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Earth's Future

RESEARCH ARTICLE

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Special Collection:

Regional Sea Level Change and Society

Key Points:

- We develop adaptive adaptation pathways that incorporate learning about sea level rise uncertainty based on future observations
- Adaptive adaptation pathways generate sea level rise thresholds for adaptation actions that can be similar across climate change scenarios
- Adaptive adaptation pathways can reduce expected costs compared to non-adaptive pathways by up to 1.8% in our study

Supporting Information:

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

Correspondence to:

V. Völz,
vanessa.voelz@globalclimateforum.org

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Learning About Sea Level Rise Uncertainty Improves Coastal Adaptation Decisions

Vanessa Völz^{1,2} , Jochen Hinkel^{1,2}, Sunna Kupfer³ , Leigh R. MacPherson⁴, and Carl Jacob Wulff Norrby³

¹Humboldt-Universität zu Berlin, Thaeer-Institute of Agricultural and Horticultural Sciences, Berlin, Germany, ²Global Climate Forum, Berlin, Germany, ³Department of Geography, Coastal Risks and Sea Level Rise Research Group, Christian-Albrechts University, Kiel, Germany, ⁴Faculty of Agricultural and Environmental Sciences, University of Rostock, Rostock, Germany

Abstract Adaptive decision-making allows decision-makers to plan long-term coastal infrastructure under uncertain sea level rise projections. To date, economic assessments of adaptive decision-making that take into account future learning about sea level rise uncertainty are rare and the existing ones have relied on simple quantification of future learning not validated against sea level science. To address this gap, we develop an economic adaptive decision-making framework that takes into account future learning about sea level rise uncertainty and apply it to a coastal case study in Lübeck, Germany, to answer the question of how adaptation to sea level rise can be improved through adaptive adaptation pathways as opposed to non-adaptive pathways. To address this question, we use a Markov decision process to formulate the stochastic optimization problem. We quantify future learning about sea level rise uncertainty through sea level rise learning scenarios based on and validated against the latest scenarios of the Intergovernmental Panel on Climate Change. Our case study results show that the city of Lübeck is currently under-protected against storm surges and that immediate adaptation actions are advisable in the face of future sea level rise. We find that adaptive adaptation pathways, in contrast to non-adaptive pathways, generate sea level rise thresholds for adaptation actions that are similar across climate change scenarios and can reduce expected costs up to 1.8%.

Plain Language Summary Climate change is causing sea levels to rise as land ice melts under higher air temperatures. By 2100, sea levels are projected to rise between 28 and 101 cm, depending on the extent of future global warming. This will increase the risk of coastal flooding in the future and require adaptation actions. Planning for coastal adaptation to sea level rise is challenged by long-lived protective infrastructure and uncertain projections of sea level rise. Adaptive decision-making methods that specifically incorporate future learning about the uncertainty of sea level rise can address this challenge. For example, observing 30 cm of sea level rise in 2060 will lead to different projections from 2050 onwards and require different adaptation actions than observing 70 cm of sea level rise in 2060. To date, economic adaptation studies that account for future learning about sea level rise uncertainty are rare, and those that do exist have relied on simple methods. We develop a decision framework to address this research gap and apply it to the city of Lübeck on the Baltic Sea in Germany. Our results show that the city of Lübeck is currently under-protected against storm surges and that immediate adaptation actions are advisable from an economic perspective.

1. Introduction

Large uncertainties in sea level rise projections, together with the long lead times and lifetimes of adaptation measures, pose a challenge to coastal adaptation planning (Fox-Kemper et al., 2021) that can be addressed through *adaptive decision-making* (Oppenheimer et al., 2019). Adaptive decision-making is an approach to decision making, where decisions are taken at multiple stages over time and decisions at future stages take into account what will be learned until then (Bellman, 1966). A number of different normative frameworks for adaptive decision-making have been proposed in recent years, including adaptive planning (Walker et al., 2001), dynamic adaptive policy pathways (Haasnoot et al., 2013) and adaptation pathway analysis (Haasnoot et al., 2012, 2020). Normative adaptive decision-making also includes some technically sophisticated methods, such as real-option analysis (Wreford et al., 2020) and dynamic planning frameworks (Herman et al., 2020), which can identify strategies that are economically efficient in terms of the timing of adaptation, taking into account future learning about the uncertainty of sea level rise (Oppenheimer et al., 2019).

As adaptive decision-making considers future learning, the results of *adaptive decision analysis methods* are *adaptive adaptation pathways*, rather than a single optimal action to be taken today, or a sequence of actions over time. Adaptive adaptation pathways, often referred to simply as adaptation pathways (Haasnoot et al., 2012), tell the decision-maker which adaptation measures to implement under which future observations of sea level rise. The majority of economic studies on coastal adaptation use a *single-stage non-adaptive adaptation pathway* (e.g., cost-benefit analysis (Anthoff et al., 2010; Bachner et al., 2022; Hallegatte et al., 2013; Hinkel et al., 2014; Lincke & Hinkel, 2018, 2021; Sassone & Schaffer, 1978; Tiggeloven et al., 2020; van Dantzig, 1956; Voudoukas et al., 2020), which are characterized as decisions that are implemented today and remain unchanged over the entire time horizon (e.g., a constant dike height). Very few cost-benefit analyses of coastal adaptation use optimal control theory to consider a *multi-stage non-adaptive adaptation pathway* (Eijgenraam et al., 2014, 2017; Zwaneveld et al., 2018), which may change over time, but the whole sequence of protection levels over time is decided today, regardless of future observations of sea level rise (e.g., a dike with incremental height upgrades).

Economically efficient adaptive adaptation pathways for coastal adaptation have rarely been developed in the literature and if so rely on simple quantification of future learning about sea level rise (Oppenheimer et al., 2019; Völz & Hinkel, 2023b). One reason for this is the unavailability of so called learning scenarios, which are a prerequisite for developing efficient adaptive adaptation pathways. Learning scenarios are an up-front quantification of the opportunity to learn about the uncertainty of sea level rise in the future (Hinkel et al., 2019; Völz & Hinkel, 2023a). While sophisticated learning scenarios and case study applications exist for precipitation (Dittrich et al., 2019; Fletcher, Lickley, & Strzepek, 2019) and groundwater level (Fletcher, Strzepek, et al., 2019), applications for sea level rise (Diaz, 2016; Garner & Keller, 2018; Gersonius et al., 2013; Linquiti & Vonortas, 2012; van der Pol et al., 2013; Webster et al., 2008; Woodward et al., 2014) use learning scenarios that are rather simple, for example, based on ad-hoc assumptions and not validated against the science of sea level rise (Völz & Hinkel, 2023b). Recently, Völz and Hinkel (2023b) have developed sea level rise learning scenarios based on and validated against sea level rise projections from the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), but a case study application remains to be seen.

The novelty of our paper is threefold: (a) for the first time we apply adaptive decision-making to a real case study using state-of-the-art sea level rise learning scenarios, (b) for the first time we couple a hydrodynamic flood model with an adaptive decision framework, and (c) for the first time we derive adaptive adaptation pathways with granular sea level rise thresholds for adaptation actions by optimizing timing and protection height. Recent studies on adaptive decision-making have presented optimal adaptive adaptation pathways with climate variable thresholds for binary adaptation actions that are flexible in time, as traditionally done in real-option analysis or engineering options analysis (Fletcher, Lickley, & Strzepek, 2019; Fletcher, Strzepek, et al., 2019). In the context of coastal adaptation decisions, adaptation options are usually not binary, but require a specific protection height of the coastal protection measure. While a few studies on economic adaptive decision-making combine simplified learning about climate change with optimization of timing and protection heights (Linquiti & Vonortas, 2012; van der Pol et al., 2013; Woodward et al., 2014), no study has presented optimal adaptive adaptation pathways with granular climate variable thresholds for adaptation actions with specific protection heights. We fill this gap by using a Markov decision process and state-of-the-art sea level rise learning scenarios to formulate a stochastic optimization problem and solve it using dynamic programming.

By applying our decision framework to a coastal case study in Germany, we aim to answer the following research question: How can adaptation to sea level rise be improved through economic adaptive decision analysis methods that incorporate future learning about sea level rise uncertainty, as opposed to non-adaptive decision analysis methods?

2. Methods

Our workflow for deriving optimal adaptive adaptation pathways for coastal adaptation to sea level rise consists of three steps: (a) modeling flood damages under a wide range of sea level rise, storm surges and adaptation options, (b) using the model output to build a statistical emulator of flood damages as the numerical model is computationally too expensive to be used in the decision framework, and (c) developing and applying an appropriate economic adaptive decision framework (Figure 1). In this section, we first describe the adaptive decision framework and then present its application to the German case study, including the flood damage modeling and emulation.

