Empirical-Statistical Downscaling & Record-Statistics

R.E. Benestad

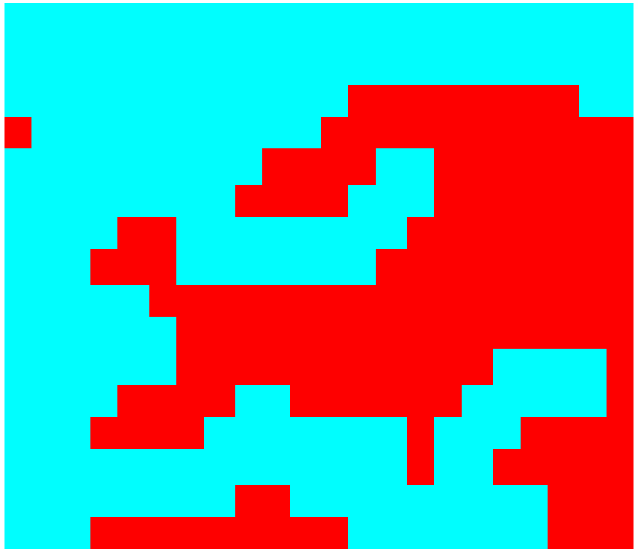
Rasmus.benestad@met.no

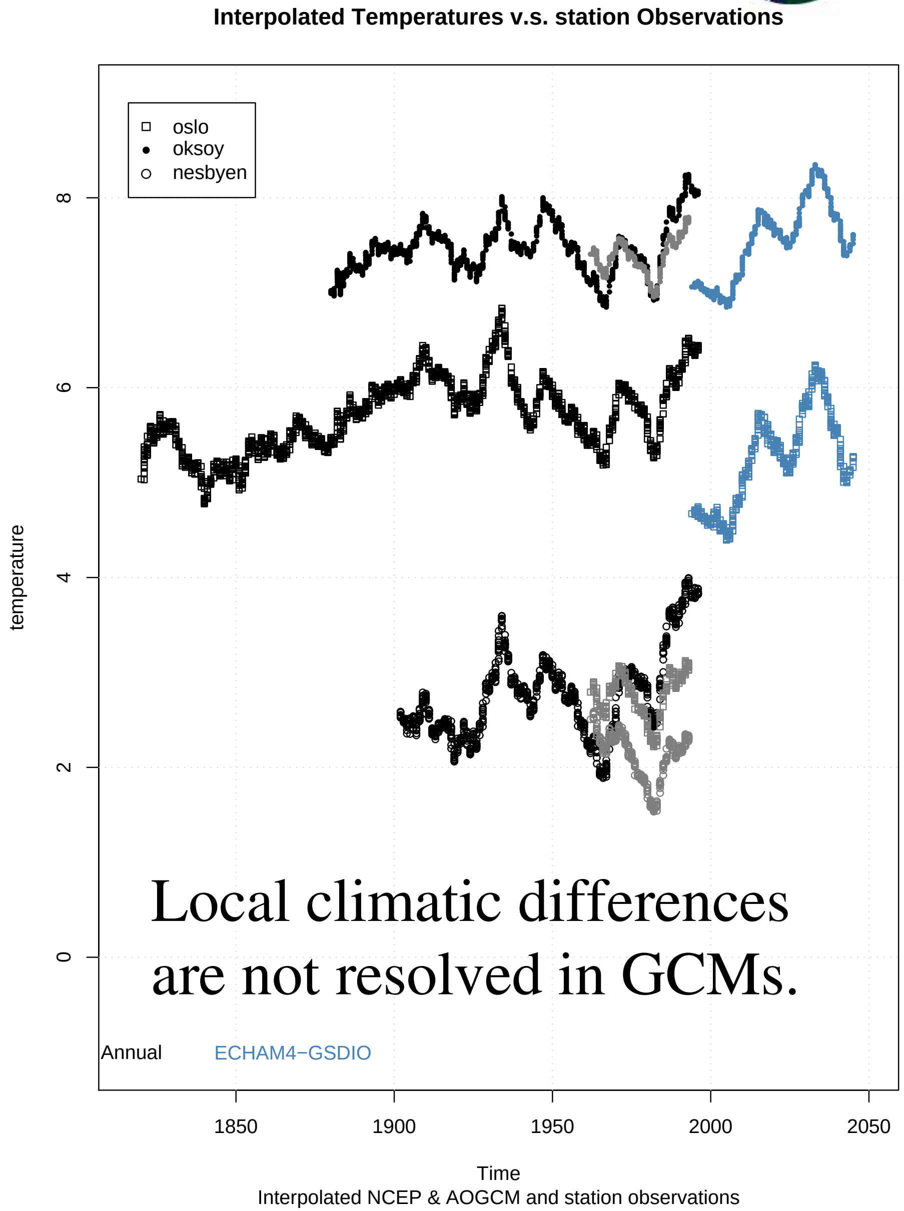
Outline

- Theoretical basis.
  - Why do we need downscaling?
- Methods.
  - Dynamical v.s. empirical-statistical
  - The common EOF frame-work
  - Statistical models: Regression, CCA, SVD, …
  - Empirical-statistical: e.g linear, analog
- Uncertainties.
- Extremes & record values.
  - Downscaling pdfs
  - Exponential law & dependency on local conditions
  - Record-events: test for non-stationarity
  - ‘Extremes’ as in ‘severe’ events

Principles of Downscaling

Why downscaling?





Local climatic differences are not resolved in GCMs.

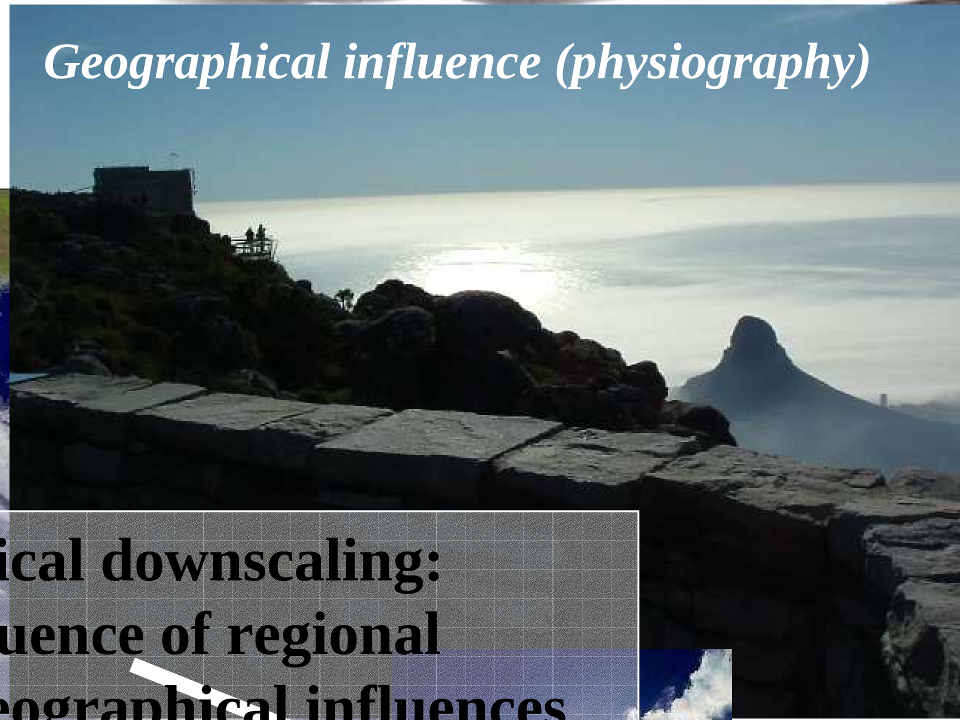
"Skillful spatial scale": ~ 8 grid-pts.

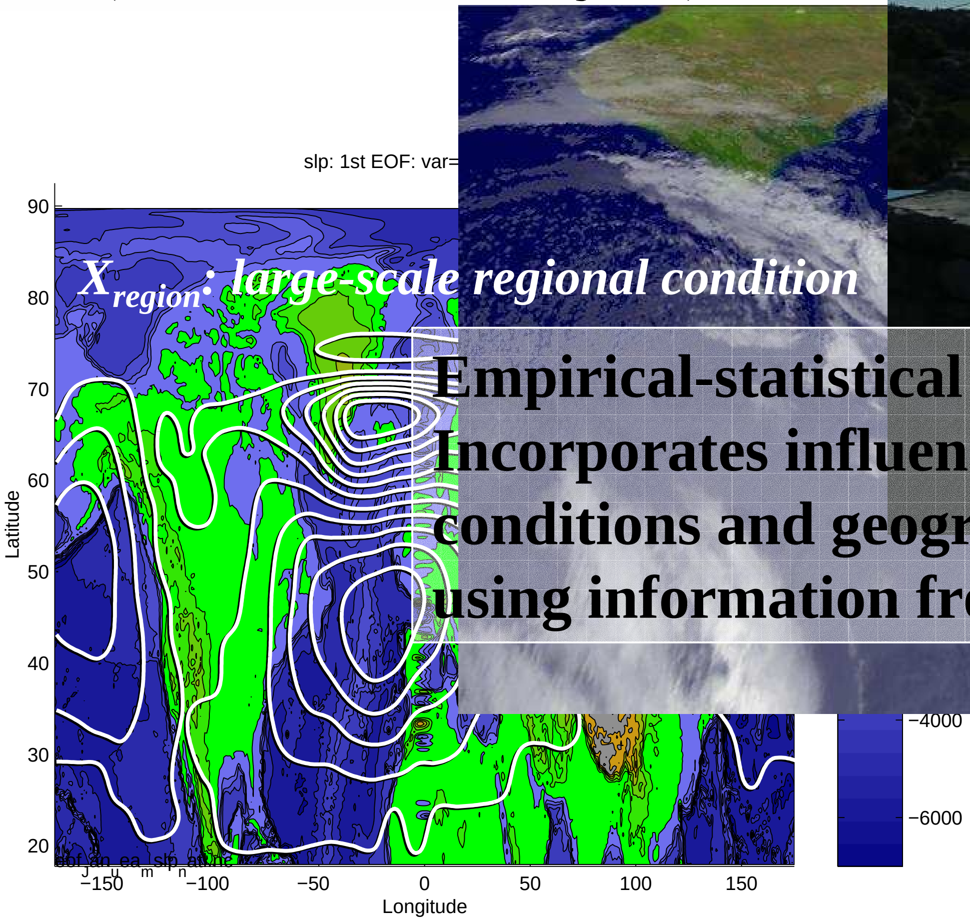
Grotch & McCracken (1991), *J. Clim*, **4**, p. 286

Principles of Downscaling

Large-scale
(GCMs, re-analysis)

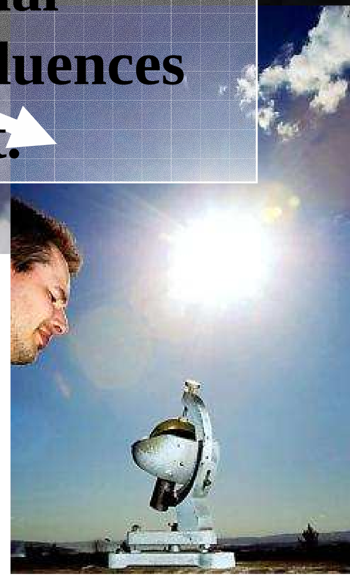
Geographical influence (physiography)





X_{region}: large-scale regional condition

Empirical-statistical downscaling: Incorporates influence of regional conditions and geographical influences using information from the past.

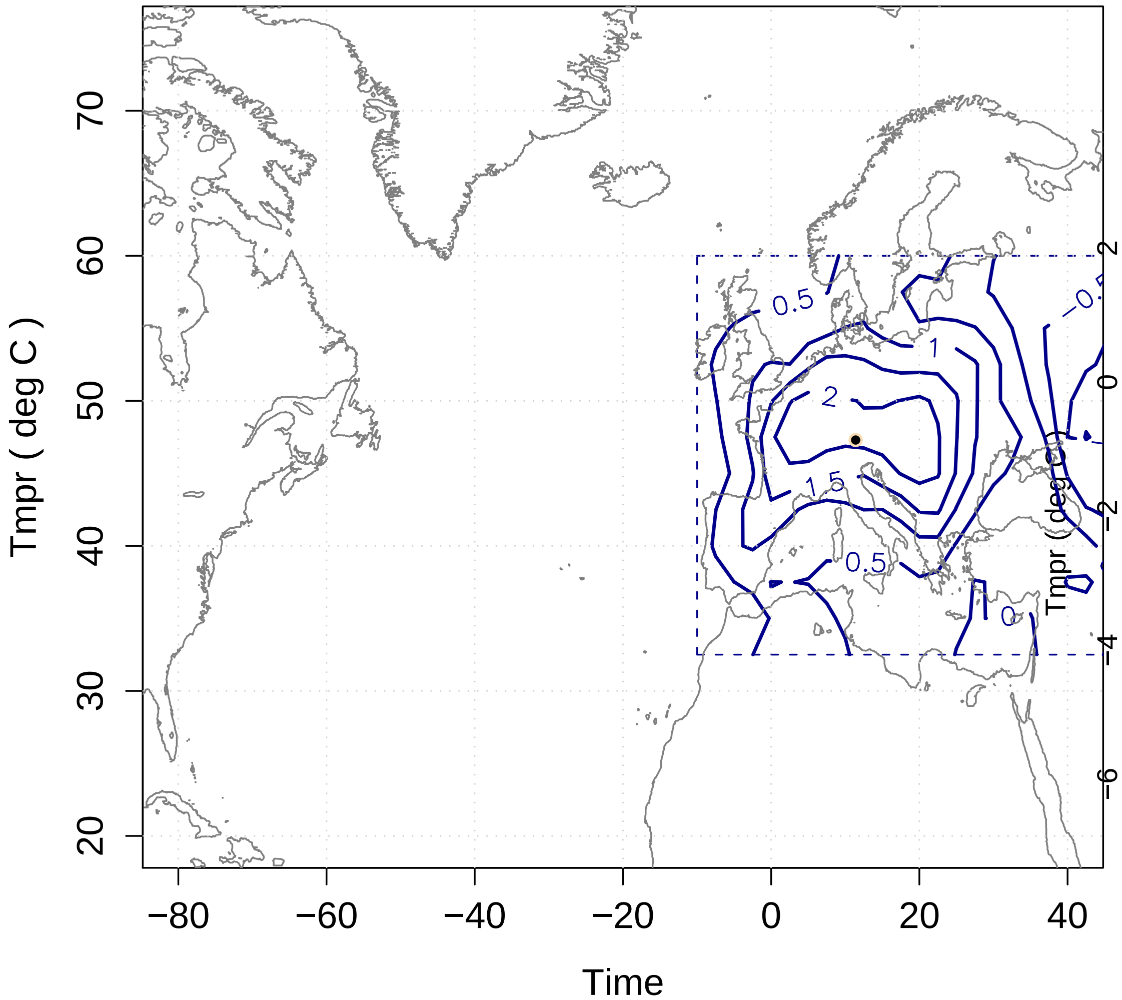


Small-scale
(Direct measurements)

$X_{local} = \psi(X_{regnion}, \text{physiography})$

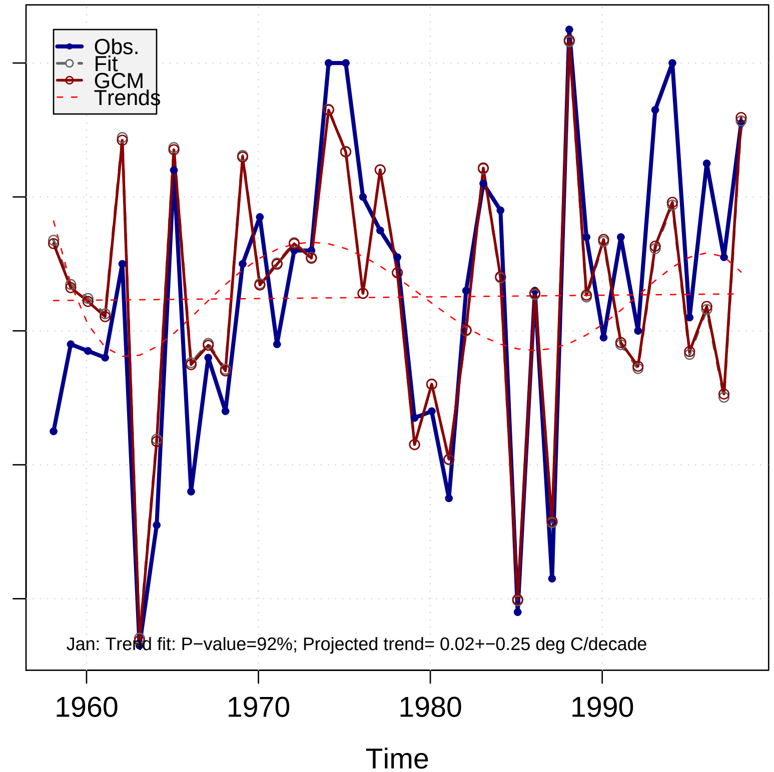
Regression example for Innsbruck…

Empirical Downscaling (ncep_t2m [10W50E−30N60N] −> Tmpr)



Calibration: Jan Tmpr at INNSBRUCK using ncep_t2m: R2=81%, p−value=0%.

