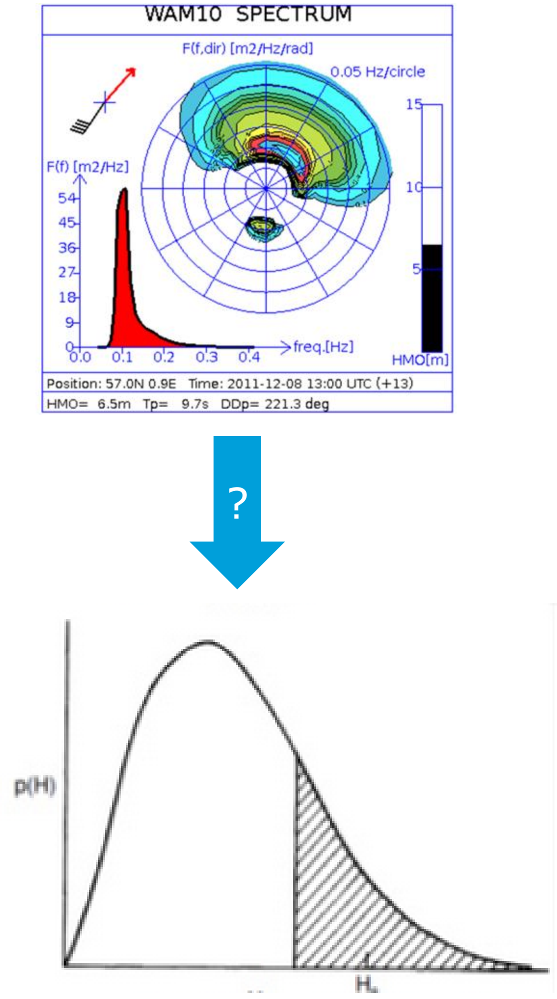
Rogue wave warning based on spectral wave forecasting

2nd International Workshop on Waves, Storm Surges and Coastal Hazards
Melbourne, Australia

Odin Gramstad, Elzbieta Bitner-Gregersen, Ole Johan Aarnes, Øyvind Breivik and Anne Karin Magnusson

12 November 2019

How much can we say about the wave statistics in a sea state, given information about the wave spectrum?



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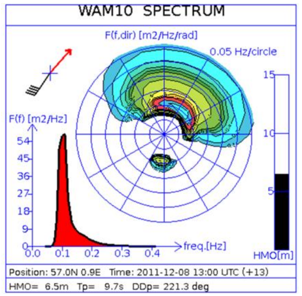
Datasets used in study

