Contribution of historical precipitation change to US flood damages

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Edited by Kerry A. Emanuel, Massachusetts Institute of Technology, Cambridge, MA, and approved December 16, 2020 (received for review August 18, 2020)

Precipitation extremes have increased across many regions of the United States, with further increases anticipated in response to additional global warming. Quantifying the impact of these precipitation changes on flood damages is necessary to estimate the costs of climate change. However, there is little empirical evidence linking changes in precipitation to the historically observed increase in flood losses. We use >6,600 reports of state-level flood damage to quantify the historical relationship between precipitation and flood damages in the United States. Our results show a significant, positive effect of both monthly and 5-d state-level precipitation on state-level flood damages. In addition, we find that historical precipitation changes have contributed approximately one-third of cumulative flood damages over 1988 to 2017 (primary estimate 36%; 95% CI 20 to 46%), with the cumulative impact of precipitation change totaling $73 billion (95% CI 39 to $91 billion). Further, climate models show that anthropogenic climate forcing has increased the probability of exceeding precipitation thresholds at the extremely wet quantiles that are responsible for most flood damages. Climate models project continued intensification of wet conditions over the next three decades, although a trajectory consistent with UN Paris Agreement goals significantly curbs that intensification. Taken together, our results quantify the contribution of precipitation trends to recent increases in flood damages, advance estimates of the costs associated with historical greenhouse gas emissions, and provide further evidence that lower levels of future warming are very likely to reduce financial losses relative to the current global warming trajectory.

precipitation | flooding | climate change

Flooding is one of the most costly natural hazards, causing billions of dollars in damage each year (1). Both the total cost of flood-related damages and the frequency of "billion-dollar disasters" have been growing over time (2–4) (Fig. 1*A*). Simultaneously, extreme, short-duration precipitation has been increasing in many areas (5–7). Many historical trends in precipitation intensity—including of individual extreme events—have been attributed to climate change (8–11), and continued global warming is very likely to yield further increases in extreme precipitation (12–15). Quantifying the impact of these precipitation changes on flood damages is a critical step toward evaluating the costs of climate change and informing adaptation and resilience planning (16).

However, the effect of changes in precipitation on historical flood damages—and the potential attribution of these damages to anthropogenic climate change—remains poorly quantified (17, 18). Such attribution requires isolating the impact of changes in precipitation from changes in other factors such as exposure and vulnerability, as well as from changes in reporting of damages. Previous studies have argued that increases in exposure (e.g., increases in property values or the number of structures) could explain most or all trends in disaster losses (19–22). While much of the research on trends in the cost of flood damage has been conducted at the national scale (2, 4, 19, 20), both the processes that cause damaging precipitation and the factors that control exposure and vulnerability occur at smaller spatial scales. Analyzing the national precipitation trend is thus not sufficient to understand historical drivers of flood damage, which result from regionally varying trends in flood hazard, exposure, and/or vulnerability. As a result, there remains critical uncertainty in the contribution of historical precipitation trends to the observed national-level increase in flood damages.

"Bottom-up" flood risk assessments (23–25)—which integrate higher-resolution socioeconomic and flood hazard information—can provide greater detail, but are often limited in temporal and geographic extent. Further, these approaches may require assumptions about the relationship between flood hazard and damage that cannot be easily verified. For example, existing flood depth–damage curves are often poor predictors of observed flood damage (26) but are commonly used in flood risk assessments. The attribution of historical precipitation trends also becomes more uncertain at finer spatial scales because of the progressively stronger influence of climate variability (27), particularly over the United States, where there is uncertainty in the signal-to-noise ratio of mean precipitation change during the historical period (17).

Here we quantify the impact of historical global warming on flood damages by combining 1) empirical approaches that integrate historical flood damages and precipitation at the subnational scale, 2) an analysis of historical changes in precipitation, and 3) ensemble climate model simulations that quantify the contribution of anthropogenic forcing to historical and future

Significance

Precipitation extremes have increased in many regions of the United States, suggesting that climate change may be exacerbating the cost of flooding. However, the impact of historical precipitation change on the cost of US flood damages remains poorly quantified. Applying empirical analysis to historical precipitation and flood damages, we estimate that approximately one-third (36%) of the cost of flood damages over 1988 to 2017 is a result of historical precipitation changes. Climate models show that anthropogenic climate change has increased the probability of heavy precipitation associated with these costs. Our results provide information quantifying the costs of climate change, and suggest that lower levels of future warming would very likely reduce flooding losses relative to the current global warming trajectory.

Author contributions: F.V.D., M.B., and N.S.D. designed research; F.V.D. performed research; F.V.D. contributed new analytic tools; F.V.D., M.B., and N.S.D. analyzed data; and F.V.D., M.B., and N.S.D. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

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This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2017524118/-/DCSupplemental.

Published January 11, 2021.