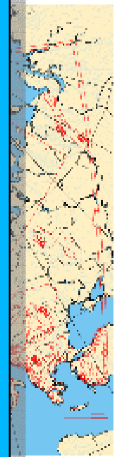
Empirical Downscaling (ncep_t2m [10W50E−30N60N] −> Tmpr)

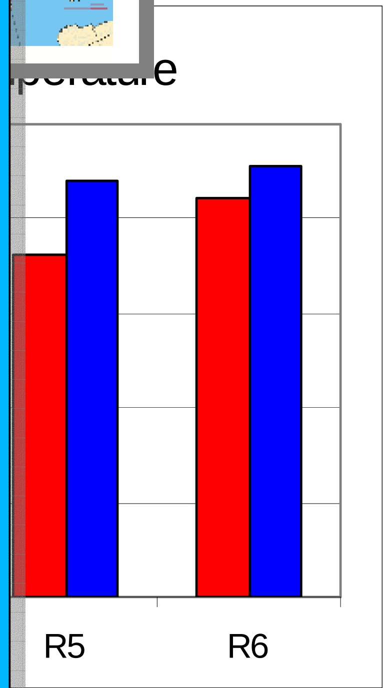


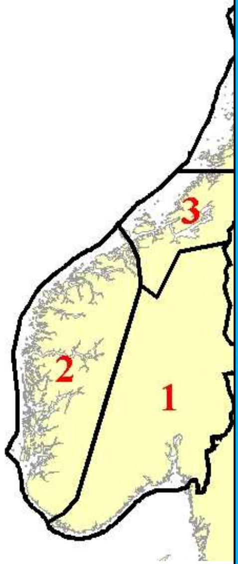
Calibration: Jan Tmpr at INNSBRUCK using ncep_t2m: R2=81%, p−value=0%.

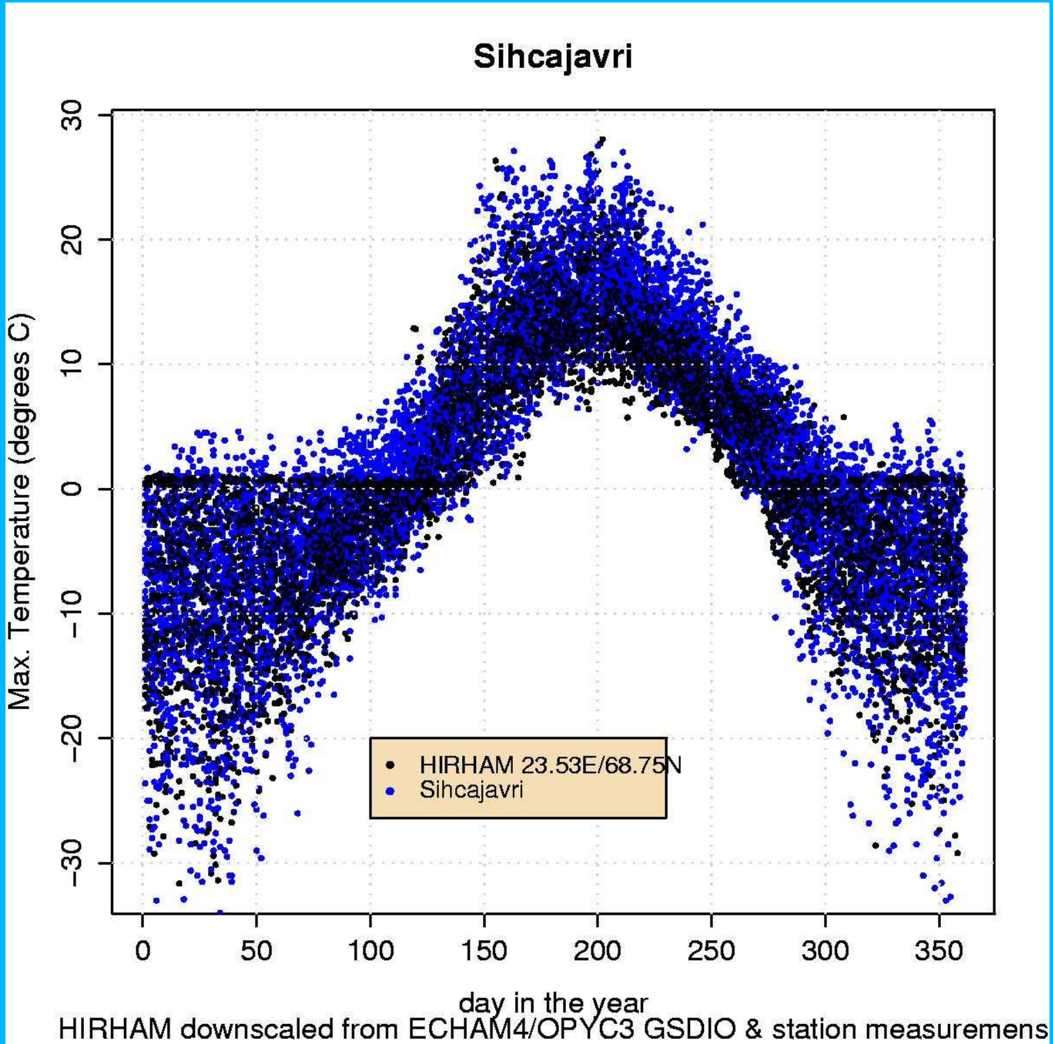
Methods

…ling: 2 completely …g strategies.







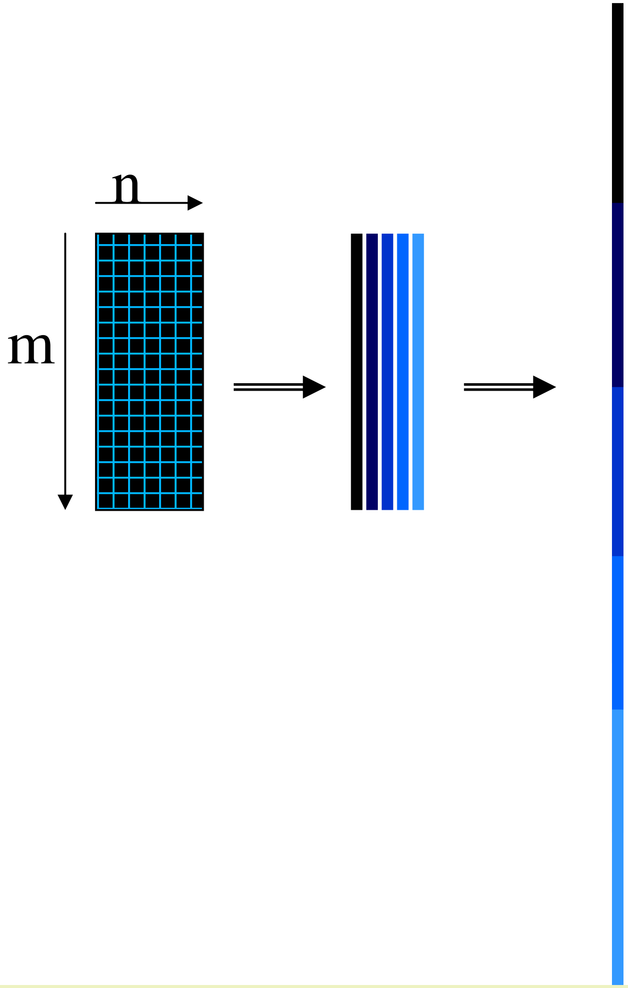


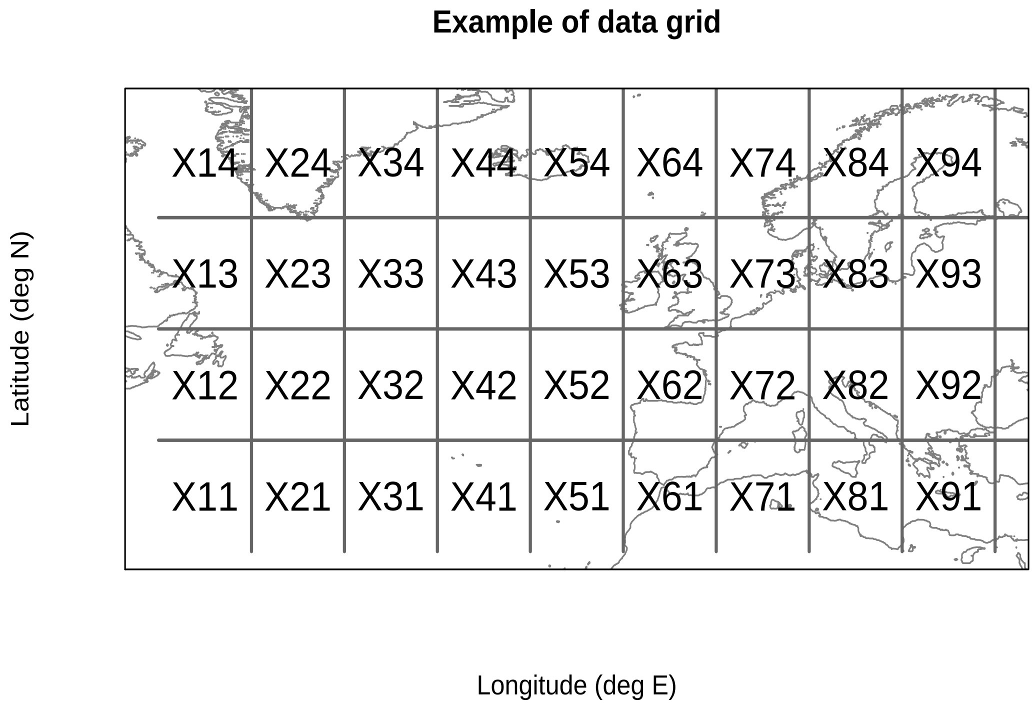
Dynamical DS not necessarily 'better' than empirical-statistical. Stationarity-problems associated with parameterisation (statistical) and not more 'physically consistent' (systematic biases – also see figure!).

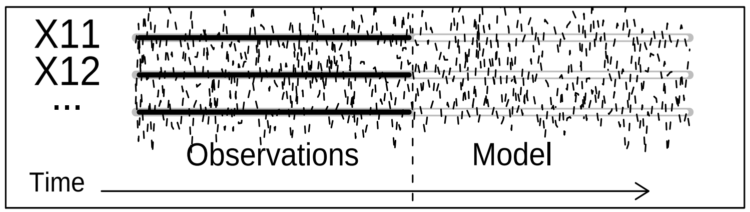
Hanssen-I…

2-dimensional data matrix converted to a 1D vector:

$$\mathbf{Y}_{ij} \rightarrow \tilde{y} \in \Re^{n\times m}$$

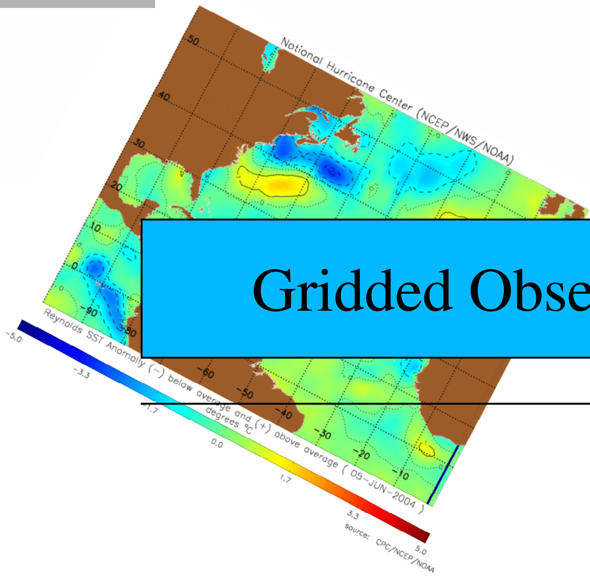






A question of how to organize the data…

Methods



common EOF : combine two different data sets

Gridded Observations/ re-analysis	GCM results	space

Time axis

PCA: Singular Vector Decomposition (SVD):

$\mathbf{X} = \mathbf{U}\,\mathbf{\Sigma}\,\mathbf{V}^T$

U Σ V

U: spatial pattern common
Σ: 'Eigenvalues' (variance)
V: time series describing the loadings (principal components)

Mathematically identical to Empirical orthogonal functions (EOF).

