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Fluvial Flood Losses in the Contiguous United States Under Climate Change

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Key Points:

- Future likelihood of flood-related property damage is quantified using probabilistic models conditioned on precipitation indicators
- Increase in the probability of flood-related property damage is projected toward the mid and end of the century across the US
- Nonstationary uncertainties in the projected flood-related property damage originate from the probabilistic models and climate scenarios

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Flooding is one of the most devastating natural disasters causing significant economic losses. One of the dominant drivers of flood losses is heavy precipitation, with other contributing factors such as built environments and socio-economic conditions superimposed to it. To better understand the risk profile associated with this hazard, we develop probabilistic models to quantify the future likelihood of fluvial flood-related property damage exceeding a critical threshold (i.e., high property damage) at the state level across the conterminous United States. The model is conditioned on indicators representing heavy precipitation amount and frequency derived from observed and downscaled precipitation. The likelihood of high property damage is estimated from the conditional probability distribution of annual total property damage, which is derived from the joint probability of the property damage and heavy precipitation indicators. Our results indicate an increase in the probability of high property damage (i.e., exceedance of 70th percentile of observed annual property damage for each state) in the future. Higher probability of high property damage is projected to be clustered in the states across the western and south-western United States, and parts of the U.S. Northwest and the northern Rockies and Plains. Depending on the state, the mean annual probability of high property damage in these regions could range from 38% to 80% and from 46% to 95% at the end of the century (2090s) under RCP4.5 and RCP8.5 scenarios, respectively. This is equivalent to 20%–40% increase in the probability compared to the historical period 1996–2005. Results show that uncertainty in the projected probability of high property damage ranges from 14% to 35% across the states. The spatio-temporal variability of the uncertainty across the states and three future decades (i.e., 2050s, 2070s, and 2090s) exhibits nonstationarity, which is driven by the uncertainty associated with the probabilistic prediction models and climate change scenarios.

Plain Language Summary Floods create significant economic losses in the United States and many other places across the world. Floods and flood-related losses are expected to change due to changes in heavy precipitation in a warmer climate. Inferring how (including when and where) flood-related losses could change in the future is crucial because of significant implications for flood risk management, insurance, and infrastructure resilience. We develop probabilistic models to project the likelihood of (fluvial) flood-related high property damage (annual total property damage exceeding a critical threshold) conditioning on precipitation indicators under two greenhouse gas emission scenarios. We estimate relatively higher probability of high property damage for the states across the western and south-western U.S. and parts of the U.S. Northwest and the northern Rockies and Plains, where projected changes range from 46% to 95% for a high-emission scenario. In these regions, future changes in the probability of high property damage compared to the historical period vary from 20% to 40%. Overall, our results identify regions with higher likelihood of high property damage in the future, and they are useful for developing long-term planning and resource mobilization, adaptation, and insurance instruments.

1. Introduction

Floods are among the most devastating natural disasters in the U.S. and many other regions around the world, causing significant losses to human lives, agriculture, and properties (Ashley & Ashley, 2008; Merz et al., 2021; Smith & Matthews, 2015). The global flood-related economic losses between 1980 and 2013 amounted to over $1 trillion and killed over 220,000 people (Winsemius et al., 2016). As per the "Billion-Dollar Weather and Climate Disasters" data inventory, there were 33 flood events across the United States between 1980 and 2018, each causing economic losses over $1 billion and totaling $120 billion (NOAA, 2021). Among other climate-related

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natural disasters, floods caused the highest mortality in the country in 2015, 2016, and 2017 (National Weater Service, 2019), leading to 449 deaths in total. In addition to fatality and mortality, flood-related economic losses mainly originate from property and crop damage.

Economic losses from floods are significant; hence, many studies have focused on quantifying flood damage at scales from local to global leveraging computationally expensive numerical models or empirical models employing statistical relationships (Alfieri et al., 2017; Alipour et al., 2020; Blöschl et al., 2019; Gerl et al., 2016; Guimarães Nobre et al., 2020; Wobus et al., 2019; Zhou et al., 2017). Traditionally, flood damage forecasting employs hydrological and hydrodynamic models to quantify the extent and depth of a flood and translate these physical characteristics to economic losses using empirical depth–damage relationships (Dutta et al., 2003). However, quantifying climate change impacts on flood damage is challenging due to large uncertainties in future depth-damage relationships as well as applying hydrological models for regional scale projections of future flood extents and inundation depths (Bates, 2012; Bubeck et al., 2011; Freni et al., 2010; Lehman & Nafari, 2016; Villarini et al., 2020; Wasko et al., 2021; Wing et al., 2020).

An alternative approach for forecasting flood damage is formulating statistical relationships between flood damage and variables that directly or indirectly drive flood damage, for example, flood recurrence, heavy precipitation, climate oscillations, and socio-economic conditions (Bhattarai et al., 2016; Lüdtke et al., 2019; Wobus et al., 2019). Among others, Alipour et al. (2020) used machine learning for predicting flash flood property damage in the U.S. Southeast building relationships with precipitation, topography, and socio-economic conditions. However, the application of statistical relationships to assess climate change impacts on flood-related property damage is challenging because the prediction model requires future values of variables, which are fraught by large uncertainty (i.e., land use, topography, and socio-economic conditions) (Bubeck et al., 2011) in addition to the uncertainty in climate variables (e.g., precipitation intensity and duration). Seasonal prediction of flood losses using relationships with large-scale climate indices was proposed by Guimarães Nobre et al. (2020). Other studies forecast flood damage using heavy precipitation as predictor (Cortès et al., 2018; Pastor-Paz et al., 2020; Van Ootegem et al., 2018; Zhou et al., 2017).

Riverine and surface water floods are generally caused by excessive precipitation (or melting of snow in the snow-dominating regions), which is one of the prominent drivers of flood-related property and agricultural damages; additional drivers include the size and characteristics of river basin and catchment, built infrastructure, and socio-economic conditions. The higher the intensity and frequency of precipitation, the larger the property and agricultural damages (Bernet et al., 2019; Rosenzweig et al., 2002). Recently, Davenport et al. (2021) showed that increases in heavy precipitation alone caused approximately one-third of the 1988–2017 cumulative U.S. flood damages. Moreover, long-term trends in flood related property damages are related to long-term changes in the heavy precipitation climatology (Pielke & Downton, 2000). The frequency and magnitude of heavy precipitation have already increased in many regions across the world due to the observed increase in temperature (Zhang et al., 2019), and they are expected to increase further in the future in response to additional global warming (Fowler & Wilby, 2010; Halmstad et al., 2013; Hoegh-Guldberg et al., 2018; Rashid et al., 2015b, 2017; Villarini et al., 2011; Wuebbles et al., 2017). This may lead to more frequent and devastating flooding and hence higher flood damage if appropriate adaptation actions are not taken (Neri et al., 2020; Willner et al., 2018; Wobus et al., 2019).

