

# Defining single extreme weather events in a climate perspective

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# Context

The analysis of single extreme weather events relates to:

- climate monitoring;
- physical understanding;
- estimation of return periods;
- attribution to climate change.

For the latter, one compares the probability of the event occurring:

- in the **factual** world ( $p_1$ );
- in a **counter-factual** world, e.g. non-anthropized ( $p_0$ ).

One defines the **Risk Ratio** and the **Fraction of Attributable Risk** as:

$$RR = \frac{p_1}{p_0} \quad \text{and} \quad FAR = \frac{p_1 - p_0}{p_1} = 1 - \frac{1}{RR}$$

# The four steps of event definition

## 1. Select the variable ( $X$ ).

Usually straightforward — not crucial here.

## 2. Define the class of events.

Here, traditional "risk-based" approach, i.e. events *equally or more intense than* the observed one:  $\Pr\{X \geq x_0\}$  with  $x_0$  the event value.

N.B. Alternative "storyline" approach: events *of about the same intensity* — not appropriate for probabilistic framework since:  $\Pr\{x_0 - \varepsilon \leq X \leq x_0 + \varepsilon\} \xrightarrow{\varepsilon \rightarrow 0} 0$ .

## 3. Define the level of conditioning.

$\Pr\{X \geq x_0 \mid Y \in \Omega\}$  with  $Y$  a concurrent climate variable (e.g. SST, atmospheric circulation, ENSO) or the time of the year (e.g. winter heat wave)?

Here only the **calendar conditioning** is explored (relevant for climate monitoring).

## 4. Define the spatio-temporal scale.

The main topic of this talk.

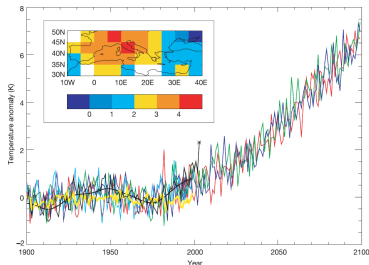
# Why spatio-temporal scale matters

Example of the European heat-wave of summer 2003 (EHW03):

- Stott et al. (2004): EHW03 becomes a **cold** extreme after 2050.
- Beniston (2007): EHW03 remains a **hot** event in 2100.

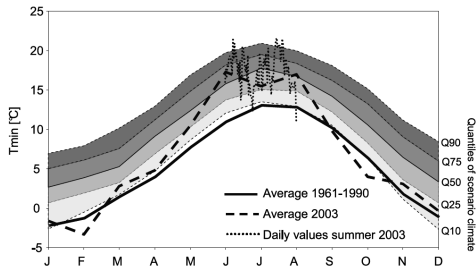
The difference? **Seasonal/European** vs. **daily/local** temperature anomalies.

a) JJA T Europe



Stott et al., Nature, 2004  
(SRES A2 scenario).

b) Daily T Basel



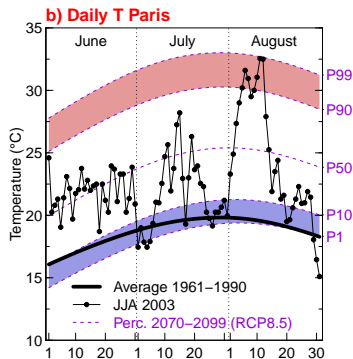
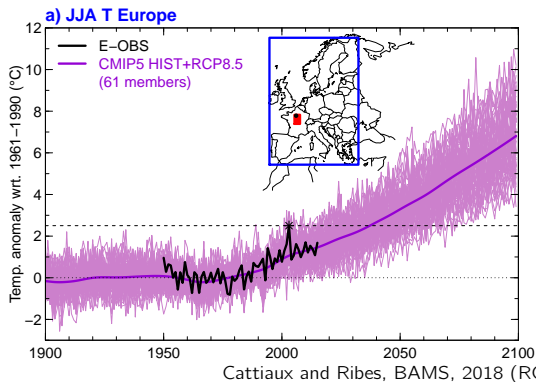
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# Choice of spatio-temporal scale

Most of the time: arbitrary.

Authors use predefined areas (e.g. a local station, a national territory) and periods (e.g., a day, a month, a season), and/or their own expertise.

**Problem #1:** this may not faithfully portray the event / be biased by our perception.

**Problem #2:** different definitions of the "same" event may lead to different attribution statements (see EHW03 example).