Methods

U Σ V

PCA: observations

U Σ V

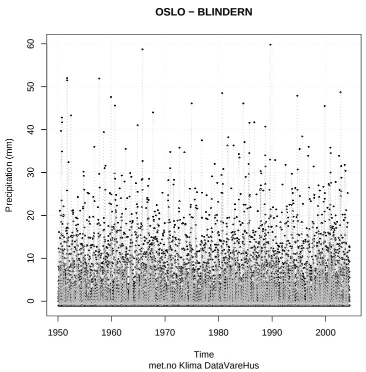
PCA: GCM

U Σ V

Common PCA

'Prefect prognosis'
Traditional downscaling

V^T



U

U

Match
Patterns→φ

V^T

φψ

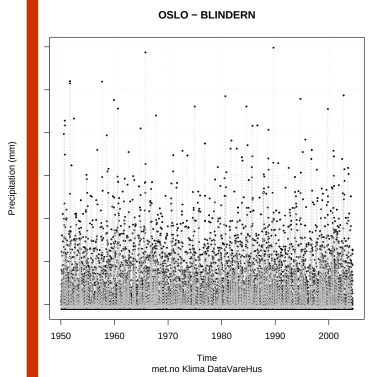
↓

scenario

Regression →ψ

Common EOF based
downscaling

V^T



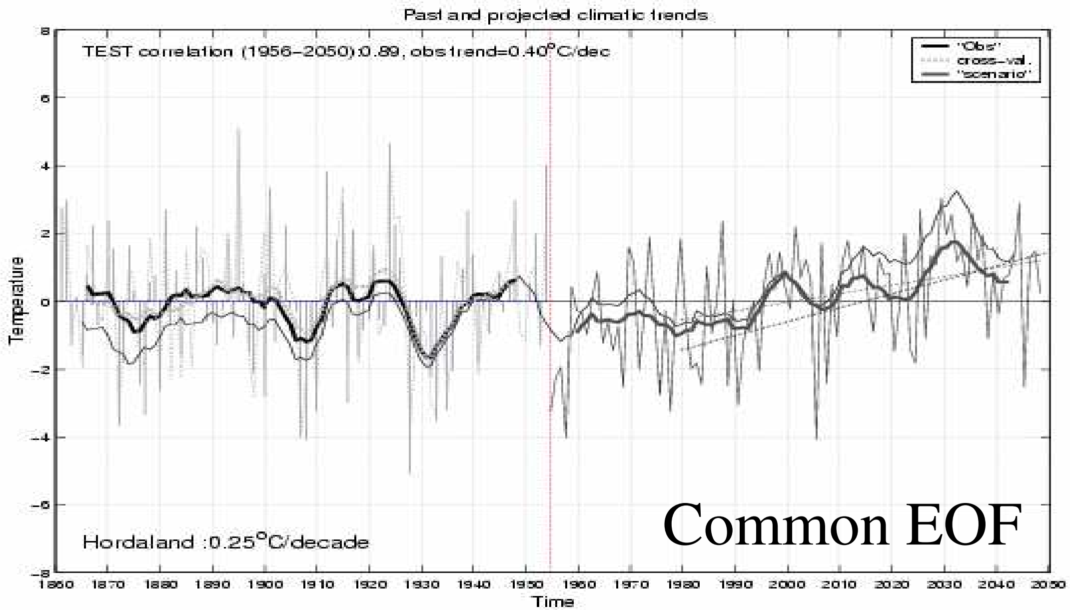
ψ

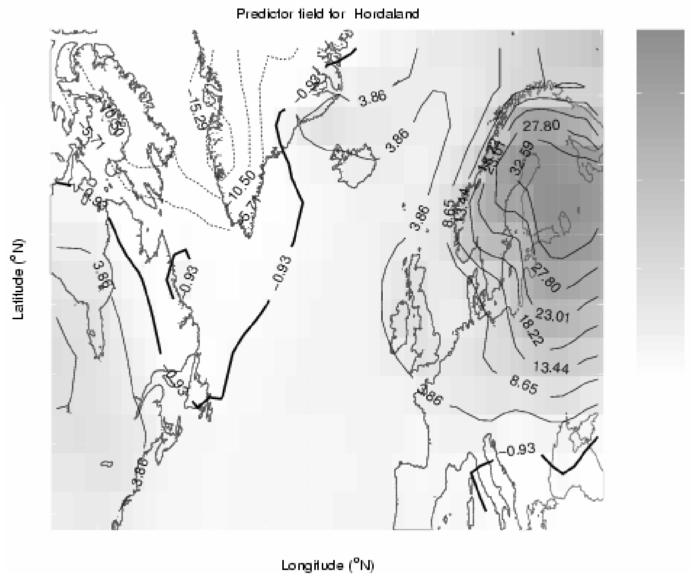
↓

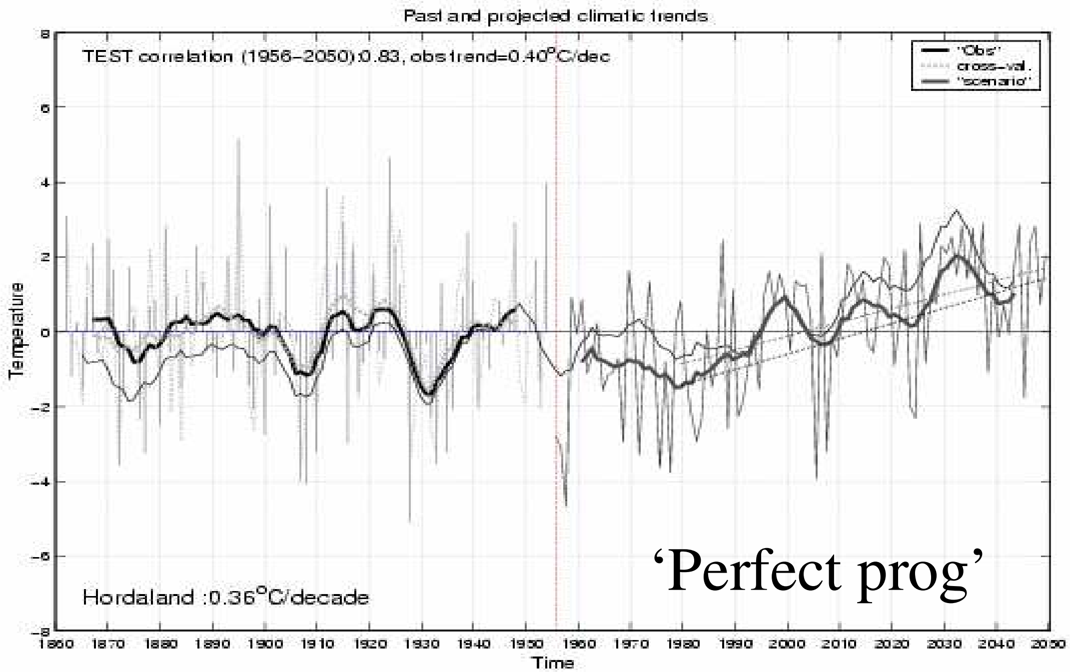
scenario

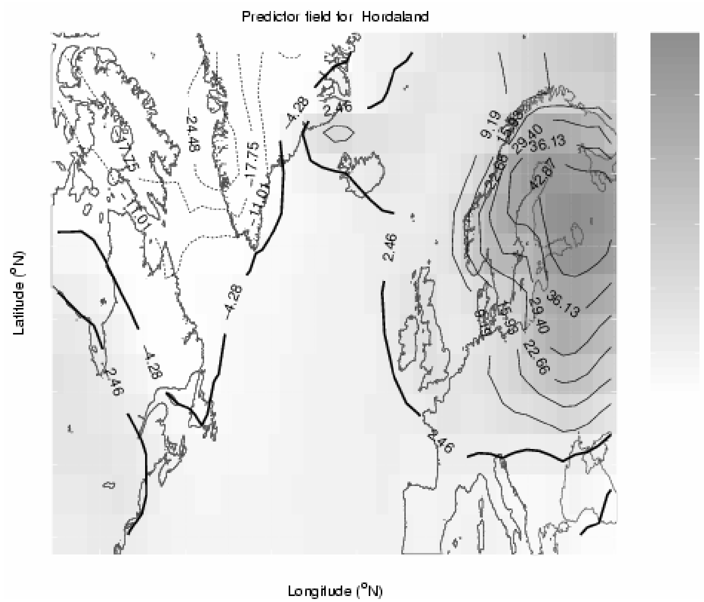
Regression →ψ

Example of downscaling: ‘Perfect prog’ & common EOF





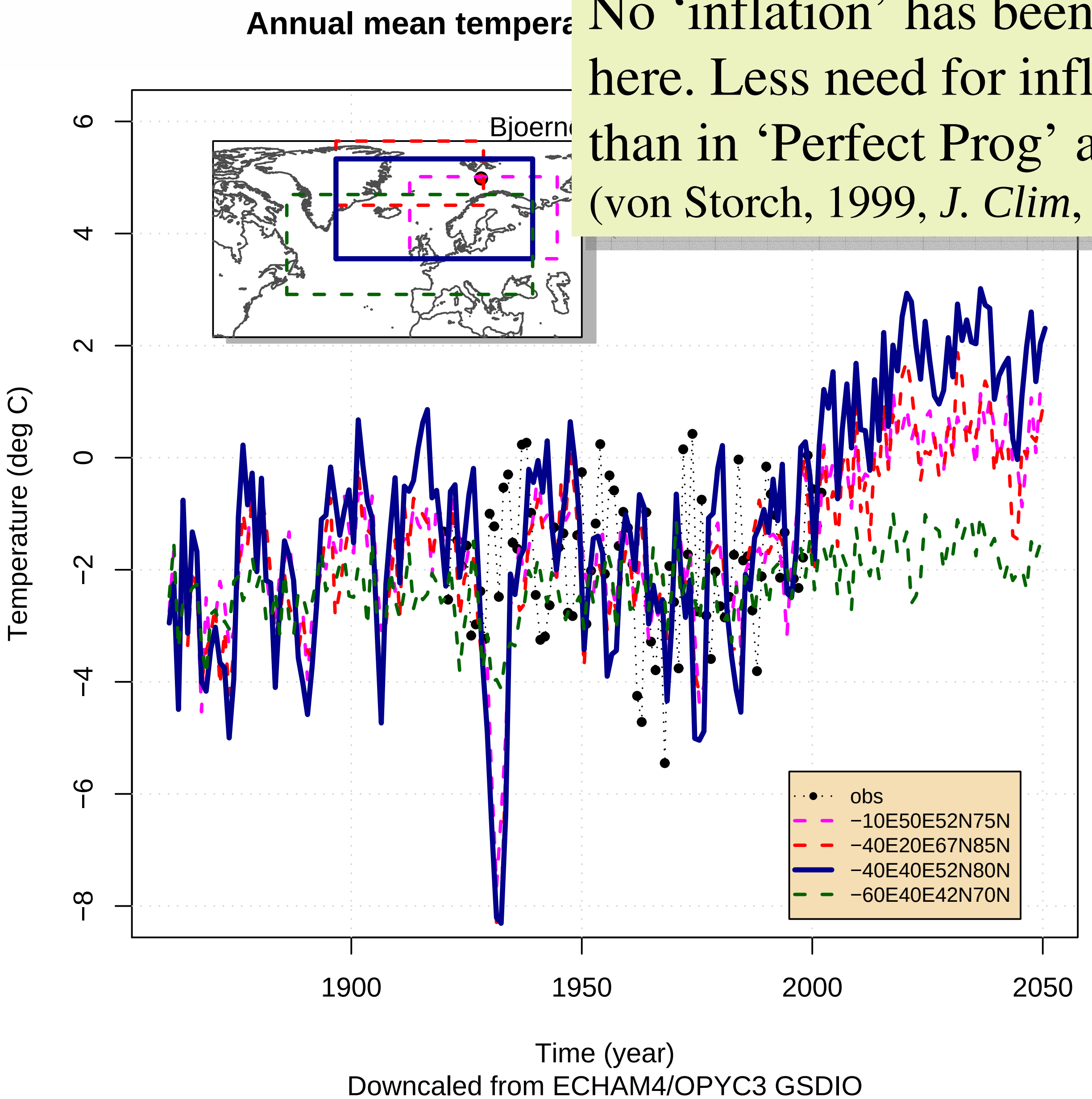




Benestad (2001) *Int. J. Clim.* **21** 1645

Choice of domain can affect your results

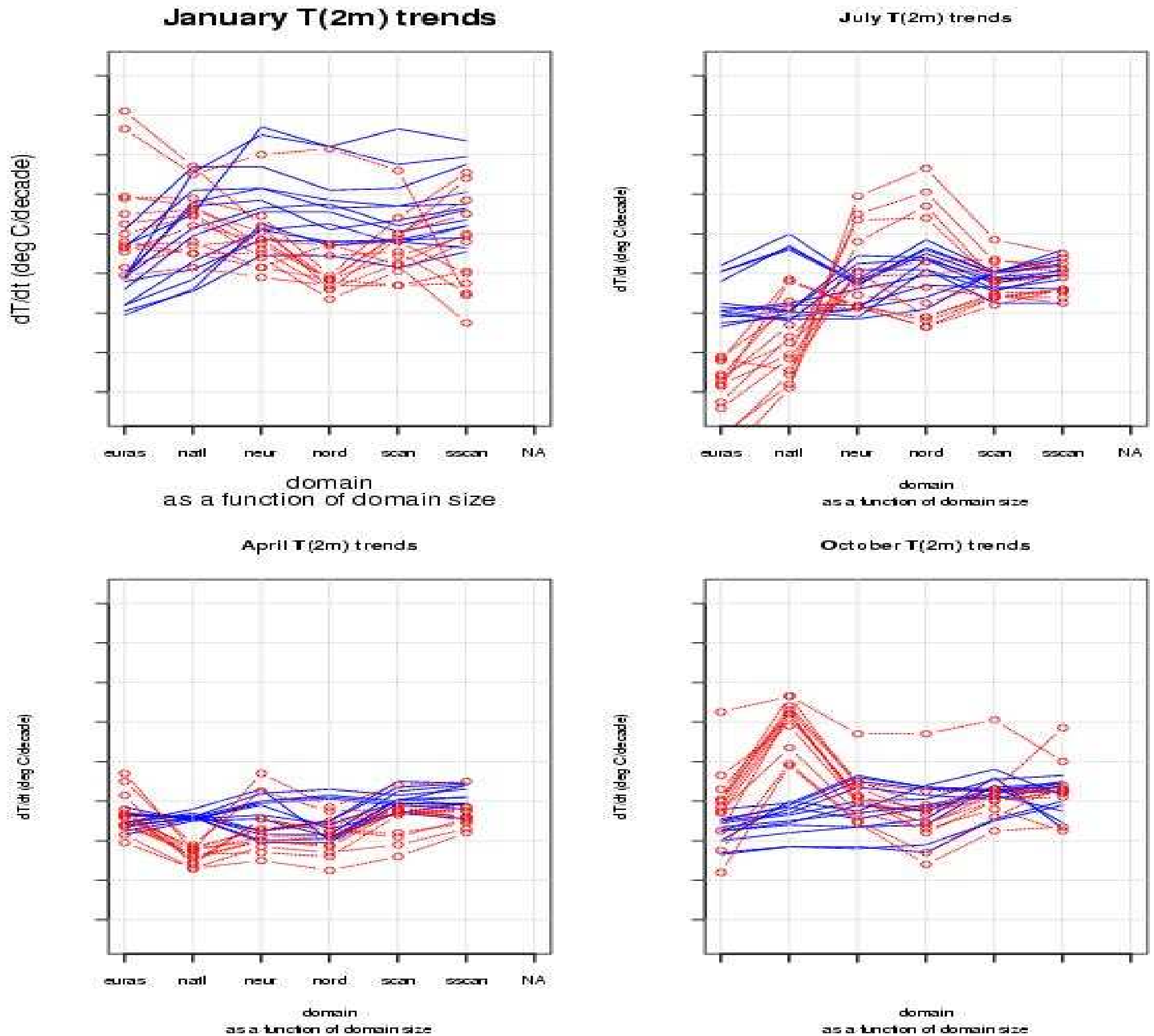
No 'inflation' has been used here. Less need for inflation than in 'Perfect Prog' approach (von Storch, 1999, *J. Clim*, **12**, 3505)



Benestad (2002) *Clim. Res.*,**21** (2), p. 105-125: warning about domain choice.

Methods

Experiment: downscaling using a set of different predictor domains. Check robustness (flat structure).



Common EOF

'Perfect prog'

Benestad (2001) *Int. J. Clim.* **21** 1645

Empirical Orthogonal Functions (EOFs) and Principal Component Analysis (PCA).

Eigenvectors of the co-variance matrix:

‘S-mode’ and ‘T-mode’

$[\vec{x}_1, \vec{x}_2, .. \vec{x}_m] \rightarrow \mathbf{X}$

Variance-covariance matrix **S** of **X’** is 1/(n-1) **X’**^{T}**X** where

$\mathbf{X}' = \mathbf{X} - \overline{\mathbf{X}}$

$\mathbf{S}\vec{e} = \lambda\vec{e}$ (Eigenfunctions)

$\vec{x}' = \mathbf{E}\vec{u}$

$\vec{u}_m = \vec{e}^T_m \vec{x}'$

$\vec{e}^T_i \vec{e}_j = \delta_{ij}$

$[\vec{e}_1, \vec{e}_2, .. \vec{e}_n] \rightarrow \mathbf{E}$

Singular Vector Decomposition (SVD)

$\mathbf{X} = \mathbf{U}\,\Sigma\,\mathbf{V}^T$

Literature:

Wilks, D.S. (1995) Statistical Methods in the Atmospheric Sciences. *Academic Press*
Press W.H., Flannery B.P., Teukolsky S.A, & Vetterling W.T..(1989) Numerical Recipes, *Cambridge*
Preisendorfer R.W. (1989) Principal Component Analysis in Meteorology and Oceanology, *Elsevier Science Press*

Regression & other Statistical models on Relationships

Regression:

single & mul

Least

multivariate

Proje

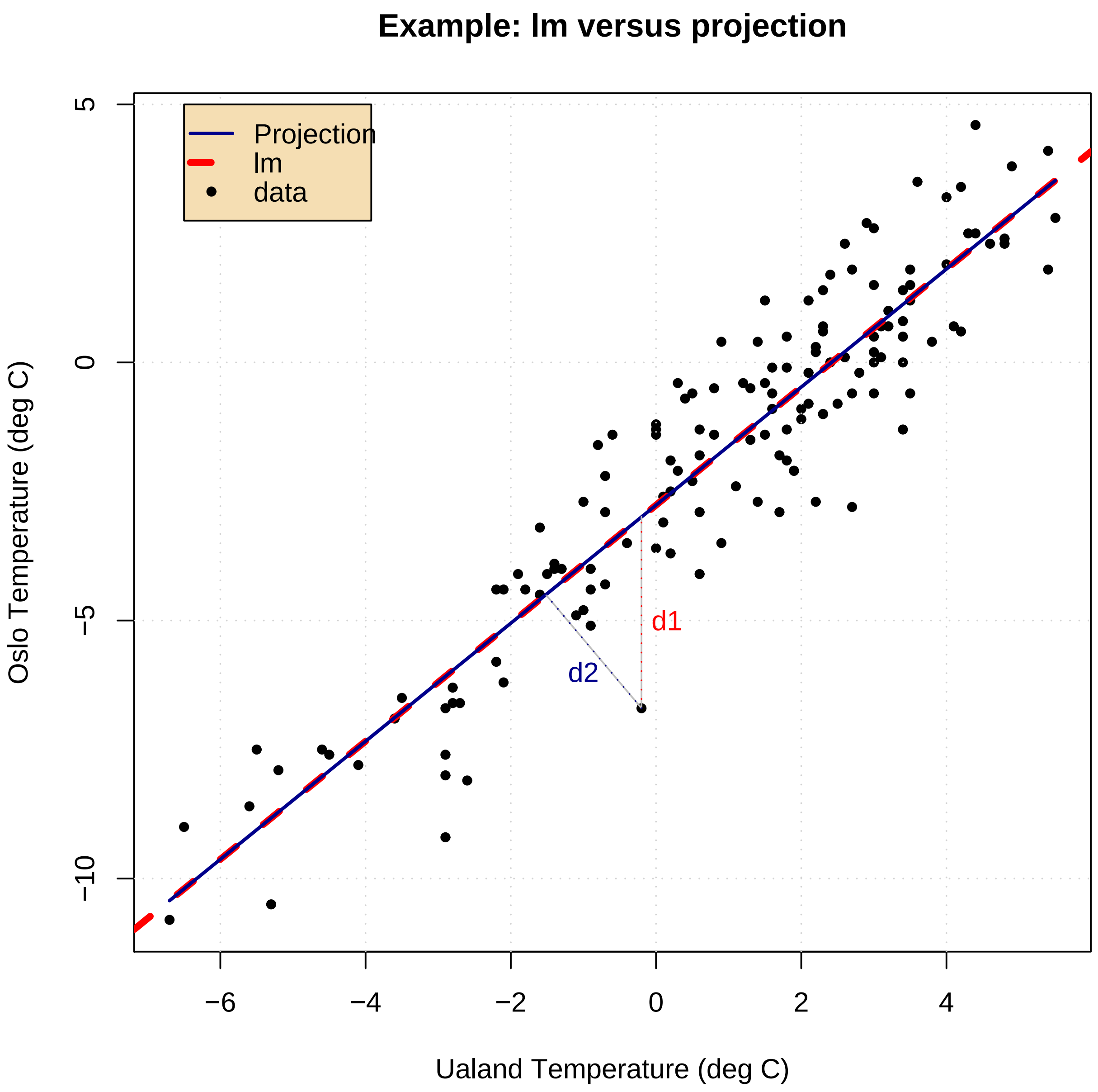
$\vec{y}$ = a

Strang,

Benesta

<u>Mean Land Surface Temperatu</u>

linear models

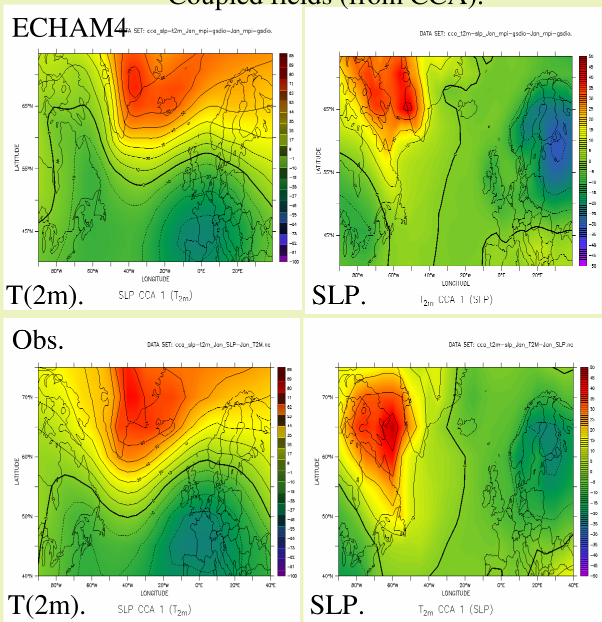


Canonical Correlation Analysis (CCA) classical & Barnet-Preisendorfe

Bretherton et al. (1992) An Intercomparison of Coupled Patterns in Climate Data, *J. Clim.*, **5**, 541.

Benestad (1998) CCA applied to Statistical Dov Monthly Mean Land Surface Temperatures: Model Docum 28/98, pp.96

Coupled fields (from CCA).