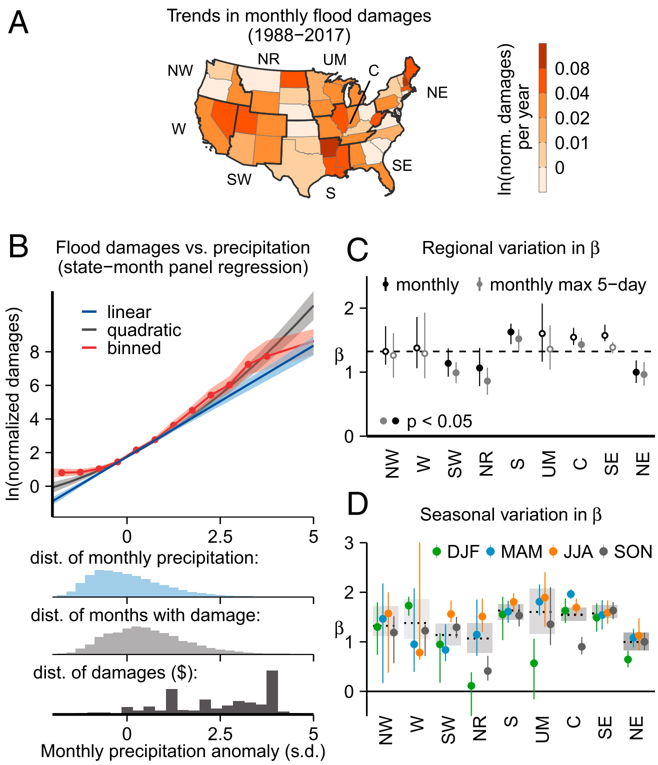

Fig. 1. Effect of state-level precipitation on flood damages. (*A*) Historical state-level trends in monthly flood damages. The nine National Centers for Environmental Information (NCEI) climate regions are outlined in dark gray: Northwest (NW), West (W), Southwest (SW), Northern Rockies and Plains (NR), South (S), Upper Midwest (UM), Central (C), Northeast (NE), and Southeast (SE). (*B*) Relationship between normalized flood damages and monthly precipitation at the state level using linear (blue line), quadratic (gray line), and binned (red line) models. Shading indicates the 95% CI estimated by bootstrapping states. Response functions are centered at mean monthly precipitation (0.04 SD) and mean log-normalized damage (1.8). Histograms show the distribution of monthly precipitation anomalies across all state-months (blue), the distribution of monthly precipitation anomalies during months with flood damage (light gray), and the distribution of total damages (in 2017 dollars) across monthly precipitation anomalies (dark gray). (*C*) Effect of precipitation on flood damages within each NCEI climate region (shown in *A*), for two precipitation variables: total monthly precipitation (black) and monthly maximum 5-d precipitation (gray). Effects are measured as the change in ln(normalized damages) per SD change in precipitation. Points show median coefficient estimates and vertical lines show the 95% CI around each point estimate. Filled circles indicate statistically significant ($P < 0.05$) differences between the regional coefficients and a pooled model (shown as a black dashed line for total monthly precipitation, same as the blue line in *B*). (*D*) Seasonal variations in the effect of monthly precipitation on flood damages for each region. Points show the median coefficient estimates for each season and region, and vertical lines show the 95% CI around each point estimate. Seasons are defined as December–January–February (DJF), March–April–May (MAM), June–July–August (JJA), and September–October–November (SON). Black dotted lines show the median coefficient estimate for each region (the same as black points in *C*), and gray shading shows the 95% CI (black lines in *C*).

precipitation change within the context of climate variability (*SI Appendix*, *Text*).

We use historical observations from 1988 to 2017 to model the relationship between precipitation and flood damages at the state-month level using fixed-effects panel regression analyses. We control explicitly for changes in income in each state, and include fixed effects that account for 1) year-to-year variations in precipitation and flood damages within each state and 2) state-specific seasonality in precipitation and flooding. In essence, we compare the effect of a relatively wet month in one state with a relatively dry month in the same calendar month and state, while accounting for year-to-year changes in average flood damage in that state. Over shorter (i.e., monthly or submonthly) timescales, variations in precipitation within each state are plausibly uncorrelated with variations in exposure or vulnerability, meaning that the regression analyses isolate the effect of a precipitation anomaly from other confounding variables that also affect flood damages.

Results and Discussion

We find a significant, positive relationship between monthly precipitation and flood damages, with a 1-SD increase in the monthly precipitation anomaly corresponding to a >3-fold increase in flood damages (Fig. 1*B*). Variation in monthly, state-level precipitation (after accounting for state-month and state-year fixed effects) explains 21% of the observed variation in monthly flood damages. The log-linear response suggests exponential growth in flood damages for a given increase in monthly precipitation, and we find a similar shape and magnitude of response using either a quadratic or nonparametric binned model (Fig. 1*B*). We also show that the presence of reporting errors in the data (such as missing damages) is unlikely to cause an overestimation of the effect of precipitation on flood damage (*SI Appendix*, *Text* and Fig. S1).

