



Analysis

Projected Increases in Hurricane Damage in the United States: The Role of Climate Change and Coastal Development



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ABSTRACT

The combined forces of climate change and coastal development are anticipated to increase hurricane damage around the globe. Estimating the magnitude of those increases is challenging due to substantial uncertainties about the amount by which climate change will alter the formation of hurricanes and increase sea levels in various locations; and the fact that future increases in property exposure are uncertain, reflecting local, regional and national trends as well as unforeseen circumstances. This paper assesses the potential increase in wind and storm surge damage caused by hurricanes making landfall in the U.S. between now and 2075 using a framework that addresses those challenges. We find that, in combination, climate change and coastal development will cause hurricane damage to increase faster than the U.S. economy is expected to grow. In addition, we find that the number of people facing substantial expected damage will, on average, increase more than eight-fold over the next 60 years. Understanding the concentration of damage may be particularly important in countries that lack policies or programs to provide federal support to hard-hit localities.

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1. Introduction

Climate change is likely to increase the frequency of the most intense categories of hurricanes in some parts of the world, including the North Atlantic Basin, and is expected to increase sea levels, leading to more destructive storm surges when hurricanes occur (see IPCC, 2013). Moreover, growing populations and rising incomes are expected to place more people and property in harm's way. This paper estimates the increase in U.S. hurricane damage between now and 2075 using a Monte Carlo framework. We simulate damage 5,000 times, with each simulation providing an estimate of expected damage based on a unique set of draws from the projected distributions of four factors that determine damage: hurricane frequencies, location-specific sea levels, and changes in population and per capita income in coastal counties (which serve as proxies for increases in property exposure). We compare the distribution of expected damage in 2075 to an estimate of expected hurricane damage based on current conditions.

The importance of accounting for the effects of both climate change and increases in exposure in estimating the damage from extreme events was highlighted in a special report by the Intergovernmental

Panel on Climate Change (IPCC, 2012) and in the most recent National Climate Assessment (Melillo et al., 2014).¹ Moreover, Nicholls et al. (2008) estimates that the total value of global assets exposed to damage from coastal flooding from storm surge and damage due to high winds (in 135 port cities) was around 5% of global GDP in 2005 (measured in international USD). In the case of hurricanes, climate change will exacerbate damage on both existing and newly constructed properties and increases in property exposure will aggravate the escalation of hurricane damage that climate change would otherwise bring about.

Our analysis builds on previous studies that have examined the effects of climate change on coastal communities in the United States. For example, Yohe (1990) develops a method of estimating nationwide damage from sea level rise (SLR) and Neumann et al. (2015) examines the joint effects of storm surge and sea level rise. Houser et al. (2015), uses estimates of future hurricane frequencies and location-specific

¹ Much of the early literature on sea level rise addressed its direct effects such as inundation and erosion rather than its effect on damage from storm surges. Besello and Cian (2014) describe the types of models used to measure effects and group them into "bottom up" and "top down" approaches, with the former providing much greater spatial resolution and the latter assessing economy-wide impacts. Our analysis would be classified as a bottom up approach.

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estimates of increases in sea levels to project how climate change will increase both wind and storm surge damage due to hurricanes; however they do not account for the effects of coastal development. (For a discussion of variation in sea level rise, see Sallenger et al., 2012). Pielke et al. (2008) demonstrates the importance of accounting for changes in property exposure in explaining historic trends in hurricane damage; however, given the infrequency of hurricanes and the importance of the point of landfall in determining damage, historic records may not be long enough to detect the effects of climate change (Hallegatte, 2007). Nordhaus (2010) uses historic data to construct a damage function that relates wind speed to damage and estimates future increases in U.S. hurricane damage due to the changes in the frequency and intensity of hurricanes that would be associated with an equilibrium doubling of CO₂-equivalent atmospheric concentrations. Mendelsohn et al. (2011) also constructs a damage function based on historic data (using barometric pressure as well as wind speed) and estimates increases in U.S. hurricane damage due to changes in hurricane frequencies. They estimate the effects of coastal development using county level estimates of changes in population and per capita income. Neumann et al. (2015) estimate U.S. damage resulting from the joint effect of SLR and storm surges through 2100. Their analysis primarily focusses

on the potential effects of mitigation and adaptation (see the discussion section below).

Our work most directly expands on the work of Hauser et al. (2015) and Mendelsohn et al. (2011). Like Hauser et al., we compare expected damage under current conditions and under future conditions (reflecting climate-induced changes in hurricane frequencies and sea levels). We expand on that work by using a much wider range of predictions about changes in U.S. hurricane frequencies (reflecting the significant underlying uncertainties about the effects of climate change on hurricane formation) and by accounting for the interaction between climate change and coastal development. Like Mendelsohn et al., we use county-level changes in population and per capita income in estimating exposure. We expand on their work by weighting county-level estimates based on each county's relative vulnerability to damage from wind and storm surges, by accounting for the location-specific effects of sea level rise on damage, and by constructing estimates of future damage that explicitly account for uncertainty in the underlying drivers of damage (changes in hurricane frequencies, sea levels, and location-specific populations and per capita incomes).

While our damage estimates are specific to the United States, our approach can be applied in other countries. That approach, however,

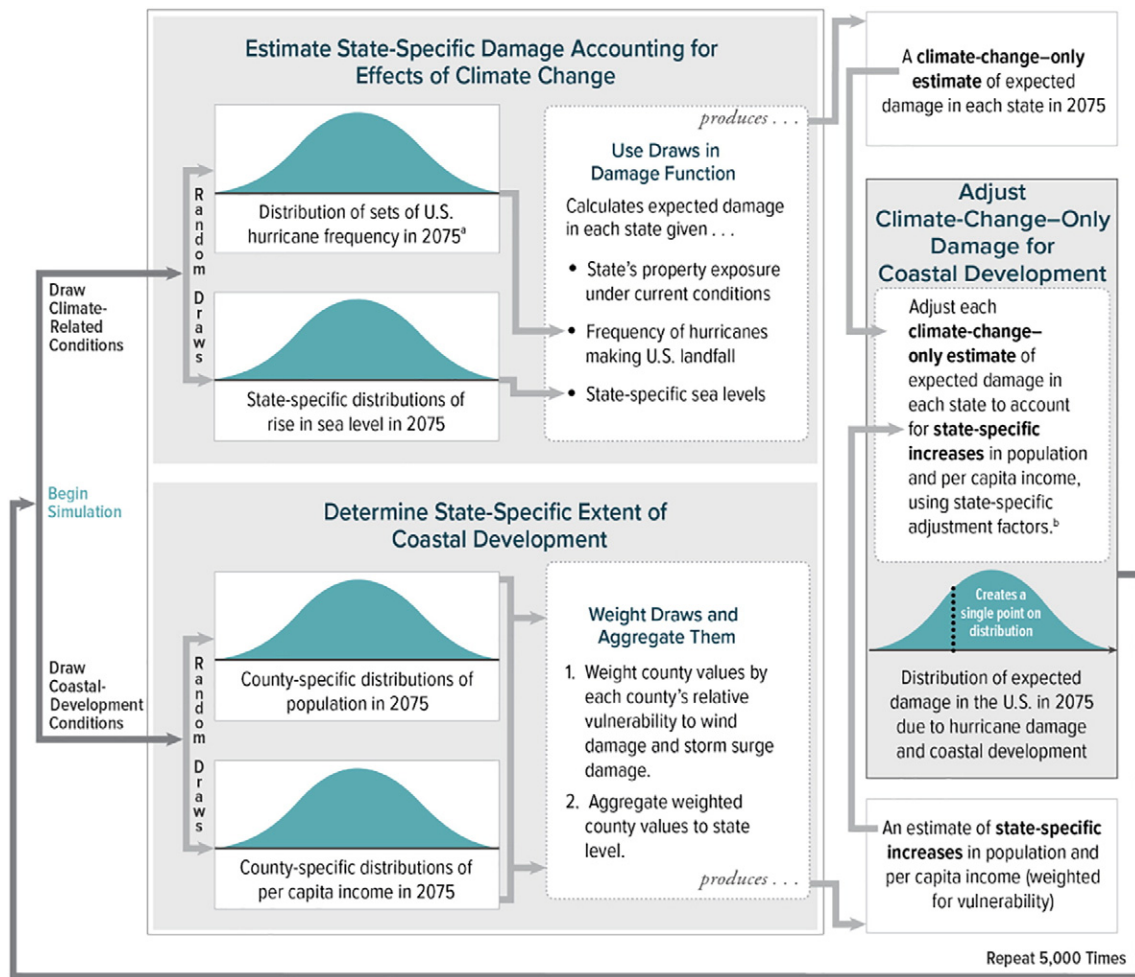


Fig. 1. Flow of the model for estimating the effects of climate change and coastal development on hurricane damage in 2075. a. Each set consists of a projection of frequency for hurricanes in each of five categories. (The five categories of hurricanes are based on peak wind speed. Category 5 storms are the most intense.) b. Each state's increase in expected damage due to an increase in its population and per capita income is uniquely determined based on the share of the state's expected damage (measured under current conditions) that comes from wind versus storm surge damage. That unique determination incorporates different responses of wind and storm surge damage to a given increase in population and per capita income.

requires detailed data on property exposure; thus, our approach may be more applicable to developed countries—with plentiful data. In contrast, Bertinelli et al. (2016) uses an approach that may be applicable to countries with limited data. They predict expected hurricane damage—based on current conditions—for islands in the Caribbean using synthetic hurricane tracks and the existing level of development on the islands. Given data limitations, they approximate local property exposure using satellite-derived measures of nightlight intensity.

