Using extreme value theory to study decadal trends in extreme ocean surface winds

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Royal Netherlands Meteorological Institute
Ministry of Infrastructure and Water Management

International Ocean Vector Wind Science Team Meeting
May 30th 2024

Towards better extreme winds

Earlier study made on 99th percentiles winds

Recent analysis of changes in extreme wind speeds over the global ocean (2007–2020) [*Giesen, Stoffelen* (2022)]

- Scatterometer observations: MetOp-A ASCAT L3 reprocessed surface winds
- Collocated model winds: ERA5 (ECMWF Reanalysis v5)—also hourly

Objective: obtain better extreme winds

Extremes are rare by definition, so working with e.g. 99^{th}-percentile winds can be very noisy

ESA MAXSS project

Decadal trends in hurricane wind speeds → need to go even higher

Idea

- Extreme value theory: apply methods used in climate attribution at KNMI
  percentile interpolation → more consistent results; consider higher percentiles
- Start with ASCAT-A, then consider earlier instruments and compare each separately against ERA5
  (different winds extreme statistics: because of calibration and rain contamination)

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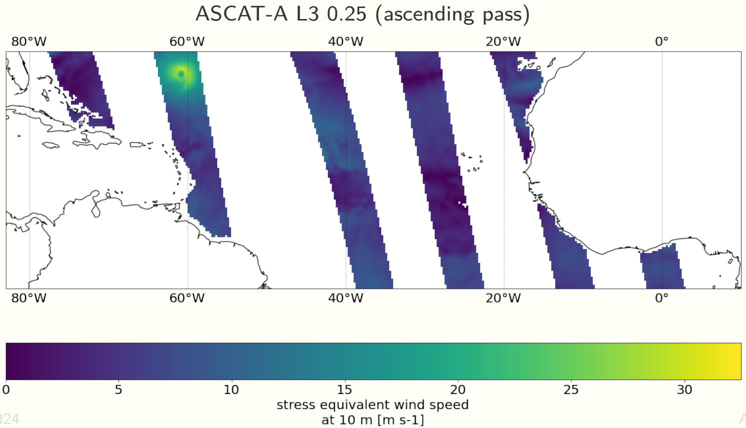
Start with ASCAT-A & collocated ERA5

- ASCAT-A L3 product: 0.25° (less noise) & 0.125° (sharper gradients and higher wind speeds): very stable, about 15 years of data; we also consider collocated ERA5 model winds.
- Consider a few tropical basins separately: the Caribbean and the Atlantic 0–30° N & S

One example day with extreme winds in the North Atlantic (264th day of 2020)



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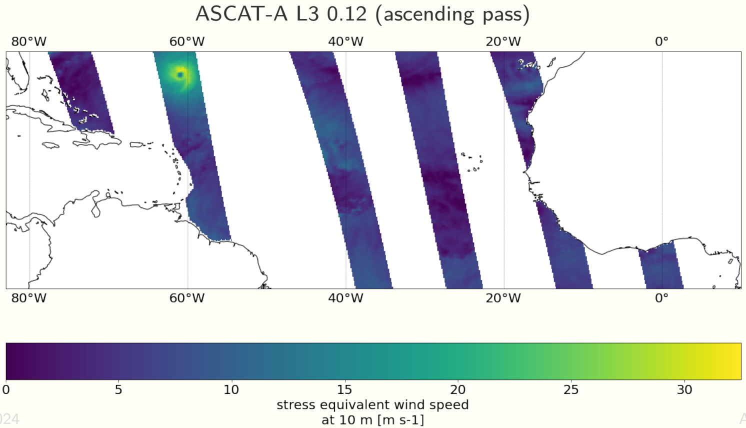

Extreme value theory

Extreme order statistics: Extreme Value Theory

Very interesting topic: used, for instance to assess the required height of dikes in the Netherlands

Royal Netherlands
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Estimation of wind speeds with very high return periods from large datasets generated by weather prediction models : statistical aspects

C.F. de Valk, H.W. van den Brink

De Bilt, 2020 | Scientific report; WR 2020-01

Extreme order statistics: Extreme Value Theory

For sequences of independent,
identically distributed random variables

$F_X(x)$: cumulative distribution function (CDF)

Extreme Value Theory, classical result:

$\exists$ three different classes of distributions to be fitted
either Gumbel, Weibull, or Fréchet
(block maxima)

1.2. *Classical extreme value theory.* The principal concern of classical extreme value theory is with asymptotic distributional properties of the maximum $M_n = \max(\xi_1, \xi_2, \dots, \xi_n)$ from an i.i.d. sequence $\{\xi_i\}$ as $n \to \infty$. Whereas the distribution function (d.f.) of M_n may be written down exactly $[P\{M_n \le x\} = F^n(x)$, where F is the d.f. of each $\xi_i]$, there is nevertheless virtue in obtaining asymptotic distributions, which are less dependent on the precise form of F, i.e., relations of the form

$$P\{a_n(M_n - b_n) \le x\} \to_d G(x), \quad \text{as } n \to \infty, \tag{1.2.1}$$

where G is a nondegenerate d.f. and $a_n > 0$, b_n, are normalizing constants.

The central result of classical extreme value theory, due in varying degrees of generality to Fréchet [47], Fisher and Tippett [46] and Gnedenko [50], restricts the class of possible limiting d.f.'s G in (1.2.1) to essentially three different types as follows.

THEOREM 1.2.1 (Extremal types theorem). *Let $M_n = \max(\xi_1, \xi_2, \dots, \xi_n)$, where ξ_i are i.i.d. If (1.2.1) holds for some constants $a_n > 0$, b_n and some nondegenerate G, then G must have one of the following forms (in which x may be replaced by $ax + b$ for any $a > 0$, b):*

$$\textit{type I}: \quad G(x) = \exp(-e^{-x}), \qquad -\infty < x < \infty,$$

$$\textit{type II}: \quad G(x) = \begin{cases} 0, & x \le 0, \\ \exp(-x^{-\alpha}), \quad \textit{for some } \alpha > 0, & x > 0, \end{cases}$$

$$\textit{type III}: \quad G(x) = \begin{cases} \exp(-(-x)^{\alpha}), \quad \textit{for some } \alpha > 0, & x \le 0, \\ 1, & x > 0. \end{cases}$$

