POTSDAM INSTITUTE FOR CLIMATE IMPACT RESEARCH

PIK

Climate extremes: Assessing trends in observational data and regional climate models

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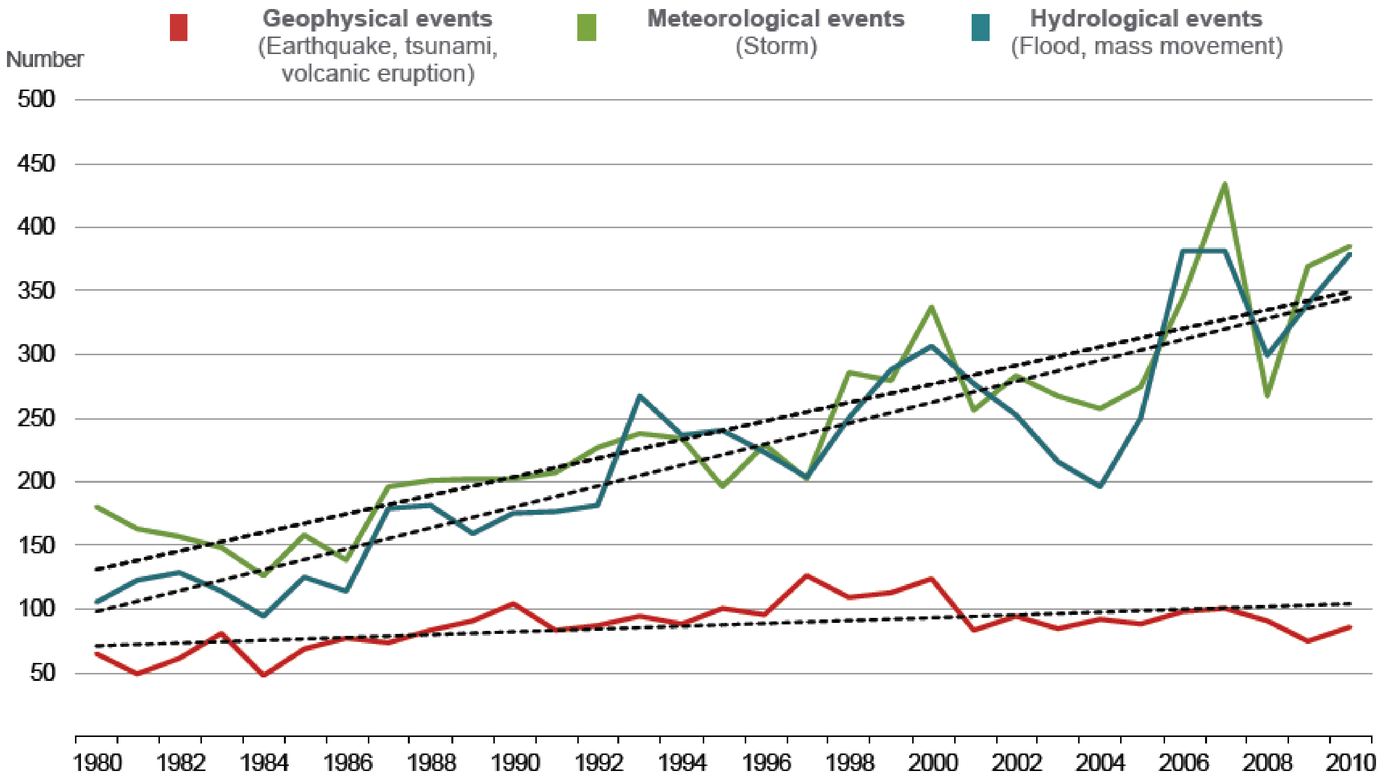
COSY CC²

Motivation

Statistics and dynamics of extreme events in a changing climate



Motivation

Statistics and dynamics of extreme events in a changing climate

- What is an extreme event in case of changing mean conditions?
  - Dependence on temporal and spatial scales of observation/aggregation
- Temporal changes in extreme events
  - Frequency and intensity of extremes
- Spatio-temporal structure of variability associated with climate extremes
  - Existence of distinct spatio-temporal patterns or scaling properties
- Effect of scales on observed space-time structure and changes
  - Consistency among data sets from different sources (in-situ, reanalysis, models)
  - Downscaling of extremes
- Representation of extremes in (climate) models
  - Bias correction for changing extremes
- Long-term climate change and stationarity of short-term variability patterns in both time and space
  - Existence of changes, representation in stochastic weather generators

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Data inter-comparison problem

Typical problems in climatological applications:

- **Validation of Earth observation products (point vs. areal data): data-data inter-comparison**
- **Model validation via model-data (and model-model) inter-comparison**

⇒ **State of the art: mostly basic statistical properties (bias, variance / uncertainty)**

Basic problems: Do different data sets actually measure the same thing and exhibit the same dynamics (beyond simple statistical properties)?

Data inter-comparison problem

Do different data sets actually measure the same thing (e.g., remote sensing vs. in-situ data)?

$\Rightarrow$ **Transfer functions (possibly nonlinear)**

- **Learning from data (fully empirical) – always possible?**
- **Learning from physical models (e.g. radiation transfer for remote sensing data)**

$\Rightarrow$ **Representativeness of in-situ / ground measurements?**

$\Rightarrow$ **Problem of different spatial and temporal resolution of data sets**

Do different data sets show the same spatio-temporal variability patterns?

- **Spatial patterns: sufficiently many representative records?**
- **Temporal patterns: time series capturing all relevant time scales (diurnal, seasonal, inter-annual, decadal,…)?**

$\Rightarrow$ **Continuum of scales to be considered**

Data inter-comparison problem

Scatter between temporally co-located measurements (if exist, otherwise interpolation) – up-/downscaling

Statistical problem:

- **regression (possibly nonlinear transfer function)**
- **residual: uncertainty / noise (basis stochastic weather generators): spatial and temporal auto- and cross-correlation structures of climatological fields of interest**
- **Implicitly assumes stationarity (e.g., no instrumental drift, no climatological trends or other “ultra low-frequency” variability), otherwise needs time as covariate**

Beyond synchronous (at most fixed-lagged) values: How to compare temporal patterns?

$\Rightarrow$ **Time series analysis problem**

Trend analysis

Classical: long-term trends in observational data from different sources – LS regression and more sophisticated variants, in most cases just linear models

⇒ Inter-comparison between single values (plus uncertainties)

Broader picture: Are changes homogeneous for all parts of the PDF of a variable, or are there differences between different data sets (e.g., due to different temporal scales or representativeness)?

- **Inter-comparison between PDFs for different time intervals (KS statistics or similar approaches)**
- **Do different parts of the PDF (especially the extremes) show the same long-term changes?**

Possible tools of choice: quantile regression, time-dependent GEV/GP statistics for the special case of extremes

⇒ Nonlinear / nonparametric versions available, but need sufficiently long records!

