A Hybrid Simulation Approach for Disaster Loss and Damage Projection Under Climate Change

By

Charles J. Doktycz

Dissertation
Submitted to the Faculty of the
Graduate School of Vanderbilt University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY
in

Civil Engineering

December 17th, 2022

Nashville, Tennessee

Approved:

Mark Abkowitz, Ph.D.

Hiba Baroud, Ph.D.

Dan Work, Ph.D.

Jonathan Gilligan, Ph.D.

Copyright © 2022 by Charles Joseph Doktycz

All Rights Reserved

Dedicated to family, friends, Haley, Bruce and Maja … who all supported me in their own way

Acknowledgements

I would like to especially thank my advisors, Dr. Mark Abkowitz and Dr. Hiba Baroud for their guidance and support during my time at Vanderbilt. I would also like to thank my committee members: Dr. Daniel Work and Dr. Jonathan Gilligan. I have learned so much working with you both, skills that have made this research possible and skills that will undoubtedly help me in the future. Lastly, I would like to thank Dr. Leah Dundon and Dr. Craig Philip for their support during my time at Vanderbilt, helping to provide me with opportunities I could never forget. I have enjoyed every moment working with you all.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Climate change is creating more frequent and more severe weather events across the world and the reality is that this trend will only continue for the foreseeable future (Masson-Delmonte, Zhai, et al. 2021). As a result, society must prepare for these impacts and adapt accordingly while recognizing that these impacts will be vastly different across geographical regions. In order to make more effective adaptation investment decisions, the future impacts of these natural disasters must be understood. Loss and damage data can be utilized to forecast these impacts. Databases on loss and damage monetary impacts have been recorded for decades, presenting a data-rich resource for use in predictive modeling of future impacts. The focus of this dissertation is to leverage this data in concert with utilizing future climate change pathways and their associated outcomes, and to evaluate non-economic and indirect damages. Such a modeling effort achieves a more comprehensive evaluation of the cost of future disaster and helps inform resource allocation towards strategies designed to mitigate the risk of extreme weather events.

1.1 Motivation for the study

Human induced climate change is already affecting the frequency and severity of extreme weather and other climate-induced events across the globe. There is evidence of observed changes in heatwaves, heavy precipitation, droughts, and tropical cyclones (Masson-Delmonte, Zhai, et al. 2021), among others. As current climate mitigation efforts fail to reach the goals set by global leaders, the new reality of increasingly severe and frequent weather events requires adaptation to these possible impacts. The Intergovernmental Panel on Climate Change states that the need for climate resilient and adaptation development is more urgent than previously stated in past assessment reports (H.-O. Pörtner 2022).

Climate change impacts will accrue at all levels, local to international. As an inevitable product of that range, there can be a great disparity in the resources allotted across those levels, and between similar locations with different assessment capabilities. By developing a model to simulate cost impacts using publicly available data online, this reduces the cost burden to access information to help in decision making, particularly important for rural communities and locations of disproportionately high socially disadvantaged populations.

By presenting the future impacts of natural hazards in a dollar value, this helps to present a business case for climate change adaptation to motivate adaptation decisions. Furthermore, by illustrating the usefulness of loss and damage data, improvements in loss and damage accounting could provide enhanced modeling at a smaller spatial resolution to help risk-informed decision-making.

1.2 Overview of the Study

The work presented in this dissertation aims to both show the potential in loss and damage information while also highlighting the need to improve this data for more effective analysis. This is first done by establishing the definitions of the many variables which comprise loss and damage, followed by. identifying the available databases and assessing their advantages and disadvantages. Once the fundamental knowledge of loss and damage data is established, this study advances with a selected database to develop a risk projection model by fitting probability distributions of loss and damage to the hazards included in the database in specific regions of the continental United States. By developing the probability distribution of damages, these cost curves are then used as the integral piece in the development of a hybrid Monte Carlo Simulation technique where parameters are adjusted based on future climate change scenarios to develop future climate change monetary impacts.

This dissertation is organized as follows. Chapter 2 outlines the state of the practice of loss and damage databases. Chapter 3 describes the hybrid simulation technique developed to model the loss and damage of specific natural hazards in individual states of the continental United States. Chapter 4 establishes the change in parameters using various climate change scenarios along different Shares Socioeconomic Pathways to introduce future expected risk. Chapter 5 introduces additional costs into the model, intangible and indirect loss and damage which are not commonly included in existing databases due to the difficulty in accounting for damage which is not formally given a dollar value. Chapter 6 contains concluding remarks and directions for future research. It should be noted that Chapters 2-5 consist of published or soon-to-be-published journal articles, respectively, that are intended to be read as separate documents, so there is some overlap in the material discussed.

Chapter 2

Loss and Damage Estimation for Extreme Weather Events: State of the Practice

Extreme weather, climate-induced events that are episodic (e.g., hurricane, heat wave) or chronic (e.g., sea level rise, temperature change) in nature, is occurring with increasing frequency and severity. This places a growing and time-sensitive need on the development and implementation of adaptation policies and practices. To motivate adaptive behavior, however, requires the ability to deliver improved risk-informed decision-making capability. At the crux of this challenge is the provision of full and accurate loss and damage accounting of the overall impact of an extreme weather event, enabling the business case to be made for adaptation investment. We define loss and damage as the manifestation of impacts associated with extreme weather that negatively affect human and natural systems. Progress in the development of adequate loss and damage accounting has been hampered by issues such as discrepancies in conceptual frameworks, problems associated with data quantity and quality, and lack of standardized analysis methodologies. In this paper, we discuss the conceptual basis for measuring loss and damage, review the state of loss and damage data collection and modeling, and offer a narrative on the future direction of the practice.

2.1 Introduction

Extreme weather events worldwide have been increasing at an alarming rate in terms of both frequency and consequence, creating a compelling need for proactive risk management (ICSU 2008). While improved disaster reporting may serve as a partial explanation of this observed trend, it does not explain the temporal and spatial impacts that are being realized (UNISDR 2009).

The 2018 Intergovernmental Panel on Climate Change report heralded the need to accelerate global climate change adaptation (IPCC 2018), stating with high confidence that human activities have caused approximately 1.0°C of global warming, and we are on pace to reach 1.5°C in the coming decades. The consequences of this forecast are that trends in intensity and frequency of weather extremes are likely to persist for the foreseeable future. Although some climate change adaptation measures are being undertaken, these efforts must be expanded and implemented more rapidly than previously anticipated.

At the crux of improving risk-informed decision-making and motivating adaptive behavior, is making the business case for investing in such policies and practices. The concept of a business case involves a full accounting of the cost of investing in a risk mitigation strategy compared to the derived benefits, creating an ability to determine if the return-on-investment warrants expenditure of resources. In the case of extreme weather, the benefits accrue in the form of cost avoidance; that is expenditures that do not have to be incurred due to strategy implementation having mitigated the severity of the impacts. A complete assessment of cost avoidance requires a comprehensive approach to and damage accounting, both in terms of accuracy, completeness and uniformity.

The United Nations Framework Convention on Climate Change defines loss and damage as “the actual and/or potential manifestation of impacts associated with climate change in developing countries that negatively affect human and natural systems” (UNFCCC 2012). While there is no question that developing countries are a key focal point of the conversation, this definition and the need for loss and damage assessment applies to first world countries as well.

Unfortunately, to date, the lack of standardized and comprehensive methods for loss and damage data collection, analysis and reporting has posed challenges. In this paper, we discuss the conceptual basis for measuring loss and damage, review the state of loss and damage data collection and modeling, and offer a narrative on the future direction of the practice. In the following discourse, we use the term "extreme weather" as including both episodic (e.g., flood, wildfire) and chronic (e.g., sea level rise, temperature change) events, both of which are climate-induced.

2.2 Conceptual Framework for Loss and Damage Estimation

Loss is commonly defined as the negative impacts in which restoration or reparation is impossible (Gall, Emrich and Cutter 2015); (Andrei, Rabbni and Khan 2015), whereas damage is considered those negative impacts for which restoration or reparation is possible. Loss and damage estimation is typically approached categorically, generally separated into tangible and intangible cost (Meyer, et al. 2013); (Gall, Emrich and Cutter 2015). Tangible loss and damage can be further sub-divided into direct and indirect impacts. Some studies define risk mitigation as a category as well.

2.2.1 Direct Tangible Costs

Direct tangible costs are considered those that occur as a direct result of the physical impact of the event (Kreibich, et al. 2014). Common examples include damage to infrastructure and property loss (e.g., cars, livestock, crops). Fatalities and injuries may appear in this category or be included elsewhere, depending on whether the cost of human harm is considered a tangible or intangible cost due to the complexity in the quantification of the value of a human life.

Direct cost measurement is most frequently performed using damage functions, which describe the relationship between a hazard parameter and the resulting monetary cost (e.g., cost per square foot of residential housing). Some models account for resistance parameters, such as building type or a risk mitigation measure that has been implemented (Meyer, et al. 2013). Market price methods are popular in assessing direct tangible costs, as these valuation techniques reflect current replacement costs, are easy to apply, and applicable to many economic sectors.

Direct cost estimation can be limited by the quality and quantity of available data, however, which can vary widely depending on the location of the event and the information source. Such inconsistencies, inaccuracies and missing data contribute to greater estimation uncertainty, leading many analysts to utilize cost ranges rather than specific values. Additionally, complexities in understanding the process leading to loss and damage often results in the use of multi-parameter models that require the introduction of additional variables, causing further uncertainty in the estimation process.

2.2.2 Indirect Tangible Costs

Indirect tangible costs are generally considered as those that occur as a result of a direct impact (Kreibich, et al. 2014). Examples include business interruption, relief efforts, lost tourism, relocation costs, disruption to transportation, and diminished living conditions.

Common approaches to indirect cost estimation include the use of surveys, econometric models, input/output models, and computable general equilibrium analysis (CGE) models (Meyer, et al.

2013). Surveys are often narrow in scope and consequently the applicability of the results can be limited. Econometric models provide an opportunity for broader application, and the results can be used in future forecasts. Input-output models contain coefficients to estimate impacts that an initial change in economic activity has on a regional economy, where the initial change and coefficients are determined based on extreme weather event severity (Bess and Ambargis 2011). Note, however, that input-output models require assumptions in economic behavior with the potential to bias the magnitude of the results (Meyer, et al. 2013). CGE models, while based on the input-output structure, place greater emphasis on price, with substitution options not included. As a result, CGE models often result in lower loss estimates than input-output models. However, CGE models assume markets function perfectly post-disaster, which is rarely the case.

2.2.3 Intangible Costs

Intangible costs are effects felt by society, but for which the accompanying loss and damage are difficult to value monetarily. Examples include environmental, educational, cultural, and health/well-being impacts. Depending on the assessment framework, human harm can be placed in this category as well. Intangible costs are typically difficult to quantify because of the subjective nature of the variables involved, as putting a dollar value on impacts such as environmental degradation or cancer risk is a complex process that can include a number of considerations.

One approach to quantifying loss and damage is through the use of revealed preference and stated preference methods (Markantonis and Meyer 2011). Revealed preference methods produce estimates of the value of a particular good or service from actual market behavior. Types of revealed preference methods include hedonic pricing, travel cost, cost of illness and replacement cost. Stated preference methods create a hypothetical or contingent market for choice analysis; methods include contingent valuation, choice modeling, and life satisfaction analysis. Whereas revealed preferences look towards related markets, where the non-market good is implicitly traded, stated preference methods take a survey-based approach that considers an individual's preference directly by determining a willingness to pay or a willingness to accept. Regardless of the approach, however, the resulting estimated value for intangible damages is not an equivalent to a market price, which is the monetary standard for comparison (Morrissey and Oliver-Smith 2013).

2.2.4 Risk Mitigation Costs

Risk mitigation costs represent the investment that is made in order to achieve a reduction in loss and damage when an extreme weather event is experienced. As such, it is considered as a cost incurred against which to compare the cost reductions in unrealized loss and damage. It is on this basis that the benefit/cost of a candidate risk mitigation strategy can be evaluated, with an ultimate goal of determining whether such an investment is warranted. Common risk mitigation costs include investments made for (Bouwer, et al. 2013): 1) management practices, 2) land use planning, 3) hazard modification, 4) infrastructure adaptation, 5) communication in advance of events, 6) emergency response and evacuation, 7) financial incentives, and 8) risk transfer (e.g., insurance). Risk mitigation costs are relatively easy to quantify and can be determined by the available market price for the cost of implementation (Meyer, et al. 2013).

2.3 Loss and Damage Data

In utilizing databases for loss and damage estimation, one must be mindful of a number of potential biases that might be present, including (Gall, Borden and Cutter 2009):

- Hazard bias - over or under representation of certain hazard types, due to selective reporting.
- Temporal bias - loss and damage exhibiting an upward trend over time as a result of increased wealth and population sizes, or perhaps improved accounting.
- Threshold bias - inconsistent inclusion criteria across databases, creating discrepancies.
- Accounting bias - inconsistencies in how loss and damage is accounted for due to the variety of input methods used.
- Geographic bias - changes in political geography, creating spatial inconsistencies in loss and damage accounting.
- Systemic bias - between and within loss and damage reporting arising from computational inconsistencies (e.g., reporting in dollar losses at the time of occurrence vs. inflation-adjusted losses).
- Measurement bias - use of different metrics to measure loss and damage, making it difficult to normalize.

While several approaches to loss and damage estimation have emerged, each embodying a unique set of cost categories and input variables, the databases they generally rely upon are limited to information made available by a small number of sources. Here, we review the most popular: 1) EM-DAT, 2) NatCatSERVICE, 3) Sigma CatNet, and 4) SHELDUS.

2.3.1 Emergency Events Database (EM-DAT)

EM-DAT is a publicly accessible, international database of global natural and technological disasters, maintained by the Centre for Research on the Epidemiology of Disasters

(CRED 2018). It is intended to provide an objective basis for vulnerability assessment and decision-making by collecting, organizing and providing access to validated data on the human impact of disasters and disaster-related economic damage estimates. The database consists of approximately 19,000 entries, covering from calendar year 1900 to present. Natural disasters are divided into six groups (geophysical, meteorological, hydrological, climatological, biological, and extraterrestrial), covering 15 disaster types and over 30 sub-types. Technological disasters are divided into three groups (industrial, transport, and miscellaneous), covering 15 disaster types (see Table 1). Data sources include governments, UN agencies (UNEP, UNOCHA, WFP, FAO), NGOs, research institutions, insurance companies, and media reports.

Geophysical	Meteorological	Hydrological	Climatological	Biological	Extraterrestrial	Industrial	Transport	Misc.
Earthquake	Extreme temperature	Flood	Drought	Epidemic	Impact	Chemical spill	Air	Collapse
Dry mass movement	Fog	Landslide	Glacial lake outburst	Insect infestation	Space weather	Collapse	Road	Explosion
Volcanic activity	Storm	Wave action	Wildfire	Animal accident		Explosion	Rail	Fire
						Fire	Water	Other
						Gas leak		
						Poisoning		
						Radiation		
						Oil spill		
						Other		

Table 1*:* EM-DAT Disaster Classifications

Criteria for database inclusion are events in which there are at least ten fatalities, at least one hundred people affected, declaration of a state of emergency, and/or a call for international assistance. Events are entered on a country-level basis, with attributes consisting of location; date; number of people killed/injured/missing; number homeless/affected; economic loss, both direct (e.g., damage to infrastructure, crops, housing) and indirect (e.g., loss of revenues, unemployment, market destabilization); international aid contributions; and composite indicators (total affected and victims). The disaster classification used in EM-DAT is adapted from Integrated Research on Disaster Risk (IRDR) Peril Classifications (IRDR 2014).