The paper consists of six sections. The following section discusses the Monte Carlo framework used in the analysis. The third section describes the data. The fourth section describes the results and sensitivity analysis and the fifth and sixth sections offer discussion and conclusions.

2. Overview of the Monte Carlo Framework

We construct a distribution of hurricane damage by simulating damage 5,000 times, with each simulation, n ($n = 1$ to 5,000), based on a unique set of values for changes in the frequency of hurricanes and for state-specific estimates of sea level, population, and per capita income selected from distributions for 2075. The model includes 22 states—all of which we estimated to have a nonzero probability of incurring hurricane damage. Because growth in some counties (directly on the coast, for example) will have a larger effect on damage than growth in other counties, measures of population and per capita income were weighted on the basis of their relative vulnerability to hurricane damage, with \tilde{p} and \tilde{y} indicating vulnerability-weighted population and per capita income, respectively, and p and y indicating unweighted values.

The 2075 values for hurricane frequencies, f , sea levels, s , vulnerability-weighted population, \tilde{p} , and vulnerability-weighted per capita income, \tilde{y} , in turn, were each selected from individual distributions. The shape of the damage distribution in a particular year depends on the shape of the distributions for f , s , \tilde{p} , and \tilde{y} and on the relationship between those variables and hurricane damage (described in detail below). Each value for f includes a set of frequency values for each hurricane Category c , $c = 1$ (for a Category 1 hurricane, which consists of the least intense storms) through $c = 5$ (for a Category 5 hurricane, which consists of the most intense storms).

We compare the distribution of expected damage in 2075 with an estimate of expected damage in a reference case. For the reference case, hurricane frequencies, f , were based on estimates for 2010, and all other variables, s , \tilde{p} , and \tilde{y} , were set at their estimated values for 2015. For notational convenience throughout this paper, the 2075 subscript is suppressed. Subscripts i , j , and k are used to indicate county, state, and region, respectively; subscript n indicates that the variable takes on a different value in each n th simulation; and subscript R indicates that the variable is set at its reference value. Thus, for example, $s_{j,n}$ denotes sea level in state j in the n th simulation, and $s_{j,R}$ denotes sea level in state j in the reference case. For general purposes, a damage estimate for state j can be described as $D_j(f_x, s_{j,x}, \tilde{p}_{j,x}, \tilde{y}_{j,x})$, where $x = R$ indicates that D_j was calculated with the variable set at its reference value, and $x = n$ indicates that D_j was calculated with the variable set at its value selected in the n th simulation.

Each simulation of the model begins with a set of draws for all four of the conditions that affect expected hurricane damage (see Fig. 1). Each n th simulation of the model determines a set of state-specific estimates of expected damage (reflecting only the effects of climate change) based on the draws for hurricane frequency, f , and sea levels, s , in that simulation; existing property exposure in each state; and a set of damage functions developed by Risk Management Solutions (RMS), which analyses risk exposure for insurance companies. Those functions estimate expected damage on a state-specific basis, given: existing exposure of residential and nonresidential property in the state, landfall of a specific category of hurricane anywhere in the United States, and state-specific

estimates of sea levels.² We then adjusted those climate-only damage estimates to reflect the effects of coastal development. That adjustment is based on draws of each county's population and per capita income in 2075—which are weighted to reflect the county's relative vulnerability to damage from wind and storm surges and then aggregated to the state level (creating variables \tilde{p} and \tilde{y})—along with state-specific inflation factors (described below).

For each simulation, n , values of the four random variables f , s , \tilde{p} , and \tilde{y} were drawn from their individual distributions, and those variables were used to estimate expected damage for each state j ($j = 1$ through 22). The n th damage estimate (corresponding to the n th simulation) for state j is:

$$D_j(f_n, s_{j,n}, \tilde{p}_{j,n}, \tilde{y}_{j,n}) = \sum_{c=1}^5 f_n(c) d_{j,n}(c, s_{j,n}, \tilde{p}_{j,R}, \tilde{y}_{j,R}) g_{j,n}(\tilde{p}_{j,n}, \tilde{y}_{j,n})$$

where:

- $d_{j,n}(c, s_{j,n}, \tilde{p}_{j,R}, \tilde{y}_{j,R})$ is the expected damage in dollars in state j , given U.S. landfall of a hurricane of Category c , the specific value of sea level for state j selected for the n th simulation, and state j 's population and per capita income in the reference case (reflecting state j 's property exposure in 2015); and

² We defined the frequency of hurricanes but relied on RMS's model to indicate the probability of landfall at various locations. RMS estimated the probability that a hurricane of a particular category will make landfall at any given location by simulating tens of thousands of stochastic events that represent more than 100,000 years of hurricane seasons under current conditions. The stochastic storms are constrained to follow physically realistic pathways with the landfall frequencies constrained to the observed frequencies over the past 100 years. To estimate the damages from the storms winds RMS uses a parametric wind hazard model to generate wind fields and peak gusts and relate the expected physical damage for buildings and contents to the modeled peak 3-second gust wind speed at that location. To estimate damages from storm surges RMS uses a hydrodynamic storm surge hazard model to generate storm surges and wave action. Large storm surges can result from the low pressure and wind stress acting for many days before the storm nears the coast and RMS's storm surge model is driven by the wind stress from the time-stepping wind fields and the hurricane's low-pressure field together with changes in sea levels that accompany tides from the genesis of each individual stochastic storm. Sea level rise can be accounted for as a higher launch point for storm surges: for example, a two foot SLR equates directly to two feet extra surge depth for any storm. A storm-surge vulnerability model relates expected physical damage to buildings and contents to modeled flood depth and wave action. Those relationships are based on observations compiled by the U.S. Army Corps of Engineers from major U.S. flood events and structural-engineering-based adjustments to account for the effects of building height and construction class. Finally, the storm-surge vulnerability functions are calibrated and validated using claims data from historic storms. For a more detailed description, see Delgado et al. (2015), pp. 290–291. We used the same version of the model as described in Delgado et al., but used our own estimates of hurricane frequencies and SLR. In addition we estimated changes in damage due to changes on vulnerability-weighted population and per capita income; the RMS model, in turn, uses current property exposure. We assessed the validity of RMS damage functions by comparing RMS's damage estimates for actual hurricanes that have occurred since 2002 with estimates generated by the National Oceanic and Atmospheric Administration (NOAA). (For a description of NOAA's method of estimating damage, see Smith and Katz (2013)). For this purpose, RMS modeled the specific storms by using current estimates of property exposure trended to the time the hurricane occurred. For individual storms, some of RMS's estimates were higher than NOAA's (most significantly for Hurricane Katrina); however, on average, RMS's estimates were lower—equal to 80 percent of NOAA's estimates. Excluding Hurricane Katrina from the calculation, RMS's estimates were, on average, 2 percent higher than NOAA's. In the case of Katrina, RMS's method for adjusting losses/property exposure (i.e. the method to adjust downward their measure of 2015 exposure to estimate exposure in 2005) is not able to replicate the significant decrease in exposure in New Orleans caused by Hurricane Katrina. As a result, the RMS model underestimates property exposure in New Orleans in 2005, and thus underestimates damage due to Hurricane Katrina. As further evidence of the validity of the RMS model we note that RMS model is certified by the Florida Commission on Hurricane Loss Projection Methodology (<https://www.sbafla.com/method/>) for use in Florida and is widely used by insurance and re-insurance companies as well as in the capital markets and in insurance linked securities. The RMS surge model in particular was used in modeling the risk associated with the purchase of insurance protection purchased by the Metropolitan Transportation Authority to help pay for future repairs for damage to its infrastructure in the event of a storm featuring destructive storm surges similar to those experienced during Superstorm Sandy.

