Addressing Uncertainty In Ensemble Sea-Level Rise Predictions

Matthew A. Thomas  
*Graduate Student, Dept. of Civil, Construction and Environmental Engineering, Marquette University, Milwaukee, USA*

Ting Lin  
*Assistant Professor, Dept. of Civil, Construction and Environmental Engineering, Marquette University, Milwaukee, USA*

**ABSTRACT:** Sea-level rise represents a looming hazard to coastal communities which remains difficult to quantify. Ensemble climate change predictions incorporate epistemic uncertainty in the climate modeling process and climate forcing scenarios help portray a range of radiative forcing changes. This study proposes a method for incorporating both model and scenario uncertainty in ensemble projections of thermosteric sea-level rise. A Markov Chain Monte Carlo algorithm is utilized to weigh the contributions of eight process-based climate models as well as the four Representative Concentration Pathways based on convergence criteria and observational data. Hazard analysis and deaggregation combine these contributions over a range of sea-level rise thresholds and quantify the relative contributions of each pathway and prediction model. The hazard maps generated suggest improved accuracy in modeling regional trends over typical ensembles. Deaggregations effectively represent model and scenario differences and the impacts of the methods used.

1. **INTRODUCTION**

Sea-level rise (SLR) is an ongoing hazard, threatening coastal communities around the world. Semi-empirical SLR models (Vermeer and Rahmstorf, 2009; Grinsted et al., 2010; Kemp et al., 2011; Jevrejeva et al., 2012) and physics-based climate models (Taylor et al., 2012; IPCC, 2013) provide a means of estimating future sea-levels. Quantifying the uncertainty inherent in these SLR predictions will help decision makers understand and account for this hazard.

Uncertainty in SLR estimates is linked to natural climate variability, an incomplete knowledge of the climate system (Paté-Cornell, 1996), and anthropogenic factors (IPCC, 2014) such as population growth, economic growth, policy decisions (Nakicenovic et al., 2000; Webster et al., 2003), and the development of new technologies. A comprehensive analysis of SLR hazard incorporates all sources of uncertainty.

Multimodel ensembles allow researchers to address epistemic uncertainty in climate model predictions, although ensemble results are often difficult to interpret and may ignore extreme behavior (Knutti et al., 2010). Models may be assigned weights to reflect characteristics of the ensemble using criteria such as expert assessments (Horton et al., 2014) or probabilistic methods (Tebaldi and Sans, 2009; Smith et al., 2009). Although powerful, the results of the latter reflect the underlying assumptions of the method used (Lopez et al., 2006). Working Group I of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change utilized equal-weight ensembles for the Representative Concentration Pathways (RCPs) of process-based climate models to project SLR (IPCC, 2013).

The RCPs include four forcing scenarios, RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, numbered by an associated radiative forcing by 2100 in $W/m^2$ (IPCC, 2013). These scenarios range from very low to very high emission pathways but avoid making explicit assumptions about anthropogenic activity. Running climate model simulations along the RCPs is informative but tells us little about the likelihood.

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In earthquake engineering, probabilistic seismic hazard analysis (Cornell, 1968) combines the contributions of many sources and models to quantify the total seismic hazard at a specific site. Lin (2012) suggested a framework for applying this concept to SLR in which the contributions of forcing factors and SLR prediction models are combined to determine total hazard. Hazard may be deaggregated to determine the contributions of individual sources and models.

This study combines a modified version of the univariate Bayesian method for quantifying uncertainty in ensembles of climate models developed by Smith et al. (2009) with Lin (2012)'s proposed framework to determine the total uncertainty in thermosteric SLR predictions, considering the contributions of process-based climate models and climate forcing scenarios. Model ensembles for each RCP scenario and RCP ensembles for each climate model are evaluated using data available from the Fifth Phase of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al., 2012). Hazard maps are developed to represent the likelihood of experiencing SLR above a certain threshold and these results are deaggregated to reveal the relative contributions of different models and scenarios.

2. METHODS

Model and RCP scenarios are evaluated using a Markov Chain Monte Carlo (MCMC) algorithm to calculate posterior distributions and weights for each ensemble. The MCMC results are combined as in Lin (2012)'s framework to generate SLR exceedence maps and deaggregated to calculate the contributions of each model and RCP. Figure 1 details this process.

2.1. Data Selection and Interpolation

This study utilizes a combination of global mean thermosteric SLR and dynamic sea-surface height projections collected by CMIP5. These data sets were combined to create sea-level prediction maps for each model and scenario combination. SLR values are evaluated relative to January 2006, the beginning of the RCP scenarios.

For the purposes of this study only climate models with high-resolution ocean components simulated for each RCP were considered. To minimize correlation between prediction models, only the newest model from each institute was utilized. An exception was made for the MIROC5 and MIROC-ESM-CHEM models which produced significantly different SLR predictions. Table 1 characterizes the climate models meeting these restrictions.

