Actionable science for sea level rise and coastal flooding: from physical hazards to social resilience

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Abstract

Rising sea levels increase the frequency of flooding of all elevations, from minor to extreme, along coastlines across the world. Impacts of flooding, including disasters, have increased the saliency of sea level rise (SLR) and the risks it presents to governments, communities, households and businesses. However, the effect of SLR on coastal flooding is complex and filled with uncertainty, including the effects of natural variability versus human-caused changes on the flood magnitude/frequency relationship. Together, these uncertainties pose methodological obstacles for integrating SLR into flood hazard projections and risk management. They also pose a quandary for decision-makers—how much to invest in building resilience and how soon to act?

A major challenge is how to distill this complexity into information geared towards public and private stakeholders to help inform adaptation decision-making. Because policy windows are limited, budgets are tight, and decisions may have long-term consequences, it is especially important that this information accounts for uncertainty to help avoid damage and maladaptation. Another challenge is that, as decision-makers face difficult choices in planning for programs and infrastructure to increase resilience in the face of these changing hazards, they are doing so with little information about how such policies and other social dynamics affect adaptation among households.

This dissertation includes actionable science to support decision-making for adaptation to coastal impacts, despite uncertainty in projections of SLR and flood frequency. As a result, this body of work applies geoscience, engineering, risk analysis, economics, and psychology to a public policy context. This dissertation is divided into two main parts. The first focuses on flood hazard and provides projections and metrics of change in coastal flooding, accounting for deeply uncertain SLR (Chapters 2 and 3). To help inform city, community, and federal level planners, the second part focuses on social resilience and provides a baseline of how households have adapted to coastal flooding and projections of how they intend to adapt amid other social stressors (Chapter 4). Chapter 5 discusses future work for modeling these

coupled physical and human systems to help inform decision-making regarding large-scale protective infrastructure and public policy.

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To my family.

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Chapter 1

Introduction

1.1 Disasters and disruptions

Flooding can be fatal and costly. After heat, flooding causes the most fatalities among natural hazards (NOAA, 2017*b*). It currently results in ∼\$27 billion in annual average losses in the form of property damage and business interruption along the U.S. East and Gulf coasts (Houser et al., 2015). Even moderate flooding can distress households, businesses and governments by interrupting transportation and communication channels as well as municipal services.

Extreme flooding can irreversibly change cities and communities. When the levees broke in New Orleans from Hurricane Katrina in 2005, approximately 80% of the city was inundated (NOAA, 2017*a*). Across the Gulf coast, this resulted in 1,200 reported deaths and an estimated \$75 billion in damage, displacing nearly a million residents (NOAA, 2017*a*).

In 2012, inundation from Hurricane Sandy crippled communities and cities across the Eastern seaboard. It damaged an upwards of 650,000 homes, predominantly from flooding (USACE, 2015*c*). Eight and a half million residents lost power and many remained without it for weeks or even months (USACE, 2015*c*). Direct damages and ensuing economic losses totaled an estimated \$65 billion and roughly 20,000 residents were relocated to shelters (USACE, 2015*c*).

Flood-related disasters have long-term economic and psychological consequences. Experiencing personal injury or injuries of a loved one, displacement, and damage to assets can cause post-traumatic stress disorder and depression (Neria and Shultz, 2012). Hsiang and Jina (2014) found that environmental disasters persistently suppress economic growth. The cumulative damage from disasters has also put national programs at risk; for example, by 2015, the National Flood Insurance Program's debt amounted to \$23 billion after losses from Hurricanes Katrina and Sandy (Worth, 2016).

Rising sea levels enhance the likelihood of disasters and disruptions by increasing the frequency of flooding at all levels, from minor to extreme, along coastlines across the world. Indeed, flood frequency has already increased; for example, 93% of measured sites in the United States experienced a significantly larger number of floods per year in 2010-2015 than in 1950-1959 (Sweet and Park, 2014). Because coastal counties are home to 39% of the national population and 28% of property values, changing flood hazards pose great risk (Houser et al., 2015). The amplification of flooding from sea level rise (SLR) is expected to change urban landscapes and increase average annual losses by \$2 to \$3.5 billion by 2030 (Houser et al., 2015).

1.2 Actionable science for coastal climate impacts

Disasters and disturbances from flooding have increased the salience of SLR and awareness of its related risks among governments, communities, households and businesses (Woodruff and Stults, 2016). However, the effect of SLR on coastal hazards is complex and filled with uncertainty that is often challenging for decision-makers (Lempert et al., 2012). Although it is certain that SLR is occurring and will continue (Church et al., 2013), its future rate remains deeply uncertain and ambiguous (Kasperson et al., 2008; Heal and Millner, 2014; Ellsberg, 1961). Because extreme flooding is by definition rare, there is also uncertainty in the effect of natural variability on flood frequency (Coles et al., 2001). These uncertainties pose methodological obstacles for integrating SLR into flood hazard projections and risk management.

A major challenge is how to distill this complexity into information geared towards public and private sectors to help inform adaptation decision-making. Because policy windows are limited, budgets are tight, and decisions may have long-term consequences, it is especially important that this information accounts for uncertainty to help avoid damage and maladaptation (Kingdon and Thurber, 1984; Lempert, 2003). The U.S. Global Research Program, and others, describe this type of science as *actionable*—"data, analyses, projections, or tools that can support decisions regarding the management of the risks and impacts of climate change" (Beier et al., 2015, p. 5).

Another challenge is that, as decision-makers face difficult decisions in planning for programs and infrastructure to increase resilience in the face of these changing hazards, they are doing so with little information about how such efforts and other social dynamics affect adaptation among households. Individuals may be motivated not only by information regarding emerging flood hazards, but also by psychological and social factors (Adger et al., 2009). For governments to develop effective adaptation policies, it is important to understand what factors tend to motivate household adaptation.

1.3 Sea level rise and flood hazard

Several global and local factors contribute to the amount of SLR projected for a given location. Global mean sea-level rises when the volume (e.g., due to thermal expansion) and mass (e.g., due to land-ice melt from glaciers, ice caps, or ice sheets) of water in the ocean increases (Church et al., 2013).

A number of local and regional factors contribute to relative sea level (RSL; the difference in height between the sea surface and the solid Earth; Kopp, Hay, Little and Mitrovica, 2015). These include static-equilibrium effects (changes in the height of Earth's gravitational field and crust associated with the large shifts of mass from ice to the ocean), which distribute water from ice-sheets to coastal areas. RSL is also affected by changes in ocean circulation and winds, and associated changes in the distribution of heat and salt within the ocean (Kopp et al., 2014). Finally, vertical land motion (VLM) affects RSL by lowering the land with respect to the sea. VLM occurs through glacial isostatic adjustment, which is the ongoing adjustment of the solid Earth to the loss of the North American ice sheet at the end of the last ice age. VLM is also caused by natural sediment compaction and groundwater withdrawal. Within recent years, scientists have synthesized multiple lines of evidence to produce time-varying probability distributions of RSL that account for its various sources and their uncertainty (Kopp et al., 2014; Grinsted et al., 2015; Jackson and Jevrejeva, 2016; Kopp et al., 2017; Slangen et al., 2017).

Flood height is driven by RSL (also known as local sea level) and storm tide, which in turn is composed of tide elevation and storm surge. SLR raises the platform for storm tide and dominates the effect of anthropogenic climate change on flooding (Tebaldi et al., 2012; Reed et al., 2015). While climate change may affect storm surge by changing sea surface temperatures and wind patterns, there is low confidence in climate model projections of future tropical cyclone behavior, particularly in individual basins (e.g., Knutson et al., 2010, 2015).

Extreme value distributions can be fit to tide-gauge observations of water levels to estimate flood frequency curves. Flood frequency curves show flood height (storm tide height above a particular datum, such as Mean Higher High Water) corresponding to a particular flood frequency (expressed as the expected annual occurrence). For example, they can be used to identify the height of the 100-year flood (equivalent to flood that has a 1% annual chance of occurrence), the standard flood protection level administered by the National

Flood Insurance Program. Because both storm tide and sea level contribute to water level observations, historical SLR rate can be used to detrend the observations to create flood frequency curves under the historic climate. These historic flood frequency curves can then be combined with projected SLR to develop flood frequency curves for future decades.

Alternatively, storm tide distributions can be simulated with hydrodynamic models, which can simulate potential changes in storm surges associated with tropical cyclones. The resulting storm tide distributions may then be fit by an extreme value distribution to estimate the storm tide frequency distribution (including or excluding SLR, e.g., Lin et al., 2012 and Muis et al., 2016, respectively). Here, we apply extreme value theory because (1) SLR dominates the effect of climate change on flooding patterns, (2) of the computational intensity of high-resolution hydrodynamic modeling, and (3) it is data-based, capturing both tropical and non-tropical storm surges. Hence, we assume there are no significant changes in tides or storm climatology that would affect storm tide distributions.

1.4 Flood risk management

To understand flood risk we need to account not only for flood hazard but also for how societies interact with flood hazard, as well as public policies that are intended to mitigate it. Risk is commonly expressed in terms of the probability of an event's occurrence and the consequence of its impact, often measured in monetary value (e.g., Kaplan and Garrick, 1981; Aerts et al., 2013). Alternatively, in the Intergovernmental Panel on Climate Change's Special Report on Extremes, Lavell et al. (2012) provide a more holistic conceptual framework useful for communicating the dynamic and integrated components of flood risk management in a changing climate. In this framework, risk is a function of an area's climate events, as well as its exposure and vulnerability:

$$Flood\ Risk = f(Hazard,\ Exposure,\ Vulnerability) \tag{1.1}$$

In the coastal context, weather and climate events relate to the physical hazard of flooding. Exposure is defined as the number of people and assets (and potentially the total value of assets). Vulnerability relates to the susceptibility of these people and assets to harm—corresponding to social and structural vulnerability, respectively.

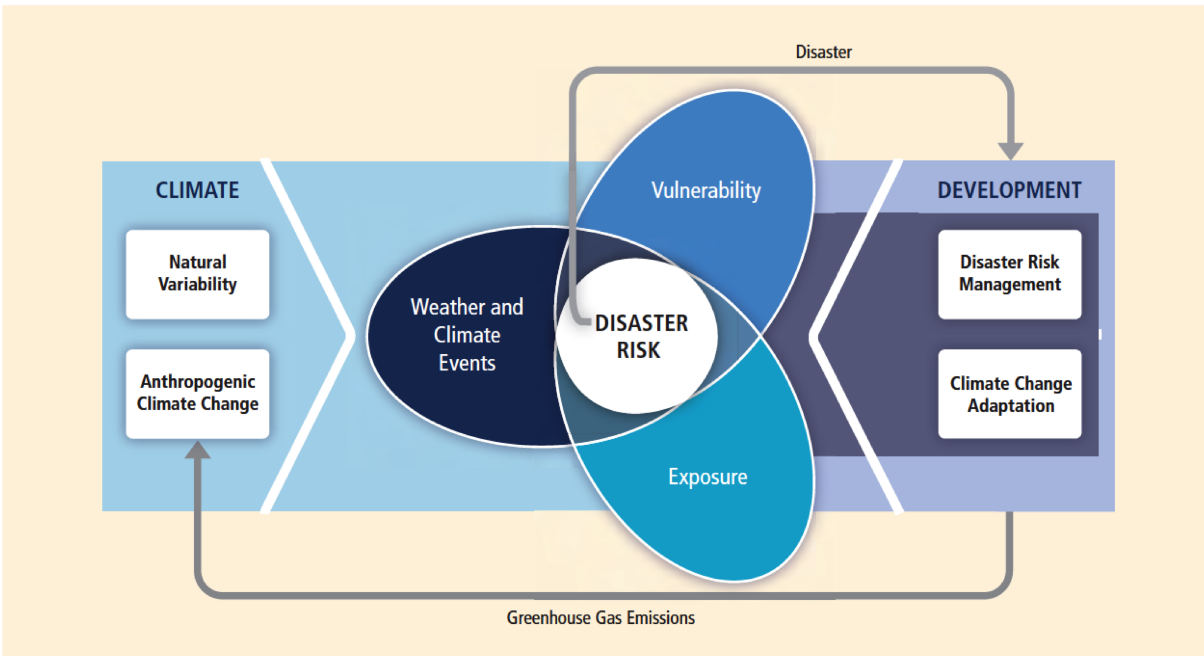

Figure 1.1: IPCC risk framework from Lavell et al. (2012)

While SLR amplifies flooding from tides and storms for coastal communities, it is people's reactions to this physical hazard that will ultimately determine the impact on coastal communities. As illustrated in Figure 1.1, these components (flood hazard, exposure, and vulnerability) interact with the broader social and governmental landscape through disaster risk management and climate change adaptation, whereby climate change adaptation can be defined as "the process of adjustment to actual or expected climate and its effects" (Mach et al., 2014). Public or private entities may implement adaptation measures to block or accommodate flooding, reducing exposure and/or vulnerability of households and assets. For example, in anticipation or reaction to flood risk, governments may implement large-scale infrastructure (such as sea walls, dunes, and barriers) or policy incentives to permanently relocate or elevate homes in at-risk areas. They may also equip emergency centers with backup electricity to help reduce social vulnerability. Adaptation measures may overlap with risk management strategies if risk calculations account for the emerging climate and its downstream effects on the build environment and social systems.

Motivated households may invest in private adaptation measures, such as buying flood insurance, elevating their homes, or permanently relocating. These household-level adaptations interact with perceptions and manifestations of flood hazard, altering the exposure and/or vulnerability of people and assets. In other words, flood hazard is actually a combination of physical hazard and human intervention. For simiplicity, I will use the term "flood hazard" from here on.

It is important to clarify that while adaptation is a process of taking actions, resilience is a state of being. Resilience is the capacity of systems to cope (or thrive) under a hazardous event or ongoing stressors (Mach et al., 2014). Resilience is not only a function of flood hazard, exposure, and vulnerability, but also the interaction of these entities with site-specific non-climatic conditions.

1.5 Dissertation

1.5.1 Research questions

The objective of this dissertation is to help produce actionable science to support decision-making for adaptation to coastal impacts, despite uncertainty in projections of SLR and human behavior. My hope is that in doing so, it can help improve the resilience of cities. Through an interdisciplinary approach, this body of work applies geoscience, risk analysis, economics, and psychology to address three central questions:

1. Given uncertainty in the magnitude of sea level rise and natural variability in flood frequency, how does sea level rise affect future flood levels and how can a decision-maker use this information to satisfy their planning criteria?

2. What is the magnitude and pattern by which the frequency of current flood levels increases along coastlines?

3. How are households adapting to emerging flood patterns among other social stressors and public policies?

For the first and second questions, I calculate emerging flood levels that account for the uncertainty in both local SLR and storm tide. I address the first question in Chapter 2 by providing a framework for decision-makers to identify how much they would need to raise infrastructure to satisfy their planning criteria. These criteria include flood risk tolerance level, confidence in SLR projections, and time period of interest. The second question is evaluated in Chapter 3 by assessing how flood frequency distributions change with local SLR over time. The final question leads to the examination in Chapter 4 of household adaptation driven by changing flood hazards, public flood protection, flood insurance premiums, peer imitation, risk perception and tolerance, and other psychological factors. Finally, Chapter 5 provides an overview of future work to couple these physical and human systems. Modeling a coupled system would allow for investigation of how public adaptation strategies affect holistic resilience outcomes under projected changes in coastal flooding and dynamic human behavior.

1.5.2 Outline and related work

Future flood levels are changing dynamically over time, and their estimation is dependent on the amount of SLR accounted for. Drawing upon geoscience and risk analysis, Chapters 2 and 3 apply extreme value statistics and comprehensive local SLR probability distributions to calculate dynamic flood hazard across the United States. Traditionally, future flood levels have been estimated without the full distribution of plausible SLR and independent of decision-making criteria, such as time horizon. Chapter 2 calculates new flood return levels and provides a framework of SLR allowances: the height adjustment from historic flood levels that maintains under uncertainty the annual expected probability of flooding. This framework employs a range of user-defined flood risk management preferences. Given non-stationary and uncertain sea-level rise, these metrics provide estimates of flood protection heights and offsets for different planning horizons in coastal areas. An illustration of the calculation of various allowance types for a set of long-duration tide gauges along U.S. coastlines is included. This work was originally published as Buchanan et al. (2016) and presented at the American Geophysical Union annual fall meeting, MIT/University of Washington Graduate Climate Conference, and Decision Making Under Deep Uncertainty Conference in 2015.

Chapter 3 outlines the magnitude and pattern by which current flood levels increase. The amplification of flood frequencies by sea level rise (SLR) is expected to become one of the most economically damaging impacts of climate change for many coastal locations. Understanding the magnitude and pattern by which the frequency of current flood levels increases is important for developing more resilient coastal settlements, particularly since flood risk management (e.g., infrastructure, insurance, communications) is often tied to estimates of flood return periods. The Intergovernmental Panel on Climate Change's Fifth Assessment Report defined the multiplication factor by which the frequency of flooding of a given height increases (referred to here as an amplification factor, AF; Church et al., 2013). However, this characterization neither rigorously considered uncertainty in SLR nor distinguished between the amplification of different flooding levels (such as the 10% versus 0.2% annual chance floods); therefore, it may be seriously misleading. Because both historical flood frequency and projected SLR are uncertain, joint probability distributions of the two are combined to calculate AFs and their uncertainties over time. Under probabilistic RSL projections, while maintaining storm frequency at a fixed level, the expected annual number of local 100-year floods for tide-gauge locations are estimated to increase by a median of 40-fold (ranging from 1- to 1314-fold) along the contiguous U.S. coastline by 2050. While some places can expect disproportionate amplification of higher frequency events and thus primarily a greater number of historically precedented floods, others face amplification of lower frequency events and thus a particularly fast-growing risk of historically unprecedented flooding. For example, with 50 cm of SLR, the 10%, 1%, and 0.2% annual chance floods are expected respectively to recur 108, 335, and 814 times as often in Seattle, but 148, 16, and 4 times as often in Charleston, SC. This work was originally published as Buchanan, Oppenheimer and Kopp (2017) and presented at the American Geophysical Union annual fall meeting in 2016, and at the National Adaptation Forum and Regional Sea-level Changes / Coastal Impacts Conference in 2017.

Chapter 4 applies principles from economics and psychology to assess how people respond to various existing adaptation options and policies, using a household survey with discrete choice experiments in New York City neighborhoods affected by Hurricane Sandy. We investigated a comprehensive set of factors that may influence household adaptive behavior (like buying flood insurance, elevating one's home, or permanently relocating), controlling for socioeconomic and cognitive variables, as well as past experience. Our study builds adds to our understanding of these factors as well as some which have been overlooked, including personal values and single-action bias. It also assesses the role of external stressors that have rarely been tested, including the influence of property value and the adaptive behavior of peers. We find that valuation of community members and avoiding flooding-related costs have moderate effects on intended adaptive behavior. Our findings suggest that single-action bias plays a substantial role in coastal adaptation, whereby homeowners who have already taken a measure that is of moderate cost are 80% less likely to relocate and 66% less likely to insure. Homeowners are also ∼10, ∼5, and ∼3 times more likely to relocate if their property values fall substantially, peers relocate, and nuisance flooding becomes a frequent occurrence, respectively. Finally, renters who are more concerned with issues like crime, gentrification, and economic security than flooding are 50 times as likely to relocate. The salience of this locale and the range of characteristics represented in the population studied may provide lessons for coastal communities elsewhere seeking to motivate adaptive behavior. This chapter was co-authored by Michael Oppenheimer and Adam Parris, and was presented at the Resilience 2017 conference as well as to several New York City and New York State agencies.

Chapter 5 discusses future work for modeling these coupled physical and human systems to investigate how public policies interact with emerging flood patterns and household behavior. This chapter was co-authored by Michael Oppenheimer, Guy Nordenson, and Robert Kopp. Chapter 6 concludes, summarizing findings and posing policy recommendations and future work.

Chapter 2

Allowances for evolving coastal flood risk under uncertain local sea-level rise

The work in this chapter is adapted from Buchanan, M. K., Kopp, R. E., Oppenheimer, M. and Tebaldi, C. (2016), 'Allowances for evolving coastal flood risk under uncertain local sea-level rise', *Climatic Change* pp. 116. DOI:10.1007/s1058401616647.

2.1 Introduction

The distribution of coastal flood events is influenced by astronomical tides, the distribution of storm events, and local mean sea level (Lin et al., 2012; Hunter, 2012). Under current practice, acceptable levels of coastal flood risk are often based upon specific flood return periods, such as the 100-year flood (1% annual expected probability of occurrence, AEP) for the U.S. National Flood Insurance Program (Galloway et al., 2006). While federally designated flood zones and often capital projects are based on flood probabilities that assume stationary sea level, sea-level rise (SLR) renders estimates of flood hazard exceedingly optimistic.

For example, Talke et al. (2014) show that stationary predictions of flood return levels fail to capture the rapidly increasing flood recurrence due to sea-level rise in Manhattan. The New York City Special Initiative for Rebuilding and Resiliency (NYC, 2013) assessed how frequently elevated flood return levels would top the NYC subway system protection level with sea-level rise (using a 90th percentile SLR estimate of 31 inches by 2050). They found that this threshold—not surpassed until Hurricane Sandy in 2012—would be susceptible to a 25% AEP flood. Similarly, since ∼50 cm of sea-level rise would increase the AEP of the current 0.1% annual chance flood to 1% at London's Thames Barrier (Conner, 2013), the barrier—originally built in the 1970s to protect against the 1% AEP flood—now faces a premature upgrade (Environment Agency, 2012). Houser et al. (2015) estimate that, in the absence of adaptation, changes in flood frequency driven by SLR would cost about 20–30 billion dollars per year in the U.S. by the end of the century (assuming current economic valuation). Aware of these growing risks, U.S. cities and states are calling for metrics to help identify how much to adapt to this threat of uncertain magnitude (e.g., Bierbaum et al., 2014; Li et al., 2014).

While some authors have developed estimates of the changes in flood levels under the influence of SLR, adjustments to stationary AEPs made assuming fixed sea-level increases (e.g., Tebaldi et al., 2012) are inadequate when applied to sea level that is rising at an uncertain rate over time. Some studies have assumed fixed sea-level increases derived from deterministic scenarios of SLR that are not conditional upon emissions scenarios (Parris et al., 2012; USGCRP, 2014; Kunkel et al., 2015). For example, in the Hurricane Sandy Tool Kit—a prominent sea-level rise adaptation tool for some Sandy-affected areas—New Jersey users are directed to follow the 'high' federally vetted SLR scenario (2.0 m of global mean SLR by 2100) if their asset has low risk tolerance and the 'low' SLR scenario (0.2 m rise by 2100) for high risk tolerance (USGCRP, 2014). Such deterministic scenarios may be insufficient to capture the uncertainty of local SLR and its implications for local flood risk management. Additionally, the majority of studies have employed global mean sea levels, while others have accounted for some but not all local factors to provide local flood estimates.

To help account for the uncertainty in SLR projections, Hunter (2012) developed the concept of SLR allowances—the vertical buffer necessary to maintain an AEP—estimated by global mean SLR (and later local SLR; Hunter et al. 2013) plus a margin for uncertainty provided by various parametric probability distribution functions (PDFs) by a fixed date (2100). This method provides an amount of freeboard for decision-makers to maintain their flood risk tolerance, using the Gumbel extreme value distribution to fit annual flood exceedances. Hunter's (2012; 2013) SLR allowances are for single time points (hereafter, 'instantaneous allowances').

Although it is certain that SLR is occurring and will continue (Church et al., 2013), its rate remains deeply uncertain and ambiguous (Kasperson et al., 2008; Heal and Millner, 2014; Ellsberg, 1961), in the sense that no single probability distribution function (PDF) is widely accepted. This deep uncertainty poses a methodological challenge for integrating SLR projections into flood hazard characterization, and ultimately risk management. Moreover, individuals, businesses, and municipalities do not currently have systematic guidance regarding how much freeboard to account for SLR that reflects their managerial preferences.

To help accommodate communities' need for resilience metrics, we combine four useful methods to expand upon Hunter's SLR allowances. First, we employ the temporally dynamic, uncertain SLR projections of Kopp et al. (2014), which provide reasonable, complete PDFs of local sea-level changes across a range of sites. Second, we address deep uncertainty by using a limited degree of confidence metric (Froyn, 2005; McInerney et al., 2012). Third, we provide an additional allowance type inspired by the work of Rootzén and Katz (2013) for hydrologic design-life levels to accommodate different assets' lifetimes in non-stationary risk management. We define the average annual design-life level (AADLL) as the flood level corresponding to a time-integrated AEP under uncertainty over the lifetime of an asset, and we define the associated design-life (DL) allowance as the adjustments from historical levels that maintain historical probability of flooding over a given design life. Fourth, because building resilience into infrastructure also requires user- and asset-specific risk preferences (Adger et al., 2009)—such as flood risk tolerance, SLR risk perception, and valuation of asset protection—we incorporate these features into the design-life and instantaneous allowances.

In Section 4.3, we lay out the formal framework underlying AADLLs and DL allowances and describe the calculation of historical flood return periods and of sea-level rise projections, and the treatment of uncertainty. Section 4.4 illustrates calculation of AADLLs and DL allowances with a representative set of 71 long-recording tide gauges along U.S. coastlines. Section 2.4 discusses how these metrics might be applied in the context of sea-level rise resilience decision-making. Conclusions are presented in Section 2.5.

2.2 Methods

2.2.1 Framework

While Rootzén and Katz (2013) discussed design-life levels in the context of hydrological flood hazard analysis, the concept is equally applicable to other extremes, including extreme coastal flood heights. As defined by Rootzén and Katz (2013), the $t_1 - t_2$ $p\%$ design-life level is the level of an extreme that has a $p\%$ probability of occurrence over the time period t_1 to t_2. We extend this concept by defining the Average Annual Design-Life Level (AADLL), which is more directly comparable to the AEPs and associated flood heights used in flood risk management. The $t_1 - t_2$ p% AADLL has an average $p\%$ per year probability of occurrence over the interval $t_1 - t_2$. For example, in the context of coastal flood risk, the 2020–2050 1% AADLL is the flood height that has an average 1% per year probability of occurrence over the 30 years between 2020 and 2050. Under stationary sea levels, the 1% AADLL is equal to the height of the historic 1% AEP flood.

Expressed more formally, let $N(z)$ be the number of expected floods per year exceeding height z under stationary sea level, which can be estimated from the application of extreme value theory to tide-gauge statistics. By definition, $1/N(z)$ is the return period of a flood of height z. For an arbitrary sea-level change Δ, assuming no change in the distribution of flood heights relative to mean sea level, the number of expected floods of height z is $N(z-\Delta)$. Letting the uncertain sea-level rise at time t be denoted by Δ_t, we define the instantaneous number of expected floods per year of height z as

$$N_e(z,t) = \mathbb{E}[N(z-\Delta_t)]. \tag{2.1}$$

The average annual expected number of floods over period t_1 to t_2 is then given by

$$\tilde{N}_e(z,t_1,t_2) = \frac{1}{t_2-t_1}\int_{t_1}^{t_2} N_e(z,t)dt. \tag{2.2}$$

Accordingly, the $t_1 - t_2$ $p\%$ AADLL is the value of z such that $\tilde{N}_e(z,t_1,t_2) = p\%$.

The instantaneous allowance of Hunter (2012) is defined as the level $A(N_0,t)$ such that

$$N_e(z+A(N_0,t),t) = N(z), \tag{2.3}$$

where $N_0 = N(z)$ is the number of expected floods in the absence of SLR. For example, $A(0.01,t)$ is the additional height above the current 1% probability flood level needed to maintain an expected 1% probability flood level at time t. (Note that, for known sea-level rise Δ, $A = \Delta$.) Similarly, the DL allowance $\tilde{A}(N_0,t_1,t_2)$ is defined by

$$\tilde{N}_e(z+\tilde{A}(N_0,t_1,t_2),t_1,t_2) = N(z). \tag{2.4}$$

For the Gumbel distribution of $N(z)$ assumed by Hunter, A is independent of N_0, but this is not generally the case.

Calculating an AADLL thus requires both an estimate of the historic extreme value distribution $N(z)$ and a probability distribution of sea level over time, $P(\Delta,t)$.

2.2.2 Flood return levels under stationary sea level

We use extreme value analysis (EVA) to assess flood return levels. EVA has commonly been used in engineering statistics since the 1950s to estimate the occurrence of extreme events, which by definition are too rare to be estimated by observations alone (Coles et al., 2001). Using the GPD and peak-over-threshold (POT) approach to estimate local extreme water level exceedances, we estimate $N(z)$ for each tide gauge, following the methodology of Tebaldi et al. (2012). We analyze National Oceanic and Atmospheric Administration (NOAA) hourly tide-gauge records for sites with a minimum 30-year record (which can be found at http://tidesandcurrents.noaa.gov/; see Appendix B Table for a list of record lengths). We consider 30 years to be the minimum required length for the trend not to exhibit significant multi-decadal cyclicity (Tebaldi et al., 2012). A declustering routine isolates events that are spaced from each other by at least one day.

Each record is linearly detrended to remove the effect of long-term sea-level rise and capture a distribution of exceedances influenced by sub-decadal sea-level variability, astronomical tides and storm surge alone. We employed a linear trend rather than removing annual mean sea level because we wished to retain interannual sea-level variability in the extreme distribution.

The GPD takes the functional form

$$P(z-\mu \leq y | z > \mu) = \begin{cases} 1-(1+\frac{\xi y}{\sigma})^{\frac{-1}{\xi}} & \text{for } \xi \neq 0 \\ 1-\exp(-\frac{y}{\sigma}) & \text{for } \xi = 0 \end{cases} \tag{2.5}$$

where μ is the water-level threshold above which exceedances are estimated, and σ and ξ are respectively the scale and shape parameters. The shape parameter ξ controls the overall shape of the distribution's tail, with $\xi = 0$ giving rise to a Gumbel distribution, $\xi > 0$ giving rise to a heavier tailed distribution, and $\xi < 0$ to a bounded distribution. Assuming the probability of $z > \mu$ is Poisson-distributed with mean λ, the expected number of annual exceedances of height z is given (for $z > \mu$) by

$$N(z) = \begin{cases} \lambda(1 + \frac{\xi(z-\mu)}{\sigma})^{\frac{-1}{\xi}} & \text{for } \xi \neq 0 \\ \lambda \exp(-\frac{z-\mu}{\sigma}) & \text{for } \xi = 0 \end{cases} \tag{2.6}$$

Compared to the GEV block maxima approach, the GPD POT approach has the advantage of extracting more information by using all of the data over the threshold (rather than just the yearly maxima), which improves the accuracy of the parameter estimates of the resulting distribution (Coles et al., 2001). POT thresholds are set to accurately approximate the Poisson distribution of actual extreme outliers—high enough to justify the limiting distributional assumption of a GPD for the threshold exceedances, yet low enough to extract enough sample points to provide a reliable estimate of the parameters of the GPD. The diagnostics for the choice of the thresholds rely on the assessment of the behavior of the exceedances according to well-established metrics for the fitting of the parameters of GPDs (Coles et al., 2001; Tebaldi et al., 2012). A threshold equal to the 99th percentile of the distribution of daily maximum water levels (computed from hourly records) gave reasonable results for all of the tide gauges tested by Tebaldi et al. (2012).

To account for parameter uncertainty, we estimate the maximum-likelihood shape and scale parameters and their covariance. Assuming the parameter uncertainty is normally distributed, we sample 1000 parameter pairs with Latin hypercube sampling. We then calculate the expected number of exceedances under parameter uncertainty, which we use for our main calculations. Sites' maximum-likelihood shape parameter values and historic 1% AEP and 10% AEP flood levels are shown in Figure 2.1. (See Appendix B Table B.1 for parameter distributions for all sites). To allow our analysis to extend approximately to events with greater frequency, we assume that flood waters exceed Mean Higher High Water (MHHW) 182.6 times per year (i.e., every other day), and that events with frequency between λ and 182.6/year are Gumbel distributed. We do not consider flood events more frequent than 182.6/year.

2.2.3 Sea-level rise projections

To estimate the time-varying probability of sea-level rise, we employ the local sea-level rise PDFs of Kopp et al. (2014) for Representative Concentration Pathway (RCP) 8.5, which is frequently taken as a 'business-as-usual' emissions pathway. Kopp et al. (2014) constructed global sea level PDFs by combining global climate model (GCM) projections of thermal expansion, glacier surface mass balance model projections, semi-empirical projections of land water storage changes, and ice sheet projections based upon a combination of the expert assessment of the Intergovernmental Panel on Climate Change's Fifth Assessment Report and the expert elicitation study of Bamber and Aspinall (2013). These global projections were localized by accounting for static-equilibrium fingerprint effects of land ice mass changes, GCM projections of atmosphere/ocean dynamics, and tide-gauge based estimates of non-climatic contributors to sea-level change, such as glacial-isostatic adjustment. From the probability distributions associated with each of these contributing factors, Kopp et al. (2014) generated 10,000 samples of relative sea-level change at each of 1091 tide gauges. Kopp et al's (2014) median projected SLR from 2000 to 2100 under RCP 8.5 is illustrated in Figure 2.1b. We combined 10,000 Monte Carlo samples from the Kopp et al distributions of relative sea-level change with the extreme water level probability distributions to compute changes in flood return periods in response to SLR.

2.2.4 Ambiguity in sea-level rise projections

The Kopp et al. (2014) projections provide one plausible, self-consistent set of local sea-level rise PDFs, but they are not the only plausible PDFs. To accommodate imperfect confidence in these PDFs, we adapt the Limited Degree of Confidence (LDC) criterion used in decision-making under uncertainty (Froyn, 2005; McInerney et al., 2012). Taking $P(\Delta, t)$ from Kopp

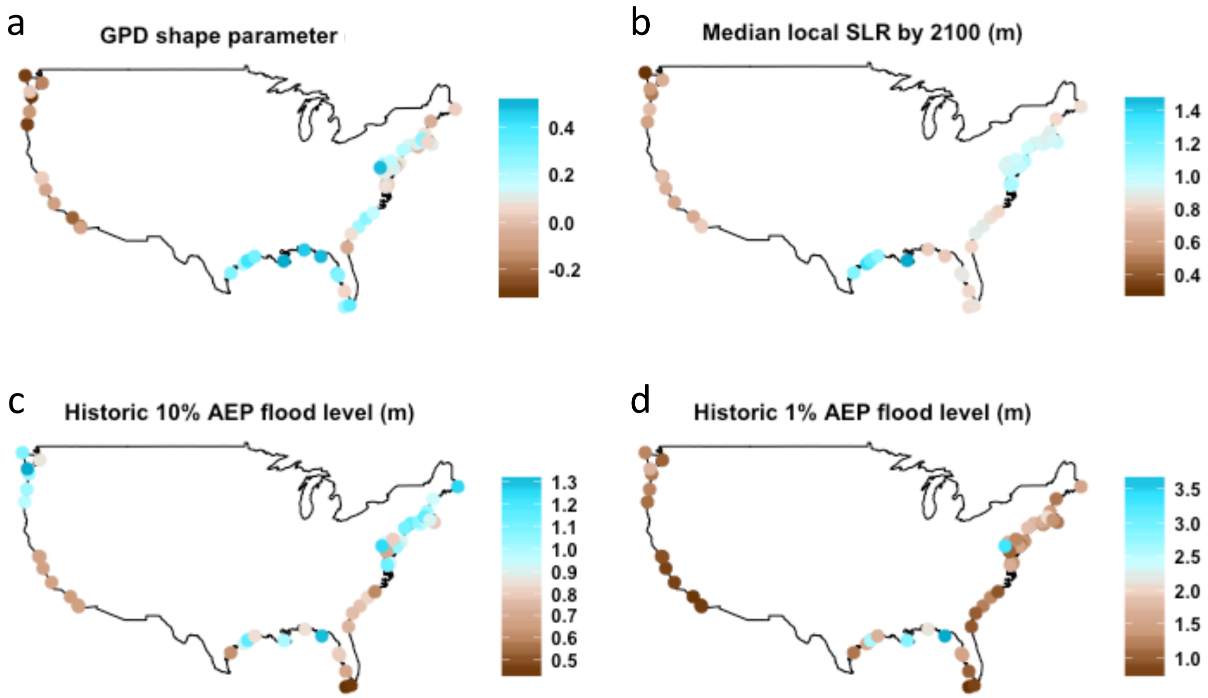

Figure 2.1: (a) Maximum-likelihood estimate of the GPD shape parameter, (b) median projected sea-level rise between 2000 and 2100 under RCP 8.5, (c) expected historic 10% AEP flood level (meters above MHHW), and (d) expected historic 1% AEP flood level for representative tide gauges (meters above MHHW).

et al. (2014), we define the LDC effective probability as

$$\tilde{P}(\Delta, t) = \beta P(\Delta, t) + (1 - \beta)\delta(\Delta - \Delta_{t,\mathrm{WC}}) \tag{2.7}$$

Here, $\beta \in [0, 1]$ is a measure of confidence in $P(\Delta, t)$, $\Delta_{t,\mathrm{WC}}$ is a worst-case projection at time t, and δ is the Dirac delta function. For $\Delta_{t,\mathrm{WC}}$, we adopt the 99.9th percentile projections of Kopp et al. (2014), which are comparable to other estimates of physically-plausible worst-case projections available in the literature (e.g., Miller et al., 2013; Pfeffer et al., 2008; Sriver et al., 2012). It follows that

$$N_{e,LDC}(z,t,\beta) = \beta N_e(\Delta,t) + (1-\beta)N(z-\Delta_{t,\mathrm{WC}}) \tag{2.8}$$

$$\tilde{N}_{e,LDC}(z,t_1,t_2,\beta) = \frac{1}{t_2-t_1}\int_{t_1}^{t_2} N_{e,LDC}(z,t) \tag{2.9}$$

Because of the extra weight given to the worst-case outcome, SLR allowances will be higher for decision-makers with incomplete confidence in the expert PDF than with full confidence.

2.2.5 Combination of methods

The allowance framework permits decision-makers to choose among several options based on their project and preferences. Figure 2.2a illustrates a simple flow chart of the combined framework's application. First, a decision-maker assesses her asset-specific flood protection and SLR preparedness preferences. Second, she selects the design life of her asset. Third, she selects an allowance type (DL or instantaneous). A DL allowance keeps annual risk below target in early years and above target in late years, while an instantaneous allowance for the end of the asset is more conservative, keeping annual risk below target throughout. Fourth, she selects a β value to reflect her level of confidence in the expert PDF. Finally, she may wish to add a margin of safety to help protect against a potential increase in the number of coastal storms, which is a source of deeper uncertainty (Christensen et al., 2013; Church et al., 2013). For example, a homeowner in Boston may wish to elevate her structure so as to maintain her current 1% AEP flood hazard over the lifetime of her mortgage, from 2020 to 2050 (Figure 2.2b). If she prefers to minimize her home's elevation to maintain her risk target on average over the period, keeping her risk below target in all years except 2050, she selects the DL allowance. Finally, if she is fully confident in the Kopp et al. (2014) local SLR PDF, her SLR allowance is 0.3 m.

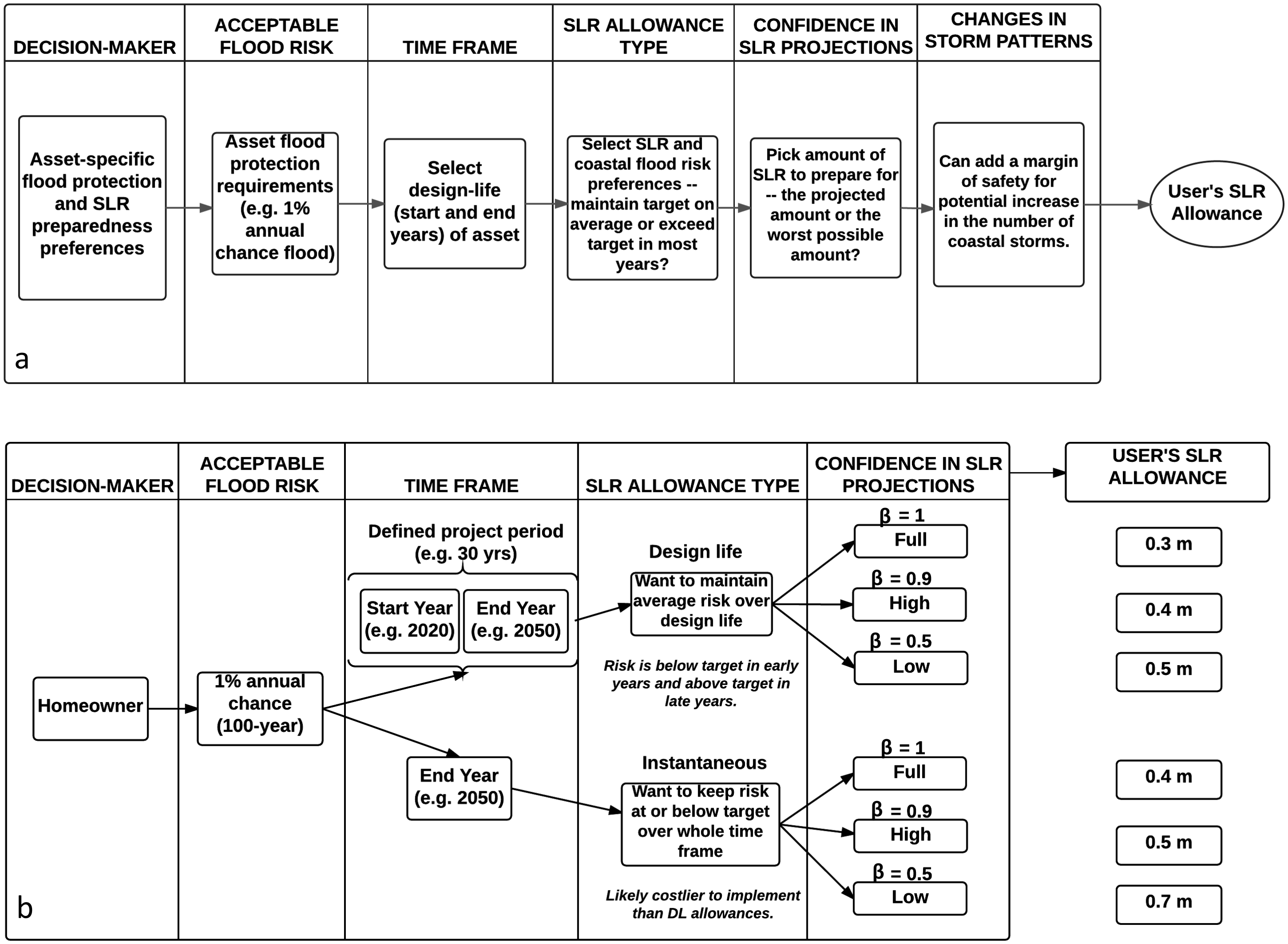

Figure 2.2: (a) A flow chart of the combined SLR allowance framework, and (b) a simple example of its application for a homeowner in Boston seeking to maintain 1% AEP flood hazard over a mortgage from 2020 to 2050. See Section 2.2.5.

