Modelling extreme ocean environments for structural design

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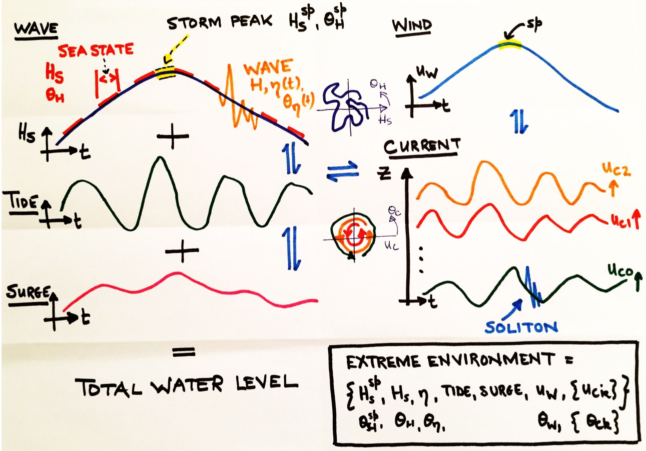
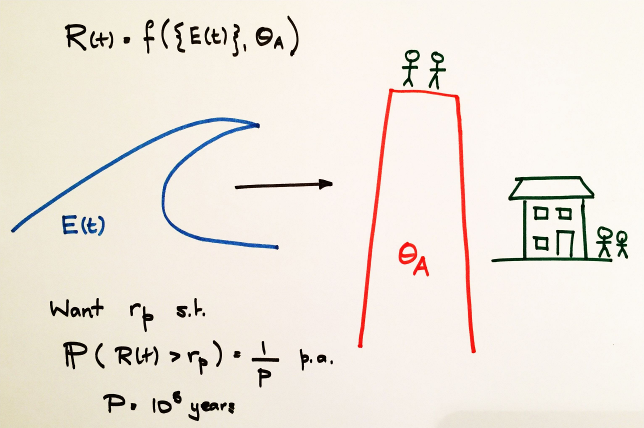
... with thanks to colleagues at Lancaster, Shell and elsewhere

Modelling ocean storm environment



- Multiple coupled physical processes
- Rare, extreme events

Modelling structural risk



- Ocean environment is harsh
- Marine structures at risk of failure
- Reliability standards must be met

Optimal design of marine structure

Set-up

- Storm storm peak events $\boldsymbol{X}^{\text{sp}}$ dependent on covariates $\boldsymbol{\Theta}^{\text{sp}}$
- An evolving within-storm environment $\{(\mathbf{X}_s, \boldsymbol{\Theta}_s)\}_{s \in S_T}$ for storm of length T
- A structural "loading" $\boldsymbol{Y}$
- Everything subject to sources of uncertainty $\boldsymbol{Z}$
- $\boldsymbol{Z}$, $\boldsymbol{\Theta}^{\text{sp}}$, $\boldsymbol{X}^{\text{sp}}$, $\{(\mathbf{X}_s, \boldsymbol{\Theta}_s)\}_{s \in S_T}$ and $\boldsymbol{Y}$ are multidimensional random variables

Unconditional distribution of loading

$$
\begin{aligned}
F_{\boldsymbol{Y}}(\boldsymbol{y}) \quad = \quad & \int_{\zeta} \int_{(\{(\mathbf{x}_s, \boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau}, \tau)} \int_{\mathbf{x}^{\text{sp}}} \int_{\boldsymbol{\theta}^{\text{sp}}} \\
\times \quad & F_{\boldsymbol{Y} | \{(\mathbf{X}_s, \boldsymbol{\Theta}_s)\}_{s \in S_T}, \boldsymbol{Z}}(\boldsymbol{y} | \{(\mathbf{x}_s, \boldsymbol{\theta}_s)\}_{s \in S_\tau}, \boldsymbol{\zeta}) \\
\times \quad & f_{(\{(\mathbf{X}_s, \boldsymbol{\Theta}_s)\}_{s \in \mathcal{S}_T}, T) | \mathbf{X}^{\text{sp}}, \boldsymbol{\Theta}^{\text{sp}}, \boldsymbol{Z}} \left(\{(\mathbf{x}_s, \boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau}, \tau \mid \mathbf{x}^{\text{sp}}, \boldsymbol{\theta}^{\text{sp}}, \boldsymbol{\zeta} \right) \\
\times \quad & f_{\mathbf{X}^{\text{sp}} | \boldsymbol{\Theta}^{\text{sp}}, \boldsymbol{Z}}(\mathbf{x}^{\text{sp}} | \boldsymbol{\theta}^{\text{sp}}, \boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{\Theta}^{\text{sp}} | \boldsymbol{Z}}(\boldsymbol{\theta}^{\text{sp}} | \boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{Z}}(\boldsymbol{\zeta}) \\
\times \quad & \mathrm{d}\boldsymbol{\theta}^{\text{sp}} \, \mathrm{d}\mathbf{x}^{\text{sp}} \, \mathrm{d}(\{(\mathbf{x}_s, \boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau}, \tau) \, \mathrm{d}\boldsymbol{\zeta}
\end{aligned}
$$

Optimal design of marine structure

Typical

- Distribution of annual maximum loading
- Assumes univariate load

$$F_A(y) \quad = \quad \int_m [F_Y(y)]^m f_C(m)\,\mathrm{d}m$$

- Annual rate of occurrence f_C of storms
- Return value for return period P years given by $F_A^{-1}(1-1/P)$

More generally

- Expected utility

$$\mathbb{E}(U_A|\boldsymbol{\mathcal{R}}) = \int_m \int_{\boldsymbol{y}_1} \dots \int_{\boldsymbol{y}_m} U_A(\boldsymbol{y}_1, \dots, \boldsymbol{y}_m|\boldsymbol{\mathcal{R}}) f_{\boldsymbol{Y}_1,\dots,\boldsymbol{Y}_m,M}(\boldsymbol{y}_1, \dots, \boldsymbol{y}_m, m)\,\mathrm{d}\boldsymbol{y}_1 \dots \mathrm{d}\boldsymbol{y}_m\,\mathrm{d}m$$

- System annual utility $U_A(\boldsymbol{Y}_1, \dots, \boldsymbol{Y}_m|\boldsymbol{\mathcal{R}})$ given system "strength" characteristics $\boldsymbol{\mathcal{R}}$
- Solve for $\boldsymbol{\mathcal{R}}$ to achieve required expected annual utility
- Or maybe "lifetime utility" (?)

Historical approach

Historical approach

Will discuss:

- Estimation for return values from small samples
    - This is still a major issue today (e.g. LOADS)

Generic historical issues:

- Weaker justification (?) for choice of distributional forms for extremes
- Neglect of covariate effects in extremes (direction, season, “climate change”)
- Neglect of spatial and temporal dependence in extremes
- Neglect of joint behaviour of extremes across multiple metocean variables (“associated values”)
- Neglect of uncertainty (“no UQ”)
- Dearth of data, data quality (measured, hindcast, ...) for extremes not clear
- Disconnect with risk (no direct connection with structural failure; “return values”, “design contours”)
- Missing interface between metocean specialists, structural engineers and “statistical modellers”
- “No full empirical model”

What is a return value?

- Random variable A represents the maximum value of some physical quantity X per annum
- Forget about all complicating issues like serial dependence, covariates and other sources of dependence and uncertainty
- The P-year return value x_P of X is then defined by the equation

$$F_A(x_P) = \Pr(A \leq x_P) = 1 - \frac{1}{P}$$

- Or

$$x_P = F_A^{-1}(1 - \frac{1}{P})$$

- Typically $P \in [10^2, 10^8]$ years

An alternative definition

- Random variable A_P represents the P-year maximum value of X
- The P-year return value x'_P of X can be found from F_{A_P} for large P, assuming independent annual maxima since

$$\begin{aligned} F_A(x_P) &= 1 - \frac{1}{P} \\ \Rightarrow F_{A_P}(x_P) &= \left(1 - \frac{1}{P}\right)^P \approx \exp(-1) \end{aligned}$$

- Use $F_{A_P}(x'_P) = \exp(-1)$ to define an alternative return value x'_P

Estimating a return value

- To estimate x_P, we need knowledge of the distribution function F_A of the annual maximum
- We might estimate F_A using extreme value analysis on a sample of independent observations of A
- Typically more efficient to estimate the distribution $F_{X|X>\psi}$ of threshold exceedances of X above some high threshold ψ using a sample of independent observations of X, and use this in turn to estimate F_A and x_P
- How is this done?

Estimating a return value

- Asymptotic theory suggests for high threshold $\psi \in (-\infty, \infty)$ that

$$F_{X|X>\psi}(x|\psi, \sigma, \xi) = 1 - \left(1 + \frac{\xi}{\sigma}(x - \psi)\right)_+^{-1/\xi}$$

for $x > \psi$, shape $\xi \in (-\infty, \infty)$ and scale $\sigma \in (0, \infty)$

- The full distribution of X is $F_X(x) = \tau + (1 - \tau)F_{X|X>\psi}(x)$ where $\tau = \Pr(X \le \psi)$
- Thus

$$F_A(x) = \Pr(A \le x) = \sum_{k=0}^{\infty} f_C(k) F_X^k(x)$$

where C is the number of occurrences of X per annum, with probability mass function f_C to be estimated (say with a Poisson model with parameter λ)

- So what's the problem?

Parameter uncertainty

- x_p can be estimated easily in the absence of uncertainty

- In reality, we estimate parameters λ, ψ, σ and ξ from a sample of data, and we cannot know their values exactly
- How does this epistemic uncertainty affect return value estimates?

- A number of different plausible estimators for return values under uncertainty
- Different estimators perform differently (bias and variance)
- Which estimators are likely to perform reasonably in fairly general circumstances?

- Is it even **sensible or desirable** to estimate return values?

