# FPSO Forum

## Uncertainty in Extreme Metocean Conditions

Offshore Consulting Group

14 October 2020

OFFSHORE
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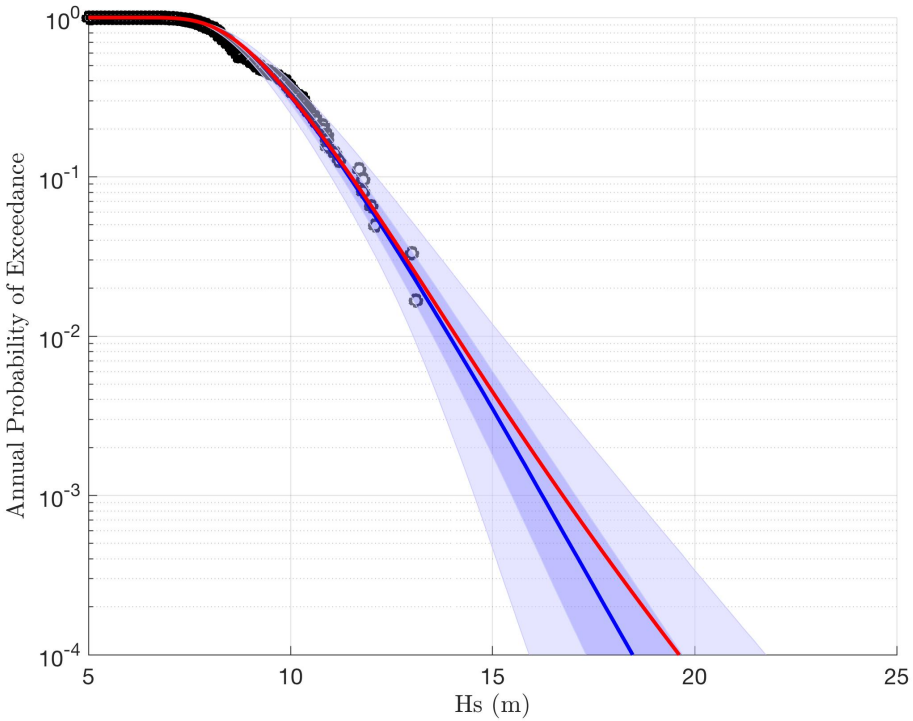
# Introduction

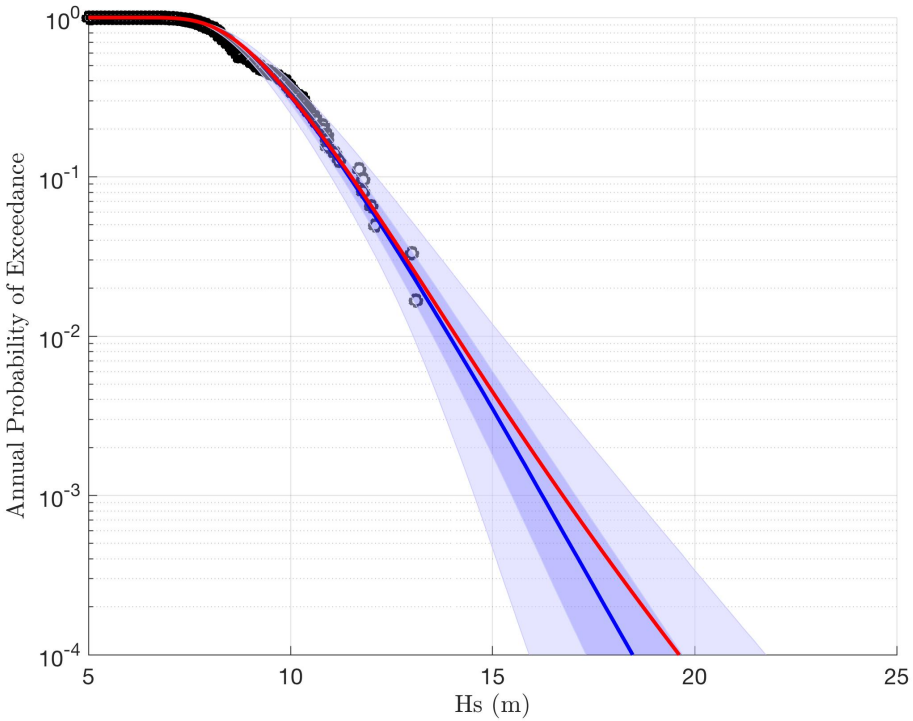
1. Motivation: uncertainty in metocean loading key component in determining the structural reliability of offshore structures.
2. Types of uncertainty:
   - 2.1 Aleatoric Randomness: natural variability of the environment.
   - 2.2 Epistemic Uncertainty: limitations in our models, knowledge and understanding.
3. Sources of epistemic uncertainty:
   - 3.1 Metocean Data: measurements, hindcasts.
   - 3.2 Statistical Models: long- and short-term extrapolations.
   - 3.3 Physical Models: waves, loads etc.
   - 3.4 Climate Change.
4. Focus on: long-term extrapolation.

# Long-term Extreme Value Analysis




Long-term distribution of storm peak significant wave height.
Bayesian MCMC analysis with covariates (season and direction).
Generalised Pareto fits over a range of thresholds.
Data (black), median (dark blue), P25-P75 (mid blue), P5-P95 (light blue), and posterior predictive (red).
Uncertainty affected by: length and type of the data set; and the prior distribution.

# Long-Term Metocean: North Sea

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Analysis based on hindcast data.
Methods for reducing the uncertainty?