2.3 Results

Across U.S. tide gauges, the instantaneous allowance A is strongly correlated with expected sea-level rise $\mathbb{E}[\Delta_t]$ (Figure 2.3a). This is to be expected; as demonstrated in Appendix B, the offset between the instantaneous allowance $A(t)$ and the expected sea-level rise $\mathbb{E}[\Delta_t]$ does not depend on the first moment of the distribution of Δ_t, although it does depend on higher-order moments and on the parameters of the extreme flood level distribution. (For example, for a zero-variance projection, the allowance is equal to the expected sea-level rise; increasing variance increases the allowance.) Accordingly, if the higher-order moments and extreme flood level distribution were identical across sites and only the expected sea-level rise differed, Figure 2.3a would show these points along a line with slope 1. Across all sites, the instantaneous allowance is larger than expected SLR on average by 4 cm in 2050 and 60 cm in 2100. This gap increases because the variance and skewness of the SLR projections increase over the course of the century.

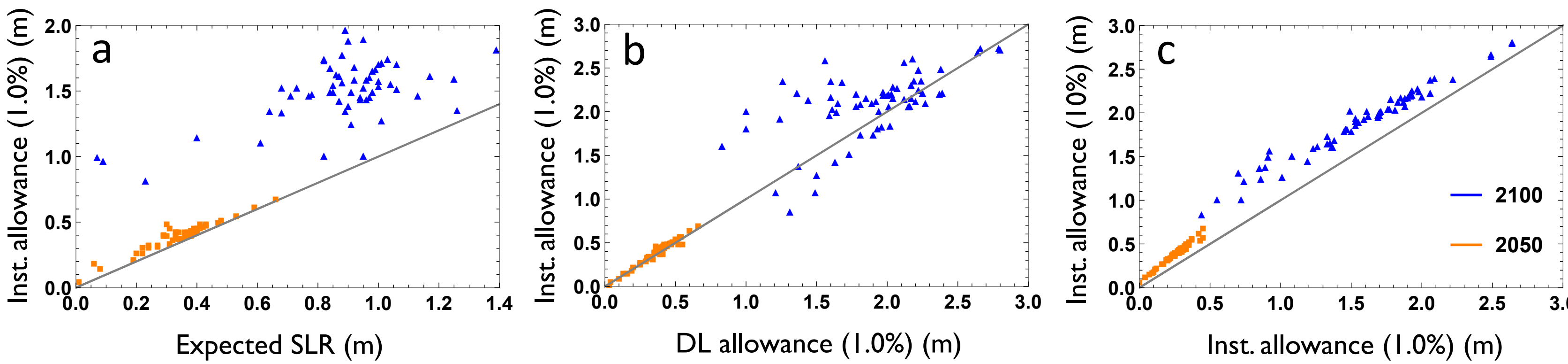

Figure 2.3: (a) 1% instantaneous allowance vs. expected SLR (2050, 2100), (b) 1% instantaneous allowance (2050, 2100) vs. 1% DL allowance (2020-2050, 2020-2100) (c) 10% instantaneous allowances vs. 1% instantaneous allowance (2050, 2100). 2050 values are indicated by orange squares and 2100 values by blue triangles. All plots include a line with slope 1 for comparison.

Figure 2.4 shows several flood return curves for Boston, Washington, D.C., and San Diego. First, it shows the historic flood curve (N), accounting for uncertainty in the GPD fit. Second, it shows flood curves adjusted for deterministic SLR estimates equal to the expected value of SLR ($N + E(SL_t)$) and the worst-case SLR ($N + SL_{99.9}(t)$) in 2050 and 2100. Third, it shows the expected flood curves under the full PDF of SLR for 2050 and 2100 ($N_e(t)$)). The instantaneous allowances for 2050 and 2100 are given by the horizontal offsets between the historic curve and the expected curves ($N_e(t)$)). Fourth, the figure shows average expectations under the full PDF of SLR integrated over 2020–2050 and 2020–2100 design lives ($N_e(t_1, t_2)$); these curves are the AADLLs. The DL allowances are given by the horizontal offsets between the historic curve and the AADLL curves.

Accounting for uncertainty in SLR shifts the flood curves farther to the right than deterministically adjusting for the expected SLR, and therefore yields a curve significantly closer to the deterministic worst-case SLR scenario. The shifts of $N(z)$ by expected and projected SLR are not parallel; the range of uncertainty in SLR over time and N-dependence of the GPD alters the width of the shifts. The kinks in the figure arise at the transition in the extreme-value distribution between the extremes represented by the GPD and the extremes represented by a Gumbel distribution from λ to 182.6 floods per year; a second kink arises at >182.6 floods per year (see Section 2.2.2). The appearance of these kinks in the $N_e(t)$ and $N_e(t_1, t_2)$ curves reflects the influence of high-end SLR projections that cause floods to transition between regimes.

Because the return levels of AEPs increase over time with SLR, the p% instantaneous allowance for year t_2 is always more conservative (higher) than the p% DL allowance over a period ending in year t_2 (Table 2.1, Figure 2.3b and Appendix B). Adjusting historical flood levels upward by the instantaneous allowance at t_2 is akin to employing the MiniMax Flood Design Level (Rootzén and Katz, 2013), which maintains a p% annual flood probability over every year in the project period (as opposed to averaged over the period).

Among the representative set of 71 U.S. coastal tide gauges, allowances are nearly independent of N in 2050, but significantly N-dependent by 2100. Table 2.1 provides the 1% instantaneous and DL allowances for every 21st century decade for various β values (1, 0.9, 0.5, and 0) under RCP 8.5 for representative sites. Among all sites in the contiguous U.S. and Hawai'i, the 1% instantaneous allowances for 2050 and 2100 have a mean and range of (0.37/ 0.03 to 0.66 m) and (1.89 / 0.83 to 2.80 m) with respect to the historic baseline, while the 1% DL allowances for 2020-2050 and 2020-2100 have a mean and range of (0.27/ 0.04 to 0.45 m) and (1.53 / 0.14 to 2.64 m). These values demonstrate the gap between current flood risk protection standards and future flood return levels. Some Alaskan sites (Juneau, Seldovia, Seward, Skagway, Unalaska, and Yakutat) have negative SLR allowances arising from the projected falls in relative sea levels, due to a combination of glacial-isostatic adjustment, gravitational and flexural responses to ongoing glacier melt, and tectonics (Kopp et al., 2014).

Figure 2.5 illustrates different instantaneous and DL allowances for an asset's risk tolerance (1%,10%, and 0.2% annual chance of flooding) and time period, local sea-level rise projection and confidence therein. For example, in Boston, there is little difference between the 10%, 1%, and 0.2% allowances before late century (Figure 2.5b-d). However, allowance amounts are sensitive to the time period of a project; a 30-year 1% risk tolerant asset will have an allowance twice as large if starting in 2050 rather than 2030 (Figure 2.5d). As noted, SLR allowances will be lower for decision-makers with full confidence in the expert SLR PDF than those with full confidence in worst-case SLR. Because of the approximately log-linear relationship between N and z, the worst-case possibility exerts a strong influence on allowances even for high degrees of confidence. For example, for an 80-year asset, the 1% DL allowance for 2020–2100 is 1.6 m with full confidence in the expert PDF ($\beta = 1.0$) and 2.5 m with no confidence in the expert PDF ($\beta = 0$) (Figure 2.5f). Due to the pull of the high end of the local SLR projection, β =0.92 yields a DL allowance that is halfway between the metrics of full confidence and a complete lack of confidence in projected SLR

Table 2.1: Vertical adjustments to infrastructure to maintain 1% annual chance flood risk with projected SLR for a specific year (instantaneous) or over a design life. 1% instantaneous and design-life allowances are in meters above the year 2000 baseline. DL allowances are integrated from 2020 to the specified year. β values of 1, 0.9, 0.5, and 0 correspond to full, high, 50%, and no confidence in the local SLR projection.

	β	2020	2030	2040	2050	2060	2070	2080	2090	2100
Boston										
Instantaneous	1	0.13	0.21	0.3	0.41	0.55	0.76	1.07	1.50	2.01
	0.9	0.16	0.25	0.36	0.53	0.79	1.15	1.58	2.05	2.56
	0.5	0.22	0.34	0.49	0.70	1.01	1.40	1.83	2.30	2.81
	0	0.28	0.41	0.58	0.81	1.13	1.52	1.95	2.42	2.93
Design-life	1		0.18	0.22	0.29	0.37	0.51	0.75	1.14	1.61
	0.9		0.21	0.27	0.37	0.56	0.87	1.27	1.71	2.21
	0.5		0.29	0.38	0.51	0.74	1.07	1.47	1.92	2.41
	0		0.36	0.46	0.60	0.84	1.17	1.57	2.01	2.5
Washington, D.C.										
Instantaneous	1	0.13	0.21	0.29	0.38	0.49	0.61	0.73	0.86	1.00
	0.9	0.14	0.23	0.32	0.43	0.58	0.74	0.93	1.17	1.47
	0.5	0.19	0.3	0.43	0.60	0.85	1.14	1.47	1.86	2.31
	0	0.25	0.39	0.56	0.79	1.13	1.50	1.92	2.38	2.91
Design-life	1		0.17	0.21	0.25	0.30	0.36	0.42	0.48	0.55
	0.9		0.19	0.23	0.28	0.34	0.42	0.50	0.61	0.76
	0.5		0.25	0.31	0.39	0.49	0.61	0.78	0.98	1.23
	0		0.32	0.40	0.50	0.64	0.82	1.04	1.29	1.60
Key West										
Instantaneous	1	0.11	0.18	0.26	0.38	0.61	0.94	1.36	1.83	2.38
	0.9	0.13	0.21	0.32	0.53	0.83	1.18	1.59	2.06	2.60
	0.5	0.17	0.27	0.42	0.67	0.98	1.33	1.74	2.22	2.76
	0	0.21	0.32	0.48	0.75	1.06	1.42	1.84	2.31	2.85
Design-life	1		0.15	0.20	0.28	0.48	0.81	1.21	1.68	2.22
	0.9		0.17	0.24	0.42	0.70	1.04	1.45	1.91	2.45
	0.5		0.23	0.32	0.52	0.80	1.14	1.53	1.99	2.53
	0		0.27	0.38	0.57	0.85	1.19	1.58	2.04	2.57
Grand Isle										
Instantaneous	1	0.24	0.37	0.51	0.66	0.82	0.99	1.18	1.37	1.56
	0.9	0.25	0.39	0.53	0.71	0.91	1.13	1.38	1.67	2.03
	0.5	0.29	0.45	0.63	0.89	1.18	1.52	1.91	2.35	2.87
	0	0.35	0.52	0.74	1.08	1.45	1.88	2.35	2.88	3.47
Design-life	1		0.31	0.38	0.45	0.53	0.62	0.71	0.81	0.92
	0.9		0.32	0.39	0.48	0.57	0.68	0.8	0.96	1.18
	0.5		0.37	0.46	0.57	0.71	0.88	1.09	1.34	1.67
	0		0.44	0.54	0.68	0.86	1.09	1.35	1.66	2.04

(i.e. no-confidence allowance, $\beta = 0$) and $\beta = 0.5$ yields a DL allowance of 2.4 m, quite close to the no-confidence allowance.

2.4 Discussion

It is important to note that the historic 1% AEP flood height (e.g., 100-year flood)—the predominant flood risk metric used by the National Flood Insurance Program—is essentially a convention which assumes near-perfect protection against flood events. As shown by the AADLL and instantaneous flood levels (Figure 2.4), that assumption no longer holds because the expected distribution of all flood return periods changes with SLR. Complementing other methods, the framework presented here is part of a larger effort to provide robust climate science to the decision-making level (e.g., Jonkman et al., 2009; Lempert et al., 2012). SLR allowances provide a means for stakeholders to account for the distribution of flood return levels and maintain a desired protection standard—such as 1% AEP—under non-stationarity.

The framework has a combination of traits to allow for some ease in transition from stationary to non-stationary flood risk management. First, its sea-level rise estimates include local factors. While global mean sea level (GMSL) change is mainly driven by land-ice melt and by thermal expansion of warming ocean water, ocean/atmosphere dynamics, static-equilibrium sea-level fingerprints, and other regional factors contribute significantly to local sea-level change (Kopp, Hay, Little and Mitrovica, 2015). Second, its sea-level rise estimates are based on complete probability distributions, as opposed to central estimates, scenarios with unspecified probabilities, or likely ranges. Complete distributions are needed in order to apply this approach. Third, its allowances reflect decision-makers' risk management preferences, such as desired protection level, limited degree of confidence in SLR projections, and preferences between protection and cost which relate to the choice of instantaneous vs. DL allowances. Accounting for different flood risk tolerance levels is critical, as households, businesses, and government entities often have divergent risk perceptions and behavior (Willis, 2007), although this generally seems to exert a minor influence on allowances before mid-century. Fourth, its allowances account for different planning periods throughout the 21st century, capturing the effects of SLR over time. Finally, similar to the majority of previous methods, the framework relies on the historic distribution of storms, as future projections are not yet well understood and only available for a few tide gauges (e.g., Lin et al., 2012).

A "project" can be any investment time period, such as a 30-year mortgage or 80-year power generation facility. Given a planner's acceptable flood risk (e.g., 1%, 10%, 0.2% AEP), she can identify the corresponding protection height during a planning horizon, such as a 30-year project from 2030-2060 or an 80-year project from 2020-2100 for various levels of confidence in SLR projections (Figure 2.5). Decision-makers can explore and adjust variables they have control over, such as potential implementation delays, *a priori*. Stochastic planning of this type is particularly important for large capital projects, especially those with lengthy lifetimes, to achieve practical maintenance expectations and avoid risk tolerance exceedances. For example, allowances can be used to explore the effect of potential delay of bridge construction or post-mortgage occupation of a house on protection height or risk taken. Similarly, the framework can inform rational thinking about trade-offs between flexibility (in terms of adding protection over time) and regrets (in terms of overprotection) in adaptation strategies. In this regard, AADLL and instantaneous flood levels can be integrated with flexible adaptation pathways (Haasnoot et al., 2013) and to help identify dates when acceptable flood risk is crossed (Kwadijk et al., 2010). Instantaneous flood levels can be used as an upfront high fixed cost adaptation strategy, which may be inflexible over time (Ranger et al., 2013). AADLLs can be used to inform terminal adaption strategies that at a certain date should either be upgraded (by adding more freeboard associated with a revisited design life) or in transition to another adaptation strategy (and abandoning the asset).

There is an implicit trade-off between instantaneous and DL allowance types in terms of flood protection and cost. Project end-year instantaneous allowances are below the target annual risk level (and therefore lead to excess protection) in all but the last design-life year, and by requiring a larger freeboard, may be costlier to implement than DL allowances. For example, to maintain 1% flood risk tolerance for an asset from 2020 to 2080, the DL and instantaneous allowances are 0.7 m and 0.4 m in Washington, D.C., respectively (Table 2.1). Raising infrastructure (or its flood defense) by the additional 0.3 m could cost upwards of $6,000 per horizontal foot (USD; Jonkman et al., 2009; USACE, 2015*c*). The increased protection cost may be preferred for projects where the lifetime of interest may extend well beyond the nominal design life or where uncertainty about the extent of SLR is very high. Conversely, DL allowances may be preferred for a well-defined design life (e.g., such as a 30-year mortgage) where minimal value is imputed to flooding after the end of the design life. As DL allowances provide a minimum freeboard to maintain desired protection on average over the project's design life, they may also be preferred as a low-regrets options when financial resources for resilience are scarce, which is a common barrier for adaptation (e.g., Moser and Ekstrom, 2010).

In some states in the U.S., political leaders have been reluctant to discuss the human-caused acceleration of SLR (e.g., Kopp, Horton, Kemp and Tebaldi, 2015). However, while a relatively modest lack of confidence in expert PDFs toward the worst-case possibility can dominate the calculation of allowances, even a modest degree of confidence allows the expert PDFs to dominate. To illustrate, we calculate a variant of the LDC allowances wherein limited confidence in the expert PDFs is expressed by belief not in the worst case scenario, but in zero sea-level rise. To distinguish these Panglossian Limited Degree of Confidence from the more traditional LDC metric, we use values of β', i.e.,

$$N_{e,PLDC}(z,t,\beta') = \beta' N_e(\Delta,t) + (1-\beta')N(z) \tag{2.10}$$

A party must be very optimistic and have quite low confidence in expert SLR PDFs to argue against preparing for SLR. For example, $\beta' = 0.5$ means a party believes there is a 50% chance that the expert PDF is correct and a 50% chance that there will be no SLR. Even if they think there is a 90% chance of no sea-level rise and a 10% chance the experts are correct ($\beta' = 0.1$), the appropriate allowance over 2020-2100 in Boston for example is still about half the allowance as if they had full confidence in the expert PDF ($\beta' = 1$), rationalizing adaptation planning.

Risk can be defined as the probability of an event's occurrence and the consequence of its impact (Lavell et al., 2012). From the perspective of a coastal decision-maker, SLR allowances capture the changing probability of an event's occurrence (and the number of annual exceedances). Although they do not directly provide information regarding the consequence of impact, by holding the decision-maker's risk tolerance constant, allowances provide an adaptation offset to counteract the adverse consequence of exceeding tolerable risk. The framework can be coupled with damage functions that account for the consequence of flooding. Accompanied by such, the allowances can provide a mechanism to translate comprehensive SLR PDFs into actionable science to meet local adaptation risk management decisions sensitive to extreme events.

We focus on flood height which is a primary metric decision-makers what to know (Jonkman et al., 2009; Neumann et al., 2010; Lempert et al., 2012; Woodward et al., 2013). Other hydraulic factors, such as surge duration, are important in assessing inundation and can be incorporated in future work. SLR allowances can also be considered holistically with other coincident hazards in our changing climate (such as riverine flooding or extreme precipitation), which are developing research areas (Wahl et al., 2015; Katsman et al., 2011). Moreover, learning to better accommodate with overtopping of defenses is critical in a non-stationary climate (Brown, 2010). Beyond methodology, accounting for SLR and its uncertainty in federal and municipal flood standards also requires institutional changes, which have proven to be an obstacle for effective risk management (e.g., Moser and Ekstrom, 2010).

Finally, our model is a 'bath tub' model in that it accounts for mean wave height, which is often but not always a good approximation (Lin et al., 2012; Georgas et al., 2014). We assumed a historic distribution of storms, which imperfectly samples the true probability distribution which may change in a warming climate (Christensen et al., 2013). Projection of changes in storminess involves deeper layers of uncertainty and is a nascent area of research for individual basins (Christensen et al., 2013). Users with a high risk aversion to potential changes in storminess may also include an additional margin of safety.

2.5 Conclusions

The availability of probabilistic local SLR projections provides an opportunity to improve coastal flood risk management. In this study, we provide a framework for local, dynamic, and actionable flood hazard information that can be used by stakeholders to inform flood risk management despite ambiguity in SLR projections. Our calculations of average annual design-life flood levels, instantaneous allowances and design-life allowances illustrate the importance of accounting for asset specific time frames and deep uncertainty in SLR projections to satisfy project design standards and risk preferences. Because of the evolution of flood levels in a non-stationary climate, failing to do so can compromise standards of protection, even from short project delays or extended durations. In this effort to provide individuals with actionable climate science, households, businesses, and government entities can select a SLR allowance that meets their planning needs among trade-offs, such as between protection and adaptation cost, and between flexibility and regret. The potential severity of flooding resulting from deeply uncertain changing storm dynamics, such as hurricane intensity, also matters and needs to be better accounted for in future local flood risk management. To summarize, our work underscores the need to readjust federal and local planning beyond the historic 100-year flood to an adaptable means of maintaining flood risk standards, such as that afforded by design-life and improved instantaneous allowances.

2.6 Acknowledgements

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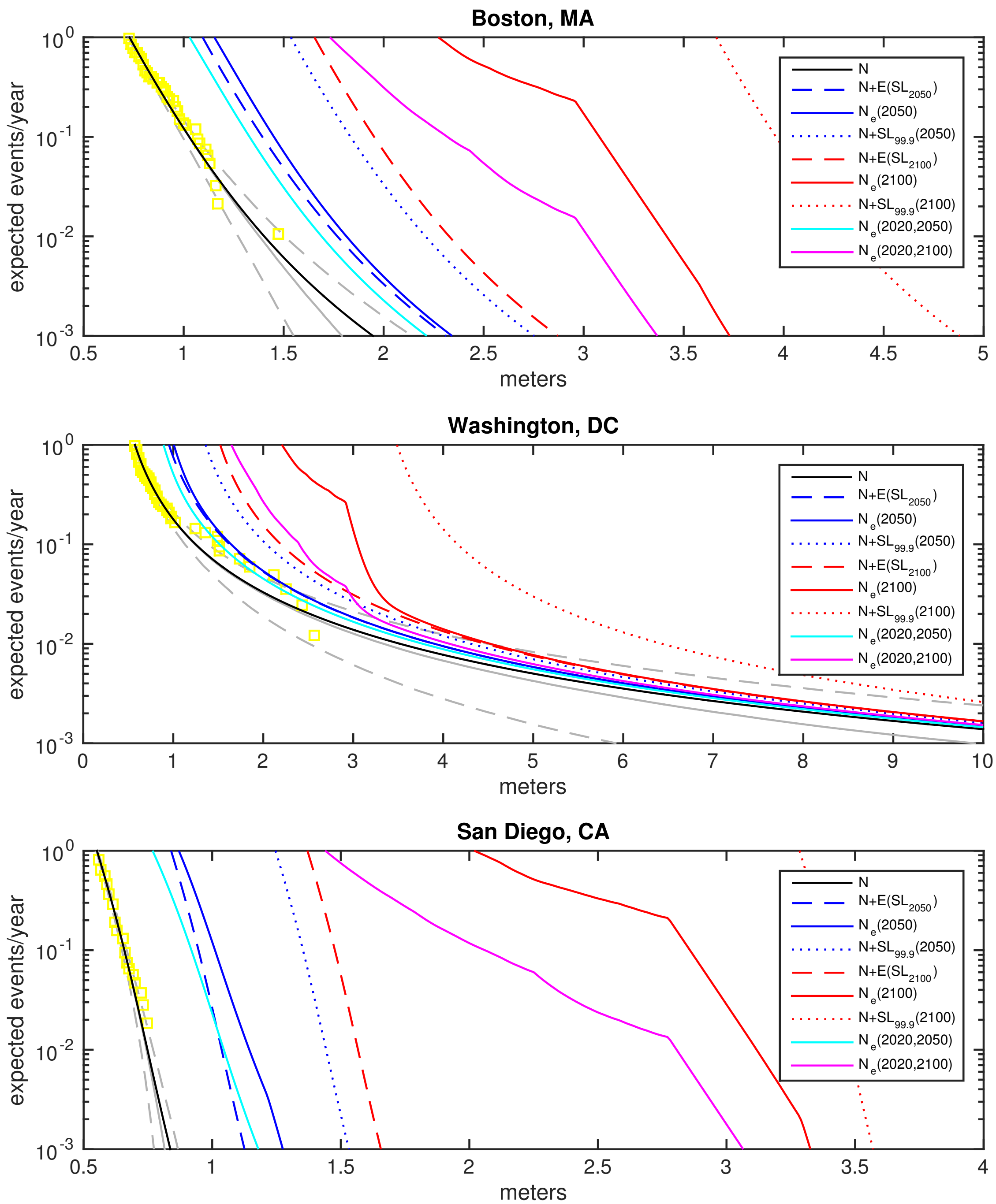

Figure 2.4: Flood return curves indicate the relationship between the number of expected flood events $N(z)$ and flood level (z) for different assumptions of SLR, date, and time period. N denotes the historic flood return curve and yellow points are empirical observations. Fixed offsets of the historic curve for expected SLR in 2050 and 2100 are represented by $N+E(SL_{2050})$ and $N+E(SL_{2100})$, and 99.9th percentile SLR by $N+SL_{99.9}(2050)$ and $N+SL_{99.9}(2100)$. Instantaneous expected flood return levels for 2050 and 2100 are $N_e(2050)$ and $N_e(2100)$. AADLLs from 2020 to 2050 and from 2020 to 2100 are denoted as $N_e(2020, 2050)$ and $N_e(2020, 2100)$.

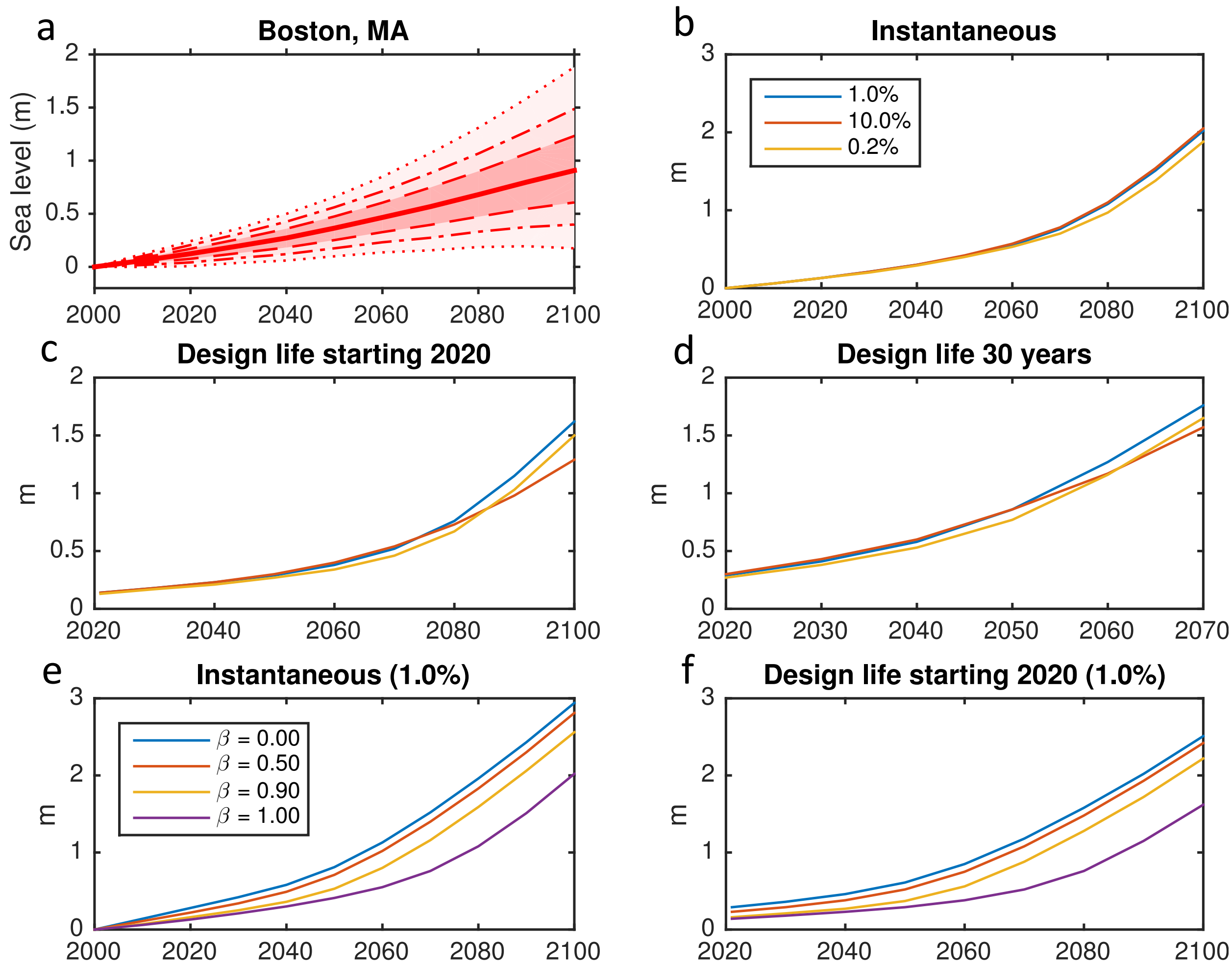

Figure 2.5: (a) Local SLR projections for Boston, (b) instantaneous allowances for various risk levels (N_0 = 10%,1%, and 0.2% AEP), (c) DL allowances starting in 2020 for variable project lengths (from 1 to 81 years), (d) DL allowances for 30-year projects with variable start dates (from 2020 to 2070), (e) 1% instantaneous allowances with Limited Degree of Confidence (LDC) metric and (f) 1% DL allowances with LDC metric.

Chapter 3

Amplification of flood frequencies with local sea level rise and emerging flood regimes

The work in this chapter is adapted from the following publication: Buchanan, M. K., Oppenheimer, M. and Kopp, R. E. (2017), 'Amplification of flood frequencies with local sea level rise and emerging flood regimes', *Environmental Research Letters* 12, 17. DOI:10.1088/17489326/aa6cb3.

3.1 Introduction

Coastal flooding is already one of the most damaging environmental hazards—responsible for a great loss of life, property, and long-term effects on municipal services and economic health (Hsiang and Jina, 2014; USACE, 2015*c*). Flood height is driven by sea level rise (SLR) and storm tide, which in turn is composed of tide and storm surge. Even a small amount of SLR augments the flood height associated with a storm surge or tidal event. Indeed, flooding amplified by SLR is projected to be the most damaging market impact of climate change for many coastal regions of the U.S. in the 21st century (Houser et al., 2015). Understanding the magnitude and pattern by which the frequency of current flood levels (such as the 1% annual chance flood, or equivalently the 100-year flood) increase is critical for developing more resilient coastal areas, particularly since coastal infrastructure management, federal flood insurance, and flood risk communications are typically tied to estimates of flood return periods (e.g., NYC, 2013; Douglas et al., 2016).

The amplification factor (AF) is a metric that measures the change in the expected frequency of a historic annual chance flood with SLR. It has been calculated explicitly (Hunter, 2012; Church et al., 2013) and implicitly (by estimating changes in flood frequency; Tebaldi et al., 2012; Lin et al., 2012) to aid stakeholder decision-making about coastal flood risk management. AFs are a function of the frequency distribution of storm tide events and the amount of local SLR—both of which are uncertain (see Methods). Storm tide distributions can be simulated with hydrodynamic models, which may then be fit by an extreme value distribution to estimate the storm tide frequency distribution (including or excluding SLR, e.g., Lin et al., 2012 and Muis et al., 2016, respectively). Alternatively, observations can be fit to an extreme value distribution to estimate a storm tide distribution, which can be adjusted for the distribution of future SLR. Extreme value theory is commonly used because of the computational intensity of high-resolution hydrodynamic modeling and also because it is data-based, capturing both tropical and non-tropical storm surges. Although hydrodynamic modeling can simulate potential changes in storm surges associated with tropical cyclones in response to warming sea surface temperatures and changing wind patterns, there is low confidence in climate model projections of future tropical cyclone behavior, particularly in individual basins (e.g., Knutson et al., 2010). Here, we assume there are no significant changes in tides or storm climatology that would affect storm tide distributions.

The Gumbel extreme value distribution was prominently used in the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (AR5; Church et al., 2013) and elsewhere (Hunter, 2012; Muis et al., 2016) because it has the advantage of simplicity, assuming an exponential relationship between the level and frequency of flooding. However, AFs estimated by it are invariant to flood levels and do not capture the distinct effects of SLR on flooding in areas with heavy- and thin-tailed flood frequency distributions. Here we present calculations of the amplification of flood return periods using extreme value theory allowing for heavy- and thin-tailed distributions and their change with SLR. We combine joint probability distributions of flood frequency using the Generalized Pareto Distribution (GPD), incorporating uncertainty in this extreme value distribution and employing probabilistic local SLR projections (conditional upon a greenhouse gas emissions pathway) to provide AFs along U.S. coastlines for various flood levels, timeframes, and SLR scenarios.

3.2 Estimating the amplification of flood frequencies

There are two main families of extreme value distributions: the Generalized Extreme Value (GEV) distribution and Generalized Pareto Distribution (GPD). The GEV family of distributions is used in block maxima analysis, in which extremes are estimated by maximum water levels over a unit of time (e.g., annual values). The GPD is used in peak-over-threshold (POT) analysis, in which the probability of having an event over a specified threshold is described by a Poission distribution and the GPD characterizes the conditional probability of an event of a given magnitude. In a POT analysis, all observations over a high threshold (e.g., the 99th percentile of hourly water levels; Tebaldi et al., 2012) are used to estimate the distribution of flood events (e.g., water level extremes). Hence, the GPD incorporates sub-annual maxima, making use of more of the available data. For these reasons, the GPD has been recognized as a hydrological standard since 1975 (NERC, 1975; Coles et al., 2001).

The number of exceedances of flood level z for the GEV and Poisson-GPD are given by:

$$N(z) = \begin{cases} \lambda(1 + \frac{\xi(z-\mu)}{\sigma})^{\frac{-1}{\xi}} & \text{for } \xi \neq 0 \\ \lambda \exp(-\frac{z-\mu}{\sigma}) & \text{for } \xi = 0 \end{cases} \tag{3.1}$$

whereby the distributions are characterized by location (μ), scale (σ), and shape (ξ) parameters. The location parameter relates to local sea level, the scale parameter to the variability in the maxima of water level caused by the combination of tides and storm surges, and the shape parameter to the curvature and upward limit of a flood frequency curve. These expressions for the number of exceedances in the GEV and Poisson-GPD are identical except for λ. For the Poisson-GPD, λ is the Poisson-distributed annual mean number of flood events; for a GEV describing annual block maxima, $\lambda = 1$ event/year (Hunter, 2012; Buchanan et al., 2016). For $\xi = 0$, the expression is identical to that for a Gumbel distribution, a simple exponential function (Fig. 3.1a).

The shape parameter dominates the tail of a flood frequency distribution (Coles et al., 2001), illustrated by the distinction between curves in Fig. 3.1a from only a variation in ξ, holding all other parameters constant. Flood frequency distributions with $\xi > 0$ are 'heavy-tailed', with a relatively high frequency of extreme flood levels. Conversely, flood frequency curves with $\xi < 0$ are 'thin-tailed', having an upper bound of extreme flood levels.

The AF of a flood of height z after SLR is $N(z-\delta)/N(z)$, where $N(z-\delta)$ is the new expected number of exceedances of the flood level with SLR:

$$AF(z) = \frac{N(z-\delta)}{N(z)} = \begin{cases} \left(1 - \frac{\delta}{(\sigma/\xi)+z-\mu}\right)^{\frac{-1}{\xi}} & \text{for } \xi \neq 0 \\ \exp(\frac{\delta}{\sigma}) & \text{for } \xi = 0 \end{cases} \tag{3.2}$$

Taking the derivative of $AF(z)$ with respect to z shows the dependence of the AF on flood height:

$$\frac{\partial AF(z)}{\partial z} = \begin{cases} \frac{-\delta\xi[AF(z)]^{(1+\xi)}}{(\xi(z-\mu)+\sigma)^2} & \text{for } \xi \neq 0 \\ 0 & \text{for } \xi = 0 \end{cases} \tag{3.3}$$

Assuming $AF(z)$ and $\delta > 0$, the sign of $\partial AF(z)/\partial z$ is equal to the sign of $-\xi$, so the AF is decreasing with flood height for positive shape factors and increasing with flood height for negative shape factors (Figs. 3.1b, 3.1c).

For $\xi = 0$ (i.e., a Gumbel distribution), $\partial AF(z)/\partial z = 0$; there is no dependence of AF on flood height, and thus its use assumes AFs are invariant to flood levels; i.e., that all flood frequencies amplify by the same magnitude (Fig. 3.1b and 3.1c). A key question thus arises among the approaches in extreme value theory to fit a distribution to flood frequencies—whether to use the simple Gumbel distribution or the GPD/GEV that requires fitting of a shape parameter. Because the shape parameter is dominant in determining a flood frequency distribution, there is a trade-off between the simplicity of the extreme value distribution used and its validity (Coles et al., 2001). Simple approximations are more tractable numerically; however, they are suboptimal when another accessible approach can differentiate between varying values of key metrics of concern—such as changes in the recurrence of the 10-year vs 500-year flood under climate change.

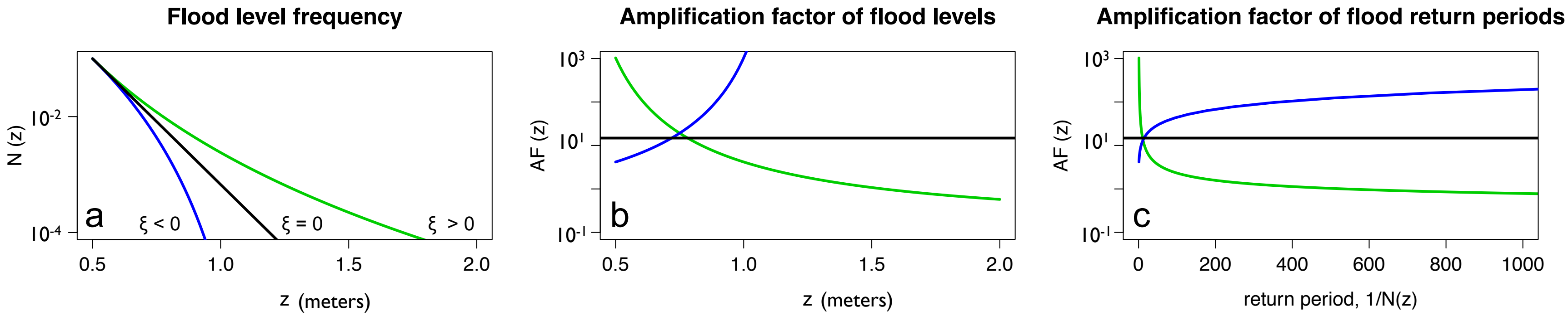

Figure 3.1: (a) Flood frequency distributions (the number of expected events of flood level z), (b) amplification factors (AFs) of flood levels z, and (c) AFs of corresponding return periods $(1/N(z))$ for 0.5 m SLR and three hypothetical GPD curves with equal parameters except for varying shape factors (ξ). The green, blue and black lines correspond to a positive ($\xi = .15$), negative ($\xi = -.15$), and zero ξ. The AF of a given flood level z is dependent on the sign of the extreme value shape parameter.

Amplification of flooding frequency is also heavily influenced by how local SLR is characterized. Under uncertain SLR, the AF equals $\mathbb{E}[(N(z) - \delta)/N(z)]$. By Jensen's inequality (Jensen, 1906), the convex transformation of the expectation of a random variable is less than or equal to the expectation of the convex transformation of the random variable. As a result of Jensen's inequality and the approximate log-linearity of flood frequency curves, the AF under expected SLR is less than the expected AF under uncertain SLR, such that $\mathbb{E}[(N(z)-\delta)/N(z)] \geq N(z-\mathbb{E}[\delta])/N(z)$. This inequality holds even if the distribution of SLR is symmetric, and the discrepancy is larger still if the distribution is positively skewed (i.e., when expected SLR is greater than median SLR). Because $N(z)$ is also a random variable, accounting for the uncertainty in the extreme value distribution fit is also important.

3.3 Methods

3.3.1 Extreme value theory

We analyze National Oceanic and Atmospheric Administration (NOAA) hourly tide-gauge records for sites with a minimum 30-year record following the methodology of Tebaldi et al. (2012) and Buchanan et al. (2016). The GPD is estimated using hourly water level exceedances above a high threshold (equal to the 99th percentile of the hourly water level; Gilleland and Katz, 2011). Hourly tide records are used to capture storm surge, astronomical tides, and interannual sea level variability, and are detrended to remove the contribution of changes in mean sea level. To account for uncertainty in fit, GPD parameters are estimated by maximum likelihood, and their covariance is estimated based on the observed Fisher information matrix (the Hessian of the negative log-likelihood at the maximum-likelihood estimate). We sample 1,000 parameter pairs with Latin hypercube sampling, assuming the parameter uncertainty is normally distributed. The expected number of exceedances under parameter uncertainty is calculated for our main calculations. Below the GPD threshold of λ events per year, we fit a Gumbel distribution with 182.6 events exceeding mean higher high water (MHHW) per year, assuming about half of all days have higher high water levels above mean higher high water. For a comparative analysis, a Gumbel distribution is also fitted to the full distribution of threshold exceedances.

3.3.2 Sea level rise projections

We use 10,000 Monte Carlo samples of Kopp et al.'s (2014) local SLR projections, accounting for global and local contributions, including land subsidence, distributional effects of land-ice melt (e.g., SLR fingerprints), and expert assessment of dynamic ice-sheet collapse. These SLR projections are asymmetric, and—due primarily to the poorly constrained but potentially large contribution of the Antarctic ice sheet (e.g., DeConto and Pollard, 2016)—positively skewed. We use two Representative Concentration Pathways (RCP) 4.5 and 8.5 which represent greenhouse gas concentrations that lead to a radiative forcing of 4.5 and 8.5 W m^{-2} by 2100 (Van Vuuren et al., 2011).

3.3.3 Amplification factors

The distribution of amplification factors and the expectation over 1,000 samples of the amplification factor are calculated for a given site. In our main calculations, amplification factors estimated by the GPD include uncertainty in local SLR and in the GPD fit, while amplification factors estimated by the Gumbel distribution include uncertainty in local SLR.

3.4 Amplification of current flood levels with sea level rise

The shape factors, ξ, reflect meteorological and hydrodynamic differences among sites (Fig. 1a in Buchanan et al. 2016). Exposed to tropical cyclones, sites along the Gulf and Atlantic coasts tend to have heavy-tailed flood frequency distributions, with positive ξ. Conversely, sites along the Pacific coast, limited by steeper coastal slopes into the seabed and fewer barrier beaches (Pugh, 1996), tend to have thin-tailed distributions, with negative ξ.

The sensitivity of flood frequency distributions to ξ (Coles et al., 2001) yields distinct behavior: AFs increase as a function of z when $\xi > 0$, decrease as a function of z when $\xi < 0$, and are greatest for z at which the slope of $N(z)$ is steepest. Hence, sites with positive ξ face a large amplification of traditionally less extreme storm surges, whereas those with negative ξ face high amplification of traditionally extreme storm surges.

Sea level rise not only amplifies flood heights but also changes the relation of flood height to flood frequency across locations. We refer to the relationship between flood height and flood frequency changes under SLR as an emerging flood regime. It can be simply illustrated by the ratio of the AF of the 500-year flood to the AF of the 10-year flood (R_{AF}). Take, for example, the flood frequency distributions of four U.S. tide gauge sites with varying ξ: Charleston, SC with a large positive shape factor ($\xi = 0.23$ [0.10, 0.36]; maximum-likelihood, median [5th and 95th percentiles]), New York City with a more moderately positive shape factor ($\xi = 0.19$ [0.07, 0.30]), San Francisco with a near-zero shape factor ($\xi = 0.03$ [-0.10, 0.16]), and Seattle, WA with a large negative shape factor ($\xi = -0.17$ [-0.27, -0.06]; Fig. 1). Fifty cm of local SLR amplifies the 10-year, 100-yr, and 500-yr floods by 148, 16, and 4 times in Charleston (yielding a R_{AF} of 0.03) and by 109, 335, and 814 times in Seattle (R_{AF} = 7.47). AFs are less divergent across $N(z)$ for places with smaller ξ (in absolute value): R_{AF} is 0.17 in New York and 0.43 in San Francisco.

