Characterizing Uncertain Sea Level Rise Projections to Support Investment Decisions

Robert Lempert[1*], Ryan L. Sriver[2], and Klaus Keller[2]

1) RAND, 1776 Main St. Santa Monica, CA 90407-2138

2) Penn State, Department of Geosciences, Deike Building University Park
PA 16802-2714

Corresponding author: Robert Lempert (lempert@rand.org)

Abstract

Many institutions worldwide are considering how to include expectations about future sea-level rise into their investment decisions regarding large capital infrastructures. This paper examines how to characterize deeply uncertain climate change projections to support such decision by examining a question facing the Port of Los Angeles (PoLA): how to address the potential for presumably low probability but large impact levels of extreme sea-level rise in its investment plans? Such extreme events – for instance, increased storm frequency and/or a rapid increase in the rate of sea level rise – can affect investments in infrastructure but have proved difficult to consider in such decisions because of the deep uncertainty surrounding them. This study uses a robust decision making (RDM) analysis to address two questions: 1) under what future conditions would a PoLA decision to harden its facilities against extreme sea-level rise at the next upgrade pass a cost-benefit test and 2) does current science and other available information suggest such conditions are sufficiently likely to justify such an investment? Given the approximations and the adopted cost-benefit framework in this study, near-term hardening merits a more detailed study only for one out of the four analyzed PoLA facilities. We compare and contrast the RDM analysis with a full probabilistic analysis. These two analysis frameworks result in similar investment recommendations, but provide different information to decision makers and envision different types of engagement with stakeholders. In particular, the full probabilistic analysis begins by aggregating the best scientific information into a single set of joint probability distributions while the RDM analysis identifies scenarios where a decision to invest in near-term response to extreme sea-level rise passes a cost-benefit test and then assembles scientific information of differing levels of confidence to help decision makers judge whether or not these scenarios are sufficiently likely to justify making such investments.

Key words: Sea-level rise, robust decision-making, climate change adaptation, cost-benefit analysis

1. Introduction

The Port of Los Angeles (PoLA) is one of the largest container shipping facilities in the world. The Port owns many square miles of land, but its main assets are twenty container ship terminals – large steel and concrete structures that serve as docking facilitates for large container ships, the foundations for the large moving cranes that load and unload these ships, and as transportation hubs for the trucks and trains that carry goods inland. Many jurisdictions worldwide (including PoLA) have been or are considering how to include sea level rise into investments and management of large infrastructure investments [cf. the case studies in *Jonkman et al.*, 2008; *Reeder and Ranger*, 2011; *Rosenzweig*, 2010; *Rosenzweig et al.*, 2011; *van Dantzig*, 1956; *Vrijling*, 2001; *Walsh et al.*, 2004]. This paper focuses on a particular question facing PoLA: how to address the potential for presumably low probability but large impact levels of extreme sea-level rise in its investment plans? Such extreme events – for instance increased storm frequency and/or a rapid increase in the rate of sea level rise – can affect investments in infrastructure but have proved difficult to consider in such decisions because of the deep uncertainty surrounding them [cf. *Vellinga et al.*, 2009].

A typical approach for estimating the risk posed by such changes begins by defining a small number of scenarios of future sea level rise and storminess, which are then used to help estimate exposure, vulnerability, and hence risk. For instance, the State of California has provided official sea level rise planning scenarios of 16” by 2050 and 55” by 2100 that local, regional, and state agencies can use as input to vulnerability analyses of their facilities [*Co-CAT*, 2010]. *Hanson et. al.* [2011] rank the potential exposure of 136 port cities worldwide to climate extremes in the years 2005 and 2070 by crafting scenarios that include changes in mean sea levels, storminess (focusing on the 1 in a 100 year event), patterns of urbanization and economic growth, and human-induced subsidence. To bound the potential exposure in the face of large uncertainties, the scenarios include what are termed high-end estimates for each of these factors.

Such scenario analyses, which begin with scientific projections of changes in key climate variables and in some cases also include projections of socio-economic factors, can provide useful information for surveys of relative exposure and risk as exemplified by Hanson et. al. [2011]. But this type of analysis, sometimes characterized in the literature as “science-first” [*Dessai and Hulme*, 2007] or “predict-then-act” [*Lempert et al.*, 2004], can prove a less useful guide for specific adaptation decisions, including those involved with investments in infrastructure, because it provides only very limited avenues to ensure that the scenarios being considered are those most relevant to the decisions that need to be made. In some cases, sufficiently reliable probabilistic projections may exist to support a traditional risk analysis, which also begins with projections of key climate and socio-economic factors. But for many adaptation decisions, in particular those sensitive to extreme events, well-characterized distributions for climate variables are not available and probabilistic projections of relevant socio-economic factors may be even more unreliable [cf. *Keller et al.*, 2008; *Knutti et al.*, 2010; *Oppenheimer et al.*, 2008; *Rahmstorf*, 2010; *Siddall et al.*, 2010].

In such cases of deeply uncertain projections, it may prove more effective to begin with the specific decisions under consideration, and then use the requirements of these decisions to identify the climate and socio-economic scenarios that should be considered. The literature offers several names for such approaches, including "context-first" [*Ranger et al.*, 2010], "decision scaling" [*Brown*, 2010], "assess risk of policy" [*Carter et al.*, 2007; *Dessai and Hulme*, 2007; *Lempert et al.*, 2004], and "vulnerability and robust response." All share the central idea of defining a proposed policy or policies; identifying vulnerabilities of that policy, defined as conditions where the policy fails to meet its goals; identifying potential policy responses to those vulnerabilities; and then organizing scenarios to help policy makers decide whether and when to adopt those responses. The Thames River barrier plan provides an important example of such an approach in the context of sea level rise. The analysis began with the current flood protection system for London, identified the level where current defenses fail, and laid out a route-map plan that showed how different actions could be taken at different times [*Reeder and Ranger*, 2011]. New York City has adopted similar adaptive approaches [*Rosenzweig*, 2010].

This paper focuses on a particular challenge in implementing such approaches – the question of how to organize a rich body of information about climate and socio-economic factors into the scenarios that can be used to inform infrastructure investment decisions. Past applications have identified simple thresholds to represent their decision-critical scenarios, such as in the Thames River Barrier work. But in general, such scenarios will be multi-faceted, combining a range of different climate and other factors.

Complicating matters further, the available information about these factors may span a wide range of different types of uncertainty, from well-characterized to deeply uncertain. Both the annual means and daily extremes of future sea levels are expected to differ from past trends due in large part to the effects of anthropogenic climate change, which result from a complex interplay of effects such as thermal expansion, changes in oceanic structure, melting of land-based ice, shifts in oceanic and atmospheric circulation, and changes in the terrestrial water balance [*Milne et al., 2009*]. While some of these processes, such as thermal expansion, are relatively well understood, others remain deeply uncertain. For instance, current models fail to resolve mechanistically key processes that could contribute to, or constraint, rapid flows of land-based ice [Pollard, 2010]. In addition, the impacts of anthropogenic climate change on the frequency and intensity of future storm surge is only poorly understood [cf. *Bromirski et al.*, 2003; *Cayan et al.*, 2008; *Menendez and Woodworth*, 2010; *Rosenzweig et al.*, 2011].

This study conducts a Robust Decision Making (RDM)-based [*Lempert and Collins*, 2007; *Lempert et al.*, 2003] vulnerability and robust response option analysis for the Port of

Los Angeles to create multivariate scenarios combining a range of different climate and socio-economic factors that can inform some of the port's infrastructure decisions. The study focuses on the question of whether PoLA should harden their container ship terminals against future sea-level rise during the next major upgrades of those terminals. Because these terminals are currently relatively high above the water, a decision to make such an investment can be thought of as purchasing relatively low-cost insurance against the potential impacts of poorly understood extreme events. To implement the vulnerability and robust response option approach, we run a cost-benefit calculation for the Port many hundreds of times to explore the implications of a wide range of different assumptions about future climate and terminal management conditions. We then conduct a "scenario discovery" cluster analysis [*Bryant and Lempert*, 2010] on the resulting database of simulation model results to succinctly characterize the conditions where an early hardening would meet a cost-benefit test. Finally, we compare these conditions to available information in the scientific literature. This process allows for a traceable combination of information from different sources and varying levels of uncertainty.

This study demonstrates three important elements of the approach, how to: i) use climate information with different levels of uncertainty, ii) combine uncertain climate information with uncertain information about relevant socioeconomic factors, and iii) display the results to decision makers. The next section of this paper describes the decision problem. The third section provides the RDM analysis on a particular PoLA facility. The fourth section compares the results to a more traditional full probabilistic risk analysis and the fifth summarizes RDM analyses on three additional PoLA facilities.

This quantitative analysis relies on models that are necessarily approximations. These approximations result in several and nontrivial caveats. We discuss these caveats towards the end of the discussion, before the conclusions.

2. PoLA's Decision Challenge

Past analyses have often suggested that future sea-level changes alone do not warrant immediate infrastructure investments. However, when an organization such as PoLA is building new infrastructure, or conducting major renovations of existing facilities, it may prove useful to consider future sea level rise (see, for instance, [*TRB, 2008*]). The effect of sea level rise on PoLA's decisions regarding its container ship terminals follows this pattern.

The edge of PoLA's terminals currently lies about 12 feet above mean sea level. As shown in Figure 1, conduits carrying high voltage electric lines run underneath the main floor and lie 9.2 feet above mean sea level. A breakwater, managed by the U.S. Army Corps of Engineers, provides the main barrier to wave action and storm surge in the harbor.

The design and use of the terminals is driven by container ship technology. PoLA first built such terminals in the 1960s and gave them a major overhaul in the 1980s when the size of container ships increased significantly. Several factors will drive the lifetime of PoLA's current terminals, including how long they take to wear out and any impending changes in container ship technology, both of which are uncertain.

PoLA's terminals are relatively high above today's mean sea level and have never been flooded in the past few decades. Given this large apparent safety margin, PoLA would only consider sea level rise when planning a major upgrade of their terminals because hardening at that time would cost much less than would such an effort undertaken not at the time of a major upgrade.

We approximate PoLA's decision challenge as a sequential decision problem as shown in Figure 2. At some time in the future the Port will upgrade one of its terminals. The Port can decide to spend an additional sum C_{harden} to make the terminal practically invulnerable to plausible future sea levels during the terminal lifetime. Such hardening might involve redesigning the electric conduits currently under the terminal and raising the terminal considerably higher. If the Port decides to harden the terminal they pay an additional $C_1 = C_{harden}$ now and then suffer no further costs from any plausible amount of sea level rise through the next upgrade which would occur no less than several decades later.

If PoLA decides not to harden, the terminal may prove vulnerable during its lifetime to sea-level rise. Storm surges combined with high tides and a higher mean sea level might then occasionally flood the terminal. Such flooding would cause damage and disrupt operations. We assume that PoLA could tolerate some small flooding frequency. But if the flooding became too frequent, the organization would need to respond at significant cost. We assume that if the frequency of flooding exceeds this critical level, which we call p_{crit}, that the Port, rather than just hardening the existing terminal, would choose to conduct a major upgrade that would include the hardening.1 If the Port chooses not to harden at the time of the next upgrade they might be forced to upgrade in the future earlier than would otherwise prove necessary, with the resulting cost of

$$C_2(\tau) = \left[C_{upgrade}\left(\frac{L-\tau}{L}\right) + C_{harden} \right] e^{-d\tau} . \tag{1}$$

where L is the lifetime of the terminal in years, d is the discount rate in percent per year, and τ is the year when the frequency of flooding first exceeds the allowable threshold. Table 1 summarizes these and the other model parameters.