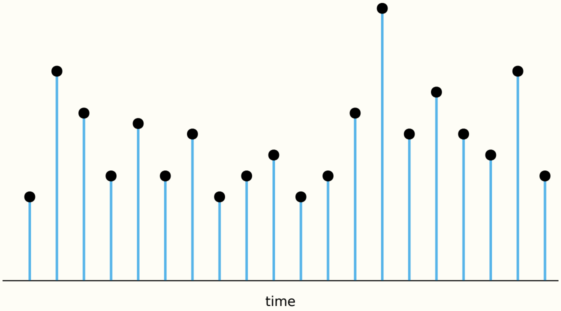
[*Leadbetter, Rootzen* (1988)]

Study the tail of distributions; look at $1 - F_X(x)$ (exceedance)

Asymptotic statistical model of tails fitted to the data

$\Rightarrow$ Interpolating or even extrapolating percentiles, using an asymptotic arguments (important caveat)

Block maxima & peak over threshold



Block maxima

- e.g. look at distribution of yearly maxima
- parameter: needs to select the block size
- throws away most of the data
- less worry about independence

Peak over threshold

- more recent approach [Leadbetter (1991)], [Coles (2001)]
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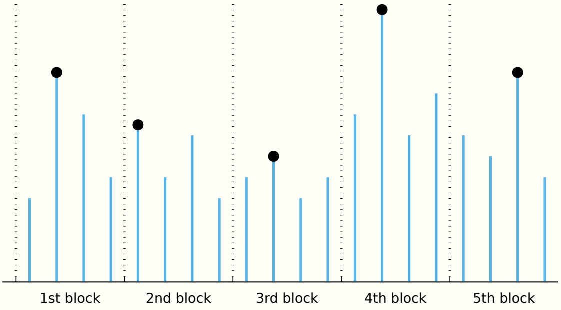

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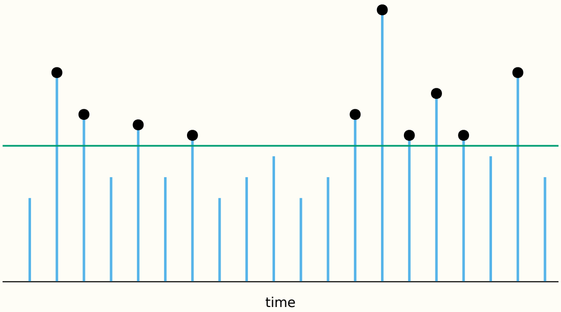

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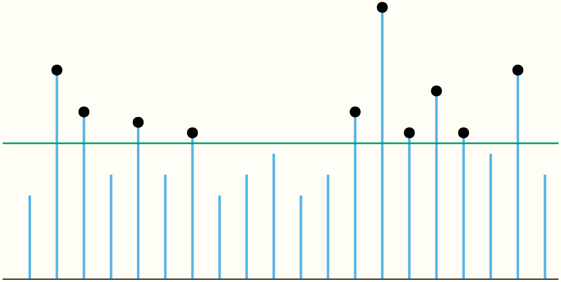

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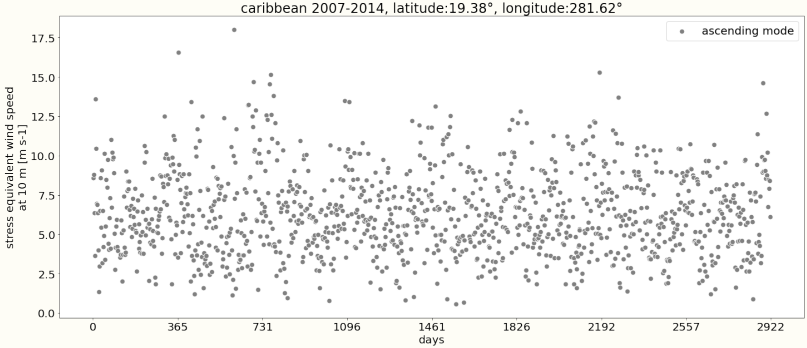
Developing our method

Motivation to work at basin level

There is a balance:

- we want to be sensitive to more extreme winds (incentive to increase the threshold)
- however, the higher the threshold, the less data available for the fit (incentive to lower it)



Time series for a pixel in the middle of the Caribbean basin (2007–2014 period)

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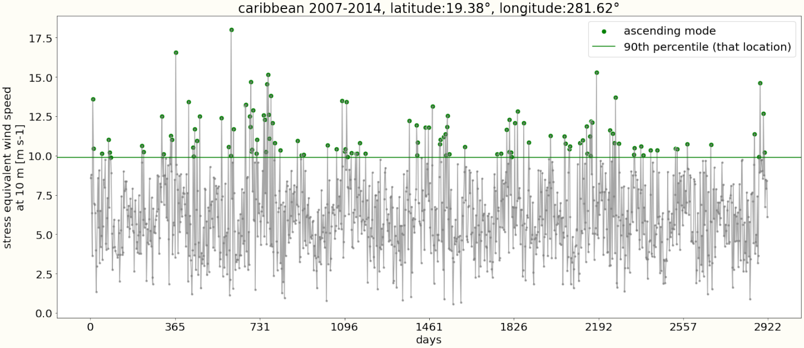

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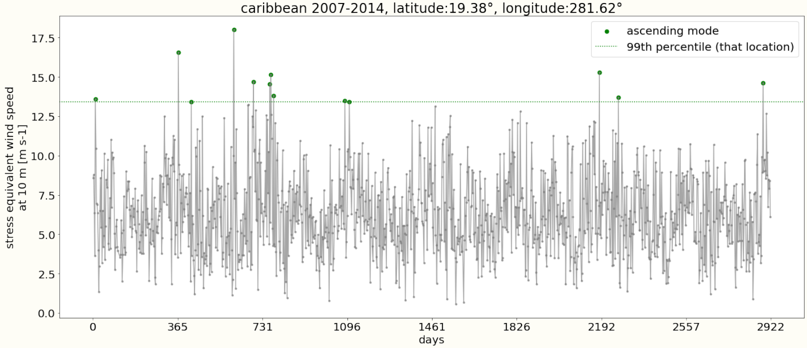

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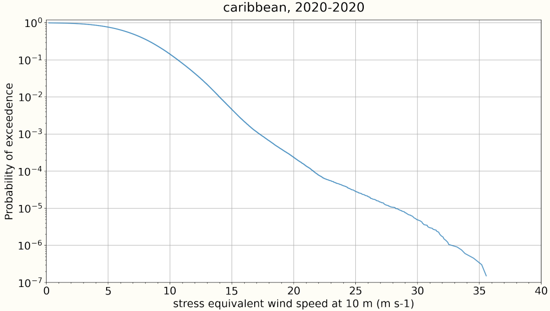
$\Rightarrow$ As we do not want to compromise on either $\rightarrow$ we work at basin level.

