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Flood Risk Projection Using a Hybrid Simulation Technique

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Abstract

Future climate conditions project an increase in the frequency and severity of flooding in many regions of the world. Evaluation of candidate flood adaptation strategies must consider risk assessment methods that capture scenario-based loss and damage (L&D) for cost-benefit analysis. There is a need to develop tools that improve understanding of a region's risk exposure while recognizing data and resource limitations available for this purpose. This study aims to address this gap by employing a novel approach that utilizes historic L&D data with an eye towards the current end-tail of extreme flood events as a prognosticator of what the future might hold. A hybrid Monte Carlo simulation technique is deployed to develop flood L&D projections under future climate change scenarios and used to estimate return periods of extreme flood events. Application of this methodology is illustrated in a case study using the Northeast region of the United States. The results show decreases in expected return periods of large flooding events, thereby expanding the geographic area of increased risk. These findings suggest this approach could function as a promising screening tool to help guide local flood adaptation planning, including the possibility of adopting this approach for other extreme weather events.

1. Introduction

Recent Intergovernmental Panel on Climate Change (IPCC) assessment reports affirm that the rise in global surface temperatures along current emissions scenarios will bring many changes to climate systems, including increases in the frequency and intensity of heavy precipitation events (Masson-Delmonte, et al. 2021). Furthermore, with each additional increment of global warming, these effects are expected to become more pronounced. Projecting these changes and the consequential impacts are fundamental to climate risk analysis. Absent this information, it is challenging for decision-makers to justify investment in adaptation strategies. Armed with better information, cost-benefit analysis can more accurately depict the efficacy of candidate adaptation strategies to address anticipated needs (Nissan, et al. 2019).

The availability of historic loss and damage (L&D) data from extreme weather events offers an opportunity to create a baseline from which to estimate future impacts. A single catastrophic event can lead to a broad range of outcomes, often with a reliance on property damage as a proxy measure for a variety of economic, social and environmental consequences (Botzen and Van Den Bergh 2009). The intent of this study is to develop a method for evaluating the cost of future disasters beyond relying solely on property damage to support climate risk-based decision-making. It builds on a hybrid simulation technique developed in prior work (Doktycz, Abkowitz and Baroud 2021) that develops a base simulation model of historic L&D costs for extreme weather events in the United States over the past two decades. Our proposed method utilizes the outcome of the simulation to develop a probabilistic framework that estimates future L&D risk using expected changes along different climate change pathways. This is performed by adjusting the L&D cost probability distributions based on the future mean annual precipitation for the region in three Shared Socioeconomic Pathway (SSP) scenarios. The SSP scenarios are used to drive climate model projections of changes in the climate system, representing illustrative scenarios that cover a range of future development of anthropogenic drivers of climate change found in literature (Masson-Delmotte, et al. 2021). The methodological approach presented

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herein is applied to flood risk as the extreme weather event type of interest. However, we see potential in applying similar principles to assess the risk of other extreme weather events.

Flood estimation under a changing climate is a difficult statistical challenge for translating into meaningful guidance due to the diversity of flood-generation processes and mechanisms that rely on location-specific information. Common flood estimation approaches include flood frequency analysis (fitting a probability distribution to gauged flood maxima); event-based approaches (combining intensity-duration-frequency design rainfall with dependent factors to produce the design flood using rainfall-runoff models); continuous simulation (long rainfall records converted to streamflow records for subsequent flood frequency analysis); and physical reasoning (informing probable maximum precipitation estimates which result in a probable maximum flood estimate using a rainfall-runoff model) (Wasko, et al. 2021). Applying climate change projections into any flood estimation model adds an additional level of difficulty and uncertainty. Our approach aims to reduce the complexity of flood modeling using a proxy measure for loss and damage.

Academic literature primarily focuses on the projection of flood frequency curves through either explicit consideration of non-stationarity using time-based statistical covariates or by downscaling climate model projections of rainfall to the point scale then simulating the resultant flood frequency curve (Wasko, et al. 2021). Obtaining credible inputs to estimate flood risk requires detailed data of the study region, including the return period of extreme flooding events, vulnerability of exposed assets, and the type of economic activity in the affected area (Pellicani, et al. 2018).

