

Quantifying the added value of downscaling in extreme precipitation attribution

EGU General Assembly

4-8 May 2020

Jonathan Eden¹ and Bastien Dieppois^{1,2}

¹ Coventry University, Centre for Agroecology, Water and Resilience, Coventry, UK (jonathan.eden@coventry.ac.uk)

² Department of Oceanography, MARE Institute, University of Cape Town, RSA



Attributing extreme precipitation events

- There is still large uncertainty about the role played by anthropogenic climate change with regard to changes in extreme precipitation; our understanding can be supported by attribution studies of individual extreme events.
- Empirical event attribution is a useful tool when large model ensembles are not always available, allowing us to make the most of observed and simulated data at our disposal.
- However, to date, attribution of precipitation extremes has not fully utilized statistical techniques that merge bias correction and downscaling.

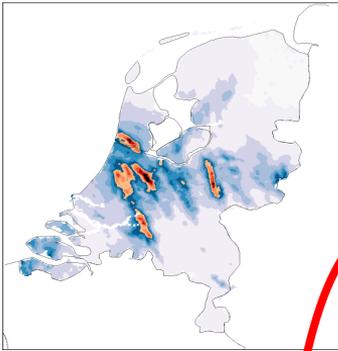
Aim: To demonstrate the benefits of:

- (a) a pointwise approach to generating attribution information for recent precipitation extremes across Europe, and
- (b) the application of a downscaling correction to bridge the gap between results from observed and simulated data.

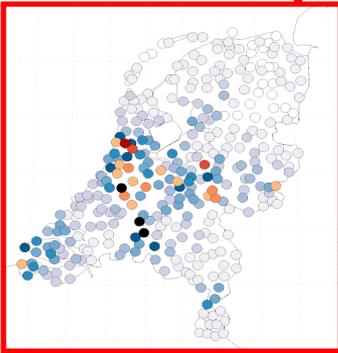
Empirical event attribution: example

Extreme event: 28 July 2014

pr 28-28Jul KNMI radar precipitation



28-29 July 2014 sum



Has the likelihood of this type of event changed as a result of anthropogenic climate change?

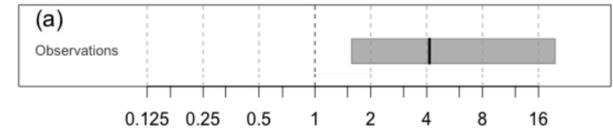
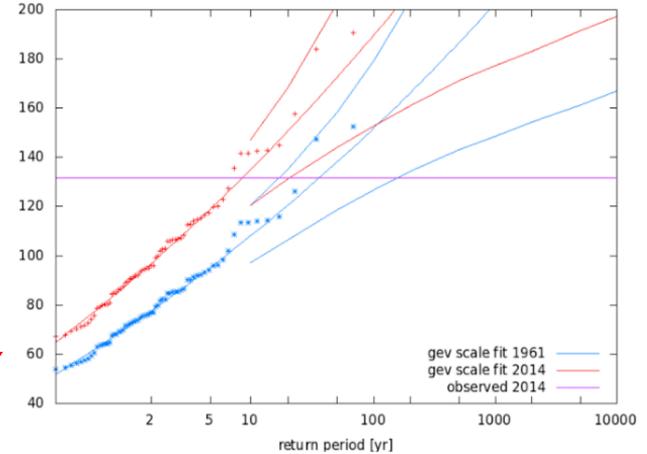
Annual maxima of summertime (AMJJAS) one-day precipitation at 324 stations (1910-2014) fitted to GEV.

$$F(x) = \exp\left[-\left(1 + \xi \frac{x-\mu}{\sigma}\right)^{\frac{1}{\xi}}\right]$$

$$\mu = \mu_0 \cdot \exp \frac{\alpha T}{\mu}$$

$$\sigma = \sigma_0 \cdot \exp \frac{\alpha T}{\mu}$$

- Distribution assumed to scale with global mean temperature T .
- Uncertainty margins estimated using non-parametric bootstrapping (sample size: 1000).