Even though heavy precipitation alone is a significant driver of flood related property damage, few studies has focused on exploring its potential for damage predictions using probabilistic approaches (e.g., Hosseini et al., 2020; Merz et al., 2010, 2013; Rözer et al., 2019; Spekkers et al., 2014). Furthermore, projections of future property damage at the continental scale using heavy precipitation indicators are rare (e.g., Pastor-Paz et al., 2020; Wing et al., 2020). In this study, we develop probabilistic models for each state across the contiguous United States (CONUS) by linking observed property damages and heavy precipitation indicators. We consider two indicators related to the amount and frequency of heavy precipitation above a certain threshold, namely heavy precipitation fraction (HPF) and heavy precipitation days (HPD). The models are calibrated and validated with the historical property damage and heavy precipitation indicators; they are then forced with projections of the physical indicators derived from precipitation downscaled from the Coupled Model Intercomparison Project 5 (CMIP5) global climate models (GCMs) under different climate change scenarios. This information is then used to estimate the probability of annual property damage to exceed a critical threshold (termed as high property damage, hereafter) and associated uncertainty for three future decades (2050s, 2070s, and 2090s).

2. Data

We consider several data sources to acquire information on flood related property damage and heavy precipitation indicators for the historical and future periods across the CONUS. The National Weather Service (NWS) provides a comprehensive *Storm Events* database with the occurrence of recorded extreme weather phenomena (e.g., flood, drought, heat, and wind) that caused loss of life, injuries, and significant damage to property and crops across the United States. In the database, there are three categories of flood events: flood, flash flood, and coastal flood. Here, we only use data from the "flood" category, where a flood event is defined as an "event with high flow, overflow, or inundation of a usually dry area caused by an increased water level in a watercourse, or ponding of water, that pose threat to life or property." This means that the flood events considered here are mainly driven by precipitation (or melting of snow particularly in the snow-dominated regions) and generally have slower onset periods and longer event durations compared to flash flood events. The *Storm Events* database provides detailed information about the flood events (e.g., location and start and end time of the event, property and crop damage, injuries, and fatalities) across the U.S. for the period from 1996 to the present. Despite the limited record length, the *Storm Event* database is currently the most complete freely available database of flood events in the United States and has been successfully used in previous studies (Ahmadalipour & Moradkhani, 2019; Alipour et al., 2020; Konisky et al., 2016; Lobell et al., 2011; Paul et al., 2018). We acknowledge the Spatial Hazard Events and Losses (SHELDUS) database (CEMHS, 2020) which considered the *Storm Events* database as the baseline and extended it back to 1960 by integrating hazards information from different sources; however, the access to SHELDUS is not free to the public. Considering potential uncertainty on the reliability of data collected (or imputed) from different sources for the pre-1996 period and limited no-cost accessibility, we decided to rely only on NWS's *Storm Events* database.

We use observed daily grided precipitation records from the Livneh climate dataset (Livneh et al., 2013) and CPC US Unified Precipitation data provided by the National Oceanic and Atmospheric Administration's Climate Prediction Center (CPC) (Chen et al., 2008). It is noted that we did not consider the latest version of the Livneh data (Livneh et al., 2015) because the earlier version (Livneh et al., 2013) was used as the observational product for downscaling precipitation from the CMIP5 GCMs which are used in this study. The gridded precipitation data sets were developed by interpolating the gauge-based observations. The CPC US Unified precipitation data are available at the daily time scale from 1948 to the present and cover the CONUS. Livneh precipitation data are available up to 2011, limiting the overlapping period with respect to the property damage data that span from 1996 to 2019. Therefore, we complemented the Livneh precipitation data with the CPC US Unified precipitation data (2012–2019) and obtained daily precipitation time series from 1996 to 2019.

The Livneh precipitation data are considered because it was the observational product for producing projections of daily precipitation that we use here. The projections of daily precipitation were developed by statistically downscaling precipitation from the CMIP5 GCMs using Localized Constructed Analogs (LOCA) method (Pierce et al., 2014). These downscaled projections (LOCA database) are obtained from the "Downscaled CMIP3 and CMIP5 climate and hydrology projections" archive (http://gdo-dcp.ucllnl.org/downscaled_cmip_projections), and we considered 32 GCMs (listed in Table S1 in Supporting Information S1) under two greenhouse gas emission scenarios (RCP4.5 and RCP8.5). The downscaled precipitation data have a spatial resolution of $1/16° \times 1/16°$ and span from 1950 to 2100.

3. Methods

3.1. Property Damage Indicators

We identify 55,760 flood events across the 48 states of the CONUS. We first derive flood-related annual total property damage time series from 1996 to 2019 for each state. Delaware was not considered because it has no damage data or zero damage for most of the years over the study period as per the *Storm Events* database. All property damage values were adjusted for inflation to the year 2019. Years with no damage were considered as zero in the time series. We are interested in quantifying the likelihood that flood related property damage exceeds a critical level; however, there are only few references in the literature that could help with this task, and there was no suggestion of any unique threshold that could be used for that purpose. Instead of using absolute damage values, percentile-based flood losses were suggested for defining critical thresholds. Among others, Guimarães Nobre et al. (2020) suggested different categories of flood losses based on percentiles. For example, low and high flood losses were defined as the 33rd and 66th percentiles of observed flood losses, respectively. Based on this guideline and our best judgment, for each state, we considered the 70th percentile of the annual property damage observed from 1996 to 2019 as the critical threshold to estimate the probability that this threshold will be exceeded under future scenarios of the heavy precipitation indicators (HPF and HPD described below); we have also performed sensitivity analysis by considering other thresholds, such as 80th and 90th percentiles, to define the high property damage.

3.2. Heavy Precipitation Indicators

We consider two indicators related to amount and frequency of heavy precipitation above a certain threshold to formulate the relationships with annual property damage at the state level for the CONUS. The first one is termed heavy precipitation fraction (HPF) and represents the percentage of annual total precipitation falling in the heaviest daily events exceeding a given threshold. The second one is heavy precipitation days (HPD), describing the total number of days in a year corresponding to the heaviest precipitation events above the given threshold. An optimum threshold is important to formulate functional relationships between heavy precipitation indicators and property damage. The optimum threshold to identify property-damaging precipitation can vary due to changes in topography, geology, geomorphology, land use, and urbanization (Bernet et al., 2019). We tested different thresholds ranging from the 90th to the 99th percentiles to find the optimum thresholds to derive the heavy precipitation indicators. The following steps are used to derive the heavy precipitation indicators.

