

Non-stationary Extreme Values Analysis of waves: a simplified approach

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Non-stationary EVA of the wave climate

Why?

Estimation of wave climate design parameters in view of climate change,
e.g. design of coastal infrastructures, probabilistic operational forecasts.

When?

- Change of the frequency of extremes with time and/or space (IPCC 2007);
- Presence of trend at the timeseries;
- Strong interannual, seasonal variability
- Influence of ocean-atmosphere climatic patterns (SOI, ENSO, NAO)



Development of non-stationary probabilistic models

- a) Include the **variability in time** at the GEV or GPD models: usually achieved by means of a MLE on a parametric GEV/GPD

$$Z_t \sim GEV[\mu(a_1, a_2, \dots, t), \sigma(a_1, a_2, \dots, t), \varepsilon(a_1, a_2, \dots, t)]$$

$$Y_t \sim GP[u(a_1, a_2, \dots, t), \sigma'(a_1, a_2, \dots, t), \varepsilon'(a_1, a_2, \dots, t)]$$

Where μ , σ , ε are the time-dependent location, scale and shape parameters, a_1, a_2, \dots are tunable parameters characteristic of system.

- b) Include the dependence on **covariates** such as climate indices at the location parameter:

$$Z_t \sim GEV(\mu(t), \sigma, \varepsilon)$$

$$\mu(t) = \beta_0 + \beta_1 SOI(t)$$

Sources:

Coles, 2001, Springer London
Mendez, 2006, JGR

...



An alternative methodology, basic concept

- transform the non stationary signal into a stationary one
- execute a stationary EVA on the transformed signal
- back transform the stationary EVA into a non stationary one

The simplicity of this approach is that it deduces the non-stationary parameters from a stationary MLE which is simpler to implement.

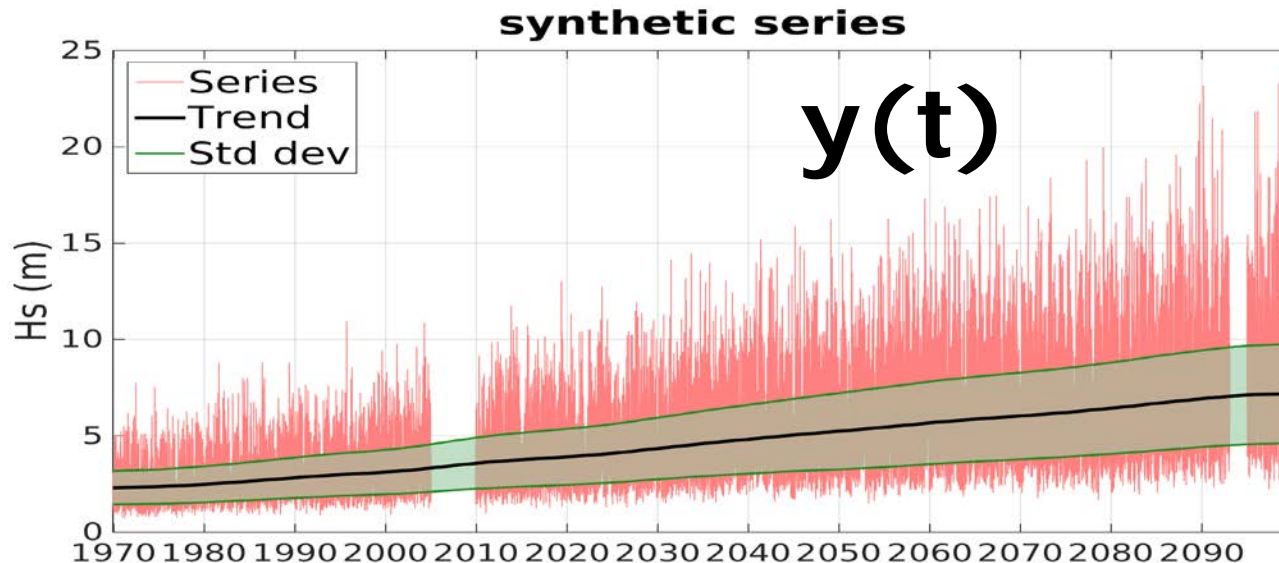
A key aspect is how transformation and back-transformation are carried out.