The MCMC algorithm updates ensemble distributions using observational data. In recent years, satellite altimetry has provided an accurate means of measuring regional sea-levels across the globe (Shepherd et al., 2012). This study utilizes a satellite altimetry data set developed by CSIRO combining data collected by the TOPEX/Poseidon, Jason-1 and Jason-2/OSTM satellites. The altimeter data covers sea-levels between 65° latitude north and south of the equator resolved over a 1° by 1° grid. This covers the majority of developed coastlines and is consistent with the resolution and precision of CMIP5 SLR predictions.

To facilitate calculations, the sea-level prediction maps were linearly interpolated to match the al-
Table 1: Process-based General Circulation Models of recent vintage incorporating high-resolution ocean components available from CMIP5

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Institute ID</th>
<th>Vintage</th>
<th>Grid Resolution</th>
<th>Layers‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSIRO-Mk3-6-0</td>
<td>CSIRO-QCCCE</td>
<td>2009</td>
<td>0.9° x 1.875°</td>
<td>31</td>
</tr>
<tr>
<td>GISS-E2R</td>
<td>NASA GISS</td>
<td>2011</td>
<td>1° x 1.25°</td>
<td>32</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>IPSL</td>
<td>2010</td>
<td>2° x 2-0.5°†</td>
<td>31</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td>MIROC</td>
<td>2010</td>
<td>1.4° x 1.4-0.5°†</td>
<td>44</td>
</tr>
<tr>
<td>MIROC5</td>
<td>MIROC</td>
<td>2010</td>
<td>1.4° x 1.4-0.5°†</td>
<td>50</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>MRI</td>
<td>2011</td>
<td>1° x 0.5°</td>
<td>51</td>
</tr>
<tr>
<td>NorESM1-ME</td>
<td>NCC</td>
<td>2012</td>
<td>1.125° x 1.125°</td>
<td>53</td>
</tr>
<tr>
<td>bcc-csm1-1</td>
<td>BCC</td>
<td>2011</td>
<td>1° x 1°</td>
<td>40</td>
</tr>
</tbody>
</table>

† For models with variable grids, resolution is higher near the equator.  ‡ The number of vertical ocean layers incorporated in the model.

Many studies such as Smith et al. (2009) account for natural climate variability through the use of decadal or multidecadal averages. This study utilizes eight year SLR means, limited by the difference between recent altimeter data and the beginning of the RCP scenarios. While not ideal, the limited average is sufficient for this study.

2.2. Bayesian Modeling of Uncertainty in Climate Ensembles

The MCMC algorithm from Smith et al. (2009) is adapted to create posterior probability distributions and weights for sea-level rise prediction models and RCP ensembles. The algorithm incorporates Bayesian updating to produce posterior probability distributions for ensembles of climate models, assigning weights based on convergence criteria and each model’s ability to reproduce sea-level observations.

Smith et al. (2009) propose univariate and multivariate versions of the MCMC algorithm which, respectively, represent regional climate predictions with a single random variable and incorporate terms for regional and model deviations from the global mean. The univariate assumptions prove to be more appropriate for this study as the multivariate assumptions do not scale well from the 22 regions used in Smith et al. (2009) to the thousands of grid points used here.

Equations (1) through (3) define algorithmic assumptions that climate data takes normal distributions with the following means and variances

\[ X_{0i} = N(\mu_{0i}, \lambda_{0i}) \]  
\[ X_{ij} = N(\mu_{i}, \lambda_{ij}) \]  
\[ Y_{ij} = N(\nu_{i}, \lambda_{ij}) \]

where \( X_{0i} \) is the observed sea-level and \( X_{ij} \) and \( Y_{ij} \) represent present and future simulation data for grid point \( i \) and model \( j \). \( \mu_{i} \) and \( \nu_{i} \) represent present and future true global sea-level while \( \lambda_{ij} \) and \( \lambda_{0i} \) represent inter model variability and natural variability as estimated from the eight years of altimeter data respectively. The relative weights of individual models, \( P(S_{ij}) \), in an ensemble are inversely related to the uncertainty for a given model and region. This method for model ensembles is extended to RCP ensembles.

\[ P(S_{ij}) = \frac{\lambda_{ij}}{\sum_{j} \lambda_{ij}} \]

The MCMC algorithm updates the hyperparameter values until they reach stable probability distributions. In this study, Gibbs sampling is used to collect 1,000 samples of each posterior distribution, drawing ensemble \( \nu_{i} \) values every 100 iterations. A
Metropolis-Hastings updating step is used to iterate $a_\lambda$ and $b_\lambda$, hyperparameters which constrain $\lambda_{ij}$. A burn-in period of 250,000 iterations ensured sampling from stable distributions.

Figure 2 depicts the posterior distributions generated by the prediction model ensembles for each RCP scenario. Ensemble distributions tend to be relatively narrow due to the differential weighing of the MCMC algorithm.