Although months with flood damages occur at a range of precipitation anomalies, the largest damages primarily occur at precipitation anomalies >2 SDs (Fig. 1*B*). As expected, the slope of the relationship is flatter across negative monthly precipitation anomalies when using a nonlinear functional form. Smaller flood damages do occur during months with negative statewide precipitation anomalies (Fig. 1*B*), possibly due to lagged effects from snowmelt, precipitation in adjacent states, or short-duration and/or localized precipitation during months that are relatively dry at the state-month scale. (We include additional models to test for some of these effects, as described below.)

Given the range of temporal and spatial scales at which flooding occurs, we compare our primary monthly, state-level regression model with regression models that use shorter- or longer-duration precipitation, or precipitation over large watersheds that span multiple states. Monthly maximum 5-d precipitation has a positive effect on monthly flood damages, but the effect is smaller compared with that of total monthly precipitation (Fig. 1*C*). Using a lagged precipitation model, we find that precipitation in previous months has a positive effect on flood damages (*SI Appendix*, Fig. S2*A*) but that these effects are much smaller than the effect of the current-month precipitation. Further, although there are additional effects from precipitation that occurs out-of-state (*SI Appendix*, Fig. S3), these effects are small compared with that of within-state precipitation. Combined, these analyses indicate that results based on the state-month regression are consistent with models that account for the effects of shorter- or longer-duration precipitation, or large-scale flooding processes.

We do find regional differences in the magnitude of the effect of monthly precipitation on flood damages (Fig. 1*C*), reflecting both regional differences in the conditions creating flood hazards (e.g., the type of weather events associated with extreme precipitation, and the primary flooding processes) and regionally specific patterns of exposure and vulnerability (e.g., patterns of land use and development). Additionally, some regions show seasonal variations in the effect of precipitation on flood damages (Fig. 1*D*). For example, there are smaller effects of precipitation on flood damages during the winter (December through February) season in the Northern Rockies, Upper Midwest, and Northeast regions. This result could reflect the fact that these cold regions receive snow in the winter, which would not have the same immediate impact on flooding as rain during

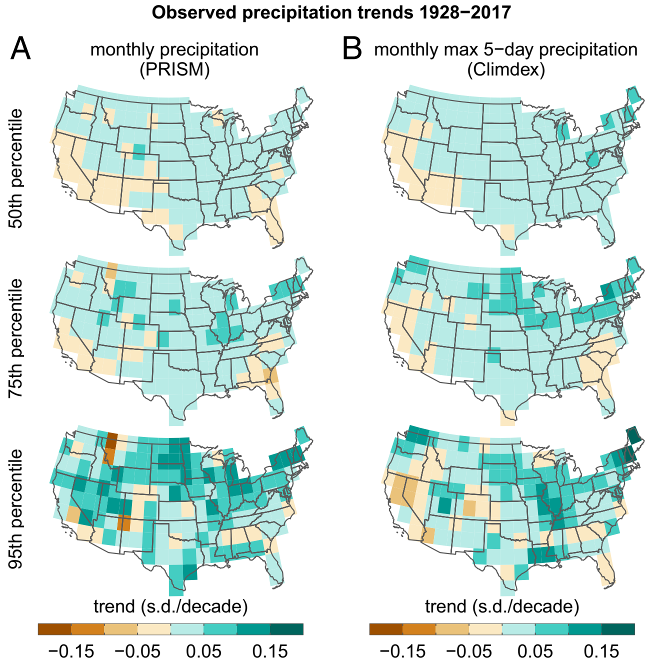

Fig. 2. Observed trends in monthly total and maximum 5-d precipitation. (*A*) Observed 1928-to-2017 trends in the 50th, 75th, and 95th percentiles of monthly precipitation, measured in SDs per decade. Trends are calculated on a 2.5 × 2.5° grid using quantile regression and the PRISM monthly precipitation product. (*B*) Same as *A*, but for monthly maximum 5-d precipitation. Trends are calculated on a 2.5 × 2.5° grid using quantile regression and the Climdex HadEX3 monthly Rx5day product.

warmer seasons. We use the regional, monthly regression model (Fig. 1*C*) as our primary model for later analyses, but we test the sensitivity of our results to these seasonal effects (see Fig. 3*B*).

We use our regression model results as a framework to understand the effect of historical precipitation changes on flood damages. Because monthly total and maximum 5-d precipitation have a similar effect on monthly flood damages (Fig. 1*C*), and because previous studies have detected changes in short-duration (e.g., daily or 5-d) precipitation extremes (5, 28), we analyze trends in both monthly total (Fig. 2*A*) and maximum 5-d precipitation (Fig. 2*B*). Further, given existing evidence that trends in extreme precipitation are larger and sometimes of opposite sign compared with trends in mean precipitation (29), we calculate trends at multiple quantiles within the distributions of monthly total and maximum 5-d precipitation. This approach allows us to distinguish between changes in the wettest months (which are associated with the largest flood damages; Fig. 1*B*) and changes in the median or drier months.