The Gumbel Distribution fits the majority of observations of extreme water levels poorly. For a subset of qualifying sites, we define $\triangle AIC$ as the difference between the Akaike Information Criterion (AIC) with the Gumbel distribution and the AIC with the GPD, whereby lower AIC values indicate higher model quality. The $\triangle AIC$ is negative for only 4 out of 23 qualifying sites and has a mean of 11.77 and $s.d.$ of 6.97 (Appendix C Table C.15). When ξ is assumed to be zero, the AF is reduced to a single scalar, invariant to flood level—196 for Charleston and 86 for Seattle (Eqn. 3.2). This underestimates the recurrence of the 500-yr flood in Seattle and overestimates it in Charleston by 1−2 orders of magnitude, respectively (Fig. 3.2, columns G and GPD). This illustrates the Gumbel distribution's poor approximation for storms in the far tail and reflects the larger problem with using the Gumbel distribution to estimate flood frequencies. Accounting for uncertainty in the GPD significantly widens the distribution of AFs for sites with positive ξ, with more uncertainty in far in the tail of storm surges (columns for *Uncertain SLR* and *Uncertain GPD* in Fig. 3.2; see Methods).

AFs are also sensitive to the characterization of SLR. Using the GPD and a central estimate of SLR—rather than a probability distribution—underestimates by an order of magnitude the AF of the 500-yr flood for places with negative ξ and by two orders of magnitude the AF of the 10-yr flood for places with positive ξ (columns for $\mathbb{E}[SLR]$ and *Uncertain SLR* in Fig. 3.2). The expected amplification factors for Seattle and San Francisco are much larger than the median estimate partly because of the large positive skewness in their local SLR distributions.

Fig. 3.3 shows the expected amplification of the current 10-year flood and its ratio to other flood levels for a set ($N = 69$) of long-duration tide gauges across U.S. coastlines under RCP 4.5, corresponding to a likely global mean temperature increases of 2.0−3.6 C by 2100 (Van Vuuren et al., 2011). While the Gumbel distribution underestimates and overestimates the AF of the current 500-year flood by 1−2 orders of magnitude (Figs. 3.3d, 3.3h), the GPD captures distinct flood regimes—the heightened AF of more extreme flooding for areas with negative ξ (and the opposite for areas with positive ξ; Figs. 3.3b, 3.3c, 3.3f, 3.3g). AFs in Fig 3.3 are drastically different than those for the U.S. in the AR5 Fig. 13.25 (Church et al., 2013), which used a Gumbel distribution. With 50 cm of SLR, the AR5 underestimates the AF of the 500-yr flood in areas with a negative ξ and overestimates it in areas with positive ξ by 1−3 orders of magnitude, respectively.

Under probabilistic RSL projections of Kopp et al. (2014) for RCP 4.5 and when accounting for uncertainty in the GPD, we project a median 25-fold increase (range of 1- to

914-fold) in the expected annual number of local 100-year floods for tide-gauge locations along the contiguous U.S. coastline by 2050 (measured with respect to detrended sea level over the entire length of the record; Buchanan et al., 2016). These values jump significantly by 2100 (median: 1729, range: 5−12,546). As SLR gets to such high levels, lower flood levels saturate first, yielding flooding influenced primarily by tidal events rather than storm surges, and dampening the growth of the AF of all flood levels along all coastlines (Figs. 3.3e, 3.3g, 3.3h). This effect is also illustrated by the red curve in Appendix C Fig. C.1, demarcating flood levels in 2100. Under RCP 8.5, a high greenhouse gas emissions pathway, a median 40-fold increase (range: 1−1314) in the annual number of local 100-year floods is expected by 2050 and a median 3467-fold increase (range: 5−16,829) by 2100. For illustrative purposes, the current 100-year flood in Seattle is expected to occur 50.9 times a year, equal to an average of one 100-year flood per week. The expected AFs of various flood levels by 2050 and 2100 under RCP 4.5 and 8.5, accounting for uncertainty in the GPD fit, are provided in Appendix C Tables C.1−C.12. Annual expected flood frequencies of the 10-year, 100-year, and 500-year floods by 2050 and 2100 are in Appendix C Tables C.16−C.19.

It should be noted that the distributions of tropical and extra-tropical cyclones may be systematically different and the significance of any such difference is uncertain. Here, contributions of tropical and extra-tropical cyclones are combined as in other studies (e.g., Hunter, 2012; Tebaldi et al., 2012). Separation of these storm events would likely lead to a scarcity of very extreme events. Inclusion of uncertainty in the extreme value distribution helps account for potential sensitivity of the shape parameter to different storm events.

3.5 Conclusion

SLR imposes slow but steady inundation of coastal land and property. However, the more immediate threat from SLR is an amplification of flooding, independent of any potential changes in the distribution of coastal storms from climatological factors (Houser et al., 2015;

Church et al., 2013). Amplification of current flood levels and emerging flood regimes have critical implications for cities, states, and federal entities interested in adapting to coastal impacts.

The expected amplification of flooding frequency is highly sensitive to the characterization of SLR and flood frequency curves; the commonly used Gumbel extreme value distribution can, depending on ξ, underestimate or overestimate flood extreme increases in the far tail. Its use cannot distinguish emerging flood regimes, the pattern by which flood frequency responds to SLR. Among the prominent uses of the Gumbel distribution was the IPCC AR5 (Church et al., 2013). Additionally, Muis et al. (2016) use the Gumbel Distribution to derive a global data set of extreme sea levels; this data now populates the Dynamic Interactive Vulnerability Analysis (DIVA) model, which is used extensively to assess impacts of sea level rise (e.g., Hinkel et al., 2014). The AR5 amplification values may be seriously misleading because using the Gumbel distribution implies that amplification of flood frequency is invariant across flood levels. For example, this assumes that the frequency of extreme events like a 500-yr flood will increase by the same magnitude as lesser extremes, potentially projecting overly catastrophic flood hazards in some areas while underestimating flood hazards elsewhere. Prominent use of the Gumbel distribution in the IPCC—which has a special influence on policy makers—and elsewhere creates a risk that policy makers will implement policy based on the wrong information. While using a rule of thumb (implicit in the Gumbel distribution) is practical, it over-simplifies flood hazard characterization and could result in costly misjudgments by planners. This is particularly important as coastal areas tend to be early adopters of climate change adaptation planning (nearly 80% of U.S. adaptation plans in a recent meta-analysis were in coastal states; Woodruff and Stults, 2016). The use of the GPD is therefore preferable for flood risk assessment of the emerging non-stationary climate.

Using the GPD, locations with positive ξ (like New York City, Baltimore, Washington D.C., and Key West) can expect disproportionate amplification of higher frequency events, whereas those with negative ξ (such as Seattle, San Diego, and Los Angeles) can expect a disproportionate amplification of lower frequency flooding. Effective policies should initially increase resilience to historical flooding in areas with emerging flood regimes associated with positive ξ, and prepare for largely unprecedented flooding in areas with negative ξ. Policies should also allow for adjustment over time to address eventual flooding dominated by tidal events and permanent inundation (Sweet and Park, 2014). Identification of areas with similar flood regimes by shape factor could facilitate the sharing of adaptation strategies across coastal areas.

3.6 Acknowledgements

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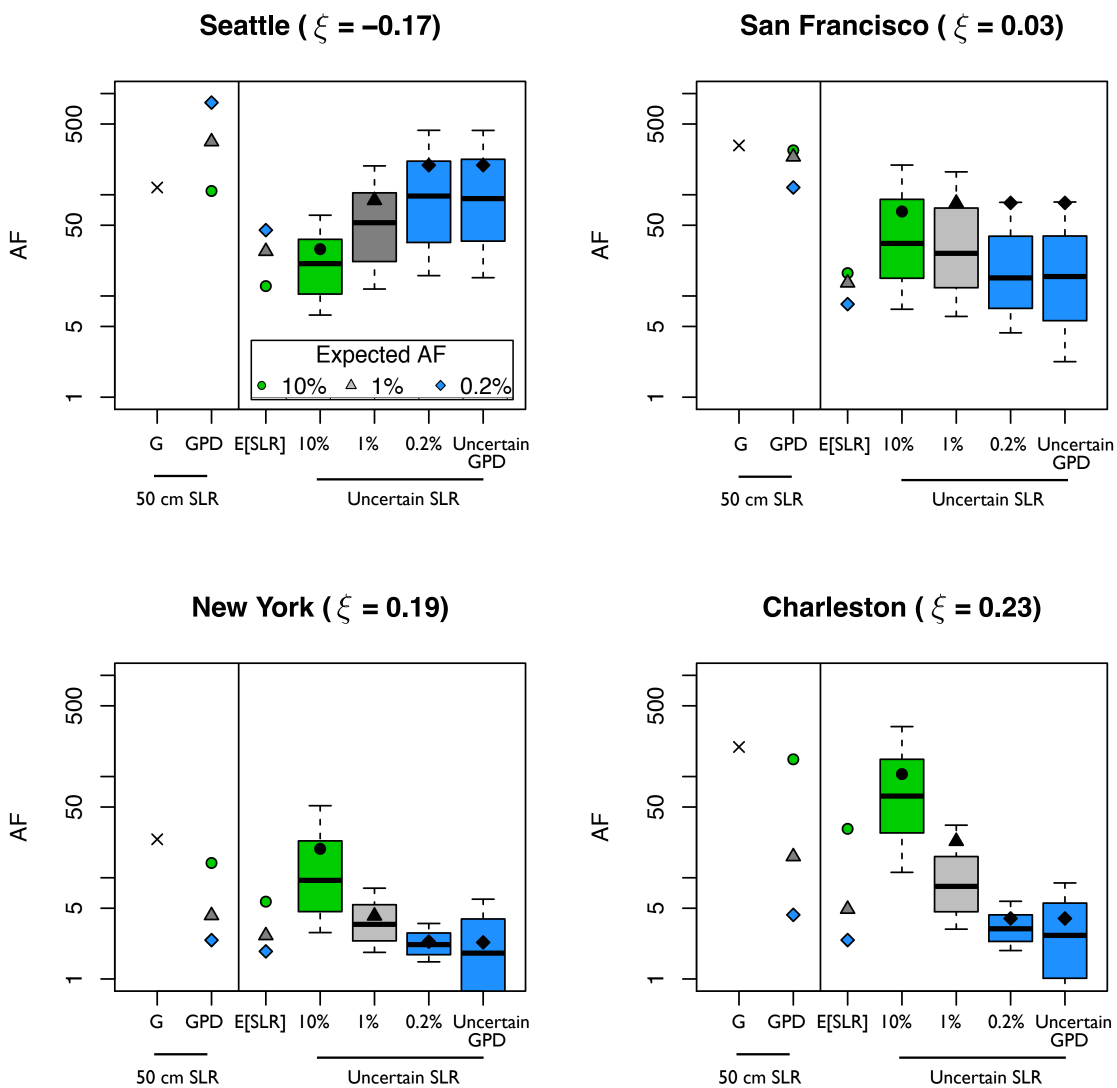

Figure 3.2: Expected amplification factors (AFs) of different flood return levels (10% (○), 1% (△), and 0.2% (◇) annual chance floods) for different extreme value distributions (GPD and Gumbel) and characterizations of sea level rise (SLR) for regional sites (Seattle, San Francisco, Charleston, and New York City) with varying shape parameters (negative, near-zero, and positive ξ). Amplification scenarios include: (1) the Gumbel distribution with 0.5 m deterministic SLR (column G), (2) the GPD with 0.5 m deterministic SLR for the 10-, 100-, and 500-yr floods (GPD), (3) the GPD with expected SLR for 2050 under RCP 4.5 for the 10-, 100-, and 500-yr floods ($\mathbb{E}[SLR]$), (4-6) the GPD with uncertain SLR for 2050, integrated over the full probability distribution for SLR under RCP 4.5 for the 10-, 100-, and 500-yr floods ($Uncertain\ SLR$), and finally (7) the GPD with uncertain SLR for 2050, integrated over the full probability distribution for SLR under RCP 4.5 and accounting for uncertainty in the GPD fit (see Methods) for the 500-yr flood ($Uncertain\ GPD$). With the Gumbel distribution, differences in the expected amplification of various flood levels with the same amount of SLR are undetectable (×). Boxplots correspond to the 5th, 17th, 50th, 83rd, and 95th percentiles of the distribution of AFs.

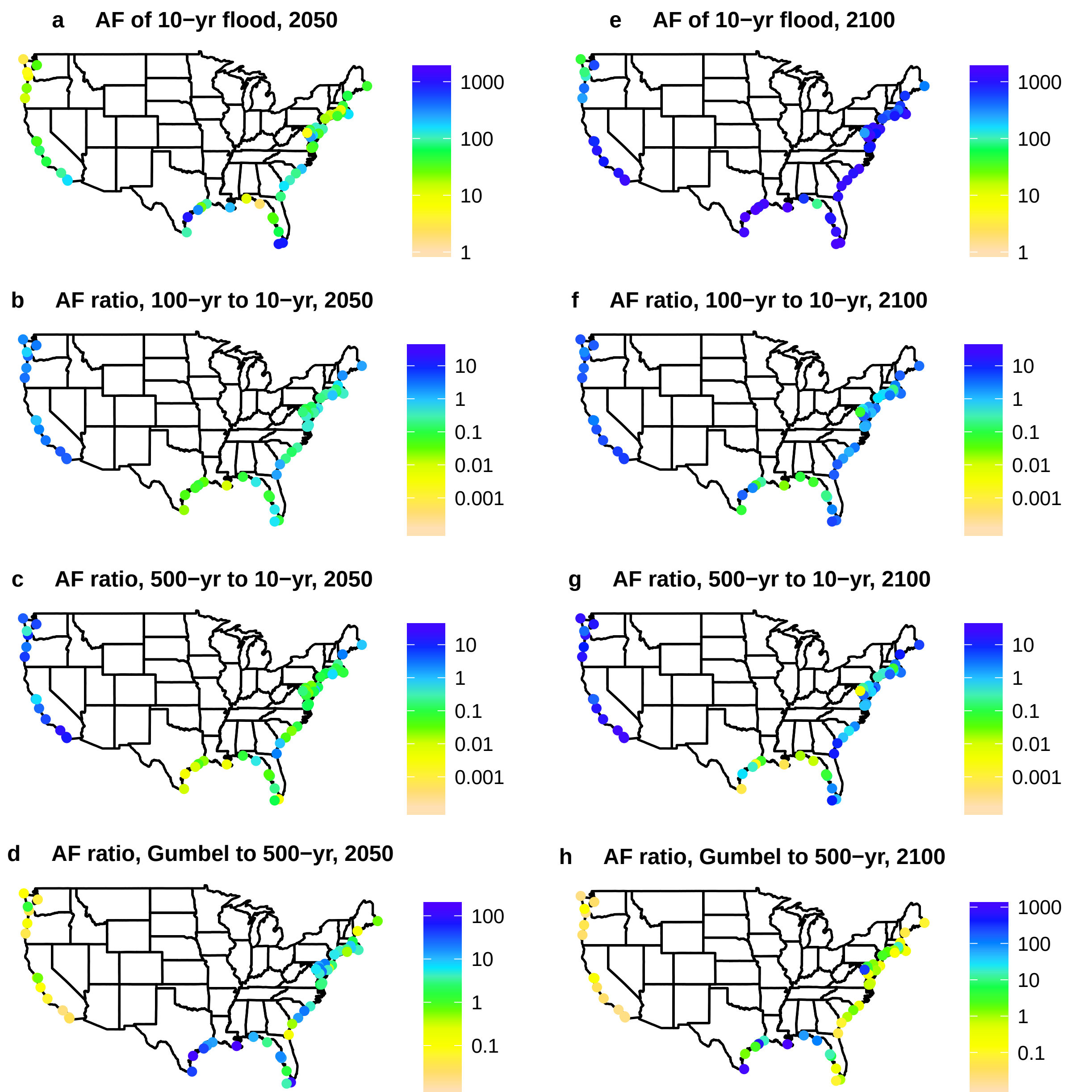

Figure 3.3: Amplification factors (AFs) and ratios thereof estimated for 2050 (a-d) and 2100 (e-h) under uncertain local sea level rise under Representative Concentration Pathway (RCP) 4.5. (a, e) AF of current 10-year flood return levels estimated by the GPD, (b, f) the ratio of the AFs of the 100- to 10-year flood estimated by the GPD, (c, g) the ratio of the AFs of the 500- to 10-year flood estimated by the GPD, and (d, h) the ratio of the AFs estimated by the Gumbel distribution to the 500-year flood estimated by the GPD. All GPD AFs account for uncertainty in the GPD fit.

Chapter 4

Values, bias, and stressors affect adaptation to coastal flood risk: evidence from New York City

4.1 Introduction

Forty percent of the world's population sits along ocean coastlines and ~10% lives on land that is within 10 meters above sea level (McGranahan et al., 2007). This urban exposure to flooding is increasing due to population growth and sea level rise resulting from anthropogenic climate change. Recent research improving the characterization of physical hazards from climate change on the coastal zone has helped cities assess their risks (e.g., Douglas et al., 2016; Griggs et al., 2017). This work includes improving our understanding of the rate and magnitude of sea level rise (Sweet and Park, 2014; Kopp et al., 2014), the change in distribution of tropical cyclones (Knutson et al., 2010; Lin et al., 2012), and the resulting frequency and severity of flooding (Buchanan et al., 2016; Buchanan, Oppenheimer and Kopp, 2017) on global to local scales. However, the ability of settlements to cope or thrive under changing climate conditions will likely depend on the cooperation and initiative of households, regardless of any governmental efforts to reduce risk (Seneviratne et al., 2012). Understanding individuals' likely responses to changing coastal hazards is thus critical for decision-makers to plan for a sustainable future.

There remains great uncertainty regarding the extent to which households will adapt to changing coastal hazards. First, households face a range of adaptation options. For instance, households may take small, 'low-hanging fruit' measures, such as elevating service equipment or supplying resources for an emergency. They may also take more costly measures to accommodate flooding, such as buying flood insurance or elevating their homes. Alternatively, they may permanently relocate, curbing their exposure and vulnerability to flood hazards. Moreover, a complex array of factors can influence their adaptation decision-making process, including several personal and non-personal factors (Botzen et al., 2009). As reviewed in Koerth et al. (2017), many studies have explored the influence of personal factors, including previous experience with flooding, knowledge of how flood frequency and severity may change in the future, as well as socioeconomic and cognitive variables. Others have explored the role of non-personal factors such as situational and geographical variables pertaining to the decision-making context (e.g., Baker, 2011).

However, there are additional personal factors that have previously been overlooked in the coastal adaptation context. These include the influence of households' personal values, which have been shown to dominate individuals' perspectives and decision-making processes (Adger et al., 2009). Also of interest is the role of single-action bias, the cognitive trade-off households make between adaptation options, whereby taking a small (and often less effective measure) may strongly discourage uptake of a more protective measure (Weber, 2006). This effect was demonstratively important in adaptation decision-making in the agricultural sector (Weber, 1997). Using a survey in New York City Jamaica Bay region, we examine how values and single-action bias affect adaptive behavior to coastal hazards, controlling for other explanatory factors, such as socioeconomic, cognitive, and situational variables, as well as past experience and knowledge of emerging flood patterns. Finally, we employ discrete choice experiments to test non-personal factors that have shown to be significant elsewhere and are particularly relevant for the study area. These include the behavior of others (Lo, 2013), the price of insurance (Botzen et al., 2013), the range of tolerable flood hazards (Botzen et al., 2015), the presence of large-scale flood risk management strategies administered by the government (Poussin et al., 2014), and sensitivity to property value and cost of rent (Bunten and Kahn, 2014).

This study focuses on neighborhoods surrounding Jamaica Bay in New York City, a city recognized for its leadership in developing policy for coastal climate impacts (e.g., NYC, 2013; New York City, 2017*b*). The Jamaica Bay region in particular has been subject to international attention not only for its devastation from Hurricane Sandy floodwaters, but also for its use of billions of federal dollars (and potentially billions more) for recovery and future resilience initiatives (Ferre-Sadurni, 2017). The area's socio-economic diversity, increasing flood exposure, and current engagement in public decisions regarding large-scale flood mitigation strategies led by city, state, and federal governments make for a timely case study (USACE, 2016). Hence, this study may pose lessons for other coastal settlements developing flood risk management policies and programs.

The remainder of this chapter is structured as follows. Section 4.2 provides a review of the literature on the drivers of adaptive behavior and provides a basis for the hypotheses to be tested. Section 4.3 describes the research methodology. Section 4.4 presents and discusses the results. Section 4.5 provides policy recommendations and concludes.

4.2 Adaptive behavior and its drivers

4.2.1 The spectrum of adaptive behavior

There is a spectrum of adaptive behavior in which coastal residents may engage, ranging in both monetary and psychological cost. Least costly are 'low-hanging fruit' measures, such as elevating service equipment or supplying resources for an emergency. Costly adaptation measures include buying flood insurance, which is increasingly expensive. Annual premiums averaged $1,500 in 2013 for homeowners of one- to four-unit homes in high-risk flood zone areas in NYC and could increase to over $9,000 with changes to the National Flood Insurance Program (Dixon et al., 2013). Participation in the insurance program can also be stressful and difficult to navigate. For example, many policyholders did not receive timely payouts after Hurricane Sandy and litigation persists over flood zone classification (e.g., PBS, 2016). Home elevation can be significantly more expensive than insurance if done privately (e.g., $140,000−$255,000 for a typical 2,400 square-foot, two-story home; State of New York, 2016). Home elevation can also be emotionally taxing, particularly when subsidized through the current city program. Several respondents who participated in the program expressed dissatisfaction with the unpredictable nature of the process, the lengthy time away from home that is required (years, often with unknown end dates), and the loss of homes' character upon completion. Permanent relocation is perhaps the costliest, since a household may sacrifice proximity to family, community members, work, and/or coastal amenities (e.g., the beach), as well as familiar surroundings and routines.

4.2.2 Determinants of adaptive behavior

A large body of research shows that a complex array of factors may influence households' response to environmental change, including coastal hazards (Koerth et al., 2017). Socio-economic characteristics, such as age, education, gender, or marital status can affect an individual's priorities, perspectives, and tolerance for environmental hazards (Cutter et al., 2003). For example, Molua (2009) and Paul and Routray (2011) found variables such as age, marital status, education and homeownership to significantly affect household adaptation in Cameroon and Bangladesh. Adaptive capacity in the form of income has an ambiguous effect on behavior (Paul and Routray, 2011; Baker, 2011; Linnekamp et al., 2011). As individuals without sufficient resources may not be able to afford *in-situ* protective measures (such as flood insurance, back-up emergency electricity generators, or home elevation), a lack of capital could discourage action or incentivize relocation.

The extensive natural hazards literature suggests that cognitive factors and previous experience of extreme events affect individuals' assessments of risk and motivations to behave proactively (e.g., Slovic, 2000; Bubeck et al., 2012). These include perception of exposure to flood events and level of concern, which are understood to heighten after an extreme event and then decay in the years following (Egan and Mullin, 2012). In the coastal context, Bichard and Kazmierczak (2012) found that awareness of climate change and flood risk significantly influenced the intentions of households in England and Wales to take adaptive measures. Botzen et al. (2009) found that homeowners in the Netherlands were more likely to buy sandbags if they were more aware of flood risk and had previous experience with flood damage. Moreover, risk perception is partly driven by emotion (Loewenstein et al., 2001), which has downstream consequences. One of these is single-action bias, a psychological effect in which people do not take additional protective action after already haven taken *an* action (that may not be particularly protective) because taking the first action reduces their concern (Weber, 2006). We examine single-action bias in the coastal adaptation context and hypothesize that households who have already taken a small adaptation measure are less inclined to take larger scale measures, such as buying flood insurance, elevating their home, and permanently relocating (H1).

Adger et al. (2009) highlight the influence of personal values in limiting adaptive behavior. For example, an individual's attachment to a community—in addition to emotional and financial investments made in one's home—may be more compelling than fears about financial loss or physical damage. If a household strongly desires to stay close to the coast to preserve their cultural identify or lifestyle, they may be more likely to take *in-situ* adaptive measures. Moreover, a household may be opposed, on principle, to pay for flooding-related costs. They may also have limited tolerance for the inconveniences that flood hazards and flood risk management can bring, such as traffic, roadblocks, or time away from home. To the best of our knowledge, this is the first study to empirically test the role of values on adaptive behavior. We hypothesize that households who highly value the coast, their community and home are more likely to insure or elevate their home and less likely to relocate (H2), and that those who highly value avoiding flooding-related costs and inconveniences are less likely to insure or elevate and more likely to relocate (H3).

Situational, external stressors have the potential to limit or spur adaptive behavior, but are rarely investigated (Koerth et al., 2017). Households have varying tolerance of hazard frequency and severity (Dow et al., 2013) and sensitivity to the price of flood insurance (Kriesel and Landry, 2004). They may relocate or abstain from coverage if rates increase above their willingness to pay. People may also be more or less inclined to take an action depending on its uptake by peers (e.g., Cialdini and Goldstein, 2004), such as home elevation or relocation. People may act less cautiously if they sense a degree of protection (whether or not that sense is accurate; Kunreuther and Slovic, 1978), whereby the presence of a protective barrier from coastal flooding may assuage fears of damage from future flood events (regardless of the integrity of the structure or its ability to protect against a range of flood levels). For example, Botzen et al. (2009) found that adaptation was less likely among households who assumed the government will help mitigate flood risk. Additionally, residents may behave differently depending on the particular public adaptation strategy (e.g., a storm surge barrier or natural features, such as wetlands), depending on how effective or adverse they think the strategy is to coastal amenities (such as the view, ease of navigation, or ecology; Adger et al., 2009). Finally, change in property value or cost of rent may drive *or* prevent relocation (Murdoch et al., 1993; Bin and Polasky, 2004; Bunten and Kahn, 2014). We hypothesize that households are sensitive to nuisance flooding and are more likely to adapt as it becomes more frequent (H4), and if their peers adapt (H5). We posit that households are more likely to relocate if their property values fall or costs of rent rise (H6). Finally, we expect households are less likely to adapt under large-scale governmental efforts to reduce flood risk (H7), and are less likely to insure under conditions of rising premiums (H8).

Because of the complexity of human behavior, it is often best to analyze behavior through revealed preferences from past actions. However, since flood hazard from climate change is emerging and increasing over time, many such observations do not yet exist. To assess intended adaptive behavior, we employed discrete choice experiments (DCEs; Louviere and Hensher, 1982). DCEs are a rigorous statistical method used across the social sciences to isolate the systematic components of an individual's utility for a particular choice under hypothetical scenarios, and are subject to less bias than contingent valuation methods for stated preferences (Hoyos, 2010). Whereas Botzen et al. (2013) used DCEs to elicit individuals' willingness to pay for flood insurance, to the best of our knowledge, this is the first study to use DCEs to examine households' intentions to take a range of different adaptation measures, including procuring flood insurance, elevating one's home, and permanently relocating from one's neighborhood.

4.3 Methodology

4.3.1 Case study area

Neighborhoods surrounding Jamaica Bay face some of the highest flood risk in NYC. Substantial damage occurred throughout the study area from Hurricane Sandy in 2012, including 10 fatalities and the destruction of over 1,000 structures (USACE, 2016). The damage from Sandy and the increasing potential for future flood damage has incited NYC, NY State, and Federal agencies to invest in public flood protection. There are two leading alternatives under consideration (USACE, 2016): a structural storm surge barrier across, sea walls or natural features. A storm surge barrier across the Jamaica Bay inlet would crest approximately 17 ft above the North American Vertical Datum of 1988 to help mitigate flooding. Alternatively, sea walls or a portfolio of natural features, including newly cultivated marshes and living shorelines, would span the Jamaica Bay perimeter to help accommodate floodwater. While a storm surge barrier would offer more protection against extreme flooding, natural features would likely be more protective against more moderate flooding (e.g., Nordenson et al., 2014; de Castella, 2014, February 11; Bridges et al., 2015; USACE, 2015*c*).

The area is culturally and socio-economically diverse and divided (Kornblum and Van Hooreweghe, 2010; U.S. Census Bureau, 2015) and approximately half of households are renters. Like many urban areas, gentrification is a growing concern (Higgins, 2016). The Rockaway Peninsula, for example, spans a gradient of wealth, from low in the east (e.g., Far Rockaway) and increasingly high toward the west (e.g., Belle Harbor and Breezy Point; Appendix D Figure 1, Appendix D Table 1). Although flood insurance is formally required for federally-backed mortgages and nearly 90.0% of structures in the area qualify for subsidized premiums, flood insurance uptake is modest (Dixon et al., 2013).

4.3.2 Sampling method and survey protocol

In-depth interviews with community leaders ($n = 15$) and residents ($n = 5$) and observations of community meetings ($n = 14$) validated the relevance of predictors on the intention to insure, elevate, and relocate. A semi-structured survey instrument ($n = 462$) collected data on personal factors and intended adaptive behavior under plausible future conditions with DCEs. To be eligible, respondents were asked if they were at least 18 years of age and could represent their household. Over 90% of surveys were taken by individuals, as opposed to couples.

Nine neighborhood areas within the Jamaica Bay region were randomly selected (Appendix Figure 1) and the survey was executed by three mechanisms to increase the generalizability of the findings. First, the survey was conducted in-person using clustered random sampling, whereby cross-streets were randomly selected from each neighborhood and every third home was approached ($n = 97$, response rate (RR) = 22%). This sampling method was used because of the natural geographical clusters within the population (exemplified by the demographic stratification in Appendix D Table 1). Second, the survey was mailed to residences in each neighborhood using stratified random sampling to identify recipients (n

= 173, RR = 16%). Finally, as online samples are an emerging surveying technique, the survey was also administered online (n = 199, RR = 8.4%) to broaden the survey's coverage and test the reliability of online sampling. This was done by testing the independence of the variables between the online sample and those from more traditional surveying approaches (i.e., administered in-person or by mail). The online panel was proportional to the general population and randomly selected respondents across neighborhoods. The response rates from all three approaches are increasingly common for the social sciences (e.g., Kohut et al., 2012; Roser-Renouf et al., 2014; Akerlof et al., 2016) and response rates from online panels are generally lower than from traditional approaches (Nulty, 2008). Tests of independence showed no significant differences in independent variables between the in-person, mailed, and online surveys (see Appendix D Tables 2−23).

4.3.3 Survey instrument

The survey had five components. First, personal values pertinent to coastal residents were measured on a 5-point Likert scale, ranging from *not important* to *extremely important*. For homeowners, these included the value of living close to current community members and the coast, avoiding flooding-related costs and inconveniences (like traffic, roadblocks, or time away from home), and keeping one's property (for personal or financial reasons). For renters, the value of avoiding inconveniences and keeping one's property were replaced by the value of home affordability and quality. Second, DCEs asked respondents to choose their most likely response to scenarios including environmental and urban stressors that may result from sea level rise and changes in the distribution of storm events. Third, instruments measured perceptions of current and future risk, past experiences with flooding, and recent adaptation measures taken. Fourth, selected demographic questions and covariates from the American Consumer Survey identified individual characteristics of the respondent and represented household. Finally, open-ended questions about recent adaptation measures and perspectives on flood risk management were included to provide additional contextual understanding.

4.3.4 Descriptive statistics of the sample

As to be expected, renters and residents in poorer neighborhoods were less responsive. As a result, the sample is primarily representative of homeowners, who tend to be wealthier, above the median age, and married; they also have a larger ratio of retirees than renters (Table 4.1). These higher response rates from females, older and more educated individuals are not uncommon for the social sciences (e.g., Gannon et al., 1971; Binder et al., 2015; Akerlof et al., 2016). Moreover, the Jamaica Bay area received a large amount of international attention after Hurricane Sandy, whereby dozens of research groups surveyed the most vulnerable residents after Hurricane Sandy (e.g., Gruebner et al., 2015). Confirmed by community leaders during in-depth interviews, survey fatigue further explains the lower response rates among lower-income households.

On average, respondents were 50 years old (median: 50, sd: 16.3, range: 20−85) and lived in their neighborhood for 26 years (median: 23, sd: 18.4, range: 0.2−80). Thirty-six percent of respondents had a mortgage and the average annual household income was \$89 k (median: \$87 k, sd: \$52.3 k, range: \$7−200 k). High school was the highest level of education for 26%. Forty-five percent had a college degree, 28% had an advanced or professional degree, and less than 1% had not completed high school. Given the size and diversity of the sample, significance tests of the hypotheses are unlikely to provide false positives. Surveyed variables and descriptive statistics of the sample are listed in Table 4.1.

All personal variables had less than 5% of missing values (except for *Income* and *Married*, both with 5.8%). Observations with missing values were removed, reducing the original sample size (n = 462) to 405 (262 homeowners and 131 renters). No variables were correlated except the independent variables *Insured* and *No adaptation* (Pearson's r = -0.79, $p < 0.001$), as well as *Expected floods* and *Flood perception* (Pearson's $r = 0.31$, $p < 0.001$). These correlations are to be expected as insurance is currently the most widely adopted adaptation and individuals who perceive current flood risk are more likely to perceive future flood risk.

Table 4.1: Survey instrument and sample characteristics

	Variable	Description	Mean	St. Dev.
Socioeconomic	Income	Household annual income ($ 1,000)	89.30	52.32
	Married	Yes = 1, No = 0	.58	.49
	Age	Age in years	49.72	16.28
	Female	Yes = 1, No = 0	.60	.49
	White	Yes = 1, No = 0	.67	.47
	Children	‘Are any children under 18 years living with you?’ Yes = 1, No = 0	.24	.43
	Education	Advanced degree = 4, College degree = 3, High School degree = 2, None = 1	2.99	.77
	Homeowner	Yes = 1, No = 0	.67	.47
	Mortgage (owners)	Number of mortgages	.55	.50
Cognitive	Climate perception	‘Do you think the world’s climate is changing causing more extreme weather and rising sea levels?’ Yes = 1, No = 0, I don’t know = 0.5,	.86	.30
	Flood perception (owners)	‘Do you live in an area prone to major flooding?’ Yes = 1, No = 0, I don’t know = 0.5	0.66	0.46
	Flood perception (renters)		0.61	0.47
	Flood concern (owners)	‘How serious of a problem do you think flooding is for your household? Serious = 1, Not serious = 0, I don’t know = 0.5	0.72	0.45
	Flood concern (renters)		0.60	0.48
	Expected floods	The expected number of major floods over the next 20 years.	2.21	2.12
Experience/Knowledge	Experience	Experienced other major flood events in lifetime. Yes = 1, No = 0	.27	.44
	Damage	Percent damage of structure from Sandy. Destroyed $\geq$ 75%, Major = 50%-75%, Minor =10%-50%, Affected $\leq$ 10%, None = 0%	21.66	22.92
	Surveyed	Surveyed/interviewed about coastal flooding/resilience before. Yes = 1, No = 0	.09	.29

Table 4.2: Continued. Survey instrument and sample characteristics

	Variable	Description	Mean	St. Dev.
Values		'On a scale of 1 to 5 with 1 being 'Not important' and 5 being 'Extremely important', how important are the following to you?':		
	Avoid flood cost	Avoiding flooding-related costs	3.95	1.19
	Community	Living near your current community	3.54	1.29
	Coast	Living close to the coast	3.54	1.34
	Avoid inconvenience	Avoiding inconveniences (like traffic, roadblocks, time away from residence; owners).	3.72	1.08
	Keep home	Keep residing in your home (owners)	4.31	.73
	Home (personal)	'On a scale of 1 to 5 with 1 being 'Not significant' and 5 being 'Extremely significant', how personally significant is your home?' (owners)	4.51	.72
	Home (asset)	'On a scale of 1 to 5 with 1 being 'Little' and 5 being 'Extremely', how much do value your home as a financial asset'? (owners)	4.50	.71
	Home quality	Quality of residence (renters)	4.25	.88
	Home affordability	Affordability of residence (renters)	4.37	.84
Situational	External network	Number of family members or close friends who live far (e.g. $\geq$ 10 miles). from the coast.	6.95	5.70
	Tenure	Years living in neighborhood	26.83	18.40
	Community hrs.	Hours per week participating in community activities	2.33	2.68
Previous adaptations	Elevated	Currently or recently elevated their home. Yes = 1, No = 0	.07	.26
	Insured	Currently or recently have flood insurance. Yes = 1, No = 0	.38	.49
	Generator	Currently or recently purchased back-up generator. Yes = 1 , No = 0	.20	.40
	'Low-hanging fruit' adaptation	Currently or recently taken other flood protection action. Yes = 1, No = 0	.09	.28
	No adaptation	Have **not** taken any flood protection action. Yes = 1, No = 0	.50	.50

4.3.5 Discrete choice experiments

DCEs were designed to elicit the systematic utility of taking a particular adaptation measure under scenarios of hypothetical (but plausible) future conditions, drawing upon rational choice theory and a conditional logistic model (Thurstone, 1927; McFadden et al., 1973):

$$U_{in} = V_{in} + \epsilon_{in}. \tag{4.1}$$

Here, U_{in} is the unobservable utility that individual n associates with adaptation measure i, and V_{in} and ϵ_{in} are the explainable and random components of that utility. The probability (P) that individual n chooses adaptation measure i from a set C_n of options j is:

$$P(i) = \exp(V_{in}) / \sum_{j \in C_n} \exp(V_{jn}). \tag{4.2}$$

V_{in}, the systematic component of an individual's utility, is a function of attributes X_{ikn} with coefficients β_{ik}:

$$V_{in} = \sum_{k=1}^{K} \beta_{ik} X_{ikn}. \tag{4.3}$$

Attributes included levels of flood hazard (nuisance, major, or extreme flooding), insurance premiums (low, medium, high), peers' adaptive behavior (whether the majority of community members do nothing, elevate their homes, or permanently relocate), changes in property value (remains unchanged, increases, or decreases), and public flood protection strategies (storm surge barrier, natural features, sea walls). Flood hazards vary in frequency and severity, whereby nuisance flooding is defined as the potential for streets to flood several times a month and extreme flooding is on par with that resulting from Hurricane Sandy. Insurance premiums are represented by \$40, \$120, and \$800 per month for homeowners covering their structures and contents, and by \$30, \$45, and \$60 per month for renters covering their contents. These values represent a wide range of typical premiums of homeowners and renters in the case study area (Dixon et al., 2013). Peers represent whomever respondents identify as community members, whereby the majority of respondents identified people living in their official neighborhood as peers. Because housing markets are volatile and it is uncertain how property values and rents respond to natural hazards (Murdoch et al., 1993; Bin and Polasky, 2004; Bunten and Kahn, 2014), we included a wide range of possible change in property values and in the cost of rent (±50%). Finally, public flood protection strategies mirrored those being proposed by the U.S. Army Corps of Engineers(USACE, 2016), including a large storm surge barrier across the Jamaica Bay inlet, expansion of natural features (e.g., marshlands) and sea walls along the perimeter of Jamaica bay. This design was reached following initial in-depth interviews with residents in the region regarding the criteria of principal relevance to them in thinking about their adaptation decision-making. Table 4.3 illustrates how attributes were described to respondents.

DCE questions were designed based on orthogonal main-effect arrays, whereby scenarios covered the parameter space of external factors and their attributes (Johnson et al., 2006). To reduce the computational burden on respondents, we distributed factors into two separate DCEs. The first DCE included attributes for flood hazard, insurance premium, and peers' adaptive behavior (Eqn. 4.4). The second DCE included attributes for flood hazard, property value, and public flood protection (Eqn. 4.5). In total, each DCE included nine choice sets, blocked into groups of three that were randomly assigned to respondents. Figure 4.1 illustrates a sample question from each DCE. For each question, respondents were asked to consider how they would likely react under a given scenario: (1) buy insurance, (2) elevate their home (with or without insurance), (3) permanently relocate from their neighborhood, or (4) take none of these actions. Homeowners who had previously elevated their homes were not allowed to select home elevation as an adaptation option.

Following the methodology of Aizaki (2012), conditional logistic regression models were used to measure the systematic utility V_{in} of taking adaption measure i given attribute X, against the alternative of taking no action. For homeowners, three separate models were used to measure the utility of buying insure, elevating a home, and relocating, respectively.

Similarly, we used two models for renters to measure the utility of buying insurance and relocating. This led to 6 regression models for homeowners (who may insure, elevate, or relocate; Models 1-6b) and 4 models for renters (who may insure or relocate; Models 7-10b). To allow for non-linearity in sensitivity to flood hazard, insurance price, and property value/cost of rent, we use a piece-wise linear function whereby X independent variables represent discrete factor levels as opposed to continuous values. For example, insurance premiums are included as low, medium, and high, not by their price in dollars. ASC is an alternative specific constant. Models for the first DCE are expressed by:

$$V_{in} = ASC_i + \beta X_E + \beta X_N + \beta X_M + \beta X_H + \beta X_{PE} + \beta X_{PR}. \tag{4.4}$$

Similarly, models for the second DCE are expressed by:

$$V_{in} = ASC_i + \beta X_E + \beta X_N + \beta X_{PD} + \beta X_{PI} + \beta X_B + \beta X_{NF} \tag{4.5}$$

whereby E and N refer to extreme and nuisance flood hazards, M and H refer to medium and high insurance premiums, PE and PR refer to peers' elevating their homes and relocating, PD and PI refer to a decrease and increase in property values (or cost of rent), and B and NF refer to a storm surge barrier and natural features. All respondents completed all DCE questions. For each model, this resulted in 1,866 observations for owners (311 people $*$ 3 scenario questions $*$ 2 choices: the given adaptation measure vs. the reference case of taking no action) and 906 for renters (with 151 people).

To examine whether personal factors are associated with these intended adaptive behaviors, we created three independent binary variables (*Insure*, *Elevate*, and *Relocate*) reflecting whether or not a respondent would consider taking a particular adaptation measure at least once under the DCE scenarios presented during the survey. We then undertook several binary logistic regressions, whereby Models 1-3a correspond to homeowners' intentions to relocate, insure, and elevate, as opposed to the alternative of taking no action (Table 4.4). Similarly, Models 4-5a relate to renters' intentions to relocate and insure (Table 4.5).

Table 4.3: Attributes of situational/external stressors included in discrete choice experiments

Factor	Attribute	Description
Flood hazard	Nuisance	“Streets may flood several times a month.”
	Major	“A major flood may occur, possibly flooding your home by a few feet.”
	Extreme	“Extreme flooding may occur, possibly damaging your home.”
Insurance premium	Low	“Flood insurance costs $40 per month.”
	Medium	“Flood insurance costs $120 per month.”
	High	“Flood insurance costs $800 per month.”
Peers’ behavior	Do nothing	“The majority of your community members take no adaptation measures.”
	Elevate	“The majority of your community members elevate their homes.”
	Relocate	“The majority of your community members permanently relocate from the neighborhood.”
Property value	Unchanged	“The value of your property remains the same.”
	Decreases	“The value of your property decreases substantially ($\sim$50%).”
	Increases	“The value of your property increases substantially ($\sim$50%).”
Public flood protection	Barrier	“The government builds a large storm surge barrier across the Jamaica Bay inlet.”
	Natural features	“The government expands natural features, like wetlands, along the perimeter of Jamaica Bay.”
	Sea walls	“The government builds sea walls along the perimeter of Jamaica Bay.”

