

Building Bridges for Troubled Water: Assessing the Possibility of Cooperative Adaptation in Boston Harbor with Agent-Based Models of Coalition Formation

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Dissertation Abstract:

As sea level rise intensifies coastal flood risk, coastal adaptation requires cooperation across jurisdictions and scales, yet cooperative agreements remain difficult to achieve. This dissertation examines **the conditions under which cooperative approaches to sea level rise adaptation emerge and reduce flood risk (or fail to), through either voluntary coalitions or a centralized regional flood authority.** We focus on the roles of economic incentives, decision-making dynamics, institutional context, and uncertainty and ambiguity, using Boston Harbor as an empirical case. The dissertation first develops an agent-based model to compare individual adaptation, voluntary cooperative coalitions, and a centralized regional flood authority under varying assumptions about sea level rise, financing access, discounting, and flood variability. Results show that cooperative governance can reduce cumulative damages and increase net benefits, but this is not consistent across all scenarios. Additionally, certain actors experience worse outcomes under cooperative regimes, particularly within voluntary coalitions. Subsequent modeling explores how alternative representations of cooperative decision-making (inspired by social contagion, network reciprocity, and flood-response mechanisms) influence coalition formation and collective implementation. Flood experiences increase cooperation, while diffusion-based mechanisms are less effective in fragmented networks and often insufficient to sustain voluntary coalitions. Qualitative analysis of stakeholder interviews and focus groups, structured using the Institutional Analysis and Development framework, reveals broad interest in cooperative adaptation but strong skepticism that voluntary cooperation will scale without significant institutional and financial change, particularly the establishment of a regional flood authority. Finally, the dissertation examines how uncertainty and ambiguity shape adaptation decisions and introduces a Decision-Making under Uncertainty and Ambiguity (DMUUA) approach that

integrates methods from decision-making under deep uncertainty (DMDU) and engineering diplomacy (EDF). Overall, the findings of this dissertation show that the feasibility of cooperative sea level rise adaptation depends less on climate uncertainty and more on the interaction of governance structures, economic conditions, institutional constraints, decision-making processes, and ambiguity. Many trade-offs exist between relying on voluntary coalitions and the formation of a regional flood authority.

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Chapter 1: Background and Motivation

1.1 Motivation

Sea level Rise (SLR) is a global phenomenon affecting coastal cities, posing risks to both natural and human-centered systems. Comprehensive studies on the potential risks of SLR across geographic scales date back decades, as scientific consensus grew on the potential implications that climate change may have on accelerating sea level rise. By 1990, the International Panel on Climate Change also addressed the need for adaptation or management strategies for sea level rise accelerated by climate change (Intergovernmental Panel on Climate Change. Coastal Zone Management Subgroup et al., 1990).

Given the risk that climate change poises to urban coastal environments (Chen et al., 2021; Gornitz, 1991; Guimarães et al., 2021; Hurlimann et al., 2014), coastal cities need to rapidly adapt in new and innovative ways. Possible adaptation management regimes include the creation of regional bodies to plan and implement adaptation, the formation of voluntary coalitions, or independent adaptations. In particular, there is growing interest in cooperative or regionally-coordinated adaptation (An Act Pertaining to Regional Resilience and Flood Protection Entities., 2025; Bonnett & Birchall, 2023; Fitzgerald et al., 2023; Shi, 2019).

Cooperative SLR adaptation is one example of a collective action problem. While many authors offer definitions or further study on applications of collective action, there tends to be agreement that these systems are affected by multiple users, exist when one individual's decisions may impact others, and are indicated when full management cannot be achieved by individual action alone (Heckathorn, 1996; Oliver, 1993; Ostrom, 1990; Wright, 2009). In the case of SLR,

adaptation is necessary to protect shared shorelines, where an individual's flood risk is closely linked not only to their own adaptation, but also to the adaptation of their neighbors.

In the consideration of multiple adaptation governance regimes, urban decision-makers must resolve two key questions relating to cooperative adaptation. First, urban planners and policymakers need to *understand and quantify benefits and trade-offs to behaving collectively (when are cooperative solutions beneficial?)*. In many collective action cases, risks and losses decrease for all participants under scenarios of full cooperation. However, not all participants may benefit equally and not all participants may benefit under every possible scenario. Despite the linkages to a SLR adaptation context, few studies have been published assessing to what extent these findings transfer to SLR adaptation. In short, decision-makers must first answer: should we behave collectively? A careful comparison of the potential benefits of cooperation against risks of incomplete or unsuccessful cooperation is necessary.

The second question that coastal urban decision-makers must answer is: if cooperation is a better strategy, *how do we encourage cooperative adaptation to emerge?* This question applies not just to SLR, but to other collective action situations, although we acknowledge that some of the drivers of cooperation may be application specific. This is an even more challenging task, requiring not only assessments of the flood risk, but also of human behavior. Developing effective policies to encourage collective adaptation for SLR will require synthesizing an understanding of the local institutional context, the decision-making process, and hydrologic flood risk. Answering this question will help to design more effective and resilient coalitions for adaptation.

Obtaining answers to either of the questions above may require utilizing more than one methodology to approach SLR adaptation from multiple distinct lenses. In general, when large-scale experiments cannot be conducted due to the technical and ethical considerations of

implementing temporary policy or interventions, researchers first turn to models. This is a useful approach for the first question. However, models require multiple assumptions that may prescribe specific cooperation outcomes under different representations of cooperative decision-making. The risk of over-simplifying these properties is a fundamental challenge of trying to mimic a human decision-making problem with mathematical representations. Distinct risks of misrepresentation occur from improperly determining or evaluating the ability of equations to adequately capture the nuances of decision-making. Testing models to understand the impact of these underlying assumptions can help to disentangle the influence our model assumptions have on outcomes. In some cases, this can be connected to what may drive collective action for SLR adaptation.

Although these models may struggle to capture decision-making and human behavior, models are well suited to calculate clearly understood and clearly defined processes. For example, they are incredibly useful for calculating dynamic flood risk over time (Nicholls et al., 1999). Additionally, they can be useful to explore the impacts of particular assumptions on model outputs (Yoon et al., 2023).

Despite the benefits of using models for those purposes, there will always be additional nuance that is not represented, either due to scope or deliberate modeling choices. In these cases, it is important to use alternative data, such as semi-structured interviews and previous literature on decision-making frameworks to better understand how models may translate to the real world. For example, while models may suggest particular adaptation financing schemes must change, qualitative research may suggest exactly where in the financing process those problems exist and propose solutions.

This dissertation seeks to understand the following research question: *How do cooperative approaches to sea level rise adaptation (including voluntary action or centralization) emerge, evolve, or fail, given economic incentives, decision-making dynamics, institutional constraints, and uncertainty?* We explore multiple aspects of coordinated sea level rise adaptation, using both quantitative and qualitative methodologies. First, we highlight the benefits of cooperative adaptation strategies in Chapter 2. These findings illustrate how coalitions and a regional flood authority reduce flood damages under uncertain futures. In Chapter 3, we explore how the choice of underlying theories and corresponding decision-making mechanisms affect adaptation coalition formation. Additionally, we demonstrate how the real-world context of Boston may reduce cooperation. In Chapter 4, we explore the current adaptation context in Boston Harbor, evaluating both mandated and voluntary cooperation management strategies. Finally, we explore how to manage uncertainty and ambiguity in complex systems, such as SLR adaptation in Chapter 5.

Overall, the chapters illustrate the promises of a Regional Flood Authority for flood management, although such an institution must be carefully designed to avoid inequities and overcome legal hurdles with its creation. We also demonstrate the risks of relying solely on voluntary cooperation, including the need for an initial environmental trigger to drive cooperation, and the risk of free-riding behavior. However, for either formulation of adaptation governance to achieve robust public support, there is a need to pre-emptively incorporate the risks of uncertain sea level rise and ambiguous concepts such as ‘equity’ or ‘fair’ financial contributions to such an organization.

1.2 Sea Level Rise from Multiple Literature Perspectives

1.2.1 The Challenge of Sea Level Rise

SLR benefits from being studied through multiple lenses, including as a scientific problem, as a complex system, and as a collective action problem. First, we consider SLR as a scientific problem, grounded in environmental processes. Current sea level rise is driven largely by three mechanisms: thermal expansion of the ocean, the melting of large glaciers, and changes in terrestrial water storage (subsidence, aquifer storage, dam impoundment etc.) (Frederikse et al., 2020). With less water held within aquifers, there is a chance that more water will be added to the oceans, increasing sea level rise. Additional influences include land rebound (Lambeck, 2001). The largest contributing factor to sea level rise since 1900 is the ice-mass loss, although thermal expansion also played a large role in the acceleration of sea level rise since the 1970s (Frederikse et al., 2020). SLR comes with three distinct risks: erosion, where coastal land is lost to the ocean, salinization, where rising seas push salt into coastal aquifers and pollute fresh water sources, and inundation, or coastal flooding (Gornitz, 1991). In this dissertation, we focus on the problem of coastal flooding due to increasing SLR.

The global mean sea level rise, while a useful metric, can be misleading to communities attempting to design and implement localized adaptations. This is because sea level rise in a particular location may be more or less than the global average. Both fingerprinting (Jeon et al., 2021) and relative sea level rise are terms used to describe how a localized pattern of sea level rise will vary from the global mean rate. Local sea level rise rates can deviate significantly from the global mean. For example, while one study calculated the rate of global mean sea level rise to be 2.6 mm per year, coastal regions with significant subsidence rates can experience SLR rates of up

to 9.9 mm per year (Nicholls et al., 2021). However, the exact amount of sea level rise that will occur in a specific location is difficult to assess, in part due to the dependence on potentially inconsistent or inaccurate historical tide gauge data (Cazenave & Nerem, 2004).

While responses to climate change are frequently separated into adaptation or mitigation, most literature on sea level rise focuses on adaptation actions due to the irreversible consequences of the melting of large glaciers. Because these reactions are largely one-way, many coastal regions will need to implement adaptations regardless of any current or future mitigation activities. Determining the optimal adaptation for any given location poses a challenge, as definitions of ‘optimal’ vary based on the specific goals of a community. Discussions for adaptation design may include the choice between engineered hard adaptations, policy interventions, soft interventions, or nature-based solutions (Van der Meulen et al., 2023).

Despite the uncertainty in the amount of sea level rise that coastal communities may face by the end of the century and beyond, the challenge of effectively responding to the increasing risks posed by SLR is a complex problem that also requires incorporating political and social systems along with natural systems.

1.2.1.1 Sea Level Rise as a Complex Problem

Despite the challenges facing coastal environments from sea level rise, adaptation provides an avenue for resilience despite rising seas. Although it may be too late for mitigation to act as an effective strategy at stalling sea level rise below 1 meter by 2100 (Mengel et al., 2018), numerous adaptation options, from hard infrastructure to nature-based solutions could be employed to protect vulnerable ecosystems and urban environments. Coastal cities are currently facing a number of questions about adaptation, including: what policies should exist for coastal adaptation? What risk should we design for? And how do we finance adaptation?

Sea level rise adaptation is well-situated to be considered through the lens of complex systems, nestled in the interaction between natural, social, and political systems. This is reflected in a definition of risk provided by an IPCC special report (Lavell et al., 2012):

$$risk = hazard * exposure * vulnerability$$

While hazard is the probability of a flood event, exposure is who and what is subject to flooding risk, and vulnerability is a reflection of how well a group can adapt or maintain resilience in the face of a flood (Koks et al., 2015). Hazard is largely a problem of natural systems, including coastal processes, while exposure can be influenced by political systems through zoning laws, Vulnerability is closely intertwined with both social and political systems (Surjan et al., 2016). The interactions between natural, political, and social systems surrounding climate adaptation is what leads to the complexity. Figure 1 below illustrates just a few of these components of each system and overlaps in the context of coastal SLR adaptation.

The complexity of SLR adaptation can be indicated by cataloguing the elements of natural, political, and social systems in which it is embedded. Figure 1 highlights just a few of these elements and their interactions. For example, both social and natural systems contribute to coastal vulnerability, while social and political systems create ripple effects to existing institutions, and political and natural systems interact for the development of adaptation infrastructure. For example, many flood risk models capture a static assumption of risk, which does not accurately reflect the true complexity of the system. Instead, flood risk shifts not only due to changes in the natural system, but also as political processes influence individual or collective adaptation construction or the purchasing of flood insurance.

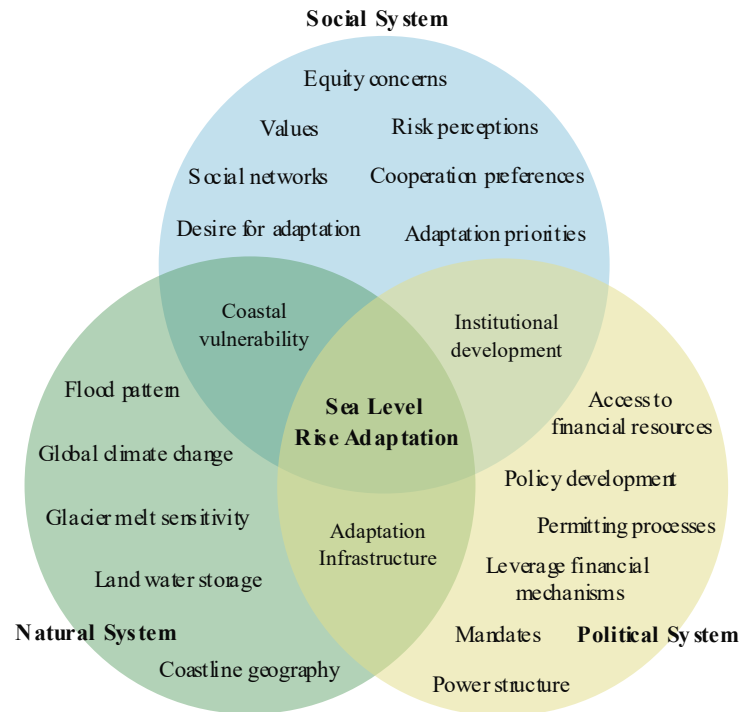


Figure 1. Interaction of natural, political, and social systems influencing sea level rise adaptation choices

Acknowledging that changes to one facet of the system may spill over to other connected systems through feedback loops is an important component of complexity. Incorporating these into feedbacks into planning can help to provide a more accurate assessment of any unexpected impacts.

One of the challenges of designing effective SLR adaptation is that complex systems are more difficult to manage. The complexity of multiple interacting systems and the multitude of agents contribute to the difficulty to quickly act and implement sea level rise adaptation. (Hinkel et al., 2018a) categorize challenges to coastal adaptation as either finance barriers, social conflict barriers, economic barriers, or technological limits. Similar research highlights these challenges within the Boston context (for example, limited capacity and fragmented jurisdictions), along with

the need for particular equity considerations (Hamin et al., 2014; P. Kirshen, Douglas, et al., 2012a).

Because of the close linkages between climate adaptation and social systems, concerns of equity must also be mentioned. While settling on a single definition of equity for coastal adaptation is a challenging task and there may never be one single correct definition (S. Walker et al., 2024), there are significant equity implications for coastal adaptation that must be considered (N. Fox et al., 2023; Pollack et al., 2025). These concerns exist across a variety of scales, from inequities between neighborhoods in the same city, to larger scale inequities between countries. For example, at a global scale, the individuals and nations most vulnerable to SLR contributed the least to the emissions driving SLR (Shi et al., 2016). When considering interventions for coastal adaptation, equity should play an important role in the selection of final adaptation plans. Every policy passed will have positive impacts and negative impacts, some of which may not become visible until decades down the line (particularly for large scale infrastructure that may re-shape the fundamental ways in which neighborhoods operate).

Uncertainty is another facet of complex systems that requires careful consideration and planning. Complex systems are characterized by a high degree of uncertainty, some of which exist due to inherent randomness in the system (maximum flood in a given year), and some that will narrow over time as more information becomes available (total SLR increase by 2200). Efforts are needed to improve how we incorporate uncertainty into planning and design. In the case of SLR, uncertainty has very real impacts on decision-makers, as coastal residents may respond differently when faced with uncertain flooding risk on an annual time scale, uncertain long-term SLR, and uncertain future political climates. While some strategies, such as purchasing flood insurance,

hedge against uncertainty, these only shift the risk between multiple purchasers, rather than providing long-term damage reductions.

1.2.1.2 Sea Level Rise as a Collective Action Problem

Throughout this dissertation, we use a collective action framing to analyze the sea level rise adaptation, which aids us in bridging disciplines from hydrology and engineering with social sciences and policy analysis. While many traditional collective action systems relate to a shared resource, such as a limited water source or fisheries management, SLR adaptation also maintains some critical characteristics that identify it as a collective action problem, including interconnections and rivalry. For example, available financial capital may be a collective resource when multiple agencies are competing for the same grants for adaptation implementation. Additionally, SLR represents collective risk, where the nature of coastal processes means that flood damages often directly or indirectly affect many individuals and organizations simultaneously.

In contrast to traditional flood risk papers, a collective action framing supports an analytical approach that considers the role of governance structures and decision-making for adaptation implementation. Such a framing also improves the generalizability of insights generated within this dissertation to other collective systems, where cooperation must be encouraged and sustained for improved resources management.

The decisions of when, how much, and where to adapt to sea level rise present a collective action problem that requires the simultaneous efforts of many agents to protect a shared coastline and shared infrastructure. Despite this, models that demonstrate adaptation to SLR rarely engage with collective action and common-pool resource literature. Generally, SLR flood model papers tend to focus on specific applications and policy experiments. More qualitative research on climate change adaptation and in some cases, explicitly on flood adaptation, has incorporated ideas from

collective action, but this research rarely incorporates modeling techniques like agent-based modelling (Adger, 2010; Boda & Jerneck, 2019; Yu et al., 2017).

The lack of connectivity between insights from collective action literature and flood adaptation models has resulted in a lack of knowledge of how to encourage and develop lasting governance strategies for sea level rise, building on the extensive existing knowledge about collective action problems and polycentric governance. While some of the flood models have begun to incorporate behavioral and social phenomenon relating to collective processes through the role of social networks and institutions in their models, these are often exogenous or simple representations. For example, Abebe, et al. incorporate social network effects by using a threshold of neighbors who have already implemented a flood adaptation measure as one branch in their decision trees (Abebe et al., 2020). To the best of my knowledge, no one has attempted to model flood adaptation using representations of cooperation and defection, such as the models proposed by Bravo, Janssen et al., or Nhim, et al (Bravo, 2011; M. Janssen, 1998; Nhim et al., 2019). This kind of modeling exercise could illustrate interesting dynamics about coalition formation if it is incorporated in flood adaptation modeling. One promising class of models for studying collective action systems is Agent-Based Modeling (ABM), a bottom-up methodology frequently used to incorporate diverse and heterogeneous agents within environmental systems. While a challenging concept to capture, integration of coalition formation in SLR adaptation plans with an ABM is a significant gap that has yet to be properly addressed.

In addition to the lack of linkages between flood adaptation models and collective action literature (including coalition formation and mechanisms for cooperation), there is a gap in exploring effects of governance structures on flood adaptation outcomes. While many contributions have been made to assess the relationship between governance strategies and

collective action (particularly with the work of Elinor Ostrom and her colleagues) (Ostrom, 1990, 2000, 2017), this has been less frequently applied to climate adaptation. Three papers that begin to explore this are the work by (Bitterman & Koliba, 2020; Haer et al., 2019; Pahl-Wostl, 2007). These authors have made significant contributions to understanding how governance and adaptation interact, but there is much left unknown. For example, these are still limited in the number and variety of governance strategies explored. Haer, et al. (2019) consider the difference between proactive and reactive government actions for flood adaptation. Pahl-Wostl, et al. (2007) begin to explore outcomes of centralized versus decentralized decision-making, but in the context of irrigation. Bitterman and Koliba (2020) begin to explore different network structures and impacts of voluntary and mandated project implementation for nutrient load reduction. While these papers begin to explore the question of governance regimes for different applications, none of them sufficiently answer the question of how different flood adaptation governance structures will affect overall adaptation outcomes and subsequent flood risk. As mentioned in some reviews of ABMs for socio-ecological systems, this could be due to the fact that government agents are rarely incorporated into ABMs as agents, but more frequently as assumptions or exogenous model levers (Bourceret et al., 2021).

Within collective action systems, one challenge to modeling is determining the representation of cooperative processes. For example, low levels of cooperation may include sharing information or passing messages. Higher and more organized patterns of cooperation may include entering binding agreements, sharing limited financial capital, or coordinating on policy. Throughout this dissertation, we significantly limit how we imagine cooperative adaptation agreements, largely due to the limitations of modeling hundreds of possible formulations of cooperation. Instead, we consider cooperation to only be either mandated through two options

throughout the research: a Regional Flood Authority or through voluntary adaptation coalitions, whose only purpose is to share financial burdens to implement large-scale adaptations. We also do not include any notion of overlapping coalitions to form polycentric governance structures (Ostrom, 2017). While this limits the nature of cooperation, we are able to compare extreme ends of cooperation because the law requires it, and cooperation because there is interest in collective adaptation. This research would benefit from future expansion of the representation of cooperation and added flexibility in the rules of how to cooperate.

1.2.1.3 Useful Methods to Study Collective Action

Collective action is a complicated topic to study with any singular methodology, in particular due to the large dependence on human systems, which can be difficult to capture in quantitative models (Bonabeau, 2002; P. K. Davis et al., 2018; Essahraoui et al., 2025). Throughout this dissertation, we use a combination of quantitative and qualitative approaches to construct and refine models for SLR adaptation and provide additional institutional analysis and context.

The class of models used throughout this dissertation are Agent-Based Models (ABMs), which are a suite of models that represent phenomena through bottom-up action of multiple heterogeneous agents. ABMs and other modeling methods have been applied both to collective action problems generally, and sea level rise adaptation specifically. While typically touted for their ability to capture emergent behavior (Bonabeau, 2002; Cenani, 2021; Dessalles et al., 2008), an ABM approach can be justified for systems where there are multiple classes of agents that interact in independent decision-making processes. Rather than presuming emergence, this justification allows for a humbler approach that does not guarantee true strongly emergent properties.

A brief review of ABMs for collective action purposes reveal applications to a variety of topics: water withdrawals, mostly for irrigation purposes (Lang & Ertsen, 2023; Nhim et al., 2019; Pahl-Wostl et al., 2007; Tamburino et al., 2020); models for cognitive modeling (D. Andersson et al., 2021; Kuhlmann et al., 2020); models pertaining to land conservation (forestry and otherwise) (Bravo, 2011; Watkins et al., 2013); applications to soil conservation (Van Oel et al., 2019), use for flood adaptation (Abebe et al., 2020; Haer et al., 2019, 2020; Han et al., 2020; Han & Peng, 2019); general resource management (M. A. Janssen et al., 2022); and pollution reduction in a shared waterway (Bitterman & Koliba, 2020). Many of these models use survey or experimental data from their modeled population to parameterize their models, including to calibrate models or represent initial beliefs towards risk and adaptation efficacy (Abebe et al., 2020; Bitterman & Koliba, 2020; Han et al., 2020; M. A. Janssen et al., 2022; Van Oel et al., 2019; Watkins et al., 2013).

One benefit of ABMs is their ability to generate unexpected or emergent large-scale outcomes based on granular agent interactions. A similar modeling approach is often demonstrated with multi-agent systems, who model distinct agents individually. One distinction between agent-based models and multi-agent systems (MAS) is the focus and design to demonstrate emergent conditions (this is not a hard rule however, and certain fields do not create a distinction between ABMs and MAS). Whether or not all published ABMs generate true emergence is up for debate based on whether you consider the title ‘ABM’ to reflect the model structure or the purpose of the model. In this dissertation, Chapter 2 uses an ABM as a multi-agent model because the purpose was not to demonstrate emergent characteristics. However, Chapter 3 demonstrates an ABM constructed with the purpose of exploring large-scale phenomena arising from the actions of

multiple distinct agents, in line with the typical purpose and application of ABMs. Papers exploring ABMs and multi-agent systems for flood adaptation include (Simmonds et al., 2020).

A Note on ABMs and Emergence

The overall definition of emergence is that it is a system-level property that cannot be estimated by the individual parts alone. Santa Fe Complexity Institute determines emergence as “the arising at the macro level of some patterns, structures and properties of a complex adaptive system that are not contained in the properties of its parts” (Singh et al., 2013). While there is agreement for the overall definition, there is a lack of consensus for the definitions of sub-categories of emergence, such as weak, strong, or spooky emergence. For example, while some consider weak emergence to be defined with some regard to the potential of computer simulation, others reject the idea. Broadly, there seems to be agreement that any computer simulation is not capable of explicitly capturing ‘strong’ emergence, and that ‘spooky’ emergence cannot even be conceptualized (similar to logic of unknown unknown/black swans, etc.) (S. Janssen et al., 2019).

Although the concept of emergence is well-understood, measuring or demonstrating emergence with ABMs is a much murkier task and there are no universally agreed upon ways to prove emergence within an ABM (Szabo et al., 2014; Tang & Mao, 2014). While some modelers defend the presence of emergence by demonstrating patterns or outcomes (for example, the way Arthur, 2021 utilizes ‘emergence’), others have begun to attempt to develop metrics that assess emergence. Often, these patterns are described by model phase states, shifting trends over time, or agent clustering. For example, (Dessalles et al., 2008) mention that one indicator of emergence can be bifurcation.

Alternatively, a few metrics have been developed to measure emergence, which strongly borrow from equations utilized to describe entropy or focus on quantifying the impact of agent

interaction and are tailored to emergence of behavior, structure, or spatial clustering, such as those in (Tang & Mao, 2014). (Szabo et al., 2014) also proposes a mathematical equation to quantify emergence based on the interactions between agents and their ‘grammar’, but the detail and complexity of those equations are well-suited to simpler models. Alternative metrics that don’t directly capture emergence but can hint at its presence include the number of interactions, clustering coefficients of the network, local entropy, and Gini-coefficient (Suda et al., 2023).

(S. Janssen et al., 2019) demonstrate how causal discovery graphs can be used to identify emergence within an ABM when used along with machine learning algorithms, although there are no specific metrics to ‘prove’ its existence. Unexpected, missing, or divergent results between machine learning outputs, sensitivity outputs, and causal inference graphs can represent emergence.

Structural Uncertainty in ABMs

ABMs face particular challenges with structural uncertainty: the choices we make in specifying decision pathways can have a large impact on outcomes than parameter uncertainty (Yoon et al., 2023). Yoon, et al. demonstrate this, exploring how different assumptions about how agents incorporate flood risk preferences has a much larger impact on uncertainty than any parameter uncertainty. However, they don’t provide any singular solution for managing this challenge.

Because of the diversity of ABMs, there is little consensus on what verification and validation even means within an ABM (Troost & Berger, 2020), particularly for models that demonstrate hypothetical futures. Troost proposes a validation framework for ABMs that emphasizes the alignment of research question, model choices, and model conclusions as critical components of the validation process (Troost & Berger, 2020). Alternative methods for validation of an ABM include face validity (animation or graphical representation), tracing, internal validity

(effect of different random seeds), historical data validation, parameter variability-sensitivity analysis, predictive validation, and Turing tests (Xiang et al., 2005).

Qualitative Methods and Mixed-Method Approaches

Combining model development with stakeholder knowledge can help to fill some of the gaps in knowledge that either can't be captured through modeling or are not well-suited to a modeling methodology. In particular, qualitative literature such as the work by (Azhar et al., 2025; P. Kirshen, Douglas, et al., 2012a; Safarpour et al., 2025) demonstrate the utility of interviews and focus groups to capture stakeholder perspectives on water systems or adaptation system. Additionally, participatory modeling approaches have demonstrated how incorporating stakeholders in model development leads to more useful models and a much richer discussion of their findings (Eitzel et al., 2020; Voinov et al., 2018).

1.3 Application to Boston Harbor

Although sea level rise is a challenge for most coastal cities, Boston (and the greater New England region) is experiencing greater than average relative sea level rise (Kruel, 2016). The urgency of the problem, coupled with the need to rapidly adapt to protect low-lying areas of the Harbor, including underground assets like the tunnel systems for both roadways and subways, means that Boston will be one of the first coastal US cities grappling with existential sea level rise. Given the risk the city is facing, Boston is a useful case study to investigate when cooperation is a useful strategy and how to make cooperative solutions sustainable and resilient.

Previous studies have looked at general barriers to coastal adaptation (P. Kirshen, Douglas, et al., 2012a) and the implementation of nature-based solutions in Boston (Lillquist, 2024), but have yet to specifically investigate challenges of cooperation. However, given the particular

challenges that many of the small coastal towns and cities face related to leadership and resource scarcity (Hamin et al., 2014), cooperative approaches may be an important strategy to ensure adequate flood protection across the Harbor.

Boston is an interesting focus of this dissertation for a few reasons. First, this work was born in the Boston area; the experts, decision-makers, and stakeholders that we spoke with were more accessible due to proximity. Second, many agents in the Boston Harbor area are engaged and active in discussions around SLR adaptation and the possibility of cooperative and regionalized governance. The city has multiple mandates for managing adaptation, and many organizations across Massachusetts have completed adaptation and flood risk assessments. Third, Boston Harbor ‘Big Dig’ project began to shift the way the public here views and manages large-scale infrastructure projects (McCarthy & Derickson, 2010). Finally, the Harbor area has multiple organizations that can serve as possible models for regionalized management, including the Massachusetts Bay Transportation Authority (MBTA) and the Massachusetts Water Resources Authority (MWRA).

Although Boston Harbor is the impetus, inspiration, and focus of this dissertation, Boston is among hundreds of coastal cities that are or will soon grapple with questions pertaining to the role of cooperation in sea level rise adaptation. Because the work is calibrated and centered in Boston, many of our findings will be Boston specific. However, we strive to also address and incorporate generalizable findings and possible applications for extensions to other locations, when possible.

The timing of this research coincides with the introduction of Bill S.658 to the Massachusetts Senate (An Act Pertaining to Regional Resilience and Flood Protection Entities., 2025), which proposes the creation of a Regional Flood Authority for Massachusetts. Although in

initial stages, the bill highlights the timeliness of many of the questions and findings put forward in this work. Although the Bill would establish a flood authority and endow it with fundraising and management power, many decisions are yet to be made about the structure of such an organization, the ease of financing their projects, and their role for coordinating adaptations with the general public in addition to larger entities. We hope that this research can contribute to the on-going discussions and commentary surrounding this bill as it is processed by the Committee on Environment and Natural Resources.

1.4 Development of Research Questions

Responding to sea level rise will require adaptation to protect vulnerable and exposed areas. In Boston, this includes protecting coastal land both along the Harbor itself and along more inland waterways that are susceptible to flooding. SLR adaptation can take many forms including hard adaptations (seawalls, rip-rap, beach nourishment) or nature-based solutions (Van der Meulen et al., 2023). In addition to the choice of adaptation pursued, urban planners and policy makers must determine how adaptation is pursued and whose job it is to construct and implement adaptations.

Throughout this dissertation, we focus on three possible ways of coordinating adaptation. The first, and simplest, is adaptation without cooperation. Whether it was due to a specific avoidance of cooperation or simply due to the absence of cooperative structures, these adaptation regimes are unregulated and piece-meal. Most coastal adaptation is currently more or less completed as an independent endeavor, without organized or large-scale coalitions and poor coordination across jurisdictions or levels of governance (Wannewitz et al., 2024). The second form of adaptation governance is through voluntary coalitions, which aligns well with Bednar and Henstra's conceptualization of networked governance (Bednar & Henstra, 2018). Here, we assume

that individual entities, such as property owners, towns, infrastructure organizations, or others agree to cooperate on adaptation outcomes without being mandated to cooperate through legislation. While these arrangements are less formal and difficult to sustain, early example of voluntary cooperation similar to this concept include the Wharf District Council in Boston (<https://www.wharfdistrictcouncil.org/climateresilience>), which brings together actors from across the Wharf district to discuss climate resilience. Finally, we consider the possibility of a regional flood authority that manages and implements coastal adaptation under one centralized organization, endowed with powers through legislation (Fitzgerald et al., 2023).

Throughout the body of this dissertation, we will explore SLR adaptation under these three adaptation regimes, largely motivated by the case study of Boston Harbor. We will review the purpose and motivating questions of each chapter below. In general, this dissertation seeks to answer: *how do cooperative to sea level rise adaptation approaches (both through voluntary action or centralization) emerge, evolve, or fail, given economic incentives, decision-making dynamics, institutional constraints, and uncertainty?*

1.5 Chapter Overviews

This research examines when collective SLR adaptation is economically advantageous, how cooperative decision-making pathways influence coalition formation, how institutions enable or constrain cooperation in Boston Harbor, and how uncertainty and ambiguity shape adaptation decisions. This dissertation offers two main categories of novelty: general and conceptual contributions, and methodological contributions. While the former focuses on looking at the outputs from modeling and qualitative data directly to reach conclusions, the latter focuses on

impacts of modeling choices, decision-making frameworks, and the synthesis of multiple disciplines for meaningful problem framings.

Chapter 1: The first chapter provides a motivation for the research and serves as a guide to navigate the dissertation. We focus on introducing the collective action framing and why it is important to consider SLR adaptation from this perspective, particularly given the pressure for cooperative adaptation structures. Additionally, we provide background information about SLR in Boston Harbor and the methods used throughout this dissertation.

Chapter 2: In the second chapter, we seek to contribute to the overall research question by asking ‘*Under what conditions are collective approaches to SLR adaptation more economically efficient?*’ We compare how different adaptation governance regimes result in improved adaptations across Boston Harbor, as measured by flood damage reduction. This chapter introduces the development of the ABM that is used throughout the dissertation to capture SLR adaptation within a coastal city. In this chapter, we demonstrate that while a Regional Authority results in reduced flood damages, there are trade-offs and specific neighborhoods are often left exposed to flood risk for longer. We also illustrate how a regional approach is not sufficient to ensure the most optimal outcomes, but it is an adequate strategy to avoid the costliest flood damage scenarios. Given the numerous uncertainties that affect SLR adaptation, institutional factors are as important to the performance of cooperative solutions than hydrologic variability.

Chapter 3: The third chapter expands on the ABM presented in Chapter 2 to focus on the successes and failures of voluntary adaptation coalitions. Here, we focus on a more methodological contribution. In particular, we ask “*how does changing cooperative decision-making pathways inspired by social contagion, network reciprocity, and flood reaction shift coalition formation and collective adaptation implementation?*” Although Chapter 2 indicated that a Regional

Authority is more successful than voluntary coalitions at reducing flood damage, the development of such an authority depends on the new legislation, which may not always be a feasible option. For this reason, we justify additional research into voluntary cooperative agreements. In this chapter, we also illustrate how there is a lack of knowledge on the integration of multiple behavioral theories, cooperative SLR adaptation, and coalition-forming ABMs. Because the decision to cooperate is so complex and varied between individuals, it is important to understand how alternate decision-making assumptions may impact cooperative behavior. Unlike general coalition forming models, cooperation for SLR adaptation is also strongly shaped by the natural system and flood risk. In this chapter, we demonstrate how the selection of the decision-making process can result in dramatically different coalition behaviors. Additionally, we demonstrate that by adding the context of Boston Harbor reduces cooperative behaviors in comparison with an idealized world. This paper builds on literature highlighting the importance of structural and parametric uncertainty in modeling.

Chapter 4: This chapter focuses on utilizing qualitative data to identify: “*what are the institutional hurdles to cooperative for adaptation in Boston Harbor and what changes are necessary to support a voluntary or mandated cooperative adaptation policy?*” One missing component of our analysis so far was stakeholder perspective on cooperative adaptation structures. Although the previous chapters benefitted from stakeholder comments for model validation purposes, many of our experts also made extensive contributions on the differences between a regional flood authority or voluntary cooperation. Chapter 4 analyses the commentary we received and utilizes the Institutional Analysis and Development Framework (McGinnis, 2011; Ostrom, 2009) to frame the results. In contrast to previous studies that generally look at coastal adaptation challenges (or their application to particular adaptation strategies, such as Nature-Based

Solutions), this chapter focuses on the possible role of cooperation in SLR adaptation in Boston Harbor.

Chapter 5: The previous chapters use qualitative and quantitative methods to explore cooperative SLR adaptation. In contrast to Chapters 2-4, this chapter focuses on making a theoretical contribution to improve our strategies for managing uncertainty and ambiguity. In particular, this chapter asks: *“how do the characterization of uncertainty and interpretation of ambiguity affect the decision-making processes in sea level rise adaptation? How can we synthesize quantifiable uncertainty and ambiguous interpretations to strengthen decision-making?”* We first assess current definitions of ‘uncertainty’ and ‘ambiguity’ and their use in decision-making literature. Next, we propose how the synthesis of two frameworks is necessary to manage uncertainty and ambiguity when they are deeply connected to each other. Decision-Making Under Deep Uncertainty (DMDU) and Engineering Diplomacy Framework (EDF) are synthesized to support an approach for Decision-Making with Uncertainty and Ambiguity (DMUUA). Finally, we demonstrate why such an approach is needed, using the case of adaptation coalition formation, again building on the ABM work previously established in the dissertation.

Chapter 6: Chapter 6 offers a conclusion to the dissertation, reviewing the contributions from each previous chapter. We also add commentary to the on-going discussions about effective policy for cooperation for SLR adaptation in Boston Harbor. We also emphasize the contributions and novel elements of this work.

Across the chapters in this dissertation, we strive to provide new context and insights to cooperative adaptation arrangements, both in Boston Harbor, but also applicable to other coastal urban centers. Thank you for taking the time to read this far and I hope that something in this dissertation resonates with all of us as we consider our roles in this rapidly changing world.

Chapter 2: Governance and Coordination Trade-offs for Sea Level Rise Adaptation in Boston: An Agent-Based Model

This chapter is in review at *Regional Environmental Change*. The paper's author list is:

Catherine Knox, Dr. Paul Kirshen, Dr. Jonathan Lamontagne, and Dr. Shafiqul Islam.

Abstract: As sea level rise intensifies coastal risk, adaptation is often hampered by fragmented governance. This study develops an agent-based model of Boston Harbor to evaluate how three adaptation regimes—non-cooperation, voluntary cooperation, and a centralized regional authority—perform under varying assumptions about sea level rise, discounting, financing access, and flood variability. Results show that cooperative governance, particularly through a regional authority, can reduce cumulative damage and increase net benefits. However, these gains are highly conditional: under scenarios with modest sea level rise or abundant financing, voluntary or uncoordinated adaptation may perform similarly or better. In some cases, agents with limited resources or disadvantaged geography fare worse under cooperative regimes, especially in voluntary coalitions. Equity and efficiency trade-offs highlight the importance of tailoring governance structures to context. Notably, governance structure, financing, and discounting explain more outcome variation than stochastic flood events—but a large share of variance remains unexplained, pointing to the influence of local dynamics and emergent behavior. These findings suggest that designing adaptive institutions may be more impactful than refining climate projections alone.

2.1 Introduction

Increasing rates of sea level rise (SLR) force coastal cities to implement adaptations to protect infrastructure and assets from floods. While this phenomenon is global, in Boston above average relative SLR will affect 20% of the land and population by 2100 (Chen et al., 2021; Douglas & Kirshen, 2022a; Kruei, 2016). Many of the locations most at risk of increased coastal flooding in Boston are considered disadvantaged communities with fewer resources to adapt to SLR (Douglas et al., 2012; P. Kirshen, Douglas, et al., 2012a).

Developing effective and equitable climate adaptation will require collaboration between individuals, private sector, and government actors along coastlines (Hamin et al., 2014; Hurlimann et al., 2014; Klein et al., 2017). Despite the need for rapid SLR adaptation, there is often a mismatch between the current institutions that plan and construct coastal adaptations, and the institutions required for collaborative strategies. To justify the effort required for collaboration, quantitative representations of the benefits of regional adaptation are necessary. Additionally, it is important to quantify how financial, behavioral, or political conditions may affect the success of collaboration (Shi, 2019).

To understand the dynamics and benefits of regionalized adaptation, we developed an agent-based model (ABM) to investigate how collective adaptation to SLR could improve adaptation outcomes in Boston Harbor. Although the model was developed for Boston, we use this location as an emblematic case study with a transferrable structure to other coastal cities with multiple private or public actors sharing a coastline. Within the model, we incorporate several key agents in the region, including geographically dispersed agents such as the subway network, and localized agents such as property owners and municipalities. The model explores how these

processes and agents interact to implement coastal adaptations under three adaptation regimes: no cooperation, voluntary cooperative coalitions, and a regional flood authority. We explore model behavior under numerous uncertainties in behavioral, coastal, legislative, and financial systems.

Although most literature will agree that ‘cooperation is better,’ our results suggest three actionable insights for the case of SLR adaptation in Boston. First, the benefits of cooperation depend on conditions such as SLR, discount rate, and external financing access (parameters with high uncertainty and political sensitivity). Second, poorly designed or underutilized coalitions can result in adaptation delays, in some cases underperforming non-cooperative adaptation strategies. Third, different adaptation governance strategies minimize different risk sets. While a regional flood authority may help to avoid worst-case flood damages, voluntary coalitions and non-cooperative strategies often have lower adaptation costs. These findings illustrate why there is no single choice for adaptation governance, but rather that adaptation measures and metrics need to be chosen with consideration for local capacity and constraints.

While our ABM provides initial assessments of how and when regionalization may create sufficient benefits to justify the efforts of mandatory regionalization, additional research is required to ensure that adaptations are implemented with attention to equity and sustainability.

2.2 Background: SLR Adaptation Governance Regimes

SLR and accompanying flooding is a substantial threat facing coastal communities across the globe. With optimistic conditions, relative SLR from 2000-2100 may be between 0.8-2.6 ft, and with extreme conditions may reach 2.36 - 4.66 ft (Douglas & Kirshen, 2022a). When faced choosing coastal adaptation or retreat, many towns in New England are considering protective infrastructure, such as seawalls (P. Kirshen, Borrelli, et al., 2018). However, their construction has

been slow, in part due to challenges in political or budgetary processes. Barriers to coastal adaptations have been explored more in detail by numerous authors (Douglas et al., 2012; Hamin et al., 2014; P. Kirshen, Douglas, et al., 2012a; P. Kirshen et al., 2020), including high costs, a lack of clear information, the need to coordinate across multiple bureaucratic agencies, values and beliefs, and environmental permitting. Based on the current adaptation ecosystem, the institutions necessary for regional collaboration may require significant effort and shifts within current political systems (Ishiwatari, 2019; Puig et al., 2025).

Climate adaptation is one example of collective action problems, which also include resource management or emissions reductions problems (Ostrom, 2010a). Despite their inherent challenge, collective systems have been managed via multiple approaches, including through the formation of coalitions, private-public partnerships, regionalization, or polycentric governance (Lubell & Robbins, 2022; Ostrom, 2010c, 2017; Pattberg, 2010). The success of collective action in multiple resource-related empirical cases raises the question about when and how some of these approaches could be applied to SLR adaptation (Ostrom, 1990, 2000).

In general, climate adaptation governance can be distinguished between four categories: hierarchy (regionalized), market (subsidies and taxes), network, or community (coalition) (Bednar & Henstra, 2018). Of these, centralizing adaptation capacity or through voluntary collaborative coalitions are often of interest for environmental management (Feiock, 2009). While many authors highlight arguments in support of collaborative and centralized governance in climate adaptation (John III & Yusuf, 2019; Mitchell et al., 2023a), mandatory regionalization may override local autonomy for the sake of more generalized goals (Shi, 2019). Understanding potential trade-offs of both mandatory and voluntary collaboration is a critical part of optimizing adaptation processes

in coastal cities (Shi, 2019). However, estimating these trade-offs and determining how to quantify financial benefits from adaptation also poses a challenge.

Although multiple papers have explored typologies of adaptation governance and their structures from a policy, institutional, or economic perspective, there is a need for the development of new quantitative models that explicitly address how different degrees of cooperation could affect adaptation outcomes in a harbor region (Bednar & Henstra, 2018). One such approach is Agent-Based Models (ABMs). ABMs are commonly used to capture dynamics arising from the interactions of many agents and have been used across literature to investigate the dynamics of numerous coupled human-natural systems, including applications in health, resource management, migration, and climate adaptation (Bonabeau, 2002; Macal & North, 2005). ABMs are well-suited to capture stochastic flood models where the risk structure shifts over time (Taberna et al., 2020; Zhuo & Han, 2020). In particular, they are well-suited to collective action systems, where management outcomes are often the result of interactions of many individual agents and institutions (Bourceret et al., 2021).

Many authors have successfully demonstrated the utility of using ABMs to explore aggregate adaptation behavior to SLR, in contrast to traditional flood modeling approaches that do not incorporate dynamic adaptation behavior (Aerts, 2020). Previous models have demonstrated the importance of specific flood sequences on adaptation patterns (Abebe et al., 2020), flood insurance reforms (De Ruig et al., 2023; Dubbelboer et al., 2017), social network impacts on flood adaptation (Erdlenbruch & Bonté, 2018; Haer et al., 2016), and the role of proactive or reactive governments on coastal adaptation (Haer et al., 2019). Other notable contributions to ABMs applied to flood adaptation include: (Han et al., 2020), (Han & Peng, 2019), and (Tierolf et al., 2023).

Despite the advances presented in these models, to the best of our knowledge, ABMs for coastal flood adaptation have yet to clearly quantify how coastal adaptations shift according to multiple governance typologies. In Boston, there is a demonstrated need for such a model, as debates over centralizing flood adaptation are ongoing (Fitzgerald et al., 2023; Shi, 2019). While the work by (Haer et al., 2019), (Pahl-Wostl, 2007) and (Bitterman & Koliba, 2020) begin to explore elements such as reactivity of governance, or governance regimes in non-flooding applications, none of them sufficiently answer the question of how flood adaptation cooperation will affect adaptation outcomes and subsequent flood risk. As mentioned in some reviews of ABMs for socio-ecological systems, this may be because that government agents are rarely incorporated into ABMs as agents, but more frequently as assumptions or exogenous model levers (Bourceret et al., 2021).

Our model contributes to closing the gap between qualitative understandings of adaptation governance and quantitative assessments of their benefits and effects on adaptation patterns. We explicitly explore how adaptation governance strategies affect adaptation outcomes using a stylized example of Boston Harbor to balance specificity with transferability. Our findings may suggest actionable insights related to the efficacy of cooperative institutions and add nuanced understanding of the benefits of cooperation.

2.3 Introduction to the ABM

We chose an ABM methodology over other modeling approaches such as generalized equilibrium or system dynamics models due to its ability to mimic interaction effects, incorporate reactivity, and preserve agent heterogeneity. Our ABM includes three distinct adaptation regimes: no cooperation, voluntary cooperation, and a regional authority. The three adaptation regimes

incorporate how agents seek to minimize their damages and implement adaptations with high benefit-cost ratios. A map of agents is shown below in Figure 2. Although we explore three separate representations of adaptation governance, the flexibility of the ABM set-up allows for us to directly incorporate how the decision-making process shifts between them. We include only three municipalities (Boston, Quincy, and Winthrop) due to computational complexity, but the study area could be expanded to include other towns on the coastline. For the purposes of these results, we consider Quincy and Winthrop to represent a sample of the nearby towns.

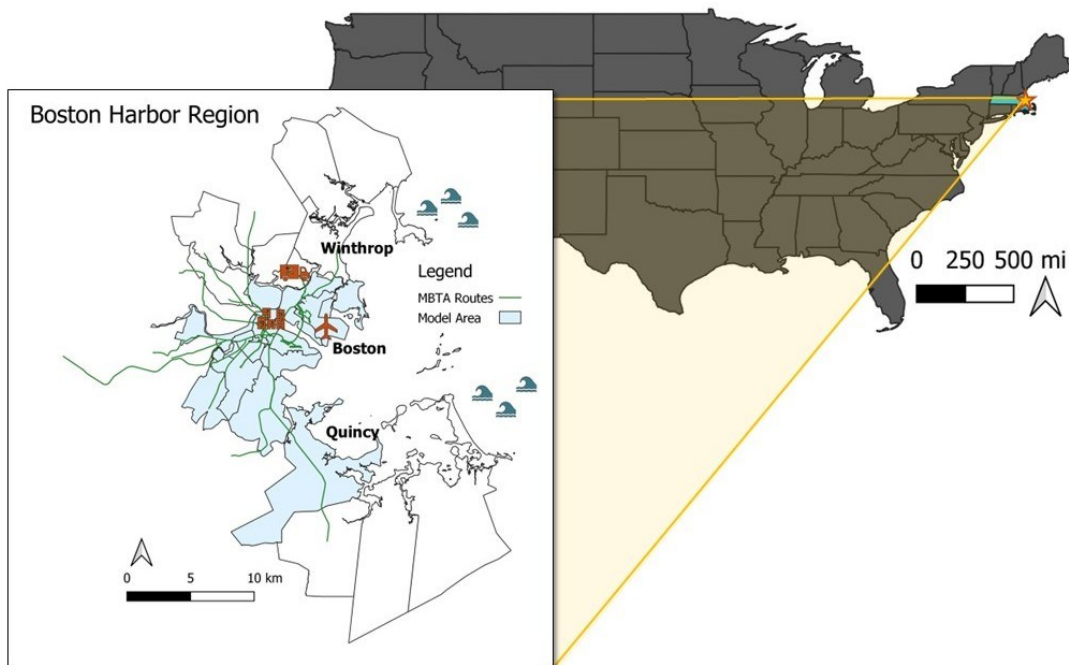


Figure 2. Map of key agents in the Boston Harbor model.

The choice of ABM as a model structure was largely due to the representation of voluntary cooperation. While the regional authority (a single optimizer) and non-cooperative adaptation regime (multiple independent optimizers) do not necessarily require the complexities of an agent-based approach due to minimal interactions, using the same framework allows for meaningful comparisons between the three adaptation governance strategies. Future work will focus on

expansions around the decision to cooperate and requires heterogeneous representations of many agents. The model makes several simplifications and assumptions to be computationally useful, including the agents we represent and their damage functions, our selected representation of adaptation behavior, assumed adaptation options, and our simplified permitting and financing system.

2.3.1 Model Structure

Our ABM uses simplified adaptation heuristics to compare the multiple adaptation regimes. We draw from existing work incorporating a distinction between SLR perception and actual SLR (Fuchs et al., 2017; Osberghaus et al., 2010; Rühlemann & Jordan, 2021). Drawing from ABMs that incorporate numerous types of agents within the model, we choose to represent four key stakeholder groups in Boston Harbor: a small sample of property owners, the Massachusetts Bay Transportation Agency (MBTA) (representing the subway system throughout Boston), municipalities (incorporating the three innermost municipalities in the Harbor), and regional assets representing Boston Logan airport and a major food distribution center in the region. While the municipalities can only consider seawall construction for their adaptation options, other agents may implement local adaptations that solely protect their properties. Although we chose to use a seawall as an illustrative hard adaptation in the model due to its well characterized cost and benefit estimates, alternative shore-based coastal flood protection choices could be included as well. Alternative adaptations could include green, gray, or hybrid adaptation approaches (Waryszak et al., 2021). Large-scale agents may only construct seawalls at the coastline (municipalities) or to protect their assets (MBTA, regional assets, etc.). Property owners may purchase flood insurance, construct an aquafence, or build a seawall on their property. The seawall height of 15 ft NAV88 was selected to represent a design height for a 100-year storm with approximately 5 feet of SLR.

We make several assumptions and simplifications throughout the model. The most significant is the representation of the decision-making process, which we assume is similar for each agent type. Although this glosses over many of the complexities associated with decision-making, it more thoroughly isolates the role of governance structures. Additionally, we assume that each governance structure bounds decision making within a set procedure, which means that this approach is not yet designed to ask questions about incentives for cooperation or to investigate how cooperation emerges. Rather, we compare the efficacy of each strategy, assuming full compliance of all agents. Figure 3 below provides a simplistic overview of key steps within the model and a few critical input parameters. The processes and calculations for expected damage calculation, adaptation decision-making, and adaptation implementation all vary depending on the adaptation regime selected: no cooperation, voluntary cooperation, or a regional authority.

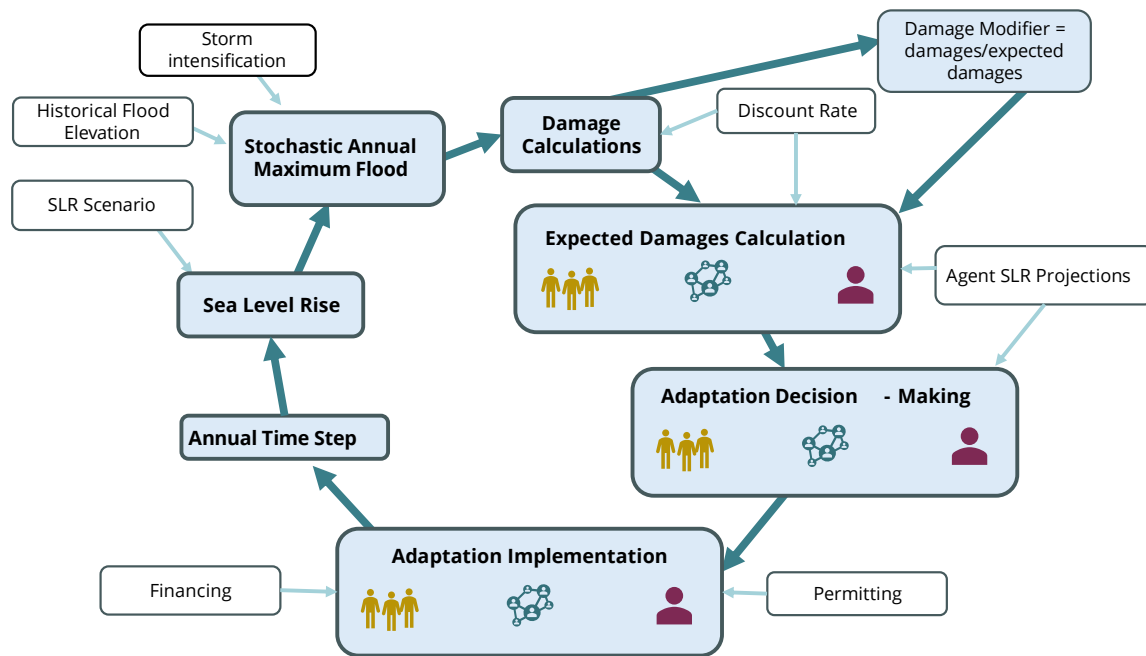


Figure 3. The model overview is illustrated by the cycle above. Key input parameters are included in white boxes and the icons indicate where detailed processes vary based on governance regimes.

2.3.2 Model Details

Simulations (built in NetLogo (Wilensky, 1999)) proceed annually, from 2020 to 2100. In each year, a stochastic annual maximum flood is generated from a Gumbel distribution fitted to the historical annual maximum floods in Boston, which incorporate both high tide flooding and storm surges due to weather (NOAA, 2021). This sample is adjusted to account for historical SLR and expected SLR into the future. SLR is assumed to be a linear increase from 2020 to 2100, following four scenarios: 0, 1, 3, or 5 feet of SLR in 2100. Additional information on storm intensification modifiers and other model details is available in the SI. Given this methodology, we only capture the worst flood in a year, so the model structure does not permit multiple back-to-back flood events within the same calendar year.

Flood elevation is used to calculate damage for each agent, considering any adaptations that an agent has in place currently, or any municipal seawalls that offer protection to inland agents within that city. Damage curves were collected from a combination of existing sources, including (S. A. Davis, 1985; P. Kirshen, Borrelli, et al., 2018; Martello, 2023). In the event that a depth-damage curve was not available, we transformed estimates of damages under future SLR scenarios into relative depth-damage curve based on the current sea level and projections for future changes. In each step, agents evaluate and decide on any potential adaptations that they may pursue. Each adaptation is evaluated to generate a benefit-cost ratio for the next thirty years, given assumptions for additional permitting and operation and maintenance costs. The benefits and costs are discounted according to the selected rate (a 3% discount rate is a common choice (Horsch et al., 2023)).

Agents determine adaptations according to a benefit-cost ratio, where benefit is calculated as:

$$\text{benefit} = \text{damage expected without adaptation} - \text{damage expected with adaptation}$$

Expected damages are calculated according to the method proposed by (P. Kirshen, Merrill, et al., 2012), which considers the use of the area under a damage-exceedance probability curve as a rough estimate of annual damage. These curves were assembled by applying key floods (exceedance probabilities varying between 1 and 0.0001) with flood damage estimates calculated by depth-damage estimates at the given flood depth or collected from other sources). This curve is adjusted annually to account for an agent's believed SLR (SLR projection) and summed over the assumed foresight of an agent, thirty years, assuming a linear increase in SLR. These benefits are divided by the adaptation costs to ultimately calculate a benefit-cost ratio. To account for the effects of reactive adaptation behavior and the possible contradictions between believed and actual SLR levels, we multiply the benefit-cost ratio by an annual modifier that adjusts for whether or not more significant flooding than expected occurred in that year. In this way, agents can respond differently depending on the flood that occurs and the alignment with their believed SLR projection, which in reality may be shaped by lived experience, political leaning, or knowledge about SLR risk (Shao et al., 2020). The modifier is represented as:

Equation 1:

$$\text{behavioral modification: } \alpha = \frac{\text{damage}_t}{E[\text{damage}_t]}$$

Where α represents the behavioral modifier, damage_t is the damage that an agent experiences in the year, and $E[\text{damage}_t]$ is the damage an agent expected to have in a year given their projected scenario of SLR and their probability-damage curve.

Agents then adapt according to:

Equation 2:

$$\text{If } \left(\frac{\text{benefit}}{\text{cost}} \right) * \alpha > 1.0, \text{adapt}$$

$$\text{else, no adaptation}$$

If the benefit-cost ratio is close to 1, this adjustment may result in the total modified ratio being greater than 1. If the damage modifier is less than 1, the opposite may occur, allowing for elements of bounded rationality (Conlisk, 1996) to be included in agent decision-making processes.

If a benefit-cost ratio is larger than 1.0, an agent proceeds to the implementation process for their selected adaptation. Agents may only implement one adaptation per year, except for property owners, who may simultaneously construct a physical adaptation and purchase flood insurance. Agents must meet two criteria to implement adaptations: they must have sufficient finances to adapt and they must have waited for permitting (a user-set parameter). Rough estimates of annual adaptation budgets were based on published city plans, municipal incomes, property values, or other simple heuristics. We also assume that agents need 10% of the adaptation cost available in the first year, but that the remaining costs can be dispersed.

The type of adaptation regime affects three steps in the model process: the calculation of expected damages, adaptation decision-making, and adaptation implementation. For the scenario of no cooperation, we assume that agents independently go through the adaptation process – calculating their personal damages, deciding to adapt, and funding projects independently. However, if a municipality adapts, then agents protected by the seawall may decide to no longer

adapt. At the other end of the spectrum, a regional authority completes the benefit-cost analysis on behalf of all agents within a geographic area (either a town or neighborhood) and implements an adaptation with pooled financial resources. To account for differences with funding availability due to agent types, we assume that external funding availability is highest for municipal governments or a regional authority, but reduced for other agent types. To account for the costs of collaboration, adaptations pursued by any coalition of agents are subject to a maintenance fee, which is also a model parameter. For voluntary cooperation, we sought to capture a simplified process. Here, agents establish an interest in adaptation, by having a benefit-cost ratio greater than one, then recalculate their benefit-cost ratios given the impacts of the maintenance fee and greater access to financing. They will pursue the adaptation within or outside of a coalition that reaches or surpasses their original adaptation protection level with the highest benefit-cost ratio, given that their contribution to collaborative adaptation is less than the individual adaptation cost. These coalition dynamics are rudimentary and not based on social networks, or other important considerations such as trust that have been explored in alternate literature (Haer et al., 2016; Rotberg, 2010). Coalition decisions are static and utility-maximizing, not emergent based on social characteristics. This is a promising direction for future research.

Extra details on model choices are included in the dissertation appendices.

2.3.3 Experiments

We run two experiments to understand how governance affects SLR adaptations. These experiments include a baseline experiment representing a realistic future for the Harbor (our best estimates of each parameter) and a full ensemble comprised of all possible combinations of each model parameter. We consider 200 stochastically generated storm surge sequences for each combination of parameters in the baseline experiment, and 10 stochastically generated storm surge

sequences for the full ensemble. Using this methodology, our baseline experiment contains approximately 25,000 simulations, while the widespread experiment contains about 140,000 simulations. The raw data, model, and directions for reproducing our results are available on [10.5281/zenodo.15546585](https://doi.org/10.5281/zenodo.15546585). The number of simulations was limited to balance computational constraints while maintaining sufficient variability in storm surge patterns to capture patterns of adaptation across a range of coastal processes. The values assigned to each parameter in both experiments are shown below in Figure 4, which only illustrates experimental design. In this work, the word ‘parameter’ is used to describe the choice of values for these levers, which are set by the user at the start of each simulation.

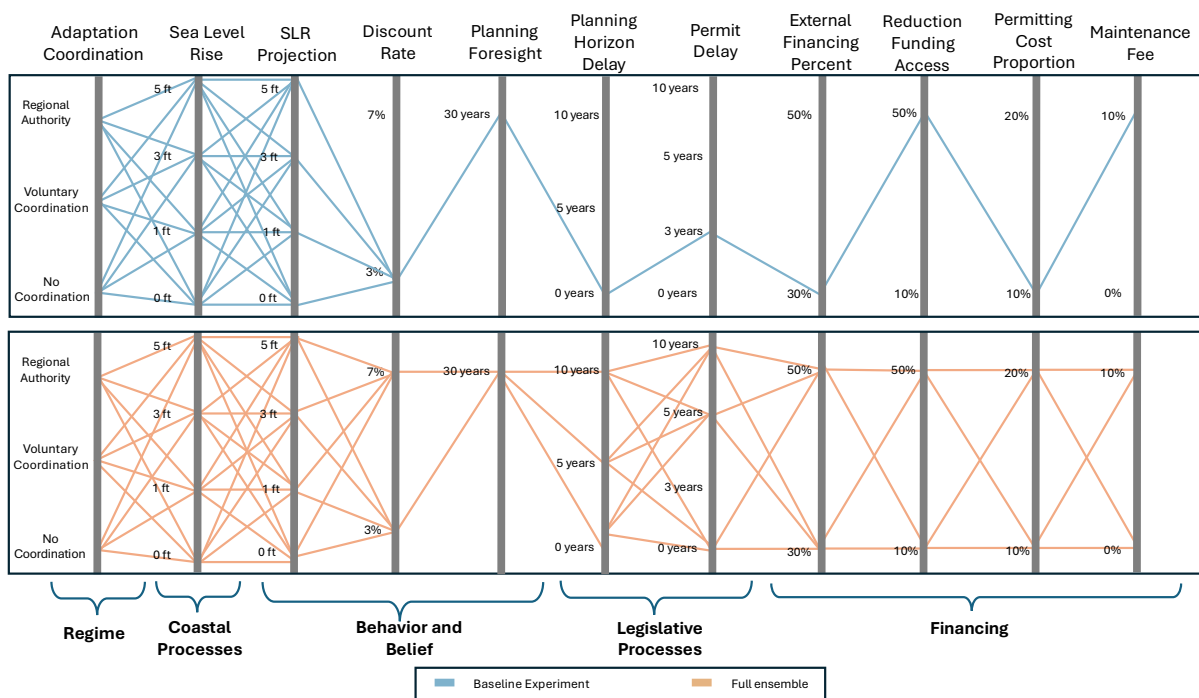


Figure 4. Figure of ensemble design for Chapter 2. The top row illustrates the combinations of parameters run for the baseline experiment, where 200 different flood patterns are tested for each combination. The bottom row, the full ensemble, contains each combination of parameters shown, with repetitions on 10 different stochastic flood patterns. The parameters are selected to capture variation in the adaptation regime, coastal processes, behavior and belief, legislative processes, and financing processes.