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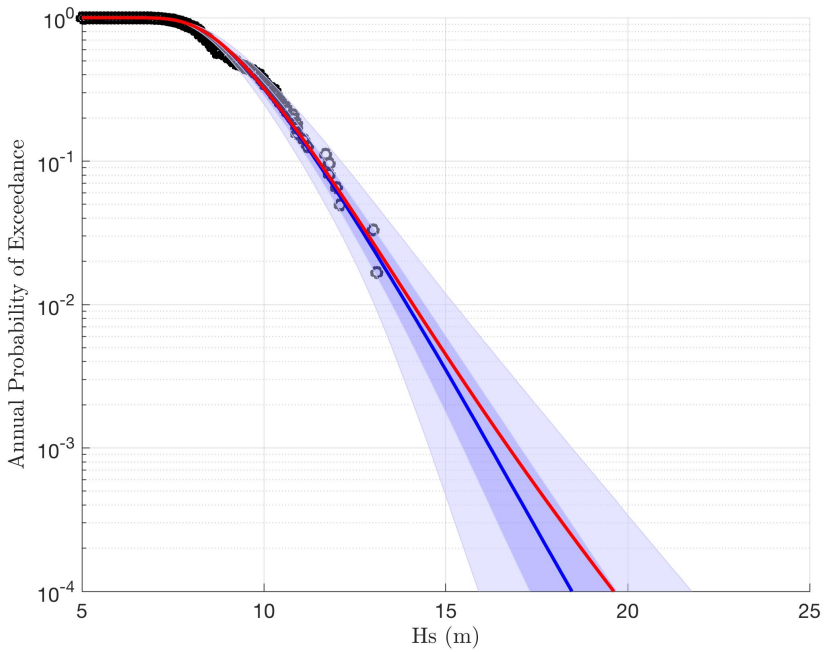
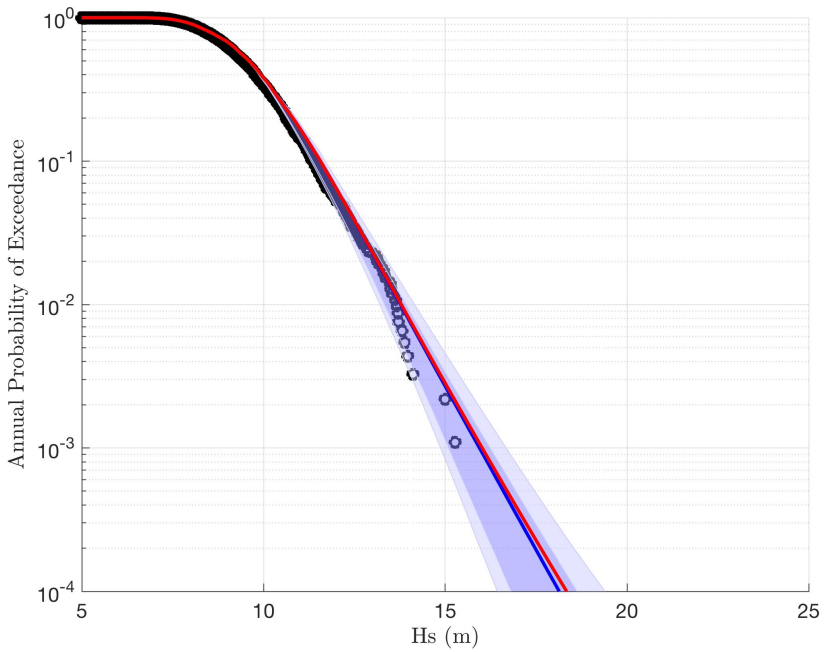
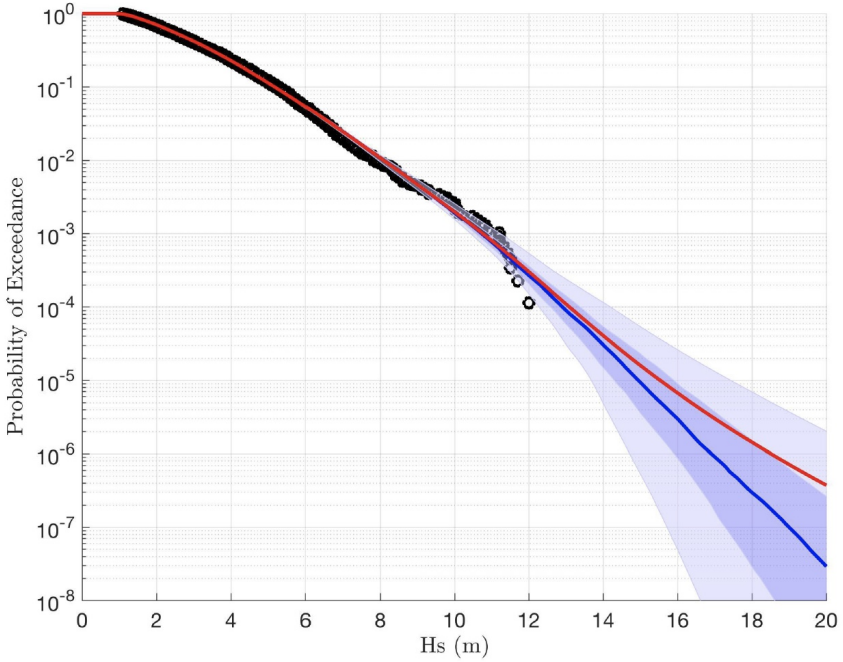
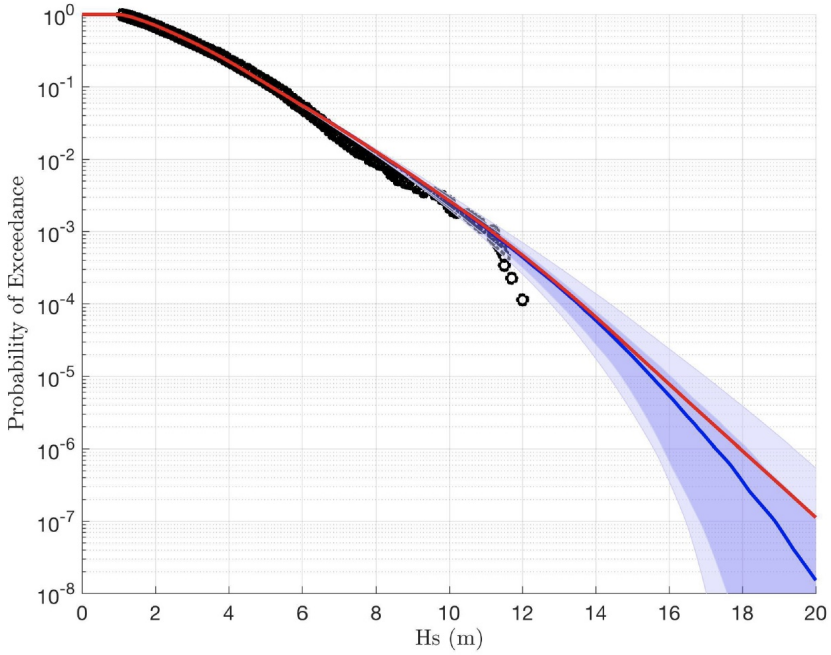



Long-term distribution of storm peak significant wave height.
NORA10 hindcast (left) and NS1200 (right).
NS1200: 1,200 year simulation of waves and winds across the North and Norwegian Seas, based on HiGEM climate model wind fields.
Extrapolation uncertainty reduced by using a very long data set.
Plots do not include the uncertainty in the underlying data itself: hindcast (left) and simulation (right).