High resolution studies at the community level are still necessary to fully prepare infrastructure planning based on expected future flood risk (Porter, et al. 2021). However, the technical and computational burden of future flood projection can be resource intensive, limiting its use for many vulnerable communities. The methodology described herein can function as a screening tool to identify hazards and scenarios requiring higher-resolution analysis or a physics-based modeling approach to more accurately evaluate the risk. This offers the potential for vulnerable communities to gain sufficient insight to invest in selective higher-resolution studies.

To evaluate future climate conditions, we use the products developed by the World Climate Research Programme's Coupled Model Intercomparison Project (CMIP) to generate hydrologic projections of the frequency of flooding events (Wobus, et al. 2017). CMIP comprises major climate models from different groups and incorporates them into a simulation of the 20th century's climate for projecting into the 21st century (Nyaupane, et al. 2018). A primary output of CMIP for flooding projection is mean annual precipitation (Raff, Pruitt and Brekke 2009). In addition, CMIP produces climate projections along socio-economic pathways based on global greenhouse gas emissions under various future emissions scenarios. Studies have found a significant positive relationship between precipitation and flood damage, along with expectations for increased damage should the world continue along current climate pathways (Davenport, Burke and Diffenbaugh 2021).

Our methodology reduces data requirements by utilizing normalized flooding costs rather than an expansive list of detailed information required to model flood events, thereby reducing the

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technical burden on local decision-makers. Normalizing the dataset using socioeconomic vulnerabilities to account for spatial and temporal differences between individual cost estimates accounts for some differences between existing urban systems and characteristics.

2. Risk Projection Methodology

2.1 Review of the Hybrid Simulation Technique

We begin with the base hybrid simulation technique which normalizes the existing L&D cost data to then be fit to a distribution to represent the probabilistic distribution of flooding costs in the spatial area of interest. A Monte Carlo simulation is then used to develop expected costs the hazard would cause in the region over a specified time period. From there, future projections can be performed by adjusting parameters in the probabilistic distribution. The changes were determined from the ensemble of 31 models utilized in CMIP, version 6 (CMIP-6). Our study utilizes a modeling methodology to project L&D for flooding events for near (2021-2040), mid (2041-2060), and long-term (2080-2099) time horizons, across three different SSP's (SSP1-2.6, SSP2-4.5, and SSP5-8.5). SSP1 represents a sustainable pathway where emissions decline to net zero around or after 2050, SSP2 represents a middle case with emissions remaining around current levels until the middle of the century, and SSP5 represents a fossil-fuel dependent future, with emissions that roughly double from current levels by 2050. The change in mean annual precipitation for the region along each scenario is used to shift the probabilistic L&D cost distribution to be simulated as the new set of parameters for future flood L&D projection.

The simulation approach uses normalized L&D cost data to model historic property damage totals from an extreme weather event type in the United States beginning from the year 2000 (Doktycz, Abkowitz and Baroud 2021). The L&D cost data comes from the NOAA Storm Events Database, which includes 49 different event types, with each record containing date, location (state and county), property damage, crop damage, injuries and fatalities (NOAA 2022). The NOAA Storm Events database is one of the only high-resolution publicly available non-aggregated national datasets with a statistically significant number of records for large data analysis. The data is then aggregated at a state level to ensure large sample sizes which can average out inconsistencies in reporting. L&D cost data has been collected using standardized recording procedures since 1996.

The initial step involves normalizing the historic data for comparison between different locations and years in which the events occurred according to Equation 1.

$$D_n = D_i * SVI_{(y,c)} * PD_{y,c} \tag{1}$$

Equation 1 calculates normalized cost (D_n) by inflation-adjusting damage to a 2018 U.S. dollar value (D_i). The cost is further adjusted using the CDC Social Vulnerability Index ($SVI_{(y,c)}$) for the respective year and county in which the event occurred (denoted with subscript y and c, respectively), to account for the variability across regions in their ability to respond to disasters (Mechler and Bouwer 2015). SVI is comprised of a percentile rank index of 15 census variables that define a community's vulnerability to potential disasters (CDC/ATSDR 2021). The CDC SVI index has measurements for the years 2000, 2010, 2014, 2016, 2018. The values in years

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between corresponding measurement indices were linearly extrapolated. The CDC SVI is one of the most widely used indicator models for social vulnerability (Wood, Sanders and Frazier 2021). Using cost as a measurement tool, it is critical to account for community differences, both for individual community development over time and the differences between regions. SVI is used in the normalization of the loss data to account for regional and temporal differences in socioeconomic vulnerabilities, recognizing a range of socioeconomic vulnerabilities across the modeled area and over the time of the accumulated historical data that may amplify loss and damage due to additional exposure to climate hazards. The final variable in the normalization equation is the percentile rank of the population density for the impacted region for the respective year and county ($PD_{y,c}$), representing exposure to households in the impacted area.