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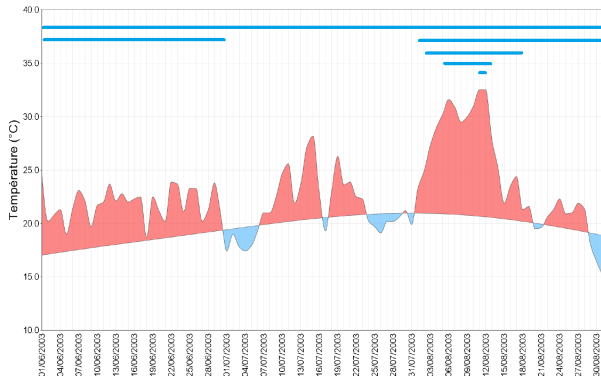
Our idea: select the scale at which the event has been the most extreme, i.e. minimize the factual probability:

$$p_1 = \Pr \{ X^{(t_1)} \geq x_{t_1} \},$$

with  $X^{(t_1)}$  the random variable describing the temperature distribution at time  $t_1 = 2003$ , and  $x_{t_1}$  the observed 2003 value.

# Optimizing the time window

Example: Daily  $T$  at Paris-Montsouris station for Jun-Jul-Aug 2003.



Data: Météo-France.

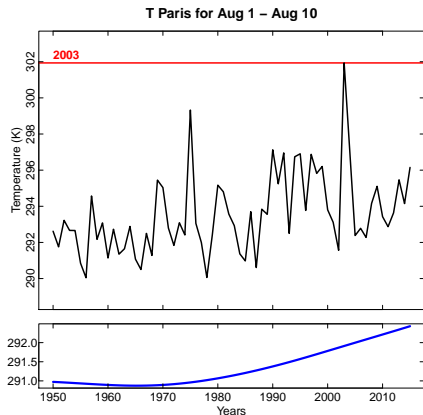
Question: Over which time window is the anomaly the most extreme?

1. Aug 11 (1 day);
2. Aug 5–12 (1 week);
3. Aug 2–17 (2 weeks);
4. August (1 month);
5. June (1 month);
6. Jun-Jul-Aug (1 season).

## Optimizing the time window – Calendar method

For each time window  $[[d_1, d_2]]$ :

- we consider the observed time series  $x_t$  & the climate change  $x_t^*$  at this location;



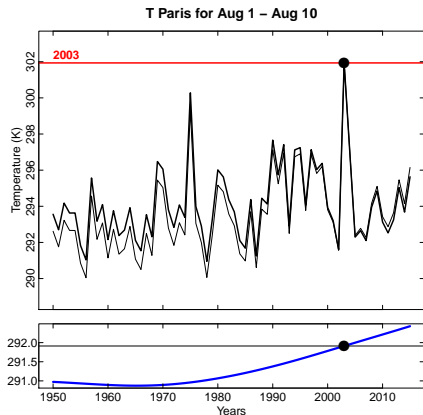
N.B.  $x_t^*$  = smoothed multi-model mean of CMIP5 JJA temperatures (common to all time windows but location-dependent).



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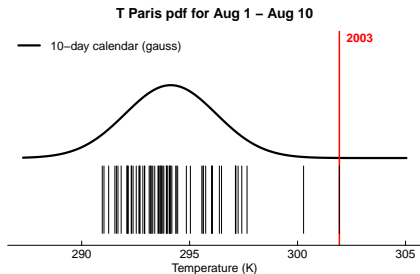
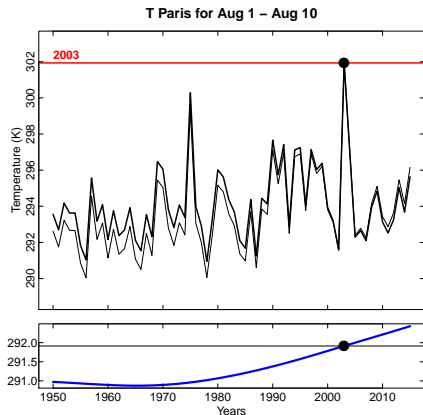