Incorporating uncertainty

- If a distribution $F_{Y|\boldsymbol{Z}}$ of random variable Y is known conditional on random variables $\boldsymbol{Z}$, and the joint density $f_{\boldsymbol{Z}}$ of $\boldsymbol{Z}$ is also known, the unconditional predictive distribution $\tilde{F}_Y$ can be evaluated using

$$\tilde{F}_Y(y) = \int_{\zeta} F_{Y|\boldsymbol{Z}}(x|\zeta) f_{\boldsymbol{Z}}(\zeta)\, d\zeta$$

- Th expected value of deterministic function g of parameters $\boldsymbol{Z}$ given joint density $f_{\boldsymbol{Z}}$ is

$$E[g(\boldsymbol{Z})] = \int_{\zeta} g(\zeta) f_{\boldsymbol{Z}}(\zeta)\, d\zeta$$

- $\zeta = (\lambda, \psi, \sigma, \xi)$, $Y = A$ (or $Y = A_P$)

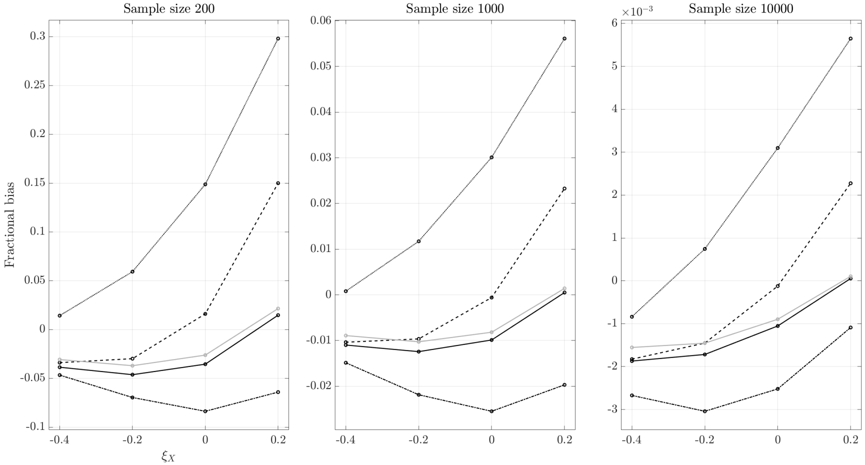
Different estimators of return value

- Uncertain estimates of GP model parameters from fit to sample represented by random variables $\boldsymbol{Z}$
- Estimate distribution $F_{A|\boldsymbol{Z}}$ of annual maximum event using $\boldsymbol{Z}$
- Estimate P-year return value by finding the $1-1/P$ quantile of $F_{A|\boldsymbol{Z}}$
- Various options available, including:

$$
\begin{aligned}
q_1 &= F^{-1}_{A|\boldsymbol{Z}}(1-1/P \mid \mathbb{E}_{\boldsymbol{Z}}[\boldsymbol{Z}]) = F^{-1}_{A|\boldsymbol{Z}}(1-1/P \mid \int_\zeta \zeta f_{\boldsymbol{Z}}(\zeta) d\zeta) \\
q_2 &= \mathbb{E}_{\boldsymbol{Z}}[F^{-1}_{A|\boldsymbol{Z}}(1-1/P \mid \boldsymbol{Z})] = \int_\zeta F^{-1}_{A|\boldsymbol{Z}}(1-1/P \mid \zeta) f_{\boldsymbol{Z}}(\zeta) d\zeta \\
q_3 &= \tilde{F}^{-1}_A(1-1/P) \text{ where } \tilde{F}_A(x) = \int_\zeta F_{A|\boldsymbol{Z}}(x \mid \zeta) f_{\boldsymbol{Z}}(\zeta) d\zeta \\
q_4 &= \tilde{F}^{-1}_{A_P}(\exp(-1)) \text{ where } \tilde{F}_{A_P}(x) = \tilde{F}^P_A(x) \\
q_5 &= \text{med}_{\boldsymbol{Z}}[F^{-1}_{A|\boldsymbol{Z}}(1-1/P \mid \boldsymbol{Z})]
\end{aligned}
$$

- For small samples, these have very different properties

Fractional bias of return value estimators



Fractional bias of return value estimates from different estimators using maximum likelihood, as a function of sample size and true GP shape ξ. LHS top to bottom: q_3, q_2, q_5, q_1, q_4.

- Knock-on effects for associated values of the form $\mathbb{E}_{\boldsymbol{Z}}(\boldsymbol{Y}|X = q, \boldsymbol{Z})$

Return value references and implications

References

- Return values: Serinaldi [2015], Jonathan et al. [2021]
- Associated values : Towe et al. [2022]
- Lots of other approaches for small samples (e.g empirical Bayes Zhang 2007, Zhang and Stephens 2009, Zhang 2010)

Implications for today

- Current EV models tend to have high effective dimensionality
- Effective number of degrees of freedom from sample for model fitting can be small ⇒ we have small effective sample size
- Momentum in metocean community (e.g. AWARE, LOADS JIPs) to use Bayesian inference ... great in principle, but ...
- Characteristics of (posterior) predictive distributions highly dependent on prior specification. Yet not clear how to advise "diverse user community" regarding "rational prior specification".

Current best practice

Current best practice: full probabilistic modelling

- Model components of "full empirical model"
  - Storm peaks
  - Within-storm evolution
  - Fluid loading
- Marginal modelling
- Dependence modelling

The full "forward" model

Unconditional distribution of loading from a "random storm"

$$
\begin{aligned}
F_{\boldsymbol{Y}}(\boldsymbol{y}) \quad = \quad & \int_{\zeta} \int_{(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)} \int_{\mathbf{x}^{\text{sp}}} \int_{\boldsymbol{\theta}^{\text{sp}}} \\
\times \quad & F_{\boldsymbol{Y}|\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},\boldsymbol{Z}}(\boldsymbol{y}|\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\boldsymbol{\zeta}) \\
\times \quad & f_{(\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},T)|\mathbf{X}^{\text{sp}},\boldsymbol{\Theta}^{\text{sp}},\boldsymbol{Z}}\left(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau \mid \mathbf{x}^{\text{sp}},\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}\right) \\
\times \quad & f_{\mathbf{X}^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},\boldsymbol{Z}}(\mathbf{x}^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{\Theta}^{\text{sp}}|\boldsymbol{Z}}(\boldsymbol{\theta}^{\text{sp}}|\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{Z}}(\boldsymbol{\zeta}) \\
\times \quad & \mathrm{d}\boldsymbol{\theta}^{\text{sp}}\,\mathrm{d}\mathbf{x}^{\text{sp}}\,\mathrm{d}(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)\,\mathrm{d}\boldsymbol{\zeta}
\end{aligned}
$$

Still missing here:

- Temporal "inter-storm" effects (clustering, climate change)
  - "Random storm" model invalid; even conditional independence assumption invalid (?)
- Spatial dependence of extremes
  - Spatial risk: e.g. de-manning multiple structures

Storm peaks

Context: unconditional distribution of loading

$$
\begin{aligned}
F_Y(y) = & \int_\zeta \int_{(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)} \int_{\mathbf{x}^{\text{sp}}} \int_{\boldsymbol{\theta}^{\text{sp}}} \\
\times & F_{Y|\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},Z}(y|\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\zeta) \\
\times & f_{(\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},T)|\mathbf{X}^{\text{sp}},\boldsymbol{\Theta}^{\text{sp}},Z}\left(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau \mid \mathbf{x}^{\text{sp}},\boldsymbol{\theta}^{\text{sp}},\zeta\right) \\
\times & f_{\mathbf{X}^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},Z}(\mathbf{x}^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\zeta) \\
\times & f_{\boldsymbol{\Theta}^{\text{sp}}|Z}(\boldsymbol{\theta}^{\text{sp}}|\zeta) \\
\times & f_Z(\zeta) \\
\times & \, d\boldsymbol{\theta}^{\text{sp}}\, d\mathbf{x}^{\text{sp}}\, d(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)\, d\zeta
\end{aligned}
$$

Storm peaks: modelling margins and dependence

$$
\begin{aligned}
f_{\mathbf{X}^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},Z}(\mathbf{x}^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\zeta) = & \left[\prod_{j=1}^{p} f_{X_j^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},Z}(x_j^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\zeta)\right] \\
\times & \; c(F_{X_1^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},Z}(x_1^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\zeta),\ldots,F_{X_p^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},Z}(x_p^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\zeta)|\boldsymbol{\theta}^{\text{sp}},\zeta)
\end{aligned}
$$

More to come in a minute!

