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Estimating monetary damages from flooding in the United States under a changing climate

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Climate change; modelling; precipitation.

Abstract

Extreme precipitation events are likely to become more frequent and more extreme under a changing climate. It follows that monetary damages from flooding would also increase relative to baseline, yet this relationship has not been quantified at the scale of the entire United States. In this paper, we quantify how climate change could affect monetary damages from flooding in the coterminous United States. With publicly available historical flooding and precipitation data, we estimate region-specific logistic regression models of the probability that severely damaging floods will occur under baseline conditions. We then use future precipitation projections driven by climate model outputs to estimate the probability that damaging floods could occur under a 'business as usual' climate change scenario. Our results project an increase in monetary damages from flooding in nearly all regions of the United States and a total increase in damages by the end of century of approximately 30% (assuming no change in built infrastructure or values). However, these changes vary between regions due to differences in the mechanisms driving flooding and general circulation model precipitation projections.

Introduction

A growing body of literature indicates that the frequency of extreme precipitation events has been increasing in recent decades (e.g. Karl and Knight, 1998; Groisman *et al.*, 2005; IPCC, 2012). Climate models and theoretical arguments further indicate that extreme precipitation events will continue to increase with rises in greenhouse gas (GHG) concentrations (e.g. Palmer and Raisanen, 2002; Trenberth *et al.*, 2003; Min *et al.*, 2011). Given these empirical and theoretical arguments for increases in the frequency and severity of extreme precipitation, it is quite possible that flood risk, and associated monetary damages from flooding, is also likely to increase in the 21st century and beyond (e.g. Pielke and Downton, 2000; Changnon *et al.*, 2001; Milly *et al.*, 2002; Allamano *et al.*, 2009; Pall *et al.*, 2011). However, quantifying the monetary damages from increased flooding remains a vexing problem for a number of reasons. First, physically based hydrologic models are both costly to implement and have a limited spatial scale of applicability; estimating climate change impacts on flood damages at large spatial scales is simply not practical using physically based hydrologic models. And second, monetary damages from flooding are complicated by socio-economic factors, including flood management practices, changes in demographics, changes in land use, and changes in wealth. Thus even if large-scale floods could be forecast, there remains substantial uncertainty as to how this might translate into changes in monetary damages (e.g. Pielke and Downton, 2000; Choi and Fisher, 2003). As a result of these complications, national-scale projections of future flood risk are relatively uncommon (e.g. Hall *et al.*, 2005; Rodda, 2005).

The goal of this study is to develop and test a methodology for estimating changes in monetary damages from flooding under a changing climate at the scale of the coterminous United States (e.g. excluding Alaska and Hawaii). Because our overall objective was to evaluate potential damages at a national scale, our approach does not utilise physically based flood routing models that could be used at local or sub-basin scales. Instead, our approach is empirically based and relies on statistical relationships between historical precipitation and flood damage data for the United States over the past two decades. Using this approach, we are able to evaluate broad regional trends, thereby obtaining reasonable national-level estimates of damages. Changes in precipitation are driven by an ensemble average of general circulation models (GCMs),

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which are applied as perturbations to the observed time series of historical precipitation and flooding. While our approach does not address the role of socio-economic changes on flood risk, it does overcome the issues associated with developing formal hydrologic/flood routing models to translate rainfall into flooding. This approach and its results are particularly useful for projecting the potential impacts of climate change, which can inform analyses of the benefits of avoiding these impacts through GHG mitigation policies.

Methods

Our approach was to formulate statistical relationships between observed precipitation and flood damages over the course of the observational record, and to utilise these relationships to estimate future damages under a changing climate. Because the atmospheric and hydrologic mechanisms that create damaging floods vary across different regions of the United States (e.g. O'Connor and Costa, 2004), our analysis of precipitation and flood damage data was conducted on a regional scale. The data were first evaluated at the scale of the 99 assessment subregions (ASRs) in the coterminous United States (Figure 1), a set of watersheds that was defined for the Second National Water Resources Assessment (U.S. Water Resources Council, 1978). However, because the data from many of these regions were too sparse to support our statistical analysis, the paired precipitation and damage data were bundled into the 18 water resource regions (WRRs), which are equivalent to two-digit hydrologic unit code regions. These regions are small enough that the mechanisms driving flooding are likely to be similar across the region, but large enough that the aggregated data provide a sufficiently robust data set for analysis.

Data sources and data processing

The data on flood damages (the dependent variable) were obtained from the National Climatic Data Center (NCDC) (NCDC, 2011b). This data set contains information on specific flood events occurring over the 1993–2008 period. Note that the severe flooding events occurring in the Upper Mississippi Valley during several months of 1993, which were the largest in the historical record at many locations within this region (e.g. Parrett *et al.*, 1993), were not included in this database. For each flood event in the database, the dates of

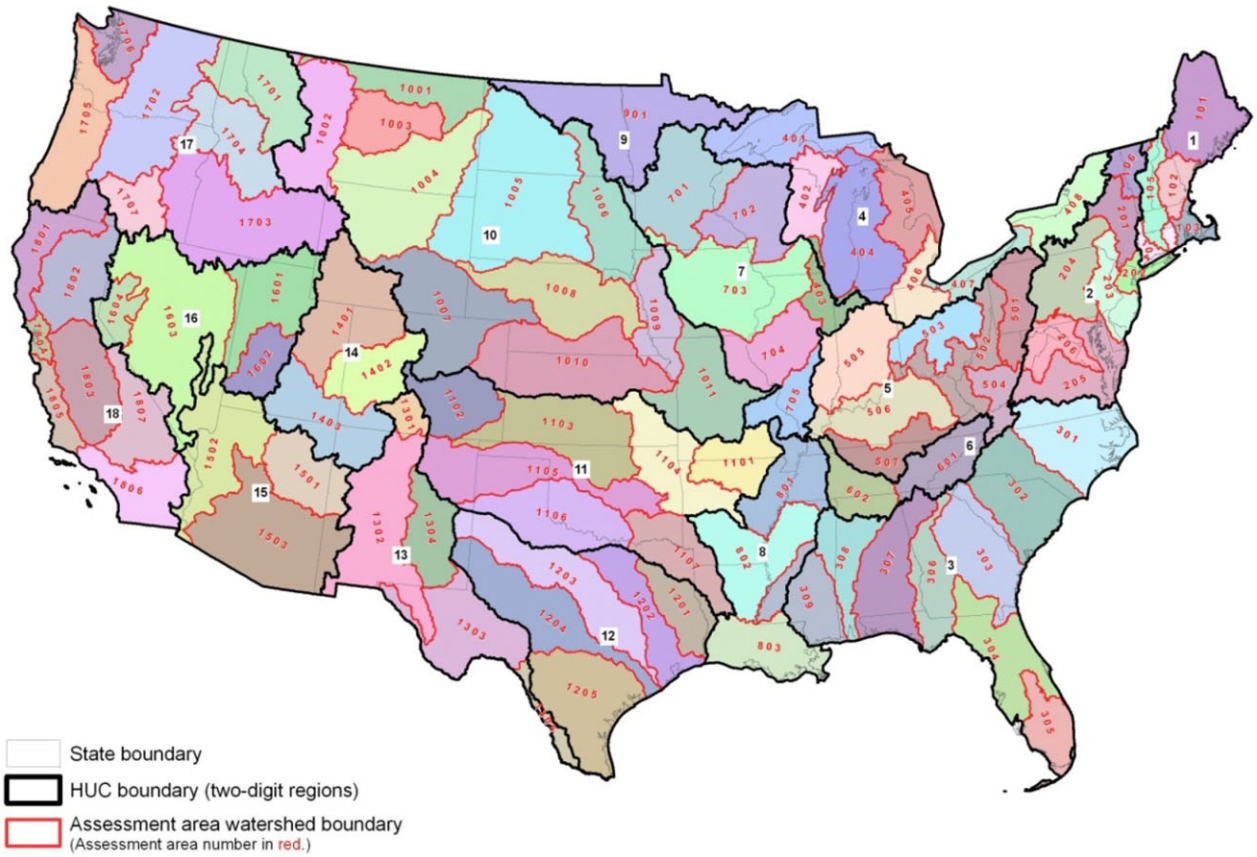

Figure 1 Two-digit hydrologic unit code (HUC) and assessment subregions boundaries used for spatial bundling of flood and precipitation data.