Risk ratio: probability of the event occurring in present vs past climates.

$$RR = P_1/P_0$$

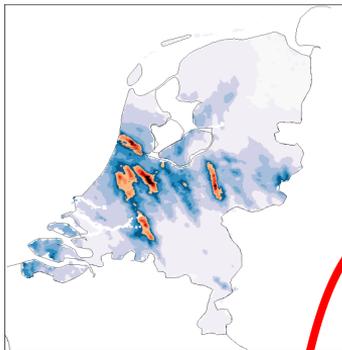
For a '2014-type' event...

$$RR = \mathbf{4.1} \text{ (CI range 1.6 to 19).}$$

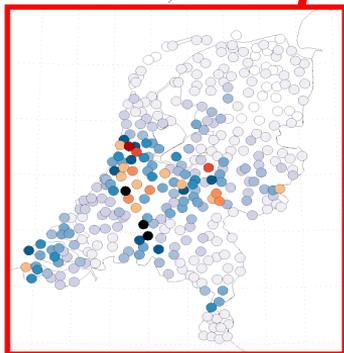
Empirical event attribution: example

Extreme event: 28 July 2014

pr 28-28Jul KNMI radar precipitation



28-29 July 2014 sum



Has the likelihood of this type of event changed as a result of anthropogenic climate change?

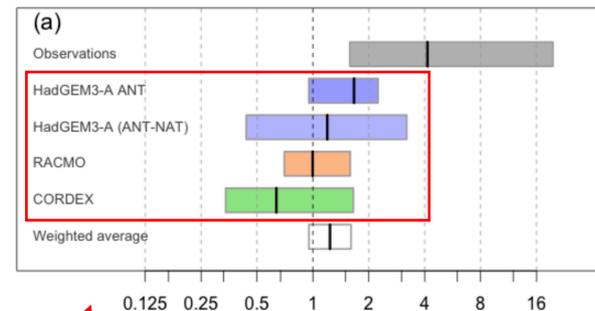
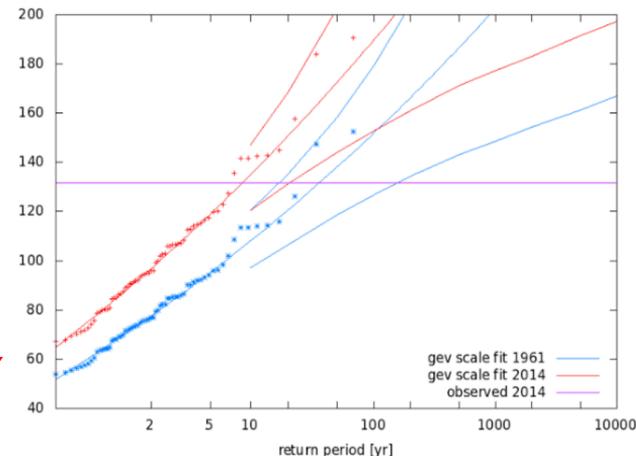
Annual maxima of summertime (AMJJAS) one-day precipitation at 324 stations (1910-2014) fitted to GEV.

$$F(x) = \exp\left[-\left(1 + \xi \frac{x-\mu}{\sigma}\right)^{\frac{1}{\xi}}\right]$$

$$\mu = \mu_0 \cdot \exp \frac{\alpha T}{\mu}$$

$$\sigma = \sigma_0 \cdot \exp \frac{\alpha T}{\mu}$$

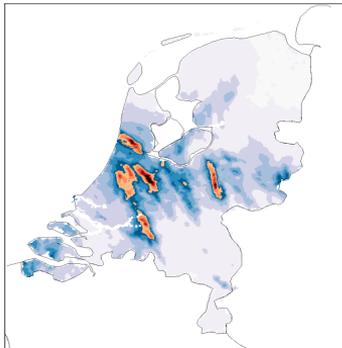
- Distribution assumed to scale with global mean temperature T .
- Uncertainty margins estimated using non-parametric bootstrapping (sample size: 1000).
- Same method applied to annual maxima from model ensembles but with considerable differences to results from observations.



Towards a pointwise approach...