Within-storm evolution

Context: unconditional distribution of loading

$$
\begin{aligned}
F_{\boldsymbol{Y}}(\boldsymbol{y}) \quad = \quad & \int_{\zeta} \int_{(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau},\tau)} \int_{\mathbf{x}^{\text{sp}}} \int_{\boldsymbol{\theta}^{\text{sp}}} \\
\times \quad & F_{\boldsymbol{Y}|\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s \in \mathcal{S}_T},\boldsymbol{Z}}(\boldsymbol{y}|\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau},\boldsymbol{\zeta}) \\
\times \quad & f_{(\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s \in \mathcal{S}_T},T)|\mathbf{X}^{\text{sp}},\boldsymbol{\Theta}^{\text{sp}},\boldsymbol{Z}}\left(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau},\tau \mid \mathbf{x}^{\text{sp}},\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}\right) \\
\times \quad & f_{\mathbf{X}^{\text{sp}}|\boldsymbol{\Theta}^{\text{sp}},\boldsymbol{Z}}(\mathbf{x}^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{\Theta}^{\text{sp}}|\boldsymbol{Z}}(\boldsymbol{\theta}^{\text{sp}}|\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{Z}}(\boldsymbol{\zeta}) \\
\times \quad & \mathrm{d}\boldsymbol{\theta}^{\text{sp}}\,\mathrm{d}\mathbf{x}^{\text{sp}}\,\mathrm{d}(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s \in \mathcal{S}_\tau},\tau)\,\mathrm{d}\boldsymbol{\zeta}
\end{aligned}
$$

Models for within-storm evolution

- History matching: Feld et al. [2019], Hansen et al. [2020]
- Extreme value time-series model (an extension of conditional extremes): Tendijck et al. [2019], Tendijck et al. [2023]

Fluid loading

Context: unconditional distribution of loading

$$\begin{aligned} F_{\boldsymbol{Y}}(\boldsymbol{y}) \quad = \quad & \int_{\zeta} \int_{(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)} \int_{\mathbf{x}^{\mathrm{sp}}} \int_{\boldsymbol{\theta}^{\mathrm{sp}}} \\ \times \quad & F_{\boldsymbol{Y}|\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},\boldsymbol{Z}}(\boldsymbol{y}|\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\zeta) \\ \times \quad & f_{(\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},T)|\mathbf{X}^{\mathrm{sp}},\boldsymbol{\Theta}^{\mathrm{sp}},\boldsymbol{Z}}\left(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau \mid \mathbf{x}^{\mathrm{sp}},\boldsymbol{\theta}^{\mathrm{sp}},\zeta\right) \\ \times \quad & f_{\mathbf{X}^{\mathrm{sp}}|\boldsymbol{\Theta}^{\mathrm{sp}},\boldsymbol{Z}}(\mathbf{x}^{\mathrm{sp}}|\boldsymbol{\theta}^{\mathrm{sp}},\zeta) \\ \times \quad & f_{\boldsymbol{\Theta}^{\mathrm{sp}}|\boldsymbol{Z}}(\boldsymbol{\theta}^{\mathrm{sp}}|\zeta) \\ \times \quad & f_{\boldsymbol{Z}}(\zeta) \\ \times \quad & \mathrm{d}\boldsymbol{\theta}^{\mathrm{sp}}\,\mathrm{d}\mathbf{x}^{\mathrm{sp}}\,\mathrm{d}(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)\,\mathrm{d}\zeta \end{aligned}$$

Models for fluid loading

- Incorporate kinematics, estimate Morison loads (e.g. LOADS, AWARE JIPs): Swan [2020], Gibson [2020]
- Interface environment and fluid loading software for full “forward model”
- Fundamentals paper: Speers et al. [2024]

Full model for fluid loading

General approach

- Linear wave spectrum model
  - e.g. JONSWAP
  - Multivariate extreme value model for all spectral model parameters
  - $\Rightarrow$ Simulation of arbitrary sea state spectra
- Linear wave theory (potential theory)
  - Linearised boundary conditions
  - Linear surface elevation and kinematics
  - $\Rightarrow$ Simulation of linear time-series given linear spectrum
- Non-linear transformation (Swan 2020, Gibson 2020)
  - Non-linear surface elevation
  - "Stretched" kinematics
  - $\Rightarrow$ Simulation of non-linear time-series given linear spectrum
- Conditional simulation of Gaussian time-series (Taylor et al. 1997)
  - Embed extreme excursions in surface elevation and associated kinematics
  - $\Rightarrow$ Efficient simulation of extreme time-series
- Estimate marginal distribution of Morison load from random storm
  - Efficient integration using importance sampling and conditional simulation
- Fundamentals paper: Speers et al. [2024]

Modelling covariate effects

Motivating marginal extremes

Storm peaks: modelling margins and dependence

$$
\begin{aligned}
f_{\mathbf{X}^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(\mathbf{x}^{\text{sp}}|\theta^{\text{sp}},\zeta) &= \left[\prod_{j=1}^{p} f_{X_j^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(x_j^{\text{sp}}|\theta^{\text{sp}},\zeta)\right] \\
&\times \quad c(F_{X_1^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(x_1^{\text{sp}}|\theta^{\text{sp}},\zeta),\ldots,F_{X_p^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(x_p^{\text{sp}}|\theta^{\text{sp}},\zeta)|\theta^{\text{sp}},\zeta)
\end{aligned}
$$

More to come on dependence later!

Generalised Pareto distribution

- Suppose we have an exceedance X of high threshold $\psi \in \mathbb{R}$
- The Pickands-Balkema-De Haan theorem states

$$\begin{aligned}
\lim_{\psi\to\infty} \mathbb{P}[X \leq x | X > \psi] &= \lim_{\psi\to\infty} \frac{F_X(x)}{1 - F_X(\psi)} \\
&= \mathrm{GP}(x|\xi, \sigma, \psi) \\
&= 1 - \left(1 + \frac{\xi}{\sigma}(x - \psi)\right)_+^{-1/\xi}, \quad \sigma > 0, \quad \xi \in \mathbb{R}
\end{aligned}$$

Theory

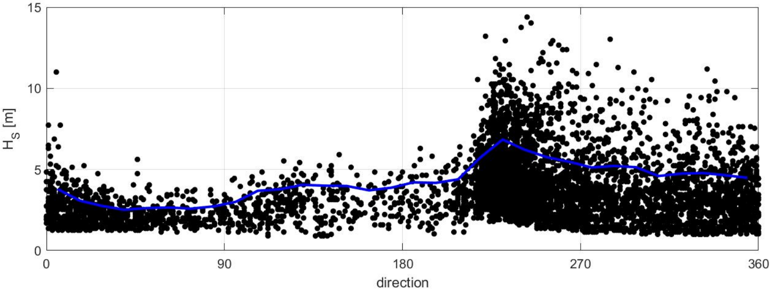
- Derived from max-stability of F_X
- Threshold-stability property
- "Poisson $\times$ GP $=$ GEV"

Practicalities

- How to isolate independent threshold exceedances from observed time-series?
- How to specify extreme threshold ψ?
- ξ, σ, ψ functions of covariates

Motivation

- Environmental extremes vary smoothly with multidimensional covariates
- Generic modelling framework for different covariate representations
- Statistical and computational efficiency for n-D covariates
- Thorough Bayesian uncertainty quantification



Typical data for northern North Sea. Storm peak H_S on direction, with $\tau = 0.8$ extreme value threshold.
Rate and size of occurrence varies with direction.

Model for size of occurrence

- Sample of storm peaks X over threshold $\psi_\theta \in \mathbb{R}$, with 1-D covariate $\theta \in \mathcal{D}_\theta$
- Extreme value threshold ψ_θ assumed known
- X assumed to follow generalised Pareto distribution with shape ξ_θ, (modified) scale ν_θ

$$f_{GP}(x|\xi_\theta, \nu_\theta) = \frac{1}{\sigma_\theta}\left(1 + \frac{\xi_\theta}{\sigma_\theta}(x - \psi_\theta)\right)_+^{-1/\xi_\theta - 1} \text{ with } \nu_\theta = \sigma_\theta(1 + \xi_\theta)$$

- Shape parameter $\xi_\theta \in \mathbb{R}$ and scale parameter $\nu_\theta > 0$
- (Non-stationary Poisson model for rate of occurrence, with rate $\rho_\theta \geq 0$)

Covariate representations in 1-D

- Index set $\mathcal{I}_\theta = \{\theta_s\}_{s=1}^m$ on periodic covariate domain $\mathcal{D}_\theta$
- Each observation belongs to exactly one θ_s
- On $\mathcal{I}_\theta$, assume

$$\begin{aligned} \eta_s &= \sum_{k=1}^n B_{sk}\beta_k, s = 1, 2, ..., m, \text{ or} \\ \boldsymbol{\eta} &= \boldsymbol{B}\boldsymbol{\beta} \end{aligned}$$

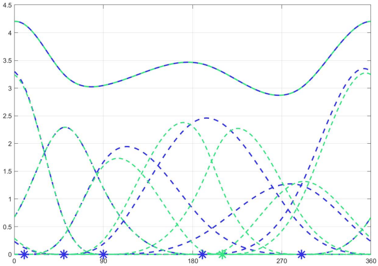
- $\eta \in (\xi, \nu)$ (and similar for ρ)
- $\boldsymbol{B} = \{B_{sk}\}_{s=1;k=1}^{m;n}$ basis for $\mathcal{D}_\theta$
- $\boldsymbol{\beta} = \{\beta_k\}_{k=1}^n$ basis coefficients
- Inference reduces to estimating $n_\xi, n_\nu, \boldsymbol{B}_\xi, \boldsymbol{B}_\nu, \boldsymbol{\beta}_\xi, \boldsymbol{\beta}_\nu$ (and roughnesses λ_ξ, λ_ν)

- P-splines, BARS and Voronoi are different forms of $\boldsymbol{B}$
- Tensor products and slick GLAM algorithms for n-D covariate representations

Basis representations ... BARS and others

Bayesian adaptive regression splines (BARS)

- n irregularly-spaced knots on $\mathcal{D}_\theta$
- $\boldsymbol{B}$ consists of n B-spline bases
- Order d
- Each using $d+1$ consecutive knot locations
- Local support
- Wrapped on $\mathcal{D}_\theta$
- Knot locations $\{r_k\}_{k=1}^{n}$ vary
- Number of basis functions n varies



Periodic BARS knot birth and death

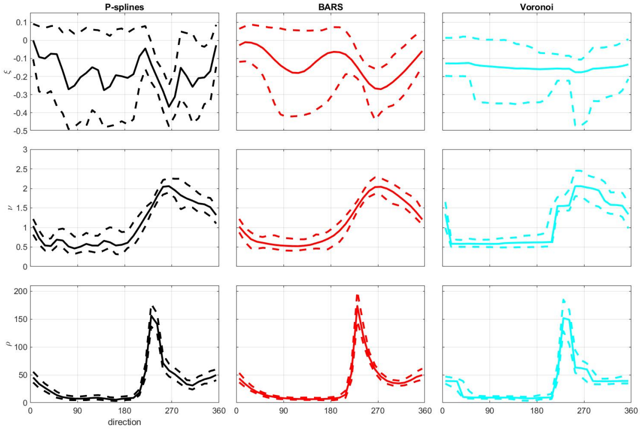
P-splines and Voronoi partition

- P-splines use fixed number of regularly-spaced knots
- Voronoi partition uses piecewise-constant representation, trivially extended to n-D

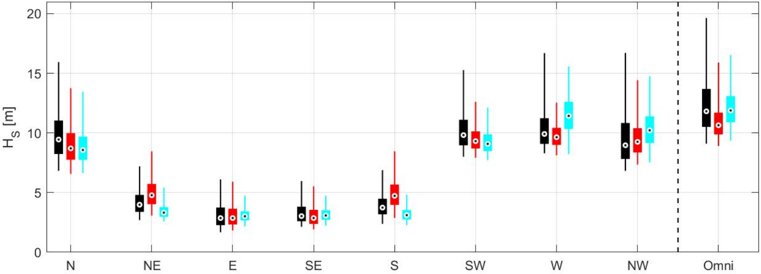
Posterior parameter estimates for ξ, ν and ρ for northern North Sea

- MCMC inference (Gibbs sampling, reversible jump, etc.)