Proposed transformation: a time varying normalization

- $y(t)$ is the non stationary series
- $x(t)$ is the transformed series
- $tr_y(t)$ is the slow varying trend of $y(t)$
- $std_y(t)$ is the slow varying standard deviation of $y(t)$

$$x(t) = \frac{y(t) - tr_y(t)}{std_y(t)}$$

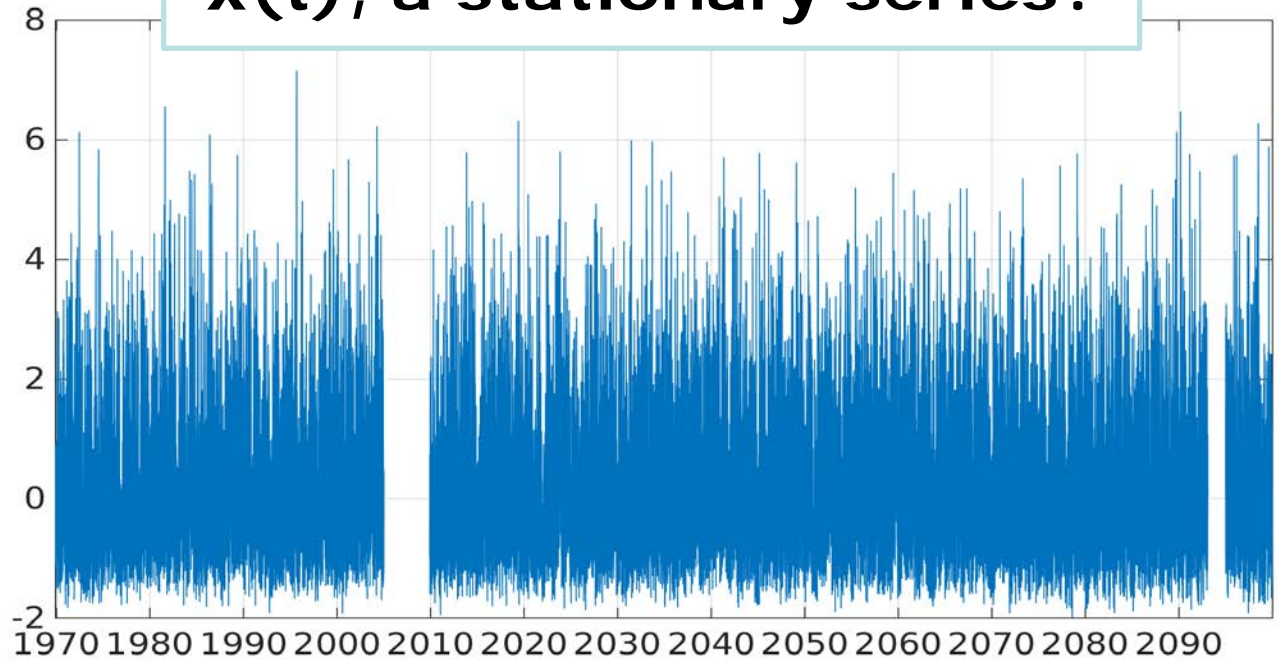




There are a lot of possible ways for estimating $tr_y(t)$ and $std_y(t)$

For example Fourier transform, polynomial regression, low pass filters, employment of climatic indexes ...
We used a running mean and a “running standard deviation” on a time window of 20 years.

$x(t)$, a stationary series?



The transformed series $x(t)$ in this case looks stationary, but a stationarity test is needed.

Check the higher order statistics



We can now find the GEV G_x best fitting the annual maxima of $x(t)$, typically through a Maximum Likelihood Estimator (MLE)

$$G_x(x) = \Pr(X < x) = \exp\left\{-\left[1 + \varepsilon_x \left(\frac{x - \mu_x}{\sigma_x}\right)\right]^{-1/\varepsilon_x}\right\}$$

How can we backtransform G_x into a non-stationary distribution G_y ?
If we call f the transformation $x(t) \rightarrow y(t)$,

$$f(x, t) = y(t) = \text{std}_y(t) \cdot x + \text{tr}_y(t),$$

$$f^{-1}(y, t) = x(t) = \frac{y(t) - \text{tr}_y(t)}{\text{std}_y(t)},$$

$$G_y(y, t) = \Pr[Y(t) < y] = \Pr[f(X, t) < y] = \Pr[X < f^{-1}(y, t)] = G_x[f^{-1}(y, t)]$$

We can always compute G_y this because $g(x, t)$ is a monotonically increasing function of x for every time t , so we can always invert it.



We find that G_y is a time varying GEV with

- Shape parameter $\varepsilon_y = \varepsilon_x$,
- Scale parameter $\sigma_y(t) = std_y(t) \cdot \sigma_x$,
- Location parameter $\mu_y(t) = std_y(t) \cdot \mu_x + tr_y(t)$

Relationship with the usual approach

It is like best fitting through MLE a non stationary GEV G_{ns} with parametric ε, σ, μ given by

$$\varepsilon_{ns} = const.,$$

$$\sigma_{ns} = std_y(t) \cdot a,$$

$$\mu_{ns} = std_y(t) \cdot b + tr_y(t) \text{ for varying parameters } a \text{ and } b.$$

The MLE in facts returns: $a = \sigma_x, \quad b = \mu_x$

Extension to GPD distribution

Generalized Pareto Distribution (GPD) is derived from the GEV as the conditional probability that an observation beyond a given threshold u is greater than x .
Therefore the arguments valid for GEV are valid also for GPD.