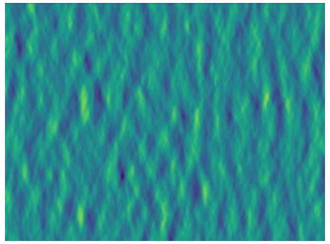


Training — 2016, 2017

Validation — 2018

Training — 2019

01-10-2016 **26 280 WAM spectra** **30-09-2019**



6200 HOSM simulations (3 hour duration)

2Hz surface elevation time series

Wave buoy

Laser

Saab radar

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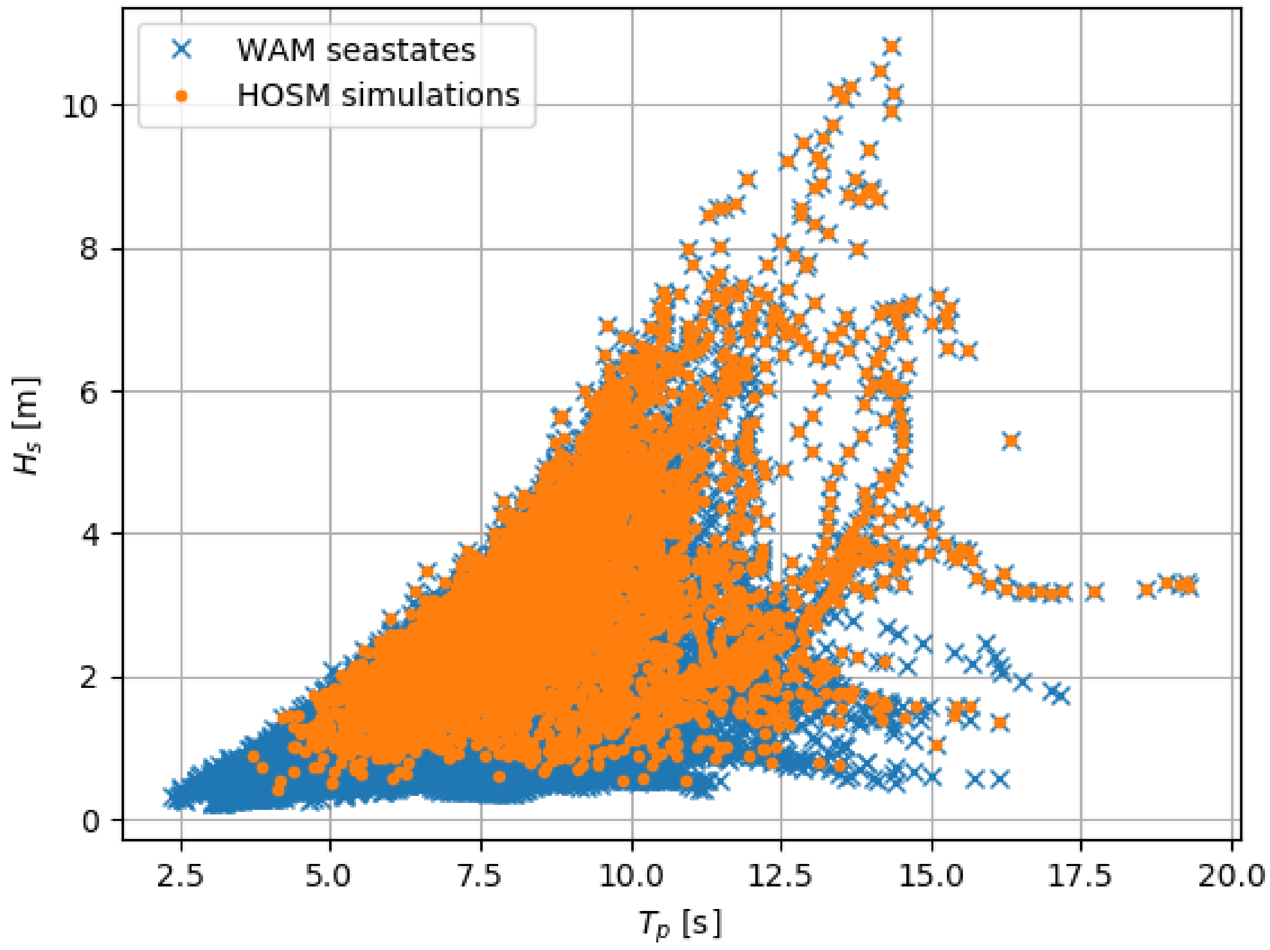
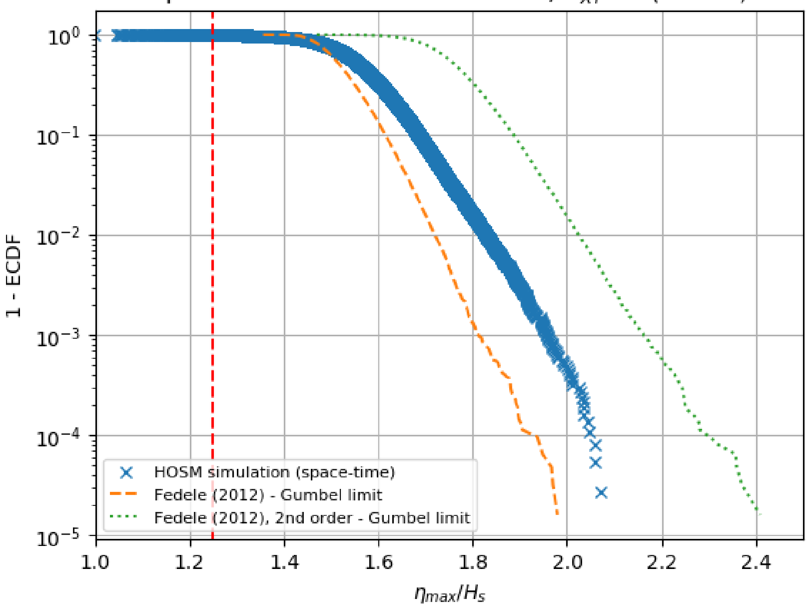
Subset of WAM spectra selected for simulation with HOSM