- $g_{j,n}(\ddot{p}_{j,n}, \ddot{y}_{j,n})$ is a damage inflation factor. It increases $d_{j,n}(c, s_{j,n}, \ddot{p}_{j,R}, \ddot{y}_{j,R})$ on the basis of the estimates of state j 's vulnerability-weighted population and per capita income in year t as selected in the n th simulation. As described below, each state's population and per capita income can be affected by rising sea levels.

The damage inflation factor, $g_{j,n}$, depends on the change in population and per capita income in each state (relative to 2015) and a set of state-specific population and per capita income elasticities (indicating the percentage change in expected damage given a percentage change in population or per capita income). Specifically,

$$g_{j,n}(\ddot{p}_{j,n}, \ddot{y}_{j,n}) = 1 + \Delta \ddot{p}_{j,n} \epsilon_j^p + \Delta \ddot{y}_{j,n} \epsilon_j^y$$

where:

- $\ddot{p}_{j,n}$ = the vulnerability-weighted population of state j in the n th simulation
- $\Delta \ddot{p}_{j,n} = \frac{\ddot{p}_{j,n}}{\ddot{p}_{j,R}} - 1$
- $\ddot{p}_{j,R}$ = the vulnerability-weighted population of state j in the reference case
- ϵ_j^p = the percentage change in expected damage in state j given a percentage change in population in state j
- $\ddot{y}_{j,n}$ = the vulnerability-weighted per capita income value for state j in the n th simulation
- $\Delta \ddot{y}_{j,n} = \frac{\ddot{y}_{j,n}}{\ddot{y}_{j,R}} - 1$
- $\ddot{y}_{j,R}$ = the vulnerability-weighted per capita income of state j in the reference case
- ϵ_j^y = the percentage change in expected damage in state j given a percentage change in per capita income in state j .

Total expected damage in the United States corresponding to the n th simulation is obtained by aggregating across the 22 state damage estimates for that simulation:

$$D_n = \sum_{j=1}^{22} D_j(f_n, s_{j,n}, \ddot{p}_{j,n}, \ddot{y}_{j,n})$$

We repeated this process 5,000 times to generate a distribution of expected U.S. hurricane damage in 2075. Next, we compared that distribution with a reference case, which is the estimate of expected damage obtained by setting all variables at their reference levels (denoted by subscript R):

$$D_R = \sum_{j=1}^{22} D_j(f_R, s_{j,R}, \ddot{p}_{j,R}, \ddot{y}_{j,R})$$

As described below, 2075 county-level mean estimates of population and per capita income are subject to both county-level and regional shocks. While those shocks result in individual county populations differing from their mean estimates, those draws are not coordinated (some counties and regions could experience negative shocks while others experience positive shock) as a result, population projections are consistent with the Congressional Budget Office's estimate of GDP for 2075.³ If this were not the case, and negative shocks implied a lower national or global output, then draws with negative shocks

could entail lower emissions and less change in sea levels and hurricane frequencies; although, the sea levels over the next few decades are generally found to be unresponsive to changes in emissions over that same time period (Kopp et al., 2014).

Draws of hurricane frequency and sea level rise are assumed to be independent, reflecting the lack of responsiveness of sea level rise to changes in emissions and the substantial uncertainty surrounding the effects of climatic conditions on hurricanes. To the extent that higher sea levels are correlated with higher frequencies of intense hurricanes over the time period that we consider, our distribution of damage could have a thinner tail than would actually be the case—that is, we would underestimate the magnitude of high damage outcomes.⁴

3. Data

As describe above, each simulation was based on a unique set of draws from projected distributions of four factors that affect the magnitude of damage: changes in hurricane frequencies, sea level rise, and growth in the population and per capita income of coastal counties (which are aggregated to the state level for use in the simulation). The method used to construct those distributions is briefly summarized in Table 1 and described in detail below.

3.1. Frequency of Hurricanes

The estimated effects of climate change on the frequency of various categories of hurricanes in the North Atlantic Basin depend on how changes in the climate alter conditions affecting hurricane formation as well as how changes in those conditions affect the occurrence of hurricanes of various intensities.

To reflect the considerable amount of uncertainty surrounding those elements, we used 18 different sets of predictions about the frequency of hurricanes in the North Atlantic Basin—with each set providing a prediction of the annual frequency of each of the five categories of hurricanes. Eleven of the 18 sets were based on a downscaling model, which translates changes in hurricane-forming conditions into changes in hurricane occurrences in a particular region, by Knutson et al. (2013) and the remaining 7 sets were based on a downscaling model developed by Emanuel (2013). Draws were determined by a two-step selection process, such that there was an equal probability (0.5) of choosing a set of projections from either modeler and, given the modeler selection, there was an equal probability of drawing any one set of his projections. This process avoided overweighting Knutson's results, simply because we had more of his projections. Based on this two-step process, the probabilities were about 4.5% (0.5/11) for each of Knutson's sets and about 7% (0.5/7) for each of Emanuel's sets. Knutson's and Emanuel's projections reflect the significant uncertainty associated with the effects of climate change on hurricane frequency (see Fig. 2). However, both researchers find a significant increase in the occurrence of major hurricanes (Category 3, 4 and 5 storms).

As inputs, Knutson and Emanuel's downscaling models relied on projections of hurricane-forming factors (such as sea surface temperature and wind shear) that were obtained as outputs from a number of coupled atmosphere-ocean general circulation models (AOGCMs). Those AOGCMs were used in the Coupled Model Intercomparison Project (CMIP), an undertaking in which all of the models are run using a particular assumption about the concentration of greenhouse gases in the atmosphere, referred to as representative concentration pathways (RCP).

Emanuel projected landfalls of hurricanes in the United States on the basis of outputs of six of the AOGCMs that were used in the most recent

³ See June 2015 long term budget projections in CBO (2015). As described below, the method we used preserves the underlying variation in counties' growth rates while ensuring that the county-specific projections are consistent with the aggregate U.S. population projection (Smith et al., 2002).

⁴ Conte and Kelly (2016) estimate that the historic distribution of hurricane damage is fat-tailed, primarily due to the fact that the distribution of coastal population is fat-tailed.

Table 1
Summary description of the development of variable used in the Monte Carlo model.

Variable	Source	Description of distribution
Set of U.S. hurricane frequencies in 2075	CMIP5 output used in downscaling models by Emanuel (2013) and Knutson et al. (2013) with supplemental data provided by the authors.	Draws from 18 sets of output (see Fig. 2) were determined by a two-step selection process, such that there was an equal probability (0.5) of choosing a set of projections from either modeler and, given the modeler selection, there was an equal probability of drawing any one set of his projections.
State-specific estimates of sea level rise in 2075	Decade-specific percentile estimates developed by Kopp et al. (2014) for 79 locations defined by latitude and longitude, which were mapped states by Risk Management Solutions.	Each of the nine percentiles that Kopp developed were translated into probabilities (see Table 2). For example, the 66.7th percentile was chosen with a probability of 0.172, or 17.2% of the time. For each simulation, the same percentile was used for all the states.
County-specific population estimate in 2075	Mean projections based on each county's population growth between 2000 and 2010 relative to that of the total U.S. population over the same period and Congressional Budget Office (2015) population projections for 2075.	Mean projections were subject to county-specific shocks and regional shocks, each of which were determined by random draws from a standard normal distribution. We defined four regions for determining regional growth patterns and estimated a correlation coefficient for each region. The standard deviation of each county was equal to 10, 11 or 12% of its mean population (with larger percentages used for larger counties).
County-specific per capita income estimate in 2075	Mean projections based on a weighted average of: (1) its growth rate between 1990 and 2000 (the decade preceding the recession), (2) its growth rate between 2000 and 2010, which reflects the effects of the recession and (3) CBO (2015) projected growth in per capita income for the United States as a whole.	County-specific per capita income projections were developed using the same method described above with income-specific correlation coefficients for each region and a standard deviation equal to 11% of the county's mean per capita income projection.

CMIP (CMIP5) as well as the “CMIP5 ensemble,” which are the values of hurricane-influencing factors obtained by averaging the results of each AOGCM.⁵ Knutson estimated hurricane occurrences in the North Atlantic by using projections from the CMIP5 ensemble as well as results from 10 individual AOGCMs used in an earlier phase of the CMIP, CMIP3.⁶ On the basis of advice provided by Knutson, we used the percentage variations found between his model's downscaling of individual CMIP3 model results and the downscaling of the CMIP3 ensemble results to build an equivalent amount of variation around his CMIP5 ensemble results. This allowed us to capture the sensitivity of his downscaling model to variation in the inputs derived from individual AOGCMs while also basing his projections on the most recent CMIP5 modeling. Our use of an expanded set of hurricane frequency predictions—reflecting a fuller range of the uncertainty about the effects of climate change on hurricane occurrences—is a primary difference between our model and that of Houser et al. (2015).