Interpolating percentiles with peak over threshold

We use a high percentile as threshold. Then:

- lower percentiles are simply calculated based on the data itself;
- beyond the threshold, the data are fully replaced by the smooth fit of the tail distribution $\rightarrow$ higher percentiles will be calculated using the fit.



Probability of exceedance $P(X > x) = 1 - F_X$:
$\rightarrow$ best suited to study tails (semi-log plot)

Link with j-th percentile:

$$P(X > x_j) = 1 - F_X(x_j) = 1 - \frac{j}{100}, \quad j \in [0, 100].$$

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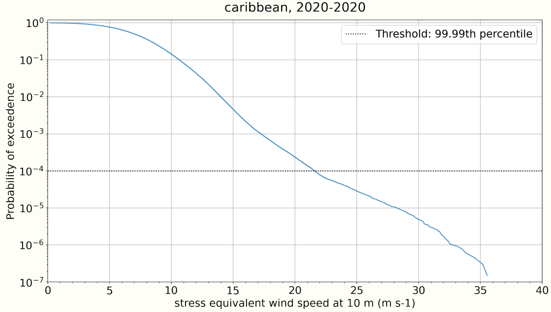

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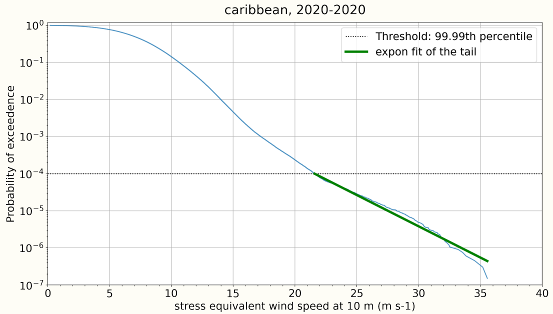

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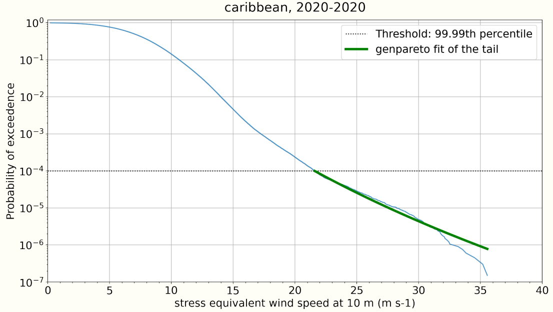

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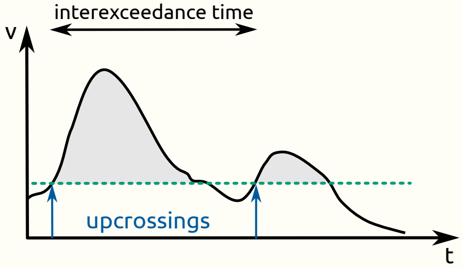
Now, the issue of dependence in the data must still be addressed

Formal requirement: independent, identically distributed random variables

Beware not to count several times the same event (assumption of independent random variables)



- Achieving independent data: problem of throwing away too much data that is already very scarce.
- Better to keep data and then assess standard error instead → use the block-bootstrap method.

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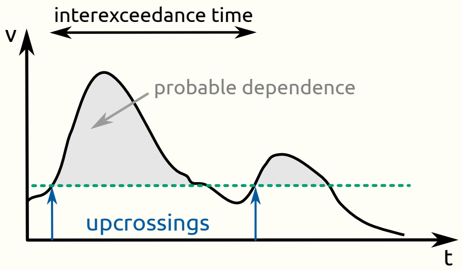

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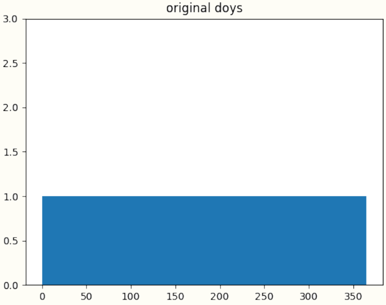
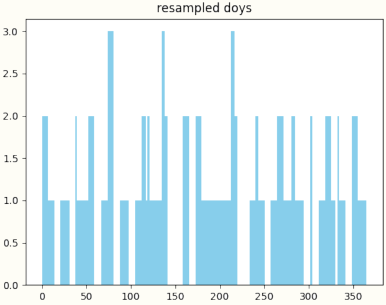
Block bootstrap

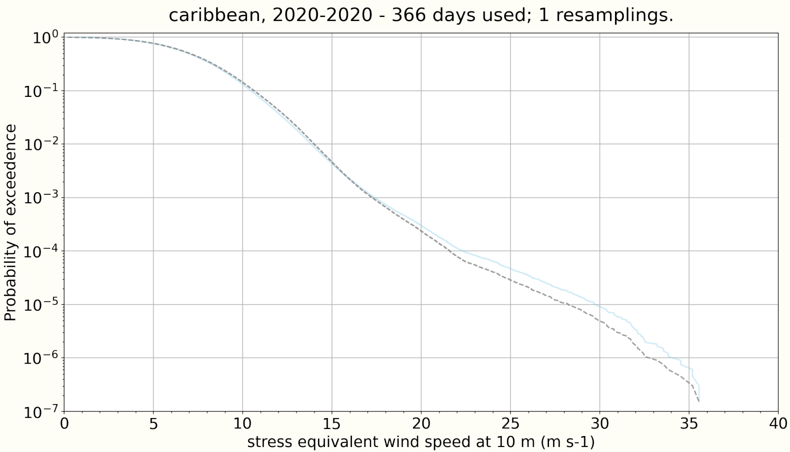




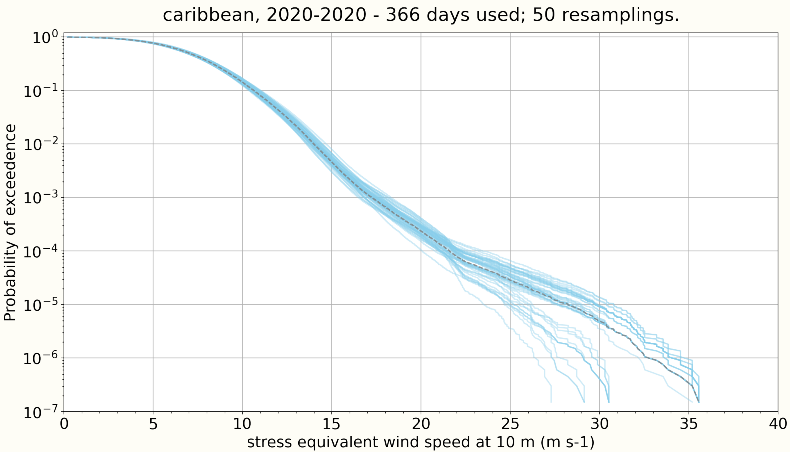
We resample randomly but make sure to preserve the temporal & spatial correlations in the data:

