Metrics used to measure climate extremes

A cautionary note: Caveats and uncertainties

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Outline

1. Introduction: Climate extremes and impacts
2. Statistical quantification of extremes: Precipitation and temperature
3. Developing benchmarking datasets for uni-/multivariate extreme detection metrics
4. Conclusions & Outlook

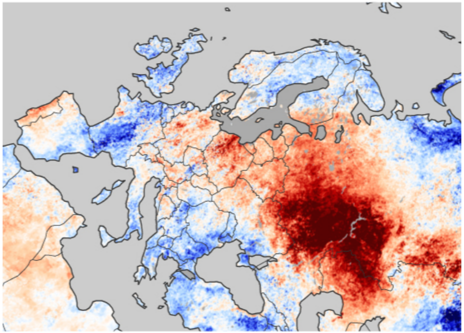
1. Introduction: Climate extremes and impacts

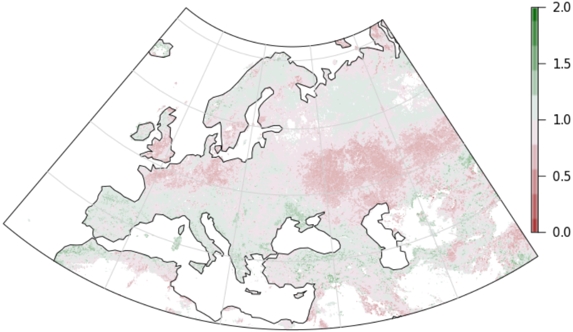
1. Several types of weather & climate extremes are changing in intensity and frequency

Points of departure

1. Several types of weather & climate extremes are changing in intensity and frequency
2. Climate extremes propagate to impacts, but in complex ways:

Example: Direct effects of Russian heat wave 2010





Points of departure

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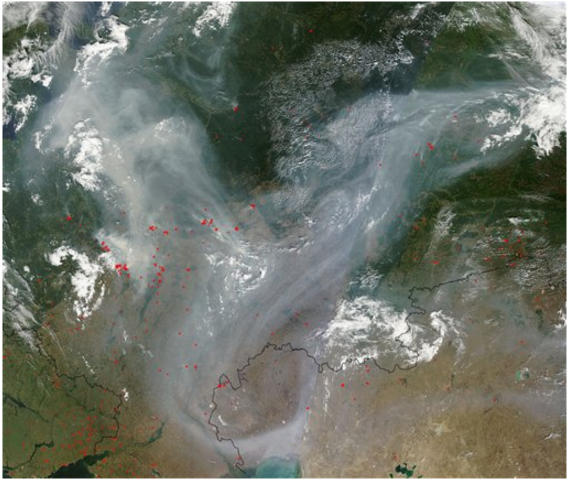
2. Climate extremes propagate to impacts, but in complex ways:

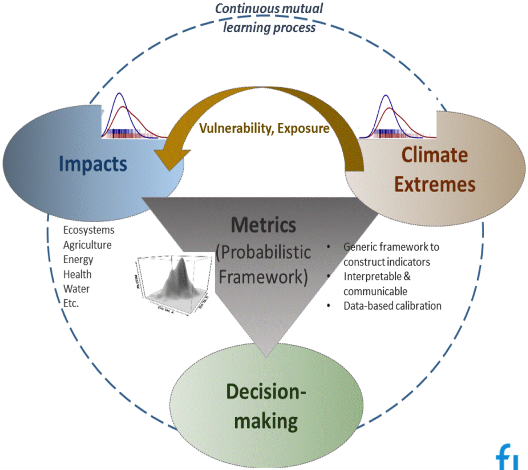
Example: Forest and peat fires of Russian heat wave (Aug 5, 2010)



Carbon losses through (indirect) wild fire effects (-256 Tg CO2, Yoshida et al. 2017, *Env. Pol.*) were about three times as large as direct carbon losses through reduced photosynthesis (-90 Tg CO2, Bastos et al. 2014, *Biogeosciences*).