Extreme event: 28 July 2014

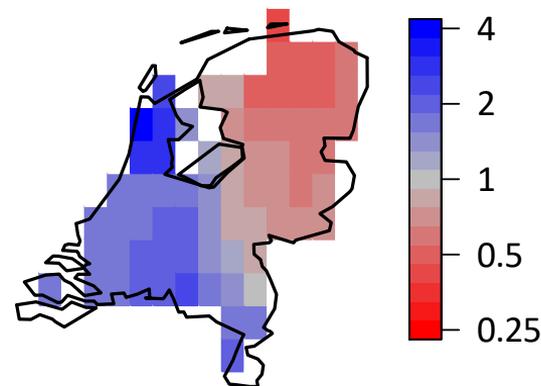
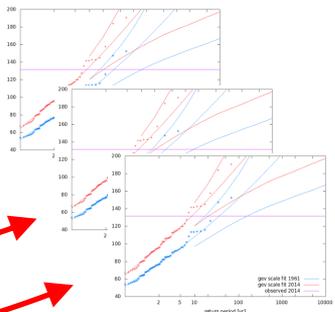
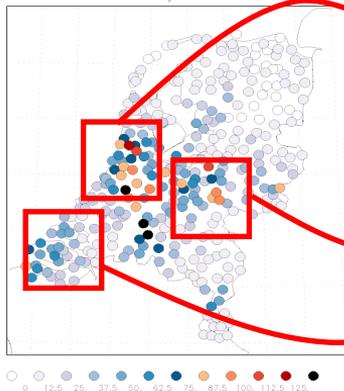
pr 28-28Jul KNMI radar precipitation



Towards a pointwise approach for generating attribution information...

- Here, the same method applied to each point using data from a predefined spatial domain.
- Risk ratios vary considerably across the Netherlands... a 'countrywide' approach ignores this variability.
- **Key question:** can downscaling bridge the gap between observations and model output?

28-29 July 2014 sum



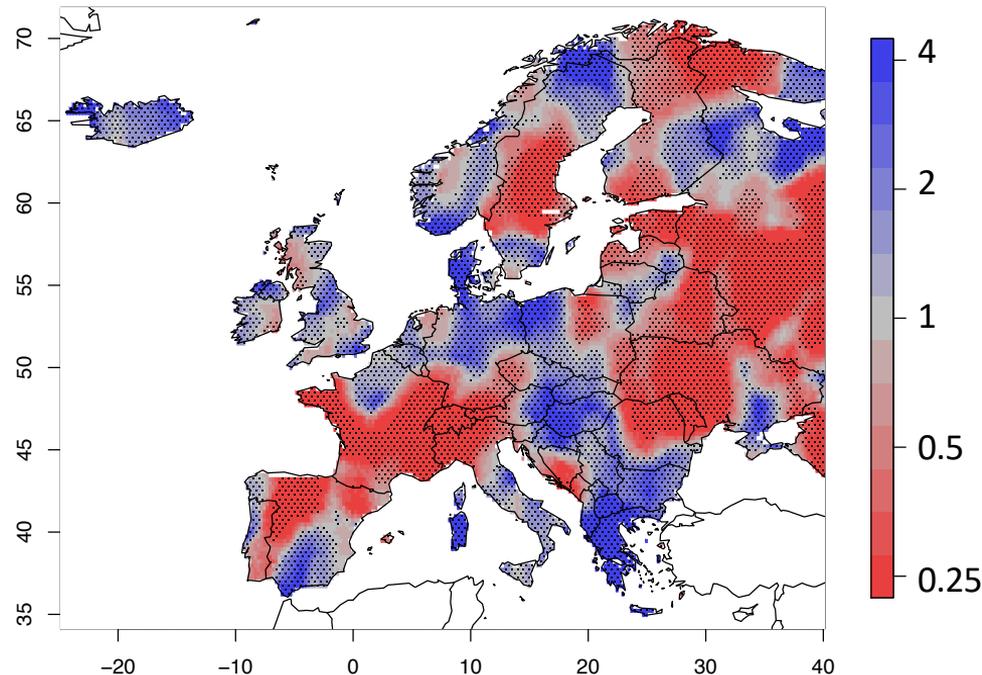
Risk ratio for 2014-type event

Towards a pointwise approach...