Figure 4.1: Example of choice cards for the first (left) and second (right) discrete choice experiments

Consider the following conditions:

- Streets may flood several times a month.
- Flood insurance costs $120 per month.
- The majority of your community members elevate their homes.

How would you likely react?

- ❑ Buy flood insurance
- ❑ Elevate your home (with or without insurance)
- ❑ Permanently relocate from your neighborhood
- ❑ Take none of these actions

Consider the following conditions:

- The government builds sea walls along the perimeter of Jamaica Bay
- A major flood may occur, possibly flooding your home by a few feet.
- The value of your property increases substantially (~50%).

How would you likely react?

- ❑ Buy flood insurance
- ❑ Elevate your home (with or without insurance)
- ❑ Permanently relocate from your neighborhood
- ❑ Take none of these actions

4.4 Results and discussion

Currently, nearly 50% of households have taken no actions to prepare for flooding. Nine percent have taken a 'low-hanging fruit' action including: emergency preparations (e.g., stocking up on water, flashlights and batteries), elevating service equipment (mechanical or electrical), lifestyle adjustments to reduce exposure (e.g., moving upstairs or downsizing), protective efforts (e.g., "building a brick wall in the garage," waterproofing walls, or procuring sandbags), or accommodations (e.g., investing in French drains, repaving gutters, or "replacing Sheetrock with Wonder board so now it's water in and water out"). While 37% of residents currently or recently had flood insurance, 20% owned backup generators, and only 7% had elevated or were in the process of elevating their homes. Fourteen percent of respondents considered relocating immediately after Hurricane Sandy in 2012, but decided to stay for their home (51%), neighborhood (39%), and/or community (33%). Others were deterred by the cost of relocation (19%), had nowhere else to go (13%), and/or were tied to their mortgage (10%).

The DCEs revealed that only 6% of homeowners and 5% of renters intend to take no action. Households who choose to adapt, opted to insure, elevate their house, and/or relocate among different scenario questions posed by the DCEs. The majority of residents intend to insure in the future (62% of homeowners, 64% of renters) and 41% intend to elevate their homes. Sixty-six percent of homeowners, and 83% of renters intend to relocate, a substantial number considering the political sensitivity of 'retreat' by city government (e.g., NYC, 2013) and the lack of regional and federal preparation for large-scale climate-induced migration.

4.4.1 Influence of personal factors on intended adaptive behavior

Binary logistic regressions were used to investigate the influence of personal factors on the intention to take an adaptation measure against the alternative of taking no action (Tables 4.4 and 4.5). Models 1-3a correspond to permanent relocation from one's neighborhood, procurement of flood insurance, and home elevation, among homeowners, respectively. Models 4a and 5a relate to the uptake of relocation and insurance among renters. The odds ratio (OR) is the exponent of the logistical regression coefficient and represents the relative increase in the odds of taking a given adaptation measure with a factor going from $x_1 = 0$ to $x_1 = 1$ holding x_2, .., x_N fixed, whereby

$$\beta = logit(p(x_1 = 1)) - logit(p(x_1 = 0)) \tag{4.6}$$

and

$$OR = \frac{p(x_1 = 1)/(1 - p(x_1 = 1))}{p(x_1 = 0)/(1 - p(x_1 = 0))} \tag{4.7}$$

which yields

$$e^{\beta} = OR. \tag{4.8}$$

If the OR equals 1, there is no association between the predictor and the uptake of an adaption measure. If the OR is greater than 1, there is a positive association and if the OR is less than one there is a negative association. When interpreting an OR, it is helpful to look at how much it deviates from 1. For example, an OR of 1.25 means that the outcome is 25% more likely. An OR of 0.25 means the outcome is 75% less likely. An OR less than one can also be translated into its counterfactual by taking the inverse. For example, if the predictor *Female* had an OR of 0.50, then females are 50% less likely to take action x and males are twice (1/0.50) as likely to take action x. For continuous variables, the OR corresponds to a one-unit increase in the level of x (see Table 4.1 for variables' units).

Looking at the effects of personal value predictors, we found that homeowners who value avoiding flooding-related costs (whether for damage prevention or recovery) are more likely to relocate ($OR = 1.44$, $p = 0.03$; Table 4.4, Model 1a). Conversely, homeowners who value their current community are less likely to relocate ($OR = 0.69$, $p = 0.02$). Moreover, we found that renters who value avoiding flooding-related costs (in their case, insurance payments or damage to contents) are less likely to buy insurance ($OR = 0.62$, $p = 0.03$), perhaps in part because they already assume coverage from their landlords. These results are to be expected; the predictiveness of these characteristics and their reported values show that respondents gave careful and consistent answers. Finally, renters who spend more hours per week with community members on average (e.g., at civic meetings or for school, athletic, cultural or religious activities) are more likely to purchase insurance ($OR = 1.22$, $p = 0.04$), suggesting that exposure to community members may increase the chance for renters to learn about their responsibility for self coverage and/or how to navigate the flood insurance bureaucracy.

We found multiple lines of evidence that suggest renters have more pressing concerns than flooding that may influence their relocation. In their written comments, renters expressed that they are most concerned with non-flooding issues, like crime, gentrification, and economic hardship, which make living in the area less desirable. Indeed, we found that renters who do not think flooding is a serious issue are 50 times as likely to relocate (OR = 0.02, $p = 0.007$). Although renters perceive flood risks, they may have a false sense of protection that helps mitigate their concern about flooding. Despite having statistically similar perception of flood risk (mean(Renters) = 0.61, mean(Homeowners) = 0.66, $t = 1.11$, $p = 0.27$), renters are less concerned about flooding than homeowners (mean(Renters) = 0.60, mean(Homeowners) = 0.72, $t = 2.66$, $p = 0.008$). Many respondents assumed they have insurance coverage through their landlords. Those in apartment buildings noted that they feel physically removed from the risk. This serves as more evidence that respondents were paying attention, and that the data are consistent as a result; also it supports the important point that action is driven by the internal evaluation of external events, as argued by Weber (2004).

Single-action bias, whereby taking a small action is enough to assuage anxiety (Weber, 2006), is a systematic deterrent of larger scale (and more effective) adaptation measures, such as insurance, home elevation, and relocation. As illustrated in Models 1a and 2a, homeowners who have already taken a ‘low-hanging fruit’ adaptation measure (such as elevating service equipment or stocking up on resources for an emergency) are 80% less likely to relocate (OR = 0.20, p = 0.002) and 66% less likely to insure (OR = 0.34, p = 0.03). These findings suggest that single-action bias is also affecting renters as they tend to perceive that their landlords have already covered their insurance and that living in an apartment building physically removes them from risk. Moreover, renters who had previously been surveyed or interviewed about flooding since Hurricane Sandy are 88% less likely to relocate ($OR = 0.12$, $p = 0.05$). This may reflect single-action bias as discussing one’s experience may feel like taking an action to cope with the problem. On the other hand, participating in an ongoing effort, like renewing flood insurance, can normalize adaptation. In Model 2a, we found that the homeowners who have previously insured are 95% more likely to insure than those who did not ($OR = 1.95$, $p = 0.04$).

Age and education have moderate effects on the intentions to elevate one's home and buy insurance. The odds for home elevation among homeowners are 3% lower per year of age ($OR = 0.97$, $p = 0.02$), while the odds of buying insurance among homeowners are 53% higher per educational degree ($OR = 1.53$, $p = 0.04$). Overall, the majority of socio-economic characteristics (e.g., gender, race, etc.)—often used as indicators of adaptive capacity (e.g., Cutter et al., 2003)—were found insignificant across adaptation measures, for homeowners and renters alike.

4.4.2 Explanatory variables on intended adaptive behavior

Conditional logistic regressions were used to test the influence of non-personal, external stressors simulated in the DCEs on the intention to take an adaptation measure against the alternative of taking no action (Tables 4.6−4.9). Models correspond to permanent relocation from one's neighborhood (1−2b), procurement of flood insurance (3−4b), and home elevation (5−6b), among homeowners. Models 7−8b and and 9−10b relate to the uptake of relocation and insurance among renters, respectively.

Adaptation by peers helps normalize adaptive behavior and signals that flood risk is high. Homeowners are 80% more likely to elevate their homes if their peers do ($OR = 1.80$, $p = 0.005$). Homeowners are nearly 5 times as likely to relocate if their peers relocate ($OR = 4.88$, $p = 0.0006$), and nearly 4 times as likely to relocate if the majority of their peers elevate their homes ($OR = 3.92$, $p = 0.0009$). This suggests that even those who cannot elevate their homes (which is often financially or structurally impractical) may imitate their peers' protective actions by relocating—the remaining alternative under worsening flood conditions. As illustrated by the interaction terms in Model 1b, these effects are slightly reduced for those who value their community members. For example, taking the exponent of the sum of the coefficients for *Peers' relocation* and the interaction term, *Peers' relocation* $\times$ *Community*, exp(1.59 - 0.25 = 1.34), yields a large and positive OR of 3.82.

Illustrated in Model 2b, high insurance premiums increase the odds of relocation by a factor of 4 ($OR = 4.01$, $p = 0.005$). Not surprisingly, the price of insurance also significantly influences homeowners' decision to buy insurance in the future. Homeowners are nearly 62% less likely to buy insurance if premiums rise to \$120 per month, and 88% less likely if premiums rise to \$800 per month. However, homeowners who have previously insured are 13% more likely to insure again despite monthly prices of \$120 per month (Model 3b, OR = exp(-0.98 + 0.86) = 1.13). Insurance prices do not appear to affect the uptake of home elevation, probably because people who would be interested in elevating their homes already tend to insure ($\chi^2 = 18.14$, $df = 1$, $p = 0.001$) and expect discounts in premiums resulting from elevating their homes. High insurance premiums discourage the uptake of insurance among renters ($OR = 0.47$, $p = 0.01$), which is to be expected as flood insurance is more of a luxury good for them, as opposed to homeowners.

A persistent drop in property value substantially increases the odds of relocating ($OR = 9.63$, $p = 3.5E^{-8}$), even if homeowners highly value their community members. Although one might expect homeowners to be trapped by a lack of resources to move, this finding supports the prospect theory of Kahneman (1979; 2011), who showed that people are more sensitive to losses than gains. When property values fall, residents may be motivated to leave before losses plummet further. Although homeowners highly value keeping their homes (mean = 4.31, sd = 0.73), these findings suggest that they are willing to depart from their homes if the market signal is strong enough, as happened after the 2008 financial crisis.

A substantial rise in the cost of rent is the dominant driver of relocation among renters, increasing their odds by a factor of 6 ($OR = 6.35$, $p = 2.40E^{-12}$). This reflects renters' highest priority: affordable housing (mean = 4.37, sd = 0.84; Table 4.1). Moreover, renters who spend more time with their community members are more likely to insure under conditions of decreased rent (Model 10b, OR = exp(-0.37 + 0.15) = 0.80), which may be because decreases in rent increase their ability to afford insurance.

Except for its interaction with previous damage, the prospect of extreme flooding was not a strong predictor of any intended adaptive behavior for homeowners or renters, resembling findings from migration studies where disasters tend not to cause permanent moves (Bohra-Mishra et al., 2014; Botzen et al., 2015). Frequent nuisance flooding, on the other hand, is a systematic driver of relocation and home elevation but inhibitor of insurance uptake. It increases a homeowner's odds of relocation by a factor of 3 ($OR = 3.32$, $p = 3.5E^{-9}$). Perception of public protection moderately reduces these odds to a factor of 2, as shown by taking the difference in OR between Model 1b (without conditions of public protection) and Model 2b (with public protection). Frequent nuisance flooding also encourages renters to relocate ($OR = 2.42$, $p = 0.01$), homeowners to elevate their homes ($OR = 3.17$, $p = 0.02$), and discourages homeowners to insure, decreasing their odds of insuring by 76% ($OR = 0.24$, $p = 0.03$). The latter may be related to the fact that nuisance flooding is not covered by the National Flood Insurance Program. As found in Botzen et al. (2015), there is an interaction between flood hazard and previous damage from flooding on homeowners' intentions to insure in the future. Illustrated in Model 3b, homeowners who suffered damage from Hurricane Sandy are more sensitive to extreme and nuisance flooding, and less inclined to insure in the future.

Inconsistent perceptions about climate change and how it affects flooding may explain why people feel less sensitive to extreme events. While 50% of respondents think local flooding is already more frequent and severe because of rising sea level, 23% expect such changes by 2030, 11% between 2040 and 2050, 7% between 2060 and 2100, and 9% think this will never happen. When asked how many *major* local floods (that could result in 2-3 ft of flooding above their ground level) would occur over the next 20 years, respondents expected an average of 2 (median = 2.21, sd = 2.12, range = $0-10$). Extreme flooding may also be a non-predictor because of a combination of low expectations of future extreme flooding and the loss of wealth among residents who already lost and repaired their homes after Hurricane Sandy. Many residents noted that they would "take their chances", stating that, even with climate change, the chance of an event occurring during their lifetime is small enough that the expected net gain of costly adaptation is lower than that of doing nothing. Yet when prompted about extreme flooding (like that from Hurricane Sandy), many used past events to qualify their expectations for the future, for example noting that they've "only seen 1 or 2 floods over decades of living here, so don't expect many more" in their lifetime. Hence, while the majority of residents (80%) think climate change is happening and that flooding is a serious and near-term issue for their household, most think that nuisance (sub-annual) and major (e.g., 1-in-100 year) but not extreme (e.g., 1-in-500) floods will amplify. In reality, the frequency of all flooding levels (minor to extreme) will increase in the near, intermediate, and long term from sea level rise alone (Buchanan, Oppenheimer and Kopp, 2017) and likely also from increases in the frequency of tropical cyclones (Knutson et al., 2010; Lin et al., 2012). As was the case in the Netherlands, these disjointed perspectives conflict with projections (Botzen et al., 2015), whereby sea level rise is expected to yield large changes in the frequency and intensity of tidal to extreme flooding. Buchanan, Oppenheimer and Kopp (2017) project that the frequency of the historic 10-, 100-, and 500-year flood levels to increase by a factor of 31, 5, and 3 times in New York City by 2050, respectively.

Overall, there is strong support for the presence of single-action bias since there are several statistically significant, negative relationships between the uptake of smaller ('low-hanging fruit') and larger adaptation measures (H1). There is only partial support for H2. Although homeowners value living near the coast and keeping their home, they do not appear to influence adaptive behavior. On the other hand, we found that homeowners who strongly value their community are less likely to relocate and that renters who strongly value their community are more likely to insure. Similarly, there is partial support for H3. There is evidence that homeowners who value avoiding flooding-related costs are more likely to relocate and that renters who value avoiding flooding-related costs are less likely to insure. However, there is no evidence that households who strongly value avoiding flooding-related inconveniences are less likely to insure and elevate, or more likely to relocate. There is strong evidence that households are more likely to adapt when nuisance flooding becomes more frequent (H4) and if their peers adapt (H5). Regarding H6, there is strong support that households are more likely to relocate if their property values fall or costs of rent rise. There is some evidence that large-scale government efforts to reduce flood risk affect adaptive behavior (H7). Although the presence of a specific strategy, like a storm surge barrier or portfolio of natural features are not statistically significant predictors, the presence of *a* strategy substantially reduces homeowners' odds of relocating. Finally, as to be expected, households are much less likely to purchase flood insurance if premiums rise, supporting H8.

Table 4.4: Influence of personal factors on intended adaptive behavior among homeowners (Models 1-3a). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Homeowners								
	Relocate Model 1a			*Insure* Model 2a			*Elevate* Model 3a		
	β	SE	OR	β	SE	OR	β	SE	OR
Income	.00	.00	1.00	.00	.00	1.00	-.01	.00	.99
Married	-.13	.36	.87	.24	.35	1.27	.57	.34	1.76
Age	-.01	.01	.99	.00	.01	1.00	-.02*	.01	**.97**
Female	.56	.32	1.75	.12	.31	1.13	-.26	.31	.77
White	-.51	.37	.60	-.05	.34	.95	-.18	.33	.83
Children	-.08	.39	.92	.50	.39	1.65	-.41	.37	.66
Education	.34	.21	1.41	.42*	.21	**1.53**	-.29	.21	.75
Mortgage	-.48	.29	.62	.25	.28	1.28	.42	.28	1.52
Tenure	.00	.01	1.00	.00	.01	1.00	.00	.01	1.00
Community hrs.	-.03	.06	.97	-.08	.06	.92	.07	.06	1.07
External network	.02	.03	1.02	.00	.03	1.00	-.03	.03	.97
Avoid flood costs	.36*	.16	**1.44**	.07	.15	1.08	-.03	.16	.97
Community	-.37*	.15	**.69**	-.12	.14	.89	.02	.14	1.02
Coast	-.23	.14	.80	-.16	.13	.85	.23	.13	1.26
Avoid inconveniences	-.02	.15	.98	-.28	.15	.75	-.16	.15	.85
Keep home	-.14	.19	.87	.28	.20	1.33	.12	.18	1.13
Flood perception	.17	.37	1.19	-.26	.35	.77	.25	.36	1.28
Flood concern	-.65	.41	.52	.47	.38	1.60	-.12	.38	.88
Climate perception	.63	.50	1.87	-.22	.49	.80	.86	.51	2.36
Experience	-.07	.36	.93	.42	.35	1.52	-.26	.35	.77
Damage level	.00	.01	1.00	-.02*	.01	**.98**	.01	.01	1.01
Surveyed	.39	.49	1.47	.66	.50	1.94	-.25	.46	.78
Insured	.14	.33	1.15	.67*	.32	**1.95**	.58	.32	1.78
Generator	.06	.36	1.06	.04	.35	1.04	.48	.34	1.61
'Low-hanging fruit' adaptation	-1.62**	.53	**.20**	-1.07*	.50	**.34**	-.85	.50	.42
Constant	1.30	1.39	3.66	-.27	1.36	.76	.29	1.33	1.33
R^2		.15			.11			.13	

Notes: *p<0.05, **p<0.01, ***p<0.001

Table 4.5: Influence of personal factors on intended adaptive behavior among renters (Models 4-5a). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Renters					
	Relocate Model 4a			*Insure* Model 5a		
	β	SE	OR	β	SE	OR
Income	-.04	.01	1.00	.01	.01	1.01
Married	-.14	.82	.86	.01	.53	1.01
Age	-.02	.02	.98	-.01	.02	.99
Female	-.49	.81	.61	-.05	.53	.95
White	-.69	.80	.50	-.72	.50	.49
Children	.00	.90	1.00	.17	.62	1.19
Education	.46	.42	1.59	.31	.34	1.37
Tenure	-.04	.02	.96	.00	.01	1.00
Community hrs.	-.18	.12	.83	.20*	.10	**1.22**
External network	-.02	.06	.98	.01	.04	1.01
Avoid flood costs	-.10	.31	.90	-.47*	.21	**.62**
Community	.40	.32	1.49	.04	.20	1.04
Coast	-.08	.28	.92	.13	.19	1.13
Home quality	-.09	.47	.91	.02	.31	1.02
Home affordability	-.24	.48	.79	.16	.31	1.17
Flood perception	2.13	1.09	8.44	-.58	.62	.56
Flood concern	-3.71**	1.38	**.02**	.57	.63	1.77
Climate perception	-.34	1.85	.71	.13	.97	1.14
Experience	-.18	.69	.83	.31	.55	1.37
Damage level	.00	.01	1.00	.01	.01	1.01
Surveyed	-2.14*	1.08	**.12**	-1.23	.93	.29
Insured	-.75	1.19	.47	2.00	1.17	7.40
Generator	-1.87	1.25	.15	-.64	1.16	.53
'Low-hanging fruit' adaptation	2.30	1.48	9.95	-.39	.85	.67
Constant	6.61	3.44	739.61	.07	2.05	1.08
R^2		.15			.11	
.13				.29		
.15						

Notes: *p<0.05, **p<0.01, ***p<0.001

Table 4.6: Influence of personal and external stressors on intended adaptive behavior among homeowners (Models 1-2b). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Relocate					
	Model 1b			Model 2b		
	β	SE	OR	β	SE	OR
Extreme flooding	.24	.20	1.27	.10	.21	1.11
Nuisance flooding	1.20***	.20	**3.32**	.82***	.20	**2.28**
Peers elevate	1.37***	.41	**3.92**			
Peers relocate	1.59***	.46	**4.88**			
Med. insurance	.54	.51	1.71			
High insurance	1.39**	.49	**4.01**			
Barrier				-.36	.57	.70
Natural features				.05	.51	1.05
Property fall				2.27***	.41	**9.63**
Property rise				1.00	.45	2.72
Peers elevate × Community	-.26*	.10	**.77**			
Peers relocate × Community	-.25*	.11	**.78**			
Medium insurance × Avoid flood costs	.03	.12	1.03			
Medium insurance × 'Low-hanging fruit'	-.43	.54	.65			
High insurance × Avoid flood costs	0.05	0.11	1.06			
High insurance × 'Low-hanging fruit'	-.60	.47	.55			
Nuisance flooding × 'Low-hanging fruit'				-1.40	.56	.25
Barrier × Avoid flood costs				-.03	.13	.97
Natural features × Avoid flood costs				.02	.12	1.02
Property fall × Community				-.41***	.10	**.66**
Property rise × Community				-.29	.12	.75
Nuisance flooding × 'Low-hanging fruit'	-.53	.53	.59			
Constant	-2.40	.28	.09	-1.53	.22	.22
R^2 (max possible = 0.5)		.13			.15	

Table 4.7: Continued. Influence of personal and external stressors on intended adaptive behavior among homeowners (Models 3-4b). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Insure					
	Model 3b			Model 4b		
	β	SE	OR	β	SE	OR
Extreme flooding	-.91	.61	.40	-.23	.56	.79
Nuisance flooding	-1.43*	.67	**.24**	-.48	.60	.62
Med. insurance	-.98***	.23	**.38**			
High insurance	-2.15***	.32	**.12**			
Barrier			-.01	.18	.99	
Natural features			-.16	.18	.85	
Property fall			-.48**	.19	**.62**	
Property rise			.03	.18	1.03	
Extreme flooding × Damage	-.02**	.01	**.98**	-.02**	.01	**.98**
Extreme flooding × 'Low-hanging fruit'	-.51	.54	.60	-.14	.47	.87
Extreme flooding × Education	.31	.18	1.36	.16	.17	1.17
Nuisance flooding × Damage	-.02*	.01	**.98**	-.01	.01	.99
Nuisance flooding × 'Low-hanging fruit'	.54	.50	1.72	-.13	.49	.88
Nuisance flooding × Education	.27	.20	1.31	.06	.18	1.06
Med. insurance × Previously insured	.86**	.27	**2.38**			
High insurance × Previously insured	.56	.38	1.76			
Constant	.10	.16	1.11	-.49	.19	.61
R^2 (max possible = 0.5)		.16			.10	

Table 4.8: Continued. Influence of personal and external stressors on intended adaptive behavior among homeowners (Models 5-6b). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Elevate					
	Model 5b			Model 6b		
	β	SE	OR	β	SE	OR
Extreme flooding	.79	.51	2.21	.37	.51	1.44
Nuisance flooding	1.15*	.50	**3.17**	1.50**	.51	**4.48**
Peers elevate	.59**	.21	**1.80**			
Peers relocate	-.08	.23	.92			
Med. insurance	.01	.38	1.01			
High insurance	.17	.36	1.19			
Barrier				.23	.22	1.26
Natural features				.16	.22	1.18
Property fall				-.17	.39	.85
Property rise				.27	.36	1.30
Extreme flooding × Age	-.02	.01	.98	.00	.01	1.00
Nuisance flooding × Age	-.02*	.01	**.98**	-.03**	.01	**.97**
Constant	-1.60	.24	.20	-1.74	.24	.17
R^2 (max possible = 0.5)		.19			.19	

Table 4.9: Influence of personal and external stressors on intended adaptive behavior among renters (Models 7-10b). Coefficients (β), standard errors (SE), and Odds Ratios (OR) are shown. ORs of significant predictors are in bold.

	Relocate						*Insure*					
	Model 7b			Model 8b			Model 9b			Model 10b		
	β	SE	OR	β	SE	OR	β	SE	OR	β	SE	OR
Extreme flooding	-.32	.33	.73	.5	.36	1.64	.21	.55	1.24	.19	.58	1.21
Nuisance flooding	.59	.32	1.81	.88*	.35	**2.42**	-.27	.58	.77	.25	.63	1.29
Peers elevate	.49	.25	1.63									
Peers relocate	.41	.25	1.51									
Med. insurance	.39	.25	1.48				-.43	.28	.65			
High insurance	.4	.25	1.5				-.75*	.29	**.47**			
Barrier				.33	.28	1.39				-.09	.27	.91
Natural features				.35	.27	1.42				-.28	.28	.76
Rent fall				-.31	.27	.74				-.37	.5	.69
Rent rise				1.85***	.26	**6.35**				-2.2	.74	.11
Extreme flooding × Surveyed	-1.56	1.09	.21	-.13	.81	.88						
Extreme flooding × Flood concern	.2	.37	1.22	-.5	.41	.61						
Nuisance flooding × Surveyed	-1.33	.84	.27	-1.47	.88	.23						
Nuisance flooding × Flood concern	-.13	.35	.88	-.23	.38	.8						
Extreme flooding × Avoid flood costs							-.04	.13	.97	-.11	.14	.89
Nuisance flooding × Avoid flood costs							.01	.14	1.01	-.2	.16	.82
Med. insurance × Community hrs.							.09	.06	1.09			
High insurance × Community hrs.							.09	.07	1.09			
Rent fall × Community										.15**	.13	**1.16**
Rent rise × Community										.28	.19	1.32
Constant	-.99	.27	.37	-1.4	.31	.25	-.2	.22	.82	-.25	.27	.78
R^2 (max possible = 0.5)		.04			.12			.04			.12	

Notes: *p<0.05, **p<0.01, ***p<0.001

4.5 Conclusion

These findings were derived from NYC and the degree to which they can be generalized to other places and other times is uncertain. However, this work provides an approach to better understand household adaptive behavior and how to shape further studies. Moreover, the saliency of this NYC study provides important lessons that may be applicable elsewhere. This work confirms that emotions and perceptions filter public information about flood risk in a changing climate and that external factors heavily influence the uptake of costly, preventative adaptation measures. Conversely, socio-economic factors—commonly used to assess vulnerability to environmental hazards—were generally poor predictors.

Households (homeowners and renters) who made small-scale adaptations are systematically less likely to take additional preventative measures. This may have large-scale implications for coastal cities and communities investing in programs to support the uptake of both small-scale (e.g., service equipment elevation) and more costly (e.g., home elevation) resilience measures among residents. This work is part of a long-term research program focusing on various actors (including local governments and businesses) in different urban contexts. More research is required to help avoid unintentional perverse incentives that may act to reduce household and community-level resilience overall.

Public programs assisting with resilience and adaptation could be adjusted to better incorporate the values, needs, and realities of community members. Future research is needed to better understand what works, and could be improved, in such programs (e.g. for home elevation and relocation buyouts). This could reduce the psychological cost of adaptation and likely yield more effective and efficient outcomes in the process. Incorporating lessons from past, recent, and ongoing climate impacts to help improve government programs is especially important since climate impacts will likely demand shorter response time for risk management.

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Chapter 5

Future Work: The Resilience Evaluation Model

5.1 Introduction

Although the extent to which flooding will increase is uncertain, coastal communities around the world are now deciding upon public adaptation measures—large-scale efforts administered by local and national governments to help cope with enhancing flood hazards. These measures may include traditional structures (e.g., sea walls and storm surge barriers) or natural and nature-based features (NNBF, e.g., wetlands and marshlands; Bridges et al., 2015); both types are investments, often with high up-front costs. For example, the average costs of a storm surge barrier and NNBF across the U.S. Northeast are ∼\$912 per cubic foot and ∼\$1,415 per linear foot, respectively (USACE, 2015*c*). The ultimate goals of public adaptation are typically to reduce flood risk (the exposure and vulnerability of people and assets to flood hazards; Seneviratne et al., 2012), and to increase the long-term sustainability and resilience of communities (USACE, 2015*a*,*c*). Evaluating how public adaptation strategies serve these goals involves modeling coupled systems of flood hazard and human behavior.

Here, we develop the Resilience Evaluation Model (REM) to assess these complexities and support community adaptation decision-making.

A common approach to decide among adaptation options is traditional cost-benefit analysis (CBA), which weighs residual flood risk (expressed in terms of expected annual damage; EAD) against the expected cost of an adaptation strategy. CBA usually omits individuals or households, and if not, assumes they have uniform preferences and are economically rational. In reality, households are dynamic agents. They respond to changing flood hazards to varying degrees, and are capable of reducing their susceptibility to harm by taking private adaptation measures, such as procuring flood insurance, elevating houses, or relocating. While public adaptations can reduce flood risk by mitigating or accommodating floodwater, they can also change the urban landscape and alter the incentives and signals that motivate households to take private adaptation measures. These interactions affect the exposure and vulnerability of different groups in a community, potentially limiting the uptake of private adaptation measures by disadvantaged groups.

As public adaptation investments are typically an immense expense, intended to leave a community better off, CBA may be insufficient to assess an adaptation strategy's holistic effect on a community. Agent-based models (ABMs) are a promising alternative and have become an increasingly attractive tool for assessing climate change impacts. They allow for interactions and feedbacks in coupled social and natural systems, lending themselves to exploration of complex and emergent behavior. A small number of ABM case studies have focused on the coastal zone to better understand emergency response (Dawson et al., 2011), the sensitivity of housing markets to flood hazards (e.g., Magliocca et al., 2011; Filatova et al., 2011; Karanci et al., 2017), the uptake of flood insurance in response to changes in premiums and SLR (Dubbelboer et al., 2017; Putra et al., 2015), and EAD from SLR (Haer et al., 2016). These models have some important limitations. They are rarely populated by spatially-explicit observations of households and, with the exception of Karanci et al. (2017), employ simplistic estimates of SLR. While Haer et al. (2016) showed that neglecting human behavior can greatly misrepresent flood risk, they did not consider non-economically motivated agents. These models have also not considered broader elements of resilience beyond flood risk or been used to evaluate large-scale flood protection strategies.

We propose a Resilience Evaluation Model (REM), a spatially explicit agent-based modeling framework assessing risk and resilience under candidate flood protection strategies. REM combines flood hazard with human behavior models and the built environment to evaluate the efficacy of large-scale flood protection strategies across socio-economic groups (Solecki et al., 2015). We measure the overall impact on flood risk and broader resilience indicators, such as the distribution and aggregate values of household uptake of adaptation measures (such as insurance, home elevation, or planned relocation; Solecki et al., 2015; Buchanan, Oppenheimer and Parris, 2017).

REM accounts not only for economically-rational household behavior but also behavior influenced by feelings, values, peers, and evolving risk perception. REM is the first to use probabilistic projections of local SLR and locally-characterized depth-damage functions. To the best of our knowledge, no other ABM has assessed resilience outcomes of government efforts to reduce flood risk. For illustration, we apply REM to neighborhoods surrounding Jamaica Bay in New York City (NYC), a socio-economically diverse area affected by Hurricane Sandy in 2012 and increasingly exposed to flood hazard.

5.2 Methods

5.2.1 Framework

REM is empirically based and spatially explicit for flood hazards, households, and residences. Household characteristics include socio-economic, psychological, and social factors, while housing characteristics include market value, geospatial coordinates, ground elevation, flood zone, flood insurance price, and flood depths associated with various flood return periods (Section 5.2.4). REM uses an agent-based model to simulate flood hazard (Section 5.2.2), flood damage (Section 5.2.3), and the adaptive behavior of households, following three alternative, utility-maximizing decision-making models: economically rational, psychological-social with static flood perception, and psychological-social with dynamic flood perception (Figures 5.1; Section 5.2.4).

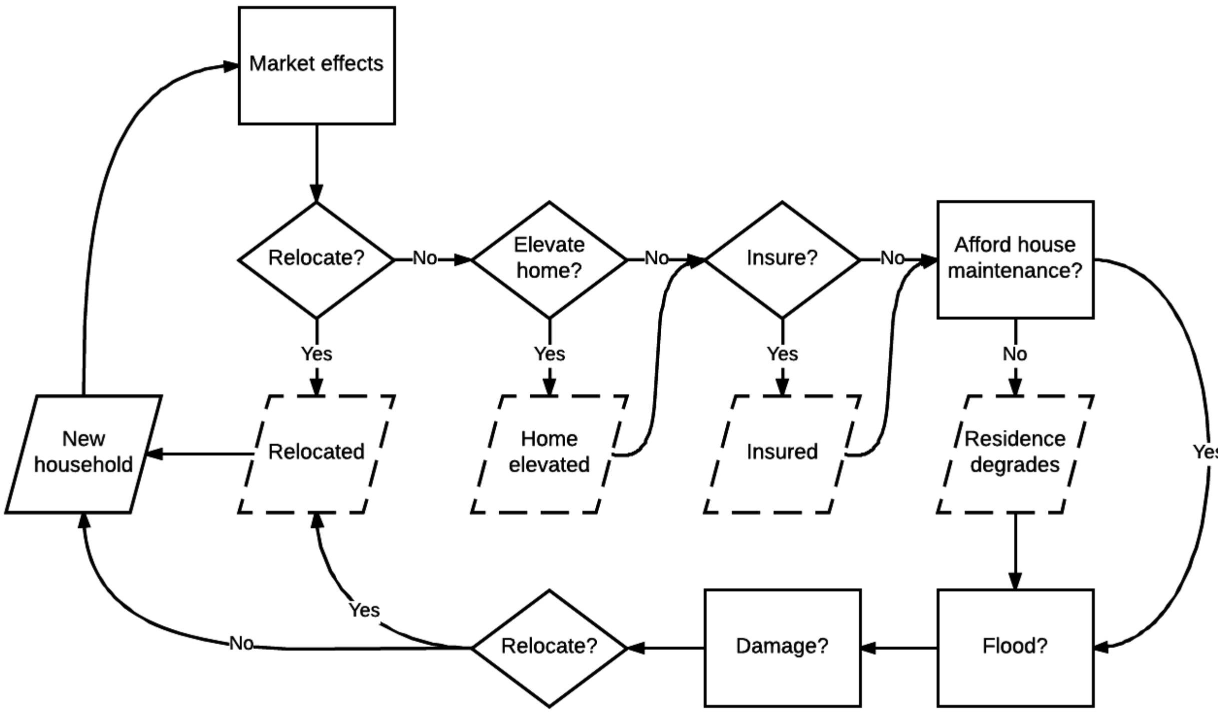

Figure 5.1: Overview of initialization and an annual time step of the model (which is repeated for 30 years). Model processes are represented by rectangles, decisions by triangles, and key state variable outcomes by slanted squares. Resilience indicators are dashed.

5.2.2 Flood hazard

Surface elevation

Topographic and bathymetric data are combined to create a topobathy Digital Elevation Model (DEM) of land and seafloor elevation above a shared vertical datum (e.g., the North American Vertical Datum of 1988, NAVD88). A baseline DEM of the existing topography is modified by public adaptation measures to create a set of DEMs representing alternative topographies. Spatial databases of property tax records are then mapped to the DEMs.

Flood return levels under stationary sea level

Storm tide distributions can be simulated with hydrodynamic models, which may then be fit by an extreme value distribution to estimate the storm tide frequency distribution (e.g., Lin et al., 2012). Alternatively, water level observations can be fit to an extreme value distribution to estimate a storm tide distribution (e.g., Buchanan et al., 2016; Buchanan, Oppenheimer and Kopp, 2017).

Historic flood levels (z), corresponding to a representative set of annual chance floods, are mapped onto the baseline and modified DEMs. This set includes extreme floods such as the 10%, 1% and 0.2% annual chance floods.

Nuisance flooding, the temporary inundation of areas (particularly streets) due to high tides, can be benchmarked as 0.5 m above Mean Higher High Water (MHHW; Sweet and Park, 2014). The frequency corresponding to this local nuisance flood level can be included in the representative set of floods.

Emerging flood frequencies with sea level rise

SLR increases the frequency of all flood levels. New flood frequencies are calculated drawing upon the methodology of Buchanan et al. (2016) and Buchanan, Oppenheimer and Kopp (2017), whereby the expected number of annual chance floods, $N(z)$, is adjusted by an amount of SLR using the Poisson-distributed GPD:

$$N(z) = \begin{cases} \lambda(1 + \frac{\xi(z-\mu-\delta)}{\sigma})^{\frac{-1}{\xi}} & \text{for } \lambda \leq 1 \text{ event/year} \\ \lambda \exp(-\frac{z-\mu-\delta}{\sigma}) & \text{for } \lambda \geq 1 \text{ event/year} \end{cases} \tag{5.1}$$

The location parameter (μ) relates to local sea level, the scale parameter (σ) to the variability in the maxima of water level caused by the combination of tides and storm surges, and the shape parameter (ξ) to the curvature and upward limit of a flood frequency curve. δ is an amount of SLR and λ is the Poisson-distributed annual mean number of flood events. Below the GPD threshold of λ events per year, we fit a Gumbel distribution with 182.6 events exceeding MHHW per year, assuming about half of all days have higher high water levels above MHHW. Nuisance flooding is considered frequent when the local 0.5 m benchmark of flooding above MHHW is experienced 30 days per year (about 2.5 times a month; Sweet and Park, 2014).

We use 10,000 Monte Carlo samples of Kopp et al.'s (2014) local SLR projections for the 21st century, accounting for global and local contributions, including land subsidence, distributional effects of land-ice melt (e.g., SLR fingerprints), and expert assessment of dynamic ice-sheet collapse. These SLR projections are asymmetric, and—due primarily to the poorly constrained but potentially large contribution of the Antarctic ice sheet (e.g., DeConto and Pollard, 2016)—positively skewed. we use Representative Concentration Pathways (RCP), RCP 8.5, which represents greenhouse gas concentrations that lead to a radiative forcing of 8.5 W m^{-2} by 2100 (Van Vuuren et al., 2011).

5.2.3 Flood damage

Local flood depth-damage functions can be used to estimate the percent damage (d) to a structure resulting from a flood depth (f) above ground elevation. The total damage cost ($c_{(d,t)}$) to a property is the product of its percent damage and structural value (v_s), where x is the amount of insurance coverage:

$$c_{(d,t)} = \begin{cases} (dv_s) - x & \text{if insured (after a deductible)} \\ dv_s & \text{if not insured} \end{cases} \tag{5.2}$$

Households with residual damage costs may take out a loan whereby c_d are the annual damage payments:

$$c_d = \frac{lr_i}{1-(1+r_i)^{-N}} \tag{5.3}$$

where l is the loan's principle, r_i is the annual interest rate, and N is the loan's duration. We assume that homeowners may borrow 85% of the total damage cost.

5.2.4 Human behavior

Household and Housing Characteristics

Household characteristics reflect important drivers of private adaptation and demographic profiles of the case study area. Included households are representative of the given population. Socio-economic characteristics, including income, age, race/ethnicity, and education are drawn from the American Consumer Survey census (U.S. Census Bureau, 2015). Observations of past uptake of adaptation measures (i.e., flood insurance, home elevation, and if possible, relocation) as well as experiments that capture predictors of projected adaptive behavior used in the psychological-social behavior models are identified by in-depth interviews and analysis of semi-structured surveys of case study households (e.g., Buchanan, Oppenheimer and Parris, 2017). Depending on the context, these factors may include personal values, peer influence, measures of risk identification, flood hazard and tolerance.

Tax records are obtained by local municipalities to represent each property individually. Market property value v_p is equal to the assessed property value divided by the local equalization rate, a measure of a municipality's level of assessment. A property's v_p is then divided by the number of its residential units. For renters, the annual cost of rent c_r is $v_p/r_{p:r}$, where $r_{p:r}$ is the price-to-rent ratio (e.g., Zillow, 2017). Household income h is initially set as:

$$h = \begin{cases} (c_t + c_m)/\tau & \text{for homeowners} \\ c_r/\tau & \text{for renters} \end{cases} \tag{5.4}$$

where τ is the fraction of income spent on housing and c_m are annual mortgage payments, estimated by:

$$c^m = \frac{l * r_i}{1 - (1 + r_i)^{-N}} \tag{5.5}$$

where l is the loan's principle, r_i is the annual interest rate, and N is the loan's duration set to 30 years.

Households' annual income levels change stochastically to reflect market variability, projected market growth, and inflation (Dinan, 2016; U.S. Census Bureau, 2016). We assume that income levels do not change with retirement and that a head-of-household dies at the age equal to the area's life expectancy, after which a new household moves in. We assume there is a large supply of new households for areas with high coastal amenity value and expected population growth (Dinan, 2016). As a result, new households with enough capital move into vacant residences.

Residences are also characterized by their property quality and other attributes affecting their flood risk, such as elevation, flood zone, insurance premium, whether or not they are elevated, and their expected flood depth and percent damage from flood events. Property quality (q) is drawn from a uniform distribution, whereby a q of 0 and 1 relates to properties that are poorly and well maintained. The cost of annual property maintenance c_p is set to 1% of the property value. If a property is maintained, its quality remains the same and its value increases by 1%; otherwise its value decreases by 1% and its quality by 10%. Property quality also decreases by an amount equal to its percent damage.

Flood insurance rate premiums depend upon a residence's flood zone, distance of its lowest floor above the base flood elevation (BFE), and whether it has a basement. They also depend on when the house was built with respect to the area's first Flood Insurance Rate Map (FIRM). Structures that pre-date this map (known as *pre-FIRM*) qualify for subsidized premiums because they were built before ensuing flood risk communications and regulations, such as improved building codes. Under the Homeowner Flood Insurance Affordability Act of 2014, subsidized rates available for pre-FIRM structures increase by 5% a year until they reach the actuarial rates of post-FIRM structures. Tax records are used to identify structures' pre- or post-FIRM status and presence/absence of a basement, while the most recent FIRM is used to identify structures' flood zones (FEMA, 2015). Premiums can be drawn from a uniform distribution using the wide range of available prices that depend on structures' flood zone, presence/absence of a basement, and pre- or post-FIRM status. Household and housing characteristics are listed in Table 5.1.