EM-DAT data entry guidelines follow three levels. Level 1 includes information regarding the disaster event, including the group, sub-group, and disaster type, sub-type, and sub-sub-type. The second level consists of geographic and temporal information, physical characteristics, and status. Spatial divisions specifying the continent, country, region, latitude/longitude of the disaster, a three letter ISO code and temporal information (start/end dates and local time) are reported. Physical characteristics of the event include origin, associated disasters and scale/intensity (reported in units linked to the disaster type, such as area covered in wildfire reports and the Richter scale for earthquake events). Status reporting lists aid contributions (total amount given in USD current value), Office of U.S. Foreign Disaster Assistance (OFDA) response, date of appeal for international assistance, and if a declaration of emergency was made. Level 3 consists of the source of the information along with a reliability score for the source, between 1 (low) and 5 (high). Level 3 also includes the human impact of the event, in terms of deaths, missing, homeless, injured, and affected people requiring immediate assistance during emergency. Economic impact is reported in Level 3, which includes total estimated damages, reconstruction costs, insured losses and the disaster impact. Total damage costs are defined as the value of all damages and economic losses directly or indirectly related to the disaster, which may be segmented by sector: social, infrastructure, production, environment, and other. Reconstruction costs are the costs for replacement of lost assets, while insured losses are the economic damages covered by insurance. The disaster impact report category specifies the sectors affected by the disaster, which include animals, electricity, water supply and sanitation, communications, cultural infrastructure, and other. Infrastructure reports include percentage of damage of destruction to certain infrastructure, and number of affected houses, bridges, businesses and schools.

2.3.2 NatCatSERVICE

NatCatSERVICE is a comprehensive global natural hazard catastrophe database maintained by Munich RE, containing records dating back to 1980, and retrospectively all great disasters since 1950 (see Table 2). Catastrophe events include those classified as geophysical (earthquake, volcano, dry mass movements), meteorological (storms), hydrological (flooding, wet mass movements), and climatological (extreme temperature, drought, wildfire). Data is made available through an online tool where the user can designate the period of interest (years), location (continent) and event type (MunichRE 2018). The loss event classification in NatCatSERVICE is closely related to the IRDR Peril classifications (also adopted by EM-DAT), defined by an overarching family of events and sub-perils that more closely describe the physical forces behind the event.

Geophysical	Meteorological	Hydrological	Climatological
Earthquake	Storm	Flooding	Extreme temperature
Volcano		Wet mass movements	Drought
Dry mass movements			Wildfire

Table 2: NatCatSERVICE Hazard Categories

Events are rated on the following scale: 0 - no fatalities and no property damage, 1 - small-scale property and structural damage and between 1-9 fatalities, 2 - moderate damage and greater than 10 fatalities, 3 - damage in excess of $60 million plus greater than 20 fatalities, 4 - damage in excess of $250 million with over 100 fatalities, 5 - damage in excess of $650 million and over 500 fatalities, and 6 - "great disaster" where a region's ability to help itself is overtaxed and international assistance is necessary, thousands of fatalities and just as many without homes, major economic losses and insured losses reaching exceptional orders of magnitude. Each record in the database is characterized by the following attributes: date; event type; geocoding of main loss areas; nature of the event; loss data (insured losses, overall losses, bodily injuries), infrastructure areas; affected industries; and event description (e.g., wind strength, precipitation levels, earthquake magnitude).

The database gathers information from a wide range of sources, using data mining and surveys among internet portals, institutions, direct contacts, and specialized companies. Any contradictory information is assessed internally. Events listed in the database have an assigned direct economic loss measured in USD. Due to potential variability in reporting accuracy and consistency, NatCatSERVICE defines five levels of loss estimates, ranging from full information to partial data or only event descriptions. Each level utilizes a separate approach for damage estimation, with loss estimates based on insurance market data offering the highest quality of reporting. In low-quality information cases, asset value assumptions are utilized, based on home value repair costs for listed damaged assets, with further assumptions made for infrastructure and agriculture sectors.

Loss and damage analysis can be performed according to: 1) country mortality rates (high, upper middle, lower middle, and low), 2) insurance penetration (high, middle, low, very low), and 3) income group (high, upper middle, lower middle, and low). The products offered by NatCatSERVICE include an analysis of the number of events, as well as overall loss/insured loss ratio, which can be tracked by inflation adjusted and normalized overall losses. The tool also provides a breakdown of the percentage distribution for relevant natural loss events worldwide as well as a map showing where each event occurred (Monti and Tagliapietra 2009).

2.3.3 Sigma CatNet

Sigma CatNet, maintained by Swiss RE, consists of a limited access global disaster database containing both manmade and natural catastrophes (SwissRE 2018). The database includes events from 1970 to present, and requires one of the following to have occurred in order to be included: 1) 20 or more deaths and/or people missing, 2) 50 or more people injured, 3) 2,000 or more people left homeless, 4) insured losses of greater than $17.9 million (marine), 5) insured losses of greater than $35.8 million (aviation), 6) insured losses of greater than $44.5 million (all other losses), or 7) total losses in excess of $88.9 million (see Table 3). This information is obtained through internal research performed by Swiss RE, natural disaster coordination agency research data, publicly released information, and press, industry and aid agency reports (CRED 2018). Minimal discussion is provided, however, regarding validation of the database sources.

Flood	Earthquake and Tsunami	Storm	Other
River flood	Seismic hazard	Wind speed	Lightning
Coastal flood	Epicenters	Tropical cyclone tracks	Volcanoes
Dyke ring projection	Plate boundaries	Hailstorms	Volcano ash thickness
Historic floods	Tsunami historical run-up	Tornado	Wildfire
	Tsunami hazard	Historic tropical cyclones	Climate change
	Historic earthquakes	Historic winter storms	Climate data

Table 3: Sigma CatNet Event Categories

Attributes for each record include fatalities, injuries, missing persons, homeless (unable to occupy their dwelling), and economic losses (direct/indirect/insured). Although some indirect economic loss is represented, such as business interruption, other such loses are not considered (e.g., loss of earnings by suppliers due to disabled businesses, estimated shortfalls in Gross Domestic Product, non-economic losses). Swiss RE cautions that total losses represent general estimates that are communicated in different ways, such that the data should not be used to perform direct comparisons between events.

2.3.4 SHELDUS

The Spatial Hazard Events and Losses Database for the United States (SHELDUS) records natural hazard events at the county level, covering the entire U.S., with the exception of U.S. territories (Gall, Borden and Cutter 2009). SHELDUS is maintained by the Center for Emergency Management and Homeland Security at Arizona State University. The database covers events from 1960 to present, and includes 18 natural hazard event types (see Table 4), populated with attributes describing date, location, and direct losses (property, crop, injuries, fatalities). The database can also be searched by specific peril, from among 139 different peril types.

Geophysical	Meteorological	Hydrological	Climatological
Avalanche	Fog	Flood	Drought
Coastal	Hail	Tsunami/Seiche	Wildfire
Earthquake	Heat		
Landslide	Hurricane/Tropical storm		
Volcano	Lightning		

	Severe storm		
	Tornado		
	Wind		
	Winter Weather		

Table 4: SHELDUS Event Categories

Most of the SHELDUS data is sourced from the National Weather Service (NWS), including the NWS process for loss estimation, including how to determine direct and indirect fatalities and injuries associated with the event. Loss estimates are recorded as actual dollar amounts if a reasonably accurate estimate is considered available. Otherwise, either an estimate is attempted or "no information available" is entered (except for flooding events, where an estimate is required by the U.S. Army Corps of Engineers). In cases where estimates are reported as ranges rather than specific values, SHELDUS enters the lower bound of the range in the database. If events are reported for regions rather than specific counties, the impacts are distributed equally across the involved counties, which often results in non-integer fatality and injury entries.

2.3.5 Further Discussion

Table 5 presents a comparative summary of the characteristics of the aforementioned databases. As noted, each database covers a different time period, geography, hazard definition, and sources of information.

From the standpoint of attempting to estimate loss and damage at the local level, SHELDUS is best suited for that purpose (Gall, Emrich and Cutter 2015). This database, although limited to the United States, provides records at the county level, the most disaggregate geographic delineation among the group, and has a lower reporting threshold such that more event information is available. Although SHELDUS also provides the most readily available loss information for analysis, even its data records are incomplete, as they do not contain any information associated with indirect or intangible loss and damage.

When considering global or national disaster trends, use of EM-DAT, CatNet or NatCatSERVICE is more desirable, given their worldwide coverage and reporting at a more aggregate scale. In each of these cases, the reporting threshold is such that only the more catastrophic events are captured, and not the entire distribution of impactful events. Moreover, none of these databases afford complete coverage of direct, indirect and intangible impacts. Also of note, only EM-DAT and SHELDUS provide an opportunity to download raw data for analysis use, whereas CatNet and NatCatSERVICE only allow viewing privileges, functioning more as an interactive online tool with a supporting database.

The bottom line is that there is a paucity of available extreme weather loss and damage data at a time when there is a compelling need to have access to such information. This creates a major gap in having the ability to make the business case for adaptation investment.

	EM-DAT	SHELDUS	NatCatSERVICE	Sigma CatNet
Total records	>20,000	>800,000	>33,000	>9,000
Record span	1900-Present	1960-Present	1980-Present	1970-Present
Loss categories	Fatalities, injuries, homeless/affected, damage (crop, property, livestock)	Direct property damage, crop damage, injuries, fatalities	Direct economic loss estimates, insured losses, fatalities	Fatalities, missing, victims (casualties), injured, homeless (unable to occupy their dwelling), and economic losses (direct/indirect/insured)
Spatial coverage	Global	United States (county level)	Global	Global
Inclusion threshold	One (or more) of the following: 10+ people killed, 100+ people affected, declaration of a state of emergency, call for international assistance	1960-1995: one fatality or $50,000+ crop or property damage 1996-Present: All events represented in the NCDC Storm Data with a specific dollar amount	Losses categorized 0-6: 0-no fatalities no property damage, 1-small scale property damage & 1-10 fatalities, 2-moderate property damage & greater than 10 fatalities, 3-property damage in excess of $60 million & greater than 20 fatalities, 4-property damage in excess of $250 million & greater than 100 fatalities, 5-property damage exceeding $650 million & over 500 fatalities, 6-great disaster with international assistance necessary	>20 deaths, and/or >50 injured, and/or >2,000 homeless, and/or insured losses >$14 million (marine), >$28 million (aviation), >$35 million (all other losses), and/or total losses >$70 million

Accessibility	Online registration, for download	Online registration, for purchase	Online registration, for viewing	Online registration, for viewing
Source	https://www.emdat.be/explanatory-notes	http://hvri.geog.sc.edu/SHELDUS/docs/SHELDUS_ReadMe.pdf	https://www.munichre.com/en/reinsurance/business/non-life/natcatservice/index.html	http://www.sigma-explorer.com/documentation/Methodology_sigma-explorer.com.pdf

Table 5: Comparison of Loss and Damage Databases (International Council for Science 2008)

2.4 Loss and Damage Methodologies and Frameworks

Several efforts have been made to incorporate loss and damage estimation either pre-disaster or post-disaster methodologies (Surminski, et al. 2012). Below, we review a representative sample of these applications.

2.4.1 HAZUS-MH

Developed by the Federal Emergency Management Agency, HAZUS-MH is a tool for assessing loss and damage associated with hurricane, flood and earthquake events (Federal Emergency Management Agency 2019). It utilizes geographic information systems to estimate hazard-related impacts before or after a disaster. The methodology accounts for loss and damage according to four categories: 1) direct damage, 2) induced damage, 3) direct losses, and 4) indirect losses. Direct damage includes general building stock, essential facilities and lifelines. Induced damages comprise those caused by fire, hazardous material exposure and debris generation. Direct losses include cost of repair/replacement, income loss, crop damage, casualties, shelter and recovery needs. Indirect losses consist of supply shortages, sales decline, opportunity costs, and economic loss. HAZUS-MH also includes demographic data in its impact reports, including age, sex, income and household characteristics.

HAZUS-MH is purported to be a comprehensive tool for loss and damage assessment in addressing a couple of extreme weather event types (i.e., flood, hurricane), and is the nationally recommended tool for flood mitigation planning at the county level. However, a recent study calls into question the accuracy of the tool's flood model impact assessment. Key study findings include that HAZUS-MH: 1) underestimates the flood extent boundaries for study regions along major rivers such as the Mississippi, 2) may be incorrectly predicting the number and location of damaged buildings, and 3) essential facility inventory data underrepresents the accessibility and response capabilities of essential facilities (Abkowitz, et al. 2019).

2.4.2 Damage and Loss Assessment (DaLA)

DaLA was developed by the United Nations Economic Commission for Latin America (ECLAC 2003), as an approach to damage and loss assessment, where the onus is on the user to obtain the necessary data for implementation. The methodology focuses on assessing the social, economic and environmental effects of disasters, separated into direct damage, indirect loss, and macroeconomic effects (i.e., repercussions of direct and indirect damage/loss, measured in terms of how the disaster modifies the performance of main economic variables of the affected country, provided that national authorities make no adjustments). A "reasonable" time frame for assessing macroeconomic effects is defined as the remainder of the year in which the disaster occurs plus up to two additional years; under exceptional circumstances, a five-year accounting can be used.

DaLA defines cost types (direct, indirect, business interruption, intangible, and risk mitigation), and how they can be quantified in monetary terms. The cost of human harm is considered a direct cost, and a suggested monetization is to estimate future income that the deceased would have generated while fulfilling the individual's average life expectancy. An alternative approach is to value the loss of life as the amount paid by insurance companies based on airline-related accidents from the Warsaw Convention of the International Civil Aviation Organization, but can be problematic due to regional variance. A final proposal for valuing a human life is to base it off the amount an individual is willing to pay to avoid premature death.

Indirect costs are defined as the flow of goods and services that will not be produced or rendered after the event and may extend throughout the rehabilitation and reconstruction periods. It is recognized that some indirect effects may have a net positive effect, such as a heightened need for a specific service or product (e.g., generators, building supplies), which should be deducted from the total cost estimate.

DaLA associates intangible costs with human suffering, insecurity, and impacts on quality of life. While the methodology recognizes the difficulty in placing a monetary value in evaluating these costs, DaLA acknowledges that a complete loss and damage assessment must include these considerations.

2.4.3 Post Disaster Needs Assessment (PDNA)

The goal of the PDNA methodology is to provide support for emergency and recovery management (World Bank 2013). It embraces the ECLAC method for assessing loss and damage.

The PDNA methodology includes the collection of pre-disaster baseline data for comparison with post-disaster conditions to determine the overall impact, and impacts by sector.

The assessment includes: 1) damage to infrastructure and physical assets, 2) disruption of access to goods and services, 3) governance and decision-making processes, and 4) increased risks and vulnerabilities. These effects are expressed in both quantitative and qualitative terms, with loss and damage estimation calculated as the value of total and partial destruction of infrastructure and assets, changes in service delivery, production of and access to goods and services, changes to government processes, and changes to risk.

Impact estimation is determined through the economic impact at macro and micro levels, considering likely effects of the disaster on economic performance and macro-economic imbalances, along with impacts on personal household incomes and employment in all sectors. This includes the extent of change in quality of human life over both medium- and long-term time scales.

Economic loss is defined as the change in economic flow arising from the disaster until full economic recovery and reconstruction is achieved. This includes the decline in output of impacted sectors due to damage to infrastructure and assets, lower revenues associated with demand reduction due to the disaster, and increased expenditure for management of new risks brought on from the disaster. Macro-economic impacts are measured from the post-disaster performance of gross domestic product, the balance of payments (increase of imports, decrease of exports), and the fiscal sector (increased operational costs). Human development impacts can be measured in terms of the human development index (HDI), hybrid HDI, inequality-adjusted HDI, multi-dimensional poverty index, and gender inequality index. The decision of which indicator(s) to include is generally governed by what is utilized in establishing pre-disaster baseline information.

2.4.4 CATSIM

A simulation model developed by the International Institute for Applied Systems Analysis (IIASA), CATSIM is designed to assess disaster risks in a certain country or region. The methodology is intended to help with natural disaster risk mitigation planning by examining fiscal and economic risk, and evaluating the benefits and costs of various risk reduction strategies. CATSIM is an interactive tool which allows for testing of assumptions through the variation of multiple parameters. The model uses Monte Carlo simulation of disaster risks in a specified region to derive an estimate of the region's financial vulnerability to the disaster (Surminski, et al. 2012). The methodology is segmented into five modules: 1) risk of direct asset losses, determined through loss distributions and probability loss curves, 2) financial and economic resilience for disaster response, measured through the financing gap concept, 3) financial vulnerability, determined by the risk and financial resilience of the government, 4) economic impacts and resource shortfall consequences, and 5) adaptation/risk management (Hochrainer-Stigler 2014). The model can be utilized at the ex-ante stage, where budget allocation is determined to make natural disaster mitigation decisions, purchase insurance or other protection of assets, or at the ex-post stage, after a disaster in guiding repair and financial decisions. CATSIM has been used by the World Bank to estimate disaster risk in over 80 countries (R. Mechler 2019).

