PROBABILISTIC SEA-LEVEL RISE HAZARD ANALYSIS

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This paper proposes a framework termed Probabilistic Sea-Level Rise Hazard Analysis (PSLRHA), to integrate the sea-level rise knowledge of current climate change scientific communities for informed engineering and policy decisions that affect coastal infrastructure, populations, and ecosystems. PSLRHA combines probabilities of all emission scenarios with predictions of the resulting sea-level rise over time, in order to compute sea-level rise hazard. PSLRHA also incorporates uncertainties in those sea-level rise predictions, by considering multiple Sea-Level Rise Prediction Models (SLRPMs). The output of the PSLRHA framework could be a Global Sea-Level Rise Hazard Map (GSLRHM) that can be used for Performance-Based Sea-Level Rise Engineering (PBSLRE).

Keywords: Climate change, sea-level rise, probabilistic hazard analysis, prediction models, emission scenarios, uncertainties, decision making, hazard map, performance-based.

1. Introduction

The release of the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4) sent an alarming message of anthropogenic warming induced sea-level rise (SLR), as a result of thermal expansion as well as ice melt from glaciers and ice sheets (Bernstein et al., 2007). More alarmingly, recent satellite observations (Cazenave et al., 2009) and tide gauge measurements (Church and White, 2006) showed even higher SLR than previously predicted by IPCC AR4. As SLR knowledge advanced, different researchers constructed and updated Sea-Level Rise Prediction Models (SLRPMs) that estimated different SLR over various time frames (e.g., WBGU, 2006; Vermeer and Rahmstorf, 2009) based on various emission scenarios (Nakicenovic et al., 2000). Significant uncertainties, both aleatory and epistemic, remain in SLR predictions, especially with regard to ice sheet contributions. Engineering and policy decisions, on the other hand, need to be made in response to SLR regarding affected coastal infrastructure, populations, and ecosystems.

Probabilistic hazard analysis has been performed for other hazards, notably that of earthquakes. Cornell (1968) introduced the concept of hazard and risk analysis to the civil engineering community for seismic design of structures, which set the foundation for Probabilistic Seismic Hazard Analysis (PSHA) and its subsequent risk assessment termed Performance-Based Earthquake Engineering (PBEE). This framework has helped the construction of the United States National Seismic Hazard Map (Petersen et al., 2008), enabled site- and structure-specific hazard analysis (McGuire, 2004) that resulted in more optimized structural design and analysis, and facilitated engineering communication with stakeholders and decision makers (Deierlein, 2004). While there are multiple prediction models for sea-level rise, and there is no consensus on which one to use, the concepts of probabilistic hazard analysis could be useful for

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combining the predictions from all the models to inform decision makers.

This paper proposes a framework termed Probabilistic Sea-Level Rise Hazard Analysis (PSLRHA), to integrate the SLR knowledge of current climate change scientific communities for informed engineering and policy decisions. PSLRHA combines probabilities of all emission scenarios with predictions of the resulting sea-level rise over time, in order to compute sea-level rise hazard at any given site. PSLRHA also incorporates uncertainties in those sea-level rise predictions, by considering multiple SLRPMs.

2. Emission Scenarios

Sea-level rise is currently understood to be related to temperature change resulting from anthropogenic activities (Bernstein et al., 2007) that increased emissions of greenhouse gases. Emission scenarios, expressed as a function of socio-economic parameters, are often used as inputs to get climate response in order to project sea-level rise. The most commonly used emission scenarios are the six illustrative scenarios from the Special Report on Emissions Scenarios (SRES): A1FI, A1B, A1T, A2, B1, and B2 (Nakicenovic et al., 2000). The driving forces underlying these emission scenarios include population, economy, technology, energy, and agriculture (land-use), among others. While these SRES scenarios are widely used in literature (e.g., Bernstein et al., 2007; Vermeer and Rahmstorf, 2009), some researchers raised questions regarding the plausibility of the scenarios that for instance assumed the implementation of sulfur dioxide emission reduction policy by 2040 in all scenarios (Webster et al., 2003) and had no likelihood assigned to each scenario leading to misinterpretations of the underlying distributions (Schneider, 2001). In the absence of better alternatives, these SRES may be used to assess sea-level rise. However, the assumptions that were used to construe these scenarios must be clearly stated, to guide the initial and subsequent users and to enable possible updates when more information is available. Alternatively, other scenarios may be used if they are deemed more appropriate.

This study proposes that in the probabilistic hazard analysis, all possible future scenarios should be considered with their corresponding probabilities. In other words, we need to account for the underlying distribution of emission scenario parameters in a fully probabilistic assessment. Aleatory uncertainties (which are naturally inherent) remain in the emission scenario parameters, and may change geographically over time. These uncertainties need to be incorporated. Emission scenarios can also be highly dependent on the absence or presence of policy, and in the case of presence of policy, the extent of control. Caution should be exercised regarding the selection of emission scenarios to represent a plausible future that considers all possibilities.