- Note colour scheme
- Rate ρ and ν very similar
- Voronoi gives almost constant ξ
- Voronoi piecewise constant
- Land shadow effects
- General agreement
- ... for other parameters also



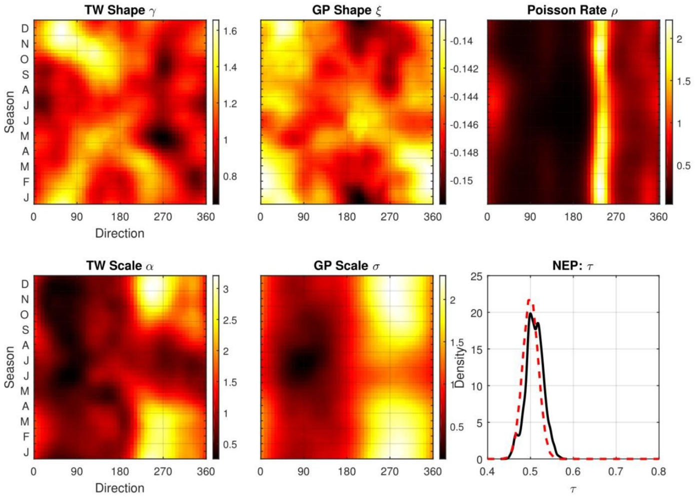
Directional posterior predictive distribution of $P = 1000$-year maximum



- Box-whiskers with 2.5%, 25%, 50%, 75% and 97.5% percentiles
- General agreement

- This is more-or-less what the engineer currently uses to design a “compliant” structure

Extension to 2D : directional-seasonal



- 2-D tensor product P-spline bases for same northern North Sea location
- Marginal posterior median estimates (plus posterior density for τ)

Practical implications of modelling choices

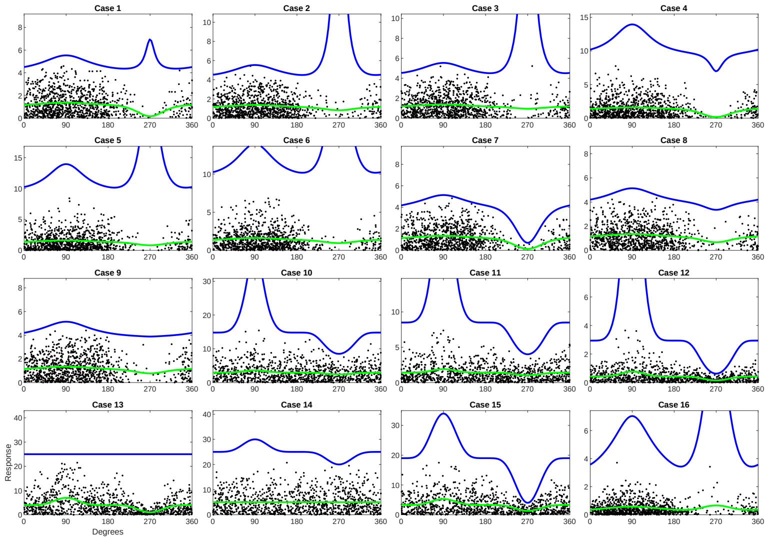
Practical implications of modelling choices

- How do "arbitrary choices" in the modelling procedure effect output?
- Case studies (like a southern North Sea location)

Effects of

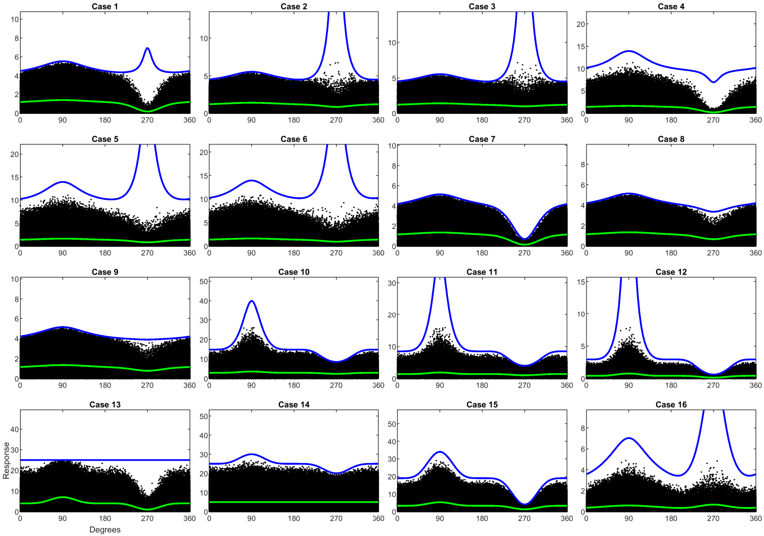
- Model parameterisation
  - Orthogonal
  - "Mean-max"
- Relative penality for GP shape and scale
  - Relatively high
  - Very high
- Cross-validation strategy
  - 10-fold
  - Repeated random 2-fold
- Choice of estimator for return value
  - Mean quantile
  - Quantile mean

Case studies



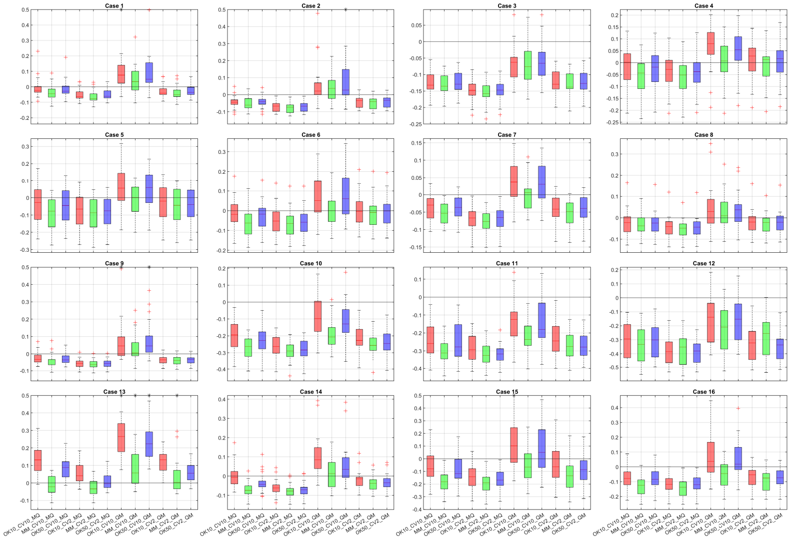
- Small samples

Case studies



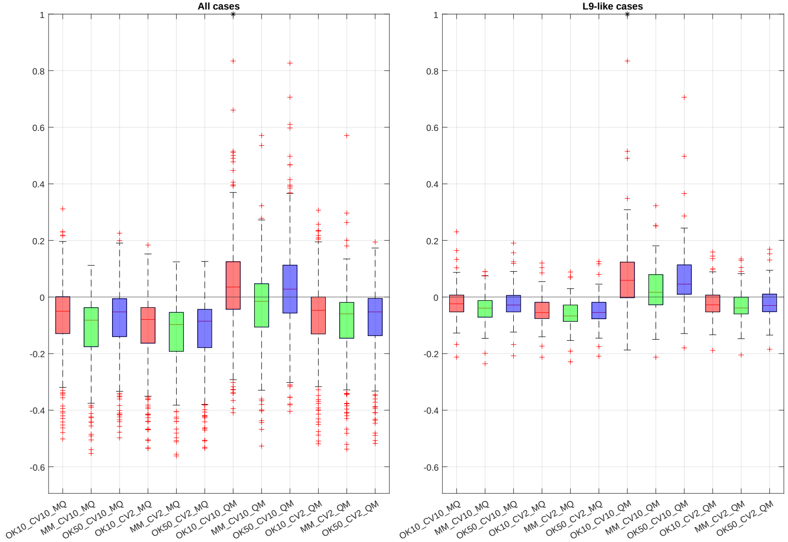
- Large samples

Case studies



- Performance by case

Case studies



- Aggregate performance

Issues and opportunities

Issues

- EV threshold modelling and UQ
- Many tuning parameters which should be optimised, but rarely are, and UQ w.r.t. these
- Model misspecification
  - Measurement scale, sub-asymptotic models
  - Missing covariates
- Prior specification (or equivalent frequentist choices)
- UQ generally

Opportunities

- Incorporate new data sources
  - Satellite (e.g. scatterometry)
  - GCM output (but CMIP6 inconsistency)
  - Large simulations (over 10^3s of years; so just "interpolate")
- Overly-complex models
  - Standard Norge [2022] "immature methodologies"
  - Diagnostics
- "Black box" AI/ML (e.g. KAUST, Saudi A.)
  - "ExaGeoStat" (Genton)
  - Sensible extremes (e.g. GP tail, "interpretable" plus "uninterpretable" covariate effects; Hüser, Richards)
- Just "do the whole planet" and be done with it!