Following normalization, the data was grouped by state and extreme weather event type to generate sufficient sample sizes to develop a damage function. Then, probability distributions were fitted, and the Kolmogorov-Smirnov test was used to identify the distribution with the best fit for each hazard-region combination. A separate distribution was considered for the top 10% of the data to better capture the end tail of extreme events. Specifically, the end tail distributions fits were assessed using Extreme Value Theory (EVT) where the Generalized Pareto distribution consistently returned a more representative distribution for the tails of losses. As a result, each end tail distribution was fit with a Generalized Pareto distribution through calculation of the L-moment statistics. This distribution has proven to be a useful method for estimating the tails of loss severity distributions (McNeil 1997).

The two distributions were then used to simulate potential costs of the extreme weather event of interest based on 1,000 samples of a Monte-Carlo Simulation (MCS) over a 20-year time period for a specific region (Figure 1A). The daily event frequency used in the MCS to determine whether an event occurs on a given day is based on the historic event frequency. The historic event frequency is calculated as the total number of events divided by the total number of days recorded in the data set. If an event does occur in the simulation, the severity of the event is determined using the L&D function discussed previously.

A process flow diagram is presented in Figure 1. The two distributions represent the overall cost, where initially a value is randomly selected from the first distribution ("C" in Figure 1B), the distribution which represents the entire range of events. If the value selected is greater than the 90th percentile threshold ("$C_{0.90}$" in Figure 1B), it is determined to be an extreme event and is removed and replaced by a new value selected from the second distribution, representing the top 10% of data in that region for the selected hazard.

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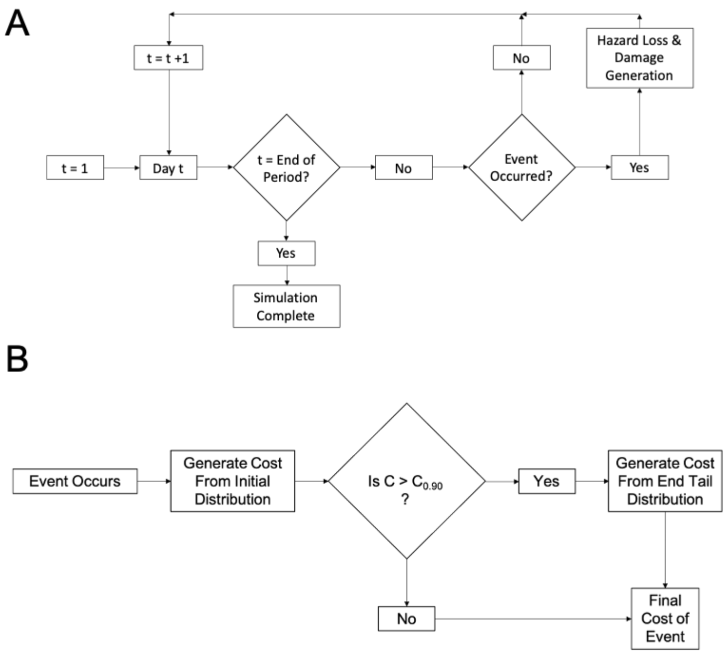

Figure 1: A) Monte Carlo Simulation process flow. B) Hazard cost generation process flow.

During the simulation, when an event occurs, the simulation generates a cost based on the representative probability distribution of losses determined in the previous steps for the specific region. The entire series of costs is subsequently collected at the end of the simulation. The data set therefore consists of 1,000 twenty-year periods, with each twenty-year period containing a record of events and costs that occurred. We found that 93% of the simulated historic cost totals were within 10% of the actual historic costs, and 77% were within 5% of the total 201 region/hazard combinations.