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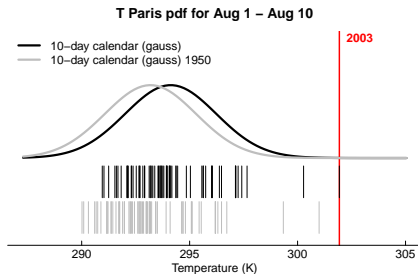
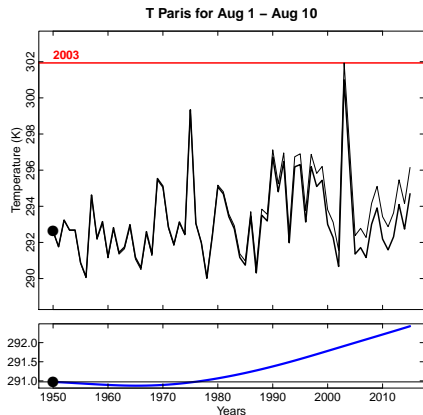


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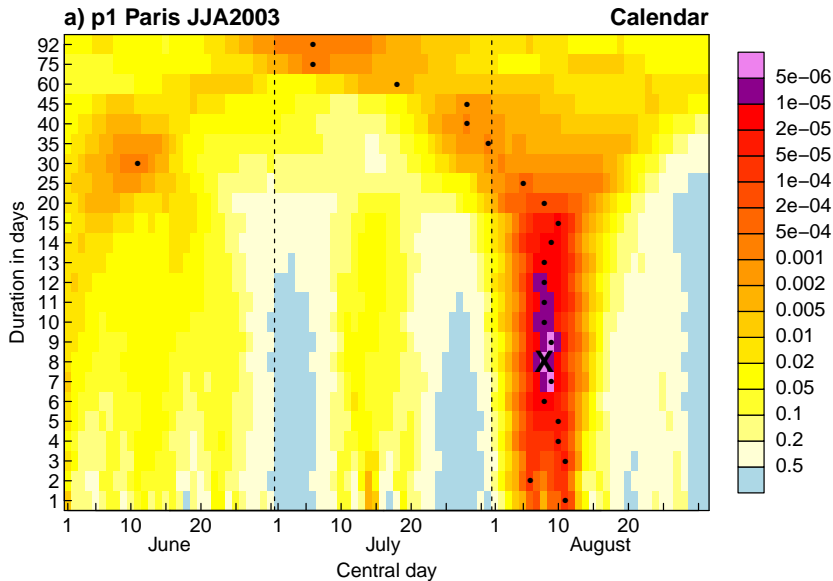
- we consider the observed time series  $x_t$  & the climate change  $x_t^*$  at this location;
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- we estimate  $p_1$  from  $x_t^{(t_1)}$ , assuming  $X^{(t_1)}$  follows a Gaussian distribution;
- we also estimate  $p_0$  by correcting wrt.  $t_0 = 1950$  (our counter-factual world).



N.B.  $x_t^*$  = smoothed multi-model mean of CMIP5 JJA temperatures (common to all time windows but location-dependent).

## Optimizing the time window – Result

The most extreme anomaly is found for **Aug 5–12** ( $p_1 = 4 \times 10^{-6}$ , 250 000 y).



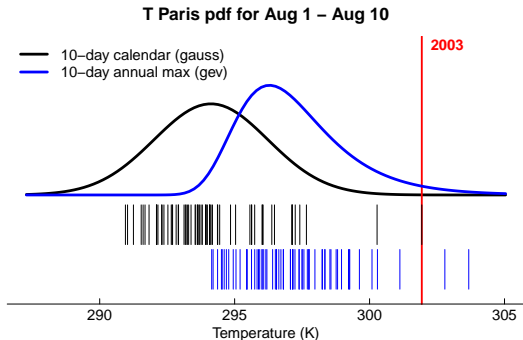
## Calendar vs. annual maxima

The calendar approach is relevant for climate monitoring (seasonal context), but the obtained  $p_1$  should not be interpreted as a formal return period.

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**Alternative approach:** consider  $x_t^{(t_1)}$  as the time series of annual maxima, (now assuming that  $X^{(t_1)}$  follows a Gumbel distribution).