A decision to harden at the next upgrade would pass an economic cost-benefit test if the cost for doing so is less than the expected present value cost of any future early upgrade

[1] Note that this assumption may underestimate the PoLA's future options, but it provides a simple representation of the current cost implications. We will return to a discussion of the implications of this and other assumptions below.

forced by sea-level rise. In other words, the expected present value of the savings due to the hardening (S_{Harden}) should be positive. In our model, S_{Harden} approximated by:

$$S_{\text{Harden}} = \begin{cases} \left[\left(\frac{L-\tau}{L}\right) + \frac{C_{harden}}{C_{upgrade}}\right] e^{-d\tau} - \frac{C_{harden}}{C_{upgrade}} & \text{for } \tau < L \\ -\frac{C_{harden}}{C_{upgrade}}\left(1 - e^{-d\tau}\right) & \text{for } \tau \geq L \end{cases} \quad . \tag{2}$$

Note that we have normalized all the costs to fractions of the upgrade cost.

The present value savings, and in particular the year τ, will depend on the future sea levels, which we approximate as a sum of two time-series:

$$y_t = z_t + x_t \tag{3}$$

where z_t is the annual mean sea level in the Port of Los Angeles for time index $_t$ and x_t is the maximum hourly anomaly. As described in Section 3, we can usefully approximate future mean annual sea level as:

$$z_t = a + bt + ct^2 + c^* \Lambda(t - t^*), \tag{4}$$

where the term *a* is the sea-level anomaly at time zero (2011), *b* is a constant rate [mm/year], and *c* is an acceleration term [mm/year^2]. (See Table 1 for a summary of the parameter definitions and symbols). These first three terms represent the effects of relatively well-understood processes, such as thermal expansion of the oceans due to rising temperatures and the melting of small glaciers, that are well-constrained by past observations. The fourth term represents currently poorly understood and poorly constrained processes, for example potentially abrupt changes in the dynamics of ice flow (cf. Alley et al, 2007), which we parameterize by an increase in the rate of sea-level rise c* [mm/a] that occurs after some time *t**.

While changes in the annual mean sea level are an important driver, any actual flooding events will happen on much shorter time-scales [e.g., *Anthoff et al.*, 2010; *Church et al.*, 2006; *van Dantzig*, 1956]. As described in Section 3, the local, hourly anomaly at PoLA, x_t, are well approximated by a generalized extreme value (GEV) distribution. Thus, we assume flooding would force PoLA into an early upgrade in the first year τ in which

$$P(x_\tau \geq H - z_\tau) = 1\text{-exp}\left\{-\left[1 + \xi\frac{H - z_\tau \text{-} \mu}{\psi}\right]^{-1/\xi}\right\} \geq \left[1 - \left(1 - p_{crit}\right)^{\frac{1}{24*365}}\right] \tag{5}$$

where μ, ψ, and ξ are the GEV distribution's location, scale, and shape parameters and the factor (24*365) translates the hourly frequencies into annual values.

We solve this model numerically by finding the smallest value of τ which satisfies Eq (5) and then evaluating the present value cost savings with Eq (2).

3. Robust Decision Making Analysis

Any savings from a decision to harden at the next upgrade, as estimated by Eq (2), are contingent on the value of fourteen parameters as shown in Table 1. The calculation would prove simple if these values were known precisely. The challenge is evaluating the decision given large and divergent levels of uncertainty regarding these parameter values.

The RDM approach addresses this challenge by answering two questions: 1) under what future conditions would PoLA find it advantageous to have hardened its terminal at the next upgrade, and 2) does current science and other available information suggest these conditions are sufficiently likely to justify a decision to harden at the next upgrade? RDM answers these questions through the following steps:

- Considering some parameters in Table 1 as deeply uncertain and evaluating Eq (2) over many cases, each described by some combinations of values of these deeply uncertain parameters;
- Concisely summarizing the common factors among those cases in which hardening at the next upgrade passes the cost-benefit test;
- Estimating the probability threshold, that is the likelihood for these cases that would justify hardening at the next upgrade; and then
- Evaluating scientific lines of evidence to help judge whether or not these cases are sufficiently likely to justify a decision to harden at the next upgrade.

The following subsections describe each of these steps.

3.1 Evaluating the decision to harden in many cases

To implement this RDM analysis, we need to construct an experimental design that effectively samples over the plausible combinations of parameters in Table 1. The table divides the parameters affecting PoLA's potential savings into two categories: eight parameters describe future sea level and six describe the terminal and its future management. The experimental design must appropriately combine parameters with different levels of uncertainty — some parameters known have known values, some are best represented with well-characterized probability distributions, and some parameters are deeply uncertain.

We treat four of the terminal management parameters – the decision year, height of the terminal, hardening cost, and discount rate – as known at the time of the decision. The other two terminal management parameters – the terminal lifetime and the maximum allowable annual flooding probability – refer to choices made by future PoLA decision makers, and are thus deeply uncertain from the point of view of the audience of this analysis. We assume that the three coefficients of the quadratic expression for the well-understood processes of sea level rise, the first three terms of Eq (4), can be accurately described with a single, well-characterized, joint probability distribution. We treat the other five parameters describing future sea level rise – the rate and starting time of any abrupt changes and the three parameters describing the future distribution of hourly anomalies – as deeply uncertain.

We now describe these distributions and the experimental design we use for the deeply uncertain parameters.

3.1.1 Well-characterized uncertainties

We estimate a single, joint probability distribution over the parameters describing the well-represented contributions to future sea level rise by fitting the first three terms of Eq (4) to observed sea levels over the past two centuries, as shown in Figure 3. Similarly to the many analyses that adopt sea-level rise projections based on simple, semi-empirical models or scenarios [e.g., *Purvis et al.*, 2008; *Rosenzweig et al.*, 2011; *van Dantzig*, 1956], we use this quadratic form that in many previous studies has provided useful insights [e.g., *Church and White*, 2006; *Douglas*, 1992; *Jevrejeva et al.*, 2008; *Woodworth et al.*, 2009]. Using more complex sea-level models [cf. *Applegate et al.*, 2011; *Irvine et al.*, 2012] would improve the physical realism of the analysis, but would require arguably unreasonable computational resources to perform the uncertainty and decision-analyses described below.

We use a simple bootstrap analysis [cf. *Solow*, 1985] to estimate the joint distribution of the parameters a, b, and c, using observations of globally and annually averaged sea-levels [*Jevrejeva et al.*, 2006]. We normalize the sea-level observations to a zero anomaly in the year 2000 to simplify comparisons with other studies such as [*Co-CAT, 2010*]. We fit the model in a least-squares sense, approximate the data-model residuals using an autoregressive model of order one, superimpose bootstrap realizations of the residuals to the original fit, and then re-estimate the parameters for each bootstrap realization. As shown in Figure 3a, this process provides a distribution of a, b, and c that approximates the past observed sea levels quite well. The distribution for each parameter is shown in Fig 3b. Note that the observed global rates are slightly larger than the local rates at PoLA (results not shown). As a result, the estimates of b and c may be high, compared to an estimate derived from local observations. We represent the projection uncertainties introduced by the discrepancies between local and globally averaged sea-levels by expanding the uncertainty range (discussed below). The use of the globally averaged data (as opposed to local observations) is an approximation. This approximation guards to some extend against the effects of the observed decadal-scale oscillations in the rate of regional sea-level rise and the resulting potential for a considerable increase in the rate of sea-level rise in the Eastern Pacific, for example due to circulation effects [cf., *Bromirski et al.*, 2011; *Jevrejeva et al.*, 2006]. In addition, this approximation makes it easier to link the sea-level rise projections affected by well-represented uncertainties to studies analysing deep uncertainties (discussed next).

3.1.2 Deep uncertainties

The other uncertainties in Table 1 – five for future sea level and two for future terminal management – are deep. We represent them by a range, or set, of plausible values. For each parameter we seek to choose a range that is consistent with physical or other constraints and sufficiently wide to contain the boundary between cases where hardening at the next upgrade does and does not meet the cost-benefit test.

PoLA has design guidance for the lifetime L of its terminals, but in practice terminals can last longer than originally planned. We thus choose a range for L between 30 and 100 years. PoLA has no experience and thus no solid estimates regarding the maximum allowable flooding probability, that is, the frequency of annual flooding that would force the organization to undertake an early terminal upgrade. We hence choose a wide range of values, between 5% and 50% chance of annual flooding, that would force an early upgrade.

The parameters c* and t* represent the contribution of poorly understood processes to future annual mean sea level rise. As described below, we choose the values of c* and t* to approximate two expert assessments. For t*, we add as an additional constraint that such a rise could begin immediately, and we take as our upper bound the end of the considered time horizon (the year 2100), where a rapid rise would no longer be relevant to any near-term hardening decision by PoLA.

To treat the future daily anomaly, we begin with the common assumption of stationarity in the intra-annual variability, modeled by superimposing an estimate of the past variability on the projected future changes in the annual mean. The State of California Sea Level Rise Interim Guidance document [*Co-CAT*, 2010] assessed this as a "reasonable starting point" because little information exists to project any future changes in this variability. We generate a time series of past anomalies at PoLA by subtracting the observed change in the annual mean from local observations (PMSL station 245, [*Caldwell, 2010*]) spanning roughly eight decades. We then fit a GEV distribution to these anomalies. A GEV distribution seems appropriate because it provides a good fit to PoLA's past hourly anomaly. As shown in Figure 4, a fit with location $\mu = -176$ mm, scale $\psi = 517$ mm, and shape $\xi = -0.305$ reproduces the observed anomaly quite well. Note also that this hourly anomaly ranges over roughly 3,000 mm, two orders of magnitude larger than the standard deviation of the unresolved interannual variability of approximately 24 mm shown in Figure 3. As an approximation in the interest of model parsimony, we hence neglect the relatively small effects of the unresolved intra-annual variability for the projection of flooding risks.

There is, however, no guarantee that the future distribution of hourly anomalies will remain stationary due to climate change and other factors. To represent these potential, deeply uncertain future changes we consider a set of GEV distributions, created by varying the scale parameter over the range $517 \text{ mm} \le \psi \le 569 \text{ mm}$, where the lower bound is the current scale and the upper bound is 10% larger. In general, we could also vary other distribution parameters (such as the shape parameter), but as we will see below there is insufficient scientific information available to justify this degree of fidelity. The mean of a GEV distribution is given by the expression $\mu + \psi\left[\Gamma(1-\xi)-1\right]/\xi$ where $\Gamma(\ )$ is the gamma function [*Hosking*, 1990]. As the scale varies, the mean of the hourly anomaly around the annual mean must remain constant (our treatment of the anomalies demand that they do not shift the annual mean), so we write the location of each distribution in our set as

$$\mu = -176 - (\psi - 517\text{mm})\left[\Gamma(1.305)-1\right] = -176 + 0.1033(\psi - 517\text{mm}). \tag{6}$$

3.1.3 Experimental design

Our initial analysis considers a decision where PoLA upgrades a terminal in 2020; the costs of hardening are small, $C_{harden}/C_{upgrade} = 1\%$; and PoLA uses a discount rate of 5% per year. As our analysis will show, we consider this low hardening cost because it is at the high end of near-term investments PoLA might reasonably make to protect its terminals against extreme sea level rise. In Section 4, we repeat the analysis for three other PoLA facilities with different combinations of heights and hardening costs to provide some summary insights.

To evaluate this decision, we generate a 500-point Latin hypercube (LHC) sample [*Bursztyn and Steinberg*, 2006] over the five deeply uncertain parameters, three for Future Sea Level rise (c^*, t^*, and ψ) and two for Future Terminal Management (L and p_{crit}), using the parameter ranges shown in Table 1. The LHC method provides a numerically efficient sample of the space of deeply uncertain parameters. For each case in the sample we treat the parameters with well-characterized uncertainty by calculating the cost savings for 700 equally likely combinations of values for the parameters a, b, and c. We then take the average to yield the expected savings for that case. Thus, for each of the 500 cases in the LHC sample, we calculate the expected savings of a decision to harden at the next upgrade, contingent on the distribution for the parameters with well-characterized uncertainty, a, b, and c, and on a particular set of values for the deeply uncertain parameters c^*, t^*, ψ, L, and p_{crit}.

The results are summarized in Figure 5. The histogram shows that in about 327 of the 500 cases a decision to harden at the next upgrade would have expected negative net costs. In 173 of the cases, such a decision would have some cost savings. In a small number of those cases the cost savings would be quite large, up to 20 times the cost of hardening.