2.4.5 Further Discussion

It is commendable that in the evolution of loss and damage frameworks and models, attempts are being made to structure a means to quantify the full impact of natural hazard disaster events. HAZUS-MH represents an all-in-one approach whereby the data and model are integrated within the tool, yet it is limited in its representation of extreme weather events, and the validity of the corresponding impact estimation results have been brought into question. The remaining modeling frameworks included in this review are indicative of idealized ways to capture the full range of disaster impacts, including recognition that post-disaster impacts are experienced over an extended period of time, which can have economic and human development impacts incurred locally and across broader spatial and jurisdictional boundaries. Data necessary to serve as inputs to populate these considerations are generally lacking, however, rendering a barrier to perform full loss and damage accounting that has yet to be overcome.

2.5 Conclusion

There is a clear need to make the business case for investments in extreme weather risk mitigation, making it imperative to perform full loss and damage accounting in evaluating the benefits and costs of various adaptation strategies. Based on our review, we find that the quality of available data and inconsistencies in loss and damage accounting methodology constrain the ability to achieve this objective. Arguably most challenging among these concerns is the difficulty in estimating intangible costs, to the point that the majority of the existing databases and models avoid its consideration altogether. This is unfortunate given the broad impact and lengthy time spans that such impacts can be experienced, such that its magnitude may dwarf the impacts that are currently taken into consideration. To the extent this is the case, the benefits of adaptation strategies may be severely underestimated, biasing the efficacy of attracting investment.

Addressing these needs will require a comprehensive effort to evaluate the full loss and damage impact of disaster events, beginning with the development of use cases based on past events where the process of full recovery has been achieved. This will provide insight into quantifying overall loss and damage, the portion attributed to direct, indirect and intangible effects, and how it is distributed temporally and spatially. Concurrently, the insurance industry should be encouraged to partner with the public and private sector to produce a methodology and practical approach to measuring loss and damage. Doing so would prove beneficial to all involved parties, as each has a vested interest in better understanding the bottom line.

While attention needs to be focused on improving extreme weather loss and damage accounting, we must also recognize that decision-makers are facing the harsh realities of extreme weather today that require immediate attention. Thus, in helping the practitioner make more risk-informed resource investment decisions in the meantime, we must straddle the fence of not requiring an overabundance of technical requirements while also effectively using available data. To that end, relying on a hybrid of quantitative and qualitative understanding of extreme weather trends may be an appropriate recourse. This particularly applies to situations where adaptation strategies are being evaluated at the screening level, or where local authorities require a simple, practical framework (and one that does not require much training or technical understanding to use) for making more risk-informed decisions given limited time and resources.

Chapter 3

Extreme Weather Loss and Damage Estimation Using a Hybrid Simulation Technique

History has shown that occurrences of extreme weather are becoming more frequent and with greater impact, regardless of one's geographical location. In a risk analysis setting, what will happen, how likely it is to happen, and what are the consequences, are motivating questions searching for answers. To help address these considerations, this study introduced and applied a hybrid simulation model developed for the purpose of improving understanding of the costs of extreme weather events in the form of loss and damage, based on empirical data in the contiguous United States. Model results are encouraging, showing on average a mean cost estimate within 5% of the historical cost. This creates opportunities to improve the accuracy in estimating the expected costs of such events for a specific event type and geographic location. In turn, by having a more credible price point in determining the cost-effectiveness of various infrastructure adaptation strategies, it can help in making the business case for resilience investment.

3.1 Introduction

Citing dire consequences, the Intergovernmental Panel on Climate Change has recently reported a compelling need to accelerate global climate change adaptation (Masson-Delmotte, et al. 2021). This finding is based on substantial evidence that the effect of global warming is causing increased frequency and severity of a variety of weather extremes, which are likely to persist for at least several decades. The consequential impacts of these developments can be expected to cause additional economic, social, and environmental suffering, creating an imperative for society to invest, post haste, in adaptation strategies that reduce community vulnerability and strengthen resilience.

The impact of an extreme weather event may be felt at several levels—local, regional, national, and global. A single catastrophic event can lead to human casualties, property damage, loss of assets, community disruption, severed supply chains, mental health issues, and other negative economic, social, and environmental impacts (Botzen and Van Den Bergh 2009). The magnitude of these impacts brings into focus the need for policy responses to prepare for what is considered a new era of natural catastrophes and ease the burden of these occurrences on society (Kunruether 2008).

Yet, widespread implementation of adaptation strategies only becomes possible if one can make a business case for investing in such initiatives. This requires an ability to quantify the full range of loss and damage (L&D) associated with an extreme weather event, such that the benefits accrued (that is, L&D avoidance) from deploying an adaptation strategy can be assessed relative to the cost of implementation. Publicly available L&D data are typically focused on quantifiable tangible direct costs, with little or no consideration of other direct costs, commonly known as tangible indirect costs and intangible costs. This limits our complete understanding of the impacts of an extreme weather event. Empirical L&D data can also suffer from inconsistent definitions and potential biases (Doktycz and Abkowitz 2019). Furthermore, utilization of L&D data for decision making follows the same difficulties as with data gathering.

Overcoming these deficiencies is a fundamental aspect of our effort, and the reason for developing a hybrid simulation approach. As development of such an approach is ultimately intended to help practitioners make more risk-informed resource investment decisions, we are mindful that local authorities require a simple, practical framework for decision making given limited time and resources. Therefore, it must balance between not requiring an overabundance of technical requirements while also effectively using available data. We develop and apply this methodology using L&D data obtained from the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database, subsequently normalizing the data to allow for spatial/temporal comparisons, fitting the data to statistical distributions, and finally using Monte Carlo simulation (MCS) to return L&D costs of specific extreme event types in a region over a specified time horizon.

The objective of the study described in this article was to generate a representative model of L&D costs for specific regions and segmented by extreme weather type, and subsequently to employ the results in a Monte Carlo simulation. This study took a unique approach in the utilization of L&D databases, to develop a cost model for hazards within the United States. Development of an accurate base historic cost model will then allow for additional cost projections and analysis in future work. As mentioned, future climate projections along with other costs such as indirect or intangible damages will help to create a more accurate picture of the impacts society will face due to climate change. This work highlights an overlooked data source, loss and damage data can provide insight towards climate impacts through use of another tool to improve cost benefit considerations for adaptation decisions in the face of future uncertainty. By building this base model, it provides opportunities to consider future climate change scenarios for cost analysis where input of different parameters can influence how the costs may change in the future.

3.2 Literature Review

When investigating trends in extreme weather events over time, it is important to account for development and wealth that may have occurred during that same period, as this affects the level of L&D exposure. To date, there have been several approaches used to normalize L&D data for spatial and temporal aggregation, with varying results. Although normalization is yet a perfect science, it is a crucial step in data analysis when comparing results by ensuring that the data can be compared consistently across all records in the database.

Weinkle et al. (2018) performed a study of normalized losses due to hurricane landfall for the period from 1900 to 2017 in the continental United States. Multiple normalization methodologies were utilized in this effort, including adjusting the historic loss data for inflation, per capita wealth, and the population of affected counties. These methodologies tried to account for wealth added in the areas in which the storms took place by using a conventional approach to L&D data normalization, one which focused on the economic value of a region. This was based on the concept that as an area develops over time, it generates more valuable assets, which increases the possible L&D outcomes that did not exist in years prior. However, this methodology does not account for the evolution of technology, building codes, improved knowledge, and investment in risk adaptation that might reduce the L&D realized in more recent extreme weather events. Furthermore, the rate of inflation or the rate of value increase over time used in these normalization methods could mask any concurrent rate changes in extreme weather frequency and severity.

Nordhaus (2010) found that annual hurricane damage in the United States increased by USD 10 billion (at 2005 incomes), 0.08% of gross domestic product (GDP), and is possibly an underestimate. The findings were based on three primary factors: (1) number of storms; (2) maximum wind speed at landfall; and (3) GDP. The assumption in development of the hurricane damage function was that damage per storm is conditional on wind speed and proportional to nominal GDP. This assumption is based on the grounds of economic growth, assuming no changes in technology and the location and structure of economic activity. His argument for why this is likely an underestimate of damage is that it omits consideration of the social impact of the destruction of communities, as well as the culture and history in the impacted areas.

In a study of various disaster trend analyses in South Korea, Choi et al. (2019) grouped normalization methods into those that used inflation, wealth, and societal factors. It was determined that each hazard type had its own characteristics and disaster-specific variables to better fit the normalization. Generally speaking, it was found that a larger spatial scope required a more simple and general normalization methodology, while a longer time period improved the quality of the statistical analysis.

Social vulnerability is a difficult metric to develop due to the array of variables that may be used to establish a representative factor. To address this consideration, the Social Vulnerability Index (SoVI) was developed by Cutter et al. (2003); it contains around 30 U.S. Census variables, including socioeconomic, household composition and disability, minority status and language, housing type, and transportation. This index provides a powerful normalization tool because the index utilizes consistent rating scales that can be employed in comparisons between regions in time or space, thus solving a major hurdle in disaster cost normalization. Additionally, social vulnerability can be measured using the U.S. Center for Disease Control (CDC) Social Vulnerability Index (SVI), which measures a community's vulnerability to respond to and recover from disasters by ranking each census tract based on 15 social factors grouped into four themes (socioeconomic status, household composition, race/ethnicity/language, and housing/transportation). The result is a vulnerability score between 0 (least vulnerable) and 1 (most vulnerable). The CDC SVI and SoVI are two of the most commonly used vulnerability indices. Various studies have compared vulnerability indices and evaluated the contribution of different factors to the assessment of community vulnerability (Flanagan, et al. 2011). The hybrid simulation technique developed in this study uses the CDC SVI, which constructs the data in a percentile rank (Tarling 2017).

Loss and damage data normalization must explain the change in exposure and vulnerability within and between areas of comparison, while controlling for the change in the value of a dollar over time. There is no standard method for cost normalization and much of it depends on the spatial region and temporal setting of analysis. The normalization input factors are dependent on the type of analysis performed and is limited to the available data. It is clear normalization for L&D must account for the socioeconomic vulnerability of an area combined with the potential exposure. Furthermore, the dollar values must be adjusted to reflect inflation that has occurred over the time period in question.

Effective disaster management policies require a full understanding of the cost of disasters. Direct damage estimations can help to provide insight from which key vulnerable sectors and mitigating factors can be determined. Furthermore, these estimates can be built upon with other costs, such as indirect, intangible damages, and future long-term climate predictions to understand the full scope of risk a community face (Botzen, Deschenes and Sanders 2020). Common natural hazard-related disaster modeling techniques build disaster loss and damage models based on physical characteristics, as in the case of catastrophe modeling. Although these models often derive costs in the form of annual expected damages, L&D databases provide actual data that can be utilized for analysis.

As an example of the application of L&D databases, Kahn (2005) examined the direct impacts of natural hazards measured by fatalities, using raw data on deaths from the Centre for Research on the Epidemiology of Disasters (CRED). Through analyzing deaths from different disasters in 57 countries, conclusions towards the role of income, geography, and institutions in minimizing death counts were made. Other studies utilize the CRED database to compare hazards on a global scale to understand the drivers of risk from extreme weather events (Shen, et al. 2018). It is worth noting that events are only included in the CRED database if they meet the database classification of an extreme event, which includes ten or more fatalities, declaration of a state of emergency, hundreds or more reported affected, or a call for international assistance. The following presented methodology uses L&D resources to develop a model for natural hazards of all cost ranges to aid decision making for future climate adaptation to natural hazard-related disasters.

3.3 Model Development

The quality and uncertainty in how extreme weather data are collected and reported makes loss and damage data difficult to utilize at a local level, particularly due to sample size limitations when the data are segmented by extreme weather type. For this reason, some level of data aggregation is recommended; one means for doing so is to adopt a geographical region approach, such as has been defined by NOAA climatological divisions (Fig. 1). These nine regions are considered to be internally climatically consistent and therefore useful for putting climate anomalies into a historical perspective (Karl and Koss 1984). Using a regional approach while maintaining internal climate consistency is an important consideration in creating a more robust sample of extreme weather events from which L&D estimation can be performed. This does not suggest, however, that smaller geographical units, such as state or county, should be ignored if a sufficient sample size exists to provide a more resolute view of L&D. Since each region is considered similar climatologically, the grouping of data by this categorization was the initial starting point to expand the modeling sample size. However, in cases where it was determined that an adequate sample size was available for a smaller geographical unit, individual state data analyses were also performed.

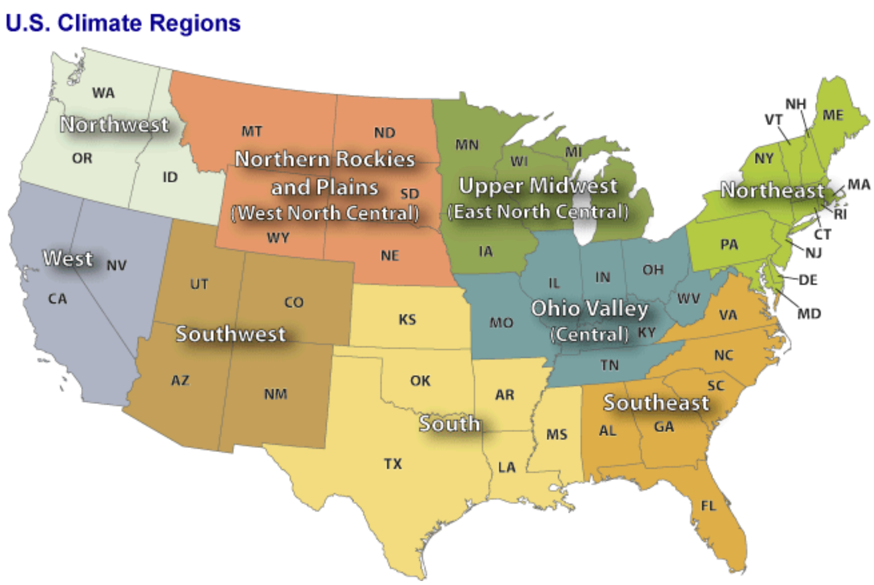

Figure 1: National Oceanic and Atmospheric Administration (NOAA) climatological divisions *Source* Karl and Koss (1984).

Socioeconomic status can be a meaningful indicator of risk exposure to extreme weather impacts, and such information is available at the county level as provided by the U.S. Census Bureau. Combining this information with the extreme weather profile for the area of interest can provide a more downscaled perspective of the risk with as suitable a level of disaggregation as the data allows.

We limited our use of extreme weather event data from the NOAA Storm Events Database to the period of 2000 to 2019. This time period is associated with an event history that reflects more recent trends, and conforms with a stretch of time where NOAA maintained consistency in how different extreme weather events were recorded.

The NOAA database includes 49 different event types, with each record containing date, location (state and county), property damage, crop damage, injuries, and fatalities. In our methodology, we aggregated the 49 event types into "main event" categories, following the Integrated Research on Disaster Risk (IRDR) peril classification and hazard glossary, as shown in Integrated Research on Disaster Risk (2014). The main event categories consisted of the following: Earthquake, Volcanic Activity, Flooding, Landslide, Wave Action, Convective Storm, Tornado, Winter Convective Storm, Heat, Cold, Fog, Tropical Cyclone, Drought, and Wildfire. These events were further sorted by the state and county in which they occurred along with the year in which the event took place, with the goal of normalizing the data based on these factors.

