

# I don't know, are you sure we want to do this? Sea level adaptation decisions under uncertainty

**T. L. Thorarinsdottir<sup>1</sup>, P. Guttorm<sup>1</sup>, M. Drews<sup>2</sup>, and K. de Bruin<sup>3,4</sup>**

<sup>1</sup>Norwegian Computing Center, Oslo, Norway

<sup>2</sup>Technical University of Denmark, Copenhagen, Denmark  
for International Climate and Environmental Research, Oslo

<sup>3</sup>Center for International Climate and Environmental Research, Oslo, Norway  
<sup>4</sup>Wageningen Environmental Research, Wageningen, The Netherlands

Wageningen Environmental Research, Wageningen, The Netherlands

## Key Points:

- Decisions on adaptation measures need to take careful account of all uncertainties
  - Modeling local sea level rise is essential
  - Decisions under uncertainty do not have to be based on precise costs

12      **Abstract**

13      Sea level rise has serious consequences for harbor infrastructure, storm drains and sewer  
 14      systems, and many other issues. Adapting to sea level rise requires comparing different  
 15      possible adaptation strategies, comparing the cost of different actions (including no ac-  
 16      tion), and assessing at what point in time the chosen strategy should be implemented. All  
 17      these decisions must be made under considerable uncertainty—in the amount of sea level  
 18      rise, in the cost of adaptation actions, and in the cost of no action. We develop two illus-  
 19      trative examples: for Bergen on Norway’s west coast and for Esbjerg on the west coast of  
 20      Denmark. Different components of uncertainty are visualized. We show that failing to take  
 21      uncertainty into account can result in the median projected damage costs being an order of  
 22      magnitude smaller.

23      **1 Introduction**

24      The potential impact of climate change on local sea level, yielding effects such as  
 25      frequent flooding, inundation and backflow of storm drainage and sewer systems, destruc-  
 26      tive erosion and contamination of wetlands and other habitats, requires city planners to  
 27      make decisions in the presence of substantial uncertainty.

28      As adaptation decision-making is an ongoing process of weighing and choosing  
 29      which measures should be taken at which moment in time [Hallegatte *et al.*, 2012], adap-  
 30      tive planning methods need to support decisions in the short term, while considering long-  
 31      term developments. Challenges of adaptation decision-making under uncertainty relate  
 32      to the incorporation of spatial, inter-temporal and flexibility aspects of adaptation priori-  
 33      ties [Fankhauser and Soare, 2013], and the linkage with specific characteristics of sectors  
 34      and contexts [Bisaro *et al.*, 2016; Hinkel and Bisaro, 2016]. Several economic decision  
 35      support tools and methods exist for adaptation assessment under uncertainty [e.g. Chamb-  
 36      wera *et al.*, 2014; Wilby and Dessai, 2010; Walker *et al.*, 2013]. However, Watkiss *et al.*  
 37      [2015] conclude that these tools are very resource intensive and complex in the context of  
 38      long-term adaptation investment decisions and call for the development of “light touch”  
 39      approaches to better support local adaptation making.

40      In this paper we employ light touch decision tools to demonstrate the importance of  
 41      combining projections of sea level rise and flood damages alongside a detailed quantifi-  
 42      cation of both hydrologic and economic uncertainties in the context of real-life decision-  
 43      problems experienced by stakeholders and authorities in two northern European cities,  
 44      Bergen in Norway and Esbjerg in Denmark, see Figure 1. Based on communications with  
 45      local end-users we highlight the value of taking into account uncertainty through two sim-  
 46      plified and complementary case studies, where in the first one planners want to know how  
 47      early they should implement costly adaptation measures, whereas in the second case the  
 48      aim is to highlight the risk of flooding in coastal areas, e.g. in order to prioritize future  
 49      adaptation actions and investments. In both cases we show that embracing the uncertain-  
 50      ties derived from economic and hydrologic models is absolutely crucial in order to answer  
 51      the question of “are we sure we want to do this?”

52      The Norwegian city of Bergen is the capital of Hordaland County. The city center is  
 53      located on Byfjorden, and is surrounded by mountains. It has the largest port in Norway,  
 54      both in terms of freight and passengers. The historic harbor area, Bryggen, is the only  
 55      Hanseatic trade center remaining in its original style, and has been declared a UNESCO  
 56      World Heritage site<sup>1</sup>. Bryggen is regularly flooded at extreme tides, and it is feared that  
 57      as sea levels rise, floods will become a major problem in other parts of Bergen as well  
 58      [Grieg Foundation, 2009].

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59      <sup>1</sup> See <http://whc.unesco.org/en/list/59>.



52           **Figure 1.** Terrain maps of central Bergen, Norway (left) and Esbjerg, Denmark (right).

60           The municipality of Bergen has, in cooperation with private actors, analyzed sev-  
 61           eral possible adaptation measures against sea level rise. The measures range from an outer  
 62           barrier that would protect the entire metropolitan area to various protection measures of  
 63           limited areas in the inner harbor [Grieg Foundation, 2009]. While the viability of the con-  
 64           structions and the associated construction costs have been carefully analyzed, the optimal  
 65           timing of potential adaptation measures and the effects of the associated uncertainties have  
 66           yet to be investigated. We perform such an analysis where we consider uncertainty in pro-  
 67           jected sea level rise, damage costs, and the effect of sea level rise on changes in damage  
 68           costs.