Points of departure

1. Several types of weather & climate extremes are changing in intensity and frequency
2. Climate extremes propagate to impacts, but in complex ways:
3. Data (Impact & Climate), methodologies, and dialogue crucially needed to link climate extremes and impacts:



futurearth
research for global sustainability

Approaches to deal with extremes:

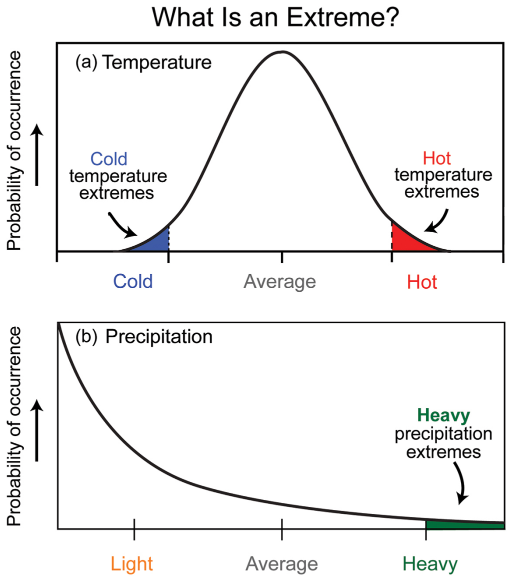
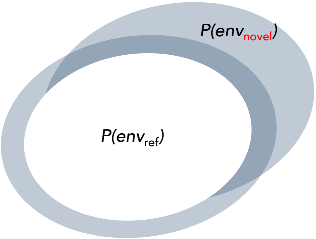


Image source: NOAA

2. Statistical quantification of extremes: Precipitation and temperature



- Building on a reference of normality

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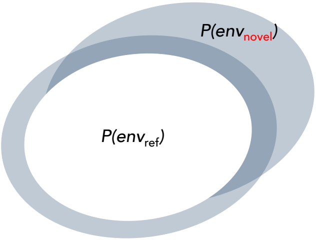
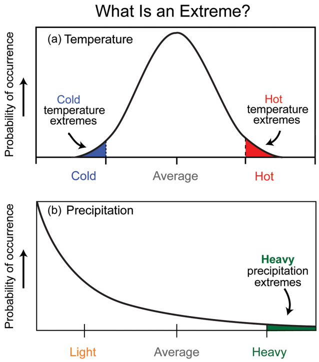
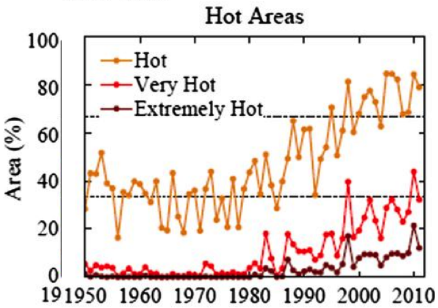




NOAA

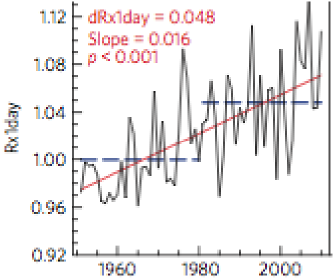
- Building on a reference of normality
- Spatial aggregation to improve S/N ratio

Temperature extremes:



Hansen et al. 2012, *PNAS*

Precipitation extremes:



Donat et al. 2016, *Nat. Clim. Change*

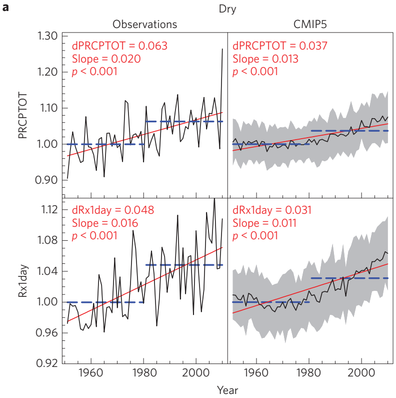
Temperature normalization:

$$z = \frac{X - \overline{X}_{ref}}{s(X_{ref})}.$$

Precipitation normalization:

$$z = \frac{X}{\overline{X}_{ref}}$$

Increasing dry region precipitation extremes?