A simple, scalable L&D normalization equation that is both spatially and temporally consistent is applied to the cost values. As outlined in the literature review, there are a variety of normalization methods implemented for trend analysis of natural hazard costs. For example, Weinkle et al. (2018) developed the following normalization equation (Eq. 1). First, the cost total (D_y) is inflation adjusted with the adjustment variable (I_y), then it is further normalized with the real wealth per capita of the impacted area ($RWPC_y$) and a county population adjuster ($P_{2018/\mathrm{y}}$). The indices functioned as multiplicative indices to generate the normalized cost data (D_{2018}) as shown in Eq. 1.

$$D_{2018} = D_y \times I_y \times RWPC_y \times P_{2018/\mathrm{y}} \quad (1)$$

A similar approach is used in this study with a focus on larger spatial scale and multiple natural hazards. The normalized damage, D_n, is calculated in Eq. 2. To adjust for inflation, the monetary value of property damage was adjusted to the CPI for calendar year 2018 from the year the event actually occurred. The CPI data were retrieved from the Bureau of Labor Statistics at the U.S. Department of Labor. The SVI is included to account for the capability of a household to withstand event impact. Finally, population density is included to explain the magnitude of the impact, based on the assumption that more people exposed increases L&D potential.

$$D_n = D_i \times SVI_{(y,c)} \times PD_{y,c} \quad (2)$$

In Eq. 2, D_i is the inflation adjusted to 2018 event cost, $SVI_{(y,c)}$ is the CDC SVI percentile rank in year *y* for county *c*, and *PD* is the population density percentile rank based on event year and county. The CDC SVI is one of the most widely used indicator models for social vulnerability (Wood, Sanders and Frazier 2021). The CDC SVI database has indices from the year 2000, 2010, 2014, 2016, and 2018 and the CDC will continue to release new data every other year. At the time of this study, the 2020 data had not been released. In this application, metrics for the years between CDC SVI release years are linearly extrapolated to fill in during normalization. The CDC SVI uses a percentile ranking for each census tract, which allows for easily interpretable data and as a result shows the spread of vulnerability more evenly without explicitly displaying vulnerability outliers (Tarling 2017). In this normalization approach the data are grouped by county rather than census tract since the loss and damage cost data are provided at the county level. This county grouping would account for the potential loss of census track outliers the percentile ranking may miss since the values would be averaged out across a county grouping. The percentile rank functions as a consistent comparative metric facilitating direct comparison across counties in the United States and across the years in which the data are sampled to account for changes in socioeconomic vulnerabilities over time. In order to keep the normalization equation variables consistent, the population density was also converted to a percentile rank. This ranking applies a homogenous vulnerability index for comparison between counties. Reducing vulnerability outliers keeps general vulnerability patterns for the impacted area but prevents unique locations from entirely changing the shape of the damage data. As loss and damage data become more resolute and accurate to impacted locations, comparison at the census tract level may be necessary, in which case vulnerability at a smaller scale will be crucial to understand.

If the desired outcome consists of cost estimates over a period of time, understanding the general distribution of costs and the nature of extreme weather occurrence in the location of interest requires statistical representation to develop a model for cost estimation. In order to account for the uncertainty in L&D estimation, we fit the natural logarithm of the data to probability distributions from which potential L&D can be generated using Monte Carlo simulation. The normalized data for a specific extreme event type and location were fitted against 85 different candidate functions using the Kolmogorov-Smirnov test to determine the best fit. Once a best-fit distribution was obtained for a specific extreme weather type and region, that function was subsequently used to represent the extreme weather type and region profile in the succeeding model simulation.

During this process, it was discovered that the fitted distributions typically did not capture rare and highly damaging events, leading to distributions with infinite moments and failing to accurately replicate the historic data consistently. This issue was addressed by Blackwell (2015), who observed a USD 200 billion difference in damages based on the distribution used to represent the hurricane impact. This is important because it strongly impacts the cost-benefit analysis results in justifying whether to invest in risk mitigation measures.

Based on the extreme value theory (EVT), using a separate distribution to replicate heavy tail events is preferred for modeling extreme losses (Katz 2020). The EVT has a growing application in measuring high-cost losses from natural hazards, for example, modeling windstorm, rainfall, wildfire, earthquake, and snowfall losses. In many cases, the goal of the application is to price the events for future expectations and probabilities to inform decision making. For example, Zimbidis et al. (2007) measured earthquake risk via the EVT to assign respective probabilities to the extreme high-cost events. Recent application has seen a similar approach using the EVT to compute probabilities of unobserved rare heatwaves not seen in historical records (French, et al. 2018).

When looking at cost extremes, studies often use a specific cost threshold to separate high-cost events from less costly events to build the end tail distributions, specifically in the case of the EVT because of the focus on modeling extremes. In one particular example, McNeil who used the EVT to estimate end tail loss of Danish wildfires fitted multiple distributions to find a single best performing distribution of extreme events (extreme events were classified as events over one million Danish Krone) from 1980 to 1990 (A. J. McNeil 1997). In our study, the application of the EVT led to similar results when compared to fitting the individual distributions to end tail. We do see, however, the need for more robust testing of EVT distributions for application within our hybrid simulation technique as a topic of future research.

Rather than establishing a specific monetary threshold as done in other EVT studies, we define the top 10% of the data for each region/hazard combination as high-cost events to be separated for data fitting in order to more accurately represent the dynamic of the data at the end tail in a region. This cutoff was implemented to both represent the unique features of the specific region/hazard combination and ensure that a large enough sample size was obtained to accurately fit the data. Furthermore, although many end tail fitting methodologies focus on fitting a single distribution to a single event data space, our approach fit many different hazard and regional data combinations to different distributions depending on the best fit found during testing. The value of the threshold can be revised and evaluated using a sensitivity analysis to determine the most appropriate threshold for different regions and hazards.

Taking the most extreme instances and fitting them separately allows for a more accurate characterization of these events. The reason for the selection of the top 10% part of the loss and damage cost distribution is that the "end tail" behavior is a unique problem due to the limited number of low probability, high consequence events in the sample. Furthermore, the top 10% of the distribution was selected using the Kolmogorov-Smirnov test in order to include enough event samples to create a confident distribution fit that can be consistently applied to each event and location. An example of the two-step data fitting process is presented in Fig. 2. The best-fit distributions for the convective storms in the Midwest were determined to be the generalized logistic and the Johnson SB distribution. This process was performed for each hazard/region combination, resulting in different distributions for each combination, depending on the distribution that fit best when tested.

For example, along with convective storms, the following list consists of the other best-fit distributions for hazards in the Midwest:

- Winter convective storm: A T-distribution for the nonextreme events and an exponential power distribution for the end tail;
- Flooding: Log-normal distribution for the nonextreme best-fit and a Gompertz (truncated Gumbel) distribution for the end tail distribution.

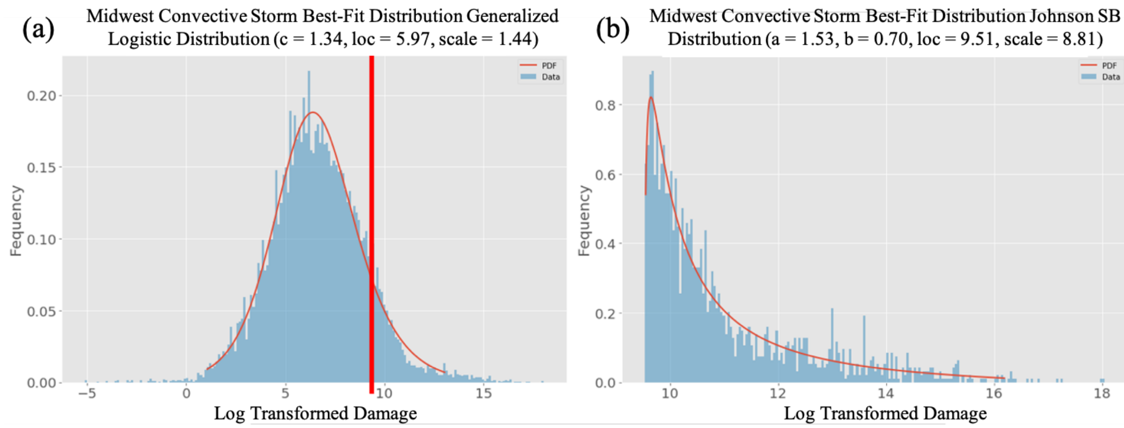

Figure 2: Two-step data fitting process. The log-normalized data for Midwest convective storms was fitted across the entire data (a) and then for the events in the top 10th percentile (b). The vertical line before 10 on (a) indicates the top 10% of the data that was fitted again on the right (b). The red curves in (a) and (b) represent the probability density function (PDF) of the best-fit distribution.

The top 10% of the data was fitted following the same process as previously described, using the Kolmogorov-Smirnov test to determine the best fit for the distribution. In many cases, the end tail distribution required truncation prior to distribution fitting in order to replicate the historic distribution. This distribution was then tested by randomly generating samples to ensure that the fit is a realistic representation of the data due to frequent cases of heavy tailed distributions resulting in disaster costs greater than the wealth in the represented area. The fitting process also occasionally required more samples than the number of samples in the top 10%, in which case the threshold was expanded to include additional events.

Once the two distributions were created, one to represent the lower 90% of the data and another for the top 10%, these distributions were placed into a Monte Carlo simulation

(MCS). The simulation uses historical event frequencies to establish the probability of occurrence of a specific extreme weather event type in the area of interest by dividing the number of records for each extreme weather event type by the observation period (in days). The historical L&D data along with the fitted distributional form from the previous step were used to generate a random cost outcome from the distribution to represent L&D.

This model was then utilized in simulation to generate samples that represent a 20-year period for the selected location and extreme weather category (Fig. 3). The 20-year period was selected to directly compare to the historic data. Each day (time = t) is represented in the simulation as an extreme weather event either happening or not, which is determined by a random outcome based on the historic event frequency (total historic events divided by the total number of days in the historic data recording period). If an event does not occur, the simulation moves to the next day ($t = t + 1$). Should an event occur, however, the model then determines the associated costs based on the corresponding event type L&D distribution. Once this is determined, the model moves to the next day in the simulation and continues this process until completion of the 20-year period. This creates a single sample and is repeated 1,000 times in the MCS. The sample size of 1,000 was determined experimentally as convergence towards a relative mean value was found in the model with reasonable computational demand.

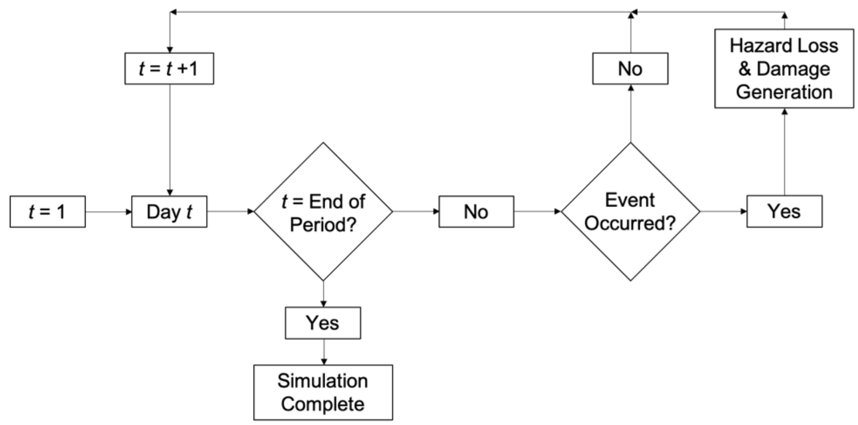

Figure 3: Simulation flowchart for a single hazard/location

The hazard loss and damage generation step in Fig. 3 uses the fitted distributions from the previous step to generate the cost based on the historic data. This process flow is displayed in Fig. 4. The variable C represents the realized cost in the simulation, $C_{0.90}$ represents the 90th percentile cost of the L&D of the specific extreme weather event type and region. These costs are compared to determine if C is greater than $C_{0.90}$; when this is the case, the end tail distribution is used to re-generate a simulated cost.

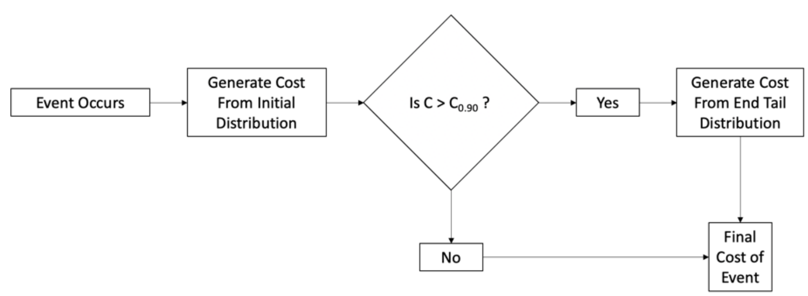

Figure 4: Generation of damage cost for a specific hazard type. C is the realized cost in the simulation, if C is greater than the 90th percentile threshold it is replaced with a cost generated from the end tail distribution.

After verifying that the simulation results fit the historic data, respective extreme weather event trends can be evaluated. The model can then be applied to future extreme weather event scenarios according to anticipated changes in event frequency/severity and demographics. These results can be compared with the status quo (base case) scenario to estimate future L&D with or without the introduction of risk mitigation strategies.

3.4 Model Validation

The aforementioned methodology was applied as separate simulations for 201 unique region and extreme weather event type combinations, each run 1,000 times over a 20-year period. The results from each individual simulation were first compared to normalized historic data in order to understand how well they represented historical observations. This was accomplished by calculating the percentage difference via the following equation for each of the 1,000 runs:

$$\%\ mean\ difference = \frac{[(Historic\ Mean) - (Simulated\ Mean)]}{Historic\ Mean} \tag{3}$$

The average p-value of the historic data following the Kolmogorov-Smirnov test of these 201 combinations was 0.680 with a variance of 0.088. The distribution fits were good considering the variety of distributions presented with the historic data.

By using the mean value, both the individual trial performance and the overall simulation performance can be examined since the mean is both a function of the total events that take place and a measure of the center of the data. Overall, 187 of the 201 simulations showed a percent mean difference below 10%. Despite a few outliers that may be addressed in further testing or re-fitting distributions, generally the simulation was able to reasonably reproduce the L&D associated with historic data representing extreme event types occurring in the areas tested.

3.5 Discussion

The efficacy of this hybrid simulation approach, as expected, relies on a sufficient sample size of historic data, which is the primary input for the model. The average percent mean difference of the combined 201 simulations was 5%. Slightly better results were achieved when the input sample size exceeded 1,000 historic events. This does not mean the simulation cannot be useful when applied to sample sizes below 1,000 historic events, only that it may somewhat reduce confidence in the results.

As seen in Fig. 5, the number of historic events is not the only variable impacting model performance. The variance represents the overall range of possible L&D that is incurred in an event. As the variance increases, there is less consistency in the event outcomes, making the ultimate modeling and data fitting process more difficult. Aside from a few clear outliers, as the overall historic cost variance increases, the percent mean difference also increases.

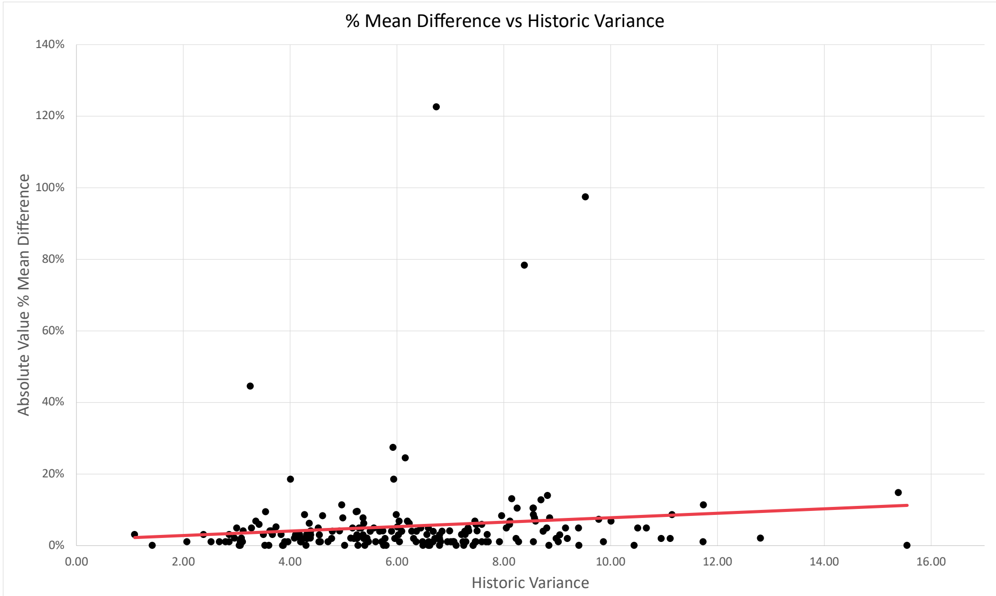

Figure 5: Percent mean difference as a function of the variance in historic cost of an event. The red line shows the trend.

