, but we have not examined alternative models here. We focus instead on the joint effect of the second and third types of uncertainty, because we have quantitative estimates for both. In the remainder of this section we first review the basis for estimating uncertainty in the emission–temperature relationship. Then we present our approach for estimating uncertainty in the damage functions. Finally, we review the joint impact of these uncertainties.

Approach for estimating emissions–temperature uncertainty

Yohe (2017) reports temperature trajectories that are designed to achieve different global mean temperature targets and compares these median scenarios for temperature against a “business as usual” scenario from Fawcett et al. (2015). Then, to illustrate the applicability and value added of the uncertain temperature trajectories, Yohe (2017) applied them to estimate U.S. economic damages using results from both Hsiang et al. (2017) and O’Neill et al. (2017), relying on their characterizations of the temperature–economic impact relationships. For both applications, Yohe (2017) presents a discrete range of damages by combining the median and the 5th and 95th percentile damage and temperature estimates. We follow a similar approach here, but rely on a Monte Carlo (i.e., random sampling) method rather than discrete probabilities for combining the estimates.

We use three representative temperature trajectories that limit increases in global mean temperature to 1.5°C, 3.0°C, and 4.5°C above the CIRA2.0 baseline period (1986–2005) (see

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21 This is reflected in the large and statistically significant regional dummy for the Southeast (see the online supplementary materials). The regional dummy measures differences in economic impact relative to the omitted Northeast regional dummy.

22 These possibilities are derived from National Research Council (2010).

23 An example of the application of these discrete probabilities to our damage functions is presented in the online supplementary materials.
Here the distributions are driven by uncertainty about the behavior of GHG sinks (e.g., the deep ocean) at higher temperatures and by uncertainty about the sensitivity of the climate to radiative forcing from GHG emissions. Based on National Research Council (2010), we assume that the 95th percentile temperature for any emission level in 2100 is 70% above the temperature associated with the median temperature and the 5th percentile temperature is 40% below the median. These assumptions allow us to estimate an uncertainty distribution of temperature trajectories (figure 4), which are then used as inputs to the damage functions.

### Uncertainty in estimating damage functions

We estimate uncertainty in the damage functions based on the statistics of the regression estimates—specifically, we use the robust standard error parameter for the temperature coefficient. Figure 5 presents an example of the resulting joint uncertainty in the damage estimation from the GHG to the temperature process and from the temperature to the damage estimation process for one sector (labor) in one region (Southern Plains). As would be expected, the larger damage estimates have larger uncertainty bounds. For all regions and scenarios, we find

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**Figure 4** Trajectories of Global Mean Temperature.

*Source: Authors, based on Yohe (2017).*

*Notes: These trajectories achieve 1.5, 3.0, and 4.5 degrees C global mean temperatures through 2100. The pathways to these end-of-century milestones are shown here with 90% confidence boundaries, indicating the likely range of outcomes under each end-of-century target temperature. Note that there are some overlaps in the likely ranges even at the end of the century, particularly between the 3.0 degree and 4.5 degree scenarios, whose median trajectories are almost identical with each others' 90% confidence boundaries.*

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24 These trajectories are derived relative to a baseline that matches the median no-policy case reported in Fawcett et al. (2015).

25 We use the prediction standard errors to define the median and 5th and 95th percentile damage estimates for each input temperature from a normal distribution.
that the uncertainty ranges in the early years are dominated by the damage function uncertainty, while in the later years they are dominated by temperature uncertainty.\footnote{Examples of uncertainty ranges for a wider range of regions can be found in the online supplementary materials.}

It is important to note that although we have estimated uncertainty ranges for individual regions and sectors, we have not attempted to estimate the uncertainty ranges associated with aggregations of these results (i.e., across regions or sectors). We did not aggregate across sectors for three reasons: damages are valued differently in each sector (e.g., lost wages in labor, lost recreational value in freshwater fish, repair costs for bridges); the 15 individual sectors do not represent the full expected damage across the entire U.S. economy, which means an aggregation would be incomplete and potentially misleading; and the models do not consistently account for substitution across sectors. We support aggregation of the mean economic damage estimates across regions (within sectors). However, aggregation of the 5th and 95th percentiles is potentially problematic because in order to aggregate the uncertainty distributions, we would need to know either that the cross-region uncertainty distributions for each sector are fully independent (which implies we could aggregate using a random sampling technique) or that they are fully correlated (which implies we could aggregate by

