Statistical downscaling:
a short excursion to history, current state, some challenges

Radan HUTH

Faculty of Science, Charles University, Prague, CZ

Institute of Atmospheric Physics, Prague, CZ

INTERNATIONAL JOURNAL OF CLIMATOLOGY

RMetS Royal Meteorological Society

Early history

- within numerical weather prediction
- since ~ 1960’s
- relatively successful prediction of upper-level flow
- but less successful prediction of surface weather (temperature, precip, …)
- statistics helps
- surface weather derived from large-scale circulation
- ‘specification’: pioneering work by W.H. Klein
- W.H. Klein – ‘grandfather’ of statistical downscaling

Less early history

- history repeated in 1980’s within climatology
- models = GCMs = General Circulation Models at those times (not Global Climate Models)
- models able to simulate large-scale flow
- models not able to simulate surface small-scale features
- this issue persists until today

Less early history

- first attempt to bridge the gap between large-scale and small-scale (local) climate

(in *Mon. Wea. Rev.*)

The Statistical Problem of Climate Inversion: Determination of the Relationship between Local and Large-Scale Climate

J.-W. KIM,[1] J.-T. CHANG,[2] N. L. BAKER,[3] D. S. WILKS AND W. L. GATES

Department of Atmospheric Sciences and Climatic Research Institute, Oregon State University, Corvallis, OR 97331

(Manuscript received 12 August 1981, in final form 9 July 1984)

ABSTRACT

The estimation of the most probable local or mesoscale distribution of a climatic variable when only the large-scale value is given may be viewed as a sort of climate inversion problem. As an initial statistical study of this question, the monthly-averaged surface temperature and monthly total precipitation for stations in Oregon are analyzed for the purpose of relating their most probable mesoscale distributions to the large-scale monthly anomalies.

The first empirical orthogonal mode of the covariance matrix of mesoscale transient departures explains 78.2 and 80.8% of the total variance of temperature and precipitation, respectively. The time structure of the first mode is predominantly seasonal and is in phase with the large-scale anomalies, and the correlation coefficient between this oscillation and the large-scale anomaly is 0.96 for temperature and 0.95 for precipitation. The most probable mesoscale distribution as specified by only the first empirical orthogonal function is predictable with relative error of less than 37.9% for temperature and 37.1% for precipitation if the corresponding large-scale anomaly is known with an error of less than 10%. These results may be useful in the study of local climatic impacts with large-scale climate models.

- statistical relationships between large-scale and local temperature & precipitation
- procedure called ‘climate inversion’
- this term has not been used later any more

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More recent history

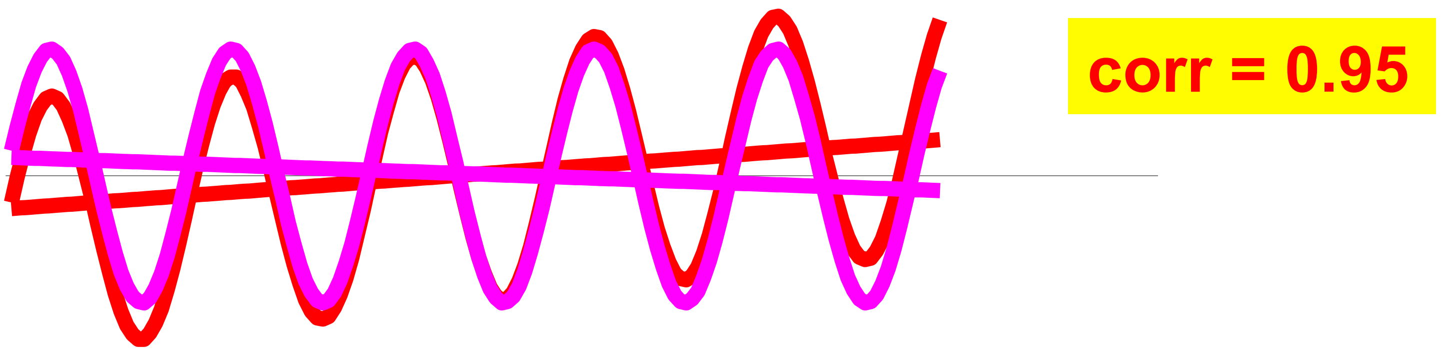
- next attempts
  - Wilks: Statistical specification of local surface weather elements from large-scale information. *Theor Appl. Climatol.,* 1989
  - Karl et al.: A method of relating general circulation model simulated climate to the observed local climate. Part I: Seasonal statistics. *J. Climate,* 1990 *(Part II never appeared)*
- term ‘downscaling’ still not used
- I thought I’d find who coined the term ‘downscaling’ (who is its father / mother) and where … but was not successful
- term ‘downscaling’ is not used even in the very influential review paper by Giorgi & Mearns (Approaches to the simulation of regional climate change: A review. *Rev. Geophys.,* 1991)
- (at the same time, first attempts to run regional models beyond their predictability limits by Dickinson and Giorgi – dawn of regional climate models)