1. For any state of the CONUS, from gridded precipitation data, estimate state average daily precipitation from all grid points within the state boundary.
2. Consider the 90th percentile as the threshold. For any year, identify days where precipitation amount exceeds the threshold. The total number of the identified days is the HPD for the year. Aggregate precipitation of the identified days to estimate the amount of annual heavy precipitation to be used in the next step.
3. Estimate annual total precipitation by aggregating daily precipitation. Estimate HPF using the following equation:

$$\text{HPF} = \frac{\text{Annual heavy precipitation}}{\text{Annual total precipitation}} * 100 \tag{1}$$

4. Repeat steps 2 to 3 for each year to generate annual time series of HPF and HPD.
5. Consider other percentiles (up to 99th with increment of 1) and estimate Kendall correlation coefficients of HPF and HPD with property damage. Identify the threshold and corresponding HPF and HPD time series for which correlation coefficient is maximum.
6. Repeat steps 1 to 5 for all selected 48 states.

In addition to the historical period (1996–2019), annual heavy precipitation indicators are derived for the future period from 2050 to 2099 from the projected daily precipitation data downscaled from the CMIP5 GCMs under two representative concentration pathways (i.e., RCP4.5 and RCP8.5) following the steps discussed earlier. To estimate the probability of high property damage in the future, three decadal periods (i.e., 2050s, 2070s, and 2090s) are considered, and the corresponding future heavy precipitation indicators are derived by averaging the annual indicators over each decade.

3.3. Probability of Future Flood Related Property Damage

The probability of high property damage (i.e., property damage that exceeds the 70th percentile of the annual property damage from 1996 to 2019) in the future is estimated by developing probabilistic models from historical annual time series of property damage, HPF, and HPD. Similar modeling approaches were adopted in earlier studies, for example, to quantify the exceedance probability of heat-related mortality conditioned on mean summer temperature and heat wave days (Mazdiyasni et al., 2017). Here, we model the links of observed annual total property damage (Y) to HPF or HPD (X) through their joint distributions, that is, $F_{XY}(X, Y)$. Using the joint distribution, we can derive distributions of property damage for different heavy precipitation conditions (i.e., different values of HPF or HPD), known as conditional probability distributions, that is, $f_{Y|X}(YIX)$. For instance, red curves in Figure 1 represent the conditional probability distributions of annual total property

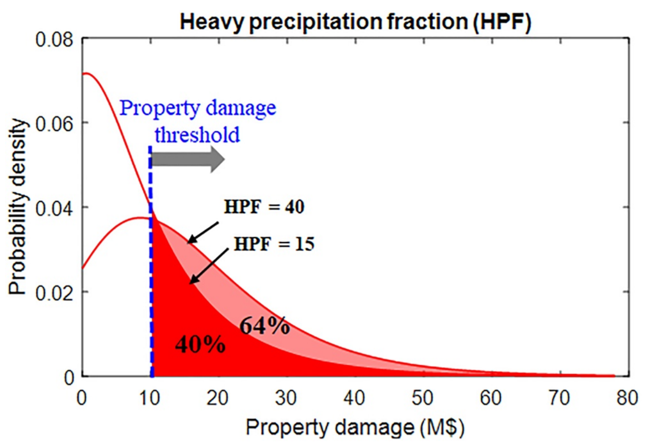

Figure 1. Conditional probability density function (PDFs) for annual property damage conditioned on certain values of HPF. The dotted line represents the high property damage threshold (i.e., 70th percentile of observed annual property damage). The likelihood of high property damage corresponding to selected HPF values is represented by the shaded areas.

damage corresponding to HPF values equal to 15 and 40. For a certain HPF or HPD value, the probability of annual property damage exceeding a threshold, that is, $F_{Y|X}(Y > Y \mid X = X)$ is the area under the curve (red shaded region in Figure 1). For example, the exceedance probability of high property damage for HPF values of 15 and 40 are 40% and 64%, respectively. With the HPF or HPD values estimated from the observed and downscaled (from different GCMs and greenhouse gas emission scenarios) precipitation, the corresponding conditional property damage distributions are developed, and exceedance probabilities of high property damage are estimated for the historical and future periods.

To derive the conditional probability, we use bivariate copula functions to define the joint probability distribution of annual total property damage and heavy precipitation indicators (HPF or HPD). We fit five widely used copula functions (i.e., Gumbel, Frank, Clayton, normal, and t copula). The Gumbel, Frank and Clayton are Archimedean copulas, while the normal and t copulas are Elliptical copulas. The best copula is selected based on the root mean square error and the Akaike Information Criterion using the maximum likelihood approach. The best marginal distributions are identified based on the AIC statistics from a selected number of univariate distributions: exponential, gamma, normal, log-normal, logistic, Weibull, extreme value, generalized extreme value, and generalized Pareto. A copula is defined as the multivariate function of an n-dimensional random vector, $X = (x_{1,} x_{2,} x_{3,} \ldots, x_n)$, with continuous marginal distribution functions $F_1(x_1), F_2(x_2), F_3(x_3), \ldots, F_n(x_n)$:

$$F(x_1, x_2, x_2, \ldots \ldots, x_n) = C\{F_1(x_1), F_2(x_2), F_3(x_3), \ldots \ldots, F_n(x_n)\} \tag{2}$$

where C is the copula function that represents the dependence between random variables. We estimate bivariate joint probability distributions of annual total property damage and heavy precipitation indicators (i.e., HPF or HPD) using historical observations following Equation 3:

$$F_{XY}(X, Y) = C\{F_X(X), F_Y(Y)\} \tag{3}$$

where X and Y represent the heavy precipitation indicators (HPF or HPD) and property damage, respectively.

Conditional probability density functions of annual total property damage for different values of heavy precipitation indictors (HPF or HPD) can be estimated as follows (Madadgar & Moradkhani, 2013; Madadgar et al., 2017; Mazdiyasni et al., 2017):

$$f_{Y|X}(Y|X) = c\{F_X(X), F_Y(Y)\}.f_Y(Y) \tag{4}$$

where c is the probability density function (PDF) of the copula function and $f_Y(Y)$ is the marginal distribution of property damage.

We developed two separate models to estimate the probability of high property damage: one conditioned on HPF and the other conditioned on HPD. We quantified the probability of high property damage in the future decades (i.e., 2050s, 2070s, and 2090s) from the conditional probability distribution functions of property damage derived for the projected HPF and HPD, as discussed earlier.