A prior probability, either uniform or from expert opinion, can be used to assign probability of occurrence for each scenario. This probability can then be updated with measurements and observations to get a posterior probability. Descriptions of this Bayesian updating procedure could be found in textbooks describing decision analysis (e.g., Benjamin and Cornell, 1970).

3. Sea-Level Rise Prediction Models

Numerous models are currently available to predict sea-level rise for various time frames. Many of these models are based on the General Circulation Models (GCMs) that simulate the physical processes and feedbacks in the atmosphere and ocean to estimate the climate response given the forcing scenario (e.g., greenhouse gas concentration input). Some are semi-empirical models that utilize the relationship between temperature change and sea-level rise as well as past observations for calibration (e.g., Vermeer and Rahmstorf, 2009). Others (e.g., Chao et al., 2008) make modifications to account for the effects of dams and reservoirs that change surface runoff into the ocean. These models result in different sea-level rise predictions that need to be reconciled. For instance, the IPCC Fourth Assessment Report (AR4) predicted a SLR of 18-59cm by 2100 (Bernstein et al., 2007), while Vermeer and Rahmstorf (2009) estimated 75-190cm. Furthermore, additional measurements showed a large discrepancy between predictions and observations, especially regarding ice sheet contribution. Recent studies, including that of Vermeer and Rahmstorf (2009), emphasized the potential contribution of ice sheet melt to future large-scale SLR that were substantially underestimated before, e.g., in IPCC AR4. Challenges remain to capture the magnitude and rate of future SLR accurately.

While the models are improving over time, decisions regarding measures to cope with sea-level rise need to be made much sooner. It would be beneficial if we can assemble the available models to arrive at a best estimate with the current state of knowledge. The models we used should capture, to the extent possible, all the relevant uncertainties, especially the uncertainty related to the contribution of ice sheets, as such contribution (consistent with recent observations) would substantially change the SLR projections and impact the subsequent engineering and policy decisions.

This framework of the assembly remains the same, while the decision on which models to include and the weights given to each model may change over time. A logic tree could be used to assign weights to the prediction models for sea-level rise projections. We can simply give equal weight to each model, utilize expert opinions to weight different models (Benjamin and Cornell, 1970), or use high-dimensional information-visualization techniques to guide weight assignment based on the proximity among various models (Scherbaum et al., 2010) in predicting similar SLR. A probabilistic treatment of epistemic uncertainties due to incomplete knowledge about fundamental phenomena is important to reduce bias held by individual experts and to lower the potential of arbitrary truncation of scientific evidence by decision makers (Pate-Cornell, 1996). The same procedures that were used for probabilistic seismic hazard analysis (an interactive procedure in which the experts exchange and debate all available information) could also be utilized here to evaluate the use of experts (SSHAC, 1997).

4. Probabilistic Hazard Analysis Framework

With the emission distribution and prediction model weights, we can obtain the total probability of exceeding a specified sea-level rise over a specified time frame. PSLRHA integrates over all j potential emission sources with their associated rates of occurrence, ν_j, an aleatory source of uncertainties expressed in terms of input parameters Θ_1, Θ_2, ..., Θ_i, in order to compute the rate of exceedance of a sea-level rise magnitude (H) of interest, $\nu(H > y)$. PSLRHA can be performed with multiple SLRPMs, an epistemic source of uncertainties, with various weights assigned to SLRPMs. We explicitly consider the epistemic uncertainty in PSLRHA by incorporating weights of SLRPMs, $P(SLRPM_k)$, into Eq. 1, to compute the total hazard rate using the total probability theorem (Benjamin and Cornell, 1970):

$$\nu(H > y) = \sum_k \sum_j \nu_j \iiint f_{\Theta_1,\Theta_2,...,\Theta_i}(\theta_1, \theta_2, ..., \theta_i) \\ P(H > y|\theta_1, \theta_2, ..., \theta_i, SLRPM_k) d\theta_1 d\theta_2 ... d\theta_i P(SLRPM_k) \tag{1}$$

where $f_{\Theta_1,\Theta_2,...,\Theta_i}(\theta_1, \theta_2, ..., \theta_i)$ is the joint probability density function for emission input parameters θ_1, θ_2, ..., θ_i, and $P(H > y|\theta_1, \theta_2, ..., \theta_i, SLRPM_k)$ is the probability of sea-level H exceeding a value y given θ_1, θ_2, ..., θ_i, and $SLRPM_k$.