Current state

- what is considered ‘statistical downscaling’ (or ‘empirical downscaling’) today?
- broader meaning than 10 years ago
- not only statistical relation between large-scale and small-scale (local) surface variables
- also
  - stochastic generators
  - MOS-like approaches
  - tools to correct statistical distributions (‘bias-correction’)
  - …
- under ‘downscaling’ it is frequently understood ‘tools for providing local climate (change) information,’ regardless of the spatial (or even temporal) scales
- but – such a ‘dynamic’ use of terminology may (and does) cause confusion and misunderstandings
- let’s stick to a ‘classical’ statistical downscaling

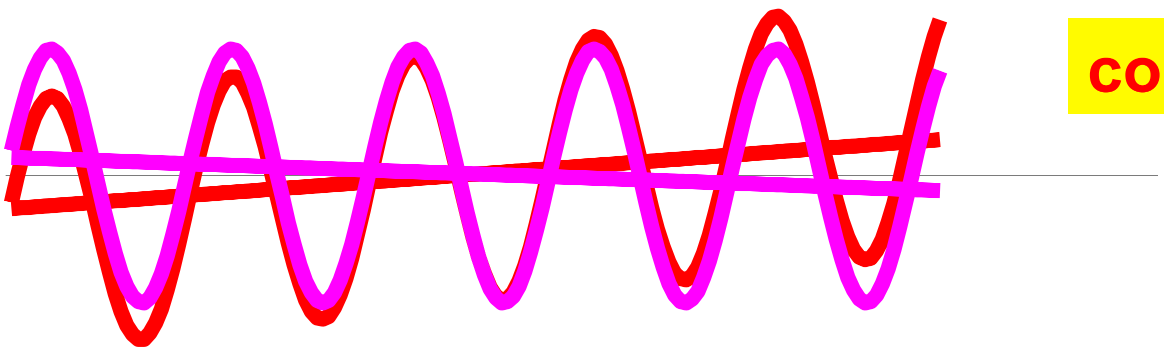
Paradox of statistical downscaling

Models are typically fitted to variability on time scales much shorter (daily) than on which climatic change proceeds (decades)