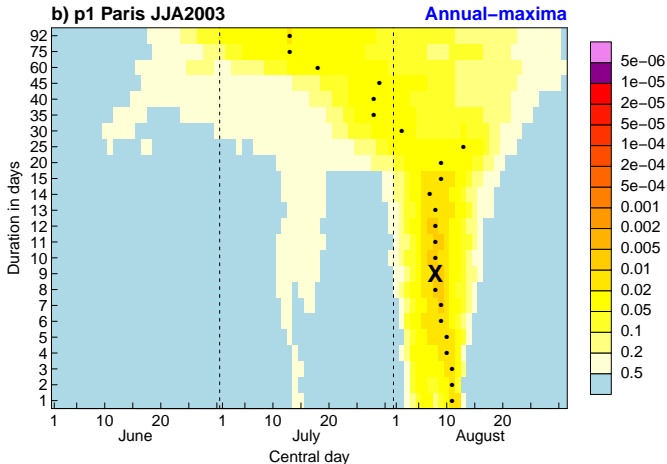
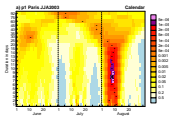


**N.B.** The question becomes: Over which time window is the **anomaly temperature** the most extreme?

# Calendar vs. annual maxima – Result

The most extreme temperature is found for **Aug 4–12** ( $p_1 = 0.008$ , 125 y).

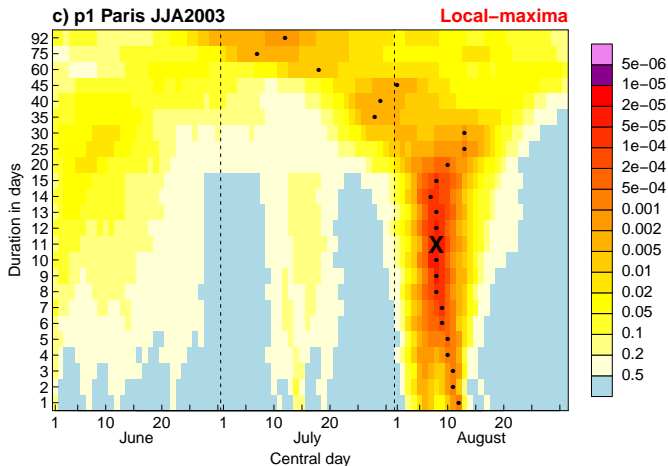
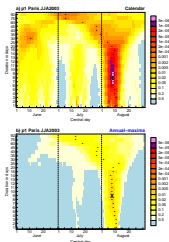
Hot anomalies distant from the annual cycle peak disappear (e.g. June).



# A compromise: local maxima

Idea : limit the search of annual maxima to a calendar neighborhood, i.e. consider  $x_t^{(t_1)}$  as the time series of **local maxima**.

Here we use  $\pm 7$  days; similar to what is done for establishing record values.



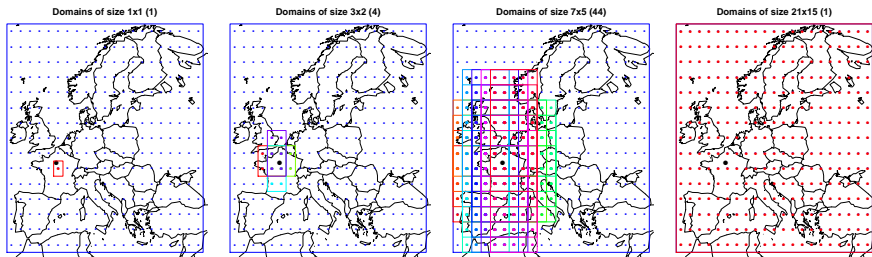


# Optimizing the space window

Idea (simple): repeat the procedure for an ensemble of spatial domains. . .

Here: squared or near-squared domains including Paris / included in Europe.

Observations: E-OBS interpolated onto a  $2.5 \times 2.5^\circ$  grid.

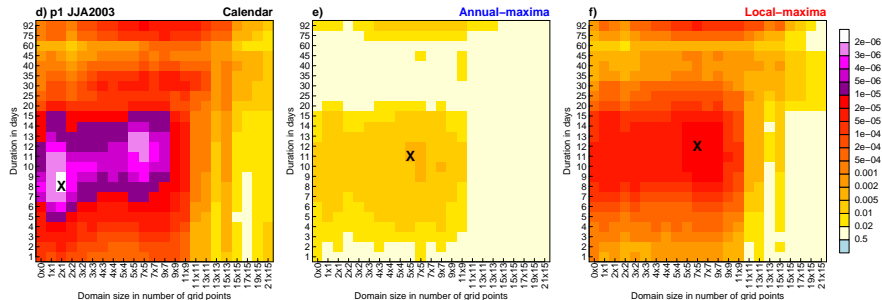


Alternative methods: successive grouping of countries or hierarchical collection of regions proposed by D.A. Stone (Climatic Change, submitted).