Marginal extremes references

- Theory : Embrechts et al. [2003], Beirlant et al. [2004]
- Method : Coles [2001], Dey and Yan [2016]
- Motivation : Davison and Smith [1990]
- Covariate effects : Wood [2003], Chavez-Demoulin and Davison [2005], Brezger and Lang [2006], Youngman [2022]

- Metocean : Jonathan and Ewans [2013], Feld et al. [2019], Vanem et al. [2022]
- Metocean applications : Randell et al. [2016], Zanini et al. [2020]
- Machine learning: Abdulah et al. [2018], Richards and Huser [2024]

- Uncertainties: Tendijck et al [2024] (in preparation)

Multivariate extremes

Multivariate extremes

- Recap
- Max-stability, AD and AI
- Conditional extremes basic
- Time-series conditional extremes
- Multivariate spatial conditional extremes
- Multivariate extremes literature
- SPAR
- covXtreme
- Summary

Modelling margins and dependence

Context

$$F_{\mathbf{X}^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(\mathbf{x}^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}) \quad = \quad C(F_{X_1^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(x_1^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta}),...,F_{X_p^{\text{sp}}|\mathbf{\Theta}^{\text{sp}},\mathbf{Z}}(x_p^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta})|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta})$$

- We already have marginal models $F_{X_j^{\text{sp}}|\mathbf{\Theta}^{\text{sp}}}(x_j^{\text{sp}}|\boldsymbol{\theta}^{\text{sp}},\mathbf{Z})$, $j = 1, 2, ..., p$
- Now we need a dependence model or copula $C = C(u_1, u_2, ..., u_p|\boldsymbol{\theta}^{\text{sp}},\boldsymbol{\zeta})$

Which dependence function?

Max-stability == multivariate extreme value distribution, MEVD

- The copula is not unique
- Max-stability is one popular assumption, which itself involves a common but often unrealistic assumption of component-wise maxima
- On uniform margins, extreme value copula: $C(\boldsymbol{u}) = C^k(\boldsymbol{u}^{1/k})$
- On Fréchet margins ($G_j(z) = \exp\left(-z^{-1}\right)$), $G(\boldsymbol{z}) = \exp\left(-V(\boldsymbol{z})\right)$, for exponent measure V such that $V(r\boldsymbol{z}) = r^{-1}V(\boldsymbol{z})$, homogeneity order -1
- Rich spatial extensions to max-stable processes, MSPs
- Multivariate generalised Pareto distribution, MGPD

AD and AI

- All MEVD distributions exhibit asymptotic dependence (AD)
- Many common distributions (e.g. the multivariate Gaussian) exhibit asymptotic independence (AI)
- So extreme value copulas are not general enough to describe extremal dependence in nature
- Other copula forms do exhibit AI
- The conditional extremes model admits AD (on the boundary) and AI

Conditional extremes

Conditional extremes ... moving beyond component-wise maxima

- Random variables $\boldsymbol{X} = (X_1, ..., X_j, ..., X_p)$ and Y
- Each X and Y have standard Laplace margins ($f(x) = \exp(-|x|)/2$, $x \in \mathbb{R}$)
- Seek a model for $\boldsymbol{X}|(Y = y)$ for $y > u$

- Assume we can find p-dimensional scaling $\boldsymbol{a}, \boldsymbol{b} > \mathbf{0}$ such that

$$\mathbb{P}(\boldsymbol{Z} \leq \boldsymbol{z}|Y = y) \quad \rightarrow \quad G(\boldsymbol{z}) \quad \text{as} \quad u \rightarrow \infty$$
$$\text{for} \quad \boldsymbol{Z} \quad = \quad \frac{\boldsymbol{X} - \boldsymbol{a}(y)}{\boldsymbol{b}(y)}$$

- Non-degenerate G is unknown, and estimated empirically

- Typical scaling is $\boldsymbol{a} = \boldsymbol{\alpha} y$ and $\boldsymbol{b} = y^{\boldsymbol{\beta}}$, $\boldsymbol{\alpha} \in [-1, 1]^p$, $\boldsymbol{\beta} \in (-\infty, 1]^p$
- So simply fit regression model

$$\boldsymbol{X}|(Y = y) = \boldsymbol{\alpha} y + y^{\boldsymbol{\beta}} \boldsymbol{Z}, \text{ for } y > u$$

- $\alpha = 1, \beta = 0$: perfect dependence and AD, and $\alpha \in (0, 1)$: AI

- Heffernan and Tawn [2004] find choices for α and β for popular bivariate cases
- Bivariate Gaussian : $\alpha = \rho^2$, $\beta = 1/2$

Developments of the conditional extremes model

Canonical extensions

- Basic: $X|(Y = y), y > u$
- Temporal: "heatwave model" $X_1, X_2, ..., X_\tau|(X_0 = x_0), x_0 > u$
- Spatial: "spatial conditional extremes" $X_1, X_2, ..., X_s|(X_0 = x_0), x_0 > u$

Idea

$$X_1, X_2, ..., X_p|(Y = y) = \boldsymbol{\alpha} y + y^{\boldsymbol{\beta}} \boldsymbol{Z}$$

- Impose appropriate structure on parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and distribution of $\boldsymbol{Z}$
  - e.g. $\boldsymbol{\alpha}$ evolves smoothly in space
  - e.g. $\boldsymbol{Z}$ follows a multivariate Gaussian or extension thereof with appropriate mean and covariance forms
- Make a simplifying assumption
  - e.g. apply a low-order model repeatedly $X_{t+1}, X_{t+2}|(X_t = x) = [\alpha_1 \alpha_2]x + x^{[\beta_1 \beta_2]}[Z_1 Z_2]$

Further extensions

- Non-stationary and multivariate temporal and spatial models

Extremal vector auto-regression (EVAR) for within-storm evolution

Context: unconditional distribution of loading

$$
\begin{aligned}
F_{\boldsymbol{Y}}(\boldsymbol{y}) \quad = \quad & \int_{\zeta} \int_{(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)} \int_{\mathbf{x}^{\mathrm{sp}}} \int_{\boldsymbol{\theta}^{\mathrm{sp}}} \\
\times \quad & F_{\boldsymbol{Y}|\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in S_T},\boldsymbol{Z}}(\boldsymbol{y}|\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in S_\tau},\boldsymbol{\zeta}) \\
\times \quad & f_{(\{(\mathbf{X}_s,\boldsymbol{\Theta}_s)\}_{s\in\mathcal{S}_T},T)|\mathbf{X}^{\mathrm{sp}},\boldsymbol{\Theta}^{\mathrm{sp}},\boldsymbol{Z}}\left(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau \mid \mathbf{x}^{\mathrm{sp}},\boldsymbol{\theta}^{\mathrm{sp}},\boldsymbol{\zeta}\right) \\
\times \quad & f_{\mathbf{X}^{\mathrm{sp}}|\boldsymbol{\Theta}^{\mathrm{sp}},\boldsymbol{Z}}(\mathbf{x}^{\mathrm{sp}}|\boldsymbol{\theta}^{\mathrm{sp}},\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{\Theta}^{\mathrm{sp}}|\boldsymbol{Z}}(\boldsymbol{\theta}^{\mathrm{sp}}|\boldsymbol{\zeta}) \\
\times \quad & f_{\boldsymbol{Z}}(\boldsymbol{\zeta}) \\
\times \quad & \mathrm{d}\boldsymbol{\theta}^{\mathrm{sp}}\,\mathrm{d}\mathbf{x}^{\mathrm{sp}}\,\mathrm{d}(\{(\mathbf{x}_s,\boldsymbol{\theta}_s)\}_{s\in\mathcal{S}_\tau},\tau)\,\mathrm{d}\boldsymbol{\zeta}
\end{aligned}
$$

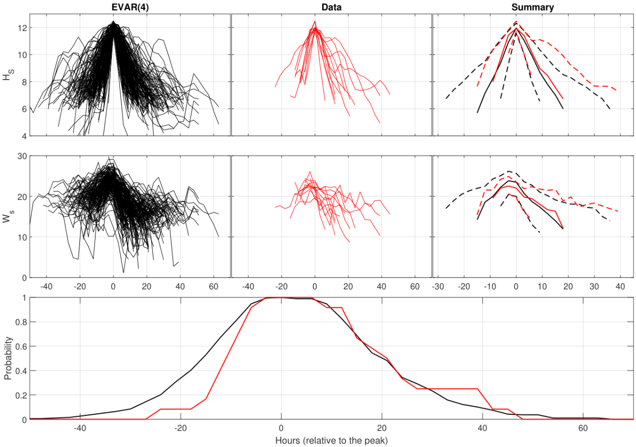
Models for within-storm evolution

- History matching: Feld et al. [2019], Hansen et al. [2020]
- Extreme value time-series model (an extension of conditional extremes): Tendijck et al. [2019], Tendijck et al. [2023]

Extremal vector auto-regression (EVAR) for within-storm evolution

On Laplace margins, with component-wise operations and $\boldsymbol{X}_t \in \mathbb{R}^d$:

$$\boldsymbol{X}_{t+k} | (\boldsymbol{X}_t, ..., \boldsymbol{X}_{t+k-1}, X_{t,1} = y) = \sum_{\ell=1}^{k} \boldsymbol{A}_\ell \boldsymbol{X}_{t+k-\ell} + y^{\boldsymbol{b}} \boldsymbol{Z}, \quad y > u \gg 0$$



Excursions of H_S (top) and W_S (middle) from EVAR(4) model (left; black), observed (middle; red) on original margins with storm peak $H_S \in [11.5, 12.5]$; right-hand plots summarise the observed (red) and EVAR(4) (black) excursions, using median (solid), 10% and 90% quantiles (dashed). In the bottom panel, we plot survival probabilities for observed (red) and EVAR(4) (black) excursions relative to the time of the excursion maximum.