69           Esbjerg, on the southwest coast of Jutland, is the fifth-largest city in Denmark and  
 70           the largest urban area in the region. The city hosts one of the largest harbours in Den-  
 71           mark, which serves as a focal point for offshore activities in the North Sea, including the  
 72           continued development of offshore wind power and extensive activities related to the ex-  
 73           traction of oil and gas. As a result critical infrastructures and commercial buildings fig-  
 74           ure prominently in the coastal zone. Esbjerg is frequently subject to substantial storms  
 75           and storm surges, causing severe flooding of the harbour and the city. The highest since  
 76           records began in 1874 was recorded in 1981, where the harbour was completely flooded  
 77           and the water level reached 433 cm above the norm, causing massive economic losses.  
 78           More generally, storm surges causing water levels in Esbjerg to rise to between 2 and 3  
 79           metres have quadrupled over the last four decades according to local records, whereas half  
 80           of the most severe events have taken place since 1975.

81           As in the case of Bergen, sea level rise caused by climate change is expected to  
 82           compound these risks, alongside parallel threats caused by increased risks of pluvial flood-  
 83           ing and rising ground water levels in Esbjerg. The municipality recently adopted its cli-  
 84           mate adaptation plan, which in its first phase is aimed at identifying present and future  
 85           flood-prone areas, e.g. to avoid urban development into such areas, to limit damages to  
 86           buildings of high societal or cultural value, and to pave the way for implementing cost-  
 87           effective adaptation measures in the second phase of the plan.

88           The remainder of the paper is organized as follows. Section 2 describes our ap-  
 89           proach to projecting sea level. In sections 3 and 4 we describe the type of decision prob-  
 90           lems that we are going to attack. We apply these tools to sea level projections for Bergen,  
 91           Norway, and for Esbjerg, Denmark in section 5. In section 6 we demonstrate the conse-

92 consequences of ignoring the uncertainty in the projections, and the paper is closed with a sum-  
93 mary and discussion in section 7.

## 94 2 Sea level projections

95 We project local sea level changes by modeling two processes, the relationship be-  
96 tween global temperature and global sea level, and the relationship between global sea  
97 level and local sea level.

### 98 2.1 Global sea level

99 Most climate models do not explicitly provide sea level as an output of the calcu-  
100 lations. Rather, the IPCC AR5 report [Stocker *et al.*, 2013, ch. 13] combines the heat ex-  
101 pansion of the ocean with temperature forced models for glacial melt, Greenland ice melt,  
102 and Antarctic ice melt and with land rise due to rebound from the last ice age and other  
103 tectonic effects. Judging from the supplementary material to Stocker *et al.* [2013, ch. 13],  
104 the uncertainty assessment is only based on the spread of the ensemble of temperature  
105 projections, not on the additional uncertainty in the ice models used.

106 We will instead use the empirical approach of Rahmstorf and collaborators [Rahm-  
107 storf, 2007; Rahmstorf *et al.*, 2011], employing the statistical modeling of Bolin *et al.*  
108 [2014] to relate global annual mean temperature anomalies to global mean sea level anom-  
109 alies. We then apply the estimated historical relationship to projected temperatures from the  
110 CMIP5 experiment [Taylor *et al.*, 2012] to obtain projected global annual mean sea level,  
111 taking into account the uncertainty in the statistical model as well as the spread of the  
112 temperature projection ensemble (see subsection 2.3). For the i'th temperature projection  
113  $T_t^i$  we estimate the corresponding global mean sea level as

$$114 H_t^{gl,i} = \int_{t_0}^t \hat{a}(T_u^i - \hat{T}_0) du + \varsigma_t,$$

115 where  $\hat{a}$  and  $\hat{T}_0$  are regression parameters of observed global sea level rise on observed  
116 global temperature and  $\varsigma_t$  the integrated time series regression error.

### 117 2.2 Local sea level

118 In order to get from global sea level projections to local ones, it is important to note  
119 that sea level rise is not uniform over the globe. Glacial and land ice melting affect the  
120 local sea level differently depending on where the melted ice is located. Another major  
121 effect in Fennoscandia is the land rise due to isostatic rebound from the glaciers of the  
122 last ice age. Again, we will use historical data to relate global sea level to isostatically  
123 corrected local sea level using a time series regression model. The local sea level projec-  
124 tions are then obtained by first relating projected temperature to global sea level, and then  
125 relating the global sea level to the local one. Each climate model temperature projection  
126 yields a different local sea level projection. The local sea level projection based on the i'th  
127 climate model for years beyond 2000 is estimated as

$$128 H_t^{loc,i} + \gamma(t - 2000) = \hat{b}H_t^{gl,i} + \varepsilon_t,$$

129 where  $\gamma$  is the annual land rise rate,  $t$  denotes year,  $\hat{b}$  is the regression coefficient relating  
130 global to local sea level and the  $\varepsilon_t$  are Gaussian errors..

### 131 2.3 Uncertainty assessment

132 Following the approach of Guttorm *et al.* [2014] we assess the uncertainty in the lo-  
133 cal sea level projections taking into account the variability between the climate projections

134 used, the uncertainties in the regressions of global mean temperature on global mean sea  
 135 level and of global on local sea level. We express the sea level projection uncertainty in  
 136 terms of a confidence band that is simultaneously of the intended level for all projection  
 137 years. This allows us, for example, to get a confidence band for the years when a given  
 138 sea level rise is obtained.