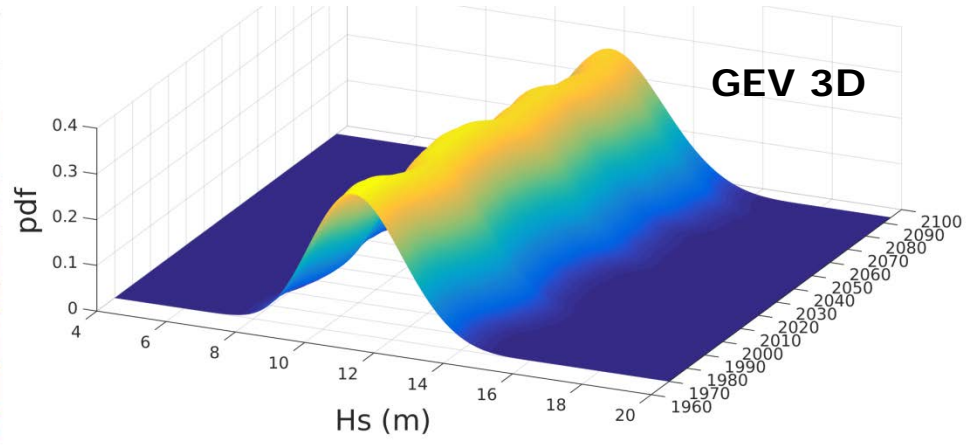
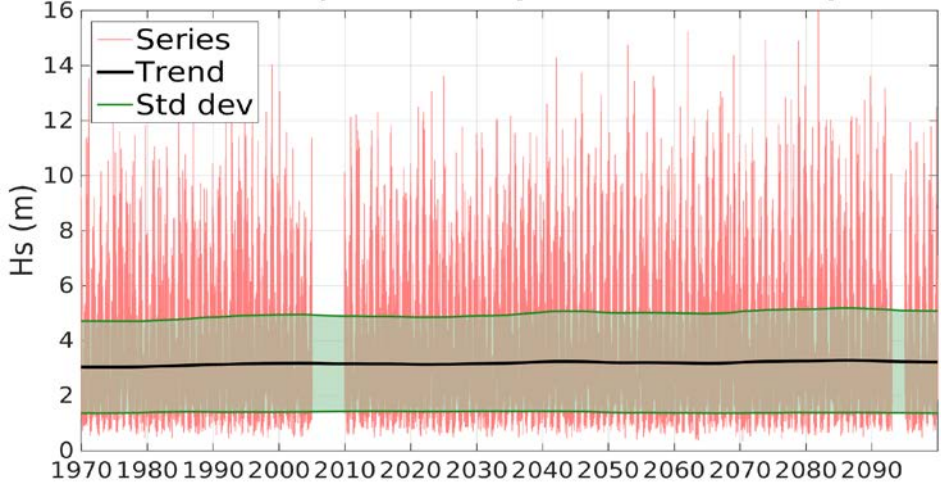
The parameters of the non stationary GPD are:

- threshold: $u_y(t) = std_y(t) \cdot u_x + tr_y(t),$
- shape parameter: $\varepsilon_y = \varepsilon_x = const.,$
- scale parameter: $\sigma_{GPD_y}(t) = \sigma_y(t) + \varepsilon_y [u_y(t) - \mu_y(t)] = std_y(t) \cdot \sigma_{GPD_x}$

