Spatial validation

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What?

- point-to-point spatial dependencies
  - spatial autocorrelation
- regions of similar temporal behaviour
  - temporal behaviour: e.g.
    - full time series (daily, monthly)
    - annual cycle
  - tools
    - cluster analysis
    - principal component analysis

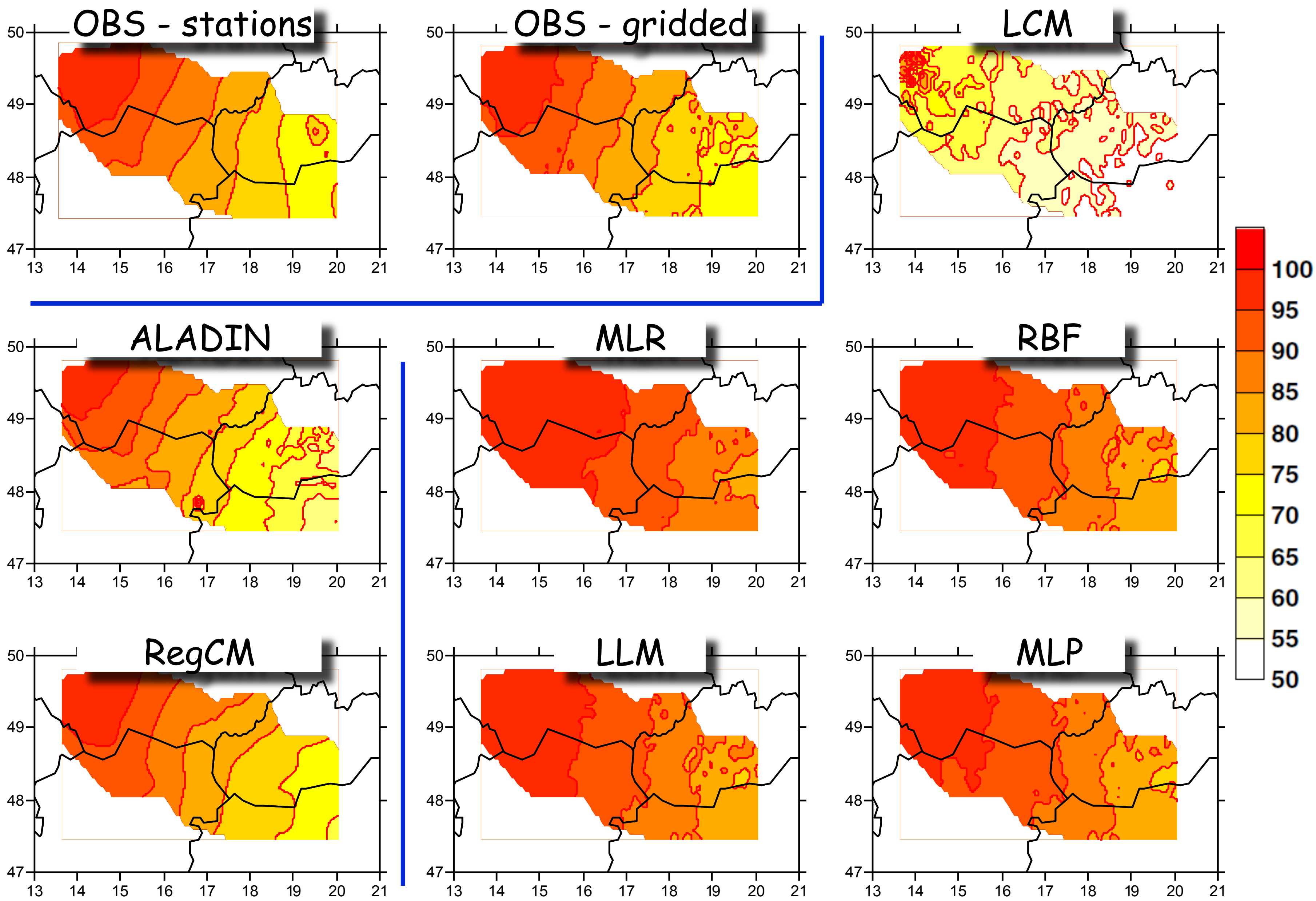
Why?

- important for various impact sectors
  - hydrology
  - ecology
  - …

Spatial autocorrelation

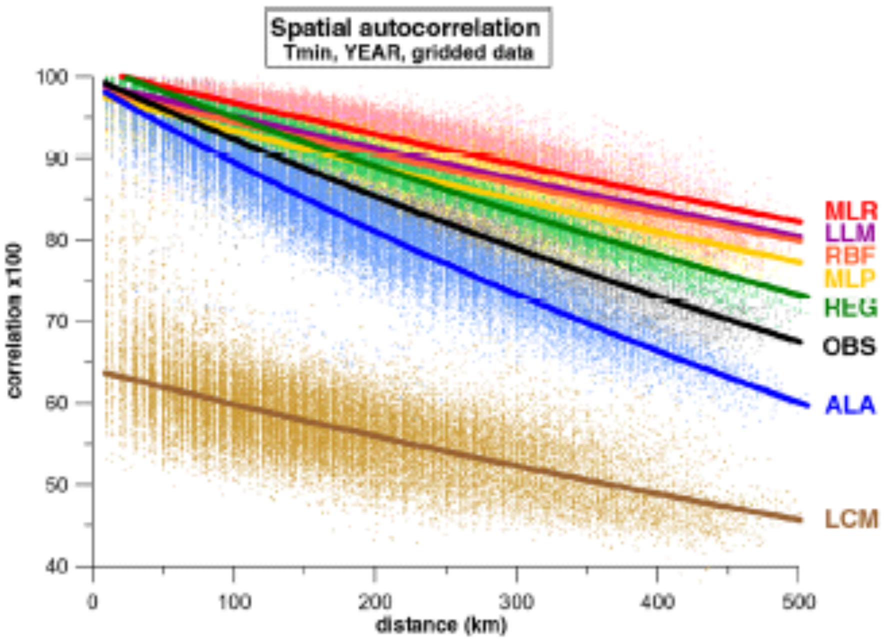
- correlations with values at a single site (station, gridpoint)
- mapped