- randomly pick blocks of 7 consecutive days ($\sim$ time for TC to cross a basin) & take all swaths
- moreover: respect seasonality when resampling the data

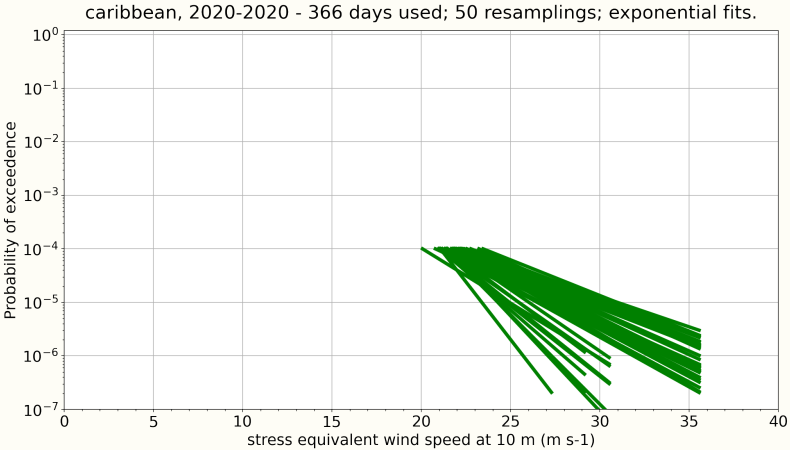
Block bootstrap: how a single resampling looks like



Block bootstrap: 50 resamplings



Fit independently each resampled dataset obtained with block bootstrap



Each new sample is fitted independently (‘exponential’ case).

For each percentile value, a mean wind-speed value and variance will then be obtained from all the fits.

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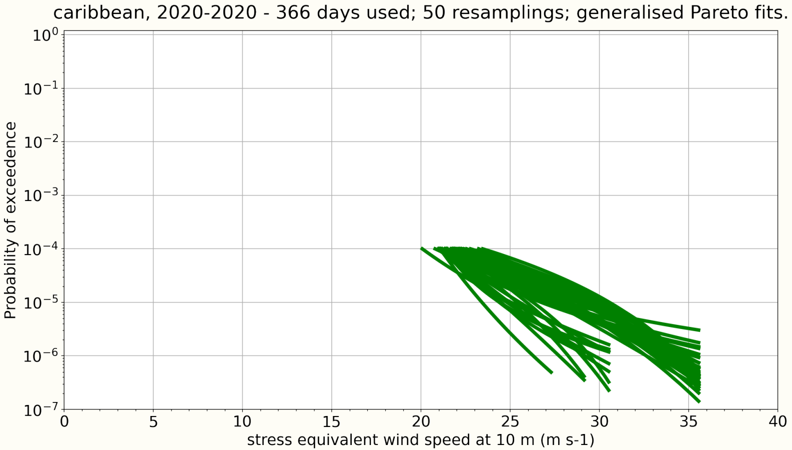
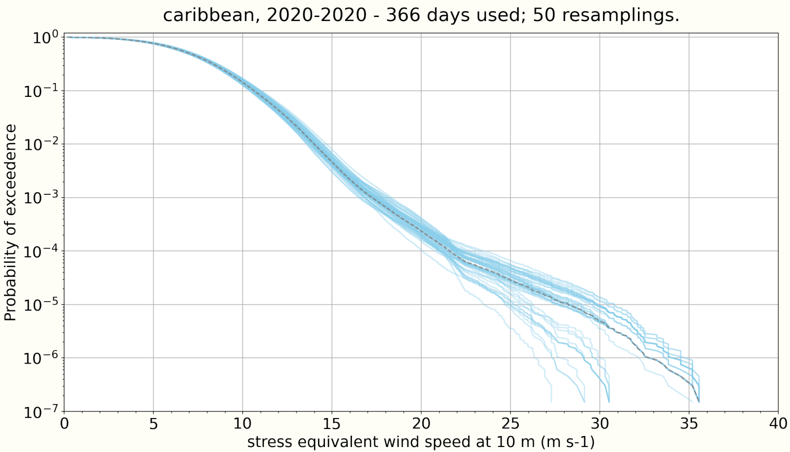


Each new sample is fitted independently ('generalised Pareto' case).

For each percentile value, a mean wind-speed value and variance will then be obtained from all the fits.

Estimate mean and variance of percentiles from block bootstrap samples

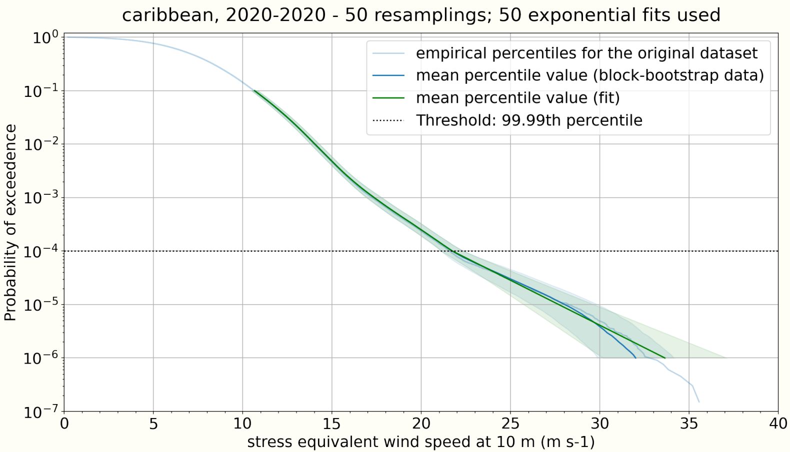


Bonus, using all these resampled datasets directly (‘raw’ case; no fit):

For each percentile value, a mean wind-speed value and variance can also be empirically obtained.