"Extreme daily precipitation averaged over both dry and wet regimes shows robust increases in both observations and climate models over the past six decades" (Donat et al., 2016, *Nature Climate Change*)

Conventional Precipitation Normalisation:

$$z = \frac{X}{\overline{X}_{ref}}$$

Sippel et al., 2017, *HESS*

Artificial example:

- simulate spatio-temporal dataset of ‘extremes’ ($X \sim GEV$): 60 artificial years
- simulated time series are stationary

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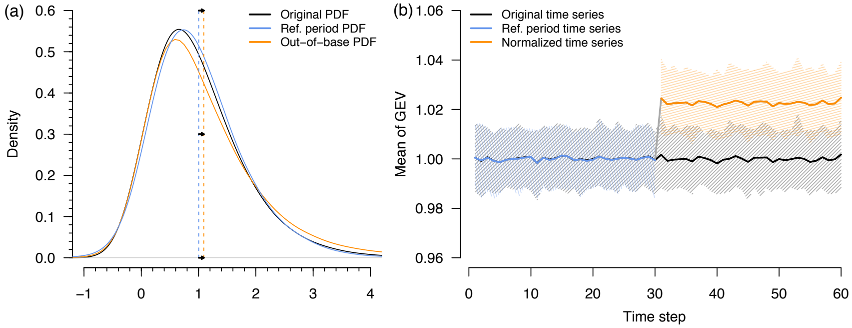

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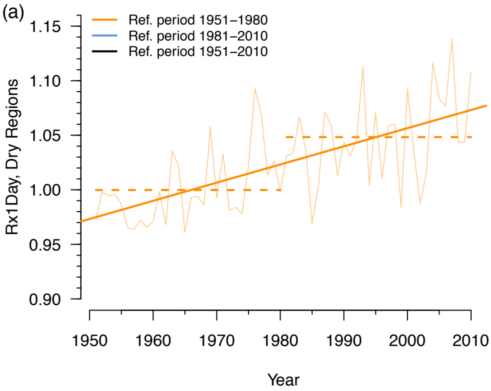

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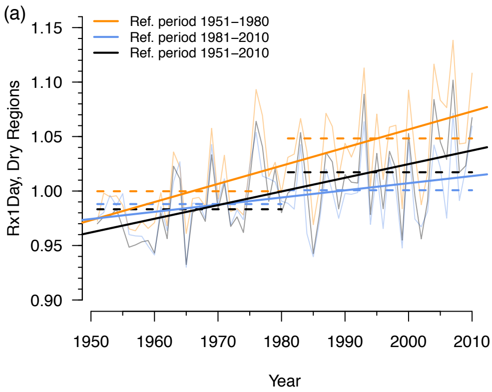

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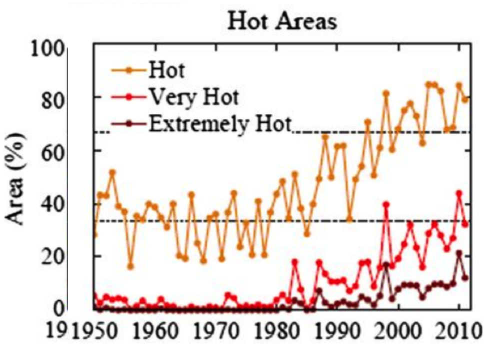
Conventional Precipitation Normalisation:

$$z = \frac{X}{\overline{X}_{ref}} \Longrightarrow \Delta_{bias} \approx \frac{\sigma^2}{\mu^2 n_{ref}}.$$

Here: Slopes reduced by 36–40%.

Sippel et al., 2017, *HESS*

What about temperature extremes?



"the emergence of [...] summertime extremely hot outliers, more than three standard deviations (3σ) warmer than [...] the 1951–1980 base period [...] now typically covers 10% of the land area."