Fig. 2 shows trends in the 50th, 75th, and 95th percentiles of the monthly total and maximum 5-d precipitation distributions from 1928 to 2017. These analyses confirm that historical precipitation trends are not uniform across the distribution, with the 95th percentile exhibiting the largest trends. The spatial pattern of changes in monthly precipitation is very similar to that of monthly maximum 5-d precipitation. Most of the northwestern, central, and eastern United States have seen increases in median (50th percentile) monthly precipitation, whereas the Southwest has experienced decreases in median monthly precipitation. This spatial pattern is very similar to reported changes in annual mean precipitation over the United States, which results from changes that vary by region and season, including increases in fall precipitation in the Southeast, Northeast, and Great Plains and decreases in spring precipitation in the Southwest (29).

Precipitation during the wettest months (i.e., the 95th percentile) has increased across most of the country, even in some areas where median monthly precipitation is decreasing (Fig. 2). This pattern is also true for monthly maximum 5-d precipitation, and is consistent with previously identified increases in short-duration (e.g., daily or 5-d) precipitation extremes (29). The largest increases in the 95th percentile have occurred in the Midwest and Northeast.

Based on the regional regression coefficients, expected state-level flood damages have increased by an average of 35, 50, and 70% for precipitation at the 50th, 75th, and 95th percentiles, respectively (*SI Appendix*, *Text* and Fig. S4). In some states, we calculate that damages from the wettest 5% of months are now more than three times what would be expected in the absence of the observed precipitation changes (*SI Appendix*, Fig. S4).

Removing the historical quantile-specific monthly precipitation trends in each state allows us to estimate the effect of state-level precipitation changes on cumulative national-level damages (Fig. 3*A* and *Methods*). We find that precipitation changes have contributed 36% ($73 billion) of the 1988-to-2017 cumulative US flood damages. Uncertainty in the regional regression coefficients (Fig. 1*C*) and observed precipitation trends (*SI Appendix*, Figs. S4 and S5) yields a 95% confidence range of 20 to 46% (39 to $91 billion) contributed by state-level precipitation trends.

Our results are robust to using alternative regression models that account for lagged and seasonal effects (Fig. 3*B*), and to calculating precipitation trends over different time periods

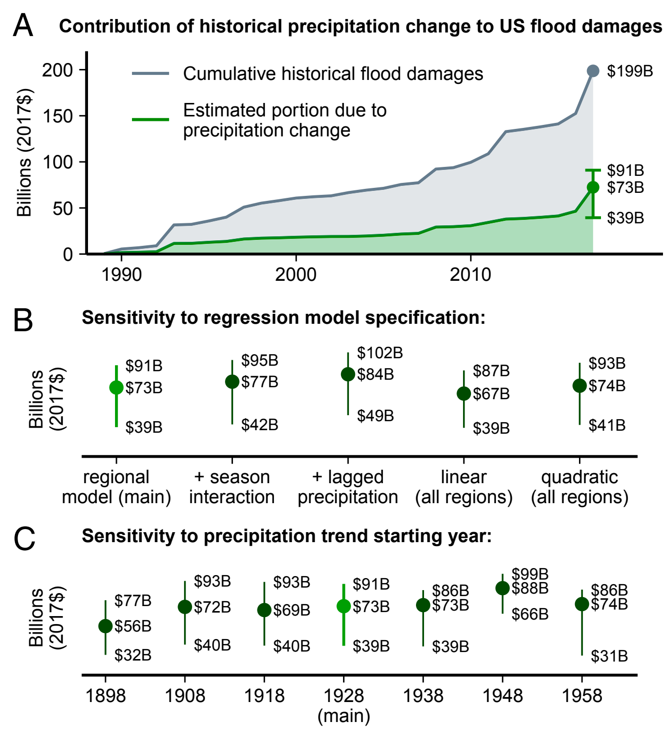

Fig. 3. Cumulative damages due to historical precipitation change. (*A*) Cumulative observed flood damages (gray) and estimated portion due to historical precipitation change (green) from 1988 to 2017. Error bars show the 95% CI for cumulative damages in 2017 (based on precipitation trends from 1928 to 2017). (*B*) Impact of historical precipitation change on cumulative flood damages in 2017 using various regression model specifications. From left to right, the models are the regional model (same as *A*), the regional-seasonal model (Fig. 1*D*), a regional model with lagged precipitation (*SI Appendix*, Fig. S2*A*), a linear model (Fig. 1*B*), and a quadratic model (Fig. 1*B*). (*C*) Sensitivity of cumulative damages from precipitation change to starting year of precipitation trend calculation. All estimates use the same regional regression model used in *A*.