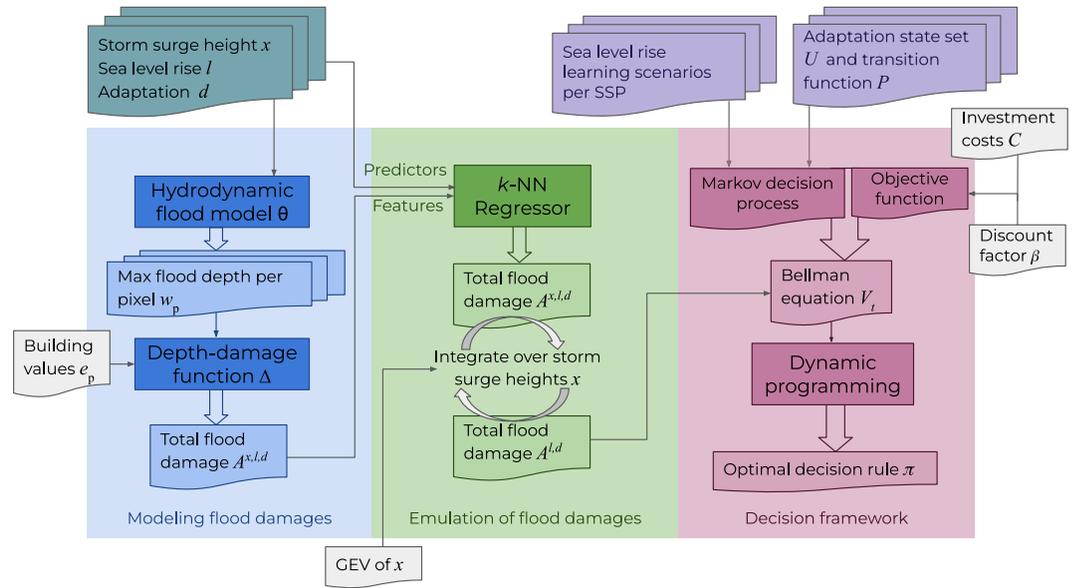


Figure 1. Workflow chart of our methods described in chapter 2.

2.1. Formulation of the Decision Framework

We use a Markov decision process to formulate our decision framework for coastal adaptation decision-making and apply dynamic programming to find optimal solutions. We create a version of the decision framework that incorporates learning about sea level rise uncertainty (Section 2.1.5) and, for comparison, another version that does not (Section 2.1.4).

2.1.1. Markov Decision Process

To model adaptation actions against increasing flood risks due to rising sea levels, we define a time-dependent state space S_t as a set of tuples containing sea level rise states l_t and adaptation states d_t , both from discrete sets \mathcal{L}_t and \mathcal{D}_t :

$$s_t = (l_t, d_t) \in \mathcal{L}_t \times \mathcal{D}_t = S_t. \quad (1)$$

The state space S , spanning the whole time horizon of discrete time steps $\mathcal{T} = \{1, \dots, T\}$, is defined by $S = \cup_{t \in \mathcal{T}} S_t$. In each time step, an action from a discrete set of actions \mathcal{U} can be applied. The transition function $P(s_{t+1} = s' | s_t = s, u_t = u)$ defines the likelihood of transitioning from state s at time t to s' when action u is implemented in t . The transition function for state s_t is a combination of two transition functions for the sea level rise and adaptation states. The transition function for sea level rise states is stochastic and independent of action u and will be defined in Section 2.1.5, whereas the transition function for adaptation states is deterministic. We already implement the deterministic transition of adaptation states by interpreting d as the protection height and u as a height upgrade:

$$\begin{aligned} & P(s_{t+1} = s' | s_t = s, u_t = u') \\ &= P((l_{t+1}, d_{t+1}) = (l^k, d^q) | (l_t, d_t) = (l^j, d^r), u_t = u') \\ &= \begin{cases} P(l_{t+1} = l^k | l_t = l^j) & \text{if } d^q = d^r + u' \\ 0 & \text{else} \end{cases}. \end{aligned} \quad (2)$$

Let $C(s, u)$ be a cost function that describes all costs occurring in state s under action u . The following collection of objects constitutes a Markov decision process that describes an adaptive adaptation problem:

$$\{\mathcal{T}, \mathcal{S}, \mathcal{U}, P(s_{t+1} = s' | s_t = s, u = u'), C(s, u)\}. \quad (3)$$

We want to find a adaptive adaptation pathway that tells us which adaptation action $u \in \mathcal{U}$ should be implemented for each state s_t over time. Hence, a adaptive adaptation pathway (also called decision rule or policy function) π is a function mapping from the state space to the action space: $\pi : \mathcal{S} \mapsto \mathcal{U}$. The set of all possible adaptive adaptation pathways is defined by:

$$\Pi = \{\pi : s \mapsto u \mid s \in \mathcal{S}, u \in \mathcal{U}\}. \quad (4)$$

2.1.2. Objective Function

We aim to find an optimal adaptive adaptation pathway that minimizes costs occurring today and in future moments in time. We discount all future costs with the discount rate β to represent costs in present values, or in other words to consider time preferences for cash flows. Our framework contains stochastic sea level rise development (see Section 2.1.5) and therefore we minimize expected costs in our objective function:

$$\min_{\pi \in \Pi} \mathbb{E} \sum_{t=1}^T \beta^t C(s_t, \pi_t(s_t)). \quad (5)$$

We want to consider costs arising from flood damages and adaptation investments in the cost function $C(s, u)$. To specify the cost function in more detail, let $I(d, u)$ be the investment cost function that defines the costs for implementing adaptation action u under current adaptation d . To account for flood damages, we use a function $\phi(l + x, d)$ that quantifies the total flood damage under sea level rise l , extreme water level x and adaptation d . We determine the average annual flood damage under sea level rise l and adaptation d by considering all possible extreme water levels and their annual likelihood of occurrence. Specifically, we multiply the flood damages by the probability density function $f(x)$ of extreme water level x and integrate over all extreme water levels:

$$\min_{\pi \in \Pi} \mathbb{E} \sum_{t=1}^T \beta^t \left[I(d_t, \pi_t(s_t)) + \int_0^{x_{\max}} \phi(l_t + x, d_t) f(x) dx \right]. \quad (6)$$

2.1.3. Solving the Optimization Problem: Bellman Equation

The objective function formulated in Equation 6 is a sequential decision problem with an optimal substructure, which allows us to solve this problem step by step rather than all at once. If we are in a given state in a given time and know the future values of being in each possible future state, we would simply need to choose the optimal action at that time, taking into account the one-period contribution and the values of the future states (Powell, 2011). Thus, we can replace the minimization over all adaptive adaptation pathways in Equation 6 with the minimization over all actions for each subproblem. We assign values V_t to each state at each time step and obtain the optimality equation, often called *Bellman equation* (Puterman, 1994):

$$V_t(s_t) = \min_{u \in \mathcal{U}} \left\{ I(d_t, u) + \int_0^{x_{\max}} \phi(l_t + x, d_t) f(x) dx + \beta \mathbb{E}[V_{t+1}(s_{t+1})] \right\} \quad (7)$$

for $s_t \in \mathcal{S}_t$ and $t = 1, \dots, T - 1$. We abbreviate $P(s_{t+1} = s' | s_t = s, u_t = u)$ with $P(s' | s, u)$ and write:

$$V_t(s_t) = \min_{u \in \mathcal{U}} \left\{ I(d_t, u) + \int_0^{x_{\max}} \phi(l_t + x, d_t) f(x) dx + \beta \sum_{s' \in \mathcal{S}_{t+1}} P(s' | s_t, u) V_{t+1}(s') \right\}. \quad (8)$$

The Bellman Equation 8 is the basis for finding optimal adaptive adaptation pathways for the objective function Equation 6. For stochastic finite-horizon discrete-time Markov decision problems with time-independent action space, the Bellman equation can be solved by dynamic programming (Powell, 2011). The dynamic programming algorithms used in this study are described in Supporting Information S1.

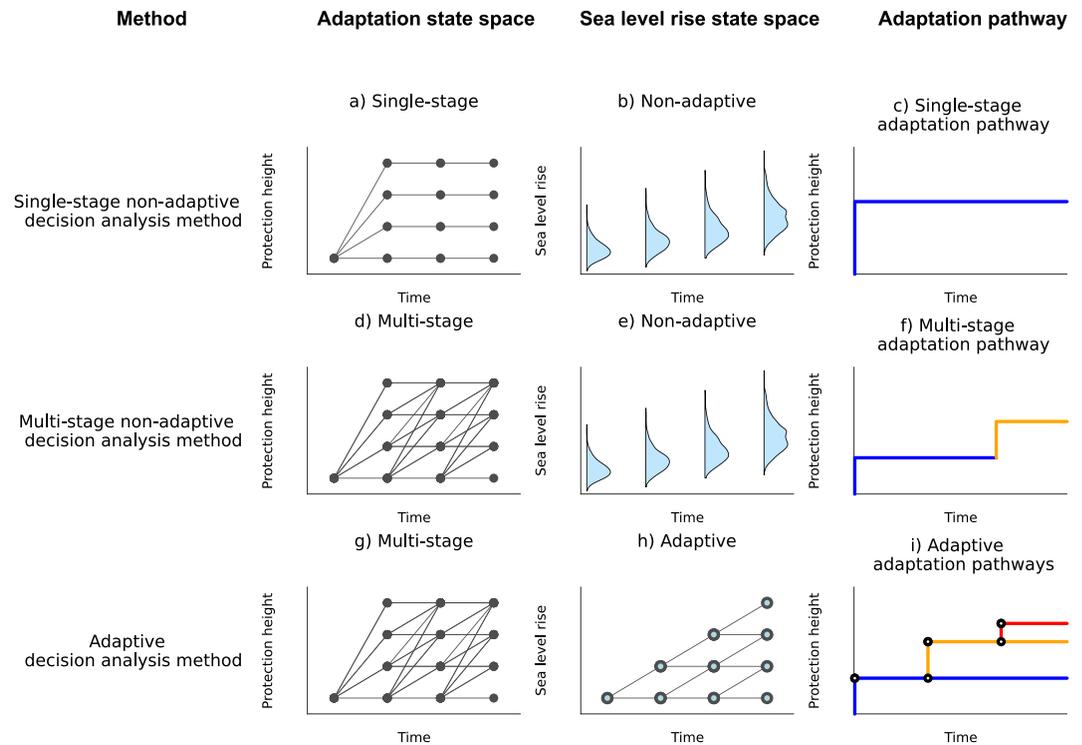


Figure 2. Illustrations of the adaptation state space, sea level rise state space and resulting adaptation pathway for single-stage non-adaptive, multi-stage non-adaptive and adaptive decision analysis methods. The non-adaptive sea level rise state space (b and e) is based on probability distribution functions per time step. The adaptive sea level rise state space (h) is a learning scenario.