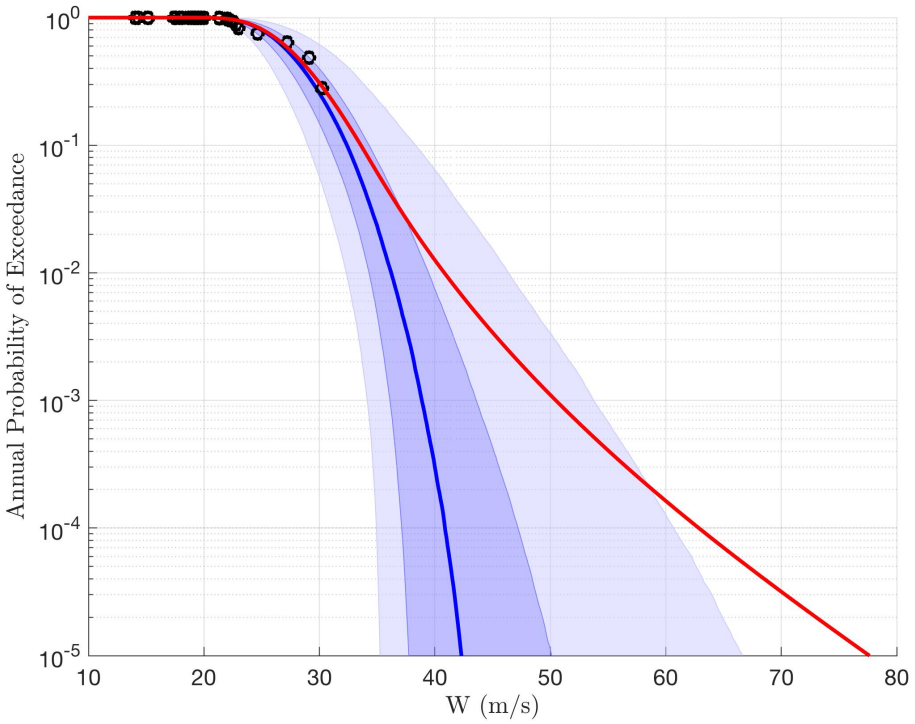
# Long-Term Metocean: North Sea



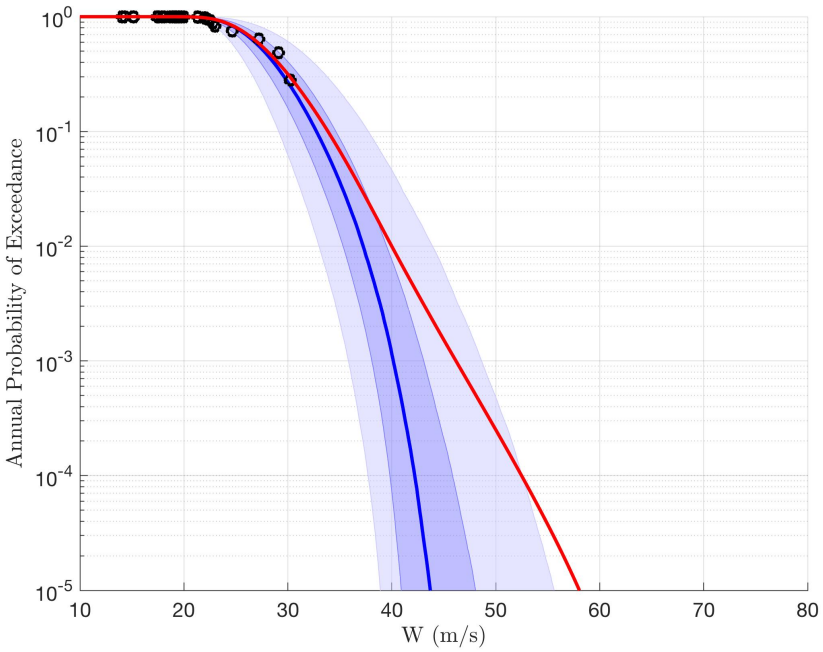

Long-term distribution of storm peak significant wave height.
Relatively uninformative prior (A, left) and prior with upper limits on significant wave height (B, right).
Prior B makes an explicit assumption about an upper limit and an implicit assumption about how that limit is approached.

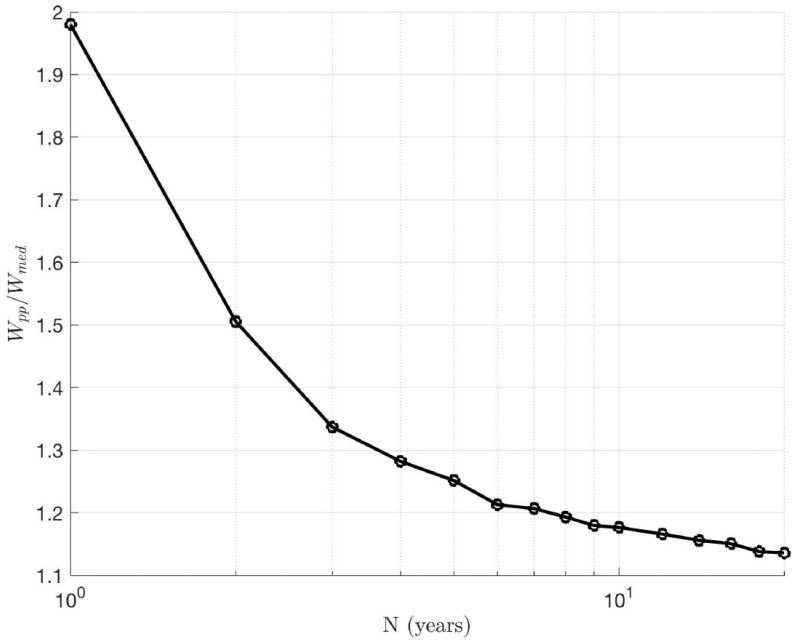
# Long-Term Metocean: Squalls




Long-term distribution of squall peak wind speed for a remote location offshore West Africa.
Analysis based on six years of measured data.
Bayesian MCMC analysis using EGP with uninformative prior.
Methods for reducing the uncertainty?

