(sfi)^2 Statistics for Innovation

Regional climate prediction comparisons via statistical upscaling and downscaling

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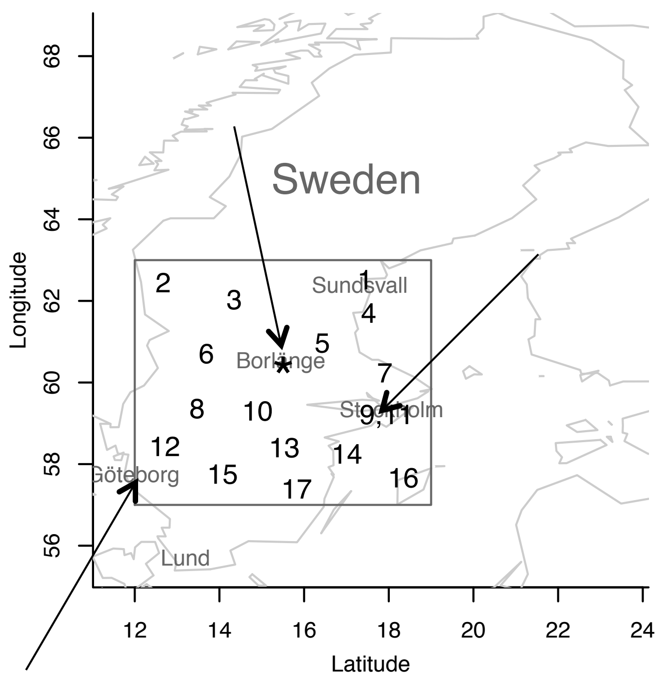
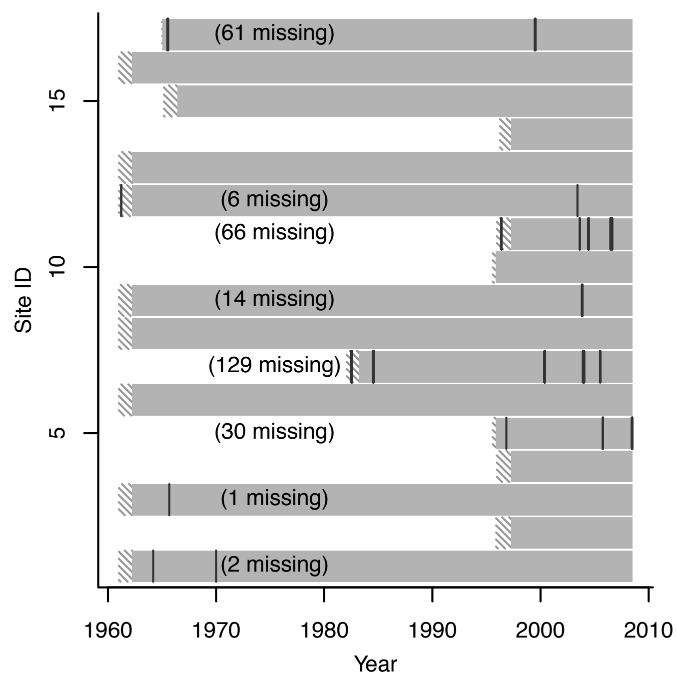
Temperature data from the Swedish Meteorological and Hydrological Institute web site

Regional model output from Gregory Nikulin, SMHI

Data

SMHI synoptic stations in south central Sweden, 1961-2008





Regional climate models

Not possible to do long runs of global models at fine resolution

Regional models (dynamic downscaling) use global model as boundary conditions and runs on finer resolution

Output is averaged over land use classes

"Weather prediction mode" uses reanalysis as boundary conditions

Comparison of model to data

- Model output daily averaged 3hr predictions on $(12.5\ km)^2$ grid
- Use open air predictions only
- RCA3 driven by ERA 40/ERA Interim
- Data daily averages point measurements (actually weighted average of three hourly measurements, min and max)
- Aggregate model and data to seasonal averages

Some terminology

Upscaling: Moving from station data to grid square level

Variant of geostatistics

Downscaling: Moving from grid square model output to station level

Variant of data assimilation

(Not the same as statistical downscaling in climatology)