2.1.4. Non-Adaptive Decision Analysis Methods

To illustrate the benefits of adaptive decision analysis methods that incorporate learning about sea level rise uncertainty, we compare their results with those of non-adaptive decision analysis methods, which do not incorporate learning about sea level rise uncertainty. We define *single-stage non-adaptive decision analysis methods* as those that analyse single-stage decisions (sometimes called one-shot decisions), that is, decisions that are implemented today and remain unchanged over the entire time horizon (Figures 2a–2c). In the literature, this method is the most widely used method for the economic analysis of coastal protection measures (Anthoff et al., 2010; Bachner et al., 2022; Hallegatte et al., 2013; Hinkel et al., 2014; Lincke & Hinkel, 2018, 2021; Tiggeloven et al., 2020; van Dantzig, 1956; Vousdoukas et al., 2020). We define *multi-stage non-adaptive decision analysis methods* as those that analyse multi-stage decisions, that is, decisions where protection measures may change over time, but decisions are non-adaptive, that is, the whole sequence of protection levels over time is decided today (Figures 2d–2f). In the literature, examples of this can be found in the Dutch context in the form of cost-benefit analyses using optimal control theory (Eijgenraam et al., 2014, 2017; Zwaneveld et al., 2018).

For non-adaptive methods we do not use a sea level rise learning scenario, but instead apply a convolution of the sea level rise and extreme water level probability distribution functions and use the probability density function of this convolution for $f(x)$ in Equation 6. We determine the convolution by a discrete sampling of the AR6 sea level rise p-box scenario for each time step with 10,000 data points and a sampling of the extreme water level distribution function, respectively, and sum both samples. Similar to Lickley et al. (2014), we then fit a log-normal distribution to the summed sample to determine an analytical solution to the convolution, see Supporting Information S1 for details.

2.1.5. Adaptive Decision Analysis Method

Uncertainty in sea level rise projections will evolve over time as new observations of sea level rise become available. Sea level rise observations will not only provide the exact value of sea level rise at that point in time,

they can also be used to learn about the uncertainty in sea level rise as sea level rise projections are updated. For example, observing 20 cm of sea level rise in 2050 will lead to different sea level rise projections from 2050 onwards than observing 40 cm of sea level rise in 2050. We define *adaptive decision analysis methods* as methods that involve future learning about sea level rise uncertainty through multi-stage adaptation actions and adaptivity (Figures 2g–2i).

In our decision framework, learning about sea level rise uncertainty is captured within the sea level rise state space, that is, the sea level rise state set \mathcal{L}_t and the sea level rise transition function $P(l_{t+1} = l^k | l_t = l^j)$. The combination of the two is a learning scenario (Figure 2h).

We apply the direct fit method by Völz and Hinkel (2023b) to define the sea level rise state set and the transition function for sea level rise. The direct fit method enumerates sea level rise states per time step and generates a binomial and recombining scenario lattice with a 50% probability of going up or down in each state. The direct fit method determines the sea level rise states positions by positioning each node in accordance with its occurrence probability in the lattice (seen from the first time step and based on the binomial distribution) and the quantile function of the underlying sea level rise data in each respective time step. For example, the two sea level rise states in the second time step both have an occurrence probability of 50% and are positioned at the 25th and 75th quantile value of the underlying sea level rise data in the year 2030. The transition function for sea level rise is then given by

$$P(l_{t+1} = l^k | l_t = l^j) = \begin{cases} 0.5 & \text{if } (k = j \vee k = j + 1) \\ 0 & \text{else} \end{cases} \quad (9)$$

Inserting Equation 9 in Equation 2 gives the joint transition function

$$\begin{aligned} & P(s_{t+1} = s' | s_t = s, u = u') \\ &= P((l_{t+1}, d_{t+1}) = (l^k, d^q) | (l_t, d_t) = (l^j, d^r), u = u') \\ &= \begin{cases} 0.5 & \text{if } (k = j \vee k = j + 1) \wedge d_{t+1}^q = d_t^r + u' \\ 0 & \text{else} \end{cases} \end{aligned} \quad (10)$$

Note that while the structure of the learning scenario is identical to a binomial and recombining scenario lattice (sometimes called binary decision tree) used in traditional real-option analysis, the underlying generation method for positioning its nodes is novel and different from existing methods. The existing sea level rise learning scenarios are based on random sampling of distribution parameters (Woodward et al., 2014), a stochastic process (Gersonius et al., 2012), updating distribution parameters (Linquiti & Vonortas, 2012), simple physical models (Webster et al., 2008), linear model regression (Garner & Keller, 2018), or ad-hoc assumptions (van der Pol et al., 2013) and are not based on state-of-the-art sea level rise projections, for example, from AR5 or AR6, and neither of these studies validated their learning scenarios against underlying sea level rise data (Völz & Hinkel, 2023b). Völz and Hinkel (2023b) validate their sea level rise learning scenarios against AR6 projections and show that the scenarios are able to reasonably represent sea level rise development over time and future learning from observations. Further, the binomial and recombining scenario lattice structure of the direct fit method outperforms existing sophisticated learning scenarios in terms of computational efficiency, as non-recombining (Erfani et al., 2018; Kind et al., 2018) or non-binomial (Dittrich et al., 2019; Fletcher, Lickley, & Strzpek, 2019) learning scenarios generate larger state spaces.

2.2. Application of the Decision Framework to Lübeck

We apply our decision framework to the coastal city of Lübeck, Germany.

2.2.1. Case Study Description and Adaptation Options

The Hanseatic city of Lübeck is located on the German Baltic coast and has a population of 222,000 (Lübeck, 2023). The city lies at the mouth of the River Trave and its old town island, which is a UNESCO World

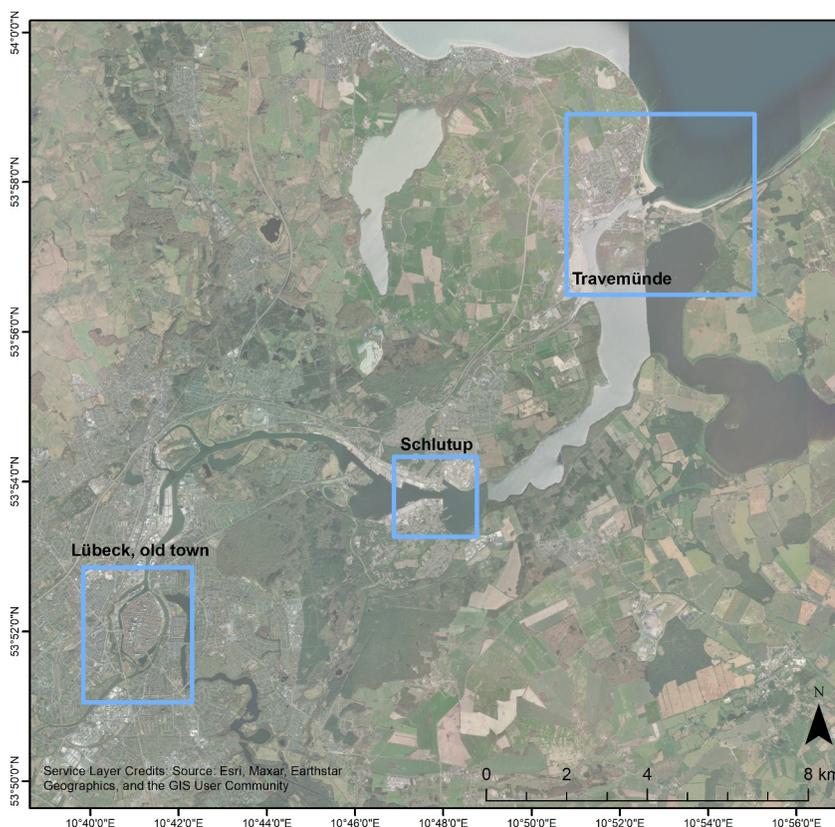


Figure 3. A map of Lübeck, Germany, showing different parts of the city, including the old town, Schlutup and Travemünde.

Heritage Site, lies 17 km inland from the estuary mouth (Figure 3). The city of Lübeck currently has no coastal flood protection infrastructure and is exposed to relatively frequent extreme events, such as the 1 in 10 years event. In October 2023, a storm surge with an extreme water level of 1.6 m flooded parts of the city of Lübeck, including the UNESCO World Heritage Site (NDR, 2023). Storm surges in Lübeck typically occur during strong westerly and northwesterly winds. Tides in the region are small (<10 cm) and thus contribute little to storm surge heights. As the Baltic Sea is a semi-enclosed basin, seiches can contribute several decimeters to the total water level. Therefore, water levels are affected by large-scale atmospheric forcing acting over the entire Baltic Sea (Jensen & Müller-Navarra, 2008).

Employees from the City of Lübeck participated in a stakeholder workshop to discuss preferences for the decision framework regarding adaptation options, confidence in sea level rise projections, and the time horizon. As a result, the majority of participants favored a longer time horizon of 100 years to take into account the lifetime of inflexible infrastructure. Further, the AR6 medium confidence sea level rise projections were preferred.