Sample results

Caribbean basin – 0.125°



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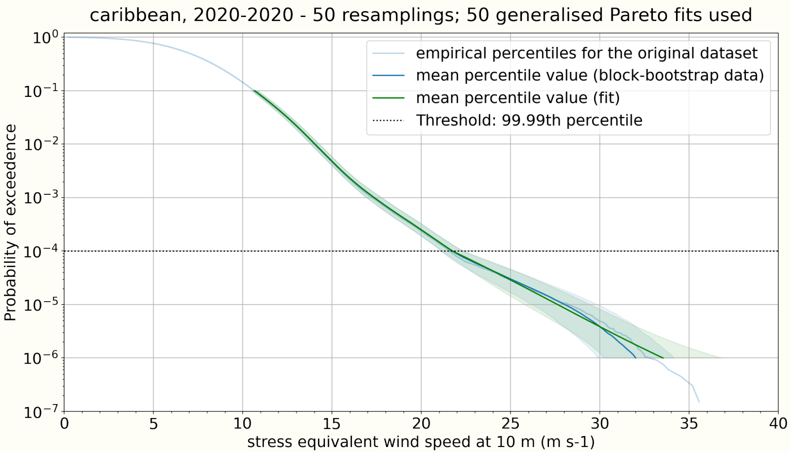
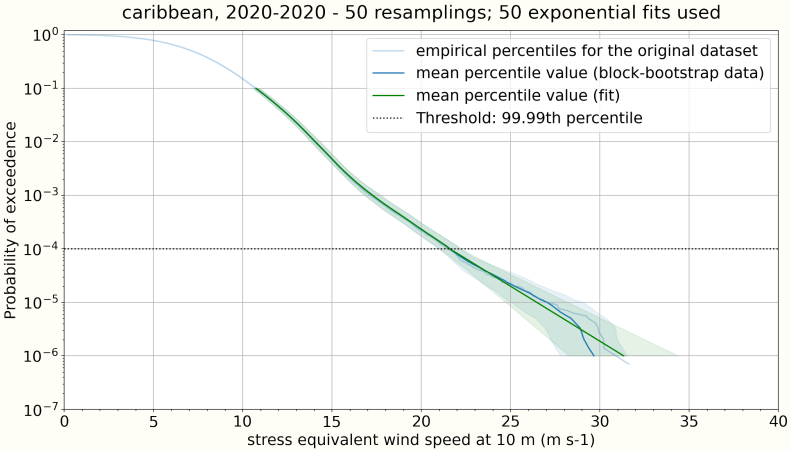


Caribbean basin – 0.25°



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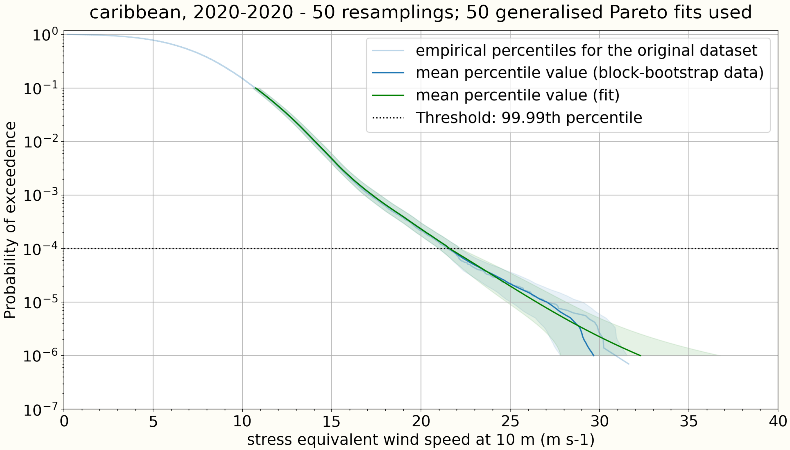
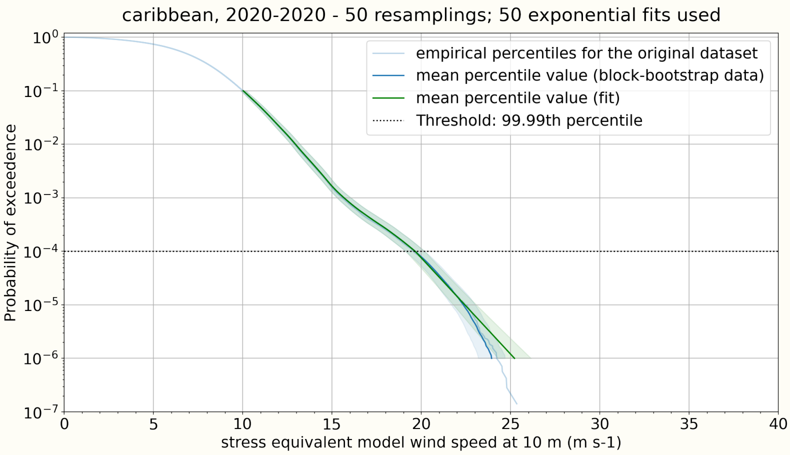


Caribbean basin – 0.125°, collocated ERA5 model winds



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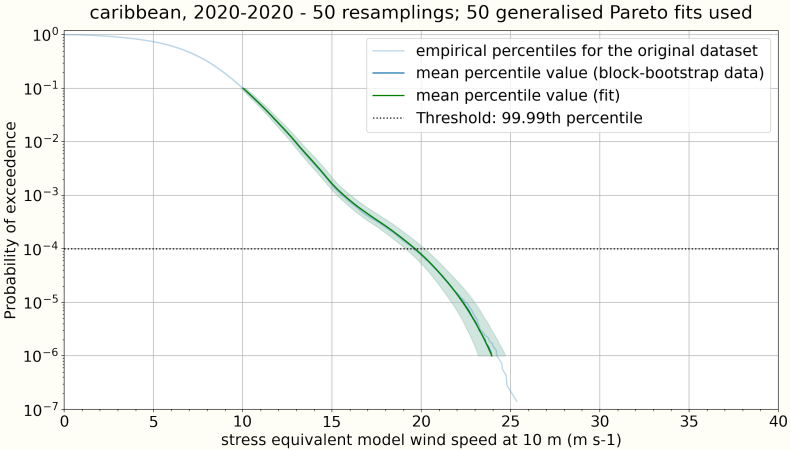
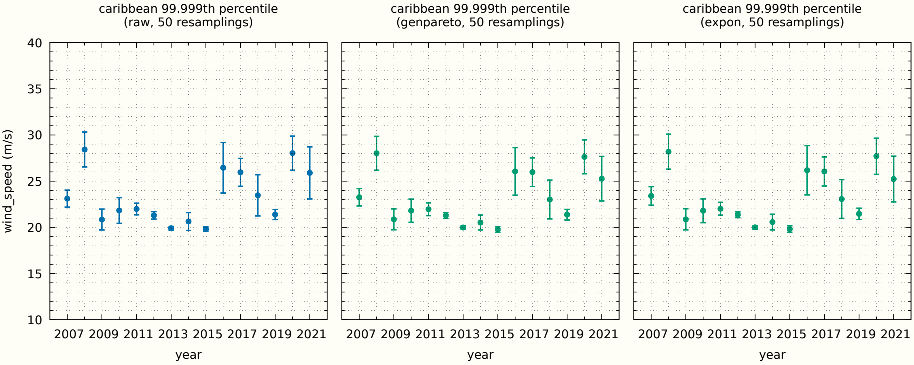