A “simple” model

$$Y_t(s) = \mu_t(s) + \varphi_t(s) + \exp(\alpha_t(s))\eta_t(s)$$

space-time trend

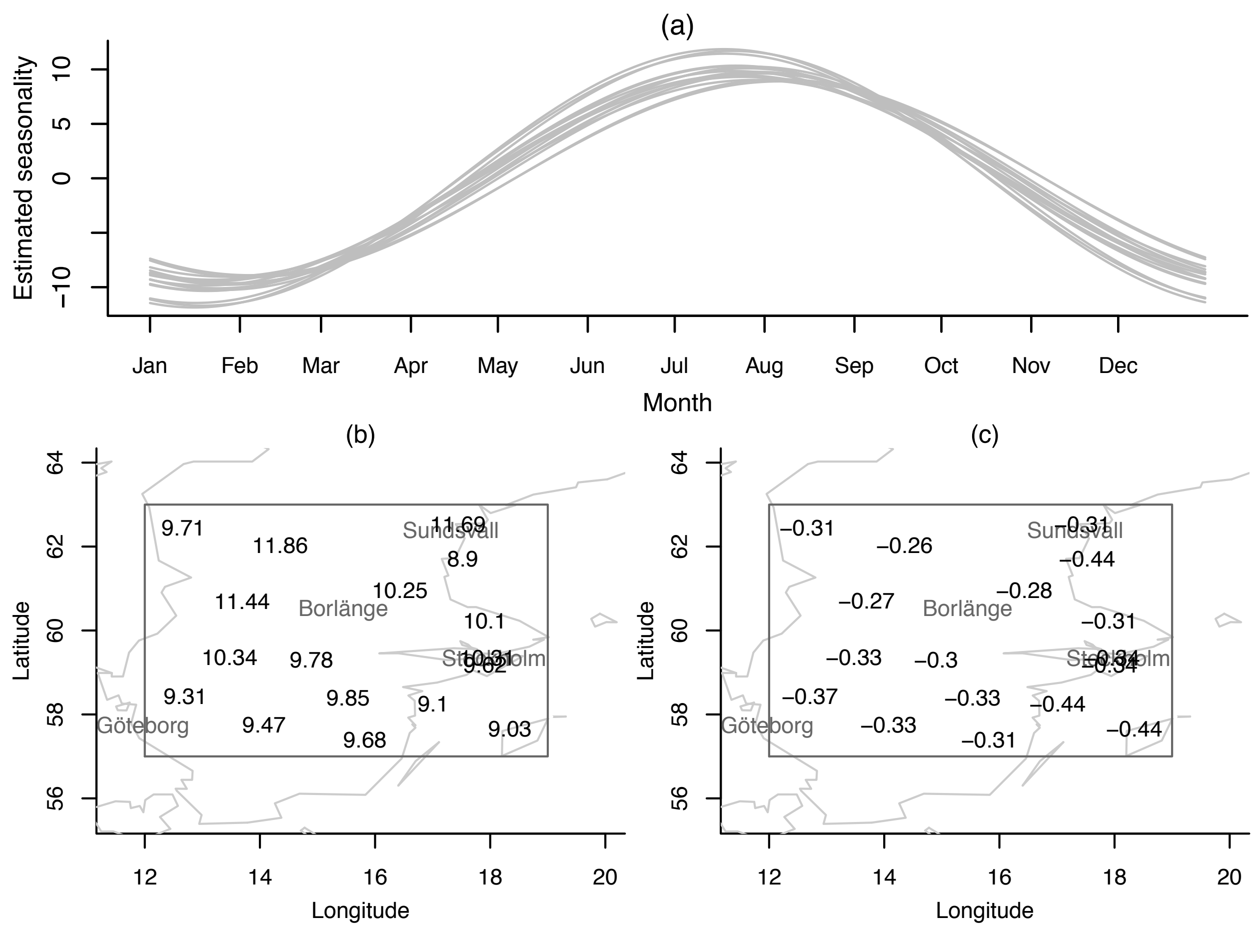
noise

periodic seasonal component

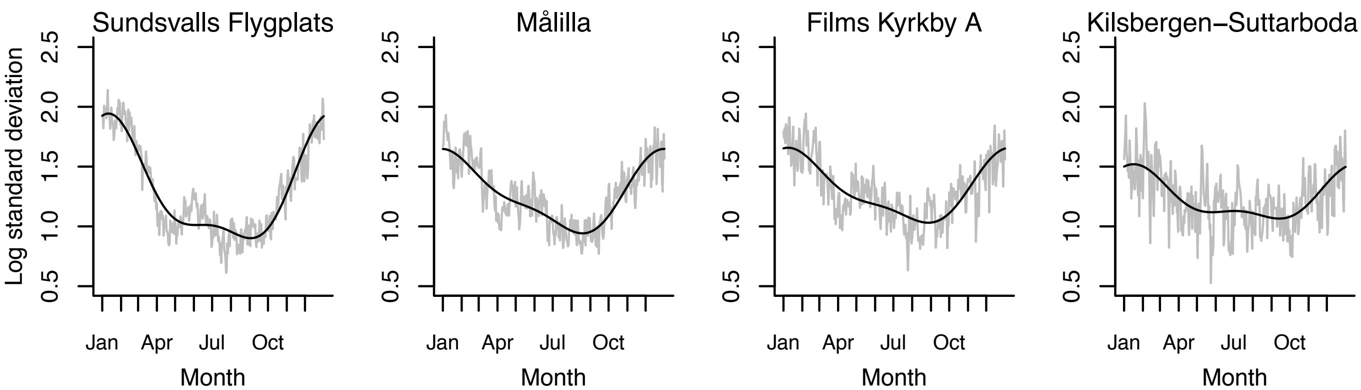
seasonal variability

Seasonal part

$$\phi_t(s) = A(s)\cos(2\pi t / 365.25 + \theta(s))$$



Seasonal variability



Modulate noise $\zeta_t(s) = \exp(\alpha_t(s))\eta_t(s)$

$\alpha_t(s)$ **two term Fourier series**

Both long and short memory

Consider a stationary Gaussian process with spectral density

$$S_\eta(f) = \underbrace{\boxed{B(f)}}_{\text{Short term memory}} \underbrace{\boxed{\left|4\sin^2(\pi f)\right|^{-\delta}}}_{\text{Long term memory}}$$