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occurrence, location (by latitude/longitude, state, county, and/or municipality), property damages, and crop damages were recorded, along with other information including (in many cases) a description of the weather event(s) responsible. Several types of floods are described and included in this database, including general flooding, flash flooding, and coastal flooding. For our analysis, we considered events that were classified as 'Flash', 'Flood_FlashFlood', 'Flooding', and 'Floods'. Events that were classified by event types 'Coastal' and 'Unclassified' were omitted from the final data set.

For the analysis of precipitation controls on flood damage, all values for property damage, crop damage, and total damage by flood event were updated to 2007 dollars using annual consumer price index values compiled from the Bureau of Labor Statistics (BLS, 2011).

On the basis of location, each damaging flood event was assigned to 1 of the 99 ASRs in the coterminous United States (Figure 1). Each entry in the final database includes the date on which the flood occurred; the ASR in which it occurred; and the crop damage, property damage, and total damage in dollars associated with the flood event. ASR assignments were retained for the purposes of correlating flood damages with precipitation events within that region. However, because the number of events in each ASR was relatively small, the ASR data were aggregated into the larger watersheds delineated by the 18 WRRs in the United States to estimate statistical relationships between flood damages and precipitation across the observational record. The WRR represents a spatial scale of analysis across which the seasonality and mechanisms of flooding (e.g. convective versus frontal storms) are likely to be similar.

The final flood damages database consisted of approximately 17 000 floods, of which approximately 8000 caused reported monetary damage. The total damages reported across all floods in the database were $26.3 billion.

Precipitation data used for analysis were from the global historical climatology network-daily (GHCN-D) database, available from NCDC (NCDC, 2011a). This data set comes from approximately 20 different sources of daily precipitation data (compiled as precipitation totals by calendar days), and is quality controlled prior to each update. Using SimCLIM software (ClimSystems, Hamilton, New Zealand) (Warrick, 2009), the daily precipitation totals from the GHCN-D database were extracted for all climate stations within each ASR, for the entire period available for each station. Each ASR typically had between 100–200 meteorological stations, with record lengths ranging from a few years to over 100 years.

Climate model output for future precipitation projections

Our analysis relies on a series of temporally correlated precipitation and flood events (see the Model Development section). To estimate the potential impact of changing precipitation on flood damages, the model framework requires that the temporal patterns of observed precipitation events are preserved, with a perturbation to the precipitation magnitude on each day. Future precipitation scenarios were therefore generated using the observed historical data as a starting point, and perturbing daily precipitation totals by an amount determined by the GCM output through SimCLIM.

To do this, we generated projected monthly changes in precipitation at each climate station in the United States and applied these monthly changes to the observed historical record. We used a monthly per cent change in precipitation from baseline (1971–2000) for the year 2100 under a business as usual (BAU) scenario, in which GHG emissions are projected to continue on their current trajectory.[1] We used a moderate climate sensitivity of 3 °C (e.g. 3 °C global average surface warming for a doubling of carbon dioxide). The results were generated in SimCLIM from an ensemble of GCMs, which included the following models: BCCRBCM2, CCSM-30, ECHO-G, GFDLCM20, GFDLCM21, MPIECH-5, MRI-232A, UKHADCM3, and UKHADGEM (see Randall *et al.*, 2007 for descriptions of these models). The monthly precipitation changes projected by this ensemble average were then applied to the observed daily historical record at each meteorological station record using scripts developed in MATLAB®.[2]

Data analysis

Damage distributions

Over the historic period of analysis, damaging floods in the United States are unevenly distributed both spatially and temporally. Monetary damages from flooding are concentrated in specific regions, and damages within any given region are typically unevenly distributed through the year.

Nationally, the distribution of monetary damages from flooding is heavy-tailed, as illustrated by the nearly log-normal distribution for all damaging floods throughout the United States (Figure 2). As an example, the upper 25th percentile of flood damages (in terms of dollars) accounts for approximately 98% of the total damages reported. This heavy-tailed distribution of flood damage data was found to be well approximated by a generalised extreme value fit to the log-transformed damages for all WRRs. As described

[1]Under the BAU scenario, US GHG emissions are benchmarked to the US Energy Information Administration's Annual Energy Outlook 2010 forecast, which reflects the Energy Independence and Security Act of 2007 and the American Recovery and Reinvestment Act of 2009. International emissions projections under this scenario are based on the Energy Modeling Forum-22 baseline (see Calvin *et al.*, 2009).

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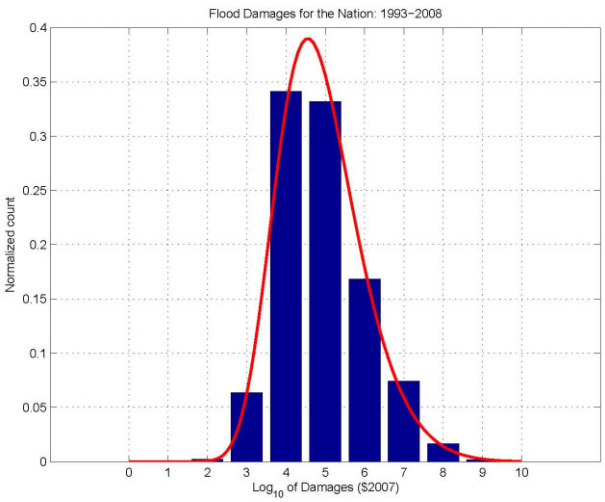

Figure 2 National distribution of monetary damages from flooding in log-bins. Red line is generalised extreme value fit to the log-transformed data.

later, the observation that nearly all of the damages can be accounted for by the uppermost 25% of individual floods also allowed us to focus our logistic regression model on explaining the upper 25th percentile of damaging floods (see the Model Development section).

Monetary damages from historical flooding are also unevenly distributed spatially across the coterminous United States. Flood damages are highest along the eastern seaboard (WRRs 2 and 3), with slightly lower contributions in the Midwest and California (WRRs 5, 7, 10, and 18). Figure 3 illustrates the spatial distribution of historical flood damages over the historical record.