The model went through code verification and model experimentation to ensure that the program operated properly. We performed single agent testing to verify that each stage of the model process worked as intended. The process of code verification was inspired by the proposed methods in (Van Dam et al., 2012).

Although ABMs cannot be validated using traditional methodologies (Troost & Berger, 2020), we utilized expert interviews to assess the applicability of the model and reasonableness of underlying assumptions. This aligns with Xiang's description of face validity of an ABM (Xiang et al., 2005). During the model development process, nine individuals representing key stakeholder groups in Boston Harbor were approached in a mixture of focus groups (7) and semi-structured interviews (2) to provide critical feedback and relate their professional experiences to model results. This process was reviewed by Tufts University Institutional Review Board. These expert consultations were used to explore the relevance of the model structure and key assumptions on the adaptation system existing in Boston Harbor. This informed numerous changes from the initial model conceptualization, including the additions of separate and explicit permitting costs and costs for coordinating across multiple agents. The addition of these parameters provided deeper nuance on the importance of permitting costs and delays for maximizing net benefits. However, they also illustrated minor additional costs of cooperation do not hinder simulations from achieving the most desired reductions in flood damages, reductions in adaptation costs, or improvements to net benefits. These changes were incorporated into the model presented in this work. Future work will build on additional commentary that we received during the focus group and semi-structured interviews.

2.4 Implications for Adaptation Governance

2.4.1 Cooperation improves outcomes-but not always by a wide margin

We compare overall outcomes under three governance regimes—no cooperation, voluntary cooperation, and regional authority—focusing on flood damages, cumulative adaptation costs, and cumulative net benefits, across the entire Harbor region. Figure 5 summarizes these metrics between 2020-2100 across the previously discussed two ensembles where the top row corresponds to the baseline ensemble and the bottom three plots to the full ensemble. Net benefits at time (t) are calculated as:

Equation 3:

Net Benefits_t

$$= (Cumulative\ Damages_{No\ Adaptation,t} - Cumulative\ Damages_{Adaptation,t}) \\ - Cumulative\ Costs_{Adaptation,t}$$

We include these three metrics separately because flood damage, adaptation costs, and net benefits are viewed differently by stakeholders.

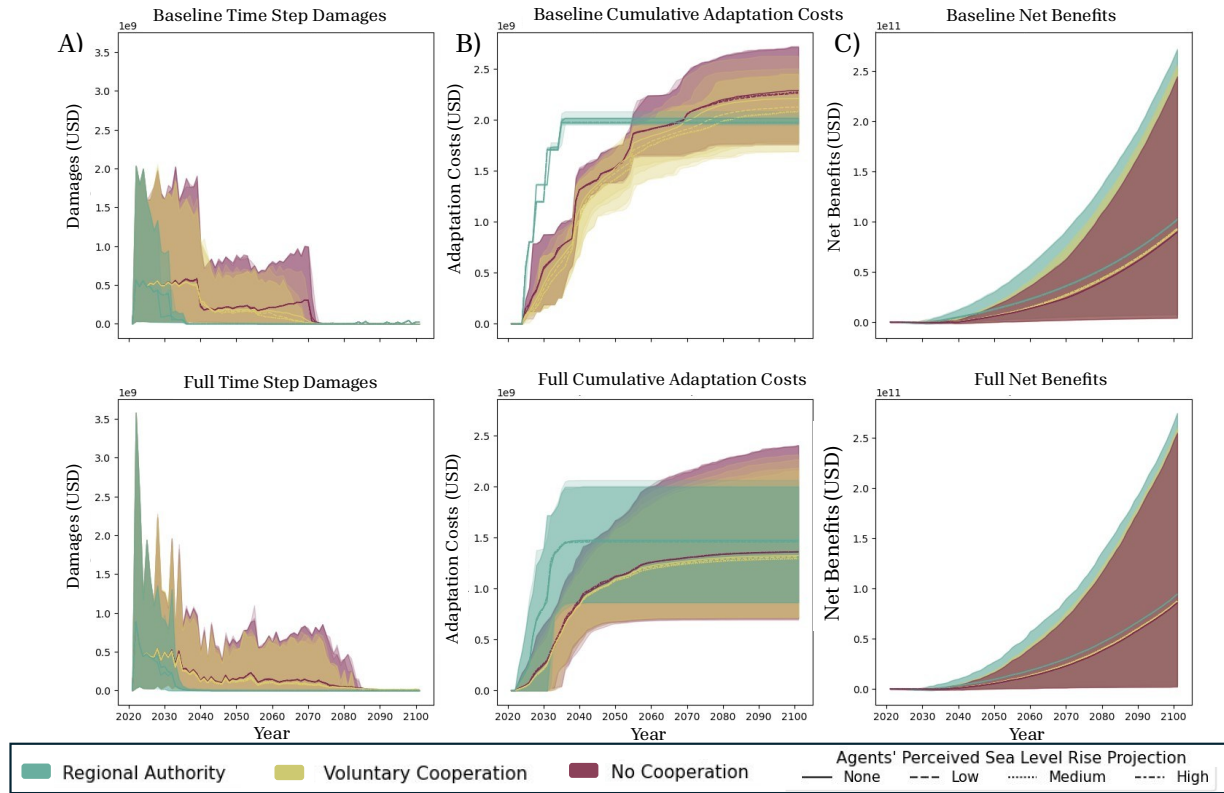


Figure 5. Flood damages, adaptation costs, and net benefits across the ensemble. The figure above shows the results of the baseline and full experiments for each selected metric cumulatively across the Harbor by 2100. The results are shaded to include 90% of the simulation results and the single lines represent the mean values across all simulations with the same adaptation coordination and perceived SLR. The top row corresponds to the baseline ensemble and the bottom row the full ensemble.

Panel A in Figure 5 illustrates the success of a regional authority at reducing flood damages over the other two adaptation regimes, demonstrated by the rapid decrease of flood damages by mid-century. This suggests that centrally coordinated adaptation is more effective in protecting infrastructure and properties from flood exposure. The close overlap under the other two regimes indicates that voluntary action often fails to prevent significant damage, particularly in scenarios with high SLR or limited access to financing.

In contrast, the story is more complex when examining total adaptation costs (Panel B). Here, costs tend to be lowest for voluntary cooperation (the least expensive regime initially. A

regional authority has the highest initial adaptation costs, reflecting its tendency to trigger earlier and more widespread action, which will require significant up-front investments, which may be politically or financially challenging to secure. The range of adaptation costs is much wider in the full ensemble, although this general pattern holds.

Panel C synthesizes these effects by showing net benefits. The distribution of net benefits is highest for the regional authority regime. However, the magnitude of net benefit gains from cooperation or regionalization is modest in many cases, particularly compared to the cost differential between regimes. However, the results from both ensembles are similar, indicating that increasing the range of tested model parameters may not always lead to a wider range of outcomes.

Taken together, Figure 5 highlights that while a regional authority tends to yield the best overall outcomes, particularly in minimizing damage, it requires a higher adaptation cost. Voluntary cooperation may achieve similar net benefits in some cases, but its effectiveness is inconsistent and context dependent. The no cooperation regime, with lowest adaptation costs, consistently leads to greater and more variable damages, resulting in inferior net benefits. These results underscore a key insight: institutional design shapes not just whether adaptation occurs, but how efficiently and equitably it unfolds. Regional coordination offers the clearest path to minimizing systemic risk, but its success depends on the financial and political feasibility of up-front investment and action. Sections 4.2-4.4 explore under what conditions cooperation is most beneficial in the Harbor.

2.4.2 Cooperation effectiveness is highly conditional on SLR, discount rates, and financing

Using aggregate measures across the entire Harbor in Section 4.1 may mask the effect of specific levers that could lead to extreme outcomes, which are often the most important to consider. In the following section, we sought to answer: what conditions lead to the extremely beneficial outcomes (top 10% of net benefits simulations)? Building on previous examples that use classification and regression (CART) trees to identify levers leading to scenarios of interest (Birnbaum et al., 2022; Loh, 2011), we apply this algorithm across our full ensemble. Early conditions can be considered drivers for specific outcomes. Results from the full CART analysis are available in our SI.

2.4.2.1 Drivers of Net Benefits

In Figure 6, we provide the results from the CART algorithm, selecting for the top 10% of net benefits. Panel A provides the results from the algorithm, while Panels B and C contextualize the two conditions across the entire set of cumulative net benefits. Two metrics are used in Panel A: coverage (C) which relates to the proportion of target classes in a node, and density (D), which relates to how many classified items are within a node. Equations for density and coverage are:

Equation 4:

$$\text{Coverage (C)} = \frac{\text{number of runs in the classification group in the node}}{\text{total number of runs in the classification group in the experiment}}$$

Equation 5:

$$\text{Density (D)} = \frac{\text{number of runs in classification group in the node}}{\text{total runs in the node}}$$

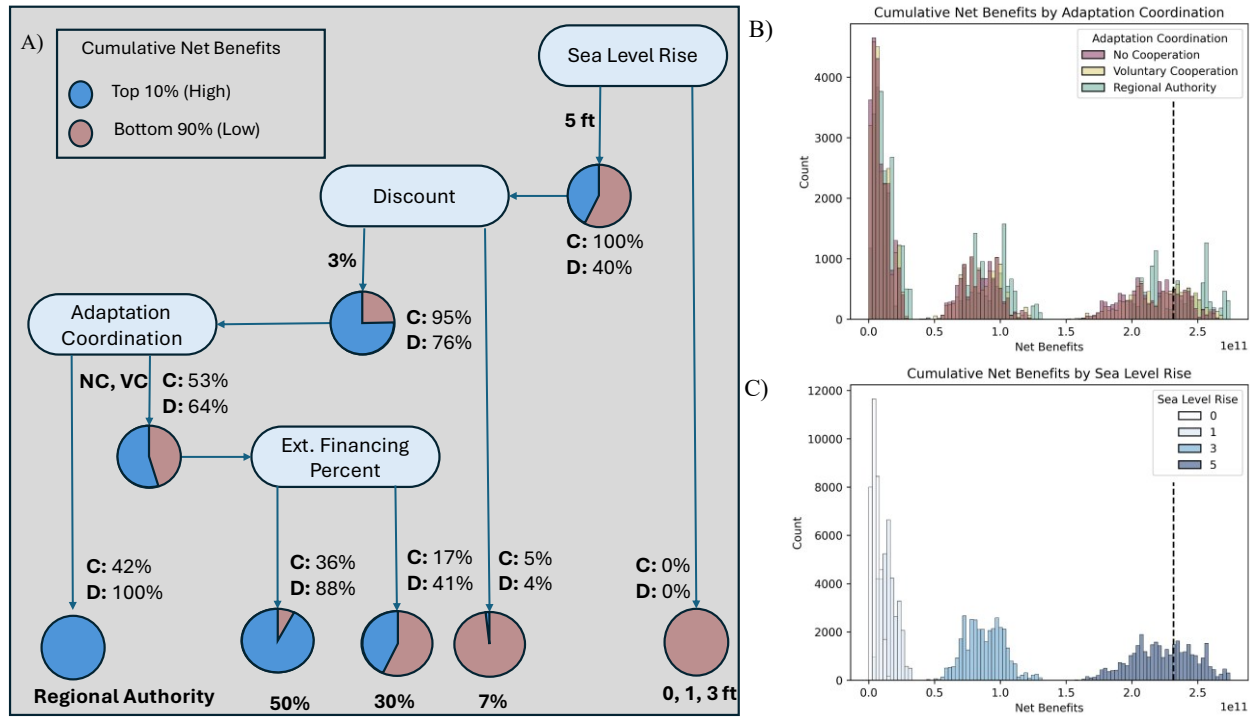


Figure 6. Results from a CART Analysis. These indicate conditions that lead to the simulations with the top 10% of cumulative net benefits across the full ensemble. Panel A is a stylized version of the CART results, indicating conditions (e.g. sea level rise, discount rate), thresholds (e.g. 5 ft SLR vs 0, 1, 3 ft SLR), and density (D) and coverage (C) values. Panel B overlays the effect of adaptation coordination on the full outcome set of net benefits, illustrating that there is significant overlap between each regime (and supporting the location of adaptation coordination as the third split on the tree). Alternatively, Panel C illustrates the effect of SLR scenario on the same histogram; the clear distinctions between colors supports the location of SLR as the first split on the CART algorithm. The dashed black line represents the cut-off for the top 10% of all simulations.

The CART tree reveals that the top conditions leading to scenarios of high net benefits include SLR above 5 feet, a discount rate of 3%, and either the presence of a regional authority or the presence of high external financing for the other adaptation regimes. Panel A also demonstrates that in the absence of a regional flood authority, having external financing available over 50% has a strong influence on improving net benefits. In other words, having easy access to adaptation financing may decrease the need and incentive for regionalized adaptation. Panels B and C illustrate the role of specific parameters on the histogram of net benefits across the entire ensemble.

These panels reiterate the effect of SLR and adaptation coordination: panel C shows clear distinctions between each SLR scenario, while panel B shows the overlap between different adaptation regimes. Notably, there are no simulations with 0, 1, or 3 ft SLR where the best net benefits outcomes are realized (large SLR incentivizes rapid adaptation that also reduces nuisance flooding). Although both panels A and B indicate that while regionalization is less critical than SLR or discount rate in reaching optimal outcomes, it is the first governance condition present; it is dependent on the design of effective institutions and is set by policy, not values or natural systems. CART trees with alternative thresholds are included in the SI.

2.4.2.2 Comparison between a Regional Authority and Voluntary Coalitions

Although the previous section computed net benefits compared to scenarios without adaptation, using a baseline of no cooperation allows us to answer questions about the comparison between voluntary coalitions and regionalization. Amongst all simulations in the full ensemble, we found that while the regional authority nearly always improves net benefits in comparison to no cooperation (99.8%), the voluntary cooperation scenarios do not outperform the no cooperation scenario about 23% of the time. This suggests that ineffective voluntary cooperation may be worse than leaving the region without organized cooperation at all.

We again use the CART methodology to compare cooperative and uncooperative strategies, answering: what are the most important levers for each adaptation metric? Figure 7 illustrates the top four parameters that lead to scenarios for the top 10% (top row) or bottom 10% (bottom row) for each of the three selected metrics: damages avoided with cooperation, adaptation costs avoided with cooperation, and net benefits from cooperation. While the algorithm identified conditions of SLR and financing parameters as the most important levers to reach best-case outcomes, adaptation coordination is the most important lever for worst-case outcomes. This indicates that

while adaptation regime is not sufficient to guarantee the best outcomes, it is largely sufficient to avoid the worst-case outcomes when compared to a baseline of no cooperation. In other words, to hedge against the worst extremes, adaptation governance is the most powerful predictor of success.

The appearance of the conditions of reduced funding access, degree of external financing, SLR, discount, and permitting as frequent nodes in our trees illustrate that these conditions are important to the performance of adaptation strategies moving forward. This suggests that creating a successful cooperative adaptation structure will require creating an appropriate enabling environment for legislative and financial concerns.

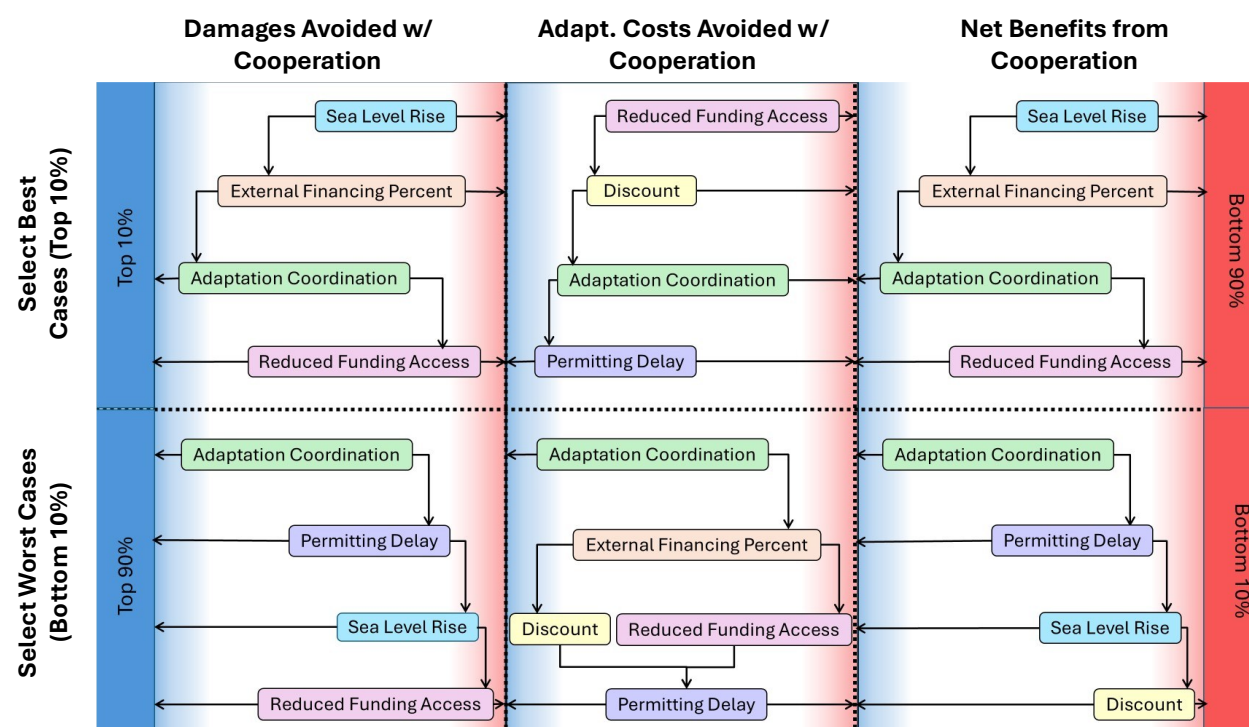


Figure 7. Strongest influences on adaptation outcomes. Results from six CART experiments demonstrate the top four parameters that lead to the most extreme scenarios according to metrics of: damages avoided with cooperation, adaptation costs avoided with cooperation, and net benefits from cooperation. The top row selects for the best outcomes (top 10%) and bottom row selects for the worst outcomes (bottom 10%).

2.4.3 Institutional design matters more than stochastic uncertainty

Analysis of variance (ANOVA) can be used to decompose overall model variation to account for the contribution of each parameter to the total variation, which can be used as a proxy to understand the relative importance of each parameter. Figure 8 shows the results of the contribution of each condition to overall variation every five years across the widespread ensemble. Here, variance is measured for the metric of total costs, which is the sum of cumulative adaptation costs and flood damage across Boston Harbor. The large contribution of residuals indicates that the model does not fully explain all of the observed outcomes, and this may be due to strong interactive effects between the various parameters.

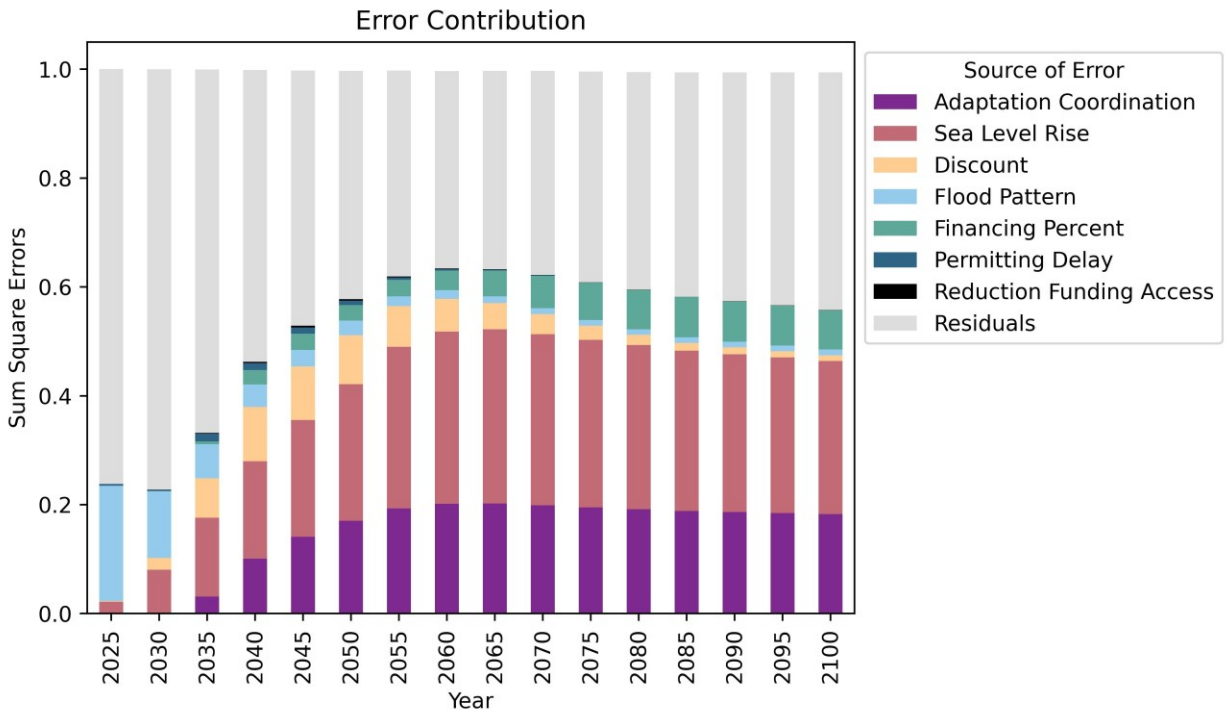


Figure 8. Results from an ANOVA experiment completed on the full ensemble to assess the relative contribution of each parameter to total costs (the sum of damages and adaptation costs). Only the top seven contributing parameters are included in the figure.

Figure 8 indicates that the importance of residual errors and specific patterns of stochastic flooding wane over time in comparison to the growing importance of SLR, adaptation coordination, and the financing percent, particularly in later years. In the future, improving our understanding and representation of coalition formation may reduce unexplained variance. The rapid decline in the contribution of flood pattern to the total error indicates that the particular pattern of storms is very important for short-term decision making, but matters less on a longer-time frame. This finding suggests that institutional factors have a much more significant impact on outcomes than scientific uncertainty. In this sense, improving our understanding and implementation of adaptation governance may yield higher returns than refining flood models alone.

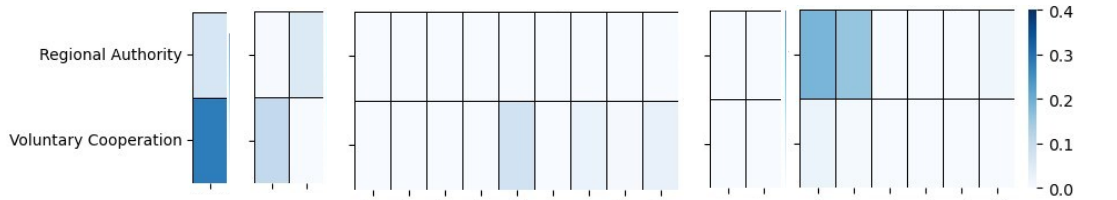
2.4.4 Cooperative Strategies do not benefit everyone equally

In addition to understanding conditions that lead to improved adaptation outcomes, our results suggest that different actors across scales experience distinct benefits or risks from cooperation. Figure 9 separates agents according to their geographic scale (indicated by the maps in Panel A) and evaluates the frequency (Panel B) and intensity (Panel C) of simulations where a non-cooperative approach reduces cumulative flood damage compared to voluntary cooperation or regionalization at the end of the century. This analysis utilizes the same ensemble as the results above, containing approximately 45,000 simulations for voluntary cooperation and regionalization each.

A) Geographic Area (Boston Harbor Reference)



B) Ratio of Simulations with Higher Cooperative Damages



C) Damages Avoided with Cooperation

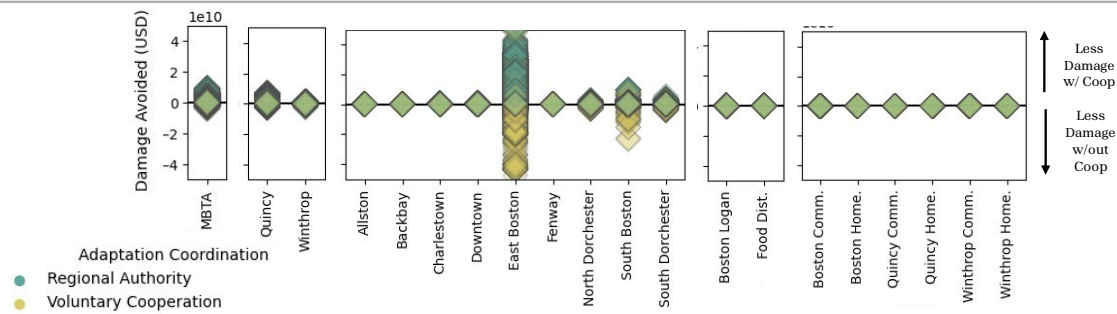


Figure 9. This figure illustrates the breakdown of the flood damage avoided from cooperation over non-cooperative adaptation regimes (*ceteris paribus*) for each agent type across scales (large, geographically dispersed agents towards the left and small, point locations towards the right). Panel A provides maps with a geographic reference for the scale and location of the agents in each column. Panel B illustrates the ratio of simulations where non-cooperative adaptation strategies resulted in lower flood damage than the cooperative approaches, providing estimates of frequency. Panel C illustrates the intensity of these simulations, where points below the horizontal line correspond to the reduction of damages that would occur using a non-cooperative approach instead of either of the cooperative approaches.

Different agents experience more frequent failures of cooperation to prevent flood damage under different adaptation regimes. While the MBTA experiences this more frequently with voluntary cooperation, a regional authority leaves Boston property owners more exposed to damage (Panel B). Panel C illustrates that even though failures from voluntary cooperation occur rarely for neighborhoods like East Boston and South Boston, the magnitude of these failures is quite large (the points below the horizontal line in Panel C). For regions such as Allston, there is

little difference between cooperation and no cooperation. These neighborhoods are often characterized by lower property values and high adaptation costs, disincentivizing their prioritization for adaptation. Overall, these figures indicate that aggregate metrics for adaptation hide nuance across scales. The figure demonstrates that different agents at different geographic scales may have different preferences for mandated or voluntary cooperation. Certain formulations of cooperation and regionalization may leave particular agents exposed to greater flood damage.

2.4.4.1 Conditions where cooperation leads to greater damages than no cooperation

Although the agents identified above experience simulations where cooperation (either voluntary or mandated) increases their cumulative damages, the conditions that lead to these outcomes may also vary based on the agent. Table 1 summarizes the top three conditions (identified using CART trees) that lead to simulations where this occurs. This table indicates that voluntary cooperation is often the most significant determinant of poor cooperative outcomes. For example, East Boston experiences worse outcomes under cooperative regimes in the presence of voluntary coalitions, low SLR, and a high discount rate, all of which disincentivize rapid adaptation. However, for certain agents, such as the Boston property owners, a regional authority is more likely to lead to higher flood damages, likely due to a mismatch between the priorities of the Regional Authority and locations of the property owners. Many of the conditions also indicate low incentives for cooperation, where the benefits of quickly joining strong coalitions are fewer. These results help to illustrate for whom and under what conditions cooperation may be worth the necessary effort.

Table 1: Conditions where No Cooperation Leads to Lower Damages than Cooperation

Agent	Condition 1	Condition 2	Condition 3
East Boston	Voluntary Cooperation	Low SLR	High Discount Rate
North Dorchester	Voluntary Cooperation	High Discount Rate	High permitting delay

South Dorchester	Voluntary Cooperation	Low SLR	Small reduction in funding access to non-coalition agents/ high discount rate
Winthrop	Voluntary Cooperation	Small permitting delay	Large Maintenance Fee
Boston Homeowners/ Commercial properties	Low SLR	Regional Authority	Low SLR projection
MBTA	Voluntary Cooperation	Low permitting delay	Small reduction in funding access non-coalition agents

2.4.4.2 Quantifying Distributional Inequality

To more systematically assess the distribution of adaptation outcomes across governance structures, we introduce a simple equity metric: the Gini coefficient of normalized flood damage.

The Gini coefficient provides a measure of statistical dispersion, commonly used to quantify inequality, where 0 represents total equality and 1 represents total inequality. To enable comparison across heterogeneous agent types (e.g., municipalities vs. households), we normalize each agent's cumulative flood damages by the highest agent-level damage observed within a given governance regime. This ensures that the equity measure reflects relative harm, rather than being biased by differences in property scale or adaptation capacity.

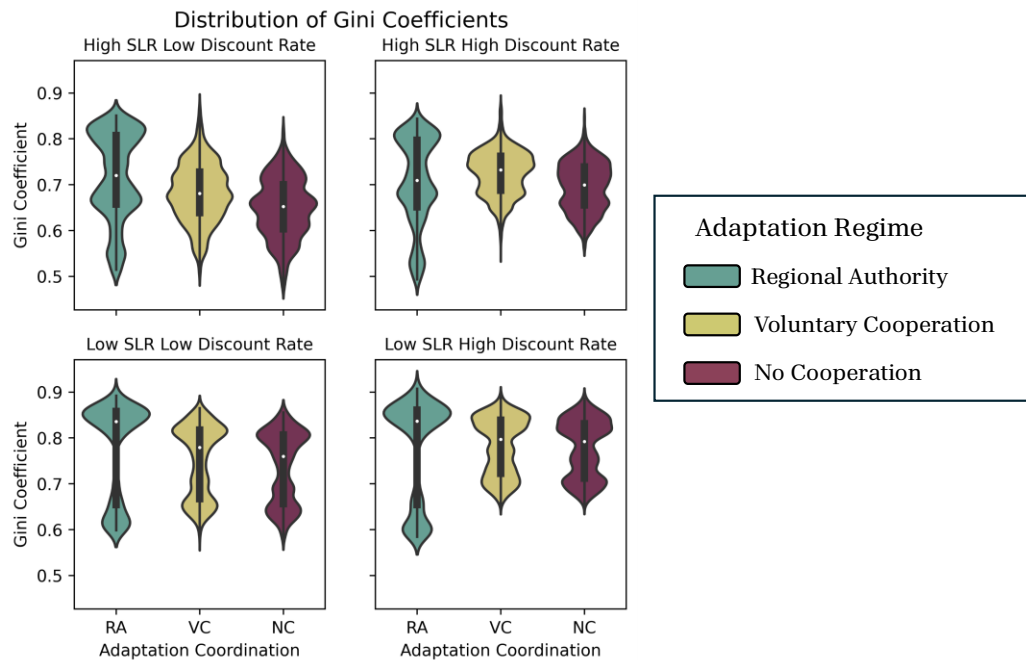


Figure 10. Measures of inequality across the Harbor. The violin plots above illustrate the distribution of the Gini coefficient for each governance strategy once the full ensemble is divided into four quadrants based on sea level rise and discount rate. The plot shows that the regional authority often experiences more inequality than the other regimes across agent types, but that in specific circumstances, such as a high discount rate, this effect is reduced.

Figure 10 summarizes the average Gini coefficient across a representative set of high- and low-risk scenarios (defined by SLR and discount rates). The results indicate that despite the previous evidence of a regional authority consistently producing lower aggregate damages, it may exhibit higher inequality in harm distribution, particularly in scenarios where centralized protection prioritizes infrastructure-dense or high-value regions. The regional authority can result in both the highest and lowest Gini values across a distribution. Voluntary cooperation also often produces higher inequality, especially when some agents are unable or unwilling to coordinate effectively, leading to uneven protection outcomes. The non-cooperative regime, while generally associated with higher damages overall, often exhibits more moderate Gini values, suggesting that

uncoordinated exposure is distributed more evenly—albeit universally worse. CART analysis, available in the SI, indicates the most equitable scenarios occur when adaptation rates are slow, due to a variety of reasons including high SLR, low SLR projections, high discount rates, and a high permitting delay, all of which slow adaptation rates. These results reinforce the idea that efficiency and equity are not always aligned, underscoring the importance of incorporating equity considerations explicitly into adaptation planning.

2.4.4.3 Intersection of Adaptation and Equity

Although we only simply address inequality and equity considerations across the ensemble, it is important to note the applications and concerns that these findings raise. Equity in flood adaptation can be defined in multiple ways depending on the desires and needs of the community involved (Pollack et al., 2025), so we do not use a specific definition or assessment. While we use simple metrics such as the frequency of outcomes where cooperation performs worse than non-cooperation (Figure 9) or the Gini coefficient (Figure 10), these are neither comprehensive nor pluralistic enough to be considered a sufficient equity analysis. Rather, our results imply that attention to unexpected impacts on adaptation equity is necessary moving forward by highlighting potential inequalities in the outcome space.

Our findings reveal that adaptation outcomes are not uniformly distributed: some agents—particularly those with limited financial capacity or higher barriers – benefit less under voluntary coalitions and bear disproportionate risk. These communities may have an extensive coastline and low property values and often receive adaptations later than other communities due to the low benefit-cost ratio of these projects. Alternative methods of decision-making may better prioritize these regions. Adaptation projects implemented by a regional authority have the potential to address equity issues or exacerbate existing inequalities in flood protection. Selecting a

prioritization that incorporates locally-accepted metrics of equity will be critical (Peck et al., 2022). Our model is equipped to add an income-weight to benefit-cost calculations according to the method proposed by Stroud, et al. (2023), although the results of this are not included in this paper (Stroud et al., 2023). Using this weighting adds preference for adaptation prioritization among regions that may have lower access to resources, as estimated by the average family income, improving adaptation timing for communities such as East Boston, highlighting the need for cooperative structures that integrate redistributive mechanisms or offer capacity-building support. Future research could incorporate spatially explicit demographic data to more systematically evaluate procedural and distributive justice in adaptation planning, ensuring that policies do not inadvertently exacerbate existing vulnerabilities.

2.3 Discussion and Conclusion

The findings of the model have numerous implications for Boston Harbor as it evaluates possible plans for cooperative structures for SLR adaptation. Our model was designed to provide quantitative estimates for on-going debates about the creation of a regional adaptation authority within Boston Harbor, such as the one suggested by (Fitzgerald et al., 2023; Fitzgerald & Hobbs, 2022). We assess the effects of cooperation with four insights.

First, our results show trade-offs between adaptation costs, flood damage, and net benefits between each governance strategy. Because many of the regions requiring adaptation already have competing demands for budgeting, extra adaptation costs may be a barrier to implementing adaptation. While the voluntary cooperation scenarios narrowly out-perform scenarios of no cooperation, the alignment between these regimes indicates that the specific institutional conditions matter to experience improved performance from coalitions. This tradeoff indicates that

there may be no one-size-fits-all adaptation governance selection for Boston and that the success of particular governance strategies may be dependent on institutional conditions and capacity.

Second, the CART trees presented in Section 4.2 emphasize the necessary institutional conditions to make adaptation cooperation effective. Our findings illustrate that financing and permitting regularly impact the extent to which adaptation outcomes are implemented, which is supported by statements made in our focus group. However, the importance of SLR suggests that future estimates of SLR may incentivize or disincentivize collective action based on predicted net benefits. Additionally, while regionalization is not sufficient to guarantee the most desired outcomes, it is the most important condition to avoid the worst outcomes.

Third, the error contribution reveals that institutional design has much more impact on total costs in the Harbor (flood damages and adaptation costs) than stochastic uncertainty of storm surges. Although detailed and accurate flood models are critical for decision-making on a household or small-scale, the findings here suggest that such refinement is likely not necessary to understand the overall mechanics of cooperation to SLR. Rather, efforts to determine optimal governance strategies should be completed in parallel to any other refinements to flood modeling. This is because adaptation governance is a human-system challenge, not just an information or scientific uncertainty challenge.

Fourth, our findings show that while cooperation appears to improve adaptation outcomes across the whole region compared to an uncooperative approach, ineffective formulations of voluntary cooperation may increase flood damage inequity. This indicates a need for strong voluntary coalitions that approach the capacity and operational processes represented by the regional authority. While voluntary cooperation may be desirable over a flood authority from a legislative perspective due to the lack of necessary institutional changes and creation of an entirely

new entity, ensuring a sustainable and strong voluntary coalition structure poses challenges to the Harbor. These coalitions will need procedures to manage equity concerns across the Harbor region.

2.4 Limitations and Future Work

Our results should be contextualized by a few of the model limitations: this is a simplified world, we do not include all agents, and we do not include all the complex facets of decision-making. These were reiterated by the focus group.

We recommend three directions for future work, motivated by both our initial findings and the focus group held to elicit stakeholder responses toward the model. First, we acknowledge the need for the incorporation of more nuanced institutional costs beyond the simplified ‘maintenance fee’ parameter. Future research into these institutional costs may reveal previously unknown thresholds and tipping points for adaptation. Additionally, work on the transferability of the model to similar coastal regions is a meaningful avenue for future research and would require tailoring the agent-set, hydrologic conditions, and institutional options to a new location.

Finally, additional work on the representation and emergence of coalition implementation is necessary through testing endogenous coalition dynamics via social or reputational heuristics. Even simple learning or reciprocity mechanisms may illustrate changing coalition dynamics over time, as successful historical cooperation motivates coalition formation while unsuccessful coalition formation may deter future cooperation. The stakeholders in our focus group emphasized this, asking questions such as: “How could we incentivize cooperation that improves the performance of voluntary coalitions?”, “Is the need really for a single entity to run all this or is it to have better coordination among the private and public sector entities?”, and “How do you coordinate?”. Future work may focus on exploring how different mechanisms for collective action may operate at a more granular level with more complex decision-making processes and exploring

how to incentivize voluntary cooperation. Such research would provide more insight into why coalitions form and evolve. Our participants identified three main challenges to coordinated adaptation: ownership, financing, and permitting challenges. Although our results confirm the need for cooperation in adaptation, understanding the strength and implications of various financial, bureaucratic, or legislative conditions that lead to meaningful collaboration is a critical next step.

2.5 Funding and Acknowledgements

This research was supported, in part, by the NSF NRT 2021874. I would like to express my deepest gratitude to my collaborators and committee members who supported this. Additionally, I would like to thank the members of the Srikrishnan Research Group at Cornell University and the Lamontagne Lab at Tufts University for their assistance in developing this project, especially Abigail Birnbaum and Jake Wessel.

Chapter 3: The Roles of Social Contagion, Network Reciprocity, and Flood Response in Agent-Based Models of Coalition Formation for Sea Level Rise Adaptation

This chapter would not be possible without the assistance and guidance of Paul Kirshen, Jonathan Lamontagne, and Shafik Islam.

Abstract: As sea level rise (SLR) threatens coastal cities, there is an urgent need for new adaptation strategies and effective systems to implement them. Understanding how collective flood risk is managed and whether cooperative adaptation coalitions can emerge organically is critical. Modeling offers a tool to explore how such cooperative arrangements form, yet the influence of different decision-making mechanisms on coalition formation and adaptation outcomes within a model structure remains unclear. This paper develops a model to examine how different mechanisms for cooperative behavior (inspired by social contagion, network reciprocity, or flood experience) shape cooperative adaptation in the context of SLR. We further explore how cooperative outcomes shift under realistic institutional constraints, flood risk profiles, and geographic details. Our results suggest that even small flood events and reactions can significantly increase coalition formation, while diffusion-based cooperation is less effective at encouraging cooperation, given our assumption of an initial preference for non-cooperative behavior. In Boston Harbor, the region's flood risk profile and institutional hurdles threaten cooperative outcomes, even when all mechanisms operate simultaneously to encourage cooperation. The findings of this work highlight that beyond structural or parametric uncertainty, the representation of decision-making processes is crucial for accurate modeling and planning. This work provides a novel

contribution to understanding how to model collective action in SLR adaptation for cooperative seawall construction.

3.1 SLR Adaptation as a Collective Action Problem

3.1.1 Sea Level Rise in Coastal Cities

In response to accelerating sea level rise (SLR), coastal cities around the world face growing pressure to invest in proactive adaptation. The threat of increasing flood risk from SLR affects governments, property owners, infrastructure systems, transportation systems, and can have far-reaching impacts on coastal ecosystems (Hauer et al., 2016; Hinkel et al., 2018b; P. Kirshen et al., 2008; Martello, 2020; Nicholls et al., 1999). Many previous studies have documented logistical and operational challenges to implementing coastal adaptations, particularly adaptations on a municipal or regional scale (Azevedo de Almeida & Mostafavi, 2016; Hinkel et al., 2018b; P. H. Kirshen, Douglas, et al., 2012).

In Boston, SLR is estimated to be between 2.4 to 7.4 feet by 2100, depending on the climate scenario (Douglas et al., 2016). Given five feet of sea level rise, vulnerable areas may be inundated and the city could experience major flooding events 75 times a year (Kruel, 2016). Although there is significant uncertainty in the exact quantity of SLR that will occur and any possible intensification of storm surges, there is a large consensus that many coastal cities need to rapidly act to protect their coastlines.

3.1.2 SLR Poses a Collective Adaptation Problem

Like many complex environmental problems, cooperation for SLR adaptation has the potential to result in mutually beneficial outcomes, but is difficult to achieve (Kalesnikaite, 2019). While

cooperation for adaptation can appear in many forms, such as binding agreements for infrastructure development, shared fundraising activities, access to coastal land, among other possibilities, we focus on cooperation as the decision to collectively fund and implement hard adaptation measures, such as a seawall. In Boston, while small-scale cooperative agreements have recently grown in number, large-scale cooperative agreements between municipalities and state-wide agencies are still underdeveloped. However, many studies explicitly find that coordinated approaches reduce damage and adaptation costs when compared to uncoordinated adaptation strategies, including Kalesnikaite, 2019; Mitchell et al., 2023b; Nichols et al., 2019. Given the potential benefits of cooperation, many coastal cities are considering regionalizing coastal adaptations, either through formal and mandated regional authorities or through the natural emergence of adaptation coalitions.

The lack of cooperation for SLR adaptation represents a problem of collective action, especially when framed around the formation of coalitions to share adaptation costs and balance flood risks. While climate change in general is frequently identified as a clear collective action problem (Adger, 2010; Colding et al., 2022; Ostrom, 2010b; Wannewitz et al., 2023; Wannewitz & Garschagen, 2023; York et al., 2021), SLR adaptation is less frequently discussed as a collective problem. Two notable exceptions to this include an analysis of the city of San Francisco and a review paper (Griggs & Reguero, 2021; Lubell, 2013), although these do not take a mathematical modelling approach. Despite the lack of frequent collective action framing, SLR adaptation shares many of the same characteristics as other collective action problems, as explained by (Khan & Munira, 2021).

Given that collective action systems are often complex and difficult to run policy experiments on in real life, mathematical modeling can be a powerful approach to explore theories

of collective action in lieu of empirical data or policy development. In this paper, we focus on agent-based models (ABMs) and their application to collective action systems, as they support the ground-up assumptions that are useful to study collective behavior.

ABMs are used in a number of applications to study phenomena where individual agents contribute to system-wide outcomes (Bonabeau, 2002; M. A. Janssen & Ostrom, 2006; Pahl-Wostl, 2002; Taberna et al., 2020). While often used to capture emergent phenomena, they also are useful in systems where there are numerous interactions between agents themselves or agents and their environment. This class of models are particularly well suited to study collective action in cases of climate change due to their ability to represent multiple heterogeneous agents responding to a shifting flood risk over time.

3.1.3 Agent-Based Modeling, Sea Level Rise, and Collective Action

Cooperation and coalition formation have been studied for multiple applications and contexts, including politics (Acemoglu et al., 2008; Sened, 1996), environmental management (Cai & Xiong, 2017; Ostrom, 2000), and operations research (Guajardo & Rönnqvist, 2015; M. Taylor, 1999). Much of the literature focuses on general cooperation, cooperation for resource management, or the formation of political coalitions. However, given growing interest in cooperative adaptation, there is a demand for new research on coalition formation for climate adaptation (Bonnett & Birchall, 2023; Shi, 2019; Shi & Moser, 2021). Although ABMs provide much potential for the study of collective action, they also generate unique challenges separate from other forms of modeling. For example, due to the need to represent decision-making processes, they tend to be characterized by higher degrees of both structural and parametric uncertainty when incorporating components such as risk aversion, information processing, and other complicated behavioral processes without detailed empirical studies.

Separate efforts have explored coalition formation through ABMs, either for the case of natural resource management or more generally. Axelrod's foundational work (Axelrod, 1997) highlights how cooperation can emerge given repeated interactions and is strengthened by network structures. (Bitterman & Koliba, 2020) demonstrate cooperation as a probabilistic function calibrated to empirical survey data for nutrient load reductions on Lake Champlain. Others incorporate game theory to compare how stable coalitions form dynamically over time (Bonnevay et al., 2005; Collins et al., 2024) or how simple rules can capture game theoretic solutions for stable coalitions (Vernon-Bido & Collins, 2021).

However, one drawback about ABMs is that they may be sensitive to assumptions about decision-making representations and structural or parametric uncertainty (N. Magliocca et al., 2024; Yoon et al., 2023). For example, (Bristow et al., 2013) compare decision rules for the graph model for conflict resolution, demonstrating how different calculations for possible coalition payoff lead to different patterns of coalition formation. Within the ABM literature, one method to account for this is through calibrating to known patterns of behavior, obtained either through behavioral experiments (M. A. Janssen et al., 2022) or detailed community surveys and interviews (Collins et al., 2024).

Alternatively, ABMs can be designed to explore how these shifts in the underlying behavioral theory or model structure influence outcomes of interest, such as (Fischbach et al., 2021; Grimm et al., 2024; Schulze et al., 2017). Model-based experimentation is essential for assessing whether these mechanisms produce realistic outcomes and for comparing the relative importance of specific drivers. In addition to identifying nuances in contrasting behavioral theories, mathematical modeling can reveal critical parameters through scenario discovery or the impacts of underlying assumptions about model processes through a sensitivity analysis of

structural uncertainty (Bojke et al., 2009; Srikrishnan et al., 2022; Yoon et al., 2023). Scenario discovery is a method that utilizes large ensembles to identify pathways that lead to particular scenarios of interest (Kwakkel, 2017).

ABM work often incorporates several behavioral theories or social phenomenon to approximate realistic decision-making. For example, the impact of trust, social networks, environmental feedback, risk aversion, and penalties on cooperative choices has been demonstrated in some models (Haer et al., 2017; M. A. Janssen et al., 2022; Kato & Sbicca, 2022). Many papers utilize prospect theory, which incorporates for the psychological phenomenon of increased sensitivity to losses when compared to possible gains (Osberghaus, 2017). Others utilize theories that incorporate multiple components, such as the Theory of Planned Behavior, which incorporates attitudes, social norms, and perceived control (Faruk & Maharjan, 2022; Jacob et al., 2021). Despite frequent usage, challenges persist in translating similar behavioral theories to a specific mathematical formulation (Schlüter et al., 2017). Finding papers that explicitly contrast these decision-making formulations for climate adaptation is therefore a necessity to understand how these representations shape outcomes.

A few papers do more explicitly begin to compare how their assumptions about decision-making representations affect model results. For example, (de Matos Fernandes et al., 2025) compare cooperation selection and social influence models but in a general cooperation context. (M. A. Janssen et al., 2022) compare the impacts of inequality, trust, and cooperation, constructing a model calibrated to empirical data on the impact of communication on cooperative outcomes in a resource harvesting game. In case of SLR adaptation, (Haer et al., 2017) compares utility theory, prospect theory, and then prospect theory with additional interaction to investigate their impact on coastal adaptation outcomes. In subsequent work, many of the same authors provide a detailed

comparison of multiple decision-making theories (Schriecks et al., 2021). Alternatively, the model presented in (Addai et al., 2025) allows agents to use one four distinct decision-making theories in their flood migration choices, although they do not present results comparing the impact of each individually. Finally, in the context of property purchasing and migration, (N. R. Magliocca & Walls, 2018) explore the impact of representing decision-making according to utility or salience. In addition to the studies above, other authors have focused on the impact of structural uncertainty, parametric uncertainty, or the incorporation of multiple objectives on decision-making, which can also contribute to significantly varied outcomes.

3.2 Research gap and research questions

Despite the meaningful contributions from the authors above, there is still a lack of knowledge on how these decision-making theories may apply to cooperative SLR adaptation. To study how adaptation coordination may emerge organically amongst a harbor region, we draw on both the literature about previous models for coalition formation and the literature on modeling coastal adaptation. Most SLR adaptation modeling papers approach SLR adaptation as an individual option, with policies stemming from policy scenarios or endogenous government agents. These papers often represent adaptation decision-making with utility functions that focus on immediate benefit, or incorporate more accurate representations of bounded rationality, including utility calculations with additional weighting, prospect theory, protection motivation theory, or the theory of planned behavior (Haer et al., 2017; Han et al., 2022; Tierolf et al., 2023). However, instead of focusing on the development of cooperation, they focus on the implementation of adaptation outcomes, including protective measures or the purchasing of flood insurance (Abebe et al., 2020; Dubbelboer et al., 2017; Han et al., 2020, 2020).

Although these have provided detailed insights into individual SLR adaptation choices, we have yet to identify a paper that combines coalition-forming behavior, the context and nuance of SLR adaptation, and the comparison between multiple decision-making mechanisms. Only a few papers even explicitly compare the role that multi-mechanism decision-making has on cooperation (Schulze et al., 2017). There is a need for research that combines all three of these elements as the need for adaptation coalitions rise, as general studies on coalition formation may not be applicable to the nature of SLR challenges. This is partly due to the fact that the decision to engage in cooperative adaptation is mitigated by an agent's benefit-cost assessment, which is influenced by its specific flood risk and property values. Additionally, SLR is time dependent, where adaptations may actively shift risk profiles for nearby agents over time, as opposed to a static flood risk. The cascading nature of flood risk, spillover impacts from piecemeal adaptation, and the significant long-range uncertainty present in SLR models creates a unique context to study cooperation. Understanding how different decision-making mechanisms may drive cooperative behavior will be an important next step for understanding how to apply knowledge from coalition and collective action studies to adaptation cooperation for coastal cities. Finally, it is critical to know how findings in a general sense may shift when faced with the constraints of a non-idealized case.

3.2.1 The role of decision-making representation

The first research question that we pursue is *how shifts in the choice of behavioral mechanism for cooperative adaptation affect SLR adaptation outcomes* to understand the sensitivity of our models to the decision-making representation. We do this by varying decision-making mechanisms to study the emergence of cooperation on an initially un-cooperative network representing a coastal community. We compare three mechanisms motivated by behavioral theory: social contagion, network reciprocity, and environmental responses. We explore social contagion influences through

the diffusion of preferences for cooperative behavior, the importance of pre-existing institutional development through demonstrated network interest and network reciprocity, and the role of environmental feedback with concepts from prospect theory (losses are felt more strongly).

To allow for clear comparison, we consider cooperation to manifest as the decision to join a coalition to construct a seawall, following the logic of Chapter 2. However, the seawall could be any large-scale hard adaptation measure. Uncooperative action is assumed to be the decision to either adapt alone (either as individual property owners or as a municipality without support of property owners) or the decision to not adapt at all.

3.2.2 Specific Application to Boston

The second research question of this paper is to explore how applying the model to a specific context (including geographic, hydrologic, and institutional details) further influences cooperative adaptation outcomes beyond what appears in the generalized and idealized model. For example, adaptation is also dependent on factors such as available external fundings and permitting challenges. We select Boston Harbor as our study location due to widely available data, the dependence on transportation infrastructure, the number of heterogeneous agents, and on-going interest in cooperation.

3.3 Model Development and Methods

For this paper, we develop an ABM for the purpose of understanding how different cooperative decision-making mechanisms influence adaptation outcomes in a general context. Secondly, to add critical context and some of the challenges posed by weak institutions that exist in reality, we build a separate procedure that applies the same structure and logic to the case of Boston Harbor, MA. This chapter builds two extensions on a previous ABM developed in Knox, et al (2025), which

develops a model to compare how different governance strategies for SLR adaptation can affect adaptation outcomes in Boston Harbor. Modeling choices were derived from literature and semi-structured interviews with stakeholders, which provided more details about decisions to adapt in Boston Harbor.

3.3.1 Semi-structured Interviews and Focus Groups

One additional component of our model and experiment design process was stakeholder engagement through a focus group and semi-structured interviews. The procedures for both processes are detailed further in Chapter 4, where we present an extended discussion on their feedbacks. In total, we spoke to 19 climate adaptation experts who work in Boston Harbor in financial sectors, local governments, NGOs, state agencies, and private sectors. All participants were selected based on their professional expertise in the climate adaptation processes in Boston. This process was overseen by the Tufts University Institutional Review Board (IRB). Participants provided feedback on the original model and influenced the way that behavioral components were incorporated into the model, including the role of underlying preferences for a cooperative or uncooperative state and the role of reciprocity. Participants were asked a series of questions, including their perceptions on cooperation in the Harbor and how it may apply to our work.

3.3.2 General model of SLR Adaptation Cooperation

Base Sequence

Both ABM models used in the work follow the same based sequence of steps in each year, which was developed to be realistic and utilize simple, rule-based processes that are easy to understand, rather than any complex mathematical representations that would require significant calibration. We initialize an uncooperative world, and highlight the decision-making required to move to a

cooperative state. The model incorporates two kinds of agents: both municipalities and property owners. Property owners include both homeowners and commercial property owners, utilizing the same adaptation possibilities for those agent categories from Chapter 2.

1. Flood Generation: Each time step begins with an annual maximum flood that has been randomly drawn from a Gumbel distribution (Gumbel, 1958) fitted to a real world Harbor. In this case, flood data is derived from the series of historical annual maximum floods in Boston Harbor and then SLR is added in, assuming a linear annual increase (NOAA, 2021). While SLR may not be a fully linear function, linear assessments are often used as simple baselines for baseline studies (Sweet et al., 2022).

2. Damage Calculation: Each agent in the model experiences damage from flooding if it occurs beyond their level of flood protection. Damage is a function of property value, base elevation, and adaptations in place (S. A. Davis, 1985).

3. Cooperative Decision-Making: We separate cooperative decision-making into two parts: the initial assessment of interest in joining a cooperation based on social, environmental, and behavioral contexts, and then the subsequent final decision incorporating estimates of expected utility, based on the financial benefit of adaptation. Details on the initial stages of this decision-making process are included below and in the supplemental materials. Utility is calculated as:

Equation 6:

$$E[U(t)] = \frac{\sum E[D(t)]_{No\ adapt} - \sum E[D(t)]_{adapt}}{\sum Cost_{adapt}(t)},$$

Where $D(t)$ represents the flood damages with and without adaptation, and the costs of adaptation are also considered. The cost-benefit calculations are discounted assuming a 3% discount rate.

We separate the process into these two stages in order to identify initial interest in cooperation based solely on social and behavioral processes, while the expected benefit provides constraints on cooperation, as the experts we met with emphasized that the most important constraint to cooperation is financial benefit. Cooperative preference is scaled between 0 and 1 and calculated according to which mechanisms are included. A value over the threshold of 0.5 indicates a larger interest in cooperation than non-cooperation, and the agent is considered to be interested in an adaptation coalition. From year to year, agents can move between cooperative and uncooperative states, which is accurate to how coalitions may form, persist, and dissolve in the real world.

Agents calculate their benefit-cost ratio for cooperative and non-cooperative adaptation and even if they are initially cooperative, a benefit-cost ratio less than 1 means that they will pursue any adaptations non-cooperatively, or no adaptation at all. Benefits of adaptation are calculated in the same manner as the model used in Chapter 2, comparing the amount of flood protection. Total adaptation costs are also consistent with Chapter 2, although agents behaving cooperatively will only pay up to the point that their benefits are equivalent to agent costs as their contribution to a collective adaptation. If agents adapt independently, they shoulder the entire burden of adaptation costs.

4. *Adaptation Implementation:* Once agents determine their interest in cooperation, they can pursue adaptation independently or with the coalition. While coalition adaptation is limited to a neighborhood scale seawall (representative of any large-scale hard adaptation), independent adaptation options include purchasing flood insurance, purchasing temporary and removable flood barriers, or constructing seawalls around one's own property. The ability to implement an adaptation is limited by the capital investment and permitting approval (see Chapter 2 for more details on those components of the model).

Figure 11 summarizes the key processes and inputs for the model.

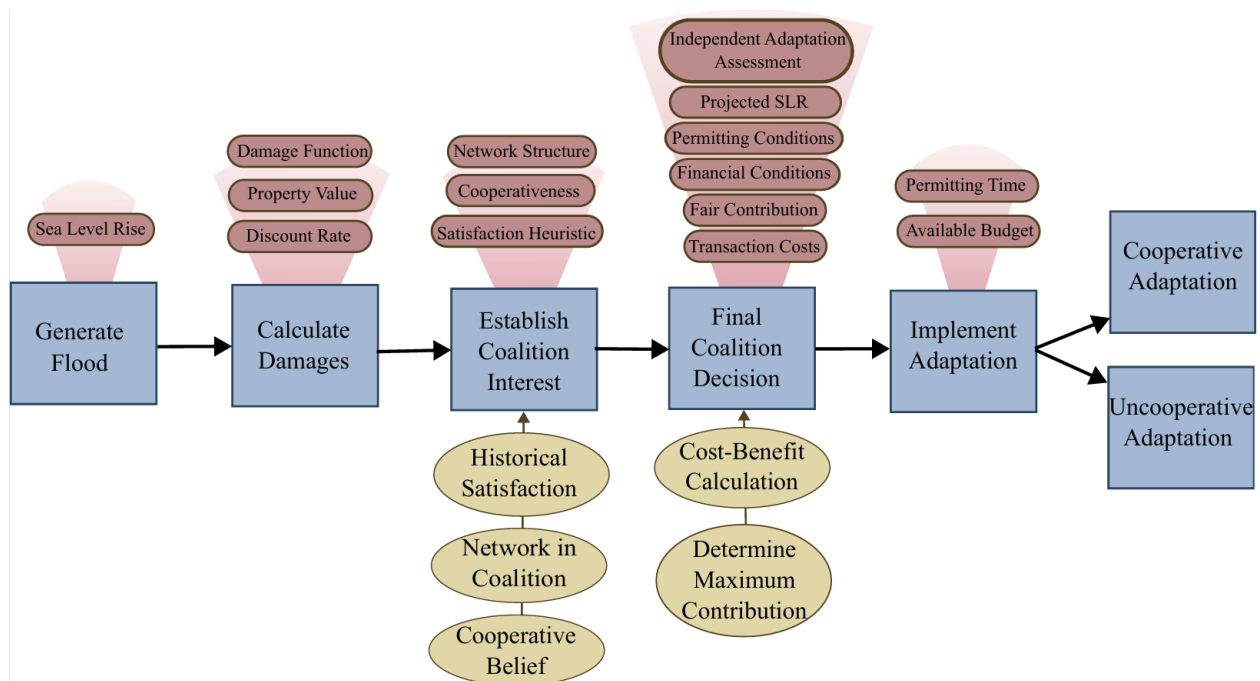


Figure 11. The basic process for the ABM is illustrated above. Inputs to each step are included in the pink, while sub-modules are included below in yellow.

Network representation:

Because decision-making is influenced by social processes, we initialize the model with a social network structure for each neighborhood in the municipality. Each neighborhood is represented by one Erdos-Renyi (ER) graph structure and connected to the broader municipality (Erdos & Rényi, 1960). To construct an ER graph, every edge is drawn with a random probability, p , to generate a scale-free graph. Agents representing commercial residents and homeowners within a neighborhood use the same depth-damage curve to estimate the cost and benefit of adaptations, but each has a random and distinct elevation and property value. The number of neighborhoods can be set by the model user.

3.3.2 Decision-making Mechanisms

In our general model, we compare the influence of three different decision-mechanisms, informed by varying behavioral theories. The three mechanisms we highlight in this work were developed based on both common uses in literature and influenced by stakeholder interviews. To do this, we focus on the use of simple heuristics to minimize the need for additional assumptions about appropriate mathematical representations.

The three mechanisms, influenced by multiple behavioral theories that we incorporate into our model for cooperative decision-making are as follows:

1. A social contagion for cooperative preference, inspired by the underlying preference of individuals towards cooperation represented in both social capital theory (Carmen et al., 2022; Gronow et al., 2021) and theory of planned behavior (Schrieke et al., 2021);
2. An assessment of demonstrated network interest reflecting theories of network reciprocity (Molm, 2010; Okada, 2020; Stojkoski et al., 2018) and institutional theory (Lie-Panis et al., 2024);

3. An interest in cooperation following an environmental trigger, inspired by the strong reactions against loss proposed by prospect theory (Osberghaus, 2017),

We also test combining these three mechanisms and the impact of the relative strength of each. A utility calculation alone, like the one presented in (Haer et al., 2017) was used for the representation of voluntary coalitions in the previous chapter. We acknowledge that translating these behavioral theories into mathematical model-based processes is a subjective assessment, and our interpretation is not the only justifiable interpretation of a theory, as pointed out by (Schlüter et al., 2017)

Social Contagion of Cooperation Preference

In this mechanism, the desire to cooperate is assessed as a social contagion, where the preference to cooperate can spread from neighbor to neighbor over time when interest in coalition formation is above a specific threshold. Previous studies that have explored cooperation through such a contagion or diffusion lens include the contagion of generosity (Tsvetkova & Macy, 2014), contagion of cooperative and selfish behavior (Jordan et al., 2013), although some suggest that this effect may be due to conformity and observation (social norms and pressure) rather than true contagion (behavior change due to repeated exposure) (Cartwright & Singh, 2018). Although an extreme simplification of social contagion, we explore what cooperation in SLR adaptation may look like in an uncooperative network where the initial interest in joining a coalition is contagious. We utilize simple contagion (see (Watts, 2002) for similar work), where coalition interest can be passed between two linked agents with probability β , if the belief in cooperation is present (i.e. above 0.5 on a scale between zero and one). The underlying distribution in our models is assumed to be uncooperative with a mean around 0.25 on a 0 to 1 scale. The probability of agent's becoming cooperative is as follows:

Equation 7:

$$P(\text{cooperation}) = 1 - (1 - \beta)^k,$$

where β is the probability that cooperation spreads and k is the number of neighbors who prefer cooperation.

Demonstrated Network Interest and Reciprocity

Another important component in the decision to cooperate is whether there is significant existing interest or membership in such a coalition within an agent's social network, reflecting institutional theory and network reciprocity (Okada, 2020; Stojkoski et al., 2018). While there is a distinction between effective institutions and network reciprocity, we assume that a reliable and pre-existing core of cooperators would strengthen existing cooperative institutions. For example, previous research that emphasizes the role of the number of 'initiators' for cooperation, such as experiments that show the importance of first-round cooperation in public goods games (Gürdal et al., 2024). Other research has demonstrated that higher initial cooperators lead to higher degrees of cooperation in heterogenous networks (Shigaki et al., 2013), but this is less important with homogeneous networks. The initial core is necessary for subsequent institutional development.

To have reciprocity occur, there is a need for a subset of initial cooperators, which is why we include a low probability of random noise in this mechanism's representation. Reciprocity also relates to concerns about free ridership indicated by our experts, as demonstrated participation and interest in cooperation is one way to build trust between agents. Within this process, an agent's preference for cooperation is represented as the ratio of their neighbors who cooperated in the last time step.