It can be seen that the variability in the historic data propagates into the model and corresponding cost outputs. This relationship is further explained in Table 1, where the extreme weather types with the most events and smallest variability lead to the smallest percent mean differences.

	Total Events	**Average Mean Difference**	**Historic Variance of Event Costs (Log Transformed)**	**No. of Test Samples**
Convective storm	393,598	5%	4.95	57
Flooding	83,167	6%	7.10	56
Tornado	26,423	4%	6.34	33
Tropical cyclone	3,759	13%	7.95	13
Wildfire	853	6%	6.89	4
Winter convective storm	29,191	4%	5.87	36

Table 1: Model performance comparison by event type. The highlighted rows include the smallest average mean difference or the smallest variance.

This is even more evident when examining the empirical distributions of the historic L&D data. For example, when comparing the historic data of convective storms in the Midwest and tropical cyclones in Texas, the percentage mean differences are 1% and 15%, respectively. Midwest convective storms had roughly 22,000 events and a historic cost variance of 5.60 compared to Texas tropical storms that consisted of 120 events and a historic cost variance of 15.39. These two combinations were selected to highlight the range of differences between region and state sample sizes in the historic data and to show inherent differences in the range of possible L&D for different event types. Although tropical cyclones have a much larger range of outcomes compared to convective storms, the sample size for Texas tropical storms is so much smaller than for Midwest convective storms, creating greater difficulty in confident data modeling.

However, even though the model is not as close to the mean in cases of smaller sample sizes, it does not necessarily imply that the results are not useful, only that the estimated results are less precise. This is a common phenomenon in any extreme weather analysis where sparse data exist for low probability, high consequence events.

3.6 Conclusion

By developing a better understanding of L&D associated with different extreme weather event types in various climate regions, it provides a basis for addressing what to expect in terms of L&D based on future climate projections. The model and methodology described herein can help guide decision making in future infrastructure adaptation investments by creating a cost comparison of inaction versus implementation of candidate risk mitigation strategies. It is based on the premise that practitioners desire to make more risk-informed investment decisions using a simple, practical framework given limited time and resources.

As previously discussed, output comparison of the end tail values, specifically the maximum cost events in the simulated period, presents a unique challenge due to the limited historic data for extreme weather events. This is further amplified if an extreme event is not present in the historic data. This issue can be potentially addressed by using an expanded data set, perhaps with a sample size threshold, to act as a benchmark for the normalized maximum costs.

Furthermore, one must be mindful that L&D model estimation is presently limited to only property damage effects of extreme weather events; intangible and indirect damages must be quantified to develop a more complete picture of the L&D impacts of an event on an area. When these empirical data become available, they can be incorporated into the approach espoused.

This methodology is unique in its approach to modeling extreme weather loss and damage. Through development of this methodology, L&D data can be used as another tool in adaptation decision making while limiting the data demands of most hazard cost projection and analysis. The added benefit of this approach is that it can become an even more impactful resource over time as the databases gain more entries from the occurrence of future events.

Chapter 4

Extreme Weather Risk Projection Using a Hybrid Simulation Technique

There are clear indications that climate change is affecting weather and other climate-induced extremes in every region across the globe, and trending in an even more concerning direction. To prepare for this increasing threat, climate adaptation measures must consider risk assessment methods that capture scenario-based loss and damage to support cost-benefit analysis. This study presents a risk projection approach that builds on historical loss and damage data from extreme weather events to evaluate potential losses under future climate scenarios. Loss and damage of historical extreme events are used as a proxy measure for severity of disasters. A hybrid Monte Carlo simulation technique is then applied to develop disaster loss projections under climate change and used to estimate return periods of extreme events based on the projected losses. Application of this methodology is illustrated using flood hazard in the Northeast region of the United States. The results are in good agreement with other literature on flooding impacts in the region in terms of expected return periods of large flooding events. These findings suggest that this approach could function as a promising screening tool to help guide climate adaptation planning.

4.1. Introduction

The most recent Intergovernmental Panel on Climate Change (IPCC) assessment report affirms that the trending rise in global surface temperatures along current emissions scenarios will bring many changes to climate systems, including increases in frequency and intensity of hot extremes, heavy precipitation, and agricultural and ecological droughts (Masson-Delmonte, Zhai, 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, including human casualties, property damage, loss of assets, community disruption, loss of supply chain, mental health issues, and other negative economic, social, and environmental consequences (Botzen and Van Den Bergh 2009). The purpose of this study is to develop a comprehensive approach for evaluating the cost of future disasters beyond relying solely on property damage to support of climate risk-based decision-making. Our study 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 (2000 to 2019). 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. While the methodological approach is applicable to any type of extreme weather event, flood risk is selected as an illustrative example in this paper.

The technical burden of 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). Recent research has made efforts to develop accurate probabilistic flood loss estimation models that incorporate fewer variables to reduce computational demands for determining flood vulnerability (Apel, et al. 2009).

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). The data demands for future flood risk projection are well-described by Bates, et al. (2021) in their flooding analysis at 30m spatial resolution for both current and future time periods under the RCP4.5 emissions pathway. The study utilized a high-resolution hydraulic model based on LISFLOOD-FP code which converts boundary conditions of rainfall, river flow or coastal extreme water level to predictions of flood depth, flow velocity, and inundations extent.

While hydraulic models provide an accurate evaluation of flood risk, reducing the technical and computation burden of future flood projection provides a complementary approach to inform risk mitigation decisions for vulnerable communities. Our proposed risk projection methodology functions 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. Moreover, while demonstrated herein for flood risk, the approach is transferable to other extreme weather and climate-induced threats.

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 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, SSP2 represents a middle case, and SSP5 represents a fossil-fuel dependent future. 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 technical burden on local decision-makers. Often methodologies require a plethora of data inputs and outputs that are not provided in ways that the public can readily utilize in decision making. It is worth nothing that the objective of our methodology is not to replace existing risk analysis approaches or physics-based, data-driven and simulation approaches, as they all contribute to a comprehensive understanding of flood risk analysis (Mosavi, Ozturk and Chau 2018). Rather, it provides an initial screening tool to determine high risk areas and to provide flood risk assessment across a defined region.

4.2 Risk Projection Methodology

4.2.1 Review of Hybrid Simulation Technique

The risk projection methodology starts 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 area of analysis. Once fit to a distribution, a Monte Carlo simulation is used to develop expected costs the hazard would cause in the region over a specified time period if no changes to the area are made. 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). Three future time periods (2021-2040, 2041-2060, and 2080-2099), under the aforementioned three different SSPs were considered. 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 database provides L&D costs dating back to January 1950, although the recording procedures were not formalized until 1996 when all 48 event types started to be recorded. The initial step involves normalizing the historic data for comparison between different locations and years in which the events occurred according to Equation 1.

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

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 between corresponding measurement indices were linearly extrapolated. 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 in order to generate sufficient sample sizes to develop a damage function. Six event types were considered, one of which was flooding. 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 been proven to be a useful method for estimating the tails of loss severity distributions (A. J. 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 and event type. 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 1), 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 1), 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.

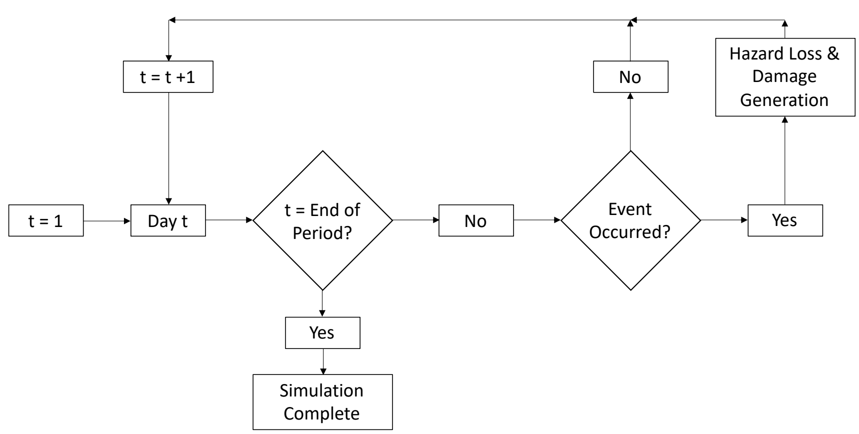

Figure 1: Monte Carlo Simulation process flow

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 and event type. 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.

4.2.2 Risk Projection Methodology

While, the risk projection approach is described in this section following a case study of flood hazard in the Northeast region of the U.S., the method can be applicable to any type of hazard-region combination. The Northeast 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 to the Northeast region. Future flooding costs are generated through use of the percentage change in mean annual precipitation in the region based on CMIP-6 generated data (Almazroui, et al. 2021). This functions as a relative measure for the expected change in the cost of flooding events (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. Using the percent change in mean annual rainfall as forecast by CMIP-6, a mean shift was then applied to the corresponding flooding probability distribution of losses (see Table 1), which is then converted to the log value in the corresponding damage probability distribution

Northeast United States			
Region/Scenario	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. Values in bold are the percent shifts which were tested in this analysis (Almazroui, et al. 2021).

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 take into 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 frequency and magnitude. More specifically, the new probability distribution of L&D increases the cost 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 a region's future scenario planning.

The future projection of flooding impacts consisted of shifts in one or both of the mean and 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.

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. Standard Deviation is abbreviated as st. dev.

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, Trenholm, 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 must 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.

4.3 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 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.

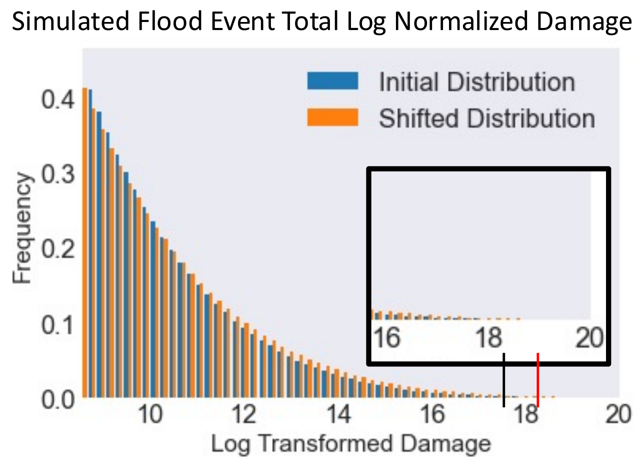

Figure 2: Distribution of log transformed normalized potential damages of the tail behavior for a flooding event. The zoomed in section shows the extended tail of the shifted distribution compared to the initial case. The two vertical lines display the historic (black) and new scenario (red) 100-year events.

Figure 2 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 was the highest resolution the L&D data allows for across all states when fitting the probability cost distributions. Figures 3-5 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 in order to visualize the impacts these shifts had on the results.

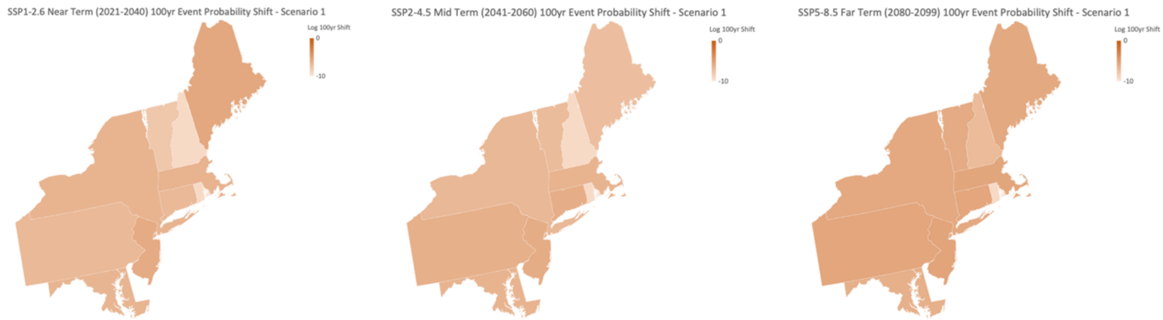

Figure 3: Scenario 1 projection of change in probability of 100-year events in the Northeast United States

Recall that Scenario 1 represents only a shift in the mean of the damage function, representing a general increase in future event magnitude. This led to minimal change in the near, mid, and far time horizons. By contrast, Figure 4 displays Scenario 2 results which represent a shift in the mean of the main body distribution and a shift to both the mean and the standard deviation of the extreme events representative damage function.

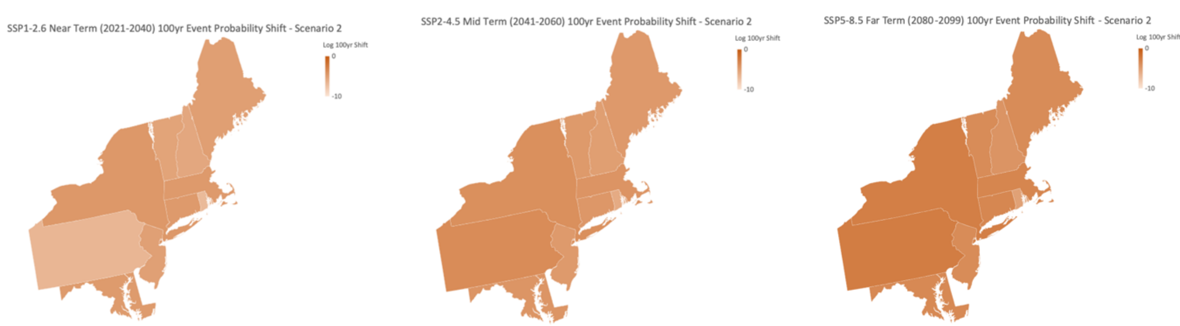

Figure 4: Scenario 2 projection of change in probability of 100-year events in the Northeast United States

Figure 4 clearly indicates a larger increase in the frequency of 100-year events relative to the historic data (base case), and particularly so for SSP5-8.5 pathway in the longer term (2080-2099). Figure 5 displays results for Scenario 3, which consists of shifts to the mean and standard deviation of both representative damage functions (the distribution body and the tail extreme events distribution).

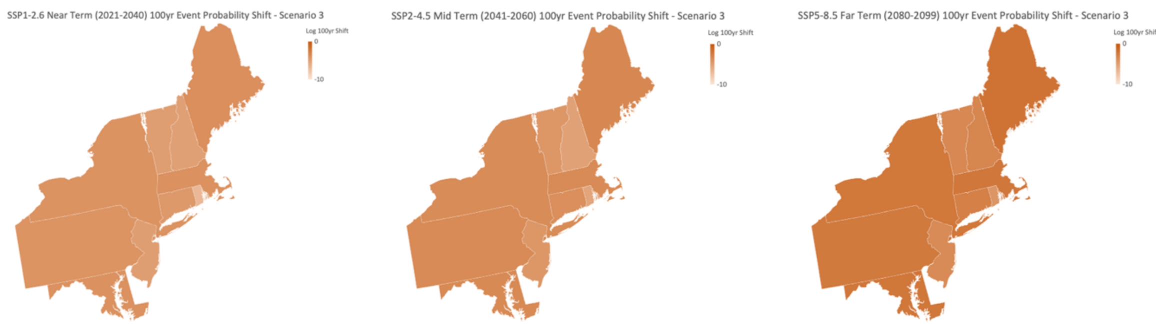

Figure 5: Scenario 3 projection of change in probability of 100-year events in the Northeast United States

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 near 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. These findings are generally consistent with other studies which conclude that flood frequency and severity will increase, and in turn increase expected L&D. Interestingly, the expected L&D for New Jersey shows a limited relative change in the Northeast. This result 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 that affirms a difference in expected damages based on the emission scenarios presented. A 2017 Natural Hazards Earth Systems Science article, which 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, found a difference of 750 million USD per year by 2100 between RCP 4.5 and RCP 8.5 scenarios. With each more intensive RCP scenario, 1% annual exceedance probabilities (AEP) increased across the entire Northeast United States, 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 (Wobus, et al. 2017).

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. Similar to the approach taken in our risk projection methodology, these results were compared to the historic records to demonstrate the change in risk over time. The analysis results 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 (Wing, et al. 2022), similar to what we observed using our risk projection methodology in the mid-term scenario.