Finally, monetary damages from flooding are also unequally distributed in time, and this intra-annual timing of damage from flooding varies regionally (Figure 4). For example, flood damages in the South Atlantic Gulf (WRR 3) are dominated by spring and fall events. Damages in the Missouri River basin (WRR 10) are concentrated in the summer months, which most likely correspond to convective summertime storms. Damages in California (WRR 18) are dominated by wintertime events, related to Pacific storms

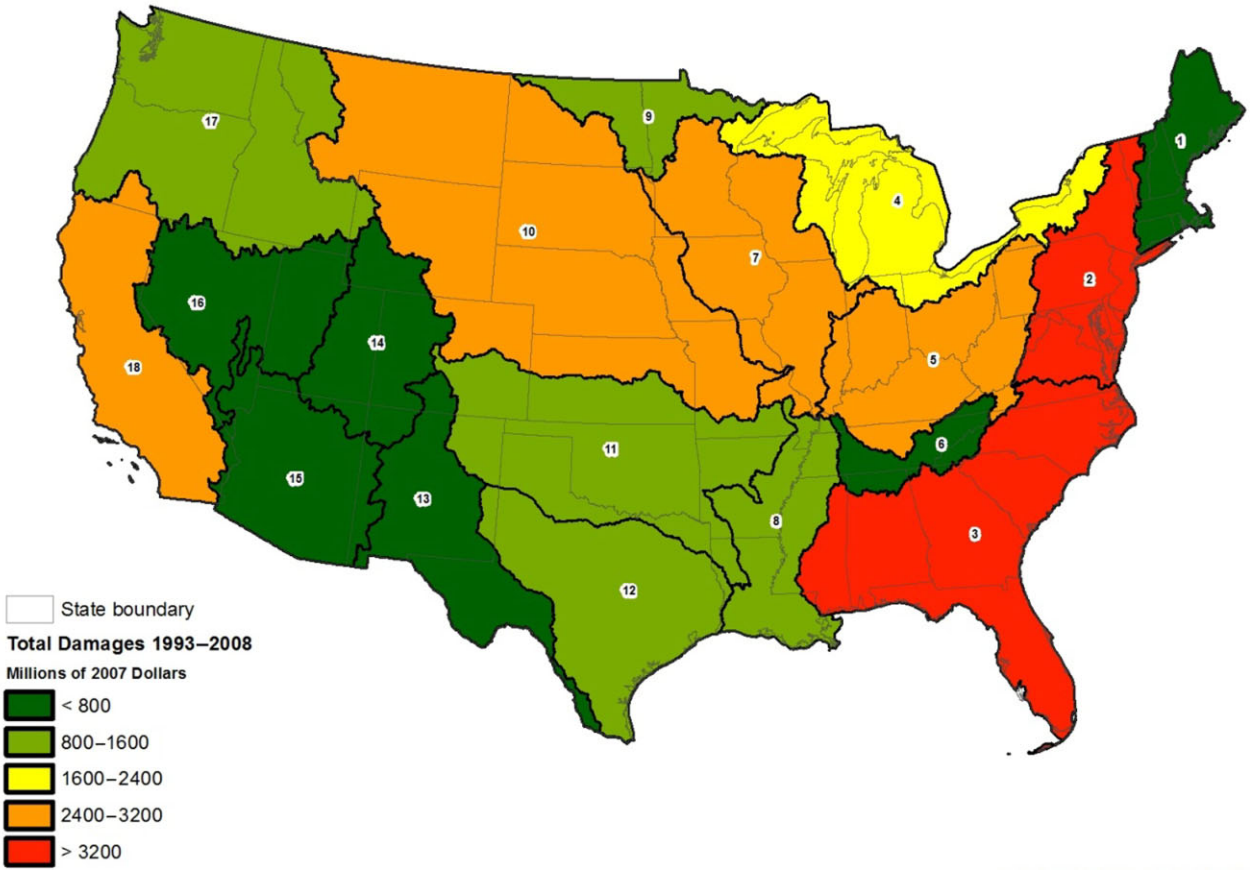

Figure 3 Spatial distribution of monetary damages from flooding, 1993–2008.

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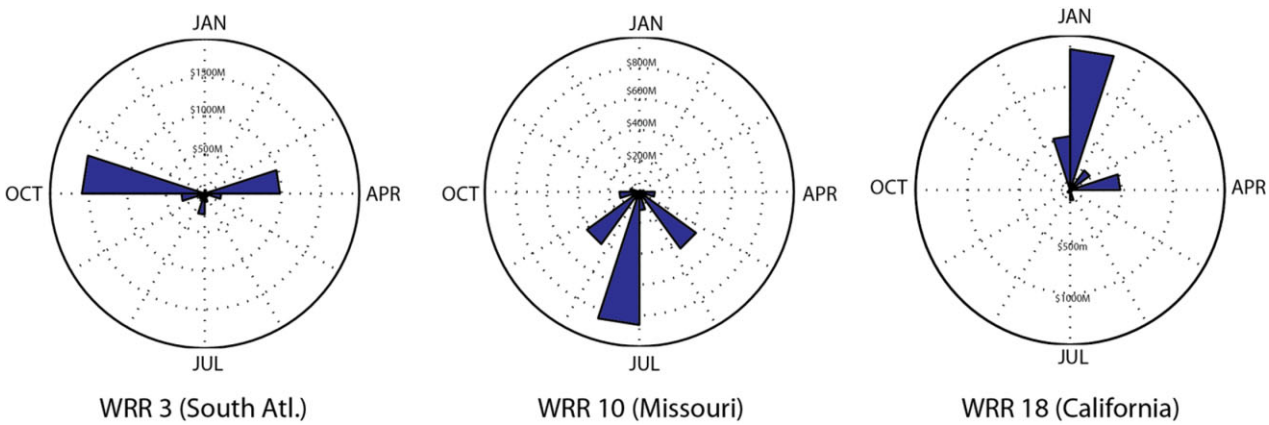

Figure 4 Seasonality of flood damages in three water resource regions (WRRs), over the period of record from 1993–2008. Dollar amounts increase radially; seasons are illustrated around the circle.

that penetrate into this region during the winter. This seasonality also played a role in the development of our logistic regression model, as described in the Model Development section.

Climate model output

GCM results predict an uneven distribution of precipitation changes, both spatially and temporally. Figure 5 shows seasonal average changes in monthly precipitation estimated by our ensemble of models for the year 2100, assuming a BAU scenario with moderate (3 °C) sensitivity.

As illustrated in Figure 5, the most pronounced changes in modelled monthly precipitation are decreases in the north-west and increases in the south-west during the summer. Moderate increases in the north-eastern half of the country and decreases in the south-western half of the country are forecast for the winter and spring months. In our regression model, these seasonal changes in forecast precipitation interact with the seasonal distribution of damaging flooding to drive changes in the magnitude of flood damages in the future.

Model development

Modelling flood probabilities

A statistical model estimating the relationship between precipitation and the precise level of monetary damages would require that both the precipitation and monetary data be collected consistently and very accurately over time and in all areas of the country. While the precipitation data methods are standardised and have a formal quality control process, the monetary data collection methods do not. These data are self-reported; therefore their accuracy may vary over time and between locations.

To account for possible inconsistencies in data collection methods while still taking advantage of the information regarding the general magnitude of flooding damages, we used a logistic regression model to estimate the probability of a large, damaging flood occurring given a suite of antecedent precipitation conditions. We identified floods that fell into the uppermost 25th percentile of monetary damages for floods in each WRR and labelled these as 'damaging floods'. Thus the model estimates when damaging floods are likely to occur given a set of precipitation conditions, but it does not estimate the exact magnitude of monetary damages.