Equation 8

$$\text{Cooperation Preference} = \frac{\text{Number of neighbors who cooperated}}{\text{Total number of neighbors}}$$

Flood Response (Inspiration from Prospect Theory)

This decision-making representation depends on a simple premise: agents are more willing to join adaptation coalitions following the experience of damaging floods themselves. Prospect Theory suggests that agents more strongly react to losses than gains, and we assume this to be part of the reason why flood experience may trigger cooperative behavior. We chose a simple heuristic: experiencing a flood drives agents to join a coalition to accelerate their protection. There are many other alternative ways to represent the impact of flood experiences on adaptation decisions, such as the work by (Haer et al., 2017). This assumes that agents are reactive to their environment and that experiencing significant flooding may be an incentive to cooperate. Previous studies have identified flood experience as the best predictor for future adaptation (Koerth et al., 2013) and that natural disasters may be motivators for cooperation (Jonsson & Jonsson, 2025) (Dai et al., 2024) within specific communities. While we acknowledge that such a strong response may not always be true for all communities, we feel that this is a valid motivation to consider, as many of our stakeholders identified a potential large flood (something similar to Hurricane Sandy) as a motivation to both adapt generally or to create new cooperative adaptation structures). Agents follow a binary process, where flood experience leads to a full cooperative interest, and lack of flooding a fully noncooperative process.

Combining the Three Mechanisms

We test the combination of the three mechanisms above on the decision to cooperate, weighing each of these influences on the cooperation decision equally. When they are combined, each mechanism executes independently. With the weighted system, extra interest in cooperation from

one component can tip an agent into a cooperative state, and there are additional possibilities for feedback between the mechanisms that spread cooperation differently. For example, once an agent decides to cooperate (perhaps as a reaction to a flood with some underlying interest), it's neighbors may be influenced to also cooperate via the network process.

We include the combination of each mechanism as a more realistic justification of the decision-making process. If the weighted combination of each contribution is above 0.5, we assume the agent will pursue a cooperative approach (see Eq. 3). We include this representation as it is unlikely that any single influence is likely to solely drive decision-making and there may be interactions between the three that do not result in a linear response due to other agents responding to the signaling in previous time steps. Additional tests of the selected threshold can be found in the SI.

Equation 9

Join coalition if:

$$[(\alpha X) + (\beta Y) + (\gamma Z)] > 0.5,$$

where $\alpha = \beta = \gamma = \frac{1}{3}$, X = flood experience, Y = the ratio of neighbors in the coalition previously, and Z = the cooperative preference of the agent.

Despite the potential of such an approach, we also wish to highlight some limitations. We acknowledge that even a single mechanism may have multiple defensible ways of representing the process within a model, and that this is a source of structural uncertainty within our model. However, a full analysis of this structural uncertainty is outside the scope of this work, as our purpose is to explore how varying our cooperative mechanism impacts cooperative adaptation

outcomes. We also acknowledge that there are many other mechanisms that are not present in our model (for example, mechanisms for punishing non-cooperators).

Application to Boston Harbor

In addition to the generalized model above, we explored how incorporating the specificities of the Boston context, including accurate damage assessments, may shed more insight on the decision to cooperate for SLR adaptation. We utilize both qualitative and quantitative data sources to explore SLR adaptation cooperation (S. A. Davis, 1985; P. Kirshen, Borrelli, et al., 2018; Martello, 2023; MassGIS, 2022b, 2022a). The qualitative data comes from expert feedback on our model and was used to help more accurately represent the Boston region. We include three municipalities in the Boston application: Quincy, Winthrop, and Boston (which is sub-divided into 9 neighborhoods), each of which utilizes a specific damage curve assembled from existing data sources (P. Kirshen, Borrelli, et al., 2018). The model incorporates agent types of the municipalities, property owners, regional assets, and regional transportation (the MBTA), all of which can adapt independently or cooperatively. Additional details are available in the supplemental information, including all equations. Both models were built in NetLogo (Wilensky, 1999)

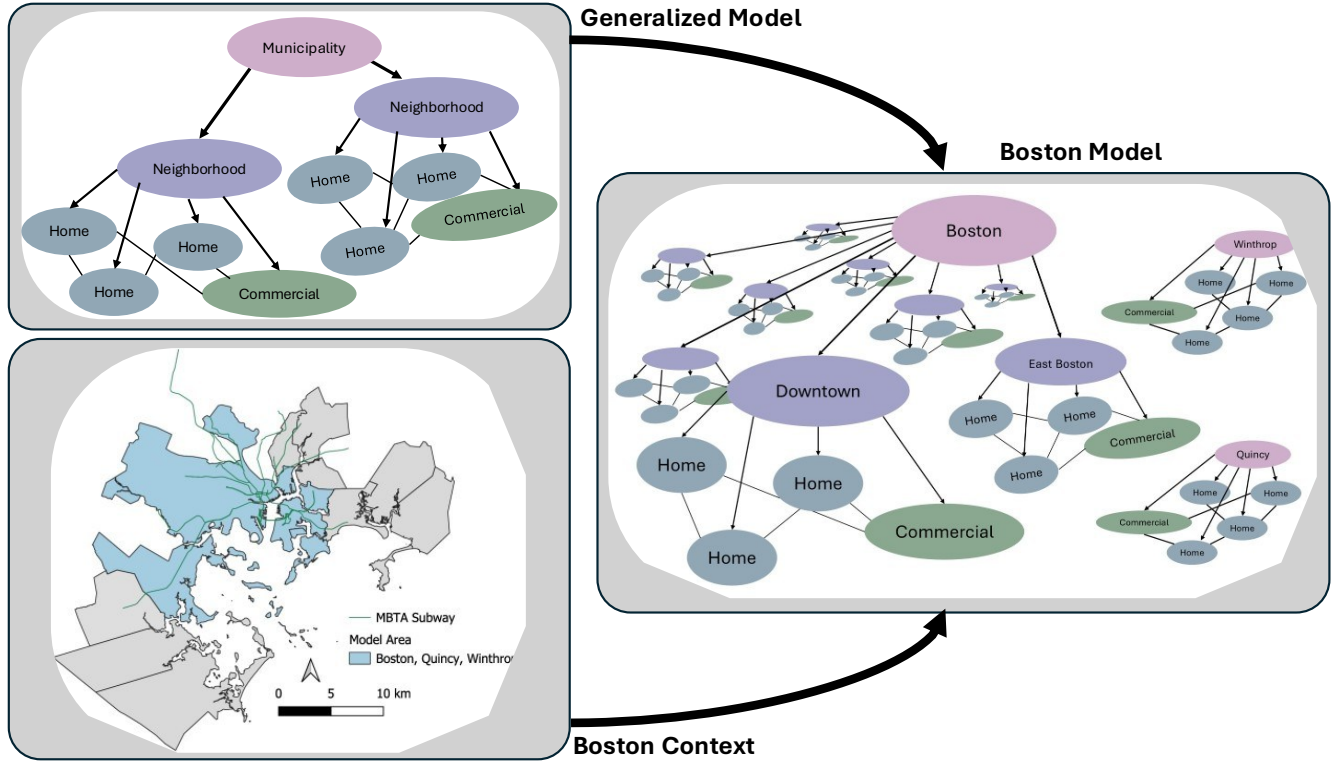


Figure 12. This figure illustrates the process to develop the Boston-specific model for our representation of SLR cooperative adaptation. The generalized model with only two neighborhoods is illustrated in the top left corner. This structure is combined with the data particular to Boston, Quincy, and Winthrop (geographic area highlighted in the lower left corner) to generate the final model. We consider 9 neighborhoods within Boston, along with simple single-neighborhood representations for the smaller municipalities of Quincy and Winthrop. The general network structure used in both models is included in the top panels.

3.4 Experimental Design

In the first half of this paper, we present results of the generalized SLR cooperation model, while the second half compares those results to the Boston context. Utilizing the general and Boston application of the model provides a number of benefits, including allowing us to better understand the mechanisms of cooperation in an idealized world, separate from the benefit-cost calculations unique to Boston. In the Boston experiment, we focus on the impact that challenging local conditions, such as permitting and financing, may play on cooperative outcomes. Within the

Boston application, we only explore results using the combination of all mechanisms, as this is the most accurate to the complexity surrounding the decision to adapt cooperatively. Tables 2 and 3 display the assumptions and conditions we test with each model. Additional details can be found in the supplemental information. The experiments utilized a full factorial sampling approach, where each combination is repeated 20 times in the generalized application and 5 times in the Boston application. While alternative sampling strategies may be justified, we selected these parameter values and the full factorial approach to fully cover parameters of interest.

Table 2: Generalized Model Experiment

<i>Parameter Name</i>	<i>Parameter Impact</i>	<i>Values</i>
Range of property values	Determines how much the property value can vary from the mean value	50%, 175%
Flood Reaction	Benefit-cost equations are modified by the ratio of experienced damages to expected damages (impact of floods is felt more strongly)	True, False
Diffusion Probability	Probability that an interest in cooperation will diffuse along a link from one agent to another, if interest is above the 0.5 threshold	0%, 1%, 5%, 10%, 20% (15%, 30%, 45%, 60%, 75% also tested in contagion experiment)
Random Coalition Initiator	Probability that an agent will randomly change to illustrate an interest in cooperating regardless of the initial cooperation (adds unpredictable stochasticity to the experiment)	0%, 1%, 5%
Network Assessment Variable	To calculate demonstrated network interest, agents can either calculate the number of linked neighbors who have indicated an interest in coalition formation or the number who have actually joined a coalition in the previous time step.	Number of links in coalition, number of links interested in coalition

Table 3: Experimental Design for the Boston-specific model

<i>Parameter Name</i>	<i>Parameter Impact</i>	<i>Values</i>
Sea Level Rise	The feet in sea level rise experienced by 2100	1ft, 5 ft
Projected Sea Level Rise	The estimate of SLR by 2100 that agents are using to make decisions	1 ft, 5 ft
Flood Reaction	Benefit-cost equations are modified by the ratio of experienced damages to expected damages (impact of floods is felt more strongly)	True, False
Maintenance Fee	Additional savings or transaction cost of cooperative arrangements	+10%, -10%
Base Cooperation	Distribution of cooperative preferences (mean of 0.25 or 0.75 on a 0 to 1 scale)	Cooperative, Uncooperative
Edge Connection Probability	Probability of an edge between two agents existing	20, 80
Permit Hurdles	Time required for permitting	High, Low
Funding Availability	Quantity of available external funding for adaptation and presence of extra grants for cooperation	High, Low
Network Assessment Variable	To calculate demonstrated network interest, agents can either calculate the number of linked neighbors who have indicated an interest in coalition formation or the number who have actually joined a coalition in the previous time step.	Number of links in coalition, number of links interested in coalition
Diffusion Probability	Probability that an interest in cooperation will diffuse along a link from one agent to another, if interest is above the 0.5 threshold	0%, 5%
Random Coalition Initiator	Probability that an agent will randomly change to illustrate an interest in cooperating regardless of the initial	0%, 5%

	cooperation (adds unpredictable stochasticity to the experiment)	
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3.5 Impact of Decision-Making Process

To discuss the impacts of each mechanism on adaptation outcomes, it is reasonable to first consider what a realistic representation of coalition formation may be. For example, in the real world, we would expect to see a slow increase in cooperation over time as the risk of flooding increased due to SLR, as extreme floods can lead to increased cooperation (Chang, 2010; Fan et al., 2020; Xiong & Li, 2024). Additionally, we would expect that interest in cooperation would fade after flood risk drops and the impetus to cooperate ends (Schilpzand, 2023). However, in many coastal systems, large-scale cooperation is still lacking, suggesting that a non-cooperative model is not necessarily an incorrect model, but rather a tool to learn about possible uncertain futures.

3.5.1 Mechanism selection drives cooperation patterns over time

The first metric we assess is the size of adaptation coalitions over time, which provides insight to the overall degree of cooperativity across the network as sea level rise leads to increasing flood occurrences. Figure 13 below illustrates the 90% interval, median, and maximum simulations for each of the four mechanisms we test.

Each mechanism (represented by a distinct panel below) leads to significantly different outcomes. In the social contagion experiment, coalition sizes remain very low or negligible throughout the ensemble, with only rare simulations reaching more notable coalition sizes of an absolute maximum around 40% (Panel A). Additionally, the coalition size is sustained through the end of the century, rather than decreasing as flood risk patterns shift due to rising seas and new adaptation construction. Without a change in flood risk, this decision-making process assumes that

agents would not lose interest in cooperation once they change their preference towards cooperation. Section 3.5.3 elaborates on the exploration of this mechanism, as it indicated the lowest rates of cooperative outcomes.

Flood reaction (Panel B) results in coalition patterns that are a stark contrast and more aligned with our original expectations for a reasonable cooperation pattern. Cooperation grows over time after a period of stagnation, peaking around the end of the century with cooperation rates above 80%, and then falling again as rising protection levels reduces agent exposure to floods, and effectively ‘turning off’ the flood incentive mechanism. This is the only individual mechanism that demonstrates a drop in coalition size near the end of the simulation.

The network reciprocity experiment (Panel C) indicates low cooperation rates, similar to the social contagion mechanism. However, coalition rates visibly increase throughout the simulations even with low rates (5% probability) of agents signaling coalition interest. Another facet of this mechanism is that rare simulations (such as the maximum, represented by the dashed line) indicate a much higher cooperation rate than the others, indicating the possibility of a critical threshold beyond which coalitions can be sustained from time step to time step.

Finally, Panel D represents the combination experiment, which presents a reasonable pattern of coalition formation and dissolution. Similar to the flood reaction mechanism, cooperation grows and falls over time, albeit less extreme, and there are significant reductions to the median coalition size from the median coalition size in the flood experiment (about a 75% reduction). Additionally, the combination of all three mechanisms appears to result in much more varied coalition sizes, as we do not see the keyhole pattern characteristic of the narrower band of simulations in Panel B. This may be because the combination mechanism balances positive and negative influences for cooperation. While an initial flood response can trigger cooperation

preferences and spread outward, overcoming the low cooperation rates in Panels A and C, a year in which there are fewer coalition members can trigger subsequent loss of interest in cooperation across the network. In other words, major coalition formation is triggered by the flood response mechanism and then sustained by the other mechanisms. This ensemble suggests that widespread coalition formation may be easier to achieve in a population that is highly motivated to cooperate after or during flood events. Additionally, the clear differences between each mechanism indicate that the choice of decision-making theory and corresponding mechanism has a strong impact on determining possible cooperation outcomes.

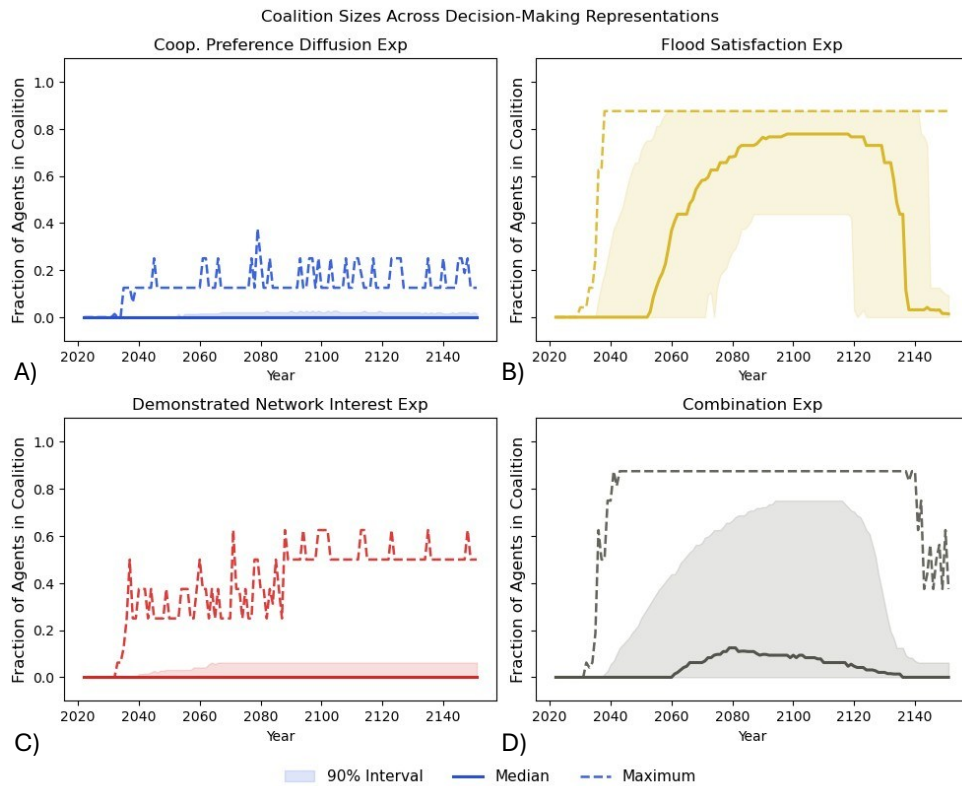


Figure 13. Coalition size as a fraction of the entire network across all four tested decision-making motivations and methods: the diffusion of cooperative preferences, the reaction to on-going flooding, demonstrated interest or follow-through on cooperation, and finally, the combination of all three influences. The plotted ensemble includes municipalities with 1-9 neighborhoods, hence

the normalization of coalition size to a fraction of the total number of agents within the network. The solid color represents the middle 90% of all simulations, while the solid color represents the media. The single dashed line represents the maximum to demonstrate that the extreme runs extend into significantly different patterns. The ensemble is approximately 10,000 simulations in total across all four experiments.

3.5.3 The importance of accounting for interactions

Because this paper seeks to understand the impact that changing mechanisms for decision-making have on cooperative adaption outcomes, we also investigate how each combination of mechanisms may create unexpected interactive effects and feedback loops. Figure 14 below mimics Figure 13 and plots coalition size over time for each mechanism (top left), each combination of two mechanisms (bottom panel), and finally the combination of all three experiments (top right). The shapes indicate the number of mechanisms used in combination in each panel. We include the top and bottom rows for comparison, despite the results repeating from Figure 13 above. The low level of cooperation that appears from combining mechanisms for cooperation contagion and network reciprocity indicates that a more significant (and likely) environmental feedback is needed to more accurately tailor cooperation interest to adaptation need. When only cooperation contagion and flood response mechanisms are included, there are only very small changes to the outcomes from using the flood response mechanism alone, suggesting that contagion is not a critical component of the model.

Finally, and of most interest to us, combining mechanisms for flood response and network reciprocity results in much of the behavior captured in the combination experiment. There is little difference between the panel that combines all three mechanisms and the results from combining network reciprocity with environmental response. Because network reciprocity requires agents to demonstrate cooperation before their neighbors are willing to cooperate (with the exception of a

small probability of noise), the initial hesitation to cooperate demonstrated in all models persists when network reciprocity is included. In this case, incorporating mechanisms that are dependent on previous decisions reduces cooperation when compared to purely reactive decision-making. This suggests that although social networks are important to add to cooperation models due to their ability to spread cooperation, certain mechanisms are equally important to reflect drops in coalition size after adaptation needs decrease.

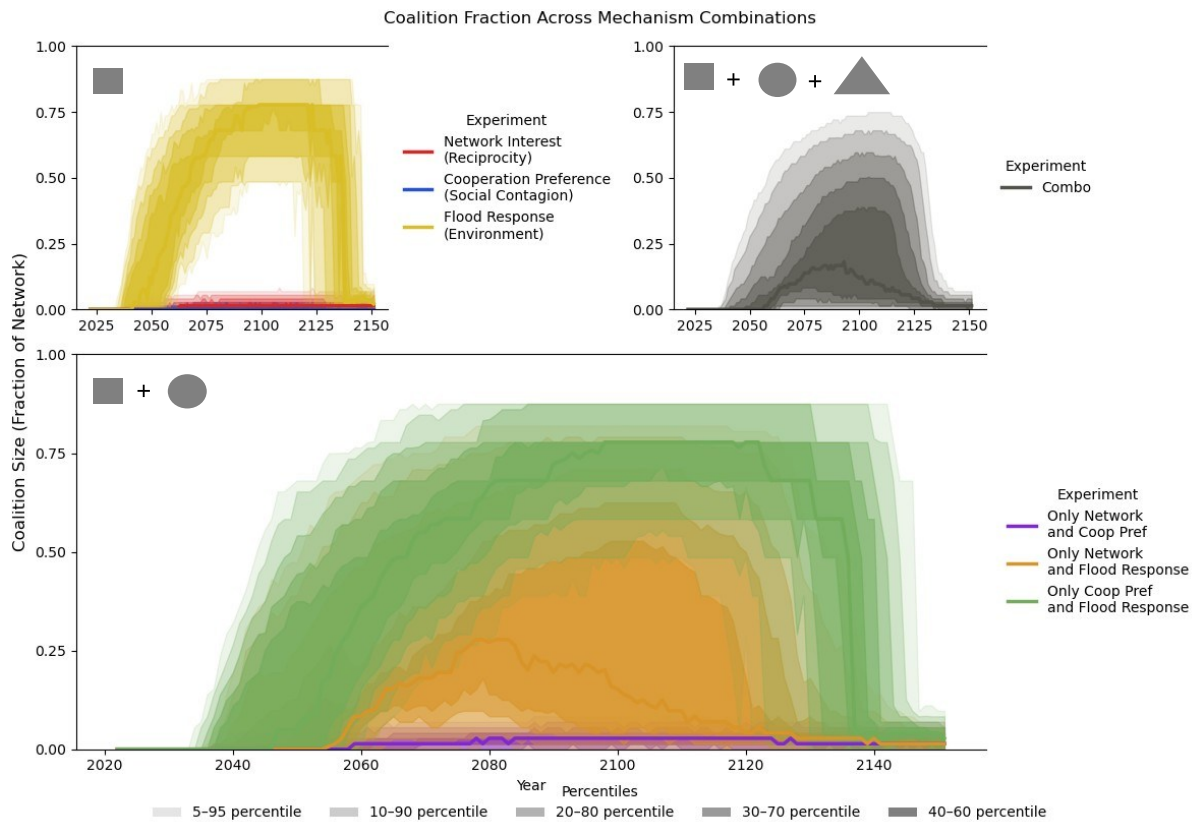


Figure 14. This figure plots coalition size across each combination of mechanisms that we tested. The first row plots three experiments: one for each mechanism run independently. In the second row, each combination of two is plotted to compare any interactive effects. Finally, the bottom row plots the results from one single experiment that turns each mechanism on simultaneously. We use the shapes to highlight how many mechanisms are simultaneously used in the decision-making process in each panel.

3.5.3 A detailed look at social contagion

The low coalition sizes that occur from the social contagion experiment were unexpected based on previous studies of social contagion and its general effectiveness (Gronow et al., 2021; Jordan et al., 2013). The mechanism is largely controlled by two variables: the probability of cooperative preference spreading from one neighbor to another, and the underlying distribution of cooperation preference. Figure 15 below provides an overview of our results of an experiment that looked at the impacts of these assumptions on coalition outcomes if only the contagion mechanism is used to inform decision-making. Panel A indicates that even very high contagion probabilities (up to 75%) do not shift the pattern of coalition size. However, shifts to the underlying preference structure do have significant impacts on coalition sizes when diffusion is the only decision-making mechanism incorporated (Panel B). Using a middle-of-the-road estimate, where preference for cooperation is distributed normally with a mean of 0.5 and standard deviation of 0.1, coalition size does stabilize around 40%, while cooperation frequently extends across the network if the underlying preference is strongly cooperative from the simulation initialization. Further experiments in the Supplemental Information illustrate that while this effect is highly pronounced when contagion is the only mechanism, the impacts of changing the underlying preference for cooperation amongst the agent population has significantly less impact on adaptation outcomes when the simulations use the combination of all three mechanisms.

This experiment highlights that the contagion parameter is less important to overall coalition sizes, largely because its importance is subdued by the more important consideration: underlying preference. These findings suggest that modelers could de-prioritize attempts to appropriately calibrate the diffusion parameter in favor of improvements elsewhere in the model, as even large changes to this mechanism's assumptions have limited impact on the simulations that

use all three mechanisms simultaneously. Finally, our results highlight how the constraints of a flood risk benefit-cost calculation may subdue coalition size, slowing the coalition growth away from the exponential increase demonstrated by unregulated contagion. The calculation of benefits and costs of adaptation are consistent with the methods used in Chapter 2.

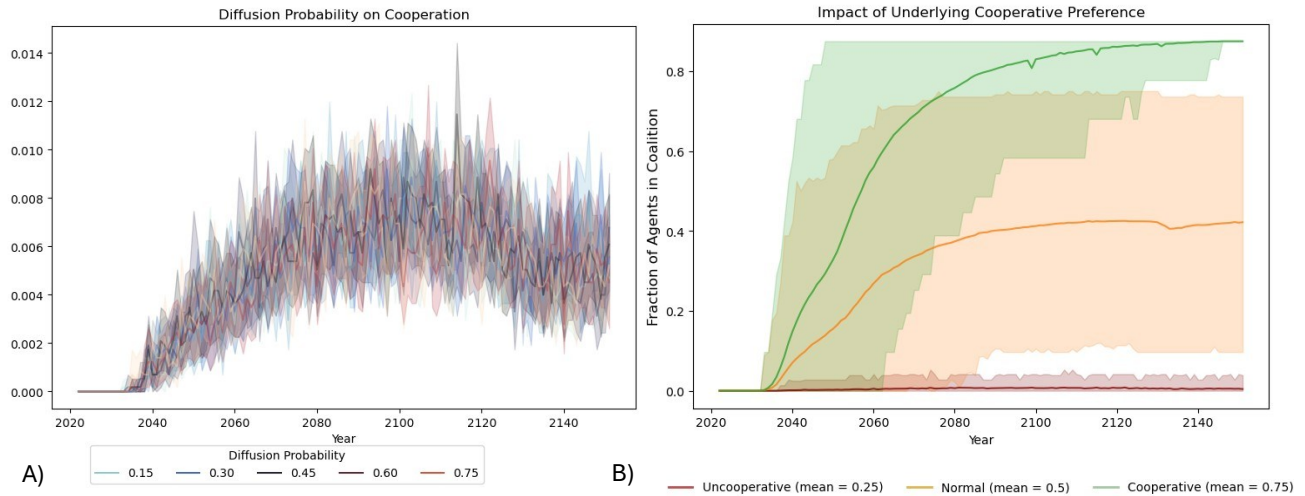


Figure 15. Panel A illustrates an experiment with 9 neighborhoods in the municipality utilizing the social contagion decision-making mechanism with an uncooperative underlying network. The overlap of all simulations, regardless of the diffusion parameter, indicate that other processes are holding back diffusion of cooperation preference. Panel B fixes the diffusion probability at 5% and instead explores cooperation outcomes across an uncooperative (mean = 0.25), normal (mean = 0.5), and cooperative (mean = 0.75) network. The large differences between each regime indicate that this parameter is what was suppressing contagion rather than the diffusion parameter. When the interest in cooperation is moderate, cooperation remains at a reduced level, while high degrees of cooperative preference rapidly result in cooperation emergence.

3.5.4 Application to Boston Harbor: Lower Cooperation in the Real World

The previous sections focused on findings from the generalized model, which lacked location-specific geography and conditions. Here, we apply the same model framework to the case of Boston Harbor to identify differences from the previous results. We incorporate a wider range of levers in the ensemble that reflect less than ideal conditions, including institutional challenges such as a lack of funding from the federal government or large permitting times and also behavioral conditions, such as a reduced perception of SLR.

Our results indicate that shifting from the generalized model and ensemble to Boston-specific context reduces cooperative adaptation. First, across the ensemble, the city of Boston experiences much lower rates of coalition formation than the equivalent municipality in the generalized experiment (for this figure, see the supplemental information). Using the same combination logic, Boston rarely experiences peak coalition sizes over 10% of the network, which directly contrasts to the wider and higher ranges of coalition size demonstrated in the generalized model. However, in Boston, despite low coalition sizes, cooperative seawalls are still constructed, just at very different times across the simulation. This may indicate that a real city, such as Boston, may face timing problems when trying to encourage regional cooperation due to inconsistent flood risk. However, because there may be sustained and slow coalitions that still achieve cooperative adaptation in Boston, we will compare the two model applications based on the number of cooperative seawalls that are constructed rather than the size of the coalition.

Even with cooperative seawalls as the metric, Boston experiences less consistent seawall construction and fewer cooperative seawalls than the combination mechanism demonstrated by the generalized model. Figure 16 below provides heat maps of seawall construction over time across each ensemble. The color of each cell indicates the distribution of cooperative to uncooperative seawall construction, while the intensity of the color represents the frequency over the entire ensemble. Cooperative seawall construction requires multiple agents to fund and implement a seawall simultaneously, benefitting from shared cost burden. For example, Panel D indicates that there is consistent seawall construction under the combination approach, and that approximately 50% of the seawalls are constructed cooperatively. The brightest band around 2140 indicates that by the end of the simulation, typically 7 out of 9 neighborhoods are protected, but

there is some variability in that value. All of the seawalls are the same length in this generalized application.

In contrast, Boston simulations often end in one of three outcomes, indicated by the intensity of the cells at 2, 5, and 9 seawalls. We only use the combination decision-making mechanism in the Boston application, as it is most realistic to real-world decision-making, which accounts for multiple simultaneous inputs and processes. The red color indicates that more than half of the seawalls in Boston are constructed uncooperatively. The range in the number of seawalls is likely due to conditions affecting the calculation of the underlying benefit-cost ratio, including perceptions of sea level rise and the actual sea level rise that occurs.

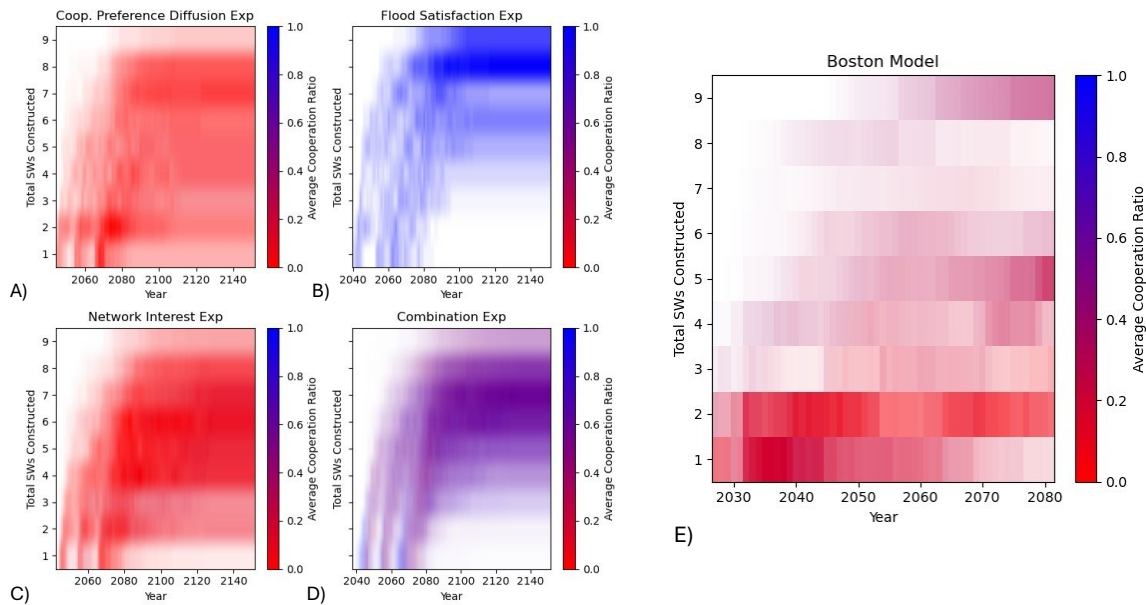


Figure 16. Heatmaps of the number of seawalls constructed overtime in the generalized model compared to Boston. The intensity of the color corresponds to the frequency of its occurrence across the ensemble, while the color corresponds to the ratio of cooperative (blue) to uncooperative (red) seawalls.

Finally, to narrow down the conditions and assumptions that lead to the lack of cooperative seawalls common in our Boston simulations, we use classification trees to identify conditions

leading to scenarios with at least one cooperative seawall segment. For more details on how our ensemble was operationalized, see the model details in Chapter 2 and the supplemental information for Chapter 3. Figure 17 illustrates the results of this analysis and specifies two metrics: density (D) and coverage (C). Density refers to the number of simulations that meet the desired criteria within the specific node (how well the pathway has purified the specific node), while coverage refers to the percentage of simulations with the desired class out of the total number of simulations with the desired class (how many simulations of interest are classified by the pathway). In the figure, the conditions are specified next to each node, and the color provides a reference for the density of each split, with blue corresponding with cooperative seawall construction, i.e. how well it separates out simulations with cooperative adaptation.

The results offer a few interesting insights into what drives cooperative adaptation within Boston. First, the most important driver is that there is a high expectation of risk amongst agents (that SLR by 2100 is 5 feet). This corresponds with the notion that there must be a high perception of risk to drive adaptation (Osberghaus et al., 2010). Second, there is a mix of influence from our decision-making mechanism representations and from external factors that drive cooperative adaptation. For example, the metric by which agents assess demonstrated network reciprocity and access to improved external funding for cooperative solutions are present as the second tier branches. Institutions and behaviors both contribute separately to the problem of cooperative adaptation: both will have to be managed to be successful. Third, the tree suggests that even if the population has a low expectation for SLR, several conditions (including improved funding and permitting for cooperation) will result in better chance for cooperative seawall construction.

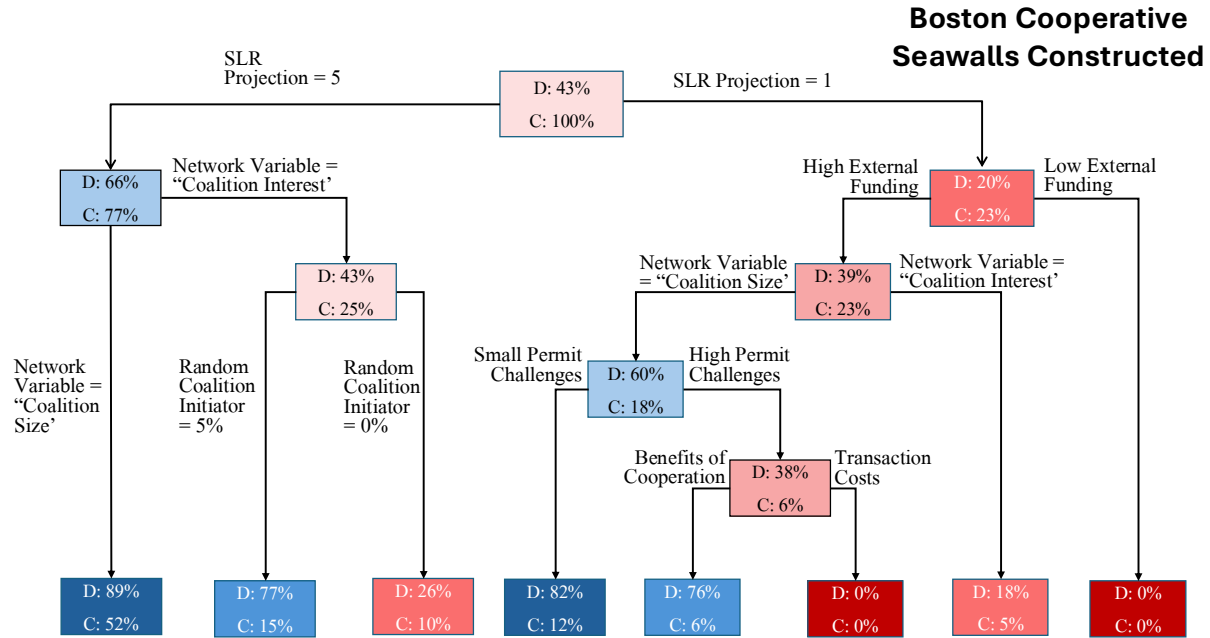


Figure 17. Classification and Regression Tree (CART) results for the Boston-specific ensemble to identify drivers of cooperative seawall construction. Blue color indicates that the majority of simulations within the node experience cooperative seawall construction, while red indicates uncooperative seawall construction.

3.6. Discussion and Conclusions

3.6.1 For modeling contexts

This paper demonstrates that implementing different decision-making mechanisms, each inspired by an alternative social and behavioral theory, has significant influence on the pattern of cooperative adaptation outcomes. First, this suggests that modelers have a duty to capture an accurate representation of the decision-making processes of their target community before any similar models are used to develop policies. While the combination of three mechanisms was our best attempt at this, there is significantly more work that could be done to incorporate additional theories of behavior and tailor them to Boston.

To help manage this problem, modelers of socio-ecological systems (SES) should consider both mechanistic or theoretical uncertainties in addition to other sources of uncertainty, including structural, parametric, or aleatoric uncertainty. Many of the same strategies suggested by authors managing these uncertainties could be applied to the uncertainty of underlying behavioral theories, including (Jackson et al., 2011; N. Magliocca et al., 2024; Srikrishnan et al., 2022; Yoon et al., 2023). One such consideration could also be the simultaneous inclusion of multiple models for comparison, such as the work completed here. Alternatively, participatory model development (Voinov et al., 2018) may provide more accurate mental model representations, although these can be difficult to reach consensus on and may not be representative of all stakeholders.

Finally, ensuring that ABMs are fit-for-purpose and appropriate use is one way to overcome this problem. If used in an exploratory context, for scenario discovery, or to compare various assumptions, having imperfect decision-making representations can even be a benefit to the model, particularly if it improves the accessibility of a model. However, such models lose strength when applied in prescriptive manners.

3.6.2 For institutional contexts

This paper also highlights that combining mechanisms that capture environmental feedback with network reciprocity result in simulations with high degrees of cooperation along with a reasonable representation of decision-making. The importance of network reciprocity suggests that frameworks for initial cooperation is an important trigger for subsequent cooperation. In the absence of such an initial institution, cooperation may fizzle out or fail to emerge.

The timing of this paper coincides with a bill presented to Massachusetts Senate (Bill S.658) to create a regional flood authority in Boston Harbor. While this bill aims to streamline

cooperative adaptation under a regional structure, providing improved access to grants and funds that prioritize voluntary cooperations between residents in Boston Harbor may also improve cooperation and compliance within the region. Additionally, creating a strong system for voluntary coalitions to manage adaptation may decrease the dependence of cooperative adaptation on the success of legislation such as S.658 to really begin. This bill should be considered within the context of this model; if an entirely new authority is unreasonable, an initial framework and structure for cooperation may alone be enough to initiate cooperation.

3.6.3 Future Work

Although this work begins to answer each of our research questions, there are still many avenues for future work, including testing many of the assumptions made in the model. First, there is a need for more qualitative work, in particular to assess surveys and other numerical feedback mechanisms to see if the representation of cooperative decision-making is realistic and if the weighting for each component is appropriate. This is a current limitation of this chapter. Secondly, future research on understanding feedback loops and tipping points between the three cooperative mechanisms is needed, as past cooperative interest can influence future cooperation across the network. Finally, while we demonstrate that the size of the network matters less, additional work is needed to see if alternative network shapes might change the findings of this result, building on the research from (Jun & Sethi, 2007).

Attempting to incorporate feedback from key experts in the Boston context throughout this project strengthened our understanding of the system we are modeling. However, appropriately moving from the varied, occasional conflicting, and detailed information collected in interviews to a mathematical model posed a significant challenge. Bridging the gap between qualitative and quantitative research methods for model development is also a fruitful avenue for research in

improved and more specific approaches. Additionally, there is much promise in surveying experts for alternative governance structures that combine both unregulated and regulated forms of cooperation.

3.6.4 Conclusion

This work demonstrates how contrasting theories for cooperative behavior significantly influence cooperative adaptation outcomes for SLR. We present a model that bridges the gap between the context of sea level rise, the formation of cooperative adaptation coalitions, and the comparison between cooperative decision-making theories. We illustrate that in this case, social contagion plays a very limited role in contribution to coalition formation across an uncooperative network. Additionally, while network reciprocity and flood reaction generate reasonable patterns of coalition formation, the model demonstrates how network reciprocity can actually act as a deterrent for cooperation.

By comparing the model to an representation of adaptation in Boston Harbor, complete with institutional challenges, we demonstrate how cooperation rates decrease even with the same decision-making logic. We use CART to illustrate that the major contributing conditions to uncooperative seawall construction in Boston contain elements from both the behavioral representation and external factors from institutional challenges, including a lack of external financing.

These efforts highlight that uncertainty in ABMs for SLR cooperation must consider structural, parametric, and mechanistic/theoretical uncertainty, supporting existing calls for their careful design and application.

3.7 Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work the author(s) used ChatGPT in order to assist in generating python code for figure development. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

3.8 Data and software availability

All of the models developed for this chapter and the code developed for data analysis are available by request to the author. Subsequent publications may also contain publicly-available versions of the software used in this chapter.

Chapter 4: Local Perceptions on Barriers to Cooperation and the need for a Regional Flood Authority

Abstract:

While the previous chapters of this dissertation explore the need for cooperation, they still simplify the background of the current adaptation systems in place in Boston Harbor. In particular, the models do not address challenges stemming from current institutional design, financing regimes, or interjurisdictional relationships in Boston Harbor. However, the complex nature of SLR adaptation cooperation calls for an approach that also considers qualitative data. In this chapter, we analyze stakeholder perspectives towards cooperative adaptation using the Institutional Analysis and Development (IAD) Framework. Despite the desire for cooperative solutions to emerge spontaneously, there is a strong belief across actors in the Harbor that widespread collaborative solutions will only be possible with a Regional Flood Authority. Additionally, stakeholders identify financing, permitting, property rights, and the current legislation as bottlenecks to both voluntary cooperation or a regional flood authority. However, our results suggest that climate adaptation experts in the region have a high perception of risk facing the Harbor and many stakeholders urgently feel pressure to adapt. This data provides valuable context to the findings in the previous chapter, which focus exclusively on models and research questions with a narrower scope.

4.1 Introduction and Motivation

One of the remaining challenges of the modeling exercises in the previous two chapters is that all mathematical models require some degree of simplification, which comes at the cost of decision-making realism (DeAngelis & Diaz, 2019). While the decision to cooperate is comprised of behavioral, financial, and institutional elements, the ensembles used in the previous chapters do not fully capture the complexity of the current state of cooperative adaptation decision-making in Boston Harbor, as they lack the inclusion of additional incentives of cooperative or non-cooperative behavior, including free-ridership or social pressure, among others. Given the uncertainties of modelling practices, the incorporation of multiple methodologies to bridge quantitative and qualitative methods in collective action research has been of interest (Poteete et al., 2010). In this chapter, we add nuanced context to cooperative adaptation processes in Boston through qualitative data collected from climate adaptation experts.

While previous authors have explored stakeholder perspectives for climate adaptation in Boston, including their perspectives on Nature-Based Solutions (NBS) (Lillquist, 2024) and general coastal adaptation (P. Kirshen, Ballesteros, et al., 2018; P. Kirshen, Douglas, et al., 2012b), to the best of our knowledge there are no studies on possible cooperative arrangements for SLR adaptation in Boston Harbor. Therefore, this chapter addresses two literature gaps: the identification of stakeholder perspectives on barriers and incentives to cooperative adaptation and the exploration of stakeholder preferences towards the adaptation regimes presented in Chapter 2 (voluntary adaptation coalitions and a regional flood authority).

The commentary presented in this chapter was collected to validate and improve the previously presented ABMs, but warranted additional explanation and focus in this chapter. While

much of the commentary was used to inform model development, many of the insights from our study participants could not be directly incorporated into the modeling portions of the dissertation. In particular, this is due to the difficulties of moving from a qualitative understanding of a process to a single mathematical representation (as discussed in Chapter 3). While some changes were implemented directly to the models, many of the comments and reflections on governance extended beyond the scope of the model itself. Therefore, the additional context from these discussions is included within this chapter as an extended discussion of the concepts presented in the previous two chapters.

To assess if our model appropriately captured some of the intricacies of cooperative decision-making, we focused our qualitative research analysis on two questions: 1) What are the largest institutional challenges to cooperative adaptation in Boston Harbor? And 2) how could a formalized regional flood authority shift the institutional landscape for cooperative SLR adaptation in Boston? We frame these questions through the lens of the Institutional Analysis and Development Framework, proposed by Elinor Ostrom (Ostrom, 2009). This framework is frequently applied to study how institutions change over time and can aid researchers in identifying key questions about existing institutions (McGinnis, 2011). While there are alternative lenses to study institutions drawing from different institutional theories (including New Institutional Economics (North, 1986), Political Economy and Institutions (Rothstein, 1996), or Sociological Institutionalism (Schofer et al., 2012)), we select the IAD Framework for its flexibility and applicability to both SLR and other collective action problems. These questions helped to distill the wide variety of interview topics.

For the first research question, our participants indicated that the largest challenges to cooperative SLR adaptation generally in Boston Harbor are the financing, legislative system, the

permitting costs, and property rights. However, many participants were also concerned about free-ridership, indicating that a lack of trust may hinder cooperative arrangements.

For the second question, we consider two alternatives for collaborative governance throughout this dissertation: cooperation via a regional authority or voluntary adaptation coalitions. A flood authority represents a centralized solution; cooperation occurs because it is mandated. Alternatively, voluntary coalitions represent a networked form of governance that emerges without mandated participation, and therefore can prioritize localized concerns (see (Bednar & Henstra, 2018) for more on climate governance typologies). The trade-offs between regionalized and localized flood adaptation regimes are studied in (Shi, 2019). While we recognize that there are also multiple alternative flood adaptation governance structures that could emerge either along this spectrum, including polycentric approaches (Lubell & Robbins, 2022; Ostrom, 2017), we focus on these two structures as contrasting ideologies. Additionally, because of model constraints, we cannot test every possible structure of cooperative arrangements. Figure 18 provides a visual depiction of the spectrum of cooperation that may exist for our climate adaptation experts, with key facets of voluntary coalitions or a flood authority emphasized.

The vast majority of our study comments seem to support the creation of a Regional Flood Authority over voluntary coalitions due to the need for a consolidated mission, the ability to raise funding, and the ability to enforce collective adaptation processes between the variety of agents who operate within Boston Harbor. However, participants also raised concerns with the development of legislation to establish such an authority. Figure 18 below summarizes this framing as two distinct management strategies for adaptation governance. Overall, there was a high awareness of the increased need for adaptation and the need to change the institutions that currently exist for coastal adaptation management.

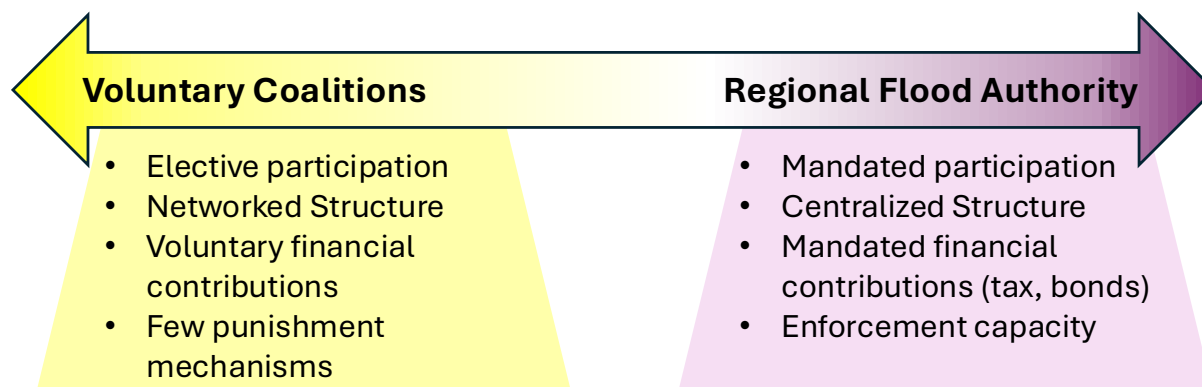


Figure 18. Illustration of the spectrum of cooperative adaptation options we use throughout the dissertation, with key characteristics of each.

4.2 Background

The previous chapters illustrated the risk that SLR poses in Boston Harbor. Multiple organizations within the Harbor are dedicated to preparing Boston for climate resilience, including the Green Ribbon Commission, Boston Harbor Now, the City of Boston via the Climate Ready Boston initiative, numerous grassroots organizations, and many others. Additionally, each town bordering the Harbor also plays a role in setting the adaptation agenda, including Quincy, Winthrop, and even inland towns that may benefit from a more resilient Boston, including commuter-friendly cities like Lexington and Concord. Additional actors with missions that include climate adaptation include the Mystic River Watershed Association, the Massachusetts Water Resources Authority (MWRA), segments of the Massachusetts Bay Transportation Authority (MBTA), MassPort, academic institutions, and the Environmental Business Council of New England, among others. Given the large number of organizations operating within Boston, effective coordination is a pressing concern. Although the need for adaptation (and collaborative adaptation) in Boston is clear (Douglas & Kirshen, 2022b; Krue, 2016), there still have been few instances of Harbor-wide

cooperation in adaptation implementation. This has led to calls for the creation of a new regional flood authority (Fitzgerald et al., 2023; Fitzgerald & Hobbs, 2022) or other cooperative structures.

Although cooperation can be studied from multiple perspectives (including modeling approaches, such as in the previous chapter), here we focus on institutions and flood risk as a common pool ‘problem’. Institutions are often described as shared ‘rules’ of the game -- for behavior, interaction, or management (North, 1990; Ostrom, 1986; Riker, 1980). Ostrom adds additional details with her definition: “institutions are the prescriptions that humans use to organize all forms of repetitive and structured interactions” (Ostrom, 2005). These rules prescribe responsibilities or interactions and these formal or informal guidelines are often the backbone for all management or governance systems. They can be as specific as particular legal arrangements or as informal as cultural norms.

This chapter focuses on an institutional lens to highlight that the systems for coastal adaptation currently in place in Boston Harbor are not sufficient for widespread cooperation. Because institutions will play a large role in facilitating cooperative adaptation within Boston Harbor, they deserve additional attention in this dissertation, hence their inclusion in this chapter. Rather than focusing on generalized knowledge about institutions, we focus on the Boston context with experts who have worked in coastal adaptation in Boston.

We utilize the Institutional Analysis and Development (IAD) Framework (Ostrom, 2005, 2009, 2011, 2019) as our method to analyze and organize data provided by the focus groups and expert interviews (see (McGinnis, 2011) for definitions of key terminology in the Framework). The framework was developed to help assess how institutions both operate and change over time. The structure of the Framework emphasizes decomposing institutions into several categories, including exogenous variables, action situations, interactions, and outcomes (see figure below).

This framework has previously been applied to climate-related institutions (K. Andersson, 2006; Roggero et al., 2018), including flood management institutions in the Netherlands (Molenveld & van Buuren, 2019). This Framework aids in understanding the present institutions for flood adaptation in Boston Harbor and conceptualizing the necessary institutional shifts that would be required for either voluntary cooperation or a regional authority. The framework provides a starting point to ask meaningful questions about adaptation institutions and to categorize the information collected from our experts.

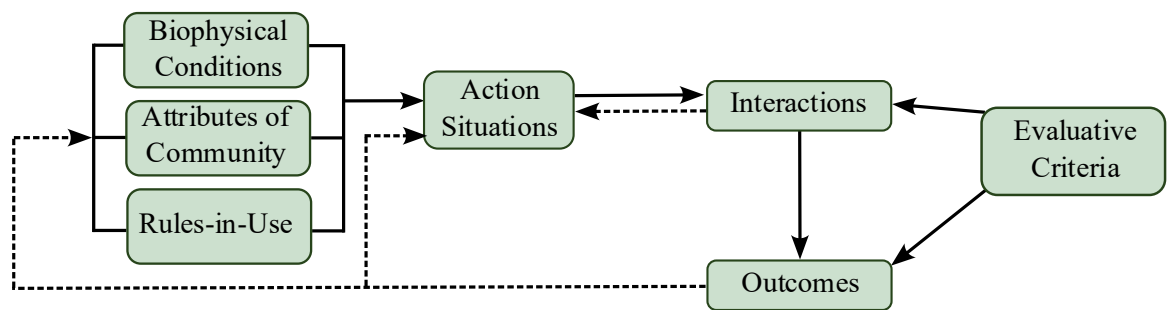


Figure 19. Overview of the IAD Framework developed by Ostrom.

4.3 Methodology: Expert Interviews

This sub-chapter utilizes semi-structured interviews with climate adaptation experts in Boston to collect more specific information about barriers to adaptation within the Boston context. In total, we spoke to 19 climate adaptation experts who work in Boston Harbor in financial sectors, local governments, NGOs, state agencies, and private sectors. Participants in the study were selected in multiple ways, including utilizing existing professional or academic network channels and collecting additional participant names during interviews. We made the decision to stop adding additional participants to our sample once the information we were receiving was largely consistent with information received previously without significant new contributions. This

process was overseen by the Tufts University Institutional Review Board and declared to be an exempt study.

During the focus group and interviews, participants were introduced to the broad motivation for our project and walked through the most up to date model structure and findings. Following our introduction, they were asked to provide feedback on our model structure, in particular our representation and assumptions about regionalization and the decision to cooperate. During the semi-structured interviews, participants were asked additional questions regarding their perceptions toward regionalization, and general barriers or incentives for cooperative adaptation.

Transcripts of the focus group and interviews were inductively coded systematically around key themes with the use of NVivo to identify patterns within the datasets. Similar methodologies have been used to study barriers to water delivery in rural Alaska (Safarpour et al., 2025), the perception of equity in extreme event communications (Azhar et al., 2025), and nature-based sea level rise adaptation (Lillquist, 2024). I developed a codebook that categorizes incentives and barriers for adaptation cooperation. During the coding process, this was expanded to include coding for particular relationships between these incentives and barriers and the decision to adapt cooperatively. Additionally, we added codes for each component of the IAD Framework and codes representing different narratives regarding voluntary cooperation or centralization of adaptation. The variety of codes provides a systematic way to analyze and consider qualitative data on adaptation in Boston Harbor. Throughout the paper, all quotes will be identified by italicized font. Throughout this analysis, italicized text indicates the use of a quote from these interviews.

Table 4: List of participants in our research study and the sector that they work in

Focus Group	<i>Sector</i>	Interview List	<i>Sector</i>
Expert 1	Private Sector	Expert 1	Private Sector

Expert 2	Infrastructure	Expert 8	NGOs/Civil Society
Expert 3	Government	Expert 9	NGOs/Civil Society
Expert 4	State Agency Official	Expert 10	NGOs/Civil Society
Expert 5	State Agency	Expert 11	Infrastructure
Expert 6	Academia	Expert 12	Public Sector
Expert 7	Financial Sector	Expert 13	Infrastructure
		Expert 14, 15, 16	NGOs/Civil Society
		Expert 17	Public Sector
		Expert 18	Private Sector
		Expert 19	Private Sector

4.4 IAD Framework Applied to Boston Cooperative Adaptation

4.4.1 Biophysical Conditions

In the IAD Framework, biophysical conditions represent the current state of ecosystems and environment to be managed. We consider relevant biophysical conditions to reflect both coastal processes like sea level rise, storm surges, and flooding, but also the broader infrastructural system that influences current flooding patterns in the Harbor. There are numerous studies that detail flood risk and the biophysical context in Boston (Douglas et al., 2016; Douglas & Kirshen, 2022b, 2022b; Fitzgerald & Hobbs, 2022; P. Kirshen, Borrelli, et al., 2018).

Multiple participants acknowledged the interdependence of flood risk in the Harbor region. Additionally, participants raised concerns about cascading effects, where damage in one area of the Harbor may have unknown or unquantified effects elsewhere in the Harbor. For example, one expert explained that even if a single highway floods, “*everybody in the greater Boston area is going to be impacted.*” While previous studies have shown that flood damages may have cascading impacts (Fekete, 2019; Guimarães et al., 2021), especially when transportation networks are

impacted, the frequency of these comments indicate that many of the major climate adaptation experts in Boston already recognize the extent to which this is a problem.

One of the challenges within the Boston context however, is the lack of a single model presenting quantified dollar estimates for potential flood risk. Despite the acknowledgement from stakeholders that Boston Harbor is a highly connected system, even the adaptation experts that we interviewed stated that there is “*no common understanding of the impact, the cost of doing nothing.*” While organizations like Coastal Zone Management (CZM) and Boston Harbor Now have started to address this, these comments suggest that the data is either not discretized enough to be useful at multiple scales for all users or not disseminated widely enough as a single, approved model of flood risk within Boston Harbor. These maps and models can be found at the following links: CZM StormSmart Coasts Program (<https://www.mass.gov/stormsmart-coasts-program>) and Boston Harbor Now flood maps (<https://www.bostonharbornow.org/what-we-do/work/climate-change-preparedness/maps/>). Compound risks only add to this struggle; three participants brought up that the compound risk from simultaneous storm surge and heavy precipitation is not fully understood, echoing calls from academic literature (Hsiao et al., 2021; Wahl et al., 2015).

One major difference between flood protection in Boston in comparison to other cities on the eastern seaboard, such as New York City, is the lack of recent history with an extreme and devastating flood. The previous chapters illustrated how quickly flood reactions could drive adaptation decisions, yet the reality is that coastal flooding recently has been a relatively isolated incident across the Boston Harbor (despite the high level of risk). Three participants compared the Boston system to cities that have experienced larger scale disasters, including Hurricane Sandy (Rosenzweig & Solecki, 2014), Hurricane Katrina (Fussell, 2015), or the recent 2025 Los Angeles, California wildfires (Clemens, 2025). As a poignant summary of the disconnect between the

current flood risk and potential of one large storm to shift adaptation perspectives, one participant stated *“this threat of sea level rise is existential. I don't know if people like have quite internalized that yet, but one day, perhaps they will... do anything to try to move this forward.”* Seven of the nineteen participants explained how a catastrophic flooding event has the potential to dramatically shift perceptions about the need for adaptation and adaptation processes during a rebuilding phase.

Taken together, these quotes frame Boston as a coastal community, largely aware of a significant flood risk (although this may be due to the criteria with which we selected climate adaptation experts as participants), with little ability to develop the adaptations that they know they need imminently. Climate adaptation is stuck in a paradox: it simultaneously seeks to prevent the catastrophe that is needed to mobilize interest and finances. The city also needs a shared and detailed model of possible risks of flooding without adaptation, building on the significant efforts and progress made by the variety of Boston flood risk organizations. To improve usability, these should incorporate cascading impacts to improve the accuracy of benefit-cost assessments and potentially compound risks from heavy precipitation.

4.4.2 Attributes of Communities

Overall, Boston Harbor is characterized by a large diversity in the actors that will need to collaborate to protect the city from sea level rise. Not only do actors have diverse needs, but they also may have significant differences between their available resources to adapt, conflicting mandates, and differing values. Other work that has begun to contextualize Boston sea level rise given the diversity of communities across Boston includes (Humphries, 2025; P. Kirshen, Douglas, et al., 2012b).

Boston Harbor, like all urban regions, also demonstrates inequities between communities in terms of income, capacity, and property values, amongst other metrics. For example, while the income per capita in the city of Boston is \$67,404, the income per capita in nearby Lynn is only \$26,189, and neighboring Nahant is up to \$79,167 per capita, according to the Massachusetts Division of Local Services in 2026, which utilizes Department of Revenue data (Department of Labor Statistics, 2025). Most towns in Boston Harbor contain census tracts identified as EJ communities and many of these directly touch the coastline, including in Rever, Lynn, and Quincy, as shown in the data available on <https://www.mass.gov/info-details/massgis-data-2020-environmental-justice-populations>.

While income is a proxy for inequity (and may overlook communities that are vulnerable in other regards), coastal adaptation costs can rise quickly in a community. Disadvantaged communities may be left behind while wealthier communities are able to construct adaptations (Venner et al., 2024; Zahnnow et al., 2025). Additionally, wealthier communities may be able to engage more in existing political processes (Ojeda, 2018).

4.4.3 Rules-in-Use: What is the coastal adaptation process?

In the IAD Framework, ‘rules’ refer to a wide range of categories, including an agent’s position, interactions, boundaries of the collective system, choices, or information access (Klok & Denters, 2018). In our interviews, experts provided feedback on adaptation decision-making, barriers to cooperation, and possible incentives to form adaptation coalitions. The following sub-sections focus on existing rules for financing adaptations, adaptation permitting, property ownership, and legislative challenges. These four topics appeared as some of the most frequent concerns raised throughout our focus group and interviews, illustrated by Figure 20. The first two are directly

included in the models in Chapters 2 and 3, while the second two are included as assumptions that agents own their own property and policy is exogenously applied.

In Figure 20, Panel A indicates the normalized frequency of each of our identified key themes in the focus group (top plot) and interviews (bottom plot), as tallied by NVivo software. Panel B breaks down the same subset of themes according to frequency of use in each of our semi-structured interviews. Taken together, these figures illustrate that certain themes appear almost universally across our participants, including financing and funding and permitting. Additionally, it reveals that for some themes, only a few experts drove the word count, including for the terms ‘uncertainty,’ ‘ownership,’ or ‘equity.’ These differences highlight that while lived experience may raise certain issues and influence participant responses throughout the interview process, certain concepts appear to be more universally recognized amongst the adaptation expert community.

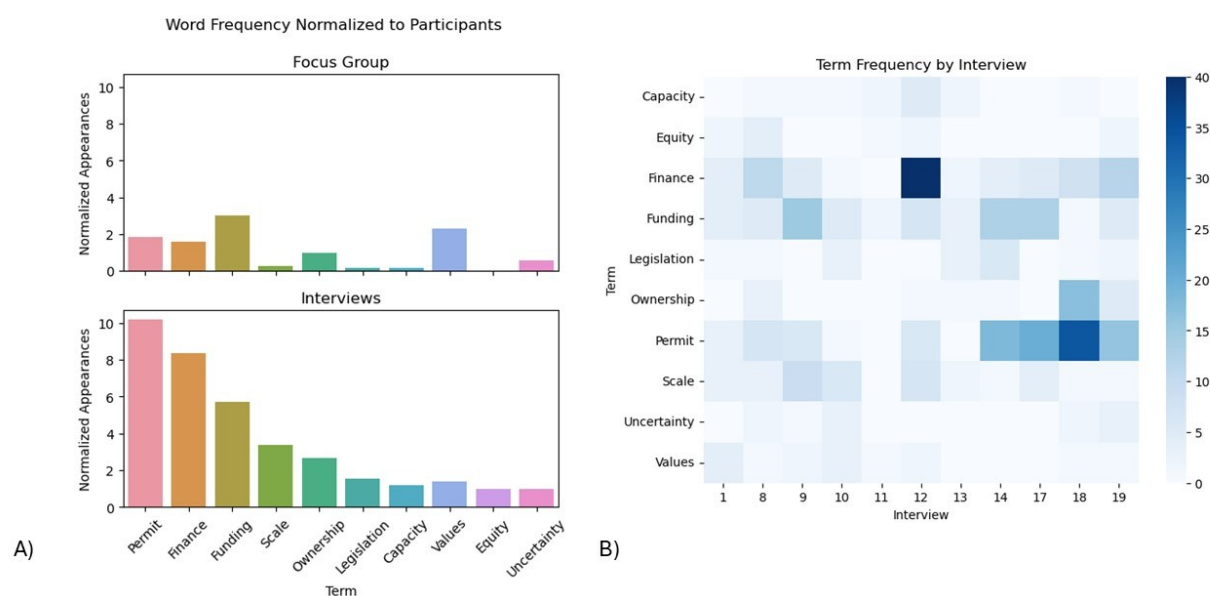


Figure 20. Panel A illustrates the number of mentions a concept received normalized by the number of individuals who we spoke to both in the Focus Group (top) and the semi-structured interviews (bottom). This reveals that across the board, permitting and financing are the greatest concerns. Panel B breaks down the terminology by interviews, illustrating that different agents focused on different concerns, although financing, funding, and permitting are still the most frequently discussed concepts. This also

illustrates that while certain concepts appear across the range of experts (i.e. “permit”), others like ‘capacity’ or ‘uncertainty’ are driven by a few individuals. The x-axis in this figure refers to a generic numbering system of each stakeholder that we interviewed independently or in small groups.