Quantile regression

Traditional trend analysis: trends in the mean

$\Rightarrow$ **What about the rest of the distribution?**

Useful tool: quantile regression analysis

- **Inference of a (parametric or nonparametric) model for the conditional quantile functions of the data distribution as a function of time**
- **Generalization of ordinary least-squares estimator replacing squared difference by asymmetric loss function**

$$\boxed{\hat{q}_\alpha(x) = \min_f \sum_{i=1}^{n} \rho_\alpha(y_i - f_\alpha(x_i))}$$

$$\begin{aligned} \rho_\alpha(u) &= \alpha u I_{[0,\infty)}(u) - (1-\alpha) u I_{(-\infty,0)}(u) \\ &= u\left(\alpha - I_{(-\infty,0)}(u)\right) \\ &= \left[\frac{1}{2} + \left(\alpha - \frac{1}{2}\right)\operatorname{sgn}(u)\right]|u| \end{aligned}$$

Examples used in this presentation

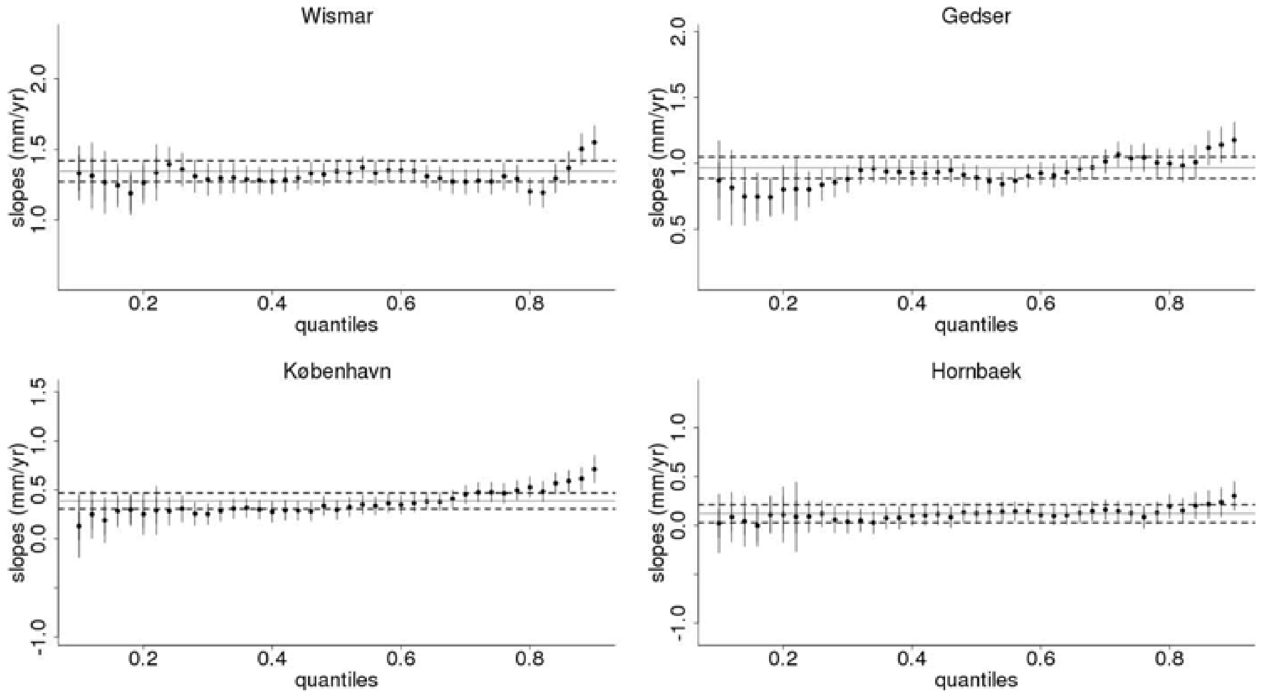
- Relative mean sea-level (Baltic Sea)
  - Daily/monthly values from long-term tide gauge records

- Daily temperature (mean/maximum/minimum)
  - In-situ station data (with spatial homogenization / interpolation) from Germany (DWD)
  - Continental-scale spatially interpolated /gridded data from Europe (E-OBS)
  - Global reanalysis data (ERA-Interim and others)

- Daily precipitation amounts
  - Homogenized in-situ station data from Germany (DWD)
  - Continental-scale spatially interpolated / gridded data from Europe (E-OBS)
  - Regional climate model hindcast runs (Euro-CORDEX), here: CCLM

Sea-level: Effect of time-scales

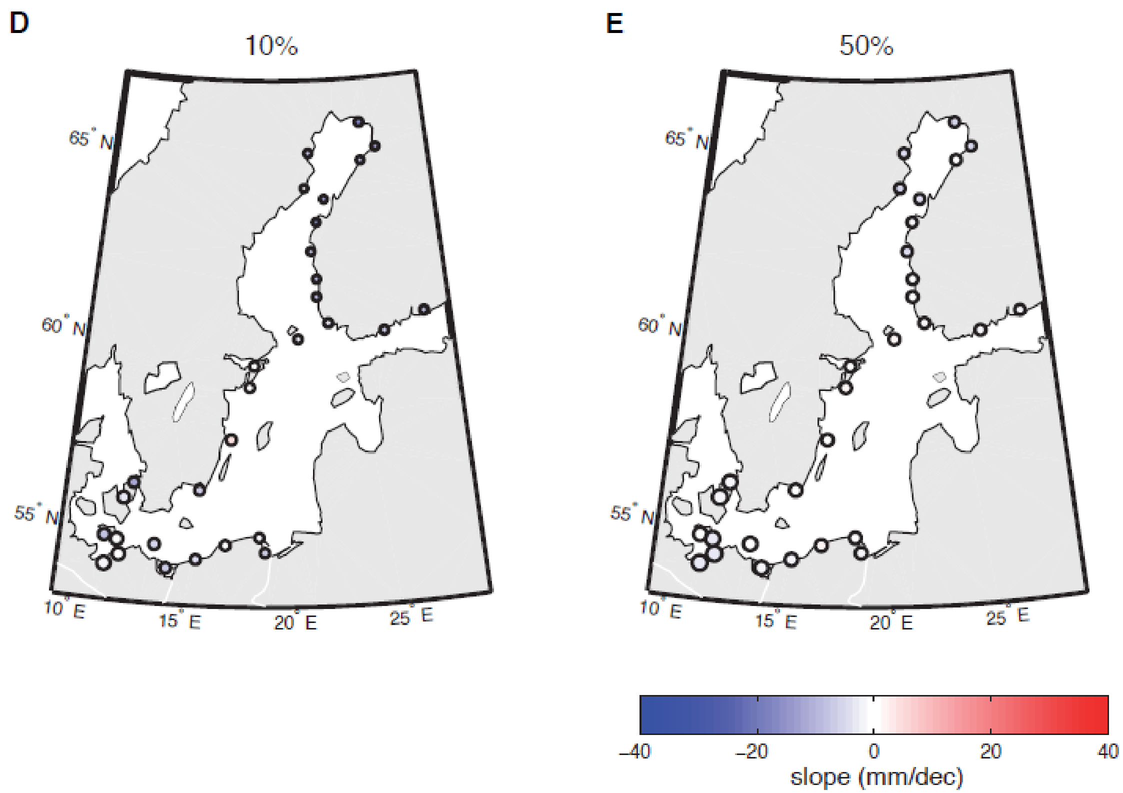
Monthly data: upper quantiles rise faster, lower ones slower than the mean (in entire Baltic Sea)



(Barbosa, 2008)