3.4. Model Validation and Uncertainty Analysis

We adopted leave-one-out cross-validation (e.g., Madadgar et al., 2017) for validating the probabilistic models; this means 1 year of property damage information is withheld from the model fit and then estimated with the model; this process is iterated for all years in the record. Additionally, to evaluate the model performance, we use a reliability statistic called α-index, which measures the distance between the Q-Q plot of the observed (i.e., empirical) and simulated distributions of property damage and the 1:1 line (Laio & Tamea, 2007; Renard et al., 2010). Uncertainty in the probability of high property damage in the future is quantified employing the square root of error variance (SREV) (Woldemeskel et al., 2012), which quantifies uncertainty as the standard

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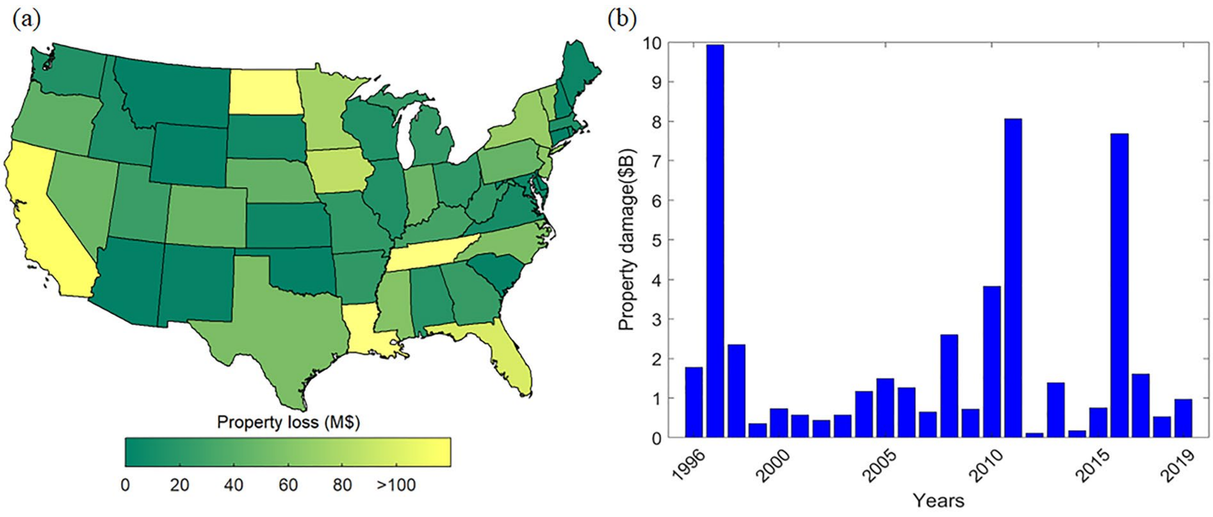

Figure 2. (a) Spatial distribution of mean annual property damage at state level across the CONUS averaged over the period 1996–2019. (b) Total Property damage summed over all states for the period from 1996 to 2019. All property damage values were adjusted for inflation to the year 2019.

deviation across different projections. This method allows decomposing all sources of uncertainty in the future projections (in our case probabilistic models, GCMs, and scenarios) and assesses their relative importance. Total uncertainty is estimated as the square root of the sum of square of individual SREV of different sources.

4. Results

Spatial and temporal variability of property damage caused by floods across the CONUS during 1996–2019 are shown in Figure 2. While no distinct spatial pattern is observed, some coastal states show higher average annual property damages, which may be related to relatively higher population density, critical infrastructure, and/or rapid urbanization (Hallegatte et al., 2013; Zhang et al., 2018). Annual total property damages across the CONUS show substantial interannual variability, varying from several million to billions of dollars. This is linked to the changes of heavy precipitation modulated by the large scale atmospheric and circulation patterns (Aryal et al., 2018; Merz et al., 2010; Špitalar et al., 2014). For instance, significant property damage from floods in 2011 was caused by widespread heavy precipitation across the CONUS due to a strong El Niño event, whereas property damage in 2012 was at its minimum due to less rainfall during a strong La Niña event.

As mentioned earlier, we tested different thresholds from 90 to 99th percentiles to derive the indicators related to heavy precipitation amount and frequency (i.e., HPF and HPD). We optimize the thresholds for HPF and HPD by achieving maximum correlation with the observed property damage. The optimum thresholds for HPD are generally higher than for HPF (Figure S1 in Supporting Information S1). An increasing pattern in the optimum thresholds is observed from east to west, indicating that flood related property damage across the western United States is linked to relatively more extreme precipitation compared to the eastern United States. The spatial variability of heavy precipitation thresholds optimized to explain flood damage variability is also evident in other studies and geographic regions (e.g., Switzerland (Bernet et al., 2019)). The temporal dependence of annual total property damage and heavy precipitation indicators (HPF and HPD) in terms of Kendall's τ are generally significant (at 5% level) varying from 0.26 to 0.61 (with mean values of 0.4 and 0.42 for HPF and HPD, respectively). The correlation follows a similar spatial pattern as the optimum thresholds. Some of the northernmost states (e.g., Montana, North Dakota, and Minnesota) showed correlations between property damage to HPF and HPD that were not significant at the 5% level. This is because flood related property damage across this region is often associated with rapid melting of snow during spring season rather than strongly linked to precipitation (e.g., Villarini, 2016). Additionally, low number of flood events could be an explanation for insignificant correlation with the precipitation indicators because many flood events might have been unreported or did not cause significant property damage because of low population and small number of infrastructure.

Probabilistic models based on the conditional distributions of annual property damage are developed to quantify the exceedance probability of high property damage for each state across the CONUS. Models are validated