## 139 2.4 Limitations of the sea level projections

140 The main assumption is using historical relationships in statistical projections of  
 141 the type used in this paper is that there is no major change in how temperature relates  
 142 to sea level, globally and locally. Among the factors that may invalidate this approach  
 143 are changes in water storage on land (in essence removing water from the oceans), ex-  
 144 cessive siphoning of groundwater (resulting in land subsidence), changes in the rates of  
 145 glacial and land ice melt, and changes in Earth's gravitational field due to transfer of mass  
 146 from land ice to ocean water. For example, the rate of ice melt on Greenland may sud-  
 147 denly increase substantially due to intense warming of both air and sea water [Bamber  
 148 and Aspinall, 2013]. A recent paper [Jevrejeva *et al.*, 2016] indicates that the upper tails  
 149 of sea level rise may be substantially higher when taking into account expert assessment  
 150 of land ice melting. Our current climate models are not able to resolve the ice processes  
 151 sufficiently to include such so called tipping points into the projections. Also, the IPCC  
 152 scenarios [*van Vuuren et al.*, 2011] do not include changes in water usage (cf. Wada *et al.*  
 153 [2012]).

## 154 3 Timing of adaptation measures

155 There is an increasing need for more detailed economic analysis, including simple  
 156 methods and tools for assessment of options, especially since Downing (2012) recog-  
 157 nizes, adaptation is moving from theory to practice, and practitioners try to deal with how  
 158 to begin adapting. This leads to an increasing need and interest in the appraisal of options.

159 Several economic decision support tools and methods exist for adaptation assess-  
 160 ment under uncertainty. Robust decision-making approaches are able to better incorporate  
 161 uncertainty and a broad range of climate scenarios to capture as much of the uncertainty  
 162 on future climates as possible (Dittrich *et al.* 2016). These approaches can be classified  
 163 according to a science-first or policy-first approach. The former has a "predict-then-act"  
 164 foundation, which starts with climate projections and impact assessments, not linked to  
 165 any specific adaptation choices (Jones *et al.*, 2014). The latter starts out with the formu-  
 166 lated adaptation plans and not impacts, and their functioning is tested against different  
 167 future projections (Dittrich *et al.* 2016).

168 We take a policy-first approach, in which we test a current adaptation plan against  
 169 different sea level and damage projections and the inclusion of different sources of un-  
 170 certainty. We focus on what this implies for the timing of adaptation measures and the  
 171 implications of including uncertainty. In particular, we employ a probabilistic extension of  
 172 the framework described by [Fankhauser *et al.*, 1999] in which we obtain a probabilistic  
 173 distribution for the net present value damage in a given year for various adaptation op-  
 174 tions. The probabilistic distribution is constructed by considering uncertainty in the local  
 175 sea level projections, in the annual damage costs, and in the effect of changes in sea level  
 176 on the annual damage costs.

### 177 3.1 Annual damage costs

178 We model the distribution of annual damage,  $F_{d,t_0}$ , for the year  $t_0 = 2015$  by the  
 179 three parameter Burr distribution [Burr, 1942] with density

$$180 f_{d,t_0}(x) = \frac{\alpha\gamma(x/\theta)^\gamma}{x[1 + (x/\theta)^\gamma]^{\alpha+1}} \quad (1)$$

for  $x > 0$ , where  $\alpha$  and  $\gamma$  are shape parameters with  $\alpha, \gamma > 0$ , and  $\theta > 0$  is a scale parameter. The Burr distribution has a heavy upper tail and is commonly used to model damage loss, see e.g. *Klugman et al.* [2012]. The parameters of the distribution are estimated using historical data for annual storm surge damage. Data prior to 2015 are adjusted to the 2015 level using the consumer price index. After adjustment, we assume stationarity over the period and independence between years.

Under a constant sea level, we can obtain a sample trajectory  $\{d_{t_1}, d_{t_2}, \dots, d_{t_{85}}\}$  of future annual damages for  $t_1 = 2016, \dots, t_{85} = 2100$  by drawing 85 i.i.d. values from the estimated distribution  $\hat{F}_{d,t_0}$ . By repeating this process  $J$  times, we obtain an empirical damage distribution for each future year  $t_i$  given by

$$\hat{F}_{d,t_i}(x) = \frac{1}{J} \sum_{j=1}^J \mathbb{1} \left\{ \frac{d_{t_i}^{(j)}}{\prod_{l \leq i} (1 + r_{t_l})} \leq x \right\}$$

for  $i = 1, \dots, 85$ , where  $r_{t_i}$  is the discount rate for year  $t_i$ . Alternatively, we obtain an empirical distribution of the total damage over the period 2016 – 2100 by considering

$$d_{\text{total}}^{(j)} = \sum_{i=1}^{85} \frac{d_{t_i}^{(j)}}{\prod_{l \leq i} (1 + r_{t_l})}$$

and similarly for the cumulative damage.