- **26 280** WAM spectra
- **6200** 3-hour HOSM-simulations over a spatial domain of about 2.5 x 2.5 km

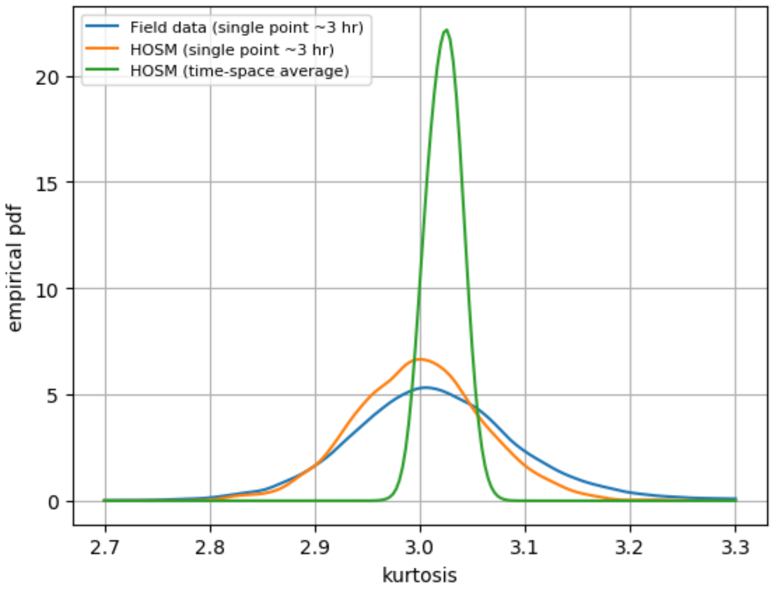


Statistics from HOSM simulations

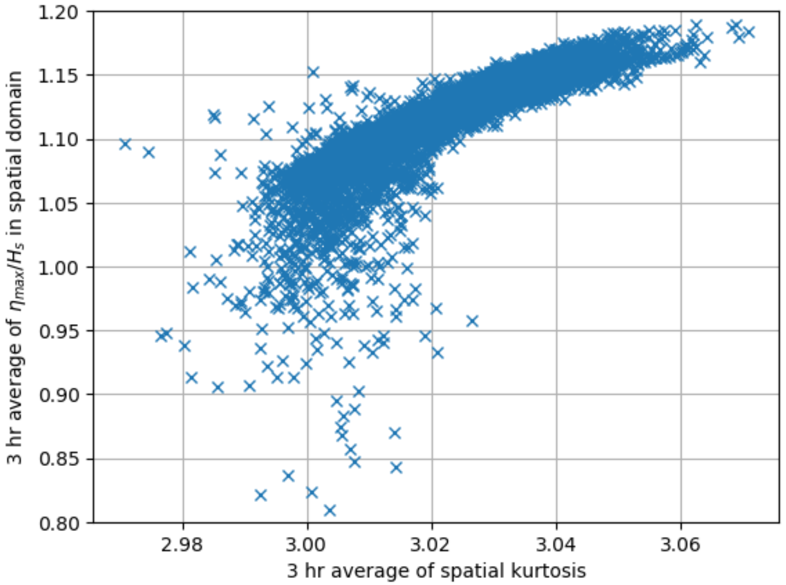
Space-time extremes



Distribution of kurtosis



Kurtosis vs η_{max}



- Simulations cover very large area
  - Rogue waves ($\eta_{max} > 1.25H_s$) are observed in almost all simulations
  - Stable estimate of kurtosis
- Clear correlation between kurtosis and extreme crests

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Prediction of kurtosis – parametric formulas

$$\mathrm{NMSE} = \frac{\sum_j \left(\kappa_{4j}^{(obs)} - \kappa_{4j}^{(pred)}\right)^2}{\sum_j \left(\kappa_{4j}^{(obs)} - \bar{\kappa}_{4j}^{(obs)}\right)^2}$$