Financing

Financing and funding sources were the most frequently discussed bottleneck to climate adaptation in Boston Harbor, both in terms of accessing capital, but also for distributing benefits and determining fair contributions. In particular, our experts often converged to discussions around external funding sources, including FEMA funding, explaining that *“if an entity is seeking funding from FEMA for example, that will dictate what solutions are able to be put into place.”* FEMA grants, such as the Building Resilient Infrastructure and Communities (BRIC) (Horn, 2022), were discussed as an avenue to increase adaptations, while also placing boundaries on the types of adaptations that could be constructed. This corresponds to the work completed by (Burnstein & Rogin, 2022), which explores how FEMA maps and funding may influence coastal adaptation planning.

Without funding coming from a large agency like FEMA, capital must be collected from the multiple actors within the Harbor. Participants explained their concerns over the lack of a clear mechanism for determining these distributed costs for collective adaptation. Additionally, they expressed concerns over not being able to accurately estimate or assess the costs of adaptation, particularly from the private side, which corresponds to findings from the Australian context (B. M. Taylor et al., 2012). Table 5 provides a list of problems for financing according to the current rules-in-use and the solutions represent possible changes that our experts identified as incentivizing cooperative behavior.

Table 5: Summary of rules-in-use that prevent cooperative adaptation and possible solutions to adjust the financing system. Each problem and solution is supported by a selected quote from an expert.

Problems	Solutions
Poor pathways to access federal funding: <i>“It doesn’t necessarily lend itself well to these types of collaborative structures, because there is a lot of money on the table from a federal funding standpoint, but there is only certain types of eligibility from a recipient standpoint.”</i>	Wait for emergency FEMA funds: <i>“I think the folks who are working on this problem are sort of quietly doing as much as we can before we get a big storm and prepping for what happens when we potentially get FEMA funds to recover from a storm, because a lot of this is not doable without the capital funds.”</i>
Timeline required for FEMA projects: <i>“Yet, FEMA is a huge problem. Every FEMA project is still not approved, some of them going back four or five years.”</i>	Obtain funding from large(r) agencies: <i>“I think about regional assets, I think about major economic drivers as well and then ...particularly entities that might be more incentivized to protect their assets and how funding/financing can be leveraged from that standpoint.”</i>
Hidden/unknown costs of cooperation: <i>“There is a cost to collaboration, both in terms of monetary costs, human cost, time. I feel personally ... that the value that they are willing to pay is actually potentially lower for the regional structure.”</i>	Collective Financing: <i>“I don’t think anyone wants to be responsible for paying for it on their own.”</i>
Ambiguous contribution rules: <i>“How do you equitably or equally, divide the money up, and who pays all the rest?”</i>	Encourage adaptation funding in annual budget: <i>“We want to get those agencies to integrate resilience in their capital planning, right?”</i>

Despite the financing system for SLR adaptation acting as a major hurdle for cooperation, creative adjustments to policies or procedures could prove to be powerful incentives for coalition formation. Table 5 suggests that there may be a few shifts to financing rules in the Harbor that may improve the feasibility of cooperative structures. First, the role and dependence on FEMA and other federal grants should be clarified. While the current rules limit the ability to mobilize funding for pre-emptive adaptation and cooperative arrangements, FEMA’s ability to mobilize significant funds post-disaster could be a transformative force in planning adaptation during re-building processes. Additionally, federal grants may need to shift eligibility structure to incentivize

cooperative behavior, while still being mindful of power imbalances between actors within the Habor. Finally, increased access to financing for cooperative structures may help to overcome some of the additional costs and efforts associated with cooperation to drive voluntary cooperation or improve compliance with a mandated regional flood authority. The work by (Levy & Herst, 2018) expands on possible financing options for large-scale adaptation within Boston Habor and the need to consider equity within the financing process.

Permitting

“I think it would be great if there was an authority that could not only lay out the requirements, but also help coordinate the permitting.”

Similarly to the challenges and opportunities that financing rules may play in encouraging the formation of cooperative institutions for sea level rise adaptation, permitting is a major consideration in adaptation decision-making. Our participants identified two main problems associated with permitting. First, that it is an expensive process, and second, that it is a difficult process to navigate, which can lead to significant delays in adaptation implementation. While experts from all sectors recognized permitting as a barrier, our experts indicated that it is a particularly strong barrier for private sector adaptation and property developers. This is for a variety of reasons, including limited resources, additional burdens from waterfront permitting regulations, and challenges with working on potentially contaminated soil. Although the burden currently posed by the permitting process towards adaptation is high, our participants recognized that streamlined permitting or additional capacity to manage permitting process provided by either a cooperative coalition or regional flood authority would be a significant incentive to cooperate. One expert even went so far as to claim that permitting is often the largest barrier facing a developer for any SLR adaptation plan.

Previous studies have identified permitting as a barrier to implementing nature-based solutions or soft-armoring flood protection (McGuire, 2018) and as a component of institutional complexity (Rasmussen et al., 2021) in multiple contexts.

Property Ownership

Given that a regional authority would require constructing adaptations on land belonging to multiple organizations or landowners, property ownership was a commonly recognized barrier to cooperative adaptation. Currently, Boston Harbor's coastline is owned by a variety of actors (see land use map in Figure 21 below), which creates challenges to building large-scale infrastructural adaptations to protect against SLR directly at the shoreline. One expert mentioned their experience attempting to coordinate many individual property owners, noting that '*it is much more complex where ownership is much more fragmented.*' Multiple participants noted that the nature of ownership can also exacerbate these issues: in particular, conflicting mandates and objectives between real estate developers, property owners, commercial properties, city assets, state assets, and federal properties create significant challenges in the current system. Private property ownership is also a challenge to coastal adaptation in small cities along the MA coastline, where there are conflicts between the strength of local governance structures and the influence of private property owners (Hamin et al., 2014).

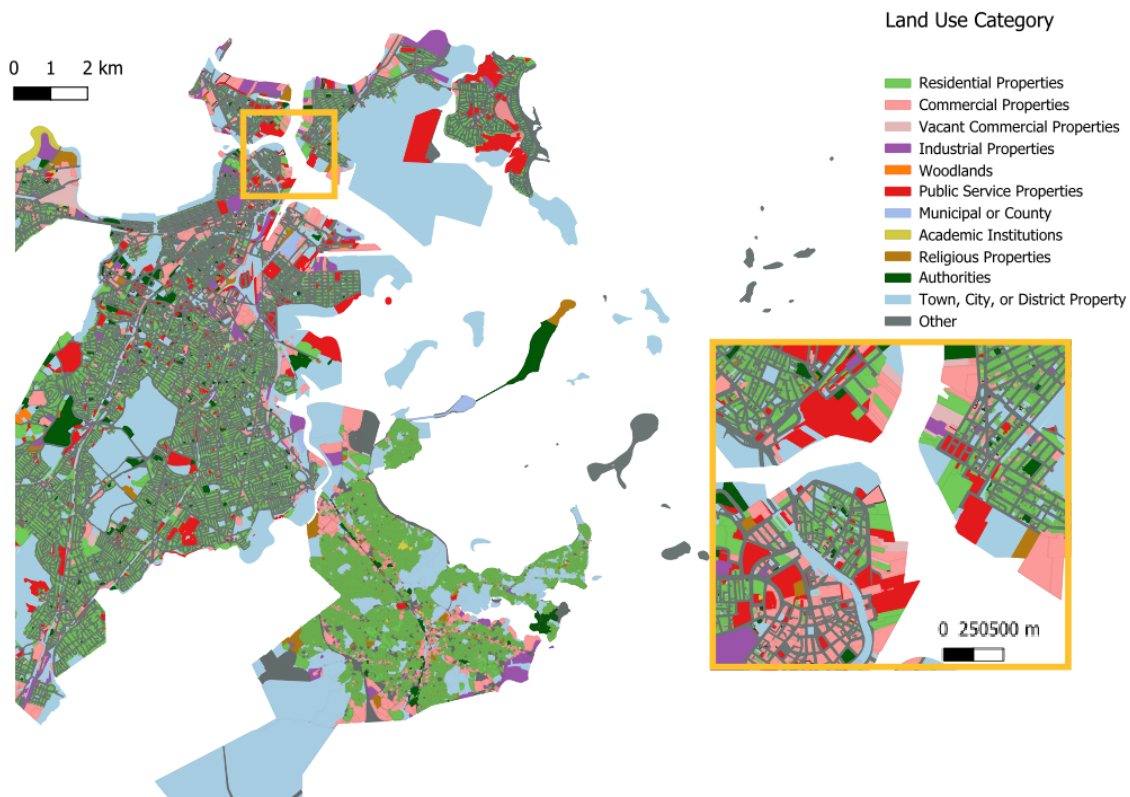


Figure 21. This map shows major land use categories for coastal property in Boston, Winthrop, and Quincy. We highlight the variety of stakeholders who own property along the coasts and the numerous uses of the parcels directly against the shore. We display Boston, Winthrop, and Quincy to match the study areas used in the previous chapters.

Previous large infrastructure projects in Boston have utilized eminent domain procedures for commercial properties, including the Big Dig (McCarthy & Derickson, 2010), which was referenced multiple times by our study participants. Despite the success of the Big Dig in moving the highway underground, there is no guarantee that future use of eminent domain processes would be perceived favorably by those impacted. As an alternative to eminent domain processes, another participant suggested consideration for the use of easements as an alternative structure.

Given the challenges to cooperation posed by the current property ownership rules, many experts felt the only way to shift the rules-in-use to support cooperation was through a mandated regional authority. However, without an effective plan to overcome challenges of property

ownership, even a regional authority will not be successful at constructing adaptation. One of the group interviews expressed significant doubt at the ability of a voluntary coalition to overcome this hurdle, as a single landowner may disrupt plans for large, collaborative solutions if their property is in the planned infrastructure area.

The Role of Legislation

Multiple participants raised concerns about the significant number of legislative changes that need to be made to develop and establish a regional flood authority. While the role of legislation is less important for voluntary coalitions, it is a pre-requisite for a flood authority. This creates a ‘*time premium*’ associated with establishing such an institution; that it could be years before the appropriate legislation is passed to create a regional authority.

One expert succinctly summarizes this concern as “*the regional authority could get completely bogged down in the legislature. There is something called a Joint Powers Act that allows, communities to opt in to doing a regional authority, which is possible to do, but would but very, very slow.*” These statements highlight the recognition of a direct tradeoff between legislative power (ability to manage the ownership challenge) and time to begin adaptation (as voluntary coalitions may be more agile from a legal perspective). In order to have a regional authority manage SLR adaptation, new policy dictating its creation, mandates, and authority should be started rapidly and considered in the decision to regionalize.

4.4.4 Action Situations: how do we decide to adapt, independently or collectively?

An action situations is described as “participants in positions who must decide among diverse actions in light of the information they possess about how actions are linked to potential outcomes and the costs and benefits assigned to actions and outcomes” (McGinnis, 2011). We use the notion

of action situations to refer to the considerations that our experts highlighted may drive the decision to cooperate for SLR adaptation or not, especially as our stakeholders are the very actors who will be determining collective adaptation plans.

Based on the relationships identified in the coding process explained above, we were able to generate a systems diagram highlighting the major factors that influence the decision to adapt in a cooperative way in the Harbor (Figure 22). In this figure, orange colored items correspond to non-financial components, green items correspond to financial components, and yellow items can be considered to incorporate both financial and non-financial elements. The thickness of the arrows indicates the frequency with which a linkage was used in the focus groups or interviews. The web reflects only clear relationships that emerged from the interviews and we recognize that other linkages are present. However, this helps to connect certain concepts. For example, permitting can be affected by a large flood and equity concerns, and it in turn feeds into the decision to adapt. Likewise, federal mandates can lead to specific organizational structures which influence how agents decide to adapt. Not all connected pathways were identified in their entirety, but assembled across the collected interviews.

While this system reveals similar dependence on financing and permitting explained in the rules-in-use section, it also highlights a dense web of overlapping and intersecting concepts on the non-financial side. This suggests that while finances are one of the strongest drivers for decision-making for cooperative adaptation, non-financial drivers may be as important and are significantly more complex. This is, in part due to ambiguous concepts such as ‘equity’ or the diversity of values that an actor may have when it comes to adaptation.

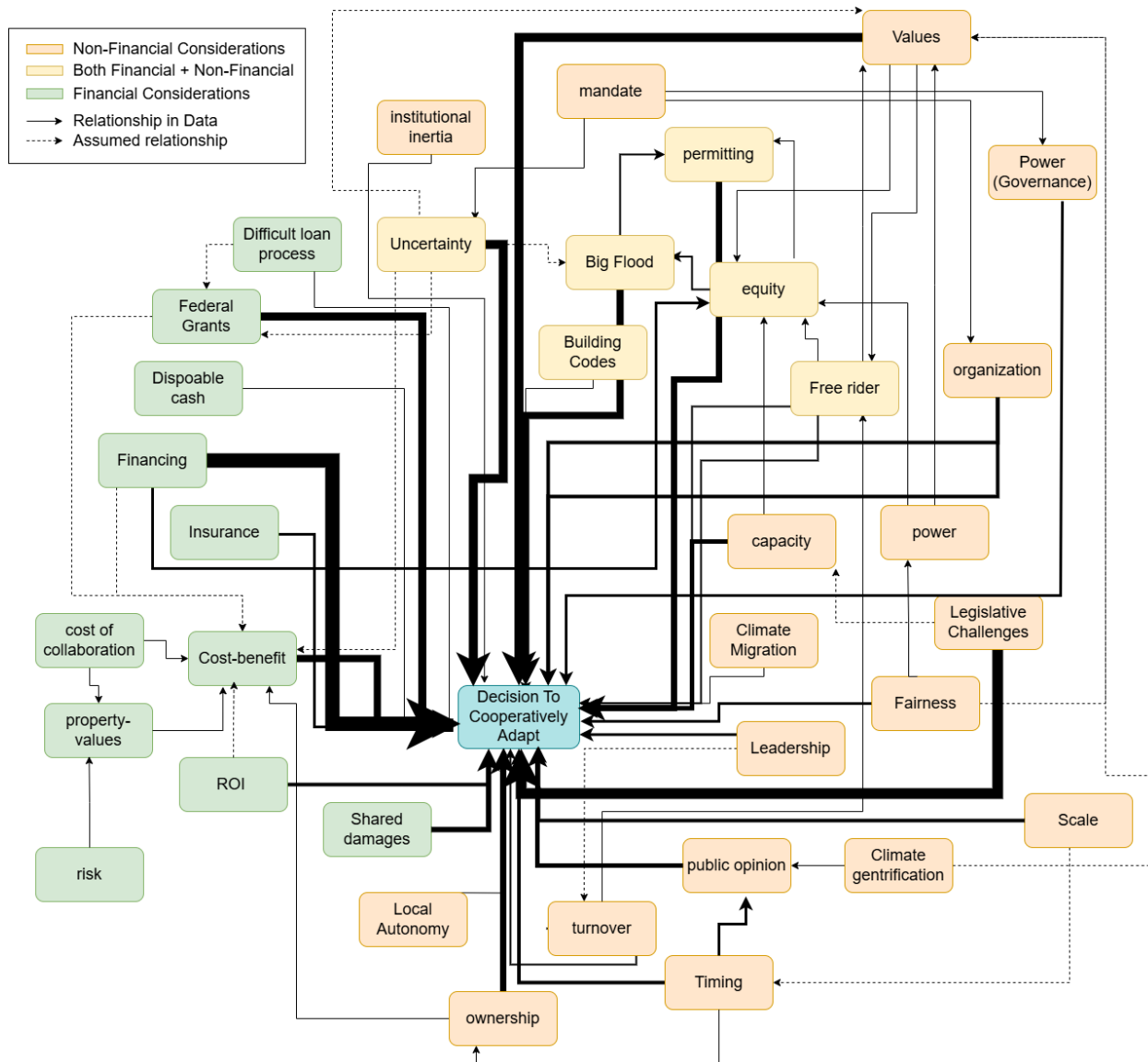


Figure 22. Diagram illustrating all relationships influencing the decision to cooperatively adapt, assembled from both the focus group and stakeholder interviews. Blocks in green represent purely financial considerations, while blocks in orange represent non-financial considerations. Yellow blocks contain both financial and non-financial elements. The thickness of the arrow is scaled to represent the frequency with which each relationship was discussed. Assumed/implied relationships (given the interviews context) are represented with the dotted lines, while the solid lines were explicitly mentioned in transcripts. Rather than using word frequency to assess frequency, each relationship was coded by hand to ensure accuracy and limit double counting of the same word within the same participant response

Uncertainty and Values

Two highly connected concepts in Figure 22 above include uncertainty and the role of values.

While our experts discussed uncertainty most frequently in the context of financial contributions,

it extends to uncertainty in coastal futures and coalition behavior. One expert this concern as “*the one thing that property owners and developers rely on or want more than anything is certainty.*”

In the absence of certainty, values are often used to drive decision-making. For example, we will never know the perfect structure of cooperation in advance, but cooperation may still be a beneficial and resilient strategy. While value alignment could be a strong incentive to agree to cooperative arrangements, one expert also pointed out the risks that strong values can pose to coordination:

“... in all these different groups who have different missions or different values overall, does it seem like there really is that desire, interest to work together?”

Determining a position on cooperative SLR adaptation will require balancing potentially conflicting values for financial and non-financial considerations.

4.4.4.1 The Choices: Regionalization, Networked Cooperation, or General Cooperation

In this dissertation, we proposed two possibilities for cooperation in coastal adaptation: regionalization or voluntary coalitions. In a regionalized system, power and financing are consolidated and centralized, and a new authority would mandate how multiple agencies and actors interact and adapt to coastal flood risk. In a system of voluntary coalitions, such an authority is either not necessary, or only has a loose organizational role, and would not require mandated participation (more closely aligned to a networked or polycentric governance structure (Bednar & Henstra, 2018; Lubell & Robbins, 2022; Ostrom, 2017)). Although many of our interviews revealed that our climate experts often had nuanced perspectives, we categorized interview transcripts according to comments coded to indicate demonstrated preferences for regionalization

or voluntary coalitions. In total, 17% of interviews are categorized as demonstrating a largely neutral, with 67% demonstrating support for a regional authority, 8% categorized by support for voluntary coalition, and 8% unspecified. Many of our study participants commented on both structures, but they were categorized according to their most frequent or supportive comments. Because participants were not directly asked which governance regime they prefer, these labels were assessed based on the specific comments within the interviews.

Neutral Preference:

Statements supporting a neutral preference are characterized by unequivocal support for the concept of collaborative solutions, but without an obvious lean towards regionalization or voluntary coalitions as the preferred or most beneficial strategy. As one participant noted, *“getting the governance right, getting the structure right is really important.”* Additional comments supporting this approach towards cooperation include: *“I think there's something that's very interesting to explore in between voluntary cooperation and centralization.”*

Our interviews highlighted the perceived benefits from cooperation among adaptation experts in the Harbor, notably potential improvements in timelines to construct adaptation and reductions in burdens created by a difficult and convoluted permitting process. Additionally, experts raised concerns about the contrast between the need for adaptation imminently and the time it may take to create and move forward with collaborative solutions, asking *“What happens in the interim?”* Another expert questioned the centralization problem, unsure if a centralized authority with decentralized contracts would out-perform a fully decentralized system. Overall, the neutral narrative is characterized by questions and curiosity; experts raised consistent questions about the structure and responsibilities from any collaborative institutions that may emerge.

The decision to form a voluntary coalition:

“What we've been able to do at a voluntary level is both extraordinary and insufficient...”

In contrast to the centralization of SLR adaptation into a regional authority, there is a possibility for voluntary networked management structures to occur. When voluntary action works, it can be a resilient and self-reinforcing governance structure, which is reflected in one expert's comments about experiencing successful voluntary cooperation in past jobs and their preference for such a structure. However, comments like this make it difficult to disentangle the desire for voluntary cooperation from many of the values underpinning a preference to cooperate on collective action problems. This can create an interesting challenge: while it may be difficult to argue against the ideas of climate adaptation democratization and meaningful collaboration, the current governance systems are not set up to encourage this kind of governance, which instead often reward free-riding behavior.

The preference for voluntary cooperation is characterized largely by a preference, behavioral, or value-based decision-making process. One expert explained that *“I do think that up here in this area, we, we collectively want to work together as much as possible. Now that means money and authority and timing and things like that. But ... all the essentials I think are in place for collaboration.”* Participants also explained that although shared asset protection encourages cooperation, there is still a need for some governance structure that assigns responsibility to a central agent.

There are multiple incentives for voluntary action over the creation of an entirely new flood adaptation authority, which would require endowing the flood authority with the power to fund, design, and implement coastal adaptations. One expert explained the tension that can exist between

regional and local agendas by referencing a separate project where a centralized authority failed to manage a beach nourishment project. They described the community's frustration that the authority had not done enough to support them, leading the community to seek control over the project. Additionally, the experts noted that there are numerous challenges to creating a new regional authority, which leaves voluntary coalitions as a more flexible and agile governance strategy. Our experts independently noted that *"figuring out the structure of a single new organization is really difficult," "the regional authority could get completely bogged down in the legislature,"* and *"it is not quick to create new organizations, staff new organizations, finance new organizations."*

In summary, the narratives about voluntary coalitions often incorporate normative values about the benefits of cooperation, emphasize the aspects of community control and flexibility offered by voluntary coalitions, and highlight that this model of governance may be easier to implement given the current political and institutional systems in Boston Harbor. However, despite interest in the idea of voluntary action across the experts, they also mention legitimate concerns about the effectiveness of such a coalition, particularly one without a key facilitator role that may be necessary to resolve permitting and financial challenges.

The decision to regionalize:

"Only a regional authority is going to get us there. I'm, I am sure of that."

The argument for a regional flood authority centers around streamlined financing and permitting, accountability through legislative mechanisms, improved governance capacity, and the ability to overcome the free-rider problem. Many of the experts referred to their knowledge of the Big Dig project, which exposed both the need for a strong authority and the challenges of projects at scale.

Many of the arguments made for regionalization praised what the Harbor has managed to achieve on a voluntary scale to-date but suggest that an authority is necessary to adapt at the scale and pace required for the current risks facing the basin.

As explored earlier, both permitting and financing were identified as some of the most significant barriers to cooperative adaptation in Boston Harbor. Many of our experts felt that a regional authority could be well-positioned to overcome these barriers, stating that *“it would be great if there was a authority that could not only lay out the requirements, but also help coordinate the permitting”* and *“a voluntary partnership will not allow you to borrow money.”* Another expert indicated that one reason a regional authority may be able to effectively overcome the financing problem is that *“there has to be some ability to levy some kind of a tax on something how do you raise some money and then allocate some for the state, for the budget?”* and that the process is more straightforward under a centralized power than through voluntary coalitions. Another expert also noted that such an authority may have the ability to issue bonds to fund adaptations at scale.

One of the most frequent explanations for an expert’s support for regionalization is the ability for such an authority to be written into law, endowed with a specific purpose and authority to plan and implement adaptations. In particular, one expert notes that *“it’s a lot easier to get people’s attention if [an organization] has mandated that I do this thing, so therefore you need to talk to me about this corrective action.”* Our interviews revealed significant reflection on how such an entity could be codified, with one expert going so far as to say *“they need to have more power given to them ... by the legislation, by the governor, whoever is the authorizing legal body.”* Interviews revealed that questions about capacity, power, and responsibility for a regional authority

are closely intertwined, in particular, asking “*who can do this for the core maintenance of work in a bunch of different environments and a bunch of different municipalities?*”

Our participants also acknowledge that often, adaptation in Boston Harbor may be delayed by a lack of capacity, particularly for smaller agents who may not have the staff, financing, or resources to focus on coastal adaptation. As one participant noted, municipalities do not have sufficient staff to allocate extra resources to cross-boundary projects, so to be feasible, cooperative adaptation structures must have independent staff at the minimum.

One of the challenges facing any collective action problem is the notion of a free rider: an agent who benefits from a collective solution without paying into the solution, and therefore reducing the incentive for anyone to participate. While certain institutional structures and community values may reduce free riding behavior, the participants expressed concern about free riding behavior in the absence of mandatory regionalization plans. The interviews reflected this concern, as participants raised this as an issue that they had experienced in their own careers. In particular, one expert mentioned that free riding only gets worse as individuals move in and out of the system, reducing the effects of previous trust or commitment to cooperative behavior. One quote mentioned: “*How do you deal with a free rider issue, the fact that there are people who will benefit, who figure, why should I cooperate if my neighbor is going to cooperate?*”

Support for the creation of a regional authority covers multiple potential benefits of regionalization: streamlined permitting, increased access to financing, reduced risk of free riding behavior, and improved capacity. However, experts acknowledge the challenges posed to creating such a new institution within the existing adaptation ecosystem in the Harbor.

4.4.5 Interactions (communication, feedback, flow of info)

Given the history of large-scale infrastructure projects, Boston Harbor has much of the groundwork for regional cooperation in place already. Future collaborative structures will benefit from the current interactive processes between actors, although cooperation will require the development of additional mechanisms to reinforce cooperative behavior and develop venues for decision-making across scales. Our climate experts referenced projects from the Mystic Watershed Association, the Metro Mayors Climate Taskforce, Boston Harbor Now, and the MWRA as examples and processes that currently encourage cooperation, interaction, and dialogue between multiple actors in the region. For example, both Boston City and the state of Massachusetts provides information and models on sea level rise risks and flood pathways that multiple organizations utilize for climate resilience planning. Additionally, organizations such as the Environmental Business Council or initiatives from the Governor's Office encourage interaction and discussion on a number of topics, SLR adaptation included. A few our of participants also elaborated on the potential of public-private partnerships within Boston Harbor to engage private and public sector actors within the existing structure.

One shortcoming of these interactions is that despite best efforts, individuals or specific communities may still be left out of these interactions. Our participants noted that this is true particularly for stakeholders who may not have the time, education, or resources to focus on SLR adaptation despite living in at-risk communities. Additionally, if there is significant turnover of property owners or elected officials, interactions may be diminished and there is little way to ensure consistent engagement in a cooperative structure across a changing actor-set.

4.4.6 Outcomes

Major outcomes can be separated into two categories: outcomes pertaining to cooperative agreements and outcomes pertaining to adaptation implementation. Although the outcomes of adaptation implementations can be summarized as the SLR adaptations they construct, ‘success’ can have significantly different meanings to different stakeholders. Setting clear evaluative criteria that is supported with consensus is therefore a necessary first step to aligning institutional goals and outcomes in the Harbor and could build on science-practice interaction (Arnott et al., 2016).

4.4.7 Evaluative Criteria

SLR adaptation can be evaluated in multiple ways, including: damage reduction, flood protection level, timing of adaptation, degree of cooperation, or by environment and equity objectives. (Goonesekera & Olazabal, 2022) explored how there is often a mis-match between adaptation goals and the metrics used to assess outcomes in cities around the world. Our stakeholders reiterated the importance of evaluative criteria for cooperative adaptation, highlighting that the way in which adaptation success is measured and reported could have critical implications for the success of SLR adaptation in general, but particularly for cooperative adaptation. In particular, clear criteria is are important because *“everyone is always going to have their opinion about what are the right outcomes”* and clear objectives and goals will help to assess project success.

Additionally, adaptation outcomes are closely entangled with environmental justice, climate gentrification, and equity concerns within any community (Coggins et al., 2021; Peck et al., 2022). Equity was a common topic brought up by participants, with one explaining that *“the prioritization issues, particularly around equity, are of certainly great importance to us.”*

Even once equity is explicitly established as a goal of adaptation, measuring and assessing ‘equitable adaptation’ poses new challenges, as one expert stated: “*whether it be the high cost of living crisis or the climate crisis, it's very hard to set equitable goals.*” One expert noted that there are also different levels of tolerance or resilience to flooding, noting that for example, in Miami, some can continue their normal lives during sunny day flooding, while others ‘*are not privileged enough to be able to wade down the street... effectiveness and fairness are kind of tied together.*’ However, coastal adaptation can also be designed to promote equity, particularly if equity is considered through distributive, procedural, systemic, and recognitional lenses (Bremer et al., 2021; N. Fox et al., 2023).

One additional component to evaluative criteria is public opinion towards adaptation projects. While a less conventional metric, maintaining positive public opinion has repercussions for future adaptation works and willingness to cooperate due to the feedbacks between public opinion and the policy agenda.

4.5 Discussion and Conclusion: New Institutions may be Possible

Within many collective systems, it is commonly accepted that cooperation (mandated or not) will lead to better outcomes (Kalesnikaite, 2019). Within this dissertation, we look at both centralized/mandated cooperation (a flood authority) and the formation of voluntary adaptation coalitions. There are multiple trade-offs between each formulation; while the voluntary coalitions are always at risk of free-riding behavior, a flood authority requires extensive policy groundwork. While both governance approaches offer avenues for potential cooperative adaptation, successfully preparing for such a future requires the Harbor region to commit to either voluntary cooperation

or a Regional Flood Authority. Because each structure corresponds to different institutional changes, early commitment to a long-term plan is critical.

This chapter sought to use our interviews about representing climate adaptation in Boston Harbor to answer two questions in addition to directly influencing model choices. These questions are: 1) What are the largest institutional challenges to cooperative adaptation in Boston Harbor? And 2) how could a formalized regional flood authority shift the institutional landscape for cooperative SLR adaptation in Boston? In particular, the first question tied directly into informing the previous models, and the second contributes to the research gap that exists on stakeholder perspectives towards cooperative adaptation solutions in Boston. Additionally, by using multiple methodologies to study cooperative adaptation, we hope that this real-world context can provide additional valuable context to the findings of the previous chapters.

While the original purpose of interviewing climate adaptation experts was to identify barriers and incentives to cooperation that should be present in our models, the qualitative data we received also highlighted the challenges with existing adaptation institutions in Boston. Participants identified barriers to each form of cooperation that they felt should be included in the model (rules-in-use), which informed many changes to the model itself (more expansive representation of permitting challenges, for example). However, their reflections on each form of governance needed to be discussed separately, as the comments could not all be directly incorporated.

Their commentary indicates that changes to current institutions could incentivize collaborative adaptation. Some of these changes exist as external systems, such as the required permitting process. Others are more deeply challenging, such as resolving trust issues between different stakeholders and communities. Our findings suggest that climate adaptation experts in

various roles across Boston Harbor demonstrate a *high* awareness of flood risk, which is motivating many of the agents and stakeholders in the area to adapt.

In regard to the second research question, despite the flexibility that voluntary coalitions offer, the experts indicated their belief a regional authority is necessary to achieve effective and resilient flood adaptation. In part, this is due to a perception that a flood authority minimizes risk through mandated action; no single agent may limit adaptation actions or funding availability.

Two organizations that may offer insight to how to manage regional coordination in Boston are the Massachusetts Water Resources Authority (MWRA) and the Massachusetts Bay Transportation Authority (MBTA). As stormwater fees may provide a model for how to regionalize and fund climate adaptation, the MWRA is often regarded as a possible home for future flood protection mandates (Levy & Herst, 2018). Additional models for a regional authority include how cities (i.e. the City of Boston or New York City) often have decision-making powers for many distinct neighborhoods or boroughs simultaneously. Although climate adaptation is just one small component of a city's daily responsibilities, the consolidation of power to design, fund, and implement adaptations could inspire the design of a regional flood authority. More detailed empirical findings and case studies will be necessary to identify the best organization structure for such a flood authority.

The work presented in this Chapter raises multiple avenues for future work. First, our choice to analyze a very broad 'action situation' is less typical of the application of the IAD Framework, which often selects a very narrow action situation to deeply consider at any given time. Future work could consider more specific action situations and focus on the interactions within, such as the actual meetings where regional cooperation is being debated at the state level. Secondly, there is significant opportunity for follow-up work that engages stakeholders to present

the findings from Chapters 2 and 3 and evaluate how their responses reinforce the findings here or perhaps shift perspectives or reveal new perspectives on the decision to cooperate.

The study participants provided multiple recommendations for both short-term and long-term changes to the institutional framework that exists in Boston Harbor. In the short term, these recommendations include creating novel funding mechanisms that reward cooperative behavior, assessing cooperative interest levels between all organizations, finalizing and communicating a shared flood model across the Harbor that includes damage estimates, and improving adaptation permitting processes. In the longer term, successful cooperation may require activities that focus on trust-building to overcome pervasive concerns of free-ridership, the selection of a final cooperative governance structure, and the selection of appropriate mechanisms to manage property right concerns, such as easements.

Despite the challenges Boston Harbor is facing for climate adaptation, swift action is necessary to avoid future flood damage. Despite the hurdles to achieving successful adaptation, our participants highlight a high awareness of the urgency and a strong desire to have sustainable and successful cooperative arrangements for adaptation in the future. Bridging large-scale city-wide infrastructure with the immediate needs of private property owners is a key next step.

Chapter 5: Managing Uncertainty and Ambiguity in Complex Systems: The Application to Sea Level Rise Adaptation in Boston

Attributions: This chapter would not be possible without the contributions from Ghazal Shabestanipour, Jonathan Lamontagne, and Shafiqul Islam. Much of the initial stages of this work was dreamed up and designed with Ghazal Shabestanipour, and early work on the need to address uncertainty and ambiguity can be found in her dissertation (Shabestanipour, 2024). She contributed extensively to the motivation, framing, and design of the DMUUA approach. Her efforts in early drafts of this work were also instrumental to the final form shown here.

Abstract:

Decision-making in complex systems faces multiple challenges from uncertainty and ambiguity. However, these concepts are difficult to define and many overlapping definitions exist across disciplines. This chapter clarifies distinctions between uncertainty and ambiguity and highlights methods well-suited to manage each. In cases when ambiguity and uncertainty are difficult to disentangle, we propose the Decision-Making Under Uncertainty and Ambiguity approach (DMUUA), which utilizes a synthesis of Decision-Making under Deep Uncertainty (DMDU) and the Engineering Diplomacy Framework (EDF). DMUUA provides a structured way to address uncertain and ambiguous facets of a decision-making problem and that they are appropriately addressed throughout the design of management strategies. We illustrate the need for such an approach, utilizing the case of Boston sea level rise cooperation, and explore both uncertainty and ambiguity pertaining to the quantity of sea level rise and heuristics used to assess a ‘fair’ financial

contribution to a cooperative adaptation coalition. We highlight how the DMUUA approach improves the robustness and legitimacy of decisions in complex systems by jointly managing uncertainty and ambiguity rather than treating them separately. While the implementation depends on the context and decision-makers, the approach has broad applications to any complex systems, including water management, climate adaptation, and public health, among others.

5.1 Motivation and Introduction

In the previous chapters of this research, we focused on providing information to decision-makers as they consider the choice to cooperate. However, we do not provide any guidance as to *how* to actually make decisions to develop policy or management strategies aligned with a cooperative or non-cooperative approach. Unlike the previous chapters, this chapter focuses on the processes of decision-making and adaptation policy development, with applications to other complex collective and environmental challenges.

Decision-makers must grapple with a number of problems when operating in complex systems: these systems are characterized by a large degree of uncertainty (Srikrishnan et al., 2022), there may be conflicting values and viewpoints between decision-makers (Hanselmann & Tanner, 2008), or there may be unknown relationships and feedbacks in the system (Taleb, 2016). These challenges are magnified in systems that require collective action and consensus among many actors. Despite these challenges, many of the world's most pressing problems are complex and often collective: adaptation to climate change, emissions reductions, pandemics, or misinformation spread, as a short list. Properly managing scientific uncertainty simultaneously with the deeply held values of decision-makers and the community will be critical to making any progress towards

effective decision-making. How do we plan and prepare for an uncertain future when we cannot fully predict the challenges that lie ahead and cannot agree on the best way to prepare?

While uncertainty relates most closely to a lack of knowledge (Beven, 2016; de Roo, 2021), ambiguity instead reflects different interpretations of a concept (Oxford English Dictionary, 2023), which often reflects the underlying values of individuals. One rule of thumb is that an uncertainty may have one objective underlying and unknown “truth,” but something that is ambiguous may have many equally defensible “truths” depending on individual preferences (Gilboa & Marinacci, 2016). For example, the amount of storm intensification in the next century is uncertain. However, determining sufficient adaptation for SLR is an ambiguous problem, as it depends on risk tolerance, individual assessments of the notion of ‘sufficient adaptation,’ and preferences for the allocation of limited adaptation capital.

While simple in that case, in practice, uncertainty and ambiguity are deeply related and disentangling them can be very difficult, posing problems for effectively managing their impacts on decision-making processes. In many situations, it may be difficult or impossible to clearly identify where uncertainty ends and ambiguity begins. If an ambiguity is improperly identified and ‘managed’ as an uncertainty, then the real (and potentially) hidden impacts of the ambiguity on decision-making may pose risks to long-term public support of any policies. In the short term, this may lead to the ultimate failure of resolutions before they ever leave the negotiation space due to irreconcilable differences between stakeholders. If a decision-maker determines an incorrect categorization, the risks of never reaching widespread support for policies increases. While methods and frameworks for individually managing uncertainty or ambiguity have made critical contributions and advancements to the management of complex systems, less attention has been

paid to managing both simultaneously. This will require synthesizing existing methodologies designed to target uncertainty and ambiguity individually.

The objectives of this paper are thus to understand why ambiguity and uncertainty have become so entangled in decision-making literature and to offer an approach that acknowledges that complex problems will require addressing both simultaneously. This paper focuses on answering the following questions: What are the variety of definitions and distinctions between the terms ‘uncertainty’ and ‘ambiguity’? What are the risks of not appropriately addressing uncertainty and ambiguity? What frameworks offer potential to simultaneously manage uncertainty and ambiguity?

This paper is divided into three major sections. In the first, we provide a short literature review of key papers that define uncertainty and ambiguity in decision-making. In the second section, we introduce a complex system (sea level rise adaptation) and a synthesis of two frameworks designed to manage uncertainty, and ambiguity, respectively. In the final section, we explore how such an approach strengthens uncertainty and ambiguity management in complex decision-making, particularly when it may be hard to clearly categorize a consideration as either an uncertainty or an ambiguity.

5.2 Classification

To appropriately manage uncertainty and ambiguity, we first need to provide a distinction between the two concepts and have a basic understanding of appropriate methodologies to manage each. The next section details common definitions of the terms ‘uncertainty’ and ‘ambiguity.’ First, we trace the usage of each term and then we will review two frameworks commonly used to manage them.

5.2.1 What is uncertainty?

Uncertainty, at its core, refers to something that is not known. However, the breadth of that definition means it is less useful for practical applications (such as assessing the uncertainty of a specific parameter in a climate model or the exact impact of the choice of radiative forcing equation used to capture climate change), which has led to the development of categories and sub-types of uncertainty. In foundational work on uncertainty, Knight and Keynes established the difference between risk and uncertainty (Keynes, 1921; Knight, 1921a). Risk (Knight, 1921b) is defined as uncertainty that is typically well characterized and relatively easily quantifiable (even if the true parameters are unknown). Uncertainty, however, is described as something that is quantifiable in theory, but our lack of knowledge makes it impossible. Concepts of Knightian uncertainty remain extremely relevant in modern uncertainty frameworks.

Since the distinction between uncertainty and risk, the proliferation of definitions for uncertainty has increased specificity, but also created conflicts and confusion between authors and academic fields. Even the simple definition of uncertainty as ‘limited knowledge’ has raised concern, with some authors pointing out that a lack of knowledge is not the root of uncertainty, as increased knowledge may illuminate more potential gaps in our knowledge, supporting an alternate definition as a lack of determinism (Kwakkel et al., 2010; van Asselt, 2000). Other contradictions may be more nuanced. For example, while the multi-sector dynamics community defines structural uncertainty as “uncertainty in the mathematical and/or rule-based representation of processes within a simulation model” (Srikrishnan et al., 2022), Jackson, et al uses a catch all for structural uncertainty, defining it as all uncertainty exclusive of either parametric or methodological uncertainty (Jackson et al., 2011).

Alternative definitions of uncertainty that focus on a more specific uncertainty theory include: deep uncertainty (uncertainty where the underlying probability distribution, processes, or model are unknown or cannot be agreed upon) (R. J. Lempert, 2003), or narrower conceptualizations of uncertainties such as parametric, sampling, normative, or scenario uncertainty (Van der Keur et al., 2008). Some of these definitions and interpretations may be application specific, such as those described by Meijer, et al. (2005) on organization development and innovation literature (Meijer et al., 2005). Others, such as structural uncertainty (as described in (Refsgaard et al., 2006)), are more universal and often recognized across disciplines and applications. Finally, some of these definitions incorporate values and uncertainty concepts, leading to the development of literature on normative uncertainty (more on this concept later) (Dietrich & Jabarian, 2022).

Uncertainty typologies (to distinguish between the nature or manifestation of uncertainty) were originally designed to reduce confusion and improve our ability to understand how different facets of uncertainty affect decision-making. Existing literature has compared various characterizations of uncertainty and frameworks for managing them (Bevan, 2022; Krupnick et al., 2006; Kwakkel et al., 2010; W. E. Walker et al., 2003). In their review of uncertainty frameworks, for example, Bevan, et al. (2016) demonstrate how some authors may categorize uncertainty according to the aleatoric/epistemic divide, levels of uncertainty, the location of uncertainty, the level of cognizance about uncertainty, or the role that human values may play in uncertainty categorization (Bevan, 2022). In one particular approach, Walker, et al. (2003) emphasize the categorization of uncertainty types along similar dimensions: the location of uncertainty, the level of uncertainty, and the nature of uncertainty (W. E. Walker et al., 2003). This matrix allows the author to propose categories for model structure uncertainties, model technical

uncertainties, statistical (measurement) uncertainty, scenario uncertainty, epistemic uncertainty, and variability uncertainty, among others. Kwakkel, et al.'s (2010) later work demonstrates how this framework has been incorporated and adjusted by various authors to better suit their specific needs or applications (Kwakkel et al., 2010). However, developing a single useful typology of uncertainty to improve complex decision-making continues to be a contentious topic of academic debates across disciplines, domains, and sectors (W. E. Walker et al., 2012).

One of the most utilized and accepted distinctions when discussing uncertainty is the difference between aleatoric uncertainty (uncertainty due to randomness) and epistemic uncertainty (uncertainty due to a lack of knowledge). This is a broad typology, but allows for a user to separate two fundamentally distinct uncertainty types. If we consider the coastal adaptation example as an illustration, projections for sea level rise by the end of the century provide a range of possible annual maximum flood heights depending on assumptions about increasing storm intensity and mean sea level rise. Mean SLR in 2100 is an epistemic uncertainty, while the specific flood that occurs in a year is aleatoric uncertainty. Epistemic and aleatoric uncertainty have different implications for modeling and decision-making and require very different approaches to manage (de Roo, 2021). The challenge of uncertainty is that we can assess it and estimate it, but we cannot eliminate it, particularly for any aleatoric uncertainty.

Although the previous contributions towards understanding uncertainty (highlighted in the paragraphs above) have made significant progress towards clarifying concepts of 'uncertainty', much overlap remains. For example, the definition of 'deep uncertainty' shares some characteristics with some types of ambiguity, particularly when 'deep uncertainty' is applied for situations where decision-makers cannot agree on relative probabilities of outcomes. Similarly, model uncertainty (Nilsen & Aven, 2003), structural uncertainty (Bojke et al., 2009), and epistemic

uncertainty (Beven, 2016) often can be applied to the same uncertainty (for example, the best way to mathematically represent sea level rise or future weather patterns in the levee case).

This has contributed to a lack of consensus and practical guidance for how to address uncertainty in a cohesive way for collective action problems within a framework (Dequech, 2000; Norton et al., 2006). This is in part due to the extremely diverse range of concepts that can be considered as part of the uncertainty umbrella; resolving all facets of uncertainty with the same methods or approaches appears to be an impossible task. In the following paper sections, we will explore epistemic and aleatoric uncertainty in contrast to ambiguity, highlight one approach for managing uncertainty, and illustrate why managing uncertainty may benefit from consensus-based approach. In particular, we will not focus on detailed identification of the categories of uncertainty discussed in this review, instead focusing only on the aleatoric/epistemic uncertainty divide. Although the more specific categorizations of uncertainty are beneficial for explicit uncertainty quantification, these broader categories are more appropriate for designing generalizable processes and knowledge.

5.2.2 What is ambiguity?

It is not a novel concept to state that not all uncertainties can be quantified. Ellsberg (1961) notes that there are cases where the nature of uncertainty is such that alternative and non-probabilistic representations of uncertainty may be required, echoing calls from previous authors (Ellsberg, 1961). Similar ideas underpin definitions of Knightian uncertainty or subsets of deep uncertainty. Despite the numerous names and definitions, they tend to share a few similarities: these ‘uncertainties’ are not easily quantifiable, they can be rooted in strongly held values, and are often open to multiple interpretations. We use ambiguity as a broad category to discuss issues when there are multiple, potentially conflicting objectives or values that need to be balanced, and there is no

clear agreement on the correct interpretation. These uncertainties are characteristically different from epistemic and aleatoric uncertainty, as they involve subjective judgments and there will never be one finite ‘truth’ or outcome that is correct. The root source of ambiguity is in value and interpretation, while uncertainty is rooted in knowledge (or more accurately, the lack thereof).

Ambiguity may arise when different stakeholders have competing interpretations, or values that are not easily resolved by data alone. Schrader, et al. (1993) note that the level of ambiguity may also vary from case to case, depending if the problem solver accepts relevant variables or their relationships as determined (Schrader et al., 1993). While multiple objective approaches (Bonham et al., 2022) may be able to address simple problems of ambiguity, multi-objective robust decision-making (MORDM) may not always be sufficient to resolve complex ambiguities where a pareto front is difficult or impossible to conceptualize.

Similar to the challenge of identifying a unifying definition of uncertainty, ambiguity is difficult to define concisely and universally. For example, one conceptualization of ambiguity is as a situation where there is uncertainty about probabilities, where the uncertainty may be resolved with further information (Camerer & Weber, 1992; Dequech, 2000; Einhorn & Hogarth, 1986). However, by focusing on the need for further information, the aspects of ambiguity related to equally valid interpretations of an unknown can be overlooked. In this regard, Dequech (2000) argues that this definition of ambiguity may be a shortcoming, as it is considered resolved when applying simple assessments of perceived risks on extreme events, which may not be sufficient. Interestingly, this definition also aligns quite closely with the definition of deep uncertainty (Dequech, 2000; R. J. Lempert, 2003). A competing understanding, which we borrow from, is the unknown elements that cannot be quantified, as their outcomes depend on equally defensible,

contrasting interpretations (Oxford English Dictionary, 2023) (typically the ‘human’ elements, as opposed to the scientific).

Clearly identifying the line between uncertainty and ambiguity can be difficult. Many elements of ambiguity are also closely related uncertainties about human values and behavior such as: normative uncertainty (MacAskill, 2014; Meiler et al., 2024; Taebi et al., 2020), institutional uncertainty (Bylund & McCaffrey, 2017), behavioral uncertainty (Krishnan et al., 2016), political uncertainty (De Figueiredo, 2002), among others. Spiegelhalter and Reisch (2011) consider some of these ‘qualitative understandings of uncertainty,’ explained by political, social, and personal responses to the unknown (Spiegelhalter & Riesch, 2011). In particular, the boundaries between epistemic uncertainty and ambiguity may be fuzzy and are context-dependent, such as in the case of structural uncertainty in model development. For example, a structural uncertainty could include uncertainty around the decision-making process that individuals actually use (reflective of the four mechanisms we implemented in Chapter 3). However, the preference of an individual to use one of these influences in their own decision-making represents an ambiguous problem.

Despite the challenges of separating problems of ambiguity from problems of uncertainty, acknowledging how ambiguities may affect decision-making is a necessary step for designing interventions in complex systems. One outcome of ambiguity is the presence of multiple problem formulations or rival framings (Quinn et al., 2017), which may vary between individuals. Additionally, ambiguity can result in conflict when compromise is difficult to achieve. For example, determining an ‘acceptable’ level of flood risk involves normative judgments about whose interests to prioritize. Should the levee be designed to protect the most vulnerable communities to an unlikely threshold, even if draws money from other sources? What if risk is felt differently between communities?

The challenges of ambiguity may also be exacerbated when cognitive processes may influence how individuals assign their perceived risk and preferred responses for climate change (Weber, 2016). For example, some cultures may demonstrate strong preferences for certain types of adaptation due to strongly held beliefs, reflecting the impact of ambiguity (Noll et al., 2020). In this case, even narrowing our uncertainty bands of climate change may not be sufficient to build consensus.

Addressing these ambiguities requires conversations and consensus-building, rather than just technical fixes. An uncertainty-focused approach would only highlight the impact of ‘guessing wrong,’ while an ambiguity-focused approach specifies how to shape decision-making regardless of conflicting values and uncertain elements. Without embedding uncertainty within a broader context of ambiguity, decision-makers run the risk of destabilizing agreements and policy planning by having no mechanism to move from uncertainty analysis to decision-making, where conflict resolution processes are necessary.

5.2.3 What are the differences between epistemic uncertainty, aleatoric uncertainty, and ambiguity?

Section 2.2 highlights some of the possible overlaps between uncertainty and ambiguity. Despite these overlaps at a fine scale, we still make a case for decision-makers to attempt to distinguish between epistemic uncertainty, aleatoric uncertainty, and ambiguity at a high level initially to understand if the root of a problem is due to knowledge or to values. In some straightforward contexts, only one may need to be addressed at a time. Understanding the differences between uncertainty (both epistemic – originating from a lack of sufficient knowledge— and aleatoric – originating from randomness) and ambiguity can help a decision-maker to pick uncertainty

analysis and quantification tools best suited to their needs. Identifying the whether a challenge is grounded as an uncertainty or as an ambiguity may require initial stakeholder engagement and assessment among decision-makers. For example, while epistemic uncertainty is reducible with better knowledge, aleatoric uncertainty is never reducible to zero and ambiguity is only reducible through negotiated processes. Given this, a feasible treatment for incorporating aleatoric uncertainty could be increased simulations, Monte Carlo processes, or the development of ensembles for robust decision-making (R. J. Lempert, 2019). However, the same methods would not be sufficient to resolve problems of ambiguity, which may require more effort and time to resolve.

Attempting to fully resolve a problem of aleatoric uncertainty could be a waste of limited resources, while focusing on an epistemic uncertainty instead of ambiguity has the potential to derail decisions when conflicts are present. The methods that we use to manage uncertainty and ambiguity are quite different; while uncertainty has long been addressed with modelling or simulation-based approaches, such as robust decision-making, info-gap, etc., ambiguity requires skillsets rooted more strongly in diplomacy and consensus-building literature to manage. Table 6 below begins to separate out some key differences between uncertainty and ambiguity. This table is adapted from work previously completed by Islam & Smith.

Table 6: Comparison of epistemic uncertainty, aleatoric uncertainty, and ambiguity

Characterization	Uncertainty		Ambiguity
	Epistemic	Aleatoric	
<i>Reducible?</i>	Reducible With better knowledge	Not reducible	Given a specific context through negotiated processes
<i>Who can resolve it?</i>	Knowledge communities (modelers/engineers)	Knowledge communities (modelers/engineers)	Relevant Stakeholders

<i>Mostly Quantifiable?</i>	Within a set bounds or structures	Within a pre-determined set of probabilities	Not usually
<i>Applicable methods and tools</i>	Decision-making under deep uncertainty, Robust-Decision Making, Scenario Discovery, etc.	Stochastic simulation, probabilistic risk assessment	consensus-building, diplomacy
<i>When are these accounted for?</i>	Model design, iterative processes	Model simulation	Problem definition, model design, interpretation

5.2.4 The Classification gets messy

Although the table above seems to clearly be able to separate these three concepts, in reality, their overlap is much less obvious for a few reasons. While we touched on the overlap before, we wish to expand on the discussion further. The overlap of definitions is messy, and based on some interpretations of ambiguity or uncertainty, the same concept could be considered as one or the other by different people, depending on which academic discipline they draw from and how these terms are used.

Even settling on terminology for use in this paper proved a challenge, given the depth of the literature that addresses uncertainty. For example, theoretically-quantifiable epistemic or aleatoric uncertainty could be referred to as deep uncertainty (R. J. Lempert, 2003; W. E. Walker et al., 2012), knowledge-based uncertainty, or unknown knowns (Rumsfeld, 2002), among others. Something that may be fundamentally unquantifiable and value-based could be considered normative uncertainty, deep uncertainty (again), or ambiguity (Oxford English Dictionary, 2023).

Because each term has a rich history with possibly overlapping applications and definitions, we use the terms uncertainty and ambiguity to differentiate between knowledge-based and value-based unknowns, although readers may prefer using other vocabulary to refer to the same concepts. We use these terms not to override decades of work, but rather select this

vocabulary due to its brevity and accessible nature to readers across disciplines. Here, we define uncertainty as a lack of knowledge that in theory is quantifiable, where there is eventually one outcome that will come to occur. Ambiguity instead is the state of multiple, equally-defensible interpretations of the same information, where the differences are not quantifiable and there is no single correct interpretation, as the variation is due to values or preferences. No amount of modeling or scientific study can resolve ambiguity.

Similar to unclear definitions, ambiguity and uncertainty in the real-world may also not be well-characterized or behaved. Occasionally, uncertainties or ambiguities may masquerade as each other or may be closely connected. For example, while many politicized scientific topics are questions of uncertainty (How bad will SLR be? How will flood patterns shift?), they become questions of ambiguity as they relate to deeply held values and perspectives on political priorities. From a SLR adaptation perspective, this may account for the impact that political affiliation has in differentiating responses to flooding and other natural disasters between individuals identifying as Democrats or Republicans in the United States (Botzen et al., 2016; Nguyen & Jud, 2025).

Every complex system will have components that are uncertain and components that are ambiguous, which makes it difficult to strictly apply methodologies that are designed for one or the other. This is particularly true when it may not be possible, or useful, to fully separate their impacts. Instead, an approach that simultaneously emphasizes appropriately identifying and managing uncertainty and ambiguity while also providing useful insights to their interactions is necessary. As a secondary benefit, such a combined approach may provide opportunities to generate mutually beneficial solutions even if an uncertainty or ambiguity is miscategorized in initial stages. The following sections will introduce a synthesis of existing methodologies that will

fulfill these objectives and apply it to the case of SLR adaptation considered in all previous dissertation chapters.

5.3 Uncertainty and Ambiguity in Decision-Making

Managing what is obviously uncertainty or obviously an ambiguity can be straightforward in a highly constrained context (for example, uncertainty quantification only); the problem arises when it may be difficult to identify which is a better fit or when there are significant feedbacks between uncertainties and ambiguities. When this occurs, an approach that synthesizes multiple methodologies is needed. Without such an approach, decision makers run the risk of selecting options that are either not robust to many possible futures or might struggle under a lack of public support.

5.3.1 A Synthesis of Methodologies

To navigate the dual challenges of quantifiable uncertainty and ambiguity, decision-makers need an approach that combines rigorous scientific methods with flexible, participatory problem-solving approaches. This is where we propose a synthesis of Decision-Making Under Deep Uncertainty (DMDU) with the Engineering Diplomacy Framework in what we refer to as the Decision-Making Under Uncertainty and Ambiguity (DMUUA) approach. Instead of proposing an entirely new method or manner to handle uncertainty and ambiguity, we hope to draw on the strengths of existing methodologies to appropriately manage each. DMDU primarily focuses on managing multiple types of uncertainties through robust modeling and scenario planning, while the Engineering Diplomacy Framework (EDF), emphasizes stakeholder engagement and negotiation to address ambiguity. By synthesizing data-driven methods to manage quantifiable uncertainties with participatory processes to address ambiguity, DMUUA provides a methodology

to design socially acceptable, economically viable, and politically feasible resolutions to complex challenges.

The most promising way to embed DMDU into the EDF is within the processes of joint fact-finding (JFF), included as a distinct step within the EDF. Susskind, et al defines joint fact-finding as: “collaborative efforts to generate information in a manner that allows stakeholders to agree on (1) the question(s) they want to answer; (2) the best ways of answering these questions; (3) the data they need to collect; (4) the ways they are going to analyze and interpret those data; and (5) the strategies they are going to use to share what they discover with others likely to be affected by decisions or actions informed by what has been learned” (L. Susskind et al., 2016). DMDU methods were developed to aid in steps 1-4 of this process, with particular attention to how to plan for requisite uncertainty. However, DMDU framings may also be useful in additional stages of the decision-making process, such as in testing possible proposed solutions during negotiations.

We will highlight why this is necessary in the context of SLR adaptation in Section 4. Using such an approach that identifies and addresses uncertainty and ambiguity explicitly ensures that even if the two are closely entangled, they can be identified and managed.

5.3.2 DMDU Approach for Uncertainty

While some uncertainties are well-characterized (risk), many of the uncertainties in complex systems like climate systems are more severe. One of the most well-known approaches for managing more severe uncertainty is Decision-Making Under Deep Uncertainty (DMDU). DMDU methods have been developed over the past decade to manage uncertainties “where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that

describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes” (R. J. Lempert, 2003).

DMDU has particular applicability to fields such as climate adaptation or water management (Bloemen et al., 2019; R. Lempert, 2025), which are characterized by diverging models and vulnerability to uncertain futures (Marchau et al., 2019). DMDU approaches, such as Robust Decision-Making (RDM), scenario discovery, and Dynamic Adaptive Policy Pathways (DAPP), are particularly well-suited for managing epistemic and aleatoric uncertainty (Dewar, 2002; Marchau et al., 2019). In the case of sea level rise adaptation, these tools can help decision-makers identify adaptation designs that are adaptive and robust for a number of potential futures. Some DMDU literature details the application of DMDU practices in practice, including the work on the Dutch Delta Programme, the Hutt River in New Zealand, and the Thames River in London, England (Bloemen et al., 2019; Haasnoot et al., 2013; Hall et al., 2019; Lawrence & Haasnoot, 2017).

While DMDU has been wildly successful at encouraging the adoption of new procedures to manage the impact of uncertainty (Groves et al., 2021), there is a lack of formalization of how to best incorporate DMDU in policy generally. In particular, future challenges to the application of DMDU include how to best integrate DMDU methods within larger contexts of decision-making, including social, cultural, and political systems that the decision-making is embedded within (Marchau et al., 2019; Stanton & Roelich, 2021; Van der Brugge & Roosjen, 2015). This may be part of the challenge to the uptake and implementation of DMDU methods (Malekpour et al., 2016).

There is no question that DMDU methods provide approaches that allow for the selection of robust or adaptive strategies to manage uncertainty. However, the methods may fall short of being able to resolve questions of ambiguity. In particular, the portion of the definition ‘parties to a decision cannot agree on’ suggests a need for more developed methods designed to create consensus. Although DMDU provides guidance for how to consider illustrating impacts of different policies and pushes away from an ‘agree on assumptions’ narrative, it may not be sufficient to resolve problems of ambiguity. This is partially due to the way in which we incorporate and respond to uncertainty; decision-makers will have different reactions and tolerances to the same uncertainty (Campos et al., 2007; C. R. Fox & Ülkümen, 2011). For example, many-objective robust decision-making (MORDM) is a methodology that builds on robust decision-making techniques (Kasprzyk et al., 2013). While MORDM is highly successful at searching the uncertainty space for potential robust solutions, the algorithm still cannot determine a single ‘optimal’ point on a pareto front. Choosing a final solution requires resolving the ambiguity around trade-offs, metrics, and tolerable risks.

5.3.3 Engineering Diplomacy for Ambiguity

Many different approaches and work have begun to build bridges between resolving problems of uncertainty and problems of ambiguity, particularly from a lens of modeling work. In particular, significant efforts have been made to tease apart problems of uncertainty from facets of ambiguity, including: differences of selected design scenarios based on climate belief, the impact of defining objectives in contrasting ways (Hadjimichael et al., 2020), and the impact of contrasting rival framings (Quinn et al., 2017).

In contrast to the efforts mentioned above that focus on modeling and quantitative work, consensus-building approaches focus on managing conflict and ambiguity through negotiated

processes (Rachmad, 2022; L. Susskind et al., 2016; L. E. Susskind et al., 1999). One approach that connects both the qualitative and quantitative elements of complex systems is the Engineering Diplomacy Framework (EDF), which is specifically designed to handle ambiguities through negotiation, stakeholder engagement, and adaptive governance. EDF is neither a technical engineering approach nor an international diplomacy method, but rather a framework for approaching complex system conflicts. This interdisciplinary framework grew out of extensive experience in conceiving, developing, and implementing the original Water Diplomacy Framework (Choudhury & Islam, 2018; Islam & Repella, 2015; Islam & Susskind, 2012). Both EDF and its precursor, WDF have been invoked in multiple practical applications, particularly for the management of transboundary water basins (Wheeler et al., 2018) and exploration of applications to existing water law (Murthy, 2014).

Key methods used in the EDF include: (a) Joint Fact-Finding: Bringing stakeholders together to collaboratively develop a shared understanding of the facts and uncertainties surrounding a decision; and (b) Mediation and Negotiation: Facilitating discussions among stakeholders to find mutually acceptable solutions. EDF recognizes that ambiguity often cannot be resolved purely through technical solutions; instead, it requires a negotiated approach that takes into account the different ways in which stakeholders perceive and value the problem. It uses the rigor of scientific methods as its guiding principle and demand commitment to a pragmatic, negotiated, and socially aware examination of the solution-space that is sensitive to the context, constraints, and capacities of a system (Choudhury & Islam, 2018; Islam & Susskind, 2013).

Despite its strengths and strong theoretical underpinning, the EDF has a limited history of being explicitly applied to climate adaptation problems, such as levee design or sea level rise. This may be due to the lack of direct integration with more targeted methodologies designed to aid

decision-making processes categorized by a high degree of uncertainty. Additionally, which it provides a high level overview of big picture methods, it is difficult to understand how these may be immediately applicable at a more granular scale. The EDF does not specify how to manage uncertainty for example, just that it should be considered.

5.4 The Case of Boston SLR

Building on the previous chapters, we use the case of SLR adaptation in Boston as an example of a complex system that could benefit from the combined DMUUA approach. The city of Boston, MA faces significant risks from increased coastal flooding due to sea level rise (Douglas et al., 2016; P. Kirshen et al., 2008; Kruei, 2016). While the exact impact of climate change on coastal flood patterns is uncertain, prioritizing adaptation spending, determining appropriate policy, and balancing risk tolerances for floods engages many ambiguous elements. In particular, the formation of cooperative adaptation structures is susceptible to conflicts due to ambiguity, as they require consensus between multiple independent actors.

Like other complex systems, it is difficult to fully separate the impacts of uncertainty and ambiguity when considering cooperative adaptation structures. Previously, we explained that combining DMDU with EDF is especially beneficial when this occurs, but we have yet to illustrate why we believe this is true. The following work illustrates how ambiguity and uncertainty are interconnected and why using both approaches can lead to new understanding and nuance.