### 3.2 Effect of changes in sea level

We assume that changes in sea level have a multiplicative effect on the annual damage cost. That is, for a sea level anomaly  $s_{t_i}$  in year  $t_i > 2015$  compared to the 2015 level, the annual damage cost becomes

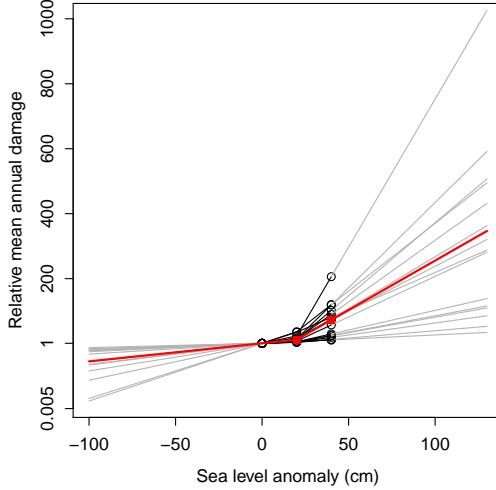
$$g(s_{t_i} | \boldsymbol{\beta}) d_{t_i},$$

where  $g(\cdot | \boldsymbol{\beta})$  is a monotonic positive function with parameter vector  $\boldsymbol{\beta}$  such that  $g(s | \boldsymbol{\beta}) > 1$  for  $s > 0$  and  $g(s | \boldsymbol{\beta}) < 1$  for  $s < 0$ . *Hallegatte et al.* [2013] estimate a similar effect function valid in 2050 for  $s \in \{0, 20, 40\}$  for 136 coastal cities. Here, we use their results for 15 European cities: Amsterdam, Athens, Barcelona, Dublin, Glasgow, Hamburg, Helsinki, Copenhagen, Lisbon, London, Marseilles, Naples, Porto, Rotterdam and Stockholm. To obtain a city-specific effect function for a large range of sea level anomalies we employ a linear extrapolation as shown in Figure 2. We then obtain a sample of effect functions  $\{g(\cdot | \boldsymbol{\beta}^{(j)})\}_{j=1}^J$  by sampling with replacement from this ensemble of trajectories with all 15 ensemble members considered equally probable.

Let further  $\{s_{t_1}^{(j)}, \dots, s_{t_{85}}^{(j)}\}_{j=1}^J$  denote a sample of projections for annual sea level anomalies compared to the 2015 value. An empirical damage distribution for the future year  $t_i$  that accounts for uncertainty in damage, sea level rise and its effect on the damage is then given by

$$\hat{F}_{d,t_i}^s(x) = \frac{1}{J} \sum_{j=1}^J \mathbb{1} \left\{ \frac{g(s_{t_i}^{(j)} | \boldsymbol{\beta}^{(j)}) d_{t_i}^{(j)}}{\prod_{l \leq i} (1 + r_{t_l})} \leq x \right\}. \quad (2)$$

The distribution in (2) describes the projected damage distribution with no adaptation measures. In addition, we can incorporate an adaptation measure of cost  $C$  that protects against  $K$  cm of increased sea level from year  $t_k$  onward. This results in a damage



210      **Figure 2.** Relative change in mean annual damage as a function of sea level rise for 15 European cities as  
211      estimated by *Hallegatte et al.* [2013] (black circles) with linearly extrapolated values indicated by gray lines.  
212      The median change and the corresponding extrapolation are indicated in red.

221      distribution given by

$$222 \quad \hat{F}_{d,t_i}^{s,a_k}(x) = \begin{cases} \frac{1}{J} \sum_{j=1}^J \mathbb{1} \left\{ \frac{g(s_{t_i}^{(j)} | \beta^{(j)}) d_{t_i}^{(j)}}{\prod_{l \leq i} (1+r_{t_l})} \leq x \right\}, & t_i < t_k \\ \frac{1}{J} \sum_{j=1}^J \mathbb{1} \left\{ \frac{g(s_{t_i}^{(j)} - K | \beta^{(j)}) d_{t_i}^{(j)} + C}{\prod_{l \leq i} (1+r_{t_l})} \leq x \right\}, & t_i = t_k \\ \frac{1}{J} \sum_{j=1}^J \mathbb{1} \left\{ \frac{g(s_{t_i}^{(j)} - K | \beta^{(j)}) d_{t_i}^{(j)}}{\prod_{l \leq i} (1+r_{t_l})} \leq x \right\}, & t_i > t_k. \end{cases}$$

223      **3.3 Limitations of the decision framework**

224      The main limitation of this light touch decision framework is that we have significantly simplified the assessment of the effect of sea level rise on the damage costs. In  
225      particular, the linear extrapolation of the results reported in *Hallegatte et al.* [2013] might  
226      provide a conservative estimate of the effect of extreme sea level rise. However, with only  
227      two data points, extrapolation approaches such as a power law or exponential growth seem  
228      difficult to justify.

229      Alternatively, a modeling framework similar to that of *Hallegatte et al.* [2013] could  
230      be applied directly to a larger range of potential changes in sea level. The elements of  
231      such a framework might include an appropriate social discount rate, valuing environmental  
232      goods in monetary terms, incorporate socio-economic assumptions and long-term policy  
233      goals of decision makers, as well as that climate change is often not the only driver that  
234      decision makers should consider, therefore costs and benefits should be studied in a wider  
235      context (Dittrich et al., 2016).

236      Our framework simplifies the cost and effect of an adaptation option during con-  
237      struction in that we assume no effect until the construction is finished with all the con-  
238      struction cost falling in the last year of the construction. Especially for larger construc-  
239      tions, these assumptions might need to be modified. Additionally, we have not specifically  
240      accounted for potential changes in storm surge patterns.