Short term memory

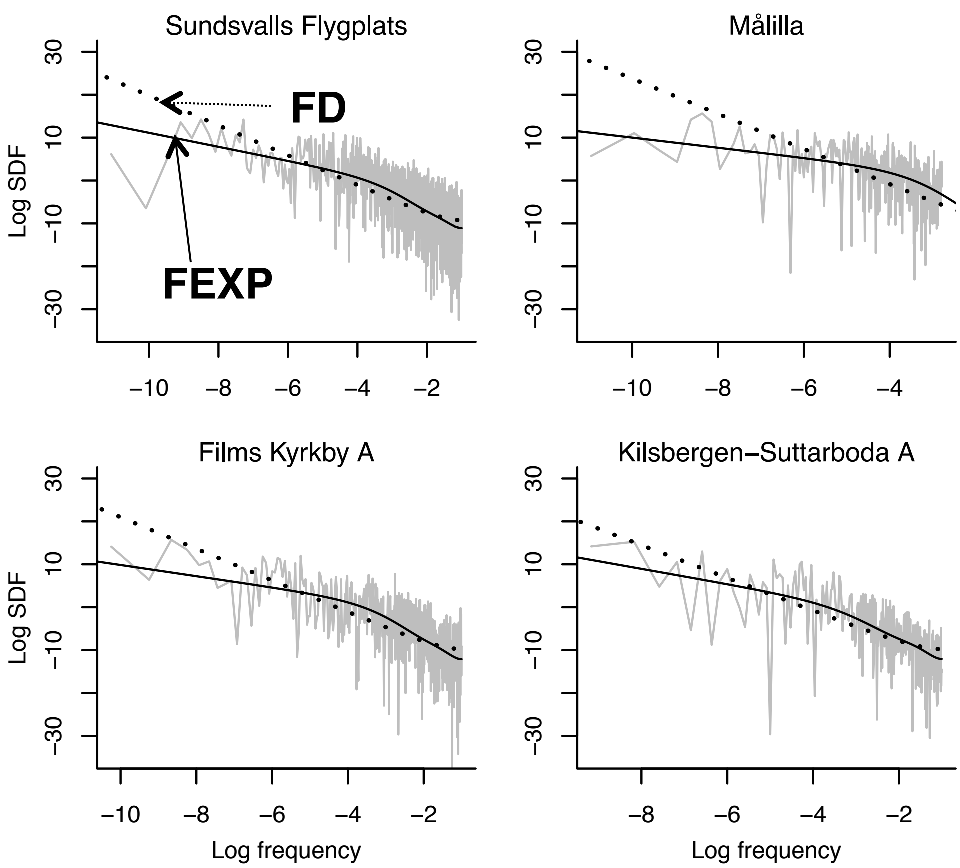
Long term memory

Examples:

B(f) constant: fractionally differenced process (FD)

B(f) exponential: fractional exponential process (FEXP) (log B truncated Fourier series)

Estimated SDFs of standardized noise



Clear evidence of both short and long memory parts

Space-time model

Gaussian white measurement error

Process model in wavelet space