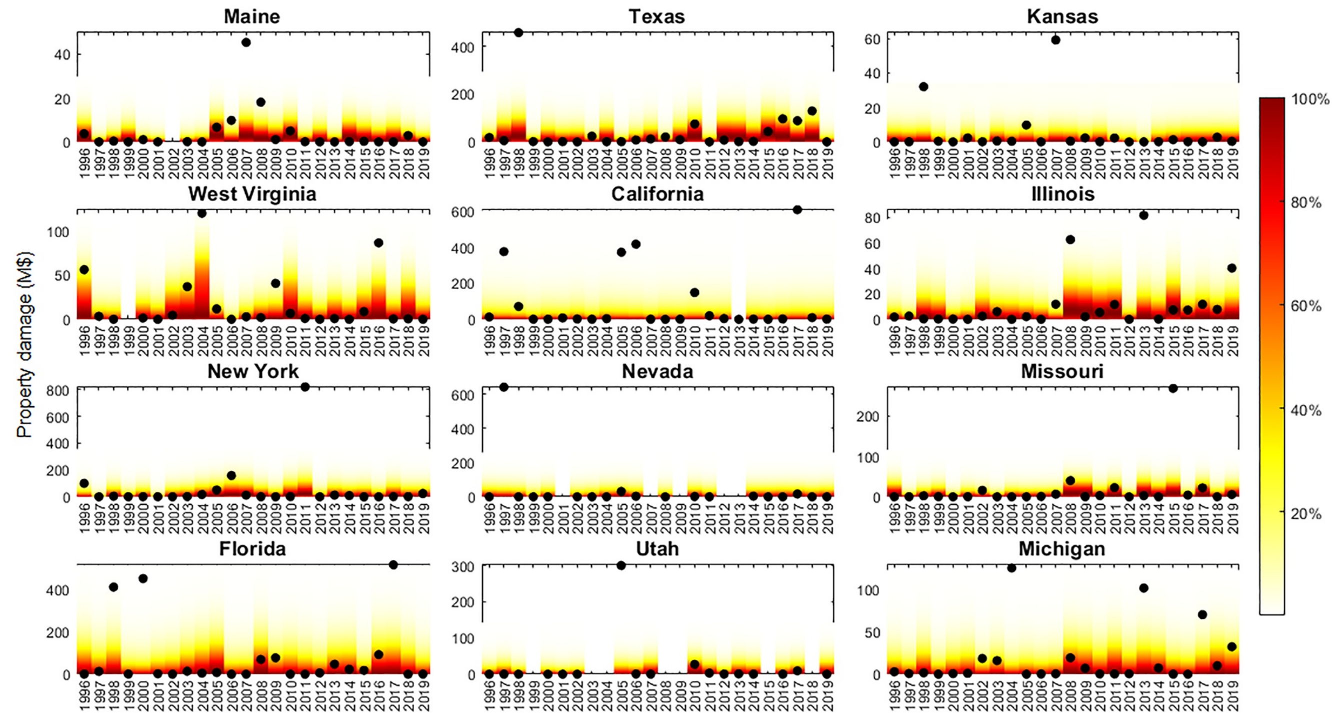

Figure 3. Comparison of estimated property damage distribution (absolute values of damage are shown on the *y*-axis and normalized probability density values between 0% and 100% are shown by the color bar) corresponding to HPF values for each cross-validated year (shown on the *x*-axis) with observed annual property damage (black circles) for the selected states. Each color bar (in each panel) represents a cross-validated property damage distribution for that year, and the black circle shows where the observed property damage is located with respect to the property damage distribution.

employing leave-one-out cross validation. Figure 3 compares the cross-validated property damage distribution with observed annual property damage for selected states (results for all states are shown in Figure S2 in Supporting Information S1). Each color panel (in each subplot) corresponds to a year and represents the cross-validated probability distribution of property damage for the corresponding HPF values. The graded colors show the normalized probability density and range from 0% for the lowest and 100% for the highest density. The vast majority of the observed annual property damage values (i.e., black circles) are located in the high-density regions of the cross-validated probability distribution functions (PDFs), indicating good model performance. The α-index, used here as a model reliability metric, is also high for all states, showing that the models adequately reproduce the observed distribution of property damage (Figure S3 in Supporting Information S1).

Mean (averaged over the selected climate models) annual probability of high property damage for three different decades in the future (2050s, 2070s, and 2090s) under the RCP8.5 scenario are shown in Figure 4 (results for the RCP4.5 scenario are shown in Figure S4 in Supporting Information S1). Ranges of probability of high property damage across all selected climate models are presented in Figure S5 in Supporting Information S1. We find a notable spatial pattern in the probability of high property damage (Figure 4a), consistent across different decades and scenarios. In general, the west, southwest, parts of the northwest and the northern Rockies and Plains regions show relatively higher probability of high property damage compared to the other regions of the CONUS. The states across the regions showing the highest probability are Washington, Wyoming, Idaho, Nevada, Utah, Colorado, and Arizona. Depending on the state, the probability of high property damage can be 38%–80% and 46%–95% by the 2090s under RCP4.5 and RCP8.5 scenarios, respectively. In the southeast region, Florida has the highest probability of high property damage (52%) in the future. Other U.S. regions and corresponding states are projected to have relatively lower probability (40% or lower) of high property damage. There are few states where projected probability is very low (<15%), including South Dakota, Kansas, Missouri, Ohio, West Virginia, and Tennessee. Differences in the probability of high property damage across the three different decades (i.e., 2050s, 2070s, and 2090s) are much more pronounced for the RCP8.5 scenario as compared to the RCP4.5 scenario (Figure S5 in Supporting Information S1). In most of the cases, differences in the probability among selected decades vary by less than 15%.

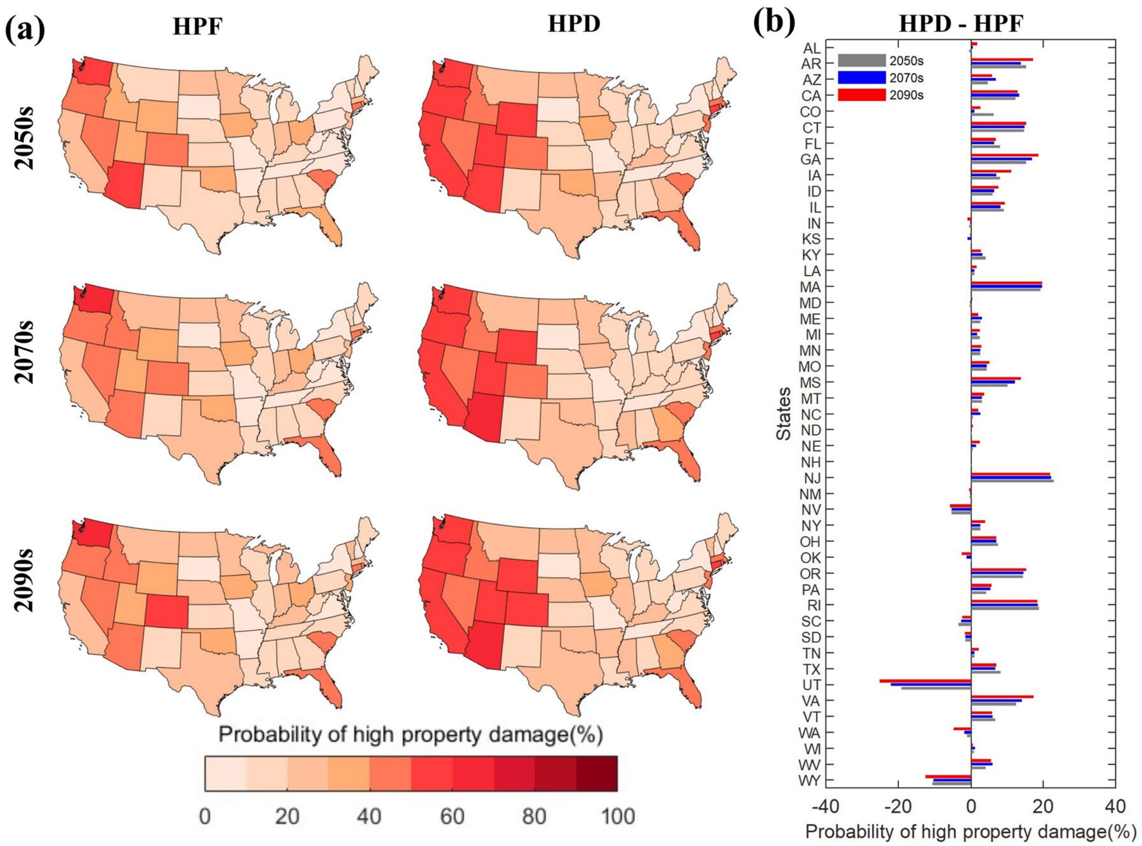

Figure 4. (a) Mean (averaged over all selected climate models) annual probability of high property damage conditioned on HPF and HPD for different future periods (top to bottom on the left: 2050s, 2070s, 2090s) under RCP8.5 scenario. (b) Differences in annual probability of high property damage conditioned on HPD and HPF for different future periods.