(Fig. 3*C*). They are also robust to using different assumptions about possible unreported damages (*SI Appendix*, Fig. S6); further, the fact that the historical flood damage values are likely underestimated and/or unreported in earlier years (1) would cause the effect of precipitation on damages to be underestimated, and thus make our estimate of the contribution of historical precipitation change conservative (*SI Appendix*, *Text* and Fig. S1*A*).

There are limitations to using the state-month as the unit of analysis, because flooding can occur on shorter or longer timescales, and over smaller or larger areas. However, we find that our primary regression model yields a similar (although slightly lower) estimate of the contribution of historical precipitation change compared with versions of the model that include effects of precipitation over longer timescales (Fig. 3*B*) or larger spatial scales (*SI Appendix*, Fig. S3). The strong similarity between historical trends in monthly total and monthly maximum 5-d precipitation (Fig. 2), as well as similarity in their effect on damages (Fig. 1*C*), indicate that an analysis based on 5-d precipitation would yield a similar estimated contribution of historical precipitation change. Together, these sensitivity analyses suggest that our primary estimate of the contribution of historical precipitation trends to total US flood damages is both robust and conservative.

Prior studies have attributed increases in short-duration precipitation extremes over the United States to anthropogenic climate forcing by comparing historical trends with climate model simulations (10, 30), isolating forced changes from those driven by modes of natural climate variability (31–34), or calculating the probability of extreme events (i.e., "risk ratio") with and without anthropogenic climate forcing (9, 35, 36). While the general circulation models that comprise the Coupled Model Intercomparison Project (CMIP5) ensemble show a thermodynamic response to warming (37, 38) (Figs. 4 and 5), they do not explicitly resolve the precipitation processes that cause flood damages (such as severe thunderstorms and tropical cyclones), and may underestimate the magnitude of extreme precipitation change (10, 28, 29, 31). Given the large uncertainties in modeled precipitation trends, particularly at the spatial scale of individual events, we do not use our regression analysis to explicitly separate the contributions of forced climate change and unforced climate variability to cumulative flood damages.

However, we do use the CMIP5 global climate model simulations to assess changes in the probability of monthly total and maximum 5-d precipitation thresholds over the recent historical period (1988 to 2017) compared with an early-industrial baseline (1860 to 1920; *SI Appendix*, *Text*). The probability of exceeding the baseline 50th and 75th percentiles of monthly precipitation has increased slightly across the central and eastern United States in the recent historical period, and decreased slightly across the Southwest (Fig. 4). In contrast, the probability of exceeding the baseline 95th or 99th percentiles has increased across most of the United States, especially for monthly maximum 5-d precipitation (Fig. 4). This analysis suggests that anthropogenic climate forcing has increased the frequency of extreme monthly precipitation, with the ensemble mean response (Fig. 4) showing many similarities to the observations (Fig. 2). However, despite the mean wetting in response to anthropogenic forcing, there is some disagreement across models on the direction of change over the recent historical period, particularly at the higher-percentile thresholds (Fig. 4). We must therefore conclude that the estimated flood damages due to precipitation change (Fig. 3) represent the combined effects of anthropogenic forcing and natural variability, and cannot be entirely attributed to anthropogenic climate change.

To understand the implications of additional global warming for the cost of future flood damages, we evaluate future precipitation change in the "high-" (RCP8.5) and "low-" (RCP2.6) emissions scenarios analyzed in the assessment of impacts, adaptation, and vulnerability in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report [IPCC AR5 (16)]. In both scenarios, the 95th and 99th percentiles of monthly total and maximum 5-d precipitation are projected to increase across most of the United States by midcentury (2046 to 2065) relative to the recent historical period (*SI Appendix*, Fig. S7). Under the high-emissions scenario (RCP8.5), there is strong model agreement that the wettest months (both in total precipitation and maximum 5-d precipitation) will continue to intensify through the end of the century (Fig. 5). In some parts of the northeastern and western United States, the 99th percentile of monthly maximum 5-d precipitation is projected to increase by more than 1 SD (Fig. 5*B*). Combined with our regression model, these analyses suggest that—absent changes in exposure or vulnerability—future global warming is very likely to increase the costs of flooding, but that those increases could be greatly reduced under a low-emissions scenario consistent with the UN Paris Agreement.

Overall, our findings are consistent with prior conclusions that flood damages are sensitive to variations in weather (39–41), and that climate change has likely increased historical damages from