Sea-level: Effect of time-scales

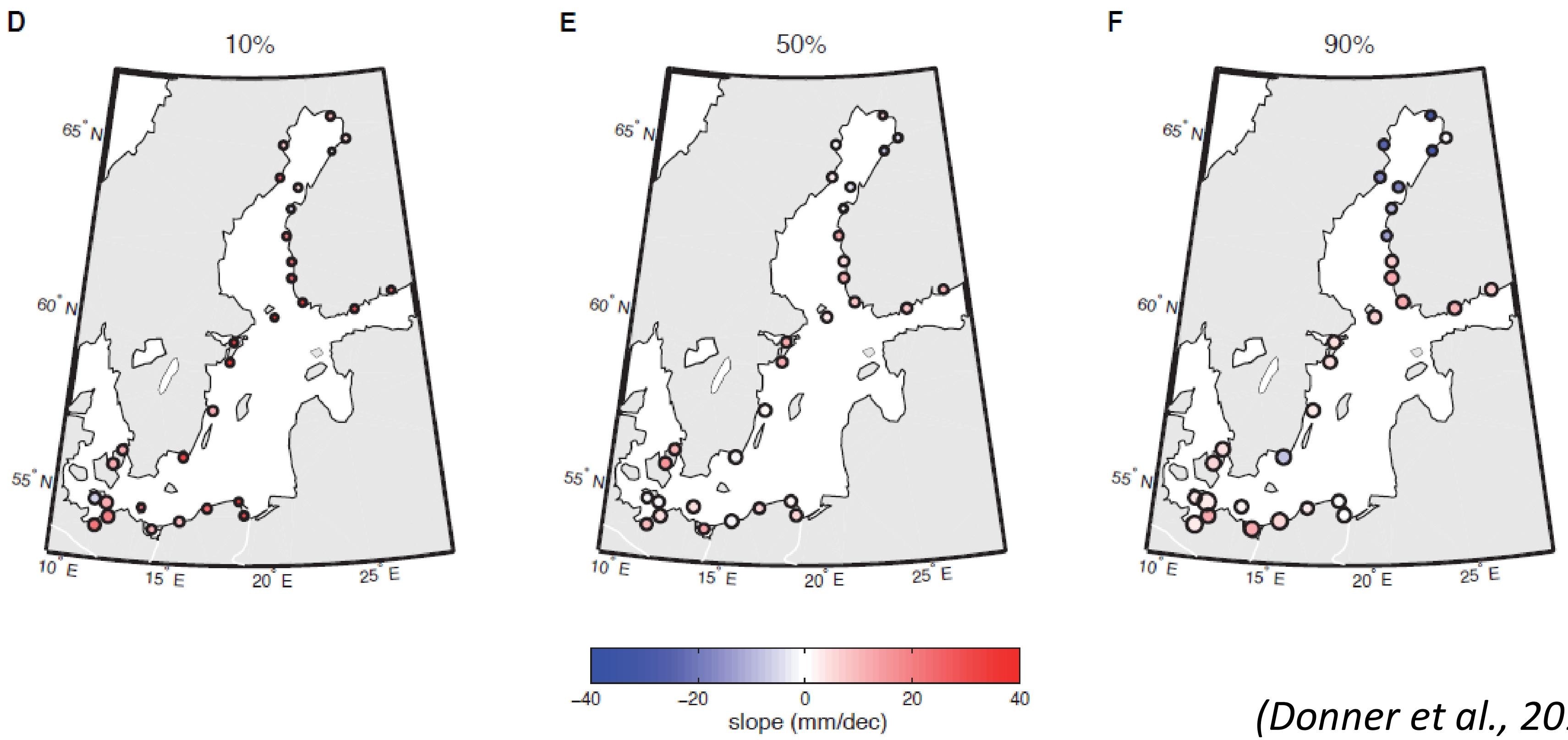
Monthly data: linear quantile trends (10%/50%/90%) relative to trend in mean



(Donner et al., 2012)

Sea-level: Effect of time-scales

Monthly data: average nonparametric quantile trends relative to mean



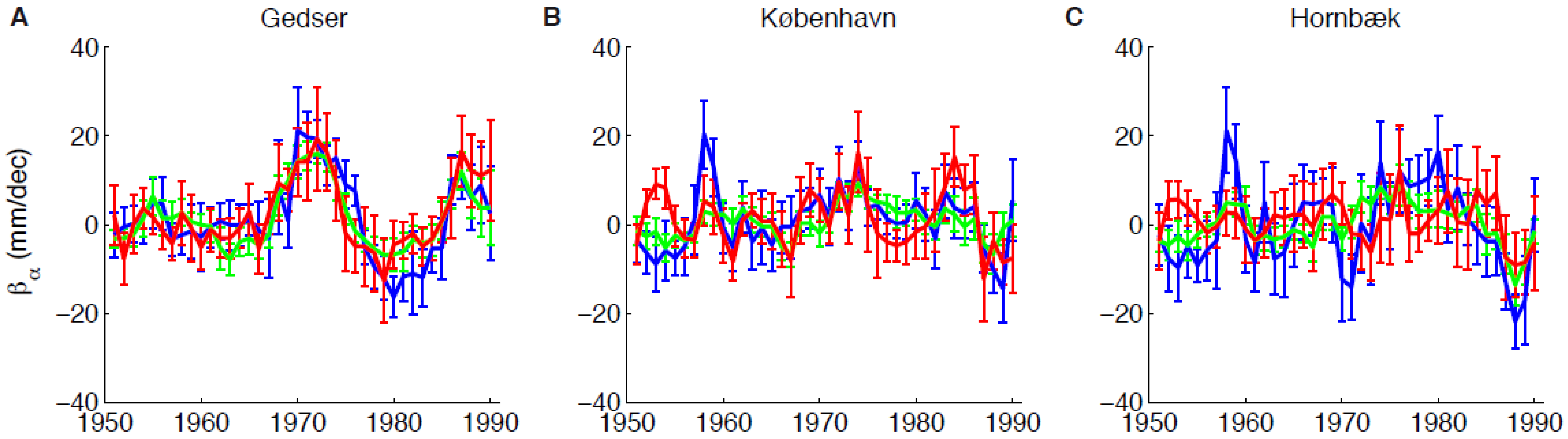
(Donner et al., 2012)

Sea-level: Effect of time-scales

Nonparametric quantile dynamics tracing low-frequency variability

$\Rightarrow$ **Quantile trends are changing with time!**

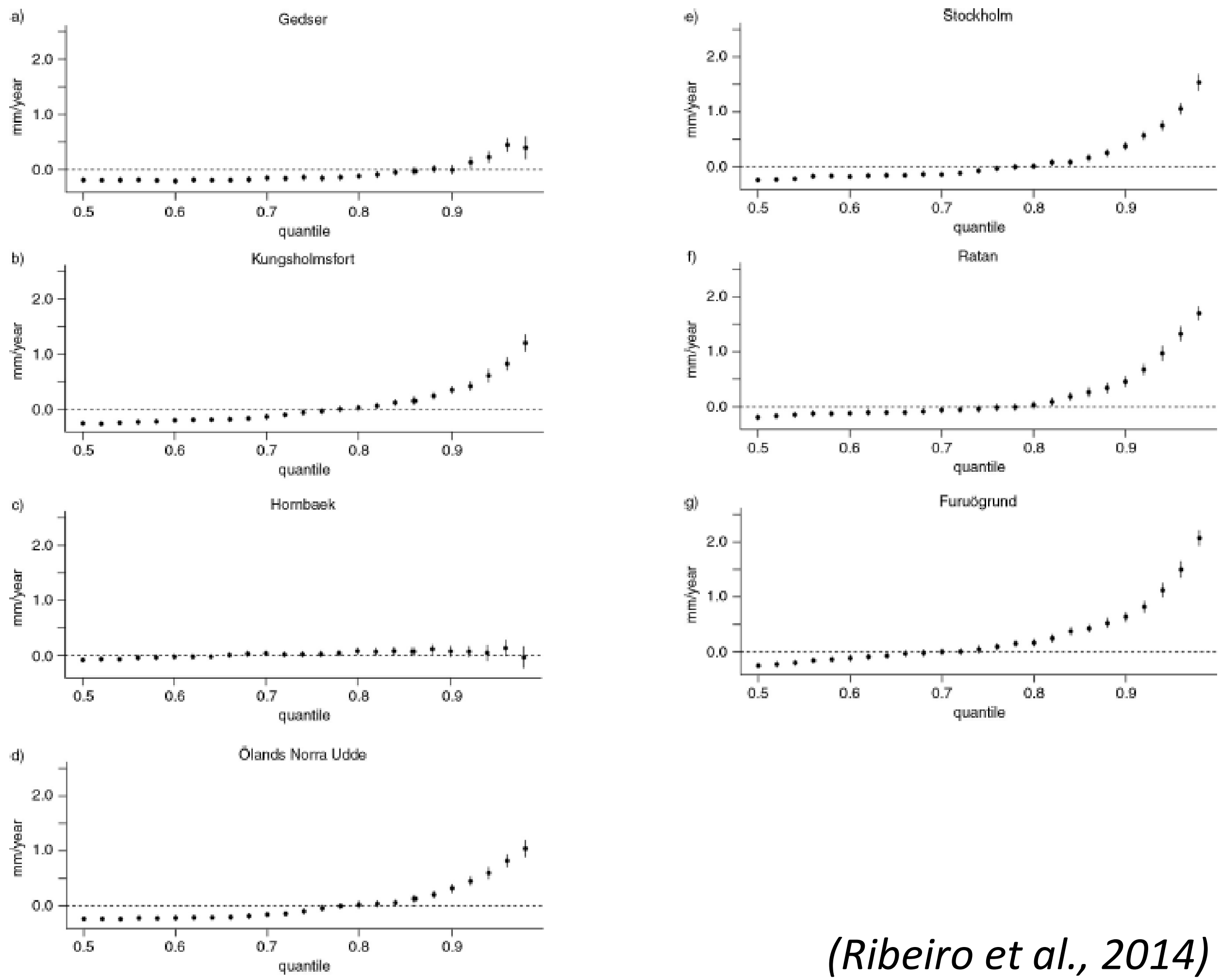
(Donner et al., 2012)



