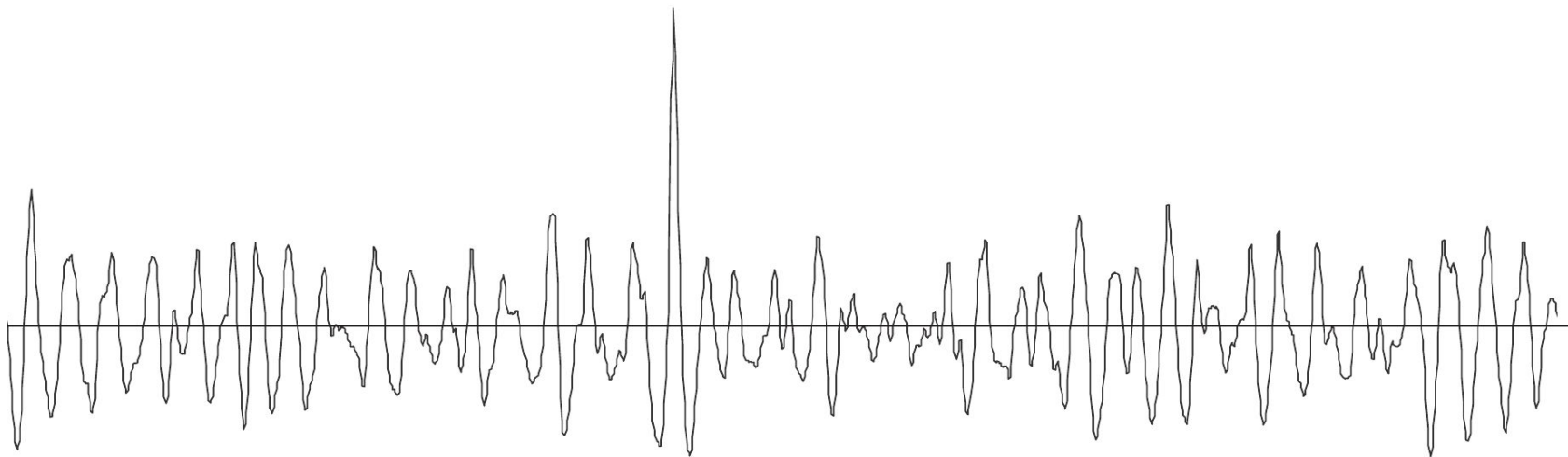
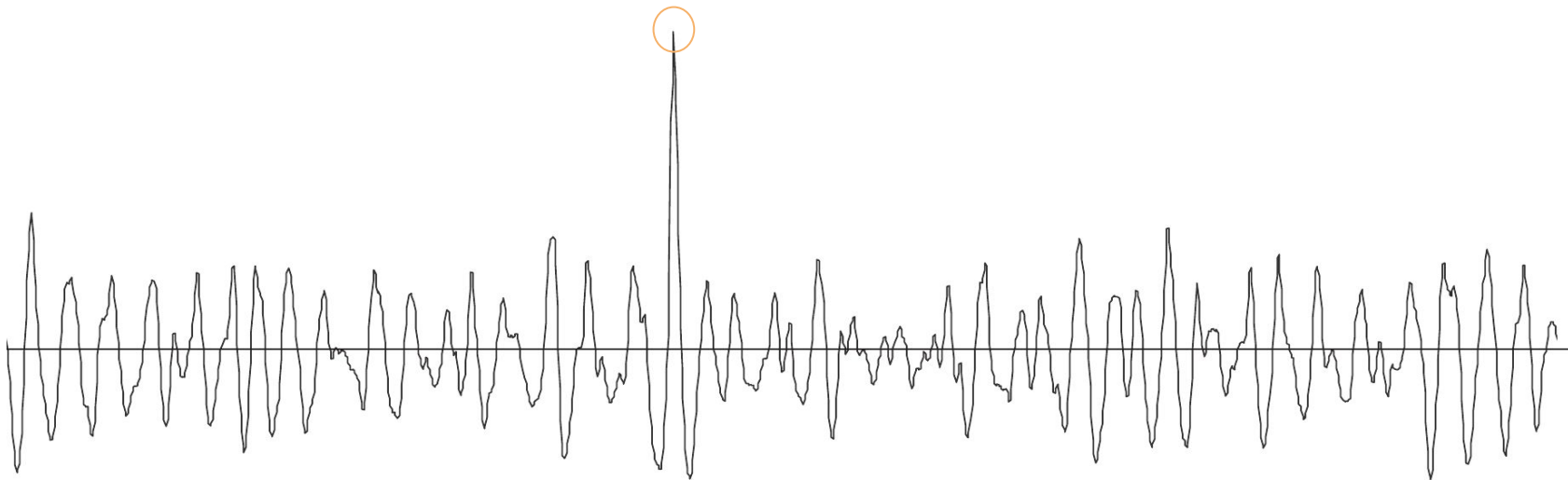