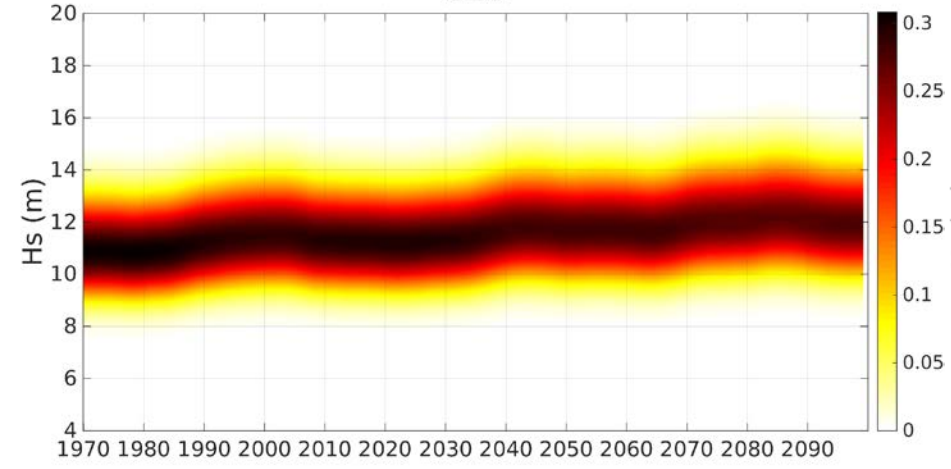
Case study 1

wind data: GFDL-ESM2M, scenario: RCP85, wave model: WWIII

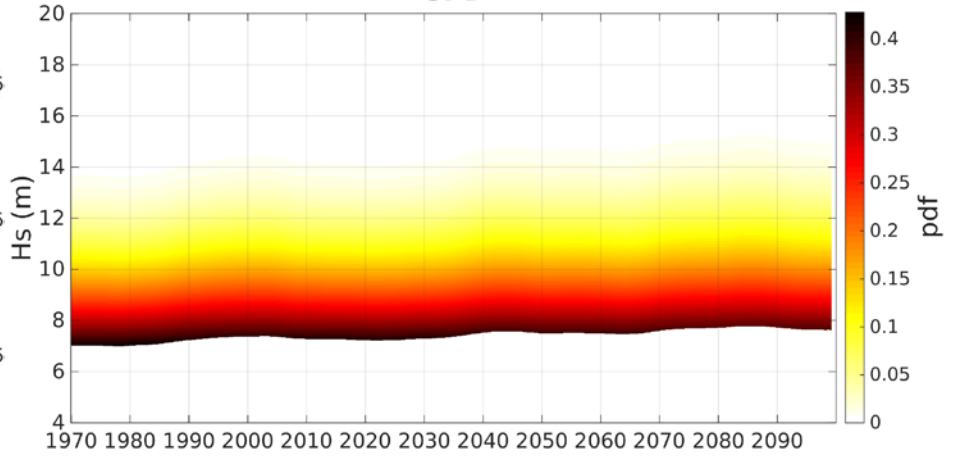
-10.53E, 53.366N (Western Ireland)