Question: Is there any systematic acceleration/deceleration of trends?

$\Rightarrow$ **Statistical tests (t-test and Mann-Kendall test for (in)/dependent data)**

Sea-level: Effect of time-scales



(Ribeiro et al., 2014)

Lessons learned from sea-level example

- **Heterogeneous long-term trends in the distribution**
  - **broadening, potentially stronger extremes**

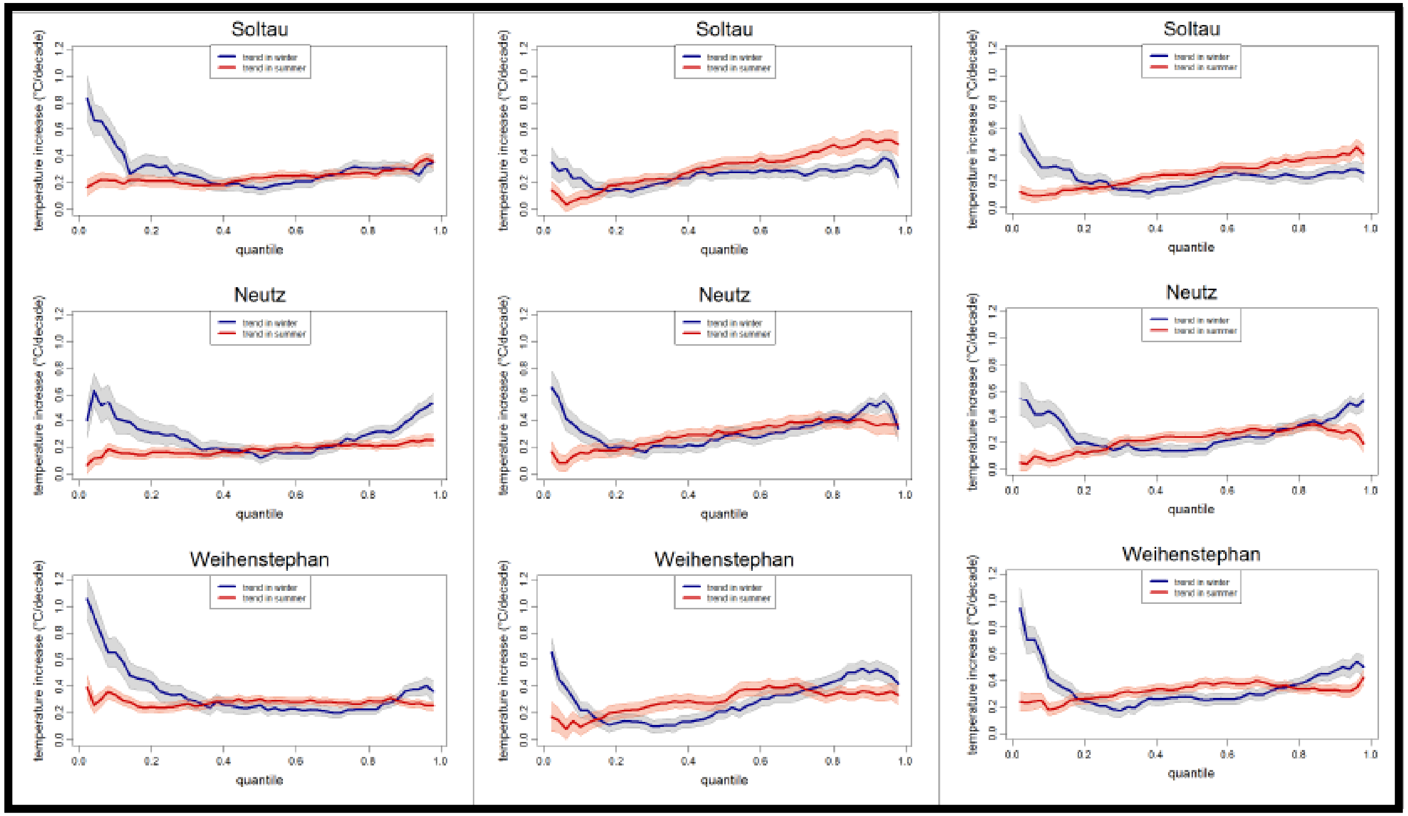
- **Quantile trends not constant, but vary with time**
  - **nonlinear / non-parametric trend models more reasonable**

- **Consistent spatial pattern of decadal-scale quantile variations**

- **Time-scale of observations matters crucially, especially for extreme quantiles**
  - **different processes involved at different time-scales (tides, storm surges, etc.)**
  - **relevance for application and interpretation of extreme value statistics**