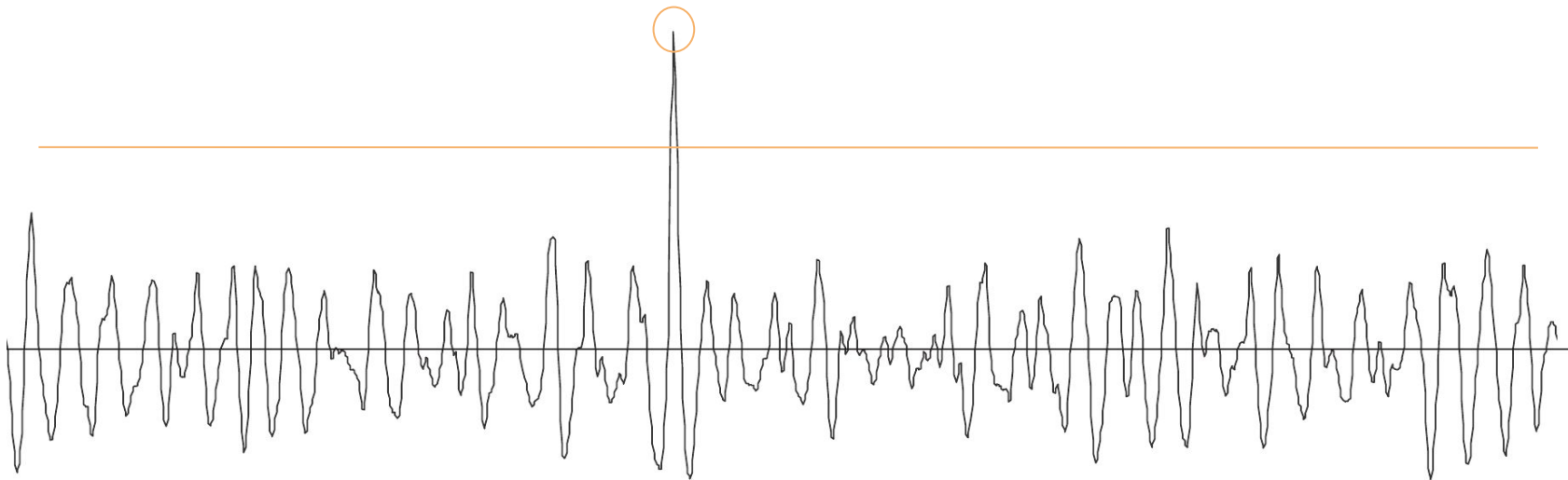
Patrik Bohlinger
patrikb@met.no

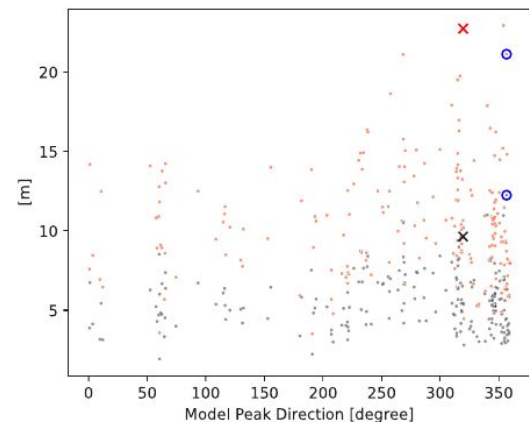