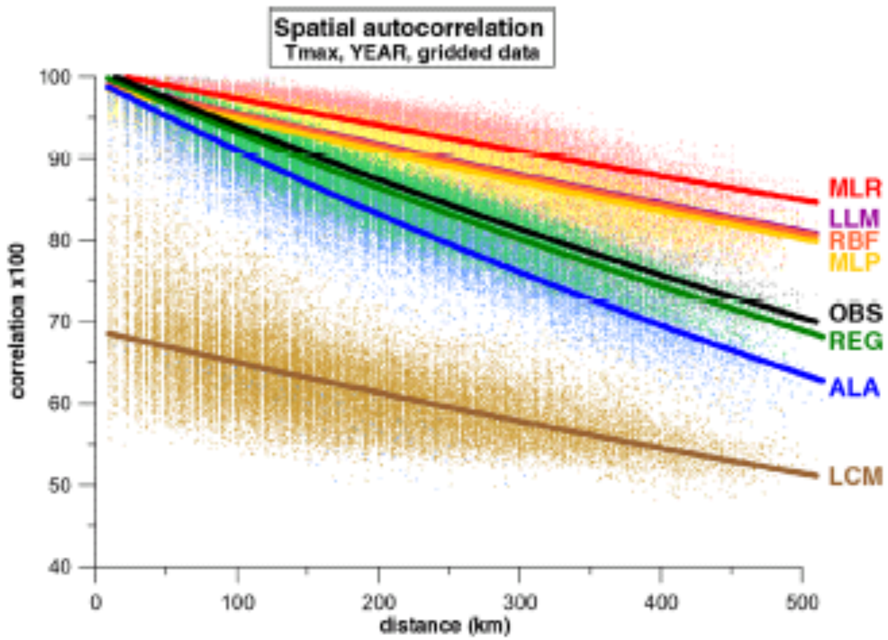
autocorrelation, Tmax, with NW-most point

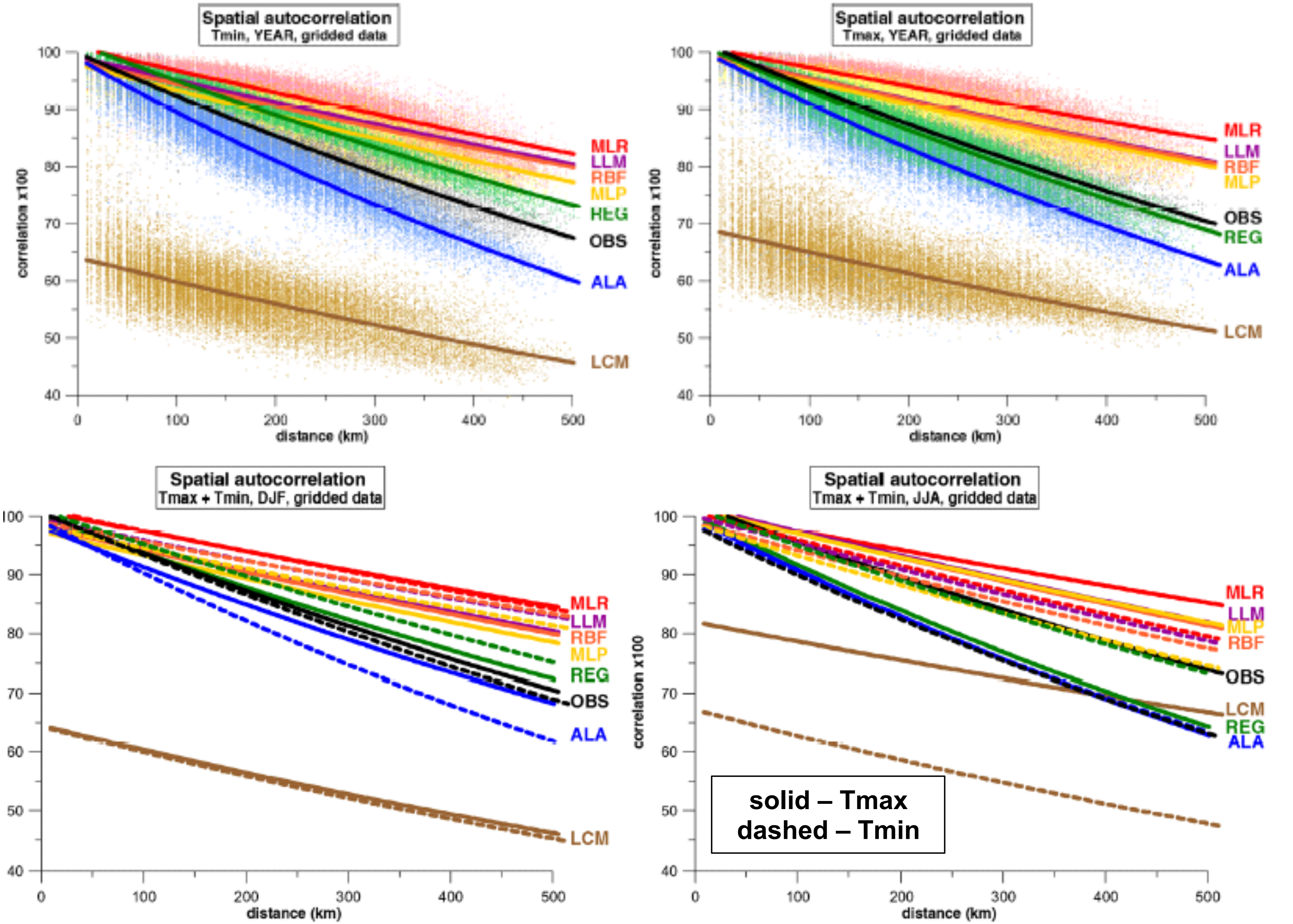


Spatial autocorrelation

- many autocorrelation maps ➔ need to aggregate information
- autocorrelation vs. distance plot (dots)
- with logarithmic fit overlaid (lines)
- another level of aggregation ➔ single number: autocorrelation distance