Temperatures: Effect of spatial resolution

Daily temperatures (max/min/mean) – German station data



Temperatures: Effect of spatial resolution

Daily temperatures (max/min) – German station data

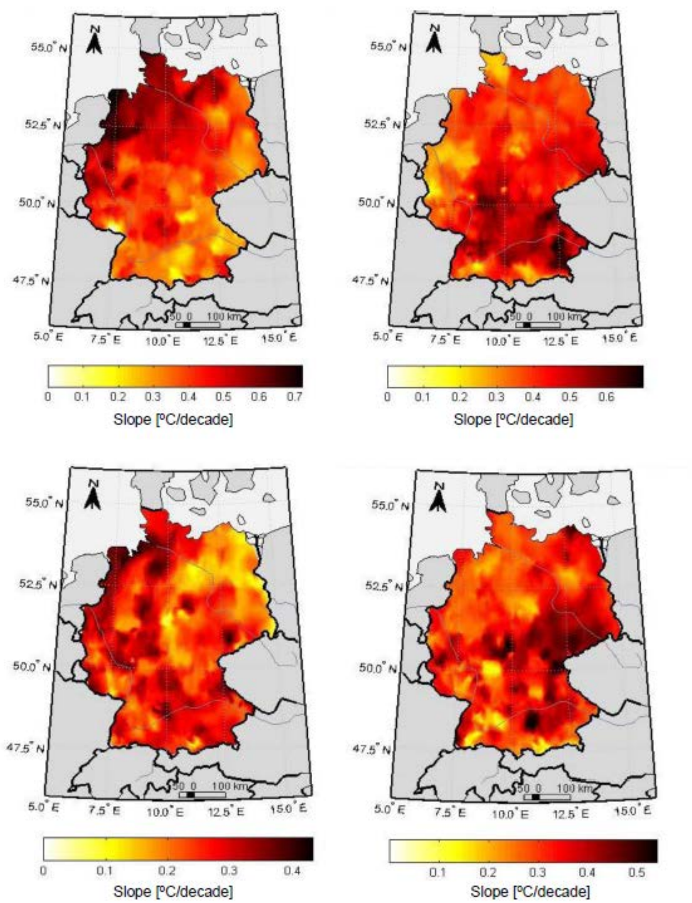
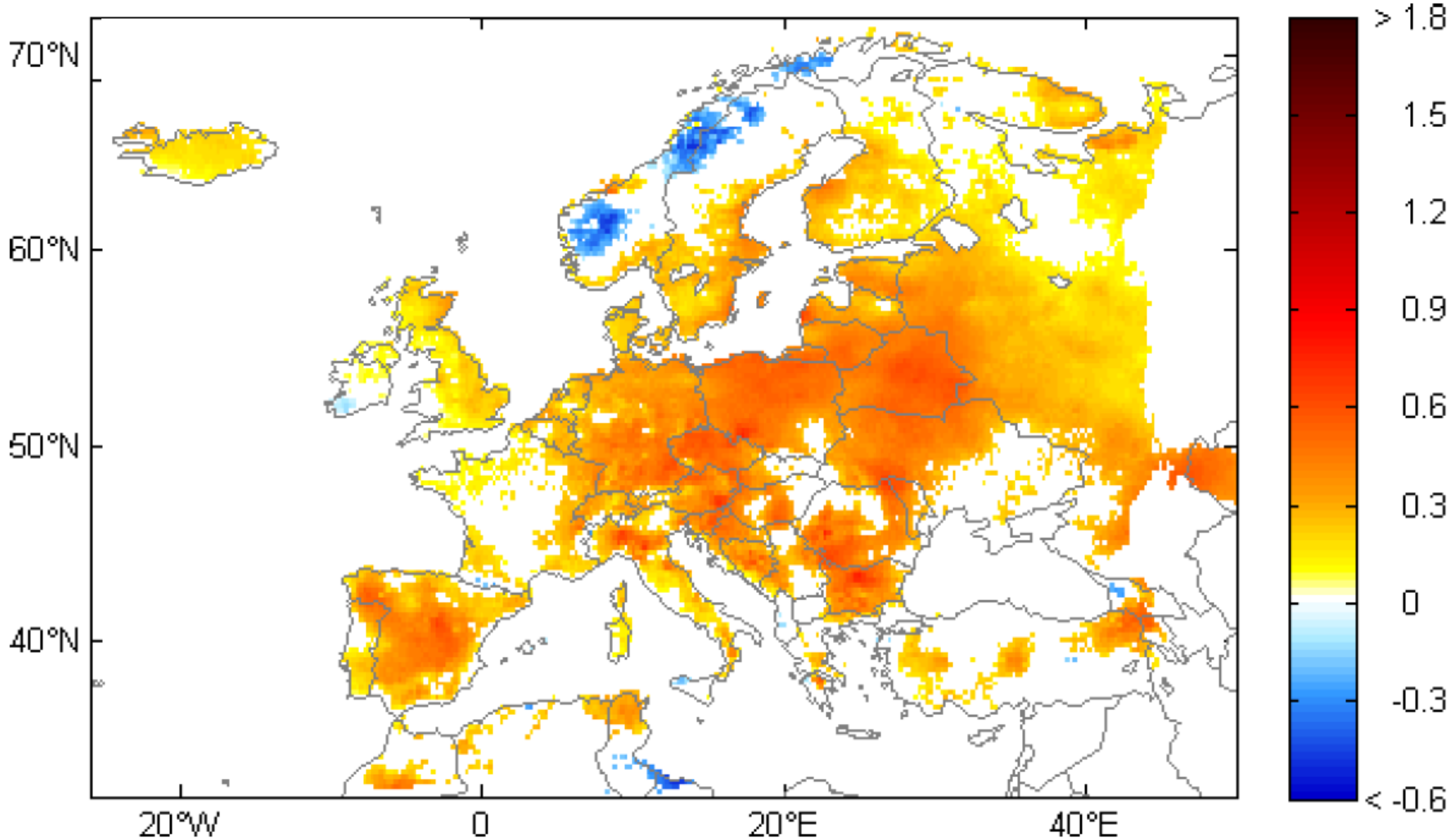


Fig. 2: Linear quantile trends in the 95% quantiles of daily maximum (top panels) and minimum temperatures (bottom panels) during summer (left panels) and winter (right panels).

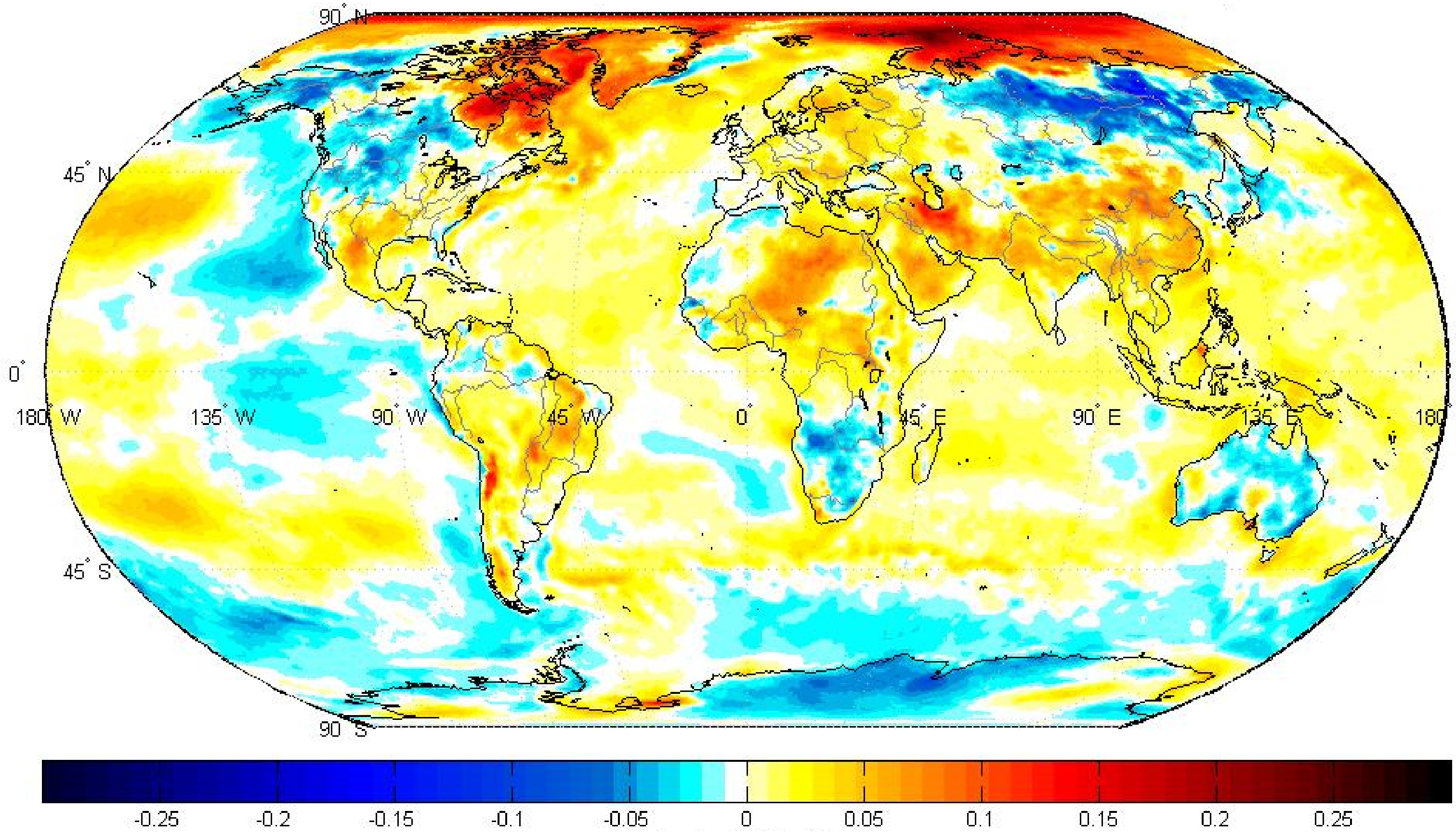
Temperatures: Effect of spatial resolution

Daily maximum temperatures DJF – EOBS: TX 95% trends [°C/decade]



Temperatures: Effect of spatial resolution

Daily mean temperatures DJF – ERA-Interim: 95% [°C/year]



Extreme quantiles versus extremes

Distribution and stationarity of extremes (equivalence to “extreme quantiles”?)