## 242 4 Danish decision framework

243 In 2014 the municipality of Esbjerg adopted its climate adaptation plan ([ref](#)), which  
 244 will cover the period from 2014-2026, and which aims to reduce the risk of flooding  
 245 caused by storm surges, heavy rainfall and rising ground water levels, respectively. In the  
 246 following (and based on interviews with end-users from the municipality) we will focus  
 247 on the harbour of Esbjerg and the nearby coastal areas, and we will only consider the hazard  
 248 of coastal flooding, though evidently in some areas the flood risk is compounded.

249 The initial scoping of the climate adaptation plan in Esbjerg includes a preliminary  
 250 value and risk mapping, considering critical infrastructure and buildings of high cultural  
 251 and societal value as identified by the municipality, while informed by spatial floods maps  
 252 for different scenarios corresponding to each of the three different kinds of hydrological  
 253 events (sea level rise/storm surges, pluvial flooding and rising ground water levels). In  
 254 terms of coastal floods the mapping considers only one type of storm surge, corresponding  
 255 to a 20-year return event (based on historical storm surge statistics), and increased sea  
 256 level due to climate change was not accounted for. We will extend these flood maps to  
 257 also deal with 100-year return events and quantiles of the projected sea level rise.

258 The risk for any given map area as the probability of, e.g., a certain flood depth,  
 259 is derived from a hydrological flood model (not including urban drainage system) times  
 260 a valuation of the consequences, which—similar to the Bergen case—is essentially a loss  
 261 function associating the flood depth with a measure of cost.

## 262 5 Case studies

### 263 5.1 Data

264 The historical global mean temperature series is obtained from *Hansen et al.* [2001].  
 265 Climate projections of global mean temperature are from the fifth climate model intercom-  
 266 parison project, CMIP5 [*Taylor et al.*, 2012]. The global mean sea level series is obtained  
 267 from *Church and White* [2011]. We use local tide gauge data from the Permanent Service  
 268 for Mean Sea Level, UK, which is the worldwide repository for national sea level data.  
 269 Glacial isostatic adjustment for Bergen is obtained from *Simpson et al.* [2014], and for Es-  
 270 bjergr in personal communication from Peter Thejll at the Danish Meteorological Institute.

271 The Bergen monthly series is missing data for 62 months, including all of the years  
 272 1942–43. To deal with occasional short stretches of missing data (at most one or two  
 273 months) we use median polish replacement [*Mosteller and Tukey*, 1977] and then com-  
 274 pute annual averages. For the years 1942-43, we use the average difference between  
 275 Bergen and the average of all other Norwegian stations in 1940 and 1943 to estimate val-  
 276 ues for 1941 and 1942, using the average of all other Norwegian stations corrected by the  
 277 average difference.

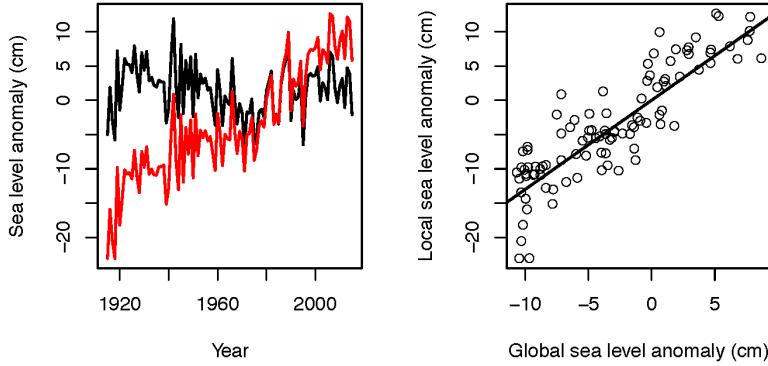
278 The Esbjerg monthly series is missing data for 19 months. Here, too, we use median  
 279 polish to fill in missing data and then compute annual averages.

280 Annual damage costs for the Bergen case study are obtained from the Norwegian  
 281 Natural Perils Pool (NPP; data are available at <https://www.finansnorge.no/statistikk/skadeforsikring/Naturskadestatistikk-NASK/>). The NPP data are available for  
 282 the period 1980-2015 and are aggregated to a county level. For improved parameter es-  
 283 timation, we include the data from Rogaland county which is the county directly south  
 284 of Hordaland and with similar characteristics. We use a discount rate of 4% for the first  
 285 40 years of the analysis, a rate of 3% for 40 to 75 years into the future and a rate of 2%  
 286 beyond 75 years (cf. Section 5.8 of *Norwegian Ministry of Finance* [2012]).

288 Storm surge data for Esbjerg are obtained from the Danish Coastal Authority [*Sorensen*  
 289 *et al.*, 2013].

290           **5.2 Sea level rise in Bergen and Esbjerg**

291           Figure 3 shows uncorrected and corrected Bergen sea level data, and the relationship  
 292           between the corrected Bergen data and the global sea level data. The glacial iso-  
 293           static adjustment is 0.26 (standard error 0.07) cm/yr. The time series regression uses an  
 294           ARMA(1,1)-model [Box and Jenkins, 1970], with AR parameter 0.82 (0.13), and MA pa-  
 295           rameter -0.61 (0.17). The regression slope is 1.30 (0.12).



296           **Figure 3.** The left figure shows raw (black) and gia-corrected (red) sea level data from Bergen. The right  
 297           figure relates the gia-corrected Bergen sea level to the global sea level series of *Church and White* [2011]. The  
 298           straight line is the time series regression line.

303           For the relationship between global annual mean temperature and global annual  
 304           mean sea level rise we use the results from *Bolin et al.* [2014]. The left panel of figure 4  
 305           shows the simultaneous 90 % confidence region for Bergen sea level rise relative to 1999  
 306           under scenario RCP 8.5, which is the scenario Norwegian authorities recommend for plan-  
 307           ning purposes.

