Storm peak validation and analysis of uncertainty in estimates of extreme sea states

HR Wallingford
Working with water

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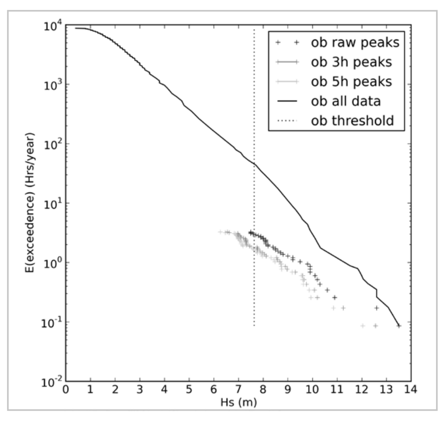
Introduction

At sites where estimates of extreme conditions are needed for engineering design, reanalysis datasets such as ERA-Interim (Dee et al, 2011) and CFSR (Chawla et al, 2013) are often the best available sources of information on past wave conditions. Published validations often focus on quantile based measures, whereas extreme conditions are estimated from distinct storm peaks. Storm peaks are often under-estimated by numerical models (Cavaleri, 2009). A peak based validation method is used and shows that model accuracy at storm peaks differs from that of the overall population. A storm peak-focussed calibration method is tested, and the remaining uncertainty in model predictions of storm peaks is propagated through the estimation of extreme conditions.

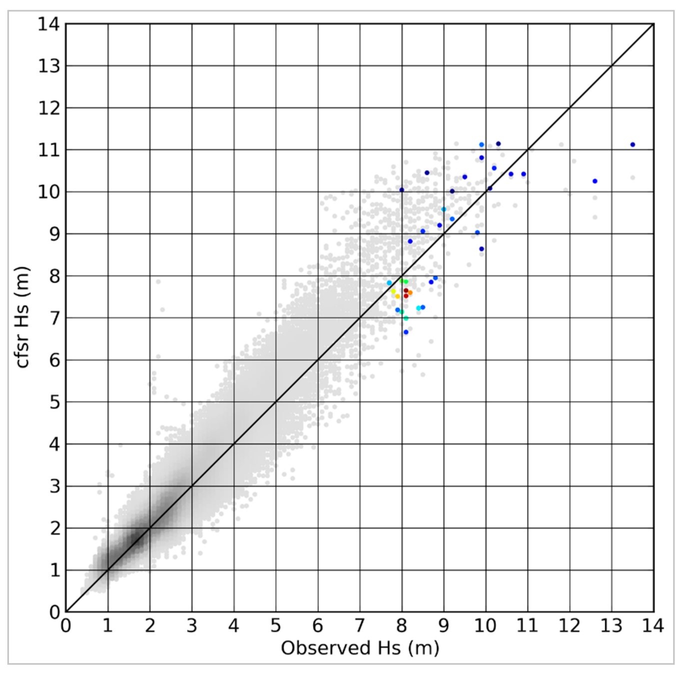
Validation at storm peaks for extremes analysis

In estimating extreme conditions, a Peaks Over Threshold approach is adopted, in which a time series is reduced to a set of independent peak values of Hs. The exceedance curve shown below shows the different distributions of the whole population and independent storm peaks at the Coruna buoy. By matching pairs of observed and modelled peaks, we can generate error statistics specific to the storm peaks. Errors at storm peaks are often different to error in the wider population.

The example shown is CFSR at the Coruña buoy. The wider population is shown in grey (with depth of grey indicating density of points), and matched peaks are coloured. Here, there is a high bias in the wider population, not present in the peaks. For most models at most buoys, the storm peaks are biased lower than the population above the 99th percentile, biased lower again than the population as a whole.



Exceedance curves of Hs at the Coruna buoy, comparing the whole population (solid) with independent storm peaks (+s)



Comparison of modelled (CFSR) and observed Hs at the Coruna buoy, whole population in grey, matched peaks coloured

Relative bias (bias normalised by observed mean) in matched storm peaks, CFSR (white), ERA-Interim (yellow)

Scatter Index (standard deviation of error normalised by observed mean) in matched storm peaks, CFSR (white), ERA-Interim (yellow)

Calibration of storm peaks

If there is a consistent relationship between modelled and observed storm peaks, then we may be able to correct the model data and achieve more accurate estimates of extreme conditions. As buoys with long records are generally not located near locations of interest, we are looking for a calibration method with relatively simple mappable coefficients.