GEV



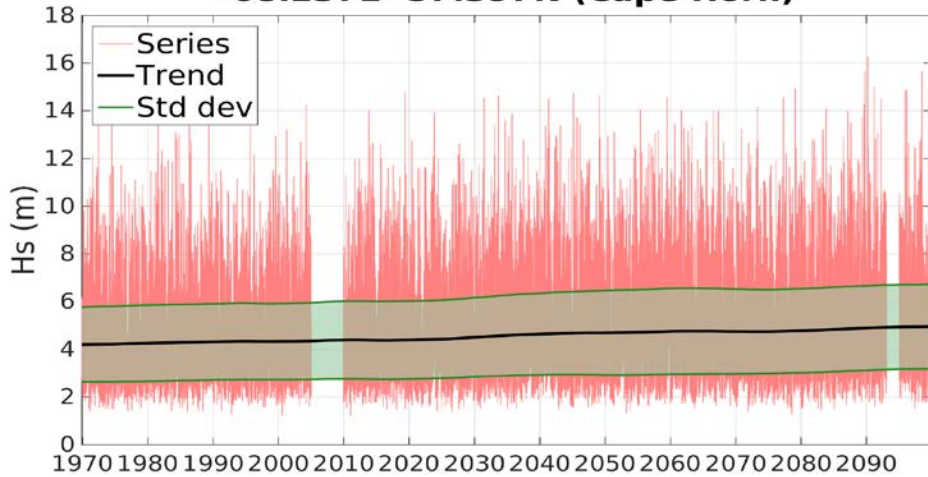
GPD



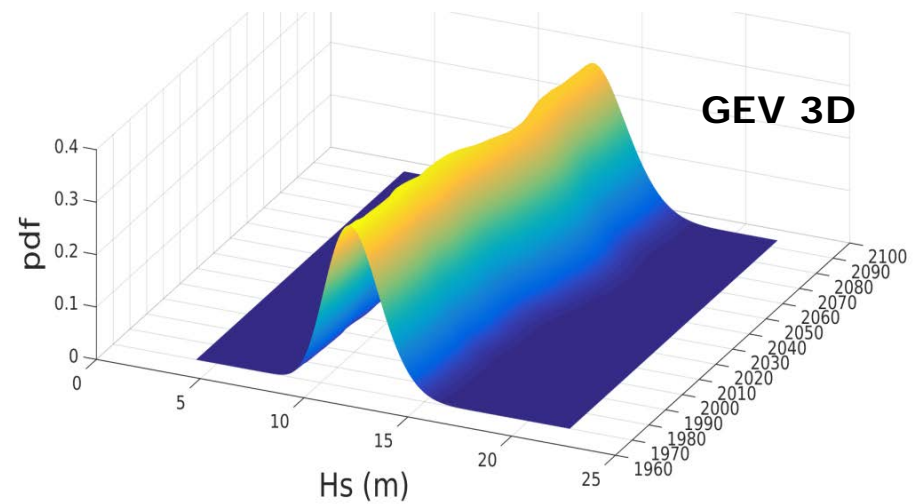
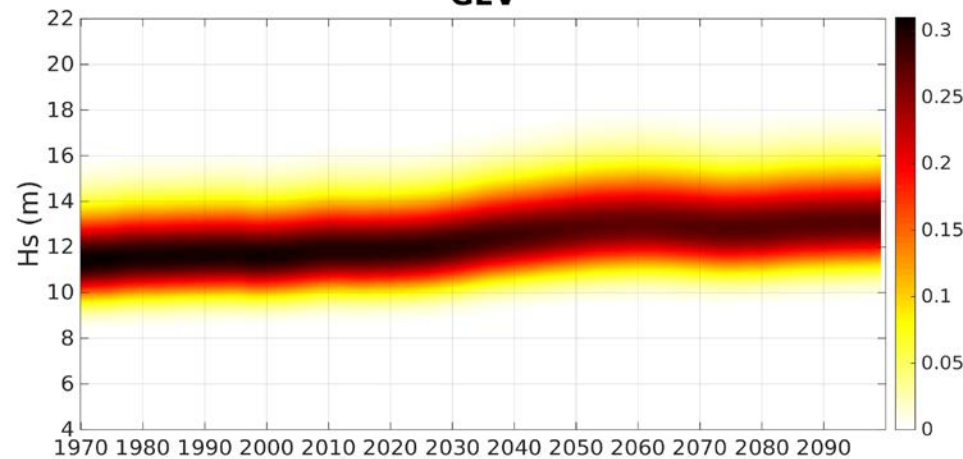
Case study 2

wind data: GFDL-ESM2M, scenario: RCP85, wave model: WWIII

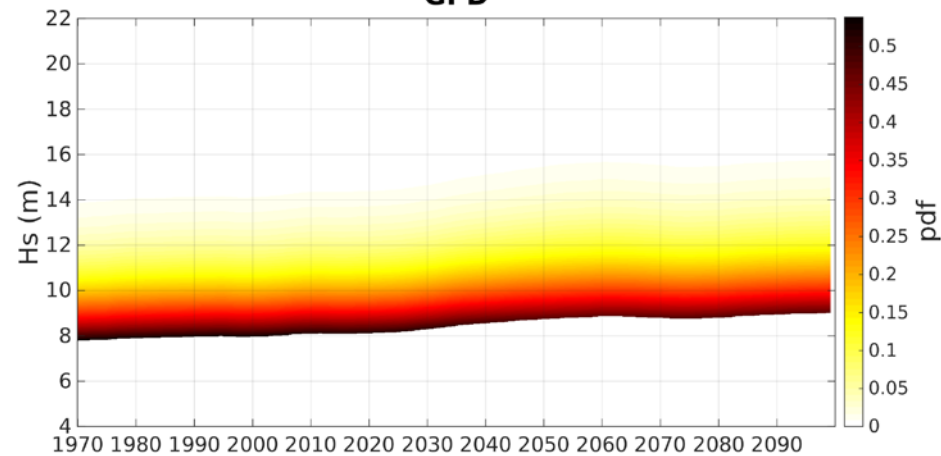
-68.237E -57.397N (Cape Horn)



GEV



GPD



Adding the seasonality

The transformation $y(t) \rightarrow x(t)$ is modified to:

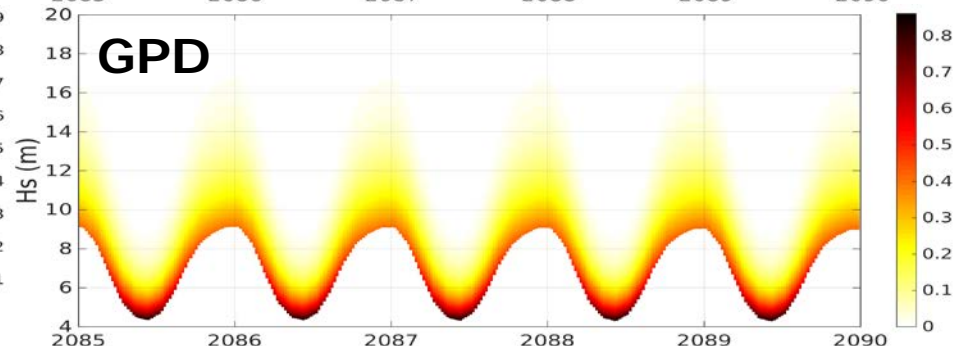
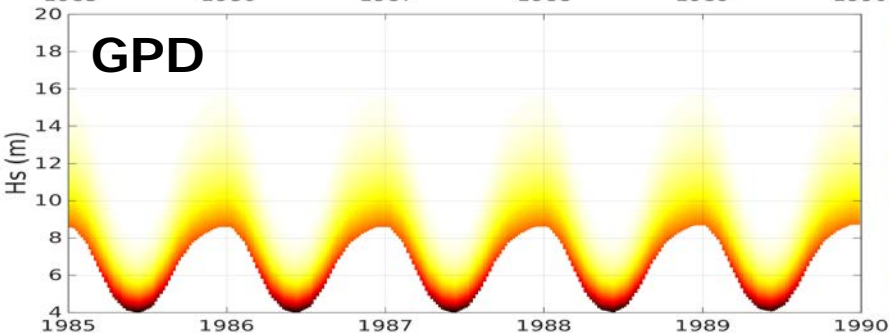
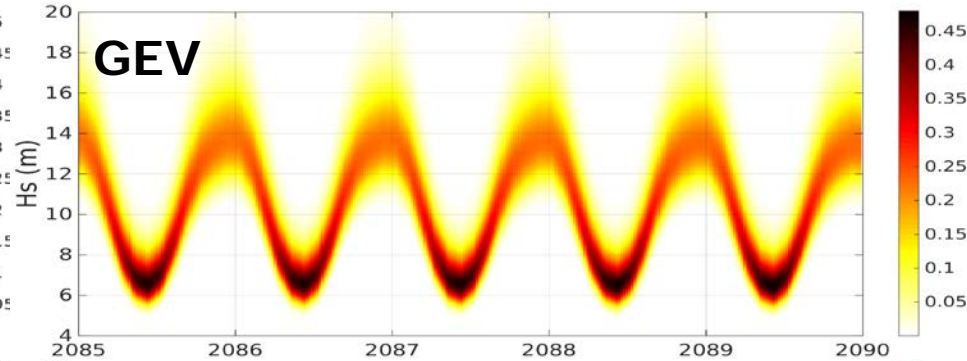
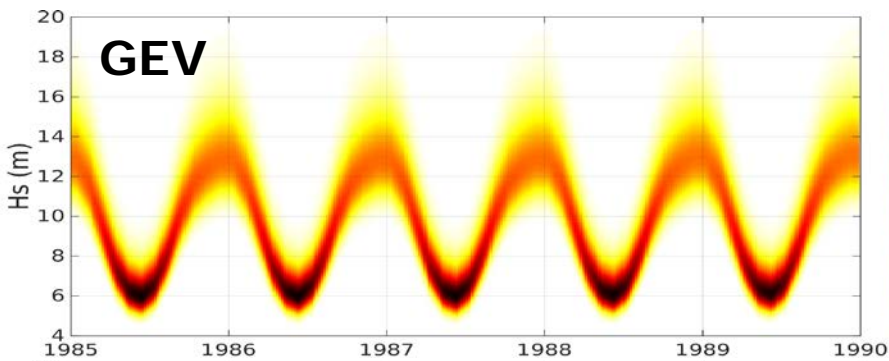
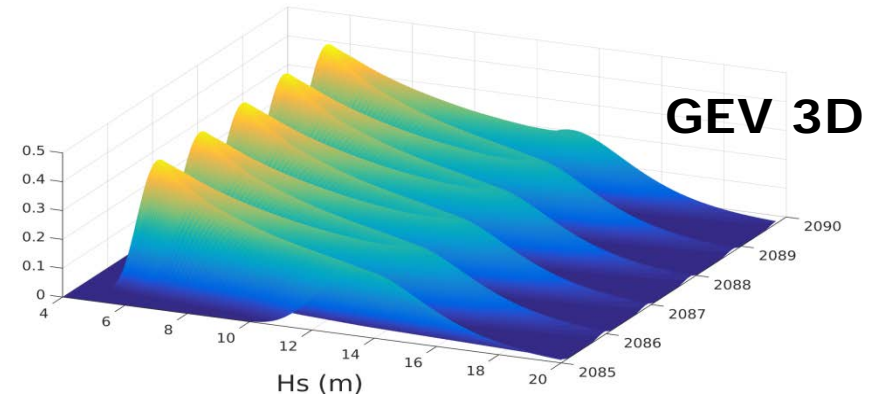
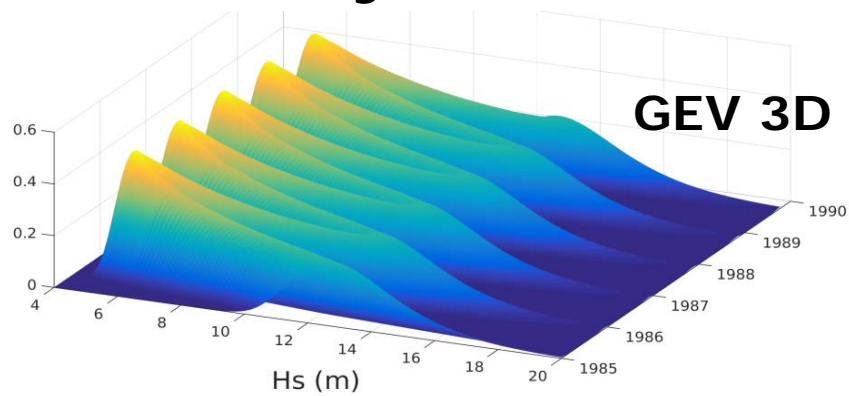
$$x(t) = \frac{y(t) - tr_y(t) - sn_{tr}(t)}{std_y(t) \cdot sn_{std}(t)}$$