Three potential adaptation infrastructures were identified for the city of Lübeck: (i) a storm surge barrier in Travemünde with adjacent dikes; (ii) a storm surge barrier in Schlutup with adjacent dikes; and (iii) sea walls along the river in the old town, Schlutup and Travemünde (see Figure 4). We assume that only one of the three adaptation options will be implemented over time and that switching between the options is impossible. The decision-maker has to decide when and how high an initial adaptation action should be implemented (if any), and if and when further height upgrades should be implemented.

2.2.2. Sea Level Rise Learning Scenarios

No vertical land motion is projected for the city of Lübeck (Peltier et al., 2015), so the relative sea level rise is equal to the regional sea level rise. We use the medium confidence sea level rise projections from the AR6 p-box scenario for Travemünde (Fox-Kemper et al., 2021; Garner, Hermans, et al., 2021; Garner, Kopp, et al., 2021) to generate learning scenarios using the direct fit method of Völz and Hinkel (2023b). The AR6 regional p-box

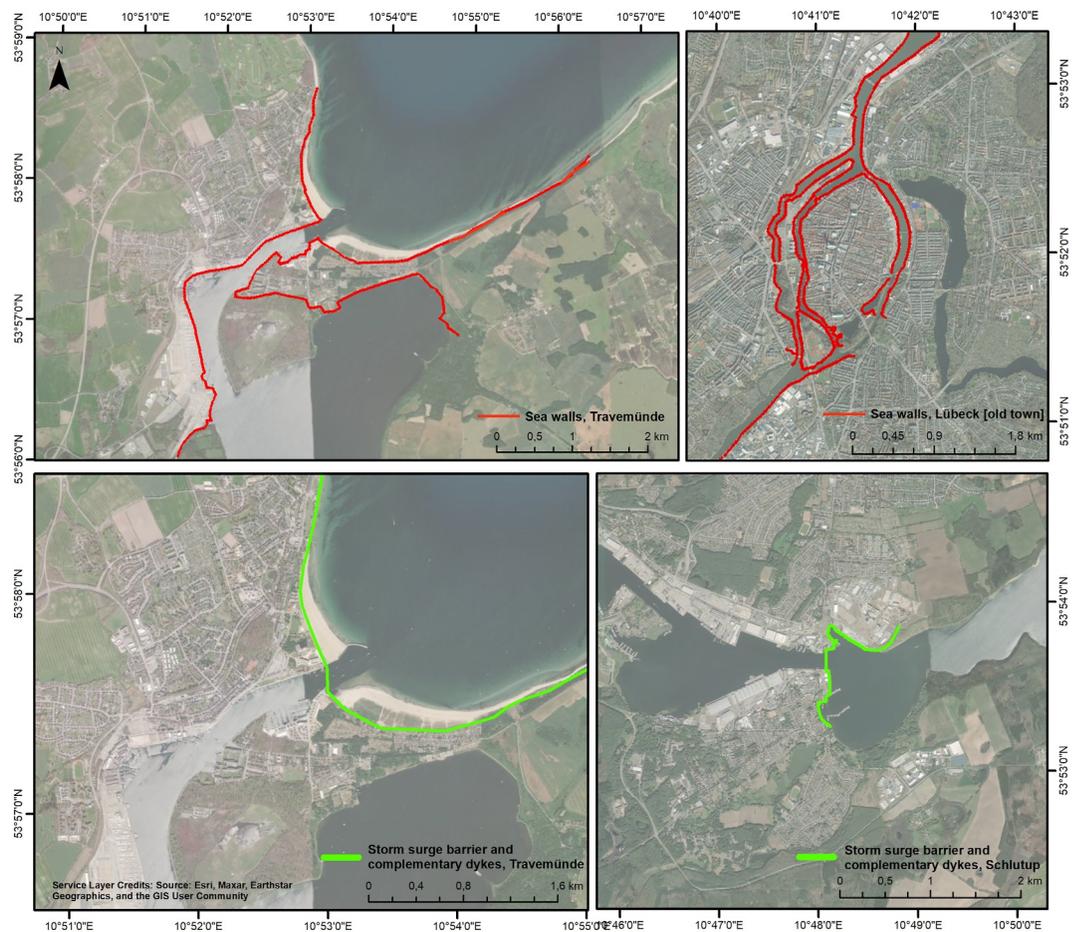


Figure 4. The three alternative adaptation options implemented in our framework: (i) sea walls along the river in the old town, Schlutup and Travemünde (top); (ii) a storm surge barrier in Travemünde with adjacent dikes (bottom left) and (iii) a storm surge barrier in Schlutup with adjacent dikes (bottom right).

scenarios combine probability distributions of several workflows into one scenario by taking the minimum quantile value of all workflow quantile values below 50%, the mean of all 50% quantile values, and the maximum quantile value of all workflow quantile values above 50% (Fox-Kemper et al., 2021; Garner, Hermans, et al., 2021; Garner, Kopp, et al., 2021). While the Monte Carlo samples of the AR6 sea level rise projections could also be used to generate learning scenarios, the use of p-box scenarios allows us to consider a wider range of uncertainty due to the alternative land ice emulators considered in the p-box scenarios, although this might overlook some other physical aspects. The resulting sea level rise learning scenarios for low and high climate change scenarios are shown in Figure 5.

2.2.3. Investment Costs

We model the initial investment costs ($d = 0$) for dikes and seawalls with a linear cost function depending on the length and height of a protection measure, as a regression analysis of Lenk et al. (2016) shows that linear cost functions are sufficient to model dike investment costs:

$$I(0, u) = c * u * b, \quad (11)$$

where c is the unit cost factor (EUR/km*cm), u is the height of protection (cm) and b is the length of the coastal protection measure (km). Following an analysis by Mooyaart et al. (2014), we model the investment costs for storm surge barriers with a linear cost function depending only on the width of the barrier. We assume that a storm

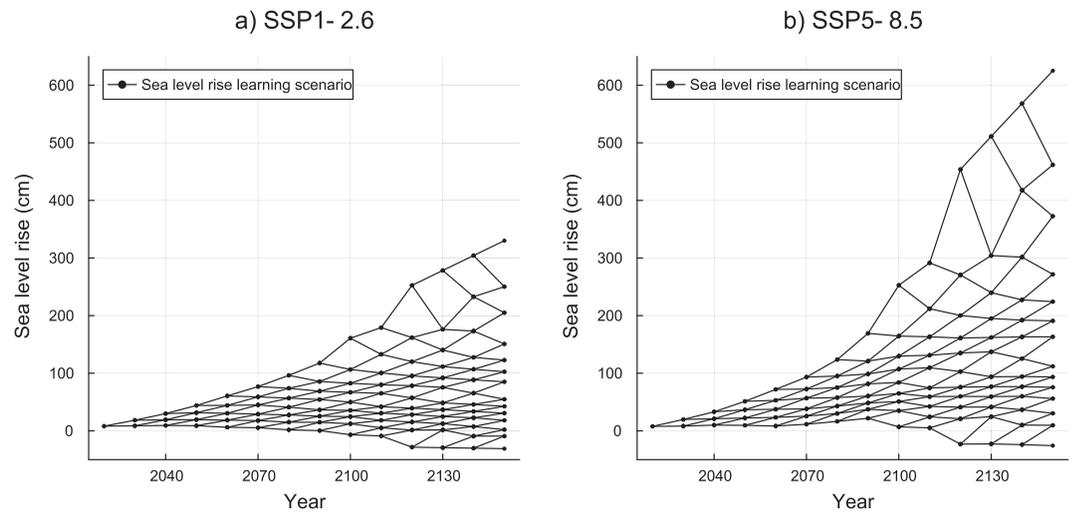


Figure 5. Sea level rise learning scenarios for Travemünde generated by applying the direct fit method of Völz and Hinkel (2023b) to the AR6 medium confidence sea level rise projections. The learning scenarios are binomial lattices with a 50% probability of either rising or falling in each state. (a) shows a learning scenarios for SSP1-2.6 (low climate change) and (b) for SSP5-8.5 (high climate change).

surge barrier is always built with a protection height of 8 m and that, unlike dikes and sea walls, no further height upgrades are possible.

In line with the findings of Jonkman et al. (2013), we assume that subsequent height upgrades of dikes or seawalls are 1.5 times more expensive than the initial investment costs. We have further extended the linear cost function for height upgrades ($d > 0$) with a fixed cost component c_{fix} , to ensure that incremental dike upgrades are more costly than combining all incremental dike upgrades into an aggregated dike upgrade (Eijgenraam et al., 2017):

$$I(d, u) = c_{fix} * 1.5 * c * 1 * b + (1 - c_{fix}) * 1.5 * c * u * b, \quad d > 0. \quad (12)$$

We estimate the fixed cost component c_{fix} to be 30%, which is consistent with data from several Dutch ring dikes (Eijgenraam et al., 2017).

In our decision framework, two different types of dikes or seawalls can be built: either a *normal* inflexible protection measure, or a *flexible* protection measure (called a “climate dike” in Germany (Schwenn, 2021)), that has a wider or deeper foundation in anticipation of subsequent height upgrades in the future. The initial investment costs for *flexible* protection measures are 30% higher than for *normal* protection measures, but in return provide the opportunity of later, cheaper height upgrades up to twice the initial height. Thus, initial investment costs for flexible dikes or seawalls are assumed to be $1.3 \times I(0, u)$ and subsequent upgrade costs are assumed to be $0.5 \times I(d, u)$ for doubling the initial protection height.