The variables used to simulate the occurrence of damaging floods capture the total amount, average amount, and seasonality of precipitation within the WRR. These variables were all calculated from the GHCN-D record for each ASR separately, creating a data set with a single record for each ASR and each day in the study period. The ASR values were then bundled to calculate a separate set of variables for each WRR. The variables include:

- Median precipitation across an ASR on each day
- Total 1-day precipitation in the ASR, measured as the sum of precipitation at all stations on that day
- Total 3-day precipitation in the ASR, measured as the sum of precipitation at all stations on the previous three days
- Total 5-day precipitation in the ASR, measured as the sum of precipitation at all stations on the previous five days
- Total 7-day precipitation in the ASR, measured as the sum of precipitation at all stations on the previous seven days
- The season.

The logit model specification is as follows:

$$\Pr\left(D_{jt} \geq P(75) \mid X\right) = \frac{e^{\beta_1 medprecip_{jt} + \beta_2 1dayprecip_{jt} + \beta_3 3dayprecip_{jt} + \beta_4 5dayprecip_{jt} + \beta_5 7dayprecip_{jt} + \underline{\beta}_6 season_t}}{\sum_{k=1}^{m} e^{\beta_1 medprecip_{kt} + \beta_2 1dayprecip_{kt} + \beta_3 3dayprecip_{kt} + \beta_4 5dayprecip_{kt} + \beta_5 7dayprecip_{kt} + \underline{\beta}_6 season_t)}}$$

where D represents the monetary damages of an individual precipitation event, j indexes an individual precipitation

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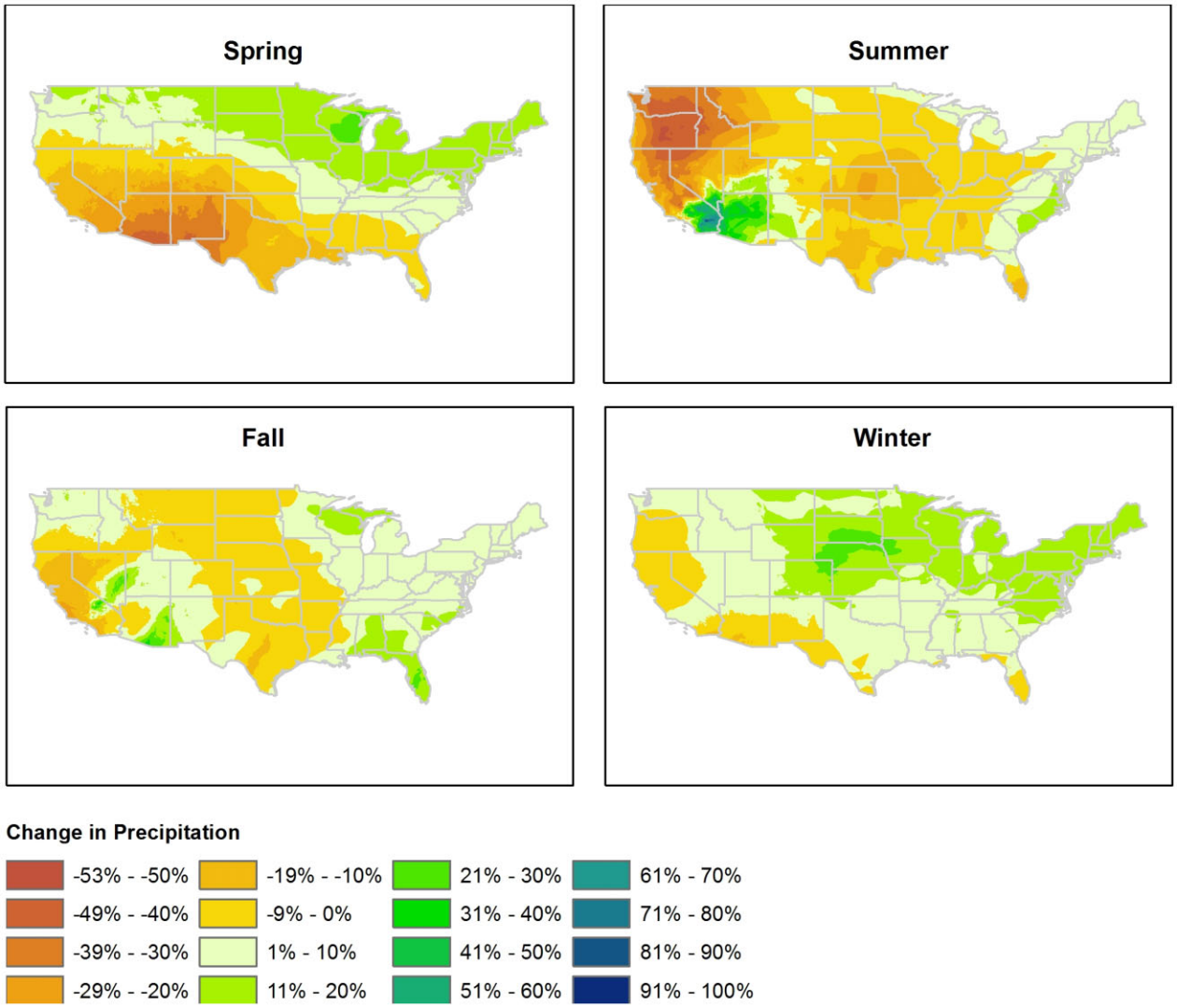

Figure 5 Per cent change in seasonal precipitation for business as usual scenario, assuming 3 °C sensitivity for the year 2100.

event, t indexes time, and k indexes all flooding events that occurred within the WRR on that day. The earlier expression translates to 'the probability that the monetary damages from an individual precipitation event exceed the 75th percentile in damages, conditional on the explanatory variables in X'. β_6 is a vector including coefficients for individual dummies for winter, spring, and summer (fall is omitted to avoid perfect collinearity).

Precipitation projections

Once the parameters of the logistic regression model were determined based on historical data, the baseline precipitation data set was perturbed by an amount defined by the GCM output. Because our method relies on correlations between an observed time series of precipitation and damage values, this time series must be preserved in the perturbed case. As a result, we applied average monthly deltas to this observed time series to make our projections.

Calculating monetary damages

For each WRR, the output of the perturbed logistic regression model is a projection of the change in the probability of a 75th percentile damaging flood event under climate change, along with the uncertainty bounds around this prediction. However, the regression model does not include projections about the monetary damages incurred by any particular flood or suite of floods. To translate the change in flood probability into a change in the estimated monetary damages from flooding, we used a Monte Carlo approach.

The Monte Carlo approach applies the estimated probability of flooding over a 100-year period. Each time a flood occurs, the simulation picks randomly from the uppermost

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25th percentile of the empirical distribution of flood damage values for that WRR. Flood damages are aggregated over the 100-year period, and the average annual damage is calculated for each WRR at the end of the model run. This is repeated 1000 times so that the final simulation output is an average of 1000 hundred-year simulations.

Results

Parameter estimates

Results from the 18 separate WRR logistic regression models are included in Table 1. Within each row in Table 1, the top number is the coefficient and the bottom number is the *t*-statistic, calculated to test the probability that the coefficient has an effect on the dependent variable (i.e. the coefficient is not equal to zero). The most important variables affecting the probability of a damaging flood, both in terms of statistical significance and magnitude, are the season in which the precipitation occurs and the total precipitation within a WRR on a given day.