Spatial autocorrelation
Tmin, YEAR, gridded data
Spatial autocorrelation
Tmax, YEAR, gridded data
Spatial autocorrelation
Tmax + Tmin, DJF, gridded data
Spatial autocorrelation
Tmax + Tmin, JJA, gridded data
correlation x100
distance (km)
MLR
LLM
RBF
MLP
REG
OBS
ALA
LCM
solid – Tmax
dashed – Tmin

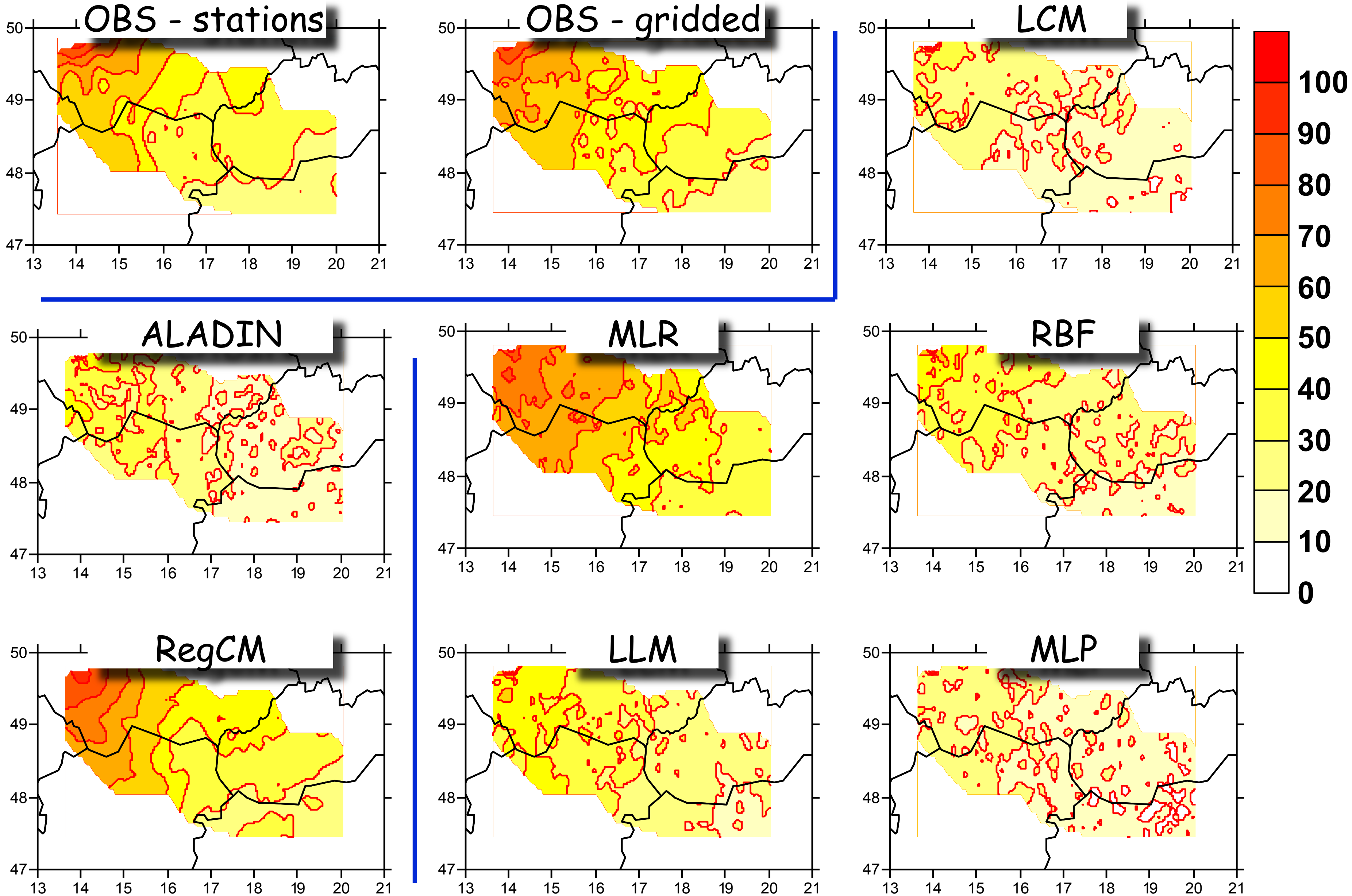
Spatial autocorrelation – precip occurrence

- binary variable
- Heidke "skill" score is used as a measure of binary correlation
- HSS = 2(ad-bc)/[(a+c)(c+d) + (a+b)(b+d)]