- **Classical approaches: block maxima, peak-over-threshold (GEV / GP statistics) – discard information on rest of PDF, thus rely on temporally sparse data(!)**
- **Time-dependent case: complex statistical models, need many data for appropriate parameter estimation, model validation and selection**
  - **Infeasible for many available data sets**
- **Quantile regression: all observations are taken into account (potentially better robustness of estimates): quantile trends as proxies for trends in extremes?**
  - **Need to be verified for specific variable and scale of interest**
  - **Only way to tackle non-stationary extremes also in relatively short records**

Problem: Do GEV statistics and quantile regression capture the same things?

Example: Daily tide gauge data

Table 3. Maximum likelihood estimates for μ, σ and ξ of the selected models (standard errors in parentheses)

Station name	μ (mm)	β_0 (mm)	β_1 (mm)	σ (mm)	ξ
Gedser	665.61 (15.66)			140.66 (10.91)	0
Hornbæk	696.69 (16.22)			145.46 (11.43)	0
Kungsholmsfort		428.61 (18.86)	0.87 (0.35)	91.61 (8.17)	0
Ölands Norra Udde	485.07 (13.28)			119.20 (9.55)	0
Stockholm	384.74 (9.87)			89.09 (7.54)	0
Ratan		466.52 (37.38)	1.87 (0.76)	159.61 (13.20)	−154.99 (70.64)
Furuögrund		467.10 (34.32)	2.56 (0.66)	154.42 (12.60)	0

Station	Slope (mm/yr)	Ensemble median (mm/yr)
Gedser	0.40* (0.22)	0.40 (0.05)
Hornbæk	−0.04 (0.18)	−0.04 (0.02)
Kungsholmsfort	1.20* (0.14)	1.23 (0.06)
Ölands Norra Udde	1.04* (0.13)	1.05 (0.07)
Stockholm	1.54* (0.15)	1.55 (0.07)
Ratan	1.70* (0.12)	1.74 (0.08)
Furuögrund	2.07* (0.14)	2.10 (0.08)

Table 5. Quantile regression trends (standard errors in parentheses) and corresponding bootstrap estimates (ensemble median and IQR) for quantile 0.98

Statistically significant trends (95% confidence level) are denoted by *.

(Ribeiro et al., 2014)

Example: Daily tide gauge data

Comments on these results:

- **Significance statements depend crucially on test:**
  - **Here: standard t-test without correction for auto-correlation (sea-level shows long-term memory) – neglecting variance inflation, too optimistic confidence bounds**
  - **Other study on E-OBS air temperatures (Mettin et al., in prep.): replacing analytical confidence bounds by block bootstrap-based estimates reduces spatial extent of significant stations markedly**

- **Block maxima and quantiles may capture different things**
  - **Monthly block maxima: 12 values per year, 95% quantile: exceedances account for about 18 values per year – more moderate "extremes"**
  - **Results from previous analysis: trends for even higher quantiles are stronger (but: confidence intervals also increase) – not intercomparable**

Example: Daily precipitation data

Significant time-dependence in GEV statistics (monthly block maxima)?

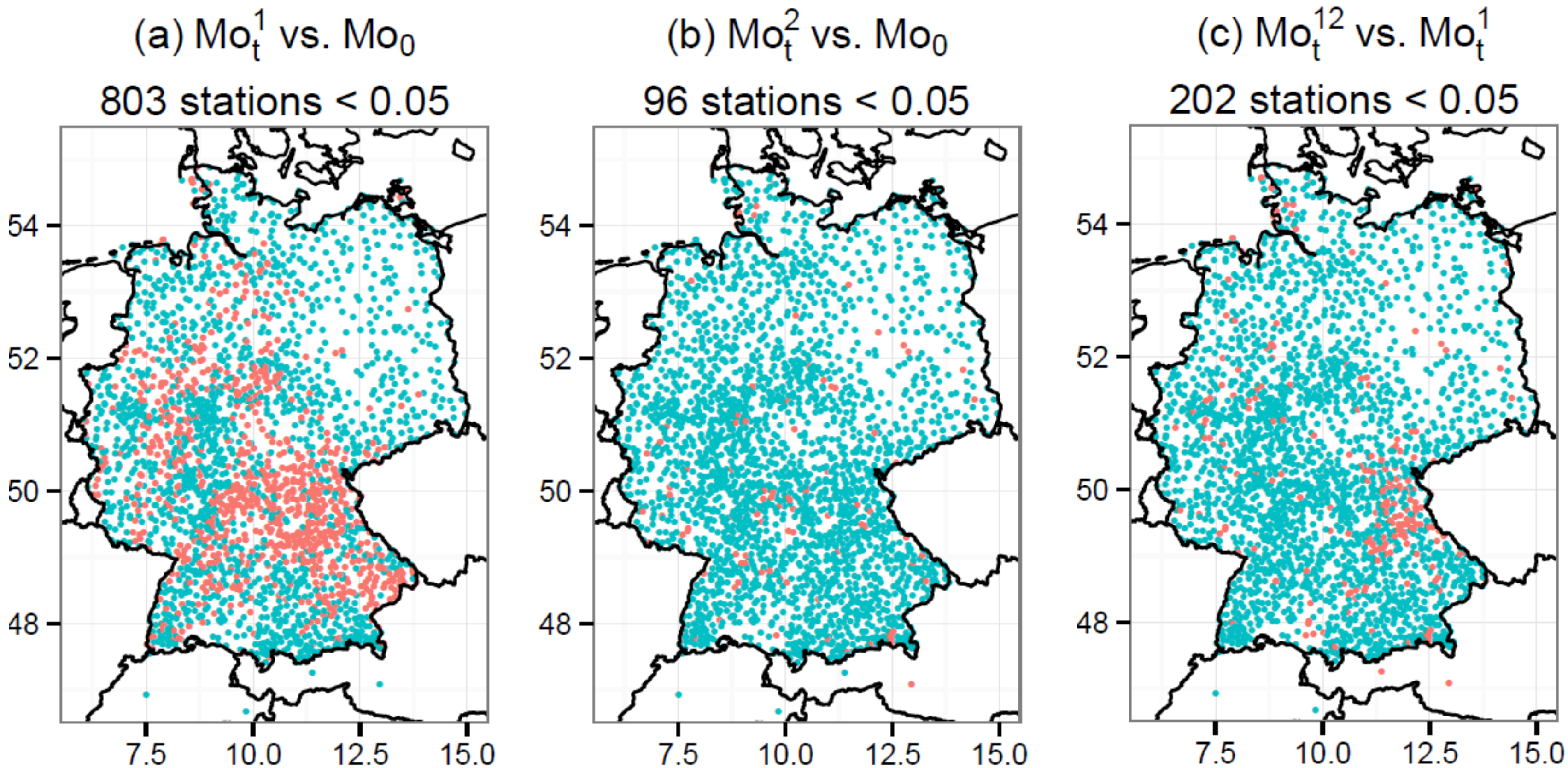
$$G(x;\mu,\sigma,\xi) = exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\}$$

$$\begin{aligned}
\mu(t) &= \mu_0 + \mu_1 t + a_\mu sin(\omega c_i) + b_\mu cos(\omega c_i),\\
ln\sigma(t) &= \sigma_0 + \sigma_1 t + a_\sigma sin(\omega c_i) + b_\sigma cos(\omega c_i),\\
\xi(t) &= \xi.
\end{aligned}$$