In 13 of 18 WRRs, damaging floods are much more likely to occur in summer than in any other season. Springtime floods in New England, the South Atlantic Gulf, the Upper and Lower Mississippi, Missouri, Arkansas-White-Red, and Texas-Gulf are also more likely to be damaging. Given the relatively large spatial scale and simple measures of precipitation, these seasonal indicators bundle a number of complex hydrologic processes that are not captured explicitly in these models.

Across all but two WRRs (the Pacific Northwest and California), greater total precipitation across the ASR is significantly more likely to result in a damaging flood. This is apparent in both the magnitude and statistical significance of the coefficients, with the strongest effects in the Great Basin, the Upper Colorado River, and the Lower Colorado River.

In the Pacific Northwest and California, damaging floods are also more likely to occur when the median precipitation across the ASR is greater. In other words, damaging floods are more likely when many stations experience a large amount of rain, rather than when single stations experience dramatically greater rainfall than other stations within the ASR. This suggests that large-scale weather systems are driving flood damages in these regions, rather than localised storms. In the South Atlantic Gulf, the Great Lakes, the Ohio River, the Lower Mississippi, the Souris Red Rainy, the Missouri and Arkansas, Texas-Gulf, Upper and Lower Colorado, and the Great Basin, greater median precipitation within the ASR actually lowers the probability of a damaging flood. In each of these cases, the coefficient on total precipitation is also significant and positive, indicating that the greatest increases (decreases) in the probability of damage occur when the total and median precipitation diverge (converge). This indicates that flooding in these areas is most severe when precipitation is extreme and localised. Climate change would have a dramatic effect in these areas if total rainfall increased, but this rainfall was isolated in a few particular ASRs. Median precipitation has no significant effect on the probability of a damaging flood in New England, the Mid-Atlantic, Tennessee, the Upper Mississippi, or the Rio Grande.

In many cases, cumulative rainfall over 3-, 5-, and 7-day periods has little effect on the probability of a damaging flood occurring. This indicates that single-day rainfall-runoff is the primary control on damaging flooding in many cases. Longer-term rainfall accumulation increases the probability of damaging floods in the Lower Mississippi, Missouri, Arkansas-White-Red, Texas-Gulf, and the Rio Grande. These areas could experience more frequent damaging floods if rainfall events under climate change were more closely spaced, or if rainfall occurred during longer duration storm events.

The Upper Mississippi, Lower Colorado, and the Great Basin had few damaging floods, limiting the variables that could be included in their respective models.

Probability of damaging flooding

Table 2 shows the current and predicted future probabilities of a damaging flood occurring, the standard errors of these estimates (calculated using the Delta method), and results of *t*-tests of the statistical significance of the difference between the predicted probabilities.

The logistic regression models estimate that damaging floods will occur more frequently in 14 of the 18 WRRs (Figure 6). These differences are statistically significant in four regions: the Great Lakes, the Ohio River, Texas-Gulf, and Lower Colorado (Figure 7a). In the other 10 regions, while the models do project that damaging floods will be more common in the future, it is possible that flooding occurrence could remain constant, or in some cases decrease, in the future (Figure 7b). Note that although increases in flood damages are not significant in any of these regions, increases in flood damages are more likely in some of these 10 regions than in others. In New England, as well as in the upper Mississippi River Valley and the Rio Grande, the distributions of current and future flood damage probabilities are not statistically different at an 80% confidence level (Figure 7c). The models predict that damaging floods will occur less frequently in the Pacific Northwest and California. However, California is the only region where this difference is statistically significant (Figure 7d).

In the Texas-Gulf region, precipitation is projected to decrease, yet the frequency of damaging floods is estimated to increase. This occurs because in the Texas-Gulf region, damages are caused more by localised flooding than by total

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Table 1 Logistic regression model results, by WRR

	New England	Mid-Atlantic	South Atlantic Gulf	Great Lakes	Ohio	Tennessee	Upper MS	Lower MS	Souris Red Rainy
WRR	1	2	3	4	5	6	7	8	9
Totalprecip	0.136	0.136	0.293	1.006	0.609	0.772	0.214	0.767	2.154
	0.8	4.05***	5.80***	4.66***	10.46***	2.47**	2.00**	4.33***	3.08***
Medianprecip	0.013	0.008	–0.009	–0.025	–0.058	0.012	0.003	–0.04	–0.569
	1.45	1.2	2.41**	2.01**	7.02***	0.56	0.19	2.21**	1.91*
Tot3day	0.101	–0.023	0.002	0.05	–0.028	–0.205	–0.02	–0.114	
	1.45	1.66*	0.1	0.76	1.61	1.79*	0.46	2.02**	
Tot5day	0.009	0.014	0.004	–0.027	0.014	0.127	0.019	0.154	
	0.13	1.09	0.25	0.41	0.87	1.15	0.42	2.53**	
Tot7day	0	0.004	0.015	0.032	0.021	0.137	0.013	–0.035	
	0	0.4	1.21	0.65	1.67*	1.5	0.41	0.72	
Spring	2.086	0.165	0.99	0.506	0.205	–0.308	1.881	1.049	12.523
	3.29***	0.47	3.49***	1.47	0.89	0.85	2.50**	2.72***	0
Summer	1.828	1.607	1.735	1.011	0.506	–0.45	2.982	0.431	14.155
	2.72***	4.98***	6.30***	2.91***	2.16**	1.01	4.01***	0.93	0
Fall	0.649	0.413	1.335	–0.746	–0.785	–0.597	0.96	0.392	11.855
	0.9	1.2	4.77***	1.68*	2.57**	1.35	1.19	0.89	0
Constant	–7.69	–6.44	–6.005	–5.943	–5.413	–6.365	–6.956	–6.671	–19.594
	11.04***	16.61***	19.90***	17.21***	22.06***	15.62***	9.73***	15.10***	0
N	5840	5840	5840	5840	5840	5840	5840	5840	5840
Pseudo R2	0.2	0.23	0.15	0.16	0.19	0.21	0.14	0.14	0.15
Chi Squared	103.51	255.28	280.07	185.46	357.37	120.56	129.34	95.35	35.4
P-value	0	0	0	0	0	0	0	0	0