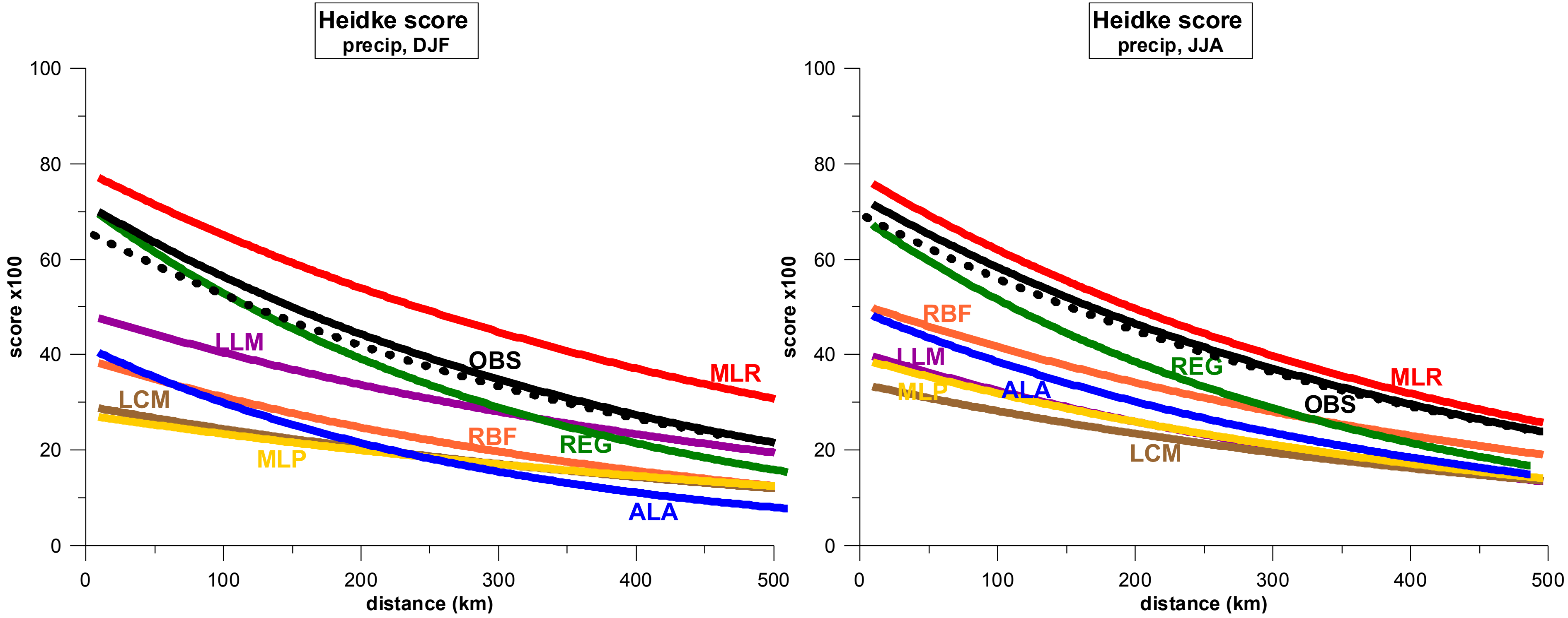
Event forecast	Event observed		
	Yes	No	Marginal total
Yes	a	b	a + b
No	c	d	c + d
Marginal total	a + c	b + d	a + b + c + d =n

- attains values from -∞ to +1 (perfect forecast)
- here, not in the context of forecasting
- "observation" = value at the reference site
- "forecast" = value at the other (target) site

spatial autocorrelation of precip occurrence – Heidke score, DJF

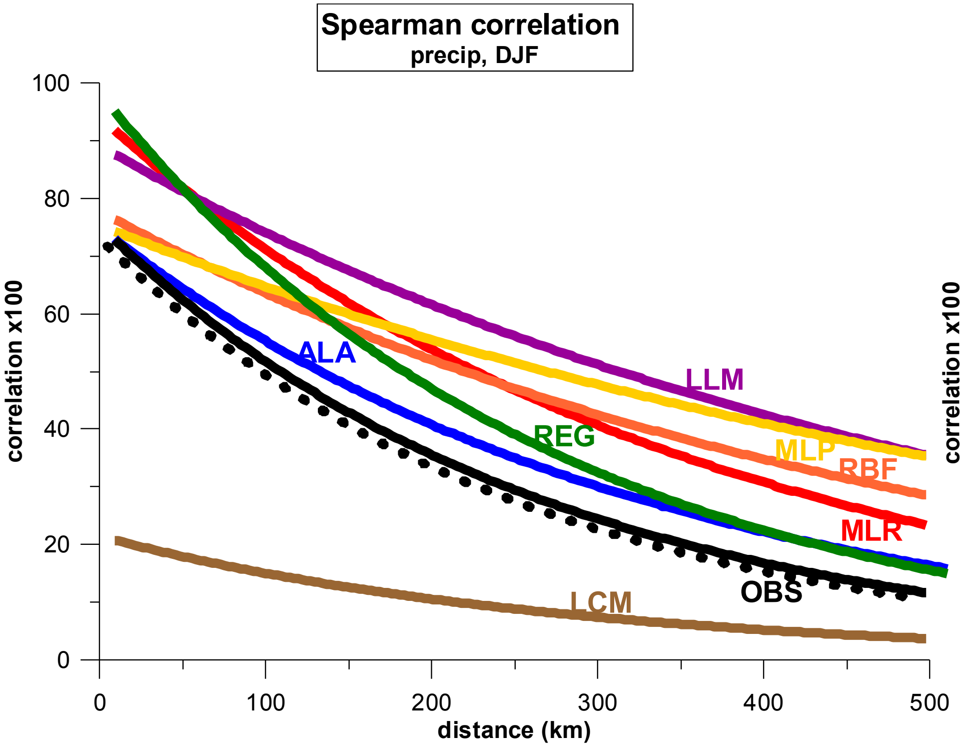


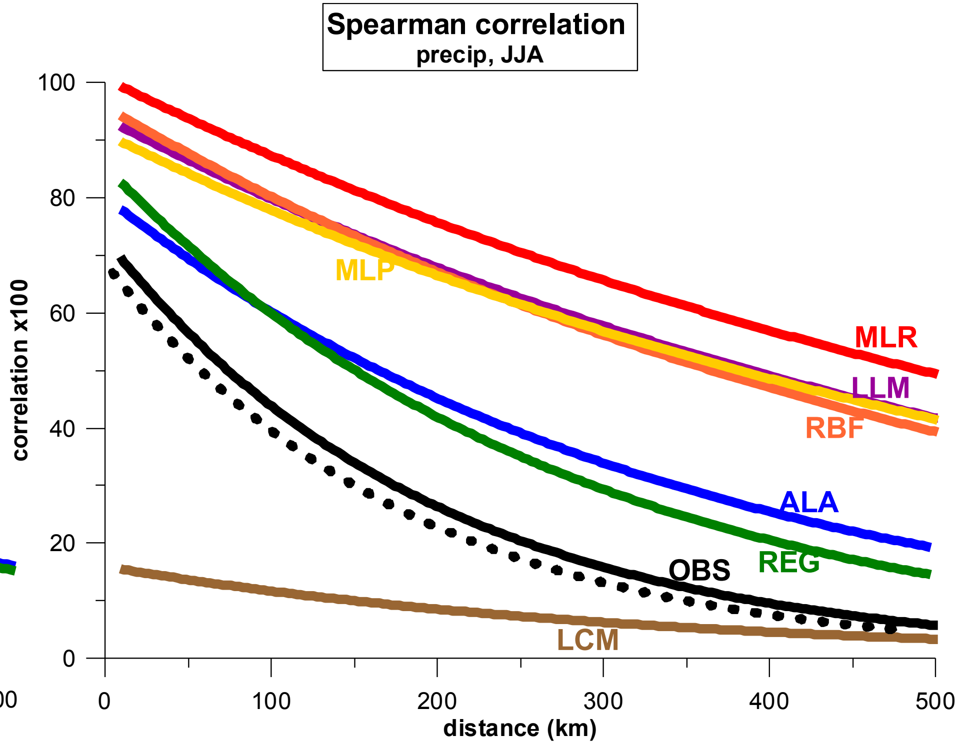
spatial autocorrelation of precip occurrence – Heidke score