2.3. Probabilistic Sea-Level Rise Hazard Analysis

Probabilistic hazard analysis combines the contributions of the eight CMIP5 models and four RCP scenarios. Hazard rate is determined using the total probability theorem described in Equation 5, where $H_i$ represents SLR at grid point $i$, $y_i$ a given SLR threshold, $S_{ij}$ an SLR prediction model $j$, and $R_{ik}$ an RCP scenario $k$. The summation along $j$ or $k$ is carried out through the generation of posterior distributions by the MCMC algorithm. These conditional distributions are then summed using the model or RCP weights as determined using the conditional probabilities calculated by Equation 4. Exceedance rates are deaggregated to quantify the relative contributions of each SLR prediction model and RCP scenario using an application of Bayes’ Rule as illustrated in Equations 6 and 7. For the purposes of this study, global mean contributions are considered in lieu of creating contribution maps or focusing on specific grid points.

3. RESULTS

Figure 3 represents these probability of exceeding various thermosteric SLR thresholds as calculated...
Figure 3: Probabilities of exceeding a global mean of (a) 0.08 m, (b) 0.16 m, (c) 0.24 m, and (d) 0.32 m of thermosteric sea-level rise between 2006 to 2013 and 2093 to 2100 weighing prediction models and RCP scenarios with the MCMC algorithm and using Equation 5.

Figure 4: Probabilities of exceeding a global mean of (a) 0.08 m, (b) 0.16 m, (c) 0.24 m, and (d) 0.32 m of thermosteric sea-level rise between 2006 to 2013 and 2093 to 2100 with all prediction models and RCP scenarios weighed equally.
using the methods described here. These maps depict SLR hazard on a regional basis, quantifying uncertainty at every grid point. Figure 4 depicts a similar hazard map for the same thermosteric sea-level rise thresholds as predicted by an ensemble in which all models and RCPs are weighed equally.

3.1. Hazard Analysis
Threshold exceedance rates tend to be significantly higher or lower for the maps generated using probabilistic hazard analysis. This results from the characteristics of the MCMC algorithm which produces relatively narrow probability distributions due to the differential weighing of models and scenarios, favoring prediction models and RCP scenarios which are near the ensemble consensus and effectively recreate altimeter measurements.

Regional deviations in hazard rate are relatively large for the maps generated using probabilistic methods. Effectively, a subset of predictions, considered accurate by the weighing criteria, determines hazard at every grid point. This allows models to contribute to regions for which they are accurate while minimizing influence on others for which they are not. Additionally, the Bayesian methods used allow models or scenarios diverging from the ensemble consensus to dominate SLR hazard in a region where they best reproduce observational data. An equal-weight ensemble cannot make such distinctions.

3.2. Deaggregation
Figure 5 depicts the deaggregation of individual prediction model and RCP contributions to global mean thermosteric sea-level rise. Visualizing these contributions demonstrates their utility as well as the impact of the modeling assumptions. The contribution of MIROC-ESM-CHEM, for instance, increases with SLR threshold as it predicts higher SLR than other models for most grid points. For similar reasons, the relative contribution of MIROC5 peaks toward the middle of the threshold range and the contribution of MRI-CGCM3 decreases with threshold.

Unsurprisingly, the contribution of RCP 8.5 also increases with SLR threshold. The contributions of RCP 4.5 and RCP 6.0 peak near the center of the threshold range as expected, but are also consistently higher than RCP 2.6 even for lower SLR thresholds. This likely results from the convergence criteria utilized in the MCMC algorithm, as moderate prediction scenarios will be favored over more extreme scenarios.

Figure 5: Deaggregated contributions of (a) CMIP5 prediction models and (b) RCP scenarios to global mean sea-level rise thresholds as calculated using Equations 6 and 7
4. CONCLUSIONS
In this study, an MCMC algorithm for creating posterior distributions of a multimodel ensemble using model weighing criteria is combined with a probabilistic hazard analysis framework to create hazard maps incorporating the projections of four RCPs and eight climate models with high-resolution ocean components. These results differ significantly from ensembles weighing each RCP and model equally, allowing hazard in particular regions to be controlled by an appropriate subset of models. Additionally, the relative contributions of each model and RCP were deaggregated, depicting how contributions change along a range of sea-level rise thresholds and the impact of the algorithmic assumptions. This represents a novel step toward fully quantifying the uncertainty in sea-level rise predictions.

The accuracy and precision of the results in this study depend on the assumptions made in the probabilistic model and the data used. A greater number of prediction models and forcing scenarios would help better account for the full range of climate uncertainty. Effectively introducing spatial and temporal dependence into the probabilistic assumptions may lead to improved predictions. Finally, incorporating mass-balance and other SLR contributions into the methods described may provide a more comprehensive assessment of SLR hazard, allowing decision makers a greater means of exploring strategies for adapting to and mitigating changes in sea-level.

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6. REFERENCES