# Optimizing the space window – Result

**Annual-maxima / local-maxima:** minimum  $p_1$  (0.005, 200 y) is found for Aug 2–13 over France & Spain (12 days,  $7 \times 5$  domain).

**Calendar approach:** other minimum at smaller scale (8 days,  $2 \times 1$  domain).



x-axis: size of the space window from local (Paris) to the entire Europe.  
y-axis: size of the time window from 1 day to the entire season (92 days).

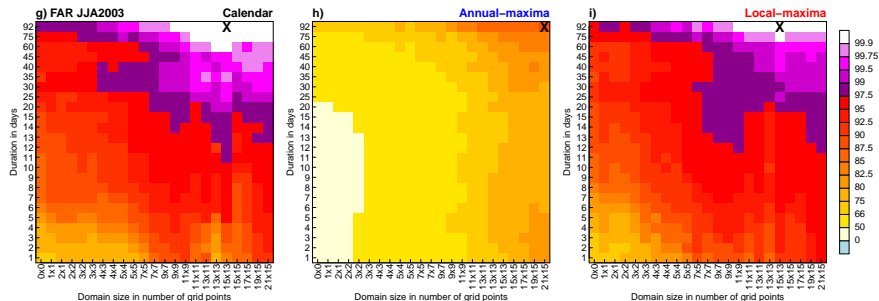
## Does it bias the FAR?

$p_1 = \Pr \{X^{(t_1)} \geq x_{t_1}\}$ ,  $p_0 = \Pr \{X^{(t_0)} \geq x_{t_1}\}$  and  $\text{FAR} = 1 - p_0/p_1$ .

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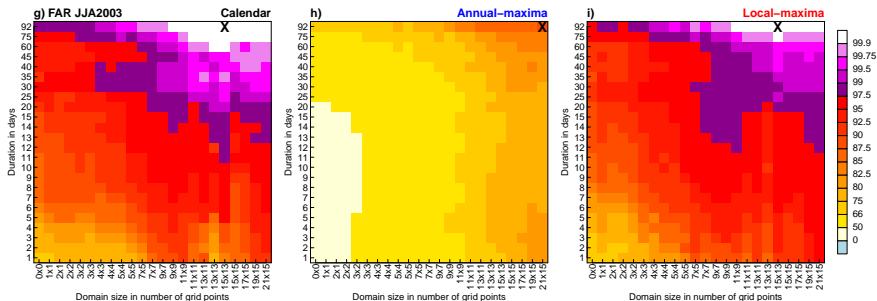
No. For this event, the FAR increases with spatio-temporal scale.  
It is maximum for the scale chosen by Stott et al. (2004).



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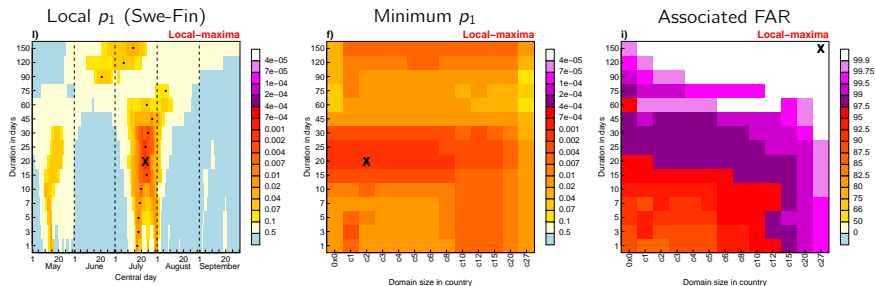
The FAR responds to the signal-to-noise ratio of the human-induced change.  
For temperatures, the signal (warming) is rather uniform across scales, while the noise (variability) is stronger for small spatio-temporal scales.

# Another temperature event

The European heat-wave of [summer 2018](#).