Emanuel and Knutson's hurricane projections were derived using different assumptions about concentrations of greenhouse gases in the atmosphere. Specifically, Emanuel projected landfalls on the basis of model runs that corresponded to an RCP of 8.5, a concentration that would be likely to result from relatively few limitations on global emissions. In contrast, Knutson estimated hurricane occurrences based on AOGCM runs that predicted results from scenarios which corresponded to a lower concentration of greenhouse gases (RCP 4.5).⁷ Ceteris paribus, constructing distributions of hurricane damage based projections of frequencies corresponding to different RCPs could provide an indication of the effects of alternative emission reduction strategies; however, differences between Knutson's and Emanuel's predictions are driven by substantial differences in their downscaling models in

addition to differences in the RCP scenarios. Model-based differences can be seen by comparing differences in Knutson's and Emanuel's predictions for 2025. Differences in emissions paths under the two different RCP scenarios should have little effect on hurricane frequencies over the course of a decade; however, the two downscaling models yield very different frequency predictions for 2025. Knutson's model yields a substantially wider range of predictions than Emanuel's—including multiple results showing decreases in frequencies relative to current conditions. Due to our inability to attribute differences in predictions to RCP scenarios, rather than due to significant differences in the models themselves, we pooled the model results. As a result, our simulations reflect uncertainty about future emissions as well as the substantial uncertainties about the manner in which changes in climatic conditions will affect U.S. hurricane landfalls. We explore the implications of pooling the two modelers' results in a sensitivity analysis described below.

3.2. Sea Levels

As the climate warms, sea levels rise because of the thermal expansion of seawater and the melting of ice sheets in Greenland and Antarctica. Moreover the amount of increase will vary along the Atlantic and Gulf coast for a variety of reasons, including non-uniform changes in ocean dynamics, heat content, and salinity. Rising sea levels, in turn, add to hurricane damage by providing a higher “launch point” for storm surges, yielding more damage from any particular storm than would otherwise be the case. Our analysis is based on regional estimates of sea level rise, developed by Kopp et al. (2014), that combine predictions associated with three different concentrations of greenhouse gases: RCPs 2.6, 4.5, and 8.5.⁸ Specifically, Kopp estimated decade-specific percentile estimates for 79 locations defined by latitude and longitude, which RMS mapped into states for use in their damage functions. (We interpolated 2070 and 2080 results to obtain 2075 estimates.) Kopp finds significant variation along the U.S. coastline. For example, the average increases in Florida, Texas, and Louisiana (which together comprise nearly two-thirds of expected hurricane damage under current conditions) are estimated to be 1.4 ft, 2.1 ft, and 2.8 ft, respectively. The probabilities that we attached to each of the nine percentiles that

⁵ The hurricane projections that Emanuel based on the CMIP5 ensemble results are shown in Kerry A. Emanuel, “Downscaling CMIP5 Climate Models Shows Increased Tropical Cyclone Activity Over the 21st Century,” *Proceedings of the National Academy of Sciences*, vol. 110, no. 30 (July 2013), pp. 12219–12224, www.pnas.org/content/110/30/12219. The results from the downscaling of individual AOGCM models were obtained directly from the author and have not yet been published.

⁶ Knutson's method and the CMIP5 ensemble results are shown in Thomas R. Knutson and others, “Dynamical Downscaling Projections of Twenty-First-Century Atlantic Hurricane Activity: CMIP3 and CMIP5 Model-Based Scenarios,” *Journal of Climate*, vol. 26, no. 17 (September 2013), <http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12-00539.1>.

⁷ For RCPs 4.5, and 8.5, the IPCC predicts an increase in global surface temperature, averaged between 2081 and 2100 (and measured relative to pre-industrial levels), of 1.8 °C, and 3.7 °C, respectively (see IPCC, 2013, p.23).

⁸ Kopp estimated decade-specific percentile estimates for 79 locations defined by latitude and longitude. (We interpolated 2070 and 2080 results to obtain 2075 estimates.) Those locations were mapped into states for use in RMS damage functions.

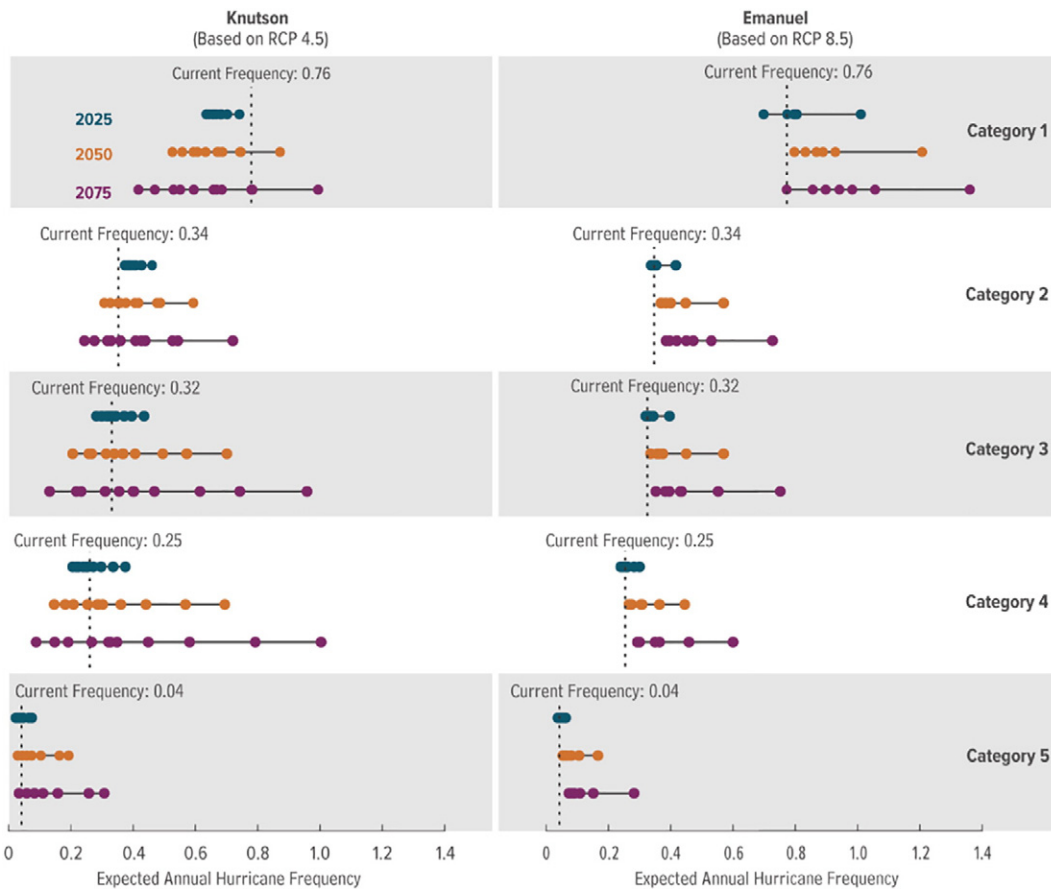


Fig. 2. Expected hurricane frequency by researcher, category, and year. Each circle indicates a projection made by the researcher on the basis of a unique set of factors that influence hurricanes, such as sea surface temperature and wind shear. Those factors were obtained from various atmospheric oceanic general circulation models, with each model projecting outcomes based on a given concentration of greenhouse gases in the atmosphere.

Kopp developed are shown in Table 2; for example, the 66.7th percentile was chosen with a probability of 0.172, or 17.2% of the time. For each simulation, the same percentile was used for all the states.

We did not have access to data on RCP scenario-specific SLR; however, differences in greenhouse gas concentrations are expected to have relatively modest effects on the magnitude of SLR over the time period that we consider. That outcome is reflected in the results of Houser et al. (2015), who did have RCP scenario specific increases. For the period 2020–2030 they found that expected hurricane damage was 8% higher under the RCP 8.5 scenario than under either the RCP 4.5 scenario or the RCP 2.6 scenario (holding the frequency of hurricanes constant at their current levels). For the period 2080–2099, they estimated that the gap with the RCP 8.5 scenario grew to 16% and 29% for the RCP 4.5 and RCP 2.6 scenarios, respectively.⁹ Because we estimate damage for 2075 (when the gap between even the two most extreme scenarios should be <29%), and are primarily focused on understanding the interaction of climate change and coastal development, we do not consider the lack of RCP-specific SLR scenarios to be a major limitation.

3.3. Vulnerability-weighted Population Estimates for Each State

As described above, we use county level projections of population and per capita income as a proxy for property exposure, a method

that is consistent with previous research on hurricane damage. Because growth in some counties (those directly on the coast, for example) will have a larger effect on the state's expected damage than growth in others, we weighted each county on the basis of its relative vulnerability to hurricane damage. Those vulnerability-weighted county estimates were then aggregated to the state level. We also allow for increases in sea level to slow growth in population and per capita income.