4.4 Further Discussion

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). In this regard, 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 achieved 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 damages. 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 as a result of added wealth and population growth in specific geographical locations, which can make the implications of these disasters even more significant.

Chapter 5

Natural Hazard Intangible Damage Quantification

5.1 Introduction

The future of climate change impacts will undoubtedly have a massive toll on life on earth. Extreme weather and other climate-induced events can be expected to leave in their wake damaged infrastructure, human casualties, environmental destruction, and otherwise test the very societal fabric upon which we depend. Typically, beyond property damage, there is no such "price of replacement/repair" for the sustained loss and damage that these events cause, such that the true cost is poorly understood. Yet, a central tenet of policy development is to rely on cost-benefit analysis to determine whether and how to invest in adaptation approaches to mitigate this risk. Because indirect and intangible (non-market) damages are not commonly measured in monetary terms, their impact is omitted from the analysis, making it more difficult to establish a compelling business case for allocating resources with this intention (Pannell and Gibson 2016).

A growing number of studies have attempted to monetize indirect and intangible loss and damage relative to direct damages experienced by extreme weather and other climate-induced events. Typically, these studies are narrow in scope, focused on a specific location, making it more challenging to apply broadly. As the number of these studies begin to accumulate, however, it creates the possibility for trends or averages to emerge that may be applicable across regions. The study reported herein was performed with this objective in mind. In this effort, we utilize available data on intangible loss and damage in a climate change cost simulation to determine a more complete estimate of loss and damage incurred from future extreme weather and or climate-induced events. Our methodology is illustrated for a use case involving flooding.

5.2 Literature Review

Intangible loss and damage refer to goods and services which are not measurable in monetary terms because they are not traded on a market (Meyer, et al. 2013). These costs often include health, environmental, and social impacts. The methods to illicit a value from intangible impacts include stated and revealed preference methods. Stated preference methods typically utilize surveys to derive a cost by asking individuals questions which can help to infer a willingness to pay (WTP) to achieve a result or willingness to make tradeoffs between different outcomes (Rogers, et al. 2019). Stated preference methods include:

- Contingent Valuation Method (CVM): Asking individuals about values they would place on non-market commodities if markets did exist (Bishop and Heberlein 2019).
- Discrete Choice Experiments/Choice Modeling: Determining a willingness to pay through use of choice experiments in which participants must decide between outcomes with varying characteristics which includes market or non-market goods (Mariel, et al. 2021).
- Life Satisfaction Analysis: Using life satisfaction survey results with a range of other objective or subjective measurable variables to assess the association those variables have on life satisfaction (Fernandez, Stoeckl and Welters 2019).

Revealed preference methods utilize market behavior to estimate the value of a good, deriving information from observed behavior to determine a willingness to pay (Meyer, et al. 2013). The most common methods include:

- Travel Cost Method: Using individual's travel cost data as a proxy for recreational value (Leh, et al. 2018).

- Hedonic Pricing Method: Determining the value of non-market characteristics based on actual market prices, such as housing market impacts (Wei, et al. 2022).

For cases of specific disaster events in an accessible area, contingent value methods are often used to survey victims to gather information about the event and to correlate those results with the level of damage experienced. This approach allows for intangible costs to be represented as a percentage of total costs. A case study in Fredericton, Eastern Canada combined extreme event analysis, the contingent evaluation method, hydrologic analysis, and down-scaled general circulation models to develop a four-step framework on a flooding event to estimate the market and non-market annual average flood damage under different population and climate scenarios (Lantz, Trenholm, et al. 2012). The authors concluded that non-market costs can represent up to 50% of total household costs of flooding events. To obtain intangible (non-market) cost estimates, the study developed CVM scenarios and questions, asking study participants to understand a hypothetical policy based on a major flood event that had previously occurred in the region and a more intense flooding scenario than the one that had occurred. The participants were asked to determine if the impacts to their household were significant enough to warrant applying for hypothetical compensation. The respondents were also asked to determine the minimum amount of financial compensation the household would need in order to make them as well off as prior to the flood event, specifying the compensation should cover damaged property, personal items, preventative measures, employment, traffic, transit, recreation, and psychological impacts, among others. These results provided a willingness to accept (WTA) that could be related to the specific flooding events in the area. The advantage to this approach is the subjectivity in what constitutes an individual's intangible costs is kept broad enough to establish a general associated non-market cost impact to an individual. Since mental health and other impacts are not traded on a market, methods such as the Fredericton case study provide a relative impact to the sector.

A second CVM approach, examining agriculture production in Vietnam, reported similar results. In this application, local authorities and farmers were asked to estimate damage rates and unit values. These results were converted to Annual Average Risk (AAR), resulting in direct intangible and indirect (tangible and intangible) being 1.5 to 2.5 times higher when compared to direct tangible risk (Nga, Takara and Nguyen 2018). Of those risks, losses associated with clean up and repair, environmental pollution and business interruption were the major contributors to the impacts of extreme events when compared to less extreme events (100-year floods compared to 10-year floods).

Similar findings have been reported for studies using life satisfaction analysis (LSA). LSA was used to value tangible and intangible costs of flooding in the Philippines used self-reported accounts as a serviceable proxy for utility. These responses, combined with regional scale environmental data and the estimated financial impact of the flood damages, allowed for inferences as to the value of ecosystem services to the individuals. Determinants of life satisfaction included gender, education, age, number of children and household size, employment, income, and health/faith/public infrastructure. These attributes were determined using ordinary least squares on the LSA model, resulting in a conclusion that tangible flooding impacts should be multiplied by a factor of between 1.4 and 1.7 to arrive at an estimate of total costs of flooding events (Fernandez, Stoeckl and Welters 2019).

The life satisfaction and social well-being approaches have been gaining popularity in economic applications because it helps to control some of the bias factors that can be introduced when surveying willingness to pay (WTP) or contingent valuation methods (CVM), as they can create hypothetical markets which do not accurately represent one's true willingness to pay (C. Fernandez 2016). A study of the monetization of social well-being impacts from flooding events found that intangible effects are about twice as large as tangible direct monetary flood losses (Hudson, et al. 2017). These effects were determined through a mail survey in France to collect a random sample in three different regions which had been impacted by flooding. The survey measured overall Subjective Well Being (SWB) and its association with health, home, living environment, financial situation, family life, social life, and amount and use of free time. The survey also asked about flood risk perceptions, namely the expectation of the possible increase in future flooding, worrying about flood probabilities, and past experiences with flooding. Lastly, the survey asked about current individual flood protection measures. Collectively, these variables were used to formulate a framework to monetize SWB. This monetization was calculated based on the trade-off between income and SWB, creating a compensating value which is the ratio of the marginal effect of the variable of interest to the marginal effect of income on SWB. Flooding was, to no surprise, correlated with a decrease in overall SWB. The intangible effects were found to be nearly twice as large as the compensation value of the tangible effects of flooding.

WTP for public investments may not always accurately reflect the expected costs in the area, further suggesting room for the non-quantified intangible damages in the expected cost assessment. One WTP study, using CVM for flood risk reduction in Germany, found an average willingness to pay of nearly double the cost as estimated by climate models for the area. One could surmise that the climate model underestimate is a result of exclusion of indirect and intangible damages and the potential for respondents to be motivated to help others by "doing their part" (Entorf and Jensen 2020). Other WTP studies found similar results. For example, a study looking at WTP for flood insurance for homeowners along a Dutch river delta aimed to elicit risk beliefs and demand for insurance from a low probability, high impact flood found individuals do not behave in accordance with the expected utility model. The study found WTP for flood insurance is considerably higher than the expected value for the flood risk homeowners face and communication of those risks has a significant impact on the level of WTP. Based on the expected risk in the area, it was found that homeowners are willing to pay flood insurance rates of between 70% and 175% higher than the expected value of average flood damage per household under the current climate conditions (Botzen and van den Bergh 2012).

Other LSA approaches contextualize intangible impacts in terms of willingness to pay a portion of household income to avoid flooding impacts. This type of analysis is useful to understand individual risk perception although makes it more difficult to place into the context of the total cost of specific flooding events. One particular study, which analyzed time series data from 16 European countries, found a sizeable negative impact of flooding on life satisfaction (Luechinger and Raschky 2009). This study utilized self-reported subjective well-being and income data as well as flooding event data. The SWB and income data were a product of the Eurobarometer Survey Series which interviews a cross-section sample of Europeans each year. On average, a person living in the study region reported a 0.035 lower life satisfaction (on a 4-point scale) compared to the reference group. Furthermore, income had a significant positive effect on individual life satisfaction. Additionally, it was found that a willingness to pay for the prevention of one sure flood disaster was valued at 23.7% of an average household income and about 0.7% of annual household income to reduce the annual flood probability by its mean of 0.026 to 0 (Luechinger and Raschky 2009).

The generalized approaches to intangible variable costs cover many of the pitfalls more specific survey measurements such as CVM or WTP can experience. Nonetheless, it is necessary to perform such analysis to achieve more focused variable costing. Considering that economic cost and benefit analysis is the standard for policy decision-making, it is necessary to continue to develop this science in order to generate more informed policy development. Furthermore, the deployment of surveys can be resource intensive and expensive, so alternatives such as benefit transfer, a method of transferring values from existing studies and adjusting them to a different context can function as an alternative if resources are limited (Johnston, et al. 2021).

The benefit transfer approach was utilized in a case study of flooding in Australia. Separate intangible loss categories were defined for morality, morbidity, recreation, electricity outage, road traffic annoyance, road traffic delays, inability to return home, and cultural heritage. For each category, annual average tangible and intangible loss values were determined for a variety of scenarios in developing a comprehensive benefit-cost analysis of flood mitigation planning in the area (Florec, Chalak and Hailu 2017). In this instance, a smaller total ratio of intangible to tangible losses was reported, with intangible costs representing between 6 and 21% of total losses. Notably, however, the study did not include much of the costs of recovery time or other mental health impacts which are typically included in life satisfaction approaches.

Business interruption costs along with site remediation costs are also crucial to the event loss and damage accounting and are often left out of cost analysis due to the length of time it takes to determine the magnitude of the costs after an event. An integrated flood risk analysis using Central Vietnam as a case study combined flood risk curves (FRCs) and annual average risk (AAR) in monetary values for the agriculture sector of a rural floodplain in multiple flooding scenarios ranging from 100-year to 10-year return periods (Nga, Takara and Nguyen 2018). The study derived the intangible damage amounts through a CVM method, using a household survey asking local authorities and farmers to estimate the damage rates and unit values of rice and crop cultivation and aquaculture production. The study found total risks (including all damage types: direct, indirect, and intangible) are significant, between 1.5 to 2.5 times higher compared to the direct tangible losses. Those losses include clean up, repair, environmental pollution, and business interruptions. Furthermore, the study suggests as direct damages increase, indirect and intangible losses increase at a higher rate (e.g., the losses in a 100-year event were found to be almost double compared to a 10-year event) (Nga, Takara and Nguyen 2018).

The definition of intangible values contains a wide umbrella of factors, which makes it difficult to measure specifically. As the above studies have shown, each study values a different set of variables using different methodologies. Furthermore, the survey approach to measuring the relationships leave a lot of the intangible definition interpretation up to the participants of the survey. As a result of the broad scope of analysis the following methodology presents an approach to use a generalized approach to account for uncertainties across the approaches to develop an associated combined intangible and indirect damage factor to the realized direct costs of a natural hazard.

5.3 Methodology

The aforementioned studies formed the database from which we were able to incorporate this information in a previously developed Monte Carlo simulation technique previously developed by the authors to develop cost projections for future climate adaptation decision making (Doktycz, Abkowitz and Baroud 2021). This approach uses normalized loss and damage (L&D) cost data to model historic direct property damage for various extreme weather events, including flooding. By adjusting the probability distribution of losses based on future climate change expectations for flooding events in the regions of analysis, future costs are determined. By including intangible damage cost factors in this methodology, a more complete cost assessment can be determined for use in performing cost-benefit analysis.

The intangible damage cost factors were defined by flooding studies shown in Table 1, which included a range of geographical locations, total cost comparisons, and methods to determine the indirect/intangible multiplying factor. Due to the variety in attributes considered in each study, combined with the different methods to calculate each attribute, the range of values were used to account for the non-exact value. Each study had an associated expected cost per year (which was either from a single event or multiple events in a year); this value was adjusted to 2018 USD to establish comparative uniformity.

Method	Scenario	Expected Cost/Year	Intangible Damage Factor	Study
CVM	'Worst-Case'	$6,000,000	0.396	(Lantz, Trenholm, et al. 2012)
CVM	'Best-Case'	$700,000	0.501	(Lantz, Trenholm, et al. 2012)
CVM	'Normal Climate'	$813,000	0.492	(Lantz, Trenholm, et al. 2012)
CVM	100yr Flood	$115,000	1.52	(Nga, Takara and Nguyen 2018)
CVM	50yr Flood	$215,000	0.83	(Nga, Takara and Nguyen 2018)
CVM	20yr Flood	$492,000	0.77	(Nga, Takara and Nguyen 2018)
CVM	10yr Flood	$910,000	0.62	(Nga, Takara and Nguyen 2018)
CVM	Annual Average	$430,000	0.65	(Nga, Takara and Nguyen 2018)
WTP	High end Estimate	$65	1.75	(Botzen and van den Bergh 2012)
WTP	Low end estimate	$65	0.7	(Botzen and van den Bergh 2012)
LSA	High end estimate	$2,000	0.7	(Fernandez, Stoeckl and Welters 2019)
LSA	Low end estimate	$2,000	0.4	(Fernandez, Stoeckl and Welters 2019)
WTP	Annual Average	$5,000	0.276	(Florec, Chalak and Hailu 2017)
WTP	Annual Average	$3,000,000	0.58	(Entorf and Jensen 2020)

Table 1: List of associated intangible damage cost factors for flooding events

To develop an intangible damage factor distribution, the factors were log transformed to fit into a truncated normal distribution. In Figure 1, the damage factor distribution used for the simulation can be seen. The initial distribution of factors from the studies was log transformed and fit to a truncated normal distribution where factors were randomly selected based on the distribution. The normal distribution, with a p-value of 0.846, was compared among 85 SciPy Statistics distributions in Python (Virtanen, et al. 2020). Although there were better fit distributions, such as the Laplace distribution with a p-value of 0.996, this distribution does not have a truncated function. The truncated normal distribution allows for the ability to retain true randomness when implemented in the simulation. The Laplace distribution would have had to be manually truncated, preventing a true random draw in the simulated model.

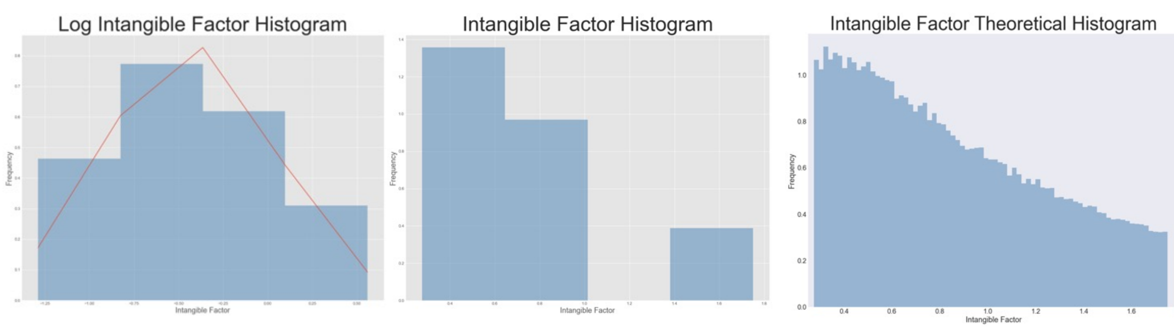

Figure 6: Left: log transformed intangible damage factors fit to a truncated normal distribution curve. Center: Actual Distribution of the intangible damage factors. Right: Theoretical truncated normal distribution using the parameters determined by the distribution fit.

The truncated normal distribution was subsequently integrated into the hybrid Monte Carlo simulation technique to function as an accessory set of costs along with the direct costs derived in the simulation. The simulation uses probabilistic cost distributions based on normalized historic property damage data to simulate a period of time for a specific region of analysis towards developing probable costs of severe weather events (in this case flooding events). Once a property damage cost total for an event is created in the simulation, the multiplication factor is randomly produced from the intangible damage distribution range and the product of the two values represents the intangible damage cost. This process can be seen in Figure 2.