Paradox of statistical downscaling

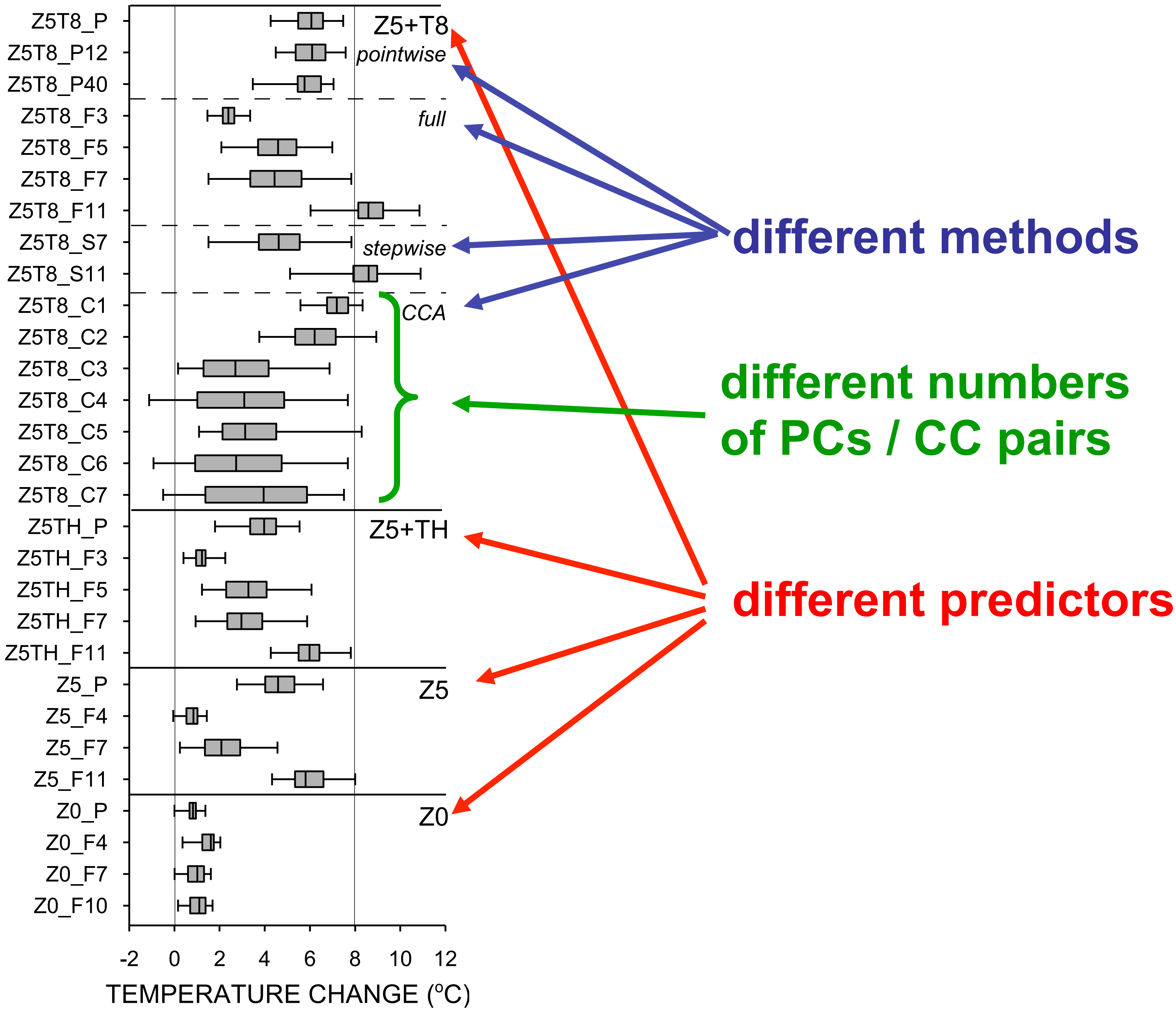
- one clear fact: degree of fit with observed data (whatever measure is used) cannot be the only criterion of which DS model to use