Mo_0: No trend at all ($\mu_1 = 0, \sigma_1 = 0$)
Mo_t^1: Only the location parameter has a trend ($\mu_1 \neq 0, \sigma_1 = 0$)
Mo_t^2: Only the scale parameter has a trend ($\mu_1 = 0, \sigma_1 \neq 0$)
Mo_t^{12}: location and scale parameter have a trend ($\mu_1 \neq 0, \sigma_1 \neq 0$)

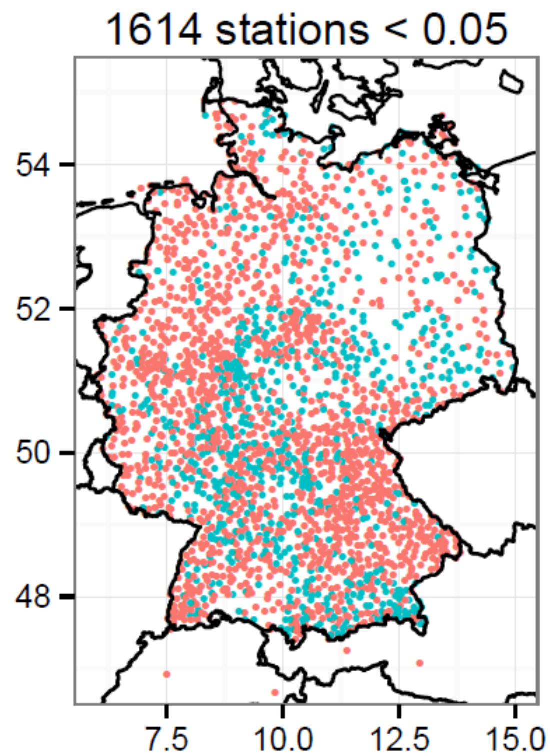
Example: Daily precipitation data

Significant time-dependence in GEV statistics (monthly block maxima)?



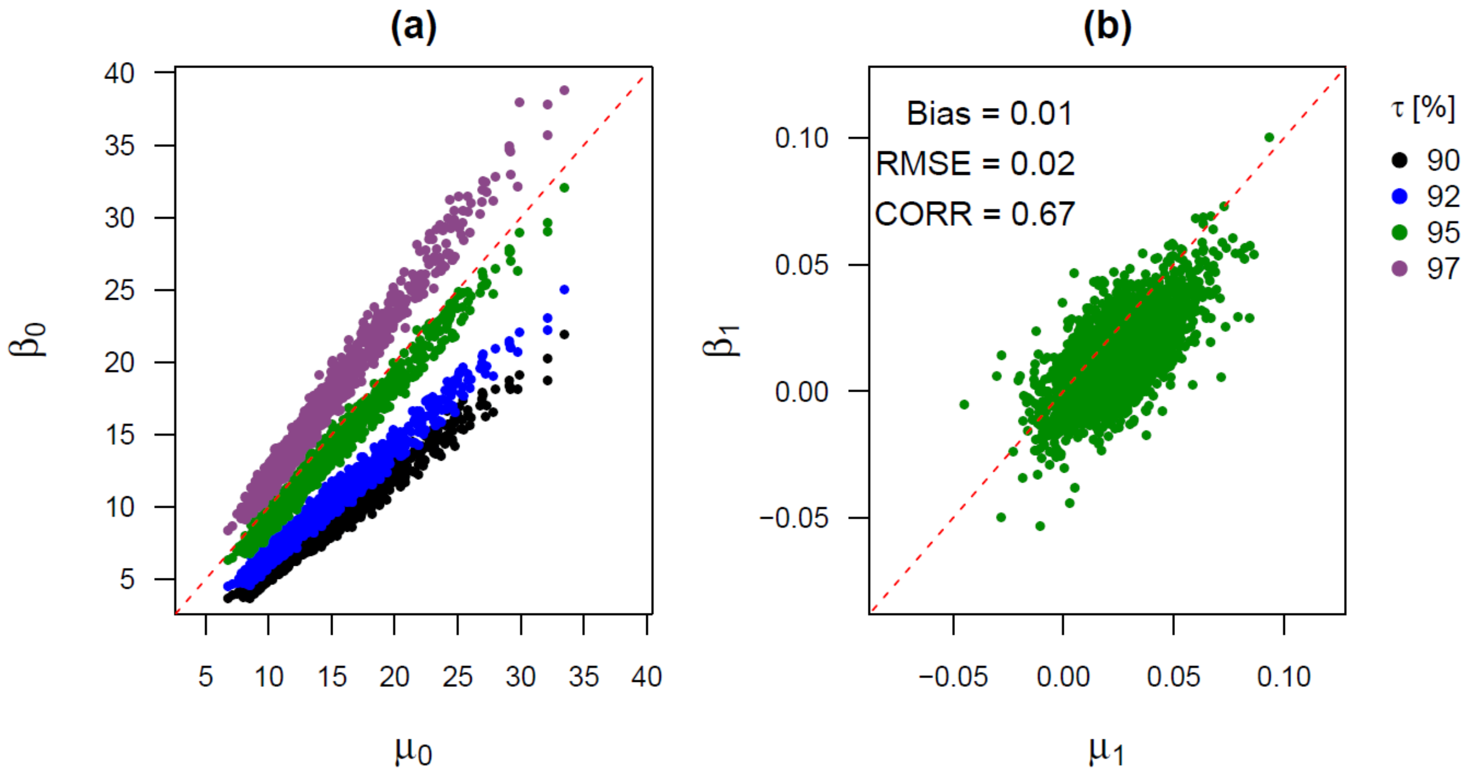
Example: Daily precipitation data

Inter-comparison with 95% linear quantile trend: many more significant stations (even though precipitation exhibits far fewer auto-correlations than temperature and sea-level)!