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**Figure 5** Estimated Economic Damage Uncertainty Range for the Labor Sector in the Southern Plains Region  
*Source:* Authors’ analysis.  
*Notes:* Gray box represents the 90 percent confidence range of the damage estimate. This shows the uncertainty associated with the estimate of damages in the Labor sector in the Southern Plains under the 3.0 degree global temperature change scenario. The uncertainty range is based on 500 draws of the estimated function applied to each of 500 draws from the 3.0 degree temperature trajectory distribution.
simply summing across regions). Most likely the factors driving uncertainty in the sectoral results across regions are characterized by both independence and correlation, and thus we did not aggregate uncertainty across regions, we only aggregated the means.

Conclusions

Our analysis of the CIRA2.0 sectoral results reported in U.S. Environmental Protection Agency (2017a) makes an important contribution to the development of an internally consistent modeling framework that significantly advances climate damage functions for the United States. In particular, the damage functions presented here increase our understanding of the marginal effect of temperature on economic impacts in the United States. This is an important step in building a “bottom-up” estimate of the marginal benefits of limiting temperature increases in the United States because we rely on a detailed set of 15 sectoral studies, each of which has been independently peer-reviewed, and our analysis covers a large share of U.S. resources that are potentially vulnerable to climate change. The damage functions presented here can be directly applied to the temperature and precipitation pathways forecast by other models and can be used to generate regional-scale damage estimates. Thus these damage functions significantly increase our ability to estimate multisector damages in the United States across multiple alternative future climate pathways.

Another important contribution of the work presented here is that we have developed and applied consistent functions across sectors. These relatively simple damage functions will be useful to researchers and policymakers because they are accessible to all researchers and allow for comparison of economic impacts across sectors. Perhaps more important is the opportunity to use these functions to assess the marginal change in impacts associated with limiting temperature increases in future periods—it is these marginal impacts that are most relevant for policy, because climate change mitigation policy can change a temperature trajectory at the margin by slowing climate change, but it is unlikely to completely eliminate the economic impacts of climate change. For example, we have shown that although the coastal property sector accounts for a larger share of overall economic impacts than any other sector, the marginal impacts of limiting temperature are smaller for the coastal property sector than for several of the health sectors (e.g., labor and extreme temperature mortality) due to the “momentum” in the physical processes that contribute to sea level rise (i.e., heat stored in the oceans over long periods of time), which are difficult to reverse. This means that the impact of policies aimed at reducing marginal changes in temperature are not merely a proportional function of the temperature change; rather they reflect complex sector- and region-specific processes. Taken together, the system of 15 sectoral damage functions provides a rich understanding of how the economic impacts of climate change in the United States depend on temperature outcomes over the twenty-first century.

Limitations of Our Analysis

Our analysis has a number of limitations, including

- the incomplete integration of cross-sectoral results into the system of sectoral economic impacts (e.g., How do climate effects on energy supply affect the deployment of air conditioning to mitigate heat stress effects in the extreme temperature mortality sector?);
the omission of important indirect effects (e.g., How might road and bridge failure affect economic impacts in the coastal property and health sectors, particularly during extreme events? Do the implications of infrastructure failure increase if climate change causes multiple infrastructure systems, such as transportation and energy, to fail at once);

- the incomplete coverage and valuation of ecosystem effects (e.g., What are the implications of sea level rise and storm surge for coastal wetland ecosystems—and what are the effects of coastal adaptation on these ecosystems?); and

- the incomplete treatment of the impacts of extreme events in general, as well as potentially catastrophic events; an example of a catastrophic event that has been at least tentatively linked to climate change is the slowing of the Gulf Stream and the associated heat-transferring ocean currents (technically known as the Atlantic Meridional Overturning Circulation, of which the Gulf Stream is a part). Catastrophic events associated with climate change have potentially large economic consequences, but are also likely to be characterized by very high uncertainty, which greatly complicates the modeling of their economic impact.