Note that Eq. 1 is expressed in terms of sea-level rise magnitude (H) for the time frame of interest as the intensity measure of sea-level rise. If other intensity measures, e.g., the rate of sea-level rise (dH/dt), are used, the equation can be modified to accommodate such changes. Care should be taken to ensure that the intensity measure used in the equation is consistent with the output of the SLRPMs, and that the distributions of the various SLRPM predictions are known. If different emission input parameters Θ_1, Θ_2, ..., Θ_i are used for each SLRPM, they need to be converted to equivalent terms to ensure consistency across various SLRPMs. There should also be efforts in quantifying the joint distribution of the input parameters, $f_{\Theta_1,\Theta_2,...,\Theta_i}(\theta_1, \theta_2, ..., \theta_i)$. The rates of occurrence for potential emission source j, ν_j, need to be determined based on available information in future emission scenarios. For instance, if various emission scenarios are used, their probabilities of occurrence can be determined from Section 2. The weights of SLRPMs, $P(SLRPM_k)$, can be obtained from the suggested methods of assigning SLRPM weights in Section 3. The SLRPMs used can be based on physical models, empirical equations, or the hybrid of the two (analogous to those for ground motions). Global models, e.g., General Circulation Models (GCMs), can be used to estimate sea-level rise at the global scale; local or regional models, e.g., Regional Circulation Models (RCMs), can be used where they are available. The local effect of land subsidence on relative sea-level rise is not caused by anthropogenic warming, but can also be incorporated if total sea-level rise, instead of anthropogenic warming induced sea-level rise, is of interest. To obtain the total hazard, convolution with respect to all the input parameters and models should be carried out.

As the sea-level rise target value y changes, the relative contribution of each emission parameter and prediction model is expected to change. Deaggregation identifies the most important contributing scenario parameters and prediction models for the target hazard of interest (Lin and Baker, 2011). Given the total hazard rate in Eq. 1, we can find the distribution of emission parameters that cause sea-level rise $H > y$ through deaggregation using Bayes' rule. For instance, the conditional distribution of Θ_1 given $H > y$, $f_{\Theta_1|H>y}(\theta_1, y)$, can be computed as follows:

$$f_{\Theta_1|H>y}(\theta_1, y) = \frac{1}{\nu(H > y)} \sum_k \sum_j \nu_j \iint f_{\Theta_1,\Theta_2,...,\Theta_i}(\theta_1, \theta_2, ..., \theta_i) \\ P(H > y|\theta_1, \theta_2, ..., \theta_i, SLRPM_k) d\theta_2 ... d\theta_i P(SLRPM_k) \tag{2}$$

The deaggregation of SLRPMs tells us the probability that the exceedance of a given

H level is predicted by a specific SLRPM, $P(SLRPM_k|H > y)$, as computed below:

$$P(SLRPM_k|H > y) = \frac{1}{\nu(H > y)} \sum_j \nu_j \iiint f_{\Theta_1,\Theta_2,...,\Theta_i}(\theta_1, \theta_2, ..., \theta_i) \\ P(H > y|\theta_1, \theta_2, ..., \theta_i, SLRPM_k) d\theta_1 d\theta_2 ... d\theta_i P(SLRPM_k) \tag{3}$$

The output of the PSLRHA framework could be a "Global Sea-Level Rise Hazard Map (GSLRHM)", similar to that of the United States national seismic hazard map (Petersen et al., 2008). This map can be used to evaluate system performance under sea-level rise hazard through "Performance-Based Sea-Level Rise Engineering (PB-SLRE)". The probabilistic hazard analysis of sea-level rise can also be combined with other hazards such as earthquakes and tsunamis, to evaluate the impact of multiple hazards on any system at any given site. Besides sea-level rise, this framework can be extended to other climate change-induced hazards to guide mitigation and adaptation efforts.

5. Conclusions

The framework of Probabilistic Sea-Level Rise Hazard Analysis (PSLRHA) is proposed to integrate the sea-level rise knowledge of current climate change scientific communities for informed engineering and policy decisions that affect coastal infrastructure, populations, and ecosystems. Global and regional/local SLR estimates can be obtained from various SLR prediction models that are based on various emission scenarios with their underlying distributions. The probability of exceeding a specified SLR over a specified time frame can be computed using the total probability theorem. This probability of SLR exceedance is informative and advantageous compared to a single deterministic value, since PSLRHA explicitly accounts for aleatory uncertainties from emission parameters and epistemic uncertainties from prediction models.

While the PSLRHA framework sets the foundation for decision making, the advancement of this framework requires extensive scientific input and updates, including appropriate treatment of epistemic uncertainties, as SLR knowledge advances. The output of the PSLRHA framework could be a Global Sea-Level Rise Hazard Map (GSLRHM) that can be used for Performance-Based Sea-Level Rise Engineering (PB-SLRE). Ultimately, informed decisions are enabled through GSLRHM and PBSLRE by the probabilistic framework that incorporates sea-level rise hazard based on multiple scenarios, from global and regional/local projections by multiple modelers, for the time frame and design/policy of interest.

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