2.2 Risk Projection Methodology

The risk projection approach is illustrated using flood hazard in the Northeast region of the U.S. as a use case. This geographic region consists of Connecticut, Massachusetts, Maryland, Maine, New Hampshire, Rhode Island, New Jersey, New York, Pennsylvania, and Vermont.

The annual percent change in mean rainfall for each time period and SSP combination is applied in the hybrid Monte Carlo simulation model. Future flooding costs are generated through use of the percentage change in mean annual precipitation for the region based on the CMIP-6 data (Almazroui, et al. 2021). This average change functions as a relative measure for the expected change in the cost of flooding events in the absence of specific flooding data (Guilbert, et al. 2015); (Zscheischler, et al. 2018); (Slater and Villarini 2016). The base costs are defined by the normalized (using calendar year 2018 monetary values) historic flood data for the Northeast region. A mean shift was then applied to the corresponding flooding probability distribution of

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losses (see Table 1), which is then converted to the log value in the corresponding damage probability distribution.

Northeast United States			
Scenario/Time Period	Near	Mid	Far
SSP1-2.6	**3.58**	3.86	5.36
SSP2-4.5	3.03	**5.22**	7.79
SSP5-8.5	3.67	5.65	**11.37**

Table 1: Percent mean shift applied to Monte Carlo Simulation probability distribution of losses in the Northeast United States (Almazroui, et al. 2021). Values in bold are the percent shifts which were tested in this analysis.

The percentage changes in Table 1 represent the broad range of possible future scenarios under the SSPs. Increased rainfall heightens future flood risk, increasing the expected costs from flooding events. Costs are a necessary component to account when evaluating the efficacy of climate adaptation practices (Prein, et al. 2017).

The mean shifts were applied to the damage function representing each state, respectively. The occurrence probabilities of various flood sizes can be determined through probability distribution techniques of varied types (Maghsood, et al. 2019); (Bhat, et al. 2019). Using the probability distribution of costs as a proxy measurement for flooding events in an area, applying the change in annual rainfall to shift the average cost of events in the probability distribution of losses also accounts for the change in event magnitude. More specifically, the new probability distribution of L&D increases the monetary outcomes in an event, making these events more costly in the future. Note, however, that this projection only accounts for future societal changes or adaptations that are included in the SSP scenarios (which derive global greenhouse gas emissions) and does not consider any further increases in exposure such as direct population increases in an area and other forms of development. This methodology projects near present day costs (2018 USD) which can be easily adjusted for future inflation, vulnerability or exposure for future scenario planning.

The future projection of flooding impacts consisted of shifts in the mean and/or standard deviation of the probability distribution of losses. A shift in the mean represents a change in the average severity of a flooding event, whereas a shift in the standard deviation represents a change in the range of possible outcomes under the scenario. This resulted in three different scenarios for each SSP (see Table 2). Note that Body represents the distribution of the common occurring flood events and Tail represents the extreme event distribution. The two distribution parameters, mean (represented as the location parameter, μ, of the distributions) and standard deviation (represented as the scale parameter, σ, of the distributions) were selected because they reflect the changes to likelihood and the severity of extreme weather and climate events. This change in distribution is reflected in Figure 2; changes to both the mean and standard deviations of the representative distributions most directly relate to changes in the type of event occurring (for example, a percent increase to the mean shifts the distribution to the right). The shape parameter (ξ) was not considered for these scenarios since the changes in mean and variance already account for some of the changes in the tail behavior; a percent change in the value that

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represents the shape parameter does not translate to as direct a shift as the mean and standard deviations. Future development of this model will consider sensitivity analysis of the shape parameter to search for better representative distributions of the data.

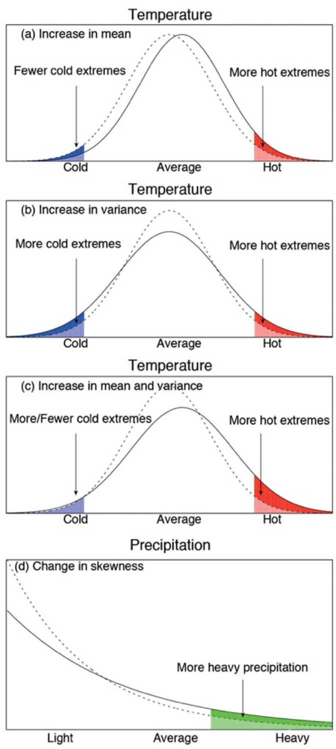

Figure 2: Schematic representations of the probability density function of daily temperature and precipitation. The change in the mean for a skewed distribution, shown for precipitation, produces a larger change in the number of extreme events. Figure adopted from (Folland 2001) and (Peterson 2008).