We assume three different scenarios of low, medium or high unit costs based on other publications (J. Aerts, 2018; Hillen et al., 2010; Jonkman et al., 2013; Mooyaart et al., 2014; Nicholls et al., 2019; Prahl et al., 2018; Rehdanz et al., 2022). Table S3 in Supporting Information S1 shows the unit cost factors for dikes, sea walls and storm surge barriers, which we assume in this study. We estimate the maintenance costs for dikes, sea walls and barriers at 1% of the respective initial investment costs (J. Aerts, 2018; J. C. Aerts et al., 2013; Mooyaart et al., 2014) and the operating costs for barriers at 5% of the initial investment costs for barriers (Jonkman et al., 2013).

2.2.4. Flood Damage Modeling and Emulation

We use a hydrodynamic flood model developed by Kupfer et al. (2024) specifically designed for the city of Lübeck to model the flood propagation of storm surge heights. The hydrodynamic model takes into account the full water level hydrographs, which were developed using the method of MacPherson et al. (2019). The hydrodynamic flood model θ determines maximum flood depths w_p for each 10×10 m horizontal pixel p under storm surge height x , sea level rise l and adaptation action d :

$$\theta(l+x, d) \mapsto w_p \quad \forall p \in P. \quad (13)$$

We apply a depth-damage function Δ to determine the relative asset damage a_p in pixel p under the maximum flood depth w_p aligned to Huizinga et al. (2016):

$$\Delta(w_p) \mapsto a_p. \quad (14)$$

Multiplying the relative damage a_p by the building value e_p gives the absolute damage $A_p^{x,l,d}$ for pixel p :

$$A_p^{x,l,d} = a_p * e_p = \Delta(\theta(l+x, d)) * e_p, \quad (15)$$

where buildings are identified using OpenStreetMaps and the building values are derived from official production cost tables published by the German Federal Ministry of Housing, Urban Development and Building. We provide a detailed explanation of the building value estimation process in Supporting Information S1. The total flood damage $A^{x,l,d}$ for the whole city of Lübeck, depending on storm surge height x , sea level rise l and adaptation action d , is determined by summing over all pixels:

$$A^{x,l,d} = \sum_p A_p^{x,l,d}. \quad (16)$$

The flood simulation model has been applied to three different input data sets, one is a Latin Hypercube Sampling ($x \in [170, 340]$, $l \in [0, 455]$, $d \in [200, 800]$), one contains samples without adaptation and one contains sample points with adaptation below 200 cm. We combine all three data sets into one and apply oversampling to avoid data bias. Specifically, we define grid cells with increments of 200 cm over the total water level ($l+x$) and adaptation height (d) and duplicate the data points in each grid cell until all grid cells contain the same number of data points.

Our decision framework requires the total flood damage $A^{x,l,d}$ for more input points than given in our data set, so we mimic the flood simulation model, the pixel-wise application of the depth-damage function, and the aggregation of housing value damages (Equations 13–16) with a k -nearest-neighbor (k -NN) regression ϕ :

$$\phi(l+x, d) \mapsto A^{x,l,d}, \quad (17)$$

with $k=2$ and distance weighting, for example, giving more weight to points which are nearby. For the adaptation option *Schlutup barrier* and *sea walls* we use two k -NN regressors for pixels that are protected by the infrastructure and those that are not.

We assign probabilities to storm surge heights using a generalized extreme value (GEV) distribution provided by MacPherson et al. (2023). Rather than relying solely on high-resolution data (at least hourly samples), MacPherson et al. (2023) apply a Bayesian approach to extreme value analysis, which allows the incorporation of historical measurements in addition to the systematic tide-gauge data. Consequently, the resulting storm surge model incorporates information from a much longer observation period compared with traditional methods (Coles, 2001), providing benefits such as reduced estimate uncertainties and better representation of extraordinary events. This is particularly useful along the German Baltic Sea coast, which experienced very large events before the introduction of systematic tide-gauge records (Jensen et al., 2022). The final distribution function is based on 195 annual maxima sea levels, observed from 1826 to 2020, and includes several large historical events dating back to 1,044. The shape, scale and location parameters are -0.0175325 , 0.28537 , and 1.24056 respectively. We use this GEV distribution for $f(x)$ in Equation 6. To make sure that we consider all possible extreme events, we set x_{\max} to 8 m, which corresponds to an extreme event with a return frequency higher than a billion years.

2.2.5. Conducted Simulations

We apply our decision framework to the Lübeck case study and perform multiple runs of our non-adaptive and adaptive decision frameworks, varying the following parameters: low, medium or high unit costs; low climate

change (limit warming to 2°C; SSP1-2.6), medium climate change (limit warming to 3°C; SSP2-4.5) or high climate change (exceed warming of 4°C; SSP5-8.5); a low discount rate (1.4% as in Stern (2006)), a medium discount rate (2.0%) or a high discount rate (4.3% as applied by Nordhaus (2006) (Goulder & Williams, 2012)); and the Travemünde barrier, the Schlutup barrier or sea walls as adaptation options. This results in 81 simulation runs for each decision type (single-stage non-adaptive, multi-stage non-adaptive and adaptive) and 243 simulation runs in total. With the exception of the sensitivity analysis of the discount rates, we choose a constant discount rate of 1.4% for our results, which corresponds to the discount rates recommended by the German Central Bank (Bundesbank, 2023). We consider an adaptation state set consisting of incremental adaptation heights of 50 cm and a maximum height of 8 m. We consider 10-year time steps and assume that it takes one time step to implement adaptation actions.

3. Results

3.1. Comparison Between the Results of the Non-Adaptive and Adaptive Decision Analysis Methods

Comparing the results of single-stage non-adaptive, multi-stage non-adaptive and adaptive decision analysis methods under the medium unit cost assumption for the Travemünde barrier, we find that multi-stage non-adaptive and adaptive adaptation pathways recommend an initial protection height of 150 cm, irrespective of the climate change scenario (Figure 6). In contrast, the single-stage adaptation pathways recommend an initial protection height of 150 cm under low climate change, but an initial protection height of 250 cm under high climate change. The multi-stage adaptation pathways recommend one future protection height upgrade under low climate change and two future protection height upgrades under high climate change. In contrast, the adaptive adaptation pathways recommend a wide range of later height upgrades that vary in timing and protection height and depend on future sea level rise thresholds.

Our results illustrate how adaptive adaptation pathways prevent over- and under-protection by recommending a wide range of cost-optimal adaptation actions, ranging from a low protection height of 1.5 m for very low sea level rise realizations (i.e., below 45 cm until 2150) to higher protection heights (e.g. 3 and 4 m) under higher sea level rise thresholds (e.g., above 90 cm until 2100 and above 160 cm until 2100) (Figures 6e and 6f). If a sea level rise threshold of 120 cm or 170 cm is reached before 2100, the adaptive adaptation pathway under high climate change for the Travemünde barrier results in an annual overtopping probability of 0.3% in 2100 (Table 1). In contrast, non-adaptive adaptation pathways can suffer greatly from under-protection if a high end sea level rise projection were to materialize (Figure 6). For example, reaching 120 cm or 170 cm of sea level rise before 2100 would result in annual overtopping probabilities in 2100 of 55.6% or 99.0% (Table 1).

The single-stage non-adaptive decision analysis method overestimates adaptation costs compared to multi-stage non-adaptive decision analysis methods, and adaptive decision analysis methods have the potential to reduce adaptation costs further (Table 2). Learning about sea level rise uncertainty, implemented in the adaptive adaptation pathway, reduces the overall expected costs of the Travemünde barrier under the medium unit cost assumption by 70 million euros (−1.8%) compared to the multi-stage adaptation pathway (Table 2). We call this cost reduction stemming from using sea level rise observations to update future sea level rise projection the value of learning. In prevalent literature this term is also called the value of information, value of flexibility or option value (Dawson et al., 2018; Kwakkel, 2020; Liu et al., 2018; Pachos et al., 2022; Skerker et al., 2023; Wreford et al., 2020). The value of learning is 29 million euro (−0.5%) for the Schlutup barrier and 41 million euro (−0.9%) for the sea walls respectively. For all adaptation options the value of multi-stage decision-making (single-stage vs. multi-stage adaptation pathways) is higher than the value of learning (Table 2). The difference in the value of learning and multi-stage decision-making between the adaptation options can be explained by the costs of height upgrades of the different options. The more costly it is to implement or upgrade the protection heights, the more beneficial it is to either postpone the protection height upgrades into the future or to learn about sea level rise in order to avoid unnecessary protection height upgrades. The upgrade costs for the Travemünde barrier are the highest, because the complementary dikes of the Travemünde barrier are more than twice as long as the complementary dikes of the Schlutup barrier (Figure 4) and the unit costs for dikes are higher than for sea walls (Table S3 in Supporting Information S1). Consequently, the value of multi-stage decision-making and the value of learning are significantly higher for the Travemünde barrier than for the Schlutup barrier or the sea walls.

