

POT METHODS: A NEW INSIGHT INTO THE ESTIMATION OF EXTREME VALUE DISTRIBUTIONS – APPLICATION TO EXTREME WAVE HEIGHTS

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CONTEXT AND PURPOSE OF THE STUDY

CURRENT SITUATION The widely spread methodology for determining extreme values of environmental variables has converged towards the so-called **GPD-Poisson model**:

- Extraction of extreme i.i.d. data from a time series using the **Peaks-Over-Threshold (POT)** approach (for wave heights: storm peaks above a physical threshold) ;
- Determination of a statistically meaningful threshold u_s ;
- Computation of the excesses above u_s then **Maximum Likelihood** estimation of a **2-parameter Generalized Pareto Distribution (GPD-2)** : $F_{Y;k,\sigma}(y) = 1 - \left(1 + k \frac{y}{\sigma}\right)^{-1/k}$, with $Y = X - u_s | X > u_s$;

- Derivation of extreme values for desired return periods (quantiles) and confidence intervals.
 - WHAT'S BOTHERING US?** Unexpected sensitivity of ML estimates to the lowest and largest data values.
 - HOW DID WE ADDRESS THIS?**
 - Classical IAHR **Haltenbanken** extreme wave heights dataset: comparison of 2-parameter MLE (MLE/GPD-2) and 3-parameter L-Moments (LMOM/GPD-3) estimations of the GPD;
 - GPD simulated data**: examination of the behavior of the model likelihood and parameter estimates;
 - Re-sampling of Haltenbanken data**: sensitivity of the estimates to the largest value of the dataset.
- The GPD-3 is defined by: $F_{Y;k,\sigma,\mu}(y) = 1 - \left(1 + k \frac{y-\mu}{\sigma}\right)^{-1/k}$, with $Y = X - u_s | X > u_s$, $k \in \mathbb{R}$, $\sigma > 0$, $\mu < y$

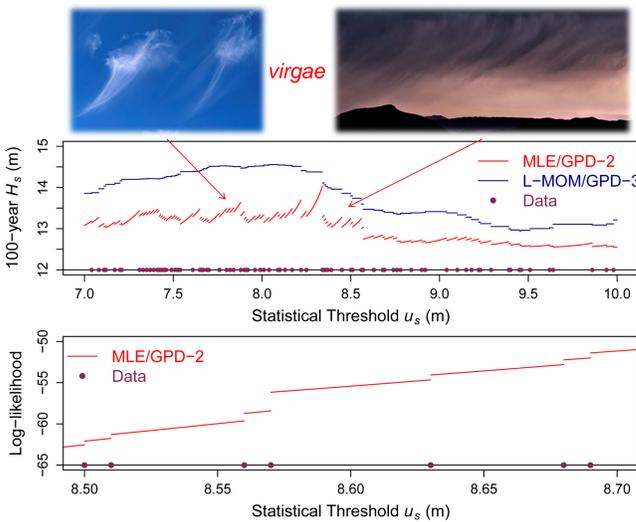


Figure 1 - Haltenbanken - Evolution of 100-year H_s (top) and maximized log-likelihood (bottom, zoom) with the threshold u_s

SENSITIVITY TO THE LOWEST DATA VALUE

WHAT'S WRONG DOC? Let's carry out an accurate sensitivity study with respect to the threshold (Fig. 1 - top) using the classical IAHR Haltenbanken dataset: the quantile (and parameter) ML estimates are **unstable** between 2 consecutive data values ("virgae"). A slight translation of the sample may lead to a significant change in the estimated quantiles! The maximum likelihood of the GPD-2 model (Fig. 1 - bottom) is continuously increasing with the threshold between two consecutive data values and shows a positive jump when the threshold reaches a new sample value.

HOW DO WE EXPLAIN THAT? Considering that:

- you still work with the **same physical events** (storms) when u_s varies between 2 data so the final result shouldn't change;
- letting u_s vary between two data sets the **origin of the distribution** while this role is usually devoted to a location parameter;
- the role of the threshold should be limited to the **selection of extreme data** to be fitted;

we claim the **need for a location parameter μ** , distinct from the threshold, to improve the stability of the results.

COMPARISON WITH A GPD-3 For comparative purpose, we fit a 3-parameter GPD (GPD-3) with the **L-Moments estimator** (Hosking, 1990). Quantile (Fig. 1 - top) as well as shape k and scale σ parameter estimates are **stable**! But the 100-yr H_s is 1 m higher...