Spatial autocorrelation – precip amount

- precip – highly non-Gaussian ➔ non-parametric correlation measure to be used





Tmean, DJF, various SDS methods

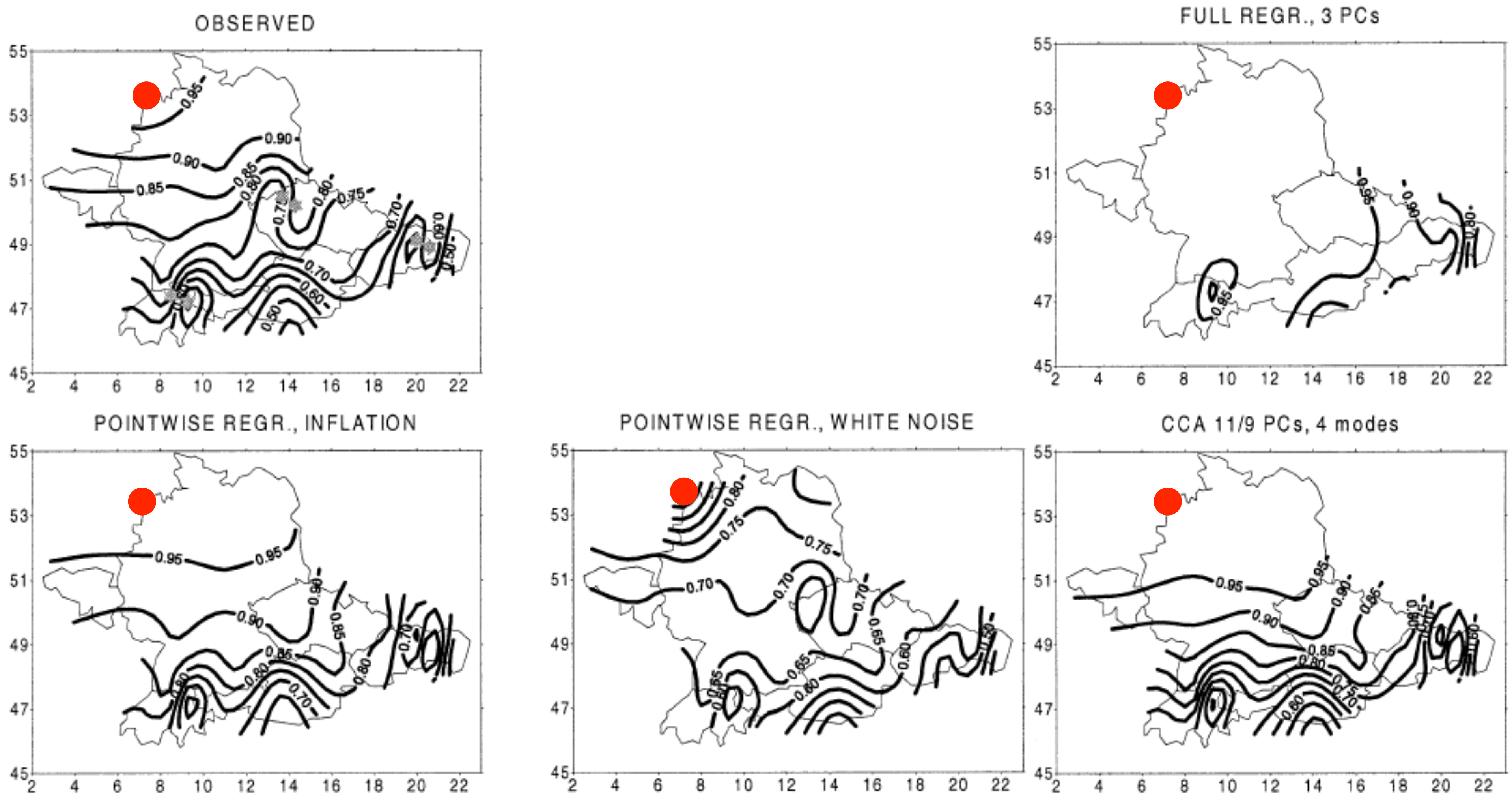


TABLE 8. Correlations (×1000) with Norderney (Germany) for pairs of close mountain/lowland stations in observations and selected downscaling methods.

	Zürich (CH)	Säntis (CH)	Poprad (SK)	Štrbské Pleso (SK)	Teplice (CZ)	Milešovka (CZ)
Observed	704	494	657	543	728	827
Pointwise regression, inflation	829	631	804	650	916	929
Pointwise regression, white noise	653	521	589	542	633	727
Full regression, 3 PCs	978	889	922	880	999	999
Full regression, 11 PCs	896	756	848	710	971	963
CCA, 1 mode	1000	1000	1000	1000	1000	1000
CCA, 11/9 PCs, 4 modes	752	543	751	586	949	924
CCA, 11/9 PCs, 7 modes	736	529	744	570	772	916

Regionalization

- goal – dividing area into regions with homogeneous (temporal) behaviour
- as usual with climate, there are no clearly separated regions
- no 'correct' solution to this task
- useful tool, nevertheless
- two (groups of) techniques
  - cluster analysis
  - principal component analysis

Regionalization

- different partitions (results of regionalization) obtained for
  - different normalizations of data
    - raw data, anomalies (from what?), standardized data
    - i.e., if we are interested in absolute values, deviations from long-term mean, deviations from areal average, …
  - different variables to cluster
    - daily time series
    - annual cycle