Janssen (2017)
Janssen & Janssen (2019)

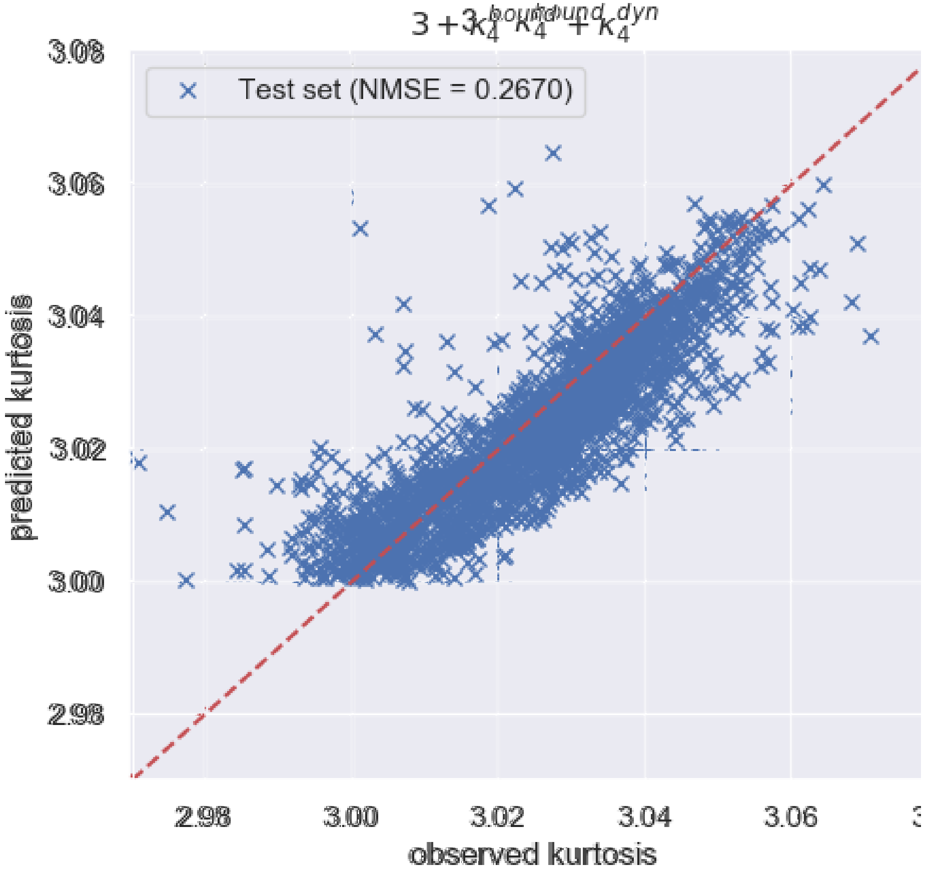
$$\kappa_4 = 3 + \kappa_4^{bound} + \kappa_4^{dyn}$$

$$\kappa_4^{bound} = 9k_0^2 m_0 = 9\epsilon^2$$

$$\kappa_4^{dyn} = BFI^2 \times \begin{cases} J(R), & R < 1 \\ -J(1/R)/R, & R > 1 \end{cases}$$

$$J(R) = \frac{\pi\gamma}{\sqrt{3}}(1 - \alpha\sqrt{R} + \beta R + \delta R^2)$$

$$BFI = \sqrt{2}\epsilon/\delta_\omega, \quad R = \frac{\delta_\theta^2}{2\nu^2}$$



	Training set	Test set
κ_4^{bound}	0.500	0.459
$\kappa_4^{bound} + \kappa_4^{dyn}$	0.291	0.267
$\alpha\kappa_4^{bound}$ (best fit)	0.331	0.286
$\alpha\kappa_4^{bound} + \beta\kappa_4^{dyn}$ (best fit)	0.275	0.244