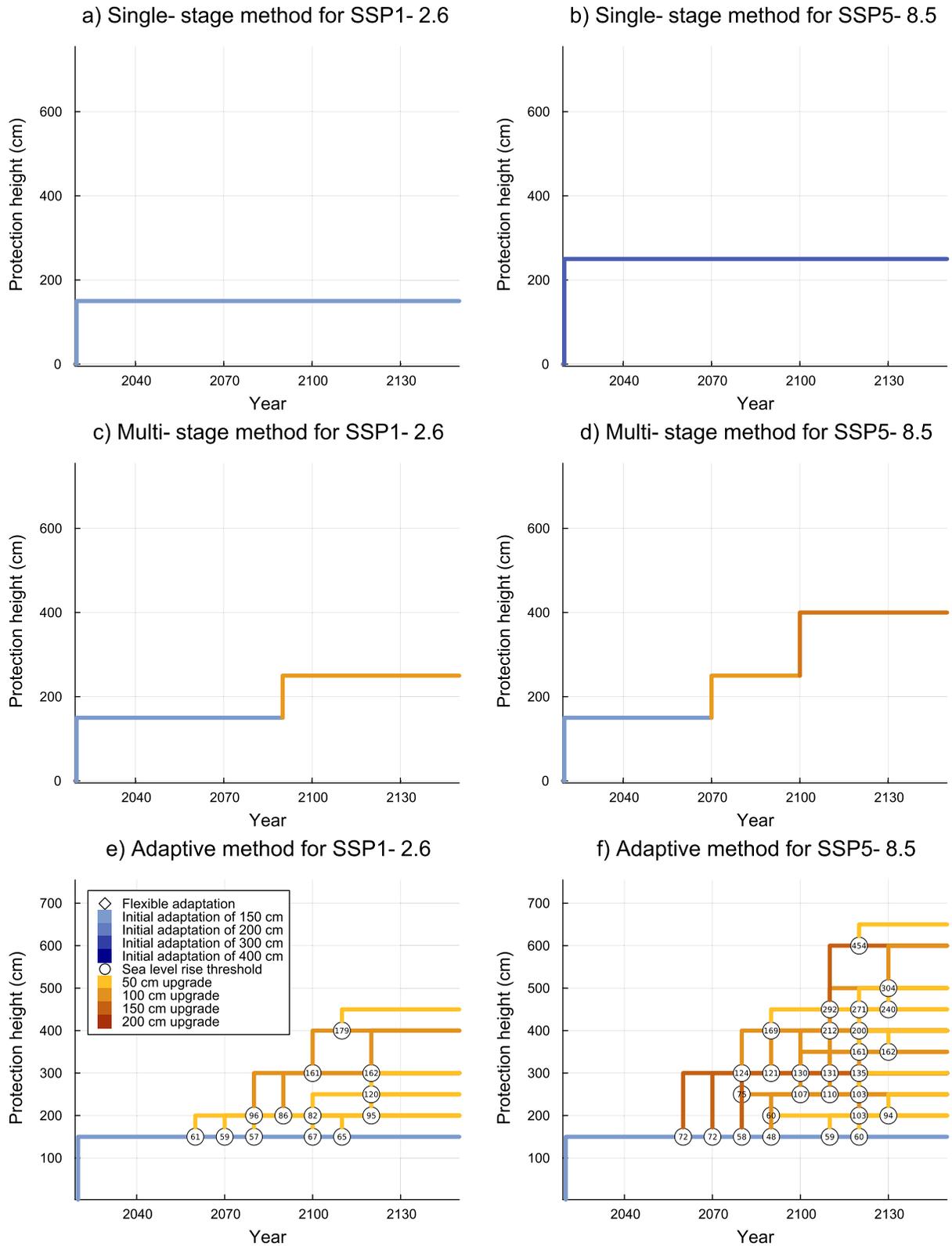


Figure 6.

3.2. Sensitivity Analyses for Adaptive Adaptation Pathways

On average, the Travemünde barrier is the most efficient adaptation option for the city of Lübeck and the sea walls are the least efficient adaptation option (Figure 7), which can be explained by the effectiveness of the Travemünde barrier in reducing flood damage due to its location at the mouth of the river. Adaptation actions are always efficient today for low or medium unit costs (Figure 9). Only in the unlikely situation of high unit costs and low end sea level rise, no adaptation action is recommended at all over the whole planning horizon (Figure 9). Sea walls have a wider range of initial protection heights from 0.5 to 3.5 m compared to barriers with 1.5–2 m (Figure 7), as this range depends on the unit cost assumption (Figure 9) and sea walls have significantly lower unit costs (Table S3 in Supporting Information S1), high initial protection heights are efficient at low unit costs and vice versa. Implementing the flexible adaptation option with a wider or deeper foundation for subsequent height upgrades is only efficient for a minority of adaptive simulation runs, namely for barriers with high unit costs under high climate change (Figures 7–9). Higher climate change increases expected flood damages and investments, but does barely affect the earliest action parameters (Figure 8). High unit costs, in contrast to low or medium unit costs, have a major impact on adaptive adaptation pathways; not only do they greatly increase overall costs, but they also lead to delays in early action and prevent adaptation options from being efficient at low end sea level rise (Figure 9). Higher discount rates devalue future capital flows and significantly reduce flood damages and investment costs, while the mean parameters of the earliest adaptation actions are almost unaffected by different discount rates (Figure S3 in Supporting Information S1).

The climate change scenarios have almost no effect on the earliest adaptation actions, only the maximum values are different when comparing the low and medium climate change scenario (Figure 8). In particular, the adaptive adaptation pathways in Figures 6e and 6f for low and high climate change scenarios recommend similar protection heights for similar sea level rise thresholds. For example, both pathways recommend an initial protection height of 1.5 m and no further protection height upgrade if sea level rise stays below 45 cm. If a sea level rise threshold of 90 cm is reached before 2100, both adaptive adaptation pathways recommend a protection height upgrade to 3 m. Similar, if a sea level rise threshold of 160 cm is reached before 2100, both pathways recommend a protection height upgrade to 4 m. This detailed example for the Travemünde barrier (Figures 6e and 6f), together with the sensitivity analysis in Figure 8, shows that adaptive adaptation pathways generate sea level rise thresholds for adaptation actions that are similar across climate change scenarios, but pathways under high climate change consider higher high-end sea level rise. In contrast, non-adaptive adaptation pathways do not generate sea level rise thresholds to trigger actions and typically have different adaptation pathways for different climate change scenarios (Figures 6a–6d).

Our results indicate that, from an economic perspective, the city of Lübeck is currently under-protected against storm surges and that adaptation actions should be implemented today. Based on our findings, an adaptation strategy for the city of Lübeck could be to implement a storm surge barrier and adjacent dikes in Travemünde and to monitor future sea level rise to trigger height upgrades. Once a certain threshold of sea level rise is observed, the adjacent dikes should be upgraded, with the exact height of the upgrade depending on the projected unit costs. A barrier option also has the advantage over sea walls that the old town island of Lübeck will not lose its status as a UNESCO World Heritage Site.

4. Discussion

Our results show that, from an economic perspective, adaptation actions should be implemented today in the city of Lübeck, in line with the call for immediate adaptation actions in AR6 (Cooley et al., 2022). Most economic assessments of coastal adaptation have considered non-adaptive decision analysis methods and thus ignored the timing of adaptation actions, that is, assumed that they need to be taken today. Adaptive adaptation pathways derived from real-option analysis or dynamic planning studies can quantify the optimal timing of adaptation

Figure 6. Adaptation pathways resulting from the applications of the single-stage non-adaptive (a, b), multi-stage non-adaptive (c, d) and adaptive (e, f) decision analysis methods for the Travemünde barrier under the assumption of medium unit costs and a discount rate of 1.4% for low climate change on the left (SSP1-2.6, 2°C) and high climate change on the right (SSP5-5.8, 4°C). For the adaptive adaptation pathways (e, f), we indicate the thresholds of observations of sea level rise l (cm) at which adaptation actions are triggered. For example, in the adaptive adaptation pathway for low climate change (e), observing a sea level rise of 59 cm or higher in 2070 triggers a protection height upgrade of 50 cm, that is, transferring from the blue to the yellow adaptation pathway.

Table 1
Annual Overtopping Probability \mathcal{P} for the Year 2100 Under Optimal Protection Heights for the Schlutup Barrier, Travemünde Barrier and Sea Walls Under High Climate Change (SSP5-8.5), Medium Unit Costs and a Discount Rate of 1.4% for the Single-Stage Non-Adaptive, Multi-Stage Non-Adaptive and Adaptive Decision Analysis Method

Adaptation option	l (SLR) (cm)	Single-stage		Multi-stage		Adaptive	
		d (cm)	\mathcal{P} (%)	d (cm)	\mathcal{P} (%)	d (cm)	\mathcal{P} (%)
Schlutup barrier	40	250	4.4	250	4.4	150	80.5
	80	250	17.7	250	17.7	200	68.4
	120	250	55.6	250	55.6	300	12.7
	170	250	99.0	250	99.0	450	0.3
Travemünde barrier	40	250	4.4	250	4.4	150	80.5
	80	250	17.7	250	17.7	300	3.1
	120	250	55.6	250	55.6	400	0.3
	170	250	99.0	250	99.0	450	0.3
Sea walls	40	350	0.1	400	0.0	300	0.7
	80	350	0.5	400	0.1	300	3.1
	120	350	3.1	400	0.3	400	0.3
	170	350	12.7	400	2.1	400	2.1

Note. We assess four different sea level rise values l that will be reached before 2100 to determine the exact overtopping probability. We determine the annual overtopping probability by integrating the GEV function describing the probabilities of storm surge heights (Section 2.2.4) and set the lower bound of the integration to the optimal protection height d (Figure 6) minus the sea level rise value. Note that for the multi-stage adaptation pathway of the Travemünde barrier a protection height upgrade is triggered in 2100, but the current protection level d in 2100 is still 250 cm (Figure 6).

actions and shed light on the urgency of coastal adaptation actions from an economic perspective (Ginbo et al., 2020; Wreford et al., 2020).