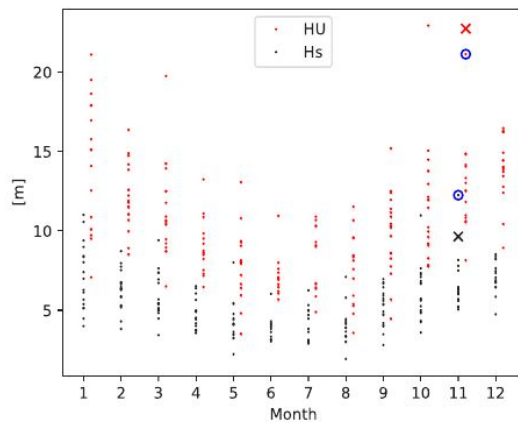
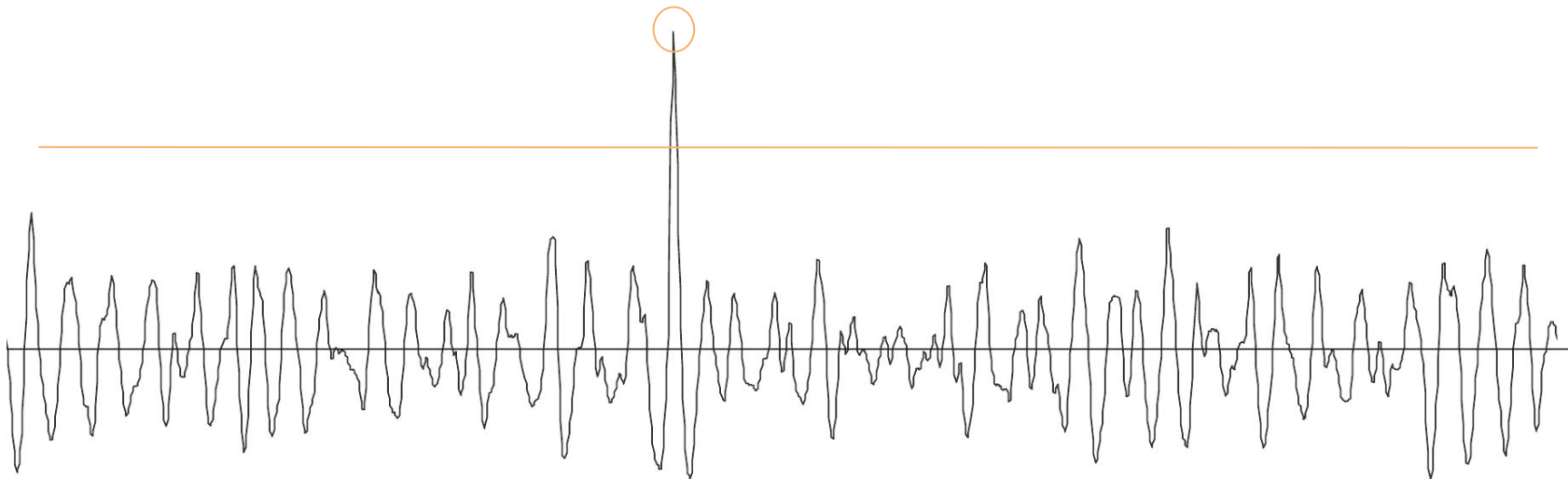
Modelling METOCEAN extremes