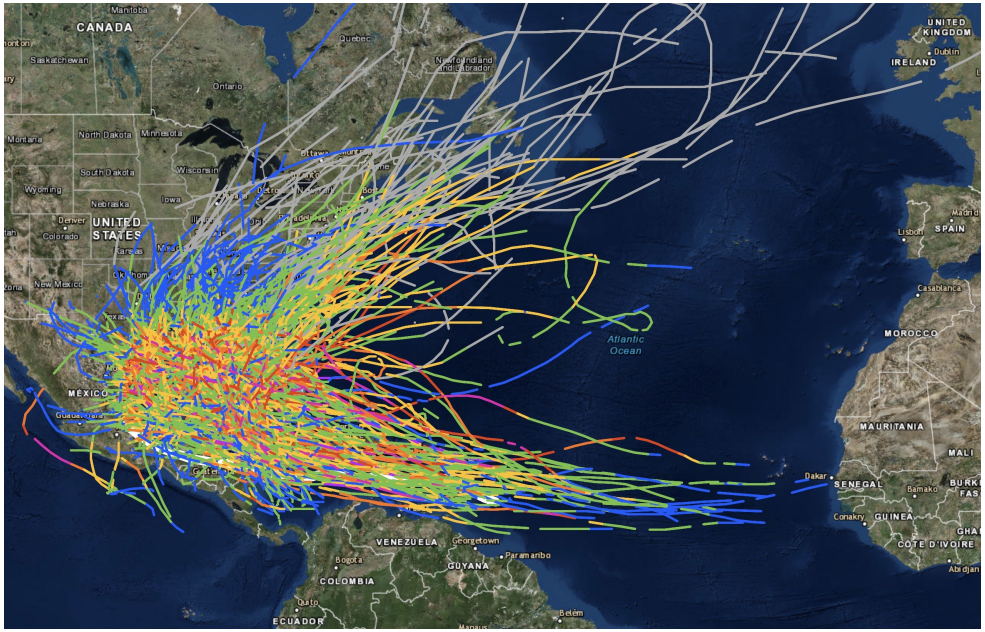
# Long-Term Metocean: Squalls

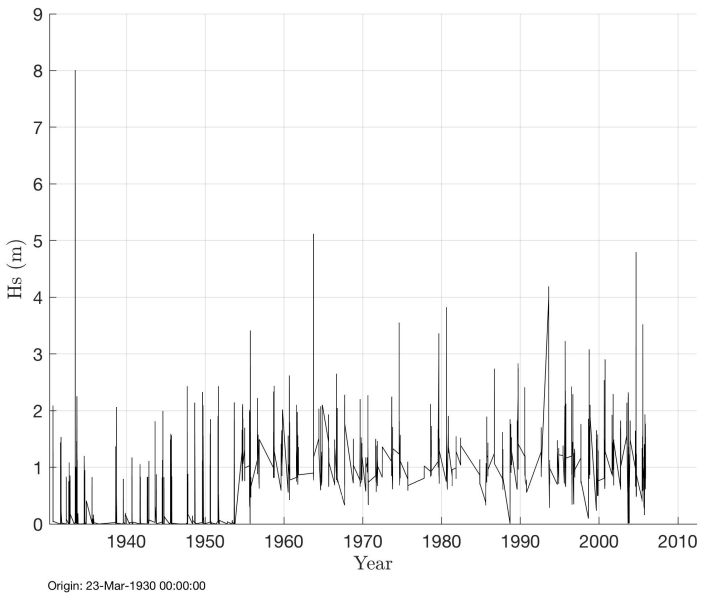



Long-term distribution of squall peak wind speed for a remote location offshore West Africa.
Analysis based on six years of measured data.
Bayesian MCMC analysis with prior on wind speed upper limit based on expert panel.
Right-hand plot shows the reduction in uncertainty for longer data sets.

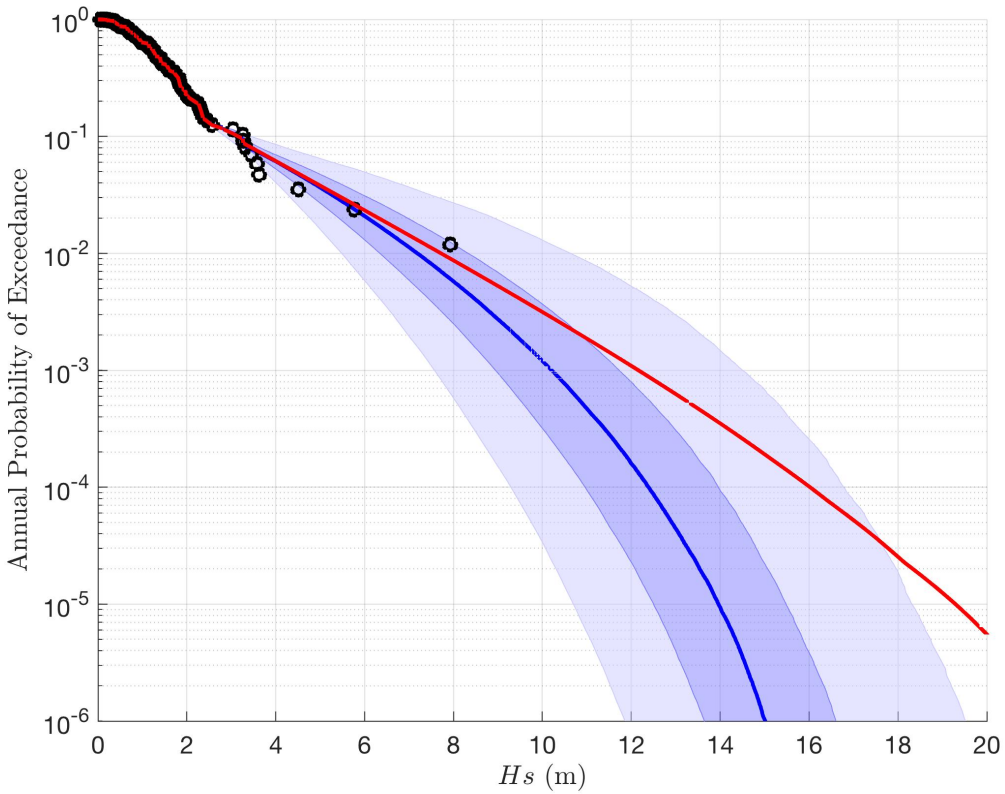
# Long-Term Metocean: Caribbean




Marginal tropical cyclone region with a handful of severe events.