3.2 Identifying Scenarios Where Early Hardening Passes a Cost-Benefit Test

We perform a scenario discovery analysis using this database of 500 cases to identify a scenario in where PoLA might regret a decision not to harden at the next upgrade. Scenario discovery [*Bryant and Lempert*, 2010] applies a cluster analysis to a database of simulation model results, seeking to identify those combinations of uncertain input parameters which most concisely predict certain policy-relevant outcomes. Here we seek those combinations of the five deeply uncertain parameters that best predict those cases where a decision to harden at the next upgrade would pass the cost-benefit test. Previous applications of scenario discovery have used PRIM (patient rule induction method) to identify these clusters of cases. Here we augment this approach by first applying a principle component analysis to the parameters c^* and t^* and then applying PRIM to the resulting rotated set of parameters as described in *Dalal et. al. (in preparation).* This PCA and PRIM combination can prove useful in situations where the scenarios can be best described by linear combinations of some uncertain input parameters, rather than just hyper-rectangular regions in the space of original input parameters.

This scenario discovery analysis suggests, as shown in Figure 6, that the decision to harden at the next upgrade might pass the cost-benefit test in cases with a near-term and rapid increase in sea level, given by $c^* \geq 14\, mm/yr + 0.3\, mm/yr\left(t^* - 2010\right)$; a long terminal lifetime, given by L>50 years; and a significant increase in the hourly anomaly, given by ψ >3% . The value of the critical threshold p_{crit} appears relatively unimportant to PoLA's decision of whether or not to harden at the next upgrade.

We can label these three conditions the *Harden At Next Upgrade* scenario. The scenario discovery process provides two measures – coverage and density -- of the quality of the scenario. This scenario has coverage of 63%, that is 109 of the 173 cases in the LHC sample where hardening at the next upgrade passes a cost benefit test meet the three conditions in Figure 6. The scenario has density of 96%, that is, of the 113 cases in the sample that satisfy the conditions shown in Figure 6, 109 of them pass the cost-benefit test.

We can calculate a probability threshold for this scenario, that is, the likelihood PoLA would have to ascribe to it so that the expected cost savings for hardening at the next upgrade are greater than zero. This probability threshold P_{thres} is the smallest value that satisfies

$$P_{thres}\bar{S}_{\text{Harden Scenario}} + \left(1 - P_{thres}\right)\bar{S}_{\text{All Other Cases}} \geq 0 \tag{7}$$

where $\bar{S}_{\text{Harden Scenario}}$ is the average savings of the cases that satisfy the conditions shown in Figure 6 and $\bar{S}_{\text{All Other Cases}}$ is the average savings of all the other cases in the considered parameter sample. We estimate these averages with a uniform distribution over the two respective sets of cases, which yields a P_{thres} >7%.

Thus PoLA might reasonably chose to harden their terminals at the next upgrade if they judged the probability of the *Harden At Next Upgrade* scenario, as defined by the conditions in Figure 6, to be at least 7%.

3.3. Scientific evidence regarding the *Harden at Next Upgrade* Scenario

We now analyze information that can help inform the judgments regarding the likelihood of the *Harden At Next Upgrade* scenario. In particular, climate science can help inform judgments about the likelihood of values of the parameters c^*, t^*, and ψ that satisfy the conditions that define this scenario.

Note first that the condition $c^* \geq 14\, mm/yr + 0.3\, mm/yr(t^* - 2010)$ implies a sea level rise contribution from poorly understood processes of about 1400 mm in 2100. When combined with the roughly 500 mm contribution from well-understood processes, the *Harden At Next Upgrade* scenario implies a roughly 2 m sea level increase by century's end. Such a level is within, but at the high end, of some current sea-level rise projections (cf. Figure 7 as well as *Pfeffer et al*. [2008], [*Co-CAT, 2010*], and [*Vellinga et al.*, 2009]). This suggests that the scenario may be less likely than the 7% threshold derived from the economic analysis. A more detailed understanding can result from estimates of joint probability distributions for c^* and t^*. While imprecise, such probability estimates can usefully contribute to judgments about the conditions under which PoLA might consider hardening their terminals at the next upgrade.

Several studies such as *Pfeffer et al*. [2008], [Co-CAT, 2010], and [*Vellinga et al.*, 2009] have used physical arguments to derive upper and lower bounds for sea-level rise in the year 2100. These bounding analyses typically extend well beyond the range of sea-level rise predictions based on empirical or Earth system models [e.g., *Grinsted et al.*, 2010; *Kemp et al.*, 2011; *Rahmstorf*, 2007] because they include processes that are typically poorly resolved in the more detailed models. We estimate joint probability distributions for c^* and t^* by sampling from broad prior distributions and applying a rejection sampling to approximate the results of these bounding analyses. We use two different sets of projections -- a modification of the analysis of *Pfeffer et al* [2008] and the California Sea Level Rise Interim Guidance document [*Co-CAT*, 2010] -- which yield two different joint probability distributions and thus a range of estimates for the likelihood of the condition $c^* \geq 14\, mm/yr + 0.3\, mm/yr(t^* - 2010)$.

Pfeffer et al. [2008] analyze kinematic constraints on the sea-level rise contributions from land-based ice and derive lower and upper bounds of 785 and 2008 mm for sea-level rise in the year 2100 and a "more plausible" estimate of about 800 mm. We introduce two adjustments to the *Pfeffer et al*. [2008] results because these previous results neglect uncertainties due to thermosteric sea-level rise and the divergence between global mean and local sea-level change. We address the lack of uncertainty assessment of about the thermosteric sea-level rise component by adding an additional rise of -230 to + 200 mm. This uncertainty range is derived from a comparison of observed sea-levels and an ensemble of runs from an Earth System Model of Intermediate Complexity, that includes a 3-dimensional dynamic ocean general circulation model and samples key parametric uncertainties [*Sriver et* *al.*, 2011].[2] We approximate the local circulation effects with an additional rise of +/- 300 mm. This range is approximately the range of projected local sea-level rise anomalies with respect to the global mean at the end of this century [*Meehl et al.*, 2007]. This range is also roughly consistent with the divergence of the simple parabolic fit to the local (PoLA) and global [*Jevrejeva et al.*, 2006] observations extrapolated to the year 2100 (results not shown). These two adjustments yield a modified lower and upper bounds for the annual mean local sea-level in 2100 of 255 mm to 2508 mm with a more plausible value of 950 mm (Figure 7). We then approximate this line of evidence using a rescaled beta distribution, chosen because it provides a good approximation of the upper and lower bounds, as well as the most-likely regions. Applying a rejection sampling approach to approximate or emulate the resulting expert assessment for the projected sea-level rise in the year 2100 allows us then to estimate joint distributions for c^* and t^* as shown in Figure 7.[3]

The California Sea Level Rise Interim Guidance document [*Co-CAT*, 2010] reviews a number of published sea-level rise projections and derives a sea-level rise of between 310 and 1760 mm for California in the year 2100. Note that these "projections do not account for catastrophic ice-melting" and are for a specific region (as opposed to the global mean). In the same way as we have modified the *Pfeffer et al* (2008) scenario, we approximate the local circulation effects with an additional rise of +/- 300. This results in a modified *Co-CAT* [2010] range of 10 to 2060 mm by the end of this century. We approximate this line of evidence using a uniform distribution, because the Co-CAT study reports no most plausible value. Using again a rejection sampling produces a joint distribution for c^* and t^* that approximates this expert judgment.

We can now use each of the *Pfeffer et. al.* (2008) and *Co-CAT* (2010) derived distribution to estimate likelihoods for the condition $c^* \geq 14\, mm/yr + 0.3\, mm/yr\left(t^* - 2010\right)$. As shown in Fig 8, the two distributions, though different, yield similar estimated likelihoods for this condition, of roughly 14% and 16% for the *Pfeffer et. al.* (2008) and *Co-CAT* (2010) bounding analyses respectively. We can thus express the probability that the inequality is satisfied as the narrow range

$$14\% \leq \Pr\left[c^* \geq 14\frac{mm}{yr} + 0.3\frac{mm}{yr}(t^* - 2010)\right] \leq 16\% \qquad (8)$$

The scientific evidence regarding the condition for the hourly anomaly, , is even more sparse than that for c^* and t^*. Some studies suggest that the future hourly anomaly may remain unchanged from that currently observed. Translated into the approximation using a

[2] The asymmetry of this range is due to the slight difference between the median thermosteric sea-level rise estimate adopted by *Pfeffer et al* [2008] and the estimate from *Sriver et al* [2012].

[3] This fit also yields a joint distribution for the parameters a, b, and c, which is largely uncorrelated with that for c* and t* and thus consistent with that used in Section 3.1.1.

GEV distribution, this implies that is the distribution parameters may be assumed to be constant over time, i.e.: $\psi \approx 517\text{mm}$. For instance, the global-scale data analyses of Woodworth and Blackman [2004] and Menendez and Woodworth [2010] conclude that the changes in the extremes are similar to the changes in the mean. In contrast, the studies of *Bromirski et al. and Mendez et al.* [2003; 2007] find that the observed variability of sea levels has been increasing at several locations. *Cayan et al* [2008] analyze model projections and place bounds on future increases in storminess near San Francisco. These bounds would correspond in our analysis to a range of $517\text{mm} \le \psi \le 533\text{mm}$.

These bounds may prove too narrow because the models used to project the short-term variability might miss important processes, such as potential changes in El Niño / Southern Oscillation properties or storm surges [*Meehl et al.*, 2007], which is why the range used in our experimental design (See Table 1) is larger. Note that the values at, the high end of our experimental design range produce an increase in storm surge of roughly 1.6 meters. This is far less than the maximum surge of up to 7 or 8 meters produced by in the U.S. Gulf Coast by storms such as Hurricanes Ike and Katarina.[4] Storm surges are affected by the intensity of storms as well as the topography of region. While it is, at this time, very difficult to define physically based bounds for future changes in storm frequency and intensity due to climate change [cf. *Cayan et al.*, 2008], future and more refined data and numerical analyses might be able to improve the estimate the maximum surge height different sized storms might produce in the Port of Los Angeles, and thus develop more plausible bounding cases for the parameter ψ to be used in future analyses.

We can summarize this disparate evidence regarding the likelihood of the *Harden At Next Upgrade* scenario by asking the question: given the estimated range of likelihood for the condition on c^* and t^* what range of likelihoods on the conditions for ψ and L would yield a probability for the scenario greater than its critical threshold? That is, what is the set of values for $\Pr[\psi > 533\text{ mm}]$ and $\Pr[L > 50\text{ years}]$, the probabilities, respectively, that ψ and L meet the conditions shown in Figure 6 such that

$$\Pr[\psi > 533\text{ mm}] \cdot \Pr[L > 50\text{ years}] \cdot \Pr[c^* \ge 14\frac{mm}{yr} + 0.3\frac{mm}{yr}(t^* - 2010)] \ge 11\% \quad (9)$$

The resulting probability region for is shown in Figure 9, which suggests that PoLA should only choose to harden its terminals at the next upgrade if it ascribes probabilities of at least about 67% to the conditions L>50 years and $\psi > 533\text{ mm}$. Given that the condition on the lifetime is longer than those PoLA has previously experiences and the condition on the hourly anomaly increase is at the high end of available scientific evidence, PoLA might reasonably choose not to harden at the next upgrade of this facility even at a cost of 1% of the cost of the upgrade.

[4] Hurricane Ike storm surge: http://www.nhc.noaa.gov/sshws_statement.shtml, Hurricane Katarina storm surge: http://en.wikipedia.org/wiki/Storm_surge

4. Comparison with Full Probabilistic Analysis

The steps of a full probabilistic analysis proceed in the opposite order from the RDM approach. To illustrate the comparison with RDM, we conduct a full probabilistic analysis of the PoLA decision considered above. As its first step, this new analysis uses the best available science to estimate a single joint probability distribution for all the uncertain input parameters in equations 2 and 5. The analysis then uses these equations and a Monte Carlo sample over their inputs to calculate a distribution for the cost of hardening at the next upgrade.[5]

The right-most column of Table 1 shows our best estimate probability distribution over the model input parameters.