MSCE

Multivariate spatial conditional extremes (MSCE)

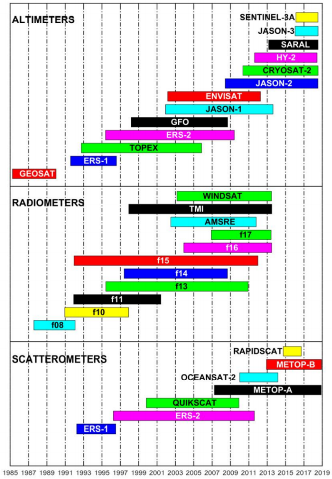
Motivation

- How useful are satellite observations of ocean waves and winds?
- Could they become the primary data source for decisions soon?
- What are the spatial characteristics of extremes from satellite observations?

Overview

- A look at the data : satellite wind, hindcast wind, hindcast wave
- Brief overview of methodology
- Results for joint spatial structure of extreme scatterometer wind speed, hindcast wind speed and hindcast significant wave height in the North Atlantic
- Implications for future practical applications

Satellite observation



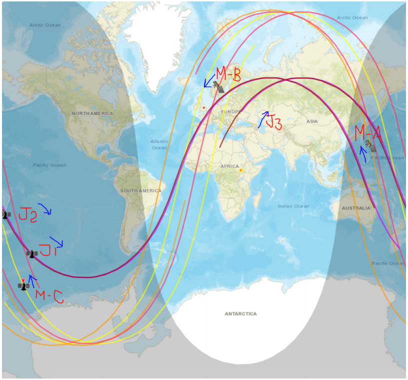
[Ribal and Young 2019]

Features

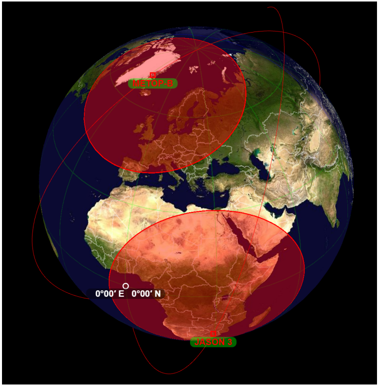
- Altimetry: H_S and U_{10}
- Scatterometry: best for U_{10} and direction
- $>$ 30 years of observations
- Spatial coverage is by no means complete: one observation daily if all well
- Calibration necessary (to buoys and reanalysis datasets, Ribal and Young 2020)
- METOP(-A,-B,-C) since 2007

H_S: significant wave height (m)
U_{10}: wind speed (ms^{-1}) at 10m (calibrated to 10-minute average wind speed)

JASON and METOP



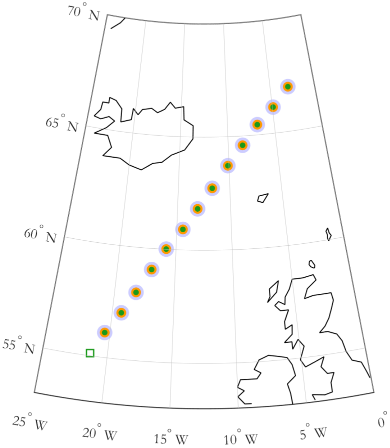
[n2yo.com, accessed 06.09.21 at around 1100UK]



[stltracker.github.io, accessed 27.08.2021 at around 1235UK]

- JASON and METOP similar polar orbits
- JASON all ascending, METOP all descending over North Atlantic
- Joint occurrence of JASON and METOP over North Atlantic rare

In a nut-shell



- Transform to standard margins using independent non-stationary GP models
- Condition on large value x of first quantity X_{01} at one location $j = 0$ (green square)
- Estimate "conditional spatial profiles" for $m > 1$ quantities $\{X_{jk}\}_{j=1,k=1}^{p,m}$ at $p > 0$ other locations (green, orange and blue circles)

$$X_{jk} \sim \text{Lpl}$$

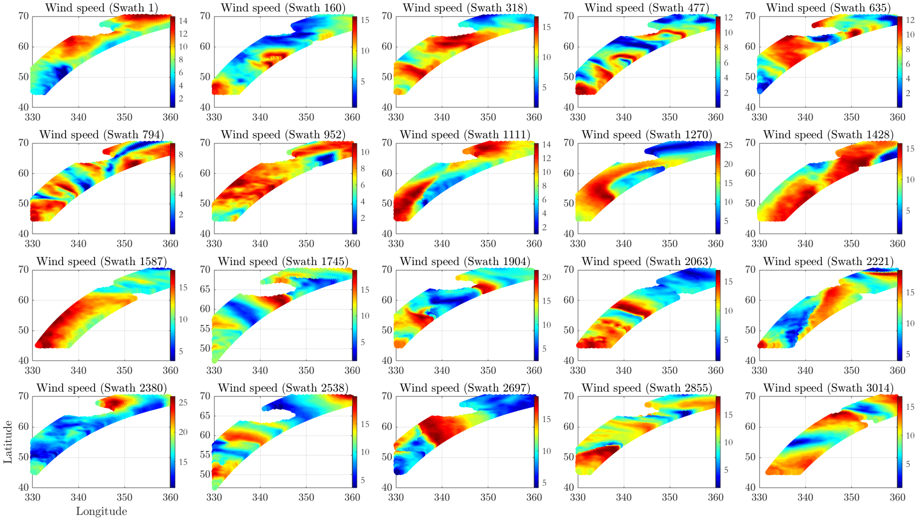
$$x > u$$

$$\boldsymbol{X}|\{X_{01} = x\} = \boldsymbol{\alpha} x + x^{\boldsymbol{\beta}} \boldsymbol{Z}$$

$$\boldsymbol{Z} \sim \text{DL}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2, \boldsymbol{\delta}; \boldsymbol{\Sigma}(\boldsymbol{\lambda}, \boldsymbol{\rho}, \boldsymbol{\kappa}))$$

- MCMC to estimate $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\boldsymbol{\delta}$ and $\boldsymbol{\rho}$, $\boldsymbol{\kappa}$, $\boldsymbol{\lambda}$
- $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\boldsymbol{\delta}$ spatially smooth for each quantity
- DL = delta-Laplace = generalised Gaussian
- Residual correlation $\boldsymbol{\Sigma}$ for conditional Gaussian field, powered-exponential decay with distance

Swath wind speeds



Daily descending METOP swaths. Satellite swath location changes over time. Spatial structure evident

Inference

$$X_{jk} \sim \text{Lpl}, \quad x > u, \quad \boldsymbol{X} | \{X_{01} = x\} = \boldsymbol{\alpha} x + x^{\boldsymbol{\beta}} \boldsymbol{Z}, \quad \boldsymbol{Z} \sim \text{DL}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2, \boldsymbol{\delta}; \boldsymbol{\Sigma}(\boldsymbol{\lambda}, \boldsymbol{\rho}, \boldsymbol{\kappa}))$$

- Delta-Laplace residual margins

$$f_{Z_{j,k}}(z_{j,k}) = \frac{\delta_{j,k}}{2\kappa_{j,k}\sigma_{j,k}\Gamma\left(\frac{1}{\delta_{j,k}}\right)} \exp\left\{ - \left| \frac{z - \mu_{j,k}}{\kappa_{j,k}\sigma_{j,k}} \right|^{\delta_{j,k}} \right\}, \quad \kappa_{j,k}^2 = \Gamma\left(1/\delta_{j,k}\right) / \Gamma\left(3/\delta_{j,k}\right)$$

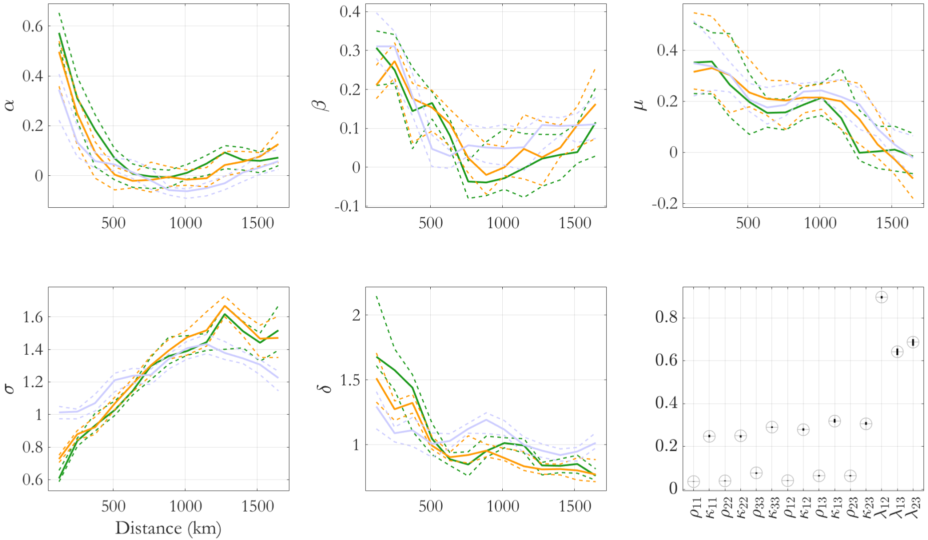
- Gaussian residual dependence

$$\boldsymbol{\Sigma}^*_{\mathcal{A}^*(j,k)\mathcal{A}^*(j',k')} = \lambda_{k,k'}^{|k-k'|} \exp\left(- \left(\frac{\text{dist}(r_j, r_{j'})}{\rho_{k,k'}} \right)^{\kappa_{k,k'}} \right)$$