First, we will specify how sea level rise and notions of fairness contain elements of uncertainty and elements of ambiguity. Table 7 below provides specific examples of when an uncertainty (SLR amount) may behave as ambiguous elements and when an ambiguity (interpretations of ‘fair’ financial contributions) may actually be benefited from uncertainty

focused approaches. Understanding how facets of each can manifest in a system and benefit from combinatory approaches is a critical part of being able to manage both. We will discuss the implications of using the full EDF joint fact-finding or DMDU methods apply to each of these in cases where uncertainty and ambiguity are well characterized, but also where they are so closely connected that they may act as the other.

Table 7: SLR and fairness as ambiguity and uncertainty

	It is uncertainty...	It is ambiguity...
It acts as uncertainty...	The amount of SLR that will happen in Boston in 2100	The heuristics that the public will use to determine a voluntary contribution to adaptation coalitions
It acts as ambiguity...	The belief in climate change (the belief in the amount of SLR that will happen in Boston in 2100)	The definition and calculation of a fair contribution to an adaptation coalition

We use the same model as in Chapter 3 to explore these ideas further. Using the combination decision-making process, we explore how coalitions form under two different criteria only: conditions and perceptions of SLR, and assessments of how to calculate ‘fair’ financial contributions to the adaptation coalitions. The decision-making process first assesses expected benefits and costs of adaptation and then also incorporates components of environmental responses, network reciprocity, and social contagion. Every year of the simulation, agents can choose to adapt independently or join a flood adaptation coalition. Simulations are run using the general application of the model, which includes municipal agents and property owners. Further information on this model can be found in Chapter 3 and in its associated appendix. We assume a municipality with a structure of six neighborhoods (chosen to maintain sufficient network size, yet

still improve computational time). Each combination of SLR, perceived SLR, and heuristic to determine financial contributions was run 200 times to generate an ensemble for analysis.

5.4.1 Uncertainty that acts as uncertainty

Some aspects of complex decision-making represent uncertainties that are easily identifiable as uncertainty. For example, ‘what is the amount of sea level rise that will occur in Boston Harbor by 2100?’ Or even, ‘what is the range of storm surge height I can expect in the year 2050?’ The first question is clearly identifiable as an epistemic uncertainty; this is a knowledge problem affected by the future rate of melting glaciers, policies to curb climate emissions, and fingerprinting effects, among others. The second question is an aleatoric uncertainty: we might not know the exact value of what a single storm will be, but as time progresses, we may be able to have a clearer idea of the probability distribution of such a storm.

Estimating and incorporating such an uncertainty for planning is frequently done in water resources management. Methods from DMDU including info-gap analysis, robust decision-making (RDM) (R. J. Lempert, 2019), scenario discovery (Kwakkel, 2017), or dynamic adaptive policy pathways (DAPP) begin to help us plan for an uncertain future. For example, in the case of the models presented earlier in the dissertation, exploring how outcomes vary across multiple rates of sea level rise can eventually be used to identify robust design choices using an RDM methodology.

While a full RDM assessment should vary more than one source of uncertainty, and along a greater range, we demonstrate this concept using an illustrative examples comparing model outputs for one and five feet of SLR by 2100 with the generalized model introduced in Chapter 3. Figure 23 plots adaptation costs, cumulative harbor damages, the number of cooperative seawall

segments, the final coalition size, and coalition interest size, normalized to their maximum value. This parallel axis plot allows for multiple objectives to be compared simultaneously, despite differences in scale. Within the plot, each line represents an individual simulation, and each of the five outcomes for that simulation are connected. The color indicates clusters according to specific conditions. These plots allow for a rapid comparison of conditions across the ensemble across multiple objectives.

The clear divide between the blue (1 ft SLR) and yellow (5 ft SLR) simulations for outcomes of flood damage indicate that SLR is a strong predictor of flood damages, which is an expected finding, given higher SLR largely means larger floods. However, ssplays an important role in the number of cooperative seawalls constructed. The majority of simulations with high SLR have a lower ratio of cooperative seawalls, while lower SLR appears to elicit a higher degree of interest in cooperation, likely due to agents rapidly changing strategies after unexpected flooding or requiring the cost reductions of cooperative adaptation to construct seawalls.

To further apply DMDU principles (in their simplest form), multiple policies (such as increased availability of external funding to coalitions) could be tested across this uncertainty to assess shifts from the baseline values presented here. A ‘robust’ policy to encourage coastal adaptations would meet the objectives for each of these metrics, regardless of the amount of SLR that occurs.

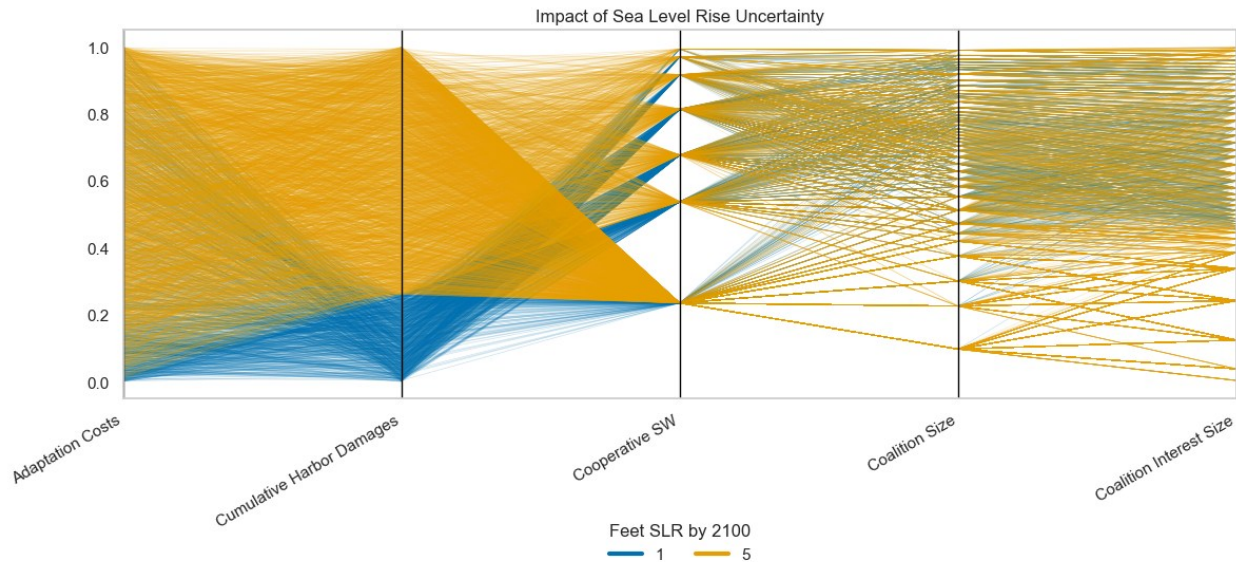


Figure 23. The parallel axis plot above compares five metrics from the model across two scenarios of sea level rise to illustrate the influence that this uncertainty has on the general system. The yellow lines correspond to high sea level rise scenarios (5 feet by 2100), while the blue lines correspond to low sea level rise (1 foot by 2100). All metrics were normalized to their maximum value to be comparable across multiple scales. Adaptation Costs and Cumulative Harbor Damages calculate the cumulative costs in 2150 for all agents in the simulations. Cooperative SW assesses the ratio of seawalls that are built cooperatively by the end of the simulation. Both coalition size and coalition interest size assess the maximum number of agents both in, or interested in joining, the coalition at any point during a single simulation.

5.4.2 Uncertainty that acts as ambiguity

While the amount of sea level rise facing Boston Harbor in 2100 is an uncertainty, the preferred planning scenario acts more as an ambiguity, as it is strongly influenced by underlying values and priorities for limited municipality resources. This is because determining a planning scenario requires balancing stakeholders interests, answering: What does a decision-maker feel is an appropriately conservative sea level rise to design for? And what does the public prefer to plan for? This preference for a specific design scenario may be based on deeply held beliefs about climate change or risk management or may reflect beliefs about the role of government in protecting private property. In short, what appears to be an uncertainty about the amount of sea level rise facing an agent is actually deeply linked to values and personal choices between multiple

alternatives when decisions must be made. Because of the linkages to decision-making, which is a human-centric challenge, the implications of this ambiguity must be considered.

Accounting for uncertainties that are embedded within larger ambiguous decisions is no longer as straightforward as applying DMDU methods; even sophisticated methods of knowledge production may not change a stubborn decision-maker. This is especially true in our era of polarization and misinformation, where stances on climate change are deeply embedded with political ideology (Botzen et al., 2016).

To illustrate the difference between sea level rise as an uncertainty and as an ambiguous planning scenario, we repeat the experiment and figure from above in Figure 24, allowing for both conservative and aggressive planning scenarios (1 and 5 feet of SLR, respectively). A planning scenario is used for decision-making differently in the model. The planning scenario is what influences an agent's expected flood damages estimates in the future, while the actual sea level rise that occurs is used to calculate damages and influence immediate decision-making based on flood experience. In contrast to the figure above, low planning scenarios (teal lines) correspond to decreased cooperative outcomes, which is demonstrated both in the number of cooperative seawalls constructed, but also in the coalition sizes. As the SLR scenario appears to have little impact on cooperative seawall construction and coalition size, while SLR projection strongly influences these outcomes (assessed by the clustering of each color on those outcomes), these results suggest that SLR planning is a more critical component for cooperation outcomes than the SLR that actually occurs, despite the multiple environmental response processes included in the model. If the municipality wishes to encourage higher rates of cooperation, then these results suggest a need to change beliefs or develop compromises. This can be encourage either through more extensive Joint Fact-Finding, which can utilize similar models, or through brainstorming for

mutually beneficial compromises between possible adaptation plans that balance cooperation with effective adaptation.

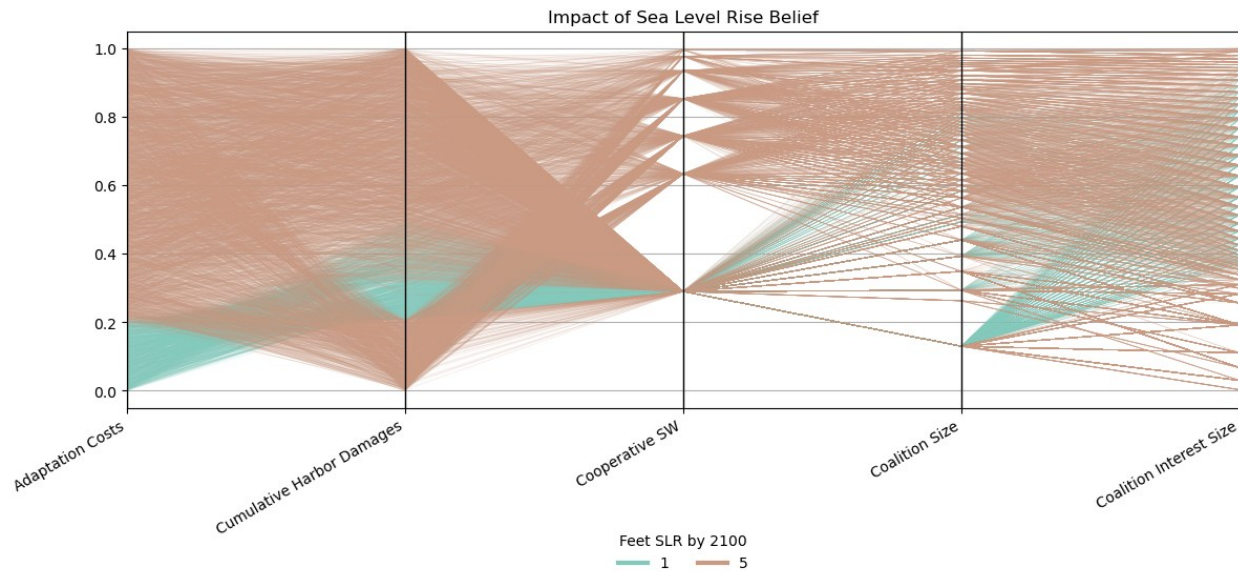


Figure 24. The parallel axis plot above compares the same metrics from the figure above for two planning scenarios, which are a reflection of underlying beliefs and preferences for how to prepare for uncertain sea level rise. The pink lines correspond to high sea level rise planning scenarios (5 feet by 2100), while the green lines correspond to low sea level rise planning scenario (1 foot by 2100). All metrics were normalized to their maximum value to be comparable across multiple scales. Adaptation Costs and Cumulative Harbor Damages calculate the cumulative costs in 2150 for all agents in the simulations. Cooperative SW assesses the ratio of seawalls that are built cooperatively by the end of the simulation. Both coalition size and coalition interest size assess the maximum number of agents both in, or interested in joining, the coalition at any point during a single simulation.

Other authors have contributed similar work that highlights the impact that preferences or beliefs may have on the ultimate selection of a planning scenario. For example, in her dissertation, Shabestanipour et al. illustrated the power of climate belief in driving the selection of a design climate scenario.

5.4.3 Ambiguity that acts as uncertainty

The collective decision-making required to form adaptation coalitions contains many ambiguous elements, particularly as coalitions emerge from individual decision-making. Using the generalized model from Chapter 3, we focus on the ambiguity pertaining to how to assess a ‘fair’

financial contribution to a cooperative coalition. While these coalitions require capital to implement adaptations, who should pay and how should those costs be distributed?

Building on the model, we explore two different possible heuristics of a ‘fair’ coalition contribution. While there are likely many possible ways that stakeholders may assess ideas of fairness in reality, we only include two for the sake of a simplified, illustrative example. The first heuristic is being willing to contribute financial capital up to the expected benefit of flood protection (the assumption used in Chapter 3). The second heuristic, is that a fair contribution is only taken from agents who would already consider a fully independent adaptation, and then the full cost of that adaptation is considered as a financial contribution to an adaptation coalition.

While similar, these heuristics shift both the quantity and timing of financial contribution based on competing assessments of what a ‘fair’ contribution would be, reflecting a deeper ambiguity in the adaptation process. While a negotiator might need to frame this as an ambiguity (as explored in the next section), a city planner may need to know what coalition sizes to expect based on the various ways people may decide to measure a fair contribution. For this reason, they may want the low and high estimates of how people may calculate ‘fair.’ In this case, an ambiguity about ‘what is fair?’ is benefitted by an uncertainty framing. This allows for more robust selection of policies to encourage cooperative coalition formations across a population.

The results from our model suggest that the second heuristic, reflecting a more conservative assessment of a population’s contribution, reduces rapid coalition formation and eventual seawall construction. Figure 25 below shows the changes in cumulative damages, the number of cooperative seawalls, coalition interest, and final coalition size over time for each heuristic. The shaded regions represent the middle 80th percentiles, while the dashed lines represent the most extreme simulations (100th percentile). While the extreme damages vary little based on the

heuristic, the city planner would be able to assess a clear high and low damage estimate based on treating this ambiguity as an uncertainty.

Additionally, these results suggest that the more conservative heuristic, requiring independent adaptation to be financially viable, frequently leads to completely negligible rates of cooperation. This suggests that a policy maker should recommend additional policies or incentives for cooperation that both reduce the threshold for cooperation and effectively communicate those reductions. In theory, such a policy would overcome the risk of individuals aligning with the belief that a 'fair contribution' is equivalent to the financial commitment of independent adaptation strategies.

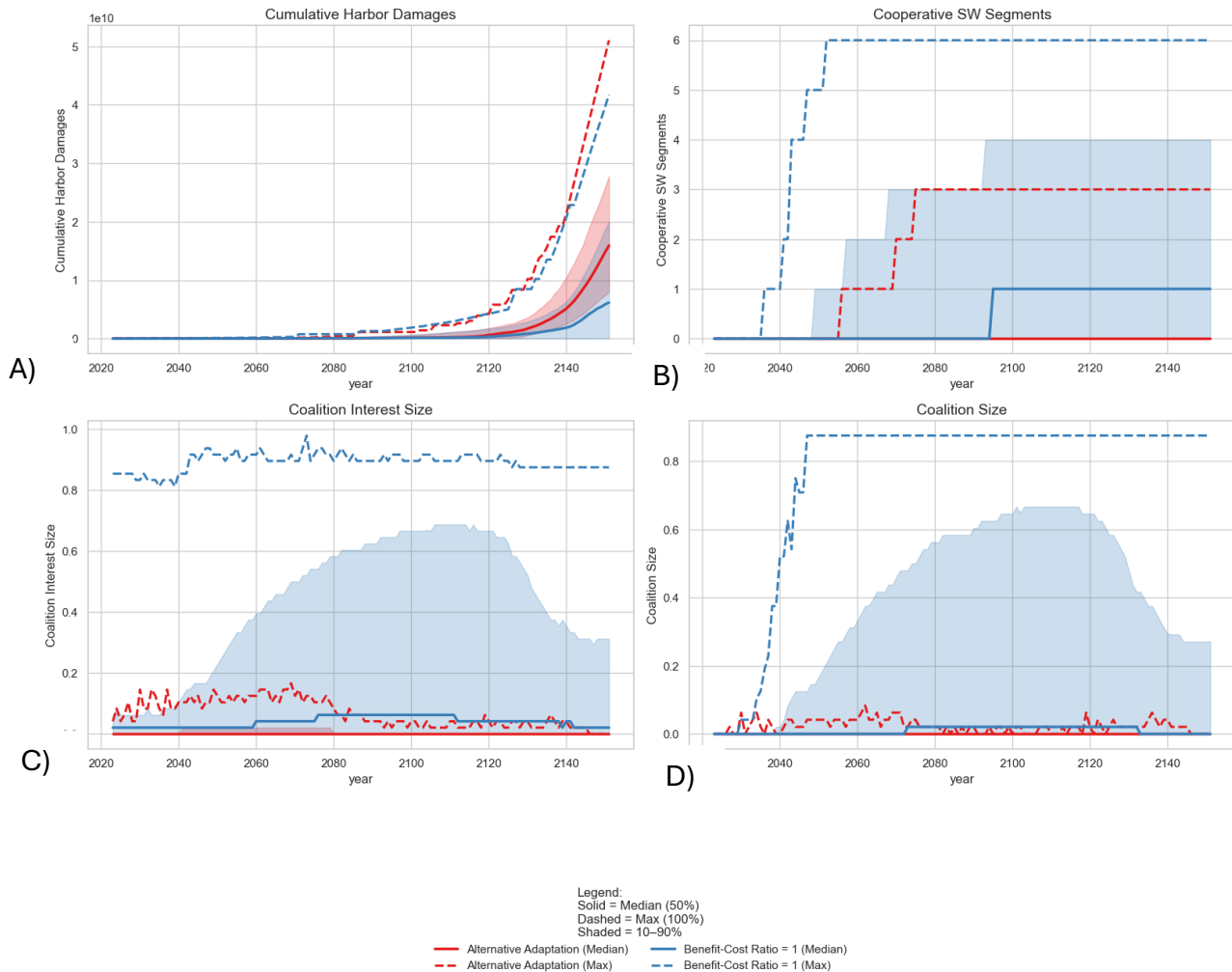


Figure 25. This figure compares four metrics over time for a municipality of six neighborhoods, using the generalized model presented in Chapter 3. Panel A plots cumulative damages, summed for all agents in the Harbor, while panel B compares the number of seawalls built cooperatively. Panel C plots coalition interest over time, and Panel D plots overall coalition sizes over time. Within each sub-plot the center 80 percentiles are included in the shaded region, and the median is reflected by the solid line. The dashed lines represent the 100th percentile simulation for each metric, showing that in rare case, significant deviations from the mean may occur.

5.4.4 Ambiguity that acts as ambiguity

The sub-section above indicated the differences in climate adaptation outcomes that may arise from conflicting interpretations of what a ‘fair’ contribution to an adaptation coalition should be. Similar ambiguous terminology presents challenges to managing other complex systems, such as conflicts in transboundary water management due to ambiguous principles of ‘equitable and reasonable’ water allocation (Smith, 1994; Vink, 2014). Because the capital to adapt often comes

with an opportunity cost of funding to other pressing concerns, climate adaptation (including considerations for migration) often are a reflection of prioritization and values, including risk tolerance (Nainggolan et al., 2023) or fears of displacement (Rubin et al., 2024). While simple in theory, the effect of ambiguity can lead different individuals to vastly different conclusions of what constitutes a ‘fair’ contribution. Generating community-wide consensus will require a negotiated approach to encourage broader coalition engagement.

DMDU methods alone are not sufficient to resolve these conflicts, although it is a powerful methodology for highlighting the impacts of multiple interpretations (as shown in Section 4.3). In our example, framing heuristics for ‘fairness’ as an uncertainty is useful in illustrating what the implications of each heuristic may be on adaptation in the long-term. However, an approach that focuses on stakeholder engagement and value creation in formal joint fact-finding is a necessary addition to the DMDU efforts. Such an approach situates the DMDU exercises within a framework that establishes a broader process for resolving conflicts in complex problems, and pushes policymakers to search for self-reinforcing mechanisms for collective risk management.

Because hosting a negotiation session is outside of the scope of this work, we propose that future applications of this work be explored through serious games, where uncertainty and ambiguity are explored in a gamified approach. This will provide insights into how participants grapple with uncertain and ambiguous approaches and if effective JFF using a DMUUA approach will aid in reaching consensus on the definition of ‘fair.’

While we cannot fully provide an illustration of how these negotiations may proceed, we use this example to highlight how ambiguity and uncertainty are deeply connected in the emergence of cooperative adaptation coalitions in a generalized city. When the implications of uncertainty or ambiguity are clear, using either Engineering Diplomacy or DMDU methods

provide valuable insights for specific applications and facets of adaptation planning. However, because both the uncertainty and ambiguities referenced here contain close ties and feedback to each other, approaching the entire system through the DMUUA lens provides a starting point for future policy development and planning that contextualizes uncertainty and ambiguity with concrete modeling efforts.

5.5 Conclusions

In complex systems, both uncertainty and ambiguity are unavoidable, yet they add challenges to developing effective policies, particularly in collective action systems. Without planning for uncertainty, any policies put in place may suffer from high regret and a failure to adapt to future changes as they emerge. Without planning for ambiguity, even mathematically ‘correct’ solutions may fail to be represented in final decisions if politics and values of the decision-makers conflict.

This paper attempts to bridge methods for mathematical modeling and consensus building with particular attention to uncertainty and ambiguity. First, we explore the definitions and use of the terms ‘uncertainty’ and ‘ambiguity,’ particularly as they related to modeling and decision-making literature. While there are multiple definitions, it is a useful framing to consider uncertainty as relating to the state of a lack of knowledge, while ambiguity relates to multiple equally-valid interpretations, stemming from different values or preferences.

Next, we explore using a synthesis of methods to manage both uncertainty and ambiguity. We acknowledge that in systems where ambiguity and uncertainty are clearly identified and separable, existing methodologies such as DMDU or the EDF are sufficient to manage them, in what we coin the DMUUA approach. However, when they are deeply intertwined and connected, a synthesis of existing approaches is necessary. For this reason, we recommend using DMDU

methods within the EDF in joint fact-finding processes to ensure both are addressed and potentially to gain additional insights into previously unexplored components of an uncertainty or ambiguity.

We illustrate how closely connected uncertainties and ambiguities benefit from simultaneous consideration as uncertainty and ambiguity using the generalized SLR cooperation model from Chapter 3. We demonstrate the impacts of the SLR scenario, the SLR planning scenario, and the heuristics that individuals may choose to assess notions of ‘fairness’ in financial contributions to a coalition.

There are numerous challenges to effectively following and implementing a DMUUA approach. Addressing ambiguity requires consensus-building among stakeholders, which can be time-consuming and may not always yield agreement. In some cases, skilled facilitation may be necessary to navigate divergent values. Additionally, while DMUUA provides a structure for decision-making, practitioners may struggle to balance the need for rigorous, data-driven models with the adaptive processes required to manage ambiguity. In cases constrained by resources or capacity for training, the approach may be difficult to adopt. A focus on synthesis demands an interdisciplinary approach, combining technical expertise with facilitation skills—a requirement that may pose resource and training challenges. Finally, DMUUA is not a one-size-fits-all solution; its application must be customized to each unique context and practitioners must carefully allocate resources and time between scientific and participatory processes.

In essence, the DMUUA approach offers a practical, flexible approach for managing complex decision-making problems characterized by both uncertainty and ambiguity. By combining DMDU and EDF methodologies, the framework not only strengthens the technical foundation of decisions but also ensures they are socially viable and adaptable to future challenges. Although implementing DMUUA may require skillful negotiation and tailored application, its

emphasis on synthesizing quantifiable uncertainty and ambiguity addresses the full spectrum of uncertainties, providing a robust model for decision-making in collective action contexts.

There is a need for future work to assess DMUUA in practice and in applications to similar sectors characterized by complex, collective, multi-stakeholder systems. This includes assessing the utility of these methods to address problems relating to other fields such as transboundary water management, urban planning, disaster management, or climate resilience projects.

Chapter 6: Dissertation Conclusions

In this dissertation, we set out with the goal of generating new knowledge about sea level rise (SLR) adaptation cooperation in coastal cities, focusing on the case of Boston, MA. We present the case that SLR adaptation should be approached as a collective action problem, particularly when there are opportunities and benefits of regionally-coordinated adaptation strategies. By the end of this dissertation, we sought to answer questions such as: under what conditions are regionally-coordinated adaptation approaches beneficial? What behavioral influences drive coalition formation for SLR adaptation? What institutions are in place that limit or support cooperative solutions? And how can we apply frameworks for complex systems to the uncertain and ambiguous elements of SLR adaptation.

This dissertation is built around the central research question: *how do cooperative approaches to sea level rise adaptation (both through voluntary action or centralization) emerge, evolve, or fail, given economic incentives, decision-making dynamics, institutional constraints, and uncertainty?* This highlights the need for a better understanding of how, when, and whether cooperative adaptation may occur. However, as this focus is quite broad, we identified a number of research gaps that exist about collective cooperation in the case of SLR adaptation. Each chapter contributes to one or more of the gaps as described below.

6.1 Research Gaps and Contributions

6.1.1 Conceptual Contributions

Much of the previous literature about cooperation in complex systems assumes that cooperation is a beneficial strategy. Although authors may acknowledge that this may not always be the case for

all individuals, estimating when and to what extent cooperation may result in unintended negative impacts is a challenge. Chapter 2 illustrates that the benefits of cooperation are conditional on context, including the extent of SLR that a basin may experience. We highlight that although a regional flood authority often leads to larger cumulative reductions in flood risk, it may disadvantage specific neighborhoods, leaving them more vulnerable to damage. In practice, this leads to equity concerns, as the ability to recover from flooding is also highly dependent on the existing social and political systems in place. Additionally, this could decrease public support from neighborhoods or regions who expect less benefit from regionalized approaches.

In addition, we depart from traditional SLR adaptation modeling approaches to assess the role of governance structures explicitly, in contrast to the more typical approaches. In many of the existing models of SLR adaptation, flood risk reductions are computed for particular adaptations or policy designs (for example, the assessment of a potential harbor barrier system (P. Kirshen, Borrelli, et al., 2018)). However, these studies rarely compare the impacts of governance structures, including cooperative approaches. Of the studies that include government, it is often as exogenous policies, while adaptation outcomes are pursued as individual approaches. Explicitly quantifying how the adaptation regime affects flood risk reduction in Chapter 2 allows for us to also assess any unintended consequences of choosing one adaptation regime over another. We also demonstrate that despite the trade-offs a regional flood authority, this adaptation regime may be best suited to avoiding the worst-case outcomes.

6.1.2 Methodological Contributions

Another gap that we focus on in Chapter 3 stems from the overlap of three key elements: the context of sea level rise, the question of cooperative coalition formation, and the comparison of decision-making representations in an ABM. While each has been studied independently, or even

as a combination of two of these elements, we were unable to identify other literature that brings all three elements together. This is an important research gap as SLR adaptation has some unique characteristics that differentiate it from other contexts. First, SLR risks are deeply shaped by environmental conditions, perhaps even more so than the traditional resource harvesting context that many coalitions models draw inspiration from. Secondly, SLR adaptation is limited by the benefit-cost ratio; cooperation interest is not sufficient alone to induce cooperation, but also depends on expected reductions in flood risk. To expand on this link, perceived flood risk is used to calculate how much an agent expects to benefit from adaptation. This in turn triggers the financial need and desire for adaptation. Finally, SLR cooperation is characterized by shifting risks over time, either when the flood risk increases due to a rising mean sea level, or when individual adaptations pursued by large agents provide protection to agents who would be otherwise exposed to floods. Therefore, the first contribution we make here is through the framing we select, which is approaching SLR adaptation governance through a collective action lens.

Additionally, we build and test an ABM to demonstrate how shifting the decision-making representation, motivated by different behavioral theories, greatly shapes patterns of coalition formation. Chapter 3 suggests that while network reciprocity can lead to coalition behavior on occasion, direct environmental feedback mechanisms are necessary for shaping coalition formation as flood risk grows and reduces with new adaptations. Despite high ‘contagiousness’ parameters in our investigation of social contagion, coalition formation was very low on an uncooperative network. This suggests that modelers must be cautious to implement adaptation decision-making strategies that align with behavioral theories actively used by the community they are trying to represent.

Chapters 2 and 3 also use scenario discovery methods to parse potential uncertainty spaces to identify conditions that are most likely to lead to flood reductions or cooperative seawall implementation, respectively. While this is not a new or novel contribution from a methodological perspective, there is limited literature that applied these methods to cooperative coastal adaptation.

6.1.3 Empirical Contributions

While using a purely general model for cooperative SLR adaptation would provide more obviously generalizable results, contextualizing our models and results to a specific city allows for more specific conclusions for policy development to be reached. In Chapter 3, we are able to highlight how the addition of location-specific flood risk and economic data shifts adaptation cooperation levels in Boston Harbor. Finally, the application of this research for Boston allowed us to interview stakeholders in a city that is already openly considering cooperative adaptation, gaining detailed insights on hesitation towards cooperative solutions.

Although previous studies have investigated challenges to SLR adaptation in Boston Harbor using qualitative methods, these studies have focused on adaptation in general and not cooperative or regionally-coordinated adaptation. We expand on previous studies by comparing stakeholder perceptions on barriers and incentives to cooperation by assessing current adaptation institutions in Chapter 4. We also begin to summarize the range of stakeholder perspectives towards different adaptation governance regimes, including voluntary cooperation and a mandated regional flood authority.

6.1.4 Theoretical Contributions

In Chapter 5, we engage extensively with existing literature on uncertainty and ambiguity, linking two frameworks that are not commonly shown together. Given the numerous definitions and

applications of uncertainty and ambiguity, this chapter explores the need for a shared set of definitions. Additionally, we propose the synthesis of Engineering Diplomacy with Decision-Making Under Deep Uncertainty in a single approach to effectively manage uncertainty and ambiguity simultaneously. This chapter both explores why there is so much confusion about uncertainty and ambiguity and why new framings may be needed.

6.1.5 Why these results matter

Across the United States, institutions and strategies to manage coastal flooding are still often fragmented and uncoordinated, which is reasonable given the challenges of designing governance structures or strategies that cross multiple jurisdictions. However, flood risk is a collective problem, both due to the nature of multiple coastal flood paths, but also due to cascading effects impacting individuals who may not even directly experience flooding. Given the possible benefits of cooperation for collective management, many policymakers are considering cooperative strategies, either in formal or informal mechanisms. However, to make informed decisions, it is important to know when cooperation is necessary, when voluntary coalitions are feasible, and how uncertainty and institutional constraints may shape collective adaptation outcomes.

This dissertation examines the conditions under which cooperation is necessary, explores how decision-making processes lead to the success or failure of cooperative coalitions, and explores how existing institutional context affects the choice to pursue voluntary coalitions or a centralized flood authority. Rather than focusing on prescribing optimal designs for cooperative arrangements, we instead explain when cooperation sometimes improves outcomes and when it fails to materialize or produces uneven benefits. Using Boston Harbor as a consistent case study throughout the dissertation allows us to explore these themes deeply within a single location, while the generalized findings can be quickly adapted to alternative coastal contexts. By grounding these

insights in both computational modeling and stakeholder perspectives, we hope to contribute to more informed discussions about the feasibility and limits of cooperative sea level rise adaptation.

6.2 Limitations and Caveats

We established throughout the dissertation that models are an imperfect representation of SLR adaptation cooperation. Although modeling allows for new policy experiments and explorations of future uncertainties, the use of models also therefore requires an acceptance of multiple limitations and the need for simplifying assumptions.

Chapter 3 explores one of the drawbacks of models: adaptation outcomes are strongly influenced by the choice of decision-making representation. Although this showed how shifting the underlying decision-mechanism greatly influenced cooperation outcomes, it also highlighted the weaknesses of ABMs: while they are powerful tools to compare behavioral theories, they are also often highly sensitive to model uncertainty, structural uncertainty, and parametric uncertainty. While some degree of uncertainty is necessary for any scenario discovery, it is important to note when uncertainty can be used productively (exploration of possible futures) and when it should be used to carefully qualify results (a limitation of the methodology).

Models will always contain components of structural uncertainty, but this is even greater when we incorporate human decision-making, as there may be many ways to represent decision-making processes with mathematical representations. Srikrishnan, et al provide a definition of structural uncertainty as “uncertainty in the mathematical and/or rule-based representation of processes within a simulation model” (Srikrishnan et al., 2022). Given this definition, we do not even fully assess structural uncertainty, as we explore four distinct processes, rather than four representations of a single behavioral process. The findings presented throughout this dissertation

would be bolstered by a more robust assessment of structural uncertainty in the array of models used.

Finally, it is important to consider alternative model limitations to the work. First, given the computational intensity requirements of ABMs, the model size and sensitivity analysis was limited. This limited the number of agents that we could include in the model and the number of calculations and processes each could undertake. Although more simulations may not change fundamental results presented here, outcomes may become less strongly influenced by stochasticity between model simulations.

One of the limitations of the dissertation that extends across all chapters of this dissertation is the dependence on data. Our models and assumptions can only be as accurate as the available data used to parameterize or design the model. While some processes are straightforward (generating a Gumbel distribution for flood simulations (Gumbel, 1958)), some require making a reasonable generalization (equal weighting on each behavioral component in Chapter 3). This provides significant space for future work improving data collection and use, particularly for the more subjective components of the research.

6.3 Future Research Directions

First, there is a desire to expand the experiment sets and model details for the models used in Chapters 2 and 3. In particular, when we quantify the trade-offs between adaptation regimes in Chapter 2, adding additional agents and incorporating cascading damages from reduced transportation routes or port closure could provide much more accurate representations. Additionally, a better array of heterogeneous agents parameterized based on parcel data would provide a much more granular and specific estimate of flood risk reduction. Additionally, this

model could be explored under a wider range of uncertain political conditions, which would allow for the analysis of more specific flood adaptation policy. Finally, while a simple flood insurance model is incorporated into the model, we do not use the module to explore how alternative insurance policies may affect the decision to form coalitions. Future research may also include an analysis of how our previous findings do or do not change when flood insurance availability also changes due to private or public flood insurance availability and pricing.

In Chapter 3, we only demonstrate coalition forming behavior under three decision-making pathways, inspired by social contagion, network reciprocity, and environmental feedback. One particularly fruitful avenue for future research here is through the use of collecting empirical data on the degree to which stakeholders agree with these heuristics or depend on alternative heuristics to decide. For example, collecting responses to surveys on what may influence the decision to cooperate among individuals and organizations in Boston Harbor may provide a clearer way to assess how our chosen decision-making structure compares to the reality.

Building on the concept of more tailed empirical data to motivate model choices, future expansions of Chapter 5 include the use of serious games (Alarcón-López et al., 2025) to see how a combination of Engineering Diplomacy with Decision-Making Under Deep Uncertainty could play out within a simulated negotiation process. Because much of this chapter focuses on hypothetical and theoretical work, exploring how decision-makers actually interact with these concepts is a key next step.

As we consider the applicability of this dissertation to other collective challenges, such as drought or water scarcity, future research is needed to explore how a changing context may shift some of the findings from this dissertation. While the benefits of cooperation are likely to be consistent, a more chronic environmental challenge may lack the acute adaptation trigger present

from SLR and associated flooding. Because Chapter 3 indicated that this may be a critical component to initiate cooperative adaptation decisions, shifting the application of this research may result in reduced cooperation until an acute event occurs.

Finally, although this dissertation focuses on many elements of SLR adaptation cooperation, we do not focus on how individuals decide with whom in particular to cooperate, instead leaning on geographical proximity. This is a key component of coalition formation and additional research that focuses on how individuals prioritize cooperation with particular individuals or organizations is necessary. Additional research is needed to also assess how stakeholders incorporate both monetary and non-monetary components into their decision to cooperate, and more broadly, on their decision to adapt or not.

6.4 Policy Implications

Although prescribing policy was not an intention of this dissertation work, our findings do suggest some considerations for policymakers in the Harbor. Drawing policy-relevant conclusions from these results requires interpreting model findings with attention to their limitations and applicability to the real world. Although the model considers an oversimplified adaptation system, there are still possible repercussions for the design of better SLR adaptation policy. For example, this dissertation suggests a clear need for any adaptation decision-makers to assess proposed adaptations under a range of natural and institutional uncertainties. Chapter 2 also emphasizes the need to assess and incorporate equity considerations, which requires effective community engagement. As adaptation plans are brainstormed, decision-makers should consider strategies like participatory modeling and should consider equity from a procedural lens, in addition to the impacts of any adaptation outcomes. Finally, even if a Regional Flood Authority is created for

Boston Harbor, there may be delays until it is capable of designing and executing adaptation, during which the city will still face flood risk. Given this possibility, legislators may still need to consider how to encourage cooperative adaptation in the interim. Policies to encourage trust amongst stakeholders and to encourage adaptation proactively and reactively should be considered in tandem.

In the question of the optimal form that cooperation should take, there are trade-offs between a centralized Flood Authority and relying on voluntary coalitions that form between the variety of actors in the Harbor. However, the results of this dissertation do support calls to strongly consider a Regional Flood Authority in the Harbor, noting that it may be the most robust governance strategy under the range of uncertainties we explored, but also it appears to be a more predictable and reliable option according to our participant interviews. While this may not hold to every city, in Boston, where there is strong interest in cooperative solutions and political will, such an Authority may be a successful case. Future research should focus on alternative existing regional bodies that engage in flood protection actions, such as the Louisiana Flood Risks Authorities or the United Kingdom's Regional Flood and Coastal Communities.

The methods presented in the research also add to ongoing debates on how to study collective action literature. As systems like climate change are deeply embedded into human and environmental systems, interdisciplinary research that bridges qualitative and quantitative processes will become more critical to capture the full range of perspectives on contrasting management strategies. Responding to global challenges, whether it is rising sea level, or allocating water resources in droughts, will require bridging environmental modeling and uncertainty management with institutional analysis and the exploration of various policies. Training modelers and scientist to comfortably engage across disciplines and methodologies will

be necessary to build institutions and policies that are robust not just to environmental uncertainty, but also political and behavioral uncertainties.

Appendices

Appendix A. List of Abbreviations

1. SLR.....Sea Level Rise
2. EDF.....Engineering Diplomacy Framework
3. DMDU.....Decision Making Under Deep Uncertainty
4. DMUUA.....Decision Making Under Uncertainty and Ambiguity
5. CART.....Classification and Regression Trees
6. ABM.....Agent-Based Model
7. IAD.....Institutional Analysis and Development
8. MBTA.....Massachusetts Bay Transportation Authority
9. MWRA.....Massachusetts Water Resources Authority
10. ANOVA.....Analysis of Variance
11. BCR.....Benefit-Cost Ratio
12. IRB.....Institutional Review Board
13. FEMA.....Federal Emergency Management Authority
14. RDM.....Robust Decision-Making
15. JFF.....Joint Fact-Finding
16. AEP.....Annual Exceedance Probability

Appendix B. Glossary of Key Terms

1. **Agent-Based Model (ABM):** This is a class of models used throughout this dissertation, based on the premise of modeling from a bottom-up perspective, by setting a series of rules or procedures for each individual agent or entities in the model. Interactions and outcomes at the low levels contribute to global phenomenon. ABMs are used in a variety of applications. References for ABMs include (Bonabeau, 2002; DeAngelis & Diaz, 2019; Fischbach et al., 2021; Schulze et al., 2017).

2. **Joint Fact-Finding (JFF):** Joint fact-finding is a key component of the Engineering Diplomacy Framework and other approaches to negotiation. In Joint Fact-Finding, multiple parties (who often are in conflict) pursue developing a shared knowledge base, develop models, and build trust through knowledge creation (L. Susskind et al., 2016).

3. **Engineering Diplomacy Framework (EDF):** The Engineering Diplomacy Framework was developed to aid modern decision-makers to synthesize scientific insights with strong negotiation frameworks, bridging concepts and disciplines to tackle complex problems. This high-level framework provides meaningful directions for incorporating uncertainty, ambiguity, scientific facts, and social facts for the development of resilient and sustainable resolutions (Islam & Madani, 2017; Islam & Susskind, 2012, 2013).

4. **Classification and Regression Trees (CART):** This is a machine learning method that aids in the identification of key contributing factors to a desired outcome (Loh, 2011). In this dissertation, we use CART to identify which parameters are most critical to contributing to particular outcomes (for example, if sea level rise or external financing more strongly are associated with reduced flood damages). In this work, we also only use classification trees,

comparing between worst case and best case outcomes, rather than use regression-based methods.

5. **Decision-Making under Deep Uncertainty (DMDU):** DMDU is a suite of methods to manage deep uncertainties, which is defined as uncertainty where the parties to a decision do not know or cannot agree upon the probability distribution or representation of an uncertainty.

Methods included in a DMDU approach are robust decision-making, dynamic adaptive policy pathways, and info-gap theory, among others. Key references include (Bloemen et al., 2019; Kwakkel & Haasnoot, 2019; R. J. Lempert, 2019; Popper, 2019).

6. **Institutional Analysis and Development (IAD) Framework:** Developed by Dr. Elinor Ostrom, the IAD Framework is designed as an effective tool to analyze and categorize institutions. By separating out numerous explanatory variables for how effective institutions arise, fail, or are supported or challenged, the IAD Framework provides a valuable analytical lens for institutions that govern commons or complex systems.

7. **Collective Action Problems:** Any problem where the actions of independent agents can affect others. Often, these problems require collaborative solutions for successful management.

8. **Uncertainty:** While a rich term with significant history in multiple disciplines (see Chapter 5), uncertainty largely stems from the state of a lack of knowledge. Uncertainty can be further specified based on its nature, source, or other characteristics. Some forms of uncertainty may be estimated or quantified.

9. **Ambiguity:** While the true definition of ambiguity is ‘ambiguous,’ the term is largely associated with the idea that individuals may draw different conclusions or interpretations given the same information. See Chapter 5 for more details on the variety of definitions here.

Appendix C. Supplemental Information for Chapter 2

C1. Overview, Design Concepts, and Details Model Documentation

C.1.1 Purpose

The purpose of the model is to explore under what conditions different adaptation governance regimes are successful in reaching specific adaptation metrics in Boston Harbor. We set up the model to quantitatively compare scenarios of no cooperation, voluntary coalitions, and regional authorities to improve coastal adaptation. The model allows for a quantitative assessment of when cooperation or regionalization is beneficial and to whom. The model is built in NetLogo with extensions for python and GIS (Wilensky, 1999).

C.1.2 Entities, state variables, and scales

Entities:

Agent Type	Names	Count	Adaptation Options	Presence in Adaptation Regimes
Municipal Agents	Boston, Quincy, Winthrop	3	Seawalls (evaluation for 9 segments in Boston, and one in each other municipality)	All
Massachusetts Bay Transportation Authority Subway (MBTA)	--	1	On-site barriers	All
Regional Assets	Boston Logan Airport, Food Distribution Center	2	On-site barriers	All
Property Owners	3 Commercial per municipality 3 Homeowners per municipality	18	On-site barriers Aquafence Flood insurance	All
Regional Flood Authority	--	1	Seawalls	Regional Authority

State variables:

Agent	Variable
Property owners and regional assets	Elevation
Property owner	Flood insurance
All	Damage Functions
All	Adaptations
All	Geographic location
All	Sea Level Rise Projections
All	Potential Seawall Heights
All	Adaptation Costs
All	Foresight for damage projections
System	External Financing Percent
System	Storm Multiplier
System	Maintenance Fee
System	Reduction of funding access
System	Planning Delay
System	Permitting Cost
System	Prioritization Method
System	Discount Rate
System	Sea Level Rise

Scales:

- The model captures a significant portion of the inner Boston Harbor.
- Agents may be located as point sources (property owners), be spread throughout the model area (MBTA), or cover sub-regions (municipalities).

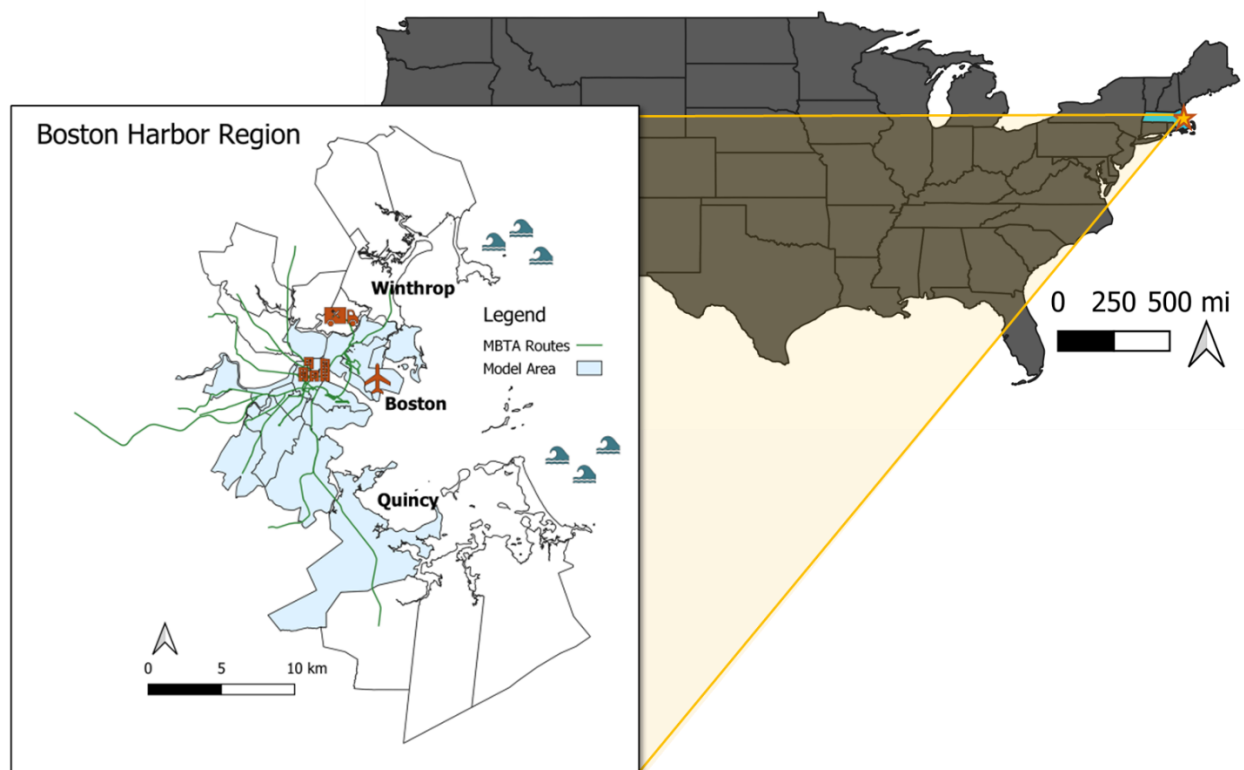


Figure S26: Map of geographic area covered by the model with key agents incorporated.

C.1.3 Process overview and scheduling

The model begins with the user selecting key parameter values for a single model run. The user must select the sea-level rise to be generated (0,1,3 or 5 feet), any storm intensity modifier (increases the mean of the storm distribution every year by the chosen parameter, but with a constant CV), the discount rate (0.03, 0.07), the agent sea-level rise projection (0,1,3,5) and the adaptation regime (no cooperation, no cooperation with a behavioral damage modifier, voluntary cooperation, or regional authority).

Additionally, the user will select the storm surge generation method (random, no extreme floods, one extreme flood, two extreme floods), whether or not flood reactive behavior occurs, the planning horizon delay (0-10 years), the permitting delay (0-10 years), the presence of the insurance module, the amount of external financing available (0 – 100%), any reduction in funding

Figure S27: Diagram of the major steps in the model process.

No Adaptation

In this version of the model, we assume a counterfactual where agents are not permitted to adapt. In this regime, agents experience damages but do not adapt in any way. This provides a useful baseline to calculate the Net Benefits of adaptation. In these simulations, there are never adaptation costs, but flood damages are tracked.

No Cooperation

In this adaptation regime, each agent is assumed to operate independently. While they are aware of and benefit from other adaptations (for example, a sea wall in front of them), they operate independently in their decision-making process. Each agent estimates the damage they will experience in the future (set by the *foresight* parameter) without an adaptation against the damage for the future with an adaptation.

If the benefit-cost ratio is greater than one, the adaptation will be adopted. In the case of two adaptations being beneficial, the one with the larger ratio of benefit to cost will be constructed. This is implemented in the following way:

Equation 10:

$$\text{If } \frac{\text{benefit}}{\text{cost}} > 1, \text{ adapt}$$

$$\text{else, no adaptation}$$

Where benefit is calculated by:

Equation 11:

$$\text{benefit} = \text{damage without adaptation} - \text{damage with adaptation}$$

Role of the behavioral modifier

The behavior calculation accounts for irrational behavior and reactivity of agents to the floods they experience. The benefit-cost ratio is modified according to an agent's most recent flood experience using this process. This supports the observation of rapid adaptation implementation following a large storm (such as the response to Hurricane Sandy). If the benefit (with the additional cost of construction) is less than the expected damages, the adaptation will be implemented. In the case of two adaptations being beneficial, the one with the larger ratio of benefit to cost will be constructed.

The equations representing this are shown below.

Equation 12:

$$\text{behavioral modification: } \alpha = \frac{\text{damage}_t}{E[\text{damage}_t]}$$

Where α represents the behavioral modifier, damage_t is the damage that an agent experiences in the year, and $E[\text{damage}_t]$ is the damage an agent expected to have in a year given their projected scenario of sea level rise and their probability-damage curve.

Equation 13:

$$\text{If } \left(\frac{\text{benefit}}{\text{cost}} \right) * \alpha > 1, \text{ adapt}$$

$$\text{else, no adaptation}$$

Where benefit is calculated again as:

Equation 14:

$$\text{benefit} = \text{damage without adaptation} - \text{damage with adaptation}$$

This means that when damage is more than an agent expects, alpha is greater than 1. If the benefit-cost ratio is close to 1, this adjustment may result in the total modified ratio being greater than 1 and spurring adaptation. If the damage modifier is less than 1, the opposite may occur, disincentivizing adaptation processes.

Voluntary Cooperation

In this version of the model, we explore how coalitions may form if multiple agents desire adaptation at the same time. It is assumed that if multiple agents in the same municipality are planning adaptations independently and can reduce the costs of adaptation through cooperation, then they will cooperate to reduce potential costs. This process occurs according to the following steps:

1. Municipalities indicate whether or not they plan to construct a seawall. We assume that if the municipality is not interested in adaptation, it is unlikely that a cooperative structure will be able to obtain permits for and construct a seawall.
2. All other agent types (property owners, MBTA, private assets) assess whether or not they would also like to implement an adaptation.
3. For agents to behave cooperatively, agents must:
 - a. Want an adaptation
 - b. Exist within a municipality that wants an adaptation
 - c. Pay less than what they would have paid for their desired adaptation (adaptation cost may be reduced due to access of municipalities to external financing, but base costs may be elevated due to the maintenance fee, which is a multiplier on the adaptation cost).

4. Agents willing to cooperate re-calculate their benefit-cost ratio according to their updated access to funding and maintenance fee if they cooperate to determine if they are better off cooperating or not
5. Agents then either implement their adaptation as a coalition or independently.

Regional Authority

For the regional authority, the only adaptations being considered are seawalls in 11 potential locations: the nine neighborhoods of Boston, and seawalls along Winthrop and Quincy. The decision-making process is similar to the decision-making process in the *no cooperation* adaptation regime without the regional modifier, except costs and benefits are calculated differently. Here, the benefit and cost of each seawall is calculated based on all agents that would be protected by the seawall. For example, the seawall in East Boston also protects Boston Logan Airport, downtown Boston protects the property owners and a portion of the MBTA, etc. Estimates for the ratio of financial protection for the MBTA based on each sea wall were made to reflect where MBTA lines are critical infrastructure are located.

Implementation

Agents experience a gap between determining adaptations to be implemented (the adaptation decision process) and the implementation process. This gap is due to both a permitting delay and the time necessary to raise funds to finance an adaptation. Agents must be able to currently have budget allocations available for 10% of the project, and can pay the remaining 90% over time (representing the effects of bonds or loans). This separation between intention and implementation means that even if downtown Boston decides to construct a seawall, other agents are not impacted by this knowledge until subsequent time steps.

C.1.4 Design Concepts

Basic Principles

Every time step, a stochastic annual maximum flood is generated, which causes damages to agents. Agents use their projections of sea level rise to complete a benefit-cost analysis on the efficacy of adaptations and then implement their selected adaptation. Each adaptation regime reflects a slightly different process of decision-making.

Emergence

Adaptation implementation patterns emerge over time under each adaptation regime.

Adaptation

Adaptation is represented in the model as agents construct physical adaptations to increasing sea level rise. Each agent has a subset of possible adaptations that they may pursue. While we use a seawall as representative of a large scale adaptation, we imagine that other large infrastructure based adaptations (either nature-based or not) could replace this adaptation option.

Objectives

The objective of all agents is to minimize future damages from sea level rise and coastal flooding through coastal adaptation.

Learning

Agents currently do not learn in the model. However, agents are reactive in each year to the differences between their expected and experienced damages. In this sense, they are responsive for predicting sea level rise correctly or incorrectly in a given year.

Prediction

Agents ‘predict’ the level of sea level rise that will happen in Boston Harbor. This prediction is set by the perceived SLR parameter. This is not a dynamic process in the model.

Sensing

There are no instances of sensing in the model.

Interaction

The nature and degree of interactions between agents varies between the three major adaptation regimes. In the Regional Authority regime, there is no interaction, as there is only one decision-maker who acts as an optimizer.

In the no cooperation regime, agents do not interact with other agents. However, as agents construct seawalls, they shift the risk profile of agents behind them geographically. Agents recognize and utilize their adjusted risk profile to make decisions.

In the voluntary cooperation regime, agents also interact through the environmental modifications of seawall construction. However, they may also choose to form coalitions to jointly finance seawall construction with other geographically-connected agents.

Stochasticity

Stochasticity is incorporated through the generation of annual maximum flood elevations in each time step. Due to the effect of the behavioral modifier, this means that both damages and adaptation time incorporates elements of stochasticity. Because of the interactions between agents, this means that multiple adaptation patterns may emerge due to the stochastic nature of the runs.

Collectives

In the voluntary cooperation formulation of the model, agents may form coalitions to adapt collectively and contribute to shared seawall costs.

Observation

Agents currently do not update their beliefs, but they observe the construction of adaptations nearby and the damages caused by flooding.

C.1.5 Initialization

Name	Variable Name	Values	Practical Meaning
Sea Level Rise Scenario	Sea-level-rise	0,1,3,5 ft	Scenario used to generate annual maximum floods as they occur
Intensity multiplier	Multiplier_storms_annual_mean	0-1 (limited in NetLogo interface)	Increases the coefficient of variation (mean and variance) of the flood distribution annually by this much
Sea level projection	Mun-slr-proj	0,1,3,5	SLR scenario that agent's expect to occur
Damage Modifier	Flood-reaction-[]	On/off for each agent type	Agents are flood reactive or not (affects benefit-cost calculations)
Discount Rate	discount	0.03, 0.07, 0.0	Value agent's place on current vs future damages
Adaptation Type	Model-version	No cooperation, voluntary cooperation, regional authority	Governance regime used in the simulation
Storm-surge method	Storm-surge-method	Random, 1 storm, 2 storms, no storms	Controls how the annual maximum floods are generated
Insurance-module	Insurance-module	True/False	Turns insurance options on/off
Delay for the planning horizon	Planning-horizon-delay	0-10	Adjust benefit-cost calculations to begin at a year in the future, rather than the present year
Permitting delay	Permitting-delay	0-10	Once agents decide to build an adaptation, delay is assumed for permits (building up financing can also occur in these stages)
Foresight	Foresight-mun-pas-mbta Foresight-property-owners	0-30	How many years are used to project forward for the benefit-cost calculations

External Financing Percent	External-financing-percent	0 - 1	The percentage of assumed external financing available to agents
Funding cap	Funding-cap	True/False	Limits funding in the simulation (against an assumption of unlimited funding)
Storm Surge Pattern	Flood-pattern	0-200	Draws a series of storm surges from pre-generated distributions for replicability
MBTA- cost-2020	Mbta-cost-2020	6.6B/3.3B	Allows the user to set the 2020 price of adaptation
Method	method	Normal/Behavior Space	Indicates whether or not the model is run through the interface or through Behavior Space
Permitting-cost-proportion	Permitting-cost-proportion	0-1	Indicates the proportion of adaptation cost that is spent on permitting
Maintenance-fee	Maintenance-fee	0-1	Indicates the proportion of adaptation cost that is required to coordinate a collaborative adaptation structure
Reduction-funding-access	Reduction-funding-acces	0-1	Reduction in external funding available to all agents except municipalities to reflect some of the current adaptation funding mechanisms
Operation and Maintenance Cost	O_M_proportion	0-1	Annual % of adaptation cost that is an OM cost
Prioritization Method for when limited money	Prioritization-method	Normal/EJ	Specifies id adaptation priority is given to top benefit-cost ratios or to benefit-cost ratios that are weighted with inverse income
MBTA Adaptation Method	Mbta-adaptation-method	All-at-once/Segments	MBTA either implements all adaptation at once or with the same

			neighborhood segments as before
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C.1.6 Input data

Data	Source
Boston Harbor Annual Max Flood Elevation	NOAA
Damage Estimates Municipalities	Feasibility of Harbor-wide Barrier Systems Preliminary Analysis for Boston Harbor (P. Kirshen, Borrelli, et al., 2018)
Flood elevation per AEP	Woods Hole MC-FRM (private communication)
Scenarios of Sea Level Rise	Taken from Feasibility Study above (P. Kirshen, Borrelli, et al., 2018)
Damage Estimate MBTA	Martello Dissertation (2023) (Martello, 2023)
Depth-damage Curves	Army Corps of Engineers (S. A. Davis, 1985)
Adaptation Costs (Aquafence, sea wall cost)	NACCS (Guise et al., 2015)
GIS Shapefiles	(MassGIS, 2022b, 2022a)
Income Data	(Department of Innovation and Technology, 2019; U.S. Census Bureau, 2015)

C.1.7 Sub-models

Flood generation

The model can run in two versions: either step-by-step, or with pre-generated flood sequences to use in the Behavior Space Experiments. In the first, where “*method*” = “normal,” a new flood is randomly generated in each time step. If “*method*” instead is set to “behavior space,” then the model will run using up to 200 pre-generated storm surge patterns corresponding to each sea level rise and a storm intensity of 1. This allows for the same pattern of storms to be tested again and again against different governance strategies or parameters.

In order to generate the floods, I fit a Gumbel distribution to the record of approximately 100 years of the annual maximum flood elevation, de-trended for sea level rise that occurred throughout the existing record. The data for historical annual maximum flood height and its fit to a Gumbel distribution is shown below.

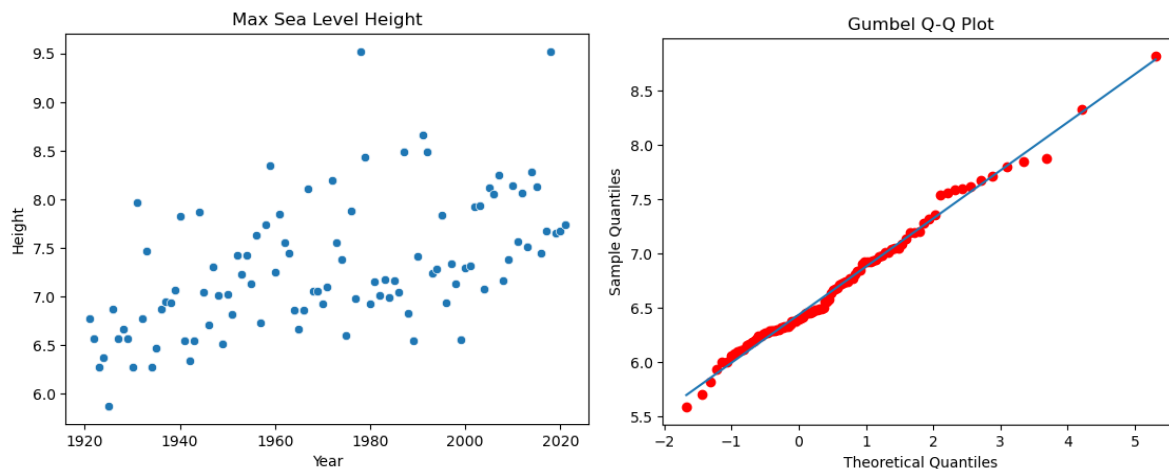


Figure S28: Plot of the annual maximum flood in Boston Harbor and Q-Q plot of these transformed to Boston Harbor.

Alternative distributions, including a GEV distribution and lognormal distribution were considered, but the two parameter Gumbel distribution fit our historic data as well or better than other 2-or-3-parameter distributions. All flood elevations use the NAV88 datum.

There are two inputs to then determine the projected floods: the *sea-level rise scenario* and the *storm intensity multiplier*. If the *storm intensity multiplier* equals 1, a random maximum flood is generated from the fitted Gumbel distribution. Sea level rise is assumed to be a linear increase from 2020 to 2100 according to the scenarios of 0, 1, 3, and 5 feet of sea level rise. Sea level rise is added back into the generated flood according to the year of the simulation and assumed sea level rise. For example, if the simulation is in the year 2100, our scenario of sea-level rise is 3 ft, and the randomly generated flood elevation is 9.2 feet NAV88, then with sea level rise, we would have a flood elevation of 12.2 feet. Additionally, the model can be run to continue the linear trend derived from historic annual maximum (approximately an increase of 0.0123 feet per year). This annual increase was determined with an ordinary least square (OLS) regression with an r-squared value of 0.3, indicating that a linear sea level rise trend only accounts for 30% of the variance in annual maximum flood elevation.

If the *storm intensity multiplier* does not equal 1, the mean and variance of the fitted distribution are changed every time step. This multiplier represents the possibility that in addition to sea level rise increasing, we may see more extreme storms every year. The multiplier affects the coefficient of variation (CV) of the fitted Gumbel distribution and is used to change the mean at each time step. The new mean is the value of the old mean multiplied by the modifier. The variance is adjusted to hold the CV constant from the original distribution (note that if the multiplier is set to 0, variance of the Gumbel distribution does not change over time, as sea level rise is added after the random flood generation). Then, the annual maximum flood is randomly generated from the new distribution and sea level rise is added back in the same method. The entire process is illustrated in the flow chart below.