The parameters driving the annual mean sea level are given by the distributions shown in Figure 7. This figure only shows the c* and t* values. But as described above, we produced these distributions by fitting to both the observational data and the extended Pfeffer and Co-CAT scenarios. These fits also generated distributions for the a, b, and c parameters. The correlations between these later parameters and c* and t* are weak. The RDM analysis in this study ignores them, while the full probabilistic analysis includes them. We have no information to distinguish the relative likelihood of the Pfeffer et al and Co-CAT scenarios, so we assume a uniform prior, that is, each are equally likely.

We use a set of GEV distributions, with the scale spanning the full range, $517 \text{ mm} \le \psi \le 543 \text{ mm}$, described in the literature. We have no information to distinguish the relative likelihood of these values, so we assume a uniform prior. As in the RDM analysis, the location of hourly anomaly distribution for value of ψ is given by Eq (6) to leave the mean annual sea level unchanged.

We have no information to determine the relative likelihood of different values of the maximum allowable overtop probability, p_{crit}, so we assume a uniform prior over the range used in the RDM analysis.

We also lack any information to determine the relative likelihood of different values of the terminal lifetime. But many analyses do show the results of full probabilistic analyses as a function of a range of values for a single parameter, a convention we will adopt here.

Figure 10 shows the results of this full probabilistic analysis, plotting the probability that hardening at the next upgrade would pass a cost-benefit test and the expected cost as a

---

[5] It is important to distinguish between two distinct roles for the stochastic samples used in this paper. In the RDM analysis, the quasi-random Latin Hypercube sample aims only to efficiently explore the full range of plausible model results. The sample makes no statement about the relative likelihood of alternative cases in the real world. In the full probabilistic analysis, the Monte Carlo sample aims to reproduce our best-estimate of the likelihood of cases in the real world in order to facilitate the calculation of expected cost.

function of the terminal lifetime L. These results use 1954 Monte Carlo samples for each value of L. The probability of a positive cost-benefit is never high, at most 16% for terminal lifetimes of 100 years. Not until the terminal lifetime exceeds about 50 years do our calculations show a greater than 1% probability that early hardening passes a cost-benefit test.

The RDM and full probabilistic analyses thus appear to give similar recommendations. Both suggest that PoLA should not harden their terminals at the next upgrade at a cost of 1% (or higher) of the total upgrade cost. Only in situations where the terminal lifetime is very long, greater than about 50 years, is there any possibility that such hardening would pass a cost benefit test and even in such cases the probability that it would do so seems low.

The two analyses do, however, provide different information to decision makers and envision two different types of engagement with stakeholders.

The full probabilistic analysis collects all the analysts' judgments at the start of the process. Once the probability distributions over future states of the world are defined, the analysis yields recommendations that follow deductively from the probability estimates and the simple, but explicit representations of the decision makers' preferences (e.g., the adopted decision-criterion of an expected benefit/cost ratio). As its primary products, the analysis provides distributions of the outputs of interest to decision makers, in this case the expected cost of an early upgrade, and a ranking of the desirability of alternative decisions. In this case, the early upgrade is less desirable because its expected cost exceeds that of not upgrading. Sensitivity analysis can also suggest which uncertain input parameters contribute most to the variance of the outputs.

The RDM analysis follows a more complicated process and one that employs analysts' and decision makers' judgments at more stages. The process begins by focusing on a specific proposed decision. Analysts then create an experimental design over the uncertain model input parameters designed to test this decision, judging which uncertainties to treat as well characterized and which to treat as deep. Next analysts and decision makers use simulation model results to identify scenarios where the policy fails to meet its goals, in this case where a decision to harden at the next upgrade fails a cost-benefit test. Analysts then present the scientific evidence that could help decision makers decide whether such scenarios are sufficiently likely to justify taking an alternative decision. The RDM analysis does not in general produce a ranking of strategies, but rather provides information to help decision makers weigh their choices. As part of this process, the RDM analysis explicitly describes the scenarios where a proposed policy may fail to meet its goals and defines a probability threshold, that is, the likelihood a decision maker would ascribe to that scenario in order to justify taking action to address it.

The two approaches also embody different treatments of uncertainty, which we can usefully summarize with reference to the IPCC uncertainty guidance. This guidance provides a template for judging confidence in scientific judgments based on the level of supporting evidence and agreement [*Mastrandrea et al.*, 2010].

Figure 11 uses this template from the IPCC uncertainty guidance [*Mastrandrea et al.*, 2010] to summarize the scientific information about future sea level rise used in our RDM and full probabilistic analyses. The figure shows the a, b, and c parameters in the upper right-hand corner because, as described above, there exists high level of both evidence and agreement that the polynomial model structure fit to past observations should provide reasonable projections of the contributions of future sea-level rise due to well-resolved processes such as thermal expansion. (Note that, as discussed in the section caveats, this is an approximation, because (i) a fraction of the past observed sea-level changes are due to less well resolved processes and (ii) the simple polynomial model neglects important physical mechanisms, cf. von Storch et al, 2008) The figure shows the c* and t* in the middle left-hand side, because there is little direct observational evidence for potential changes in the system dynamics (for example by "rapid dynamical changes in ice-flow" (Alley et al, 2007). However, there exists some agreement on the upper bounds on such contributions to sea level rise over the next century [*Alley et al.*, 2005; *Allison et al.*, 2009; *Pfeffer et al.*, 2008]. There figure shows ψ in the lower middle left because few studies and little agreement exists on how climate change might affect the future hourly anomaly at PoLA, but the worldwide diversity of current storm surge patterns in different locations with different topographies may provide useful evidence for estimating upper bounds on what the port might expect over the 21st century.

The RDM analysis in Section 3, as would an analysis of variance in the full probabilistic analysis of Section 4, makes clear that PoLA's decision whether or not the harden at the next upgrade depends more strongly on scientific estimates in which we have low confidence than those in which we have high confidence. The full probabilistic analysis does not distinguish between these levels of confidence when informing PoLA's decision. The RDM analysis, in contrast, distinguishes between information with different levels of confidence, differentiating between relatively well-characterized uncertainty (e.g., sea-level rise that follows the past observed dynamics) and deeply uncertain information (e.g., abrupt potential future dynamic changes of land ice, the hourly anomaly, or the characteristics of future terminal management).

In brief, the full probabilistic analysis embodies a concept where experts assemble the best available science so that this information can be used to inform a ranking of alternative decision options. The RDM analysis embodies a scenario concept that explicitly distinguishes among differing levels of scientific confidence and in which the analysis facilitates decision makers in recognizing potentially stressing cases, considering how they might respond, and in communicating this information within and externally to their organization. In other work, we have suggested that in many situations quantitative analyses that incorporate such scenario concepts to describe and communicate deep uncertainty can support decision making more effectively than full probabilistic descriptions [*Bryant and Lempert*, 2010; *Lempert and Popper*, 2005; *Lempert et al.*, 2003] .

5. Results for Additional PoLA Facilities

The analyses, thus far, consider one specific PoLA facility. Here we expand the analyses to three additional facilities of interest to the Port's staff. Table 2 summarizes the results of the analysis in Section 3, along with similar ones for each of three additional facilities: the top of the terminals, which lie 12.14 ft (3700 mm) above mean sea level; Berths 206-209, which lie 7.62 ft (2323 mm) above MSL; and the Alameda and Harry Bridges Crossing, which lies 6.13 ft (1868 mm) above MSL. For each facility the table lists two infrastructure characteristics, height above mean sea level and the hardening cost we assumed; the conditions describing the *Harden at Next Upgrade Scenario* for those infrastructure characteristics (including the coverage and density for that scenario as discussed in Section 3.2); and the resulting probability thresholds and estimates. The *Harden at Next Upgrade Scenario* for each facility and the corresponding probability threshold for that scenario is identified following the procedure described in Section 3.2. The likelihood for the conditions on c* and t* for each facility's *Harden At Next Upgrade* scenario are calculated as described in Section 3.3 and shown in Figure 8.

As described in Section 3.1.3, we assume a hardening cost at the next upgrade for each of the facilities that is sufficiently low that PoLA might reasonably consider such an investment. The hardening costs for the three additional facilities, as shown in Table 2, are 0.1% for the terminal top, 5% for Berths 206-209, and 25% for the Alameda and Harry Bridges Crossing. Figure 10 compares the range of threshold probabilities to the probability region for the terminal bottom upgrade decision. (It is important to note however in comparing these probability ranges that the conditions on L and differ for each facility as shown in Table 2.) Not surprisingly, given this choice of costs, the conditions on the *Harden at Next Upgrade Scenarios* for each of these facilities becomes progressively less extreme -- that is, require less rapid sea level rise, shorter facility lifetimes, and less increase in storminess -- as the height of the infrastructure above mean sea level becomes lower.

PoLA estimated that the cost of hardening at the next upgrade would be roughly 25% of the upgrade cost for each of the four facilities shown in Table 2, a much higher cost for all the examples except the Alameda and Harry Bridges Crossing. The results in Table 2 thus suggest two main conclusions for PoLA. First, of the facilities considered, the Alameda and Harry Bridges Crossing is the only location, which merits serious consideration to harden against rapid sea level rise at the currently estimated costs. Second, PoLA would have to develop strategies for hardening five or 250 times lower than their current estimates to make a hardening at the next upgrade decision reasonable for the other facilities considered here.

6. Caveats

The scientific and decision-analyses hinge on many simplifications that introduce important caveats and also point to future research. In general, these simplifications are intended to reduce the computational complexity of the decision analysis to manageable (but still nontrivial) levels and to simplify the communication with decision-makers. Below, we briefly discuss key examples of these simplifications.

First, the analysis neglects many, likely important uncertainties and processes. For example, the sea-level projections neglect the observed sensitivities on different climate forcing projections (cf. Meehl et al, 2007, Pardaens et al, 2011). Furthermore, the simple sea-level rise model fails to account for the complex mixture of response time-scales (cf. Holgate et al, 2007; Siddall et al, 2010, Kemp et al, 2011). One case in point is the approximation that future changes in the dynamics of the system (e.g., due to changes in ice-flow dynamics) intruce a step-function change in the rate of sea-level rise. One promising strategy to mitigate these issues is to use more complex models that resolve more of the relevant processes using physically motivated parameterizations (cf. Irvine et al, 2012).

Second, sorting the parameters into just two categories (i.e., either "well characterized" or "deeply uncertain") is a crude approximation. As an example, there are considerable structural uncertainties about the most appropriate mixture of functional forms to adopt for the sea-level rise model (cf. von Storch et al, 2008). In addition, some fraction of past sea-level changes are due to changes in land-ice and model hindcasts and projections of this component are deeply uncertain (e.g., Church et al, 2008; Milne et al, 2009, Pollard, 2010; Pfeffer 2011).

7. Concluding Observations

This study examines how an organization such as the Port of Los Angeles can evaluate the potential for presumably low probability but large impact levels of extreme future sea level rise in its infrastructure investment decisions. Considering such extreme climate changes can prove difficult because of the deep uncertainty involved, not only in any scientific projections, but also regarding any expectations of future socio-economic conditions that may affect judgments about the value of alternative near-term infrastructure investments.

This study addresses this challenge by employing robust decision making (RDM) to address the question: should PoLA make an additional investment to harden its facilities against potential extreme future sea level rise during the next major upgrade of those facilities? RDM represents one of a number of new decision analytic approaches that address deep uncertainty by beginning with a specific set of options facing a decision maker and then identifying specific information about the uncertain future that might affect the decision makers' choice among those options. RDM implements what has been called a "context first" or "vulnerability and robust response" analysis by answering two questions: 1) under what future conditions would a PoLA decision to harden its facilities at the next upgrade pass a cost-benefit test and 2) does current science and other available information suggest such conditions are sufficiently likely to justify such an investment?

In particular, this study's RDM analysis conducts a cost-benefit analysis of a PoLA decision to harden at the next upgrade over 500 cases representing a wide range of assumptions about future sea level rise and its future facility management; uses a cluster analysis on the resulting database of simulation model outcomes to concisely describe scenarios where a decision to harden passes a cost-benefit test; estimates a probably threshold for those scenarios, that is the likelihood PoLA would need to ascribe to the scenario to choose to harden; and then evaluating the scientific evidence that would suggest whether the scenario is sufficiently likely or unlikely to justify a decision to harden.