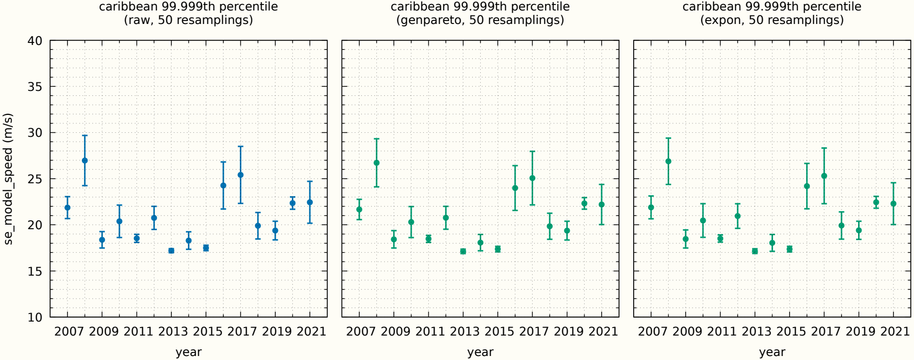
Summary results for Caribbean basin, 99.999th percentile



Extremely robust and stable up to the 99.999th percentile

This is our main result. The 3 cases are hard to distinguish.

Summary results for Caribbean basin, 99.999th percentile (ERA5)



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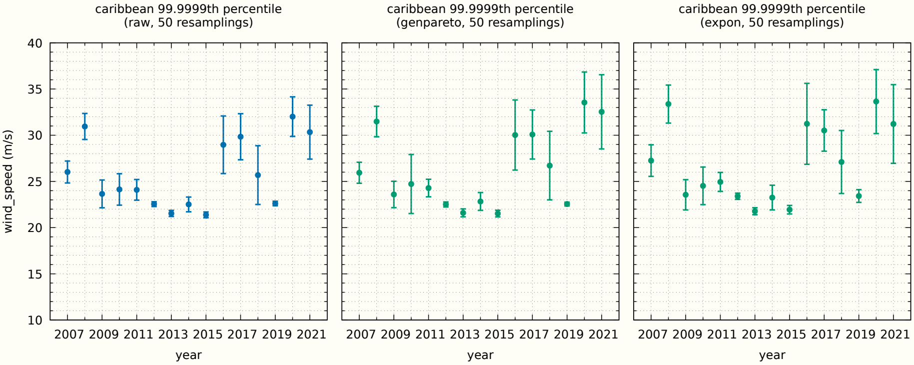

Still very consistent even at the 99.9999th percentile.

If decadal trends in tropical cyclones exist, they will be visible at these levels
Simply no need to go further (only making conclusions conditional on further assumptions)

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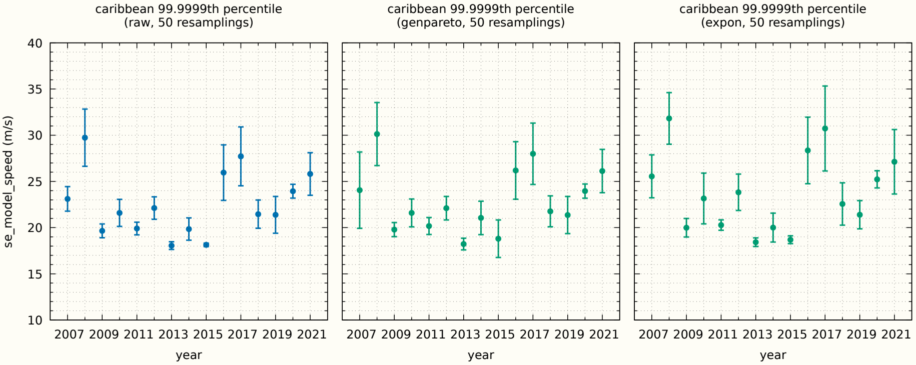

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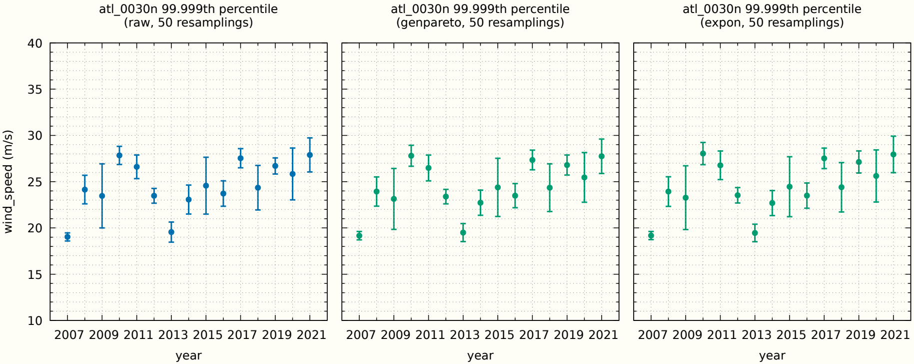

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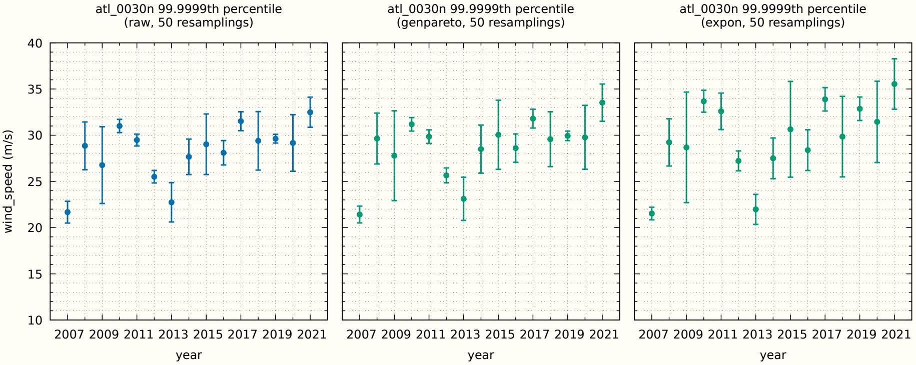