Table 5.1: Housing characteristics in Jamaica Bay

Category	Attribute	Description
Location	Region	Neighborhood region: Brooklyn, Central Jamaica Bay, East Rockaway, and West Rockaway
	Geospatial	Longitude and latitude coordinates
Structural	Resident type	House or apartment building
	Property quality (q)	Maintenance level of housing structure: on a scale from 0 to 1 from poorly to well maintained
Financial	Property value (v_p)	Market value of housing structure and land ($k)
	Structure value (v_s)	Market value of housing structure ($k)
	Adaptation cost (c_a)	Total annual cost of all adaptation measures, including insurance and home elevation payments ($k)
	Total damage cost ($c_{(d,t)}$)	Gross damage cost from a flood event ($k)
	Damage payments (c_d)	Cumulative annual cost from damage to housing structure ($k)
	Home elevation payments (c_e)	Annual loan payment ($k)
	Flood insurance cost (c_i)	Annual ($k)
	Mortgage payments (c_m)	Annual ($k)
	Property maintenance cost (c_p)	Annual ($k)
	Rent cost (c_r)	Annual ($k)
	Property tax cost (c_t)	Annual ($k)
	Flood Insurance premium	Federal flood insurance price ($ per month)
Flood risk	Elevation (e)	Home elevation level above the ground
	Elevated?	Whether property has been elevated (yes/no)
	Flood depth (f)	Annual inundation level resulting from flood events (feet)
	Percent damage (d)	Percent of structure damaged from inundation

Behavior Models and Adaptation

Homeowners may insure and/or elevate their homes, while renters may insure their contents. Both renters and homeowners can relocate. Adaptation decision-making occurs annually, reflecting annually updated insurance policies and the ongoing salience of flooding. While home elevation and relocation are permanent adaptations, insurance can be canceled every year. To analyze the sensitivity of results to household behavior, REM is run separately for three adaptive behavior models which assume households are either (1) economically rational, (2) influenced by psychological and social factors (psycho-social), or (3) influenced by psycho-social factors as well as the salience of flooding.

Economically Rational Behavior Model Under this adaptive behavior model, people will only take actions that increase their overall expected utility (EU), i.e., for which subjective benefits exceed subjective costs. As in Haer et al. (2016), the EU of taking an adaptation measure is calculated over the sum J possible flood events j with a probability p_j of occurring. For example, J may include flood levels with 10%, 1%, and 0.2% annual chance of occurrence. Utility ($U(x)$) is based on the outcome of these events, determined by the cost (C) of an adaptation measure, the insurance premium discount (D) available to households with elevated homes, and the residual damage (R_j) to property despite the presence of adaptation measures. If no flood occurs, there is no residual damage and $R_j = 0$. The expected utility of taking no adaptation measures is based on the potential for loss (L_j). While insurance and relocation are measures that can be taken annually, home elevation requires a commitment to a future stream of payments for years 1 to N. Thus, the expected utility for home elevation is the net present value of the investment;

$$\mathbf{EU} = \begin{cases} \sum_{j=1}^{J} p_j U(-L_j) & \text{for no action} \\ \sum_{j=1}^{J} p_j U(D - C - R_j) & \text{for flood insurance or relocation} \\ \sum_{n=1}^{N} \sum_{j=1}^{J} p_j U(D - C - R_j)/(1+r)^n & \text{for home elevation} \end{cases} \tag{5.6}$$

Psychological-Social Behavior Model Under this model of human behavior, an array of internal and external factors influence the expected utility of adaptation measures. These may include personal values and psychological motivations related to risk identification and previous adaptations, along with external stressors such as floods and the behavior of peers. F_j is a reduced set of households' internal or external factors drawn from semi-structured surveys in the case study area. The set of adaptive measures $a \in \{i, e, r\}$, represents insurance, home elevation, and permanent relocation, respectively. Households' intention to take adaptive measure a is determined by the following logistic regression model:

$$\ln\left(\frac{P(a)}{1 - P(a)}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j F_j \tag{5.7}$$

which is transformed into probability,

$$P(a) = \frac{\exp(\beta_0 + \sum_{j=1}^{k} \beta_j F_j)}{(1 + \exp(\beta_0 + \sum_{j=1}^{k} \beta_j F_j))} \tag{5.8}$$

Psychological-Social Behavior Model with Dynamic Flood Risk Perception This behavior model mirrors that of the Psychological-Social model, except that residents update their flood risk perception annually based on the occurrence (or non-occurrence) of floods. 'Focusing events' inflict harm, have the potential to inflict future harm, and reinforce the perception of harm (Kingdon and Thurber, 1984). Large floods often serve as focusing events, as demonstrated by the aftermath of Hurricanes Katrina and Sandy, among others. We assume there is a small annual decay in risk perception after a year with no floods and a potentially large increase in perception following a 'focusing' event (e.g., Egan and Mullin, 2012). In a given year, flood risk perception (p) is:

$$p(t) = p_0 \exp^{-\lambda t} \tag{5.9}$$

whereby $t = 1$, $\lambda \in [0, 0.05]$ in a year with no major floods, and $\lambda \in [-0.3, 0]$ in a year with a major flood.

Adaptation We follow the approach of Kniveton et al. (2012) to determine whether an intention to adapt leads to action, whereby a household takes an adaptation measure if the probability of their intention is larger than a random number, uniformly distributed between zero and one. A household's adaptation is also constrained by its budget. They may not take intended adaptation actions if their income less mortgage and property tax payments leaves insufficient capital. Households' annual budget can be simplified as:

$$(0.5 * h) \geq \begin{cases} (c_m + c_t + c_d + c_a + c_p) & \text{for homeowners} \\ (c_r + c_a) & \text{for renters} \end{cases} \tag{5.10}$$

where adaptation costs include annual insurance payments and/or home elevation costs for homeowners. We assume that residents cannot afford to pay more than 50% of their income on housing-related costs (Putra et al., 2015). Homeowners may not buy flood insurance or elevate their homes if their property quality is below 0.5 and 0.8, respectively. Residents who are below their housing spending threshold prioritize damage costs, then adaptation costs, and finally, routine maintenance costs. No homes are elevated or insured at initiation to allow for model validation.

5.3 Application to Jamaica Bay

We apply REM to neighborhoods surrounding Jamaica Bay, an area facing some of the highest flood risk in NYC. Substantial damage occurred throughout the study area from Hurricane Sandy in 2012, including 10 fatalities and the destruction of over 1,000 structures (USACE, 2016). The damage from Sandy and the increasing potential for future flood damage has incited NYC, NY State, and Federal agencies to invest in public flood protection. There are two leading alternatives under consideration (USACE, 2016): (1) a structural storm surge barrier and, (2) natural and nature-based features (NNFB). A storm surge barrier across the Jamaica Bay inlet would crest approximately 17 ft above NAVD88 to help mitigate flooding. Alternatively, a portfolio of NNBF including newly cultivated marshes and living shorelines would span the Jamaica Bay perimeter to help accommodate floodwater. While a storm surge barrier would offer more protection against extreme flooding, NNFB would likely do so for more moderate flooding (e.g., Nordenson et al., 2014; de Castella, 2014, February 11; Bridges et al., 2015; USACE, 2015*c*).

The area is culturally and socio-economically diverse and divided (Kornblum and Van Hooreweghe, 2010; U.S. Census Bureau, 2015). Like many urban areas, gentrification is a growing concern (Higgins, 2016). The Rockaway Peninsula, for example, spans a gradient of wealth, from low in the east (e.g., Far Rockaway) and increasingly high toward the west (Table 5.5). The area can be grouped into four major neighborhood regions: Brooklyn, Central Jamaica Bay, East Rockaway, and West Rockaway (excluding John F. Kennedy International Airport (JFK); Figure 5.2). Together, these regions encompass over 7,000 apartment buildings and nearly 59,000 houses. 53.9% of households are renters and 46.1% are homeowners. Although flood insurance is formally required for federally-backed mortgages and nearly 90.0% of structures in the area qualify for subsidized premiums, flood insurance uptake is modest (Dixon et al., 2013). While approximately 35.7% of homeowners and 6.0% of renters have insured, 4.9% of homeowners have elevated their homes (Buchanan, Oppenheimer and Parris, 2017).

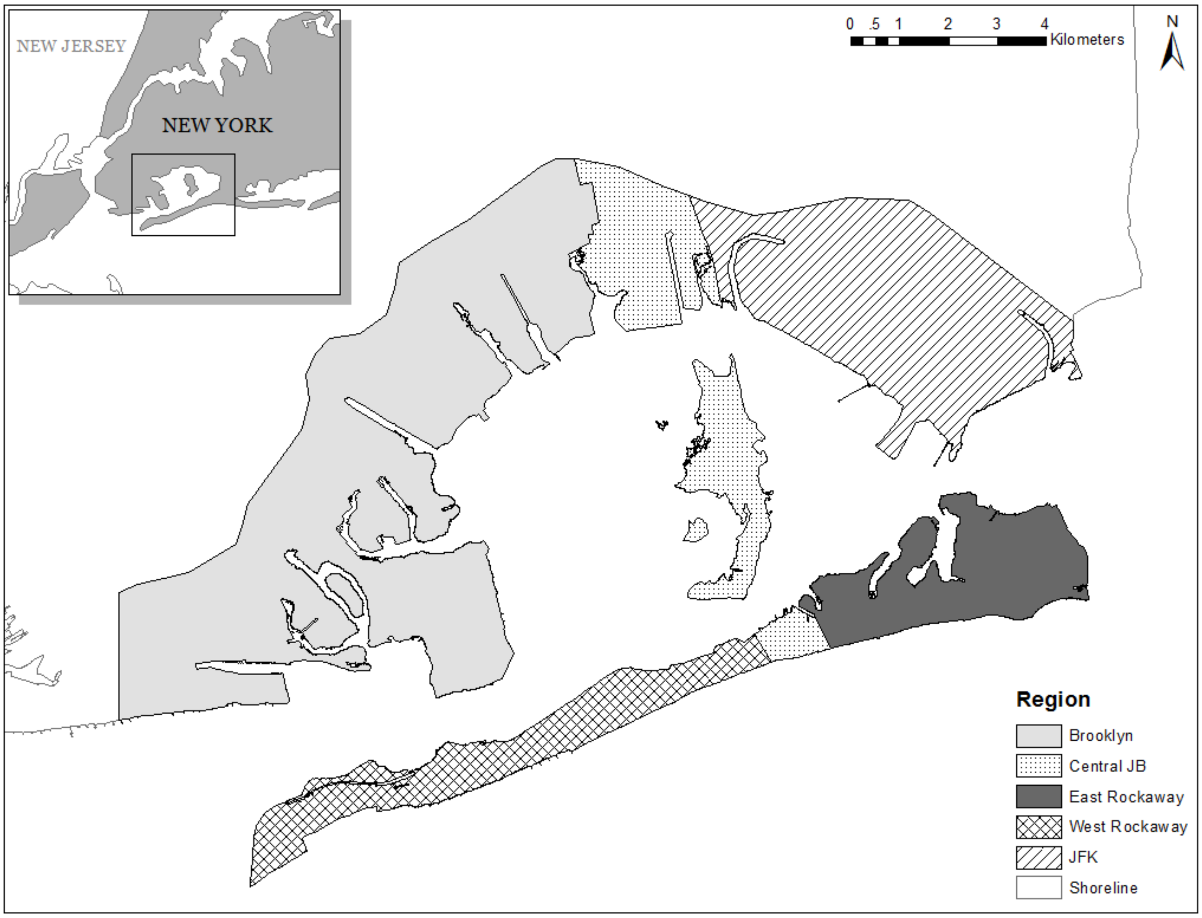

Figure 5.2: Jamaica Bay study area divided into four major regions: Brooklyn, Central Jamaica Bay (JB), East Rockaway and West Rockaway.

5.3.1 Flood hazard and damage

The topobathy DEM of Nordenson et al. (2014), combining coastal elevation and bathymetric data, were used for the baseline topography. NNBF Landscape designs from Nordenson et al. (2014) were used as the NNBF topography. Because the candidate barrier exceeds flood depths associated with the 500-year flood (across properties), we assume it is 90% reliable in protecting against the 100-year and 500-year floods. However, as use of the barrier is expensive and it is not likely operational for less extreme floods, we assume the barrier offers no protection under the 10-year flood or nuisance floods. The NYC Department of City

Table 5.2: Annual expected number of floods under RCP 8.5

	3/yr	10yr	100yr	500yr
2010	10	0.2	0.01	0.003
2020	21	0.3	0.02	0.003
2030	42	0.5	0.02	0.003
2040	83	1.0	0.03	0.004
2050	126	3.2	0.05	0.005
2060	153	10.2	0.18	0.007
2070	166	28.2	0.58	0.041

Planning's MapPLUTO was used as the spatial database of property tax records (NYC, 2010).

Flood depths associated with the set of annual chance floods (the 10%, 1%, and 0.2% annual chance flood levels) over ground elevation were calculated by Nordenson et al. (2014) following the methodology of Lin et al. (2012), which uses a statistical-deterministic hurricane model to generate synthetic storms. These storms are simulated with observed wind and pressure data from the National Center for Environmental Protection and the National Center for Atmospheric Research. Two hydrodynamic models, the Sea, Lake, and Overland Surges from Hurricanes Model and the Advanced Circulation Model, are used to simulate 3,000 storms and calculate storm tide frequency distributions.

Following the methodology of Buchanan et al. (2016) and Buchanan, Oppenheimer and Kopp (2017), Eqn. 5.1 is used to calculate the new frequencies of annual chance floods with SLR over time. In New York City, 0.5 m above MHHW occurs an average of 3 times per year. Hence, this 3/year annual chance flood frequency is added to the representative set of floods to account for nuisance flooding. Ten thousand Monte Carlo samples of local SLR projections of Kopp et al. (2014) for the Battery tide gauge were combined with the storm tide distribution for each decade to account for changes in SLR over time.

A depth-damage function is calibrated by fitting the extent of property damage resulting from observed water levels during Hurricane Sandy. We subset the NYC building-level dataset of damage and flood depths compiled by Hatzikyriakou et al. (2015), whereby the percent damage of a residential structure d resulting from flood depth f is $d = 0.01 + 0.07f$ (p-value < 0.001, $R^2 = 0.76$, $n = 31{,}306$).

5.3.2 Human behavior

Household and housing characteristics

Predictors of adaptive behavior used in the psychological-social behavior models are drawn by in-depth interviews and a semi-structured survey of case study households ($n = 465$; Buchanan, Oppenheimer and Parris, 2017). These factors include personal values, peer influence, measures of risk identification, flood hazard tolerance, and past and present adaptations. Tables 5.3 and 5.4 illustrates the survey instrument and descriptive statistics for households.

Table 5.5 shows housing and household characteristics for Jamaica Bay neighborhood regions. Equalization rates for properties in Queens and Brooklyn are 12.75 and 11.21, respectively (New York City, 2017*a*). For renters, the price-to-rent ratio from 2010-2016 is $\mu = 19.4$, $sd = 1.0$ (Zillow, 2017). Household annual income levels change stochastically by an average of 2% ($sd = 0.005$) to reflect market variability, projected market growth, and inflation (Dinan, 2016; U.S. Census Bureau, 2016). We assume that a head-of-household dies at age 81 (the overall 2013 life expectancy for NYC) and that there is a large supply of new households given the area's high coastal amenity value and expected population growth (Dinan, 2016). Property quality q is drawn from a uniform distribution, whereby $q \in [0, 1]$.

The area's first FIRM was instituted in 1983. Approximately 40% of properties in Jamaica Bay are in a high-risk flood zone (i.e., zones A or V) and over 90% are pre-FIRM. Premiums are drawn from a uniform distribution using the wide range of available prices in Dixon et al. (2013) that depend on structures' flood zone, presence/absence of a basement, and pre- or post-FIRM status (Table 5.6). These rates assume coverage of \$200,000 for the structure and \$80,000 for contents, with a \$1,000 deductible for homeowners. Renters are eligible for coverage of \$50,000 for contents, as is typical for insured renters in the area (Dixon et al., 2013).

Table 5.3: Survey instrument in Jamaica Bay

Category	Attribute	Description
Socio-economic	Resident type	Homeowner or renter
	Region	Neighborhood region: Brooklyn, Central Jamaica Bay, East Rockaway, and West Rockaway
	Income (h)	Annual household income ($k)
	Age	Age of head-of-household
	Education	Highest degree of head-of-household: none = 1, high school = 2, college = 3, advanced degree = 4
	Race/ethnicity	Whether a head-of-household is non-white/non-hispanic (yes/no).
Values		*On a scale of 1 to 5 with 1 being 'Not important' and 5 being 'Extremely important':*
	Community	The importance of living near one's current community.
	Coast	The importance of living close to the coast.
	Avoid flood costs	The importance of the avoiding flood-related costs.
	Avoid inconveniences	The importance of avoiding inconveniences (like traffic, road blocks, time away from residence.)
	Keep home	The importance of keeping one's home.
	Home affordability	The importance of an affordable residence.
	Home quality	The importance of residential quality.
Risk identification	Flood perception (p)	Degree to which one perceives they live in an area prone to major flooding: yes = 3, uncertain/reconsidering = 1, no = 0.
	Flood concern	How serious of an issue flooding is considered for a household: very = 4, somewhat = 3, uncertain/reconsidering = 2, not = 1.
	Community hours	Average number of hours per week spent with neighborhood community members.
	Other adaptation?	Previous uptake of small resilience effort, excluding insurance (yes/no).
Behavior	Insured?	Whether a household buys flood insurance (yes/no).
	Elevated?	Whether a household elevates their home (yes/no).

Table 5.4: Survey instrument and sample characteristics

	Variable	Description	Mean	St. Dev.
Socioeconomic	Income	Household annual income ($ 1,000)	89.30	52.32
	Age	Age in years	49.72	16.28
	Education	Advanced degree = 4, College degree = 3, High School degree = 2, None = 1	2.99	.77
	Homeowner	Yes = 1, No = 0	.67	.47
Cognitive	Flood perception (owners)	'Do you live in an area prone to major flooding?' Yes = 1, No = 0, I don't know = 0.5	0.66	0.46
	Flood perception (renters)		0.61	0.47
	Flood concern (owners)	'How serious of a problem do you think flooding is for your household? Serious = 1, Not serious = 0, I don't know = 0.5		
	Flood concern (renters)		0.60	0.48
Values		'On a scale of 1 to 5 with 1 being 'Not important' and 5 being 'Extremely important', how important are the following to you?':		
	Avoid flood cost	Avoiding flooding-related costs	3.95	1.19
	Community	Living near your current community	3.54	1.29
	Coast	Living close to the coast	3.54	1.34
	Avoid inconvenience	Avoiding inconveniences (like traffic, roadblocks, time away from residence; owners)	3.72	1.08
	Keep home	Keep residing in your home (owners)	4.31	.73
	Home quality	Quality of residence (renters)	4.25	.88
	Home affordability	Affordability of residence (renters)	4.37	.84
Situational	Community hrs.	Hours per week participating in community activities	2.33	2.68
Previous adaptations	Elevated	Currently or recently elevated their home. Yes = 1, No = 0	.07	.26
	Insured	Currently or recently have flood insurance. Yes = 1, No = 0	.38	.49
	'Low-hanging fruit' adaptation	Currently or recently taken other flood protection action. Yes = 1, No = 0	.09	.28

Table 5.5: Initial values for Jamaica Bay households. Note: mean and standard deviation values are shown, unless otherwise specified.

Attribute	*Brooklyn*		*Central Jamaica Bay*		*East Rockaway*		*West Rockaway*	
	Owners	Renters	Owners	Renters	Owners	Renters	Owners	Renters
Households	66,124	75,406	7,889	6,355	7,889	17,798	4,156	4,244
Income ($1,000)	138.86 (51.73)	33.09 (15.96)	135.06 (49.22)	30.95 (9.36)	105.50 (37.58)	29.92 (12.37)	179.52 (65.04)	28.54 (11.71)
Resident type	34%	66%	62%	38%	30%	70%	74%	26%
Mortgage	64%	-	65%	-	72%	-	53%	-
Age	57 (14.5)	50 (16.6)	56 (14.3)	47 (14.4)	53 (14.2)	49 (16.3)	59 (14.9)	56 (13.6)
Education	1.97 (0.00)		1.88 (0.00)		1.76 (0.00)		2.29 (0.00)	
Race/ethnicity	61%		67%		82%		13%	
Community hours	1.69 (2.33)	1.06 (1.91)	2.75 (2.64)	2.11 (2.47)	2.25 (3.05)	0.09 (0.30)	2.75 (2.74)	3.52 (2.99)
Avoid flood costs	3.81 (1.15)	3.10 (1.36)	4.29 (1.16)	3.95 (1.08)	4.62 (0.75)	4.10 (0.83)	4.10 (1.05)	4.15 (1.19)
Avoid inconveniences	3.71 (1.04)	4.26 (0.98)	3.61 (1.15)	4.26 (0.99)	4.04 (1.00)	4.09 (0.94)	3.58 (1.16)	4.35 (0.75)
Community	3.24 (1.23)	2.69 (1.42)	4.04 (1.10)	3.79 (1.36)	3.65 (1.23)	3.00 (1.27)	3.96 (1.20)	3.73 (1.19)
Coast	2.96 (1.31)	2.73 (1.37)	3.69 (1.30)	3.37 (1.64)	3.92 (1.44)	3.46 (1.29)	4.36 (0.85)	4.08 (1.02)
Keeping one's home	4.10 (1.02)	4.39 (0.87)	4.52 (0.92)	4.32 (1.06)	4.54 (0.71)	4.27 (0.79)	4.42 (0.84)	4.23 (0.82)
Flood perception	1.00 (1.36)	1.28 (1.47)	2.44 (1.13)	2.63 (0.90)	1.73 (1.43)	2.55 (1.04)	2.63 (0.97)	2.39 (1.17)
Flood concern	2.27 (1.23)	1.98 (1.19)	3.04 (1.17)	3.32 (1.00)	2.77 (1.18)	2.64 (1.36)	3.15 (0.97)	3.19 (0.94)
Other adaptation	0.05 (0.21)	0.08 (0.27)	0.11 (0.32)	0.05 (0.23)	0.12 (0.33)	0.18 (0.41)	0.15 (0.36)	0.12 (0.33)
Elevated	3%	-	19%	-	4%	-	10%	-
Insured	29%	6%	60%	21%	50%	0%	69%	8%

Table 5.6: Annual flood insurance prices based on housing characteristics.

Pre-/Post-FIRM	Flood zone	Basement?	Distance of lowest floor above BFE	Subsidized premium ($)	Actuarial premium ($)
-	X	No	-	390	390
-	X	Yes	-	429	429
Post	A	No	4	-	487
Post	A	No	2	-	601
Post	A	No	0	-	1,723
Post	A	No	-1	-	5,090
Post	A	No	-3	-	7,922
Post	A	No	-5	-	1,2296
Post	A	Yes	3	-	506
Post	A	Yes	1	-	640
Post	A	Yes	-5	-	4,100
Post	A	Yes	-7	-	5,710
Post	A	Yes	-9	-	8,045
Post	V	No	2	-	6,456
Post	V	No	0	-	8,706
Post	V	No	-3	-	19,107
Post	V	No	-5	-	27,460
Pre	A	No	0	2,922	1,722
Pre	A	No	-1	2,922	5,090
Pre	A	Yes	3	3,377	506
Pre	A	Yes	1	3,377	640
Pre	A	Yes	-5	3,377	4,100
Pre	A	Yes	-7	3,377	5,710
Pre	A	Yes	-9	3,377	8,045
Pre	V	No	0	6,016	7,094
Pre	V	No	-1	6,016	9,530

Behavior models

In the Psychological-Social behavior model, adaptation is driven by personal values and psychological motivations related to risk identification and previous adaptations, along with external stressors such as flood events and the behavior of peers. F_j is a reduced set of households' internal or external factors from a semi-structured survey using discrete choice experiments in the case study area (Buchanan, Oppenheimer and Parris, 2017; Table 5.7 and 5.8).

Table 5.7: Influence of internal factors on adaptive behavior from logistic regression (β parameter values).

Attribute	*Owners*			*Renters*	
	Retreat	Insure	Elevate	Retreat	Insure
Intercept	1.50	0.14	0.48	4.48	0.28
Income	0.00	0.00	0.00	-0.01	0.00
Age	-0.01	-0.01	-0.02	-0.02	-0.01
Education	0.41	0.41	-0.28	0.34	0.23
Community hours	-0.02	-0.08	0.05	-0.20	0.15
Avoid flood costs	0.35	0.18	0.00	-0.12	-0.34
Community	-0.34	-0.06	0.05	0.29	0.05
Coast	-0.22	-0.21	0.21	-0.22	0.00
Keeping one's home	-0.09	0.24	0.09		
Avoid inconveniences	-0.01	-0.25	-0.14		
Residence affordability				0.18	0.09
Residence quality				-0.06	0.00
Flood perception	0.11	-0.13	0.08	0.48	-0.04
Flood concern	-0.20	0.07	0.14	-1.18	0.20
Other adaptation	-1.61	-1.02	-0.64	1.36	-0.01
R^2	0.12	0.07	0.07	0.21	0.06

Table 5.8: Influence of external factors on adaptive behavior from Discrete Choice Experiments (β parameter values).

Attribute	*Owners*		
	Relocate	Insure	Elevate
Intercept	-1.407	-.464	-1.497
Extreme flooding	.130	-.309	-.075
Nuisance flooding	.945	-.766	-.113
Peers elevate	.277	-.453	.582
Peers relocate	.551	0.899	-.095
R^2	.084	.113	.179
Max. Possible R^2	.500	.500	.500

5.4 Discussion and next steps

The climate impacts literature is rich with simplified national and global aggregate CBA models to help account for the uncertainty in the extent of SLR (e.g. Fankhauser et al., 1999; Yohe and Schlesinger, 1998; Diaz, 2016). However, CBA generally assumes households have uniform preferences and are economically rational (e.g., Neumann et al., 2010, 2015).

Households are often assumed to remain in place and their vulnerability is often judged solely by the physical vulnerability of their structures (Aerts et al., 2013; de Moel et al., 2014). When social vulnerability is considered, it is often represented by supplemental static distributions of exposed households' age, race/ethnicity, and income (USACE, 2015*c*), disregarding *how* a public adaptation strategy may affect different socio-economic groups over time. While CBA yields helpful insights about the financial solvency of public adaptation investments, it overlooks how households' decisions can interact with those of the government, the environment, and each other, potentially leading to unintended policy outcomes. CBA is currently mandated for important institutions responsible for implementing long-lasting infrastructure, such as the U.S. Army Corps of Engineers (USACE, 2000). We propose an alternative method for consideration: the Resilience Evaluation Model.

This exploratory model of future scenarios of flood risk and social response allows for interactions between households and the coastal environment, providing a more comprehensive assessment of their combined effect on the resilience of a coupled natural and human system. While flood protection assessments commonly focus primarily on flood damage estimation, broader resilience indicators can be used by decision-makers to assess the efficacy of public adaptation strategies to reduce vulnerability and risk (Solecki et al., 2015). Here, we assess not only expected damage cost but the effect of a given public adaptation strategy on the distribution of private adaptation among socio-economically disadvantaged groups.

REM will be implemented for homeowner and renter households in the four Jamaica Bay neighborhood regions. This application will employ a series of experiments to examine the effect of SLR, public adaptation strategies, and human behavior on the distribution of flood risk and adaptive capacity across households. Illustrated in Table 5.9, experiments will test the influence of public adaptation strategies (i.e., storm surge barrier, NNBF, or no action) on resilience outcomes, accounting for the three models of household adaptive behavior, with and without SLR resulting from RCP 8.5, leading to 18 experiments. Each experiment will be simulated 100 times to understand how much of the variability in REM's results is due to its stochastic processes. Aggregate flood risk (accounting for total damage and the cost of public adaptation strategies) as well as the distribution of resilience outcomes (property quality, and uptake of insurance, home elevation, and relocation) across groups (minority and lower-income homeowners and renters) will be shown for each experiment.

Table 5.9: Resilience Evaluation Model Experiments for Jamaica Bay

	SLR		Behavior model			Public Strategy		
Experiment	None	RCP 8.5	Economic	Psycho-Social	Psycho-Social Dynamic	None	Barrier	NNBF
1	X		X			X		
2	X		X				X	
3	X		X					X
4	X			X		X		
5	X			X			X	
6	X			X				X
7	X				X	X		
8	X				X		X	
9	X				X			X
10		X	X			X		
11		X	X				X	
12		X	X					X
13		X		X		X		
14		X		X			X	
15		X		X				X
16		X			X	X		
17		X			X		X	
18		X			X			X

Chapter 6

Conclusion

Sea level rise (SLR) imposes slow but steady inundation of coastal land and property. However, the more immediate threats of SLR are that it increases the height of floods and shortens their return periods, independent of any potential changes in the distribution of coastal storms from climatological factors (Houser et al., 2015; Church et al., 2013). Hence, flooding, which is already one of the most critical environmental issues of our time, is expected to worsen significantly as a result of anthropogenic climate change.

This dissertation focuses on SLR, which is one of the more well-understood and influential effects of a warming climate (Church et al., 2013). At the same time, the amount and rate of SLR for a given location is deeply uncertain and could result in moderate to large changes in flooding severity and frequency (Kasperson et al., 2008; Heal and Millner, 2014; Ellsberg, 1961). The wide range in local SLR projections and the complexity of the effect of SLR on flooding levels and patterns pose obstacles for decision-makers, businesses, communities, and households to adapt. This dissertation provides an analysis of physical and social aspects facing policy-makers in managing coastal flood risk in a non-stationary climate.

My first research question was, given uncertainty in the magnitude of SLR and natural variability in flood frequency, how does SLR affect future flood levels and how can a decision-maker use this information to satisfy their planning criteria? I addressed this question in

Chapter 2, “Allowances for evolving coastal flood risk under uncertain local sea-level rise”, by using joint probability distributions of local SLR across U.S. coastlines and accounting for decision-makers’ planning criteria, such as planning horizons and risk tolerance preferences. In that chapter, I provide local, dynamic, and actionable flood hazard information that can be used for flood risk management despite ambiguity in SLR projections. My calculations of average annual design-life flood levels, instantaneous allowances and design-life allowances illustrate the importance of accounting for asset specific time frames and deep uncertainty in SLR projections to satisfy project design standards and risk preferences. Because of the evolution of flood levels in a non-stationary climate, failing to do so can compromise standards of protection, even from short project delays or extended durations. This effort to provide actionable climate science allows households, businesses, and government entities to select a SLR allowance that meets their planning needs among trade-offs, such as between protection and adaptation cost, and between flexibility and regret.

The second question underpinning this dissertation asks: What is the magnitude and pattern by which the frequency of current flood levels increase along coastlines? This question was examined in Chapter 3, “Amplification of flood frequencies with local SLR and emerging flood regimes”, by calculating the emerging annual chance frequencies of historic flood return levels across U.S. coastlines. The analysis presented in that chapter is the first to show how flood patterns may change with SLR across coastlines. I provide site-specific amplification factors (AFs), a metric that measures the change in the expected frequency of a historic annual chance flood from SLR. While some places can expect disproportionate amplification of higher frequency events and thus primarily a greater number of historically precedented floods, others face amplification of lower frequency events and thus a particularly fast-growing risk of historically unprecedented flooding. In this chapter, I demonstrated the importance of including the shape parameter (ξ)—which reflects meteorological and hydrodynamic differences among sites—in flood frequency calculations made by extreme value statistics. While the Generalized Pareto distribution (GPD) includes ξ, the Gumbel distribution does not. I showed that flood frequency distributions are quite sensitive to ξ and that the Gumbel distribution is a poor approximation for extreme water levels. Though a popular distribution in flood risk management for its simplicity, the Gumbel distribution can bias expected flood frequencies, for example, by underestimating the recurrence of the 500-yr flood in Seattle and overestimating it in Charleston by $1-2$ orders of magnitude. Moreover, accounting for uncertainty in the GPD significantly widens the distribution of AFs for sites with positive ξ, which have more uncertainty far in the tail of storm surges. Finally, amplification of flooding frequency is also heavily influenced by how local SLR is characterized, whereby the AF under expected SLR is less than that under uncertain SLR. This means that using the mean of SLR projections is likely to underestimate flood risk. Overall, SLR not only amplifies flood heights but also changes the relation of flood height to flood frequency across locations. Accounting for uncertainty in the GPD and in SLR, locations with positive ξ (like New York City) can expect disproportionate amplification of higher frequency events, whereas those with negative ξ (such as Seattle) can expect a disproportionate amplification of lower frequency flooding.

Finally, for governments to develop effective adaptation policies, it is important to understand what factors tend to motivate household adaptation. This need led to my third research question: How are households adapting to emerging flood patterns among other social stressors and public policies?, which I addressed in Chapter 4, "Values, bias, and stressors affect adaptation to coastal flood risk: evidence from New York City". In that chapter, I applied principles from economics and psychology to investigate how people respond to various existing adaptation options, using a household survey with discrete choice experiments. The survey captured a comprehensive set of 45 drivers that may influence household adaptive behavior, controlling for socioeconomic and cognitive variables, as well as past experience. My study built upon existing work by examining factors that have been previously overlooked—namely, the role of personal values and single-action bias. It also observed the role of important external stressors that have rarely been tested, including peer adaptation and property values, among others. My work confirmed that emotions and perceptions filter public information about flood risk in a changing climate and that situational, external stressors heavily influence the uptake of large, preventative adaptation measures. There is strong evidence that households who make small-scale adaptations are systematically less likely to take additional, more preventative measures. Some values, such as avoiding flood-related costs and staying close to community members, significantly affect intended adaptive behavior. Renters are more likely to relocate because of gentrification, crime, and economic instability rather than directly from flood risk. Finally, several external stressors significantly influence household adaptation. The adaptation of peers, frequent nuisance flooding, falling property values and rising costs of rent strongly encourage households to relocate. I found that socio-economic factors, commonly used to assess adaptive capacity to environmental hazards, were generally poor predictors of adaptation among homeowners and renters in this coastal zone. Overall, a striking 64% of homeowners and 83% of renters intend to relocate among different plausible future conditions.

6.1 Policy implications and recommendations

Chapter 2 illustrates the importance for infrastructure, flood maps, and insurance to reflect the evolving flood risk imposed by the wide range of plausible sea level rise. It underscores the need to readjust federal and local planning beyond the historic 100-year flood to an adaptable means of maintaining flood risk standards, such as that afforded by design-life and improved instantaneous allowances. While instantaneous SLR allowances provide a more conservative protection height, design-life allowances allow for a more cost-effective amount of protection. Both allowance types can be incorporated into adaptive management, in which additional protective measures can be added as uncertainty in the future evolution of flood risk is reduced.

In 2015, a substantial effort to help account for SLR in infrastructure planning was established by the Federal Flood Risk Management Standards (FFRMS) through Executive Order (Executive Order No. 13690, 2015). The FFRMS mandated federal agencies to account for SLR when designing new infrastructure by using climate science (e.g., SLR allowances), or approximations, such as by building two feet above the historic 100-year flood elevation. However, the standards were revoked two years later by the Trump Administration (Executive Order No. 13807, 2017). As even small increases in sea level can lead to significant changes in flood risk (Miller et al., 2013), I strongly recommend that the FFRMS be reinstated. Because extreme flooding poses a series of downstream consequences for communities (including property damage, power loss, road blockages, and water contamination, among others), similar standards should be applied to utilities and public and private real estate to help avoid economic losses and societal hardship.

As shown in Chapter 3, minor floods will become much more frequent in many East coast cities (with positive shape factors), and extreme floods will become more frequent in many West coast cities (with negative shape factors). These emerging flood regimes have critical implications for cities, states, and federal entities interested in adapting to coastal impacts. Effective policies should initially increase resilience to historical flooding in areas with emerging flood regimes associated with positive shape factors, and prepare for largely unprecedented flooding in areas with negative shape factors. Policies should also allow for adjustment over time to address eventual flooding dominated by tidal events and permanent inundation (Sweet and Park, 2014). It is important that large-scale, costly, public flood protection strategies account for emerging flood regimes to help avoid mal-adaptation. For example, a costly storm surge barrier may be built to protect parts of New York City from extreme flood levels. However, these barriers are not often used to protect against smaller floods because they are expensive to operate and obstructive to navigation and ecological systems. As the current 10-yr flood will become a nuisance flood and amplify much more than extreme floods in this area, large episodic protection may not be especially helpful.

Finally, I suggest that areas with similar shape factors (and hence flood regimes) develop networks to identify and share adaptation strategies.

My findings in Chapter 4 have several important policy implications. The tendency of households who make small-scale adaptations to avoid taking additional, more preventative measures may pose ramifications for coastal cities and communities investing in programs to support the uptake of *both* small-scale (e.g., service equipment elevation) and more costly (e.g., home elevation) resilience measures. I suggest that public programs work to bundle adaptation measures to help avoid inaction resulting from single-action bias. As household relocation is sensitive to more frequent minor flooding (which will increase across all coastlines, and specifically by a factor of 31 in NYC by 2050; Buchanan, Oppenheimer and Kopp, 2017), efforts should be taken to prepare for some degree of managed retreat. On the brighter side, the role of peer imitation poses an opportunity for adaptation, as homeowners are much more likely to elevate their homes if their peers do so. They are also more likely to relocate if their peers relocate *or* elevate. This may have positive implications if more public-private partnerships and programs (like NYC's Build it Back) can help normalize adaptation by facilitating home elevation among residents. As insurance premiums will likely rise across the country from updates in Flood Insurance Rate Maps and the grandfathering of subsidized rates through the Homeowner Flood Insurance Affordability Act of 2014, vouchers and other efforts to retain coverage for households are increasingly important. Although renters are more likely to relocate because of gentrification, crime, and economic instability rather than flood risk, increased flood frequency from SLR may well intensify these issues and weaken the overall vitality of coastal locations. Finally, the amount of residents intending to relocate under different plausible future conditions is substantial, considering the political sensitivity of 'retreat' and the lack of preparation for large-scale climate-induced migration. The immense cost of relocation and lack of long-term alternatives requires more commitment from government agencies (local, regional, and federal), as well as non-governmental partners, to identify mechanisms for managing retreat of this scale.

6.2 Future work

This dissertation is part of a long-term research program focusing on various elements of flood risk and actors (including local governments and businesses) in different urban contexts. Chapter 5 proposed future research for combining physical and social aspects of SLR and flooding to evaluate the efficacy of public flood protection strategies. This built upon and integrated the work presented in Chapters 2, 3, and 4. Here, I provide five additional areas of research that can build upon this work in the future.

First, while this dissertation focuses on the effect of SLR on flood hazards, the influence of potential changes in storm dynamics, although less robustly constrained, also matters and needs to be better accounted for in local flood risk management. Second, the metrics developed in Chapters 2 and 3— SLR allowances and amplification factors—could be coupled with damage estimates. Doing so would provide decision-makers with a mechanism to plan for adaptation that accounts for their tolerable amount of potential damage cost. Third, additional factors that influence flood risk management (and potential damage), such as erosion, subsidence, logistical challenges to evacuation, and potential for facilities and locations to function without interruption should also be considered when planning for adaptation. Fourth, additional studies along the lines of Chapter 4 could improve our understanding of household perspectives, needs, and values, and the influence of these factors on adaptive behavior. If leveraged, this information could improve public resilience and adaptation programs by reducing the psychological cost of adaptation and likely yield more effective and efficient outcomes in the process. For example, it could help avoid unintentionally perverse incentives that ultimately reduce household and community-level resilience. Fifth, because the incorporation of climate change adaptation into public programs is relatively new, ongoing monitoring and evaluation is critical to reveal barriers and creative solutions. Incorporating lessons from past, recent, and ongoing climate impacts to help improve government programs is especially important since climate impacts will likely demand shorter response time for risk management.

Appendix A

Acronyms, Terms and Expressions

A.1 Acronyms

ABM Agent-based model

AEP Annual expected probability of occurrence

AF Amplification factor

BFE Base flood elevation

CBA Cost-benefit analysis

DEM Digital Elevation Model

EAD Expected annual damage

FIRM Flood insurance rate map

GPD Generalized Pareto distribution

JB Jamaica Bay

JFK John F. Kennedy International Airport

MHHW Mean Higher High Water

NNBF Natural and nature-based features

NYC New York City

RCP Representative concentration pathway

REM Resilience Evaluation Model

RSL Relative sea level

SLR Sea level rise

USACE U.S. Army Corps of Engineers

VLM Vertical land motion

A.2 Key terms

Annual expected probability of occurrence (AEP) Probability of flooding in any given year considering the full range of possible floods (USACE, 2015*b*). The 1% AEP is equivalent to the 100-year return level.

Amplification factor The change in the expected frequency of a historic annual chance flood with SLR.

Average annual design life level (AADLL) The return level associated with sea-level rise for a given AEP and design life, integrated over the full probability distribution of SLR and its uncertainty.

Sea-level rise (SLR) allowance The vertical distance to raise a piece of infrastructure (e.g. a house, sea wall) to maintain current flood risk tolerance under projected SLR.

Instantaneous allowance SLR allowance for a single year.

Design life (DL) allowance SLR allowance integrated over a time period.

A.3 Key expressions

Table A.1: Key expressions

Symbol	Definition
a	An adaptation measure.
a_e	The elevation of one's home.
a_i	The procurement of flood insurance.
a_r	Permanent relocation from the coast.
$\beta \in [0, 1]$	Degree of confidence in SLR projections, in which full confidence in SLR projections is denoted by $\beta = 1$ and full confidence in worst-case SLR projections is $\beta = 0$.
c_a	Total annual cost of all adaptation measures, including insurance and home elevation payments ($k).
c_d	Cumulative annual cost from damage to housing structure ($k).
$c_{(d,t)}$	Total damage cost from a flood event ($k).
c_e	Annual loan payment for home elevation ($k).
c_i	Annual flood insurance cost ($k).
c_m	Annual mortgage payment ($k).
c_p	Annual property maintenance cost ($k).
c_r	Annual cost of rent ($k).
c_t	Annual property tax cost ($k).
d	Percent of structure value that is damaged from inundation.
e	Home elevation level above the ground.
f	Annual inundation level resulting from flood events (feet).
h	Household income ($k).
l	A loan's principle.
N	The duration of a loan in years.
$N(z)$	Number of expected flood events per year exceeding height z under stationary sea level. N and AEP are not exactly identical numerically, although they are very close for small N. p Flood risk perception.
q	Property quality. The maintenance level of housing structure: on a scale from 0 to 1 from poorly to well maintained.
r_i	Annual interest rate.
$r_{p:r}$	Price-to-rent ratio, the ratio of home prices to annual rental rates.
τ	The fraction of a household's income spent on housing.
v_p	Market value of housing structure and land ($k).
v_s	Market value of housing structure ($k).
x	Amount of insurance coverage.

Appendix B

Allowances for evolving coastal flood risk under uncertain local sea-level rise

Table B.1: Station information, estimated GPD parameters (maximum-likelihood (ML), Median (5th, 95th)). Meters above MHHW.