Find patterns with the maximum correlation.

$$X_1 = G\,U^T,\ X_2 = H\,V^T$$

$$U^T V = L\,M\,R^T = C$$

Downscaling:

$$\widehat{X}_1 = G\,M\,(H^T H)^{-1}\,X_2$$

Singular Vector Decomposition (SVD)

not to be confused with Singular Vector Decomposition (SVD)

Benestad (1998) SVD applied to Statistical Downscaling for Prediction of Monthly Mean Land Surface Temperatures: Model Documentation, *DNMI Klima*, 30/98, pp. 38

$$\widehat{\mathbf{X}_1} = \mathbf{G}_{svd}\, \mathbf{S}_{12}\, \mathbf{S}_{22}^{-1}\, \mathbf{H}^T_{svd}\, \mathbf{X}_2$$

Maximize co-variance (CCA maximizes correlation)

Other types of models…

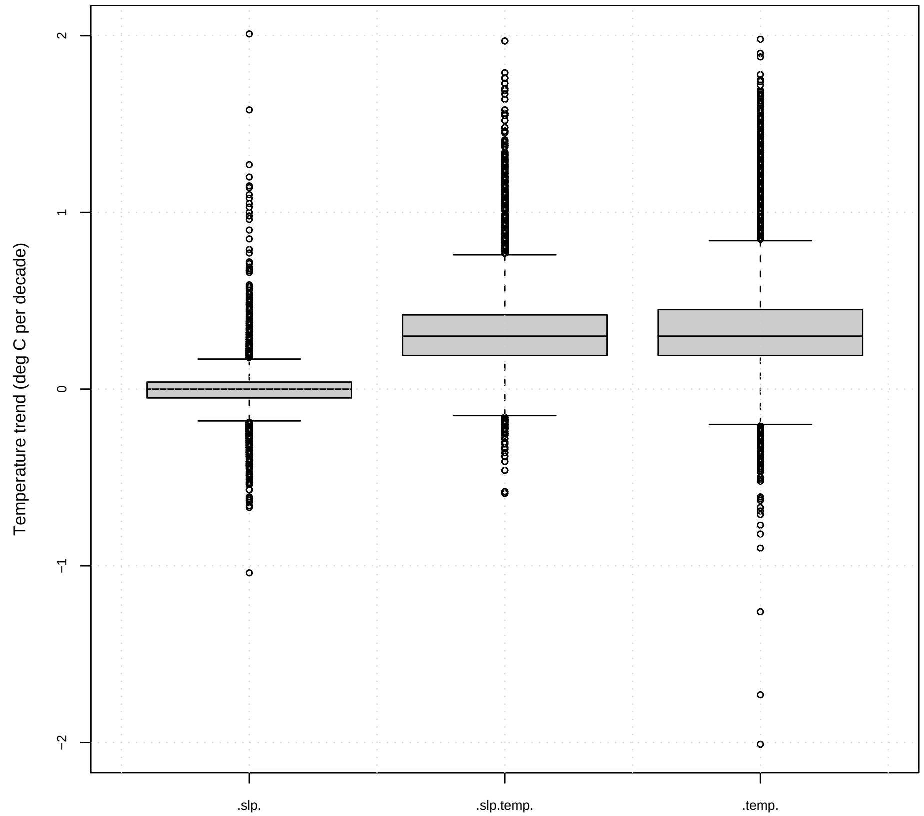
Neural nets and Self-Organising Maps…

Which parameters as predictors?

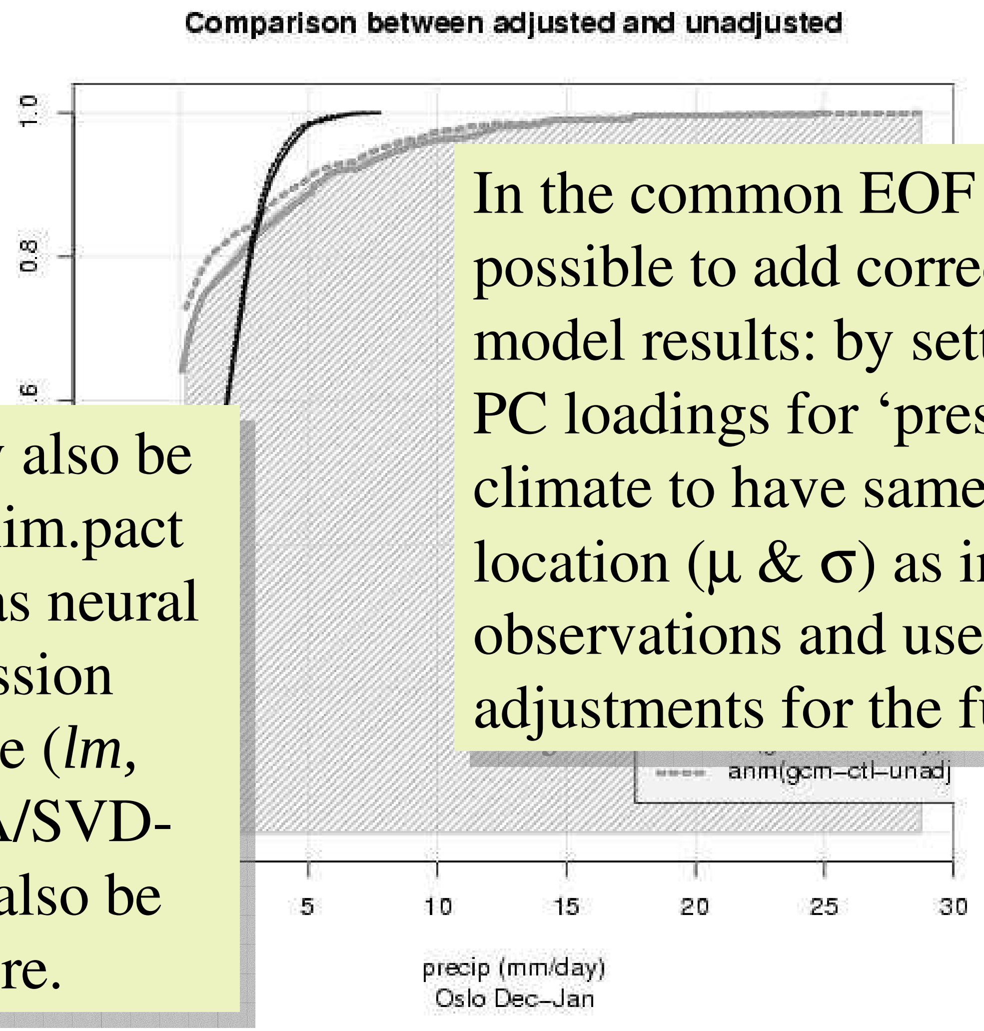
Strong & well-understood relationship (reflecting a physical mechanism)

Field that GCMs can skilfully reproduce

Parameters that carry the essential signal (e.g. a gradual global warming is not well-represented in SLP)



Choice of method: e.g. linear v.s. analog

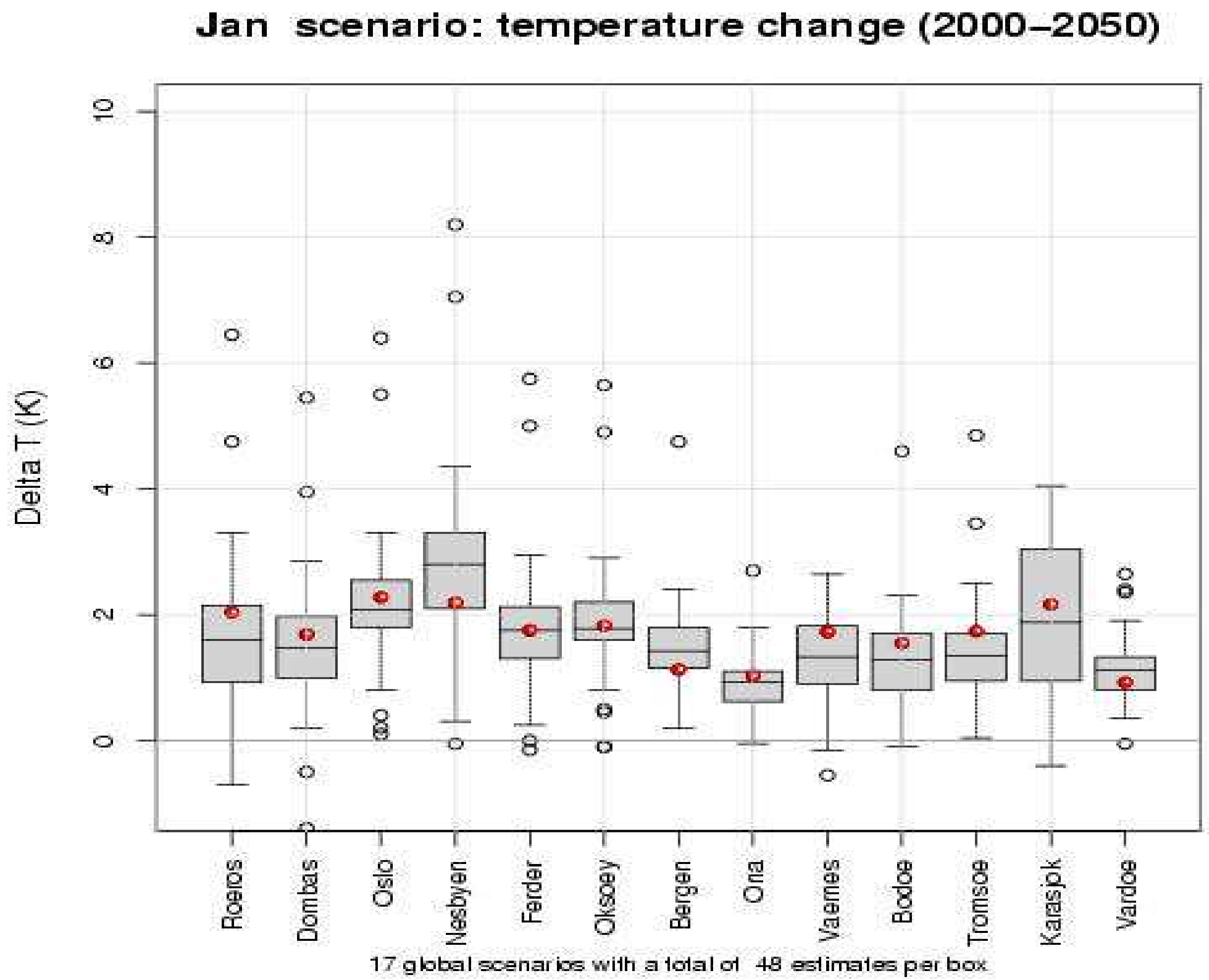


In the common EOF framework it is possible to add corrections to the model results: by setting PC loadings for 'present-day' climate to have same spread and location (μ & σ) as in the observations and use the same adjustments for the future.

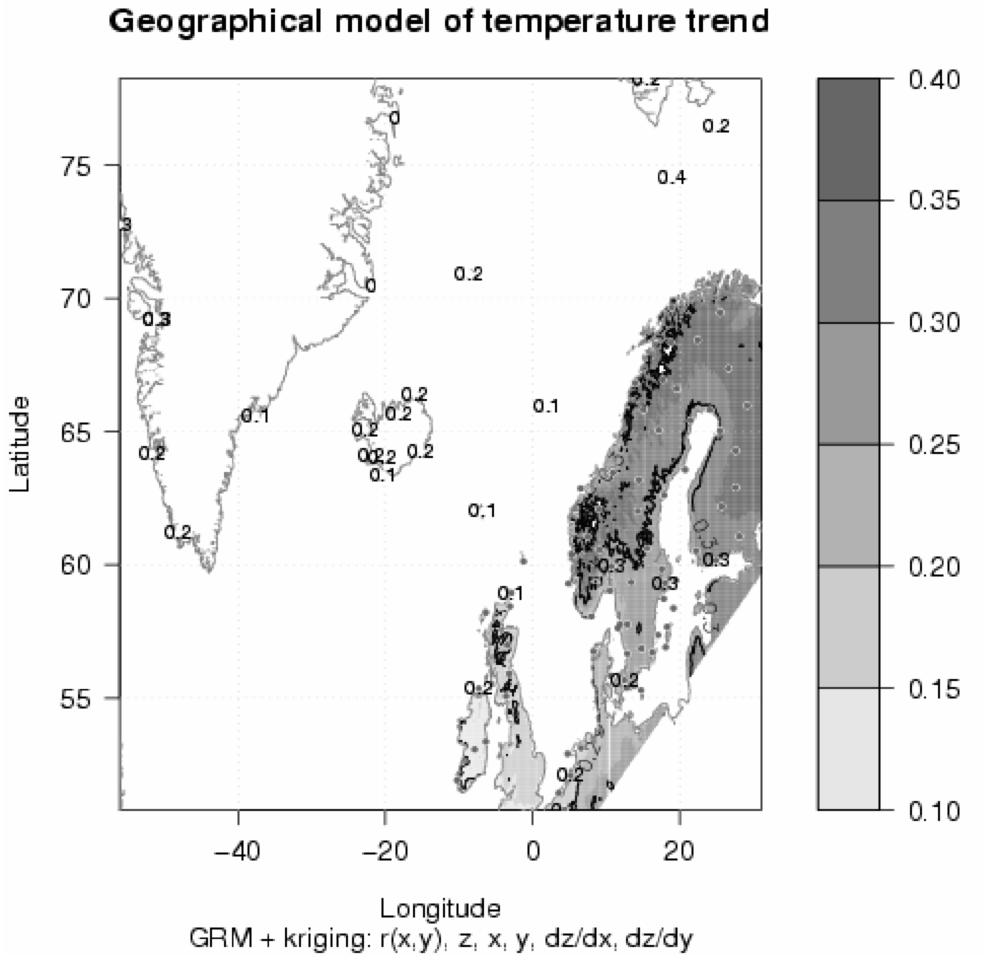
Other methods may also be incorporated into clim.pact in the future, such as neural nets. Various regression models are available (*lm, glm, etc.*), and CCA/SVD-based models may also be included in the future.

Probing uncertainties through multi-model ensembles:

Spread caused by different model shortcomings, natural variability & different initialisation processes.



Downscaling, ensembles & geographical distributi



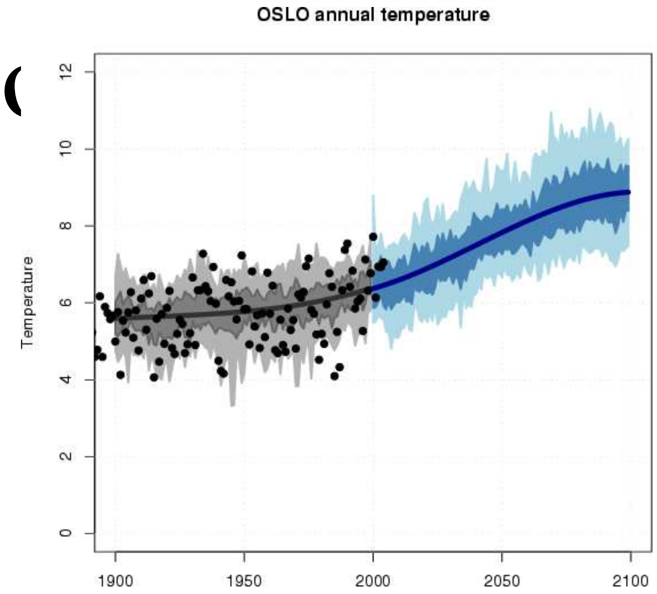
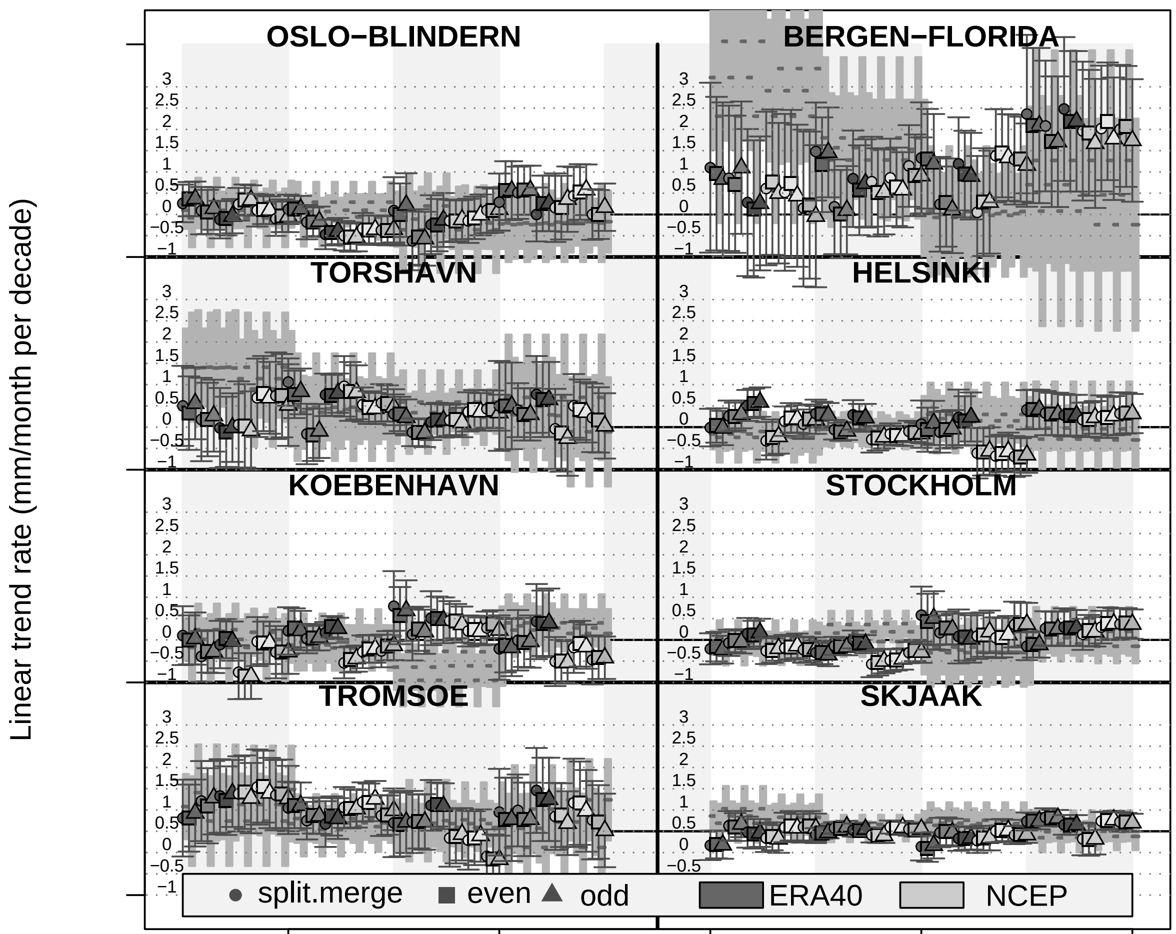


Table 3. Results from quality-control for GCMs with SRES A1b results for T(2m). The values are given in %.