This study conducts such an RDM analysis for four PoLA facilities of varying height above mean sea level: the underside of the container ship terminals, the top of those terminals, Berths 206-209, and the Alameda and Harry Bridges Crossing. Given the assumptions and decision-criteria embedded in our analysis, a decision to harden at the next upgrade merits serious consideration only for one out of the four facilities considered, the Alameda and Harry Bridges Crossing. PoLA would need to identify hardening costs 5, 25 and 250 times lower than current estimates to warrant additional study for Berths 206-209, the terminal bottoms, and terminal tops, respectively.

This study also compares its RDM analysis of a decision to harden the terminal bottoms to a full probabilistic analysis. Such an analysis begins by using the best available science to estimate a single joint probability distribution for the uncertain model inputs parameters and then uses these distributions to estimate the expected savings from an investment to harden and the probability that such an investment passes the cost-benefit test.

The RDM and full probabilistic analyses give similar recommendations to PoLA regarding the investment considered here, but provide different information to decision makers and envision different types of engagement with stakeholders. The full probabilistic analysis begins with the best scientific estimate and provides decision makers with a probability distribution of the expected savings from an investment to harden. The RDM analysis describes the conditions where such an investment would pass a cost-benefit test, estimates the probability such a scenario would have to have to justify making the investment, and assembles the scientific evidence that can help a decision maker judge whether or not the investment is worthwhile. In situations where decision makers have confidence in the best scientific estimates of the probability distributions, the full probabilistic analysis provides a more streamlined approach. But in situations, such as those faced by PoLA as it considers the potential for extreme sea level rise, where the scientific estimates of probabilities are at best imprecise, approaches such as RDM may provide a more convenient and transparent framework for organizing the relevant scientific information and applying it to the decision.

Acknowledgements

This study was partially supported by the U.S. National Science Foundation (Grant SES-0345925) and the Penn State Center for Climate Risk Management. Helpful discussions and comments from Nathan Urban, Patrick Applegate, Brian Tuttle, Tad Pfeffer, and one anonymous reviewers are gratefully acknowledged. All errors and opinions are those of the authors.

REFERENCES

Alley, R. B., P. U. Clark, P. Huybrechts, and I. Joughin (2005), Ice-sheet and sea-level changes, *Science*, *310*(5747), 456-460.

Allison, I., R. B. Alley, H. A. Fricker, R. H. Thomas, and R. C. Warner (2009), Ice sheet mass balance and sea level, *Antarctic Science*, *21*(5), 413-426.

Anthoff, D., R. J. Nicholls, and R. S. J. Tol (2010), The economic impact of substantial sea-level rise, *Mitigation and Adaptation Strategies for Global Change*, *15*(4), 321-335.

Applegate, P. J., N. Kirchner, E. J. Stone, K. Keller, and R. Greve (2011), Preliminary assessment of parametric uncertainty in projections of Greenland Ice Sheet behavior, *The Cryosphere - Discussion.*, *www.the-cryosphere-discuss.net/5/3175/2011/*, doi:10.5194/tcd-5195-3175-2011.

Bromirski, P. D., R. E. Flick, and D. R. Cayan (2003), Storminess variability along the California coast: 1858-2000, *J Climate*, *16*(6), 982-993.

Bromirski, P. D., A. J. Miller, R. E. Flick, and G. Auad (2011), Dynamical suppression of sea level rise along the Pacific coast of North America: Indications for imminent acceleration, *Journal of Geophysical Research-Oceans*, *116*.

Brown, C. (2010), The End of Reliability, *Journal of Water Resources Planning and Management*, 143-145.

Bryant, B. P., and R. J. Lempert (2010), Thinking inside the box: A participatory, computer-assisted approach to scenario discovery, *Technological Forecasting and Social Change*, *77*(1), 34-49.

Bryant, B. P., and R. J. Lempert (2010), Thinking inside the box: A Participatory, computer-assisted approach to scenario discovery, *Technological Forecasting and Social Change*, *77*, 34-49.

Bursztyn, D., and D. M. Steinberg (2006), Comparison of designs for computer experiments, *Journal of Statistical Planning and Inference*, *136*(3), 1103-1119.

Caldwell, P. (2010), Joint Archive for Sea Level: Research Quality Data, edited, p. http://uhslc.soest.hawaii.edu/jasl.html, University of Hawaii, Honolulu.

Carter, T. R., R. N. Jones, S. B. X. Lu, C. Conde, L. O. Mearns, B. C. O'Neill, M. D. A. Rounsevell, and M. B. Zurek (2007), New Assessment Methods and the Characterisation of Future Conditions, in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by M. L. Parry, O. F. Canziani, J. P. Palutikof, P. J. v. d. Linden and C. E. Hanson, pp. 33-171, Cambridge University Press, 1, Cambridge, UK,.

Cayan, D. R., P. D. Bromirski, K. Hayhoe, M. Tyree, M. D. Dettinger, and R. E. Flick (2008), Climate change projections of sea level extremes along the California coast, *Climatic Change*, *87*, S57-S73.

Church, J. A., and N. J. White (2006), A 20th century acceleration in global sea-level rise, *Geophysical Research Letters*, *33*(1).

Church, J. A., N. J. White, T. Aarup, W. S. Wilson, P. L. Woodworth, C. M. Domingues, J. R. Hunter, and K. Lambeck (2008), Understanding global sea levels: past, present and future, Sustainability Science, 3(1), 9-22.

Church, J. A., J. R. Hunter, K. L. McInnes, and N. J. White (2006), Sea-level rise around the Australian coastline and the changing frequency of extreme sea-level events, *Australian Meteorological Magazine*, *55*(4), 253-260.

Co-CAT (2010), State of California Sea-Level Rise Interim Report, edited, Coastal and Ocean Working Group of the California Action Team, www.opc.ca.gov/webmaster/ftp/project.../SLR_Guidance_Document.pdf, accessed March 03, 2011.

Dessai, S., and M. Hulme (2007), Assessing the Robustness of Adaptation Decisions to Climate Change Uncertainties: A Case Study on Water Resources Management in the East of England, *Global Environmental Change*, *17*(1), 59-72.

Douglas, B. C. (1992), Global sea-level acceleration, *Journal of Geophysical Research-Oceans*, *97*(C8), 12699-12706.

Grinsted, A., J. C. Moore, and S. Jevrejeva (2010), Reconstructing sea level from paleo and projected temperatures 200 to 2100 ad, *Climate Dynamics*, *34*(4), 461-472.

Hanson, S., R. Nicholls, N. Ranger, S. Hallegate, J. Corfee-Morlot, C. Herweijer, and J. Chateau (2011), A global ranking of port cities with high exposure to climate extremes, Climate Change, 104, 89-111.

Holgate, S., S. Jevrejeva, P. Woodworth, and S. Brewer (2007), Comment on "A semi-empirical approach to projecting future sea-level rise", Science, 317(5846).

Hosking, J. R. M. (1990), L-moments – Analysis and estimation of distribution using linear-combinations of order statistics, *Journal of the Royal Statistical Society Series B-Methodological*, *52*(1), 105-124.

Irvine, P. J., R. Sriver, and K. Keller (2012), Tension between reducing sea-level rise and global warming through solar radiation management, *Nature Climate Change*mailto:, Advanced online publication, doi:10.1038/nclimate1351 .

Jevrejeva, S., A. Grinsted, J. C. Moore, and S. Holgate (2006), Nonlinear trends and multiyear cycles in sea level records, *Journal of Geophysical Research-Oceans*, *111*(C9).

Jevrejeva, S., J. C. Moore, A. Grinsted, and P. L. Woodworth (2008), Recent global sea level acceleration started over 200 years ago?, *Geophysical Research Letters*, *35*(8).

Jonkman, S. N., M. Kok, and J. K. Vrijling (2008), Flood risk assessment in the Netherlands: A case study for dike ring South Holland, *Risk Analysis*, *28*(5), 1357-1373.

Keller, K., M. Schlesinger, and G. Yohe (2008), Managing the risks of climate thresholds: Uncertainties and information needs, *Climatic Change*, *91*, 5-10.

Kemp, A. C., B. P. Horton, J. P. Donnelly, M. E. Mann, M. Vermeer, and S. Rahmstorf (2011), Climate related sea-level variations over the past two millennia, *Proceedings of the National Academy of Sciences of the United States of America*, *108*(27), 11017-11022.

Knutti, R., R. Furrer, C. Tebaldi, J. Cermak, and G. A. Meehl (2010), Challenges in Combining Projections from Multiple Climate Models, *J Climate*, *23*(10), 2739-2758.

Lempert, R., N. Nakicenovic, D. Sarewitz, and M. Schlesinger (2004), Characterizing climate-change uncertainties for decision-makers - An editorial essay, *Climatic Change*, *65*(1-2), 1-9.

Lempert, R. J., and S. W. Popper (2005), High-Performance Government in an Uncertain World,, in *High Performance Government: Structure, Leadership, and Incentives*, edited by R. K. a. P. Light, The RAND Corporation., Santa Monica: .

Lempert, R. J., and M. Collins (2007), Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches, *Risk Analysis*, *27*(4), 1009-1026.

Lempert, R. J., S. W. Popper, and S. C. Bankes (2003), *Shaping the next one hundred years: new methods for quantitative, long-term policy analysis*, 187 pp., RAND corporation, Santa Monica, CA.

Lempert, R. J., S. W. Popper, and S. C. Bankes (2003), *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-term Policy Analysis*, xxi, 187 p. pp., RAND Corporation, Santa Monica, CA.

Mastrandrea, M. D., et al. (2010), Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties*Rep.*, Intergovernmental Panel on Climate Change.

Meehl, G. A., et al. (2007), Global Climate Projections, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor and H. L. Miller, pp. 747-845, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Mendez, F. J., M. Menendez, A. Luceno, and I. J. Losada (2007), Analyzing monthly extreme sea levels with a time-dependent GEV model, *Journal of Atmospheric and Oceanic Technology*, *24*(5), 894-911.

Menendez, M., and P. L. Woodworth (2010), Changes in extreme high water levels based on a quasi-global tide-gauge data set, *Journal of Geophysical Research-Oceans*, *115*.

Milne, G. A., W. R. Gehrels, C. W. Hughes, and M. E. Tamisiea (2009), Identifying the causes of sea-level change, *Nature Geoscience*, *2*(7), 471-478.

Oppenheimer, M., B. C. O'Neill, and M. Webster (2008), Negative learning, *Climatic Change*, *89*(1-2), 155-172.

Pardaens A. K.; Lowe J. A.; Brown S. et al, (2011), Sea-level rise and impacts projections under a future scenario with large greenhouse gas emission reductions, *Geopshyical Research Letters*, L12604, DOI: 10.1029/2011GL047678.

Pfeffer, W. T., J. T. Harper, and S. O'Neel (2008), Kinematic constraints on glacier contributions to 21st-century sea-level rise, *Science*, *321*, 1340–1343.

Pfeffer, W. T. (2011), Land ice and sea level rise: A thirty-year perspective, Oceanography, 24(2), 94-111.

Pollard, D. (2010), A retrospective look at coupled ice sheet-climate modeling, *Climatic Change*, *100*(1), 173-194.

Purvis, M. J., P. D. Bates, and C. M. Hayes (2008), A probabilistic methodology to estimate future coastal flood risk due to sea level rise, *Coastal Engineering*, *55*(12), 1062-1073.

Rahmstorf, S. (2007), A semi-empirical approach to projecting future sea-level rise, *Science*, *315*(5810), 368-370.

Rahmstorf, S. (2010), A new view on sea level rise, *Nature*, *4*(April), 44-45.

Ranger, N., A. Millner, S. Dietz, S. Fankhauser, A. Lopez, and G. Ruta (2010), Adaptation in the UK: a decision making process*Rep.*

Reeder, T., and N. Ranger (2011), How Do You Adapt in an Uncertain World? Lessons From the Thames Estuary 2100 Project*Rep.*, World Resources Report, Washington DC.