We investigate the sensitivity of our results to different thresholds to define high property damage. While the results discussed throughout the manuscript are for the case where the threshold of high property damage is the 70th percentile of the observed annual total property damage, Figures S8 and S9 in Supporting Information S1 represent the results for the cases for thresholds equal to the 80th and 90th percentiles, respectively. As expected (comparing the results shown in Figures S6–S9 in Supporting Information S1), the overall spatial and temporal patterns of the probability of high property damage are consistent for all selected thresholds but the probability of high property damage is higher for lower thresholds and vice versa.

Figure 5 shows the percent changes of mean (averaged across all selected climate models) annual probability of high property damage over the period 2090 to 2099 (i.e., 2090s) compared to the historical period 1996–2005 for the two probabilistic models and scenarios. All states across the CONUS are expected to experience an increase in the probability of high property damage in the future of at least 10%. Some states like Utah, Wyoming, Washington, Idaho, Colorado, Michigan, and Virginia are likely to experience significantly larger increases (~20–40%). The probabilities of high property damage in California and Florida are expected to increase by 17% and 19%, respectively, under the RCP8.5 scenario for the probabilistic model conditioned on HPD. As expected, the future increase in the probability of high property damage compared to the selected historical period is larger for RCP8.5 compared to the RCP4.5 scenario.

We also find differences between the probability of high property damage conditioned on HPF and HPD. Unrelated to climate models and scenarios (with few exceptions), the probability of high property damage conditioned on HPD is higher than the probability conditioned on HPF as depicted in the bar chart in Figure 4b. This indicates that the number of days with heavy precipitation (i.e., frequency) is more likely to cause higher property damage compared to the amount of heavy precipitation (i.e., intensity). More states are expected to experience an increased probability of high property damage in the future when considering the RCP8.5 scenario and the prediction model conditioned on HPD, whereas the highest increase in the probability of high property damage

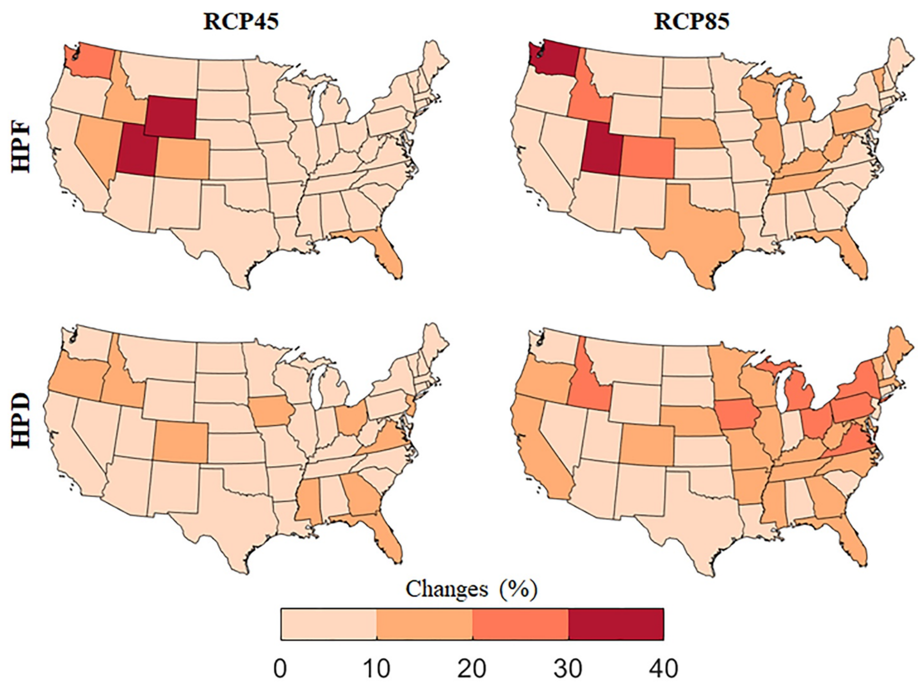

Figure 5. Percent change in the mean (averaged across selected climate models) annual probability of high property damage over the period 2090–2099 (i.e., 2090s) compared to the historical period 1996–2005 for the prediction models conditioned on HPF and HPD for two different scenarios RCP4.5 and RCP8.5.

is evident for the prediction model conditioned on HPF. In addition to the spatial variability across the CONUS, probabilities of high property damage vary with climate models and scenarios (Figure S4 in Supporting Information S1). Overall, results show that the probability of high property damage varies depending on the probabilistic modeling approach (i.e., two separate models conditioned on HPF and HPD), selected GCMs, and scenarios. Hence, uncertainty in the projections of the probability of high property damage can be accumulated from different sources. Modern design approaches, especially in light of climate change and adaptation efforts, are moving toward integrating and embracing uncertainties and our approach does not only quantify the total uncertainty but also the relative contributions from different sources. The latter opens the door for targeted future research to reduce certain types of uncertainties and derive more robust estimates of future flood losses.

Figure 6a represents the total uncertainty in the annual probability of high property damage (expressed in percent), for different states across the CONUS, analogous to that reported in Kim et al. (2020) with a focus on flood causing precipitation extremes. Total uncertainty ranges from 14% to 26% with a median (mean) value of 17.5% (18.2%). Wyoming, Utah, California, Colorado, Virginia, and Arizona are the states with the largest uncertainty. The total uncertainty is decomposed into its source components (i.e., prediction models, GCMs, and scenarios) showing that the relative contribution of individual uncertainty sources varies spatially (Figure 6b). In general, prediction models and climate change scenarios contribute the largest portions to the total uncertainty for most states, with values ranging from 25% to 50% and 25%–46%, respectively. The contribution of GCMs to the total uncertainty ranges from 6% to 43%. Figures 6c and 6d represent the PDFs of the total uncertainty and different sources of uncertainty for different future decades (2050s, 2070s, and 2090s) across all 48 CONUS states. The distribution of total uncertainty across the states is nonstationary and will increase over time, with median values of 12%, 15%, and 17% for 2050s, 2070s, and 2090s, respectively. This nonstationarity is further evident from the different values of dispersion (i.e., standard deviation) and distribution parameters for the three future decades (Table S2 in Supporting Information S1). This spatio-temporal variability of the uncertainty is mainly driven by the uncertainty originating from the prediction models and climate change scenarios. As shown in Figure 6d, the median values of the uncertainty from the prediction models and climate change scenarios are different for selected future decades and increase over time resulting in an increase in the total uncertainty over time (Figure 6c). The uncertainty PDF for climate models, on the other hand, does not change significantly in the future, revealing that GCMs' contribution to the nonstationarity of the total uncertainty is less important.