EXAMINATION OF THE GPD-3 LIKELIHOOD Test: random generation of an ordered sample of simulated GPD data $Y_{1:N}$ ($N = 25$), then computation of the likelihood for each triple (k, σ, μ) within $\mathbb{R}^+ \times \mathbb{R}^+ \times]-\infty; Y_{1:N}[$, with the condition $\sigma > -k(Y_{N:N} - \mu)$. For each constant value of μ , there is a maximum likelihood in the (k, σ) plane (Fig. 2). But the global maximum for the full (3D) parameter space is reached at the **open upper bound** of the interval of validity of μ (i.e. $Y_{1:N}$), with **non-null derivatives** (Fig. 3), while $(\hat{k}, \hat{\sigma})$ doesn't converge (Fig. 4). Still, the asymptotic properties of the MLE require that the maximum be reached on an **interior point of an open set** (Lehmann, 1983). These properties are not proven!

→ The use of MLE is quite **dubious**.

→ An accurate and robust estimation of μ is **necessary!**

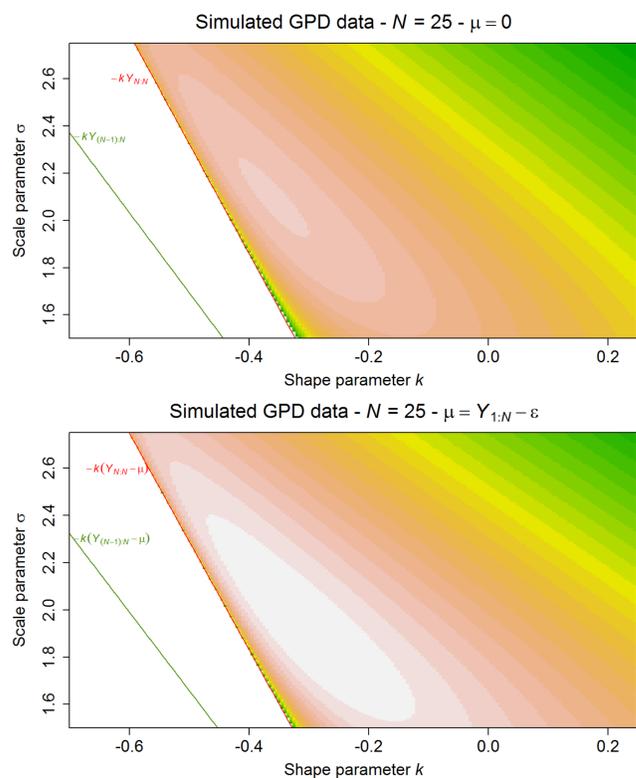


Figure 2 - GPD simulated data ($N = 25$) - 3-parameter log-likelihood function for two hyperplanes of the parameter space $\mu = \text{constant}$ (max for grey shades)

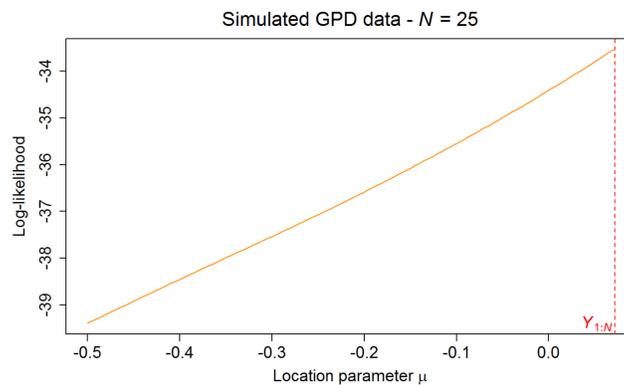


Figure 3 - GPD simulated data ($N = 25$) - Evolution of the 2-parameter maximized log-likelihood profile function with respect to μ

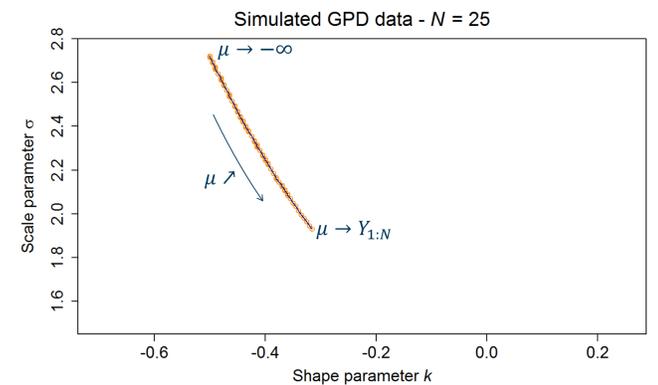


Figure 4 - GPD simulated data ($N = 25$) - Evolution of the ML estimates of $(\hat{k}; \hat{\sigma})$ when μ increases