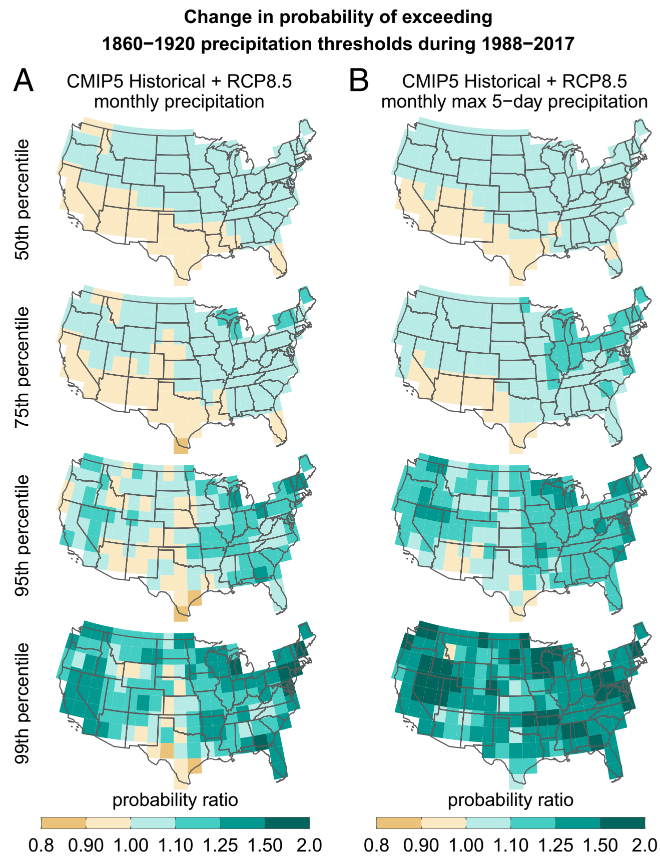

Fig. 4. Change in probability of exceeding early industrial baseline precipitation thresholds during the recent historical period, simulated by the CMIP5 global climate model ensemble. (*A*) Probability of exceeding the early industrial baseline (1860 to 1920) 50th, 75th, 95th, and 99th percentile monthly precipitation thresholds during the recent historical period (1988 to 2017). Probabilities are shown as a ratio relative to the probability during the baseline period, and are based on a 24-model ensemble (*SI Appendix*). Solid colors indicate strong model agreement (following the IPCC AR5 definition, when ≥66% of models agree with the direction of change shown on the map). Black stippling indicates <66% of models agree with the direction of change shown. (*B*) Same as *A* but for monthly maximum 5-d precipitation.

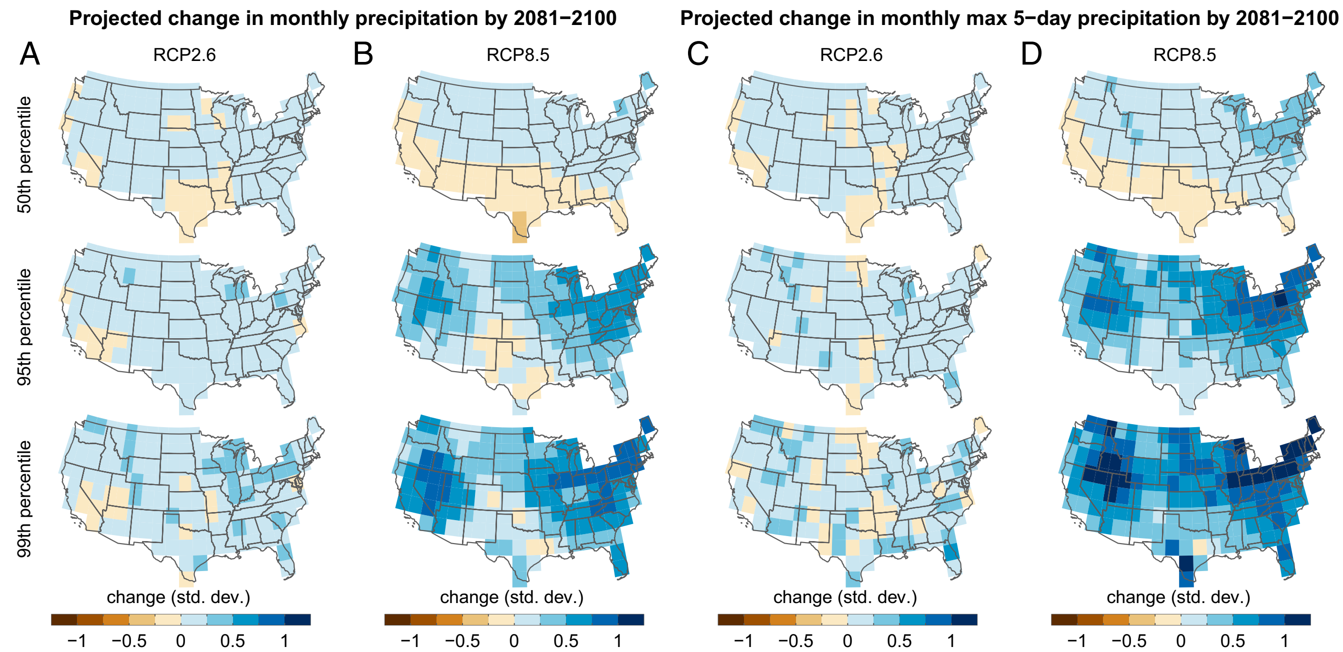

Fig. 5. Projected changes in monthly total and maximum 5-d precipitation. (*A*) Projected change in the 50th, 95th, and 99th percentiles of monthly precipitation by 2081 to 2100 for RCP2.6. Changes are relative to the recent historical (1988 to 2017) period. Maps show the mean change across a 17-model ensemble (*Methods*). Solid colors indicate strong model agreement (following the IPCC AR5 definition, when ≥66% of models agree with the direction of change shown on the map). Black stippling indicates <66% of models agree with the direction of change shown. (*B*) Same as *A* but for RCP8.5. (*C*) Same as *A* but for monthly maximum 5-d precipitation. (*D*) Same as *B* but for monthly maximum 5-d precipitation.