The adaptive adaptation pathways for the city of Lübeck are similar across climate change scenarios, showing that scenario-based application for each climate change scenario (Oppenheimer et al., 2019) and comparison of the adaptive adaptation pathways can address the problem of deep uncertainty in the case of sea level rise (i.e., it is not possible to assign probabilities to future scenarios). A major criticism of real-option analysis and other economic decision-making methods based on expected values is that they are impractical when there is deep uncertainty, as is the case with climate change scenarios (Kwakkel, 2020; Oppenheimer et al., 2019). We have shown that adaptive adaptation pathways can be similar across climate change scenarios, that is, the sea level rise thresholds and triggered protection heights of the adaptive adaptation pathway for low climate change and high climate change are similar, and one can follow the adaptive adaptation pathway for high climate change to account for potential high-end sea level rise. In contrast, the non-adaptive adaptation pathways are not similar across climate change scenarios in our results, and are indeed impractical in settings with deep uncertainty.

The values of learning in our study (Table 2) indicate that learning about sea level rise uncertainty is valuable for coastal decision settings with planning horizons beyond 2050, high investment costs of changing adaptation

Table 2
Today's Expected Costs (V_{2020} From the Bellman Equation 8) of All Future Flood Damages and Adaptation Investments for the Schlutup Barrier, Travemünde Barrier and Sea Walls Under High Climate Change (SSP5-8.5), Medium Unit Costs and a Discount Rate of 1.4% for the Single-Stage Non-Adaptive, Multi-Stage Non-Adaptive and Adaptive Decision Analysis Method

	Single-stage (Mio. EUR)	Multi-stage (Mio. EUR)	Adaptive (Mio. EUR)	VoM (Mio. EUR)	VoL (Mio. EUR)
Schlutup barrier	5,217	5,095	5,066	122	29
Travemünde barrier	4,347	3,992	3,922	355	70
Sea walls	4,888	4,675	4,634	213	41

Note. We define the value of multi-stage decision-making (VoM) as the difference between the single-stage non-adaptive and the multi-stage non-adaptive decision analysis method and the value of learning (VoL) as the difference between the multi-stage non-adaptive and the adaptive decision analysis method.

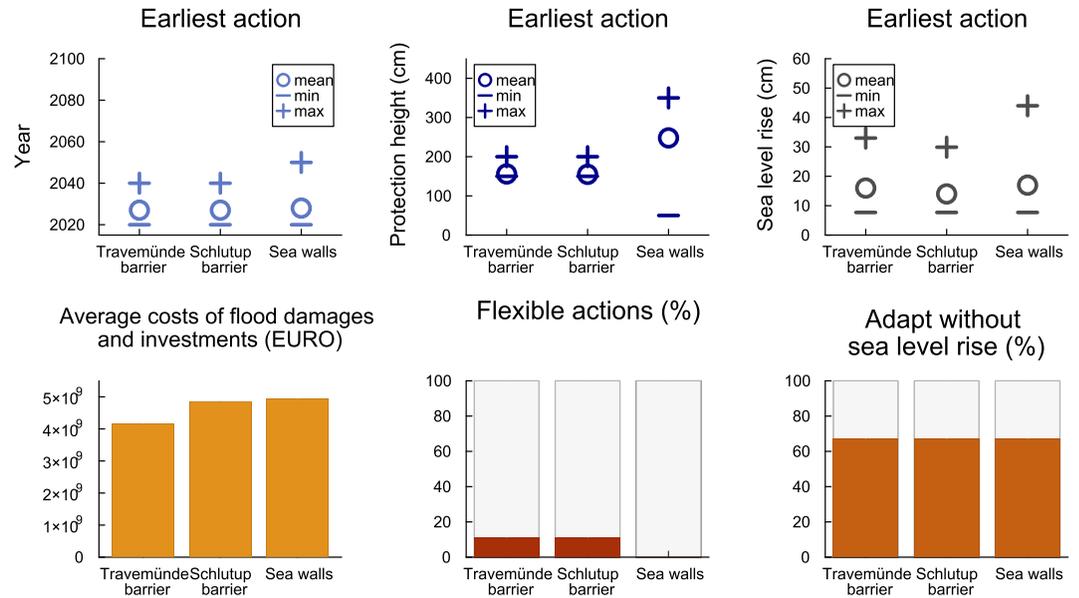


Figure 7. Comparison of adaptive adaptation pathways for the Travemünde barrier, the Schlutup barrier and sea walls. The statistics shown consider low, medium and high unit costs and low (SSP1-2.6), medium (SSP2-4.5) and high (SSP5-8.5) climate change. In the first row we present statistics on the height of protection, year and sea level rise value of the earliest possible initial investment of each adaptive adaptation pathway. The second row shows the average total costs, the ratio of adaptive adaptation pathways that use flexible options, and the ratio of adaptive adaptation pathways that apply adaptation even if there is no sea level rise (the lowest sea level rise path in the learning scenario is realized).

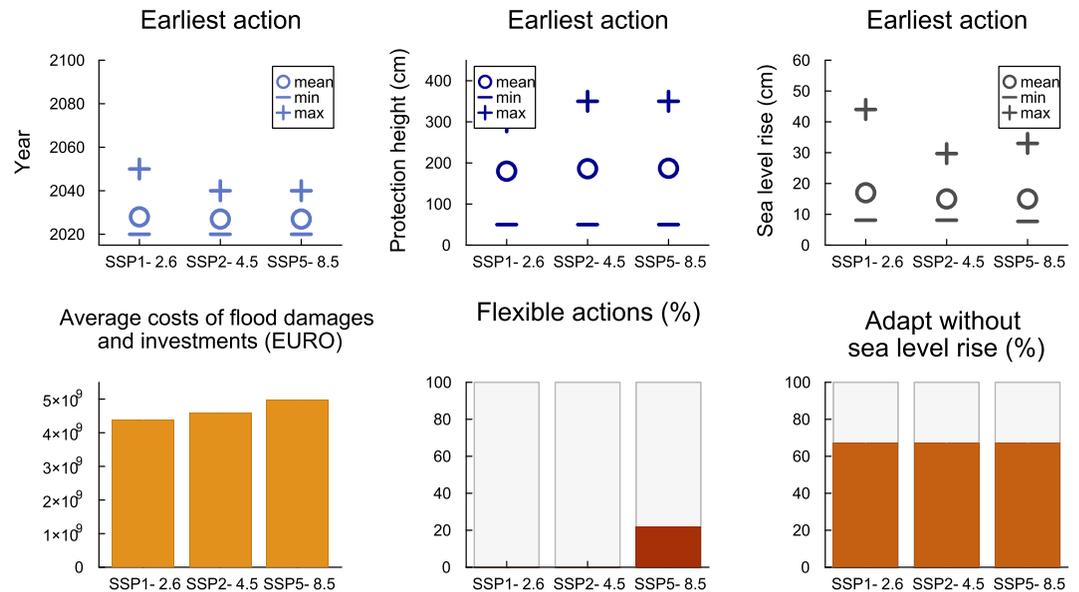


Figure 8. Comparison of adaptive adaptation pathways for the low (SSP1-2.6), medium (SSP2-4.5) and high (SSP5-8.5) climate change scenario. The statistics shown consider low, medium and high unit costs and the three different adaptation options (Travemünde barrier, Schlutup barrier and sea walls). In the first row we present statistics on the height of protection, year and sea level rise value of the earliest possible initial investment of each adaptive adaptation pathway. The second row shows the average total costs, the ratio of adaptive adaptation pathways that use flexible options, and the ratio of adaptive adaptation pathways that apply adaptation even if there is no sea level rise (the lowest sea level rise path in the learning scenario is realized).

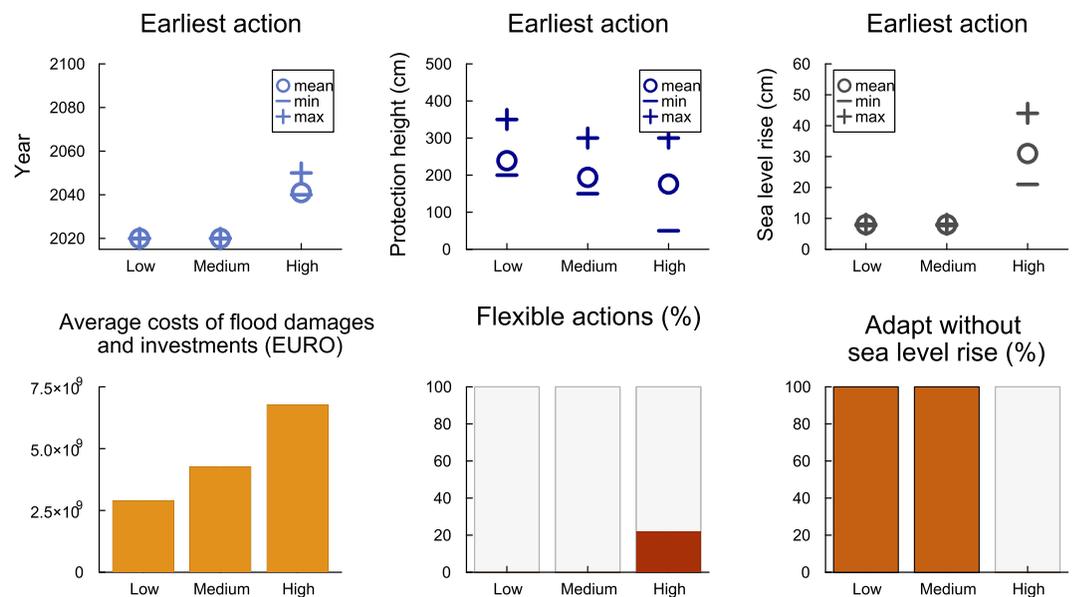


Figure 9. Comparison of adaptive adaptation pathways for a low, medium and high unit costs as indicated in Table 2. The statistics shown consider low (SSP1-2.6), medium (SSP2-4.5) and high (SSP5-8.5) climate change, the three different adaptation options (Travemünde barrier, Schlutup barrier and sea walls) and a discount rate of 1.4%. In the first row we present statistics on the height of protection, year and sea level rise value of the earliest possible initial investment of each adaptive adaptation pathway. The second row shows the average total costs, the ratio of adaptive adaptation pathways that use flexible options, and the ratio of adaptive adaptation pathways that apply adaptation even if there is no sea level rise (the lowest sea level rise path in the learning scenario is realized).

pathways, and/or no need for adaptation action until the middle of this century. Our results indicate that significant learning about sea level rise uncertainty takes place beyond 2050, as this is not only when the earliest height upgrades are recommended in our adaptive adaptation pathways (Figure 6), but also when the uncertainty in sea level rise projections increases significantly (Fox-Kemper et al., 2021). As it is inefficient to delay the initial adaptation action in our case study, the value of learning is higher for adaptation options with higher costs of changing adaptation pathways, as future learning can avoid unnecessary protection height upgrades, as in the case of the Travemünde barrier (Table 2). We also expect a high value of learning in decision settings where adaptation actions can be delayed until the middle of this century, as the initial adaptation can then be adjusted to sea level rise observations and respective learning. Similarly, adaptive pathway analysis and real-option analysis are particularly valuable in decision contexts involving long-term decisions, costly investments, uncertainty, and expected future learning opportunities (Haasnoot et al., 2020; Wreford et al., 2020).