- Here, the same approach is applied to annual precipitation maxima (RX1day) during AMJJAS from ERA5.
- For each grid point, data from a 3° x 3° domain is again fitted to a GEV, which is assumed to scale with global mean surface temperature.

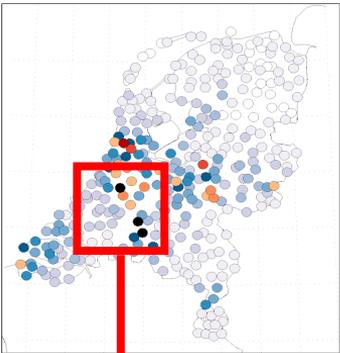
$$F(x) = \exp\left[-\left(1 + \xi \frac{x-\mu}{\sigma}\right)^{\frac{1}{\xi}}\right]$$
$$\mu = \mu_0 \cdot \exp \frac{\alpha T}{\mu}$$
$$\sigma = \sigma_0 \cdot \exp \frac{\alpha T}{\mu}$$

- Risk ratios (shown right) represent the change in likelihood of the 99th percentile at each grid point between 1961 and 2019 (with 95% significance where stippled).
- The variability further illustrates the implications of choosing an arbitrary event definition (i.e. countrywide, drainage basin).



Correcting simulated precip maxima

OBSERVATIONS

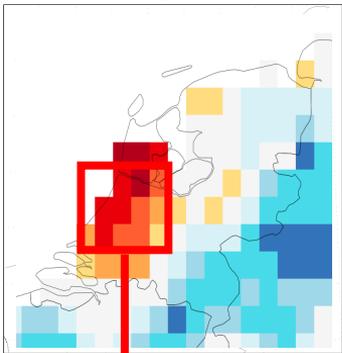


Stations within a 3° x 3° domain identified.

Stations with **homogeneous** precip statistics ($r > 1/e$) fitted to GEV.

$$F(x) = \exp\left[-\left(1 + \xi \frac{x-\mu}{\sigma}\right)^{\frac{1}{\xi}}\right]$$

MODEL



Ensemble data from all grid points within the **same spatial domain** fitted to GEV.

$$F(x) = \exp\left[-\left(1 + \xi \frac{x-\mu}{\sigma}\right)^{\frac{1}{\xi}}\right]$$

EVALUATION

Model is evaluated on the basis of the similarity of the σ/μ ratio in the GEV fit.

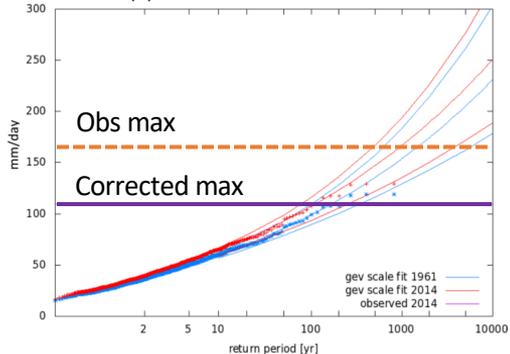


Models that are dissimilar are discarded.