flooding and/or tropical cyclones (42, 43). While some studies have not found an impact of climate change on historical flood damages (20, 21), this contrast may be explained by different methodology, including 1) the scale of the analysis (for example, country-year in previous studies vs. state-month in our study); 2) our use of fixed effects to isolate precipitation variation from the many other time-invariant and time-varying factors that might also affect flood damages (such as variations in exposure and vulnerability); and 3) our use of precipitation trends at different percentiles of the distribution to isolate trends affecting the wettest months (in which damages are most likely to occur).

Conclusions

Our results show that historical increases in precipitation are very likely responsible for a substantial fraction of recent increases in US flood damages. Not only does precipitation in the upper tail of the distribution cause the largest historical damages (Fig. 1*B*) but the most intense precipitation has also shown the greatest increase over the historical period (Fig. 2), along with the strongest imprint of anthropogenic climate forcing (Fig. 4). Our panel regression models, combined with our analyses of quantile-specific precipitation trends, provide an empirical framework for quantifying the contribution of historical precipitation changes to recent increases in flood damages, and more broadly the costs associated with global warming.

This framework provides empirical evidence that climate change has affected the cost of flood damages at the national scale, along with comprehensive quantification of the magnitude and uncertainty of that impact. The framework could be extended to calculate the costs due to changes in other natural hazards, or to calculate the global costs of regional precipitation change. Given the importance of evaluating the costs of climate change versus the costs of mitigation options (44), the empirical quantification of losses due to changing natural hazards provides critical information to inform policy and decision making.

Methods

Precipitation and Flood Damage Data. We calculate historical monthly precipitation in each state using 4-km gridded monthly precipitation observations from the PRISM (parameter-elevation regressions on independent slopes model) Climate Group (45, 46) and state boundaries from the US Census Bureau. Monthly precipitation for each state is calculated as the average of all grid cells within each state boundary. We standardize the precipitation time series in each state by subtracting the mean monthly precipitation and dividing the anomaly by the SD of monthly precipitation, with the mean and SD for each state calculated over the IPCC's 1986-to-2005 baseline period (16). To test the regression model with shorter-duration precipitation, we also calculate monthly maximum 5-d precipitation in each state using the PRISM daily precipitation data. The maximum 5-d precipitation in each month is defined as the maximum total precipitation over 5 consecutive days within each calendar month. We standardize the monthly maximum 5-d precipitation time series in each state using the same procedure described above.

We analyze monthly, state-level flood damage estimates over 1988 to 2017 from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) version 17.0 (47). SHELDUS compiles flood damage estimates from the National Climatic Data Center *Storm Data* publications. Details of the SHELDUS dataset, including a comparison with other flood damage datasets and discussion of how uncertainty in reported damages could impact our results, are included in *SI Appendix*.

Regression Model. To estimate the relationship between monthly precipitation and flood damages (Fig. 1*B*), we use a least-squares log-linear regression model:

$$\ln(y_{ilm}) = \beta P_{ilm} + \delta_{il} + \mu_{im} + \varepsilon_{ilm}, \quad [1]$$

where y_{ilm} is normalized flood damages in state i during month m of year l, P_{ilm} is the standardized precipitation anomaly during the same state-month, δ_{il} and μ_{im} are state-year fixed effects and state-calendar month fixed effects, respectively, and ε_{ilm} is an error term. We normalize flood damages by annual state income, which is strongly correlated with exposure (see details in *SI Appendix*). The fixed effects in Eq. **1** subtract out year-to-year and seasonal variations in average damages in each state, allowing us to estimate the effect of monthly precipitation on flood damages after controlling for

https://doi.org/10.1073/pnas.2017524118

long-term changes in flood damage in each state. In other words, we can directly compare flood damages during a relatively wet month in a given state (e.g., June 2008 in Iowa) with flood damages during a relatively dry month in the same calendar month and state (e.g., June 2012 in Iowa), after accounting for average differences in flood damages and precipitation between the two different years (e.g., 2008 and 2012) that could have arisen from simultaneous changes in exposure or vulnerability. We calculate CIs around the estimated coefficients using bootstrap resampling (*SI Appendix*).

We test a number of variations of Eq. **1** by including additional interaction terms and testing nonlinear functional forms. The remaining regression models (including those shown in Figs. 1 *C* and *D* and 3*B*) are described in *SI Appendix*, *Text*.