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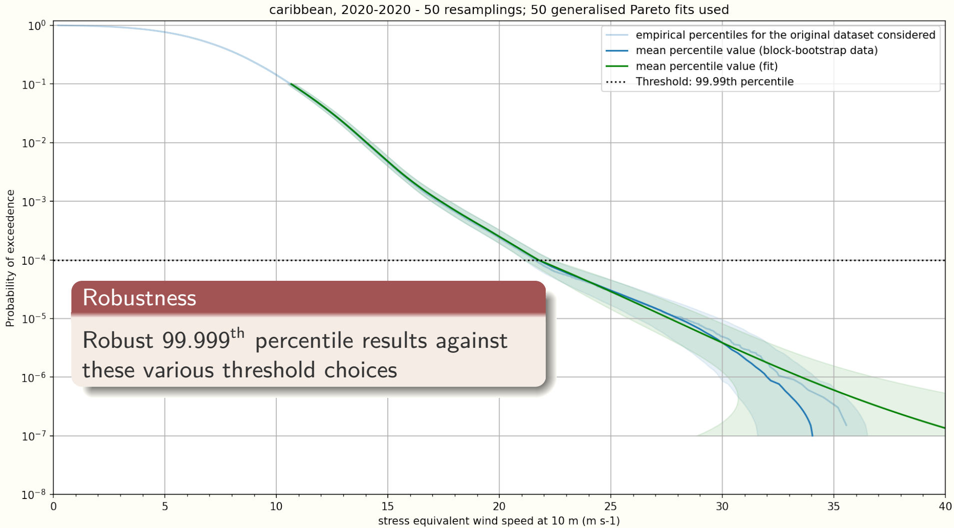

Robustness

Robust 99.999[th] percentile results against these various threshold choices

Our choice for the amount of data, and we further restrict ourselves down to 10^{-6} at most

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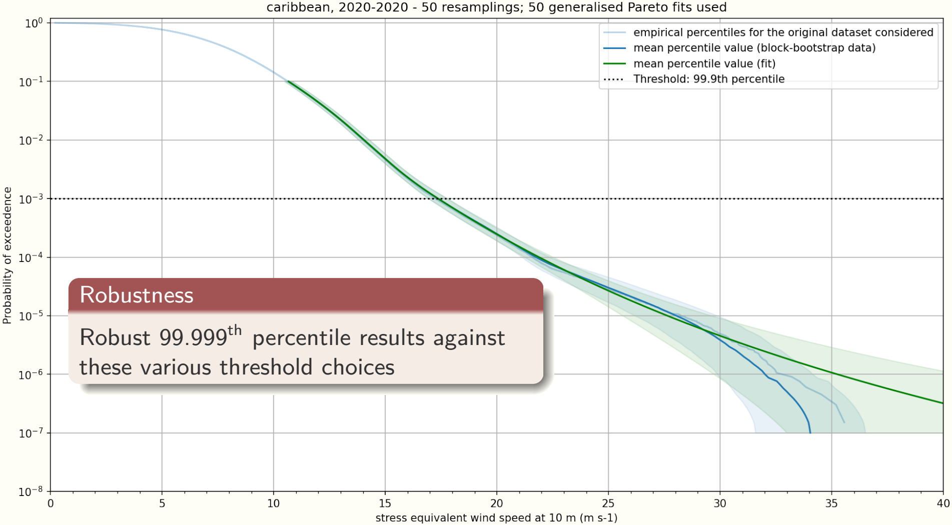

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Likely too much weight/trust on winds not associated with tropical cyclones and/or the tail model

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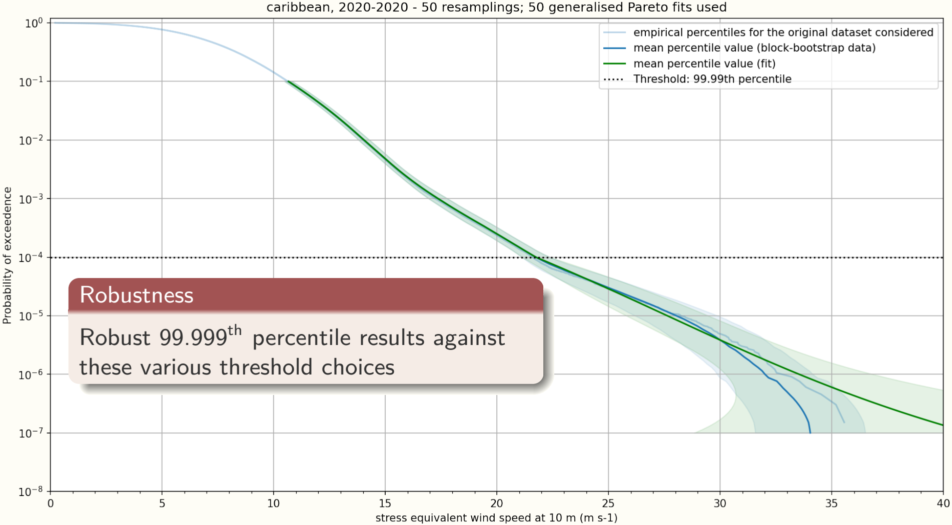

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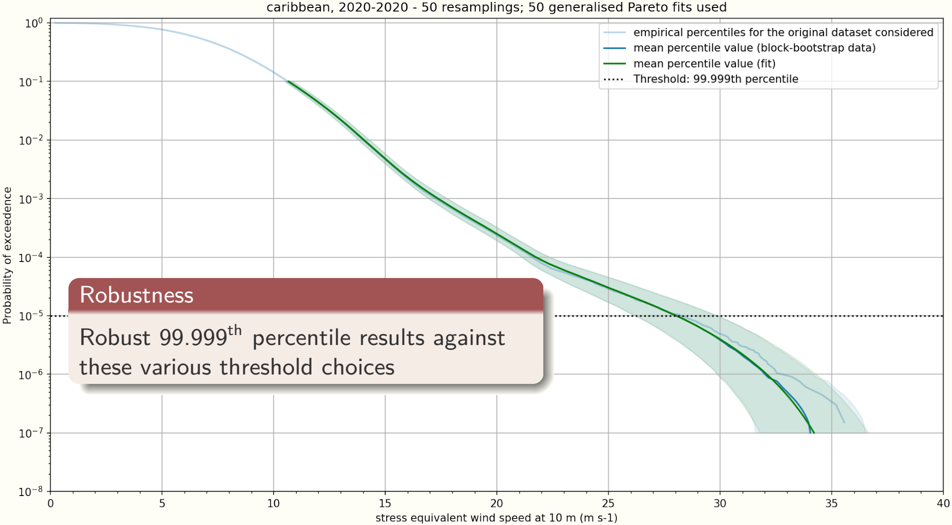