GCM	f_s	f_m	$n_{m<0}$	$n_{R^2<0.6}$	$n_{p<0.1}$	D	f_{var}	r_{xy}	n_m	N^*
CNRM-CM3	10.34	0.57	4.02	8.05	2.30	4.885	46.265	45.98	1.72	174
GFDL-CM2.0	4.60	0.57	0.57	7.47	2.30	4.885	20.405	43.68	0.57	174
GFDL-CM2.1	5.78	0.00	16.76	7.51	2.31	4.915	29.190	43.93	1.73	173
GISS-AOM	15.52	0.29	29.60	7.18	1.72	4.885	49.715	44.83	0.57	348
GISS-EH	3.26	0.19	6.32	6.90	2.30	4.885	34.005	41.38	0.57	522
GISS-ER	5.75	0.00	2.87	10.34	2.87	4.885	46.550	43.10	1.72	174
INM-CM3.0	17.82	0.57	0.57	7.47	2.30	4.885	41.380	44.83	7.47	174
IPSL-CM4	16.67	0.00	1.15	6.90	2.30	4.885	25.575	44.83	0.00	174
ECHAM5/MPI-OM	13.63	0.38	0.77	7.49	2.69	4.895	42.805	47.60	0.77	521
MRI-CGCM2.3.2	16.91	0.57	0.00	6.97	2.29	4.855	50.345	45.03	1.37	875
CCSM3	18.29	0.57	0.57	7.14	2.29	4.855	43.430	45.14	1.43	350
PCM	0.57	0.57	1.14	7.43	2.29	4.855	29.145	41.71	0.57	175
UKMO-HadCM3	23.43	0.57	1.14	6.86	2.29	4.855	41.715	45.71	0.00	175

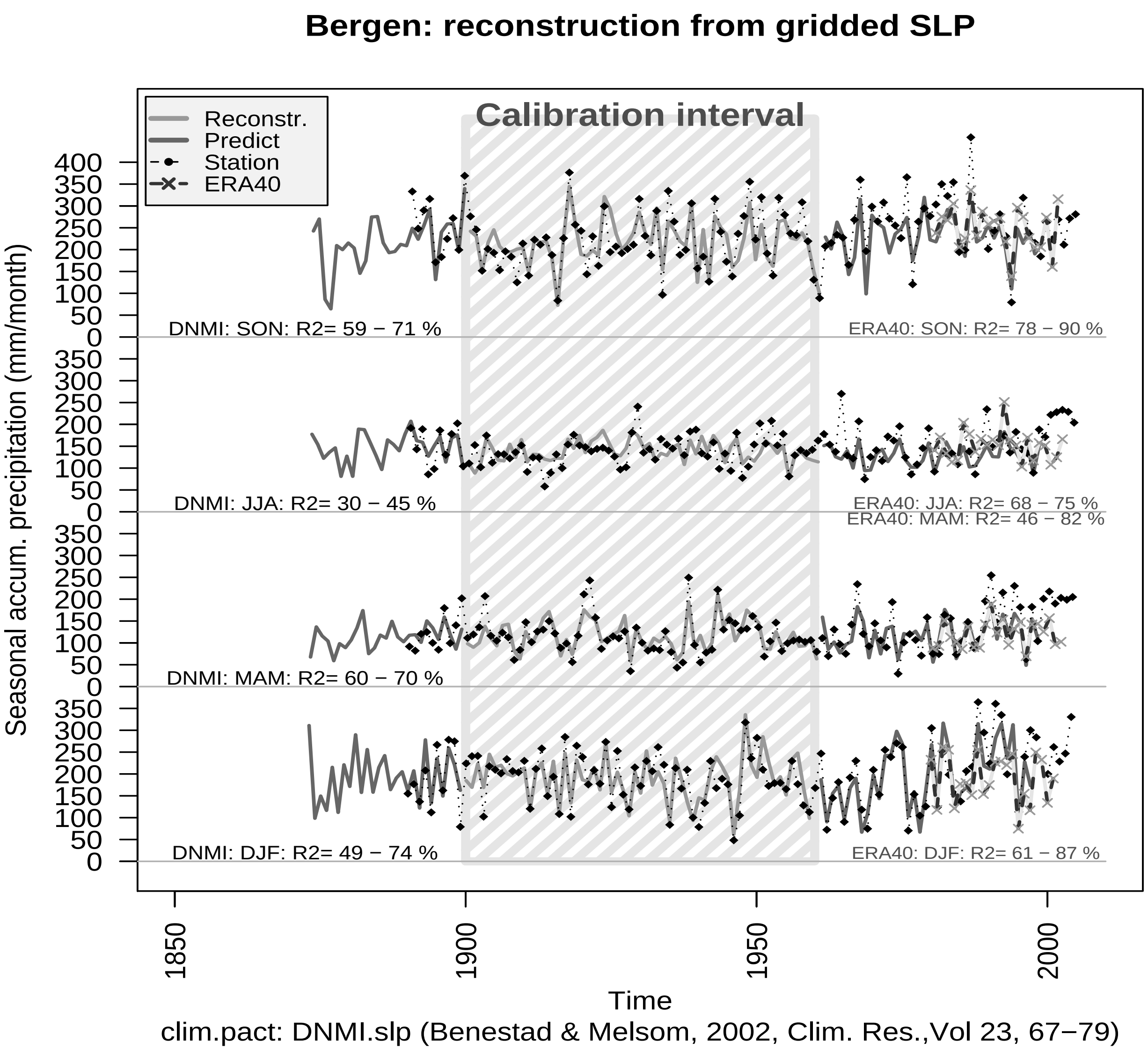
Precipitation

Slope estimates

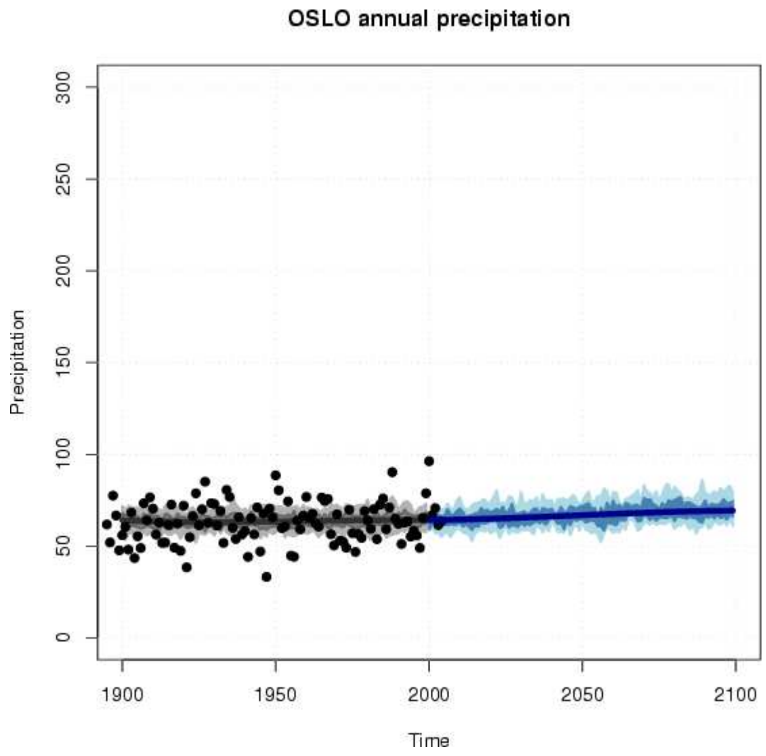


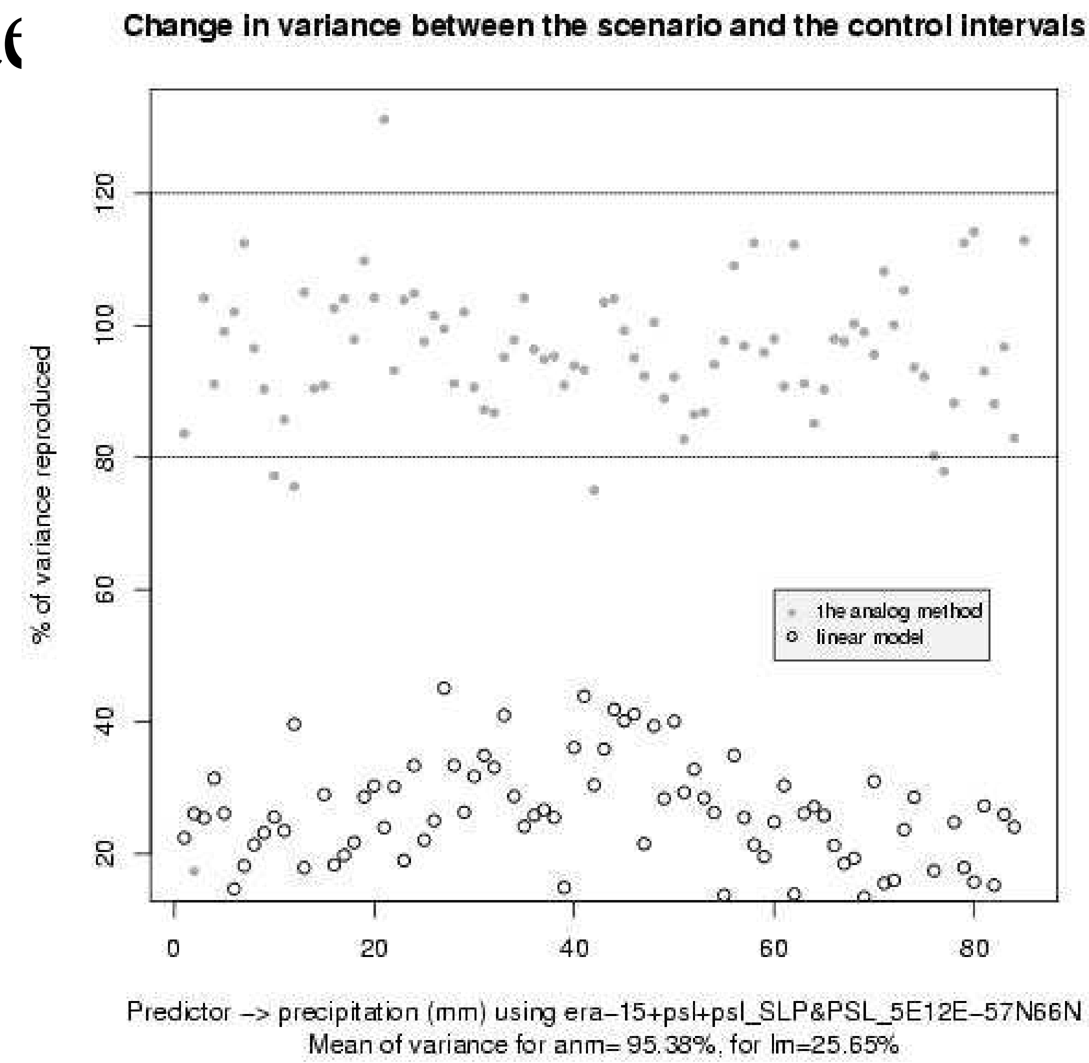
Predictors= prec , slp & mix

Validation of models



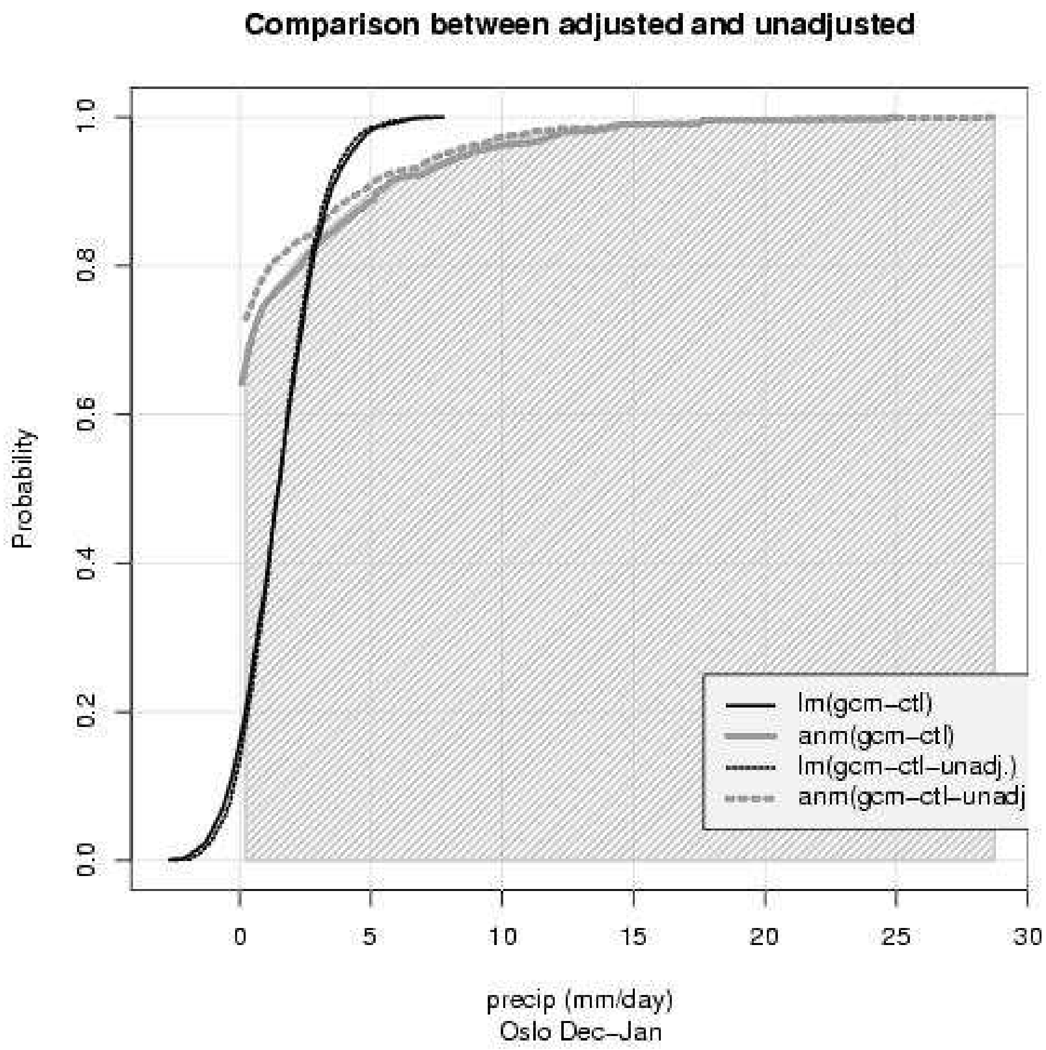
When a fraction of the variance can be accounte



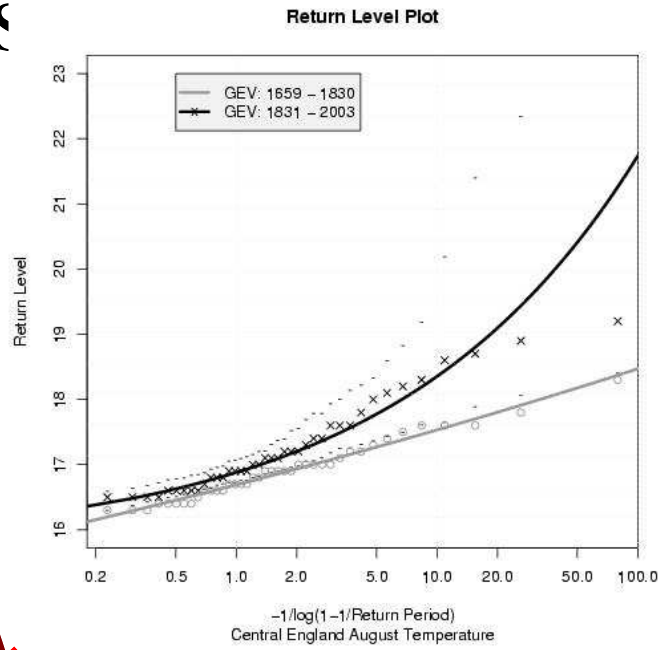


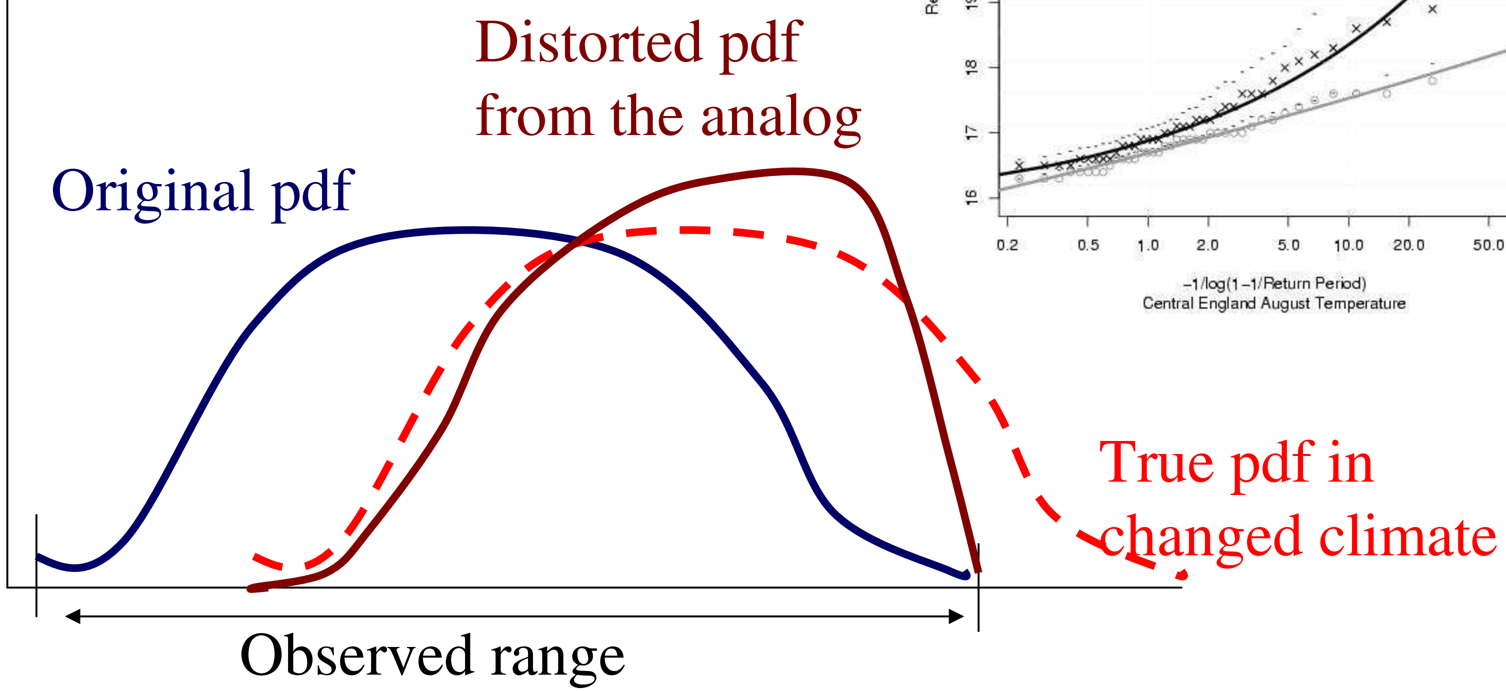
Daily rainfall

Linear (regression) models fail to give a good representation of the tails of the disribution. Other approach: **the analog model.**