Prediction of kurtosis – machine learning

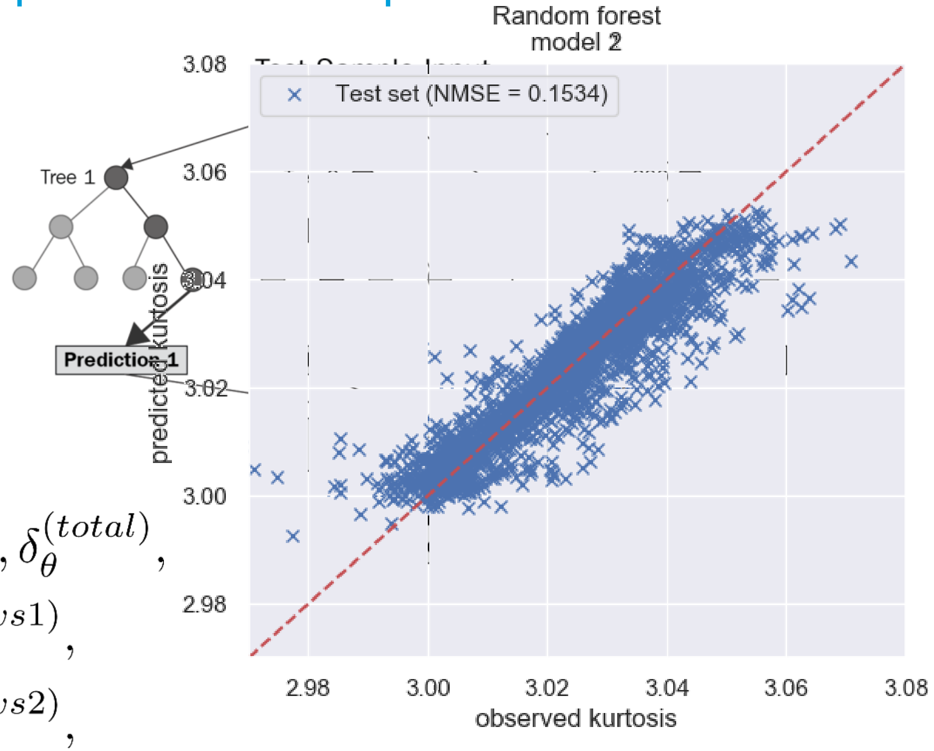
- Can kurtosis be better predicted if we include additional spectral properties and allow for more complex relationships between parameters?

- Random forest – model 1

$$k_p, m_0, m_1, m_2, \delta_\omega, \delta_\theta, n_{ws}, \Delta\theta_m$$

- Random forest – model 2

$$k_p^{(total)}, m_0^{(total)}, m_1^{(total)}, m_2^{(total)}, \delta_\omega^{(total)}, \delta_\theta^{(total)},$$
$$k_p^{(ws1)}, m_0^{(ws1)}, m_1^{(ws1)}, m_2^{(ws1)}, \delta_\omega^{(ws1)}, \delta_\theta^{(ws1)},$$
$$k_p^{(ws2)}, m_0^{(ws2)}, m_1^{(ws2)}, m_2^{(ws2)}, \delta_\omega^{(ws2)}, \delta_\theta^{(ws2)},$$
$$n_{ws}, \Delta\theta_m$$