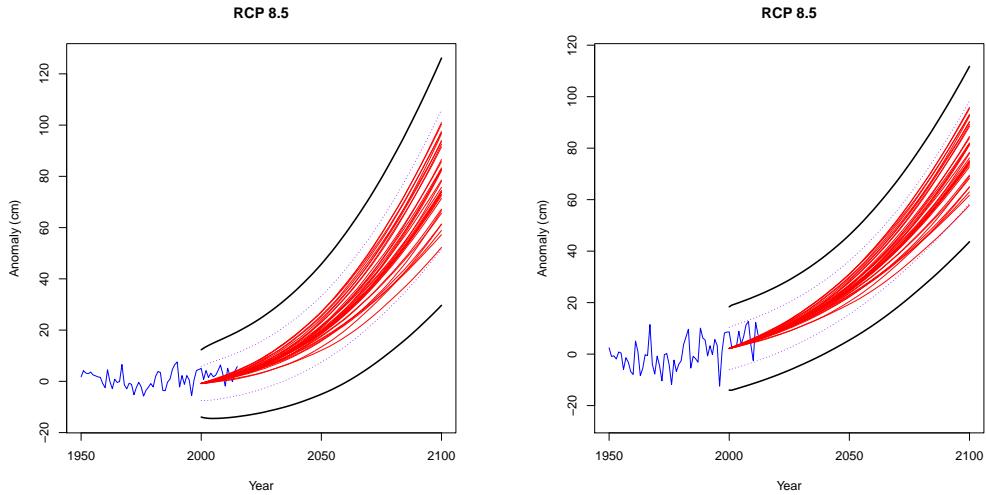
308           For Esbjerg, the glacial isostatic adjustment is 0.06 (0.03) cm/yr. The time series re-  
 309           gression model relating glacial isostatic adjustment to global sea level is an MA(1) model with pa-  
 310           rameter 0.17 (0.09). The regression slope is 1.02 (0.06). The right panel of figure 4 shows  
 311           the simultaneous 90% confidence region for sea level rise relative to 1999 under scenario  
 312           RCP 8.5.

313           **5.3 Timing of adaptation measures in Bergen**

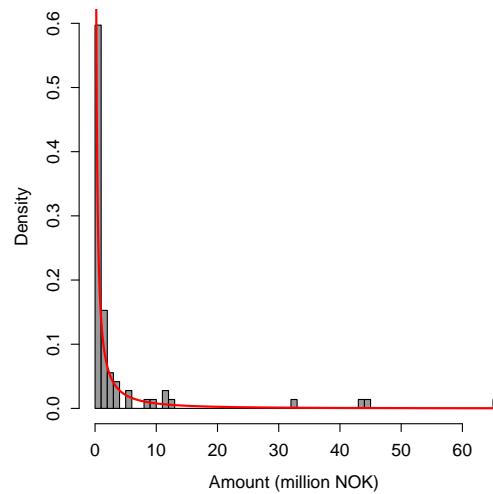
316           Figure 5 shows the histogram of observed annual damage costs for Bergen and the  
 317           associated Burr distribution. The parameter estimates are  $\hat{\alpha} = 7.84$  (3.6),  $\hat{\gamma} = 0.40$  (0.04)  
 318           and  $\hat{\theta} = 0.007$  (0.01). *Grieg Foundation* [2009] discuss several different adaptation options  
 319           for Bergen. In Figure 6 we consider the optimal timing of an adaptation option that in-  
 320           cludes two inner barriers at Vågen and Damgårdssundet, that is, one on each side of cen-  
 321           tral Bergen. The combined construction cost of the two barriers for a protection against 75  
 322           cm sea level rise is estimated at 1.13 billion NOK (2015 level)<sup>2</sup>.

323           Applying the methodology from section 3 we find that the optimal time of building  
 324           the barriers is in 2046 (Figure 6), and that by the year 2100 this decision will on average

<sup>2</sup> 100 NOK is about 11 EUR.

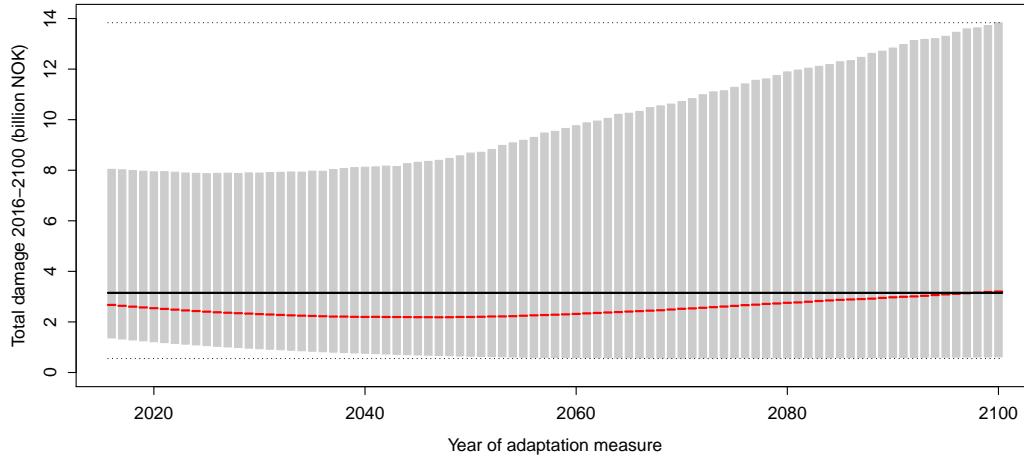


299 **Figure 4.** Simultaneous 90% confidence set (thick black lines) for Bergen (left) and Esbjerg( right) sea  
 300 level projections for the years 2000-2100 using RCP8.5. The sea level data are shown in blue and end in  
 301 2015. The thin red lines are the projections without uncertainty based on each of the climate models. The  
 302 dashed purple lines connect pointwise confidence intervals for each year.