P. Bohlinger, P. Jonathan, B. Youngman, T. Economou, Ø. Breivik

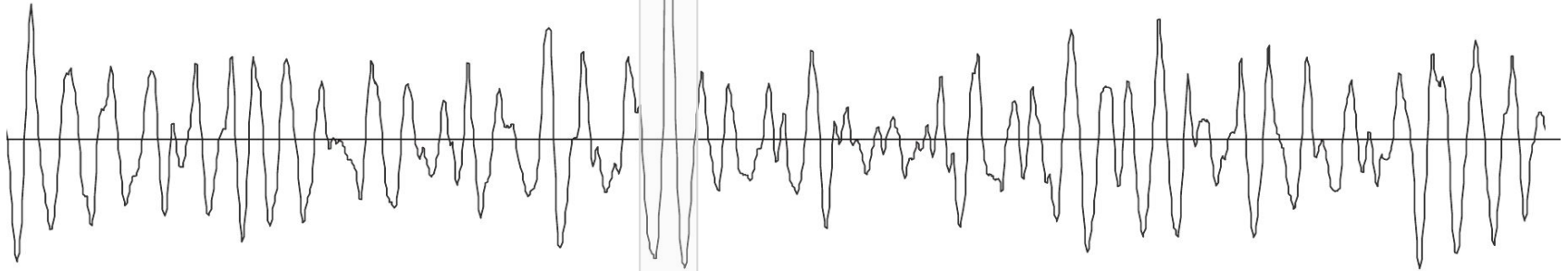




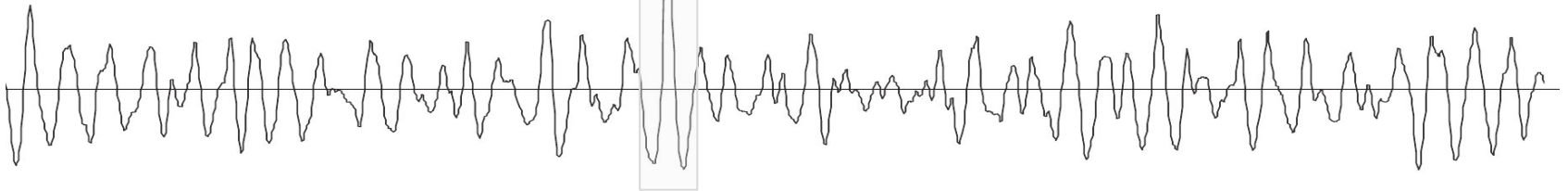




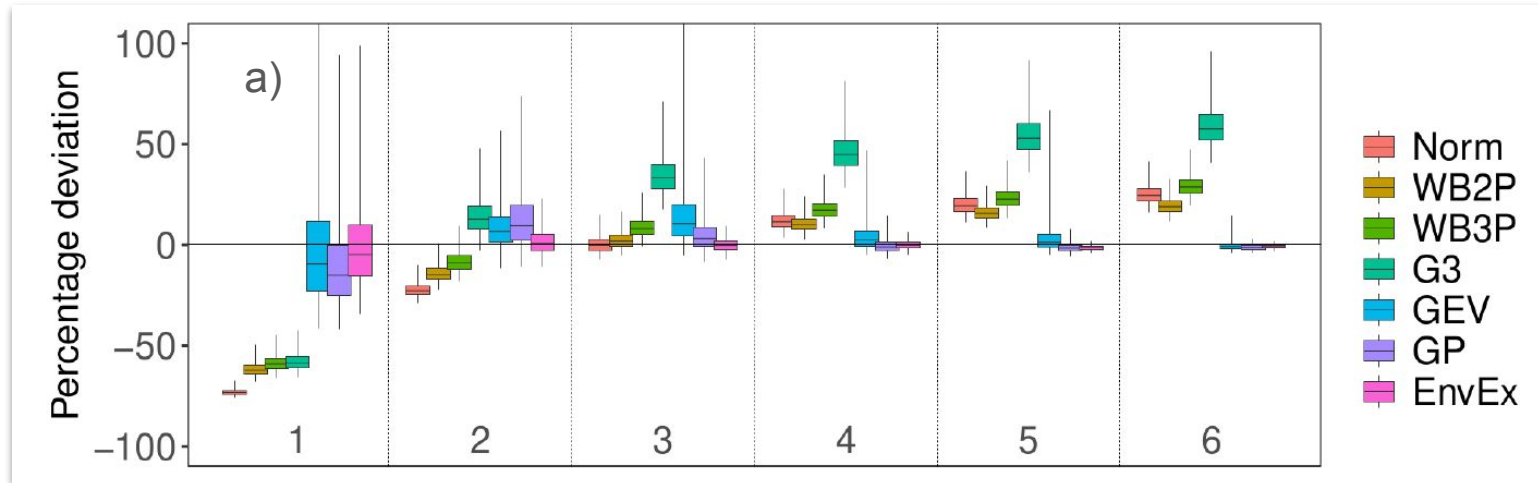
Waves, ...