Site	NOAA Station ID	Record Length (yrs)	λ	ξ	σ
Adak Island, AK	9461380	64	1.65	0.05 (-0.17, 0.27)	0.07 (0.05, 0.09)
Alameda, CA	9414750	38	1.79	0.04 (-0.17, 0.24)	0.09 (0.06, 0.11)
Anchorage, AK	9455920	35	2.43	-0.20 (-0.35, -0.05)	0.13 (0.10, 0.17)
Annapolis, MD	8575512	85	2.75	0.26 (0.13, 0.39)	0.08 (0.07, 0.1)
Apalachicola, FL	8728690	34	2.46	0.50 (0.20, 0.80)	0.12 (0.08, 0.16)
Astoria, OR	9439040	66	1.84	-0.32 (-0.47, -0.16)	0.18 (0.14, 0.21)
Atlantic City, NJ	8534720	102	2.63	0.09 (-0.02, 0.20)	0.11 (0.10, 0.13)
Baltimore, MD	8574680	111	2.73	0.25 (0.14, 0.36)	0.10 (0.08, 0.11)
Beaufort, NC	8656483	34	2.40	0.22 (-0.04, 0.47)	0.07 (0.05, 0.10)
Boston, MA	8443970	92	2.57	0.07 (-0.05, 0.19)	0.11 (0.09, 0.13)
Bridgeport, CT	8467150	34	2.83	0.13 (-0.04, 0.31)	0.15 (0.11, 0.18)
Cambridge, MD	8571892	34	3.15	0.18 (0.00, 0.36)	0.08 (0.06, 0.09)
Cape May, NJ	8536110	48	2.59	-0.07 (-0.24, 0.10)	0.14 (0.11, 0.17)
Charleston, OR	9432780	35	1.58	-0.29 (-0.48, -0.09)	0.16 (0.12, 0.21)
Charleston, SC	8665530	92	2.33	0.23 (0.10, 0.36)	0.07 (0.05, 0.08)
Chesapeake Bay, VA	8638863	38	2.36	0.04 (-0.17, 0.25)	0.16 (0.12, 0.20)
Clearwater Beach, FL	8726724	34	2.83	0.33 (0.09, 0.57)	0.08 (0.06, 0.10)
Eastport, ME	8410140	55	2.33	0.03 (-0.12, 0.18)	0.10 (0.08, 0.12)
Fernandina Beach, FL	8720030	116	1.83	-0.06 (-0.16, 0.03)	0.11 (0.09, 0.13)
Fort Pulaski, GA	8670870	78	2.24	0.07 (-0.04, 0.18)	0.07 (0.06, 0.08)
Freeport, TX	8772440	54	2.18	0.21 (0.03, 0.40)	0.11 (0.08, 0.13)
Galveston Pier 21, TX	8771450	109	2.20	0.28 (0.16, 0.40)	0.12 (0.10, 0.13)
Galveston Pleasure Pier, TX	8771510	54	2.16	0.41 (0.21, 0.61)	0.11 (0.08, 0.13)
Grand Isle, LA	8761724	34	2.14	0.52 (0.24, 0.80)	0.09 (0.06, 0.11)

Table B.2: Continued. Station information, estimated GPD parameters (maximum-likelihood (ML), Median (5th, 95th)). Meters above MHHW.

Site	NOAA Station ID	Record Length (yrs)	λ	ξ	σ
Honolulu, HI	1612340	103	1.44	-0.16 (-0.25, -0.06)	0.04 (0.04, 0.05)
Juneau, AK	9452210	35	2.37	0.00 (-0.17, 0.17)	0.14 (0.10, 0.17)
Kahului, HI	1615680	60	2.11	0.25 (0.11, 0.38)	0.03 (0.02, 0.03)
Ketchikan, AK	9450460	96	2.14	-0.29 (-0.39, -0.19)	0.19 (0.16, 0.22)
Key West, FL	8724580	100	1.72	0.23 (0.08, 0.39)	0.04 (0.03, 0.05)
Kiptopeke, VA	8632200	34	2.37	0.03 (-0.19, 0.25)	0.14 (0.10, 0.17)
La Jolla, CA	9410230	89	1.92	-0.21 (-0.34, -0.08)	0.07 (0.05, 0.08)
Lewes, DE	8557380	56	2.65	0.11 (-0.05, 0.28)	0.13 (0.10, 0.16)
Lewisetta, VA	8635750	34	2.57	0.21 (0.02, 0.40)	0.07 (0.05, 0.09)
Los Angeles, CA	9410660	90	1.90	-0.22 (-0.32, -0.13)	0.07 (0.06, 0.08)
Mokuoloe, HI	1612480	33	1.69	-0.36 (-0.60, -0.12)	0.05 (0.03, 0.06)
Montauk, NY	8510560	54	2.98	-0.04 (-0.17, 0.08)	0.17 (0.14, 0.20)
Monterey, CA	9413450	40	1.68	-0.09 (-0.27, 0.09)	0.08 (0.06, 0.10)
Nantucket Island, MA	8449130	48	2.78	0.10 (-0.05, 0.24)	0.10 (0.08, 0.12)
Naples, FL	8725110	34	2.43	0.05 (-0.15, 0.25)	0.11 (0.08, 0.13)
Nawiliwili, HI	1611400	60	1.49	0.17 (0.03, 0.31)	0.03 (0.03, 0.04)
Neah Bay, WA	9443090	77	1.83	-0.29 (-0.43, -0.14)	0.18 (0.15, 0.22)
New London, CT	8461490	75	3.04	0.11 (-0.01, 0.24)	0.15 (0.13, 0.18)
Newport, RI	8452660	83	2.79	0.19 (0.06, 0.31)	0.10 (0.09, 0.12)
Pensacola, FL	8729840	90	2.42	0.47 (0.30, 0.63)	0.07 (0.06, 0.08)
Port Isabel, TX	8779770	36	1.68	0.49 (0.17, 0.82)	0.07 (0.04, 0.09)
Port San Luis, CA	9412110	65	1.89	-0.11 (-0.24, 0.02)	0.08 (0.06, 0.09)
Portland, ME	8418150	103	2.52	-0.05 (-0.15, 0.05)	0.11 (0.09, 0.13)
Providence, RI	8454000	34	2.94	0.28 (0.05, 0.50)	0.11 (0.08, 0.14)

Table B.3: Continued. Station information, estimated GPD parameters (maximum-likelihood (ML), Median (5th, 95th)). Meters above MHHW.

Site	NOAA Station ID	Record Length (yrs)	λ	ξ	σ
Reedy Point, DE	8551910	34	3.00	0.17 (-0.03, 0.38)	0.08 (0.06, 0.11)
Rockport, TX	8774770	76	1.45	0.29 (0.09, 0.49)	0.07 (0.06, 0.09)
Sabine Pass, TX	8770570	34	1.86	0.31 (0.10, 0.52)	0.10 (0.07, 0.13)
San Diego, CA	9410170	108	1.97	-0.09 (-0.19, 0.01)	0.05 (0.05, 0.06)
San Francisco, CA	9414290	112	1.78	0.03 (-0.10, 0.16)	0.08 (0.07, 0.10)
Seattle, WA	9447130	112	2.10	-0.17 (-0.27, -0.06)	0.12 (0.10, 0.14)
Seldovia, AK	9455500	35	2.32	-0.02 (-0.18, 0.13)	0.12 (0.09, 0.15)
Seward, AK	9455090	36	1.55	-0.13 (-0.34, 0.08)	0.17 (0.12, 0.22)
Sewells Point, VA	8638610	85	2.35	0.07 (-0.05, 0.19)	0.17 (0.14, 0.20)
Sitka, AK	9451600	69	2.12	-0.05 (-0.22, 0.12)	0.14 (0.11, 0.17)
Skagway, AK	9452400	32	2.30	0.00 (-0.20, 0.20)	0.13 (0.10, 0.17)
Solomons Island, MD	8577330	34	2.60	0.11 (-0.10, 0.31)	0.08 (0.06, 0.10)
South Beach, OR	9435380	46	1.98	-0.13 (-0.30, 0.03)	0.14 (0.10, 0.17)
Springmaid Pier, SC	8661070	37	1.92	0.27 (0.05, 0.49)	0.06 (0.04, 0.08)
St. Petersburg, FL	8726520	67	2.84	0.29 (0.13, 0.44)	0.08 (0.07, 0.10)
The Battery, NY	8518750	93	2.81	0.19 (0.07, 0.30)	0.13 (0.11, 0.15)
Toke Point, WA	9440910	34	2.43	0.02 (-0.17, 0.21)	0.15 (0.11, 0.19)
Unalaska, AK	9462620	32	1.93	-0.23 (-0.41, -0.06)	0.08 (0.06, 0.10)
Vaca Key, FL	8723970	34	2.00	0.35 (0.14, 0.57)	0.03 (0.02, 0.04)
Washington, DC	8594900	82	2.23	0.50 (0.32, 0.67)	0.11 (0.08, 0.13)
Wilmington, NC	8658120	78	2.18	0.17 (0.03, 0.31)	0.07 (0.06, 0.08)
Woods Hole, MA	8447930	55	2.88	0.05 (-0.09, 0.19)	0.14 (0.11, 0.17)
Yakutat, AK	9453220	53	1.92	-0.24 (-0.43, -0.06)	0.17 (0.13, 0.21)

Table B.4: Historic return levels for the 10% and 1% AEP (maximum-likelihood (ML) Median (5th, 95th) and expected). Meters above MHHW.

Site	10% AEP (ML)	1% AEP (ML)	10% AEP (expected)	1% AEP (expected)
Adak Island, AK	0.81 (0.77, 0.86)	1.00 (0.88, 1.23)	0.81	1.03
Alameda, CA	0.70 (0.64, 0.76)	0.93 (0.77, 1.20)	0.70	0.97
Anchorage, AK	1.60 (1.56, 1.65)	1.74 (1.65, 1.84)	1.61	1.75
Annapolis, MD	0.85 (0.77, 0.94)	1.47 (1.16, 1.96)	0.85	1.52
Apalachicola, FL	1.29 (0.98, 1.81)	3.69 (1.76, 9.33)	1.30	4.29
Astoria, OR	1.02 (0.98, 1.05)	1.13 (1.07, 1.21)	1.02	1.14
Atlantic City, NJ	0.92 (0.86, 0.98)	1.30 (1.13, 1.55)	0.92	1.32
Baltimore, MD	0.93 (0.86, 1.02)	1.63 (1.32, 2.07)	0.94	1.66
Beaufort, NC	0.71 (0.62, 0.85)	1.15 (0.80, 1.96)	0.71	1.24
Boston, MA	1.03 (0.97, 1.09)	1.38 (1.21, 1.63)	1.03	1.40
Bridgeport, CT	1.14 (1.00, 1.32)	1.76 (1.33, 2.53)	1.14	1.85
Cambridge, MD	0.76 (0.68, 0.88)	1.17 (0.88, 1.71)	0.77	1.24
Cape May, NJ	0.87 (0.82, 0.95)	1.11 (0.97, 1.37)	0.88	1.15
Charleston, OR	0.96 (0.91, 1.01)	1.09 (1.01, 1.18)	0.96	1.10
Charleston, SC	0.77 (0.72, 0.83)	1.19 (0.98, 1.48)	0.77	1.21
Chesapeake Bay, VA	1.06 (0.96, 1.19)	1.48 (1.18, 2.03)	1.06	1.55
Clearwater Beach, FL	0.83 (0.69, 1.05)	1.63 (1.01, 3.06)	0.83	1.8
Eastport, ME	1.26 (1.20, 1.32)	1.51 (1.36, 1.73)	1.26	1.54
Fernandina Beach, FL	0.74 (0.71, 0.77)	0.93 (0.86, 1.02)	0.74	0.94
Fort Pulaski, GA	0.76 (0.72, 0.80)	0.97 (0.87, 1.12)	0.76	0.99
Freeport, TX	0.91 (0.81, 1.04)	1.52 (1.14, 2.22)	0.91	1.6
Galveston Pier 21, TX	0.99 (0.90, 1.10)	1.89 (1.46, 2.47)	0.99	1.93
Galveston Pleasure Pier, TX	1.15 (0.97, 1.41)	2.58 (1.65, 4.56)	1.16	2.79
Grand Isle, LA	0.99 (0.76, 1.37)	2.86 (1.38, 6.82)	1.00	3.23

Table B.5: Continued. Historic return levels for the 10% and 1% AEP (maximum-likelihood (ML) Median (5th, 95th) and expected). Meters above MHHW.

Site	10% AEP (ML)	1% AEP (ML)	10% AEP (expected)	1% AEP (expected)
Honolulu, HI	0.35 (0.34, 0.37)	0.41 (0.39, 0.43)	0.35	0.41
Juneau, AK	1.90 (1.82, 2.00)	2.22 (2.01, 2.52)	1.90	2.26
Kahului, HI	0.40 (0.37, 0.43)	0.59 (0.48, 0.74)	0.40	0.60
Ketchikan, AK	1.53 (1.49, 1.56)	1.65 (1.60, 1.72)	1.53	1.66
Key West, FL	0.42 (0.40, 0.46)	0.66 (0.54, 0.86)	0.43	0.67
Kiptopeke, VA	0.92 (0.83, 1.04)	1.27 (1.01, 1.79)	0.92	1.35
La Jolla, CA	0.64 (0.63, 0.66)	0.71 (0.68, 0.75)	0.64	0.71
Lewes, DE	1.04 (0.95, 1.16)	1.54 (1.24, 2.06)	1.04	1.60
Lewisetta, VA	0.74 (0.66, 0.86)	1.17 (0.87, 1.75)	0.75	1.24
Los Angeles, CA	0.64 (0.63, 0.65)	0.70 (0.68, 0.73)	0.64	0.71
Mokuoloe, HI	0.36 (0.34, 0.37)	0.38 (0.36, 0.41)	0.36	0.39
Montauk, NY	0.95 (0.87, 1.04)	1.27 (1.09, 1.53)	0.95	1.30
Monterey, CA	0.66 (0.62, 0.70)	0.78 (0.71, 0.90)	0.66	0.80
Nantucket Island, MA	0.79 (0.72, 0.88)	1.13 (0.93, 1.47)	0.79	1.17
Naples, FL	0.69 (0.61, 0.78)	0.99 (0.77, 1.36)	0.69	1.04
Nawiliwili, HI	0.37 (0.34, 0.39)	0.51 (0.44, 0.62)	0.37	0.52
Neah Bay, WA	1.09 (1.05 , 1.12)	1.22 (1.16, 1.30)	1.09	1.23
New London, CT	1.07 (0.97, 1.18)	1.65 (1.35, 2.11)	1.07	1.70
Newport, RI	0.94 (0.87, 1.04)	1.49 (1.22, 1.91)	0.94	1.53
Pensacola, FL	0.85 (0.73, 1.00)	2.10 (1.39, 3.41)	0.85	2.22
Port Isabel, TX	0.74 (0.59, 0.98)	1.86 (0.95, 4.62)	0.74	2.13
Port San Luis, CA	0.67 (0.64, 0.70)	0.79 (0.73, 0.86)	0.67	0.79
Portland, ME	0.92 (0.89, 0.96)	1.13 (1.04, 1.25)	0.93	1.14
Providence, RI	1.15 (0.98, 1.40)	2.07 (1.36, 3.70)	1.15	2.26

Table B.6: Continued. Historic return levels for the 10% and 1% AEP (maximum-likelihood (ML) Median (5th, 95th) and expected). Meters above MHHW.

Site	10% AEP (ML)	1% AEP (ML)	10% AEP (expected)	1% AEP (expected)
Reedy Point, DE	0.80 (0.71, 0.93)	1.22 (0.91, 1.88)	0.81	1.31
Rockport, TX	0.61 (0.54, 0.69)	1.13 (0.83, 1.69)	0.61	1.17
Sabine Pass, TX	0.83 (0.69, 1.03)	1.68 (1.10, 2.93)	0.84	1.82
San Diego, CA	0.66 (0.64, 0.67)	0.74 (0.71, 0.79)	0.66	0.75
San Francisco, CA	0.67 (0.64, 0.70)	0.88 (0.78, 1.02)	0.67	0.89
Seattle, WA	0.86 (0.84, 0.89)	1.00 (0.95, 1.07)	0.86	1.01
Seldovia, AK	2.02 (1.95, 2.10)	2.27 (2.11, 2.53)	2.02	2.31
Seward, AK	1.38 (1.31, 1.46)	1.62 (1.47, 1.86)	1.38	1.65
Sewells Point, VA	1.12 (1.03, 1.22)	1.66 (1.39, 2.06)	1.12	1.70
Sitka, AK	1.22 (1.16, 1.28)	1.48 (1.32, 1.71)	1.22	1.50
Skagway, AK	2.02 (1.94, 2.13)	2.33 (2.11, 2.72)	2.03	2.39
Solomons Island, MD	0.70 (0.64, 0.79)	0.99 (0.79, 1.40)	0.71	1.05
South Beach, OR	1.02 (0.97, 1.07)	1.20 (1.10, 1.36)	1.02	1.22
Springmaid Pier, SC	0.81 (0.74, 0.91)	1.23 (0.94, 1.84)	0.81	1.30
St. Petersburg, FL	0.80 (0.70, 0.93)	1.49 (1.09, 2.25)	0.80	1.57
The Battery, NY	1.11 (1.01, 1.21)	1.80 (1.46, 2.27)	1.11	1.84
Toke Point, WA	1.33 (1.23, 1.46)	1.71 (1.45, 2.16)	1.34	1.78
Unalaska, AK	0.76 (0.73, 0.79)	0.83 (0.79, 0.89)	0.76	0.84
Vaca Key, FL	0.44 (0.39, 0.52)	0.77 (0.55, 1.31)	0.44	0.84
Washington, DC	1.24 (1.06, 1.49)	3.34 (2.15, 5.57)	1.25	3.52
Wilmington, NC	0.60 (0.55, 0.65)	0.92 (0.74, 1.18)	0.60	0.95
Woods Hole, MA	0.91 (0.83, 1.00)	1.31 (1.08, 1.67)	0.91	1.35
Yakutat, AK	1.51 (1.47, 1.56)	1.66 (1.57, 1.79)	1.52	1.68

Appendix C

Amplification of flood frequencies with local sea level rise and emerging flood regimes

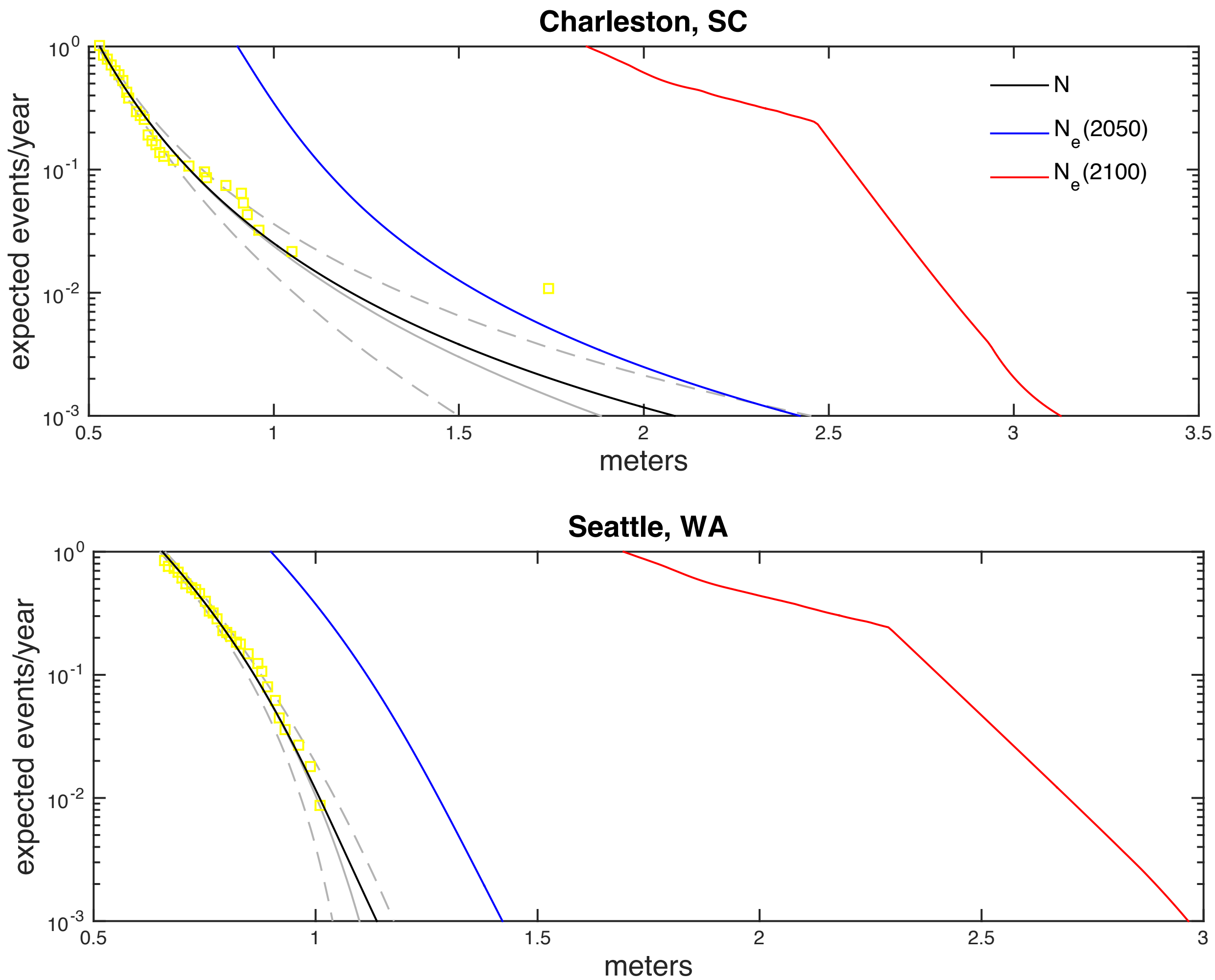

Figure C.1: Expected number of floods ($N(z)$) for Charleston and Seattle with positive and negative shape factors (ξ). The black curve is the maximum likelihood estimate of the historic flood return curve (N). The blue curve represents the expected flood return curve resulting from the complete probability distribution of local sea level rise by 2050 under RCP 8.5 ($N_e(2050)$).Yellow points are empirical observations and grey lines are the 5th, 50th, and 95th percentiles of the GPD uncertainty range. The kinks in the figure arise at the transition in the extreme value distribution between the extremes represented by the GPD and the extremes represented by a Gumbel distribution from λ to 182.6 floods per year; a second kink arises at >182.6 floods per year (see Methods). The appearance of these kinks in the $N_e(2100)$ curves reflects the influence of high-end SLR projections that cause floods to transition between regimes.

Table C.1: Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-year for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Adak Island, AK	8.7 (0.4, 24.9)	162.3 (0.2, 1235.9)	11.5 (0.0, 16.1)	660.4 (0.0, 2217.2)
Alameda, CA	30.1 (3.2, 80.0)	715.4 (10.0, *)	30.9 (1.0, 40.1)	2023.0 (5.5, *)
Anchorage, AK	5.2 (0.0, 21.2)	30.8 (0.0, 86.6)	15.1 (0.0, 65.2)	192.7 (0.0, 541.8)
Annapolis, MD	76.5 (4.7, 257.6)	1146.2 (21.5, *)	5.8 (1.2, 10.4)	872.3 (3.1, 3890.2)
Apalachicola, FL	2.5 (0.9, 3.6)	84.4 (1.5, 352.4)	1.2 (0.0, 3.3)	5.0 (0.0, 3.8)
Astoria, OR	7.4 (1.4, 14.7)	116.0 (2.0, 506.0)	27.9 (1.5, 64.9)	716.2 (3.2, 2249.9)
Atlantic City, NJ	98.1 (7.8, 326.3)	1182.1 (24.6, *)	44.9 (4.2, 103.8)	4008.2 (11.5, *)
Baltimore, MD	35.8 (3.5, 111.3)	869.8 (10.4, *)	4.1 (1.2, 8.1)	464.5 (2.5, 917.8)
Boston, MA	44.6 (4.5, 125.7)	659.9 (9.3, *)	30.1 (2.6, 78.6)	1715.7 (5.4, 12099.6)
Bridgeport, CT	15.5 (2.4, 38.3)	472.1 (3.7, *)	4.2 (0.4, 10.5)	337.5 (1.2, 525.6)
Cambridge, MD	161.7 (10.4, 545.0)	1372.2 (65.7, *)	28.9 (1.7, 47.8)	3361.1 (8.5, *)
Cape May, NJ	96.5 (9.6, 322.7)	1197.7 (36.1, *)	115.2 (9.8, 274.8)	5722.3 (44.8, *)
Charleston, OR	14.0 (3.1, 29.0)	259.3 (7.0, *)	50.0 (4.8, 106.9)	1404.4 (18.1, 7633.9)
Charleston, SC	105.8 (11.4, 311.7)	1223.8 (77.2, *)	23.0 (2.3, 32.5)	2248.8 (9.1, *)
Chesapeake Bay, VA	32.7 (5.5, 83.5)	836.6 (19.8, *)	14.1 (1.6, 31.4)	1144.5 (9.3, 6347.3)
Clearwater Beach, FL	27.6 (3.3, 70.2)	935.8 (10.5, *)	2.1 (0.1, 5.4)	209.3 (0.5, 49.8)
Eastport, ME	38.5 (4.4, 91.6)	345.8 (7.7, *)	63.0 (2.7, 247.3)	1318.5 (5.2, 5945.3)
Fernandina Beach, FL	78.2 (8.4, 234.6)	1078.1 (33.4, *)	129.4 (10.6, 301.5)	5409.5 (46.6, *)
Fort Pulaski, GA	145.7 (26.0, 395.4)	1295.2 (120.3, *)	210.5 (13.3, 559.7)	6623.6 (139.9, *)
Freeport, TX	313.4 (40.3, 1105.6)	1786.8 (* ,*)	15.8 (3.2, 24.8)	4214.3 (33.4, *)
Galveston Pier 21, TX	64.0 (9.3, 178.6)	1560.7 (220.7, *)	4.0 (1.5, 7.0)	515.1 (5.5, 947.6)
Galveston Pls. Pier, TX	24.2 (5.1, 60.1)	1216.3 (65.8, *)	1.8 (0.3, 4.1)	56.2 (0.9, 12.4)
Grand Isle, LA	209.2 (15.7, 762.9)	1801.4 (*, *)	1.6 (0.1, 4.2)	43.3 (0.4, 8.5)

Table C.2: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-yea floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Honolulu, HI	1288.0 (132.9, *)	1774.8 (*, *)	8712.4 (432.1, *)	17304.7 (7162.7, *)
Juneau, AK	0.0 (0.0, 0.1)	1.0 (0.0, 0.0)	0.1 (0.0, 0.3)	5.7 (0.0, 0.1)
Kahului, HI	1176.1 (124.8, *)	1779.9 (*, *)	1617.0 (18.6, 7896.1)	15295.9 (754.7, *)
Ketchikan, AK	4.7 (1.3, 9.8)	38.8 (1.4, 84.9)	14.6 (1.5, 36.7)	250.1 (1.7, 512.3)
Key West, FL	856.5 (55.5, *)	1727.4 (762.6, *)	496.5 (7.7, 1583.4)	12545.6 (90.4, *)
Kiptopeke, VA	55.6 (6.3, 163.1)	1044.5 (23.2, *)	25.0 (2.0, 50.2)	2218.0 (10.5, *)
La Jolla, CA	166.4 (32.7, 463.3)	1362.6 (141.1, *)	914.0 (156.1, 2443.1)	11652.7 (744.2, *)
Lewes, DE	32.5 (4.5, 88.8)	786.3 (13.3, *)	9.1 (1.3, 19.6)	859.6 (4.6, 3865.7)
Los Angeles, CA	87.5 (14.1, 220.4)	972.1 (42.1, *)	472.4 (38.9, 1157.8)	7645.8 (221.3, *)
Mokuoloe, HI	1232.1 (138.0, *)	1773.2 (*, *)	10224.0 (822.9, *)	17522.0 (10894.1, *)
Montauk, NY	36.8 (4.7, 100.4)	871.6 (9.4, *)	35.9 (3.8, 79.0)	2606.7 (9.6, *)
Monterey, CA	71.7 (8.0, 197.2)	1016.4 (35.3, *)	189.7 (9.2, 478.5)	6155.2 (64.3, *)
Nantucket Island, MA	151.8 (7.3, 593.6)	1256.5 (22.8, *)	58.1 (2.9, 124.8)	4583.5 (8.4, *)
Naples, FL	62.1 (6.1, 192.7)	1167.0 (19.8, *)	33.5 (1.8, 42.8)	3037.0 (8.7, *)
Nawiliwili, HI	1061.7 (61.5, *)	1745.1 (1037.8, *)	2449.0 (22.2, 15126.6)	15240.2 (614.9, *)
Neah Bay, WA	2.8 (0.2, 6.7)	45.9 (0.1, 107.2)	7.3 (0.0, 19.5)	281.4 (0.0, 443.5)
New London, CT	15.3 (2.7, 34.5)	558.5 (4.4, *)	5.5 (1.1, 12.2)	477.1 (2.4, 892.0)
Newport, RI	43.3 (3.7, 135.4)	854.0 (7.2, *)	7.4 (1.3, 15.0)	956.4 (2.6, 5201.7)
New York City, NY	19.3 (2.8, 51.5)	588.3 (4.8, *)	4.2 (1.1, 9.0)	370.0 (2.0, 657.0)
Pensacola, FL	12.5 (2.0, 23.5)	659.8 (3.7, *)	1.5 (0.4, 3.0)	61.3 (0.6, 6.7)
Port Isabel, TX	97.7 (5.8, 347.5)	1491.9 (87.2, *)	1.6 (0.1, 4.2)	122.7 (0.2, 11.5)
Port San Luis, CA	55.2 (6.2, 147.2)	831.0 (21.2, *)	180.1 (8.6, 460.4)	5172.6 (42.9, *)
Portland, ME	56.1 (4.6, 170.2)	672.1 (7.8, *)	118.1 (5.1, 376.0)	3251.3 (9.0, *)
Providence, RI	11.4 (1.9, 28.8)	405.9 (2.9, *)	2.0 (0.1, 5.2)	91.8 (0.3, 27.0)

Table C.3: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Reedy Point, DE	111.2 (6.3, 376.2)	1194.9 (28.5, *)	18.1 (1.0, 30.5)	2208.0 (4.1, *)
Rockport, TX	935.8 (70.5, *)	1800.3 (*, *)	35.5 (3.1, 34.2)	8003.1 (24.4, *)
Sabine Pass, TX	92.7 (7.2, 331.6)	1565.1 (150.9, *)	2.9 (0.4, 6.6)	436.8 (2.1, 356.1)
San Diego, CA	154.5 (32.2, 410.5)	1324.9 (131.1, *)	729.7 (99.7, 1862.9)	10632.7 (595.0, *)
San Francisco, CA	68.4 (7.5, 196.6)	1151.6 (45.9, *)	82.9 (5.8, 167.9)	5143.4 (35.5, *)
Seattle, WA	29.0 (6.7, 62.8)	572.1 (21.0, *)	88.0 (11.9, 192.8)	2916.3 (55.4, *)
Seldovia, AK	0.1 (0.0, 0.2)	1.8 (0.0, 0.1)	0.1 (0.0, 0.4)	11.0 (0.0, 0.2)
Seward, AK	0.7 (0.0, 1.8)	10.7 (0.0, 11.2)	0.9 (0.0, 2.7)	58.1 (0.0, 17.9)
Sewells Point, VA	21.9 (4.7, 53.1)	748.6 (14.9, *)	9.1 (2.2, 19.0)	695.3 (7.4, 2417.8)
Sitka, AK	1.6 (0.3, 3.2)	25.5 (0.1, 44.4)	1.9 (0.0, 4.3)	115.5 (0.0, 73.5)
Skagway, AK	0.0 (0.0, 0.1)	0.5 (0.0, 0.0)	0.0 (0.0, 0.2)	2.8 (0.0, 0.1)
Solomons Island, MD	274.4 (18.4, 1071.8)	1514.3 (127.1, *)	110.0 (4.7, 285.9)	7115.1 (29.4, *)
South Beach, OR	22.7 (6.0, 45.5)	406.5 (20.6, *)	51.9 (7.5, 115.3)	1729.5 (40.7, 9446.2)
Springmaid Pier, SC	82.5 (9.8, 226.4)	1002.9 (50.4, *)	13.8 (0.8, 19.8)	1314.0 (4.0, 7922.9)
St. Petersburg, FL	32.0 (3.7, 88.0)	1025.0 (11.9, *)	3.1 (0.6, 5.9)	420.3 (1.7, 363.1)
Toke Point, WA	4.9 (1.4, 9.9)	77.5 (2.6, 241.0)	3.6 (0.1, 8.6)	178.4 (1.0, 245.4)
Unalaska, AK	1.6 (0.0, 2.8)	43.4 (0.0, 88.7)	7.9 (0.0, 4.4)	328.1 (0.0, 476.7)
Vaca Key, FL	832.2 (46.5, *)	1721.7 (640.0, *)	68.6 (1.3, 59.7)	7509.5 (7.0, *)
Washington, DC	4.7 (1.6, 7.7)	262.9 (2.8, *)	1.3 (0.3, 2.7)	15.6 (0.4, 3.9)
Wilmington, NC	194.3 (7.6, 907.2)	1396.9 (55.2, *)	52.8 (2.6, 72.1)	4357.7 (9.2, *)
Woods Hole, MA	41.5 (3.9, 132.4)	907.4 (7.5, *)	19.9 (1.9, 39.2)	1969.6 (4.5, *)
Yakutat, AK	0.1 (0.0, 0.1)	3.7 (0.0, 0.2)	0.1 (0.0, 0.1)	28.0 (0.0, 0.2)

Table C.4: Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Adak Island, AK	8.5 (0.0, 9.7)	1450.3 (0.0, 1839.4)
Alameda, CA	21.0 (0.0, 18.8)	2982.4 (0.6, 6862.0)
Anchorage, AK	28.1 (0.0, 110.5)	690.2 (0.0, 1937.7)
Annapolis, MD	2.2 (0.2, 5.7)	332.8 (0.6, 28.0)
Apalachicola, FL	1.3 (0.0, 4.9)	1.4 (0.0, 5.2)
Astoria, OR	72.5 (0.1, 177.8)	2741.0 (2.3, 7011.1)
Atlantic City, NJ	14.8 (1.1, 34.6)	4202.9 (4.6, 21124.3)
Baltimore, MD	2.1 (0.3, 5.0)	208.7 (0.7, 18.8)
Boston, MA	12.1 (0.6, 30.0)	2121.7 (2.2, 5117.0)
Bridgeport, CT	2.2 (0.0, 8.1)	195.7 (0.0, 34.5)
Cambridge, MD	3.8 (0.0, 11.8)	1424.9 (0.5, 867.4)
Cape May, NJ	104.4 (2.5, 241.4)	11391.5 (30.2, *)
Charleston, OR	117.0 (2.1, 276.5)	4847.0 (25.3, 19843.1)
Charleston, SC	4.0 (0.3, 8.7)	1285.8 (1.7, 705.4)
Chesapeake Bay, VA	5.0 (0.0, 16.6)	885.2 (0.6, 537.1)
Clearwater Beach, FL	1.3 (0.0, 5.0)	68.0 (0.0, 7.1)
Eastport, ME	36.7 (0.5, 110.1)	2652.2 (2.0, 8813.2)
Fernandina Beach, FL	207.6 (9.8, 387.8)	14299.3 (53.4, *)
Fort Pulaski, GA	145.1 (4.9, 283.2)	13313.2 (48.1, *)
Freeport, TX	3.2 (0.1, 9.4)	686.5 (1.5, 140.3)
Galveston Pier 21, TX	2.0 (0.3, 4.8)	147.2 (0.9, 13.6)
Galveston Pls. Pier, TX	1.3 (0.0, 3.9)	2.2 (0.0, 5.0)
Grand Isle, LA	1.2 (0.0, 4.2)	1.3 (0.0, 4.8)

Table C.5: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Honolulu, HI	30467.6 (1021.9, *)	84249.9 (16938.0, *)
Juneau, AK	0.1 (0.0, 0.7)	20.0 (0.0, 0.3)
Kahului, HI	358.6 (2.0, 279.8)	41546.2 (23.1, *)
Ketchikan, AK	33.8 (0.4, 92.5)	989.9 (1.1, 1951.6)
Key West, FL	116.3 (0.9, 35.1)	19398.6 (6.3, *)
Kiptopeke, VA	6.7 (0.0, 20.7)	1705.3 (0.7, 2023.1)
La Jolla, CA	2953.6 (315.9, 7733.1)	50683.1 (2355.7, *)
Lewes, DE	3.6 (0.0, 11.2)	610.5 (0.6, 208.9)
Los Angeles, CA	1797.9 (95.3, 4393.6)	34114.9 (774.0, *)
Mokuoloe, HI	44042.5 (2915.7, *)	86795.9 (38599.7, *)
Montauk, NY	25.9 (1.0, 67.9)	3974.2 (5.5, 16675.0)
Monterey, CA	298.2 (3.5, 682.5)	18030.4 (51.2, *)
Nantucket Island, MA	14.1 (0.3, 29.5)	4408.0 (2.0, 21846.0)
Naples, FL	13.7 (0.0, 19.6)	2870.8 (0.8, 4357.6)
Nawiliwili, HI	1188.4 (3.9, 2546.6)	52663.5 (56.6, *)
Neah Bay, WA	15.1 (0.0, 38.8)	1096.7 (0.0, 1339.5)
New London, CT	3.0 (0.1, 8.6)	395.4 (0.6, 85.2)
Newport, RI	2.9 (0.2, 7.6)	549.4 (0.7, 113.6)
New York City, NY	2.3 (0.2, 6.1)	204.0 (0.5, 31.2)
Pensacola, FL	1.2 (0.1, 3.1)	10.5 (0.1, 3.7)
Port Isabel, TX	1.1 (0.0, 4.2)	1.4 (0.0, 4.8)
Port San Luis, CA	372.4 (6.3, 962.7)	17131.9 (50.2, *)
Portland, ME	156.8 (3.4, 461.5)	8610.7 (7.1, 63736.2)
Providence, RI	1.3 (0.0, 5.1)	24.8 (0.0, 7.1)

Table C.6: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by ∗.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Reedy Point, DE	3.0 (0.0, 10.3)	879.4 (0.1, 236.0)
Rockport, TX	2.7 (0.1, 7.5)	1193.1 (1.0, 173.5)
Sabine Pass, TX	1.5 (0.0, 5.2)	85.9 (0.0, 9.2)
San Diego, CA	2176.0 (141.2, 5500.3)	44155.8 (1756.7, *)
San Francisco, CA	83.2 (2.1, 85.7)	9657.7 (18.6, *)
Seattle, WA	196.1 (15.1, 435.7)	9573.4 (102.6, 67010.3)
Seldovia, AK	0.1 (0.0, 0.7)	36.2 (0.0, 0.4)
Seward, AK	1.0 (0.0, 3.7)	186.2 (0.0, 16.1)
Sewells Point, VA	5.1 (0.4, 13.4)	654.9 (2.6, 283.5)
Sitka, AK	1.8 (0.0, 5.5)	328.6 (0.0, 55.7)
Skagway, AK	0.1 (0.0, 0.5)	10.9 (0.0, 0.2)
Solomons Island, MD	23.4 (0.0, 33.6)	6394.7 (3.3, 48440.8)
South Beach, OR	75.2 (3.0, 160.9)	4669.7 (44.9, 17570.1)
Springmaid Pier, SC	2.1 (0.0, 7.1)	559.5 (0.1, 43.2)
St. Petersburg, FL	1.6 (0.1, 4.9)	173.6 (0.2, 10.5)
Toke Point, WA	2.3 (0.0, 8.8)	302.8 (0.0, 79.1)
Unalaska, AK	27.6 (0.0, 4.9)	1395.6 (0.0, 1616.5)
Vaca Key, FL	3.2 (0.0, 7.1)	1877.4 (0.2, 298.1)
Washington, DC	1.1 (0.1, 3.0)	1.2 (0.1, 3.3)
Wilmington, NC	18.8 (0.4, 15.4)	3336.7 (2.3, 8461.5)
Woods Hole, MA	7.4 (0.2, 21.0)	1855.4 (1.3, 1878.7)
Yakutat, AK	0.3 (0.0, 0.2)	116.9 (0.0, 0.2)

Table C.7: Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-year for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Adak Island, AK	12.6 (0.5, 34.0)	299.4 (1.7, *)	18.8 (0.1, 28.7)	1257.2 (0.9, 9042.9)
Alameda, CA	45.2 (4.6, 123.2)	1161.2 (57.9, *)	44.3 (1.7, 63.7)	4415.2 (30.1, *)
Anchorage, AK	5.0 (0.0, 20.9)	30.6 (0.0, 95.8)	14.9 (0.0, 62.0)	200.6 (0.0, 599.1)
Annapolis, MD	132.7 (6.2, 530.0)	1659.5 (478.1, *)	8.9 (1.4, 14.4)	1824.9 (12.3, *)
Apalachicola, FL	3.1 (1.1, 4.4)	232.3 (3.1, *)	1.2 (0.0, 3.3)	5.5 (0.1, 4.2)
Astoria, OR	9.5 (2.0, 18.5)	214.2 (7.5, *)	38.6 (3.0, 85.1)	1321.6 (25.1, 7093.6)
Atlantic City, NJ	164.3 (9.3, 649.8)	1654.7 (501.9, *)	78.3 (5.0, 198.8)	7011.6 (154.7, *)
Baltimore, MD	61.6 (4.2, 198.6)	1432.7 (163.7, *)	5.4 (1.3, 10.4)	900.0 (8.2, 3901.2)
Boston, MA	67.9 (5.7, 203.2)	1096.3 (102.3, *)	50.7 (3.4, 144.5)	3022.9 (58.7, *)
Bridgeport, CT	24.3 (2.6, 72.1)	839.8 (24.6, *)	5.4 (0.5, 13.6)	543.6 (5.3, 1353.9)
Cambridge, MD	266.6 (15.6, 1103.4)	1764.9 (1349.8, *)	49.4 (2.4, 88.9)	7120.8 (105.9, *)
Cape May, NJ	157.6 (11.4, 611.1)	1673.8 (557.8, *)	183.1 (12.3, 520.4)	10680.0 (475.0, *)
Charleston, OR	18.1 (4.1, 38.8)	474.8 (21.6, *)	68.3 (8.0, 138.9)	2681.9 (78.4, *)
Charleston, SC	172.7 (19.5, 544.8)	1707.1 (790.5, *)	40.3 (3.1, 64.0)	5627.8 (95.0, *)
Chesapeake Bay, VA	50.6 (7.0, 146.9)	1396.9 (203.4, *)	21.2 (2.2, 45.3)	2441.6 (54.7, *)
Clearwater Beach, FL	58.3 (4.2, 200.1)	1493.8 (141.1, *)	2.4 (0.1, 6.1)	481.4 (1.5, 624.8)
Eastport, ME	51.2 (6.2, 127.1)	567.3 (52.3, *)	98.4 (4.0, 343.1)	2193.6 (81.7, 9943.9)
Fernandina Beach, FL	138.4 (12.4, 481.2)	1644.5 (481.2, *)	223.2 (16.7, 618.2)	11312.5 (618.2, *)
Fort Pulaski, GA	226.0 (36.6, 658.5)	1744.8 (1007.3, *)	347.7 (21.4, 932.1)	12701.3 (1425.7, *)
Freeport, TX	514.3 (60.2, *)	1824.3 (*, *)	24.0 (4.0, 35.8)	9352.6 (176.6, *)
Galveston Pier 21, TX	116.4 (11.9, 374.3)	1790.7 (*, *)	4.6 (1.7, 8.1)	1355.2 (12.2, 11967.4)
Galveston Pls. Pier, TX	39.9 (6.3, 112.8)	1661.1 (474.7, *)	2.0 (0.3, 4.3)	114.9 (1.6, 25.5)
Grand Isle, LA	375.4 (23.2, *)	1825.7 (*, *)	1.7 (0.1, 4.3)	74.1 (0.6, 11.7)

Table C.8: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-year for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Honolulu, HI	1507.1 (233.0, *)	1822.0 (*, *)	11707.6 (757.7, *)	18147.4 (*, *)
Juneau, AK	0.0 (0.0, 0.1)	1.7 (0.0, 0.1)	0.1 (0.0, 0.4)	8.8 (0.0, 0.2)
Kahului, HI	1419.7 (206.4, *)	1822.5 (*, *)	3174.6 (36.0, *)	17647.2 (15443.0, *)
Ketchikan, AK	5.9 (1.8, 12.4)	66.2 (4.1, 177.6)	20.1 (2.5, 49.3)	437.0 (10.4, 1071.6)
Key West, FL	1206.5 (111.7, *)	1816.1 (*, *)	1146.8 (13.0, 5377.4)	16829.5 (3184.3, *)
Kiptopeke, VA	93.6 (7.9, 312.5)	1591.4 (342.9, *)	39.7 (2.9, 80.0)	4892.6 (84.8, *)
La Jolla, CA	236.2 (43.0, 668.0)	1689.3 (668.0, *)	1313.7 (226.7, 3521.9)	15692.0 (3521.9, *)
Lewes, DE	51.1 (5.3, 157.3)	1328.3 (133.6, *)	13.3 (1.6, 28.6)	1822.0 (24.0, 14291.8)
Los Angeles, CA	125.9 (22.1, 349.0)	1423.2 (201.0, *)	690.1 (81.6, 1833.6)	12299.7 (1056.1, *)
Mokuoloe, HI	1467.7 (231.3, *)	1821.3 (*, *)	13023.0 (1379.5, *)	18177.3 (*, *)
Montauk, NY	65.1 (5.3, 223.5)	1383.7 (100.4, *)	57.0 (4.6, 124.0)	4915.5 (75.1, *)
Monterey, CA	105.5 (12.6, 327.1)	1440.0 (178.3, *)	287.0 (16.0, 793.6)	10383.4 (432.5, *)
Nantucket Island, MA	258.7 (9.5, 1213.6)	1689.1 (536.0, *)	101.6 (3.8, 252.5)	8363.7 (114.7, *)
Naples, FL	135.2 (8.6, 555.3)	1655.2 (327.2, *)	56.7 (3.0, 83.3)	7916.9 (59.6, *)
Nawiliwili, HI	1334.5 (130.6, *)	1816.0 (*, *)	4350.4 (56.2, *)	17620.4 (15126.6, *)
Neah Bay, WA	3.8 (0.4, 8.5)	78.0 (1.0, 275.8)	10.9 (0.0, 27.8)	469.2 (0.8, 1141.4)
New London, CT	24.6 (3.0, 66.8)	961.4 (31.3, *)	7.3 (1.3, 16.6)	744.6 (9.9, 2283.7)
Newport, RI	75.2 (4.3, 253.8)	1350.5 (113.2, *)	11.5 (1.5, 22.2)	1647.6 (12.1, 13953.6)
New York City, NY	31.5 (2.9, 98.6)	1022.3 (40.4, *)	5.3 (1.2, 11.7)	623.9 (6.5, 1885.5)
Pensacola, FL	22.5 (2.4, 57.6)	1249.8 (30.4, *)	1.6 (0.4, 3.2)	116.8 (1.0, 12.2)
Port Isabel, TX	201.8 (8.7, 914.8)	1781.0 (*, *)	1.7 (0.1, 4.5)	249.6 (0.6, 39.3)
Port San Luis, CA	81.4 (9.9, 216.8)	1284.0 (110.1, *)	272.7 (16.0, 678.2)	9293.9 (344.3, *)
Portland, ME	86.6 (6.3, 263.0)	1102.6 (89.1, *)	193.9 (7.1, 581.0)	5797.5 (178.0, *)
Providence, RI	17.9 (2.2, 50.6)	724.9 (19.7, *)	2.2 (0.1, 5.7)	141.0 (0.8, 44.7)

Table C.9: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 10-year and 100-year for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by ∗.