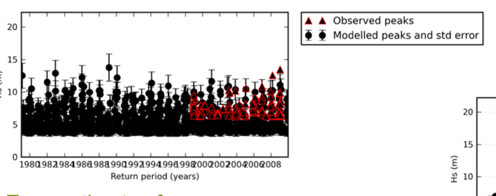
Here we use a simplified omni-directional version of the Minguez (2011) scheme, where $Hs_{calib} = a * Hs_{orig}^{\ b}$, and coefficients a and b are found through an iterative process minimising bias in storm peaks. Estimated calibration coefficients are geographically consistent (open ocean vs marginal sea, offshore vs nearshore).

Area	Model	Relative bias above 99%ile	Scatter Index above 99%ile	Relative Bias at peaks	Scatter Index at peaks	Calibration factor (a)	Calibration power (b)	Calibrated RelBias at peaks	Calibrated SI at peaks
Mean (Spanish Atlantic Coast)	CFSR	0.05	0.17	-0.08	0.17	1.03	1.04	-0.01	0.14
	ERA-Interim	-0.14	0.22	-0.22	0.26	1.06	1.11	-0.01	0.16
Mean (Spanish Mediterranean Coast)	CFSR	-0.20	0.27	-0.25	0.28	1.09	1.13	-0.02	0.17
	ERA-Interim	-0.10	0.22	-0.16	0.23	1.04	1.06	-0.04	0.19

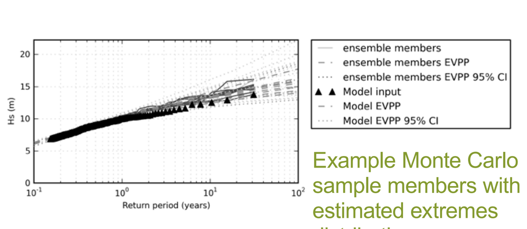
Uncertainty in extremes

If we assume that model errors at storm peaks are normally distributed, then we can use error statistics from the validation and combine Monte Carlo sampling of model error with Bayesian estimation of extreme value distributions to generate estimates of extreme conditions that include both the uncertainty due to input conditions and estimated uncertainty due to sampling of the distribution.

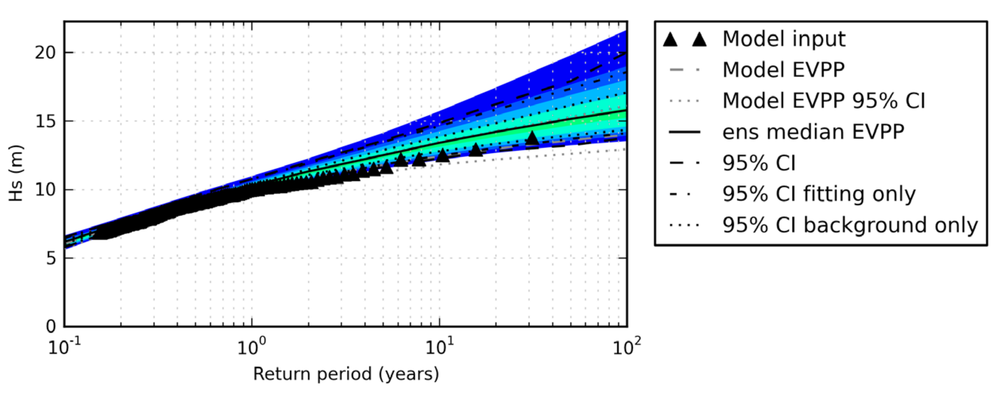
Each member in the ensemble of series is generated by adding random errors to the peaks. An Extreme Value Poisson Process (EVPP) is estimated for each series using Markov-Chain Monte Carlo techniques in a Bayesian framework. The resulting ensemble of posterior distributions can be sampled to analyse uncertainty either in fitting, background/input data or the combination. It is notable that the median EVPP estimate from the ensemble is significantly higher than the EVPP from the model alone. In this analysis, the estimate of the 100 year return period condition is increased significantly by the inclusion of uncertainty in the input data.