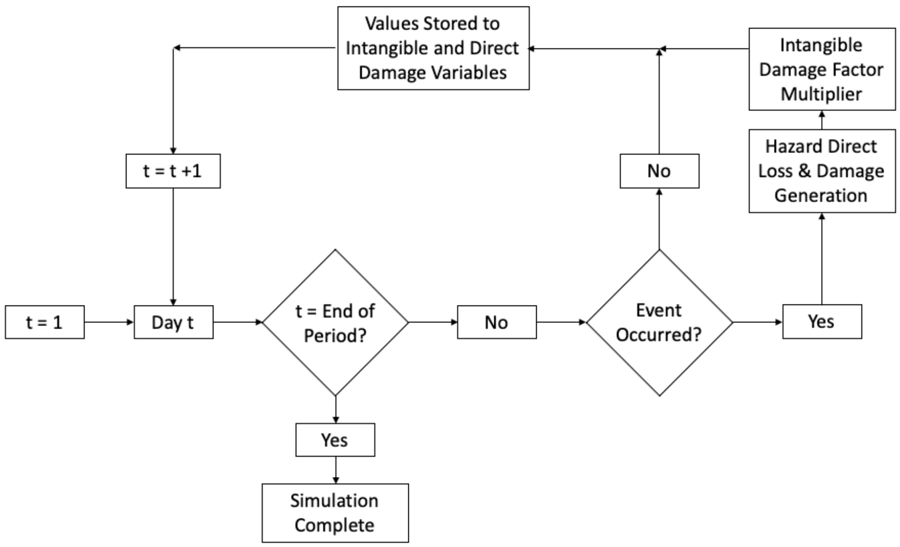

Figure 7: Monte Carlo Simulation process.

The direct and intangible damage estimates are saved as separate values for comparison. The total combined costs are calculated after the simulation period is completed. Each simulation consisted of 1,000 iterations of a twenty-year period. Different climate change pathways are also considered in the simulation technique to adjust the possible outcomes for scenario-based risk analysis by adjusting mean and standard deviations of the probability distribution of losses for the specific regions. The Shared Socioeconomic Pathways (SSPs) represent projected socioeconomic global changes up to the year 2100. SSP1 represents a sustainable pathway, SSP2 represents a middle of the road pathway and SSP5 displays a fossil fuel dependent future.

5.4 Results

We illustrate this approach using the future expected costs of flooding in the State of New York as a case study. The simulated results are presented in normalized monetary values for comparison purposes. The historic baseline simulated results serve as the metric for comparison. The data gathered from the simulation results include the direct costs and intangible damage costs for the future time horizon, the cost of a 100-year event (an event with the probability of 0.01) and the total cost (the sum of direct and intangible costs). These values were calculated for three different Shared Socioeconomic Pathways. These results are also presented in three different time periods to display the range of possible risk scenarios (see Table 2). Near-term represents the years 2021-2040, Mid-term represents the years 2041-2060 and Far-term represents 2080-2099.

Scenario	Direct Costs	Intangible Costs	Total Costs
Historic Baseline	$635,000,000	$544,600,000	$1,179,600,000
SSP1-2.6 Near Term	$954,220,000	$819,800,000	$1,774,020,000
SSP2-4.5 Mid Term	$1,179,000,000	$1,015,000,000	$2,194,000,000
SSP5-8.5 Far Term	$2,297,000,000	$1,978,000,000	$4,275,000,000

Table 2: Normalized dollar costs of flooding events in presented climate scenarios.

Based on the simulation results, the intangible damages comprise roughly 46% of the total flooding damage across all of the future climate scenarios. Furthermore, the direct damage totals over time increase 262% from the historic baseline costs to the far term fossil fuel dependent scenario of SSP5-8.5.

Scenario	100yr Event Cost (Direct)	100yr Event Cost (Intangible)	Total Cost
Historic Baseline	$121,000,000	$117,270,000	$238,270,000
SSP1-2.6 Near Term	$178,000,000	$165,350,000	$343,350,000
SSP2-4.5 Mid Term	$219,300,000	$214,230,000	$433,530,000
SSP5-8.5 Far Term	$408,300,000	$404,100,000	$812,400,000

Table 3: Normalized expected cost of a 100-year flooding event

The 100-year flooding event cost represents the expected costs of a single 100-year event (see Table 3). The intangible damages represent nearly 50% of the total costs based on simulation results. Across each scenario tested, the ratio of direct to intangible damages remains largely the same. Note that the expected costs of a 100-year event increase significantly over the three time periods, suggesting what is currently considered a 100-year event will become more frequent in the future.

5.5 Concluding Remarks

This study synthesizes recent research on intangible and indirect impacts from flooding events and integrates those results into an actionable methodology to produce a more comprehensive assessment of the monetary impacts associated with such events. As there is a considerable range of outcomes in a flooding event, creating a scenario-based simulation places into context the relative contribution of intangible and indirect damages. Generally speaking, it appears that direct damages only reveal about one-half of the total costs, which highlights a significant gap in current risk assessment.

The results reveal a significant cost burden that is simply too large to continue to be overlooked in performing benefit-cost analysis of risk mitigation strategies. Intangible and indirect damages such as network, public service disruptions, mental and physical health impacts, employment and academic outcomes, along with damage to environmental services or recreation areas unveils an entirely new set of costs that must be factored into a BCA if it is to continue to be the standard for investment decision-making as it relates to climate change (Masson-Delmonte, Zhai, et al. 2021). This is likely to be the case, as alternative methods to BCA often require significant expertise, time, and data (Helgeson and Li 2022). As research directed at intangible and indirect cost estimation for extreme weather events continues to evolve, our methodology will be able to evolve with it, as a richer database will become available to support the simulation technique.

Chapter 6

Conclusion

As a theme throughout this dissertation, loss and damage data functions as a crucial resource in educating benefit cost decisions towards climate change adaptation. There are regional variances in the impacts realized by natural hazards and in order to effectively implement tools to mitigate these hazard impacts, future cost projection at improved spatial resolutions will allow for effective strategies to be considered through benefit cost analysis. By providing the business case for adaptation decision making, the impacts can be placed in context of dollar values to help to realize the demand to develop proactive cost mitigation strategies. Loss and damage data relies on long periods of time of consistent data reporting to develop usable datasets and this accounting must continue in order to be able to narrow the spatial resolution for future analysis. Through development of the probability cost distributions for natural hazards in different regions we have displayed the potential for loss and damage data to be used for future analysis.

In Chapter 2, we outlined the current state of loss and damage databases, highlighting the accounting practices and tools available for data gathering depending on the type of analysis. This chapter also focused on the many biases which appear based on different inclusion thresholds and measurement focuses. Furthermore, the different types of losses were defined, showing the range of cost impacts and which impacts are included or excluded across the different available loss and damage databases. The synthesis of this knowledge is essential for further research to establish definitions and understanding of the possibilities and limitations of loss and damage databases and provide direction for improvement in loss and damage accounting practices.

Chapter 3 aimed to establish a baseline simulation of the historical loss records. Development of this model paves the way for future parameter changes to forecast possible future risk scenarios. Due to the nature of loss and damage data, aggregation required grouping for a sufficient sample size and normalization of the damage data to be able to compare between time and regions. The goal was to obtain a representative sample for data fitting to a probabilistic distribution, which resulted in data to be grouped at a state level to retain a large enough sample size. The average percent mean difference of the 201 combinations of region and hazard tests was about 5%, and the best results were found when the sample sizes were above 1,000 events. The success in establishing this base model allowed for progressing to future risk projection in subsequent updates to the model.

The methodology for future risk projection was established in Chapter 4. The probability distribution of losses developed in Chapter 3 were modified to represent future climate change scenarios. The following simulations developed the risk outlook for the case study application to illustrate the potential of the base model. The simulation results found agreement with other future flooding expectations under climate change trends, finding the return period of what are considered today's 100-year event will decrease.

Chapter 5 was the culmination of the previous chapters. The establishment of the expected costs from direct damages only explained a part of the picture. As outlined in Chapter 2, there is a plethora of other impacts that are not quantified in traditional loss and damage databases. This chapter synthesized the current research attempting to quantify intangible and indirect damages in relation to direct costs to develop a multiplying factor to derive a general cost from the probability distribution of losses. Developing a rough cost estimate using a fuzzy statistics-based approach gives an idea of the magnitude of costs not represented in most discussions regarding climate change impacts, highlighting the mental health, business interruption, recreational, and many other losses which occur when an event interrupts daily life. This research highlights the importance of this consideration in climate change adaptation decision making, especially in terms of benefit-cost analysis to more accurately understand the full range of impacts society faces in the future of climate change.

The work presented in this dissertation has also identified several needs for future research in loss and damage data. Chapter 2 showed how crucial it is to continue to record this data in a consistent manner in order to be able to compare past costs with future ones to avoid any systemic biases in the databases. Setting a consistent definition and set of variables is also important to be able to compare between other databases and to help establish a standard for global loss and damage accounting. The subsequent chapters displayed the potential applications to improve benefit-cost decision making through establishment of a methodology to project future costs using future climate change scenarios to estimate an expected cost for the price of inaction in the face of climate change.

Improved and sustained loss and damage accounting will only help the validity of this methodology by supplying more data to develop and compare the probability distribution of loss and damage created in Chapter 3 and 4, while also providing the potential to narrow the resolution of analysis from a state level to a regional or county analysis. Validation of this methodology can be accomplished with the stated additional future data to function as the comparison baseline to the model projections. Furthermore, additional applications of the developed model on other future climate change pathways and different time horizons will create a more robust portfolio of case studies from which to perform validation.

Future analysis would also benefit from sensitivity testing of the model parameters. For example, testing the weight of the population density or social vulnerability index in the normalization equation on future loss and damage estimates will help to understand the potential of proposed adaptation strategies.

As outlined in Chapter 5, it is important to continue to understand the relationship between direct costs and other compounding impacts of natural disasters, notably indirect and intangible damages, in order to better understand the full extent of realized costs of an event. Climate change adaptation is necessary at all levels, local to global, and through improved understanding of the costs and impacts communities will face in the future, more impactful adaptation decisions can be made and the research outlined in this dissertation serves as a contribution towards that effort.

References

Abkowitz, M., J. Camp, L. Gillespie-Marthaler, and M. Allen. 2019. "Development and Implementation of Sustainable Transportation Resilience Indicators." *Maritime Transportation Research and Education Center.*

Almazroui, Mansour, M. Nazrul Islam, Fahad Saeed, Muhammad Ismail, Muhmmad Azhar Ehsan, Ismaila Diallo, Enda O'Brien, et al. 2021. "Projected Changes in Temperature and Precipitation Over the United States, Central America, and the Caribbean in CMIP6 GCMs." *Earth Systems and Environment* 1-24. doi: https://doi.org/10.1007/s41748-021-00199-5.

Andrei, S., G. Rabbni, and H.I. Khan. 2015. *Non-economic loss and damage caused by climatic stressors in selected coastal districts of Bangladesh.* Bangladesh Centre for Advanced Studies (BCAS).

Apel, H., G.T. Aronica, H. Kreibich, and A.H. Thieken. 2009. "Flood risk analyses -- how detailed do we need to be?" *Natural Hazards* 79-98. doi: https://doi.org/10.1007/s11069-008-9277-8.

Bates, Paul D., Niall Quinn, Christopher Sampson, Andrew Smith, Oliver Wing, Jeison Sosa, James Savage, et al. 2021. "Combined Modeling of US Fluvial, Pluvial, and Coastal Flood Hazard Under Current and Future Climates." *Water Resources Research.*

Bess, R., and Z. Ambargis. 2011. *Input-output models for impact analysis: suggestions for practitioners using RIMS II multipliers.* Morgantown, WV: Southern Regional Science Association.

Bhat, M. Sultan, Akhtar Alam, Bashir Ahmad, Bahadur S. Kotlia, Hakim Farooq, Ajay K. Taloor, and Shabir Ahmad. 2019. "Flood frequency analysis of river Jhelum in Kashmir basin." *Quaternary International* 288-294, doi: https://doi.org/10.1016/j.quaint.2018.09.039.

Bishop, Richard C., and Thomas A. Heberlein. 2019. *"The contingent valuation method." Economic valuation of natural resources.* Routledge.

Blackwell, Calvin. 2015. "Power Law or Lognormal? Distribution of Normalized Hurricane Damages in the United States, 1900–2005." *Natural Hazards Review.*

Botzen, JW, and J Van Den Bergh. 2009. "Managing Natural Disaster Risks in a Changing Climate." *Environmental Hazards* 209-225.

Botzen, JW, and J Van Den Bergh. 2009. "Managing Natural Disaster Risks in a Changing Climate." *Environmental Hazards* 209-225. doi: 10.3763/ehaz.2009.0023.

Botzen, W.J. Wouter, Oliver Deschenes, and Mark Sanders. 2019. "The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies." *Review of Environmental Economics and Policy* 167–188, doi: 10.1093/reep/rez004.

Botzen, WJ Wouter, and JC van den Bergh. 2012. "Risk attitudes to low-probability climate change risks: WTP for flood insurance." *Journal of Economic Behavior & Organization* 151-166. doi: https://doi.org/10.1016/j.jebo.2012.01.005.

Botzen, WJ Wouter, Oliver Deschenes, and Mark Sanders. 2020. "The economic impacts of natural disasters: A review of models and empirical studies." *Review of Environmental Economics and Policy* doi: https://doi.org/10.1093/reep/rez004.

Bouwer, L., E. Papyrakis, J.K. Poussin, C. Pfurtscheller, and A. Thieken. 2013. "The costing of measures for natural hazard mitigation in Europe." *Natural Hazards Review.*

CDC/ATSDR. 2021. "Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program." 08 27. Accessed 02 15, 2022. https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html.

Cheong, Lisa, Christoph Kinkeldey, Ingrid Burfurd, Susanne Bleisch, and Matt Duckham. 2009. "Evaluating the impact of visualization of risk upon emergency route-planning." *International Journal of Geographical Information Science* 1-29.

Choi, Donghyun, David Oliver Kasdan, and D. K. Yoon. 2019. "Analyzing Disaster Loss Trends: A Comparison of Normalization Methodologies in South Korea." *Risk Analysis* 859-870. doi: https://doi.org/10.1111/risa.13208.

CRED. 2018. *Emergency Events Database (EM-DAT).* https//www.emdat.be.

Cutter, Susan, Bryan Boruff, and W.L. Shirly. 2003. "Social Vulnerability to Environmental Hazards." *Social Science Quarterly* 242-261. doi: https://doi.org/10.1111/1540-6237.8402002.

Davenport, Frances V., Marshall Burke, and Noah Diffenbaugh. 2021. "Contribution of historical precipitation change to US flood damages." *Proceedings of the National Academy of Sciences.*

Doktycz, Charles, and Mark Abkowitz. 2019. "Loss and damage estimation for extreme weather events: State of the practice." *Sustainability* https://doi.org/10.3390/su11154243.

Doktycz, Charles, Mark Abkowitz, and Hiba Baroud. 2021. "Extreme Weather Loss and Damage Estimation Using a Hybrid Simulation Technique." *International Journal of Disaster Risk Science*.

ECLAC. 2003. *Handbook for Estimating the Socio-Economic and Environmental Effects of Disasters.* Santiago: LC/MEX/G.5. LC/L.1874; UN-ECLAC:.

Entorf, H., and A. Jensen. 2020. "Willingness-to-pay for hazard safety–A case study on the valuation of flood risk reduction in Germany." *Safety Science* doi: https://doi.org/10.1016/j.ssci.2020.104657.

Federal Emergency Management Agency. 2019. *Multi Hazards Models.* https://www.fema.gov/multi-hazard-models.

Fernandez, C. J., N. Stoeckl, and R. Welters. 2019. "The cost of doing nothing in the face of climate change: a case study, using the life satisfaction approach to value the tangible and intangible costs of flooding in the Philippines." *Climate and Development* 825-838. doi: https://doi.org/10.1080/17565529.2019.1579697.