Applying the flexible adaptation option for sea walls or complementary dikes next to storm surge barriers is inefficient in most of our simulation runs. Vogelsang et al. (2023) find that flexible adaptation options are particularly valuable when there is a fast learning rate, but most of the learning about sea level rise uncertainty takes place after 2050. Because coastal protection is needed today in our study, but there is no fast speed of learning until 2050, building flexible adaptation options today is often inefficient in our simulation runs. Similar to Skerker et al. (2023), we also find that the use of the flexible adaptation option is highly depended on the discount rate. We find that at a discount rate of 1.4%, a flexible adaptation option is only efficient in 7% of our simulation runs, but at a discount rate of 0%, a flexible adaptation option is efficient in 48% of our simulation runs. As the discount rate devalues future capital flows, it also reduces the efficiency of flexible adaptation options that involve higher expenses today in return for future cost savings.

In our application, the main uncertainty in adaptive adaptation pathways comes from unit costs, but these can be resolved once concrete planning of adaptation actions begins. The sensitivity analysis of unit costs shows the largest differences between unit costs compared to the sensitivity of the discount rate, climate change and adaptation options (Figures 7–9 and Figure S3 in Supporting Information S1). Once specific unit costs are known, the results can be filtered to show only results for the appropriate unit cost.

Non-adaptive decision analysis methods that ignore future learning through observations, although widely used in normative analysis of coastal adaptation decisions (Bachner et al., 2022; Eijgenraam et al., 2014, 2017; Lincke & Hinkel, 2018; Tiggeoven et al., 2020; van Dantzig, 1956; Van der Pijl & Oosterlee, 2012; Voudoukas et al., 2020), are less likely to represent real-world decisions than adaptive decision analysis methods that take into account future learning. It is unrealistic to assume that decision-makers would implement adaptation measures designed a century ago without revision. In fact, recent literature on coastal adaptation to climate change strongly recommends iterative decision-making and frequent reassessment of actions (Hinkel et al., 2019; Oppenheimer et al., 2019).

By presenting optimal coastal adaptive adaptation pathways for the next 130 years, we do not mean to recommend following these pathways for the next century without revising them. Rather, these results serve, similarly to any other result of normative decision analysis over time, as a valuable basis for informing choices in the short term. But even for this, it is important to include the long planning horizon in the economic assessment, as the flexibility to change course and learn in the long-term also influences optimal decisions in the short term (Zwaneveld et al., 2018), for example, by reducing today's expected costs (Table 2). The multi-stage non-adaptive coastal adaptation model of Eijgenraam et al. (2017), which has been applied for finding optimal protection levels in the Delta Program 2015 (the official coastal protection guideline of the Netherlands), considers a time horizon of 300 years. The Dutch government plans to follow the results of Eijgenraam et al. (2017) in the short term, that is, the next 20 or 30 years, and then revise the strategies. In general, it is always advisable to monitor sea level rise and update adaptation strategies over time, regardless of the method used to develop the original strategy (Oppenheimer et al., 2019). As this is a relatively new field of research, there is little experience of the real-world challenges of applying such a framework. Apart from Eijgenraam et al. (2017), we are not aware of any other examples of coastal adaptation where multi-stage non-adaptive or adaptive decision analysis methods from economic assessment studies have been used. Given the rather technical and complex nature of the methodology, we note that well-trained staff and sufficient resources are required to carry out such an analysis.

A limitation of our model is that we only consider flood damage to buildings and ignore flood damage to infrastructure, such as the sewage treatment plant in Travemünde, and cascading effects, such as lost revenue from closed businesses. Previous studies have addressed infrastructure damages and cascading effects of flood events and found that the impacts of floods can be much broader than their direct effects, but economic evaluations are scarce (Fekete, 2019, 2020; Hilly et al., 2018; Unterberger, 2018). While our underlying hydrodynamic model results can be used to analyse flood hazards to critical infrastructure, the inclusion of critical infrastructure and cascading effects in the economic evaluation is difficult due to data scarcity. For example, the data source we use to estimate the value of buildings in Germany does not include information on the value of wastewater treatment plants. As we only consider direct flood damage to buildings, we have a rather conservative estimate of annual flood damage in our study.

Another limitation of our study is that we assume static building values over time, whereas in reality buildings are likely to increase over time with socio-economic development in the floodplain. This assumption of our study, similar to the one discussed in the previous paragraph, also leads to a rather conservative estimate of flood damage. A follow-up study could include socio-economic development over time and explore the effect of different pathways of socio-economic development. Considering future learning about socio-economic development in combination with future learning about sea level rise would provide interesting insights into the interdependencies between exposure and hazard and their effect on efficient adaptation strategies, which have so far only been analysed with highly simplified quantifications for future learning (Völz & Hinkel, 2023a).

We assume a stationary extreme value distribution to model storm surge heights in our decision framework, which does not incorporate potential changes in storm surge heights due to the effects of climate change. To date, model results along the German coastline have been inconsistent, and no conclusions could be drawn about the effects of climate change on storm surge heights. For example, Gräwe and Burchard (2012) considered the non-linear effects of sea level rise on future storm surges at the western Baltic Sea and found that, at the location of our case study, increases to future storm surges are equivalent to changes in sea level rise. However, according to Voudoukas et al. (2017), the Baltic Sea region is expected to experience large changes in the height of future storm surges. While it is likely that the distribution of storm surge heights will change in the future, it is unclear how this will unfold, and further insights are needed.

Our hydrodynamic flood model limits our choice of adaptation options because it is based on 10×10 m grid cells. This allows us to model large infrastructure protection, but not smaller adaptation options such as mobile flood barriers or nature-based adaptation such as salt marshes. We note that alternative adaptation options such as mobile flood barriers, dry- or wet-proofing of buildings and nature-based solutions could be alternatives or extensions to the adaptation options proposed in our paper. Exploring the efficiency of these alternative adaptation options would be an interesting follow-up study. For example, consideration of dry- or wet-proofing could be done through specific depth-damage functions, as empirically developed by Endendijk et al. (2023). Recent work in the context of river floods and droughts by Vogelsang et al. (2023) applies real-option analysis to consider retention areas as a nature-based adaptation option with respect to learning about climate change. To date, there are no economic studies of adaptive decision-making that consider any of the above alternative adaptation options in combination with future learning about sea level rise uncertainty (Völz & Hinkel, 2023a).

Alternative adaptive decision analysis methods, such as online optimization, policy search, Bayesian approaches and reinforcement learning, could be explored to advance economic adaptive adaptation pathways for dealing with sea level rise. In addition, comparing the performance of these normative adaptive pathways with descriptive real-world decision-making practices can provide valuable insights. One could model real-world coastal decision-making practices, such as incrementally increasing dike heights in response to observed sea level rise, or taking immediate risk-averse adaptation actions to prepare for high-end sea level rise scenarios. By comparing the performance of these descriptive approaches with normative adaptive adaptation pathways, the effectiveness and efficiency of different strategies in managing sea level rise can be evaluated.

5. Conclusion

In this paper, we present an adaptive decision framework for developing efficient coastal adaptation, taking into account future learning about sea level rise uncertainty. We formulate a stochastic optimization problem and integrate a quantification of the opportunity to learn about future sea level rise uncertainty through learning scenarios. We apply this framework to a coastal case study in Germany and use hydrodynamic flood modeling to estimate annual flood damages. We find three main advantages of adaptive decision analysis methods over non-adaptive decision analysis methods that do not take into account future learning about sea level rise uncertainty. First, adaptive adaptation pathways generate sea level rise thresholds with corresponding optimal protection heights that can be similar across climate change scenarios. Second, adaptive adaptation pathways prevent costly over- or under-protection against flood risks by taking into account future observations of sea level rise, for example, two protection height upgrades are recommended for the Travemünde barrier option if sea level rises above 1.2 m before 2100, resulting in an annual overtopping probability of 0.3%, compared to 56% for non-adaptive methods. Third, adaptive adaptation pathways reduce the expected costs of adaptation investments and flood damages compared to non-adaptive pathways, in our study by up to 1.8%.

Data Availability Statement

The data and code used in this study are publicly available in Völz et al. (2024) under <https://zenodo.org/doi/10.5281/zenodo.10262546>.

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