Rosenzweig, C. (2010), Climate Change Adaptation in New York City: Building a Risk Management Response*Rep.*, New York.

Rosenzweig, C., et al. (2011), Developing coastal adaptation to climate change in the New York City infrastructure-shed: process, approach, tools, and strategies, *Climatic Change*, *106*(1), 93-127.

Siddall, M., et al. (2010), The sea-level conundrum: case studies from palaeo-archives, *Journal of Quaternary Science*, *25*(1), 19-25.

Siddall, M., M. R. Kaplan, J. M. Schaefer, A. Putnam, M. A. Kelly, and B. Goehring (2010), Changing influence of Antarctic and Greenlandic temperature records on sea-level over the last glacial cycle, Quaternary Science Reviews, 29(3-4), 410-423.

Solow, A. R. (1985), Bootstrapping correlated data, *Math. Geol.*, *17*, 769–775.

Sriver, R., R. Tonkonjenkov, N. Urban, and K. Keller (2012), What is the defensible upper limit of projected sea-level rise in 2100?, *projected for submission to Nature Climate Change*, *in prep.*, available from the authors in request: please email: klaus@psu.edu.

TRB (2008), Potential Impacts of Climate Change on U.S. Transportation:*Rep.*, Transportation Research Board.

van Dantzig, D. (1956), Economic decision problems for flood prevention, *Econometrica*, *24*(3), 276-287.

Vellinga, P., et al. (2009), Exploring high-end climate change scenarios for flood protection of the Netherlands*Rep.*, http://www.knmi.nl/bibliotheek/knmipubWR/WR2009-2005.pdf pp, KNMI, De Bilt.

von Storch, H., E. Zorita, and J. F. Gonzalez-Rouco (2008), Relationship between global mean sea-level and global mean temperature in a climate simulation of the past millennium, Ocean Dynamics, 58(3-4), 227-236.

Vrijling, J. K. (2001), Probabilistic design of water defense systems in The Netherlands, *Reliability Engineering & System Safety*, *74*(3), 337-344.

Walsh, K. J. E., H. Betts, J. Church, A. B. Pittock, K. L. McInnes, D. R. Jackett, and T. J. McDougall (2004), Using sea level rise projections for urban planning in Australia, *Journal of Coastal Research*, *20*(2), 586-598.

Woodworth, P. L., and D. L. Blackman (2004), Evidence for systematic changes in extreme high waters since the mid-1970s, *J Climate*, *17*(6), 1190-1197.

Woodworth, P. L., N. J. White, S. Jevrejeva, S. J. Holgate, J. A. Church, and W. R. Gehrels (2009), Evidence for the accelerations of sea level on multi-decade and century timescales, *International Journal of Climatology*, *29*(6), 777-789.

TABLES

	RDM Uncertainty Characterization	Full Probabilistic Uncertainty Characterization
Future Sea Level Sea level rise in 2011 (a)	Well-characterized joint probability distribution for a, b, and c as show in in Figure 3b.	Well-characterized joint probability distribution for a, b, c, c*, and t*.
Normal rate of sea level rise (b)		
Normal sea level rise acceleration (c)		
Rate of abrupt sea level rise (c*)	**Deeply uncertain** with range: 0 to 30 mm/yr	
Year abrupt rise begins (t*)	**Deeply uncertain** with range: 2010 to 2100	
Daily anomaly location (μ)	**Deeply uncertain** set of GEV distributions, with scale ranging from $\psi = 517$ to 569, constant shape $\xi = -0.305$, and location $\mu = -176 + 0.1033(\psi - 517)$ (constant mean).	Set of GEV distributions with constant shape $\xi = -0.305$, uniform distribution over scale $517\text{ mm} \le \psi \le 543\text{ mm}$, and corresponding location $\mu = -176\text{mm}$ $+0.1033(\psi - 517\text{mm})$
Daily anomaly scale (ψ)		
Daily anomaly shape (ξ)		
Future Terminal Management Lifetime (L)	**Deeply uncertain** with range: 30 to 100 years	Consider a range of 30 to 100 years
Max allowable overtop probability (p_{crit})	**Deeply uncertain** with range: 5% to 50% per year	Consider uniform distribution over range 5% to 50% per year
Decision Year	Known at decision time: 2020	Known at decision time: 2020
Height (H) above mean sea level	Known at decision time: 2804 mm	Known at decision time: 2804 mm
Current hardening cost ($C_{Harden}/C_{upgrade}$)	Known at decision time: 1%	Known at decision time: 1%
Discount rate (d)	Known at decision time: 5%	Known at decision time: 5%

Table 1: Parameters affecting PoLA's decision whether or not to harden terminals at next upgrade and the treatment of the uncertainty in those parameters. Height and hardening cost values for decision regarding PoLA terminals discussed in Section 3.

	Terminal (top)	Terminal (bottom)	Berths 206-209	Alameda and Harry Bridges Crossing
Infrastructure Characteristics				
MSL Height (H)	12.14 ft 3700 mm	9.20 ft 2804 mm	7.62 ft 2323 mm	6.13 ft 1868 mm
Cost (% of upgrade)	0.1%	1%	5%	25%
Harden at Next Upgrade Scenario				
Year 2010 intercept and slope of condition for c* and t*	14 mm/yr 0.3 mm/yr^2	14 mm/yr 0.3 mm/yr^2	11 mm/yr 0.4 mm/yr^2	5 mm/yr 0.4 mm/yr^2
L > (years)	75	50	50	30
ψ >	543 mm (5%)	533 mm (3%)	522 mm (1%)	527 mm (2%)
Coverage/ Density	40% / 68%	63% / 96%	66% / 98%	78% / 91%
Probability Thresholds and Estimates				
P_{Thres}	11%	7%	10%	14%
$P_{c*,t*}$ =	14-16%	14-16%	13-16%	34-35%
$P_L * P_\psi$ >	69-79%	44-50%	63-77%	40-41%

Table 2: Characteristics and results of RDM analysis for four sets of PoLA infrastructure: terminal (bottom) discussed in Section 3; terminal (top), Berths 206-209, and the Alameda and Harry Bridges Crossing.

FIGURES

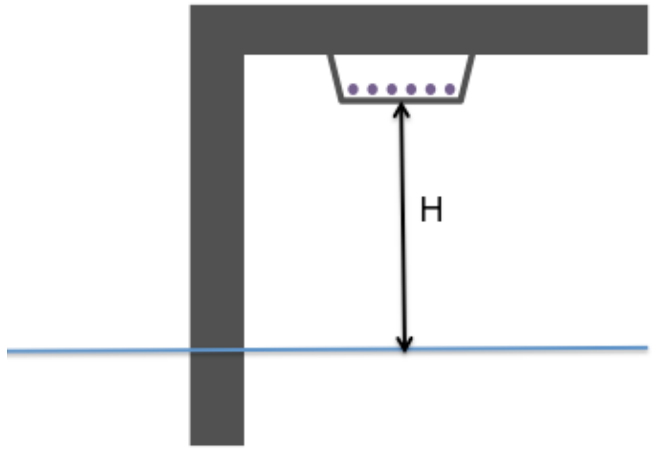

Fig 1: Schematic of PoLA container ship terminal showing height (H) above mean sea level

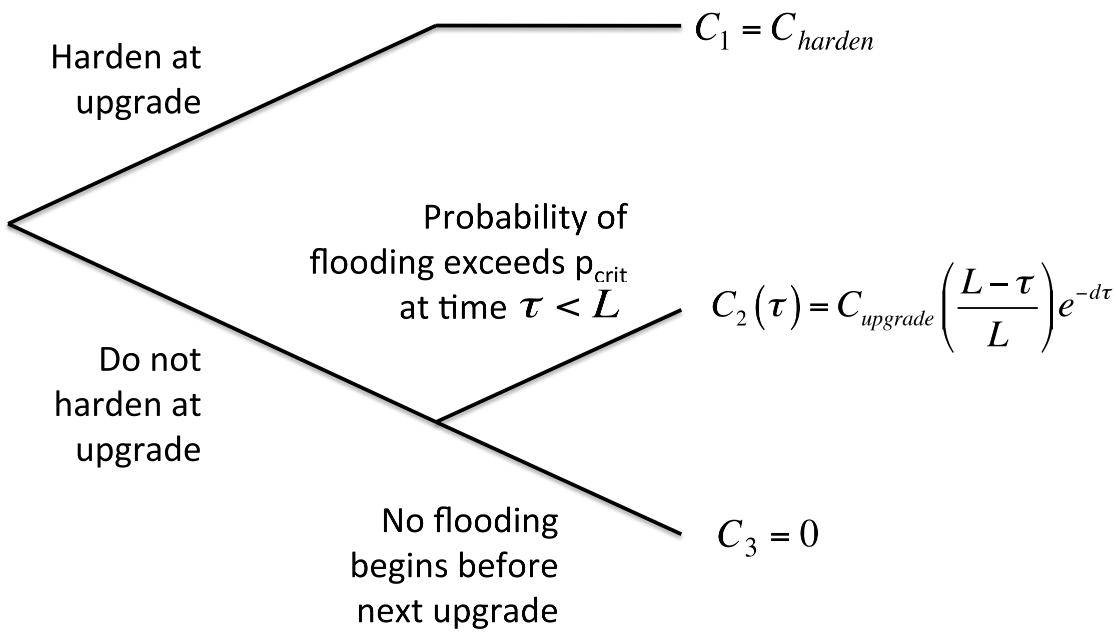

Fig 2: Simplified representation of PoLA's decision regarding whether or not to harden their terminal at its next upgrade and the costs resulting from its choices.

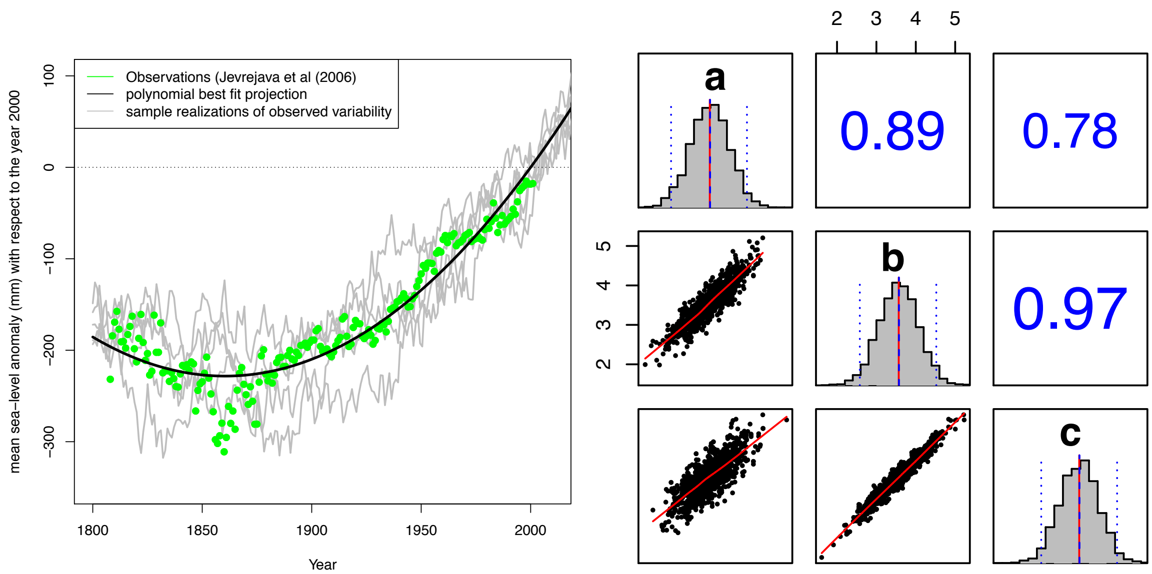

Figure 3: Observed annually and globally averaged sea-level anomalies [*Jevrejeva et al.*, 2006] (green circles), the polynomial model best fit to the observations (black line) and model hindcast scenarios (grey lines) that sample the unresolved variability (left panel). The uncertainties in the resulting parameter estimates for a, b, and c as well as the absolute value of the parameter correlation coefficient (numbers in blue font) are shown in the right panel.