Scenario	SSP	Time Frame	Body Shift	Tail Shift
Scenario 1	SSP1-2.6	near	mean	mean
Scenario 1	SSP2-4.5	mid	mean	mean
Scenario 1	SSP5-8.5	far	mean	mean
Scenario 2	SSP1-2.6	near	mean	mean + st. dev.
Scenario 2	SSP2-4.5	mid	mean	mean + st. dev.
Scenario 2	SSP5-8.5	far	mean	mean + st. dev.
Scenario 3	SSP1-2.6	near	mean + st. dev.	mean + st. dev.
Scenario 3	SSP2-4.5	mid	mean + st. dev.	mean + st. dev.
Scenario 3	SSP5-8.5	far	mean + st. dev.	mean + st. dev.

Table 2: The applied shift among climate scenarios. The Body shift represents the distribution of the common occurring events and the Tail Shift is the distribution of the less frequent high-cost events.

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The output is expressed in the normalized expected annual cost, which can be utilized in estimating the change in the expected return periods of flooding events and associated L&D cost.

The results from the simulated scenarios are measured in the change in return period of a 100-year cost event. This flooding return frequency change allows for comparison between different climate scenarios (Lantz, et al. 2012). Through use of the benchmark flood scale, more direct cost applications can be used for the local area although this is primarily used to highlight the change in risk due to future climate change expectations. Furthermore, the key output of the simulation is a normalized dollar value; those costs can be adjusted to the specific region to obtain direct cost projections for the studied area. For this case study, only the change in return periods will be highlighted.

3. Application Results

We define an initial return period based on the historic data and then use it as a basis of comparison with the calculated return periods from the simulation data to establish expected changes in flood risk. It is important to understand that communication of risk and return periods has considerable influence on the estimate of risk (Ward, de Moel and Aerts 2011), so through use of associated L&D costs of flooding events, this form of risk analysis can be utilized as a screening tool for where fine resolution modeling applications are warranted, reducing the overall technical burden. The results in this study are displayed in the form of the change in expected return period over time. For example, in the base simulation using the historic data distributions, a 100-year cost threshold (annual probability of 0.01) may become more common in the future scenarios.

Return periods are commonly used in frequency analysis, including its application to flood risk. We define the return period of an event as the inverse of the probability that the event will be exceeded in any given year. In this study, return periods are represented based on the probability of damage and losses incurred from floods instead of discharge thresholds. Specifically, we use the projected probability distribution of losses evaluated using the hybrid simulation technique (Doktycz, Abkowitz and Baroud 2021) and corresponding mean and standard deviation shifts based on climate projections.

The simulation outputs a data set containing flood events and associated normalized costs, with the resulting event costs gathered (cost is used as a proxy measure for flood severity) to determine the overall frequency of occurrence over time. The resulting values are associated with a return period based on the calculated probability as the mean number of years for which the value will be surpassed once. After the completed simulation, the events are categorized by percentiles for determining their return period based on the amount of time (in years) elapsed in the simulation. For example, the simulation spans 1,000 twenty-year periods, resulting in a total of 20,000 years of simulated flood data for the region based on the probability distribution of L&D derived from the historic data. This simulation primarily functions to represent a range of future expected costs to understand future expected flood risks. A direct way to display this change in risk is through the expected change in return periods at the cost thresholds determined from the historic base simulations. Using this data, return periods can be determined using the normalized cost as a proxy measure for the severity of an event. Events with a 0.01 probability in

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this model are defined as a 100-year event, meaning that there is a one in one hundred chance the cost will be exceeded in any one simulated year. The shift in the potential damage distributions based on this approach is displayed in Figure 2.