	Missouri	Arkansas-White-Red	Texas-Gulf	Rio Grande	Upper Colorado	Lower Colorado	Great Basin	Pacific Northwest	California
WRR	10	11	12	13	14	15	16	17	18
Totalprecip	0.2	0.388	0.436	2.181	4.725	3.265	8.018	–0.319	–0.044
	4.52***	9.82***	11.57***	3.03***	3.08***	6.20***	3.89***	0.93	0.23
Medianprecip	–0.02	–0.042	–0.067	–0.023	–0.37	–0.204	–1.51	0.096	0.039
	1.91*	5.26***	7.98***	0.74	1.99**	4.18***	2.69***	2.24**	2.61***
Tot3day	–0.017	–0.02	–0.009	0.44	0.028	0.231	–0.724	0.071	0.013
	1.04	1.11	0.52	1.32	0.04	0.91	0.81	0.56	0.19
Tot5day	0.029	–0.006	–0.011	–0.531	–0.692	–0.139	0.856	0.08	0.03
	1.69*	0.37	0.7	1.62	1.09	0.53	0.78	0.58	0.49
Tot7day	–0.01	0.025	0.031	0.403	0.534	0.141	–0.424	–0.103	0.025
	0.76	2.05**	2.74***	1.94*	1.33	0.84	0.49	1.06	0.6
Spring	2.709	1.026	1.523	14.79	–0.063			0.715	–0.368
	3.71***	2.81***	4.27***	0.01	0.04			0.8	0.62
Summer	2.952	1.487	1.956	15.676	2.514	2.489	16.526	2.237	1.31
	4.03***	4.03***	5.51***	0.01	2.40**	4.98***	0.01	2.65***	2.12**
Fall	0.67	0.815	0.99	14.088	–0.26	2.034	13.805	0.931	0.418
	0.82	2.15**	2.65***	0.01	0.18	4.05***	0.01	1.19	0.74
Constant	–6.936	–6.258	–6.58	–20.199	–8.601	–7.416	–23.074	–7.053	–6.58
	9.76***	17.30***	18.22***	0.02	7.79***	13.61***	0.01	8.04***	12.56***
N	5840	5840	5840	5840	5840	4368	4368	5840	5840
Pseudo R2	0.17	0.21	0.24	0.19	0.2	0.2	0.27	0.09	0.21
Chi Squared	227.62	302.45	392.54	170.42	47.63	151.78	37.67	26.88	100.49
P-value	0	0	0	0	0	0	0	0	0

One asterisk beside the *t*-statistic indicates that there is less than a 10% chance that the coefficient is equal to zero;
two asterisks indicate that there is less than a 5% chance that the coefficient is equal to zero;
three asterisks indicate that there is less than a 1% chance that the coefficient is equal to zero.
MS, Mississippi; WRR, water resource region.

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Table 2 Current and future probability of damaging floods occurring

WRR	Region	Current		Future		Change from current	*t*-statistic	Probability that current and future distributions are equal
		Mean	Standard error	Mean	Standard error			
1	New England	0.7%	0.0011	0.7%	0.0016	94.8%	–0.19	0.85
2	Mid-Atlantic	1.9%	0.0017	2.0%	0.0030	106.1%	0.34	0.73
3	South Atlantic Gulf	3.8%	0.0024	4.5%	0.0038	118.4%	1.55	0.12
4	**Great Lakes**	**2.0%**	**0.0018**	**2.9%**	**0.0041**	146.2%	**2.03**	**0.04**
5	**Ohio**	**3.7%**	**0.0023**	**6.7%**	**0.0053**	182.0%	**5.22**	**0.00**
6	Tennessee	0.9%	0.0012	1.0%	0.0016	113.2%	0.58	0.56
7	Upper MS	1.6%	0.0016	1.6%	0.0018	101.3%	0.09	0.93
8	Lower MS	1.0%	0.0013	1.3%	0.0021	123.6%	0.99	0.32
9	Souris Red Rainy	0.3%	0.0007	0.4%	0.0011	133.8%	0.75	0.45
10	Missouri	2.5%	0.0020	2.7%	0.0026	110.4%	0.80	0.43
11	Arkansas-White-Red	2.7%	0.0020	3.1%	0.0026	113.9%	1.15	0.25
12	**Texas-Gulf**	**3.2%**	**0.0022**	**3.9%**	**0.0028**	122.4%	**2.03**	**0.04**
13	Rio Grande	1.5%	0.0015	1.4%	0.0018	96.6%	–0.21	0.83
14	Upper Colorado	0.3%	0.0007	0.6%	0.0024	194.1%	1.18	0.24
15	**Lower Colorado**	**1.7%**	**0.0019**	**3.6%**	**0.0047**	210.1%	**3.68**	**0.00**
16	Great Basin	0.2%	0.0007	0.5%	0.0018	214.8%	1.39	0.17
17	Pacific Northwest	0.4%	0.0008	0.3%	0.0007	76.0%	–0.86	0.39
18	**California**	**0.7%**	**0.0010**	**0.4%**	**0.0009**	60.0%	**–2.01**	**0.04**

Regions in bold type had statistically significant changes in flood damages under climate change at a 95% confidence level.
MS, Mississippi; WRR, water resource region.

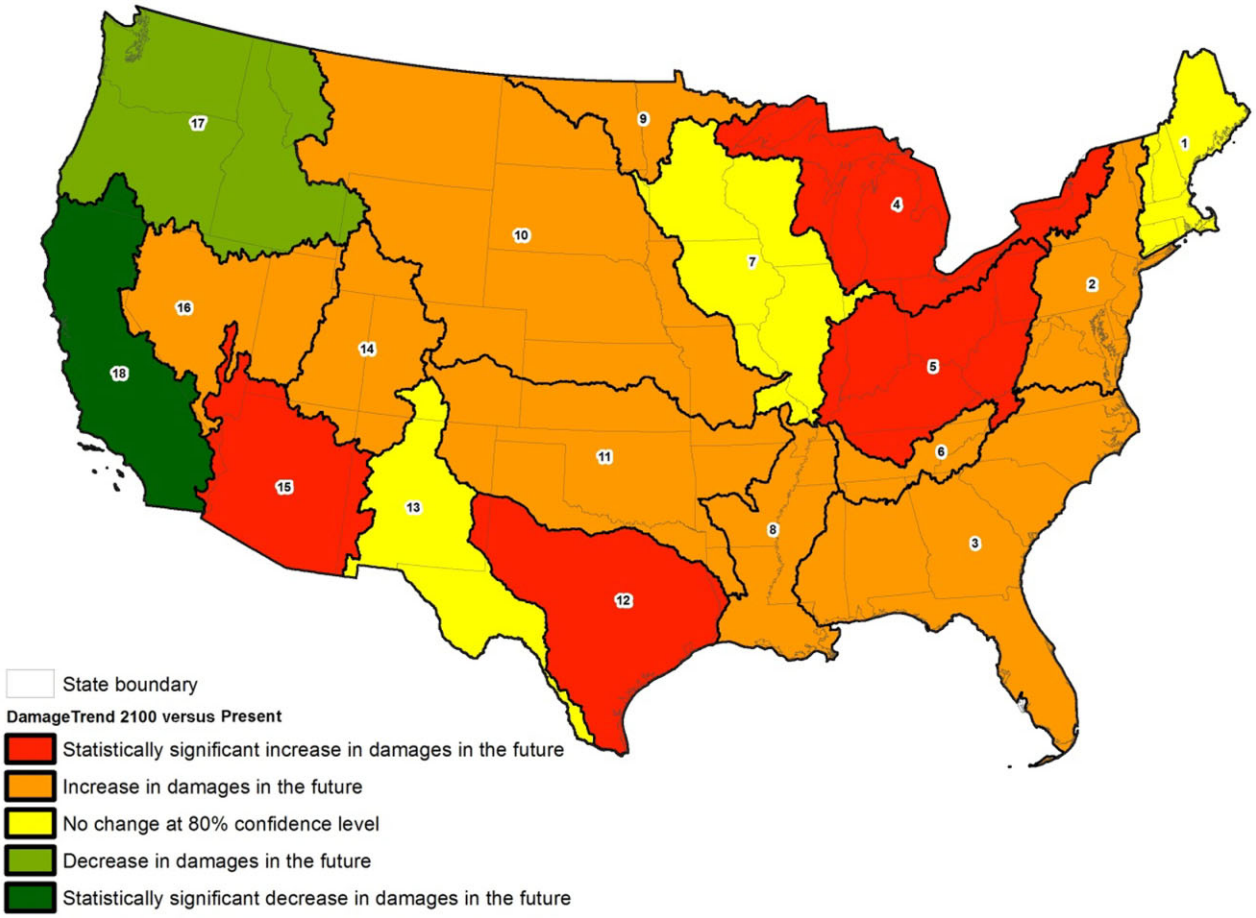

Figure 6 Spatial distribution of changes in damaging flood frequency.