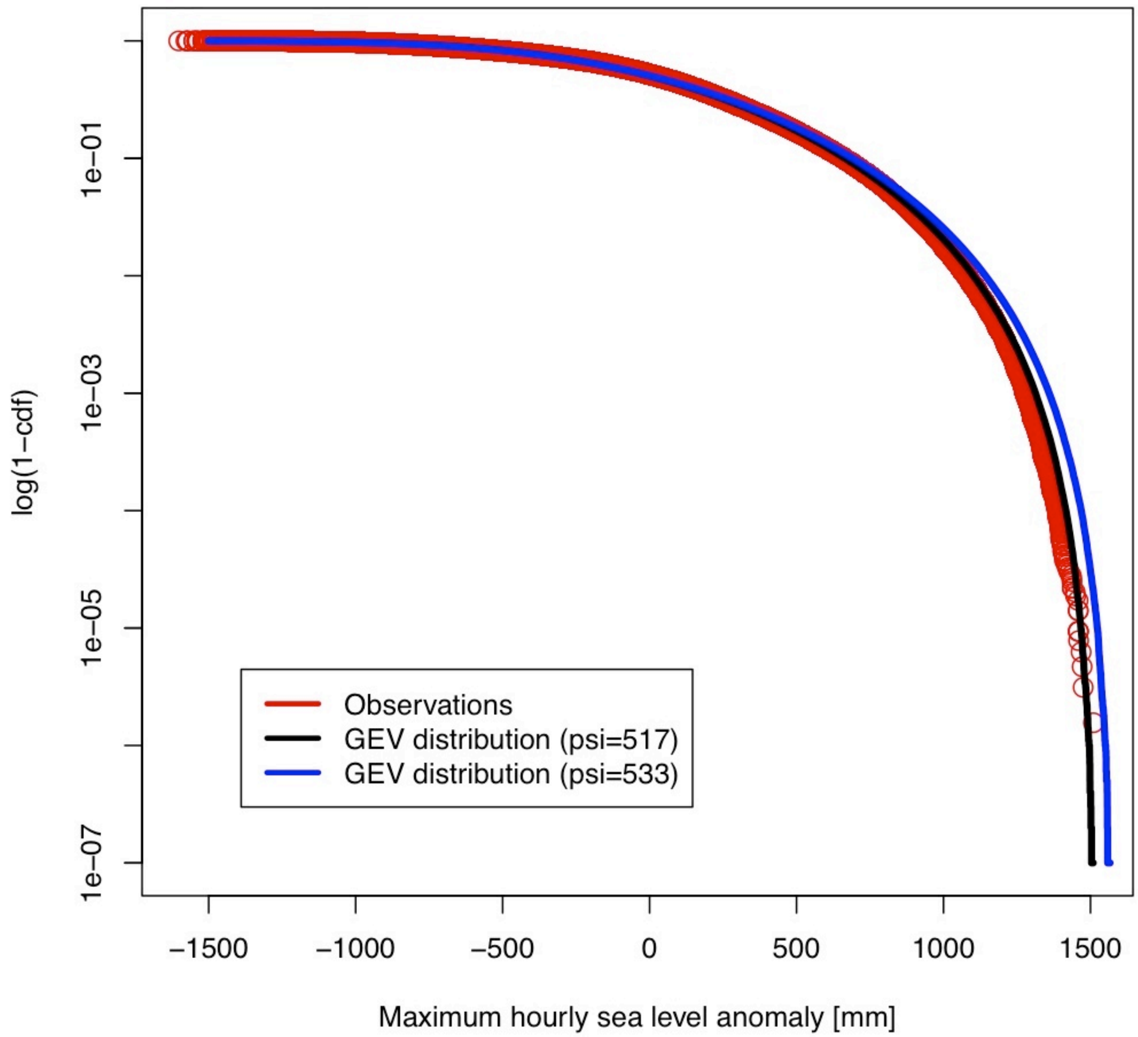

Figure 4: Black line shows General Extreme Value (GEV) distribution fitted to the hourly sea-level anomalies with respect to the annual mean value observed close to PoLA [*Caldwell*, 2010]. The estimated GEV distribution parameters are given in Table 1. Blue line shows GEV distribution with an expanded scale parameter of $\psi = 533\text{mm}$ considered in the decision analysis as described in the text.

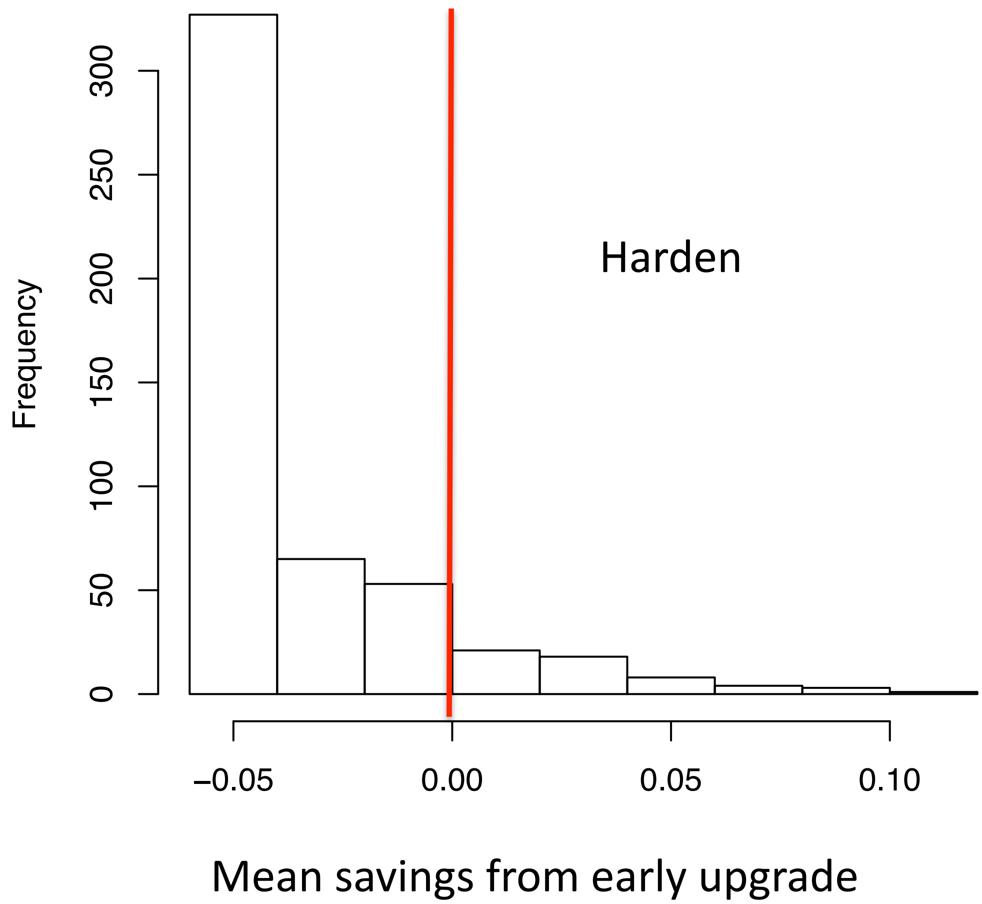

Figure 5: Histogram of model results generated with 500-point Latin hypercube sample over deeply uncertain parameters in Table 1. Positive values indicate cases in which hardening at next upgrade passes a cost-benefit test.

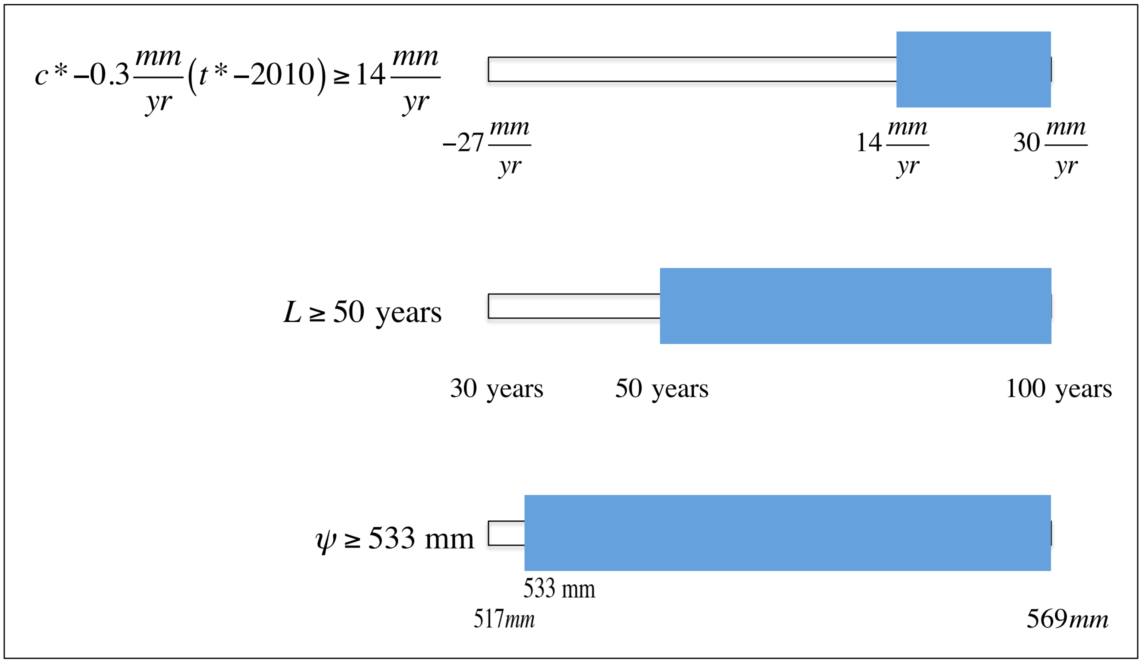

Figure 6: Parameter ranges defining the *Harden at Next Upgrade Scenario*. The blue boxes represent show the conditions under which a decision to harden at the next upgrade would pass a cost-benefit test.

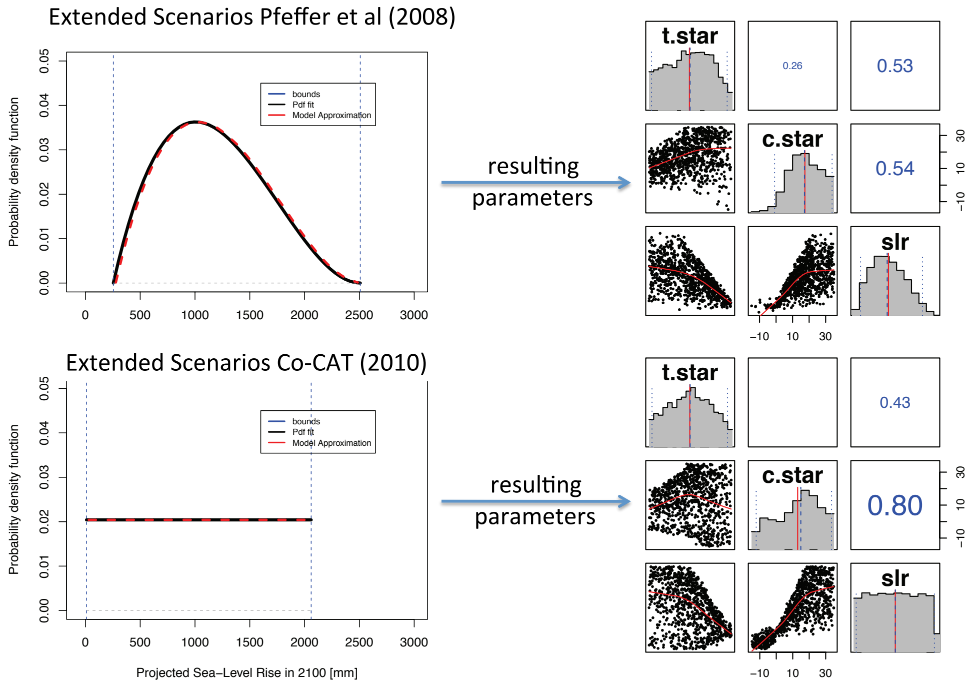

Figure 7: Parameter estimates resulting from the model calibration to the: a) extended scenarios of *Pfeffer et al* [2008] and b) the *Co-Cat* (2010) scenarios. The former uses a beta distribution and the latter a uniform distribution, and both begin with a uniform prior, as described in text.