3.3.1. Estimates of County Population

Our model incorporates 777 counties, including all counties that were found to have a nonzero probability of incurring hurricane damage. For each simulation, we used a county population estimate that was based on a mean projection and on both a regional shock and a county shock, such that the shocks affecting counties within a region had a joint normal distribution. We adjusted county means on the

Table 2
Percentiles and corresponding probabilities of rising sea levels.

Percentile observation for rising sea levels	Probability of drawing the percentile observation
0.5	0.017
5.0	0.078
16.7	0.146
33.3	0.172
50.0	0.171
66.7	0.172
83.3	0.146
95.0	0.078
99.5	0.017

⁸ Kopp estimated decade-specific percentile estimates for 79 locations defined by latitude and longitude. (We interpolated 2070 and 2080 results to obtain 2075 estimates.) Those locations were mapped into states for use in RMS damage functions.

⁹ See Houser et al. (2015), Figure 11.5, p. 114.

basis of potential increases in damage in a given state resulting from rising sea levels, allowing significant increases in expected damage from storm surges to slow the county's population growth:

$$p_{i,n}(\theta_{i,n}, z_{k,n}^p, v_{i,n}^p) = (\bar{p}_i - \theta_{i,n} \sigma_i^p) + z_{k,n}^p \sigma_i^p \rho_k^p + v_{i,n}^p \sigma_i^p [1 - (\rho_k^p)^2]^{1/2}$$

where:

- $p_{i,n}$ county i 's estimated population projection in the n th simulation
- $\theta_{i,n}$ an adjustment to county i 's mean population projection on the basis of the extent to which rising sea levels in the n th simulation are estimated to increase damage in the state in which county i resides (see a more detailed description of $\theta_{i,n}$ below)
- $z_{k,n}^p$ the draw for the population shock for region k (in which county i resides) in the n th simulation, obtained from a standard normal distribution
- $v_{i,n}^p$ the draw for the population shock for county i in the n th simulation, obtained from a standard normal distribution
- \bar{p}_i county i 's mean population projection (a fixed value estimated by the method described below)
- σ_i^p the standard deviation of county i 's population distribution, a fixed value that is equal to $x\bar{p}_i$, where $x = 0.1, 0.11, \text{ or } 0.12$, depending on the county's 2010 population)
- ρ_k^p the correlation between the historical population growth rate of region k and the population-weighted growth rates for the individual counties within the region (estimated by the method described below).

The standard deviations that we used were based on Smith et al. (2002). Standard deviations are likely to be larger for smaller cities because a given change in population (for example, if the opening of a new manufacturing plant attracted 7,000 new residents) corresponds to a larger share of the existing population of a small city than of a larger one.

For all but 26 of the 777 counties, we projected their population growth between 2010 and 2040 on the basis of their historic population growth between 2000 and 2010 relative to that of the total U.S. population over the same period. For example, if a county accounted for 1% of the growth in the total U.S. population between 2000 and 2010, then it would account for 1% of the growth in the U.S. population over the forecast period. That method preserves the underlying variation in counties' growth rates while ensuring that the county-specific projections are consistent with the aggregate U.S. population projection (Smith et al., 2002). County-specific projections were designed to be consistent with the Congressional Budget Office's projections for 2075.¹⁰

For the remaining 26 counties we used county-specific population projections that were made for regional planning purposes by county or city planning departments, state governments, or state universities. Those counties included the 20 counties with the largest populations in 2010 and 6 counties that had populations of > 100,000 in 2010 and had a difference of two or more percentage points between the average annual growth over the 1950–2010 period and the 2000–2010 period. Those two criteria captured counties, such as the parishes surrounding New Orleans, which experienced a sharp decline in population after Hurricane Katrina in 2005. For 2040 and beyond we estimated that all 777 counties would grow at the same rate as the United States as a whole.

County-specific population shocks and regional shocks were each determined by random draws from a standard normal distribution.

We defined four regions for determining regional growth patterns and estimated a correlation coefficient, ρ_k^p , for each region:

- Florida Gulf (Alabama, Florida, Louisiana, Mississippi, and Texas)— $\rho^p = 0.287$
- Southern Coastal (Georgia, North Carolina, and South Carolina)— $\rho^p = 0.184$
- Mid-Atlantic and Northern (Connecticut, Delaware, Maryland, Massachusetts, New Jersey, New York, Pennsylvania, Rhode Island, Virginia, and West Virginia, as well as Washington, D.C.)— $\rho^p = 0.149$
- Far Northern (Maine, New Hampshire, and Vermont)— $\rho^p = 0.469$.

The values for ρ_k^p were obtained by regressing each county's decade-specific population growth rate (for each decade between 1950 and 2010) against the decade-specific population growth rate for the region in which the county resides. Each county's decade-specific growth rate was weighted by its population in that decade.

We accounted for the potential for rising sea levels—and the resulting increase in expected hurricane damage from storm surges—to slow population growth in vulnerable states. Our adjustment factor incorporates a threshold effect and an upper bound. A rise in sea level must increase the state's expected hurricane damage by at least 25% before its counties' population means are adjusted and it cannot reduce mean population estimates by > 1 standard deviation from the unadjusted mean.

The adjustment factor, $\theta_{j,n}$, reduces the county's mean population estimate, \bar{p}_i , if the rise in sea level in the state j (in which county i resides) increases state j 's damage in the n th simulation by > 25% relative to its damage in the reference case. For each state j :

$$\theta_{j,n} = 0; \text{ if } \Delta \hat{d}_{j,n} \leq 0.25, \\ = \min(1, \Delta \hat{d}_{j,n}); \text{ if } \Delta \hat{d}_{j,n} > 0.25,$$

Where:

$$\Delta \hat{d}_{j,n} = \frac{D_j(f_R, s_{j,n}, p_{j,R}, y_{j,R})}{D_j(f_R, s_{j,R}, p_{j,R}, y_{j,R})} - 1$$

For example:

$$\text{if } \Delta \hat{d}_{j,n} = 0.5, \text{ then } \theta_{j,n} = 0.5 \\ \text{if } \Delta \hat{d}_{j,n} = 1.2, \text{ then } \theta_{j,n} = 1.$$

On the basis of that adjustment factor, county i 's mean population, \bar{p}_i , would be set at 1 standard deviation below the unadjusted mean if the sea level draw in the n th simulation (holding all other variables at their reference levels) led to at least a doubling of estimated damage in the state in which county i is located.

3.3.2. Vulnerability Weights for County Populations

The extent to which additional development in a coastal state is expected to increase the damage depends on where the development occurs. To account for that, we weighted the growth in population and per capita income for each county in the state on the basis of its vulnerability to damage from storm surges and wind damage:

$$\check{p}_{i,n} = p_{i,n} [\lambda_i (1 - w_j) + \gamma_i w_j]$$

where:

- $\check{p}_{i,n}$ vulnerability-weighted population of county i in the n th simulation
- λ_i the weight used to indicate vulnerability of county i (in state j) to storm surge damage relative to all other counties in state j

¹⁰ See June 2015 long term budget projections in CBO (2015).

- $(1 - w_j)$ share of damage in state j that comes from storm surges (as opposed to wind)¹¹
- γ_i the weight used to indicate vulnerability of county i (in state j) to wind damage relative to all other counties in state j
- w_j share of state j 's damage that comes from wind (as opposed to storm surges).

Our surge damage weight for each county i , in state j , is equal to the probability-weighted loss ratio from storm surges in county i , relative to the total of such probability-weighted losses, summed across all counties in state j (in which county i resides):

$$\lambda_i = \frac{\sum_{c=1}^5 m_i(c)q_j(c)}{\sum_{i=1}^{I_j} \sum_{c=1}^5 [m_i(c)q_j(c)]}$$

where:

- $m_i(c)$ the maximum potential total building losses in county i (in state j), given that a hurricane of Category c imposes losses on state j , divided by estimates of the total value of the buildings in the county¹²
- $q_j(c)$ probability that a hurricane of Category c occurs and imposes losses on state j
- I_j the number of counties in state j .

In essence, the weight λ_i is county i 's share of the total increase in probability-weighted damage from storm surges that state j would experience if an additional \$1 of property was added to each county in the state. For example, the weight for Rockingham, New Hampshire, is 0.79, indicating that it accounts for 79% of the total additional expected storm surge damage that New Hampshire would incur if \$1 of additional property was added to each county in the state. In contrast, Hillsborough, New Hampshire (which is land-locked), has a zero weight, indicating that adding more property to Hillsborough would not increase expected storm surge damage in New Hampshire. Surge weights for all the counties in any given state sum to one; that is, $\sum_{i=1}^{I_j} \lambda_i = 1$.