corr = 0.95

Paradox of statistical downscaling

- illustration: oldish example from Huth, *J. Climate* 2004
- various simple (linear) SDS methods
  - with different settings (no. of predictors, PCs, CC pairs, …)
  - with different predictor sets
- application to one GCM, one emission scenario
- 39 stations in central Europe
- temperature, winter (DJF)
- … don’t think that more sophisticated methods would behave better!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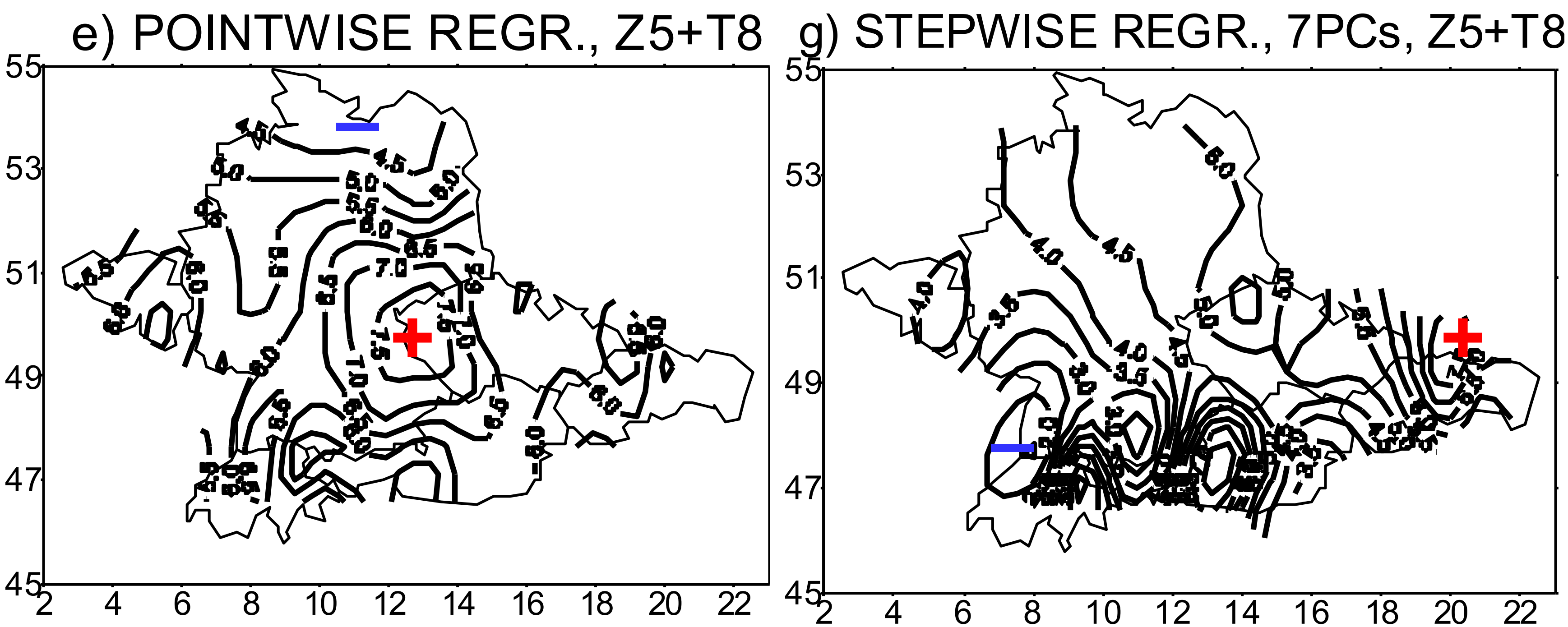
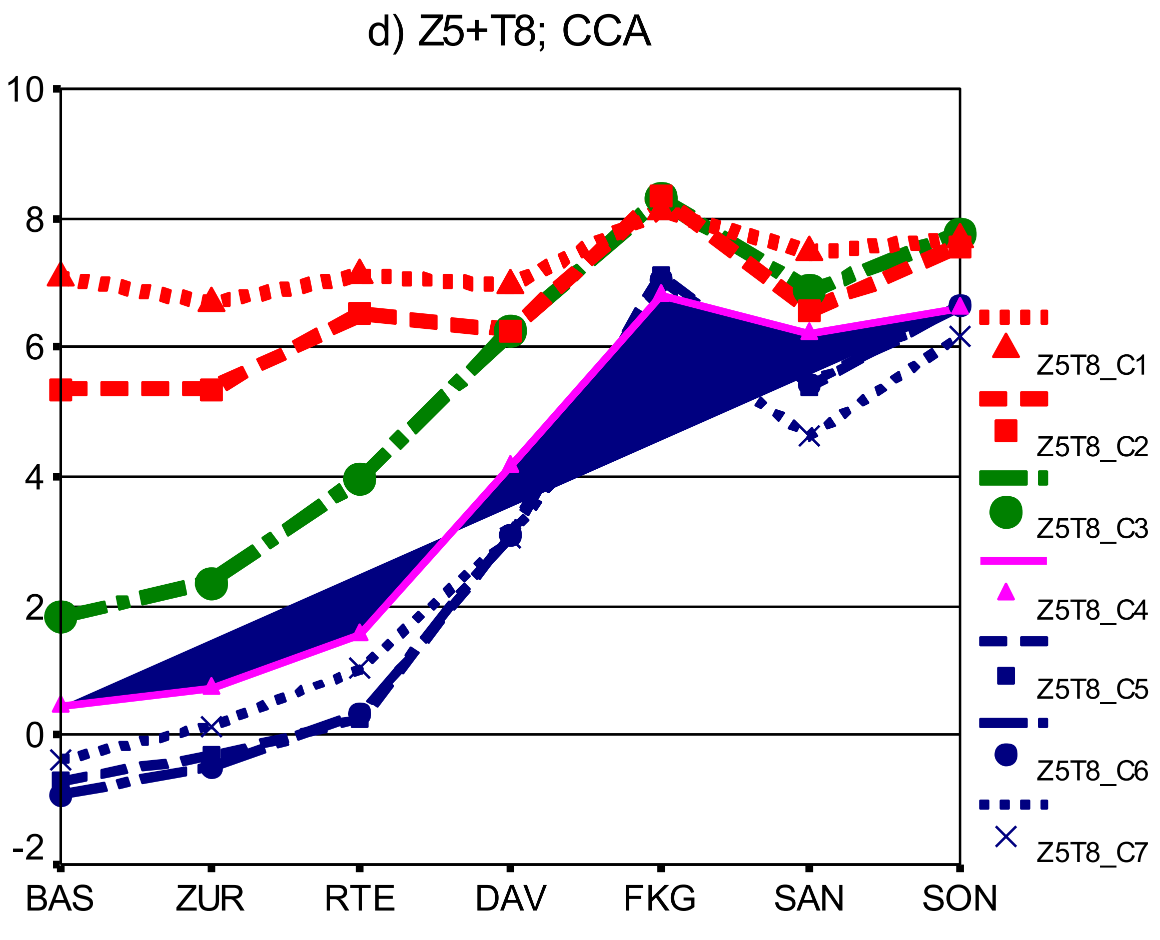
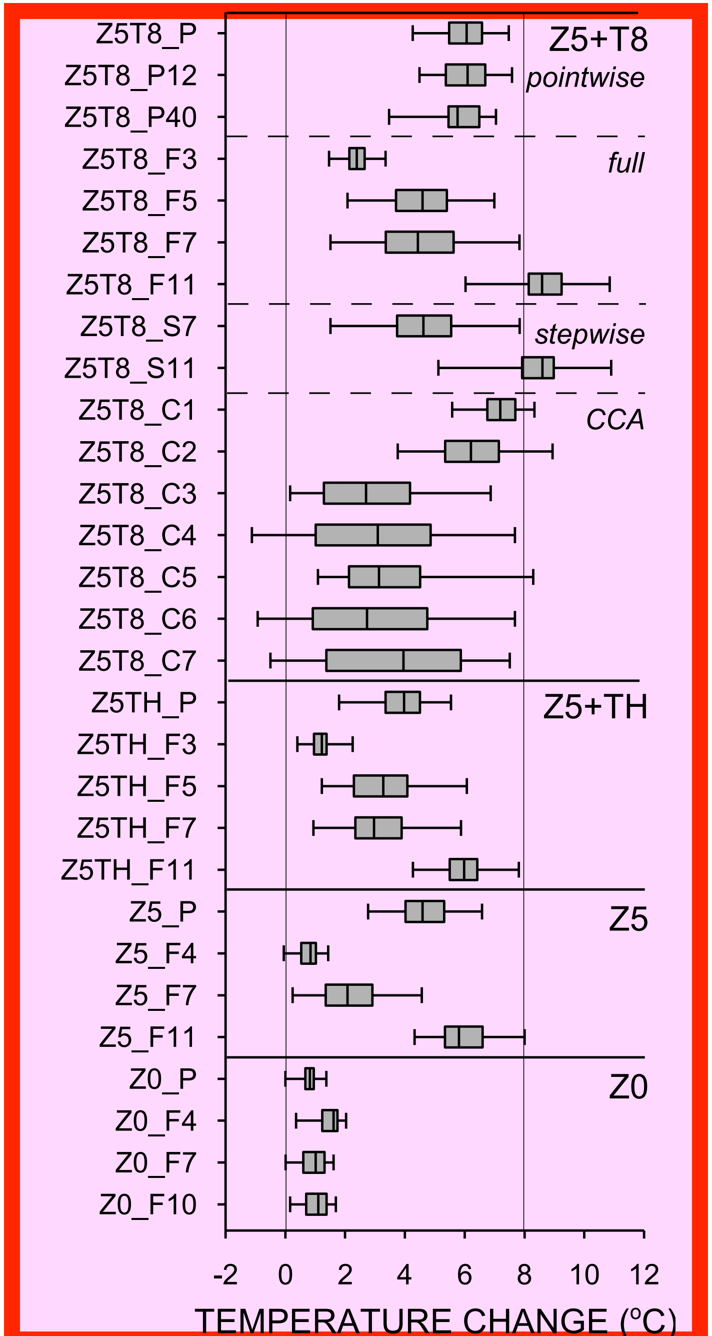
Z5_F11
Z0_P
Z0_F4
Z0_F7
Z0_F10
Z5+T8
pointwise
full
stepwise
CCA
Z5+TH
Z5
Z0
-2 0 2 4 6 8 10 12
TEMPERATURE CHANGE (°C)
different methods
different numbers of PCs / CC pairs
different predictors