	10-year flood		100-year flood	
	2050	2100	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)	AF (5th, 9th)
Reedy Point, DE	185.7 (8.2, 750.9)	1668.9 (458.3, *)	30.6 (1.3, 52.6)	4862.6 (34.3, *)
Rockport, TX	1258.4 (131.1, *)	1825.7 (*, *)	58.6 (4.0, 67.3)	13889.2 (379.6, *)
Sabine Pass, TX	182.2 (9.8, 830.9)	1791.0 (*, *)	3.5 (0.5, 7.6)	1157.5 (5.3, 10803.4)
San Diego, CA	217.7 (45.7, 583.3)	1667.4 (583.3, *)	1044.1 (207.5, 2646.7)	14947.3 (2646.7, *)
San Francisco, CA	103.0 (11.0, 307.0)	1550.9 (274.7, *)	123.9 (8.6, 264.5)	9265.1 (236.6, *)
Seattle, WA	36.4 (8.9, 79.4)	899.4 (67.9, *)	115.2 (17.3, 245.1)	5093.4 (209.6, *)
Seldovia, AK	0.1 (0.0, 0.2)	2.5 (0.0, 0.2)	0.1 (0.0, 0.4)	17.1 (0.0, 0.4)
Seward, AK	0.8 (0.0, 2.1)	14.7 (0.0, 18.9)	1.1 (0.0, 3.1)	74.8 (0.0, 36.8)
Sewells Point, VA	33.1 (5.6, 88.0)	1301.7 (134.1, *)	12.9 (2.9, 26.9)	1559.2 (31.7, 11016.0)
Sitka, AK	2.1 (0.4, 4.2)	46.1 (0.4, 117.1)	2.6 (0.0, 5.4)	192.2 (0.1, 259.2)
Skagway, AK	0.0 (0.0, 0.1)	0.6 (0.0, 0.0)	0.0 (0.0, 0.2)	4.2 (0.0, 0.1)
Solomons Island, MD	441.1 (28.6, *)	1802.1 (*, *)	195.4 (6.8, 602.8)	12727.7 (746.1, *)
South Beach, OR	28.6 (7.7, 59.3)	687.1 (55.5, *)	69.7 (10.7, 153.4)	3189.7 (142.8, *)
Springmaid Pier, SC	132.1 (17.7, 406.2)	1583.5 (406.2, *)	23.5 (1.1, 36.8)	3466.6 (37.6, *)
St. Petersburg, FL	70.1 (4.7, 241.8)	1562.3 (165.5, *)	4.4 (0.7, 7.4)	1080.2 (4.6, 8555.4)
Toke Point, WA	6.1 (1.8, 12.3)	133.4 (6.7, 553.2)	4.5 (0.2, 10.0)	295.2 (3.5, 563.2)
Unalaska, AK	2.9 (0.0, 6.5)	94.9 (0.0, 487.8)	13.6 (0.0, 14.9)	707.7 (0.0, 2620.8)
Vaca Key, FL	1194.9 (93.6, *)	1817.4 (*, *)	179.3 (2.2, 390.6)	13951.5 (231.2, *)
Washington, DC	6.8 (1.8, 11.2)	562.3 (11.1, *)	1.4 (0.3, 2.8)	18.3 (0.6, 4.5)
Wilmington, NC	379.4 (11.2, *)	1784.3 (*, *)	96.9 (3.4, 184.8)	10152.0 (147.9, *)
Woods Hole, MA	74.9 (4.6, 276.1)	1418.2 (107.3, *)	31.3 (2.5, 62.2)	3556.9 (33.4, *)
Yakutat, AK	0.1 (0.0, 0.1)	5.6 (0.0, 1.8)	0.2 (0.0, 0.2)	40.8 (0.0, 2.3)

Table C.10: Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Adak Island, AK	15.5 (0.0, 13.4)	2727.2 (0.0, 7502.2)
Alameda, CA	33.4 (0.0, 24.8)	6521.6 (6.9, 66072.4)
Anchorage, AK	28.3 (0.0, 102.8)	746.7 (0.0, 2142.6)
Annapolis, MD	2.4 (0.2, 6.3)	561.5 (1.4, 54.8)
Apalachicola, FL	1.4 (0.0, 4.9)	1.5 (0.0, 5.3)
Astoria, OR	104.1 (1.1, 246.9)	5007.5 (54.6, 22104.9)
Atlantic City, NJ	24.1 (1.5, 54.1)	6704.8 (41.7, 45851.7)
Baltimore, MD	2.3 (0.3, 5.5)	385.2 (1.5, 32.3)
Boston, MA	19.1 (0.9, 47.2)	3436.5 (20.0, 10922.8)
Bridgeport, CT	2.5 (0.0, 8.8)	312.9 (0.2, 53.7)
Cambridge, MD	5.2 (0.0, 14.2)	2683.2 (4.0, 5434.3)
Cape May, NJ	174.1 (4.4, 400.7)	24569.4 (370.6, *)
Charleston, OR	167.9 (6.3, 380.5)	9255.0 (178.6, 73422.2)
Charleston, SC	5.6 (0.5, 10.7)	2709.7 (6.4, 6147.0)
Chesapeake Bay, VA	6.6 (0.0, 20.2)	1675.9 (8.8, 1700.4)
Clearwater Beach, FL	1.4 (0.0, 5.2)	95.2 (0.0, 8.7)
Eastport, ME	63.1 (0.8, 199.1)	4366.3 (32.4, 14740.8)
Fernandina Beach, FL	355.1 (16.8, 748.1)	35579.6 (746.8, *)
Fort Pulaski, GA	270.3 (8.8, 658.6)	32932.4 (1196.0, *)
Freeport, TX	3.6 (0.1, 10.4)	1449.9 (4.6, 881.0)
Galveston Pier 21, TX	2.1 (0.3, 5.1)	220.5 (1.5, 23.6)
Galveston Pls. Pier, TX	1.3 (0.0, 4.0)	11.0 (0.1, 5.5)
Grand Isle, LA	1.2 (0.0, 4.2)	1.4 (0.0, 4.9)

Table C.11: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Honolulu, HI	45438.6 (1791.9, *)	90305.0 (*, *)
Juneau, AK	0.1 (0.0, 0.7)	27.4 (0.0, 0.4)
Kahului, HI	777.0 (3.1, 1379.7)	68650.4 (918.9, *)
Ketchikan, AK	49.5 (1.6, 133.8)	1741.4 (18.4, 4082.5)
Key West, FL	198.9 (1.5, 82.2)	48284.7 (53.8, *)
Kiptopeke, VA	9.6 (0.0, 27.0)	3295.3 (14.5, 8947.0)
La Jolla, CA	4290.3 (601.1, 11148.0)	72883.3 (11148.0, *)
Lewes, DE	4.4 (0.0, 13.3)	1082.8 (3.5, 609.4)
Los Angeles, CA	2652.2 (228.8, 6957.8)	57082.8 (4007.6, *)
Mokuoloe, HI	58858.5 (4887.8, *)	90735.2 (*, *)
Montauk, NY	45.8 (1.7, 116.2)	7337.3 (63.4, 61203.2)
Monterey, CA	507.6 (10.4, 1304.0)	36230.0 (700.9, *)
Nantucket Island, MA	26.5 (0.4, 46.5)	7841.6 (20.9, 74838.1)
Naples, FL	25.0 (0.0, 28.1)	8266.2 (11.1, *)
Nawiliwili, HI	2611.3 (7.5, 7886.4)	76809.0 (2546.6, *)
Neah Bay, WA	24.1 (0.0, 59.0)	1803.7 (0.0, 3447.1)
New London, CT	3.6 (0.2, 9.9)	597.0 (2.2, 134.7)
Newport, RI	3.4 (0.3, 9.1)	861.1 (2.3, 234.5)
New York City, NY	2.6 (0.2, 6.8)	337.4 (1.4, 52.4)
Pensacola, FL	1.2 (0.1, 3.2)	11.9 (0.1, 4.1)
Port Isabel, TX	1.2 (0.0, 4.3)	10.6 (0.0, 5.3)
Port San Luis, CA	582.2 (14.6, 1418.2)	34047.8 (659.3, *)
Portland, ME	279.9 (5.2, 878.4)	15146.3 (192.2, *)
Providence, RI	1.4 (0.0, 5.2)	56.2 (0.0, 8.2)

Table C.12: Continued. Expected amplification factors (and 5th and 95th percentiles) for the 500-year floods for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

	500-year flood	
	2050	2100
Site	AF (5th, 9th)	AF (5th, 9th)
Reedy Point, DE	3.7 (0.0, 12.1)	1670.1 (1.1, 1427.2)
Rockport, TX	3.1 (0.1, 8.5)	2907.7 (3.2, 4118.2)
Sabine Pass, TX	1.6 (0.0, 5.4)	134.6 (0.1, 12.1)
San Diego, CA	3162.0 (318.5, 7814.6)	67237.4 (7814.6, *)
San Francisco, CA	139.4 (3.4, 135.2)	21326.3 (112.1, *)
Seattle, WA	272.6 (24.3, 559.9)	17303.5 (494.9, *)
Seldovia, AK	0.2 (0.0, 0.8)	55.9 (0.0, 0.6)
Seward, AK	1.3 (0.0, 4.1)	248.0 (0.0, 34.3)
Sewells Point, VA	6.2 (0.5, 16.0)	1195.4 (10.6, 729.1)
Sitka, AK	2.5 (0.0, 6.5)	521.0 (0.0, 227.4)
Skagway, AK	0.1 (0.0, 0.5)	13.5 (0.0, 0.2)
Solomons Island, MD	44.9 (0.1, 50.9)	14244.6 (49.8, *)
South Beach, OR	105.4 (5.7, 226.1)	8714.7 (199.4, 57559.7)
Springmaid Pier, SC	2.4 (0.0, 8.1)	1026.7 (0.4, 302.2)
St. Petersburg, FL	1.8 (0.1, 5.2)	279.7 (0.3, 17.3)
Toke Point, WA	2.7 (0.0, 9.5)	463.6 (0.1, 207.0)
Unalaska, AK	47.3 (0.0, 21.5)	2947.9 (0.0, 8887.4)
Vaca Key, FL	7.6 (0.0, 8.2)	5354.2 (0.9, 54053.8)
Washington, DC	1.1 (0.1, 3.1)	1.3 (0.1, 3.6)
Wilmington, NC	34.5 (0.6, 23.1)	9026.6 (14.8, *)
Woods Hole, MA	10.5 (0.3, 28.1)	2926.7 (10.7, 5960.7)
Yakutat, AK	0.6 (0.0, 0.2)	169.0 (0.0, 2.2)

Table C.13: Amplification factors using the Generalized Pareto (GPD) distributions with 0.5 m of local SLR, without accounting for uncertainty in the extreme value distribution. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

Site	10-year flood	100-year flood	500-year flood
Adak Island, AK	162.2	291.0	94.7
Alameda, CA	211.3	111.9	29.9
Anchorage, AK	44.3	277.2	752.3
Annapolis, MD	49.5	4.7	2.3
Apalachicola, FL	3.2	1.2	1.4
Astoria, OR	54.5	242.2	773.7
Atlantic City, NJ	49.1	19.6	8.9
Baltimore, MD	26.0	4.1	2.2
Boston, MA	48.1	25.6	11.8
Bridgeport, CT	13.6	4.6	2.4
Cambridge, MD	120.2	13.0	3.6
Cape May, NJ	57.0	65.6	48.2
Charleston, OR	64.5	233.1	622.4
Charleston, SC	148.1	16.2	4.3
Chesapeake Bay, VA	20.1	10.1	4.4
Clearwater Beach, FL	39.2	2.5	1.4
Eastport, ME	52.3	78.9	33.8
Fernandina Beach, FL	155.7	200.0	261.2
Fort Pulaski, GA	200.3	283.5	101.3
Freeport, TX	29.8	4.5	2.2
Galveston Pls. Pier, TX	6.5	1.6	1.2
Grand Isle, LA	6.3	1.3	1.1
Juneau, AK	28.7	27.9	14.0
Kahului, HI	*	3414.0	95.7
Ketchikan, AK	33.4	197.0	655.7
Key West, FL	*	937.6	23.4
Kiptopeke, VA	36.9	15.9	5.9
La Jolla, CA	507.7	2677.0	8473.5
Lewes, DE	22.4	7.4	3.6
Los Angeles, CA	504.1	2648.6	10050.7
Mokuoloe, HI	*	*	*
Montauk, NY	23.7	26.9	20.8

Table C.14: Continued. Amplification factors using the Generalized Pareto (GPD) distributions with 0.5 m of local SLR, without accounting for uncertainty in the extreme value distribution. An amplification factor that results in flooding that is dominated by tidal events, rather than storm surges, is demarcated by $*$.

Site	10-year flood	100-year flood	500-year flood
Monterey, CA	361.9	878.1	1304.0
Nantucket Island, MA	94.4	25.5	8.5
Naples, FL	147.9	35.1	10.5
Nawiliwili, HI	*	12529.2	2109.3
Neah Bay, WA	44.4	183.6	571.3
New London, CT	12.8	5.9	3.4
Newport, RI	35.3	6.5	3.1
Pensacola, FL	20.4	1.8	1.2
Port Isabel, TX	66.1	1.7	1.2
Port San Luis, CA	351.9	1100.7	2301.8
Portland, ME	82.9	167.4	180.3
Providence, RI	10.6	2.2	1.4
Reedy Point, DE	85.5	9.8	3.1
Rockport, TX	332.2	7.0	2.3
Sabine Pass, TX	21.1	2.5	1.5
San Diego, CA	448.2	2033.9	6005.0
San Francisco, CA	274.7	236.6	117.8
Seattle, WA	108.7	335.4	814.1
Seldovia, AK	32.3	59.3	38.7
Seward, AK	26.5	56.9	56.2
Sewells Point, VA	13.0	7.4	4.4
Sitka, AK	37.8	58.7	42.2
Skagway, AK	28.5	29.9	11.6
Solomons Island, MD	194.7	45.0	8.5
South Beach, OR	59.3	153.4	223.2
Springmaid Pier, SC	137.2	11.2	2.6
St. Petersburg, FL	41.2	3.6	1.8
The Battery, NY	14.0	4.2	2.5
Toke Point, WA	23.0	15.0	6.7
Unalaska, AK	242.5	1302.9	4418.2
Vaca Key, FL	*	35.5	2.7
Washington, DC	4.1	1.4	1.1
Wilmington, NC	450.7	40.9	9.0
Woods Hole, MA	25.9	14.3	7.3
Yakutat, AK	33.5	171.8	410.5

Table C.15: Goodness of fit of the Gumbel compared to the GPD for extreme water levels (10% to 0.1% annual chance flood levels). We use the Akaike Information Criterion corrected for small samples (AIC$_c$) for sites in the contiguous U.S. whereby the number of k parameters is at least 30% of the sample size. Lower AIC$_c$ values indicate higher model quality. $\triangle$AIC$_c$ is the difference between the AIC$_c$ with the Gumbel and the AIC$_c$ with the GPD. There is only a fraction of sites for which $\triangle$AIC$_c$ is negative. The AIC$_c$ for the GPD is smaller than the AIC$_c$ for the Gumbel for all sites with moderate shape parameters ($\xi \geq |0.10|$).

Site	ξ	AIC$_c$ (Gumbel)	AIC$_c$ (GPD)	$\triangle$AIC$_c$
Portland, ME	-0.05	-84.04	-73.96	-10.08
Boston, MA	0.07	-57.65	-61.66	4.01
Newport, RI	0.19	-52.33	-70.39	18.06
New London, CT	0.11	-46.39	-51.18	4.79
New York City, NY	0.19	-39.21	-48.62	9.4
Atlantic City, NJ	0.09	-66.49	-67.31	0.82
Baltimore, MD	0.25	-54.09	-66.19	12.1
Washington, DC	0.5	-43.58	-55.43	11.86
Sewells Point, VA	0.07	-41.16	-41.37	0.21
Wilmington, NC	0.17	-36.73	-39.33	2.6
Charleston, SC	0.23	-55.44	-68.94	13.5
Fort Pulaski, GA	0.07	-52.34	-45.25	-7.09
Fernandina Beach, FL	-0.06	-69.54	-74.37	4.83
Key West, FL	0.23	-68.39	-72.65	4.26
St. Petersburg, FL	0.29	-34.58	-45.17	10.58
Pensacola, FL	0.47	-47.13	-79.15	32.02
Galveston Pier 21, TX	0.28	-64.23	-76.74	12.51
Rockport, TX	0.29	-46.91	-56.18	9.27
Los Angeles, CA	-0.22	-35.17	-49.46	14.29
San Francisco, CA	0.03	-64.4	-58.54	-5.86
Astoria, OR	-0.32	-34.76	-42.6	7.84
Seattle, WA	-0.17	-49.35	-62.85	13.5
San Diego, CA	-0.09	-72	-67.18	-4.81

Table C.16: Annual expected number of the 10-year, 100-year, and 500-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD.

	10-year flood		100-year flood		500-year flood	
Site	2050	2100	2050	2100	2050	2100
Adak Island, AK	0.9	16.2	0.11	6.60	0.017	2.901
Alameda, CA	3.0	71.5	0.31	20.23	0.042	5.965
Anchorage, AK	0.5	3.1	0.15	1.93	0.056	1.380
Annapolis, MD	7.6	114.6	0.06	8.72	0.004	0.666
Apalachicola, FL	0.2	8.4	0.01	0.05	0.003	0.003
Astoria, OR	0.7	11.6	0.28	7.16	0.145	5.482
Atlantic City, NJ	9.8	118.2	0.45	40.08	0.030	8.406
Baltimore, MD	3.6	87.0	0.04	4.65	0.004	0.417
Boston, MA	4.5	66.0	0.30	17.16	0.024	4.243
Bridgeport, CT	1.5	47.2	0.04	3.37	0.004	0.391
Cambridge, MD	16.2	137.2	0.29	33.61	0.008	2.850
Cape May, NJ	9.6	119.8	1.15	57.22	0.209	22.783
Charleston, OR	1.4	25.9	0.50	14.04	0.234	9.694
Charleston, SC	10.6	122.4	0.23	22.49	0.008	2.572
Chesapeake Bay, VA	3.3	83.7	0.14	11.44	0.010	1.770
Clearwater Beach, FL	2.8	93.6	0.02	2.09	0.003	0.136
Eastport, ME	3.9	34.6	0.63	13.18	0.073	5.304
Fernandina Beach, FL	7.8	107.8	1.29	54.10	0.415	28.599
Fort Pulaski, GA	14.6	129.5	2.10	66.24	0.290	26.626
Freeport, TX	31.3	178.7	0.16	42.14	0.006	1.373
Galveston Pls. Pier, TX	2.4	121.6	0.02	0.56	0.003	0.004
Grand Isle, LA	20.9	180.1	0.02	0.43	0.002	0.003
Kahului, HI	117.6	178.0	16.17	152.96	0.717	83.092
Ketchikan, AK	0.5	3.9	0.15	2.50	0.068	1.980
Key West, FL	85.7	172.7	4.97	125.46	0.233	38.797
Kiptopeke, VA	5.6	104.5	0.25	22.18	0.013	3.411
La Jolla, CA	16.6	136.3	9.14	116.53	5.907	101.366
Lewes, DE	3.2	78.6	0.09	8.60	0.007	1.221
Los Angeles, CA	8.8	97.2	4.72	76.46	3.596	68.230
Mokuoloe, HI	123.2	177.3	102.24	175.22	88.085	173.592
Montauk, NY	3.7	87.2	0.36	26.07	0.052	7.948

Table C.17: Continued. Annual expected number of the 10-year, 100-year, and 500-year floods for 2050 and 2100 under RCP 4.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD.

	10-year flood		100-year flood		500-year flood	
Site	2050	2100	2050	2100	2050	2100
Monterey, CA	7.2	101.6	1.90	61.55	0.596	36.061
Nantucket Island, MA	15.2	125.6	0.58	45.83	0.028	8.816
Naples, FL	6.2	116.7	0.33	30.37	0.027	5.742
Nawiliwili, HI	106.2	174.5	24.49	152.40	2.377	105.327
Neah Bay, WA	0.3	4.6	0.07	2.81	0.030	2.193
New London, CT	1.5	55.8	0.05	4.77	0.006	0.791
Newport, RI	4.3	85.4	0.07	9.56	0.006	1.099
New York City, NY	1.9	58.8	0.04	3.70	0.005	0.408
Pensacola, FL	1.2	66.0	0.01	0.61	0.002	0.021
Port Isabel, TX	9.8	149.2	0.02	1.23	0.002	0.003
Port San Luis, CA	5.5	83.1	1.80	51.73	0.745	34.264
Portland, ME	5.6	67.2	1.18	32.51	0.314	17.221
Providence, RI	1.1	40.6	0.02	0.92	0.003	0.050
Reedy Point, DE	11.1	119.5	0.18	22.08	0.006	1.759
Rockport, TX	93.6	180.0	0.36	80.03	0.005	2.386
Sabine Pass, TX	9.3	156.5	0.03	4.37	0.003	0.172
San Diego, CA	15.5	132.5	7.30	106.33	4.352	88.312
San Francisco, CA	6.8	115.2	0.83	51.43	0.166	19.315
Seattle, WA	2.9	57.2	0.88	29.16	0.392	19.147
Seldovia, AK	0.0	0.2	0.00	0.11	0.000	0.072
Seward, AK	0.1	1.1	0.01	0.58	0.002	0.372
Sewells Point, VA	2.2	74.9	0.09	6.95	0.010	1.310
Sitka, AK	0.2	2.6	0.02	1.16	0.004	0.657
Skagway, AK	0.0	0.0	0.00	0.03	0.000	0.022
Solomons Island, MD	27.4	151.4	1.10	71.15	0.047	12.789
South Beach, OR	2.3	40.6	0.52	17.29	0.150	9.339
Springmaid Pier, SC	8.3	100.3	0.14	13.14	0.004	1.119
St. Petersburg, FL	3.2	102.5	0.03	4.20	0.003	0.347
Toke Point, WA	0.5	7.7	0.04	1.78	0.005	0.606
Unalaska, AK	0.2	4.3	0.08	3.28	0.055	2.791
Vaca Key, FL	83.2	172.2	0.69	75.09	0.006	3.755
Washington, DC	0.5	26.3	0.01	0.16	0.002	0.002
Wilmington, NC	19.4	139.7	0.53	43.58	0.038	6.673
Woods Hole, MA	4.1	90.7	0.20	19.70	0.015	3.711
Yakutat, AK	0.0	0.4	0.00	0.28	0.001	0.234

Table C.18: Annual expected number of the 10-year, 100-year, and 500-year floods for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD.

	10-year flood		100-year flood		500-year flood	
Site	2050	2100	2050	2100	2050	2100
Adak Island, AK	1.3	29.9	0.19	12.57	0.031	5.454
Alameda, CA	4.5	116.1	0.44	44.15	0.067	13.043
Anchorage, AK	0.5	3.1	0.15	2.01	0.057	1.493
Annapolis, MD	13.3	165.9	0.09	18.25	0.005	1.123
Apalachicola, FL	0.3	23.2	0.01	0.05	0.003	0.003
Astoria, OR	1.0	21.4	0.39	13.22	0.208	10.015
Atlantic City, NJ	16.4	165.5	0.78	70.12	0.048	13.410
Baltimore, MD	6.2	143.3	0.05	9.00	0.005	0.770
Boston, MA	6.8	109.6	0.51	30.23	0.038	6.873
Bridgeport, CT	2.4	84.0	0.05	5.44	0.005	0.626
Cambridge, MD	26.7	176.5	0.49	71.21	0.010	5.366
Cape May, NJ	15.8	167.4	1.83	106.80	0.348	49.139
Charleston, OR	1.8	47.5	0.68	26.82	0.336	18.510
Charleston, SC	17.3	170.7	0.40	56.28	0.011	5.419
Chesapeake Bay, VA	5.1	139.7	0.21	24.42	0.013	3.352
Clearwater Beach, FL	5.8	149.4	0.02	4.81	0.003	0.190
Eastport, ME	5.1	56.7	0.98	21.94	0.126	8.733
Fernandina Beach, FL	13.8	164.5	2.23	113.12	0.710	71.159
Fort Pulaski, GA	22.6	174.5	3.48	127.01	0.541	65.865
Freeport, TX	51.4	182.4	0.24	93.53	0.007	2.900
Galveston Pls. Pier, TX	4.0	166.1	0.02	1.15	0.003	0.022
Grand Isle, LA	37.5	182.6	0.02	0.74	0.002	0.003
Kahului, HI	142.0	182.2	31.75	176.47	1.554	137.301
Ketchikan, AK	0.6	6.6	0.20	4.37	0.099	3.483
Key West, FL	120.7	181.6	11.47	168.29	0.398	96.569
Kiptopeke, VA	9.4	159.1	0.40	48.93	0.019	6.591
La Jolla, CA	23.6	168.9	13.14	156.92	8.581	145.767
Lewes, DE	5.1	132.8	0.13	18.22	0.009	2.166
Los Angeles, CA	12.6	142.3	6.90	123.00	5.304	114.166
Mokuoloe, HI	146.8	182.1	130.23	181.77	117.717	181.470
Montauk, NY	6.5	138.4	0.57	49.15	0.092	14.675

Table C.19: Continued. Annual expected number of the 10-year, 100-year, and 500-year floods for 2050 and 2100 under RCP 8.5. Using the Generalized Pareto Distribution (GPD) and the full probability distribution of local sea level rise and uncertainty in GPD.

	10-year flood		100-year flood		500-year flood	
Site	2050	2100	2050	2100	2050	2100
Monterey, CA	10.5	144.0	2.87	103.83	1.015	72.460
Nantucket Island, MA	25.9	168.9	1.02	83.64	0.053	15.683
Naples, FL	13.5	165.5	0.57	79.17	0.050	16.532
Nawiliwili, HI	133.5	181.6	43.50	176.20	5.223	153.618
Neah Bay, WA	0.4	7.8	0.11	4.69	0.048	3.607
New London, CT	2.5	96.1	0.07	7.45	0.007	1.194
Newport, RI	7.5	135.0	0.11	16.48	0.007	1.722
New York City, NY	3.2	102.2	0.05	6.24	0.005	0.675
Pensacola, FL	2.2	125.0	0.02	1.17	0.002	0.024
Port Isabel, TX	20.2	178.1	0.02	2.50	0.002	0.021
Port San Luis, CA	8.1	128.4	2.73	92.94	1.164	68.096
Portland, ME	8.7	110.3	1.94	57.97	0.560	30.293
Providence, RI	1.8	72.5	0.02	1.41	0.003	0.112
Reedy Point, DE	18.6	166.9	0.31	48.63	0.007	3.340
Rockport, TX	125.8	182.6	0.59	138.89	0.006	5.815
Sabine Pass, TX	18.2	179.1	0.04	11.57	0.003	0.269
San Diego, CA	21.8	166.7	10.44	149.47	6.324	134.475
San Francisco, CA	10.3	155.1	1.24	92.65	0.279	42.653
Seattle, WA	3.6	89.9	1.15	50.93	0.545	34.607
Seldovia, AK	0.0	0.2	0.00	0.17	0.000	0.112
Seward, AK	0.1	1.5	0.01	0.75	0.003	0.496
Sewells Point, VA	3.3	130.2	0.13	15.59	0.012	2.391
Sitka, AK	0.2	4.6	0.03	1.92	0.005	1.042
Skagway, AK	0.0	0.1	0.00	0.04	0.000	0.027
Solomons Island, MD	44.1	180.2	1.95	127.28	0.090	28.489
South Beach, OR	2.9	68.7	0.70	31.90	0.211	17.429
Springmaid Pier, SC	13.2	158.3	0.24	34.67	0.005	2.053
St. Petersburg, FL	7.0	156.2	0.04	10.80	0.004	0.559
Toke Point, WA	0.6	13.3	0.04	2.95	0.005	0.927
Unalaska, AK	0.3	9.5	0.14	7.08	0.095	5.896
Vaca Key, FL	119.5	181.7	1.79	139.52	0.015	10.708
Washington, DC	0.7	56.2	0.01	0.18	0.002	0.003
Wilmington, NC	37.9	178.4	0.97	101.52	0.069	18.053
Woods Hole, MA	7.5	141.8	0.31	35.57	0.021	5.853
Yakutat, AK	0.0	0.6	0.00	0.41	0.001	0.338

Appendix D

Values, bias, and stressors affect adaptation to coastal flood risk: evidence from New York City

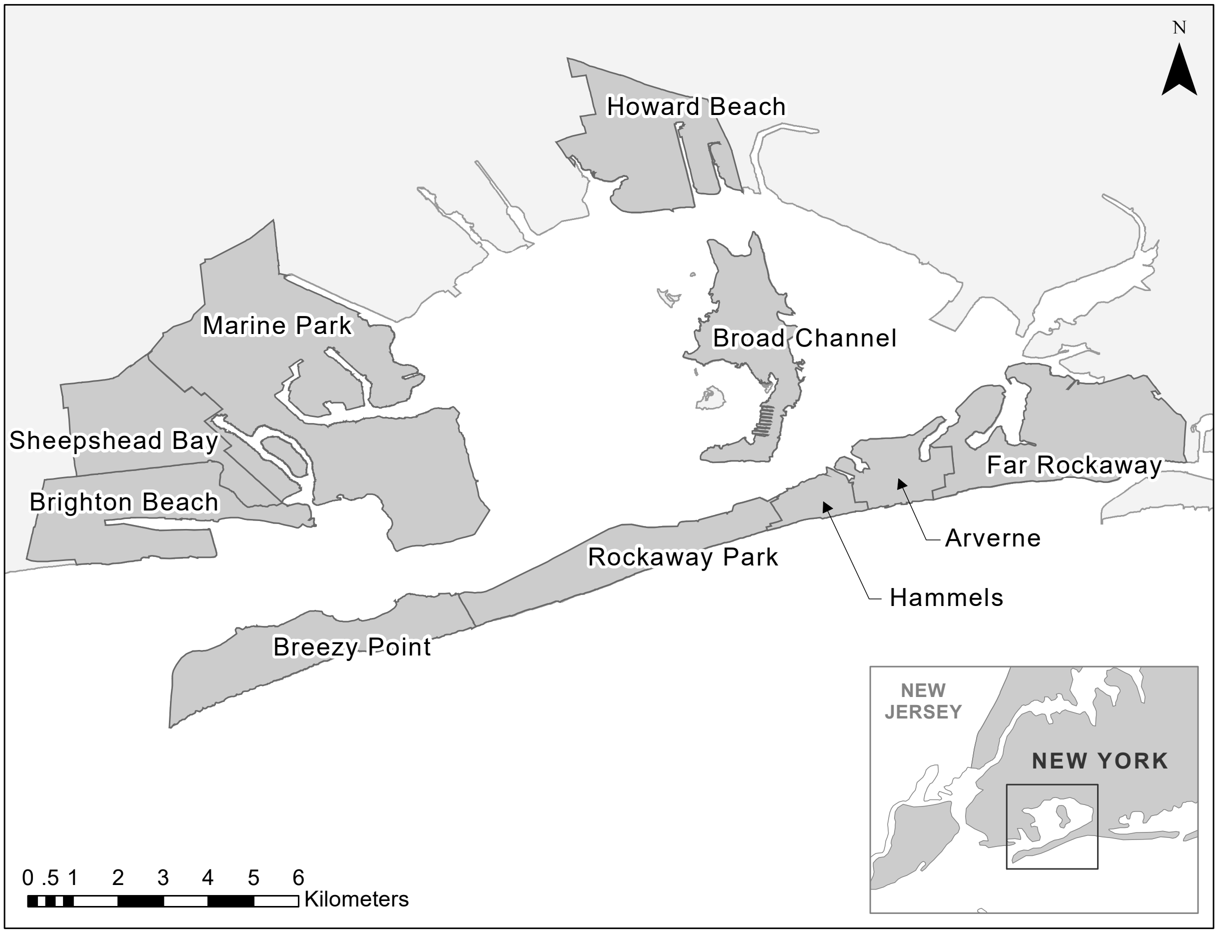

Figure D.1: The Jamaica Bay region and neighborhood areas included in the case study.

Table D.1: Descriptive statistics of Jamaica Bay neighborhoods. All values are in percentages, except where otherwise noted.

	Arverne	Breezy Point	Brighton Beach	Far Rockaway	Hammels	Howard Beach	Marine Park	Rockaway Park	Sheepshead Bay	Weighted
Zip code	11692	11697	11235	11691	11693	11414	11234	11694	11229	–
Households (count)	5,974	1,701	31,958	18,942	4,518	11,059	31,989	8,190	30,892	–
Households children ≤ 18	43	25	25	42	34	27	38	32	29	32
Age (median)	35	50	44	31	39	45	38	44	41	40
Household income (median, $k)	40	87	42	39	50	65	68	74	50	53
Property value (median, $k)	363	537	530	461	335	501	496	638	526	507
Rent cost (median, $)	839	654	1019	945	795	1,258	1,119	1,088	1,093	1,032
Female	53	50	54	54	54	54	53	51	53	53
White	14	98	75	23	47	73	42	76	67	56
Hispanic	23	1	9	27	19	20	9	13	8	13
Married	32	41	42	31	40	40	34	38	38	37
Employed	72	82	83	73	80	85	80	80	80	80
Homeowners	34	97	40	26	44	74	67	56	46	49
Mortgage	7	18	9	6	10	16	17	13	10	11

Table D.2: Comparison of in-person and mailed samples for owners in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	110.14	122.09	0.45	-0.77	-43.61	19.72
	Married	0.86	0.61	0.06	1.93	-0.01	0.52
	Age	53.57	49.39	0.38	0.90	-5.47	13.83
	Female	0.57	0.45	0.48	0.72	-0.22	0.45
	White	0.79	0.76	0.84	0.21	-0.25	0.31
	Children	0.21	0.36	0.30	-1.05	-0.44	0.14
	Education	3.50	3.18	0.16	1.45	-0.13	0.77
	Tenure	30.21	34.42	0.48	-0.72	-16.28	7.86
	Mortgage	0.36	0.64	0.11	-1.65	-0.63	0.07
	Community hrs.	2.86	2.71	0.83	0.22	-1.20	1.49
	External network	8.43	10.27	0.32	-1.02	-5.56	1.88
	Avoid flood costs	4.07	4.12	0.88	-0.15	-0.74	0.64
	Avoid inconviences	3.71	3.52	0.61	0.52	-0.60	0.99
	Keep home	4.71	4.30	0.09	1.77	-0.06	0.88
	Community	4.43	3.94	0.16	1.43	-0.21	1.19
	Coast	4.50	4.36	0.63	0.48	-0.45	0.73
	Flood perception	0.93	0.85	0.40	0.86	-0.11	0.27
	Flood concern	1.00	0.79	0.01	2.94	0.06	0.36
	Climate perception	0.86	0.86	0.95	-0.07	-0.21	0.20
	Experience	0.29	0.30	0.91	-0.12	-0.33	0.29
	Damage	50.00	36.52	0.00	3.59	5.83	21.14
	Surveyed	0.07	0.21	0.17	-1.38	-0.35	0.07
	Generator	0.36	0.48	0.43	-0.80	-0.46	0.20
	Insured	0.64	0.79	0.35	-0.96	-0.46	0.17
	Other adaptation	0.14	0.12	0.85	0.19	-0.21	0.26
	No adaptations	0.29	0.09	0.17	1.44	-0.09	0.48
Dependent	Relocate	0.57	0.52	0.73	0.34	-0.28	0.39
	Insure	0.43	0.64	0.21	-1.29	-0.54	0.13
	Elevate	0.57	0.42	0.37	0.90	-0.19	0.48

Table D.3: Comparison of in-person and mailed samples for owners in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	91.44	88.10	0.86	0.18	-34.38	41.07
	Married	0.50	0.52	0.89	-0.14	-0.36	0.31
	Age	46.11	51.43	0.36	-0.92	-16.99	6.35
	Female	0.67	0.57	0.55	0.60	-0.23	0.42
	White	0.50	0.57	0.67	-0.44	-0.40	0.26
	Children	0.28	0.24	0.79	0.27	-0.25	0.33
	Education	3.11	3.00	0.61	0.52	-0.32	0.55
	Tenure	24.78	31.33	0.30	-1.04	-19.27	6.16
	Mortgage	0.67	0.57	0.63	0.49	-0.30	0.49
	Community hrs.	3.50	2.52	0.34	0.96	-1.09	3.04
	External network	10.44	6.71	0.05	2.05	0.04	7.42
	Avoid flood costs	4.44	3.95	0.21	1.27	-0.29	1.28
	Avoid inconviences	3.83	4.00	0.67	-0.43	-0.95	0.61
	Keep home	4.72	3.95	0.01	2.68	0.18	1.36
	Community	3.78	3.57	0.63	0.48	-0.66	1.08
	Coast	4.44	3.76	0.06	1.95	-0.03	1.40
	Flood perception	0.81	0.55	0.07	1.87	-0.02	0.54
	Flood concern	0.94	0.71	0.05	2.00	-0.01	0.47
	Climate perception	0.97	0.81	0.05	2.08	0.00	0.32
	Experience	0.28	0.24	0.79	0.27	-0.25	0.33
	Damage level	26.11	15.24	0.11	1.67	-2.41	24.16
	Surveyed	0.17	0.24	0.59	-0.54	-0.34	0.19
	Generator	0.39	0.14	0.09	1.74	-0.04	0.54
	Insured	0.56	0.48	0.63	0.48	-0.25	0.41
	Other adaptation	0.11	0.10	0.88	0.16	-0.19	0.22
	No adaptations	0.33	0.43	0.55	-0.60	-0.42	0.23
Dependent	Relocate	0.67	0.67	1.00	0.00	-0.32	0.32
	Insure	0.61	0.57	0.81	0.25	-0.29	0.37
	Elevate	0.39	0.43	0.81	-0.25	-0.37	0.29