# Long-Term Metocean: Caribbean

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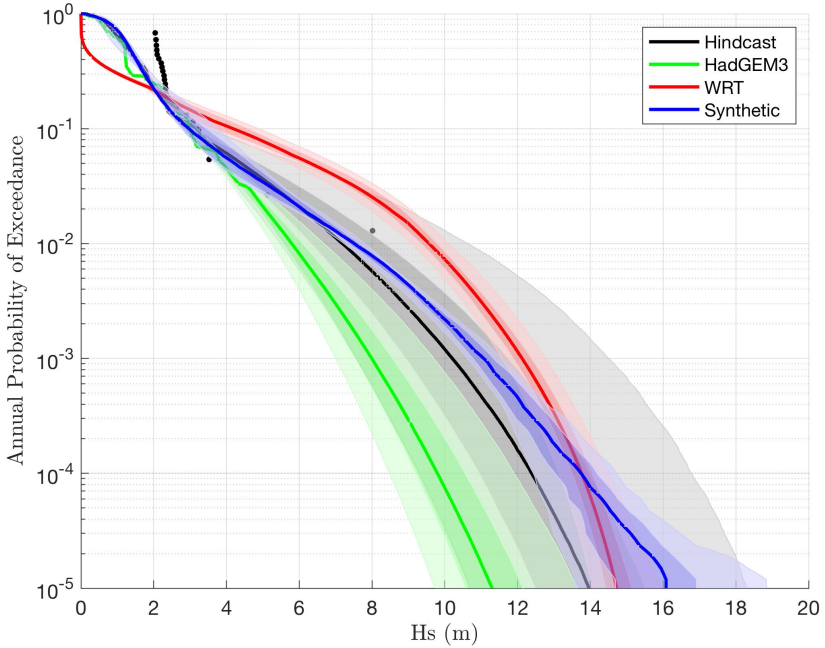
# Long-Term Metocean: Caribbean




Long-term distribution of storm peak significant wave height.
Four data sets: hindcast (90 years, black); climate model (260 years, green); WRT seeding approach (12,000 years, red); and synthetic (100,000 years, blue).
All of the data sets have limitations.
Model ensemble to be weighted by expert panel.
Final estimates consider all inter- and intra-model uncertainties.

# Summary

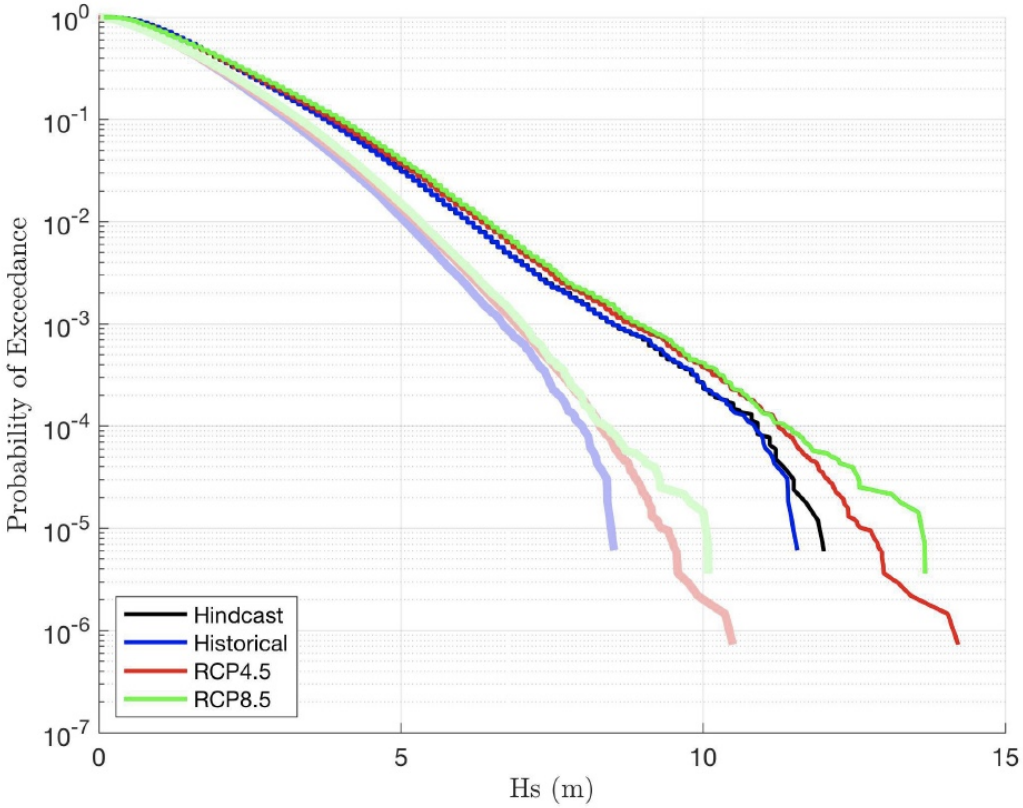
1. Epistemic uncertainty in long-term extrapolation.
2. Other sources include: data, short-term statistical and physical models, and climate change.
3. Uncertainty in the long-term metocean can be reduced by:
   3.1 Extending the data set.
   3.2 A more informative prior.
4. Examples from: North Sea, West Africa and Caribbean.