Regionalization

- comparison of partitions reality vs. model
  - by eye (if not too many sites)
  - contingency tables → several indices to quantify the correspondence
    - Rand, adjusted Rand, Jaccard, …

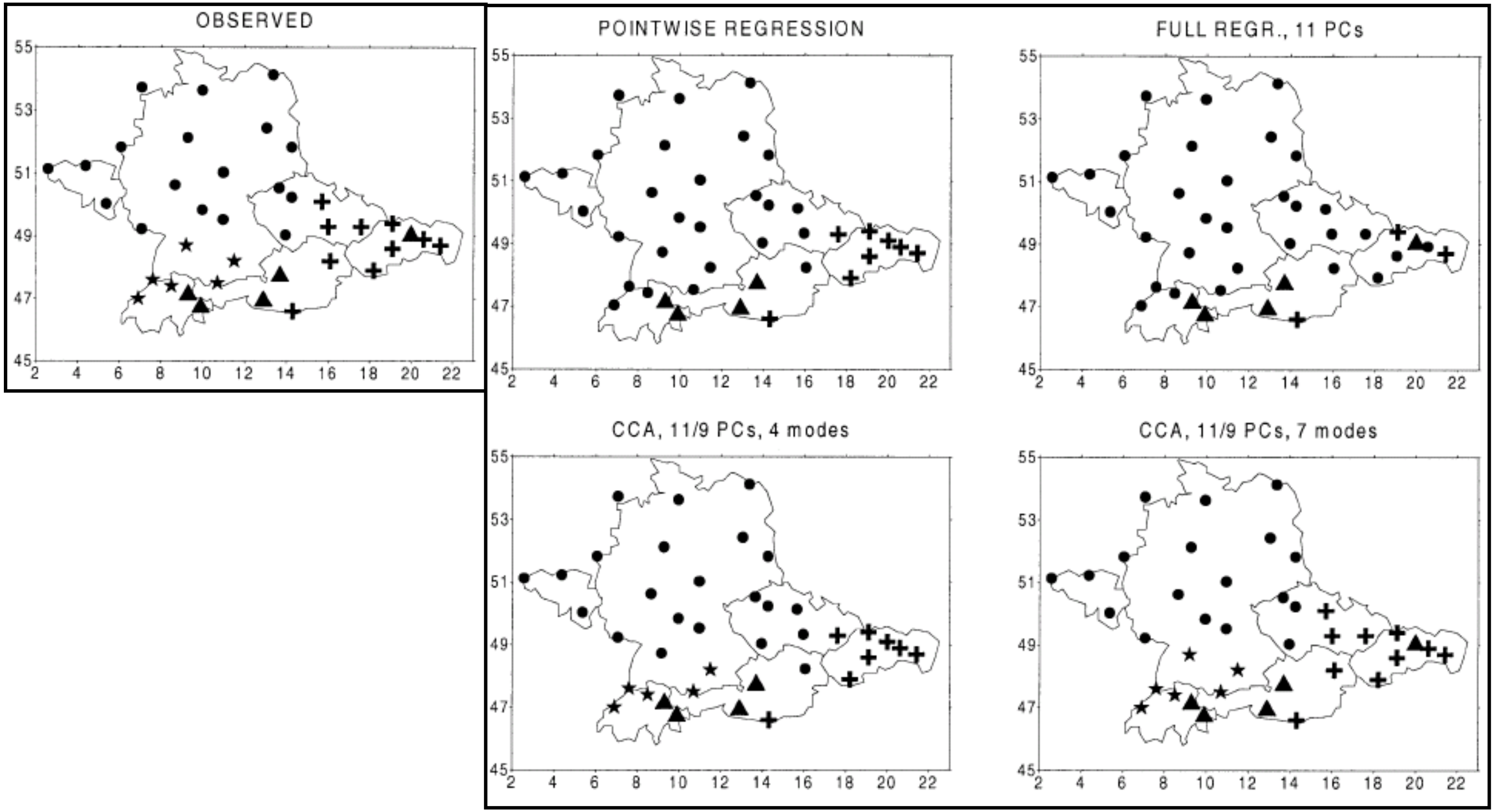
Cluster analysis

- hierarchical vs. non-hierarchical techniques
- hierarchical
  - succession of partitions
  - tree diagram (dendrogram)
  - no. of clusters (regions) to be determined by an 'experienced eye' of the researcher from the tree diagram
- non-hierarchical
  - no. of clusters to be determined prior to analysis

Principal component analysis

- S-mode
  - most common arrangement of input matrix
  - sites (stations, gridpoint) in columns
  - time (days, months, …) in rows
- choice of similarity matrix (correlation, covariance, …) has a strong effect on results
- results must typically be rotated in order to get regionalization
- rotation = mathematical transformation of a subset of relevant (not noise) components
- no. of retained relevant components = no. of regions
- output from PCA:
  - eigenvalues ('strength' or 'importance' of components)
  - loadings (weights) – maps
  - scores (amplitudes) – time series
- every site assigned to the component (region) on which it has the highest loading