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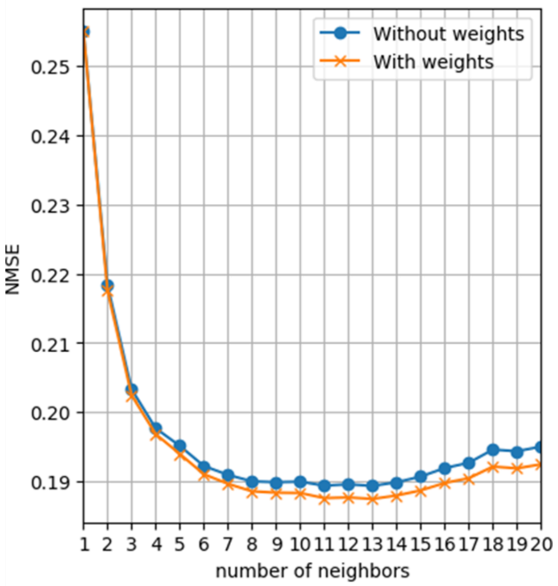
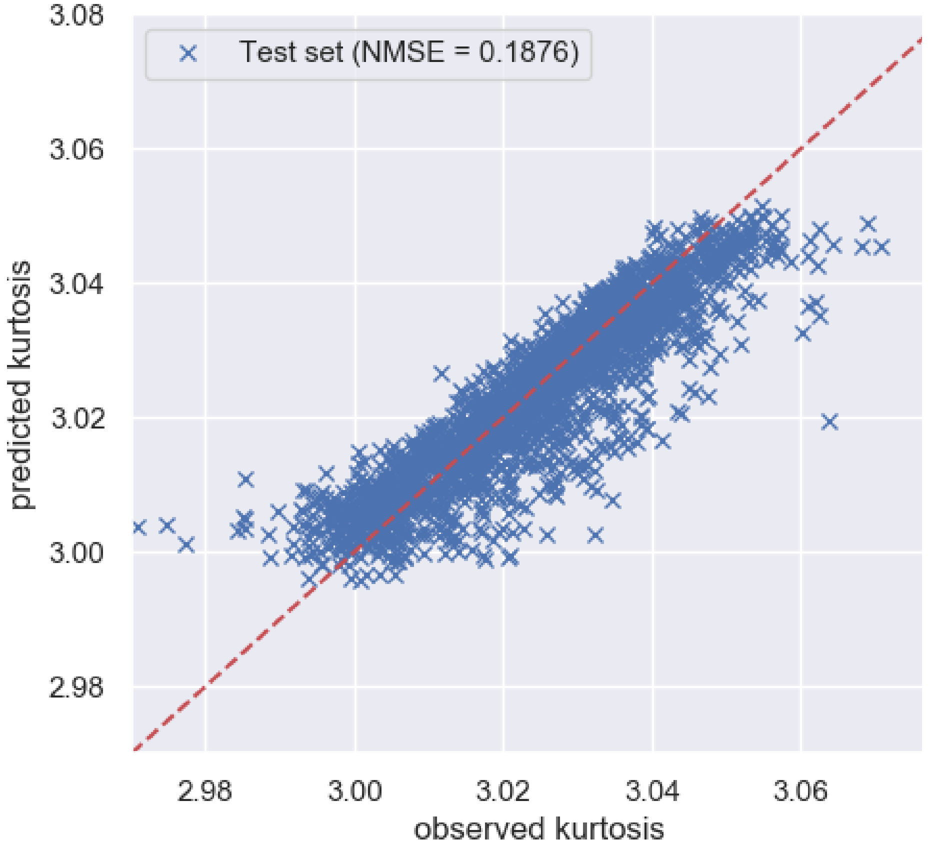
$\alpha\kappa_4^{bound}$ (best fit)	0.331	0.286
$\alpha\kappa_4^{bound} + \beta\kappa_4^{dyn}$ (best fit)	0.275	0.244
Random forest model 1	0.015	0.159
Random forest model 2	0.016	0.153

Prediction of kurtosis – similar sea states

- Predict kurtosis by considering existing simulations of sea states with similar spectra
- For each spectrum in test set -> Select the N most similar spectra in the training set