# Climate Change: Models

| | Model | Time Step (hours) | Resolution (deg) | Historical | RCP4.5 | RCP8.5 |
|---|---|---|---|---|---|---|
| 1 | EC-EARTH | 3 | 1.12 | 3 | 6 | 3 |
| 2 | GFDL-CM3 | 3 | 2.00 | 1 | 3 | 1 |
| 3 | GFDL-ESM2G | 3 | 2.00 | 1 | 1 | 1 |
| 4 | GFDL-ESM2M | 3 | 2.00 | 1 | 1 | 1 |
| 5 | HADGEM2-CC | 6 | 1.25 | 2 | 1 | 2 |
| 6 | HADGEM2-ES | 3 | 1.25 | 1 | 1 | 1 |
| 7 | MIROC | 3 | 1.40 | 5 | 3 | 3 |
| 8 | MPI-ESM-LR | 6 | 1.86 | 3 | 3 | 3 |
| 9 | MPI-ESM-MR | 6 | 1.86 | 3 | 3 | 1 |
| 10 | MRI-CGCM3 | 3 | 1.12 | 5 | 1 | 1 |

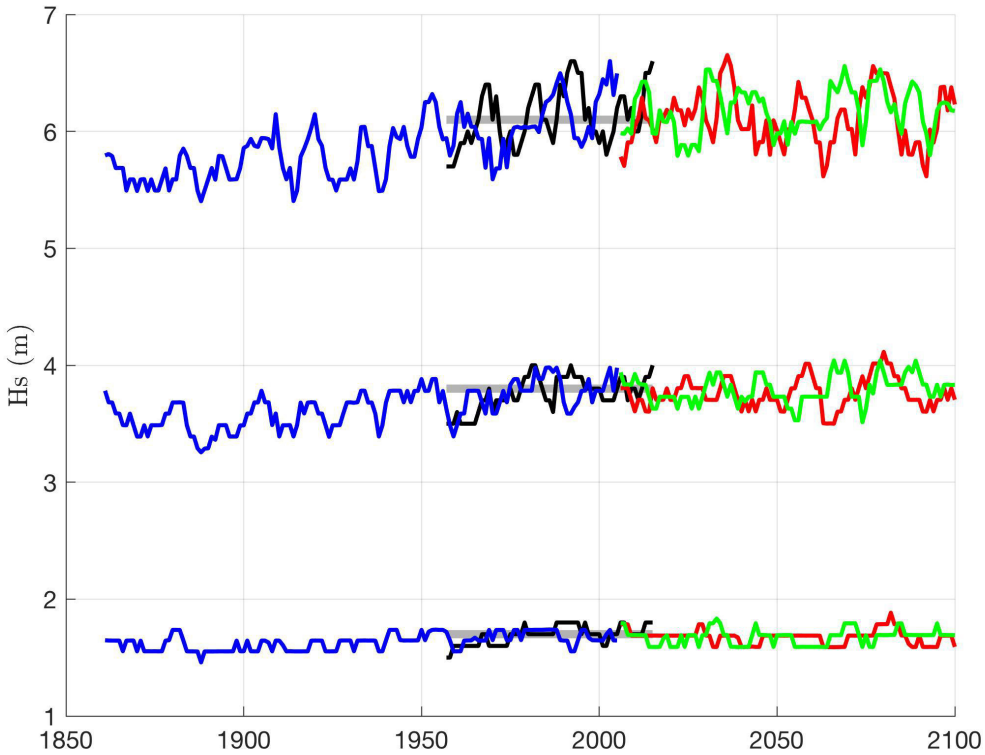
Zappa et al. (2013) identified these as having reasonable or good skill at modelling North Atlantic extra-tropical cyclones.

# Climate Change: Calibration



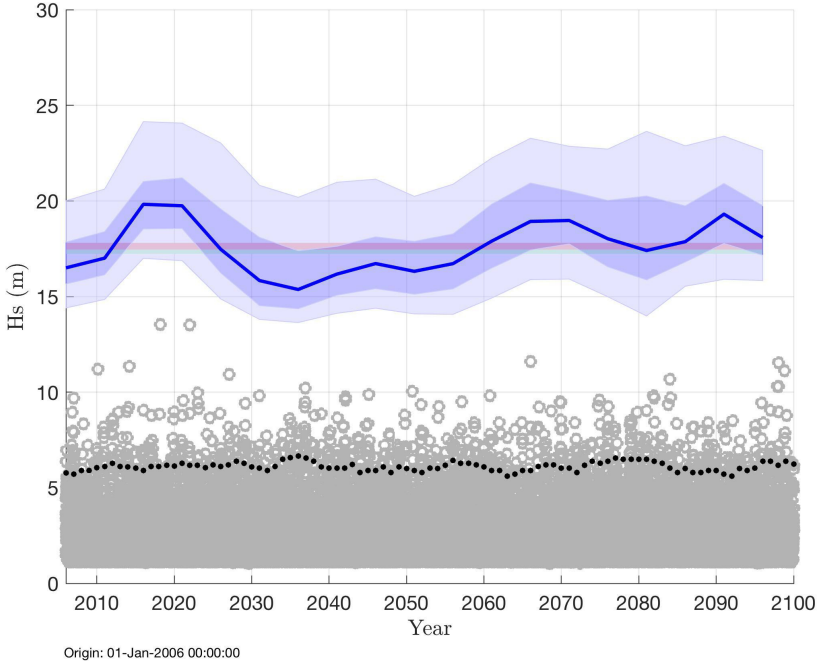

Models must be calibrated based on their performance over the historical period: uncalibrated (light); and calibrated (dark).

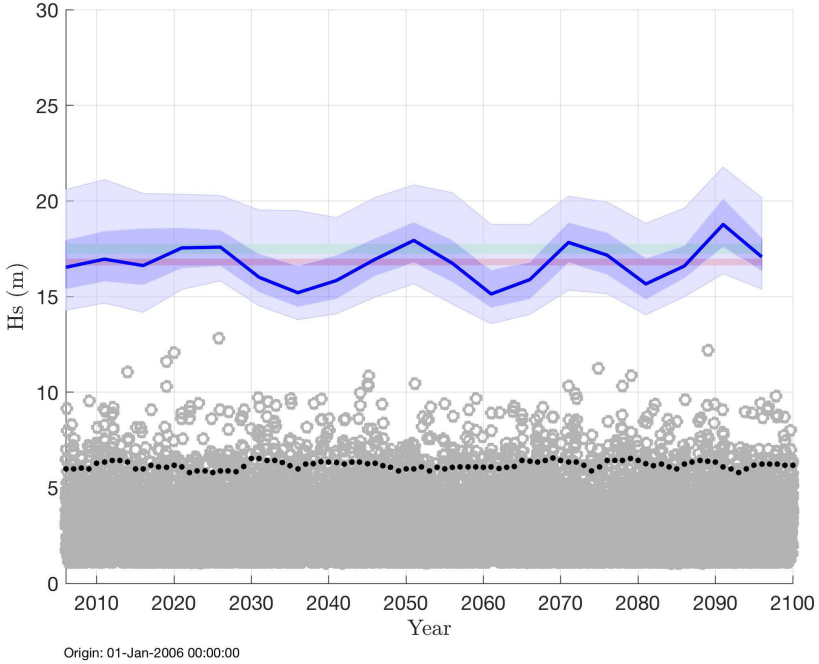
# Climate Change: Time Series




Quantiles (P50, P90 and P99) of significant wave height through time.