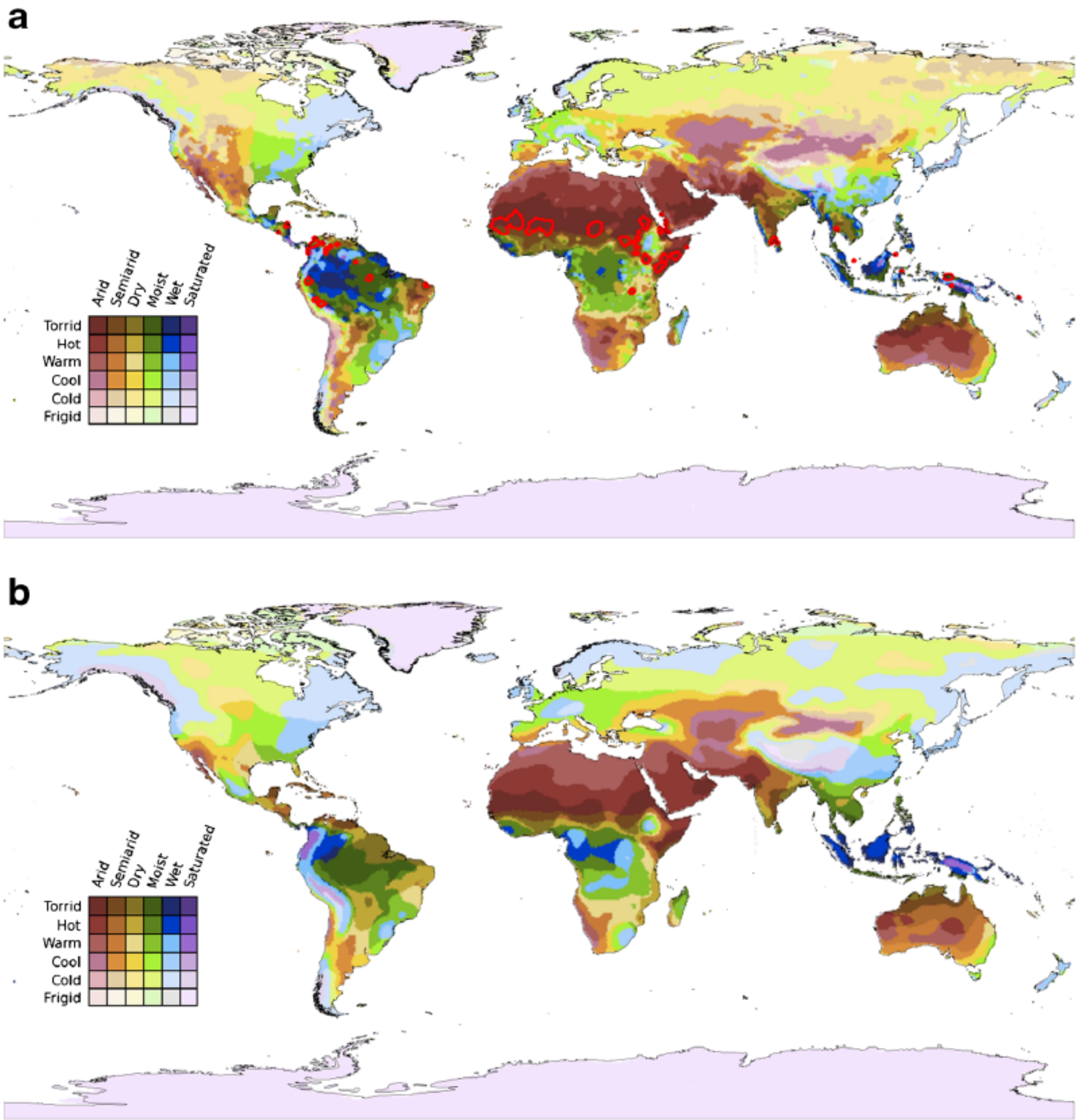
Example of regionalization



- regionalization based on PCA (correlation matrix, obliquely rotated)

Climate classification

- specific way to assess spatial characteristics of model outputs, together with inter-variable consistency
- usually used to validate GCMs
- suitable to compact description of future climate changes
- classifications used for this purpose
  - Köppen-Geiger-Trewartha
  - Thornthwaite