State j 's share of damage that comes from storm surges, as opposed to wind— $(1 - w_j)$ —was based on the breakdowns of state-specific damage in the reference case. Each state's total damage is attributed either to storm surge damage or to wind damage.

Wind damage weight for each county i , in state j , is equal to the probability-weighted wind loss ratio in county i , relative to the total of such probability-weighted losses, summed across all counties in state j :

$$\gamma_i = \frac{\sum_{c=1}^5 h_i(c)q_j(c)}{\sum_{i=1}^{I_j} \sum_{c=1}^5 [h_i(c)q_j(c)]}$$

where:

- $h_i(c)$ loss ratio due to wind damage in county i of state j , given U.S. landfall of a hurricane of Category c .

We used two sources in generating estimates of $h_i(c)$. Maps of sustained surface wind speeds produced by the National Hurricane Center were used to identify the maximum winds each county would be expected to experience if a hurricane in Category c made landfall along its

state's coastline. Relationships between wind speed and damage were derived from FEMA's Hazus loss-estimation model. Those relationships, termed wind loss ratios, indicate a county's maximum building damage as a share of its total building valuations for a given wind speed.¹³

As was the case for the surge weight, the wind weight calculated for county i , γ_i , is equal to i 's share of the total increase in state j 's probability-weighted wind damage that would occur if \$1 of additional property was added to each county in the state. Wind weights for all the counties in any given state sum to 1; that is, $\sum_{i=1}^{I_j} \gamma_i = 1$.

3.3.3. Aggregating Vulnerability-weighted County Population Estimates to the State Level

Each state's vulnerability-weighted population is simply the sum of the vulnerability-weighted populations of the counties within it:

$$\ddot{p}_{j,n} = \sum_{i=1}^{I_j} \ddot{p}_{i,n}$$

where:

- $\ddot{p}_{j,n}$ the vulnerability-weighted population of state j in the n th simulation.

3.4. Vulnerability-weighted State Per Capita Income Estimates for Each State

We projected each state's vulnerability-weighted per capita income using the same method that we used to project the state's vulnerability-weighted population. Counties' per capita incomes were projected on the basis of a mean projection and both regional- and county-level shocks, such that the shocks affecting counties within a region have a joint normal distribution. Mean per capita income estimates were adjusted on the basis of increases in hurricane damage, and county estimates were weighted on the basis of their relative vulnerability to wind and storm surge damage as well as the state's share of damage from wind and storm surges. County estimates were aggregated to obtain state totals. Only significant differences between the method used to project per capita income and the method used to project population (described above) are discussed below.¹⁴

For the period 2015 through 2040 we modeled each county's mean per capita income as growing at a weighted average of:

- Its growth rate between 1990 and 2000 (the decade preceding the recession),
- Its growth rate between 2000 and 2010, which reflects the effects of the recession and is the most recent decade for which census data are available, and
- The growth rate projected for the United States as a whole.¹⁵

Specifically, each of the county's two historic growth rates was assigned a weight of 0.1, and the U.S. growth rate was assigned a weight of 0.8. That method allows each county's historic growth to influence its future growth but also ensures a degree of consistency between the growth rates of the counties included in this analysis and the rate of growth for the United States as a whole. As was the case with estimates of population growth, we projected that, after 2040, each county's per

¹¹ The RMS-provided damage estimates are broken down by wind and storm surge. A discussion of the validity of these estimates is provided in footnote 2.

¹² We estimated $m_i(c)$ based on version 3.0 of FEMA's Coastal Flood Loss Atlas (CFLA). The CFLA combines the National Hurricane Center's SLOSH model, which models storm surge heights, with FEMA's Hazus model, which is a regional multi-hazard loss-estimation model. We used an output attribute (C#_BLDG_LR) from the CFLA for building loss ratios.

¹³ We used building loss ratios generated by running the Hazus Hurricane Model and selecting only for wind damage. The loss ratios sustained in a particular location were correlated with the maximum wind speeds experienced at that location to produce a wind-speed-to-damage curve. For more information on the Hazus Hurricane Model and wind damage curves, see Department of Homeland Security (2015).

¹⁴ For a more detailed discussion, see CBO (2016c) working paper.

¹⁵ CBO (2016b), Data and Supplementary Materials.

capita income would grow at the same rate as that projected for the United States as a whole.

We estimated a distribution of county-level per capita income by using a standard deviation set at 11% of each county's mean per capita income, the same standard deviation that was used for estimates of the population growth of midsized counties (those with populations of 50,000 to 100,000).

We estimated correlation coefficients between the growth in counties' per capita income and growth in the per capita income of the region, k , in which they reside (ρ_k^y) as follows:

- Florida Gulf— $\rho^y = 0.727$
- Southern Coastal— $\rho^y = 0.794$
- Mid-Atlantic and Northern— $\rho^y = 0.504$
- Far-Northern— $\rho^y = 0.810$.

The values for ρ_k^y were obtained by regressing each county's decade-specific per capita income growth rate (for each decade between 1960 and 2000) against the decade-specific per capita income growth rate for the region in which the county resides. Each county's decade-specific growth rate was weighted by its population in that decade.

3.5. Elasticities

Estimates of hurricane damage are sensitive to assumptions about how much hurricane damage will increase in response to increases in population and per capita income in vulnerable areas; but information on the elasticity of hurricane damage with respect to socioeconomic variables—that is, the percentage change in damage given a percentage change in population or per capita income—is limited (Bouwer, 2013). Some researchers have assumed that increases in damage are proportionate to increases in population and per capita income (for example, Pielke et al., 2008) or to GDP (Nordhaus, 2010); however, empirical evidence suggests that the responses may not be proportionate (Mendelsohn et al., 2012). In addition, recent research suggests that the United States has significantly different elasticities from those of other countries (Bakkensen and Mendelsohn, 2016).

In particular, Bakkensen and Mendelsohn found no statistically significant evidence that increases in population led to increases in hurricane damage in the United States (an elasticity of 0), but estimated a population elasticity of 0.3 for OECD countries (excluding the United States). With respect to income, Bakkensen and Mendelsohn estimated an elasticity of 1.15 for the United States and no statistically significant result for OECD countries (excluding the United States). Mendelsohn et al. (2011) also estimated elasticities for the United States. They did not find that population density and income were significant in explaining the magnitude of damage for 111 historic hurricanes in the United States; however, based on non-significant parameters they use income elasticities of 0.4 and 1 and conduct sensitivity analysis on those values.

We allowed wind and storm surge damage to each have unique responses to changes in population and per capita income using elasticities that were informed by the estimates of Bakkensen and Mendelsohn. We modified Bakkensen and Mendelsohn's elasticities because they did not allow individual responses for wind and storm surge and because the reliability of their estimates is likely to be limited by the size of their data set: They had 110 observations for the United States.¹⁶ Given the thin evidence about the magnitude of the elasticities, we chose to make their effects transparent by applying them after the Monte Carlo draws and by constructing results based on alternative estimates.¹⁷ In addition to the medium response elasticities that we

used for our base case we constructed results using higher and lower estimates, as well as using the unadjusted elasticities obtained by Bakkensen and Mendelsohn. (These results are described below in the discussion on sensitivity analysis.) For our base case we used the following estimates:

- For storm surge damage, we assumed an income elasticity of 0.75 and a population elasticity of 0.5
- For wind damage, we assumed a per capita income elasticity of 1 and a population elasticity of 0.25.

We assumed that damage from storm surges would increase less in response to increases in per capita income (an elasticity of 0.75) than would damage from wind (an elasticity of 1.0) because higher per capita income could motivate either public or private entities to invest in infrastructure (such as seawalls) that is designed to limit damage from storm surges. In contrast, we expect that damage from storm surges would respond more to increases in population (an elasticity of 0.5) than would wind damage (an elasticity of 0.25). Unlike with wind damage, increases in population density would not necessarily provide protection from storm surge damage: Increasing the number of single-story buildings in a given area would probably result in a proportional increase in the amount of damage from storm surges. However, increases in damage from storm surges would be less than proportional to increases in population to the extent that increased population led to the construction of taller buildings or of public infrastructure designed to limit damage from storm surges. To reflect the fact that potential differences in storm damage would depend on whether population growth led to the construction of more single-story homes or taller buildings, we used an elasticity of 0.5.

A specific set of elasticities is calculated for each state based on the share of its damage (under current conditions) that stems from wind and storm surges. Thus,

$$\epsilon_j^p = 0.5(1-w_j) + 0.25w_j$$

$$\epsilon_j^y = 0.75(1-w_j) + w_j$$

where:

- ϵ_j^p percentage increase in damage in state j , given a percentage increase population
- ϵ_j^y percentage increase in damage in state j , given a percentage increase in per capita income
- $(1-w_j)$ the share of total damage in state j that comes from storm surges
- w_j the share of total damage in state j that comes from wind.