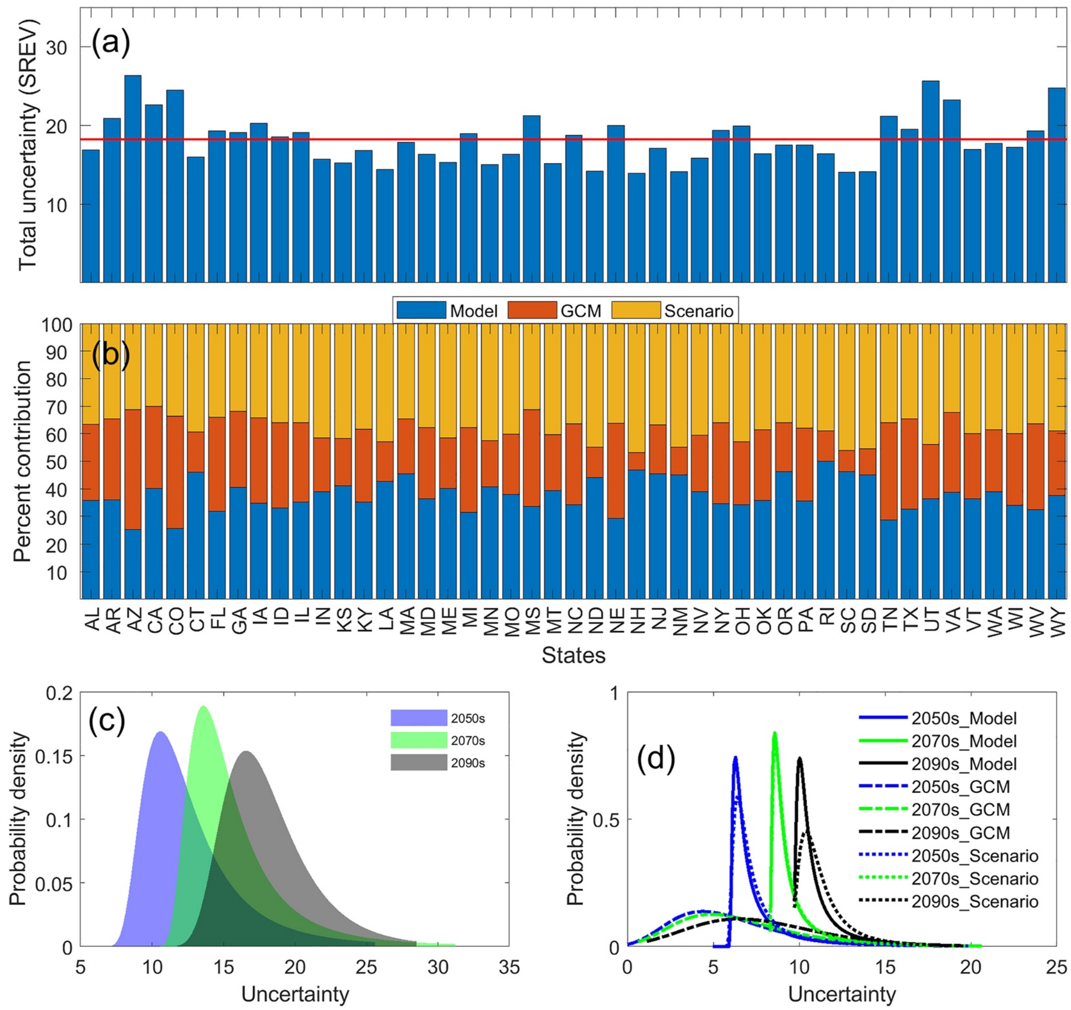

Figure 6. (a) Total uncertainty (in %) and (b) relative contribution of prediction models, GCMs, and scenarios to the total uncertainty for different states across the CONUS for 2090s. Red horizontal line in (a) illustrates the median value of the total uncertainty across all states. Probability density functions of uncertainty of all CONUS states for different future decades (i.e., 2050s, 2070s and 2090s) for (c) total uncertainty and (d) uncertainty from prediction models, GCMs, and scenarios.

5. Discussions

This study investigates the likelihood of high property damage (exceeding a critical threshold (specified here as the 70th percentile on a statewide basis) from fluvial floods across the United States conditioned on heavy precipitation indicators (i.e., HPF and HPD). We account for future climate change considering projections from 32 GCMs and two greenhouse gas emission scenarios (i.e., RCP4.5 and RCP8.5). Typically, flood risk assessments quantify property damage by assessing hazard, vulnerability, and exposure, which requires several models (e.g., flood inundation and depth-damage models) and datasets (e.g., assets/property exposure and vulnerability data). Such data are known to exhibit significant uncertainties, especially when performing risk assessments for future conditions (Bates, 2012; Bubeck et al., 2011; Freni et al., 2010; Lehman & Nafari, 2016; Villarini et al., 2020; Wasko et al., 2021; Wing et al., 2020). One of the challenges is that exposure and vulnerability data for the future are driven by complex human behavior, particularly in urban spaces (Hemmati et al., 2021). For example, future projections of urbanization and infrastructure growth, increase in human adaptive capacity, change in human behavior, and improvements in hazard forecasting are not readily available. Hence, in this study, we focus on the hazard component and assume that exposure and vulnerability remain the same. This helps quantify and isolate the impacts of changes in precipitation patterns in a warming world on flood risk. Traditional approaches for flood risk assessments are also deterministic. While those are generally well suited for analyzing catastrophic events at a local to regional scale, they are challenging to implement at a continental scale. In contrast, the approach used in this study is probabilistic and estimates the likelihood of property damage conditioned on heavy precipitation, making it very efficient for rapid continental scale assessments. The modeling framework could be extended to incorporate exposure and vulnerability, but in the absence of readily available data for future climate conditions, we consider this an avenue for future research.