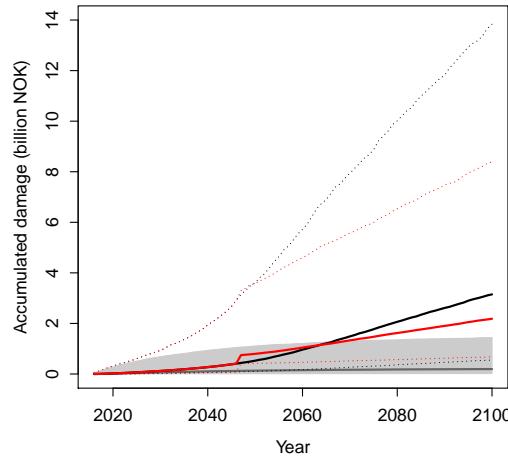


314 **Figure 5.** Estimated distribution of annual damage costs in Bergen for 2015 (red) based on observed annual  
 315 damage in Hordaland and Rogaland counties 1980-2015 (gray bars).

325 save about 1/3 of the median damage costs without adaptation (Figure 7). At the high end  
 326 (or the 95th percentile of the damage distribution) adaptation saves even more, about 43%.



327 **Figure 6.** Projected total damage costs in Bergen for the time period 2016-2100 as a function of the timing  
 328 of an adaptation measure consisting of the construction of two inner barriers. The median projection under  
 329 each adaptation scenario is indicated in red with gray bars denoting the 90% projection intervals. The median  
 330 projected total damage cost under no action is shown with a black line with the corresponding 90% projection  
 331 interval indicated by dotted lines.



332 **Figure 7.** Median projected cumulative damage costs in Bergen under constant sea level (gray line), under  
 333 sea level rise according to RCP 8.5 with no adaptation action (black line) and with the construction of two  
 334 inner barriers in 2047 (red line). The shaded gray area denotes the 90% projection interval under constant sea  
 335 level. Dotted lines indicate the 90% projection intervals with sea level rise according to RCP 8.5.

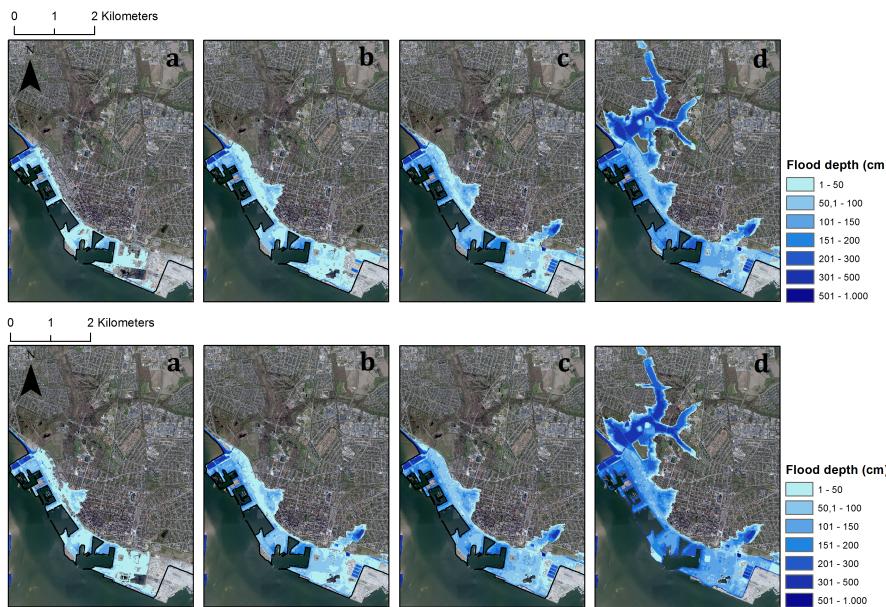
Storm surge	No sea level rise	5th percentile	RCP 8.5	
			median	95th percentile
RP 20	388 cm	431 cm	464 cm	500 cm
RP100	405 cm	448 cm	481 cm	517 cm

340      **Table 1.** Storm surge water levels [Sorensen *et al.*, 2013] with a return period of 20 years (RP20) and 100  
 341      years (RP100) with no sea level rise and with sea level rise corresponding to RCP 8.5 (5th percentile, median,  
 342      and 95th percentile).

#### 336      5.4 Identifying flood-prone areas

337      Table 1 contains the total projected storm surges for Esbjerg, corresponding to the  
 338      20-year and 100-year historical surges, with and without sea level rise. We see that the  
 339      historical maximum 433 cm is very likely to be exceeded by 2100.

346      Figure 8 shows flooding maps corresponding to the entries in Table 1. These maps  
 can be used to further develop adaptation policies for Esbjerg.