These limitations suggest that we have likely underestimated overall climate damages in the United States, largely because our damage functions do not account for some potentially important indirect and ecosystem effects and the impact of some extreme events. Moreover, there are other factors that contribute to both overestimation and underestimation within each sector. For example, in the heat-stress mortality sector we omit adaptation (overestimation bias), but we also do not have complete population coverage (underestimation bias). In the coastal property sector we do not include endogenous reactions by people and markets to limit their exposure to coastal risks that might reduce vulnerability (overestimation bias), but we also omit effects on coastal wetland ecology and nonproperty-related infrastructure (underestimation bias).

Priorities for Future Research

These limitations and their implications for bias in our estimates also suggest some important areas for future research that could improve the usefulness of damage functions for policy analysis. First and foremost is the need to improve the data and methods to fill the gaps in sectoral coverage, indirect economic effects, and impacts of extreme and catastrophic events. Expansion of the damage function estimates to sectors and research that are not included in the CIRA2.0 project, such as the assessment of climate change impacts on property and violent crime (as described in Hsiang et al. 2017), is a logical next step. It may also be possible to use other sectoral analyses in order to better characterize the uncertainty in the choice of economic impact models—for example, impacts in the U.S. coastal property sector have been examined by at least two research groups that are not part of the CIRA2.0 project (see Dinan [2017] and Hsiang et al. [2017]).

Important questions also remain concerning the best way to treat GDP in these types of damage functions. The lack of regional GDP projections in our analysis prevented us from

27 See Neumann and Strzepek (2014) for a more complete discussion.
28 See Martinich and Crimmins (2019) for a more detailed discussion of uncertainties in all of the underlying sectoral models.
exploring in detail (in this article) the effect of GDP on damages. Many IAMs (e.g., Policy Analysis of the Greenhouse Effect [PAGE], Regional Integrated Climate–Economy [RICE] and Dynamic Integrated Climate–Economy [DICE], Framework for Uncertainty, Negotiation, and Distribution [FUND], Integrated Model to Assess the Global Environment [IMAGE]) calculate climate damages based on a combination of temperature and GDP. Thus the results of the reduced-form analysis presented here will be most useful if they can identify the marginal impact of GDP on damages.

There are also other methodological challenges, because the relationship between damages and GDP-driven exposure to climate stressors is complex. On the one hand, economic growth may increase vulnerability to climate (see, e.g., Fisher-Vanden, Popp, and Wing [2014] and Moore and Diaz [2015]); for example, economic growth can lead to expansion of climate-vulnerable infrastructure. On the other hand, economic growth can also reduce the sensitivity to climate by, for example, hardening existing infrastructure networks such as coastal defenses and bridges or improving delivery of health services. We are nonetheless optimistic that future research that includes regional GDP trajectories will be able to identify the marginal impact of GDP on damages.

Finally, a clear research priority is to improve our understanding of how adaptation might affect estimates of the economic impacts of climate change. The CIRA2.0 sector studies for which we have estimated both “no adaptation” and “with adaptation” results suggest that adaptation is likely to be very cost effective. Although adaptation investments can be shown to be cost effective, recent experience with hurricane damages indicates that the United States is poorly adapted to the current climate, perhaps due to financial, behavioral, or institutional barriers (Chambwera et al. 2014; Yohe and Mann 2018). It is also increasingly clear in sectors such as coastal property that the level of capital investment needed to substantially reduce climate impacts through adaptation (see figure 3) has not yet been mobilized (Fleming et al. 2018). Because important barriers to implementing cost-effective adaptation remain, even in developed countries like the United States, it is important to continue research on the issue of how to best use damage functions that assume “no adaptation,” “optimal adaptation,” or something in between when developing climate policy.

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