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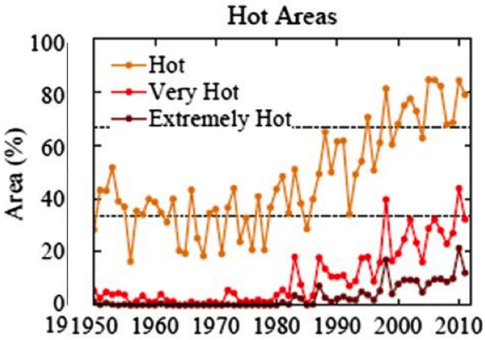

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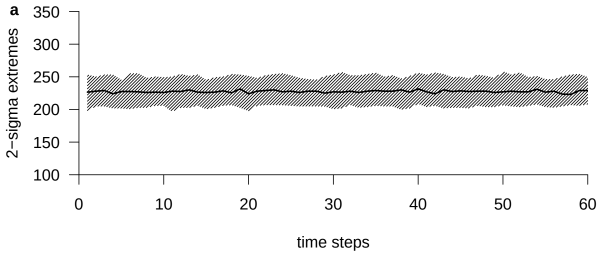
The normalisation issue: Conceptual scenario

- simulate for many "grid cells" ($n = 10.000$) each 60 random Gaussian variables (i.e. "60 years")
    a. *count "2-sigma" extremes across all grid cells for each time step*



Sippel et al., 2015, *Geophys. Res. Lett.* **42**(22), 9990–9998 (Chapter 2).

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- simulate for many "grid cells" ($n = 10.000$) each 60 random Gaussian variables (i.e. "60 years")
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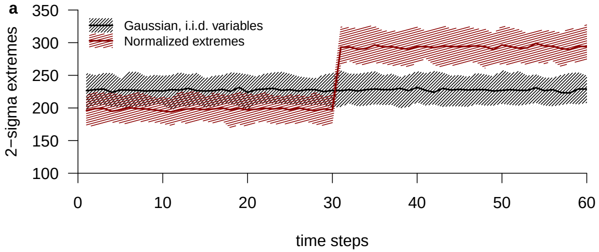
  b. normalise with $\overline{X}_{1951-1980}$ and $s(X_{1951-1980})$, and *count "2-sigma" extremes across all grid cells for each time step*



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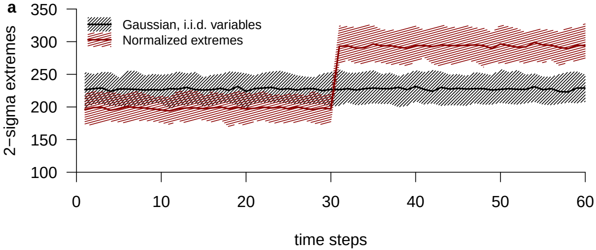

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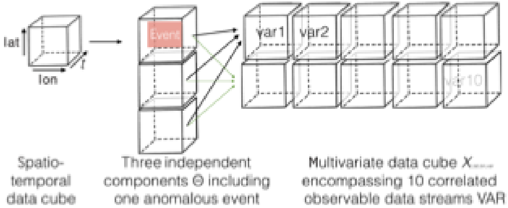
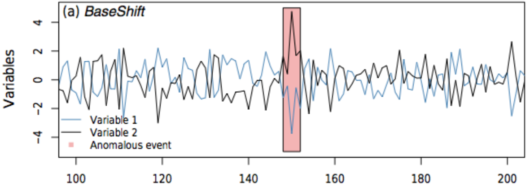
- 48.2% overestimation of "2-sigma" extremes

3. Developing benchmarking datasets for uni-/multivariate extreme detection metrics

Generation of "Artificial data farm", 10 observables from 3 intrinsic dimensions:

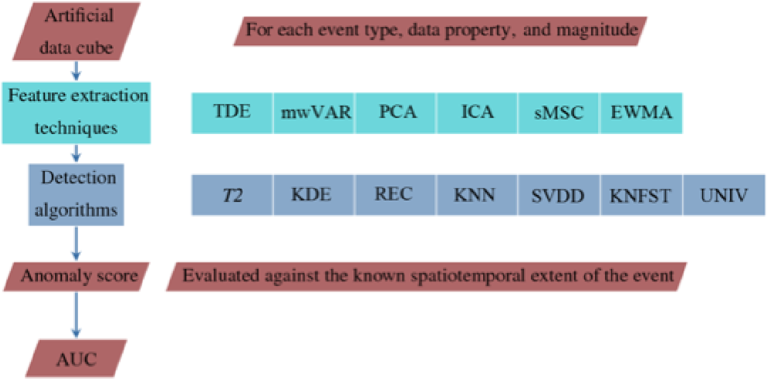


Evaluation of extreme detection algorithms and feature extraction methods:



Flach et al., 2017, *Earth Syst. Dyn.* **8**, 677–696.

Workflow for evaluation experiments:



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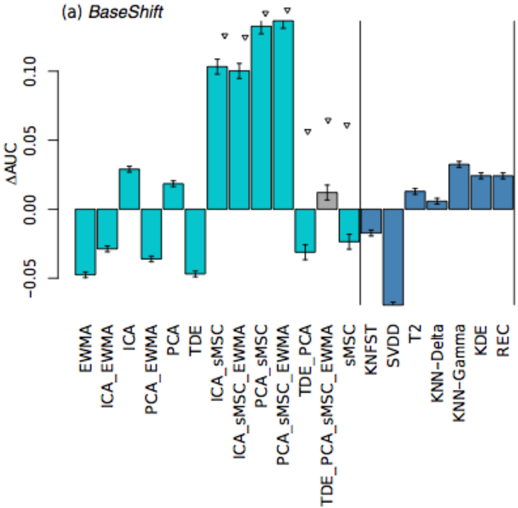
Results of algorithm evaluation experiment:



Data processing (feature extraction) methods are critical for event detection

Flach et al., 2017, *Earth Syst. Dyn.* **8**, 677–696.

Conclusion: **Quantification of extremes**

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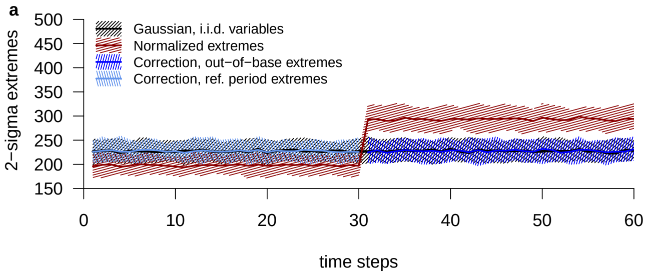
- An analytical understanding and correction has been developed
  - Temperature extremes*



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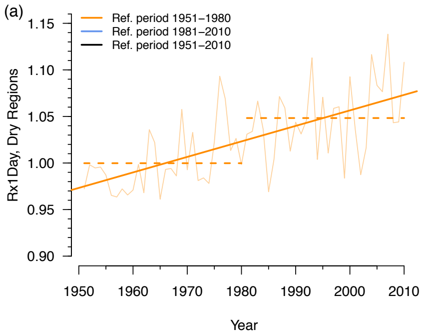

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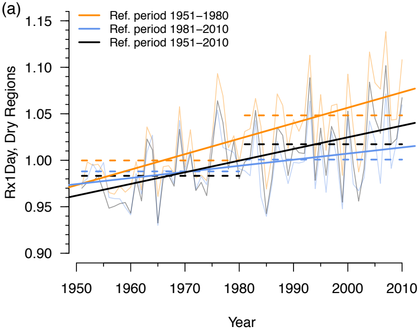

Sippel et al., 2017, *Hydrol. Earth Syst. Sc.* **21**, 441–458.

*Hansen et al., 2012, *PNAS* **109**(37), E2415–2423.