Fernandez, Cheryl Joy. 2016. "Fernandez, Cheryl Joy. Methods for determining how much to spend on flood prevention: an empirical case study in the Philippines." (Doctoral dissertation), James Cook University.

Fernandez, Cheryl Joy, Natalie Stoeckl, and Riccardo Welters. 2019. "The cost of doing nothing in the face of climate change: a case study, using the life satisfaction approach to value the tangible and intangible costs of flooding in the Philippines." *Climate and Development* 828-838. DOI: https://doi.org/10.1080/17565529.2019.1579697.

Findlater, Kieran, Sophie Webber, Milind Kandlikar, and Simon Donner. 2021. "Climate Services Promise Better Decisions but Mainly Focus on Better Data." *Nature Climate Change* 731-737.

Flanagan, Barry E., Edward W. Gregory, Elaine J. Hallisey, Janet L. Heitgerd, and Brian Lewis. 2011. "A Social Vulnerability Index for Disaster Management." *Journal of Homeland Security and Emergency Management* Vol. 8: Iss. 1, Article 3. doi: 10.2202/1547-7355.1792.

Florec, Veronique, Morteza Chalak, and Atakelty Hailu. 2017. "Integrating intangible values in economic analyses of flood mitigation: a case study of the Brown Hill and Keswick creeks catchment in Adelaide." *The Australian Journal of Emergency Management.*

French, Joshua, Piotr Kokoszka, Stilian Stoev, and Lauren Hall. 2018. "Quantifying the risk of heat waves using extreme value theory and spatio-temporal functional data." *Computational Statistics and Data Analysis* 176-193. https://doi.org/10.1016/j.csda.2018.07.004.

Gall, M., C. Emrich, and S. Cutter. 2015. *Who Needs Loss Data?* Geneva: UNISDR.

Gall, M., K. Borden, and S. Cutter. 2009. "When do losses count? Six fallacies of natural hazards loss data." *Amareican Meteorological Society* 799-810.

Guilbert, Justin, Alan K. Betts, Donna M. Rizzo, Brian Beckage, and Arne Bomblies. 2015. "Characterization of increased persistence and intensity of precipitation in the northeastern United States." *Geophysical Research Letters* 1888-1893.

H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds. 2022. *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* IPCC, Cambridge, UK and New York, NY, USA: Cambridge University Press, 3-33.

Helgeson, J., and J. Li. 2022. "New Ways to Get to High Ground." *Issues in Science and Technology.*

Hochrainer-Stigler, S. 2014. *User Interface of the CatSim Model and Practical Guidelines.* Laxenburg, Austria: IIASA.

Hudson, Paul, W.J. Wouter Botzen, Jennifer Poussin, and Jeroen C.J.H. Aerts. 2017. "Impacts of Flooding and Flood Preparedness on Subjective Well-Being: A Monetisation of the Tangible and Intangible Impacts." *Journal of Happiness Studies* 665–682. DOI: https://doi.org/10.1007/s10902-017-9916-4.

ICSU. 2008. *A Science Plan for Integrated Research on Disaster Risk: Addressing the Challenge of NAtural and Human-Induced Environmental Hazards.* Paris: International Council for Science.

Integrated Research on Disaster Risk. 2014. *Peril Classification and Hazard Glossary (IRDR DATA Publication No. 1).* Beijing: Integrated Research on Disaster Risk.

International Council for Science. 2008. *A Science Plan for Integrated Research on Disaster Risk: Addressing the Challenge of Natural and Human-Induced Environmental Hazards.* Paris: International Council for Science.

IPCC. 2018. *Summary for Policymakers, Global warming of 1.5°C - IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways .* IPCC.

IRDR. 2014. *Integrated Research on Disaster Risk; Peril Classification and Hazard Glossary.* Beijing: IRDR DATA Publication.

Johnston, Robert J., Kevin J. Boyle, Maria L. Loureiro, Ståle Navrud, and John Rolfe. 2021. "Guidance to Enhance the Validity and Credibility of Environmental Beneft Transfers." *Environmental and Resource Economics* 575–624. doi: 10.1007/s10640-021-00574-w.

Jongman, Brenden. 2018. "Effective Adaptation to Rising Flood Risk." *Nature Communications* 1-3. DOI: 10.1038/s41467-018-04396-1.

Kahn, Matthew E. 2005. "The death toll from natural disasters: the role of income, geography, and institutions." *Review of Economics and Statistics* 271-284. doi: https://doi.org/10.1162/0034653053970339.

Karl, Thomas R., and Walter James Koss. 1984. *Regional and National Monthly, Seasonal, and Annual Temperatures Weighted by Area, 1895-1983.* Asheville: Historical Climatology Series 4-3, National Climatic Data Center.

Katz, Richard W. 2020. *"Statistical Issues in Detection of Trends in Losses from Extreme Weather and Climate Events." Evaluating Climate Change Impacts.* Chapman and Hall/CRC.

Kreibich, H., J.C. Van Den Bergh, L.M. Bouwer, P. Bubeck, P. Ciavola, C. Green, S. Hallgatte, et al. 2014. "Costing Natural Hazards." *Nature Climate Change* 303-306.

Kunruether, Howard. 2008. "Reducing Losses from Catastrophic Risks Through Long Term Insurance and Mitigation." *Social Research: An international Quarterly* 905-930. https://www.muse.jhu.edu/article/527618.

Lantz, Van, Ryan Trenholm, Jeff Wilson, and William Richards. 2012. "Assessing market and non-market costs of freshwater flooding due to climate change in the community of Fredericton, Eastern Canada." *Climatic Change* 347–372. DOI 10.1007/s10584-011-0063-3.

Lantz, Van, Ryan Trenholm, Jeff Wilson, and William Richards. 2012. "Assessing market and non-market costs of freshwater flooding due to climate change in the community of Fredericton, Eastern Canada." *Climatic Change* DOI 10.1007/s10584-011-0063-3.

Leh, Fauziah Che, Farah Zulaikha Mokhtar, Norimah Rameli, and Kamarul Ismail. 2018. "Measuring Recreational Value Using Travel Cost Method (TCM): A Number of Issues and Limitations." *International Journal of Academic Research in Business and Social Sciences* 1381-1396. doi: http://dx.doi.org/10.6007/IJARBSS/v8-i10/5306.

Luechinger, Simon, and Paul Raschky. 2009. "Valuing flood disasters using the life satisfaction approach." *Journal of Public Economics* 620-633.

Maghsood, Fatemeh Fadia, Hamidreza Moradi, Ali Reza Massah Bavani, Mostafa Panahi, Ronny Berndtsson, and Hossein Hashemi. 2019. "Climate Change Impact on Flood Frequency and Source Area in Northern Iran under CMIP5 Scenarios." *water* 11, 273; doi:10.3390/w11020273.

Mariel, Petr, David Hoyos, Jürgen Meyerhoff, Mikolaj Czajkowski, Thijs Dekker, Klaus Glenk, Jette Bredahl Jacobson, et al. 2021. *Environmental Valuation with Discrete Choice Experiments Guidance on Design, Implementation and Data Analysis.* Springer Nature.

Markantonis, V., and V. Meyer. 2011. *Valuating the intangible effects of natural hazards: a review and evaluation of the cost-assessment methods.* European Society for Ecological Economics Conference.

Masson-Delmonte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al. 2021. "IPCC, 2021: Summary for Policymakers." *In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group 1 to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*

Masson-Delmonte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al. 2021. "IPCC, 2021: Summary for Policymakers." *In: Climate Change 2021: The Physical cience Basis. Contribution of Working Group 1 to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*

Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, et al. 2021. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* IPCC, Cambridge University Press.

McNeil, Alexander J. 1997. "Estimating the Tails of Loss Severity Distributions Using Extreme Value Theory." *ASTIN Bulletin: The Journal of the IAA* 117-137.

McNeil, Alexander J. 1997. "Estimating the tails of loss severity distributions using extreme value theory." *ASTIN Bulletin: The Journal of the IAA* 27.1: 117-137.

Mechler, R. 2019. *CATSIM.* www.iiasa.ac.at/web/home/research/researchPrograms/RISK/CATSIM. en.html.

Mechler, Reinhard, and Laurens M. Bouwer. 2015. "Understanding trends and projections of disaster losses and climate change: is vulnerability the missing link?" *Climatic Change* 23-35. DOI 10.1007/s10584-014-1141-0.

Meyer, V., N. Becker, V. Markantonis, R. Schwarze, J. C. Van Den Bergh, L. M. Bouwer, P. Bubeck, et al. 2013. "Review article: Assessing the costs of natural hazards – state of the art and knowledge gaps." *Natural Hazards and Earth System Sciences* 1351-1373. doi:10.5194/nhess-13-1351-2013.

Monti, A., and C. Tagliapietra. 2009. "Tracking insurance industry exposures to CAT risks and quantifying insured and economic losses in the aftermath of disaster events: a comparative survey." *2nd Conference on the financial management of large-scale catastrophes.* Bangkok.

Morrissey, J., and A. Oliver-Smith. 2013. *Perspectives on Non-Economic Loss and Damage: Understanding values at risk from climate change.* Bonn: Loss and Damage Series, United Nations University Institute for Environment and Human Security.

Mosavi, Amir, Pinar Ozturk, and Kwok-wing Chau. 2018. "Flood Prediction Using Machine Learning Models: Literature Review." *water* 10, 1536; doi:10.3390/w10111536.

MunichRE. 2018. *MunichRE.* https://natcatservice.munichre.com/,.

Nga, Pham Hong, Kaoru Takara, and Cam Van Nguyen. 2018. "Integrated approach to analyze the total flood risk for agriculture: The significance of intangible damages – A case study in Central Vietnam." *International Journal of Disaster Risk Reduction* 832-872. DOI: https://doi.org/10.1016/j.ijdrr.2018.08.001.

Nissan, Hannah, Lisa Goddard, Erin Coughlan de Perez, John Furlow, Walter Baethgen, Madeleine C. Thomson, and Simon J. Mason. 2019. "On the use and misuse of climate change projections in international development." *Wiley Interdisciplinary Reviews: Climate Change* e579. doi: https://doi.org/10.1002/wcc.579.

NOAA. 2022. *NOAA Storm Events Database.* https://www.ncdc.noaa.gov/stormevents/.

Nordhaus, William. 2010. "The Economics of Hurricanes and Implications of Global Warming." *Climate Change Economics* 1-20.

Nyaupane, Narayan, Balbhadra Thakur, Ajay Kalra, and Sajjad Ahmad. 2018. "Evaluating Future Flood Scenarios Using CMIP5 Climate Projections." *water* doi:10.3390/w10121866.

Pannell, David J., and Fiona L. Gibson. 2016. "Environmental cost of using poor decision metrics to prioritize environmental projects." *Conservation Biology* 382-391. DOI: 10.1111/cobi.12628.

Pellicani, Roberta, Alessandro Parisi , Gabriele Iemmolo, and Ciro Apollonio. 2018. "Economic Risk Evaluation in Urban Flooding and Instability-Prone Areas: The Case Study of San Giovanni Rotondo (Southern Italy)." *Geosciences.*

Porter, Jeremy R., Evelyn Shu, Michael Amodeo, Ho Hsieh, Ziyan Chu, and Neil Freeman. 2021. "Community Flood Impacts and Infrastructure: Examining National Flood Impacts Using a High Precision Assessment Tool in the United States." *Water* 13, 3125. https://doi.org/10.3390/ w13213125.

Prein, Andreas F., Changhai Liu, Kyoko Ikeda, Stanley B. Trier, Roy M. Rasmussen, Greg J. Holland, and Martyn P. Clark. 2017. "Increased rainfall volume from future convective storms in the US." *Nature Climate Change* 880–884. doi: https://doi.org/10.1038/s41558-017-0007-7.

Raff, D. A., T. Pruitt, and L. D. Brekke. 2009. "A framework for assessing flood frequency based on climate projection information." *Hydrology and Earth System Sciences* 2119-2136.

Rogers, Abbie A., Fiona L. Dempster, Jacob I. Hawkins, Robert J. Johnston, Peter C. Boxall, John Rolfe, Marit E. Kragt, Michael P. Burton, and David J. Pannell. 2019. "Valuing non-market economic impacts from natural hazards." *Natural Hazards* 1131–1161. doi: https://doi.org/10.1007/s11069-019-03761-7.

Shen, Guoqiang, Long Zhou, Yao Wu, and Zhiming Cai. 2018. "A Global Expected Risk Analysis of Fatalities, Injuries, and Damages by Natural Disasters." *Sustainability* doi:10.3390/su10072573.

Slater, Louise J., and Gabriele Villarini. 2016. "Recent trends in US flood risk." *Geophysical Research Letters* 428-436.

Surminski, S., A. Lopez, J. Birkmann, and T. Welle. 2012. *Current knowledge on relevant methodologies and data requirements as well as lessons learned and gaps identified at different levels.* Bonn: Assessing the Risk of Loss and Damage Associated with the Adverse Effects of Climate Change.

SwissRE. 2018. *SwissRE.* https://www.swissre.com/reinsurance/property-and-casualty/solutions/property-specialty-solutions/catnet.html.

Tarling, Hannah Andrea. 2017. "Comparative analysis of social vulnerability indices: CDC's SVI and SoVI®." [Masters Thesis, Lund University]. http://lup.lub.lu.se/student-papers/record/8928519.

UNFCCC. 2012. *A Literature Review on the Topics in the Context of Thematic Area 2 of the Work Programme on Loss and Damage: A Range of Approaches to Address Loss and Damage Associated with the Adverse Effects of Climate Change.* United Nations Framework Convention on Climate Change.

UNISDR. 2009. *Global Assessment Report on Disaster Risk Reduction: Risk and Poverty in a Changing Climate.* Geneva: United Nations International Strategy for Disaster Reduction.

Virtanen, Pauli, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, and Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Pearu Peterson. 2020. "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python." *Nature Methods* 261-272.

Ward, P.J., H. de Moel, and J. C. J. H. Aerts. 2011. "How are flood risk estimates affected by the choice of return-periods?" *Natural Hazards and Earth System Sciences* 3181-3195.

Wei, Cankun, Meichen Fu, Li Wang, Hanbing Yang, Feng Tang, and Yuqing Xiong. 2022. "The Research Development of Hedonic Price Model-Based Real Estate Appraisal in the Era of Big Data." *Land* 334. doi: https://doi.org/10.3390/land11030334.

Weinkle, Jessica, Chris Landsea, Douglas Collins, Rade Musulin, Ryan P. Crompton, Philip J. Klotzbach, and Roger Pielke Jr. 2018. "Normalized Hurricane Damage in the Continental United States 1900-2017." *Nature Sustainability* 808-813.

Wing, Oliver E.J., William Lehman, Paul D. Bates, Christopher C. Sampson, Niall Quinn, Andrew M. Smith, Jeffrey C. Neal, Jeremy R. Porter, and Carolyn Kousky. 2022. "Inequitable patterns of US flood risk in the Anthropocene." *Nature Climate Change* 156-162.

Wobus, Cameron, Ethan Gutmann, Russell Jones, Matthew Rissing, Naoki Mizukami, Mark Lorie, Hardee Mahoney, Andrew W. Wood, David Mills, and Jeremy Martinich. 2017. "Climate change impacts on flood risk and asset damages within mapped 100-year floodplains of the contiguous United States." *Nat. Hazards Earth Syst. Sci.* 2199–2211.

Wood, Erik, Monica Sanders, and Tim Frazier. 2021. "The practical use of social vulnerability indicators in disaster management." *International Journal of Disaster Risk Reduction* (63): 102464. doi: https://doi.org/10.1016/j.ijdrr.2021.102464.

World Bank. 2013. *Post-Disaster Needs Assessment Guidelines.* Washington DC: World Bank Group.

Zimbidis, Alexandros, Nickolaos Frangos, and Athanasios Pantelous. 2007. "Modeling Earthquake Risk Via Extreme Value Theory and Pricing the Respective Catastrophe Bonds." *ASTIN Bulletin: The Journal of the IAA* (37.1): 163-183.

Zscheischler, Jakob, Seth Westra, Bart JJM van den Hurk, Sonia I. Seneviratne, Philip J. Ward, Andy Pitman, Amir AghaKouchak, et al. 2018. "Future Climate Risk from Compound Events." *Nature Climate Change* 469-477.