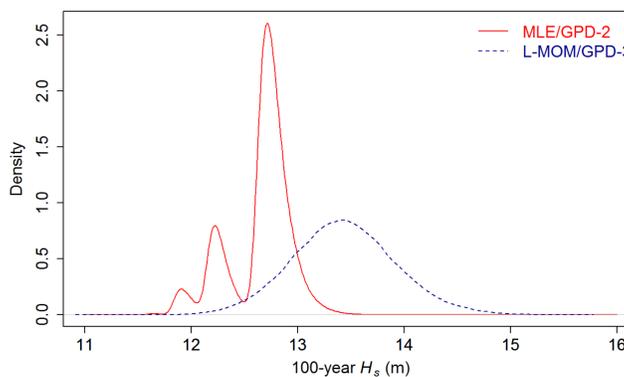
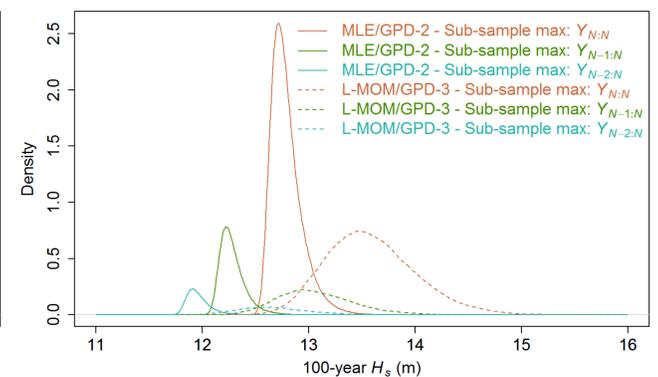


Figure 5 - Re-sampling of Haltenbanken dataset (sample rate = 75%) - Density of 100-year H_s



SENSITIVITY TO THE LARGEST DATA VALUE

LINK WITH REAL WORLD, PLEASE! Imagine wave height measurements from a buoy that could randomly fail 25% of the time... or never! What will be the influence of statistics on the results?

STATISTICAL RECIPE Ingredients: 1 appropriate dataset, 1 computer, 1 statistical software, 1 brain, coffee.

- Take the Haltenbanken dataset ($N = 46 H_s$ storm peak measurements).
- Create a **random sub-sample** with 75% of the data... then reiterate to get 100,000 sub-samples out of the 13,340,783,196 possibilities!
- Fit both models (MLE/GPD-2 and LMOM/GPD-3) to the 100,000 subsamples and compute 100-yr H_s .
- Compare. Get some coffee. Search an explanation. Get some more coffee.

WHAT WE SEE The density (Fig. 5 - left) of 100-yr H_s for ML-estimated GPD-2 exhibits **several narrow and sharp peaks**, while the L-Moments-estimated GPD-3 shows a **single broad and flat peak**.

WHY WE SEE THAT Each peak corresponds to the family of the sub-samples whose maximum is the largest ($Y_{N:N}$), second largest ($Y_{N-1:N}$), third largest ($Y_{N-2:N}$)... of the original sample (Fig. 5 - right).

There is a strong sensitivity of both models to the value of the sample maximum. This sensitivity is less visible for the LMOM/GPD-3 because of a large variance, but still exists: bad luck, not a perfect model!

→ In practice, if the analysis is based on incomplete data, this may yield incorrect estimates of extreme waves or other environmental data.

→ Significant difference between estimates from both models. Large dispersion for LMOM/GPD-3 while estimates of MLE/GPD-2 are focused on a few peaks linked with the sub-sample maximum.

CONCLUSIONS AND PERSPECTIVES

CONCLUSIONS

- The statistical threshold u_s selects the data to be fitted and defines the "extreme domain", while the location parameter μ sets the origin of the distribution. These two roles are distinct and u_s and μ should NOT be confused.
- A comparison MLE/GPD-2 vs LMOM/GPD-3 shows that introducing μ yields stable results between two consecutive storm peaks, consistent with the physics.

- The global maximum of the 3-parameter likelihood function is reached at an open bound of the parameter space with non-null derivatives: the asymptotic properties of the MLE are not proven.

- Estimation may be quite sensitive to the value of the sample maximum.

- Results are similar with other distributions such as Weibull or Gamma (Mazas & Hamm, 2011).

PERSPECTIVES

→ Which estimator for GPD-3? Can hybrid estimators perform better than L-Moments?

→ Application of local influence approach (Cook, 1986) in progress.

References :

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