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Conclusion: **Quantification of extremes**

- Conventional reference period standardisation approaches are systematically biased. This includes any data processing based on reference period statistics!
- An analytical understanding and correction has been developed
  - Temperature extremes*
  - Precipitation extremes†
  - Spatio-temporal variance‡ or asymmetry§ of temperature

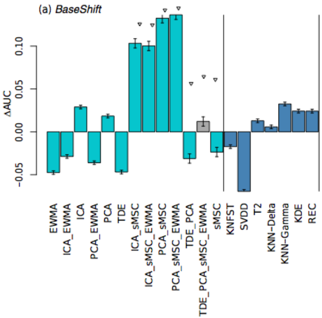
*Hansen et al., 2012, *PNAS* **109**(37), E2415–2423.
†Donat et al., 2016, *Nat. Clim. Chang.* **6**, 508–513.
‡Huntingford et al., 2013, *Nature* **500**, 327–330.
§Kodra and Ganguly, 2014, *Sci. Rep.* **4**, 5884.

Conclusion: **Quantification of extremes**

- Conventional reference period standardisation approaches are systematically biased. This includes any data processing based on reference period statistics!
- An analytical understanding and correction has been developed
- Scrutinizing data analytical tools is crucial
  - Statistical bias correction (often based on ref. period in Obs.)
  - Generation of anomaly-based gridded observations (based on fixed ref. periods)
  - Multivariate indicators for quantifying extremes

Conclusion: **Quantification of extremes**

- Conventional reference period standardisation approaches are systematically biased. This includes any data processing based on reference period statistics!
- An analytical understanding and correction has been developed
- Scrutinizing data analytical tools is crucial
- Data processing (feature extraction) can be more important than the choice of detection method.



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Outlook

Scrutinising data analytic tools and development of impact metrics using large, high-resolution model ensembles:

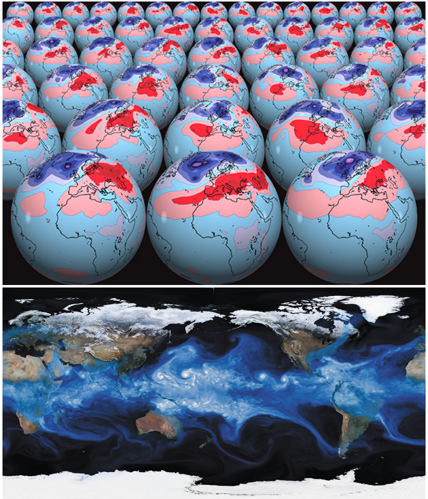
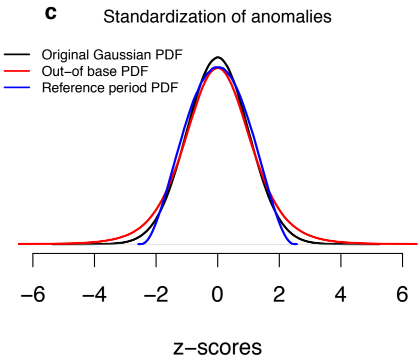


Figure Courtesy ECMWF and Michael Wehner.

Thanks for the attention!

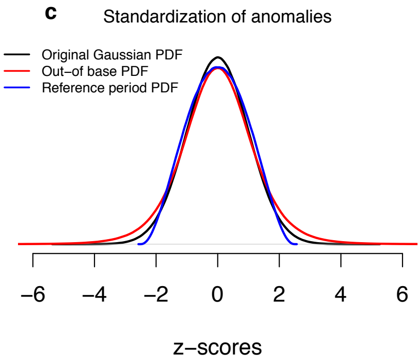
Artificial experiment yields the following pdf's:



- variability and extremes show a distinct change

The underlying problem

Artificial experiment yields the following pdf's:



- variability and extremes show a distinct change

Analytical understanding of biases:
... what is meant to be done:

$$z = \frac{X - \mu}{\sigma}$$

... and what is really being done:

$$z = \frac{X - \hat{\mu}_{ref}}{\hat{\sigma}_{ref}}$$

- Out-of-base period: *Independent* normalisation
- Reference period: *Dependent* normalisation

Sippel et al., 2015, *Geophys. Res. Lett.* **42**(22), 9990–9998 (Chapter 2).