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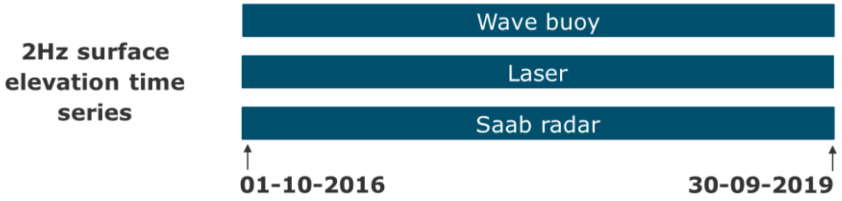
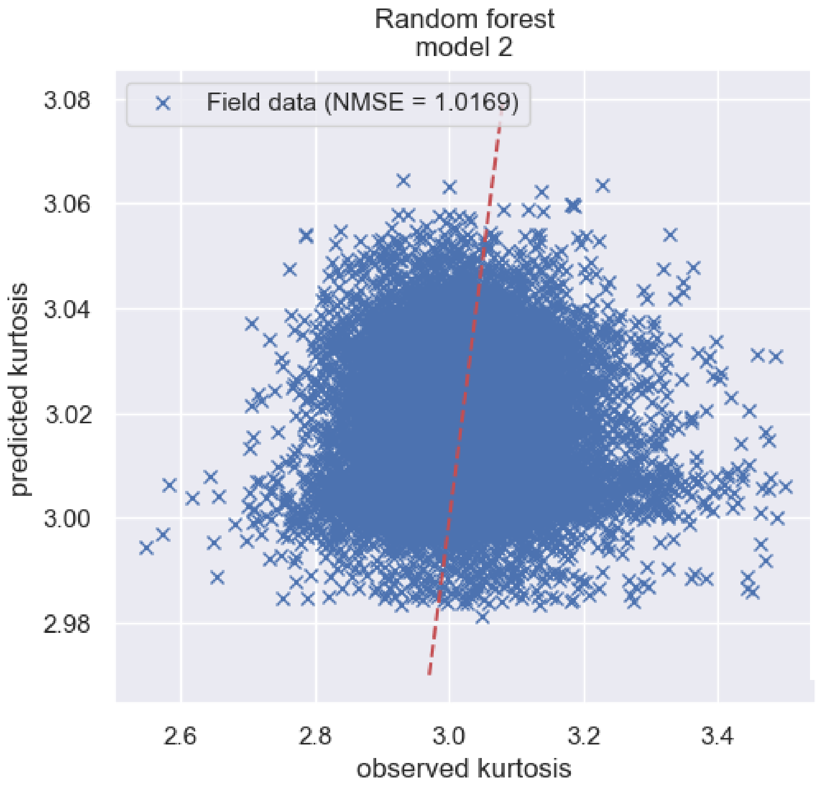
Random forest model 1	0.015	0.159
Random forest model 2	0.016	0.153
Most similar spectra	0.000	0.188