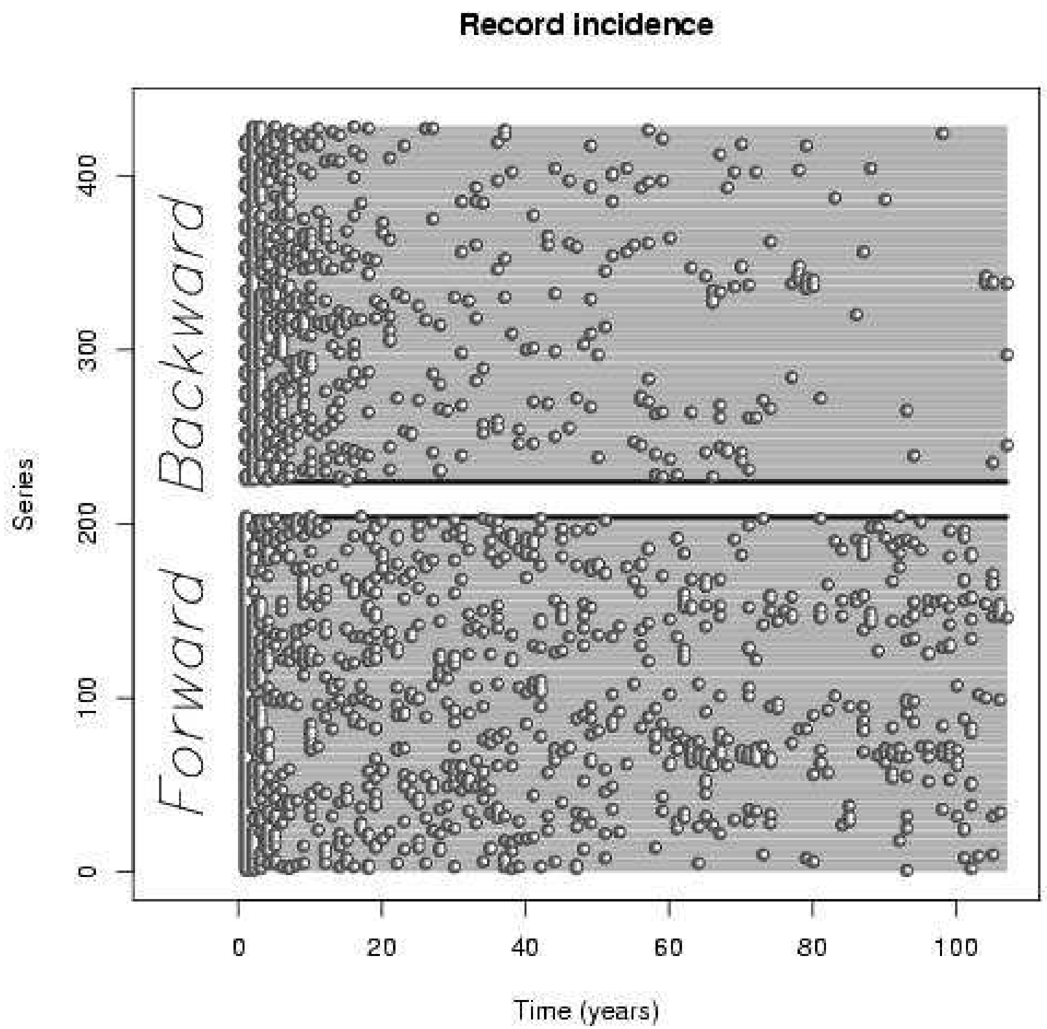


Analog model not representative for a situation where the upper tail of the distribution (pdf) is being s

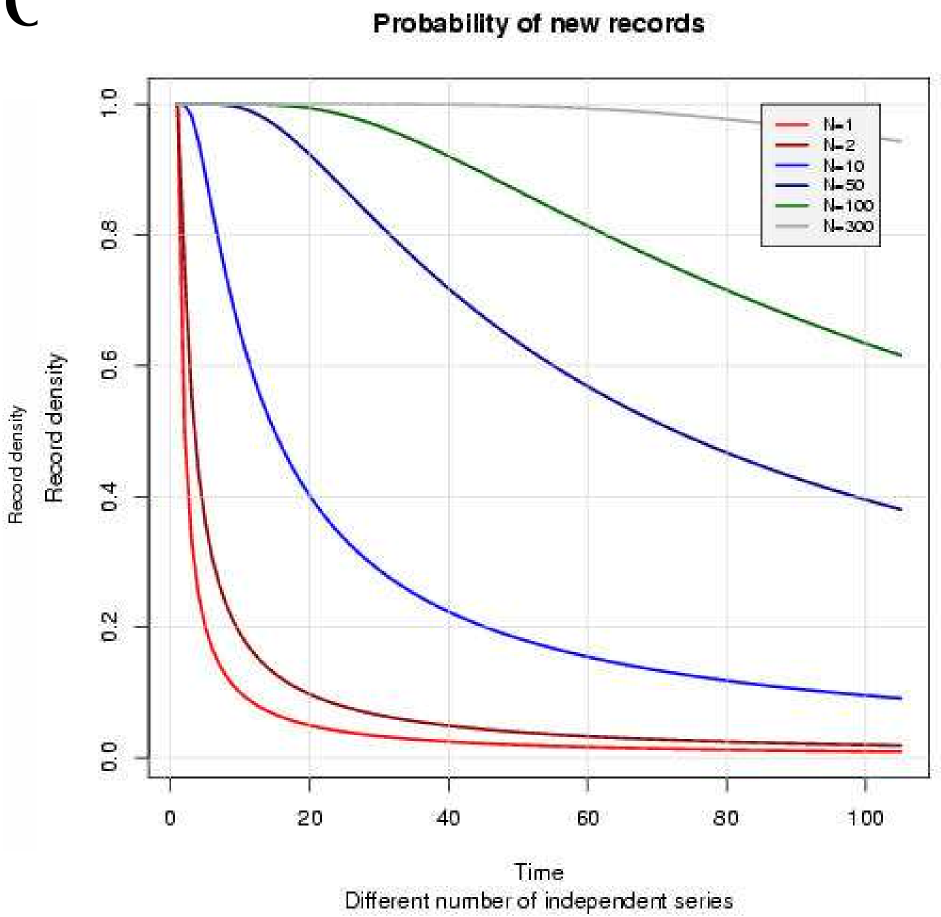




Record-events= values outside historical sample range



Caveat: the traditional analog model cannot predict values outside the c

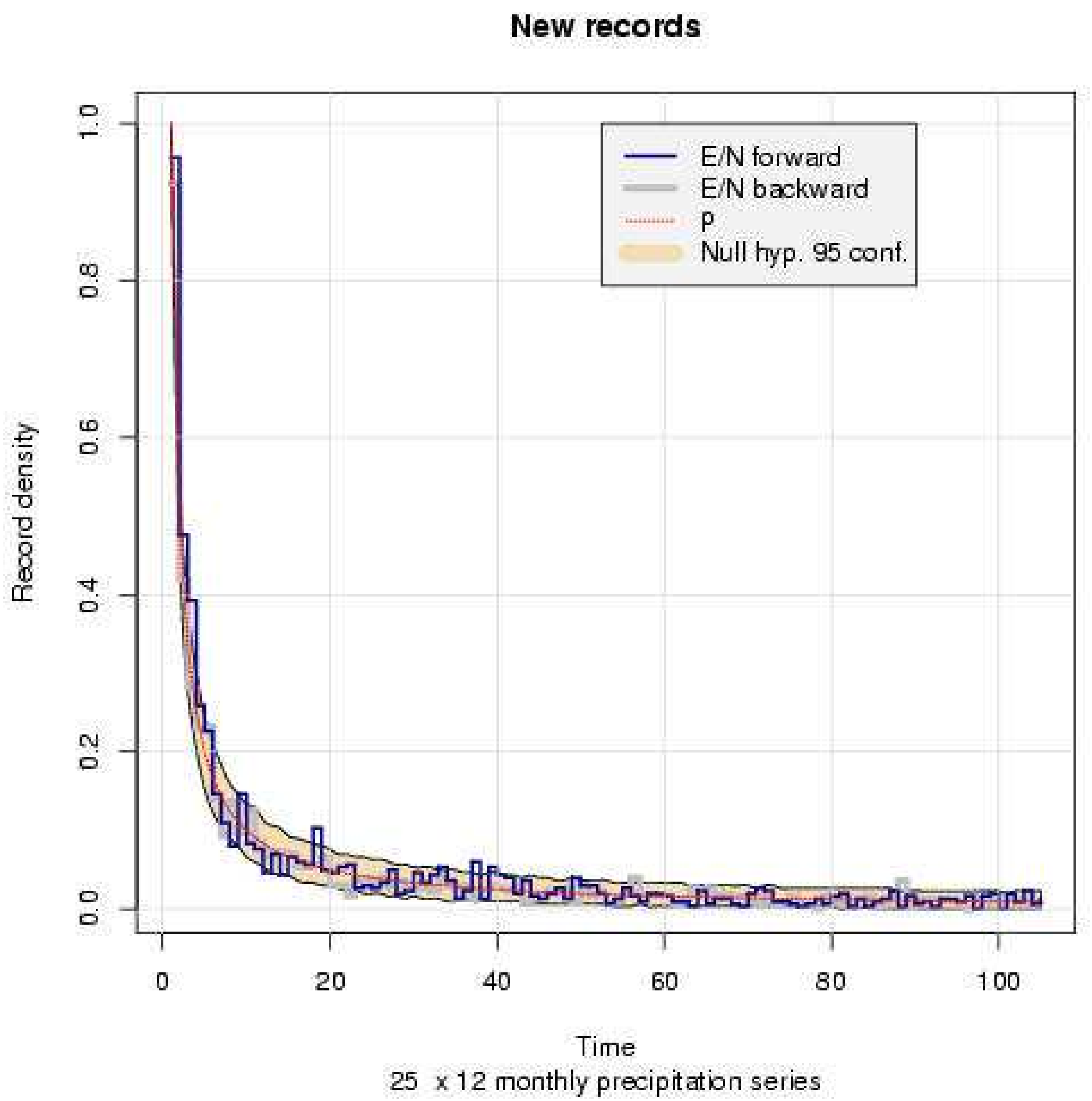


A random variable of rational numbers with independent and identical distribution (iid) has following property:

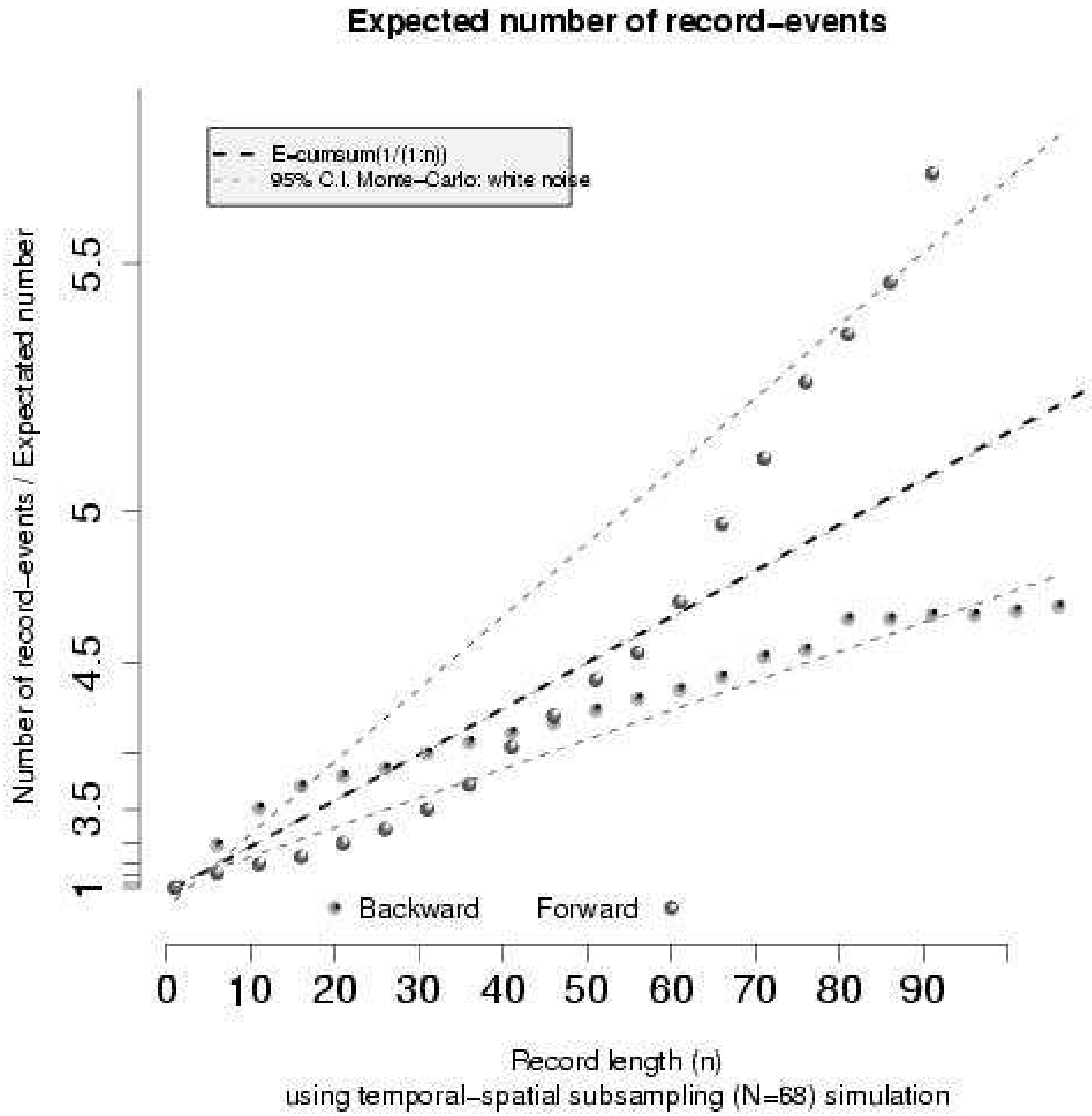
Pr(n=record) = 1/n

(assuming no ties)

Record-event statistics



Test of number of record-events: iid test



Re-cap of Uncertainties…

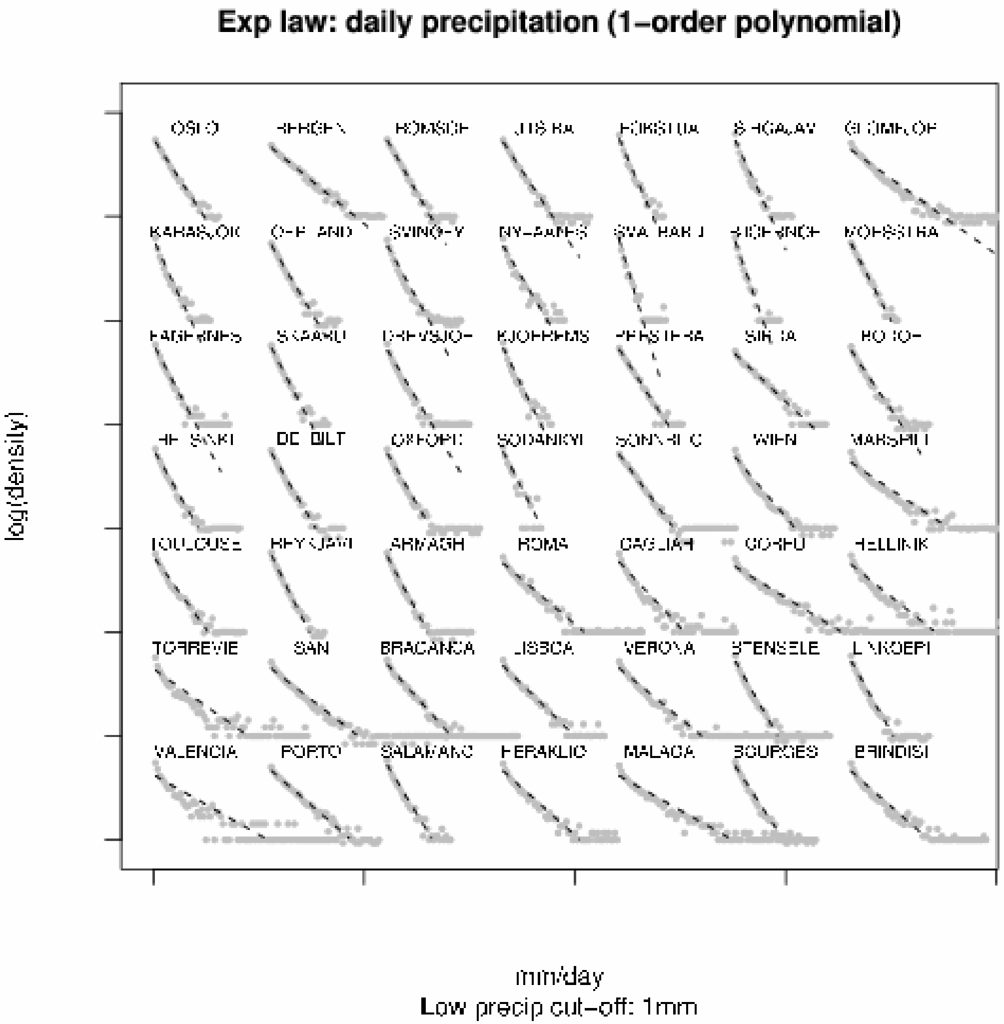
- Mean values – extremes are difficult
- Model shortcomings (systematic biases).
  - *Can be explored to a certain extent through multi-model ensembles.*
  - *Analysis, validations, & diagnostics (clim.pact)*
- Imperfect downscaling methods and choice of set-up.
  - *Can be explored through different choices and methods (eg clim.pact, SDSM, & nested models)*
  - *Validation exercises.*
- Natural variability, GCM initiation, & additional forcing factors.
  - *Ensembles of GCM exmperiments.*
- Emission scenarios.
  - *Multi-emission scenario ensembles.*

Possible solution

- Downscale the pdf?
- If the type of pdf shape is given (eg Gaussian, gamma, etc), and the parameters determining the exact structure of the pdf are systematically influenced by a set of conditions, then it may be possible to downscale the parameters for the pdfs.