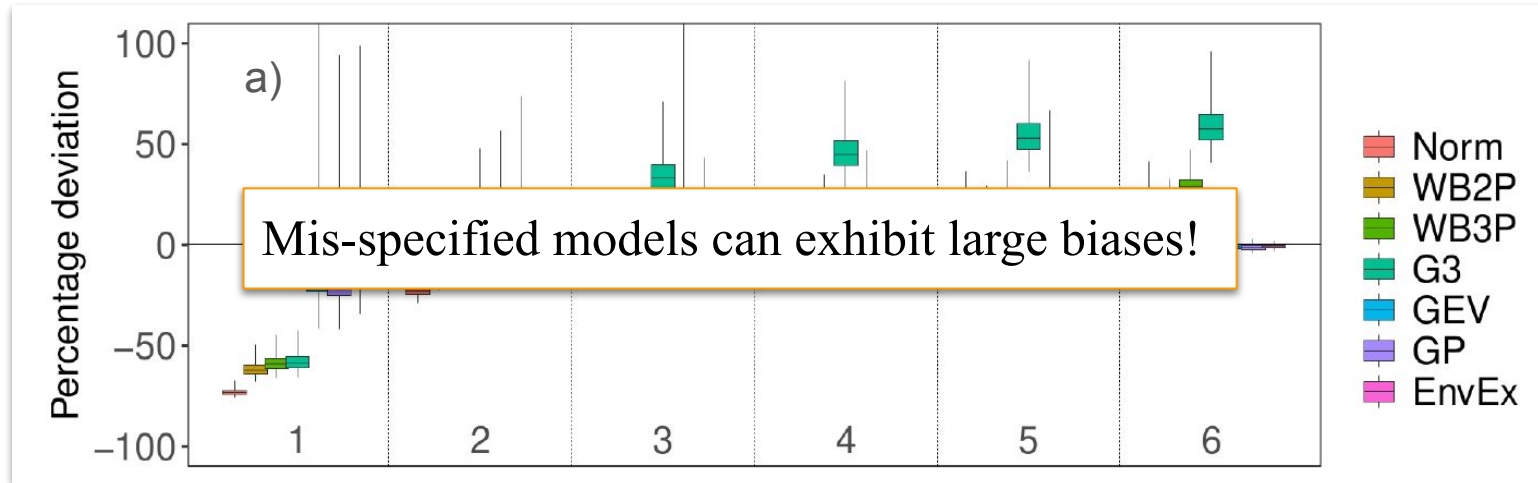
Wind, Steepness, etc, ...



100 year return value (non-stationary process)

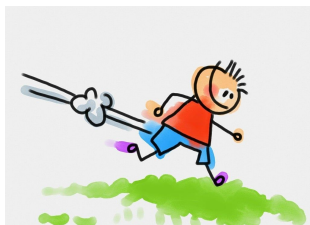


100 year return value (non-stationary process)



- modelling of non-stationary and joint extremes?
- how modern methods compare against standard approaches?
- have any comments?

Drop by!



Modelling metocean extremes using GAMs - a comparison study

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Motivation

Marine standards recommend approaches to calculate return levels and exceedance probabilities for extreme values of marine key variables (such as wind, wave, surge). However, some approaches date back many decades. Examples include the initial distribution method using a Weibull distribution for marginal models on all data, modelling directional wave heights using independent models for each sector and the Weibull log-normal model for joint probability [1,2], while they have a critical appeal, these approaches do not take into account recent developments in extreme value theory (EVT), when extrapolating far into the tail in particular, empirical models should be inferred by EVT.