4. Results

The combined effects of climate change and coastal development will cause hurricane damage to increase in the future. Our primary measure of damage is the dollar value of hurricane damage measured as a share of GDP. GDP, in turn, provides a measure of the nation's ability to pay for the damage.¹⁸ Because hurricane damage will not be evenly spread throughout the United States, we also present the percentage

¹⁶ The modified estimates were informed by conversations with both Bakkensen and Mendelsohn.

¹⁷ Changes to hurricane frequencies, sea level rise, population and per capita income are also uncertain but their uncertainties, we believe, can be more meaningfully described by the distributions identified in Table 1. In contrast, we did not have sufficient evidence to construct a distribution of elasticities because of the thin evidence base, and used our best estimate and several illustrative scenarios instead.

¹⁸ For a discussion of the potential effects that increases in hurricane damage might have on the federal budget, see CBO (2016a).

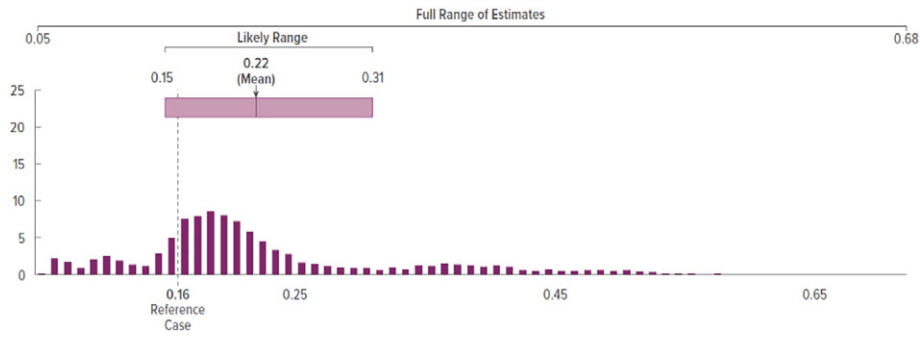


Fig. 3. Estimates of expected hurricane damage as a percentage of GDP, 2075. The “likely range” includes the middle two-thirds of the distribution of estimates from the simulations.

of the U.S. population living in counties where expected damage is particularly burdensome.

4.1. Damage as a Share of GDP

The size of the economy is expected to be nearly four times larger in 2075 than it is today; however, our projections indicate that hurricane damage will grow more quickly.¹⁹ Based on today’s conditions (current sea levels, hurricane frequencies and property exposure) expected hurricane damage is 0.16% of GDP, or \$28 billion, measured as a share of GDP in 2015. By 2075, we estimate that, on average, expected hurricane damage will grow to 0.22% of GDP (see Fig. 3). That percentage corresponds to \$39 billion measured as a share of 2015 GDP, or \$151 billion measured as a share of 2075 GDP (and reported in 2015\$). Substantial uncertainty surrounds that estimate. For example, the likely range—encompassing the middle two-thirds of the simulation results—spans from 0.15% of GDP (meaning that hurricane damage would grow more slowly than the economy, therefore declining as a share of GDP) to 0.31% of GDP.

4.1.1. The Relative Contribution of Climate Change and Coastal Development to Increasing Damage

Climate change and coastal development will occur simultaneously, with each factor compounding the increase in expected damage caused by the other. For example, rising sea levels—and the resulting increase in expected damage from storm surges—will compound the increase in expected damage resulting from expanding state populations. As a result, the combined effects of climate change and coastal development will increase expected damage by a greater amount than the sum of the increases in expected damage that each would bring about on its own.

Accounting only for the effects of climate change (holding property exposure at current levels), we estimate that mean expected damage in 2075 would be \$63 billion, an increase of \$35 billion compared to the \$28 billion of expected damage under current conditions, and \$88 billion less than the \$123 billion increase in projected damage that results of the combined effects of both climate change and coastal development (see Table 3). These climate change only results are comparable to those obtained by Houser et al. (2015), who, as indicated above, used a similar model (with a more limited set of hurricane projections, but with results differentiated by RCP scenario) to examine effects of climate change only. They estimated expected mean damage for 2090 to be \$59 billion under the RCP 4.5 scenario and \$65 billion under the RCP 8.5 scenario.²⁰

Accounting only for the effects of coastal development, we estimate that mean expected damage in 2075 would be \$69 billion, an increase of \$41 billion compared to expected damage under current conditions, and \$82 billion less than the increase due to the combined effects.

In total, we estimate that the increase in expected damage caused by the combined effects of climate change and coastal development (\$123 billion) exceeds the sum of the increases caused by the individual effects (\$76 billion) by \$47 billion. That \$47 billion reflects the *additional damage* that climate change has on the *additional property exposure* attributable to coastal development.

A key question is how to allocate the additional damage due to the interaction between climate change and coastal development. Mendelsohn et al. (2012), who estimated the effects of climate change and coastal development on global hurricane damage in 2100, took coastal development as a given and attributed the full interaction effect to climate change. Thus, they estimated the impact of climate change as the difference between damage with both future climate and future development and damage with current climate and future development. In contrast, one could take climate change as given (particularly in the near term when mitigation is likely to have relatively little impact on damage) and attribute the entire interaction effect to coastal development.

Our approach is to allocate that \$47 billion to climate change and to coastal development on the basis of the ratio of the increase in damage caused by each individual force on its own and the sum of the increase in damage caused by each of the two individual forces. For example, on its own, climate change is estimated to increase damage by \$35 billion, 46% of the \$76 billion sum of the increases in hurricane damage resulting from climate change only and from coastal development only. As a result, we attribute 46% of the \$47 billion interaction effect to climate change (\$22 billion) and the remaining 54% (\$25 billion) to coastal development. On the basis of this allocation method, climate change accounts for \$57 billion of the \$120 billion increase in the average expected hurricane damage in 2075 (or 47%)—relative to the reference case—and coastal development accounts for the remaining \$63 billion (or 53%).

4.1.2. Sensitivity of Results to Alternative Estimates of Elasticities

Our estimates of expected damage are sensitive to assessments of how much increases in population and per capita income will increase hurricane damage. Given the importance of those effects, we constructed a distribution of damage in 2075 under three alternative sets of elasticities (see Table 4):

- *Higher-response case.* In this case we increased all of the elasticities used in our reference (medium response) case by 0.25, making our expected damage estimates more sensitive to increases in population and per capita income.
- *Lower-response case.* In this case we decreased all of the elasticities used in our reference case by 0.25, making our expected damage estimates less sensitive to increases in population and per capita income.

¹⁹ We use CBO’s estimates of GDP which are calculated as population in 2075 multiplied by per capita income in 2075 (CBO, 2016b).

²⁰ Houser et al. (2015) present their results in 2011 dollars. For comparisons purposes, we present their results in 2015 dollars.

Table 3
Combined and individual effects of climate change and coastal development. Billions of 2015 dollars.

Source of change in damage	Mean expected damage estimate	Increase in damage relative to \$28 Billion in the reference case
Combined effects of climate change and coastal development	151	123
Individual effects		
Climate only	63	35
Coastal only	69	41
Sum of individual effects	n.a.	76

n.a. = not applicable. The individual mean expected damage estimates cannot be summed because doing so would double count the \$28 billion of expected damage in the reference case.

- *Bakkensen–Mendelsohn case.* In this case we used the U.S. only elasticity estimates obtained by Bakkensen and Mendelsohn for their base case (0 for population and 1.15 for per capita income, as described above). Because Bakkensen and Mendelsohn did not differentiate between wind and storm surge damage we used the same elasticities for both.

We found that the mean estimate of expected damage for 2075 was roughly 20% higher in the higher-response case (0.26% of GDP) and roughly 20% lower in the lower-response case (0.17% of GDP) than in the medium-response case (0.22% of GDP). Using the elasticities that Bakkensen and Mendelsohn estimated for the U.S. yielded results that were very close to our reference case.

4.1.3. Sensitivity of Results the Two Different Hurricane Models

The results discussed above are based on the combination of estimates of hurricane frequency developed by Knutson and Emanuel. To test the sensitivity of our results to that, we repeated the analysis using predictions of hurricane frequency made by each researcher. That analysis indicated that average expected damage was not sensitive to the choice of researcher, varying by only 0.01% of GDP (see Table 5). In contrast, the width of the likely range varied significantly depending on which researcher's estimates were used. Relative to the likely range in 2075 that was obtained when both researchers' predictions were used (from 0.15 to 0.31% of GDP), the range was much wider (from 0.10 to 0.34% of GDP) when only Knutson's predictions were used, but much narrower (from 0.17 to 0.26% of GDP) when only Emanuel's predictions were used.