Impact of Historical Precipitation Trends on Flood Damages. Following the approach of Diffenbaugh and Burke (48), we estimate the impact of historical precipitation trends on cumulative flood damages by calculating the "counterfactual" flood damages that would have occurred in the absence of precipitation changes. To create the counterfactual monthly precipitation time series, we remove observed trends at each decile of the distribution, which allows us to account for nonuniform changes in the distribution of monthly precipitation (*SI Appendix*). We next estimate counterfactual flood damages associated with this counterfactual precipitation time series. For each month with flood damages, we calculate the difference between the observed and detrended precipitation. While there are limitations to using counterfactual "treatments" and fixed-effects regression models to extrapolate impacts of large within-unit changes (49), in this case the changes in precipitation due to the historical trends are much smaller than the historical precipitation variability within each state (*SI Appendix*, Fig. S9). Because many of the observed trends are positive (Fig. 2), the detrended precipitation anomalies in the counterfactual scenario are less extreme than the observed precipitation anomalies, and this analysis does not require extrapolating the regression model beyond the observed data.

Based on the difference between the observed and detrended precipitation anomalies, we estimate counterfactual damages using the regional regression coefficients (*SI Appendix*, Eq. **S4**). We calculate the cumulative damages due to precipitation change as the sum of all observed damages minus the sum of the counterfactual damages. We calculate a 95% confidence range for our estimate of cumulative counterfactual damages based on 1) uncertainty in the regional regression coefficients and 2) uncertainty in the observed precipitation trends (*SI Appendix*, *Text*). We also evaluate the sensitivity of the counterfactual damage analysis to using other regression models, or using precipitation trends over shorter or longer time periods (*SI Appendix*, *Text*). The various alternatives lead to slightly higher or lower estimates of counterfactual damage, with our main result falling in the middle of the distribution (Fig. 3 *B* and *C* and *SI Appendix*, Fig. S6).

Climate Model Analysis. We analyze historical and future climate model simulations from CMIP5 (50) to understand the impacts of anthropogenic climate forcing on extreme monthly and 5-d precipitation. To assess the influence of anthropogenic climate forcing on historical changes, we calculate risk ratios (i.e., changes in the probability of exceeding various monthly total or maximum 5-d precipitation thresholds) for 24 simulations over the recent historical period (1988 to 2017) compared with an early-industrial baseline (1860 to 1920). To understand the impact of additional global warming on the future costs of flooding, we analyze changes in monthly total and maximum 5-d precipitation by 2046 to 2065 and by 2081 to 2100 in 34 simulations and two future emissions scenarios (17 simulations with the RCP2.6 forcing and 17 simulations with the RCP8.5 forcing). A detailed description of the CMIP5 simulations and analyses, including the limiting factors on the number of simulations analyzed, is provided in *SI Appendix*, *Text*.

Data Availability. The PRISM monthly and daily precipitation products are available from the PRISM Climate Group (http://www.prism.oregonstate.edu/). The SHELDUS dataset is a subscription-based dataset available from the Center for Emergency Management and Homeland Security at Arizona State University (https://cemhs.asu.edu/sheldus). State boundary files are available from the US Census Bureau (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html). Watershed boundary files can be downloaded from the Watershed Boundary Dataset (https://www.usgs.gov/core-science-systems/ngp/national-hydrography/watershed-boundary-dataset). Data on annual state income and national net stock of reproducible fixed assets are available from the US Bureau of Economic Analysis (https://www.bea.gov/). Data on state-level housing values and number of housing units are available from the US Census Housing Tables (https://www.census.gov/topics/housing/data/tables.html) and the American Community Survey (https://www.census.gov/programs-surveys/acs). The Climdex HadEX3 gridded monthly Rx5day product is available from the Climdex project archive (https://www.climdex.org/access/), and the Climdex CMIP5 data are available through Environment Canada (https://crd-data-donnees-rdc.ec.gc.ca/CCCMA/products/CLIMDEX/). CMIP5 data are available from the Program for Climate Model Diagnosis & Intercomparison through the Earth System Grid Federation data portal (https://esgf-node.llnl.gov/projects/cmip5/). Code and data supporting the findings of the study are available in GitHub at https://github.com/fdavenport/DBD2021.

ACKNOWLEDGMENTS. We thank the editor and two anonymous reviewers for insightful and constructive comments, which greatly improved the manuscript. We thank the PRISM Climate Group for access to the PRISM monthly precipitation product, the Center for Emergency Management and Homeland Security at Arizona State University for access to SHELDUS 17.0, the US Bureau of Economic Analysis for providing access to state income data, Climdex for calculating and archiving the observed and simulated Rx5day climate indices, and the Program for Climate Model Diagnosis & Intercomparison for access to CMIP5 data. Computational resources were provided by the Center for Computational Earth & Environmental Sciences and the Stanford Research Computing Center at Stanford University. Funding was provided by Stanford University.

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