**Result:** Sweden-Finland, Jul 14 - Aug 2, estimated return period 50 y.

- Higher  $p_1$  than 2003: less extreme event.
- Higher FAR values: stronger signal-to-noise ratio in 2018 vs. 2003.
- Same behavior for the FAR: it increases with spatio-temporal scale.



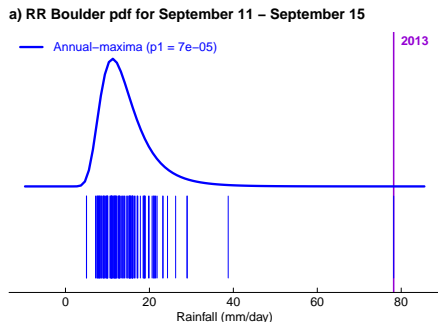
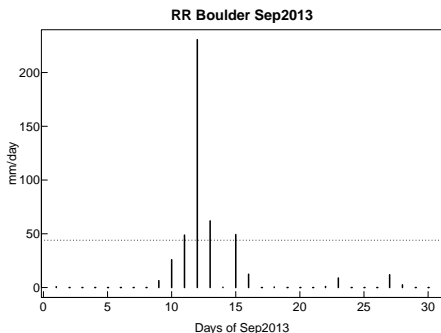
Yiou et al., BAMS report on 2018 extremes, in prep.

# A precipitation event

The intense rainfall in Boulder, Colorado, September 2013.

**Method:** annual maxima, with a different correction for climate change.

1. We estimate the local long-term  $T$  change  $x_t^*$  (in K, CMIP5).
2. We estimate the scaling of the annual  $n$ -day  $P$  maxima (in % par K, CMIP5).  
→ *2.5 %/K for 1-day maxima, 0.7 %/K for 92-day maxima.*
3. We rescale the  $P$  annual max time series wrt. 2013 ( $p_1$ ) or 1901 ( $p_0$ ).
4. We use GEV distributions with shape parameter  $\xi = 0.1$  across all time windows.



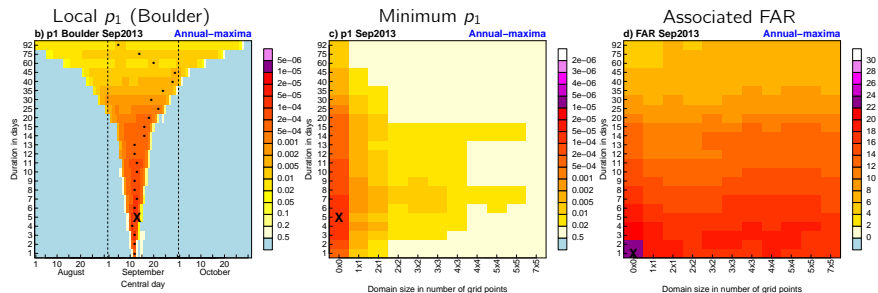
Data: GHCN daily data at Boulder station + regridded at  $0.1 \times 0.1^\circ$  by M. Hoerling.

# A precipitation event – Result

- $p_1$  is found to be minimum for Boulder local station, Sep 11–15.
  - Large estimated return period:  $p_1 = 7 \times 10^{-5}$ , i.e. 15 000 y.
  - Rather small FAR values, typically between 10 and 25 %.
- ↪ Consistent with previous attribution studies (Hoerling et al., 2014; Eden et al. 2016).

For this event, the FAR decreases with spatio-temporal scale.

The signal-to-noise ratio is more complex for  $P$  than for  $T$ .





# Summary

Select the space-time window that maximizes the event rarity (minimizes  $p_1$ ) provides an *as-objective-as-possible* event definition.

Maximizing the rarity does not systematically maximize (or minimize) the attributable risk, contrarily to some arbitrary definitions.

Using  $p_1$  allows to compare the rarity of different events and/or select the events that have been the most extreme within a year (e.g. for BAMS reports).

We have used very simple detrending + probability estimation procedures, future work may involve including more sophisticated techniques.

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Cattiaux, J. and A. Ribes, Defining single extreme weather events in a climate perspective, *Bulletin of the American Meteorological Society*, 99, 1557–1568. doi:[10.1175/BAMS-D-17-0281.1](https://doi.org/10.1175/BAMS-D-17-0281.1)