4.2. Percentage of the U.S. Population Facing Substantial Expected Damage

As described above, expected hurricane damage comprises a small but growing share of GDP. Such damage, however, would not be uniformly distributed. In particular, it will constitute a larger share of per capita income for people living along the East and Gulf coasts than for the average person in the United States. Currently, roughly 1.2 million people—0.4% of the U.S. population—live in counties facing substantial

Table 4
Sensitivity of results to alternative elasticities.

Cases	Elasticities				Results					
	Population		Per capita income		Percent of GDP			Billions of 2015 dollars		
	Wind	Surge	Wind	Surge	Mean	Likely Range		Mean	Likely Range	
						Low	High		Low	High
Medium-response (base case)	0.25	0.5	1.0	0.75	0.22	0.15	0.31	151	102	220
Higher-response	0.5	0.75	1.25	1.0	0.26	0.17	0.37	181	122	262
Lower-response	0	0.25	0.75	0.5	0.17	0.11	0.25	121	80	173
Bakkensen and Mendelsohn	0	0	1.15	1.15	0.23	0.15	0.34	162	107	238

Table 5
Sensitivity of results to alternative hurricane models.

Researcher	Mean	Likely range		
		Low End	High End	Width
Knutson	0.21	0.10	0.34	0.24
Emanuel	0.22	0.17	0.26	0.09
Both	0.22	0.15	0.31	0.16

expected damage. For the purposes of this analysis, “substantial expected damage” is defined as expected per capita damage that is >5% of the county's average per capita income. We project that by 2075, 10 million people—2.1% of the U.S. population in 2075—will face expected damage that exceeds the 5% threshold (see Fig. 4). The likely range spans 0.3% (or 1.6 million people) to 5.2% (or about 25 million people).

The low end of the likely range includes the people in 13 counties, while the high end includes the people in 68 counties (roughly five times as many counties). Because we estimate that damage grows more slowly than population, our estimates of per capita damage in 2075 tend to be higher in states with smaller populations than in states with larger populations. Consequently, the 13 counties exceeding the 5% threshold at the low end of the likely range (corresponding to lower damage estimates) have an average population that is less than one-third of the average population for the 68 counties exceeding the threshold at the high end of the likely range (corresponding to higher estimates of damage). This result leads to the very wide likely range that we estimate.

5. Discussion

Hurricane damage in the United States is likely to increase substantially in the coming decades as a result of both climate change and coastal development. Two primary strategies for limiting such increases are mitigation, which entails reducing global emissions of greenhouse gases, and adaptation, which entails reducing exposure or reducing the vulnerability of exposed property.

A coordinated global effort to significantly reduce greenhouse gas emissions could lessen hurricane damage between now and 2075, but the extent of the reduction would be uncertain and it would probably occur in the latter half of this century. Of the two ways in which climate change is expected to increase hurricane damage—an increase in the frequency of hurricanes and a rise in sea levels—the latter is the more certain; however, increases in sea levels between now and 2075 are expected to be relatively insensitive to changes in emissions over the same period. Specifically, in the first half of the 21st century, the global increase in sea levels will be caused primarily by expansion of the oceans resulting from the warming of the water. That response is relatively insensitive to changes in emissions. Differences in emissions will begin to be more important in the second half of the century, when the melting of ice sheets is projected to play a more significant role (Kopp et al., 2014).

Policies that slow the growth of property exposure in vulnerable locations would directly reduce damage. To the extent that households,

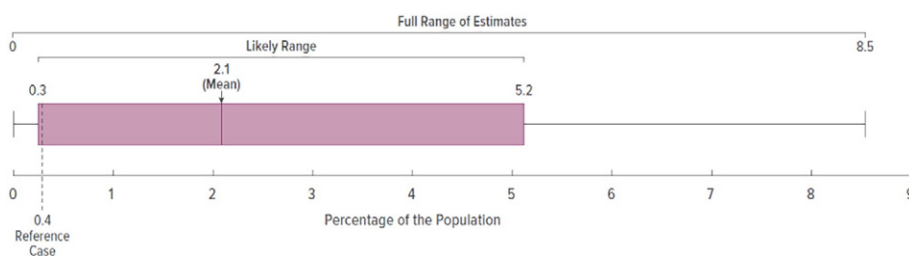


Fig. 4. Percentage of the U.S. Population Living in Countries with Substantial Expected Hurricane Damage, 2075. The “likely range” includes the middle two-thirds of the distribution of estimates from the simulations.

businesses, and state and local governments do not bear the full cost of hurricane damage, they lack the appropriate incentives to balance the costs and benefits of locating homes, business, and public buildings in coastal areas. In the United States, such development has been subsidized by a national flood insurance program in which the premiums that many homeowners pay do not fully reflect the actuarial risk that they face (Erwann, 2010; Kousky and Shabman, 2014); by limited market penetration of flood insurance (Erwann et al. 2012); by substantial growth in the provision of federal funds following hurricanes, measured as a share of the amount of damage that occurred (CBO, 2016a); and by state policies designed to attract businesses (Bagstad et al., 2007). In addition, infrastructure projects have had the unintended consequence of both promoting development and destroying wetlands, which can reduce damage from storm surges (Bagstad et al., 2007).

Several studies have examined the costs and benefits of adaptation measures. Some of those analyses are situation specific. For example, Camare and Lane (2015) examine the options of protecting, or retreating for a community in Nova Scotia and Hallegate et al. (2011) examine the avoided damage associated with various levels of flood protection for a virtual city based on Copenhagen. Other studies provide global estimates of the cost of SLR with and without adaptation (for example, Hinkel et al., (2014), Yohe and Schlesinger (1998), and Neumann et al. (2000)). Moreover, there are a wide variety of types of adaptive measures to consider, including “grey infrastructure,” such as dikes and “green infrastructure,” such as wetlands. We account for some level of adaptation by our assumption that substantial increases in storm surge damage (which would likely be accompanied by loss of land due to inundation and erosion) would slow the pace of coastal development. However, our estimate is primarily a placeholder for this effect and we have little basis for determining how its magnitude is likely to vary across communities or time. Fine tuning that assessment is beyond the scope of this analysis, but is an important area for future research.

Finally, decisions about mitigation and adaptation are complex and can entail unintended consequences. For example, Tol et al. (2008) point out that adaptation is a social, political, and economic process, rather than just a technical exercise. Further Hallgate et al. (2011) point out that building defenses against flooding will reduce damage for some storms but also greatly increase the cost of defense failure (in part, by facilitating construction in areas that would be vulnerable in the absence of the protection). Moreover, maintaining the same level of expected damage in the presence of SLR requires achieving lower flood probabilities (through higher defenses). In addition, Tol (2007) points out that expenditures of global resources on mitigation can reduce resources available for adaptation. As a result, in the case of SLR, which is expected to be relatively insensitive to changes in emissions over the next few decades, increases in mitigation could lead to higher levels of damage than would otherwise be the case.

6. Conclusions

Hurricane damage in the United States and elsewhere is likely to increase significantly in the coming decades, driven by the combined

forces of climate change and coastal development. Our paper demonstrates the importance of accounting for both effects and offers a method of estimating increases in expected damage using location-specific data about causal factors. We do this by constructing a Monte Carlo model that draws on: projections of sets of U.S. hurricane frequencies developed by two modelers based on a wide variety of potential climatic conditions, distributions of state-specific estimates of SLR, and distributions of county-level estimates of population and per capita income that are weighted to reflect each county’s vulnerability to wind and storm surge damage.

We estimate that the sum of the increase in annual expected damage that climate change and coastal development would each bring about in 2075 (relative to today) if they occurred in isolation is \$47 billion (or 38%) less than the increase that is estimated to result from their combined effects. Thus, failing to account for the interaction of the two forces can result in a considerable underestimate of total future costs, as well as the incremental cost of each individual force. On its own, we estimate that coastal development would cause hurricane damage to grow less rapidly than the economy—thus falling relative to the nation’s ability to pay for damage. In contrast, we estimate that the combined forces of climate change and coastal development will cause hurricane damage to comprise a growing share of GDP. In addition, we estimate that the number of people exposed to substantial damage in the United States will grow by more than eight-fold over the next 60 years. Understanding the concentration of hurricane damage is likely to be particularly important in nations that lack policies and programs designed to marshal national resources to address local damage.

The income and population elasticities used in this analysis are an important source of uncertainty. While few estimates are available, those that exist indicate that elasticities differ significantly among countries. Improving information about location-specific elasticities will be important in improving estimates of future expected damage. Finally, better understanding the likely effects of mitigation and potential forms of adaptation on the magnitude of hurricane damage will be important both for accessing the costs and benefits of such measures and to prepare for the costs of the residual expected damage.

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Appendix A. Supplementary Data

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