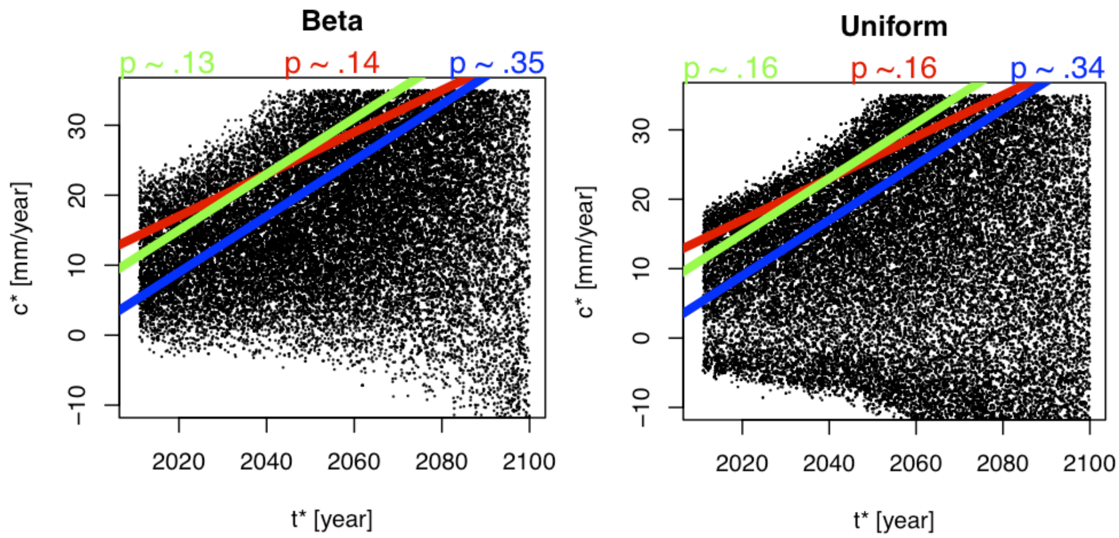

Figure 8: Red line shows estimates of the likelihood of the first condition describing the Harden at Next Upgrade Scenario shown in Figure 6, using the: a) beta distribution fit to the projections of *Pfeffer et al* [2008] and b) the uniform distribution fit to the projections of *Co-Cat* (2010) shown in Figure 7. Green and blue lines show analogous condition for two other PoLA facilities, Berths 206-209 and Alameda and Harry Bridges Crossing, respectively, as shown in Table 2.

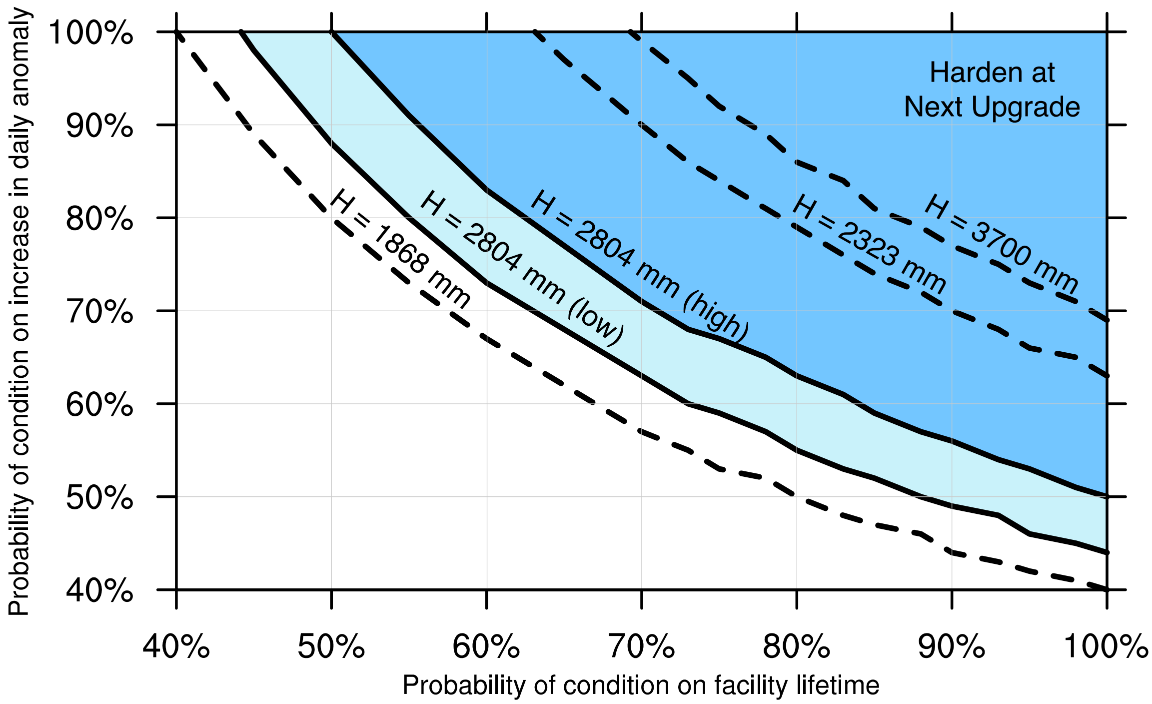

Fig 9: Probabilities of a long terminal lifetime (L> 50 years) and significant increase in the daily anomaly (ψ > 533 mm) required for decision to harden terminal bottoms (H = 2804 mm) at next upgrade to pass a cost-benefit test. Dark and light shaded regions show probabilities required using high and low estimates, respectively, of likelihood of condition on c* and t*. Dashed lines show boundary of probability regions for decisions to harden the other three facilities described in Table 2, which also lists the specific conditions for L and ψ in each case.

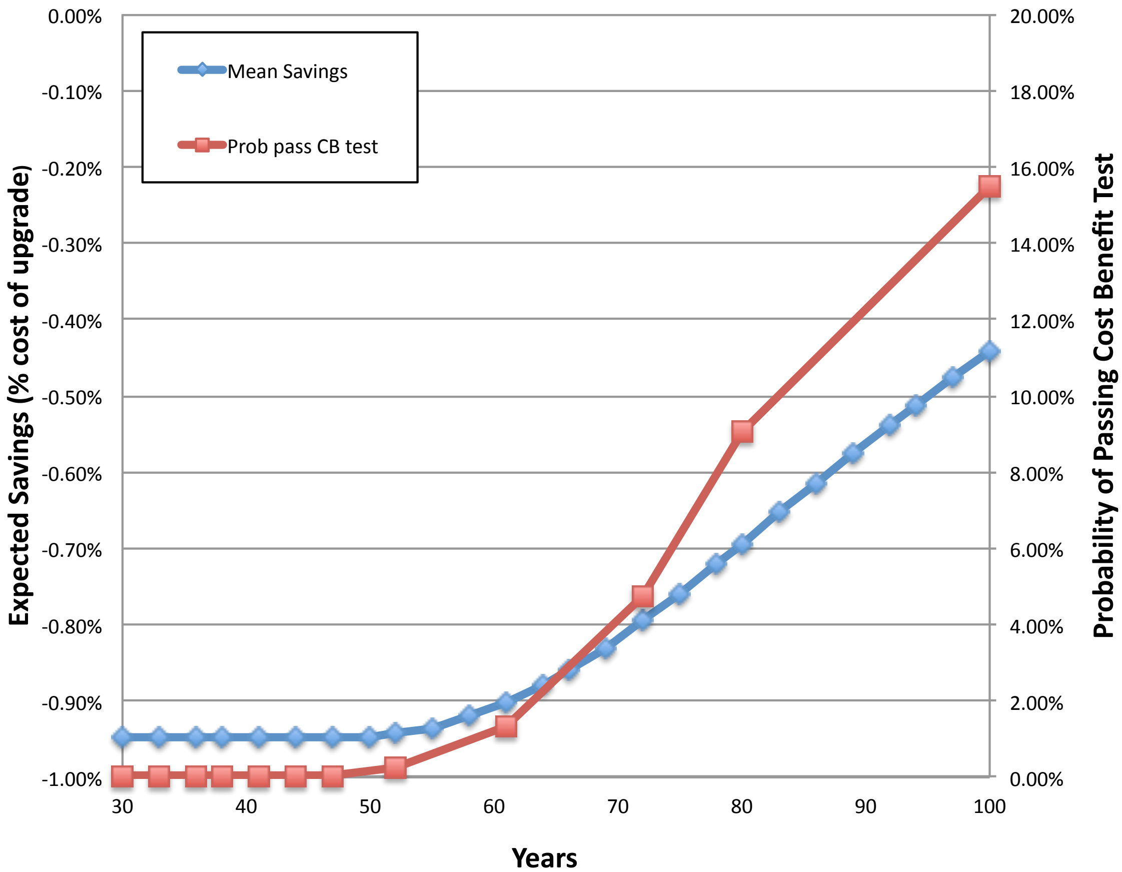

Fig 10: Results of full probabilistic analysis showing expected cost of hardening at next upgrade and probability of passing a cost benefit test as a function of the terminal lifetime.

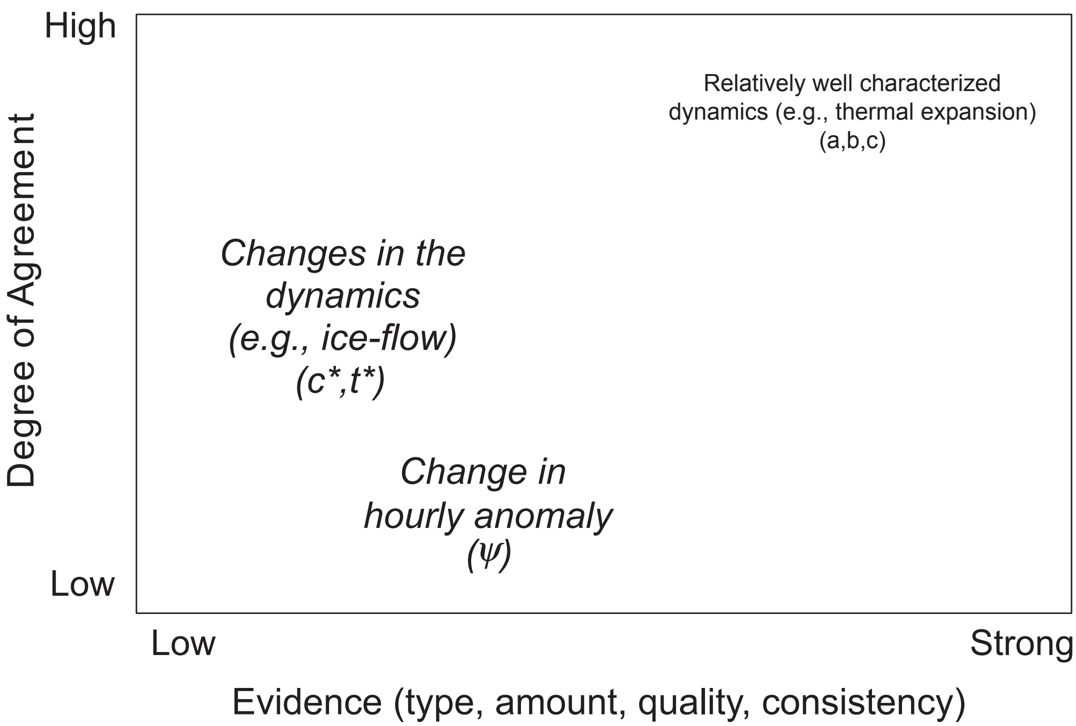

Fig 11: Assessment of the evidence and level of agreement underlying the scientific information used in this analysis, following the characterization method of [*Mastrandrea et al.*, 2010]. Size of text reflects importance of information to PoLA's decision. Italics show factor considered deeply uncertain in the RDM analysis.