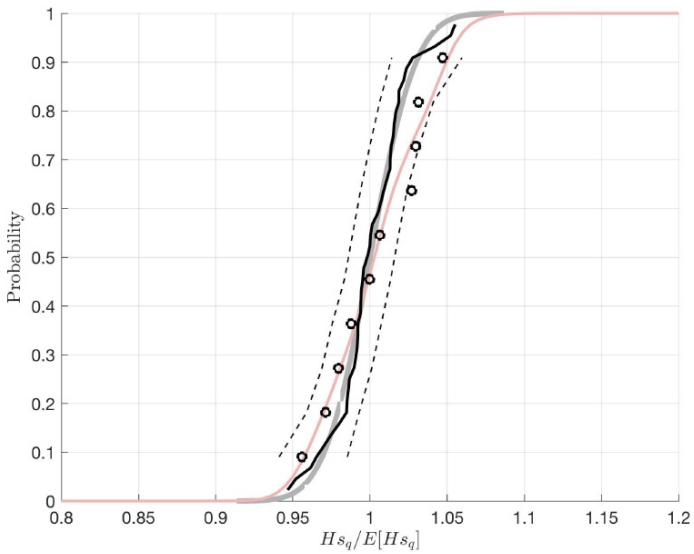
# Climate Change: Extreme Value Analysis

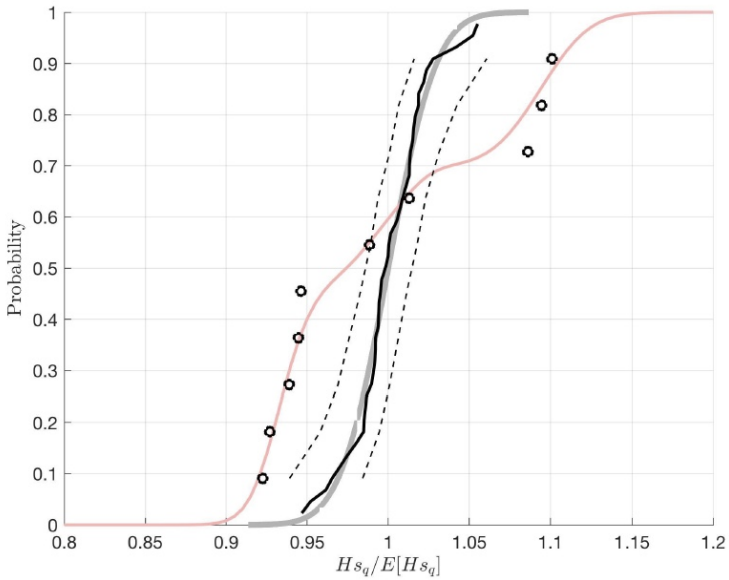



Estimate of the ten thousand year return period significant wave height in CNS using GFDL-ESM2G for the future period: RCP 4.5 (left) and RCP 8.5 (right).

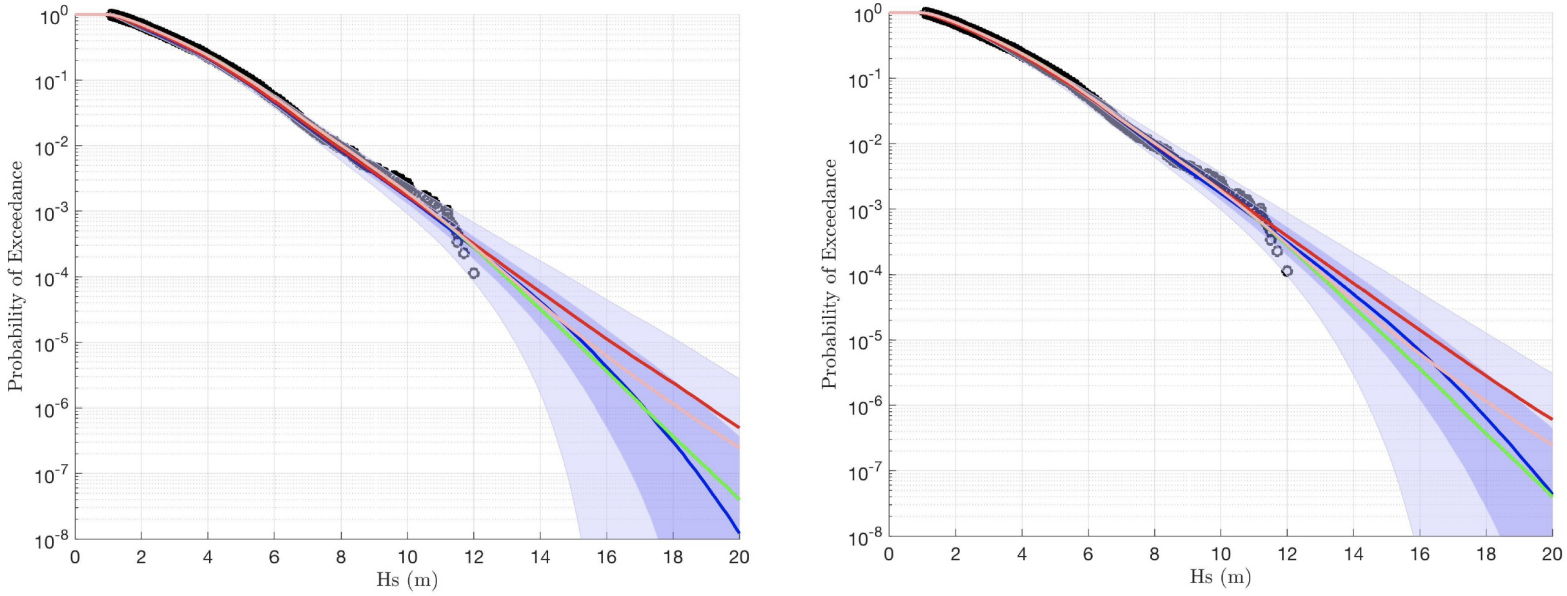
# Climate Change: Extreme Value Analysis