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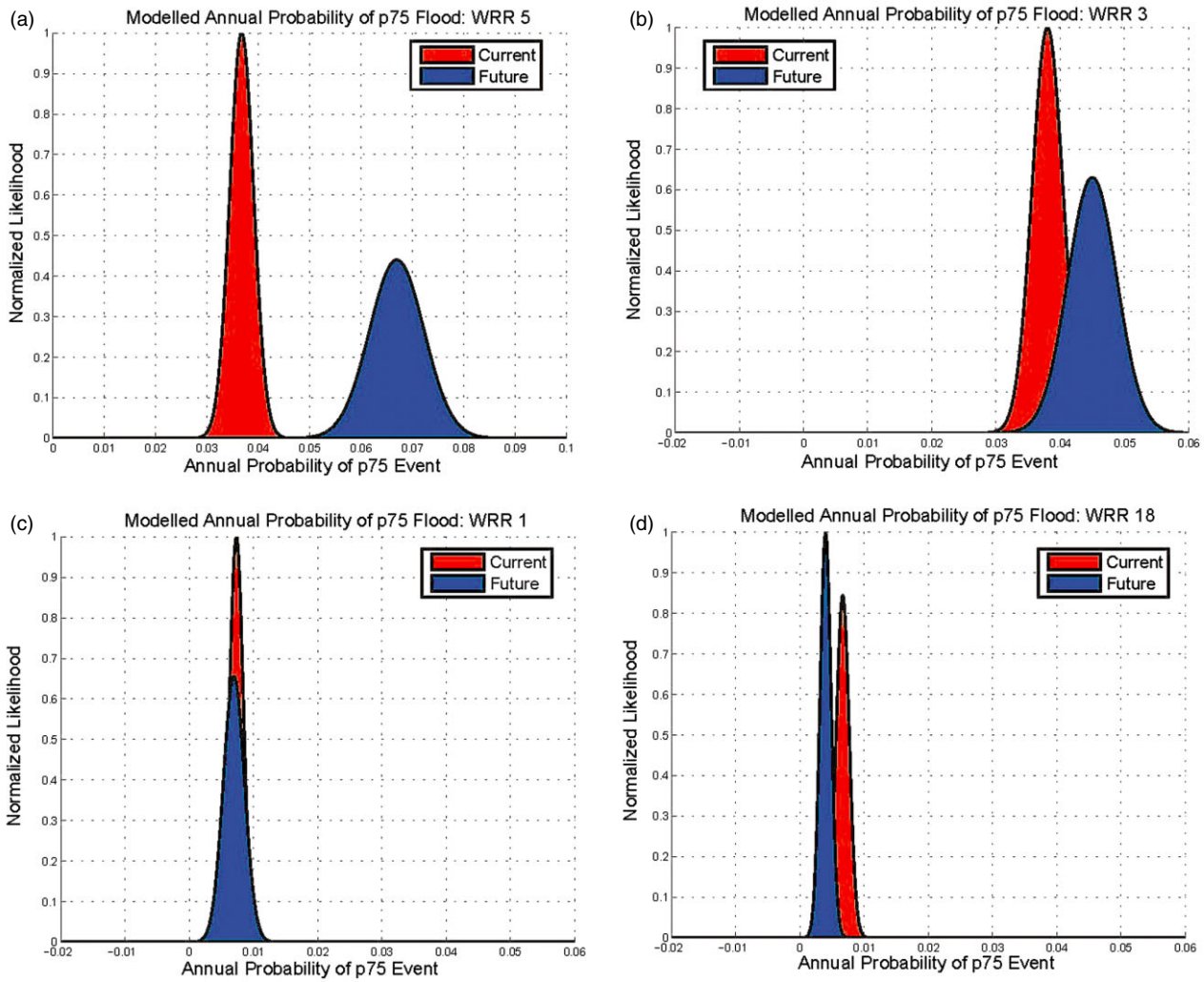

Figure 7 Examples of modelled current and future probabilities of damaging floods. Statistically significant increase in damaging floods for water resource region (WRR) 5 (a); modelled increase in flood probability, but not statistically significant for WRR 3 (b); statistically indistinguishable change in flood probability for WRR 1 (c); and statistically significant decrease in flood probability WRR 18 (d).

precipitation across the region. In this region, the GCMs estimate that total precipitation decreases slightly (by 7.5%), but median precipitation decreases by 50%. These projections indicate that precipitation events could become more localised and therefore more damaging. To be sure, GCMs are simulating precipitation over grid boxes that are more than a hundred miles across and thus are not capturing localised changes in precipitation. This result should be interpreted with caution and could be further investigated using downscaled projections of changes in precipitation.

Monetary changes in flood damages

Table 3 summarises current flood occurrence, mean damages per flood, current average annual damages, future mean and 95% confidence intervals for damages, and the mean and 95% confidence intervals for projected changes in annual damages. These calculations assume that the mean monetary damages per flood remain constant in the future.

For the four WRRs with statistically significant changes in the frequency of damaging floods, the mean and lower and upper 95% confidence intervals for monetary damages are all above zero. Summing damages across all WRRs, we estimate that the mean additional annual monetary damages in the future will be $747 million per year (a 31% increase from current levels), ranging from $3 million less damages to $1.5 billion more damages (undiscounted). The analysis assumes no change in the built environment or value of affected buildings and property.

Figure 8 displays the current and projected future distributions of monetary damages by WRR based on the Monte Carlo model output. While the mean increase in monetary

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Table 3 Current and projected future annual damages from flooding

WRR	Region	Damaging floods/year	Mean damages/event	Current annual damages	Future		
					Mean	Lower 95% CI	Upper 95% CI
1	New England	5.375	$8 190 581	$44 024 373	$41 744 591	$22 481 807	$61 007 376
2	Mid-Atlantic	13.88	$32 491 140	$450 814 568	$478 334 468	$340 774 130	$615 894 806
3	South Atlantic Gulf	27.75	$11 921 720	$330 827 730	$391 566 262	$326 456 053	$456 676 472
4	Great Lakes	14.38	$6 494 201	$93 354 139	$136 496 967	$98 142 314	$174 851 621
5	Ohio	26.88	$7 626 838	$204 971 271	$373 063 150	$315 240 650	$430 885 650
6	Tennessee	6.38	$17 466 130	$111 346 579	$126 082 066	$85 840 816	$166 323 316
7	Upper MS	11.63	$6 189 748	$71 955 821	$72 882 568	$57 022 547	$88 742 589
8	Lower MS	7.5	$4 703 467	$35 276 003	$43 595 828	$29 664 697	$57 526 959
9	Souris Red Rainy	2.125	$1 419 412	$3 016 251	$4 034 534	$1 804 568	$6 264 499
10	Missouri	18	$6 073 650	$109 325 700	$120 728 724	$98 500 894	$142 956 553
11	Arkansas-White-Red	20	$3 639 200	$72 784 000	$82 869 258	$69 247 988	$96 490 529
12	Texas-Gulf	23.5	$17 242 620	$405 201 570	$495 892 600	$426 528 590	$565 256 609
13	Rio Grande	10.625	$2 971 435	$31 571 497	$30 505 861	$22 928 596	$38 083 127
14	Upper Colorado	2.25	$11 879 560	$26 729 010	$51 886 638	$11 740 923	$92 032 354
15	Lower Colorado	9.25	$31 716 510	$293 377 718	$616 320 426	$456 818 666	$775 822 186
16	Great Basin	1.25	$8 528 340	$10 660 425	$22 898 541	$6 874 007	$38 923 075
17	Pacific Northwest	2.75	$4 272 614	$11 749 689	$8 931 319	$4 696 113	$13 166 525
18	California	4.875	$22 235 440	$108 397 770	$65 028 306	$37 781 433	$92 275 179
	Total	208.38	$205 062 606	$2 415 384 111	$3 162 862 108	$2 412 544 792	$3 913 179 424