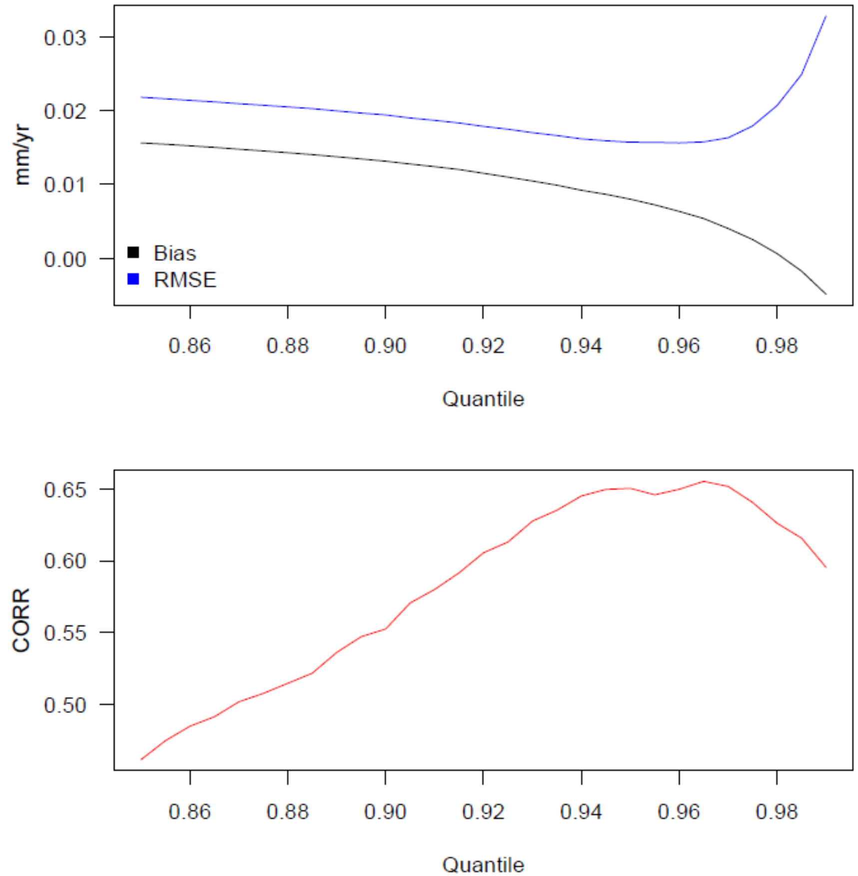
Example: Daily precipitation data

GEV model with linearly time-dependent location parameter (monthly block maxima) vs. linear quantile trends



Example: Daily precipitation data

Different quantile trends vs. linear trend in GEV scale parameter



Application: Model evaluation / bias correction

Suppose we have two time series:

$O(t)$ – observation

$M(t)$ – model (hindcast run)

Step 1: Fit quantile regression models for many quantiles to both $O(t)$ and $M(t)$ – obtain coarse-grained estimates of time-dependent PDFs

Step 2: Assign to each value of $M(t)$ the corresponding (time-localized) quantile of the contemporary distribution of M – new time series $\tau_M(t)=\tau(M(t),t)$

Step 3: For the same time t, find the value that corresponds to the (time-localized) quantile of the contemporary distribution of $O(t)$, i.e., $\tau_O(t)=\tau_M(t)$; take this as the corrected model value $M^*(t)$

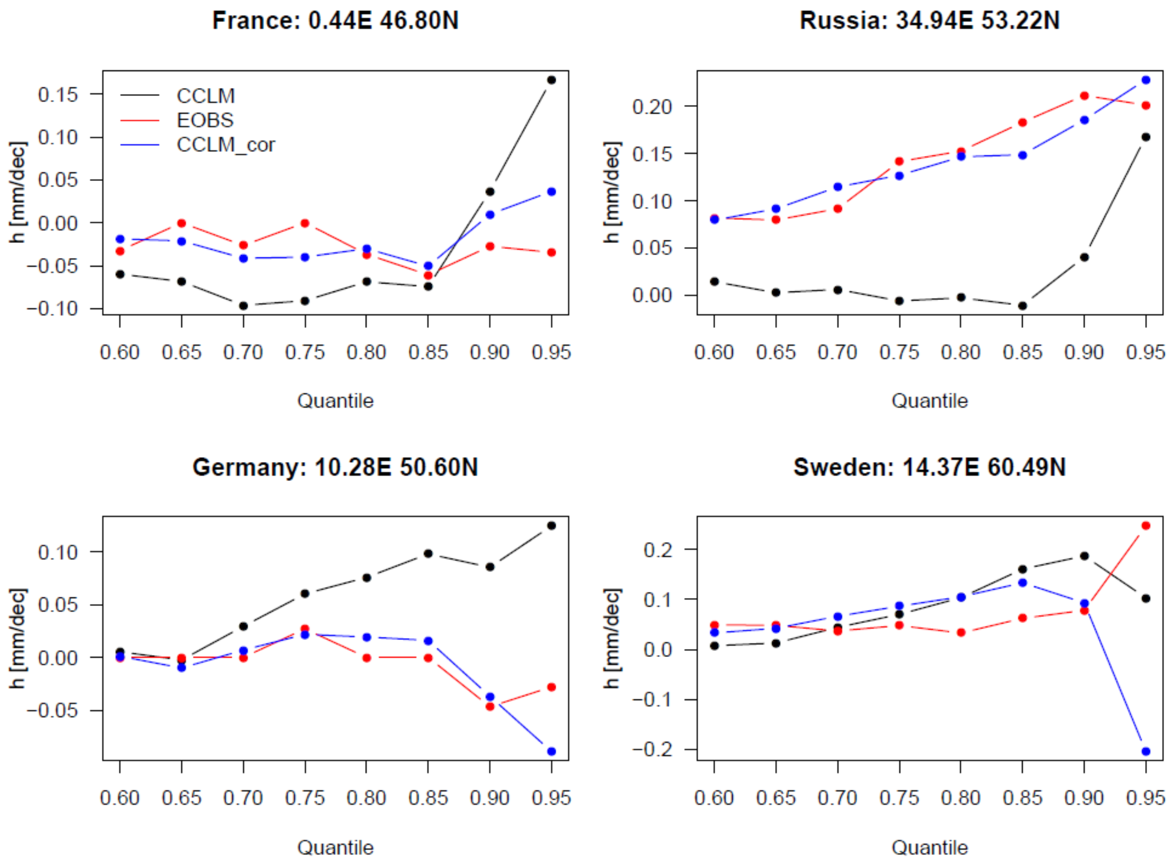
Application: Model evaluation / bias correction

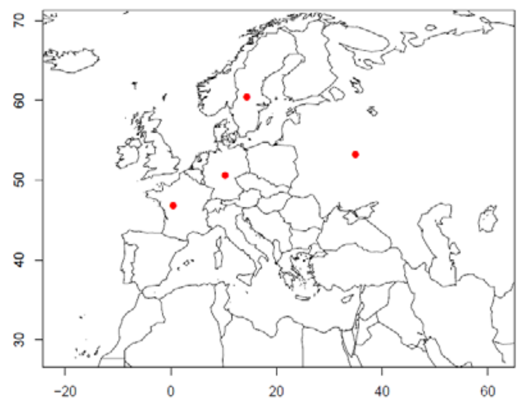
Comments on this procedure:

- **Coarse-graining of quantile range may matter**
- **Linear quantile models: quantile crossing, so contemporary quantile transformation is not monotonic and needs to be post-processed (smoothed)**
- **Alternative: use nonlinear (non-parametric) quantile estimates, e.g., kernel estimates or quantile smoothing splines**

Initial results: Bias correction for Euro-CORDEX

Observations: E-OBS daily precipitation, model: CCLM hindcasts





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Conclusions

- Temporal changes in PDF of climate observable and extremes closely linked
- Tracing quantile changes as powerful alternative to modeling time-dependent extremes
- Temporal and spatial scales strongly affect trends (low-frequency variability) in the PDF estimated from different data sources
- Upcoming application: Dynamical bias correction for (regional) climate models – calibration based on mismatch between hindcast runs and observational data
- Direct relevance for stochastic weather generators: recalibration to changing climatology in terms of PDF (residuals about mean)

References

S.M. Barbosa: *Quantile trends in Baltic sea-level*. Geophysical Research Letters, 35, L22704, 2008.

R.V. Donner, R. Ehrcke, S.M. Barbosa, J. Wagner, J.F. Donges, J. Kurths: *Spatial patterns of linear and nonparametric long-term trends in Baltic sea-level variability*. Nonlinear Processes in Geophysics, 19, 95-111, 2012.

A. Ribeiro, S.M. Barbosa, M.G. Scotto, R.V. Donner: *Changes in extreme sea-levels in the Baltic Sea*. Tellus A, 66, 20921, 2014.

C. Passow, R.V. Donner: *A rigorous statistical assessment of recent trends in intensity of heavy precipitation over Germany*. In prep.

R. Koenker: *Quantile Regression*. Cambridge University Press, 2005.