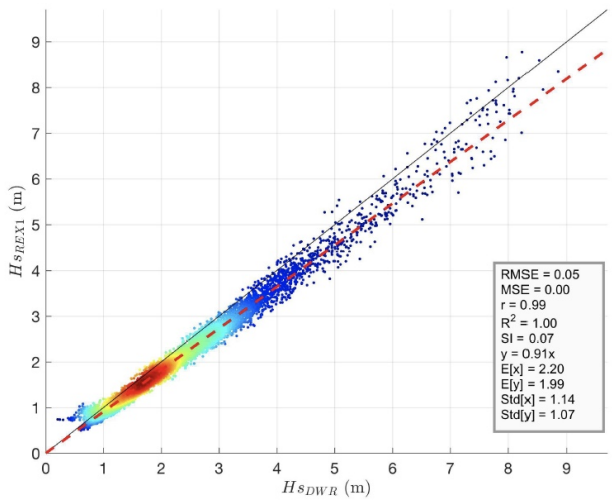

P99 significant wave height in the central North Sea: RCP4.5 2025-2045 (left) and RCP8.5 (2080-2100).
Historical variability (grey and black lines), climate model estimates (black circles), and posterior distribution (red).

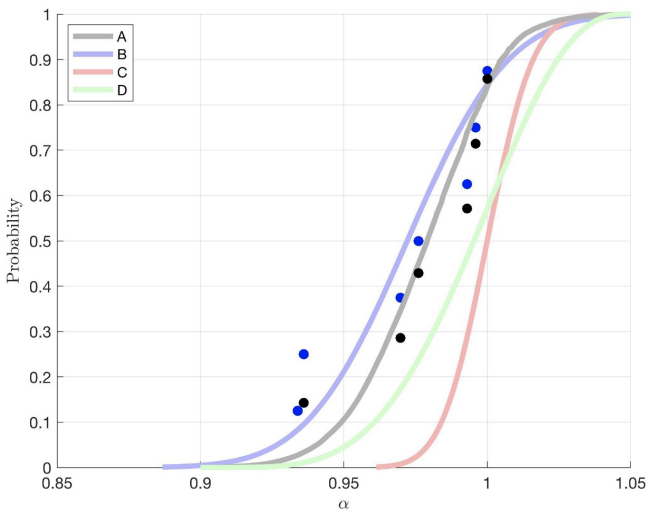
# Climate Change: Extreme Value Analysis




Long-term distribution of storm peak significant wave height in the central North Sea: RCP4.5 2025-2045 (left) and RCP8.5 (2080-2100).
Historical: data (black), median (green) and posterior predictive (pink).
Future climate: median (blue), credible intervals (blue fan), and posterior predictive (red).

# Measurement Uncertainty




Scatter plot comparing simultaneous measurements of significant wave height (left). Measurement device biase (right).

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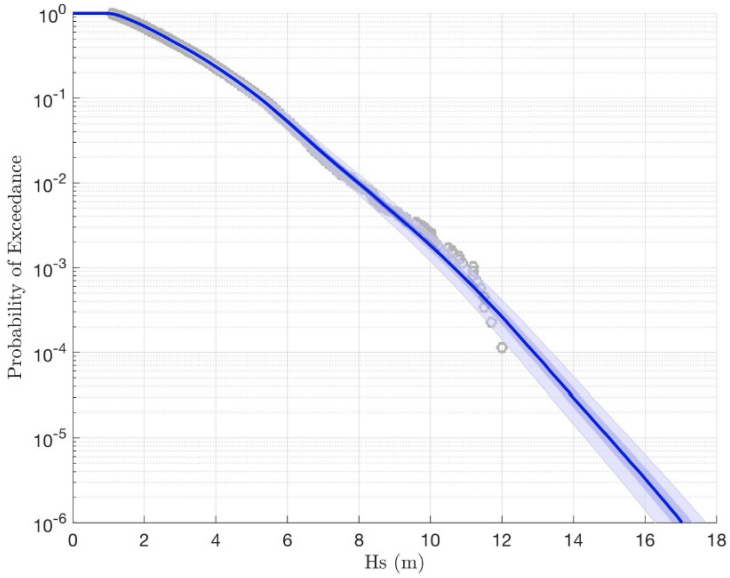


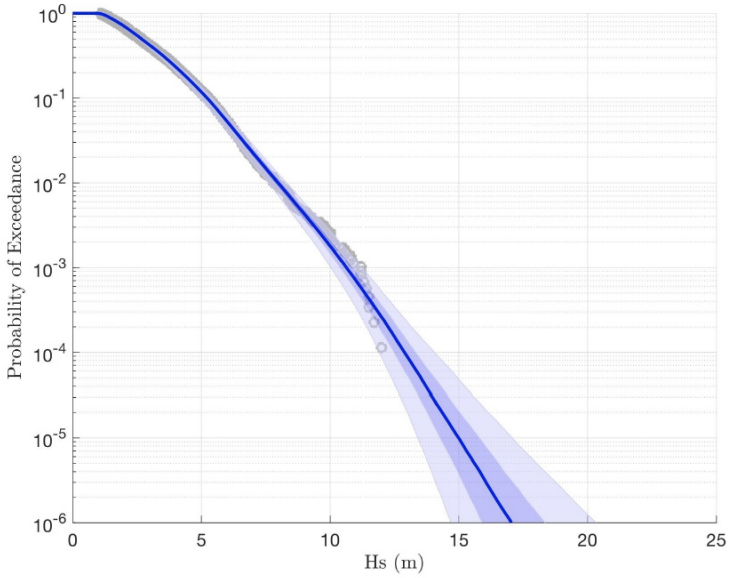


Effect of measurement uncertainty on the long-term distribution of significant wave height.

# Bibliography

Giuseppe Zappa, L.C. Shaffrey, and Kevin I. Hodges. The ability of CMIP5 models to simulate North Atlantic extratropical cyclones. *Journal of Climate*, 26(15):5379–5396, 2013. ISSN 08948755. doi: 10.1175/JCLI-D-12-00501.1.