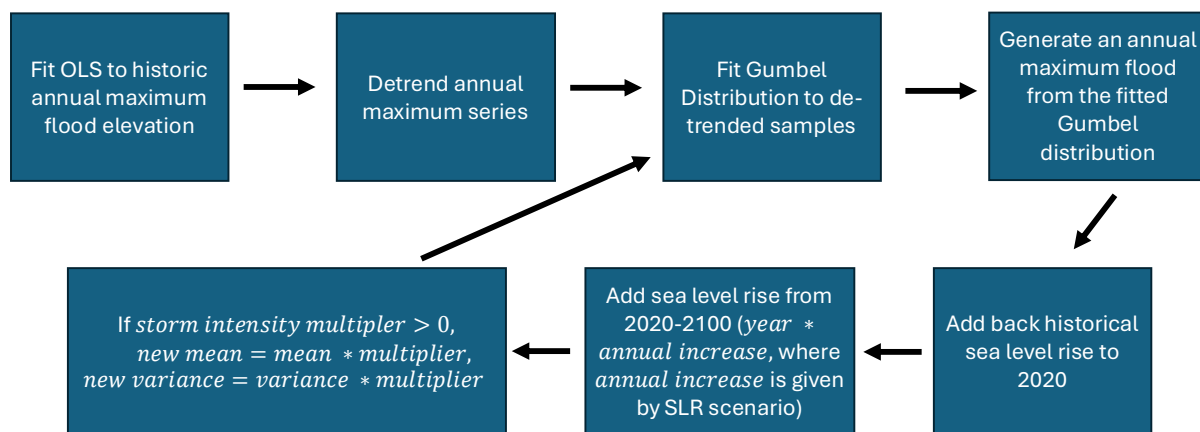


Figure S29: Process for generating an annual maximum flood elevation in each year of simulation.

The model also includes the possibility of incorporating known flood patterns as tests. These include a scenario where an artificially low flood occurs in every year except 2050, a scenario where a flood occurs in 2025 and 2075, and a scenario where there are no floods. The 1000-year

storm surge is used as the extreme flood in these scenarios. These are built into the NetLogo model and were used as sanity checks when testing model behavior.

Damage Calculations Details

Once the stochastic annual maximum flood elevation is generated, agents calculate the damage that they experience. The process for damage calculation varies based on agent type.

Municipalities:

Damages are calculated for each separate municipality. Damages in Boston are broken down into 9 regions, corresponding to seawall segments that may be constructed. These segments are: Allston, Back Bay, Charlestown, Downtown, East Boston, Fenway, North Dorchester, South Boston, and South Dorchester. Benefits to inland neighborhoods were allocated to the neighborhood where the seawall would prevent flood pathways reaching inland areas. To calculate damage for each neighborhood in Boston and the municipalities of the North Shore and the South Shore, we used data from the Sustainable Solutions Lab Analysis of the Feasibility Study on an Outer Harbor Barrier (P. Kirshen, Borrelli, et al., 2018), and data from NOAA and Woods Hole Group's MC-FRM model on flood elevations corresponding to specific AEPs. The data from the MC-FRM estimate was provided to us in private communication from an individual at the Woods Hole Group and is shown below. We use the 2008 MC-FRM estimates of flood elevations for this model.

The Storm of Today...is not the Storm of Tomorrow

Exceedance Probability	Present Water Surface Elevation (ft-NAVD88)		2030 Water Surface Elevation (ft-NAVD88)		2050 Water Surface Elevation (ft-NAVD88)	2070 Water Surface Elevation (ft-NAVD88)	
	BH-FRM	MC-FRM	BH-FRM	MC-FRM	MC-FRM	BH-FRM	MC-FRM
0.1	10.5	10.95	11.3	11.99	13.95	14.1	15.64
0.2	10.4	10.54	11.1	11.59	13.49	14.0	15.19
0.5	9.7	9.99	10.6	11.07	12.87	13.5	14.58
1	9.4	9.58	10.4	10.68	12.40	12.8	14.12
2	9.1	9.17	10.2	10.28	11.93	12.5	13.67
5	8.6	8.61	9.6	9.75	11.29	12.1	12.56
10	8.2	8.17	9.3	9.33	10.79	11.6	12.04
20	7.8	7.70	8.7	8.88	10.26	11.0	11.85
25	7.3	7.54	8.4	8.72	10.07	10.8	11.69

Figure S30: Exceedance probabilities of storm surges complied from the Woods Hole MC-FRM model.

The data from (P. Kirshen, Borrelli, et al., 2018) provides estimates of single-event damages avoided by the construction of an outer harbor barrier (assuming for the purposes of this model that there is full damage protection). These estimates were provided for 12 neighborhoods of Boston and municipalities along the North and South shores of the Harbor. The damages are separated by both scenario of sea level rise (0, 1, 3 and 5 ft) and flood frequency. A brief snapshot of the data is provided below.

Community	Sea Level Rise Scenario	Barrier System	Frequency	Building Damage	Contents Losses	Displacement	Total
Allston	5-Foot	Outer Barrier	.1	\$199,000,000	\$284,000,000	\$26,000,000	\$509,000,000
Back Bay	5-Foot	Outer Barrier	.1	\$628,000,000	\$851,000,000	\$90,000,000	\$1,569,000,000
Charlestown	5-Foot	Outer Barrier	.1	\$429,000,000	\$481,000,000	\$49,000,000	\$959,000,000

The first data transformation was to change the damage estimates from the Outer Harbor Barrier Feasibility Study to be dependent only on flood elevation, rather than frequency and sea level rise scenario. This was accomplished by assigning the MC-FRM flood elevation to each return period, effectively replacing the 'Frequency' column with a base elevation established in 2008 (note: this

will introduce some error). In order to then account for the effect of sea level rise, the value of sea level rise was added to the base elevation corresponding to the frequency. For example, given a 1000-year flood elevation of 10.95 feet, the flood elevation corresponding to the damages shown in the first three rows of the figure above would be replaced with 15.95 ft NAV-88. This provides a reference of expected flood damages given a flood elevation in NAV88.

Once this was completed, we were left with datasets for each neighborhood in Boston and for each municipality that provided flood damages according to various flood elevations. Because these are rough transformations, an equation was fit to each neighborhood or municipality to represent the relationship between flood elevation and damages to smooth the damage curve, leaving us with a specific relationship between flood elevation and damage for each geographic area. For datasets that experienced little or no damage until the flood elevation reached a specific height, the near-zero damages were removed prior to fitting a curve and assumed that any damages below said height would be negligible, and represented by zero damages in the model. The figures below demonstrate how the different municipalities may have different damage curve shapes.

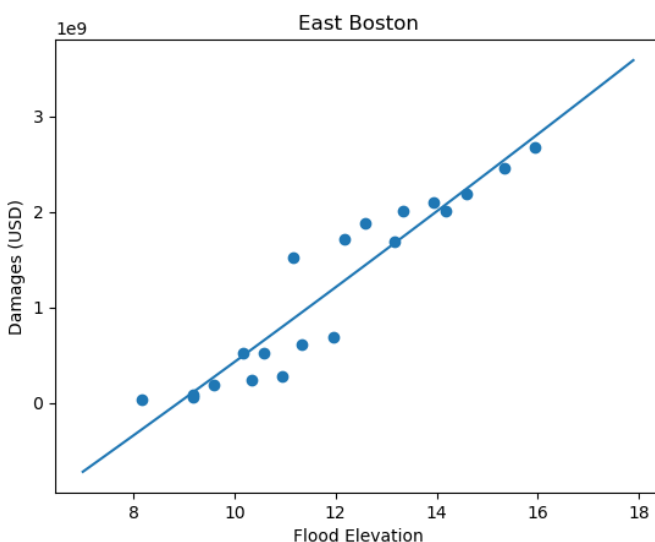


Figure S31: Fitted curve of estimated Damage compared to flood elevation in ft NAV88 for the East Boston neighborhood.

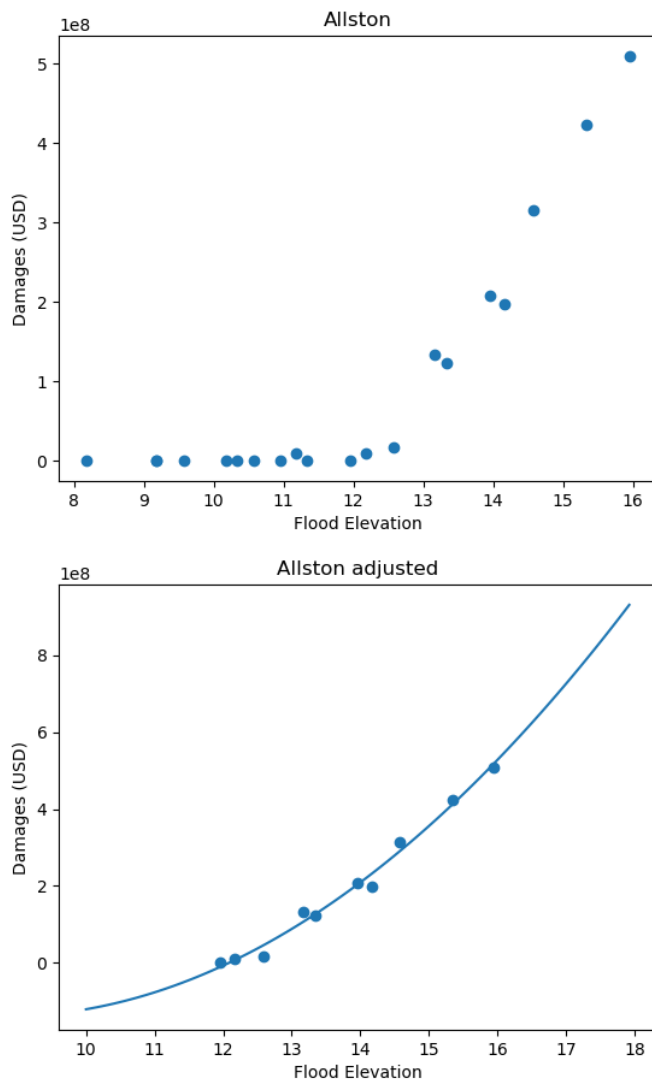


Figure S32: Fitted Damage curves for Allston. The top figure demonstrates that damages to Allston are negligible with floods less than approximately 12 ft NAV88, so the fitted damage curve is only applied to flood elevations above that elevation.

When a municipality constructs a seawall, our model assumes that the seawall protects up to 15 ft NAV88. Any flood elevation below this level results in no damage, and damage above this level is calculated according to the previous elevation-damage relationships established. Boston cumulatively calculates damages by summing the damages according to each of the 9 neighborhoods we were able to establish an elevation-damage relationship for based on the data from (P. Kirshen, Borrelli, et al., 2018).

Property Owners:

Property owners experience damage based on their elevation and a depth-damage curve provided by the Army Corps of Engineers (S. A. Davis, 1985). Inundation value is calculated if the flood elevation is greater than the elevation of the property owner, which is a variable assigned at initialization.

Equation 15:

$$Inundation = |flood\ elevation - elevation|$$

Using the inundation value, damage percent is assigned based on the depth-damage curve and then the percent is used to calculate total damage to a structure based on the structure's total assumed value.

If a property owner has constructed an aquafence, it is assumed that there is no damage with an inundation less than 3 ft above the structure's elevation. If the property owner has constructed an on-site barrier or seawall, it is assumed no damage when the flood elevation is less than 15 ft NAV-88. Property Owners also experience no damage when floods are less than 15 ft NAV-88 if their municipality has constructed seawalls that protect them.

MBTA:

Damage for the MBTA is calculated similarly to the methodology used with the municipalities, although our input data for damages based on scenarios of sea level rise and exceedance probability is from Martello (2023) (Martello, 2023). The same data transformations are completed and a curve is fit to create a relationship between flood elevation and damages for the MBTA.

Despite the similarities to the methodology for the municipalities, the impact of adaptations is calculated differently. The MBTA can decide to protect all vulnerable assets for a cost of \$6.6 billion for floods up to 15 ft NAV-88. Additionally, municipal seawalls may protect components of the MBTA system. For example, a seawall in South Boston that protects vital storage facilities for the MBTA would reduce damage by a significant amount, while a seawall in Quincy may only be assumed to reduce damage by 5% due to the lack of assets in Quincy. When the MBTA is allowed to adapt with segments corresponding to the same neighborhoods, the degree of damage attributed to each segment is estimated according to the amount of exposed assets within that segment. For example, segments that protect rail yards or tunnel entrances are considered to contribute more to damages. The costs are estimated according to the length of the segment and the complexity of the project (for example, East Boston tunnel is assumed to be both expensive and complex). These estimates are stored as an array of damage percentage and cost percentage that can be adjusted by the model user.

Regional Assets:

Damages for regional assets are calculated differently. It is assumed that these assets can tolerate up to three feet of inundation, after which damage is assumed to be catastrophic (\$1 Billion of damages). These assets can similarly be protected by on-site barriers up to 15 ft NAV-88 and will be protected by the construction of municipal seawalls if a municipality decides to construct sea walls along their flood pathways.

Expected Costs and Benefits Details

Expected benefits for all adaptations are calculated for the length of the time corresponding to the value selected for the *foresight* parameters. We use 30 years as our selected value. We assume that there is a delay equivalent to the length of the *permitting delay* parameter to construct the

adaptation, and therefore account for the cumulative benefits with an adaptation as the sum of expected damages without adaptation for the first years (length of the delay) and expected damages with the adaptation for the remaining time. The year in which agents begin their assessment of future damages is set by the planning-horizon-delay. All adaptation costs and benefits are discounted according to the selected discount rate. Additionally, the final cost of an adaptation is determined by the selected values for the *maintenance fee* for cooperative adaptation, *permitting-cost-proportion*, *external-financing-percent*, and any *reduction-funding-access* that may be selected.

Municipalities:

The method for municipalities to assess annual expected damages is established in the work of Kirshen, et al. (P. Kirshen, Merrill, et al., 2012), where the area below the damage-flooding depth probability exceedance curves represents an estimated annual expected damage value. These curves are taken from (P. Kirshen, Borrelli, et al., 2018), and shown graphically below for Boston.

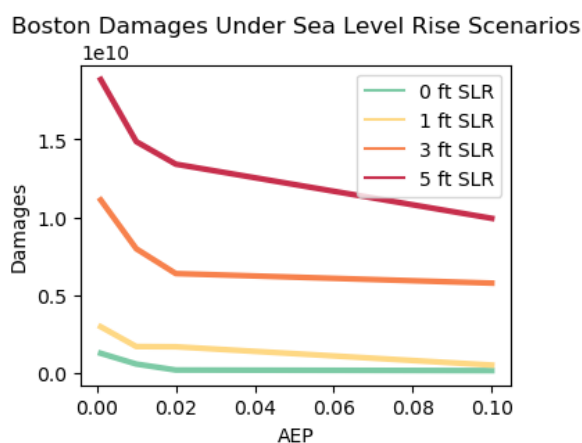


Figure S33: Example curves for Boston connecting flood annual exceedance probability to damages under different sea level rise scenarios.

In our experiments, municipalities use 30 years of discounted annual estimates to estimate the cost of future storms. The damage-flooding depth probability exceedance curves are linearly interpolated from the curves assembled previously (corresponding to 0, 1, 3, and 5 feet of sea level rise) to correspond to the agent's believed sea level in each year of the simulation. This process can be represented by the equation below:

Equation 16:

$$30\text{year damage estimate} = \sum_{i=0}^{30} \left(\frac{\int \text{damage curve}}{(1+d)^i} \right),$$

where d is the discount rate and i is the year of calculation from the present simulation year. The damage curve shifts with each iteration of the iterative process to reflect sea level rise expectations. The $\int \text{damage curve}$ is approximated through a trapezoidal integration of the damages and exceedance probabilities present from our input data source (P. Kirshen, Borrelli, et al., 2018; P. Kirshen, Merrill, et al., 2012).

The cost of municipal seawalls is assumed to be 7500/ft. Assessments of the length of the seawall needed are based on GIS files using QGIS software.

In order to assess the efficacy of seawall construction, the exceedance curves were altered so that any flood corresponding to a level of less than 15 feet NAV-88 corresponded to a damage of 0 (representing a seawall height of 15 ft NAV-88). 30-years of these altered discounted damages were summed, allowing agents to determine the benefit of constructing a seawall.

This process was done once per municipality, with the exception of Boston, which maintained the division of nine potential seawall segments determined in the damage calculations.

Property Owners:

In order to be able to calculate annual expected damages for property owners, damage curves had to be developed for each agent in order to be able to complete the same process as for the municipalities. Using the flood heights for various exceedance probabilities, under 0 feet of SLR, the elevation of the structure, and the depth-damage curves used to calculate flood damage, I was able to assign certain inundation depths to each exceedance probability. Sea level rise adjustments were added in each predicted year linearly for each of the projections up to 30-years out, as it was assumed that an increase in MSL affected the depth of the expected floods equally. The depth-damage curve then was used to estimate damages from the new inundation heights, resulting in the same style curve: expected damages for floods corresponding to various exceedance probabilities. Once again, using the method in (P. Kirshen, Merrill, et al., 2012), the area under this curve was taken to estimate annual expected damages. The same equation to calculate 30-year expected damages for the municipalities could then be used for the developer agents.

The aquafence costs property owners \$500,000 to install and \$40,000 to deploy. Property owners currently assume a worst-case rate of one deployment per year. On-site barriers are assumed to cost \$3.2 million per building, which assumes \$5300 construction cost per foot and a perimeter of 600 feet. We assume that the aquafence protects structures up to 3 feet of inundation, while the on-site barriers protect for floods up to 15-ft NAV-88.

MBTA:

The MBTA process for assessing risk mimics that of the municipalities in the case where no seawalls are constructed throughout the Harbor. When municipalities choose to construct seawalls, annual damage estimates are altered to reflect the reduction in damage that the seawalls would provide according to their specific location. This allows the agent to update expected damages as seawalls are constructed. However, the MBTA does not have information about future planned municipal seawalls or speculate on their construction.

Reductions in risk from seawall construction or on-site barriers is completed in the same manner as the municipal assessments. Cost estimates for on-site barriers is taken from Martello (2023) [4].

Regional Assets:

Damage estimates for regional assets was completed similarly to the procedure for property owners. Assuming catastrophic damages (\$1B) at inundation depths of more than 3 feet, a curve was created plotting exceedance probabilities against damages. This curve is shifted with each projected year of sea level rise according to the agent's projection. Thirty years of these projections are discounted and summed to get the 30-year estimate of potential damage.

Costs of on-site barriers are expected to be similar to on-site barriers for property owners (\$5300/ft). I used GIS to estimate the perimeter of these assets and estimate construction costs. It is assumed that these barriers protect agents up to 15 ft NAV-88. The damages coming from flood exceedance probabilities that correspond to an elevation less than 15 ft NAV-88 are assumed to cause no damage in the case of an on-site barrier.

Flood Authority

The flood authority uses calculations from all agents above. However, instead of considering individual adaptations for each agent, the agent only considers constructing seawalls across 11 locations: the nine neighborhoods in Boston, Quincy, and Winthrop. 30-year damage estimates from all other agents are summed based on their locations to estimate the cumulative damages that could be avoided from the construction of each segment of seawall.

Additional cost considerations

The cost of an adaptation is not only the costs specified in the section above. Adaptation costs are also affected by a few user selected parameters: discount rate, operations and maintenance percent, permitting cost, and maintenance fee. The operations and maintenance costs and permitting costs are both represented as percentages of the total adaptation cost that are added to the cost estimate. The maintenance fee is also represented by a percentage, assumed to represent the additional transaction costs due to cooperation for both voluntary coalitions or the regional flood authority. The discount rate is applied according to the following equation:

Equation 17:

$$discounted\ cost = \frac{final\ cost}{(1 + discount\ rate)^{year-2020}}$$

Insurance Module

Some property owners are required to have insurance. We model our insurance market off of the NFIP flood insurance process. Any household in the 100-year flood plain with a mortgage is often required to by NFIP insurance by their lender. De Ruig, et al estimate the percentage of households in the flood plain that are required to comply to be around 55%, with around 78% of

those actually purchasing the insurance (De Ruig et al., 2023). Although there will be discrepancies between these values and large scale property owners, we use this as an approximation of how many agents are required to purchase NFIP insurance. Out of agents within the 100-year flood plain, we assume 43% of these agents must purchase flood insurance. It is assumed that these agents will always purchase this insurance regardless of the cost of the insurance. We distinguish insurance options between homeowners and commercial properties both for price and coverage. Although not all properties may be eligible for NFIP insurance, we do consider this to be representative of all insurance in the Harbor and do not model private insurance markets.

In each time step, property owners have the option to purchase flood insurance. Prior to the year 2022, the insurance premium is assumed to be \$1482, the average value in Massachusetts, following the procedure used by (De Ruig et al., 2023). For commercial properties, we set this to \$4,224. In 2022, we begin to price the premiums to better reflect NFIP's Risk Rating 2.0, which has been updated to better reflect an accurate assessment of property risk (National Flood Insurance Program, 2022). Insurance is then priced according to the following procedure:

1. For each property owner, the annual expected damage is assessed according to the same area methodology as the benefit-cost ratio.
2. The premium is set to either an 18% increase from the current premium or the expected annual damage, whichever is smaller.
3. Premium minimums are set at \$100 so no household would pay less than \$100 for coverage.

If property owners purchase insurance, they are assumed to be eligible for the maximum NFIP coverage in a given storm (350,000 for homeowners and 1,000,000 for commercial structures),

subject to a 10% deductible. While this does not reduce the damage, it does alter who pays for the damage that occurs to a property owner.

Property owners may purchase flood insurance in addition to other adaptations or may purchase flood adaptation on their own.

We estimate the role of the CRS system on insurance premiums by reducing the cost of a premium by 30% for any agent protected by a seawall (FEMA, 2017).

Funding and Budgeting

The model can be run with or without budget constraints. Without budget constraints, we assume that financing is not an obstacle for adaptation. In this case, adaptation implementation would be limited only by a permitting delay.

With a budget constraint, some available funds are required to allow an agent to adapt. We assume a 10% down payment for adaptation implementation. Assumed annual budgets are based on published capital improvement plans, municipal plans, and percentages of structure value.

Adaptation prioritization for the MBTA, Boston Harbor, and Regional Authority can be completed in one of two ways. In the first, prioritization of particular segments is completed in order of the highest benefit to cost ratio (*prioritization-method = normal*). The second methodology (*prioritization-method = EJ*) utilizes the method proposed by (Stroud et al., 2023), where potential benefits of adaptation are weighted by:

Equation 18:

$$\omega_{Y_{CT}} = \left(\frac{Y_{Census\ Tract}}{Y_{Boston\ Median}} \right)^{-\epsilon}$$

Where epsilon is 1.35.

Rather than calculating these at the census tract level, we identified weights at the scale of the model: neighborhoods or towns in 2017. This resulted in the following weights for each neighborhood and municipality considered in the model:

<i>Municipality/Neighborhood</i>	<i>Income Weight</i>
Allston	1.454823548
Backbay	0.510401236
Charlestown	0.502590867
Downtown	0.666944919
East Boston	1.238426983
Fenway	1.835616468
North Dorchester	1.4452918
South Boston	1.109159906
South Dorchester	1.349865209
Quincy	0.911733669
Winthrop	1.002224514

Permitting

Permitting manifests through two variables in our model: *permitting_cost_proportion* and the *permitting_delay* parameter. These work together to account for the direct costs on permitting on adaptation decision-making and the time that it may take to permit large adaptation projects, during which storm damages will still occur. For example, the total cost of an adaptation is calculated as follows:

Equation 19:

Total adaptation cost

$$\begin{aligned}
 &= \text{discounted adaptation cost} + (\beta * \text{discounted adaptation cost}) \\
 &+ (\gamma * \text{discounted adaptation cost}) - (\delta * \text{discounted adaptation cost})
 \end{aligned}$$

Where β is the *permitting_cost_proportion*, γ represents any cooperation maintenance fee, and δ represents any reduction in funding due to external grant accessibility.

In addition to increasing the number of years that an agent is exposed to damaging floods while awaiting adaptation, the *permitting_delay* parameter is also taken into account directly when calculating benefits of an adaptation into the future. In this way, large *permitting_delays* both reduce the calculated benefits of an adaptation (because it is a longer time before the benefits can be realized) and increase damages that an agent experiences before the adaptation is in place. Expected benefits of an adaptation, which drive the adaptation decision-making are calculated as below:

Equation 20:

$$Benefits = \sum_{pd}^{t=f} E[Damages_{No\ Adapt}]_t - E[Damages_{Adapt}]_t,$$

Where t indicates the year of calculation, f is the *foresight* parameter, which controls how far into the future agents project their calculated benefits, pd is the *permitting_delay* and the terms $E[Damages_{No\ Adapt}]_t$ and $E[Damages_{Adapt}]_t$ correspond to the expected damages with and without an adaptation in the calculated year. All agents experience the same permitting delay and permitting cost proportion within a single simulation.

Adaptation Metrics

Metrics in the paper are reported in 6 different ways that can be separated into two categories: using a baseline of no adaptation and using a baseline of no cooperation. The first is useful to understand the relative behavior of each form of adaptation governance independently. However, using the scenario of no cooperation as a baseline provides insights on the benefits of cooperation in direct contrast to a scenario that is likely reflective of a business-as-usual adaptation strategy (we consider it to be unlikely that no adaptation will occur in the absence of

cooperation, which provides a strong case for the second set of metrics. Regardless of the baseline, we directly quantify three metrics: flood damages, adaptation costs, and net benefits.

These are calculated in the following ways for use in analysis:

Flood damages (no adaptation baseline):

Equation 21:

$$cumulative\ damage = \sum_{2020}^{2100} damage_t$$

Flood damages (no cooperation baseline):

Equation 22:

$$cumulative\ damage\ avoided = \sum_{2020}^{2100} damage_{no\ cooperation} - \sum_{2020}^{2100} damage_{cooperation}$$

Adaptation costs (no adaptation baseline):

Equation 23:

$$cumulative\ adaptation\ costs = \sum_{2020}^{2100} adaptation\ costs_t$$

Adaptation costs (no cooperation baseline):

Equation 24:

cumulative adaptation costs avoided

$$= \sum_{2020}^{2100} adaptation\ costs_{no\ cooperation} - \sum_{2020}^{2100} adaptation\ costs_{cooperation}$$

Net benefits (no adaptation baseline):

Equation 25:

$$\begin{aligned} \text{net benefits} = & \text{cumulative damage}_{\text{no adaptation}} - \text{cumulative damage}_{\text{adaptation}} \\ & - \text{adaptation costs} \end{aligned}$$

Net benefits (no cooperation baseline):

Equation 26:

$$\begin{aligned} \text{net benefits of cooperation} \\ = & (\text{cumulative damage}_{\text{no cooperation}} - \text{cumulative damage}_{\text{cooperation}}) \\ & + (\text{adaptation costs}_{\text{no cooperation}} - \text{adaptation costs}_{\text{adaptation}}) \end{aligned}$$

GIS

The map in NetLogo is generated using GIS files of the Boston Harbor Area. These files were also used to estimate seawall length needed for each municipality (and in the case of Boston, each neighborhood). These files are use to generate a map and demonstrate where seawalls are constructed, but the patches in NetLogo do not directly interact with the agents. The following table displays both the estimated seawall length required for each designated segment and the neighborhoods that it protects.

Seawall Segment	Length (ft)	Additional Neighborhoods?
Allston	14505	
Backbay	4146	
Charlestown	16676	
Downtown	13842	
East Boston	73993	
Fenway	5428	
North Dorchester	20811	Jamaica Plain, Roxbury
South Boston	44647	Roxbury, South End
South Dorchester	20811	

North-Shore	54530	Assumed to be Winthrop
South-shore	105324	Assumed to be Quincy

Python Extension

The NetLogo model is run with the python extension. Python is utilized to complete some of the more complicated benefit-cost calculations. Model users will need to have python and a corresponding environment to run the model. The packages of Scipy and Sys must be downloaded.

C.2 Example Dashboard

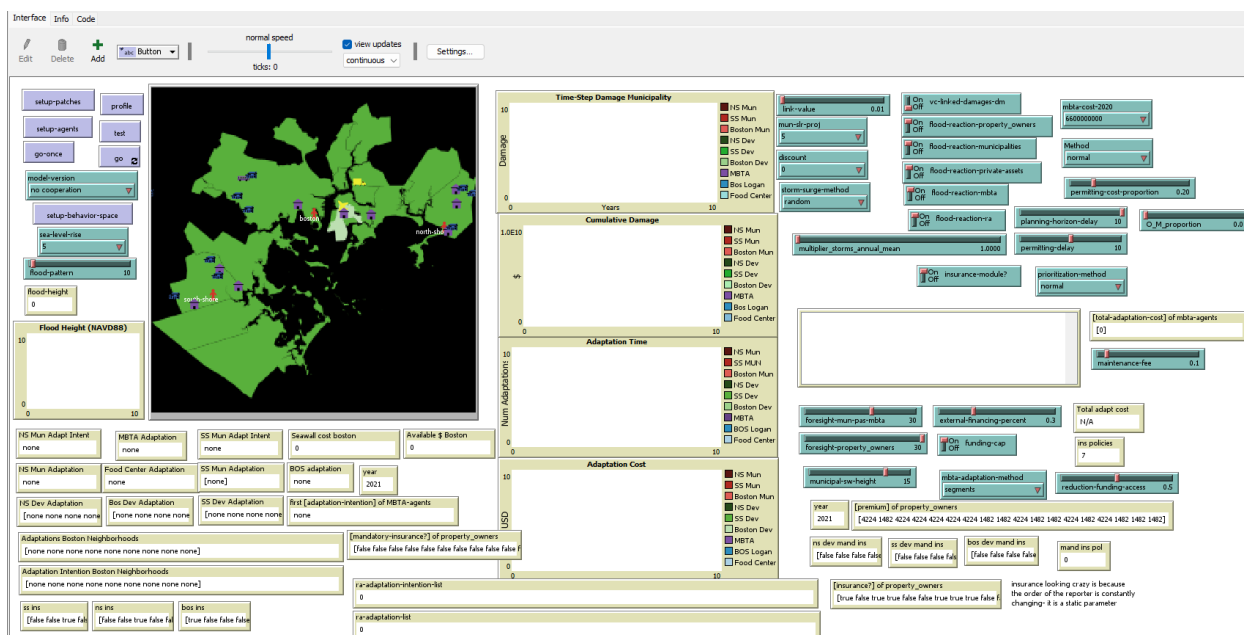


Figure S34: Snapshot of the GUI for the model in NetLogo.

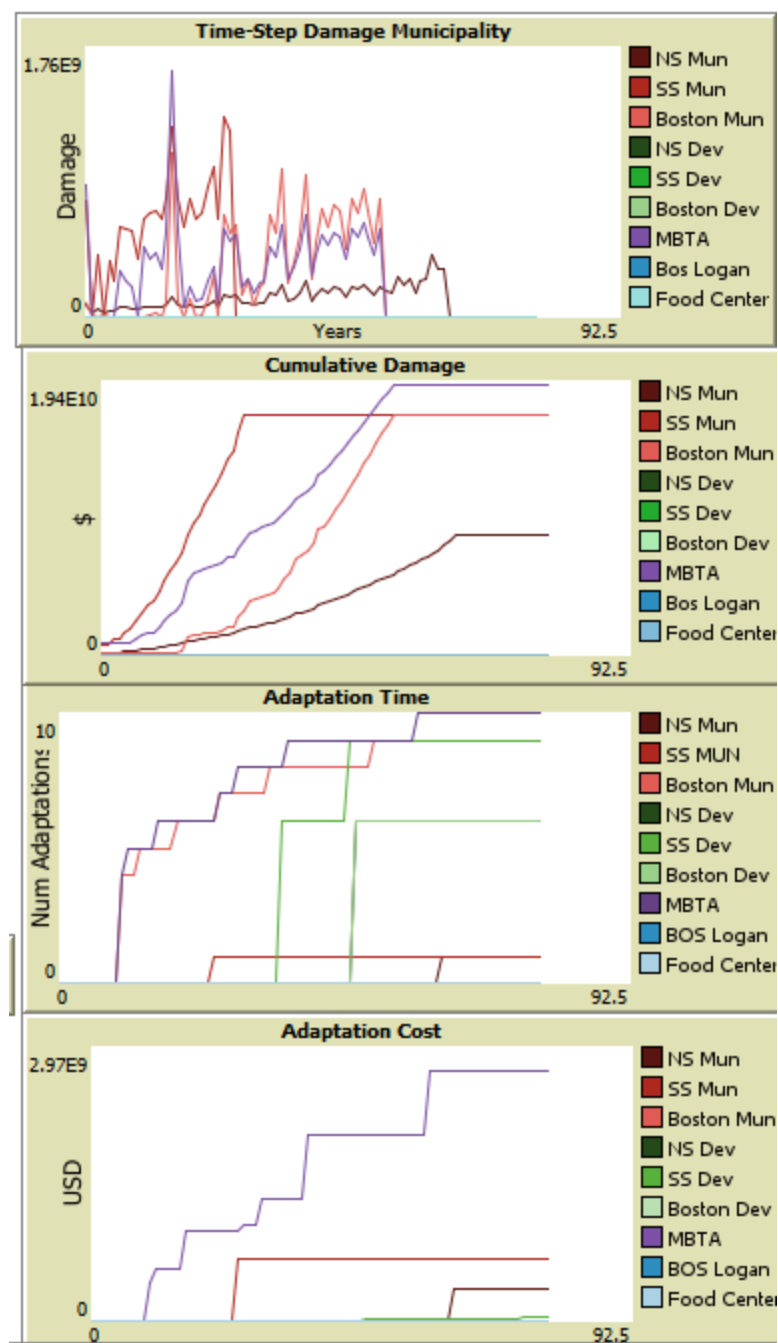


Figure S35: Close-up on graphs from a single simulation on the NetLogo interface.

C.3 Key Assumption List

Assumption	Details
Max Storm Surge Distribution	Captured with Gumbel distribution based on historical data

Flood Heights corresponding to AEPs	For AEPs of [.001, 0.002, 0.01, 0.02, 0.05, 0.1, 0.2, 0.25], we use flood heights of [10.95, 10.54, 9.99, 9.58, 9.17, 8.61, 8.17, 7.7, 7.75] determined from the MC-FRM with linear interpolation
Assumed damages municipalities	Values calculated in Outer-harbor feasibility study
Annual Adaptation Budget of Airport	\$50M
Annual Adaptation Budget of Food Distribution	\$50M
MBTA Cost per Neighborhood Adaptation	In order of: North Shore, South Shore, Allston, Back Bay, Charlestown, Downtown, East Boston, Fenway, North Dorchester, South Boston, South Dorchester; [2.5, 2.5, 5, 5, 10, 25, 25, 5, 2.5, 15, 2.5]
Annual MBTA Adaptation Budget	\$40M
Annual municipality adaptation budget	Calculated as the same ratio that Boston has allocated to climate out of tax income; Boston has a budget of 20000000, NS of 560000, and Quincy 2720000
Property Owners annual budget	10% of property value
Property Value of property owners	Homeowners: 1000000 Commercial: 8000000
Property owners with mandatory NFIP insurance	43% if elevation < 9.58 ft NAV88
Minimum NFIP premium	100
Aquafence Protection	Structure elevation + 3 ft
Seawall protection	15 ft NAV88 (~5ft above 100-year flood)
Insurance Coverage Caps	Homeowners: 250,000 Commercial: 500,000
Insurance deductible	10% damages
MBTA Exposure	In order of: North Shore, South Shore, Allston, Back Bay, Charlestown, Downtown, East Boston, Fenway, North Dorchester, South Boston, South Dorchester; [2, 2, 2, 10, 15, 2, 5, 40, 2]
Cost of municipal seawall	7500/ft
CRS Discount with municipal seawall in place	30%
Aquafence cost	500,000
Modifier value in case of no expected damage	0.5
Prioritization of adaptation in case of limited budget	Maximum benefit-cost ratio
Voluntary cooperation requirements	Agents are already willing to adapt Agents pay less than current adaptation plans
Adaptation down payments	10%

C.4 Supplemental CART Results

The following results show the raw CART trees highlighted throughout the paper. We present both raw trees and results from any alternative thresholds that were tested. For all of the trees included in the following sections the condition is listed above each node (for example, Sea Level Rise = 3) and the left branch indicates if the condition is true, while the right branch indicates false. The majority class (Low/High) is listed within the box for each node, along with the number of simulations in each class. The percentage given at the bottom of each box is the percentage of simulations across the entire ensemble that exist within that node.

C.4.1 Top 10% Net Benefits across the Full Ensemble

Chapter 2 presents the results of a CART algorithm for the conditions that lead to the top 10% of outcomes for the highest net benefits across our full ensemble. Figures S11 and S12 are the raw outputs from the R file used for data analysis, with S12 demonstrating the tree with an expanded depth.

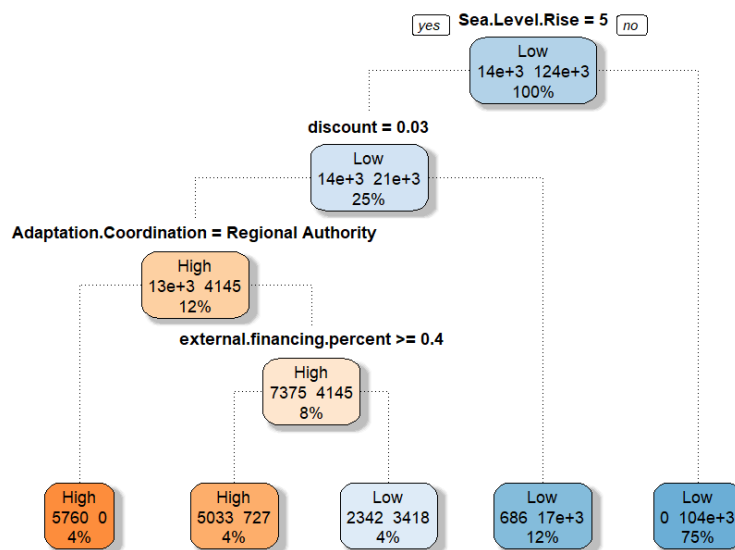


Figure S36: Tree for Net Benefits in the top 10% of simulations for the full ensemble.

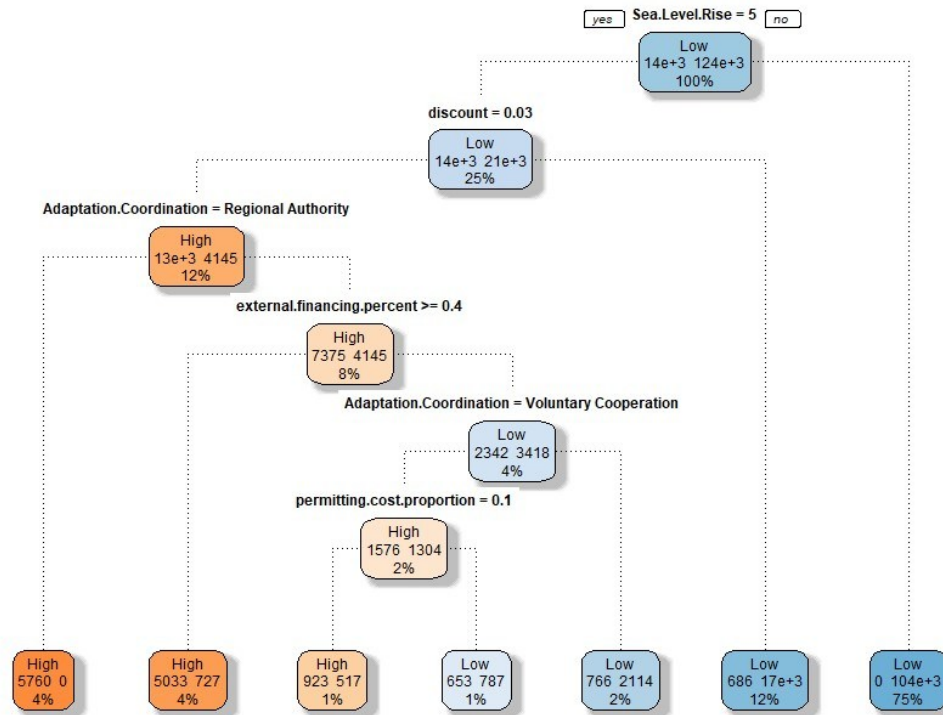


Figure S37: Expanded tree for Net Benefits in the top 10% of all simulations containing additional branches and nodes.

C.4.2 Comparison of Cooperative to Non-Cooperative Strategies

The figures below expand on Figure 6 in the manuscript. In the previous figures, we assumed a baseline worst-case scenario of no adaptation, using outcomes with no adaptation at all to calculate Net Benefits. However, this may be unrealistic, as a no cooperation outcome may be a more appropriate business-as-usual scenario. To address this and provide analysis on the *nature* of cooperation necessary, we analyze the ensemble by comparing voluntary cooperation and regionalization to scenarios of no cooperation. This methodology allows for statements to be made about the relative effectiveness of mandated or voluntary cooperation over a lack of cooperation

in adaptation planning. We include the raw CART algorithm outputs for the 10% best and 10% worst case outcomes, along with results for alternatives thresholds using 9% and 11% (results greater than 9, 10, 11% and results less than 9, 10, 11%).

Damages Avoided by Cooperating

The first metric we include in the paper is the calculation of damages avoided by cooperative behavior. This metric is calculated by comparing simulations with a regional authority or voluntary coalitions to simulations with no cooperation, when all other parameters are identical within a single simulation. These comparisons are then carried out for each combination of parameters and stochastic runs, resulting in an ensemble of approximately 90,000 simulations.

Damages avoided are calculated as:

Equation 27:

Damages avoided

$$= \text{Cumulative Flood Damages}_{No\ Coop} - \text{Cumulative Flood Damages}_{Coop}$$

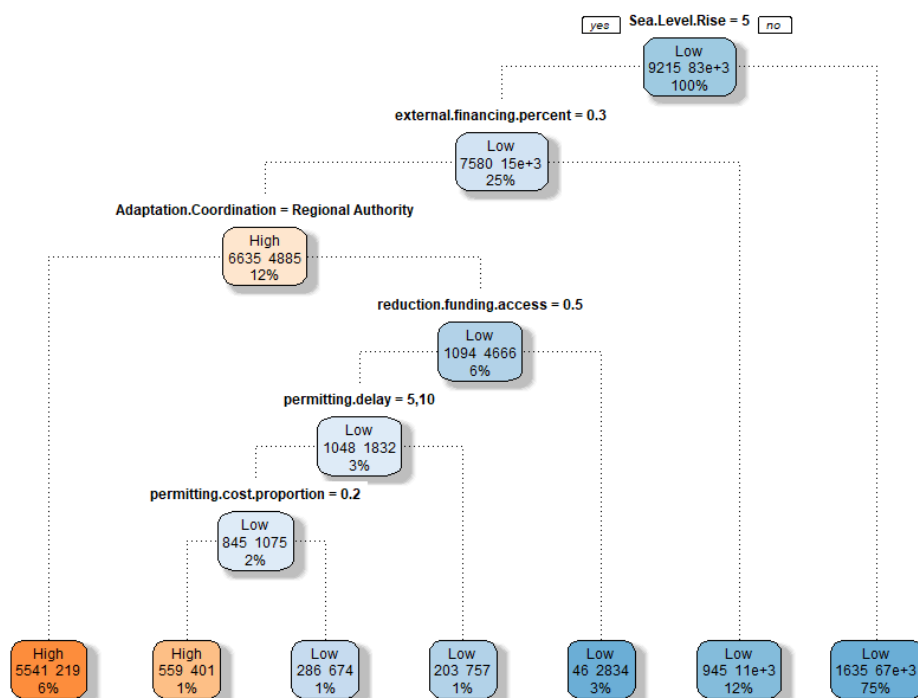


Figure S38: CART results where the classification is set for damages avoided to be greater than 90% of the simulations. The importance of sea level rise, financing percent, and adaptation regime are highlighted by their presence in the early conditions.

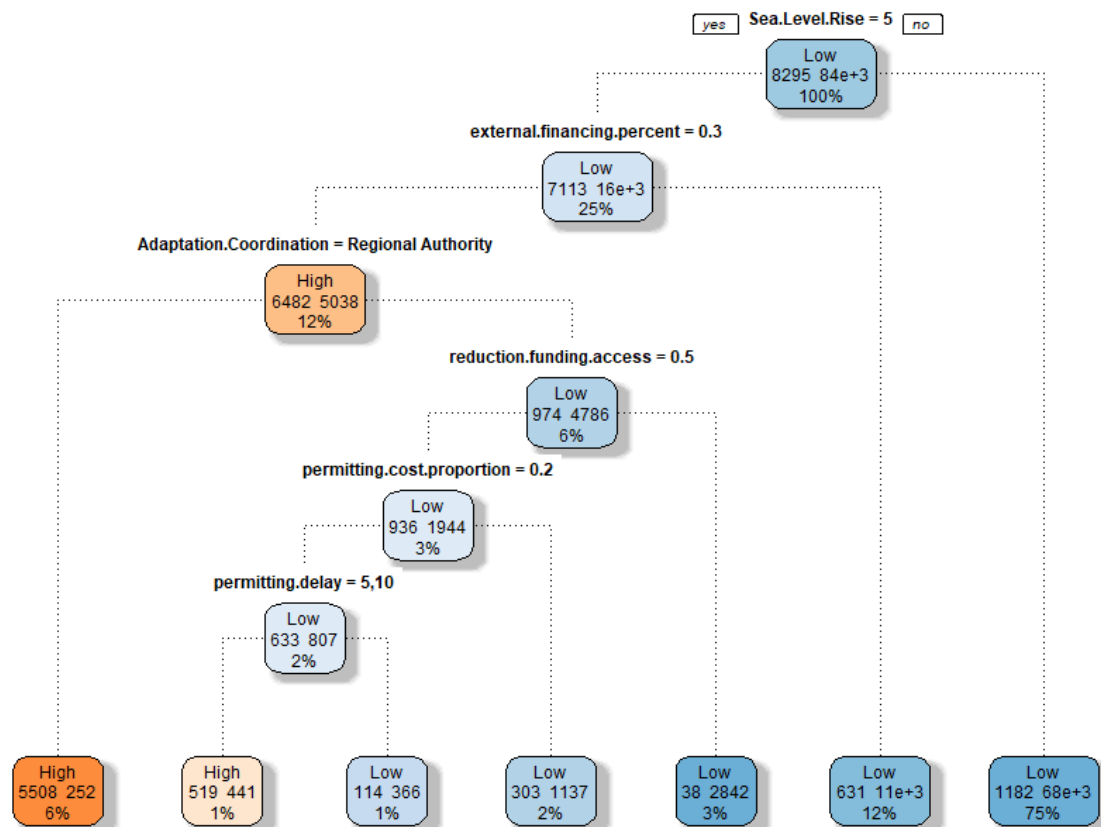


Figure S39: Here, the threshold for 'High' is adjusted to 91% instead of 90%, such that only the top 9% of simulations are included in the classification algorithm. The top 4 conditions are the same as Figure S3.

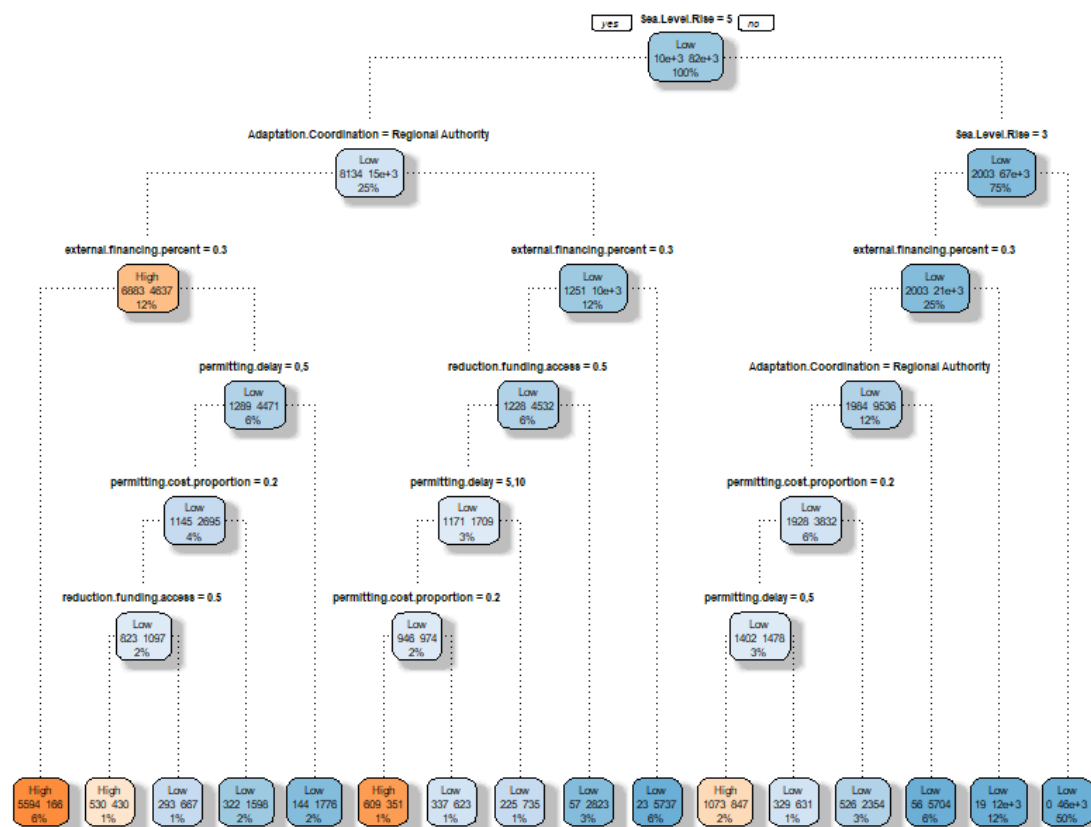


Figure S40: When the threshold is adjusted to 89%, the tree gets slightly more complicated, though the top parameters remain largely unchanged from the results before.

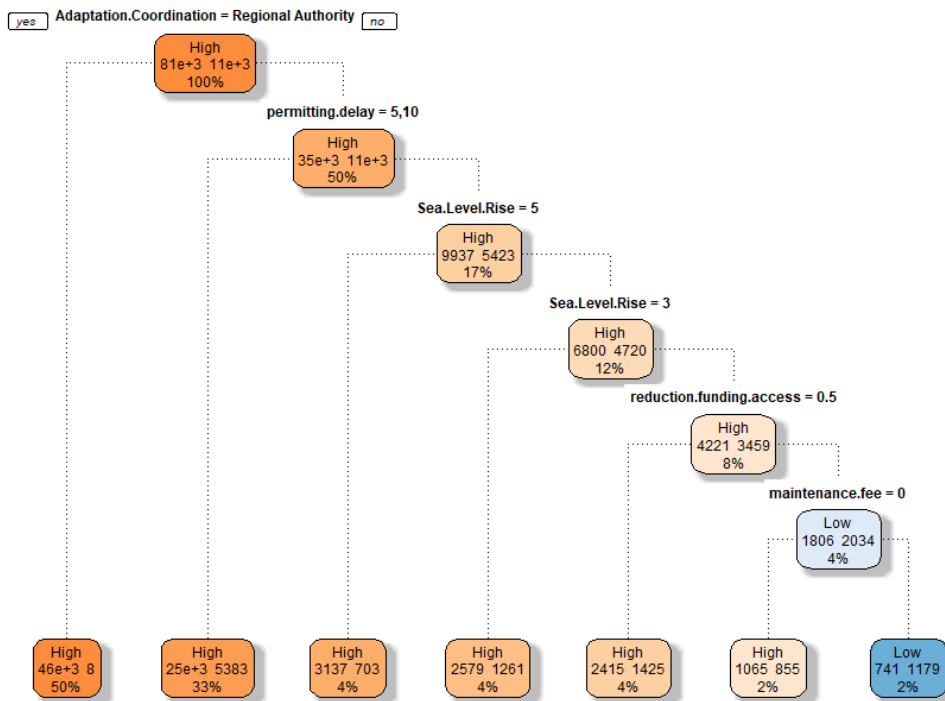


Figure S41: This figure represents the CART outputs for the classification for damages avoided less than 11%, 10%, and 9% of the simulations. The conditions for each node are identical for all three trees, although the exact values of simulations in each classification shifts slightly from the 10% tree here. Because we utilize these trees only for parameter identification, we do not include the repetitive 11% and 9% tree below.

Adaptation Costs Avoided by Cooperating

The next metric of interest is adaptation costs avoided by cooperating. Similarly to the ‘damages avoided’ metric above, this is calculated by comparing outcomes from simulations with either voluntary cooperation or a regional authority with simulations from no cooperation scenarios. The metric is also calculated cumulatively at the end of the century as:

Equation 28:

Adaptation Costs Avoided

= Cumulative Adaptation Costs_{No Coop}

– Cumulative Adaptation Costs_{Coop}

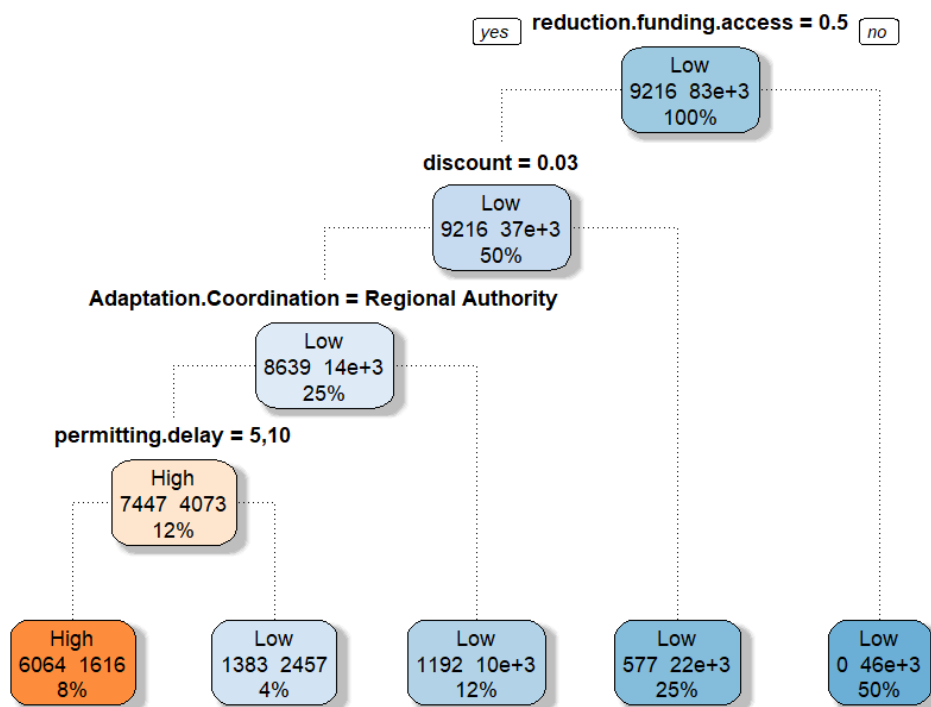


Figure S42: This tree presents the results of CART analysis for when adaptation costs avoided are greater than 90% (the best outcomes).

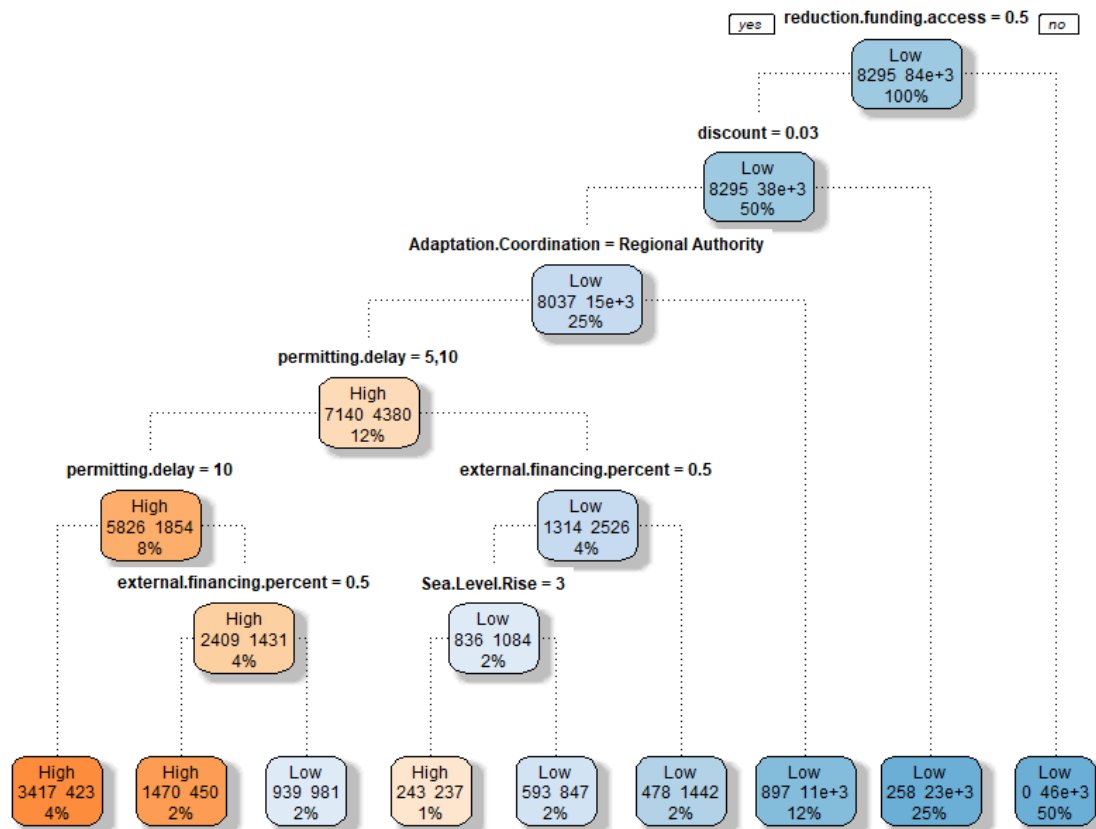


Figure S43: This tree mimics the tree above, except a cut-off of 91% of simulations is used. The first four conditions are again static, justifying the selection of the 10% threshold.

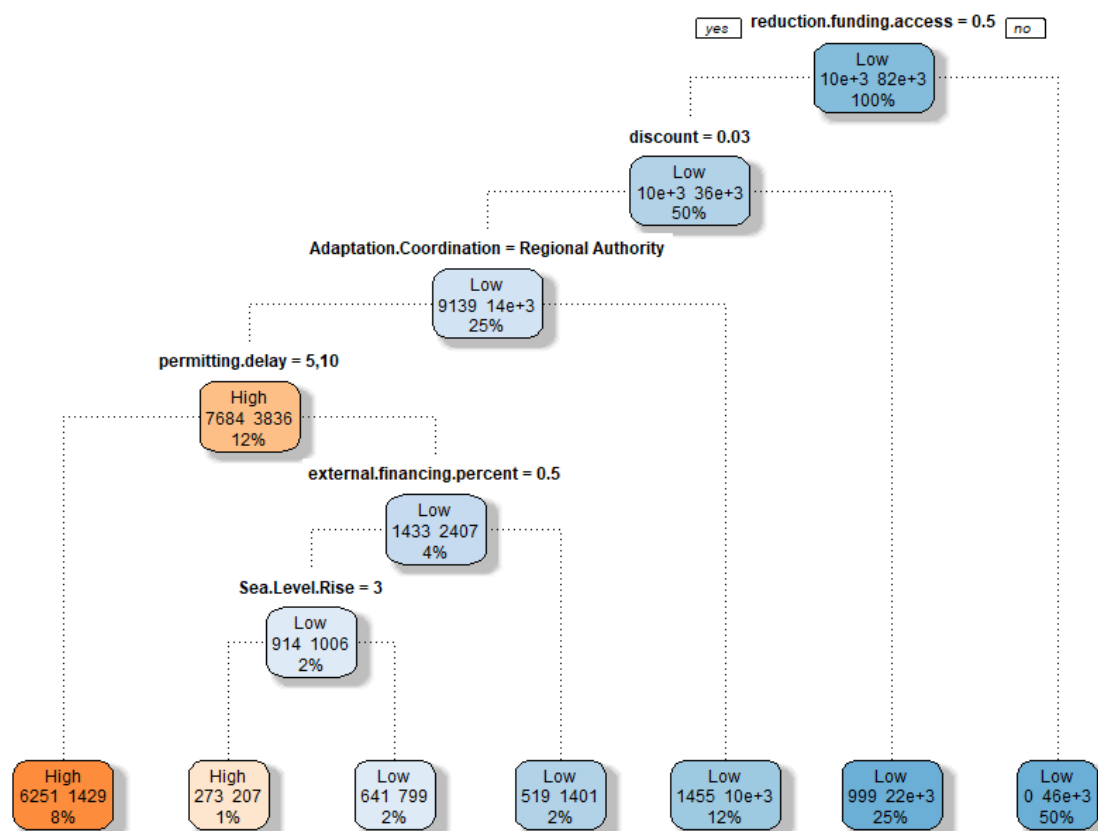


Figure S44: This tree was generated using a threshold of 89% for adaptation costs avoided. Similar to the two figures above, the top four conditions are reduction in funding access, discount rate, adaptation coordination, and permitting delay.

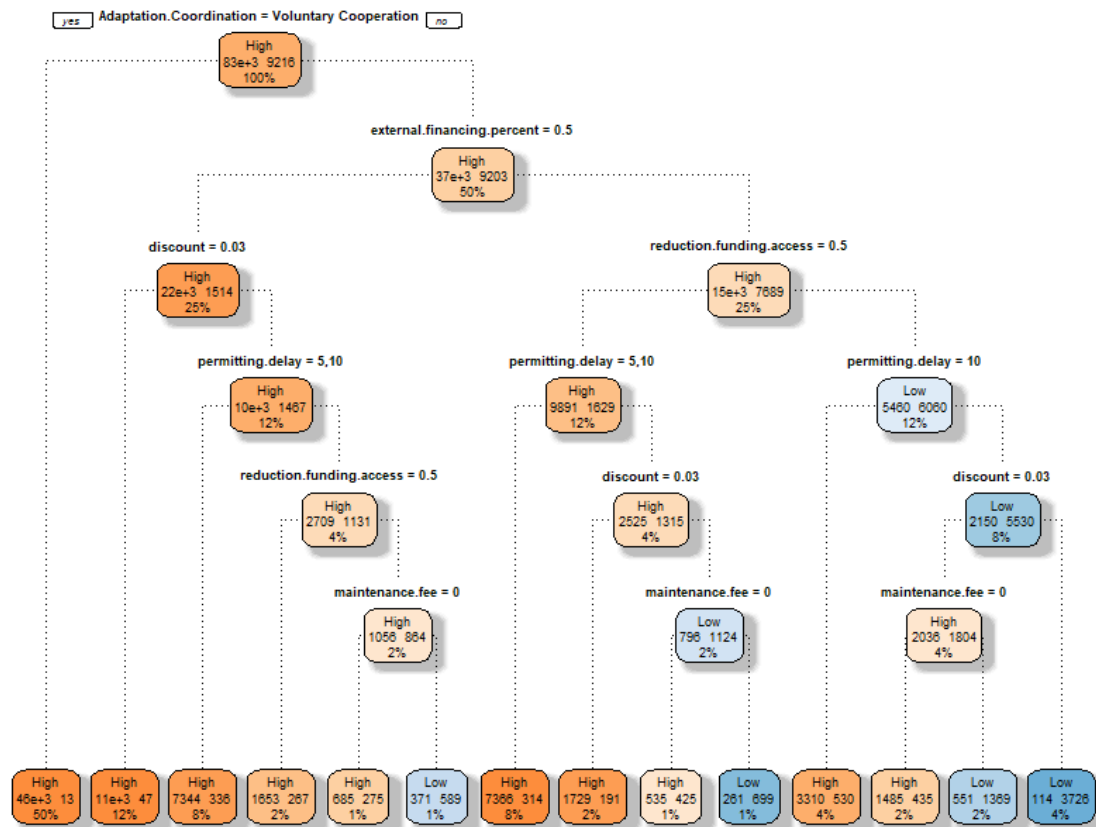


Figure S45: In contrast to the trees above, this tree sorts for the worst case outcomes, the bottom 10% of simulations for adaptation costs avoided by cooperation. Although complicated, the top conditions are adaptation coordination, external financings, discount, reduction of funding access, and permitting delay.