where $sn_{tr}(t)$ and $sn_{std}(t)$ are the seasonality of the trend and of the standard deviation respectively. The parameters of the GEV get:

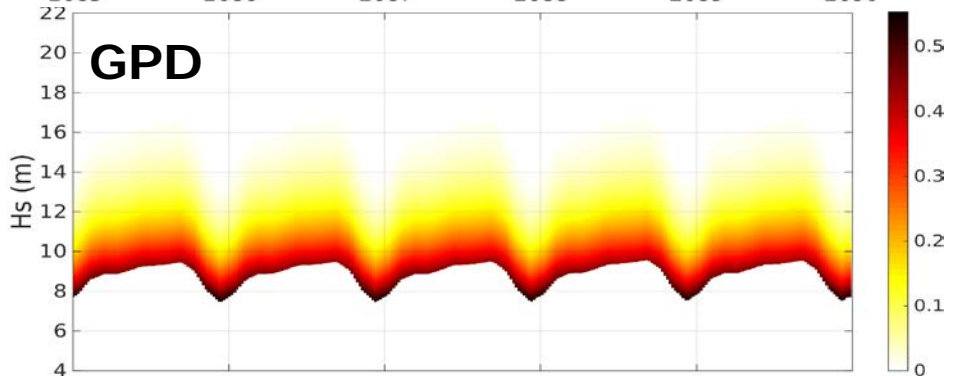
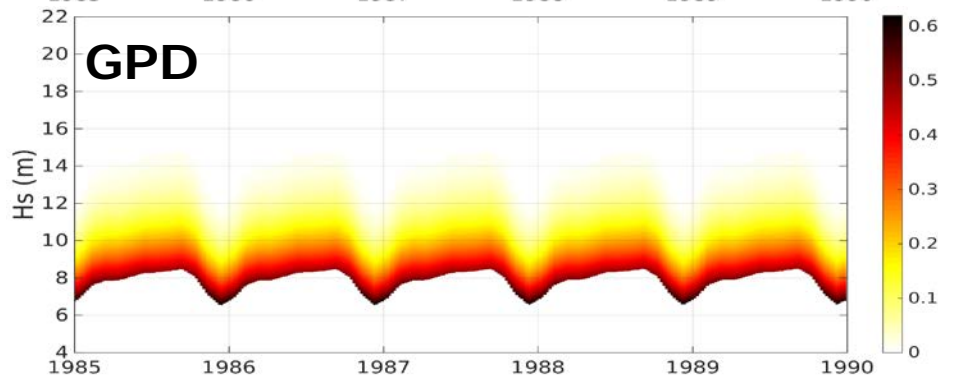
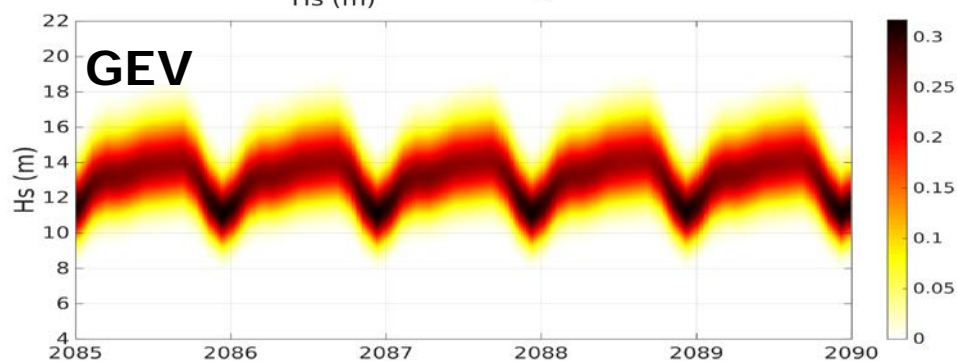
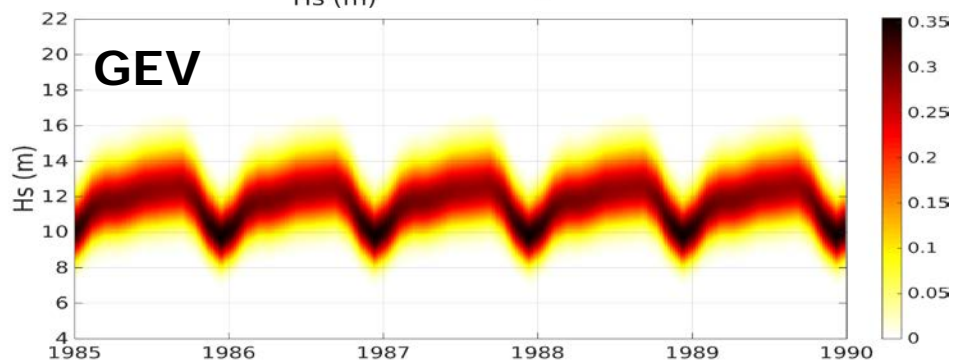
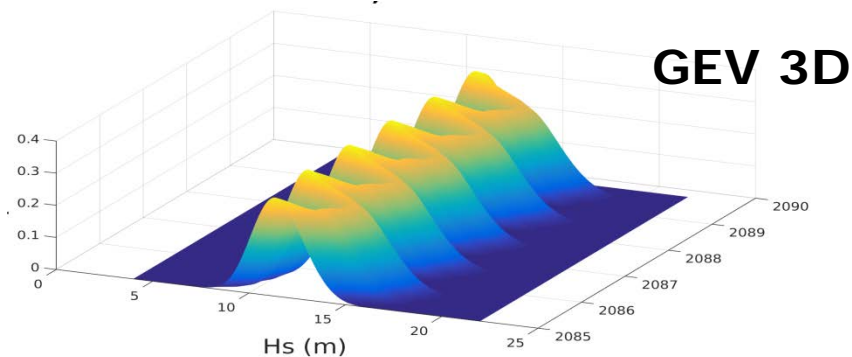
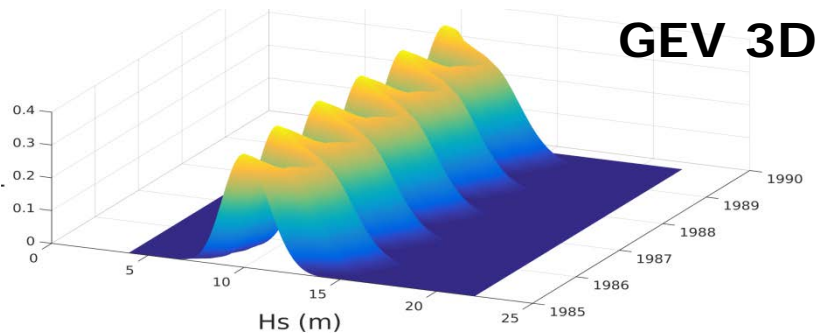
- Shape parameter $\varepsilon_y = \varepsilon_x$,
- Scale parameter $\sigma_y(t) = std_y(t) \cdot sn_{std}(t) \cdot \sigma_x$,
- Location parameter $\mu_y(t) = std_y(t) \cdot sn_{std}(t) \cdot \mu_x + tr_y(t) + sn_{tr}(t)$

The seasonality coefficients $sn_{tr}(t)$ and $sn_{std}(t)$ can be estimated from the monthly means respectively of the detrended series and of the ratio between a monthly-varying standard deviation and the slow-varying standard deviation.

Case study 1: Western Ireland



Case study 2: Cape Horn



Advantages of this approach

- simple to implement and fast to run (with the formulations of $\text{tr}(t)$ and $\text{std}(t)$ illustrated in these slides)
- all you need is the series itself
- the transformation of the series to stationary makes it possible to verify the applicability of EVA and MLE

Disadvantages

- the current implementation is not so general as the usual approach, you limit your analysis to 2 parameters. However some resources (e.g. Coles 2001) suggest that simple models should be preferred to complex ones

Possible generalization?



Thank you!

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