- Piecewise linear forms for $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\boldsymbol{\delta}$ with distance using n_{Nod} spatial nodes

- Adaptive MCMC, Roberts and Rosenthal [2009]
- Total of $m(5n_{\text{Nod}} + (3m+1)/2)$ parameters
- Rapid convergence, 10k iterations sufficient

Parameter estimates



Estimates for α, β, μ, σ and δ with distance, and residual process estimates ρ, κ and λ. Model fitted with $\tau = 0.75$
StlWnd (green), HndWnd (orange), HndWav(blue)
Residual Gaussian field : ρ=scale (need to $\times$100km), κ=exponent (need to $\times$5), λ=cross-correlation

Applied conditional extremes references

- Non-stationary : Jonathan et al. [2014]
- Time-series : Winter and Tawn [2016], Tendijck et al. [2019], Tendijck et al. [2023]
- Mixture model : Tendijck et al. [2021]
- Spatial : Shooter et al. [2021b], Shooter et al. [2021a], Shooter et al. [2022]
- Lots more

SPAR

Semi-parametric angular radial (SPAR) representation

Basics

- Radial R and angular Q components. Then joint density factorised as

$$f_{R,Q}(r,q) = f_Q(q) f_{R|Q}(r|q)$$

- Assume GP conditional tail for $R|(Q=q)$, with parameters varying smoothly with angle q above some threshold $\psi(q)$ with non-exceedance probability $\tau(q)$

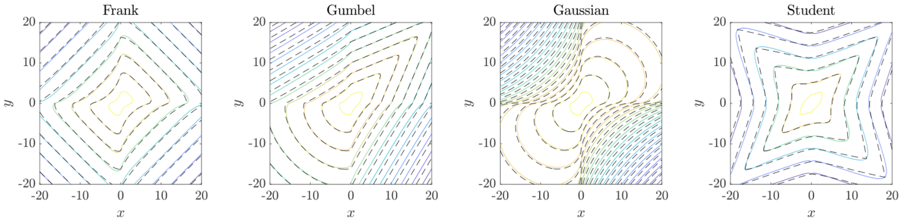
$$f_{R,Q}(r,q) = f_Q(q) \times \tau(q) f_{GP}(r - \psi(q)|\xi(q), \sigma(q)), \quad r > \psi(q)$$

  with smoothly varying $\psi(q)$, $\tau(q)$, $\xi(q)$ and $\sigma(q)$. Also assume angular density $f_Q(q)$ varies smoothly with q

- SPAR representation shown to provide good approximations to a large set of copula functions on standard margins
- Is transformation to standard margins necessary?
- Different possible angular-radial decompositions using "generalised co-ordinates"

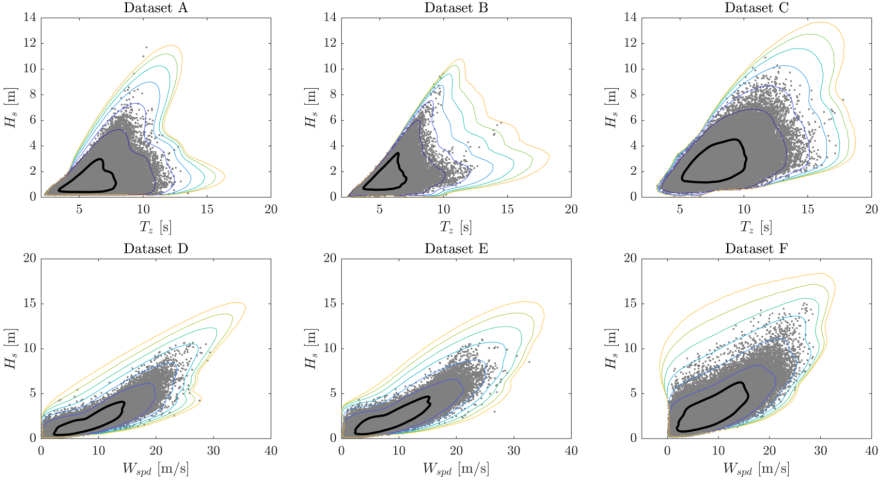
- $\Rightarrow$ multivariate extremes is just "non-stationary univariate" extremes!

SPAR fits to extreme value copulas



Density contours of various copulas on Laplace margins. All copulas have Pearson correlation coefficient 0.6. Student-t copula has two degrees of freedom. Solid lines: true contours at logarithmic increments. Dashed lines: SPAR-estimated contours.

Density contours from SPAR fits to data



Density contours from SPAR model for 6 samples.

covXtreme

Pragmatic non-stationary multivariate extremes with UQ

- Fit generalised Pareto marginal models for peaks over threshold data $\dot{\boldsymbol{X}}$ and $\dot{Y}$
  - Physics-based identification of peaks from time-series
  - Multiple thresholds, simple piecewise constant model for covariates $\boldsymbol{\Theta}$
  - Diagnostics: threshold stability
- Transform to standard Laplace scale $\boldsymbol{X}$ and Y
  - Transform full sample
- Fit conditional extremes model $\boldsymbol{X}|(Y = y)$ for $y > u$
  - Multiple thresholds, simple piecewise constant covariate model for α
  - Diagnostics: threshold stability, residual structure
- Calculate probabilities of extreme sets
  - MC simulation, importance sampling
  - Estimate environmental contours

- Free covXtreme software for MATLAB does all of above
  - UQ: incorporates epistemic uncertainty using bootstrapping cradle to grave
  - Model averaging: incorporates multiple models for different threshold combinations
  - Multidimensional X and covariates
  - Cross-validation for optimal parameter roughness in marginal and dependence models
  - Careful return value and associated value definitions
  - `https://lfenergy.org/projects/covXtreme/`, Towe et al. [2024]

Multivariate extremes references

- Theory : Beirlant et al. [2004]
- Copulas : Joe [2014]
- Method : Dey and Yan [2016]
- Key ideas in AI : Ledford and Tawn [1996], Ledford and Tawn [1997], Coles et al. [1999], Heffernan and Tawn [2004]
- Modelling across dependence classes : Wadsworth et al. [2017], Huser and Wadsworth [2022]
- Limit sets and SPAR : Nolde and Wadsworth [2022], Simpson and Tawn [2024], Mackay and Jonathan [2023], Murphy-Barltrop et al. [2024], Mackay et al. [2024], Huser et al. [2024]
- Metocean : Parametric conditional models (e.g. Haver 1987), design contours (e.g. Haselsteiner et al. 2021).
- covXtreme: Towe et al. [2024]

Summary

Summary

Why?

- Careful quantification of "rare-event" risk
- Characterise tails of (multivariate) distributions
- Limited observations
- Combine solid theory and pragmatic application, UQ
- Immediate real-world consequences

The next 10 years?

- Univariate : fuller covariate descriptions, exploit measurement scale / sub-asymptotics, UQ, provide real-world decision-support
- Multivariate : theoretical development, computational tractability, expansion in scope (time-series, spatial), serious real-world applications
    - Limit sets (Simpson and Tawn 2024), SPAR (Murphy-Barltrop et al. 2024)
- More demanding regulatory framework

Tusen takk! / Diolch yn fawr!

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Backup

Generalised extreme value distribution

- F_X^n is the distribution of the maximum of n independent draws of X
- If F_X^n "looks like" $F_X^{n'}$, we say F_X is max-stable

- More formally, F_X is max-stable if there exist sequences of constants $a_n > 0$, b_n, and non-degenerate G_ξ such that

$$\lim_{n\to\infty} F_X^n(a_n x + b_n) = G_\xi(x)$$

- We say $F_X \in D(G_\xi)$ or that F_X lies in the max-domain of attraction of G_ξ
- The Fisher–Tippett–Gnedenko theorem states that G_ξ is the generalised extreme value distribution with parameter ξ

$$G_\xi(y) = \exp\left(-(1+\xi y)^{-1/\xi}\right), \quad \xi \in \mathbb{R}$$

- For large n, makes sense to model block maxima of n iid draws using G_ξ (with $(x-\mu)/\sigma$ in place of y above)

Multivariate extreme value distribution, MEVD

- $\boldsymbol{X}_i = (X_{i1}, \ldots, X_{ij}, \ldots, X_{ip}), i = 1, \ldots, n$ iid p-vectors, distribution F
- $M_{n,j} = \max_i X_{ij}$, component-wise maximum
- The component-wise maximum is not "observed" (especially as $n \to \infty$)

- Then for $Z_{n,j} = (M_{n,j} - b_{n,j})/a_{n,j}$, normalised with scaling constants:

$$\mathbb{P}(\boldsymbol{Z} \leq \boldsymbol{z}) = F^n\left(\boldsymbol{a}_n \boldsymbol{z} + \boldsymbol{b}_n\right) \to G(\boldsymbol{z}) \quad \text{as} \quad n \to \infty$$

- Non-degenerate $G(\boldsymbol{z})$ must be max-stable, so $\forall k \in \mathbb{N}$, $\exists\ \boldsymbol{\alpha_k} > \boldsymbol{0}, \boldsymbol{\beta_k}$ s.t.

$$G^k(\boldsymbol{\alpha}_k \boldsymbol{z} + \boldsymbol{\beta}_k) = G(\boldsymbol{z})$$

- We say $F \in D(G)$
- Margins $G_1, \ldots, G_p$ are unique GEV, but $G(\boldsymbol{z})$ is not unique

MEVD on common margins

- On standard Fréchet margins with pseudo-polars $(r, \boldsymbol{w})$

$$\begin{aligned} G(\boldsymbol{z}) &= \exp\left(-V(\boldsymbol{z})\right) \\ \text{with } V(\boldsymbol{z}) &= \int_\Delta \max_j \{\frac{w_j}{z_j}\}\, S(d\boldsymbol{w}), \quad \text{on } \Delta = \{\boldsymbol{w} \in \mathbb{R}^p : ||\boldsymbol{w}|| = 1\} \\ \text{and } 1 &= \int_\Delta w_j\, S(d\boldsymbol{w}), \quad \forall j, \text{ for angular measure } S \end{aligned}$$