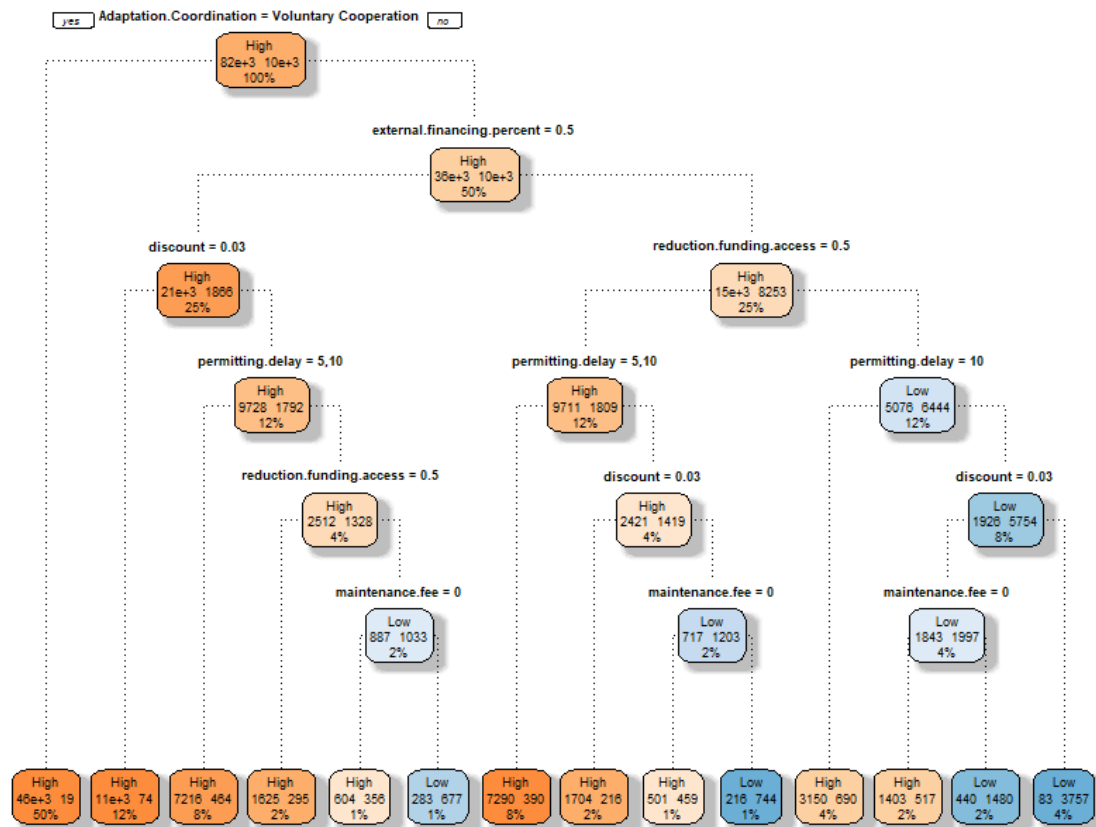


Figure S46: This figure repeats the metric above, but sets the threshold at the bottom 11% of all simulations. The conditions and order of the splits are identical to the 10% threshold above.

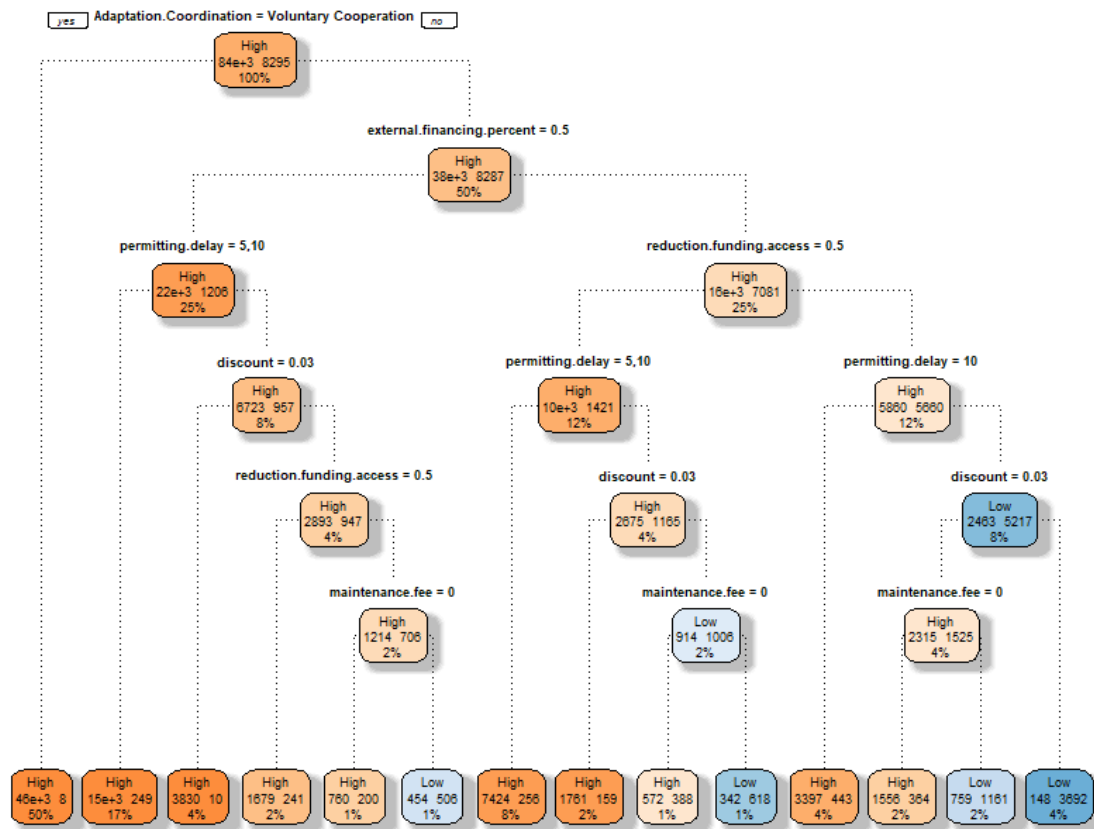


Figure S47: With a threshold of 9%, the identified conditions are also identical to the 10% and 11% cut-off for adaptation costs avoided.

Net Benefits from Cooperation

Net benefits are designed to measure how much benefit is derived from cooperative behavior in contrast to non-cooperative behavior. This is a useful metric, because it incorporates both damages that are avoided and the costs required to adapt. This metric is applied across the entire Harbor region cumulatively and calculated based on cumulative flood damages and adaptation costs at the end of the simulation. Net benefits are calculated as:

Equation 29:

Cumulative Net Benefits

$$\begin{aligned}
 &= (\text{cumulative damage}_{no\ cooperation} - \text{cumulative damage}_{cooperation}) \\
 &+ (\text{adaptation costs}_{no\ cooperation} - \text{adaptation costs}_{adaptation}) \\
 &= (\text{flood damages avoided with cooperation}) \\
 &+ (\text{adaptation costs avoided with cooperation})
 \end{aligned}$$

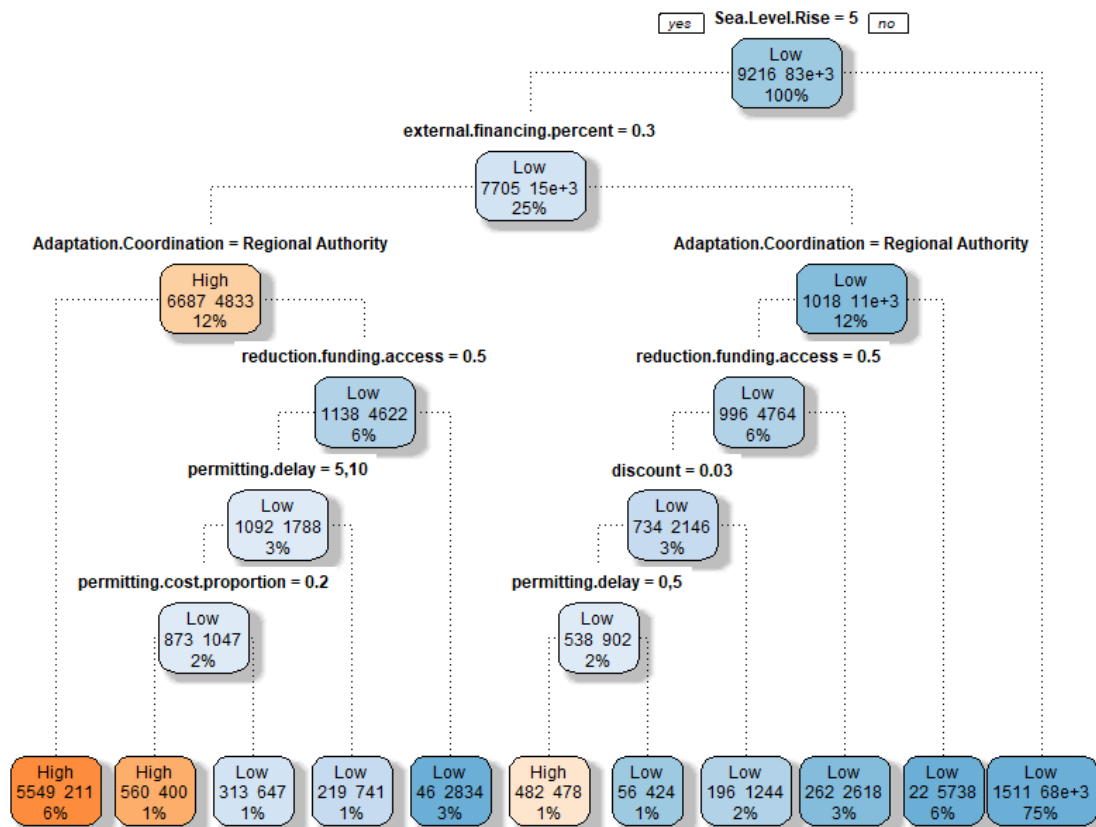


Figure S48: The tree above provides the results of the CART algorithm when selecting for the top 10% of net benefits of cooperation. Here, the top conditions in order of their importance are sea level rise, external financing percent, adaptation coordination, and a reduction in funding access.

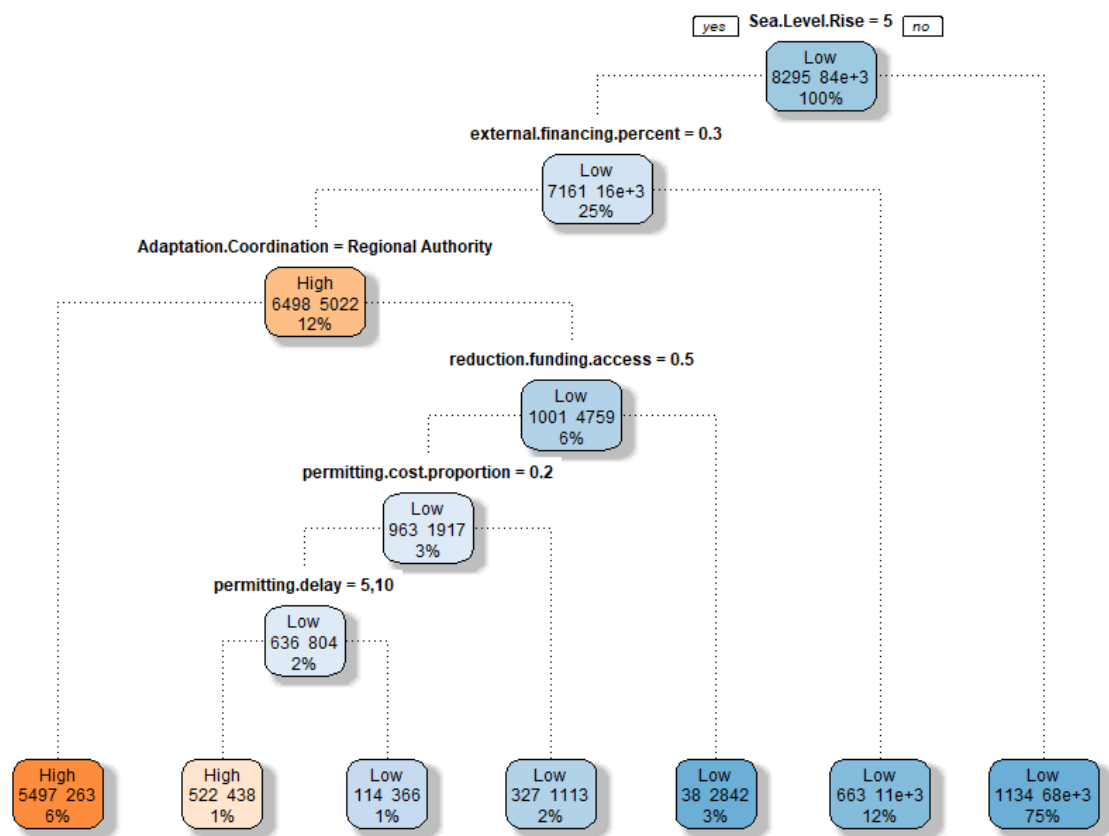


Figure S49: The tree above reflects the results when selecting for the top 9% (net benefits > 91% of all simulations). Although the tree has fewer branches, the top 4 conditions are consistent.

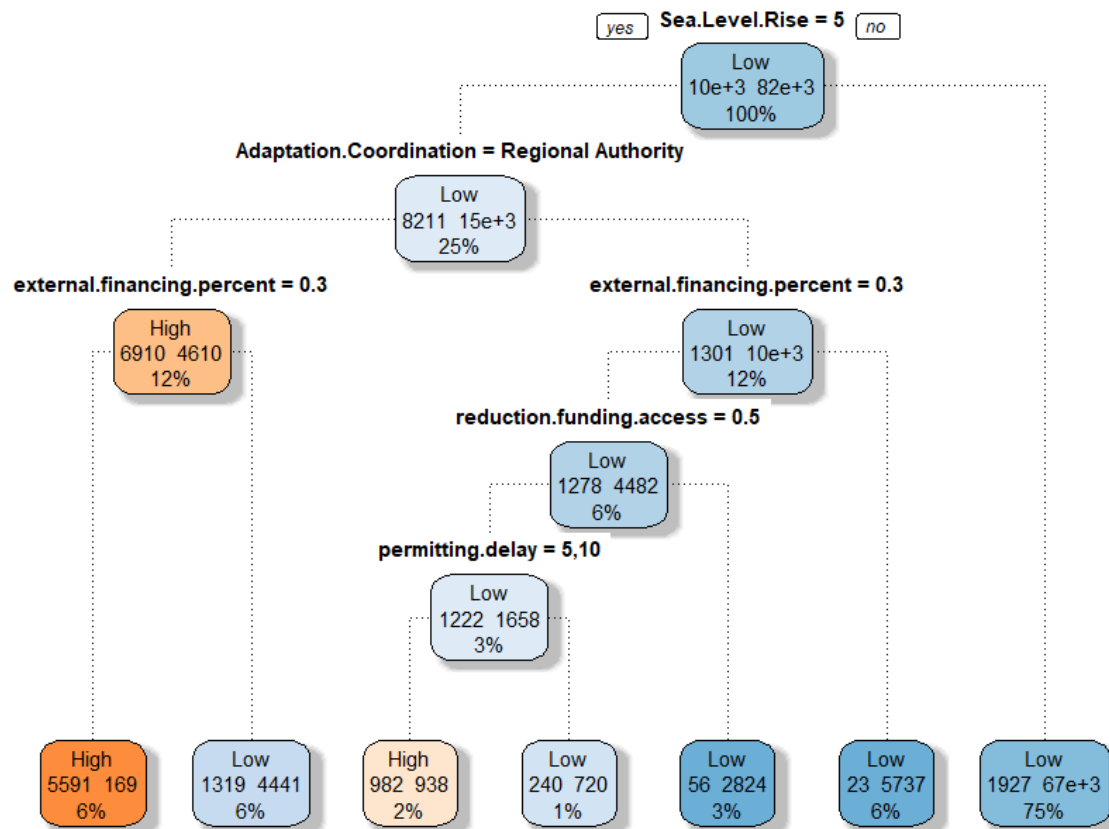


Figure S50: This tree was used with a cut-off for the top 11% of the simulations for net benefits. Here, a reversal is visible between the order of the adaptation coordination and external financing conditions, although the same conditions are present within the top four selected for Figure 6 in the manuscript.

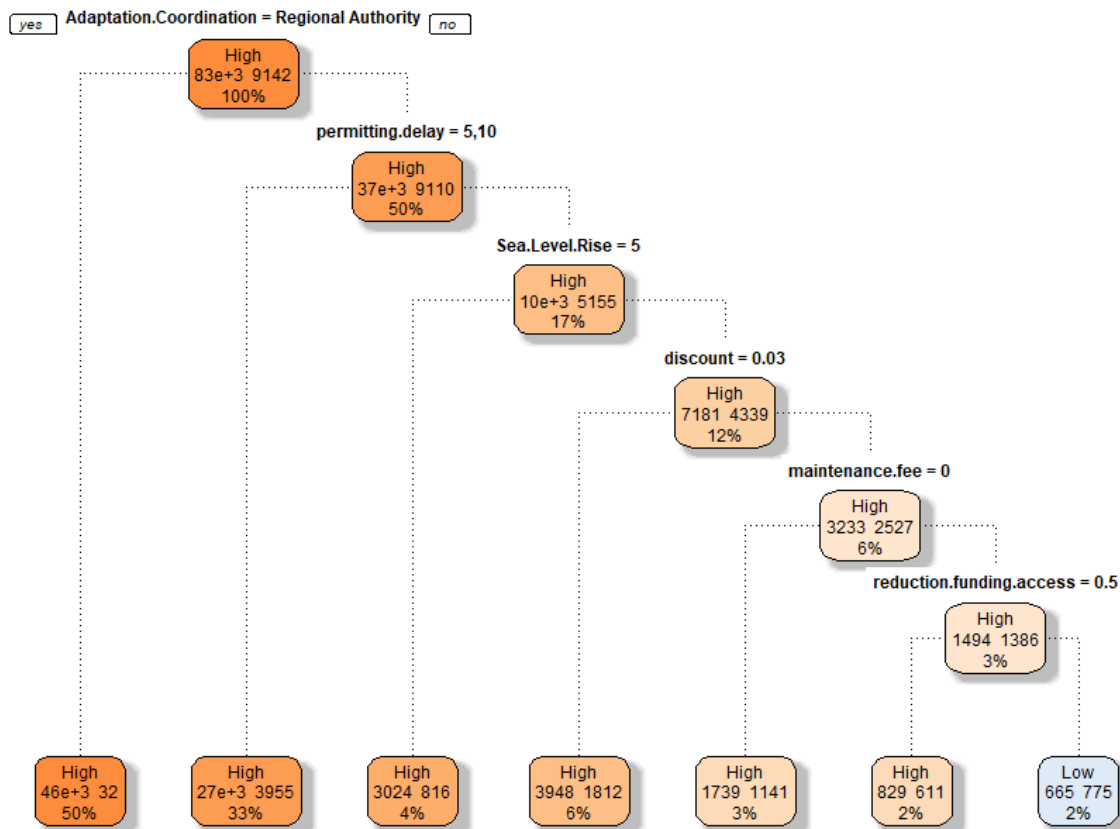


Figure S51: In contrast to the three figures above, here the algorithm was applied to select for cases where net benefits were in the lowest 10% of all simulations. The most important four conditions include adaptation coordination, permitting delay, sea level rise, and discount rate.

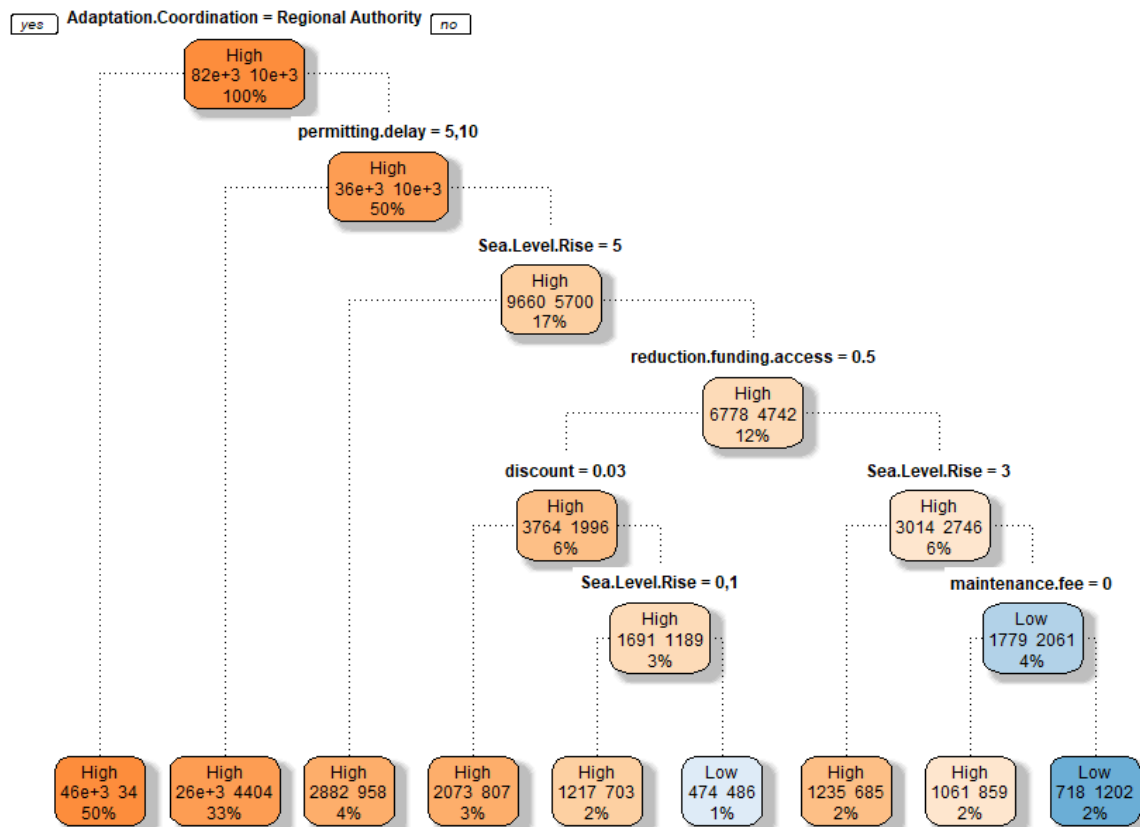


Figure S52: This figure presents the results of the CART tree for a threshold of bottom 11% percent of simulations. In contrast to the figure above, a reduction in funding access replaces discount rate as the fourth most important condition.

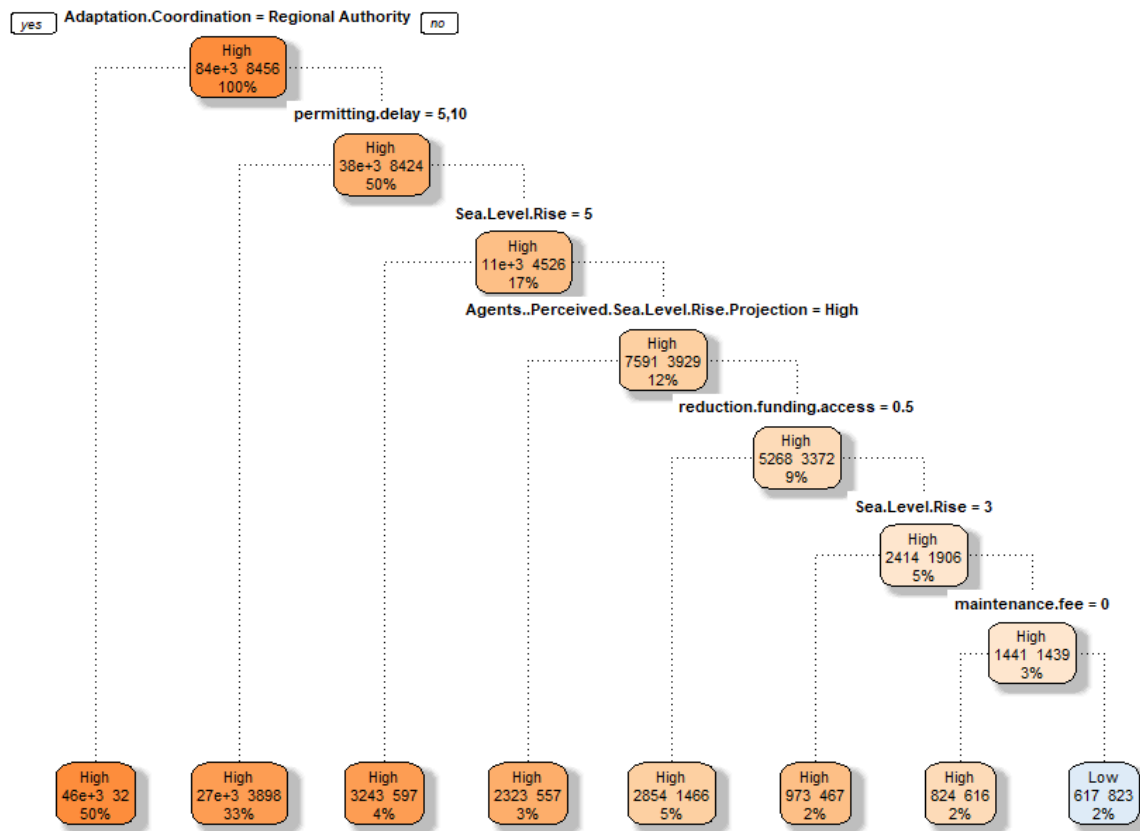


Figure S53: This figure, which uses as threshold of bottom 9%, again utilizes a separate condition for the 4th split of the tree.

Here, the perceived sea level rise projection is used, which is a parameter that reflects an actor's expectation of sea level rise (noting that this can vary from experienced sea level rise).

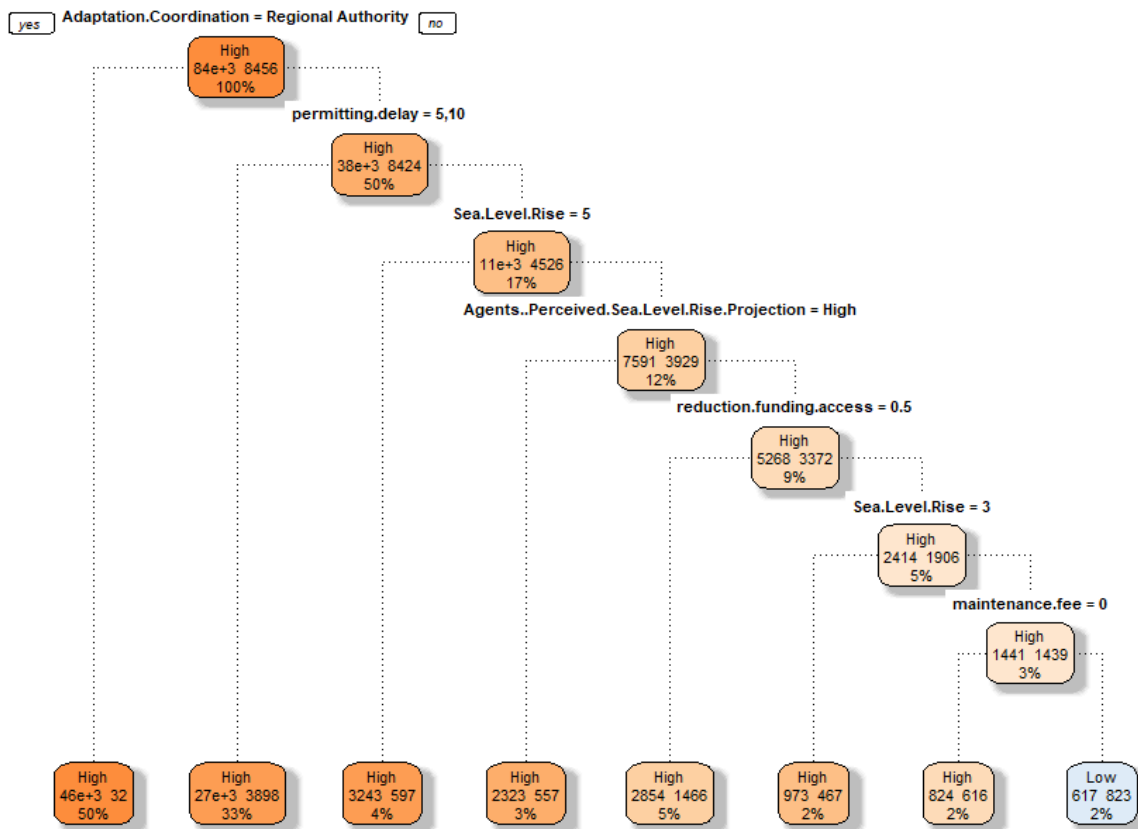


Figure 54: Rather than utilizing a classification based on the best or worst outcomes, here, the CART tree was used to identify conditions that lead to higher net benefits from cooperation than no cooperation (the difference between the two is greater than 0). A classification of 'High' indicates that cooperation results in higher net benefits than the corresponding non-cooperative approach. This tree demonstrates that adaptation coordination, permitting delay, sea level rise, and perceived sea level rise largely contribute to this phenomenon. Non-cooperation out-performs cooperation approximately 10% of the time across the ensemble.

C.4.3 Breakdown by Agent type

Chapter 2 displayed the conditions that lead to the best and worst outcomes for total flood damages summed across all agents in the Harbor. In contrast, Table 2 focuses on conditions that lead to poor outcomes based on an agent scale. The following figures demonstrate the trees used to identify conditions that lead to cooperative solutions resulting in less flood damage than non-cooperative

adaptation for a variety of agent types. In the figures below, 'High' indicates that the benefits from cooperation are present, while 'Low' indicates that non-cooperative approaches reduce flood damages more than cooperative approaches.

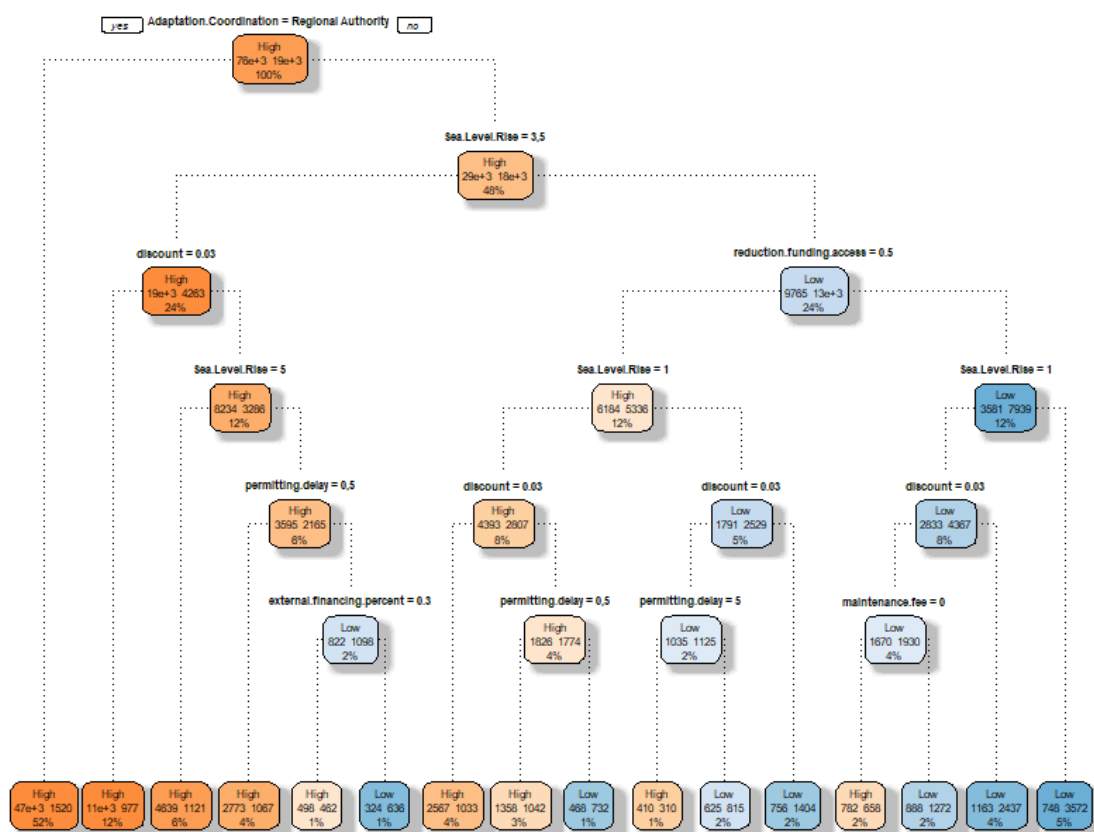


Figure S55: Conditions that lead to reduced damages in East Boston from cooperative approaches. Leading conditions are Regional Authorities, high sea level rise, low discount rate, and large reduction in funding access.

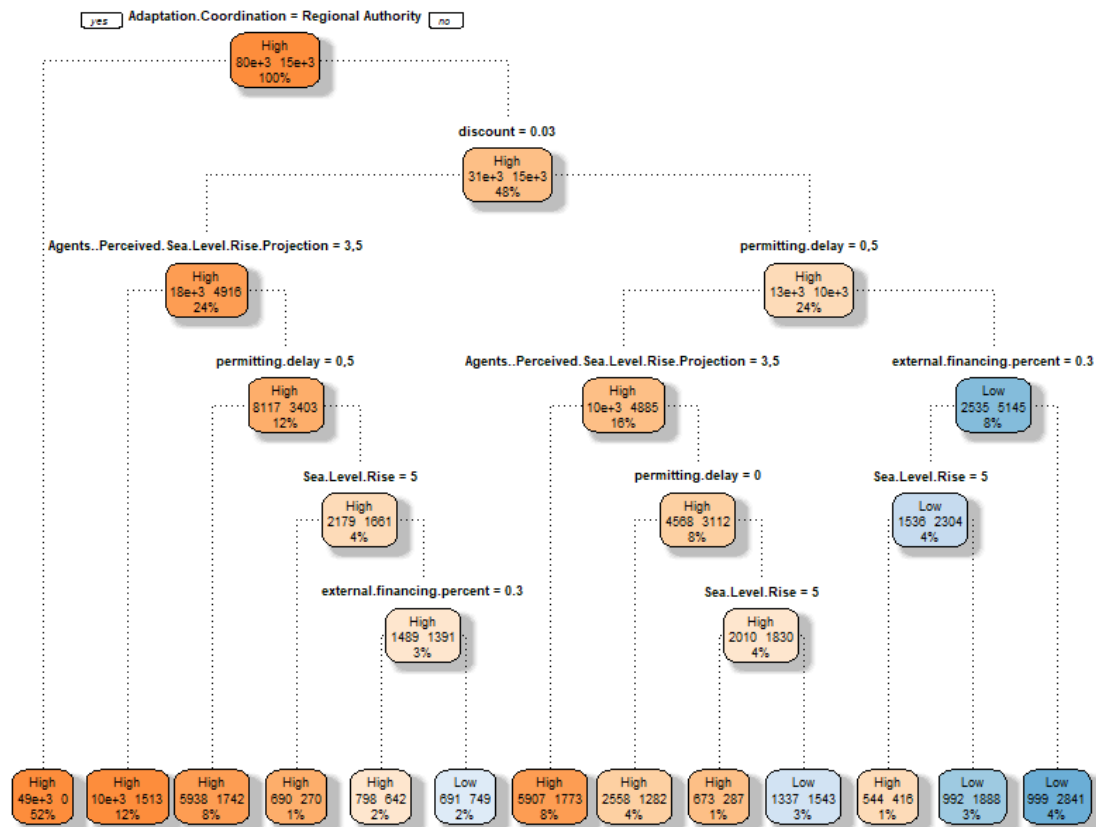


Figure S56: This figure illustrates conditions that lead to simulations where cooperative adaptation approaches reduce flood damages in comparison to non-cooperative approaches. Leading conditions are a regional authority, low discount rate, high projection of sea level rise, and low permitting delay.

Figure 1 is a decision tree diagram illustrating the impact of various parameters on the probability of a high or low outcome. The tree starts with a root node 'Adaptation.Coordination = Regional Authority' (High: 156x3, 27x3, 100%; Low: 0%). It branches into 'SeaLevelRise = 3.5' (High: 21x3, 25x3, 85%; Low: 0%) and 'discount = 0.03' (High: 15x3, 82x3, 24%; Low: 0%). Further branches include 'permitting.delay = 0.5', 'SeaLevelRise = 1', 'Agents.Perceived SeaLevelRise Projection = 3.5', and 'external financing.percent = 0.5'. The final outcomes are listed at the bottom, showing the probability of high or low results for each path.

Path	High Outcome	Low Outcome
Adaptation.Coordination = Regional Authority	High: 156x3, 27x3, 100%	Low: 0%
SeaLevelRise = 3.5	High: 21x3, 25x3, 85%	Low: 0%
discount = 0.03	High: 15x3, 82x3, 24%	Low: 0%
permitting.delay = 0.5	High: 6517, 5005, 12%	Low: 0%
SeaLevelRise = 1	High: 1252, 72x3, 12%	Low: 0%
Agents.Perceived SeaLevelRise Projection = 3.5	High: 1541, 1339, 5%	Low: 0%
external financing.percent = 0.5	High: 1091, 629, 1%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
High Outcome	High: 156x3, 27x3, 100%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%
Low Outcome	Low: 916, 100x, 2%	Low: 0%

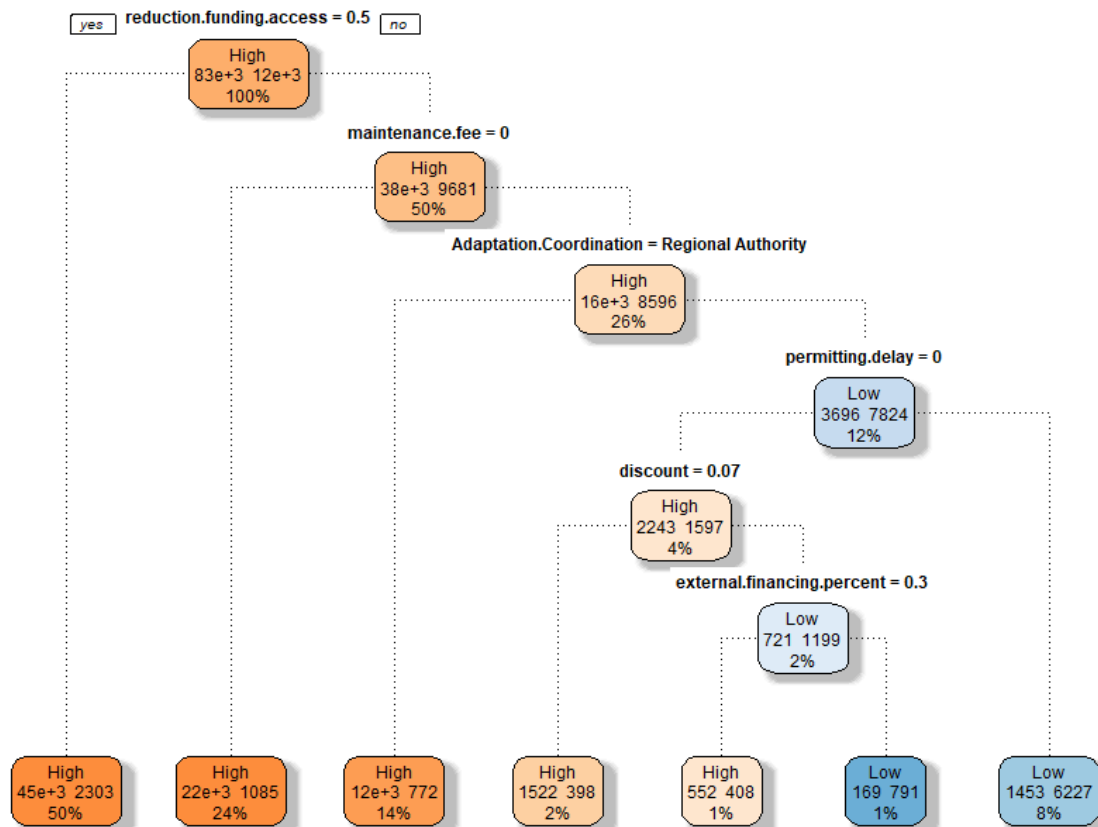


Figure S58: The tree above repeats the same analysis of previous figures for Winthrop. Here, conditions leading to improved outcomes includes the reduction of funding access, no maintenance fee, and a regional authority.

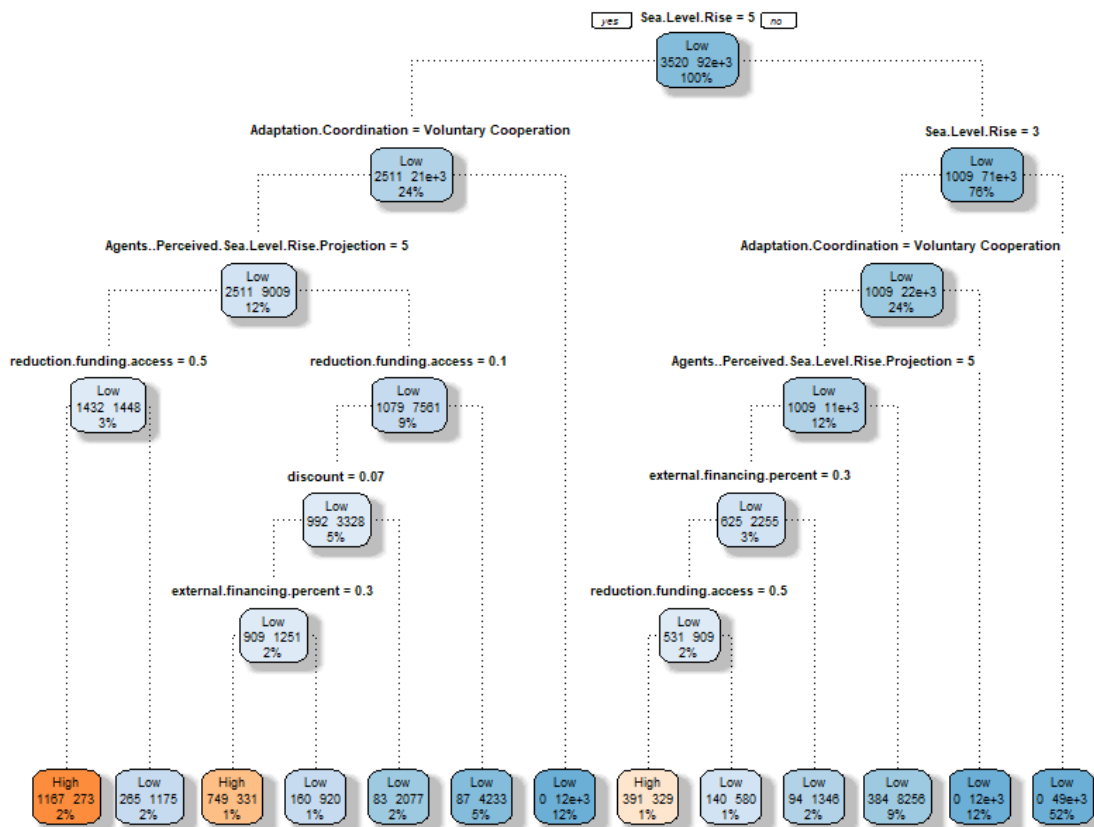


Figure S59: Here, the figure explores when Boston homeowners experience fewer damages from cooperations. Here, the conditions that lead to these outcomes include high sea level rise, voluntary cooperation, and high reductions in funding access for non-municipal agents.

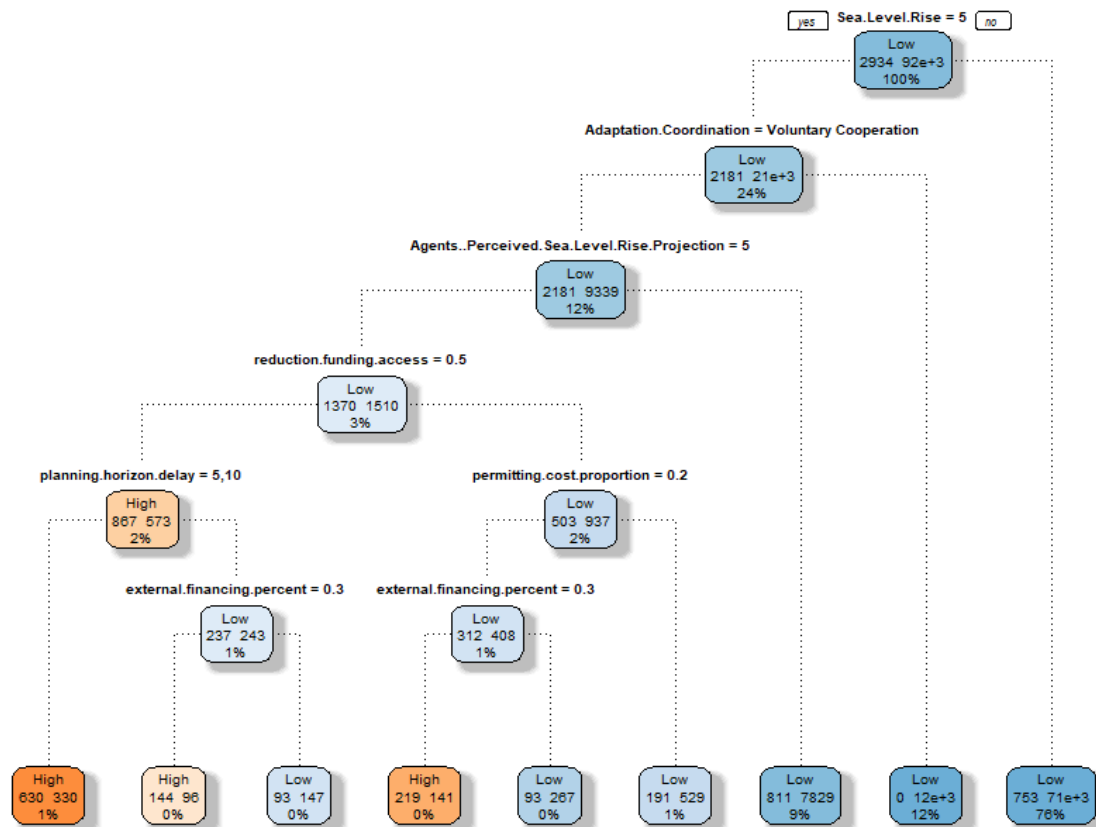


Figure S60: The same analysis reveals that Boston commercial properties experience reduced damages with cooperation when sea level rise is high, cooperation is through voluntary coalitions, and high perceptions of sea level rise.

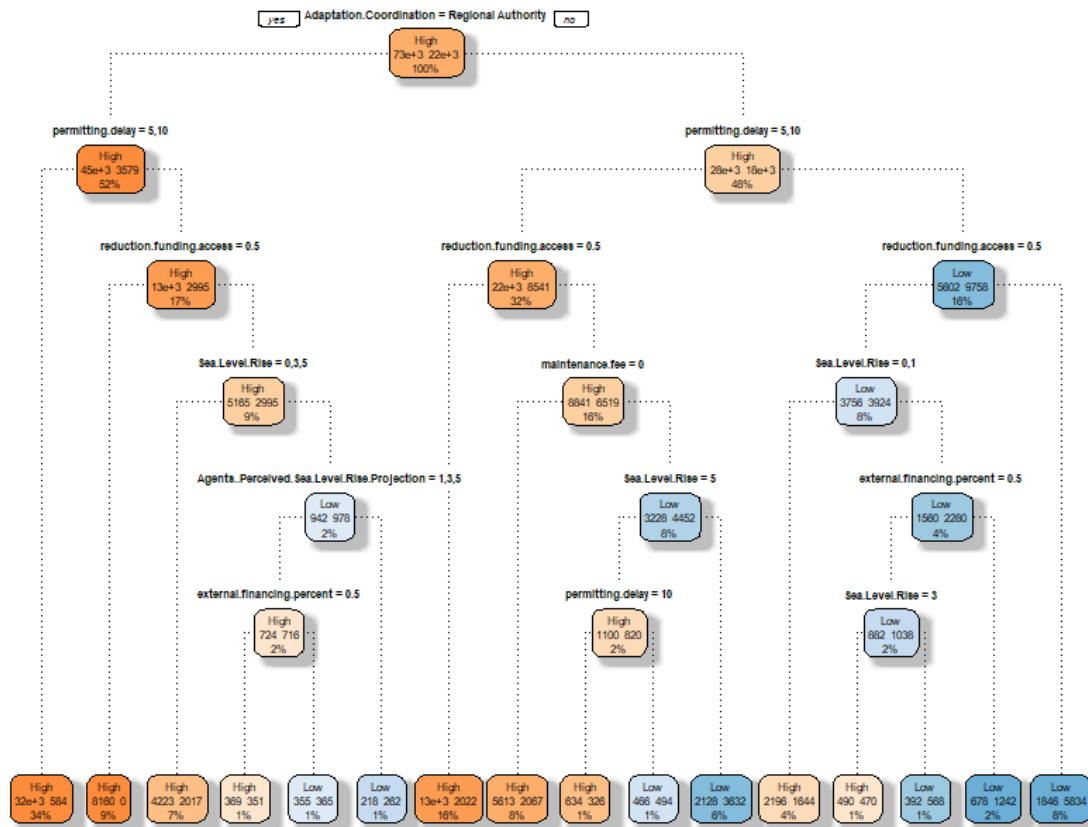


Figure S61: For the MBTA, the conditions that lead to improved flood damage outcomes under cooperative approaches are a regional authority, low permitting delay, and low reduction in funding access.

C.4.4 CART Trees for the Gini Index

In Chapter 2, we present distributions of the Gini Index to measure inequality in normalized flood damages between agent types. We plot the distributions among four key scenarios (combinations of high/low SLR and high/low discount rate) and stated that we did a CART analysis on the Gini values to identify conditions leading to more and less unequal outcomes, as measured by the extreme Gini values. Each simulation has a unique value for the Gini Index, calculated by the floods that occur in that given year. The trees used to identify the best outcomes (lowest Gini values across 10-11% of simulations) are shown below.

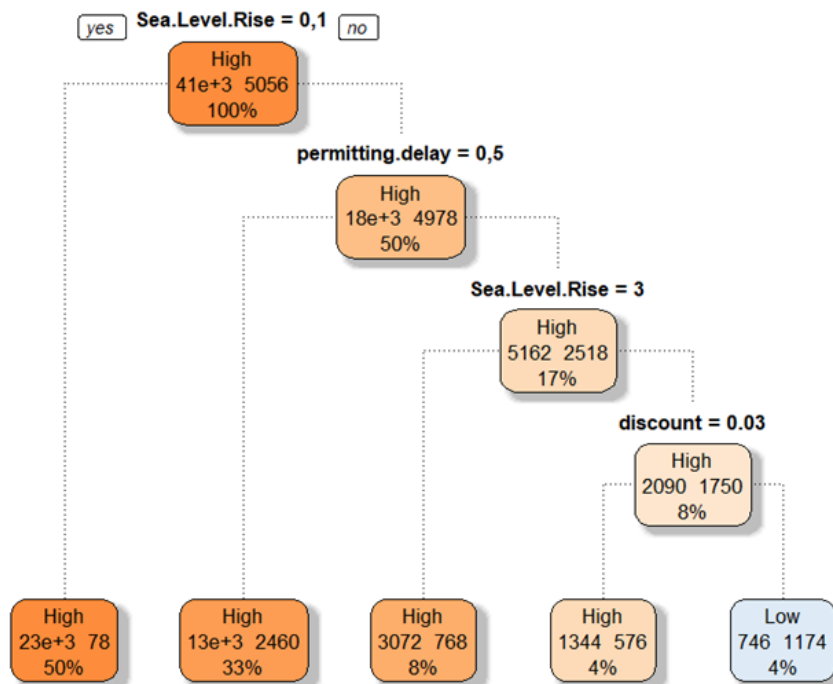


Figure S62: This tree is the output when sorting for the conditions that lead to the lowest 11% of Gini coefficients across all simulations for the regional authority. The values for flood damages were normalized based on the agent type and worst damages in the corresponding governance strategy.

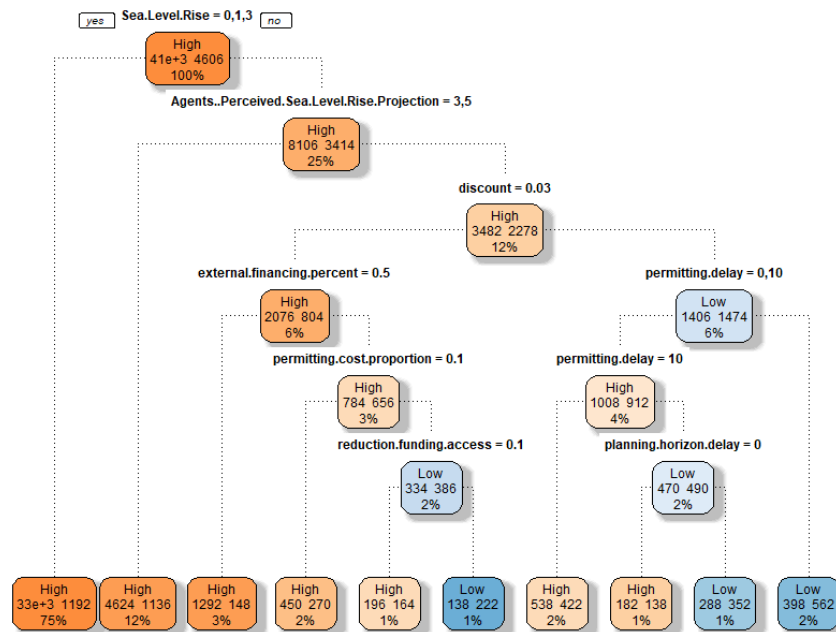


Figure S63: This is the same experiment as Figure S37, but for the no cooperation governance regime. Here, the conditions that lead to the best (lowest) Gini values are high sea level rise, low projections, and high discount rates.

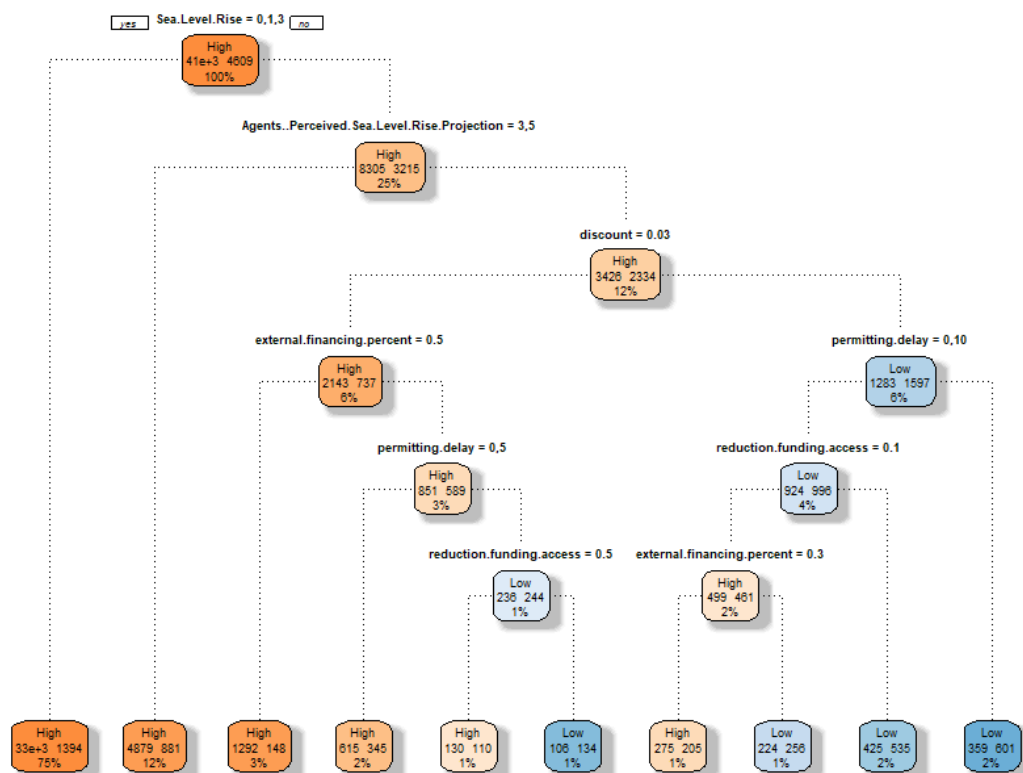


Figure S64: These results indicate the conditions that lead to the lowest gini coefficient values across the no cooperation regimes, very similar to the two trees above.

Appendix D. Supplemental Information for Chapter 3

D.1 Supplemental Results

Results included here either did not fit in the paper or were not deemed critical enough to be selected for the paper. However, we feel that they add extra context both to the choices we made in the modelling process and to the narrative presented in the paper.

D.1.1 Extra results generalized model

In Chapter 3, we plot the coalition size over time for the general ensemble. Here, we add plots for coalition interest, which is calculated only off of the decision-making process, before the benefit-cost ratio is calculated.

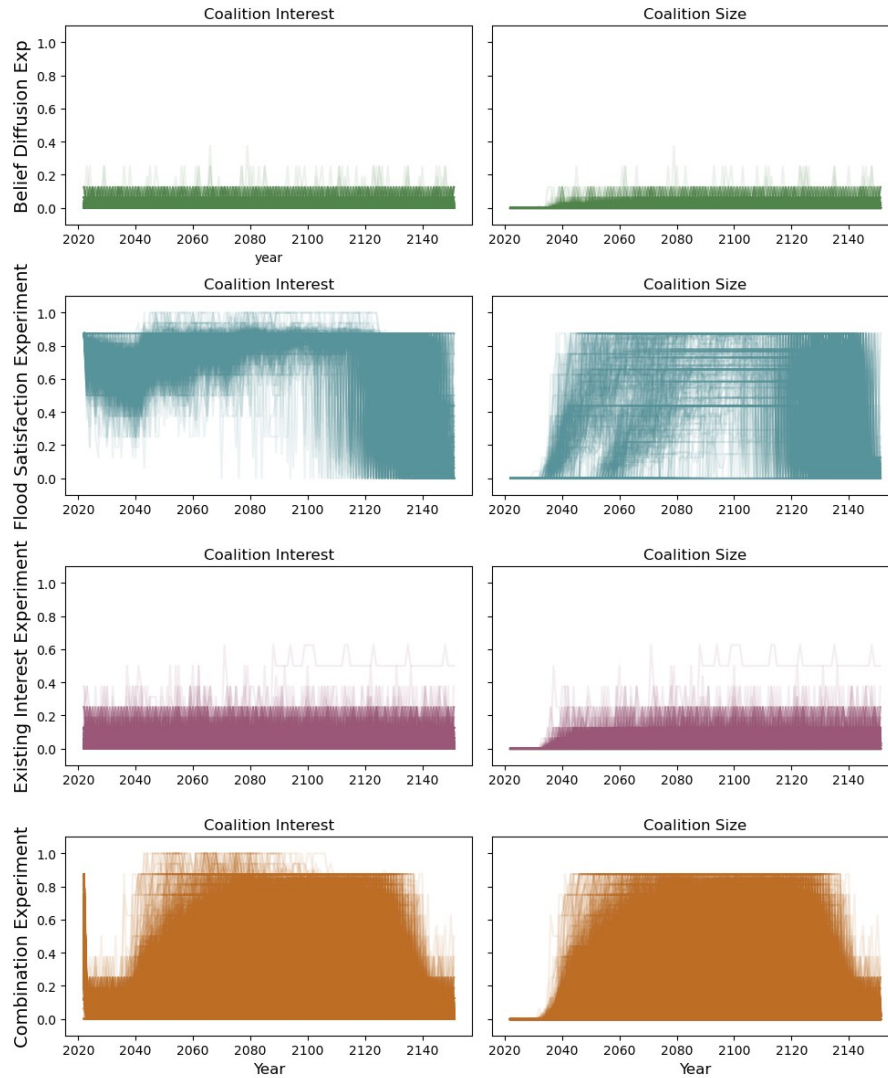


Figure S40: The left-hand side of the figure plots coalition interest across time for the municipality in the generalized ensemble (normalized to the total number of agents within the model). The right-hand side plots the actual coalition size that emerges. Each row of plots represents a different decision-making representation that was explored in the model.

In Figure S41 below, we demonstrate the role that changing the probability that a random property owner will change from being uninterested in cooperation to being interested in cooperation. The point of this parameter is both to add noise, but also to acknowledge that by simplifying the decision-making process, we do not address every incentive for cooperation and there may be other draws to it. The figure shows that while there is not a huge difference between have 0 and 1%

probability, the 5% shows a marked increase in coalition interest and size. This effect is stronger when the decision-mechanism is the demonstrated network interest mechanism (top row), while it is less pronounced in the combination experiment, where the median coalition size increases slightly, but the range largely remains the same. This figure shows that even a small percentage of coalition initiators can accelerate cooperative behavior.

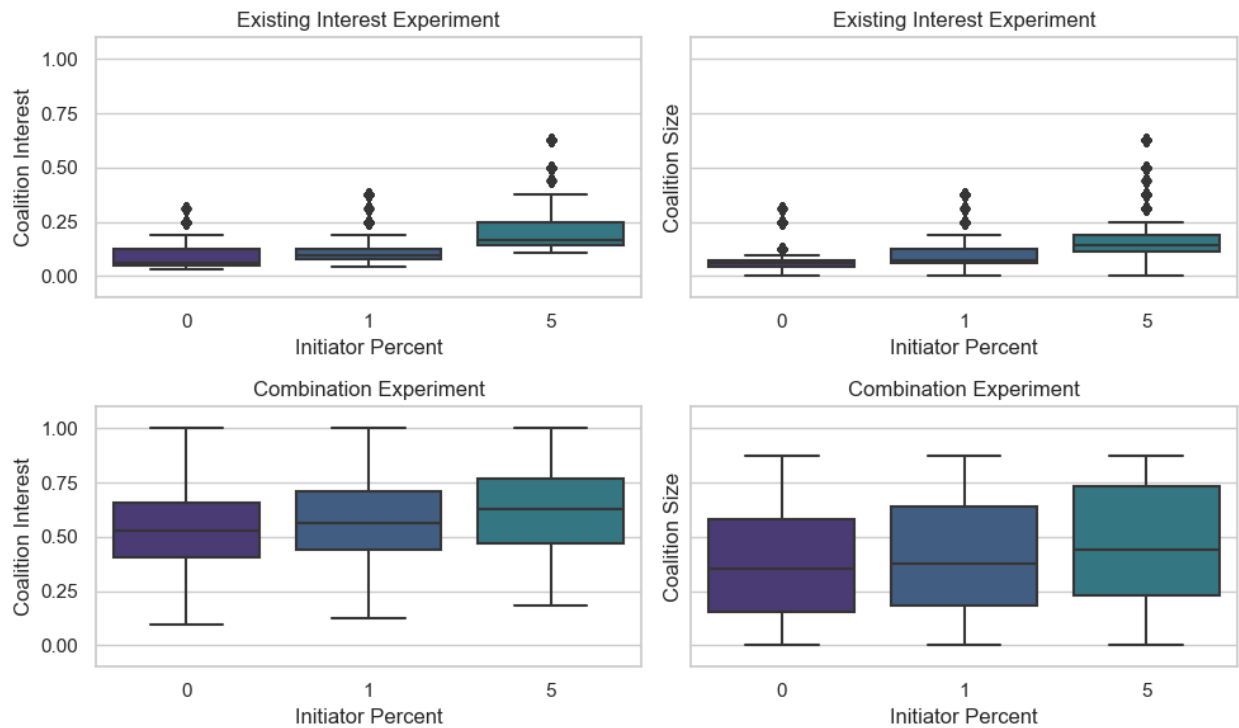


Figure S41: The impact of the value of the random initiator percent (turns an agent cooperative) is shown on coalition interest size (left column) and final coalition size (right column), across experiments for demonstrated network interest mechanisms (top row) and combination experiments (bottom row).