- scaling coefficients have mean linear in time and latitude
- separable space-time covariance
- trend occurs on scales $\geq 2^j$ for some j
- obtained by inverse wavelet transform with scales < j zeroed

Gaussian spatially varying parameters

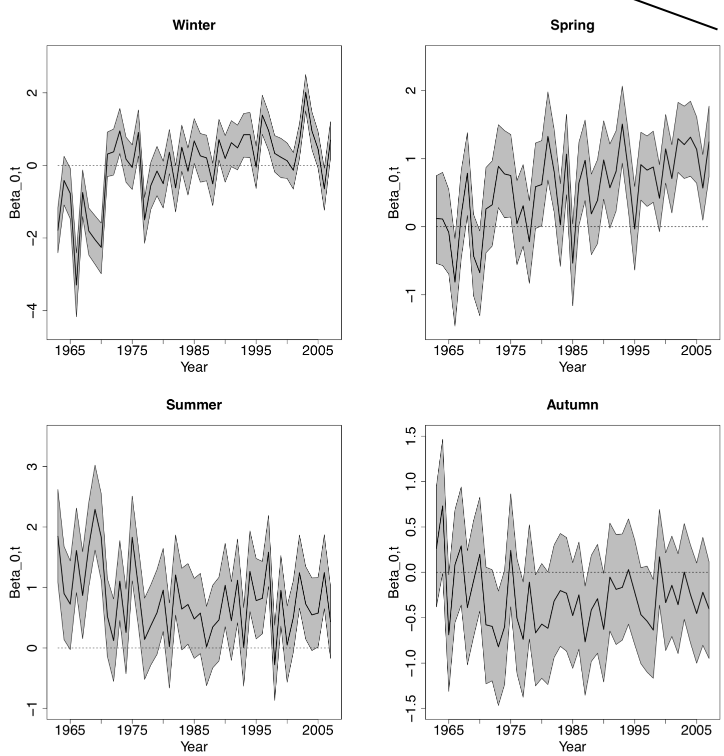
Downscaling model

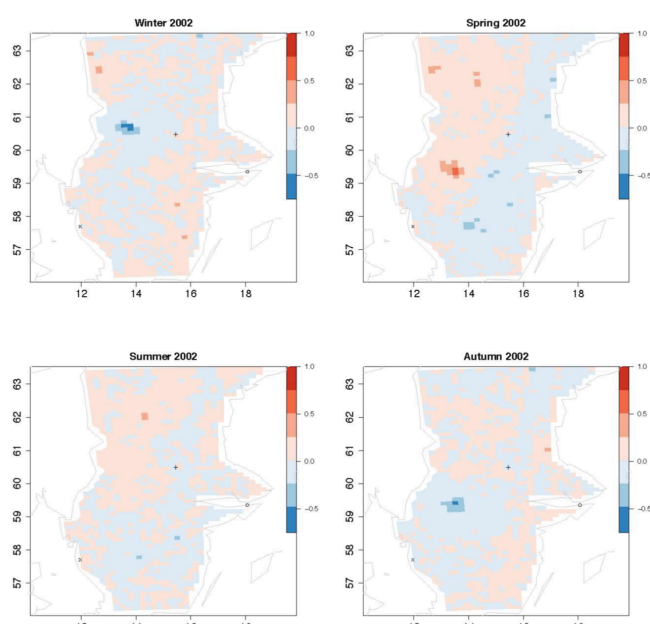
(0.91,0.95)

$$Y(s,t) = \boxed{\tilde{\beta}_0(s,t)} + \boxed{\beta_1}\tilde{x}(s,t) + \varepsilon(s,t)$$