MS, Mississippi; WRR, water resource region; CI, confidence interval.

WRR	Region	Change		
		Mean	Lower 95% CI	Upper 95% CI
1	New England	–$2 279 781	–$21 542 565	$16 983 003
2	Mid-Atlantic	$27 519 900	–$110 040 437	$165 080 238
3	South Atlantic Gulf	$60 738 532	–$4 371 677	$125 848 742
4	Great Lakes	$43 142 828	$4 788 175	$81 497 481
5	Ohio	$168 091 879	$110 269 379	$225 914 379
6	Tennessee	$14 735 487	–$25 505 763	$54 976 737
7	Upper MS	$926 747	–$14 933 274	$16 786 769
8	Lower MS	$8 319 825	–$5 611 306	$22 250 956
9	Souris Red Rainy	$1 018 283	–$1 211 682	$3 248 248
10	Missouri	$11 403 024	–$10 824 806	$33 630 853
11	Arkansas-White-Red	$10 085 258	–$3 536 012	$23 706 529
12	Texas-Gulf	$90 691 030	$21 327 020	$160 055 039
13	Rio Grande	–$1 065 635	–$8 642 901	$6 511 630
14	Upper Colorado	$25 157 628	–$14 988 087	$65 303 344
15	Lower Colorado	$322 942 708	$163 440 949	$482 444 468
16	Great Basin	$12 238 116	–$3 786 418	$28 262 650
17	Pacific Northwest	–$2 818 369	–$7 053 576	$1 416 837
18	California	–$43 369 464	–$70 616 337	–$16 122 591
	Grand total	$747 477 997	–$2 839 319	$1 497 795 313

MS, Mississippi; WRR, water resource region; CI, confidence interval.

damages is high in regions such as the Mid-Atlantic, the South Atlantic Gulf, and the Upper Colorado River, the variance around these means is often large, illustrating the uncertainty in this outcome.

Discussion

This study developed and tested a framework for estimating changes in the monetary damages due to flooding under a changing climate. This framework can be applied to estimate flooding damages under a broader range of future GHG emission and climate scenarios, and this is a focus of future work. Due to the large spatial scale of this analysis, physically based hydrologic models were not used to make these projections; instead, our approach combines GCM output with an evaluation of the statistical correlations between local and regional rainfall and flood damages. While this approach provides a national-scale method of estimating how mon-

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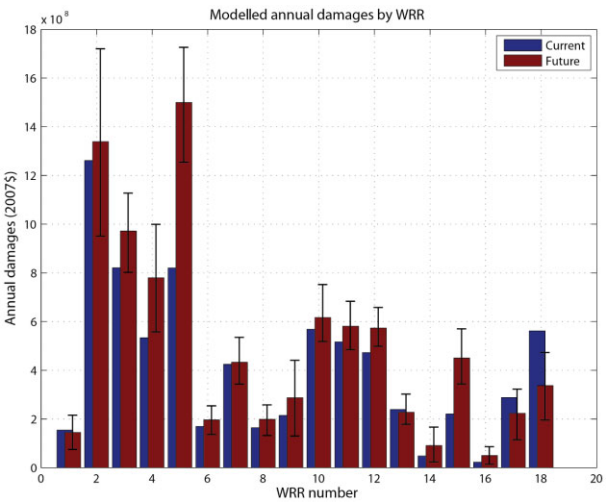

Figure 8 Modelled current and future annual damages by water resource region (WRR), with 95% confidence intervals.

etary damages from flooding might change under a changing climate, it also introduces some key limitations that are described here.

First, because our model relies on statistical correlations between precipitation and flooding, it requires that we preserve an observed time series of precipitation and flooding events. As a result, GCM-derived changes in precipitation are incorporated as monthly changes to an observed time series, rather than as changes in the distribution of storm frequency and magnitude. This introduces a potential limitation to this modelling framework: many studies suggest that changes in the frequency-magnitude distribution of storms may occur under climate change, and in particular that extremes may become more extreme (e.g. Meehl *et al.*, 2000; Emori and Brown, 2005; Tebaldi *et al.*, 2006; IPCC, 2012). Our approach to applying an average monthly delta to an observed time series may therefore underestimate the effect of potential increases in the severity of storms, particularly in regions where isolated, convective events drive flooding.

In addition, because the logistic regression model considers only 1-, 3-, 5-, and 7-day precipitation totals, there is very little hydrologic 'memory' in our approach. The model therefore will not capture potential changes in flood damages due to snowmelt events or rain-on-snow events. Analysis of the seasonality of flood damages indicates that this could be a shortcoming in regions such as New England, the Mid-Atlantic, the Ohio River, Upper Mississippi, and Souris Red Rainy basins (WRRs 1, 2, 5, 7, and 9). In each of these WRRs, flood damages in the spring represent a significant fraction of total damages, and snowmelt is a potential source of these damaging events.

Finally, our approach to estimating damages assumes stationarity in the distribution of monetary damages from flooding in the future. In reality, this distribution is likely to change: changes in demographics, modifications to flood protection infrastructure, or changes in wealth could all influence the damage incurred by a given magnitude of flood event in the future (e.g. Pielke and Downton, 2000; Bouwer, 2011). However, these future demographic and infrastructure changes could either increase or decrease damages from flooding in the future: flood protection could decrease damages, while increases in overall wealth or additional development in the floodplain could increase them. Without an *a priori* means of evaluating which path to follow, the assumption of stationarity in this distribution was deemed appropriate.

Conclusions

The results of our analysis indicate that monetary damages from flooding will increase in 14 of the 18 WRRs in the United States under a BAU scenario, with statistically significant increases in damages in four of these regions: the Great Lakes, the Ohio River, the Texas-Gulf region, and the Lower Colorado. The mechanisms behind these forecast changes vary regionally. For example, increases in flood damages in the Lower Colorado are due to substantial increases in projected summertime precipitation, when most of the flood damages in this region occur. In the Great Lakes and Ohio River, increases in damages may be driven by increases in fall, winter, and spring precipitation.

Nationally, the model estimates that the annual monetary damages from flooding may increase by up to $1.5 billion by 2100, with a mean estimate of approximately $750 million or 31% higher than the historic baseline. Nearly all of the projections within the 95% confidence limits are positive, indicating that it is unlikely that monetary damages from flooding will decrease in the future.

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