Additionally, we can explore the impact of the diffusion probability for a preference for cooperation on cooperative outcomes. Similarly to the experiment above, we test probabilities of 0%, 1% and 5%. In the combination experiment however, we only test 0% and 5%, as the original results indicated that this parameter has little influence on the outcomes. In Figure S42 below, we

plot the impact of the diffusion probability on the cooperative preference experiment (top row) and combination experiment (bottom row). There is very little impact from varying this parameter between 0 and 5 in any of the experiments.

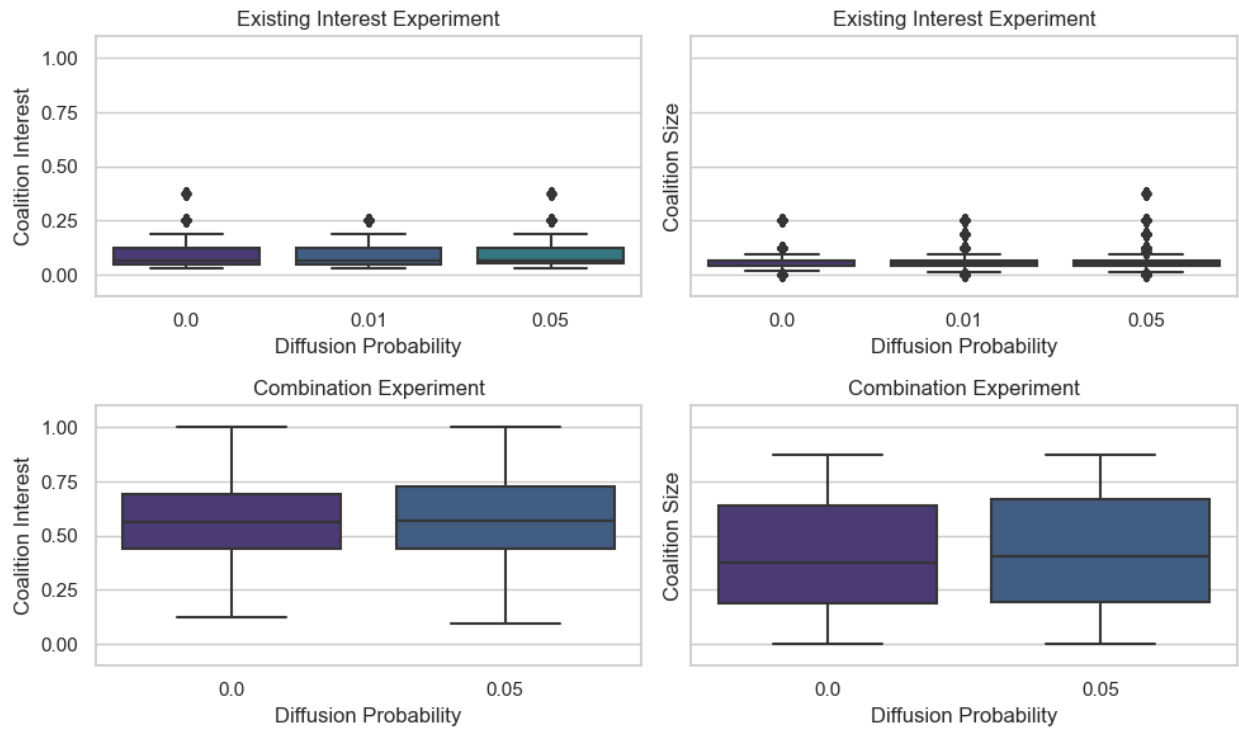


Figure S42: Boxplots demonstrating the impact of changing the probability of cooperative preferences spreading from one agent in a community to another. The top row only includes simulations where the only decision-making mechanism for cooperation is cooperative preference, while the bottom row explore the combination experiment.

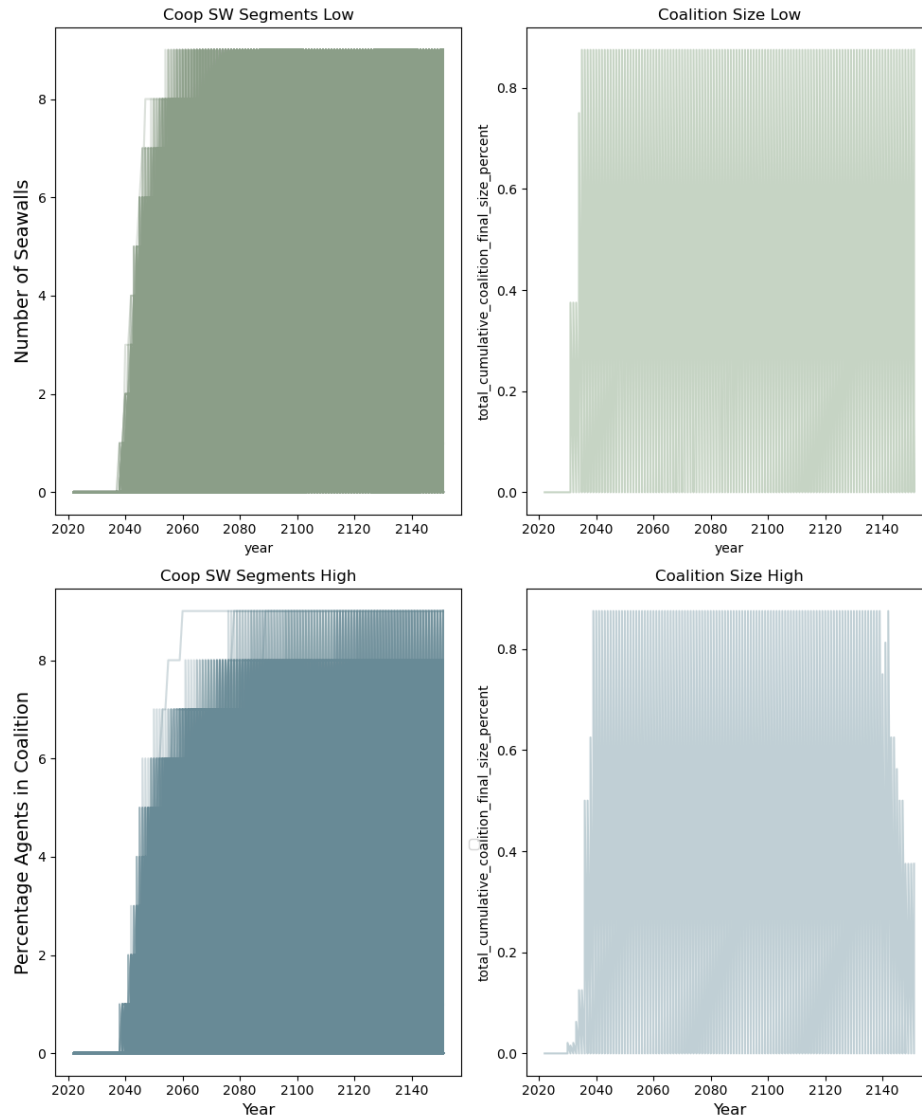


Figure S43: The top row of this figure in Green demonstrates the impact of lowering the threshold for cooperation from 0.5 (shown in the bottom row) to 0.3, which should increase the number of cooperative agents. The left panels illustrate the number of cooperative seawalls constructed in each simulation, while the coalition sizes are shown in the right hand side panels.

Figure S43 above looks at the impact of shifting our assumption about the threshold parameter, which dictates when agents cooperate. Using the combination decision-making mechanism, we explore simulations where the threshold is set to 0.3 (top row) and 0.5 (bottom row). While there are some overall shifts to the patterns shown between the top and bottom panels, the impact is

still quite small compared to the impact from changing our assumption of cooperation decision-making representation.

While the paper displays a similar figure that compares the maximum coalition size to the ratio of cooperative seawalls constructed, here we compare the ratio of cooperative seawalls to the ratio of any seawalls constructed across experiments and the number of neighborhoods in the municipality. This figure demonstrates that in lieu of cooperative adaptation, noncooperative seawall construction will still occur. We do not study if delaying non-cooperative adaptation options would encourage cooperative adaptation.

Another sensitivity that we run is particular to the simulations that only includes network reciprocity. In these simulations, we include a random noise parameter that sets the probability that an agent spontaneously indicates cooperation interest, such that other connected agents would be incentivized to also display cooperative behavior. We explored how shifting this noise parameter between 0%, 1% and 5% shifts the overall coalition sizes. Our results suggest that on an uncooperative network, there is a response to this noise parameter, but that the impact is quite low (the median value only increases coalition size from by about 5% of the total population).

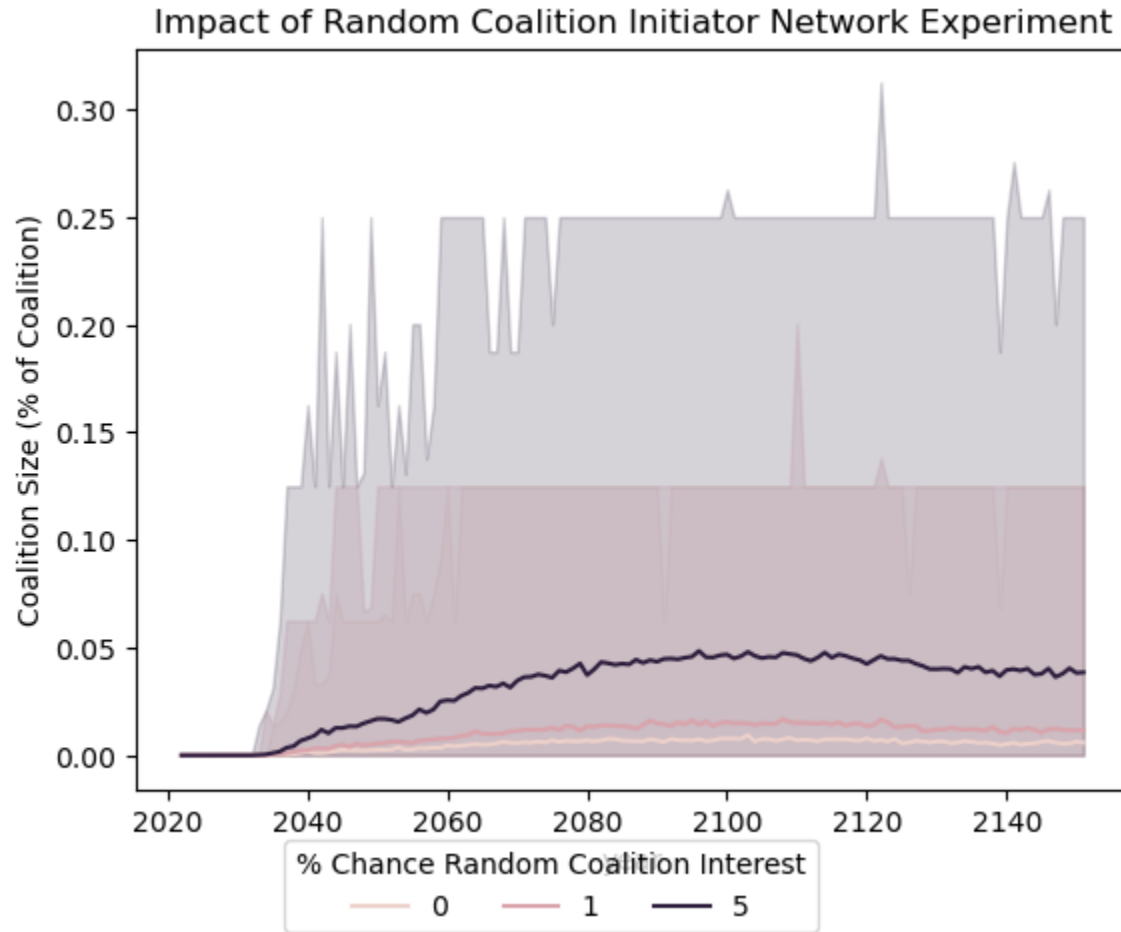


Figure S44: This figure highlights the role of the parameter that controls the probability of an agent randomly signaling an interest in cooperation, which can trigger cascading cooperation responses due to network reciprocity. We explore three different values of this noise parameter: 0%, which indicates no noise, 1% and a 5% probability. While the overall 99% range (given by the shaded region) indicates a clear increase due to noise, there is a less significant shift in the median runs. There is little difference between 0% and 1% noise.

In the chapter manuscript, we mention that we combine the influence of each mechanism with an even weight. Although this assumption was meant to ensure that we don't bias our results to one mechanism over another, individuals may place different weights on the way they incorporate multiple influences into their decision-making. For this reason, we also explored how using different weights on social contagion, network reciprocity, and environmental feedback mechanisms may shift patterns of cooperative adaptation.

The figure below shows the combinations of weighting factors used for each combination of experiments we ran. We explored the model using one, two, or three mechanisms simultaneously. In particular, the combination of weights between all three factors allows us to explore how changing the assumption of equal influence between each factor may shift coalition formation within the coastal community.

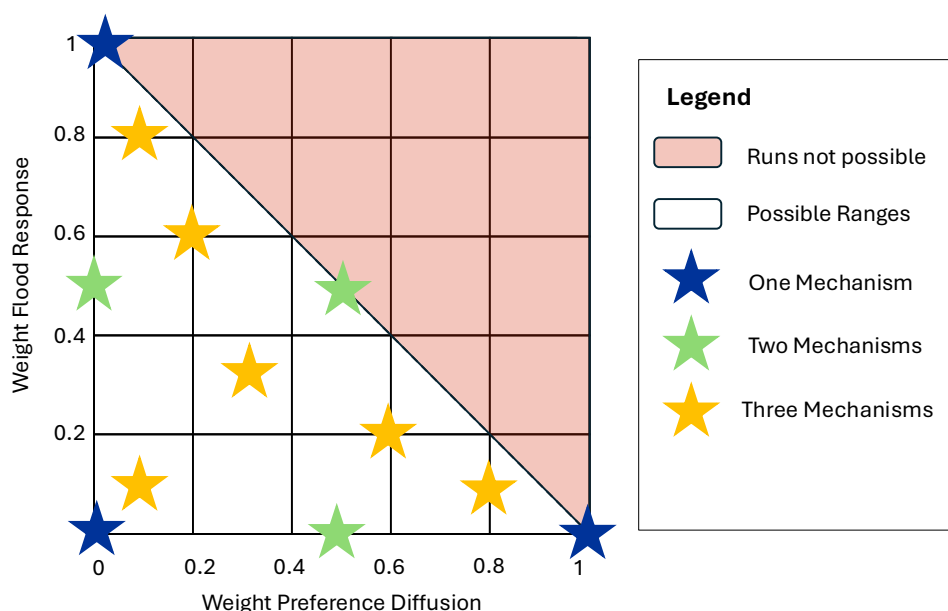


Figure S45: Mapping of weights explored in the experiment onto a 2-D grid of weights for social contagion (diffusion) and the flood response mechanism. When the sum of these two weights is less than one, any additional weight is placed on the network reciprocity mechanism.

The figure below demonstrates how changing the weights between the experiments above shifts coalition formation behavior. The first plot demonstrates how only utilizing an environmental response (weight = 1.0) results in a rapid proliferation of coalitions, which drop over time. Moving

down, the weights placed on flood responses are 0.8, and 0.6, which show little change from the first plot, where decision-making is solely driven by flood response.

By the time we move to an even combination of each mechanism, the coalition formation patterns suggest a greater risk of uncooperative behavior, with some simulations resulting in very low rates of cooperation, represented by the pathways that hover near zero cooperation.

In the subsequent combinations, when the flood reaction weight is very low, coalition sizes rarely surpass 20%, with the exception of combining the environmental response with network reciprocity. This results in coalition sizes that mimic the shape of the combination experiment, albeit with lower overall rates of cooperation. Unlike when social contagion is used as the dominant adaptation decision-making approach, this combination appears to trigger feedback loops between environmental responses and network reciprocity to generate more persistent coalitions.

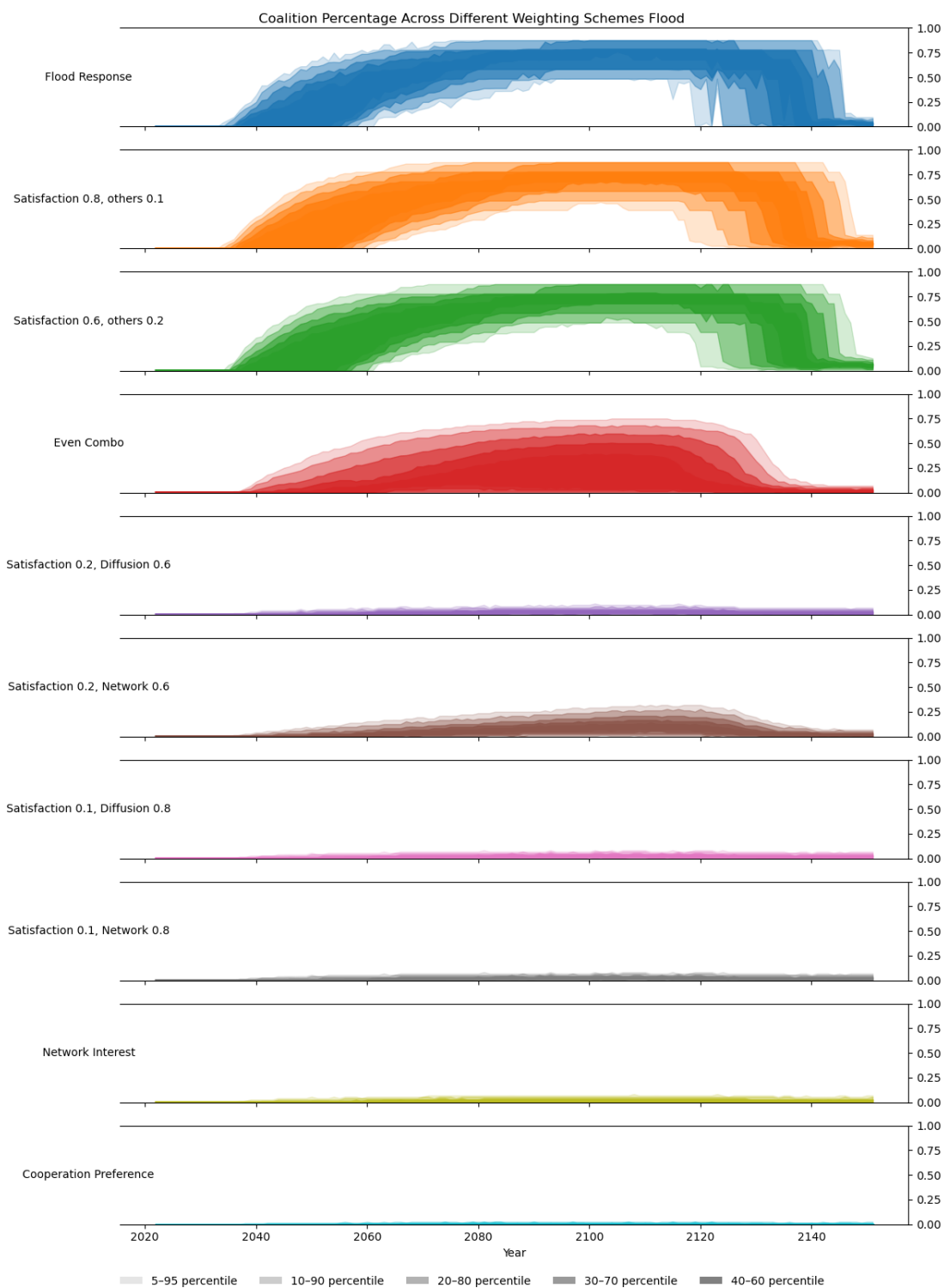


Figure S46: Comparison of coalition sizes throughout the simulations according to each combination of weights for network reciprocity, social contagion, and environmental response. The order of simulations corresponds to a decreasing weight on the environmental response mechanism.

In the manuscript, we include an analysis of the contagion parameter and underlying cooperation preference on the social contagion mechanism. However, we do not extend our analysis of how these parameters affect coalition sizes using the combined mechanism. While changing the contagion parameter from 5% to 75% still results in insignificant changes in coalition size with a combination mechanism, changing the underlying distribution still affects coalition outcomes. Below, we highlight the impacts that changing the underlying preference for cooperation has on coalition size when moving from an uncooperative (mean = 0.25, SD = 0.05) to neutral population (mean = 0.5, SD = 1). These results suggest that in contrast to the fundamentally different shape that coalition formation takes when changing the underlying cooperation preference when social contagion is considered in isolation, the impacts of shifting the distribution on overall cooperation outcomes is more moderate. The general shape of coalition formation is preserved, although the neutral population using a normal distribution centered at 0.5 does result in some extent of cooperation in every single simulation (the range never remains at zero across all time).

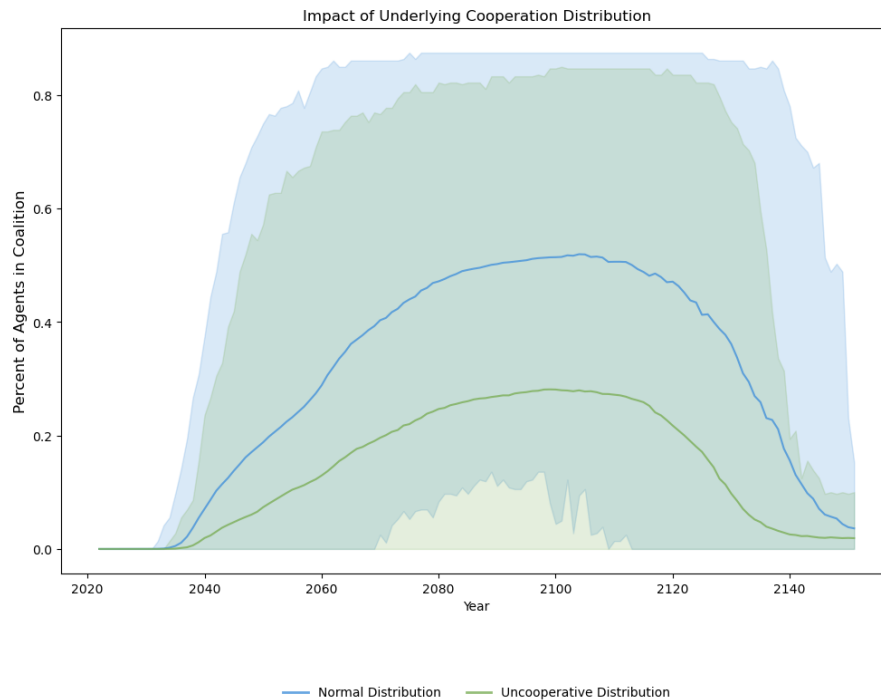


Figure S47: This plot shows the impact of changing the underlying distribution of cooperation preferences when using a combination of all three decision-making processes. The 99% percentile, avoiding the most extreme runs, are shaded in blue or green, while the median values are highlighted in the darker lines.

In addition to an exploration of our assumptions about decision-making processes, we also explored how the size of the network may or may not impact cooperative outcomes. These results are explored below in Figure S48.

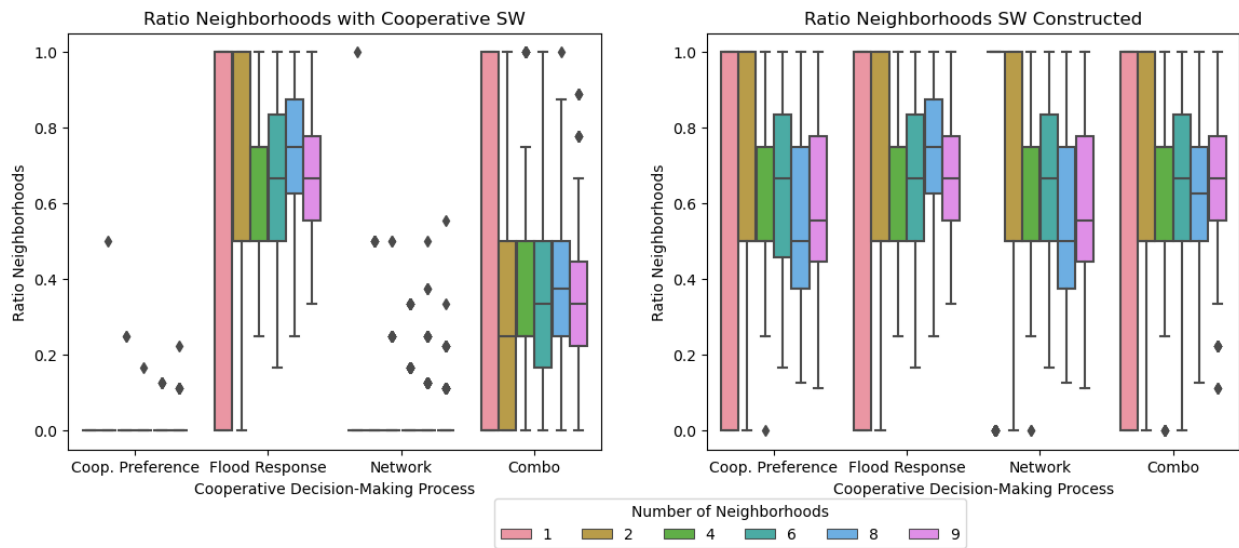


Figure S48: Boxplots comparing the ratio of cooperative seawalls to the ratio of the total number of seawalls constructed by the end of the simulations. The clusters correspond to the ensemble based on a specific decision-making process, while the colors correspond to the number of neighborhoods incorporated into the municipality.

Although the coalition size for both the cooperative preference experiment and the network experiment is lower than the other two, we were curious if cooperative seawall construction is still feasible. The figures below (S49 and S50) show an alternative representation of the heatmaps in Chapter 3. Although less intuitive, these figures better show the simulations with any cooperative construction. Red lines indicate the total number of seawalls constructed in any single simulation.

Blue lines indicate the total number of cooperative seawalls constructed in the same simulations. Unlike the chapter, which uses a color gradient to represent the ratio of cooperativity, clear examples of cooperative seawall construction are visible in the two figures below (Figure S49 illustrating simulations with only 9 neighborhoods and Figure S50 illustrating across the ensemble). This photo clearly demonstrates that despite the low coalition sizes, there are still simulations where cooperation (albeit) lower emerged in both the experiments for cooperation preference diffusion and demonstrated network interest.

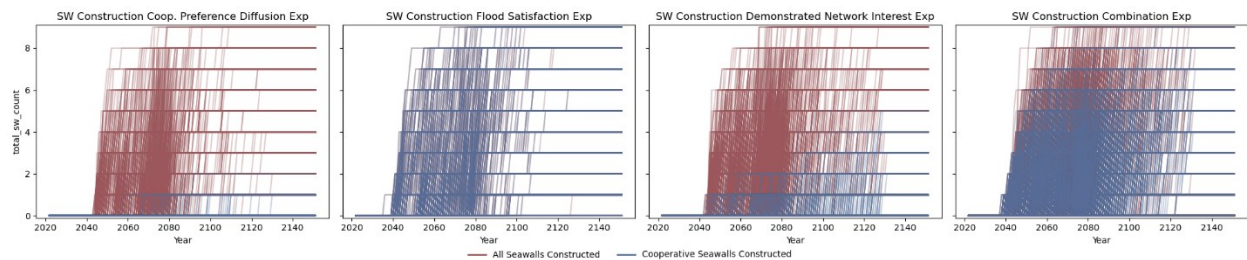


Figure S49: Plots of all seawalls constructed over time (red) and cooperative seawalls constructed over time (blue) for all simulations in the generalized ensemble with nine neighborhoods).

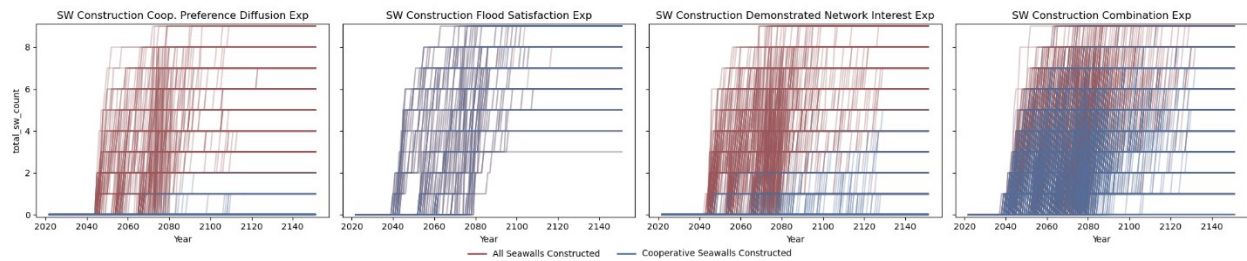


Figure S50: The same figure as above, but repeated for the entire ensemble (not just simulations where there are 9 neighborhoods included in the municipality).

While not included in the final paper, we also explore how maximum coalition size relates to both the number of cooperative seawalls constructed and the flood damages that occur for simulations that have nine neighborhoods and utilize the combination decision-making representation.

The heatmaps below in Figure S51 demonstrate the relationship between maximum coalition size in a simulation (x-axis), number of seawalls constructed or total flood damage (y-axis), and the frequency with which these simulations occur. In the figure below, we only plot the part of the generalized experiment that can be compared to Boston: nine neighborhoods, and the combination decision-making method. On first sight, the figure appears to show two clusters that vaguely trend from the lower left to upper right according to both flood metrics. Subsequent testing revealed that these clusters correspond to the network assessment parameter: when agents assess coalition interest only, they experience lower cooperation rates than if they assess coalition size. Taken separately, the trend indicates seawall construction increase with cooperation size (desirable), but that flood damages also increase as coalition size increases (less desirable). This suggests that a larger extent of cooperation may eventually result in more seawall construction, but they are delayed in time, which increases flood damages temporarily.

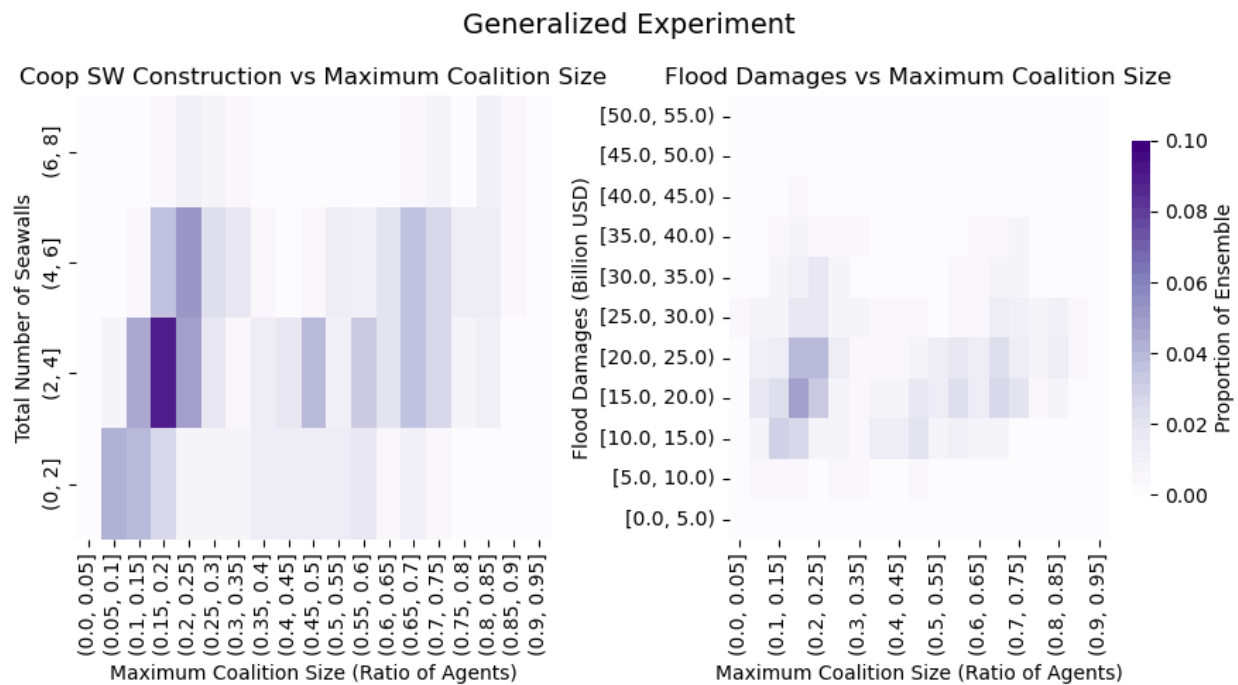


Figure S51: Heatmap of comparing maximum coalition size to both the total number of seawalls constructed (left) and cumulative flood damages (right). The intensity of the color corresponds to the frequency of the appearance across the ensemble. We only consider simulations with nine neighborhoods and the combination decision-making. Additionally, we remove the impact of timing by only capturing the maximum value of each variable in a single simulation.

One way that we compare the influence of multiple conditions on a specific outcome in the paper is through classification and regression trees (CART). This algorithm identifies which conditions lead to a more ‘pure’ outcome set, i.e. of the simulations that meet a parameter combination, how many of them meet the objective that we are searching for. While we apply this methodology to the/. Boston case in the paper, we demonstrate its applicability to the generalized experiment below as well.

Figure S52 below searches across the generalized experiment for conditions where the coalition size exceeds 50% at any point in time. We chose 50% as a critical threshold, noting that the simulations almost always lead to coalitions of some size. Re-emphasizing the paper’s findings, the first two splits relate to the decision-making representation, the far left branches correspond to the flood response mechanism, the far right to the network and diffusion mechanisms, and the middle nodes to the combination experiment. Looking at the far right, we can see that there are a few simulations where cooperation exceeds 50%, but that these are extremely uncommon.

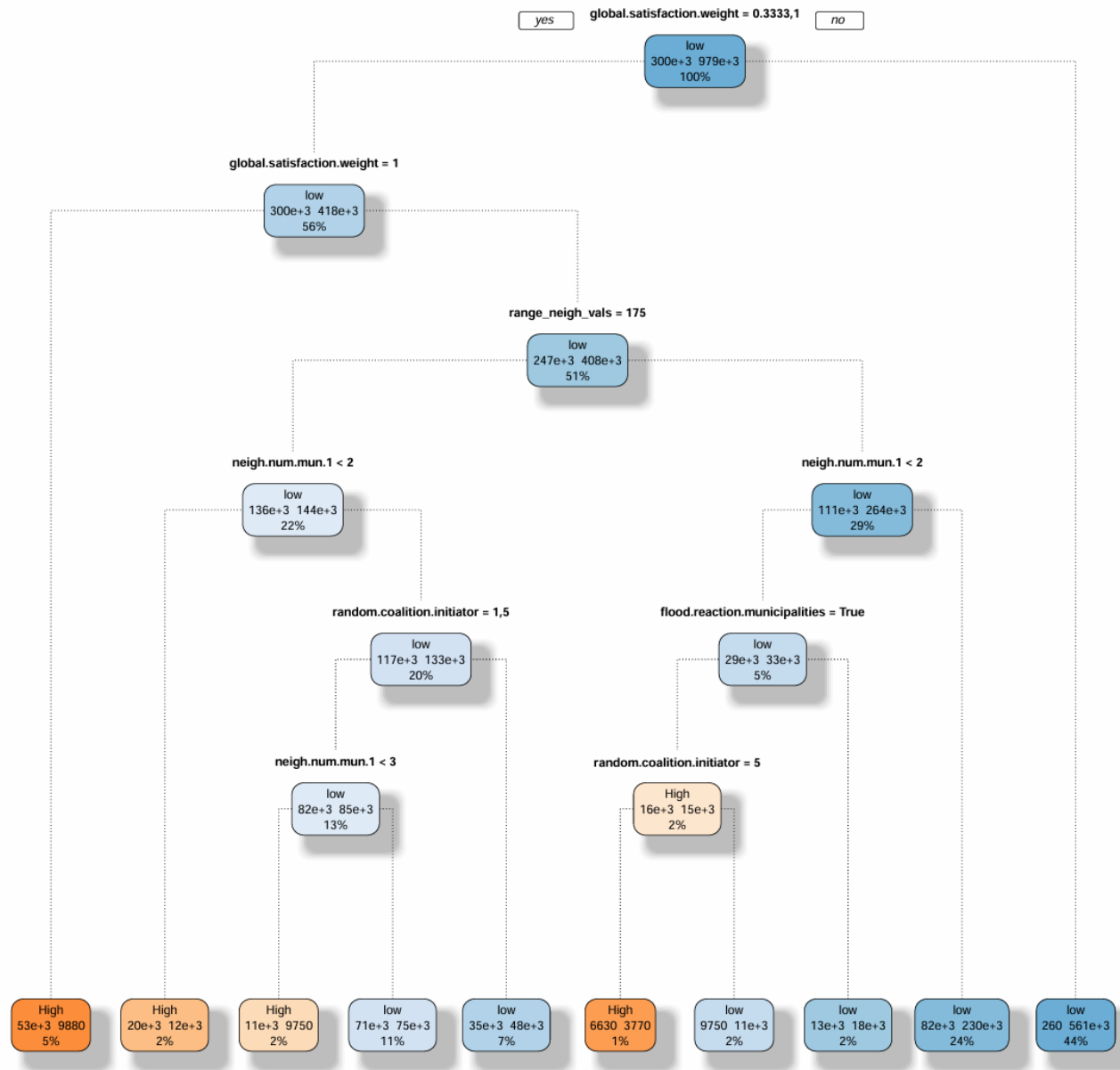


Figure S52: Conditions in the generalized model that lead to more than 50% of the agents being in a coalition at a single time.

Each cell is rated high or low, based on the frequency of the scenarios that have large coalition sizes. The numbers in each node correspond to the simulations with large coalition sizes (left) and low coalition sizes (right). The percentage in the bottom is the percentage of the ensemble within that cell.

Further inspection of the figure reveals that within the combination experiment, smaller municipalities with greater heterogeneity in their property values (corresponding to some highly valued properties) actually experience larger coalition sizes.



D.1.2 Extra results Boston model

In addition to the findings presented in the paper, we explored alternative figures and findings for the Boston-specific context. The two figures below present alternative illustrations of seawall construction, but were removed from the chapter. The figure below repeats the same structure of Figures S49 and S50 above, where the red color indicates the total number of seawalls constructed in Boston across the ensemble, while the blue overlays which of those seawalls were built cooperatively. Here, we see that although Boston experiences a lot of non-cooperative seawall construction, there is a small subset of ensembles that achieves some degree of cooperativity.

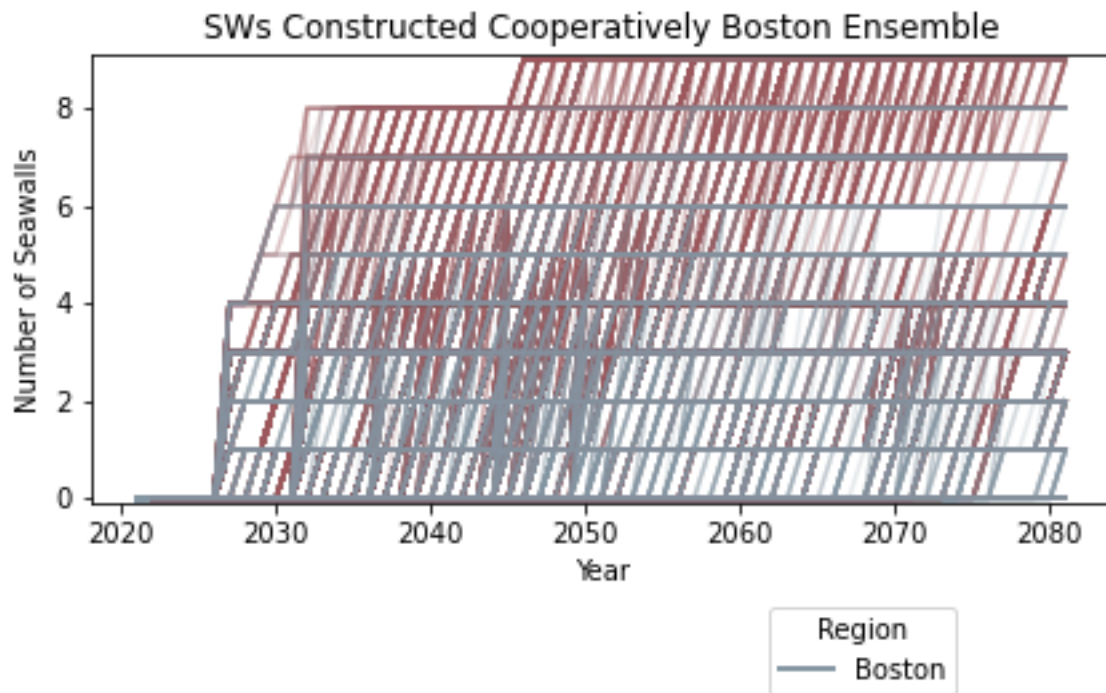


Figure S54: This figure first plots the total number of seawalls constructed in Boston throughout the ensemble in red and overlay cooperative seawalls in blue. This demonstrates that while many simulations demonstrate high levels of non-cooperative adaptation, there are still numerous simulations where cooperative adaptation emerges.

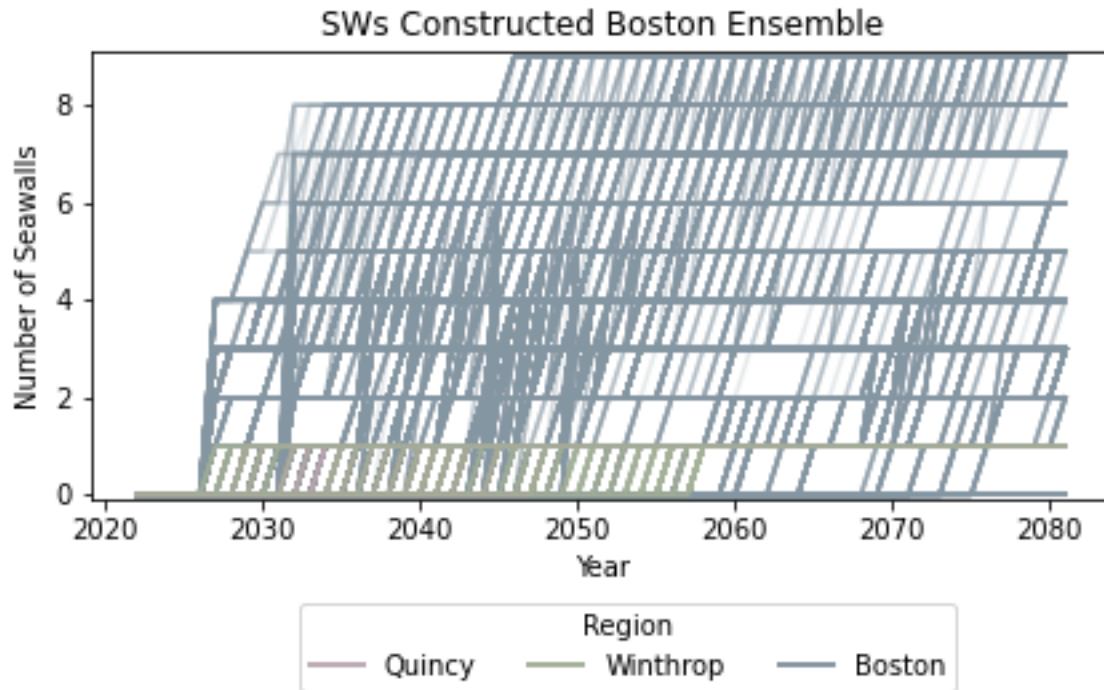


Figure S55: Similar to the Figure above, these lineplots show the total number of seawalls constructed for Quincy (pink), Winthrop (green) and Boston (blue). The Figure demonstrates the gradual increase of seawalls in Boston, and the earlier construction of seawalls in Quincy and Winthrop.

In Chapter 3, we present results using the CART algorithm to identify the most important conditions that lead to cooperative seawall emergence in Boston Harbor. The figures below also utilize the CART algorithm, but rather than classifying the number of cooperative seawalls, we set the classification criteria for all simulations where the coalition sizes are greater than one agent, regardless if the seawalls are eventually completed in a collaborative way.

Below, we show the figure for all agents across Boston municipality. Coalition formation is highly dependent first on risk assessment, and then on the permitting and funding conditions. Even with a low risk perception, with high levels of funding for cooperative solutions and reductions in the permit burden for cooperative coalitions, many of the simulations still result in coalition formation.

Of interest, for all three municipalities, the initial cooperative preference does not appear as a driving factor for the formation of coalitions.

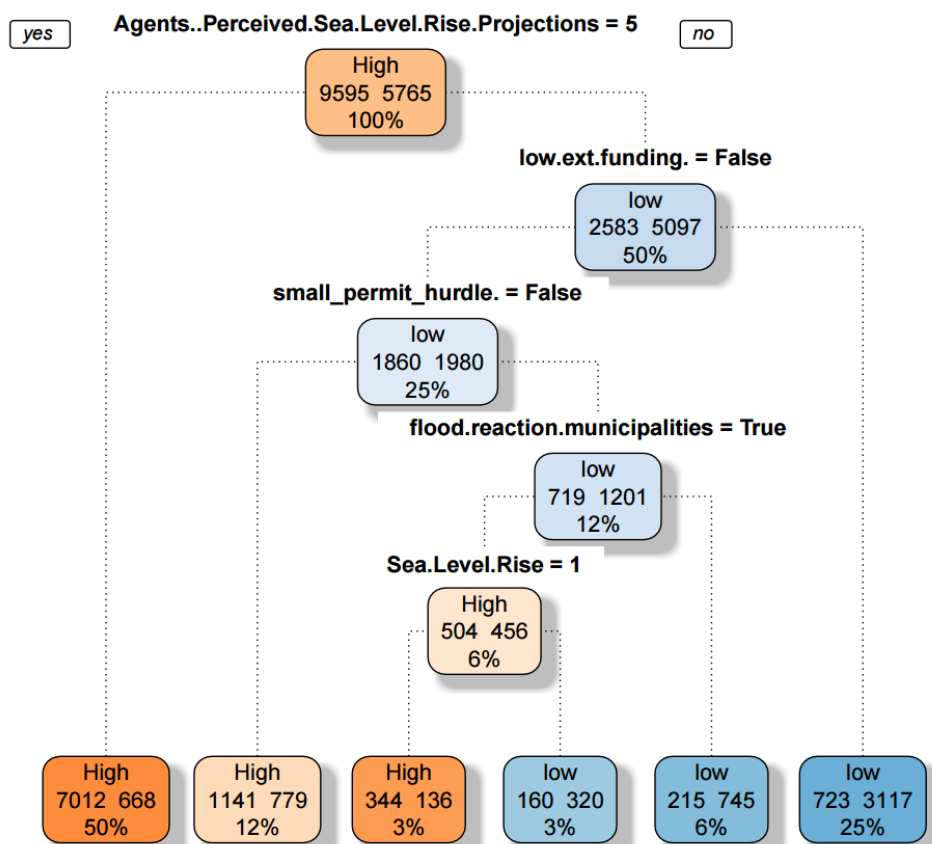


Figure S56: This CART tree sorts for Boston coalition sizes when more than 1 agents selects to join the coalition. “High” corresponds to 2+ agents in the coalition for Boston, while “Low” is just one or no agents.

In Winthrop, coalition formation is similarly initially dependent on having a high enough risk assessment to warrant adaptation. Interestingly, in many simulations, cooperation does not emerge. Interestingly, Winthrop experiences many simulations without coalition formation, in nearly 2/3 of the simulations we ran. For Winthrop, high sea level rise is absolutely a pre-requisite for cooperation. However it is not always sufficient for cooperation.

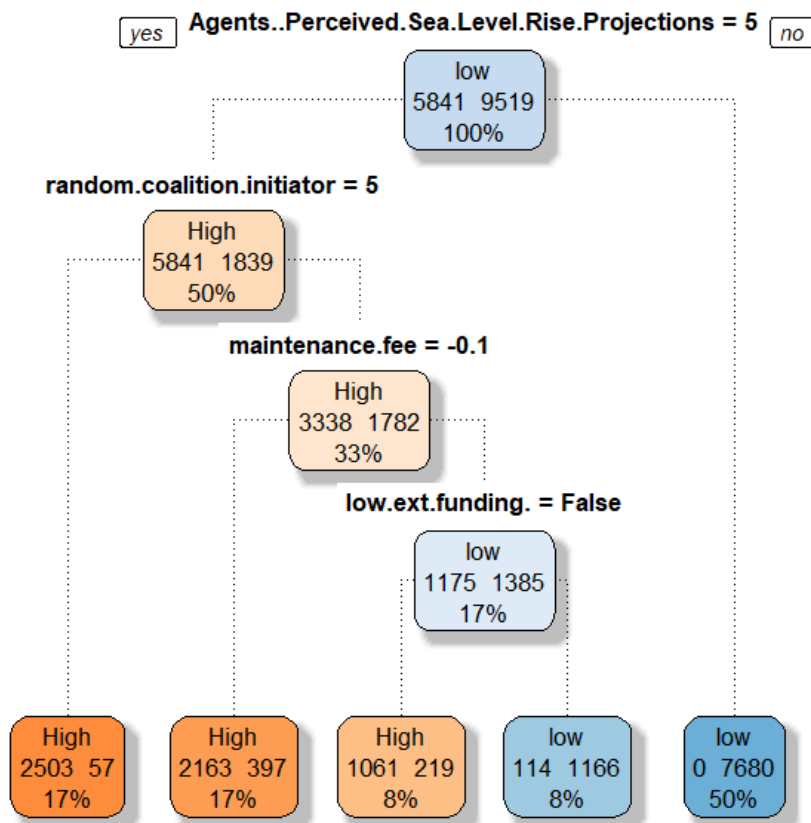


Figure S57: Repeating the figure above, this CART tree sorts for Winthrop coalition sizes when more than 1 agents selects to join the coalition. “High” corresponds to 2+ agents in the coalition for Winthrop, while “Low” is just one or no agents.

In the large majority of simulations, Quincy experiences cooperative coalition formation.

However, like Boston, low sea level rise expectations can be overcome by high external funding sources and a permitting process that favors cooperation.

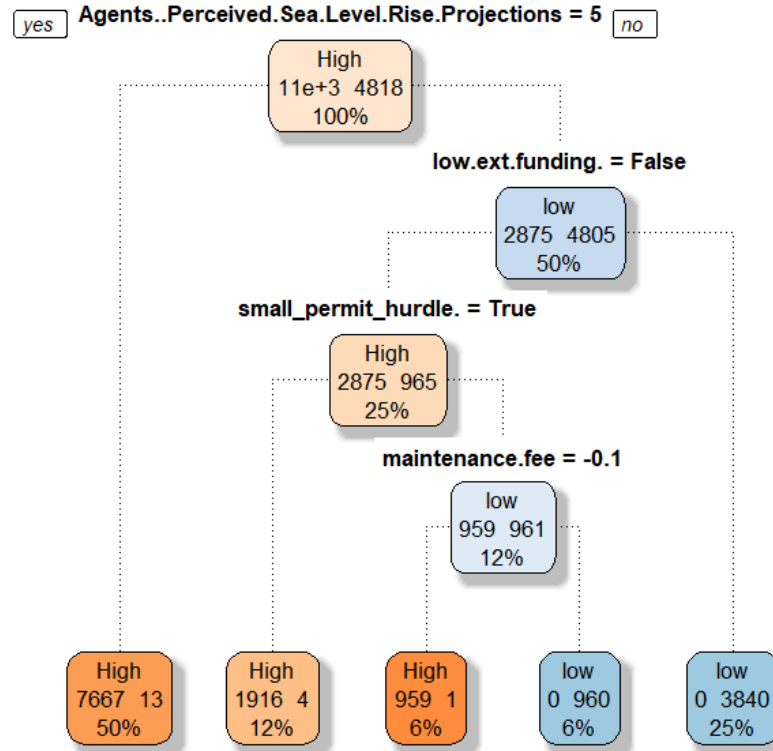


Figure S58: Repeating the figure above, this CART tree sorts for Quincy coalition sizes when more than 1 agents selects to join the coalition. “High” corresponds to 2+ agents in the coalition for Quincy, while “Low” is just one or no agents

In addition to the analyses shown in the paper, we explored the ensemble with additional metrics and additional methods. We utilized causal discovery through algorithms that assemble causal inference graphs (S. Janssen et al., 2019), with the python package constructed by (Zheng et al., 2024). We use the PC algorithm (Spirtes et al., 2000) to look for causal dependencies between the input and outcome variables. For this analysis, we include the output variables of cumulative harbor damages, cumulative adaptation costs, the year of maximum coalition size, and the maximum interest in and final size of coalitions. The edges included in the figure provide a rough assessment of the linkages between the levers we used and output variables.

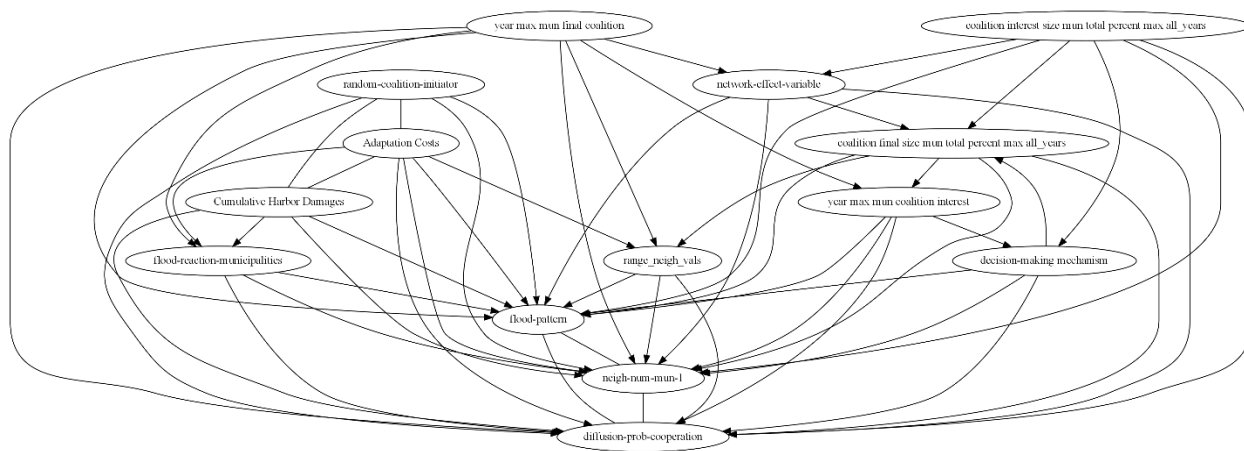


Figure S59: Causal inference graph assembled with the PC algorithm from the general model. This provides an overview of the linkages between different elements.

D.2. Experiment Design

The two tables below highlight every parameter that could be changed in the simulations, the values we picked, and the justification for both the generalized model and Boston-specific model.

General Model: 9840 (small exp) simulations with 20 different flood patterns for each combination of parameters

Parameter	Meaning	Values	Justification
Permitting Time Reduction (General only)	The reduction in permitting time available with a cooperative structure	0	Set to 0 to simplify model
External Financing (General only)	The amount of financing available for agents from external funding agents (FEMA, ACE)	0	Set to 0 to simplify model
Planning Horizon Delay	How far in advance agents start their calculations for expected benefits and damages.	5	Planning a large-scale adaptation will take at least 5 years
Maintenance Fee	Any additional costs or savings for adaptations from cooperative structures	0	Set to 0 to simplify model

	(representing transaction costs or reduced redundancy)		
Permitting Cost	Cost of permitting as a percentage of adaptation cost	10%	Low, static value. Any changes will just shift final adaptation costs
Range-neigh-vals (General only)	Sets limits on the extent of heterogeneity between property owner asset values	175%, 50%	Represents significant or minor heterogeneity between the asset value of property owners
Permitting cost reduction (general only)	Reduction in permitting costs due to cooperative arrangements	0	Set to 0 to simplify model
Sea level rise	The sea level rise in feet by 2100	5	High end estimate (high risk)
Sea level rise projection	The amount of SLR in feet by 2100 that agents use for planning	5	Assumes population has accurate assessment of the risk profile.
Cooperative belief	Determines the distribution that the agents are initialized with for their internal preference for cooperative or uncooperative solutions	uncooperative	Representative of the current state with no cooperation
Permit delay	The amount of time it will take to receive a permit before adaptation is in place	5	Best guess at the time required to permit large-scale infrastructure projects
Threshold (combination experiment and Boston only)	The tipping point in calculating coalition interest at which an agent decides their initial commitment to cooperating	0.5	50% indicates an agent is more interested in cooperating than not.
Edge probability	The probability that an edge is placed between any two agents within a neighborhood	20%	This provides a relatively large number of linkages between agents.
Flood reaction	Modifies the benefit-cost ratio to allow learning (underestimation adds weight, while overestimation takes it away)	True, False	Explore both possibilities.
Diffusion probability	Probability of an agent “catching” the interest to cooperate from a neighbor	0%, 1%, 5% in the diffusion-specific model	The chances of ‘catching’ a belief are low. This allows us to explore how even small diffusion rates could trigger cooperative behavior. Range of values inspired by (Haer et al.,

			2016), who set the probability of adjusting strategies at apprx. 16%.
Random coalition initiator	Probability of an agent deciding to randomly adapt an interest or commitment to cooperation despite the initial calculation (represents a stochastic process of what may not be explicitly present here)	0%, 1% 5%	This adds just a small amount of stochasticity of interest in cooperating that could trigger the cascade for demonstrated network interest. This aligns with the noise parameter in (Haer et al., 2016)
Discount	Discount rate for all monetary estimates	0	Set to 0 to simplify model
Foresight	Amount of years that agents consider in their calculations	30 years	Rough estimate of how far out municipalities calculate flood risk
Operation and maintenance cost (Boston only)	Additional O&M costs as a proportion of the adaptation cost	--	--
Permit hurdles (Boston only)	A general variable that increases the permitting burden for noncooperative solutions and decreases for cooperative solutions	--	--
Access to financing (Boston only)	A general variable that increases the permitting burden for noncooperative solutions and decreases for cooperative solutions	--	--
Network effect variable	When calculating demonstrated network interest, agents wither use demonstrated coalition interest or coalition size to determine their cooperativity.	Coalition interest, coalition size	Agents calculate demonstrated network interest based off on the final cooperation decision or off of their signal of intent to cooperate from the initial individual cooperative assessment.

In the model specific to the Boston context, we complete an ensemble of 15,360 runs. In comparison to the large number of repetitions completed before, each parameter combination is

only repeated 5 times. We complete a full factorial of each combination of the parameters shown below. The number of repetitions is limited due to the large number of parameters tested.

Parameter	Meaning	Values	Justification
Permitting Time Reduction (General only)	The reduction in permitting time available with a cooperative structure	--	--
External Financing (General only)	The amount of financing available for agents from external funding agents (FEMA, ACE)	--	--
Planning Horizon Delay	How far in advance agents start their calculations for expected benefits and damages.	5	Planning a large-scale adaptation will take at least 5 years
Maintenance Fee	Any additional costs or savings for adaptations from cooperative structures (representing transaction costs or reduced redundancy)	-10%, 10%	Set to 0 to simplify model
Permitting Cost	Cost of permitting as a percentage of adaptation cost	10%	Low, static value. Any changes will just shift final adaptation costs
Range-neigh-vals (General only)	Sets limits on the extent of heterogeneity between property owner asset values	--	--
Permitting cost reduction (general only)	Reduction in permitting costs due to cooperative arrangements	--	--
Sea level rise	The sea level rise in feet by 2100	1, 5	High and low end estimate
Sea level rise projection	The amount of SLR in feet by 2100 that agents use for planning	1, 5	Assumes population has accurate assessment of the risk profile or very inaccurate
Cooperative belief	Determines the distribution that the agents are initialized with for their internal preference for cooperative or uncooperative solutions	Uncooperative, cooperative	Representative of the current state with no cooperation

Permit delay	The amount of time it will take to receive a permit before adaptation is in place	5	Best guess at the time required to permit large-scale infrastructure projects
Threshold (combination experiment and Boston only)	The tipping point in calculating coalition interest at which an agent decides their initial commitment to cooperating	0.5	50% indicates an agent is more interested in cooperating than not.
Edge probability	The probability that an edge is placed between any two agents within a neighborhood	20%, 80%	This provides a relatively large number of linkages between agents, while 80% is an almost fully linked network within a neighborhood
Flood reaction	Modifies the benefit-cost ratio to allow learning (underestimation adds weight, while overestimation takes it away)	True, False	Explore both possibilities.
Diffusion probability	Probability of an agent “catching” the interest to cooperate from a neighbor	0%, 5%	The chances of ‘catching’ a belief are low. This allows us to explore how even small diffusion rates could trigger cooperative behavior. Range of values inspired by (Haer et al., 2016), who set the probability of adjusting strategies at approx. 16%, and a zero chance.
Random coalition initiator	Probability of an agent deciding to randomly adapt an interest or commitment to cooperation despite the initial calculation (represents a stochastic process of what may not be explicitly present here)	0%, 0.5%, 5%	This adds just a small amount of stochasticity of interest in cooperating that could trigger the cascade for demonstrated network interest. This aligns with the noise parameter in (Haer et al., 2016). We add in minimal noise (0.5%) to compare to no noise (0%).
Discount	Discount rate for all monetary estimates	0.03	Frequently used estimate in flood adaptation planning

Foresight	Amount of years that agents consider in their calculations	30 years	Rough estimate of how far out municipalities calculate flood risk
Operation and maintenance cost (Boston only)	Additional O&M costs as a proportion of the adaptation cost	1%	Low, but not insignificant addition to adaptation costs
Permit hurdles (Boston only)	A general variable that increases the permitting burden for noncooperative solutions and decreases for cooperative solutions	Low, High	'Low' sets the permitting conditions to a preference for cooperative adaptation. "High" increases the permit challenges.
Access to financing (Boston only)	A general variable that increases the permitting burden for noncooperative solutions and decreases for cooperative solutions	Low, High	'Low' limits external financing availability, while "high" financing represents more favorable financing.
Network effect variable	When calculating demonstrated network interest, agents wither use demonstrated coalition interest or coalition size to determine their cooperativity.	Coalition interest, coalition size	Agents calculate demonstrated network interest based off on the final cooperation decision or off of their signal of intent to cooperate from the initial individual cooperative assessment.

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