The trends in the annual property damage from riverine floods are found to be insignificant (at 95% level) for most of the states, although the length of the data length is relatively short. Hence, assuming that the relationships between the annual property damage and heavy precipitation indicators observed in the historical period remains unchanged for the future is reasonable. We identified differences in the heavy precipitation indicators derived from the historical observations and downscaled precipitation from the GCMs' current climate simulations. The downscaled data used in this study are formulated by statistically downscaled daily precipitation, which was not explicitly designed to match the observed heavy precipitation indicators, hence can have biases. Therefore, we consider the probability of high property damage derived from the downscaled precipitation for the current climate as reference instead of the observed precipitation to quantify the future changes in the likelihood of high property damage. Consequently, we adopt a simple factor change bias correction in quantifying future changes in high property damage.

We found substantial increases in the likelihood of high property damage in the future conditioned to the frequency and magnitude of heavy precipitation (i.e., HPF and HPD). The increases vary from only a few percent (relative to present-day) to 40% depending on the location, the precipitation indicator used in the probabilistic prediction model, and the climate change scenario. Increase of property damage across the United States from riverine flooding in a warmer climate was reported in other studies; for example, Wobus et al. (2019) found 5%–25% increase in expected annual damage from riverine flooding under a 1°C warming scenario. Bates et al. (2021) estimated a significant increase in flood hazard (i.e., 16% increase in 100-year flood inundation area) across the eastern seaboard and western states by 2050 under the RCP4.5 scenario. We found that future changes in the property damage generally follow the changes in the heavy precipitation indicators. The same is also concluded by Wobus et al. (2017), with minor differences in some regions due to localized influences because we assume no changes in the built infrastructure and flood protection. In general, relatively higher increases in the likelihood of high property damage are projected across the Midwest, Southeast, and Northeast United States. This is consistent with the higher increase of heavy precipitation indicators across these regions. Similar patterns of projected increases in the frequency and intensity of heavy precipitation are reported in the Fourth National Climate Assessment (NCA4) Report (Wuebbles et al., 2017).

By conducting a leave-one-out cross-validation, we show that the probabilistic models used in this study reasonably capture the annual property damage variability. However, the models are unable to reproduce extreme property damage associated with the most catastrophic events in several instances. This is because probabilistic models are trained with samples including events ranging from low through moderate to extreme. This challenge could be overcome by fitting separate models for the different classes of events or by using hybrid distributions (e.g., Rashid et al., 2015a). However, fitting separate models would also lead to smaller training samples while increasing the complexity of the modeling framework. Here, we derive results at the state level where spatially averaged precipitation indicators may smooth out some of the variability which would be required to accurately capture the most catastrophic property damage events. Nevertheless, the models allow for rapid assessments of the state-level future property damage due to plausible changes in heavy precipitation. For example, the probability of high property damage in Florida (exceedance of 70th percentile of observed property damage i.e., $30 million for Florida) for the 2090s is 52%, indicating that there is, on an average, 52% likelihood that the annual property damage would exceed $30 million over 2090–2099 compared to the 33% likelihood in the historical period 1996–2005. Despite the limitations, the probabilistic models are a valuable tool for projecting the likelihood of property damage under different climate change scenarios at the continental scale.

6. Conclusions

Flood-related property damage is one of the major contributors to the climate induced economic losses in the United States and many other places across the world, but its future impacts have not been investigated in depth. Producing deterministic projections of flood-related property damage at the continental scale is often challenging in terms of the inclusion of future changes of built environments, socio-economic conditions, or resilience of infrastructure, while other challenges lie in employing regional scale hydrological and hydrodynamic models and using uncertain depth-damage relationships. In contrast, probabilistic models can be developed from historical flood-related property damage and climate variables (e.g., heavy precipitation) to predict changes in the likelihood of property damage into the future. In this study, we developed probabilistic models where conditional probability distributions of historical flood related property damage were derived using heavy precipitation frequency and intensity related indicators (i.e., HPF and HPD). The conditional probability distributions were then used to estimate the exceedance probability of high property damage for different values of HPF or HPD corresponding to historical and future periods.

Results show that the western, southwestern, and parts of the northwestern United States and the northern Rockies and Plains are expected to experience a larger probability of high property damage compared to the other regions; depending on the state, the probabilities could range from 38% to 80% and from 46% to 95% at the end of the century (2090s) under RCP4.5 and RCP8.5 scenarios, respectively. In 2090s compared to the present day (1996–2005), relatively higher increases in the probability of high property damage are likely for the states across the U.S. southwest and northwest regions (i.e., Colorado, Utah, Idaho, and Washington). These future increases range from 20% to 40% depending on the states, prediction models, and climate scenarios. Thus, uncertainty is apparent in the projections of probability of high property damage. Uncertainty estimates vary substantially across states and selected future decades (i.e., 2050s, 2070s, and 2090s); this suggests that the uncertainty exhibits nonstationary spatio-temporal variability which is mainly driven by the nonstationary uncertainty associated with the prediction models and climate change scenarios. We have considered a wide range of future climate conditions including one downscaled precipitation database derived from 32 CMIP5 GCMs, and two greenhouse gas emission scenarios; yet we did not consider other future climate change possibilities (we considered 32 out of 40 GCMs and 2 out of 4 greenhouse gas emission scenarios). Therefore, we did not cover the whole range of plausible climate change uncertainty. Following previous climate change impact studies, we assume that the historical relationships between annual total property damage and heavy precipitation indicators remain the same in the future, that is, we do not account for future socio-economic development.

Despite the uncertainty and unavoidable limitations associated with the projections of probability of high property damage explored in this study, the results can benefit long-term decision and policy making. However, potential changes in property damage from infrastructure vulnerability and exposure are not considered. While those can pose a wide range of impacts on the probability of high property damage, incorporating them in the continental scale probabilistic framework is challenging. We modeled future probability of high property damage conditioning on the heavy precipitation indicators. The model can be extended to condition solely on infrastructure vulnerability and exposure or in combination with precipitation indicators, which would require reliable vulnerability and exposure data (both historical and future) and the framework would have to be extended to employ more complex multivariate statistical models (e.g., vine copulas). Nevertheless, the outputs of this study can be used for developing long-term planning and resource mobilization, adaptation strategies, and insurance instruments. Our detailed assessment of uncertainties and their sources reveals a nonstationary behavior over three future decades. Such information can help framing time varying adaptation strategies to maximize the adaptation benefits, while ensuring that the adaptation investments and associated uncertainties are relatively low.

Data Availability Statement

All data used in this study are available in publicly accessible data repositories. The precipitation data downscaled from the CMIP5 GCMs are available and free to download from the data repository at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/. CPC US Unified Precipitation data can be accessed from https://psl.noaa.gov/data/gridded/data.unified.daily.conus.html. Livneh daily precipitation data are stored at https://psl.noaa.gov/data/gridded/data.livneh.html. NWS's *Storm Events* database can be accessed from https://www.ncdc.noaa.gov/stormevents/details.jsp.

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