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Likely too much trust put on the overly scarce data: risk of overfitting

Summary

Summary

We obtain very robust results at basin level, without relying on a strong assumption for the tail

- Exponential fits
- Generalised Pareto fits
- Empirical mean & variance from block-bootstrap resampled data

} Very consistent results

Results are extremely stable down to a probability of exceedence of 10^{-5} $\leftarrow$ main result

- still quite consistent within the uncertainties, down to 10^{-6} $\leftarrow$ slight differences can then appear
- robust against changes in the approach, such as the number of resamplings, or the threshold

This allows peering at extreme percentiles high enough to correspond to tropical cyclone winds

$\rightarrow$ powerful tool to assess the existence significant of decadal trends, once applied to 30 yr of data

Continuing this work

A longer period is needed to enable conclusions on decadal trends in tropical cyclone winds
(also e.g. to avoid being too sensitive to El Niño-index variations)

Our method is ready for use with earlier scatterometer datasets, also generated at KNMI

We now want to apply it to ERS, QuikSCAT, ASCAT data, using ERA5 as comparison

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Appendix

Earlier study made on 99th percentiles winds (scatterometers & ECMWF)

[*Giesen, Stoffelen* (2022)]

99th percentile study, per basin and smaller subregions

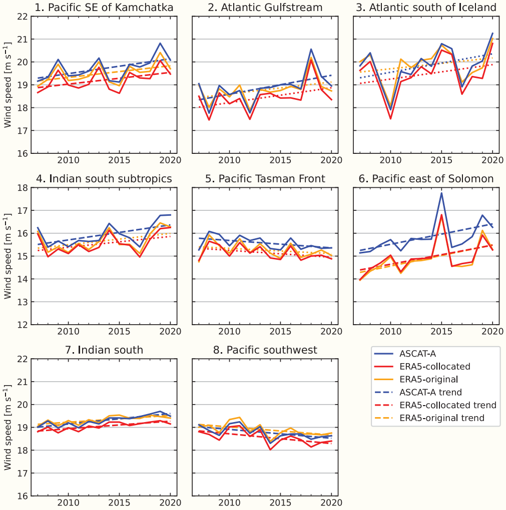


Figure 2.1.3. Time series (2007–2020) and linear trends of annual 99th percentile extreme wind speeds over selected regions with large trends (see Figure 2.1.2(c)), for ASCAT-A, collocated and original ERA5. Trends not significant at the 90% confidence level are shown with dotted instead of dashed lines.

Earlier study made on 99th percentiles winds (scatterometers & ECMWF)

[*Giesen, Stoffelen* (2022)]

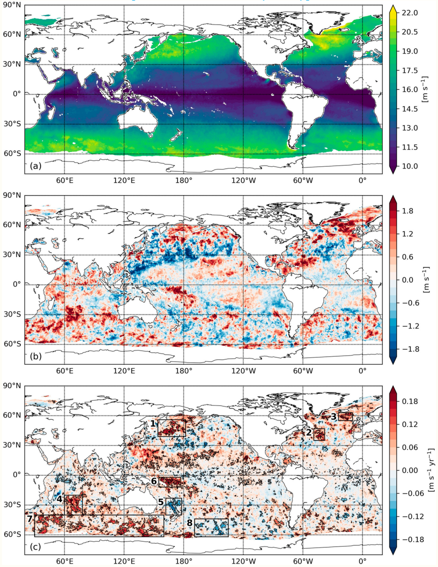
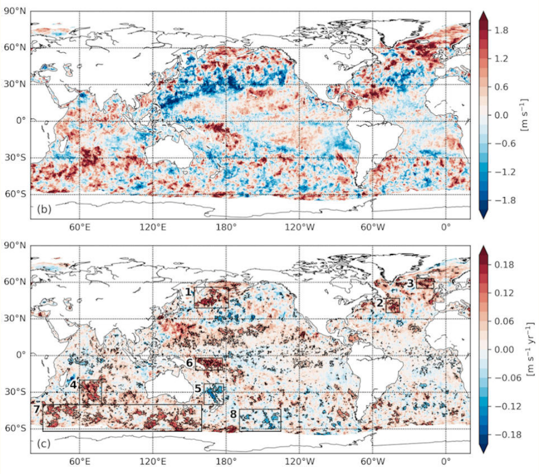


Figure 2.1.2. ASCAT-A 99th wind speed percentile (a) climatology (2007–2014), (b) annual anomaly for 2020 and (c) annual trend (2007–2020). Areas with trends significant above the 90% confidence level are outlined in black. Regions examined in more detail are indicated with numbered boxes.

On deriving trends using only a few years

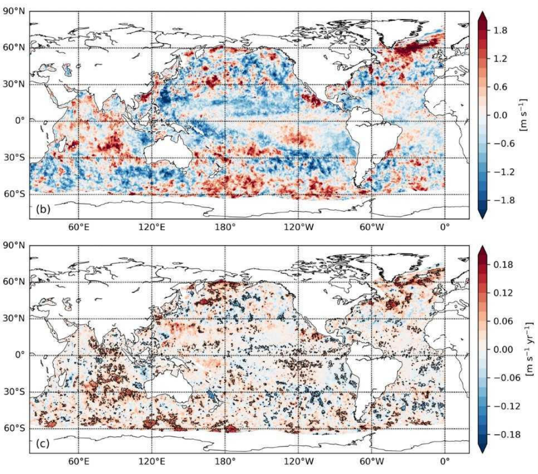
2020 anomalies and 2007–2020 trends (OSR6)



[*Giesen, Stoffelen* (2022)]

On deriving trends using only a few years

2022 anomalies and 2007–2022 trends
(will appear in OSR8)



[*Giesen, Stoffelen* (202X)]

Wind speeds: buoys vs dropsondes

[*Giesen, Stoffelen* (2022)]

Wind speed [m s^{-1}]	Wind speed scaled [m s^{-1}]
5.5–7.9	5.5–7.9
8.0–10.7	8.0–10.7
10.8–13.8	10.8–15.3
13.9–17.1	15.4–21.3
17.2–20.7	21.4–28.0
20.8–24.4	28.1–35.2
24.5–28.4	35.3–43.3
28.5–32.6	43.4–52.0
>32.6	>52.0