Table D.4: Comparison of in-person and mailed samples for owners in Central Jamaica Bay neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	104.63	114.00	0.71	-0.39	-64.81	46.08
	Married	0.73	0.75	0.92	-0.10	-0.42	0.38
	Age	49.76	50.00	0.96	-0.05	-11.63	11.14
	Female	0.61	0.62	0.94	-0.08	-0.46	0.43
	White	0.93	1.00	0.08	-1.78	-0.16	0.01
	Children	0.37	0.38	0.96	-0.05	-0.45	0.44
	Education	2.78	2.50	0.23	1.24	-0.20	0.77
	Tenure	33.88	31.00	0.70	0.39	-13.53	19.29
	Mortgage	0.71	0.75	0.82	-0.23	-0.45	0.36
	Community hrs.	2.78	4.31	0.27	-1.18	-4.50	1.43
	External network	7.02	9.38	0.30	-1.09	-7.19	2.49
	Avoid flood costs	4.54	4.62	0.71	-0.38	-0.58	0.40
	Avoid inconviences	3.44	3.88	0.34	-0.99	-1.41	0.54
	Keep home	4.68	4.75	0.74	-0.34	-0.49	0.35
	Community	4.15	4.25	0.73	-0.36	-0.74	0.53
	Coast	3.59	4.50	0.01	-2.74	-1.62	-0.21
	Flood perception	0.87	0.94	0.39	-0.88	-0.24	0.10
	Flood concern	0.95	0.88	0.57	0.59	-0.22	0.37
	Climate perception	0.87	0.94	0.36	-0.95	-0.23	0.09
	Experience	0.44	0.62	0.37	-0.93	-0.63	0.26
	Damage	34.88	48.12	0.09	-1.85	-28.91	2.41
	Surveyed	0.07	0.25	0.33	-1.05	-0.57	0.21
	Generator	0.44	0.50	0.77	-0.30	-0.52	0.40
	Insured	0.66	0.75	0.62	-0.51	-0.49	0.31
	Other adaptation	0.17	0.00	0.01	2.87	0.05	0.29
	No adaptations	0.12	0.00	0.02	2.36	0.02	0.23
Dependent	Relocate	0.66	0.38	0.18	1.43	-0.16	0.73
	Insure	0.59	0.38	0.32	1.06	-0.23	0.66
	Elevate	0.61	0.75	0.46	-0.78	-0.54	0.26

Table D.5: Comparison of in-person and mailed samples for owners in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	92.67	90.70	0.92	0.11	-37.55	41.48
	Married	0.78	0.60	0.43	0.81	-0.29	0.64
	Age	48.89	39.00	0.13	1.59	-3.27	23.05
	Female	0.56	0.60	0.86	-0.19	-0.55	0.46
	White	0.89	0.60	0.16	1.46	-0.13	0.71
	Children	0.44	0.20	0.28	1.11	-0.22	0.71
	Education	3.11	3.10	0.97	0.04	-0.67	0.69
	Tenure	25.22	26.70	0.83	-0.21	-16.29	13.33
	Mortgage	0.67	0.60	0.82	0.23	-0.55	0.68
	Community hrs.	3.17	4.45	0.44	-0.78	-4.74	2.18
	External network	5.67	6.80	0.69	-0.40	-7.12	4.85
	Avoid flood costs	4.22	3.40	0.23	1.24	-0.58	2.23
	Avoid inconviences	3.89	3.40	0.39	0.88	-0.69	1.67
	Keep home	4.22	4.40	0.72	-0.37	-1.24	0.88
	Community	3.56	3.90	0.59	-0.55	-1.65	0.97
	Coast	3.89	4.10	0.66	-0.45	-1.21	0.79
	Flood perception	0.78	0.70	0.72	0.37	-0.37	0.53
	Flood concern	0.56	0.70	0.54	-0.62	-0.64	0.35
	Climate perception	0.94	0.95	0.94	-0.07	-0.16	0.15
	Experience	0.22	0.40	0.43	-0.81	-0.64	0.29
	Damage	15.56	34.00	0.07	-1.97	-38.18	1.29
	Surveyed	0.11	0.20	0.62	-0.51	-0.46	0.28
	Generator	0.44	0.20	0.28	1.11	-0.22	0.71
	Insured	0.56	0.50	0.82	0.23	-0.46	0.57
	Other adaptation	0.22	0.20	0.91	0.11	-0.40	0.44
	No adaptations	0.44	0.40	0.86	0.19	-0.46	0.55
Dependent	Relocate	0.78	0.50	0.23	1.25	-0.19	0.75
	Insure	0.56	0.40	0.53	0.65	-0.35	0.66
	Elevate	0.56	0.50	0.82	0.23	-0.46	0.57

Table D.6: Comparison of in-person and mailed samples for renters in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	49.67	63.50	0.57	-0.65	-85.52	57.86
	Married	0.00	0.42	0.02	-2.80	-0.74	-0.09
	Age	53.33	45.00	0.57	0.64	-35.44	52.10
	Female	1.00	0.25	0.00	5.74	0.46	1.04
	White	1.00	0.83	0.17	1.48	-0.08	0.41
	Children	0.00	0.17	0.17	-1.48	-0.41	0.08
	Education	3.67	3.00	0.17	1.61	-0.43	1.77
	Tenure	21.67	22.17	0.97	-0.04	-33.39	32.39
	Community hrs.	2.17	3.96	0.14	-1.60	-4.29	0.71
	External network	8.00	6.08	0.67	0.47	-11.92	15.75
	Avoid flood costs	4.33	4.42	0.92	-0.11	-2.49	2.33
	Home quality	4.33	4.50	0.71	-0.39	-1.26	0.93
	Home affordability	3.67	4.42	0.38	-1.08	-3.35	1.85
	Community	4.33	4.17	0.71	0.39	-0.93	1.26
	Coast	4.67	4.33	0.48	0.76	-0.77	1.43
	Flood perception	0.67	0.83	0.67	-0.48	-1.47	1.14
	Flood concern	0.67	0.92	0.53	-0.73	-1.58	1.08
	Climate perception	1.00	0.88	0.19	1.39	-0.07	0.32
	Experience	0.00	0.42	0.02	-2.80	-0.74	-0.09
	Damage	20.00	29.58	0.61	-0.56	-62.89	43.72
	Surveyed	0.33	0.25	0.83	0.23	-1.15	1.31
	Generator	0.00	0.25	0.08	-1.91	-0.54	0.04
	Insured	0.00	0.08	0.34	-1.00	-0.27	0.10
	Other adaptation	0.00	0.08	0.34	-1.00	-0.27	0.10
	No adaptations	1.00	0.67	0.04	2.35	0.02	0.65
Dependent	Relocate	0.67	0.58	0.83	0.23	-1.11	1.28
	Insure	0.33	0.58	0.54	-0.68	-1.45	0.95
	Elevate	0.00	0.00				

Table D.7: Comparison of in-person and mailed samples for renters in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	39.94	68.27	0.12	-1.69	-64.76	8.10
	Married	0.24	0.55	0.12	-1.63	-0.71	0.09
	Age	35.29	40.91	0.30	-1.06	-16.55	5.32
	Female	0.82	0.73	0.58	0.57	-0.26	0.45
	White	0.29	0.55	0.21	-1.29	-0.66	0.15
	Children	0.29	0.18	0.51	0.67	-0.23	0.46
	Education	2.76	2.73	0.90	0.13	-0.57	0.64
	Tenure	18.53	17.75	0.90	0.13	-11.68	13.25
	Community hrs.	3.38	3.14	0.84	0.20	-2.33	2.82
	External network	5.47	9.18	0.09	-1.79	-8.02	0.60
	Avoid flood costs	3.88	3.91	0.94	-0.07	-0.82	0.76
	Home quality	3.94	3.82	0.69	0.41	-0.50	0.75
	Home affordability	4.35	4.18	0.55	0.60	-0.42	0.76
	Community	3.65	3.27	0.41	0.84	-0.57	1.31
	Coast	3.47	2.82	0.29	1.09	-0.64	1.94
	Flood perception	0.65	0.41	0.21	1.28	-0.15	0.62
	Flood concern	0.79	0.45	0.06	1.98	-0.02	0.70
	Climate perception	0.94	1.00	0.33	-1.00	-0.18	0.07
	Experience	0.41	0.18	0.20	1.33	-0.13	0.59
	Damage	16.18	10.91	0.53	0.63	-11.88	22.41
	Surveyed	0.24	0.00	0.04	2.22	0.01	0.46
	Generator	0.06	0.09	0.77	-0.30	-0.26	0.20
	Insured	0.06	0.09	0.77	-0.30	-0.26	0.20
	Other adaptation	0.06	0.09	0.77	-0.30	-0.26	0.20
	No adaptations	0.82	0.82	0.97	0.03	-0.32	0.33
Dependent	Relocate	0.82	1.00	0.08	-1.85	-0.38	0.03
	Insure	0.82	0.73	0.58	0.57	-0.26	0.45
	Elevate	0.00	0.00				

Table D.8: Comparison of in-person and mailed samples for renters in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Mailed sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	45.60	68.60	0.36	-0.97	-78.45	32.45
	Married	0.20	0.20	1.00	0.00	-0.65	0.65
	Age	42.00	46.00	0.71	-0.38	-28.30	20.30
	Female	0.80	0.60	0.55	0.63	-0.53	0.93
	White	0.40	0.80	0.24	-1.26	-1.13	0.33
	Children	0.40	0.20	0.55	0.63	-0.53	0.93
	Education	3.00	2.80	0.69	0.41	-0.94	1.34
	Tenure	11.20	24.80	0.15	-1.65	-34.24	7.04
	Community hrs.	4.20	4.20	1.00	0.00	-5.37	5.37
	External network	6.00	9.00	0.10	-1.90	-6.67	0.67
	Avoid flood costs	3.20	3.60	0.65	-0.48	-2.43	1.63
	Home quality	4.20	4.00	0.61	0.53	-0.69	1.09
	Home affordability	4.20	3.80	0.47	0.76	-0.82	1.62
	Community	3.00	3.00	1.00	0.00	-2.31	2.31
	Coast	4.40	2.40	0.01	3.54	0.70	3.30
	Flood perception	0.80	0.60	0.55	0.63	-0.53	0.93
	Flood concern	0.80	0.80	1.00	0.00	-0.65	0.65
	Climate perception	1.00	0.80	0.37	1.00	-0.36	0.76
	Experience	0.20	0.40	0.55	-0.63	-0.93	0.53
	Damage	4.00	16.00	0.25	-1.33	-35.85	11.85
	Surveyed	0.00	0.20	0.37	-1.00	-0.76	0.36
	Generator	0.00	0.00				
	Insured	0.20	0.20	1.00	0.00	-0.65	0.65
	Other adaptation	0.00	0.40	0.18	-1.63	-1.08	0.28
	No adaptations	0.80	0.40	0.24	1.26	-0.33	1.13
Dependent	Relocate	0.80	0.40	0.24	1.26	-0.33	1.13
	Insure	0.80	0.60	0.55	0.63	-0.53	0.93
	Elevate	0.00	0.00				

Table D.9: Comparison of online and in-person samples for owners in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	136.18	122.09	0.39	0.87	-19.74	47.92
	Married	0.73	0.61	0.47	0.73	-0.23	0.47
	Age	52.73	49.39	0.62	0.51	-10.67	17.34
	Female	0.64	0.45	0.32	1.03	-0.19	0.55
	White	1.00	0.76	0.00	3.20	0.09	0.40
	Children	0.27	0.36	0.59	-0.55	-0.44	0.25
	Education	3.36	3.18	0.46	0.75	-0.33	0.69
	Tenure	21.64	34.42	0.01	-2.81	-22.11	-3.47
	Mortgage	0.64	0.64	1.00	0.00	-0.49	0.49
	Community hrs.	1.64	2.71	0.22	-1.27	-2.84	0.69
	External network	11.09	10.27	0.64	0.47	-2.77	4.40
	Avoid flood costs	4.55	4.12	0.12	1.59	-0.13	0.97
	Avoid inconviences	3.91	3.52	0.20	1.31	-0.22	1.01
	Keep home	4.36	4.30	0.84	0.21	-0.55	0.68
	Community	3.36	3.94	0.14	-1.54	-1.35	0.20
	Coast	4.09	4.36	0.44	-0.80	-1.01	0.46
	Flood perception	0.91	0.85	0.58	0.56	-0.17	0.29
	Flood concern	0.91	0.79	0.31	1.04	-0.12	0.36
	Climate perception	0.77	0.86	0.51	-0.67	-0.38	0.20
	Experience	0.00	0.30	0.00	-3.73	-0.47	-0.14
	Damage	37.73	36.52	0.88	0.15	-15.59	18.01
	Surveyed	0.09	0.21	0.31	-1.04	-0.36	0.12
	Generator	0.45	0.48	0.87	-0.17	-0.41	0.35
	Insured	0.55	0.79	0.18	-1.40	-0.61	0.13
	Other adaptation	0.09	0.12	0.78	-0.28	-0.26	0.20
	No adaptations	0.27	0.09	0.25	1.21	-0.14	0.51
Dependent	Relocate	0.82	0.52	0.06	2.01	-0.01	0.62
	Insure	0.64	0.64	1.00	0.00	-0.37	0.37
	Elevate	0.27	0.42	0.37	-0.91	-0.50	0.20

Table D.10: Comparison of online and in-person samples for owners in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	102.73	88.10	0.49	0.70	-28.31	57.57
	Married	0.73	0.52	0.27	1.13	-0.17	0.58
	Age	49.09	51.43	0.72	-0.36	-15.59	10.91
	Female	0.45	0.57	0.55	-0.61	-0.52	0.28
	White	0.55	0.57	0.89	-0.13	-0.43	0.38
	Children	0.09	0.24	0.27	-1.12	-0.42	0.12
	Education	3.00	3.00	1.00	0.00	-0.68	0.68
	Tenure	22.16	31.33	0.23	-1.23	-24.69	6.34
	Mortgage	0.64	0.57	0.78	0.28	-0.43	0.56
	Community hrs.	1.27	2.52	0.16	-1.44	-3.03	0.53
	External network	6.64	6.71	0.97	-0.04	-4.10	3.94
	Avoid flood costs	4.64	3.95	0.06	1.94	-0.04	1.40
	Avoid inconviences	4.27	4.00	0.47	0.74	-0.48	1.03
	Keep home	4.27	3.95	0.40	0.86	-0.45	1.09
	Community	4.18	3.57	0.13	1.56	-0.19	1.41
	Coast	3.27	3.76	0.41	-0.85	-1.70	0.72
	Flood perception	0.55	0.55	0.99	-0.01	-0.40	0.39
	Flood concern	0.55	0.71	0.38	-0.90	-0.56	0.22
	Climate perception	0.59	0.81	0.21	-1.32	-0.57	0.13
	Experience	0.18	0.24	0.72	-0.36	-0.38	0.26
	Damage	17.27	15.24	0.79	0.27	-13.88	17.94
	Surveyed	0.18	0.24	0.72	-0.36	-0.38	0.26
	Generator	0.18	0.14	0.79	0.27	-0.27	0.34
	Insured	0.45	0.48	0.91	-0.11	-0.42	0.38
	Other adaptation	0.00	0.10	0.16	-1.45	-0.23	0.04
	No adaptations	0.45	0.43	0.89	0.13	-0.38	0.43
Dependent	Relocate	0.73	0.67	0.73	0.34	-0.31	0.43
	Insure	0.64	0.57	0.73	0.35	-0.33	0.46
	Elevate	0.55	0.43	0.55	0.61	-0.28	0.52

Table D.11: Comparison of online and in-person samples for owners in Central Jamaica Bay neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	104.82	114.00	0.73	-0.35	-67.06	48.70
	Married	0.55	0.75	0.38	-0.90	-0.69	0.28
	Age	51.82	50.00	0.81	0.25	-13.66	17.30
	Female	0.55	0.62	0.75	-0.33	-0.59	0.43
	White	0.73	1.00	0.08	-1.94	-0.59	0.04
	Children	0.18	0.38	0.40	-0.88	-0.67	0.28
	Education	2.91	2.50	0.17	1.44	-0.19	1.01
	Tenure	24.45	31.00	0.46	-0.76	-25.02	11.93
	Mortgage	0.55	0.75	0.38	-0.90	-0.69	0.28
	Community hrs.	1.27	4.31	0.05	-2.22	-6.09	0.01
	External network	8.09	9.38	0.65	-0.47	-7.10	4.53
	Avoid flood costs	3.64	4.62	0.07	-1.95	-2.08	0.11
	Avoid inconviences	3.73	3.88	0.77	-0.29	-1.22	0.93
	Keep Home	4.18	4.75	0.14	-1.56	-1.35	0.21
	Community	3.45	4.25	0.13	-1.59	-1.86	0.27
	Coast	2.82	4.50	0.01	-3.14	-2.82	-0.54
	Flood perception	0.59	0.94	0.05	-2.16	-0.69	-0.00
	Flood concern	0.27	0.88	0.01	-3.20	-1.00	-0.20
	Climate perception	1.00	0.94	0.35	1.00	-0.09	0.21
	Experience	0.00	0.62	0.01	-3.42	-1.06	-0.19
	Damage	15.00	48.12	0.00	-3.41	-53.61	-12.64
	Surveyed	0.00	0.25	0.17	-1.53	-0.64	0.14
	Generator	0.00	0.50	0.03	-2.65	-0.95	-0.05
	Insured	0.36	0.75	0.10	-1.73	-0.86	0.09
	Other adaptation	0.09	0.00	0.34	1.00	-0.11	0.29
	No adaptations	0.55	0.00	0.01	3.46	0.19	0.90
Dependent	Relocate	0.82	0.38	0.07	2.02	-0.03	0.92
	Insure	0.64	0.38	0.29	1.10	-0.25	0.77
	Elevate	0.00	0.75	0.00	-4.58	-1.14	-0.36

Table D.12: Comparison of online and in-person samples for owners in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	101.01	90.70	0.41	0.86	-15.43	36.06
	Married	0.71	0.60	0.54	0.64	-0.27	0.49
	Age	55.00	39.00	0.01	3.27	5.31	26.69
	Female	0.49	0.60	0.53	-0.65	-0.49	0.27
	White	0.65	0.60	0.77	0.30	-0.33	0.43
	Children	0.16	0.20	0.79	-0.27	-0.34	0.27
	Education	3.09	3.10	0.97	-0.04	-0.43	0.42
	Tenure	28.80	26.70	0.65	0.46	-7.74	11.94
	Mortgage	0.50	0.60	0.57	-0.58	-0.48	0.28
	Community hrs.	1.53	4.45	0.04	-2.39	-5.64	-0.19
	External network	5.33	6.80	0.52	-0.67	-6.40	3.45
	Avoid flood costs	3.80	3.40	0.43	0.82	-0.69	1.49
	Avoid inconviences	3.70	3.40	0.49	0.72	-0.62	1.22
	Keep home	4.13	4.40	0.29	-1.10	-0.80	0.26
	Community	3.26	3.90	0.18	-1.42	-1.65	0.36
	Coast	2.97	4.10	0.01	-3.28	-1.88	-0.39
	Flood perception	0.35	0.70	0.05	-2.19	-0.70	0.00
	Flood concern	0.53	0.70	0.31	-1.06	-0.53	0.18
	Climate perception	0.81	0.95	0.04	-2.19	-0.27	-0.01
	Experience	0.12	0.40	0.12	-1.70	-0.66	0.09
	Damage	8.02	34.00	0.00	-3.89	-40.88	-11.07
	Surveyed	0.03	0.20	0.25	-1.22	-0.47	0.14
	Generator	0.08	0.20	0.41	-0.87	-0.42	0.19
	Insured	0.29	0.50	0.25	-1.20	-0.59	0.17
	Other adaptation	0.03	0.20	0.25	-1.22	-0.47	0.14
	No adaptations	0.65	0.40	0.17	1.47	-0.13	0.63
Dependent	Relocate	0.72	0.50	0.23	1.27	-0.16	0.60
	Insure	0.76	0.40	0.06	2.10	-0.02	0.73
	Elevate	0.29	0.50	0.25	-1.20	-0.59	0.17

Table D.13: Comparison of online and in-person samples for renters in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	141.67	63.50	0.02	4.20	19.73	136.61
	Married	1.00	0.42	0.00	3.92	0.26	0.91
	Age	43.33	45.00	0.85	-0.20	-23.63	20.30
	Female	0.67	0.25	0.34	1.16	-0.81	1.65
	White	1.00	0.83	0.17	1.48	-0.08	0.41
	Children	0.33	0.17	0.67	0.47	-1.10	1.43
	Education	3.67	3.00	0.17	1.61	-0.43	1.77
	Tenure	21.33	22.17	0.96	-0.05	-52.52	50.85
	Community hrs.	2.33	3.96	0.32	-1.10	-5.47	2.22
	External network	8.67	6.08	0.30	1.14	-2.96	8.13
	Avoid flood costs	5.00	4.42	0.07	2.03	-0.05	1.22
	Home quality	4.67	4.50	0.71	0.39	-0.93	1.26
	Home affordability	5.00	4.42	0.01	3.02	0.16	1.01
	Community	3.00	4.17	0.17	-1.83	-3.22	0.88
	Coast	3.33	4.33	0.07	-2.28	-2.10	0.10
	Flood perception	1.00	0.83	0.10	1.77	-0.04	0.37
	Flood concern	1.00	0.92	0.34	1.00	-0.10	0.27
	Climate perception	1.00	0.88	0.19	1.39	-0.07	0.32
	Experience	0.67	0.42	0.54	0.68	-0.95	1.45
	Damage	50.00	29.58	0.02	2.64	3.36	37.47
	Surveyed	0.00	0.25	0.08	-1.91	-0.54	0.04
	Generator	0.00	0.25	0.08	-1.91	-0.54	0.04
	Insured	0.00	0.08	0.34	-1.00	-0.27	0.10
	Other adaptation	0.00	0.08	0.34	-1.00	-0.27	0.10
	No adaptations	1.00	0.67	0.04	2.35	0.02	0.65
Dependent	Relocate	1.00	0.58	0.02	2.80	0.09	0.74
	Insure	0.33	0.58	0.54	-0.68	-1.45	0.95
	Elevate	0.00	0.00				

Table D.14: Comparison of online and in-person samples for renters in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	45.50	68.27	0.26	-1.18	-63.67	18.13
	Married	0.25	0.55	0.21	-1.30	-0.78	0.19
	Age	50.00	40.91	0.24	1.23	-6.98	25.16
	Female	0.62	0.73	0.66	-0.44	-0.60	0.39
	White	0.25	0.55	0.21	-1.30	-0.78	0.19
	Children	0.00	0.18	0.17	-1.49	-0.45	0.09
	Education	2.75	2.73	0.94	0.07	-0.66	0.70
	Tenure	21.75	17.75	0.64	0.48	-14.01	22.02
	Community hrs.	0.38	3.14	0.02	-2.70	-5.01	-0.51
	External network	7.38	9.18	0.47	-0.74	-7.01	3.39
	Avoid flood costs	3.88	3.91	0.94	-0.08	-1.00	0.93
	Home affordability	4.25	3.82	0.28	1.12	-0.40	1.26
	Home quality	4.38	4.18	0.63	0.49	-0.66	1.04
	Community	2.75	3.27	0.39	-0.88	-1.79	0.74
	Coast	3.50	2.82	0.34	0.98	-0.79	2.15
	Flood perception	0.75	0.41	0.11	1.71	-0.08	0.76
	Flood concern	0.38	0.45	0.74	-0.34	-0.58	0.42
	Climate perception	0.88	1.00	0.17	-1.53	-0.32	0.07
	Experience	0.25	0.18	0.74	0.33	-0.37	0.51
	Damage	14.38	10.91	0.75	0.33	-19.56	26.49
	Surveyed	0.00	0.00				
	Generator	0.00	0.09	0.34	-1.00	-0.29	0.11
	Insured	0.12	0.09	0.83	0.22	-0.30	0.37
	Other adaptation	0.25	0.09	0.41	0.85	-0.25	0.57
	No adaptations	0.75	0.82	0.74	-0.33	-0.51	0.37
Dependent	Relocate	0.88	1.00	0.35	-1.00	-0.42	0.17
	Insure	0.50	0.73	0.35	-0.96	-0.73	0.28
	Elevate	0.00	0.00				

Table D.15: Comparison of online and in-person samples for renters in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (In-person sample)	p	t	CI	
Independent	Income	64.69	68.60	0.85	-0.19	-56.32	48.49
	Married	0.43	0.20	0.33	1.07	-0.32	0.77
	Age	46.94	46.00	0.90	0.13	-17.50	19.39
	Female	0.76	0.60	0.56	0.63	-0.51	0.83
	White	0.46	0.80	0.17	-1.59	-0.88	0.21
	Children	0.20	0.20	0.99	0.02	-0.54	0.55
	Education	3.06	2.80	0.54	0.67	-0.77	1.28
	Tenure	18.72	24.80	0.48	-0.78	-26.71	14.56
	Community hrs.	1.14	4.20	0.14	-1.83	-7.60	1.48
	External network	5.56	9.00	0.05	-2.37	-6.81	-0.08
	Avoid flood costs	3.13	3.60	0.33	-1.06	-1.55	0.61
	Home quality	4.31	4.00	0.40	0.92	-0.54	1.17
	Home affordability	4.44	3.80	0.16	1.64	-0.37	1.66
	Community	2.72	3.00	0.72	-0.38	-2.21	1.65
	Coast	2.72	2.40	0.49	0.73	-0.76	1.41
	Flood perception	0.41	0.60	0.48	-0.76	-0.86	0.48
	Flood concern	0.40	0.80	0.12	-1.91	-0.95	0.14
	Climate perception	0.86	0.80	0.78	0.30	-0.49	0.61
	Experience	0.20	0.40	0.47	-0.78	-0.87	0.48
	Damage	6.76	16.00	0.35	-1.04	-33.18	14.70
	Surveyed	0.00	0.20	0.37	-1.00	-0.76	0.36
	Generator	0.02	0.00	0.32	1.00	-0.02	0.06
	Insured	0.06	0.20	0.51	-0.71	-0.70	0.41
	Other adaptation	0.07	0.40	0.26	-1.32	-1.00	0.35
	No adaptations	0.85	0.40	0.14	1.81	-0.22	1.13
Dependent	Relocate	0.93	0.40	0.10	2.12	-0.15	1.20
	Insure	0.67	0.60	0.80	0.26	-0.60	0.74
	Elevate	0.00	0.00				

Table D.16: Comparison of online and mailed samples for owners in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	136.18	110.14	0.17	1.41	-12.18	64.26
	Married	0.73	0.86	0.46	-0.76	-0.49	0.23
	Age	52.73	53.57	0.91	-0.12	-16.08	14.39
	Female	0.64	0.57	0.75	0.32	-0.36	0.49
	White	1.00	0.79	0.08	1.88	-0.03	0.46
	Children	0.27	0.21	0.75	0.32	-0.32	0.44
	Education	3.36	3.50	0.62	-0.51	-0.69	0.42
	Tenure	21.64	30.21	0.17	-1.42	-21.08	3.93
	Mortgage	0.64	0.36	0.27	1.15	-0.23	0.79
	Community hrs.	1.64	2.86	0.15	-1.50	-2.93	0.49
	External network	11.09	8.43	0.20	1.31	-1.54	6.86
	Avoid flood costs	4.55	4.07	0.19	1.34	-0.26	1.21
	Avoid inconviences	3.91	3.71	0.62	0.51	-0.60	0.99
	Keep home	4.36	4.71	0.25	-1.19	-0.97	0.27
	Community	3.36	4.43	0.02	-2.59	-1.92	-0.21
	Coast	4.09	4.50	0.32	-1.02	-1.25	0.43
	Flood perception	0.91	0.93	0.87	-0.17	-0.26	0.22
	Flood concern	0.91	1.00	0.34	-1.00	-0.29	0.11
	Climate perception	0.77	0.86	0.58	-0.57	-0.40	0.23
	Experience	0.00	0.29	0.04	-2.28	-0.56	-0.02
	Damage	37.73	50.00	0.11	-1.76	-27.84	3.29
	Surveyed	0.09	0.07	0.87	0.17	-0.22	0.26
	Generator	0.45	0.36	0.64	0.47	-0.33	0.53
	Insured	0.55	0.64	0.64	-0.47	-0.53	0.33
	Other adaptation	0.09	0.14	0.70	-0.39	-0.33	0.22
	No adaptations	0.27	0.29	0.95	-0.07	-0.40	0.38
Dependent	Relocate	0.82	0.57	0.19	1.34	-0.13	0.63
	Insure	0.64	0.43	0.32	1.01	-0.22	0.63
	Elevate	0.27	0.57	0.14	-1.52	-0.71	0.11

Table D.17: Comparison of online and mailed samples for owners in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	102.73	91.44	0.58	0.56	-30.27	52.84
	Married	0.73	0.50	0.23	1.22	-0.16	0.61
	Age	49.09	46.11	0.63	0.49	-9.67	15.63
	Female	0.45	0.67	0.29	-1.09	-0.62	0.19
	White	0.55	0.50	0.82	0.23	-0.37	0.46
	Children	0.09	0.28	0.20	-1.32	-0.48	0.10
	Education	3.00	3.11	0.71	-0.38	-0.74	0.52
	Tenure	22.16	24.78	0.72	-0.36	-17.66	12.42
	Mortgage	0.64	0.67	0.91	-0.12	-0.57	0.51
	Community hrs.	1.27	3.50	0.03	-2.28	-4.23	-0.22
	External network	6.64	10.44	0.06	-1.95	-7.85	0.23
	Avoid flood costs	4.64	4.44	0.56	0.58	-0.48	0.87
	Avoid inconveniences	4.27	3.83	0.22	1.25	-0.28	1.16
	Keep home	4.27	4.72	0.16	-1.48	-1.10	0.20
	Community	4.18	3.78	0.28	1.11	-0.35	1.15
	Coast	3.27	4.44	0.04	-2.27	-2.29	-0.05
	Flood perception	0.55	0.81	0.17	-1.43	-0.64	0.12
	Flood concern	0.55	0.94	0.03	-2.39	-0.76	-0.04
	Climate perception	0.59	0.97	0.03	-2.53	-0.71	-0.05
	Experience	0.18	0.28	0.56	-0.59	-0.43	0.24
	Damage	17.27	26.11	0.30	-1.06	-26.14	8.46
	Surveyed	0.18	0.17	0.92	0.10	-0.30	0.33
	Generator	0.18	0.39	0.23	-1.22	-0.56	0.14
	Insured	0.45	0.56	0.62	-0.51	-0.51	0.31
	Other adaptation	0.00	0.11	0.16	-1.46	-0.27	0.05
	No adaptations	0.45	0.33	0.54	0.62	-0.28	0.53
Dependent	Relocate	0.73	0.67	0.74	0.33	-0.32	0.44
	Insure	0.64	0.61	0.90	0.13	-0.38	0.43
	Elevate	0.55	0.39	0.44	0.80	-0.25	0.57

Table D.18: Comparison of online and mailed samples for owners in Central Jamaica Bay neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	104.82	104.63	0.99	0.01	-29.68	30.05
	Married	0.55	0.73	0.30	-1.08	-0.56	0.18
	Age	51.82	49.76	0.74	0.34	-11.13	15.25
	Female	0.55	0.61	0.72	-0.37	-0.44	0.31
	White	0.73	0.93	0.20	-1.36	-0.52	0.12
	Children	0.18	0.37	0.22	-1.28	-0.49	0.12
	Education	2.91	2.78	0.61	0.53	-0.39	0.64
	Tenure	24.45	33.88	0.15	-1.50	-22.71	3.86
	Mortgage	0.55	0.71	0.37	-0.92	-0.54	0.21
	Community hrs.	1.27	2.78	0.04	-2.17	-2.96	-0.06
	External network	8.09	7.02	0.61	0.52	-3.37	5.50
	Avoid flood costs	3.64	4.54	0.09	-1.82	-1.98	0.18
	Avoid inconveniences	3.73	3.44	0.43	0.81	-0.46	1.04
	Keep home	4.18	4.68	0.17	-1.46	-1.25	0.24
	Community	3.45	4.15	0.16	-1.51	-1.69	0.30
	Coast	2.82	3.59	0.15	-1.52	-1.85	0.32
	Flood perception	0.59	0.87	0.10	-1.75	-0.62	0.07
	Flood concern	0.27	0.95	0.00	-4.68	-1.00	-0.36
	Climate perception	1.00	0.87	0.00	3.13	0.05	0.22
	Experience	0.00	0.44	0.00	-5.60	-0.60	-0.28
	Damage	15.00	34.88	0.03	-2.42	-37.39	-2.37
	Surveyed	0.00	0.07	0.08	-1.78	-0.16	0.01
	Generator	0.00	0.44	0.00	-5.60	-0.60	-0.28
	Insured	0.36	0.66	0.10	-1.74	-0.66	0.07
	Other adaptation	0.09	0.17	0.47	-0.73	-0.31	0.15
	No adaptations	0.55	0.12	0.02	2.56	0.06	0.78
Dependent	Relocate	0.82	0.66	0.28	1.12	-0.14	0.46
	Insure	0.64	0.59	0.77	0.30	-0.31	0.41
	Elevate	0.00	0.61	0.00	-7.91	-0.77	-0.45

Table D.19: Comparison of online and mailed samples for owners in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	101.01	92.67	0.61	0.52	-27.34	44.03
	Married	0.71	0.78	0.67	-0.44	-0.41	0.28
	Age	55.00	48.89	0.21	1.34	-3.96	16.18
	Female	0.49	0.56	0.72	-0.37	-0.48	0.34
	White	0.65	0.89	0.08	-1.94	-0.51	0.03
	Children	0.16	0.44	0.15	-1.56	-0.69	0.13
	Education	3.09	3.11	0.95	-0.07	-0.63	0.59
	Tenure	28.80	25.22	0.56	0.61	-9.57	16.73
	Mortgage	0.50	0.67	0.51	-0.69	-0.72	0.38
	Community hrs.	1.53	3.17	0.19	-1.43	-4.24	0.97
	External network	5.33	5.67	0.86	-0.18	-4.69	4.01
	Avoid flood costs	3.80	4.22	0.40	-0.87	-1.50	0.66
	Avoid inconveniences	3.70	3.89	0.65	-0.47	-1.10	0.72
	Keep home	4.13	4.22	0.84	-0.21	-1.11	0.92
	Community	3.26	3.56	0.53	-0.65	-1.34	0.74
	Coast	2.97	3.89	0.03	-2.43	-1.76	-0.09
	Flood perception	0.35	0.78	0.02	-2.77	-0.77	-0.08
	Flood concern	0.53	0.56	0.89	-0.14	-0.44	0.39
	Climate perception	0.81	0.94	0.07	-1.95	-0.27	0.01
	Experience	0.12	0.22	0.50	-0.70	-0.45	0.24
	Damage	8.02	15.56	0.30	-1.10	-23.06	8.00
	Surveyed	0.03	0.11	0.52	-0.68	-0.33	0.18
	Generator	0.08	0.44	0.07	-2.04	-0.77	0.04
	Insured	0.29	0.56	0.18	-1.45	-0.68	0.15
	Other adaptation	0.03	0.22	0.24	-1.26	-0.53	0.15
	No adaptations	0.65	0.44	0.29	1.13	-0.20	0.62
Dependent	Relocate	0.72	0.78	0.72	-0.37	-0.40	0.29
	Insure	0.76	0.56	0.30	1.10	-0.21	0.61
	Elevate	0.29	0.56	0.18	-1.45	-0.68	0.15

Table D.20: Comparison of online and mailed samples for renters in West Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	141.67	63.50	0.02	4.20	19.73	136.61
	Married	1.00	0.42	0.00	3.92	0.26	0.91
	Age	43.33	45.00	0.85	-0.20	-23.63	20.30
	Female	0.67	0.25	0.34	1.16	-0.81	1.65
	White	1.00	0.83	0.17	1.48	-0.08	0.41
	Children	0.33	0.17	0.67	0.47	-1.10	1.43
	Education	3.67	3.00	0.17	1.61	-0.43	1.77
	Tenure	21.33	22.17	0.96	-0.05	-52.52	50.85
	Community hrs.	2.33	3.96	0.32	-1.10	-5.47	2.22
	External network	8.67	6.08	0.30	1.14	-2.96	8.13
	Avoid flood costs	5.00	4.42	0.07	2.03	-0.05	1.22
	Home quality	4.67	4.50	0.71	0.39	-0.93	1.26
	Home affordability	5.00	4.42	0.01	3.02	0.16	1.01
	Community	3.00	4.17	0.17	-1.83	-3.22	0.88
	Coast	3.33	4.33	0.07	-2.28	-2.10	0.10
	Flood perception	1.00	0.83	0.10	1.77	-0.04	0.37
	Flood concern	1.00	0.92	0.34	1.00	-0.10	0.27
	Climate perception	1.00	0.88	0.19	1.39	-0.07	0.32
	Experience	0.67	0.42	0.54	0.68	-0.95	1.45
	Damage	50.00	29.58	0.02	2.64	3.36	37.47
	Surveyed	0.00	0.25	0.08	-1.91	-0.54	0.04
	Generator	0.00	0.25	0.08	-1.91	-0.54	0.04
	Insured	0.00	0.08	0.34	-1.00	-0.27	0.10
	Other adaptation	0.00	0.08	0.34	-1.00	-0.27	0.10
	No adaptations	1.00	0.67	0.04	2.35	0.02	0.65
Dependent	Relocate	1.00	0.58	0.02	2.80	0.09	0.74
	Insure	0.33	0.58	0.54	-0.68	-1.45	0.95
	Elevate	0.00	0.00				

Table D.21: Comparison of online and mailed samples for renters in East Rockaway neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	45.50	39.94	0.67	0.44	-22.03	33.15
	Married	0.25	0.24	0.94	0.08	-0.41	0.44
	Age	50.00	35.29	0.06	2.04	-1.03	30.45
	Female	0.62	0.82	0.36	-0.96	-0.65	0.26
	White	0.25	0.29	0.83	-0.22	-0.47	0.38
	Children	0.00	0.29	0.02	-2.58	-0.54	-0.05
	Education	2.75	2.76	0.97	-0.04	-0.71	0.69
	Tenure	21.75	18.53	0.67	0.44	-13.05	19.49
	Community hrs.	0.38	3.38	0.00	-3.87	-4.63	-1.38
	External network	7.38	5.47	0.41	0.85	-2.90	6.70
	Avoid flood costs	3.88	3.88	0.99	-0.02	-0.93	0.92
	Home quality	4.25	3.94	0.42	0.83	-0.50	1.11
	Home affordability	4.38	4.35	0.95	0.06	-0.78	0.83
	Community	2.75	3.65	0.11	-1.77	-2.02	0.22
	Coast	3.50	3.47	0.95	0.06	-1.03	1.08
	Flood perception	0.75	0.65	0.56	0.59	-0.26	0.47
	Flood concern	0.38	0.79	0.07	-2.03	-0.87	0.04
	Climate perception	0.88	0.94	0.52	-0.66	-0.28	0.15
	Experience	0.25	0.41	0.44	-0.79	-0.60	0.27
	Damage	14.38	16.18	0.87	-0.17	-24.60	20.99
	Surveyed	0.00	0.24	0.04	-2.22	-0.46	-0.01
	Generator	0.00	0.06	0.33	-1.00	-0.18	0.07
	Insured	0.12	0.06	0.64	0.48	-0.24	0.37
	Other adaptation	0.25	0.06	0.30	1.10	-0.20	0.59
	No adaptations	0.75	0.82	0.70	-0.39	-0.49	0.34
Dependent	Relocate	0.88	0.82	0.75	0.33	-0.28	0.39
	Insure	0.50	0.82	0.16	-1.53	-0.79	0.14
	Elevate	0.00	0.00				

Table D.22: Comparison of online and mailed samples for renters in Central Jamaica Bay neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	46.00	64.91	0.43	-0.94	-92.64	54.82
	Married	0.00	0.27	0.08	-1.94	-0.59	0.04
	Age	50.00	50.91	0.97	-0.04	-199.79	197.97
	Female	1.00	0.91	0.34	1.00	-0.11	0.29
	White	1.00	0.82	0.17	1.49	-0.09	0.45
	Children	0.50	0.18	0.64	0.62	-4.76	5.39
	Education	2.50	2.55	0.94	-0.08	-3.28	3.19
	Tenure	32.50	29.00	0.83	0.26	-87.38	94.38
	Community hrs.	3.00	1.50	0.70	0.49	-33.48	36.48
	External network	2.00	4.91	0.06	-2.09	-6.01	0.19
	Avoid flood costs	2.00	4.36	0.24	-2.30	-12.51	7.79
	Home quality	4.50	4.55	0.95	-0.08	-2.95	2.86
	Home affordability	4.50	4.45	0.95	0.07	-2.32	2.41
	Community	3.00	4.18	0.66	-0.58	-24.44	22.07
	Coast	1.00	3.82	0.00	-6.35	-3.81	-1.83
	Flood perception	0.75	1.00	0.50	-1.00	-3.43	2.93
	Flood concern	1.00	0.91	0.34	1.00	-0.11	0.29
	Climate perception	1.00	0.95	0.34	1.00	-0.06	0.15
	Experience	0.00	0.45	0.02	-2.89	-0.81	-0.10
	Damage	25.00	34.55	0.77	-0.37	-256.32	237.23
	Surveyed	0.00	0.00				
	Generator	0.00	0.00				
	Insured	0.00	0.27	0.08	-1.94	-0.59	0.04
	Other adaptation	0.00	0.00				
	No adaptations	1.00	0.73	0.08	1.94	-0.04	0.59
Dependent	Relocate	0.50	0.73	0.73	-0.44	-4.99	4.53
	Insure	0.50	0.73	0.73	-0.44	-4.99	4.53
	Elevate	0.00	0.00				

Table D.23: Comparison of online and mailed samples for renters in Brooklyn neighborhoods. Differences in means for each variable within a sample, p-values (p), t-statistic (t), and confidence intervals (CI) are shown.

	Variables	Mean (Online sample)	Mean (Mailed sample)	p	t	CI	
Independent	Income	64.69	45.60	0.25	1.28	-17.92	56.09
	Married	0.43	0.20	0.33	1.07	-0.32	0.77
	Age	46.94	42.00	0.58	0.59	-16.90	26.78
	Female	0.76	0.80	0.85	-0.20	-0.59	0.50
	White	0.46	0.40	0.82	0.25	-0.61	0.73
	Children	0.20	0.40	0.47	-0.78	-0.87	0.48
	Education	3.06	3.00	0.87	0.17	-0.81	0.92
	Tenure	18.72	11.20	0.09	1.95	-1.40	16.44
	Community hrs.	1.14	4.20	0.14	-1.83	-7.60	1.48
	External network	5.56	6.00	0.73	-0.35	-3.27	2.38
	Avoid flood costs	3.13	3.20	0.93	-0.09	-2.08	1.94
	Home quality	4.31	4.20	0.64	0.48	-0.44	0.67
	Home affordability	4.44	4.20	0.56	0.62	-0.77	1.26
	Community	2.72	3.00	0.72	-0.38	-2.21	1.65
	Coast	2.72	4.40	0.01	-3.82	-2.76	-0.59
	Flood perception	0.41	0.80	0.12	-1.86	-0.94	0.15
	Flood concern	0.40	0.80	0.12	-1.91	-0.95	0.14
	Climate perception	0.86	1.00	0.00	-3.62	-0.22	-0.06
	Experience	0.20	0.20	0.99	0.02	-0.54	0.55
	Damage	6.76	4.00	0.39	0.89	-4.13	9.65
	Surveyed	0.00	0.00				
	Generator	0.02	0.00	0.32	1.00	-0.02	0.06
	Insured	0.06	0.20	0.51	-0.71	-0.70	0.41
	Other adaptation	0.07	0.00	0.04	2.06	0.00	0.15
	No adaptations	0.85	0.80	0.81	0.25	-0.50	0.60
Dependent	Relocate	0.93	0.80	0.57	0.62	-0.42	0.68
	Insure	0.67	0.80	0.55	-0.63	-0.68	0.41
	Elevate	0.00	0.00				

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