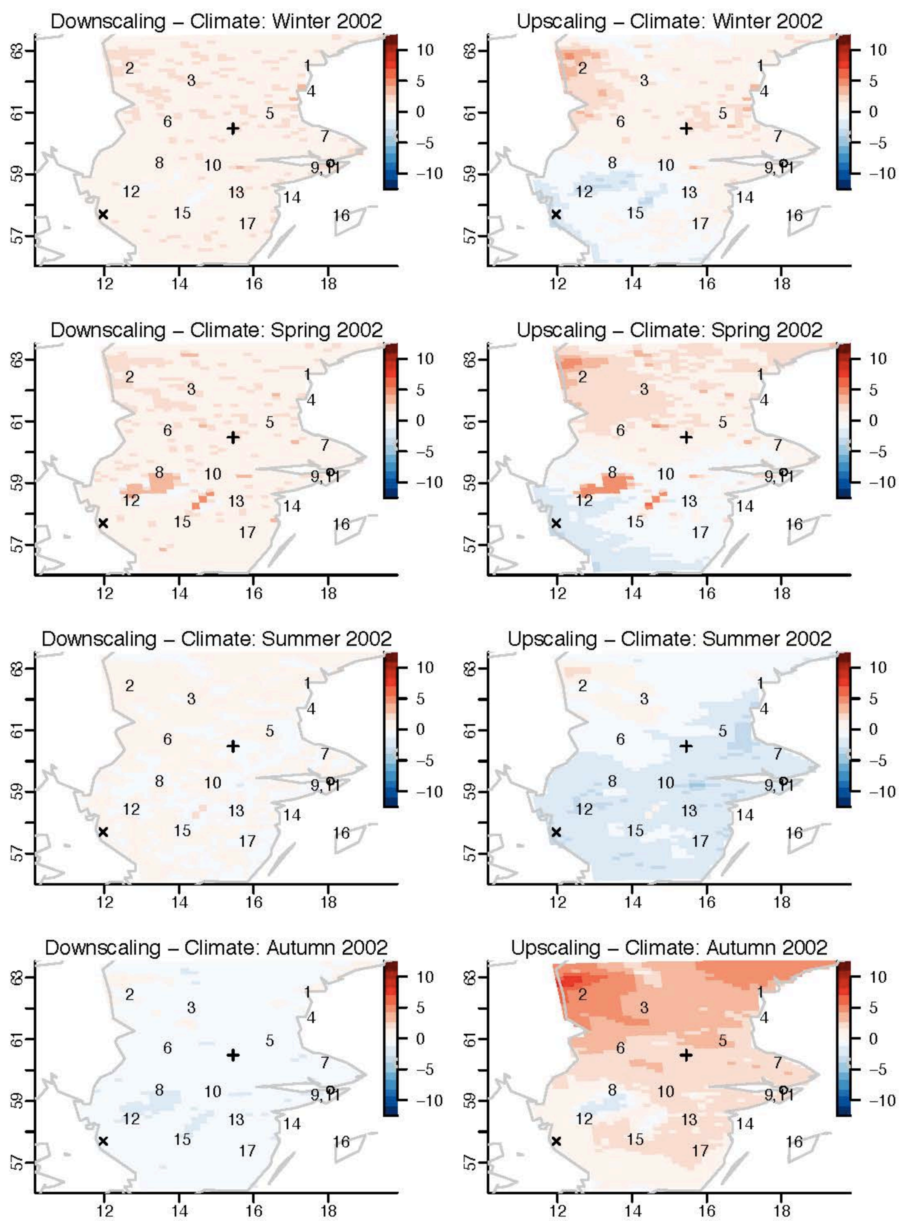
$$\tilde{\beta}_0(s,t) = \boxed{\beta_0(t)} + \boxed{\beta(s,t)}$$