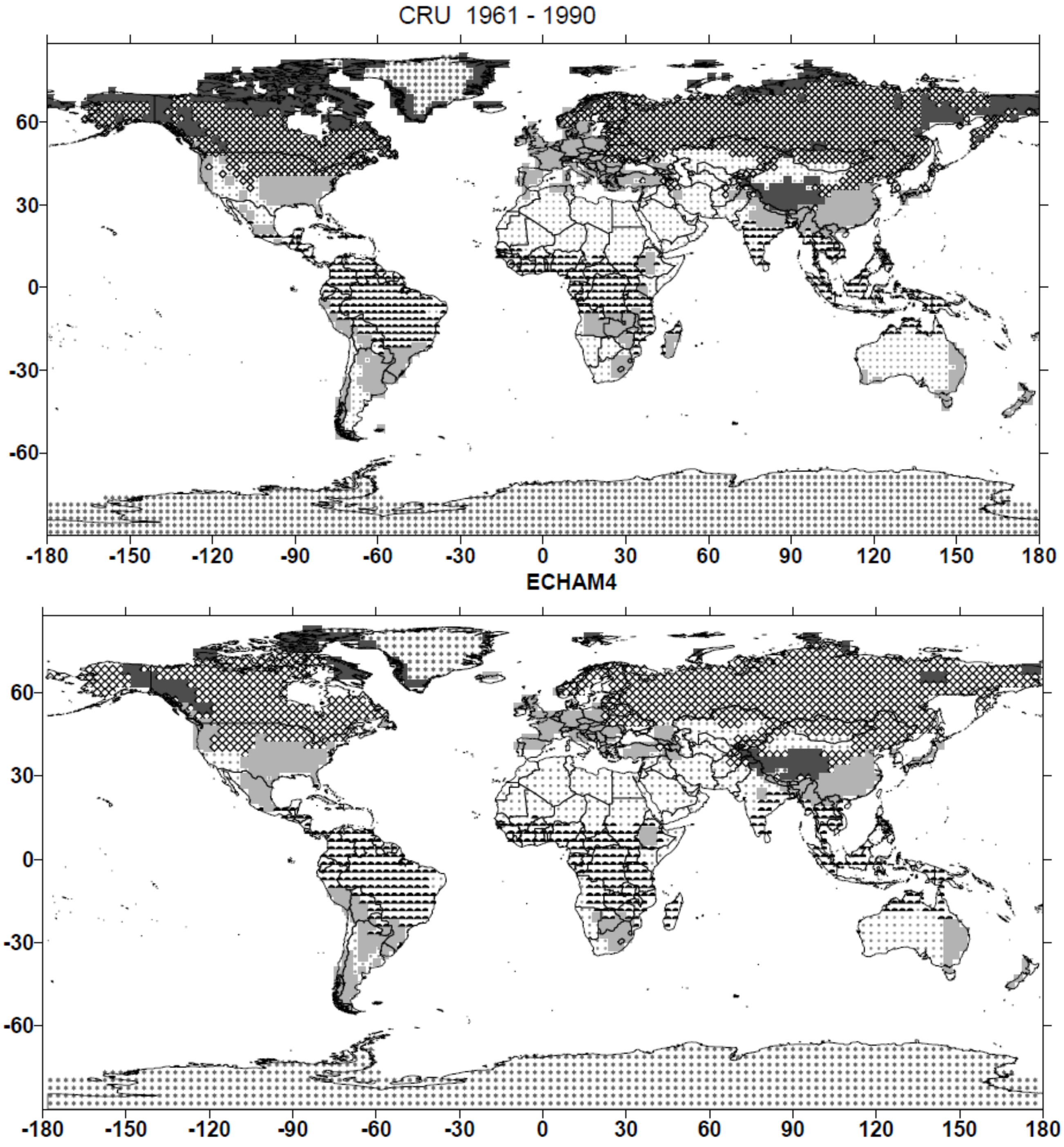


Thornthwaite climate types

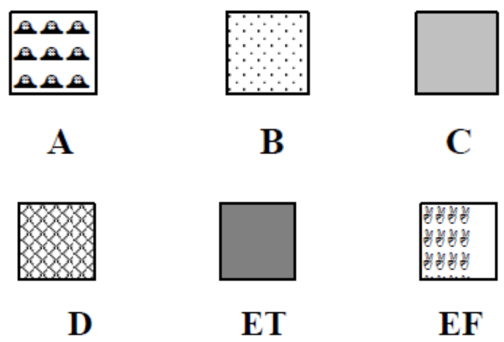
OBS (top)

CMIP5 ensemble for recent climate (bottom)

Elguindi et al., *Clim. Change* 2014



- Köppen climate types
- Kalvová et al., *Studia Geophys. Geod.* 2003



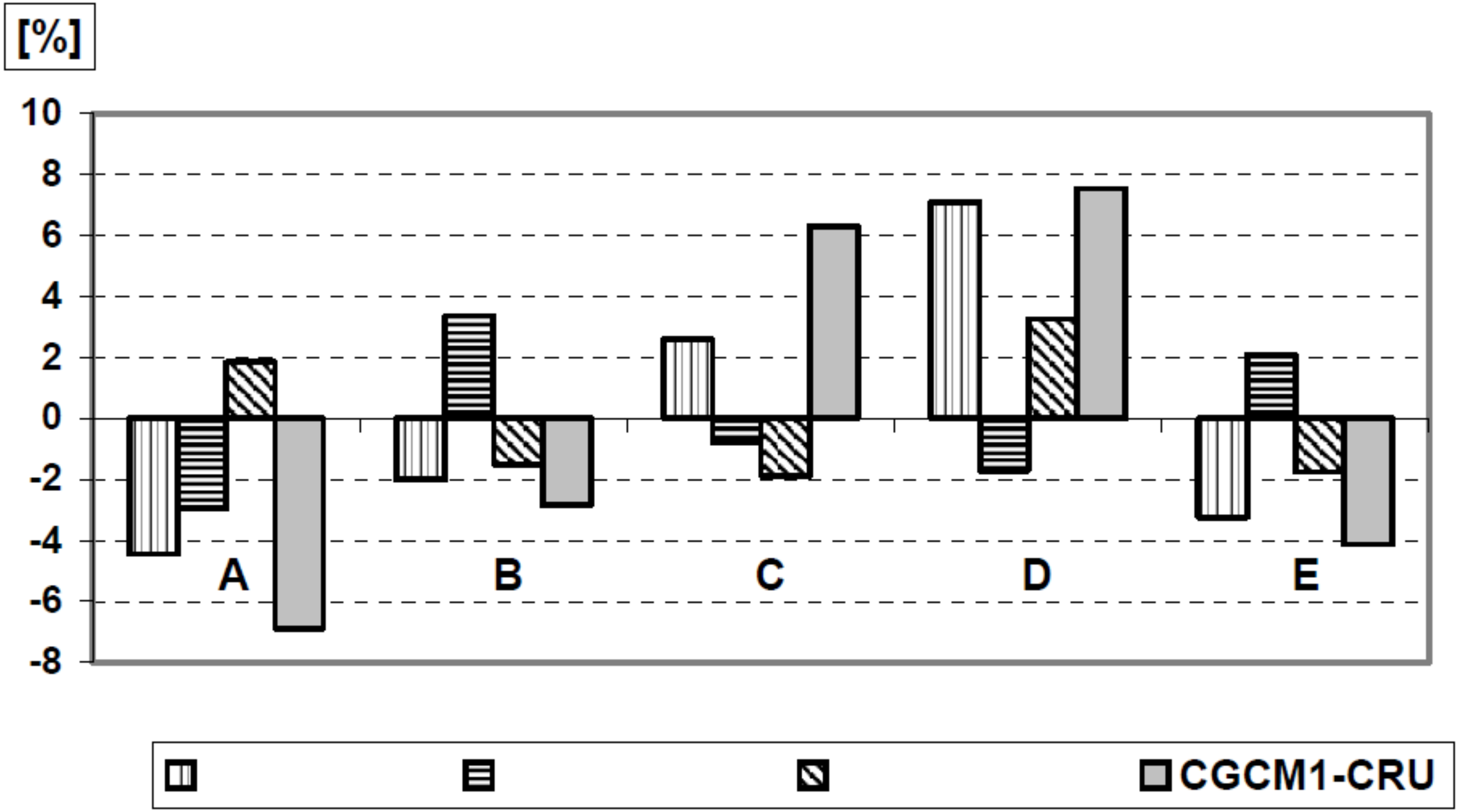


Fig. 3. Differences (in %) between the Köppen climatic types derived from GCMs and real data (for the period of 1961–1990).

A sort of conclusions…

- a wide variety of validation criteria
- criteria driven by
  - model developers
  - model users (end-users)
- studies comparing performance of a wide range of DS methods (e.g., RCMs with SDS models) are rather scarce
- performance of different DS methods is comparable – none can be seen as ‘best’ or ‘worst’
- model good in one aspect may fail in another aspect
- impossible to rectify all the aspects of downscaled variables at the same time