- Condition of multivariate regular variation, MRV

$$\frac{1 - F(t\boldsymbol{x})}{1 - F(t\mathbf{1})} \to \lambda(\boldsymbol{x}) \text{ as } t \to \infty, \boldsymbol{x} \in \mathbb{R}^p$$

useful to prove that $F \in D(G)$ for some MEVD G

- Lots more

Asymptotic dependence ... admitted by MEVD

- On uniform margins

$$\chi(u) = \frac{\mathbb{P}(U > u, V > u)}{\mathbb{P}(U > u)} = \frac{\bar{C}(u,u)}{1-u} \quad \to \chi \text{ as } u \to 1$$

- $\chi = 1$ perfect dependence
- $\chi \in (0,1)$ asymptotic dependence, AD
- $\chi = 0$ perfect independence

$$\theta(u) = \frac{\log \mathbb{P}(U \leq u, V \leq u)}{\log \mathbb{P}(U \leq u)} = \frac{\log C(u,u)}{\log u} \quad \to \theta \text{ as } u \to 1$$

- $\theta = 2 - \chi$

- χ and θ describe AD
- MEVD admits AD

Asymptotic independence ... not admitted by MEVD

- On uniform margins

$$\bar{\chi}(u) = 2\frac{\log \mathbb{P}(U > u)}{\log \mathbb{P}(U > u, V > u)} - 1 = 2\frac{\log(1-u)}{\log \bar{C}(u,u)} - 1 \quad \to \bar{\chi} \text{ as } u \to 1$$

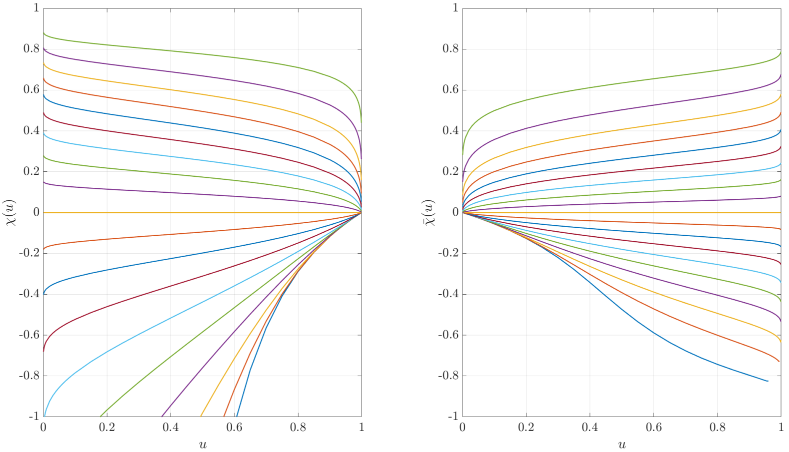
- $\bar{\chi} = 1$ perfect dependence and AD
- $\bar{\chi} \in (0,1)$ asymptotic independence, AI
- $\bar{\chi} = 0$ perfect independence
- On Fréchet margins ($F(z) = \exp\left(-z^{-1}\right)$), assume

$$\frac{\mathbb{P}(Z_1 > z, Z_2 > z)}{\left(\mathbb{P}(Z_1 > z)\right)^{1/\eta}} = \mathcal{L}(z)$$

where $\mathcal{L}$ is slowly varying : $\mathcal{L}(xz)/\mathcal{L}(z) \to 1$ as $z \to \infty$
- $\bar{\chi} = 2\eta - 1$
- Idea : use non-extreme value copulas or inverted EV copulas
- Also $\mathbb{P}(Z_2 > z | Z_1 > z) \approx Cz^{1-1/\eta}$ from above
- Idea : assume a max-stable-like normalisation for conditional extremes

Extremal dependence (bivariate Gaussian)

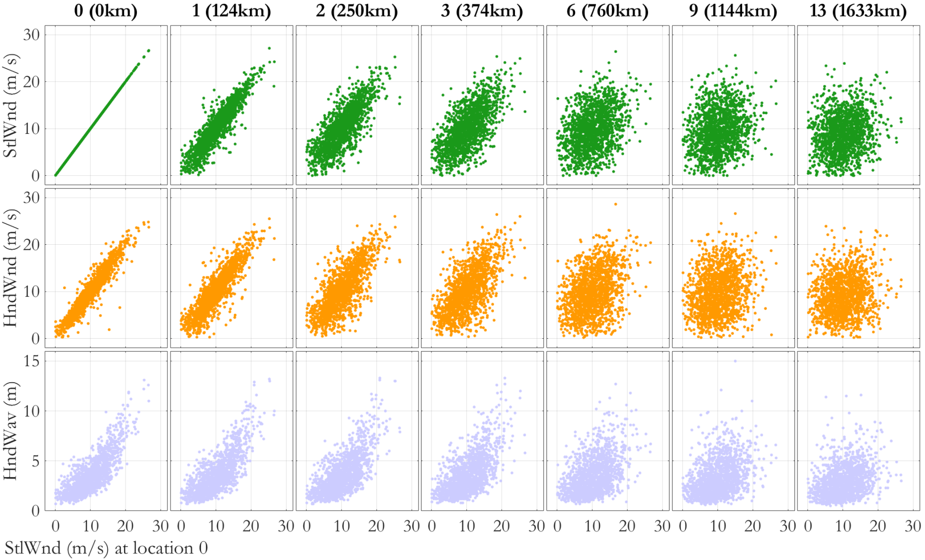
- Many (almost all?) environmental extremes problems involve asymptotic independence, at least in part ... bivariate Gaussian is one example!



$\chi(u)$ and $\bar{\chi}(u)$ for bivariate Gaussian ($\Rightarrow \chi = 0, \bar{\chi} = \rho$)

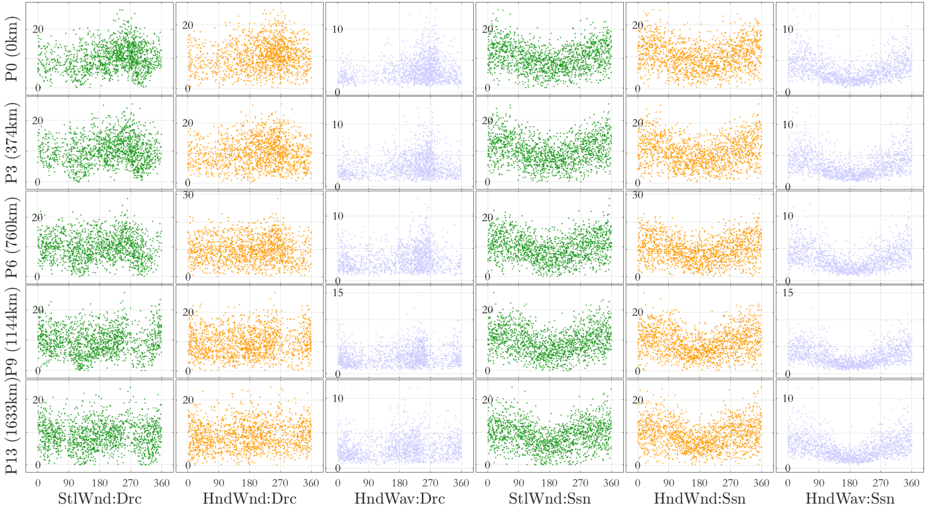
Colours are correlations ρ on -0.9, -0.8, ..., 0.9 (Recreated from Coles et al. 1999)

Scatter plots on physical scale



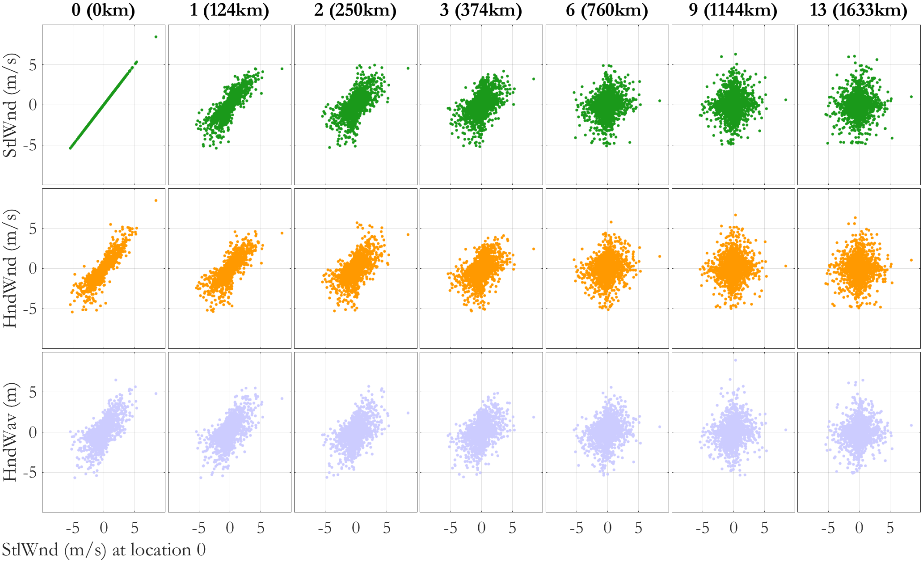
Scatter plots of registered data : StlWnd (green), HndWnd (orange), HndWav(blue)

Covariate dependence on physical scale



Directional and seasonal dependence. "Direction" is that from which fluid flows measured clockwise from North
StlWnd (green), HndWnd (orange), HndWav(blue)

Scatter plots on Laplace scale



Registered data on Laplace scale: StlWnd (green), HndWnd (orange), HndWav(blue)