SSPipeline: A pipeline for estimating and characterizing uncertainty in coastal storm surge levels

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Summary

Effective management of coastal risks demands projections for flood hazards that account for a wide variety of potential sources of uncertainty. Two typical approaches for estimating flood hazards include (1) direct physical process-based modeling of the storms themselves and (2) statistical modeling of the distributions and relevant characteristics of extreme sea-level events. Recently, flexible and efficient mechanistically-motivated models for sea-level change have become widely used for characterizing uncertainty in projections of mean sea levels (Oppenheimer & Alley, 2016). Although the information obtained from modeling mean sea levels if useful, there is also a need for additional research for measuring extreme sea levels. The above is a motivating factor in the focus within the SSPipeline (Storm Surge Pipeline) project, that characterizes uncertainty in estimates of extreme sea levels, using a statistical modeling approach. Specifically, the SSPipeline project includes processes for raw sea-level data and fits a statistical distribution to the extreme sea levels, which in turn permits estimation of the probabilities associated with extreme sea levels.

To satisfy the demand for fast estimation of flood hazard and characterization of uncertainty, we implemented an API that only requires a user to configure a text file, which includes arguments for the tide gauge data set, some statistical modeling paramters, and output options. The program will run, from a single terminal command, resulting in a suite of calibration and diagnostic routines. Importantly, the output consists of a set of diagnostic plots, data sets of calibrated parameters, and storm-surge-return-level estimates. Secondly, the program is modular so that developers can extend the options for statistical modeling or calibrate the methods employed if they so choose.

To begin, the user will need to input a raw tide gauge data set for hourly sea levels, formatted in the manner of the University of Hawaii Sea Level Center (UHSLC) data repository in CSV format (Caldwell, Merrfield, & Thompson, 2015). Our choice for the format of the data set was motivated by the fact that the UHSLC repository provides hundreds of widely used, freely available, and research-quality data sets, spread across the globe. The user must designate the location of this data, as well as a number of data processing options to establish the processed data set that will serve as calibration data to which we fit a distribution. At present, a generalized extreme value (GEV) distribution fitting annual block maximum sea levels is the only option, as it is both commonly used in the literature [REFS] and the proper limiting distribution for a sequence of block maxima (Coles, 2001). Future code enhancements will include adding options for other statistical models, for example, generalized Pareto or lognormal distributions. The GEV distribution is specified by three parameters: (1) a location parameter, which governs the center of the distribution (μ); (2) a scale parameter, which governs the width of the distribution (σ); and (3) a shape parameter, which governs the weight of the upper tail (ξ). The program estimates the three parameters, using a Markov chain Monte Carlo parameter calibration approach to sample from the posterior distribution of the model parameters given the processed tide gauge data set (Higdon, Kennedy, Cavendish, Cafeo, & Ryne, 2004). In this
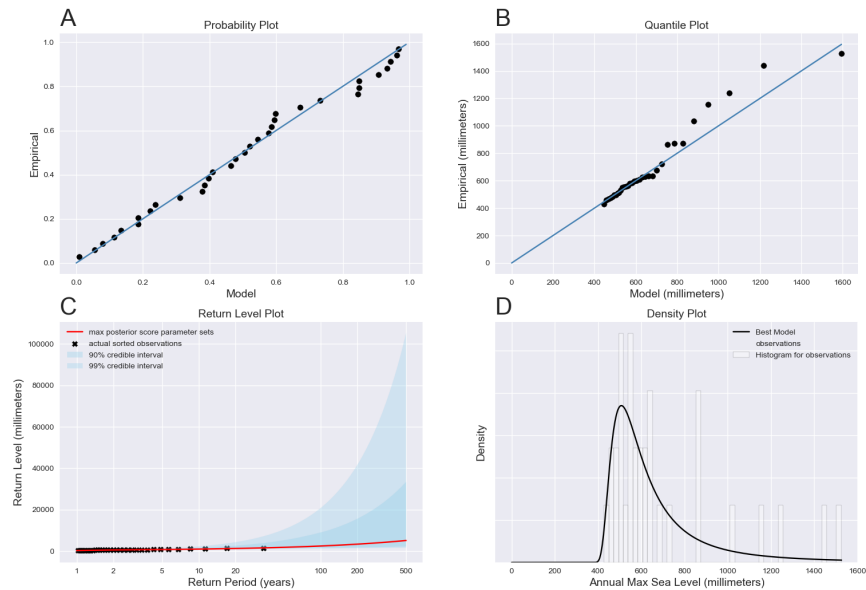
Figure 1: Diagnostic output plots using tide gauge data from Grand Isle, Louisiana, USA.

calibration approach, the goodness-of-fit of the GEV distribution given by a candidate set of parameters is quantified by comparing the modeled probability of a given storm surge height against the observed probabilities from the tide gauge data. The user configuration file also specifies a variety of settings for the calibration method, including the number of parallel Markov chains to use for estimation, number of iterations to simulate, and thresholds for autocorrelation and convergence of the Markov chains.

The final output from the program includes a data set of GEV posterior parameter samples, data tables of flood heights and associated probabilities, and a set of figures to assess model goodness-of-fit and the estimated flood probabilities. Figure 1 provides an example of this diagnostic figure set: (1A) a probability plot where each data point corresponds to an observed sea-level extreme in which the x-value gives the modeled probability of observing that sea level in a given year, and the y-value gives the empirical probability of observing that sea level in a given year; (1B) a quantile plot that shows the model-estimated sea levels (x-axis) associated with the observed sea levels (y-axis); (1C) a return levels plot that shows the storm surge heights ("return levels", y-axis) associated with given return periods (how frequently one expects to observe such a storm, x-axis); and (1D) the best-fit GEV distribution, superimposed on the processed tide gauge data.

The modular nature of the project codes allows the addition of new features and extensions of the base codes, including options to fit alternative statistical models and projecting future flood hazard by incorporating potential non-stationary processes into the model (Wong, Klufas, Srikrishnan, & Keller, 2018). By providing base code to the community, our aim is to (1) enable others to incorporate more modeling uncertainties into their own flood hazard estimate, (2) provide a foundation on which a user community might work together to develop extensions on the existing codes, and (3) provide a pipeline with standard output diagnostics to facilitate comparisons of the extensions and features that users may add over time. This, in turn, may lead to a more thorough understanding and careful accounting of the impacts of various uncertainties and processes that affect flood hazard estimates.

Acknowledgements

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