Error estimates from validation associated with modelled storm peaks



Example Monte Carlo sample members with estimated extremes distributions



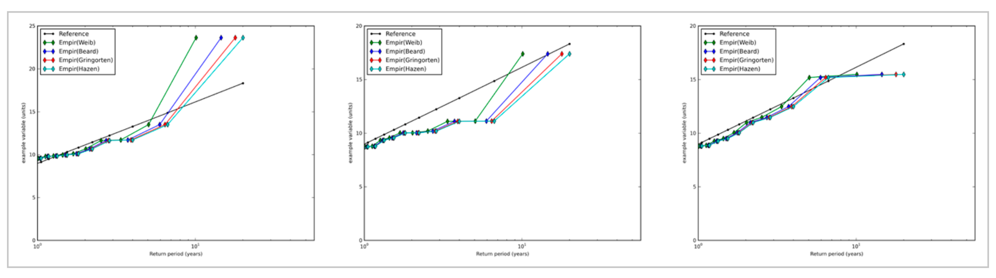
Density of large Monte Carlo sample, with 95% credible limits representing uncertainty in extreme estimates due to uncertainty in input data, estimation of the extremes distribution, and their combination

Validating uncertainty in extremes

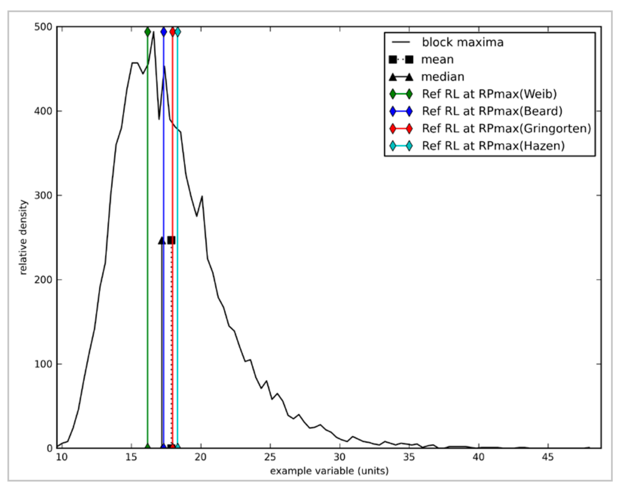
Validating uncertainty in estimates requires analysis at a large number of sites - still in progress - and depends to an extent on the probability associated with the most extreme events in a series, the so-called plotting position.

The formulation of the plotting position has been debated for many years. Although no longer used in the generation of estimates of extreme conditions, empirical plotting positions are still used to compare estimated extreme distributions with data.

Numerical experiments using synthetic data from a known distribution are shown in the adjacent figure suggesting that the optimal formulation lies within a narrow subset of the debated schemes, and depends on whether the mean or median of the posterior distribution of interest. The example is typical of a large number of distributions tested.



Example synthetic events sampled from a known distribution (in black) and plotted against empirical return periods associated by four candidate plotting position schemes



Distribution, mean and median of block maxima from 10,000 series of synthetic data from a known distribution (at 10 events per year over 10 years) compared to the return level (from the known distribution) corresponding to the return period associated with the block maxima by four candidate plotting position schemes

Conclusions and further work

A peaks-based validation is needed to assess the accuracy of modelled datasets for use in estimation of extreme conditions.

Uncertainty in extreme conditions can be estimated, including the effect of uncertainty in input conditions, using combined Monte Carlo techniques and Bayesian statistical approaches.

Validation of uncertainty estimates requires collation of validations of multiple datasets at many buoys - this is on-going.

The increase in median estimate of extreme conditions due to uncertainty in the input was not expected and may yet be identified as an artefact of the analysis. If real, it may be interpreted as a contribution to the estimate due to the lack of skill of the estimator.

The confidence intervals/credible limits of the extremes estimates seem wider than our perception of the uncertainty. It is likely that work is needed on both the statistical analysis and our appreciation of what it is saying.

Further work will include building into analysis the uncertainty in buoy data (e.g. as analysed by Bitner-Gregersen and Magnusson (2014)) and extending analysis to higher resolution datasets such as NORA10 (Aarnes et al, 2012), and forecast models.

References

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