However, despite multiple studies it is still not obvious how these modern approaches perform compared to existing standards in various settings. Therefore we contribute with a comparison of our in-house developed workflow for non-stationary, joint Environmental Extremes (EnvEx) applying modern EVT methodology [3,4]. Here, we focus on the fair comparison of the sea state parameters and joint variables because Hmax and Cmax are downstream response variables with their quality being contingent on the correct estimation of the sea state parameters and the distribution functions for the individual waves and crests.

Conclusion

EnvEx provides a framework for applying non-stationary extreme value analysis including LQD for our metocean variables of interest. The impact of variations on return variables and exceedance probabilities can be investigated as all dependencies are traceable through the model.

EnvEx is able to predict a meaningful distribution of 100-year maxima. Models that do not take into account nonstationarity (i.e. serial correlation and covariate effects) are misspecified and develop biases that are most severe for long-tailed data.

Depending on the purpose it may be beneficial to consider the full predictive distribution of 100-year maxima rather than the return levels to better account for the variability in the underlying stochastic process.

Plans

- Incorporate outperforming based uncertainty
- Incorporate more models for Hmax and Cmax
- Create publicly available software package
- Benchmark using different datasets and
- Investigate more sensitivity

Acknowledgements

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Non-stationary and joint modelling strategy in EnvEx

We assume that 1) storm events and their storm peak values are independent given storm peak covariates, 2) storm events can be sufficiently characterized by their respective storm peak variables and their storm peak covariates. Additionally, the storm evolution itself can be described by the probability density of a multivariate time series of sea state characteristics throughout the storm event, other sea state covariates, and the unknown and variable storm length.

Following [3,4] we can now design the hierarchical model for the distribution of the maximum individual wave height within any storm. The hierarchy consists of A) a model for Hmax within a storm event with random length $1 \leq T$ consisting of sea states of

$$F_{H_{max}}(h) = \int_{\mathcal{S}} \int_{\mathcal{C}} \prod_{t=1}^T f_{H_{max}}(h_t | \mathbf{X}_{t-1}, \mathbf{C}_{t-1}) d\mathbf{X}_{t-1} d\mathbf{C}_{t-1}$$

- $f_{H_{max}}(h_t | \mathbf{X}_{t-1}, \mathbf{C}_{t-1})$
- $f_{H_{max}}(h_t | \mathbf{X}_{t-1}, \mathbf{C}_{t-1})$
- $f_{H_{max}}(h_t | \mathbf{X}_{t-1}, \mathbf{C}_{t-1})$
- $f_{H_{max}}(h_t | \mathbf{X}_{t-1}, \mathbf{C}_{t-1})$

unknown length T . B) the evolution of A multivariate storm events characterized by A multivariate storm peaks given their covariates, C) the joint model (Jeffreys and Tawn) [5] or non-stationary marginal modelling of sea state characteristics throughout the storm event, other sea state covariates, and the unknown and variable storm length, D) the dependence between individual waves given their sea state is negligible.

Comparison using artificial data (the truth is known)

We fit a range of candidate models as commonly applied and let them predict a distribution of 100-year maxima. Those should group around the true 100-year return value for the probability: $P(\hat{\mu}_{100}^{(T)} > \mu_{100}^{(T)})$. All models are provided with the same 50 years of data to which they are fitted to. The predictions based on these models are subsequently compared.

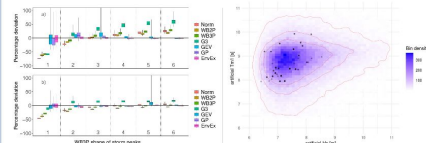


Figure 1: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 2: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 3: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 4: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 5: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 6: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 7: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 8: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 9: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 10: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 11: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 12: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 13: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 14: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 15: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 16: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 17: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 18: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 19: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.

Figure 20: Comparison of different models. The top row shows the percentage of peaks predicted by the models. The bottom row shows the percentage of peaks predicted by the models. The plots show that the models generally predict the 100-year return value correctly, with some models showing more bias than others.