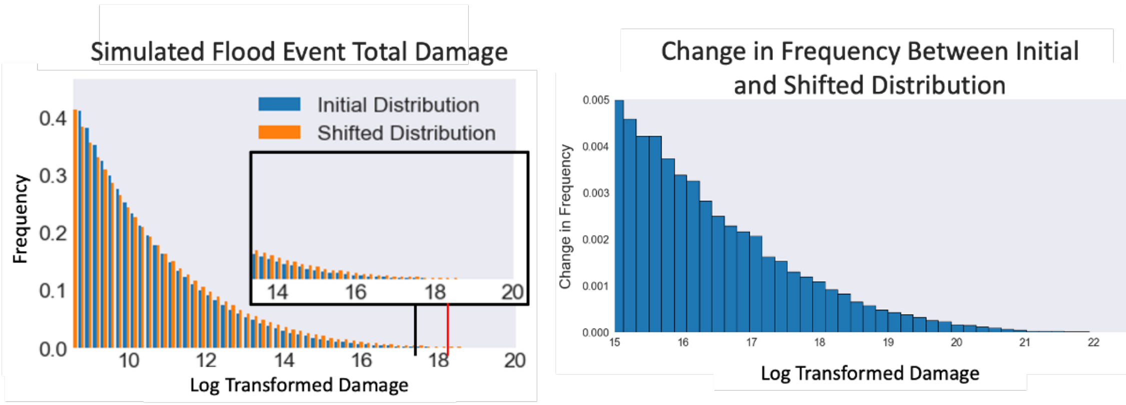

Figure 3: Distribution of log transformed normalized potential damages of the tail behavior for a flooding event (Left). The zoomed in section shows the extended tail of the shifted distribution compared to the initial case. The two vertical lines display the historic (black) and new scenario (red) 100-year events.Change in end tail frequency between initial and shifted distribution (Right).

Figure 3 shows the range of costs associated with the tail of a representative damage probability distribution in the model simulation. All costs calculated in this analysis have been normalized to 2018 USD for direct comparison across time. Shown in blue is the distribution of costs from flood events using the historic case damage distribution and displayed in orange is the distribution based on the expected change in mean annual precipitation in the region. As seen in Figure 2, there is a shift towards increased costs when considering the expected change in mean annual precipitation in the region. As a result, what was a 100-year event in the initial distributions can be expected to become a more common event under the new climate scenarios due to the shifts applied from the expected climate change pathways.

To understand the impact of a changing climate on loss and damage from flood events, we evaluated the shift in the likelihood of a 100-year event (based on the simulated loss and damage probability distribution) for each state across the entire Northeast region. These figures are developed at the state level as this represents the highest resolution the L&D data allows for across all states when fitting the probability cost distributions. Figures 4-6 show this shift in the likelihood under the three scenarios listed in Table 2. The scenarios follow three different SSP pathways combined with different applied shifts visualize the impacts these shifts have on the results. The SSP1-2.6 pathway, which represents the low end, optimistic carbon concentration pathway, is combined with the near-term time horizon to anchor the projected shifts and represent the minimum potential change. SSP2-4.5 represents the middle of the road carbon concentrations and is combined with the mid-term projections. The SSP5-8.5 pathway, which represents the high end of carbon concentrations, is combined with the far-term time horizon to display the worst-case and largest potential shifts. The combination of the three scenarios represent the full range of potential outcomes.

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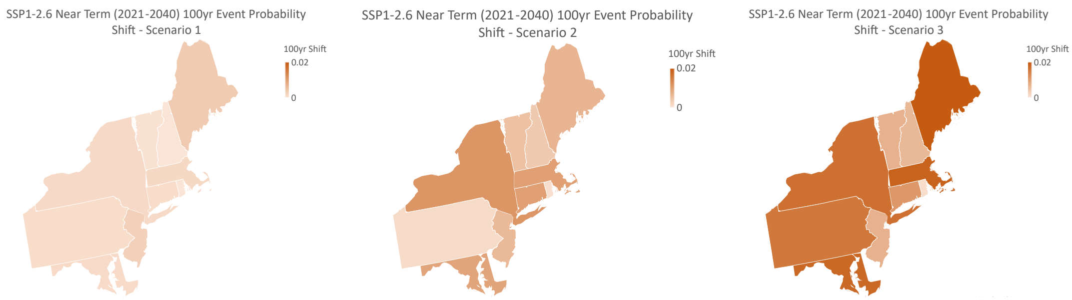

Figure 4: Near-Term (2010-2040) + SSP1-2.6 projection of change in probability of 100-year events in the Northeast United States across the three future projection scenarios.