Dependency of pdf on local conditions

For many situations, the linear-log relationships are approximately linear, indicating that an exponential law provides a reasonable fit. But, still some discrepancies in the upper tail.

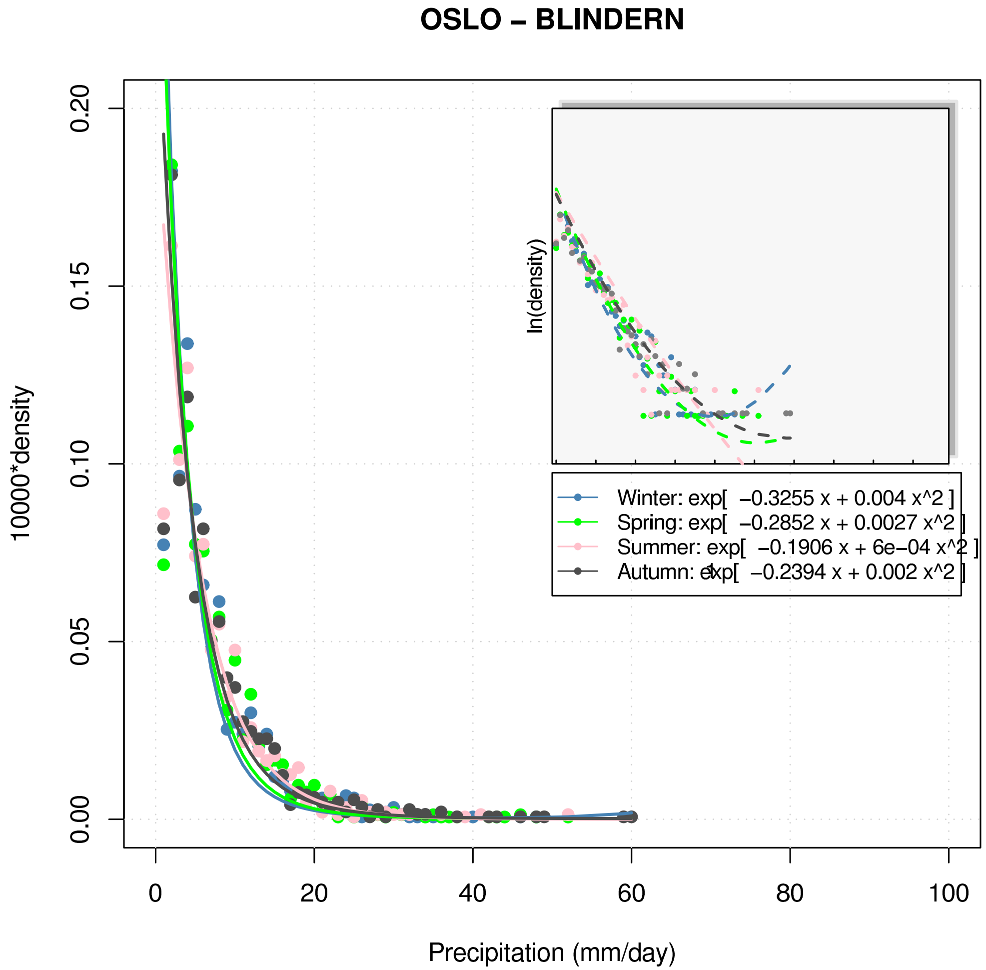


Exponential law: simpler than the gamma distribution

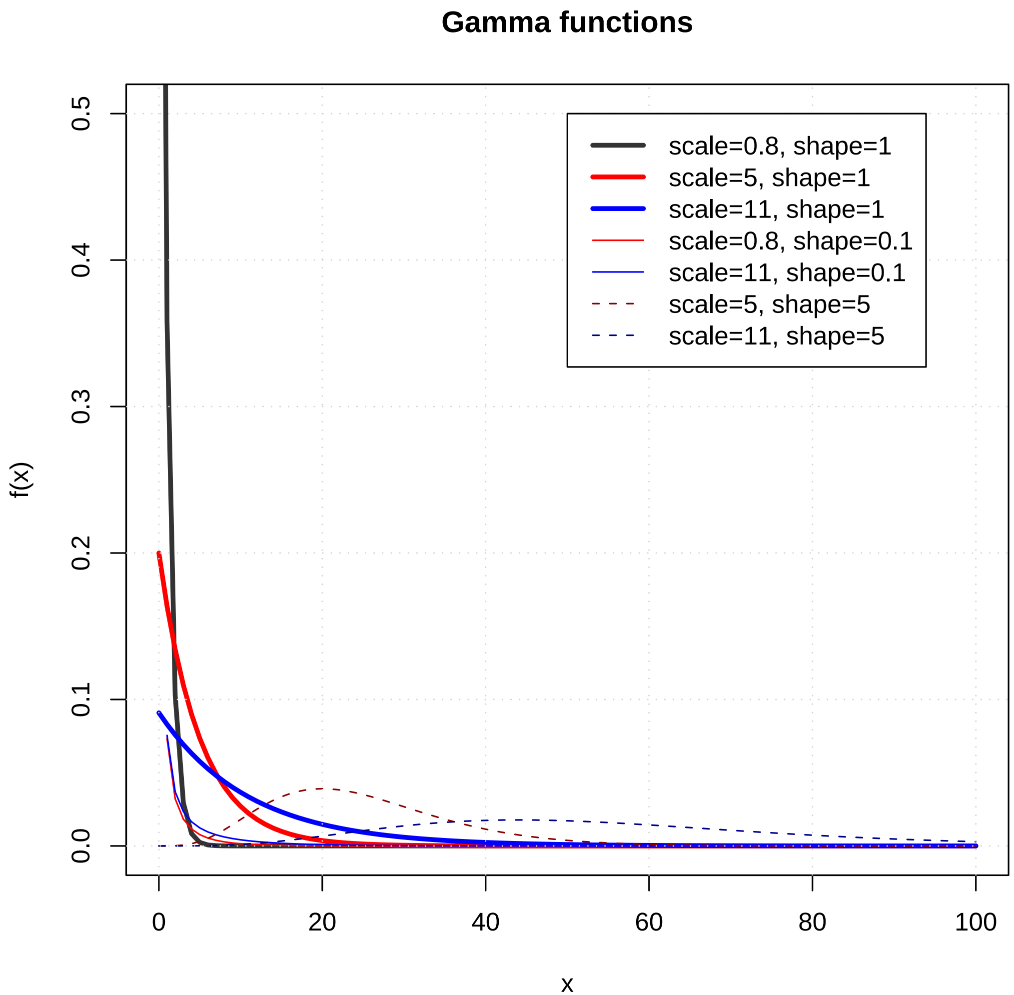
pdf:

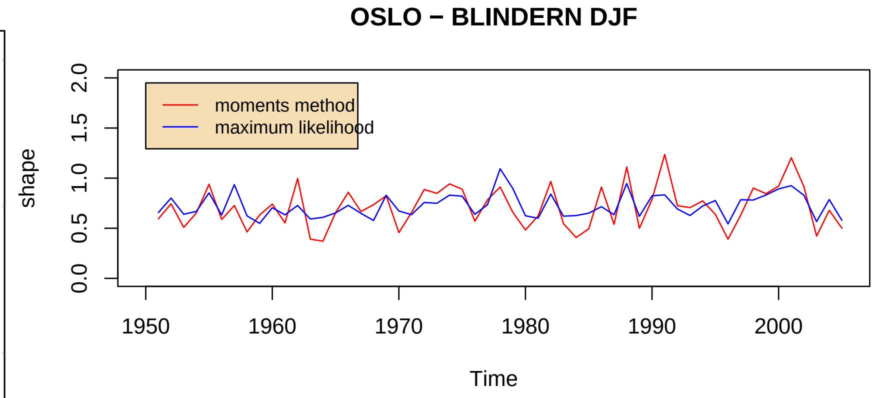
$p(x) = -m \exp\{-mx\}$

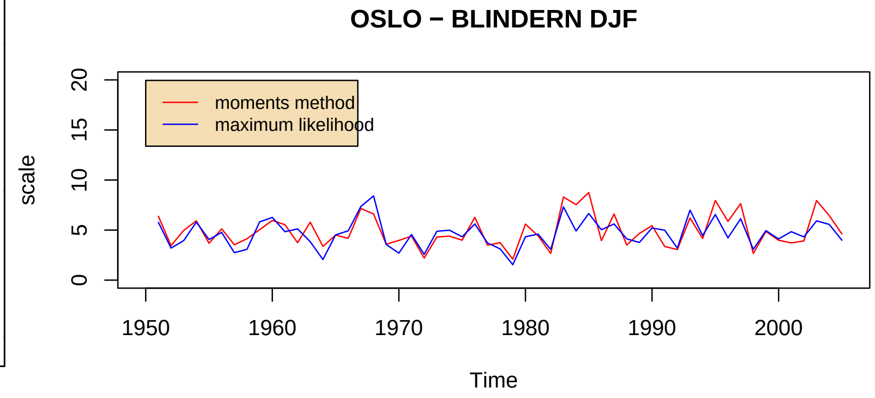
m varies with local mean temperature and precipitation



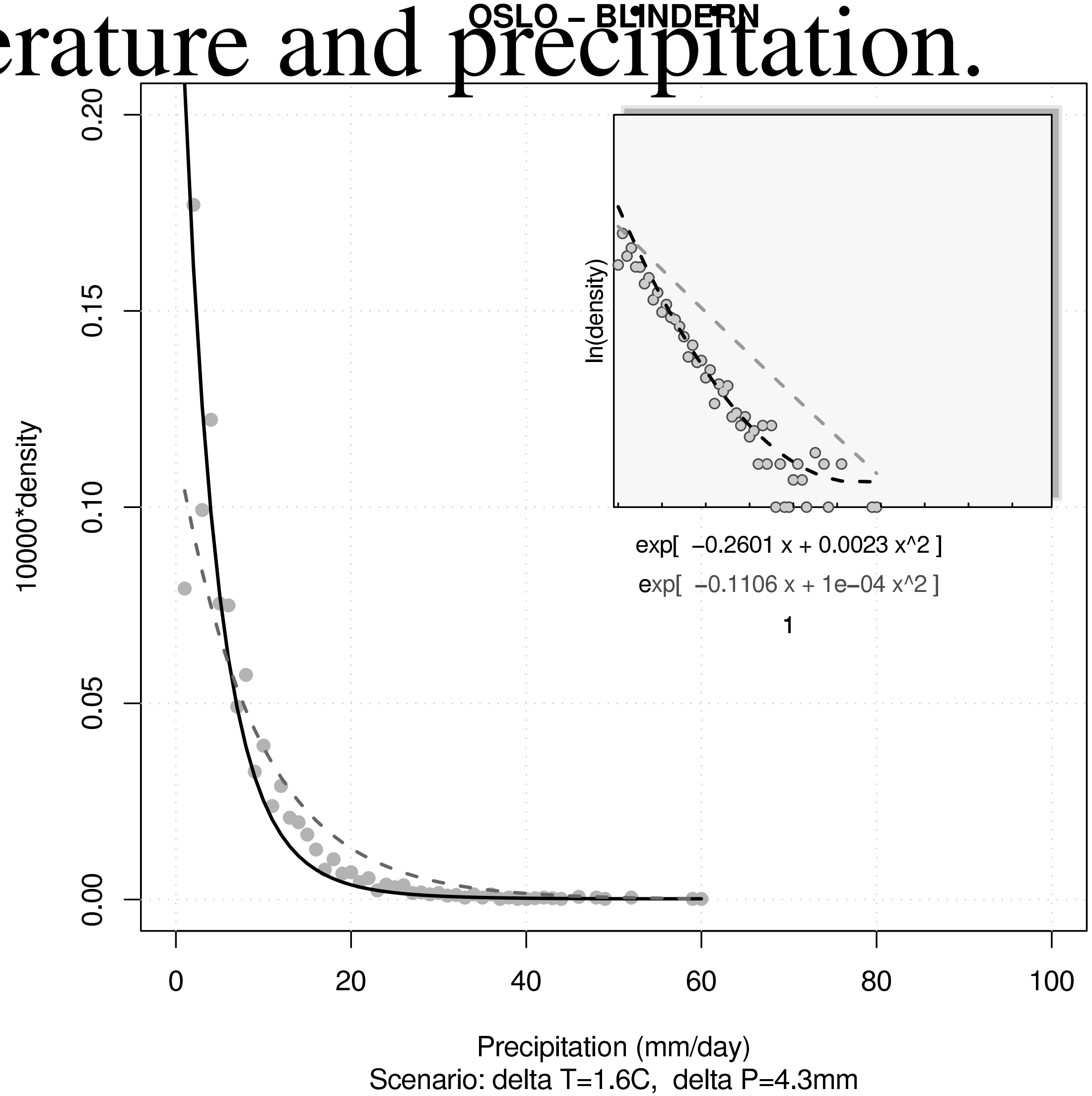
Ways of modelling the tails







Scenario for the future: derived from downscaled changes in the mean temperature and precipitation.