CORRECTION

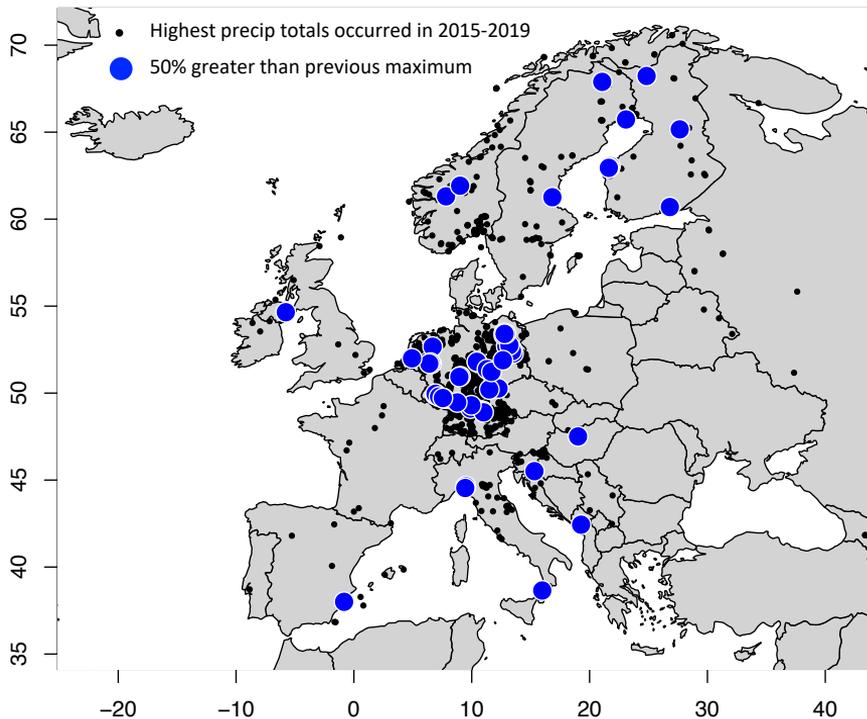
Observed maximum is scaled with $\sigma_{\text{mod}}/\sigma_{\text{obs}}$ to reflect model bias. GEV is evaluated at the **corrected** maxima.

(b) HadGEM3-A return levels



Application to recent extreme events

Analysis of a collective of recent 'exceptional' events from ECA&D observations (where precip total is 50% greater than second highest annual maxima; below).

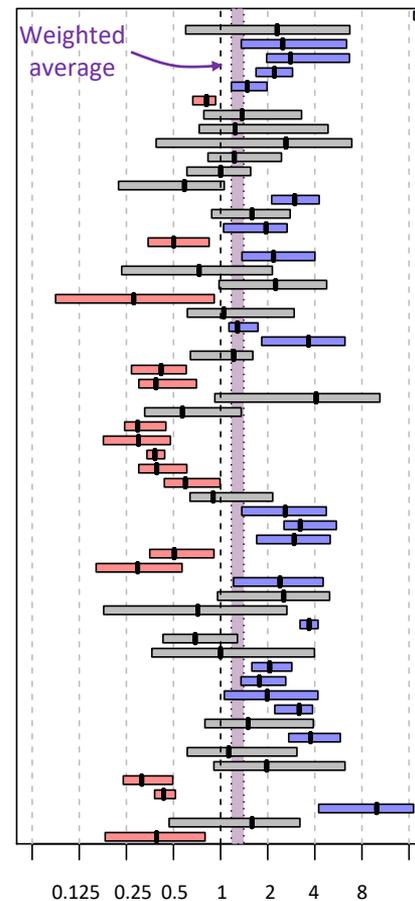


Eden and Dieppois (in prep.)

- For each station, annual AMJJAS maxima at corresponding grid points taken from 105-member HadGEM3-A ensemble.
- Observed 2015-2019 maxima adjusted using pointwise correction.
- HadGEM3-A data fitted to scaled GEV; non-parametric bootstrapping using to estimate 95% CIs.

Risk ratios calculated at each grid point (right). A common methodology and consistent event definition permits comparison; changes in **61%** of these event types have a global warming fingerprint.

Risk ratios and errors combined to produce a **weighted average**. Collectively, these event types are between 1.2 and 1.4 times more likely as a result of global temperature change since 1961.



Summary and outlook

While potentially more computationally-demanding, a pointwise approach to attributing precipitation extremes has several key benefits:

- Enabling a more meaningful comparison of information produced by different data sources at different resolution.
- Corrections of model bias can be tailored to regions of homogenous precipitation characteristics.
- Common methodology and consistent event definition permits comparison of complementary studies of different events in different regions.

Next steps:

- Application to additional global and regional model ensembles.
- Analysis of 3- and 5-day precipitation extremes and for different seasons.
- The gradual adoption of more sophisticated postprocessing methods to correct and downscale for simulated precipitation.