Recall that scenario 1 portrays only a shift in the mean of the damage function, representing a general increase in future event magnitude. Scenario 2 represents only a shift in mean for the body of the distribution and a shift in both mean and standard deviation of the end tail distribution. Scenario 3 represents a shift in both the mean and standard deviation of the body and end tail distributions. The Near-Term + SSP1-2.6 projection shows the low-end of the future changes, and that is apparent in the figure which only displays a shift in event probability on the scale 0 to 0.02. A minimal shift in 100-year event probability in scenario 1, contrasted with the other scenarios display the increase in event probability across the three scenarios. Additionally, Figure 5 displays the Mid-Term results across the three scenarios. In this figure, the largest shift in probability (found in scenario 3) is nearly double the largest shift in the Near-Term, showing the significance of the change in time horizon following this climate pathway.

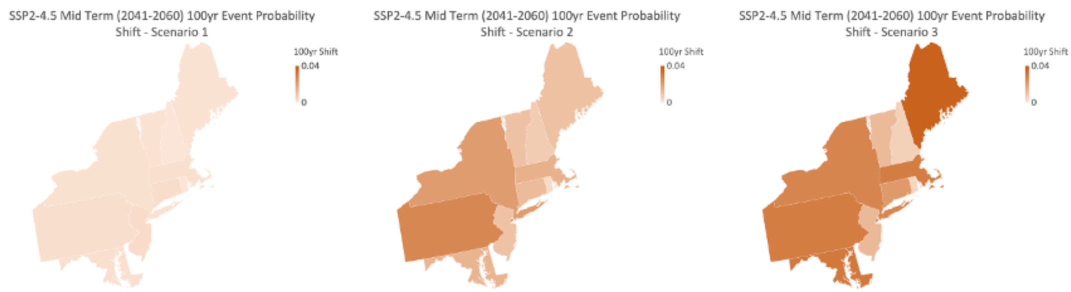

Figure 5: Mid-term + SSP2-4.5 projection of change in probability of 100-year events in the Northeast United States across the three future projection scenarios.

Figure 5 clearly indicates a larger increase in the frequency of 100-year events relative to the SSP1-2.6 + Near-Term time horizon, now measured on a scale from 0 to 0.04. Figure 6 displays results for the worst-case climate pathway SSP5-8.5 along the Far-Term time horizon, representing the highest end risks across the three scenarios. The largest shifts in probability in this time horizon are about 4 times the shifts in the Mid-Term projections.

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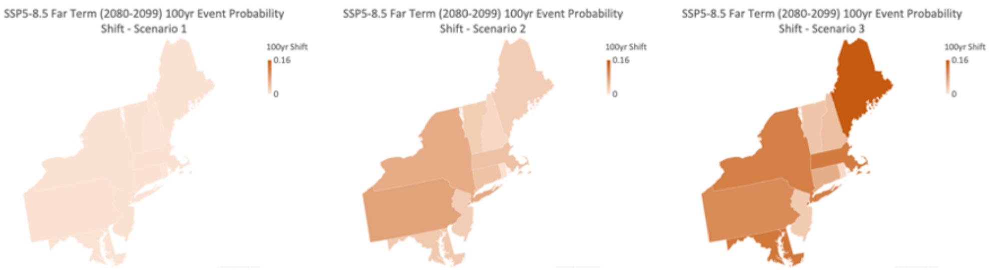

Figure 6: Far-term + SSP5-8.5 projection of change in probability of 100-year events in the Northeast United States across the three future projection scenarios.

As expected, there is a larger increase among all SSP's, again with the most intense change associated with the longer-term scenario, where almost every Northeast state experiences an average increase in annual probability to 0.08. Even in the near-term simulation (SSP1-2.6), each state realizes an increase from the historic 100-year return period (probability greater than 0.01). This increase means the probability of what is currently considered a 100-year event level of damage will develop a shorter return period than 100 years in the future. More specifically, today's 100-year event in the Northeast following scenario 3 projections would become a 12.5-year event in the next 80 years since the annual probability of a similar outcome magnitude is 0.08.