Validation against field data



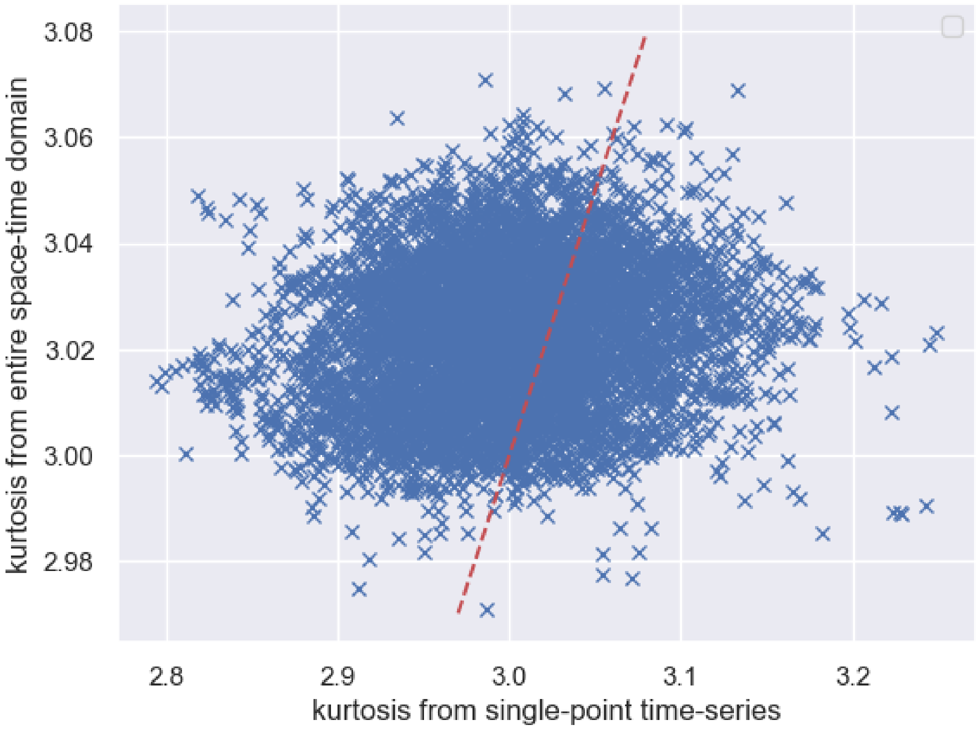


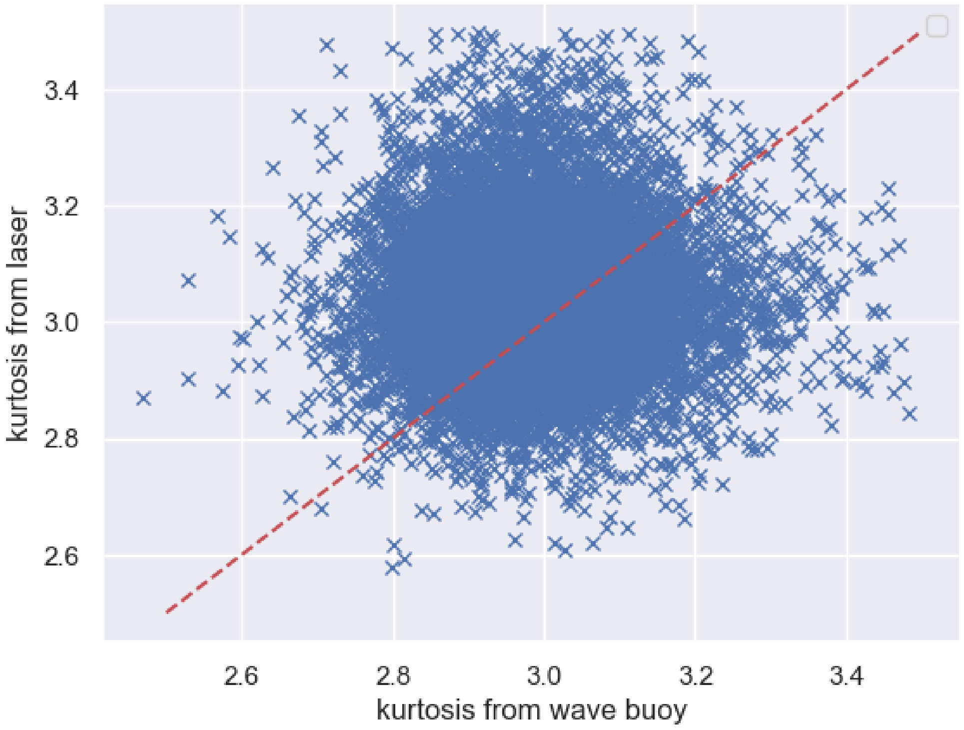
	Training set	Test set	Field data	
	Training set	Test set	Field data	Simulations timeseries
κ_4^{bound}	0.500	0.459	1.003	1.224
$\kappa_4^{bound} + \kappa_4^{dyn}$	0.291	0.267	1.009	1.292
$\alpha\kappa_4^{bound}$ (best fit)	0.331	0.286	1.006	1.331
$\alpha\kappa_4^{bound} + \beta\kappa_4^{dyn}$ (best fit)	0.275	0.244	1.008	1.316
Random forest model 1	0.015	0.159	1.019	1.334
Random forest model 2	0.016	0.153	1.017	1.334
Most similar spectra	0.000	0.188	1.019	1.316

spectra

- Very poor prediction when validated on field data
- Sampling variability of kurtosis from single-point wave records is much larger than difference in kurtosis due to sea-state differences

Point measurements – sampling variability dominates





No correlation between kurtosis from a 30-minutes time-series and the “real” underlying kurtosis obtained as an average over the full space-time domain

Same goes for kurtosis from two point measurement (at the same time and in nearby locationa)

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Predicting increased risk of rogue waves from wave spectrum - conclusions

- Sea-state kurtosis (and hence increased risk of rogue waves) can in principle be “forecasted” from knowledge about the wave spectrum
  - Wave steepness is (not surprisingly) the most important factor
  - …but including information such as BFI and spectral bandwidths improves prediction
  - Machine learning methods that are not restricted to simple parametrizations → Even better predictions
- However:
  - The predictability of rogue waves/kurtosis in single-point measurements is non-existing
  - Hence, the relevance of such prediction seems to be very limited for marine structures, since sampling variability will always dominate. Unless the area of interest is quite large.
- Further work: Validate prediction of kurtosis using stereo-camera space-time measurements, where sampling variability is reduced

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