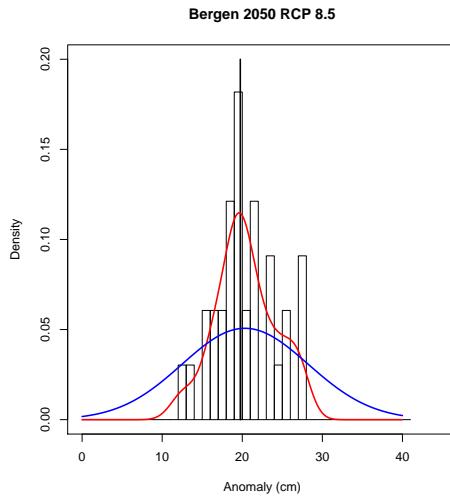


343      **Figure 8.** Flood extents and depths for the city of Esbjerg in year 2100 during storm surges with a 20 year  
 344      return period (upper row) and a 100 year return period (lower row) with (a) no sea level rise and with sea level  
 345      rise corresponding to RCP 85 (5th percentile (b), median (c) and 90th percentile (d)).

## 348 6 The value of including uncertainty

### 349 6.1 Sea level projections

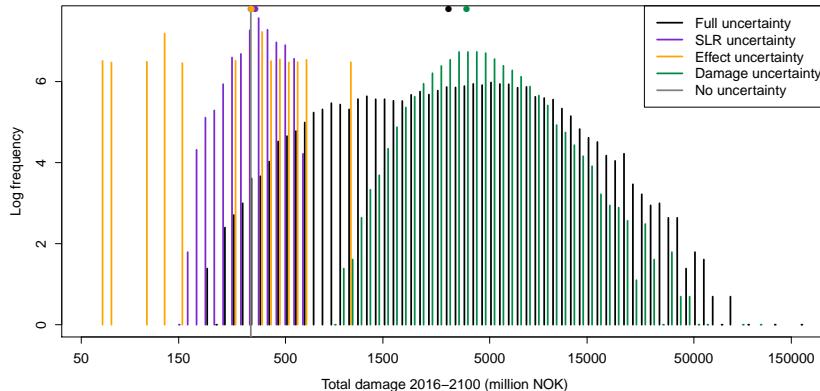
350 In many cases sea level rise projections are given as a single number for each sce-  
 351 nario, usually the mean or median of the ensemble of projections from different climate  
 352 models (e.g. *Mote et al.* [2008]). Sometimes the spread of the ensemble is used to as-  
 353 sess the uncertainty in the projections (e.g., the Norwegian Environmental Agency rec-  
 354 ommends using the upper ensemble value for RCP 8.5 as the basis for planning decision,  
 355 pers. comm. from Even Nilsson, Norwegian Mapping Authority). In our analysis there are  
 356 two more sources of uncertainty, namely the two regression models. Figure 9 shows the  
 357 single number (vertical black line), the ensemble spread (histogram), the uncertainty in-  
 358 cluding only the global model (red) and the full uncertainty (blue) for Bergen projections  
 359 of sea level rise relative to 1999 under RCP 8.5. We see that the ensemble range is about  
 360 16 cm, whereas the overall uncertainty range is about 40 cm.



361 **Figure 9.** 2050 Bergen sea level projections with uncertainty due to different sources for RCP 8.5. The  
 362 black vertical line is the median projection (with no uncertainty), while the gray histogram corresponds  
 363 to the spread of the climate models, the red curve adds the uncertainty due to the relation between global  
 364 temperature and global sea level, and the blue line that due to downscaling global sea level to Bergen.

### 365 6.2 Damage costs

366 A simplistic analysis of projected damage costs at the year 2100, not taking into  
 367 account the uncertainty, would use the median historical damage cost multiplied by the  
 368 median damage effect factor at 2100 at the median sea level rise projected for 2100. This  
 369 yields a damage cost of NOK 338 million (the grey vertical line in Figure 10). Similar  
 370 results obtain when allowing sea level or effect factor to vary, holding the other quantities  
 371 at the median (yellow and purple dots on top of Figure 10). However, allowing only the  
 372 damage cost to vary yields a median cost of 3.85 billion (green dot on top of Figure 10).  
 373 The appropriate uncertainty analysis for our model should draw each of sea level, effect  
 374 factor and damage cost at random from their 2100 distributions. This corresponds to a  
 375 median cost of 3.15 billion NOK, over 9 times higher than the simplistic value. Over 99%  
 376 of the costs in our simulation are higher than the simplistic median.



**Figure 10.** Simulated distribution of total damage cost for 2100 without adaptation on log-log scale (black histogram). We also show the distributions of costs varying only one aspect of the uncertainty (sea level rise in blue, effect multiplier in yellow, and damage cost in green), holding the other two at their median values. The grey vertical line is the result of holding all three factors at their median value. The median of each distribution is shown as a dot on top of the figure.

## 7 Conclusions and discussion

Important to continue an iterative and interactive with end-users, as the decision framework provides actionable information to decision-makers, who will then make their own decisions. These decision are then incorporated into the current adaptation strategy. Continued loop to identify potential vulnerabilities of the approaches across a wide-range of possible futures.

### Take home message

- It is possible to account for uncertainty even if you do a light touch decision-making approach – Explain what it implies if you don't account and if you do
- Proof of concept – connect in a probabilistic way (normally done in a discrete way) – consider uncertainty in both ways
- Improve the accessibility and demonstrating the general applicability of policy first approaches – towards more generic toolkit

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