Interestingly, the expected L&D for New Jersey shows a limited relative change in the Northeast. This can be explained by the historic New Jersey data supporting the hybrid simulation technique. In New Jersey, the historic L&D data has a left skew, which creates a distribution that contains a larger number of costly events, in turn, the increases reflected in the simulation created a smaller relative increase than the surrounding states.

These results are consistent with other literature focused on flooding in the Northeast, affirming a difference in expected damages based on various emission scenarios (Kirshen, Watson and Douglas 2007) (Kim and Villarini 2023). Additionally, a Gilroy and McCuen (Gilroy and McCuen 2012) study projects a 30% increase in the 100-yr flood on the Little Patuxent River in Maryland by 2100 resulting from climate change and urbanization.

Taking a broader view of projected flooding studies as comparisons, Wobus, et al. (2017) used hydrologic projections based on CMIP-5 to estimate changes in frequency of modeled 1% annual exceedance probability flood events in the contiguous United States. With each more intensive RCP scenario, 1% annual exceedance probabilities (AEP) increased across the entire Northeast U.S., finding between two and six times the frequency of occurrence. The heavier concentrations of increased 1% AEP frequency in the Northeast were observed mainly in Pennsylvania, New York, New Jersey, Connecticut, Maine, and Massachusetts. When aggregated across the U.S., national annual flood damages were estimated to increase from approximately USD 3 billion between 2000 and 2020 to approximately USD 4 billion by the end of the century under RCP 4.5, and to USD 7 billion under RCP 8.5.

A study looking at the inequitable patterns of U.S. flood risk in the Anthropocene also found an increased flood risk of about 26.4% along RCP4.5, including increases in the inland Northeast region (Wing, et al. 2022). Similar to the approach taken in our risk projection methodology,

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these results were compared to the historic records to demonstrate the change in risk over time. The study concluded that U.S. flood losses are currently around $32.1 billion on average and are expected to rise to $40.6 billion by 2050 under the RCP4.5 scenario. More specifically, the largest expected increases of absolute annual losses by the year 2050 in the Northeast region were observed in New York, New Jersey, Massachusetts, Connecticut and Rhode Island, similar to what was observed using our risk projection methodology in the mid-term scenario.

4. Conclusion

Decision-making under uncertainty necessitates a risk-informed approach, particularly as it impacts an assessment of the benefits and costs of risk mitigation strategies (Cheong, et al. 2009). There is cause for optimism in adaptation to flood disasters, as positive achievements have been witnessed through economic development, technological improvements and targeted adaptation interventions. In Europe, for example, fatalities and normalized economic losses have decreased over recent decades despite an increase in flooded area and absolute loss (Jongman 2018).

However, additional improvements can be accomplished through better understanding of expected changes in return periods which, in turn, can help make a more convincing case for adaptation investment. The 100-year event is a well-understood standard for risk analysis which can help make that argument. Understandably, the methodology described herein does not supply the level of granularity necessary for evaluating the efficacy of specific adaptation measures, but it can serve as a screening tool to identify and prioritize locations where risk is heightened, from which risk analysts can perform a more detailed assessment of viable adaptation strategies.

There is broad agreement that climate science tends to produce outputs that are difficult to use, incompatible with the decisions at hand, or too technical for decision-makers to utilize (Findlater, et al. 2021). It is our hope that this effort provides a simple and practical approach to help overcome these challenges. Although it is limited by the resolution of available data for both climate projections and historic events, it demonstrates a proxy-based methodology from which one can develop future scenario planning through cost-benefit analysis with publicly available data.

Note, however, that our methodology was limited to the inclusion of only tangible property damage. Inclusion of indirect and intangible L&D would provide a more complete and comprehensive assessment of the full cost associated with extreme weather events. Additionally, this methodology provides an underestimate of future costs from disasters because economic and population growth continue to act as key drivers of rising impacts from natural disasters (Botzen, Deschenes and Sanders 2019). Future costs will likely be greater than currently predicted due to added wealth and population growth in specific geographical locations, which can make the implications of these disasters even more significant.

Code/Data Availability: Code can be made available by request.
Competing Interest Statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution: Charles Doktycz led modeling and data development, additionally with paper outline and development. Mark Abkowitz led revisions/editing and paper scoping. Hiba Baroud provided technical insight into model development and paper revisions/editing.

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