smoothed RCM





Comparisons



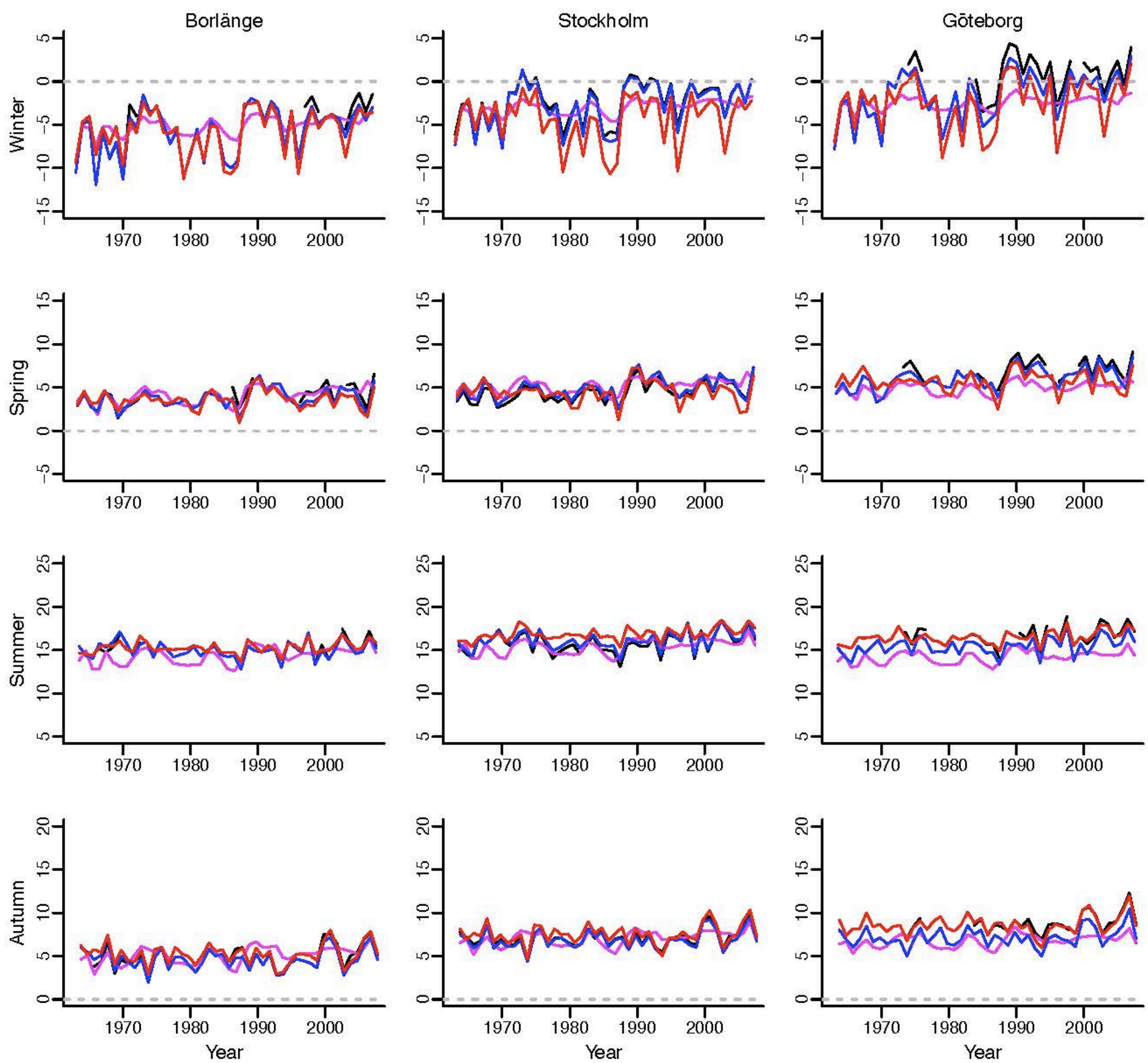
Reserved stations

Borlänge: Airport that has changed ownership, lots of missing data

Stockholm: One of the longest temperature series in the world. Located in urban park.

Göteborg: Urban site, located just outside the grid of model output

Predictions and data



Comments

Nonstationarity

in mean

in covariance

Uncertainty in model output

”Extreme seasons” where down- and upscaling agree with each other but not with the model output

Model correction approaches