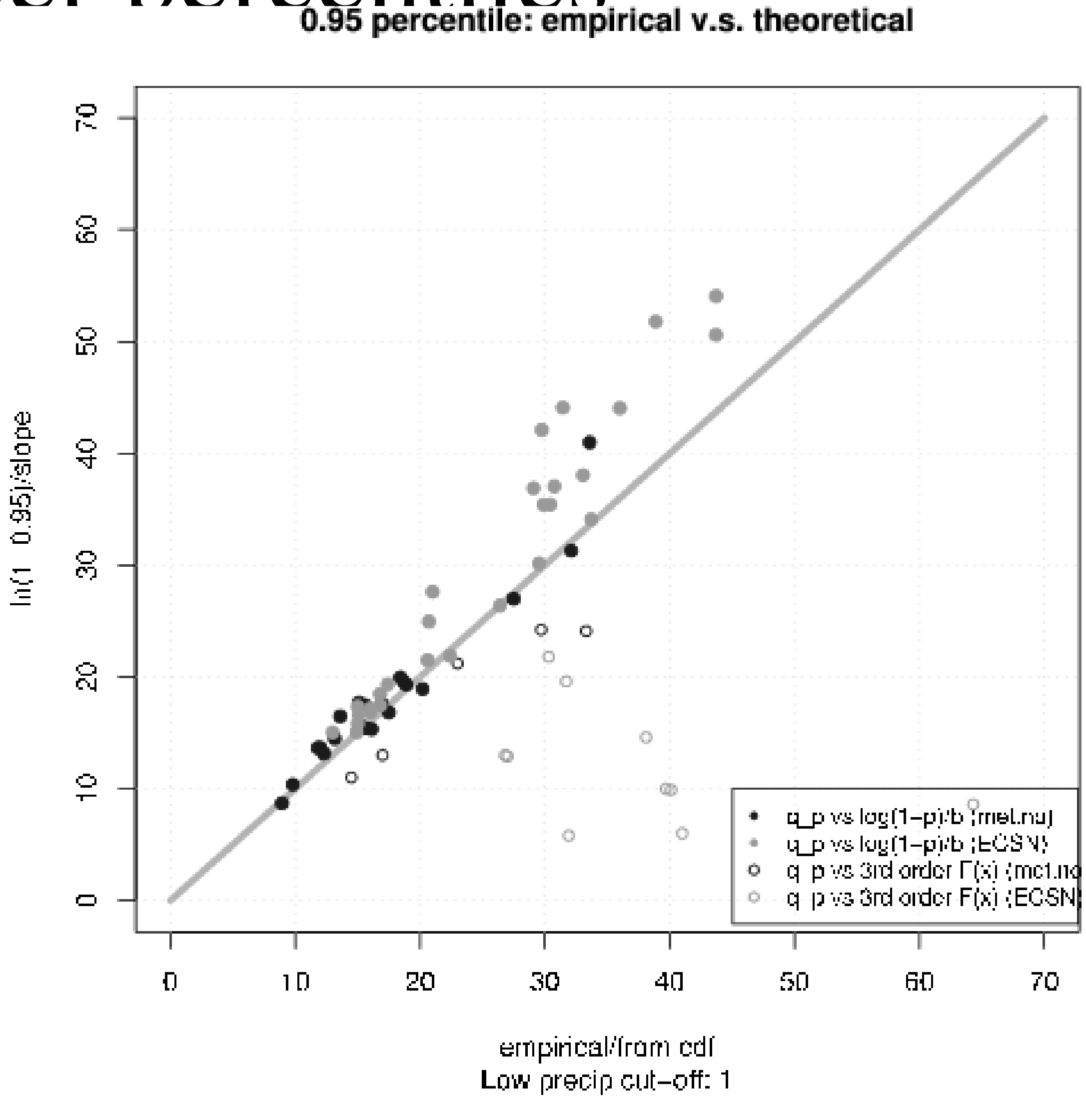


Exponential law: simple expression for upper percentiles

$Q_p = \log(1-p)/m$

$M = -1/m$

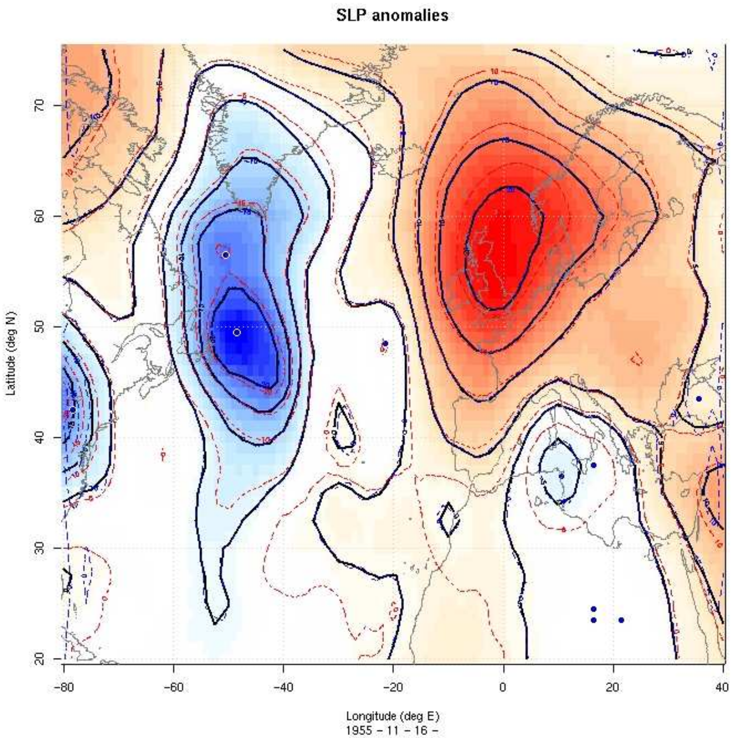
$S = -2/m^2$

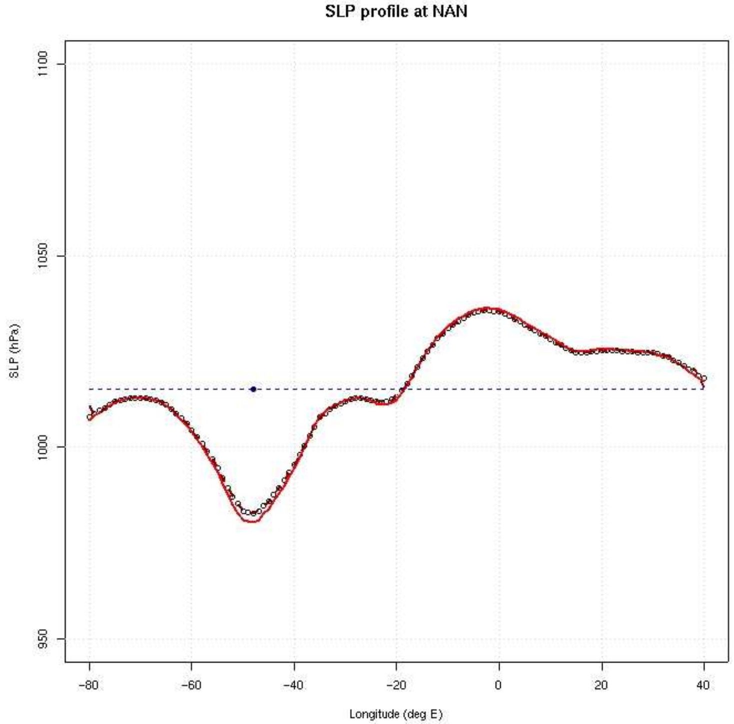


extremes – severe events: cyclones

(usually, we are not particularly interested inextremes because they

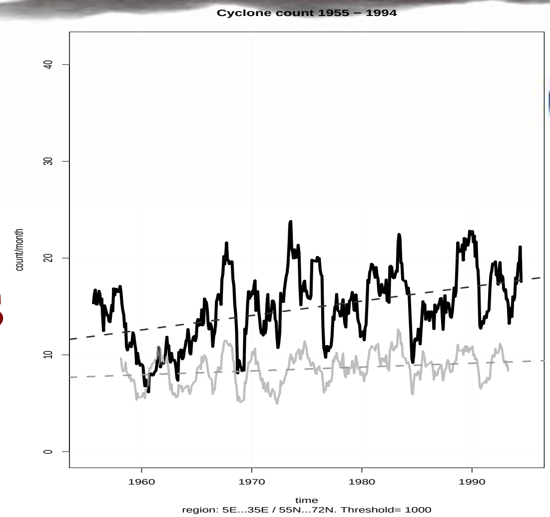
se

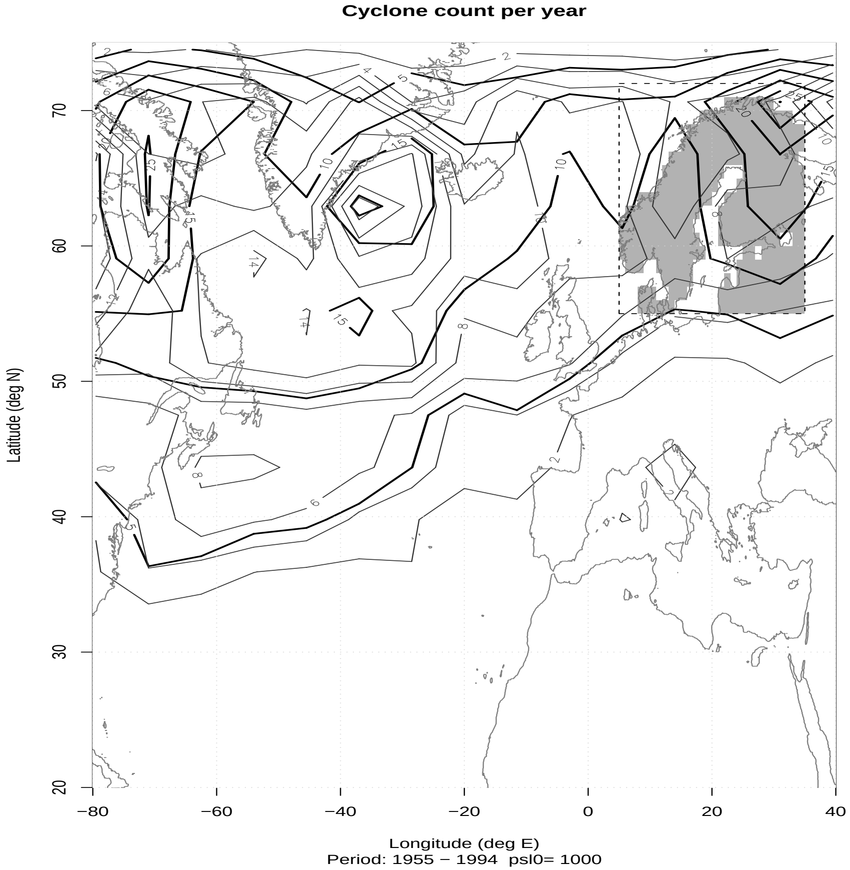


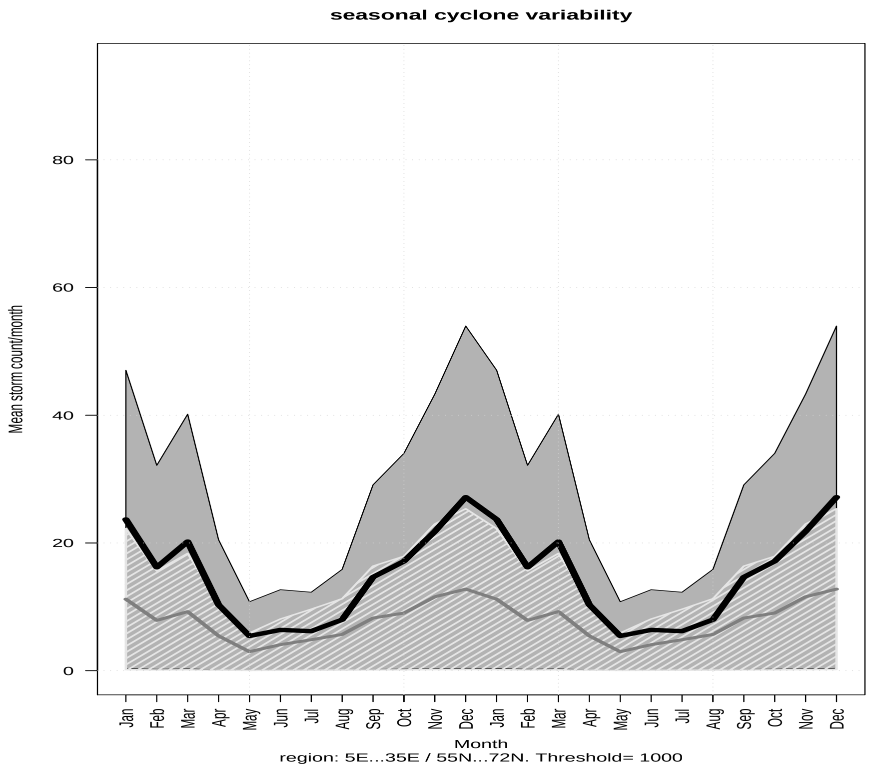


Downscaling cyclones

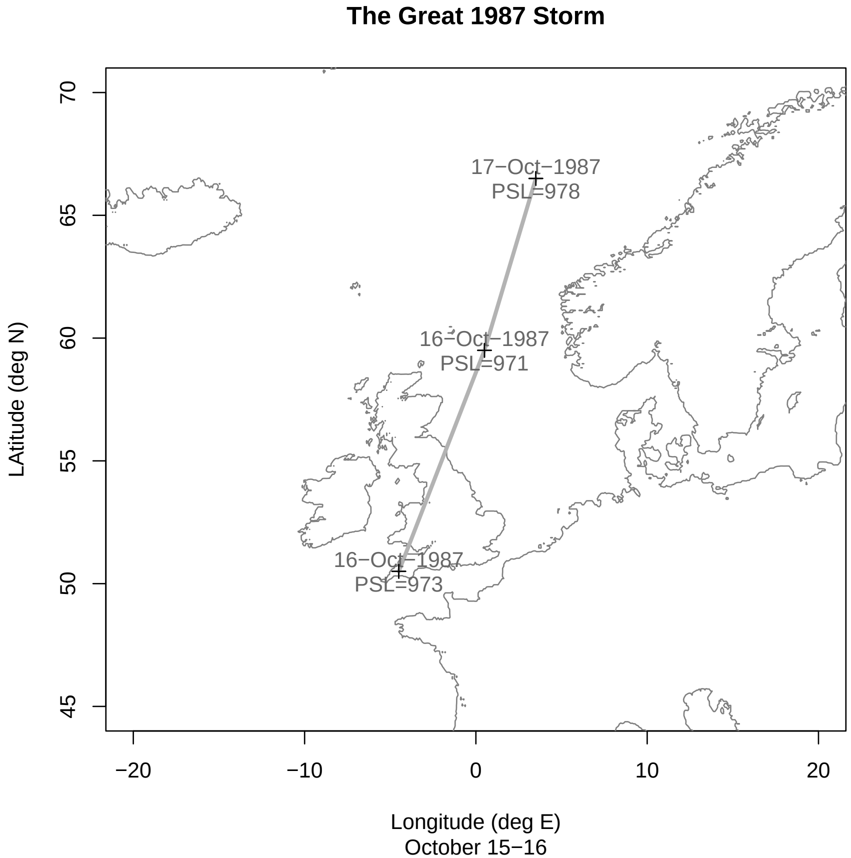
Validation: analysis of observations



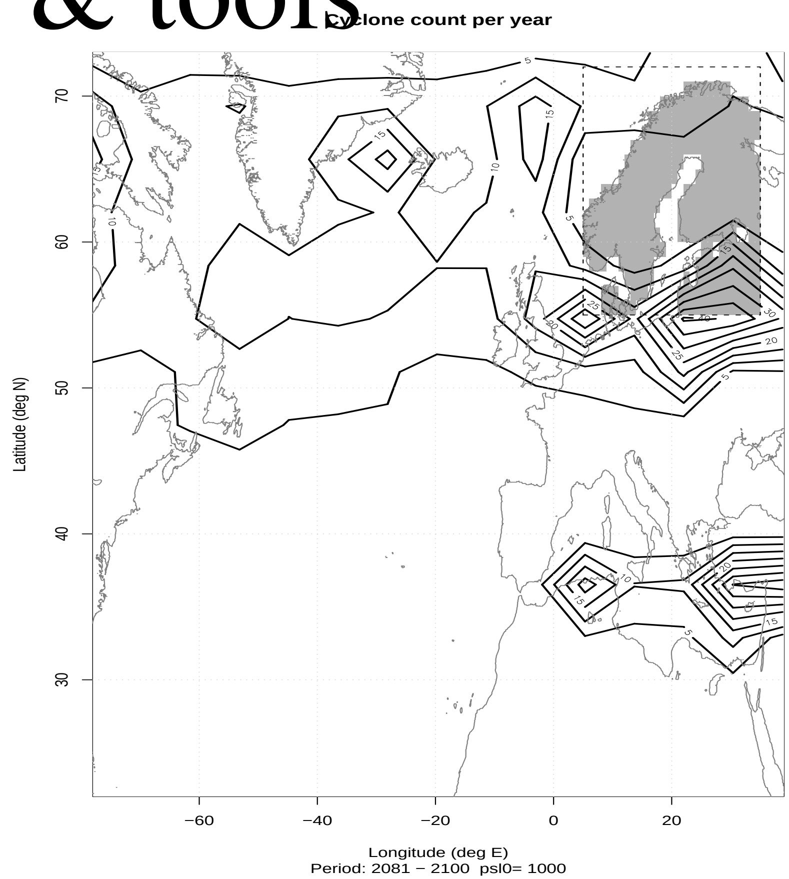




Testing the models & tools



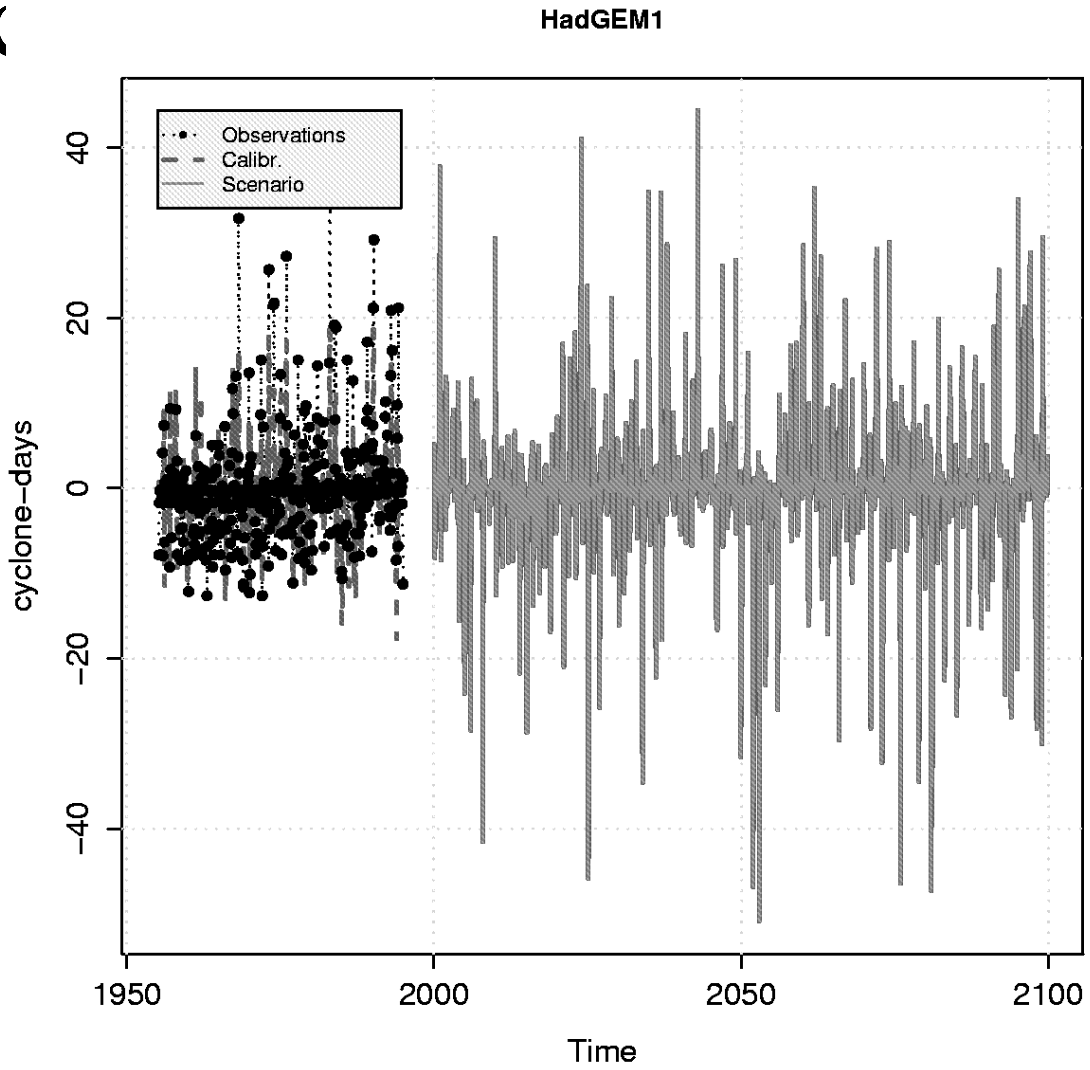
Reproduces known storms



GCMs may not have sufficient spatial resolution for proper representation of cyclones.

Downscaled storm frequency over Fennos

Use the observed time series of cyclone counts as predictand – treating it like a station series – and applying an ordinary downscaling analysis to this, based on monthly SLP.



Summary

- Downscaling as a tool for analysis
  - Methods: strengths and weaknesses
  - Uncertainties
  - Applications
- Extremes
  - Tails of the pdf
  - Record-events & test of non-iid behaviour
  - In the meaning of severe events

Thank you for you attention