- not only amplitude of temperature change differs
- also spatial patterns



- not only amplitude of temperature change differs
- also elevation dependence





- all models are good in terms of fit to observations (e.g. rmse)
- mean temperature change varies from +0.5 to +8.5 °C
- other aspects also vary widely
- **so how to decide which model to prefer???**
- indeed, ensemble approach would help, but wouldn’t the range of values be too wide?

Remedy to the paradox

- possible REMEDY – 2 ways:
  - validation: use appropriate criteria (motivation for my talk on validaton of temporal aspects)
  - a priori selection of predictors (outside of our current topic)

Remedy – validation

- validate trends (but recent and future trends may result from different mechanisms!)
- check ability to simulate contrasting climatic states (cold / warm; dry / wet years) (similar objection)
- verify consistency with driving GCM (but GCM may be wrong! – or at least have large systematic biases)

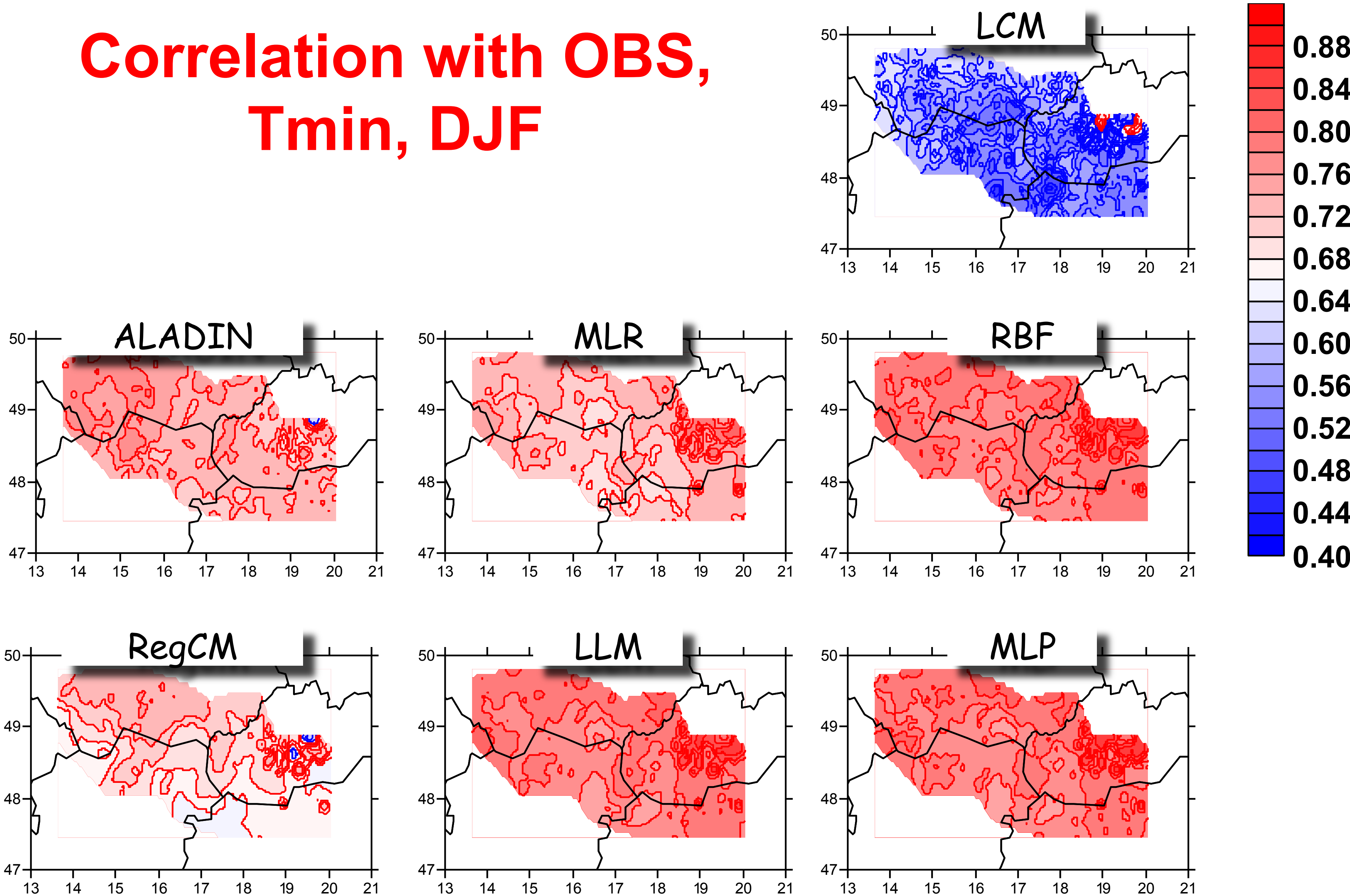
Statistical vs. dynamical downscaling

- statistical downscaling – tendency to be viewed as inferior, simplistic
  - *(example – ENSEMBLES project, CORDEX initiative where it was/is an appendix of RCM efforts)*
- but: the few comparison studies ➔ statist. and dynam. downscaling have similar performance

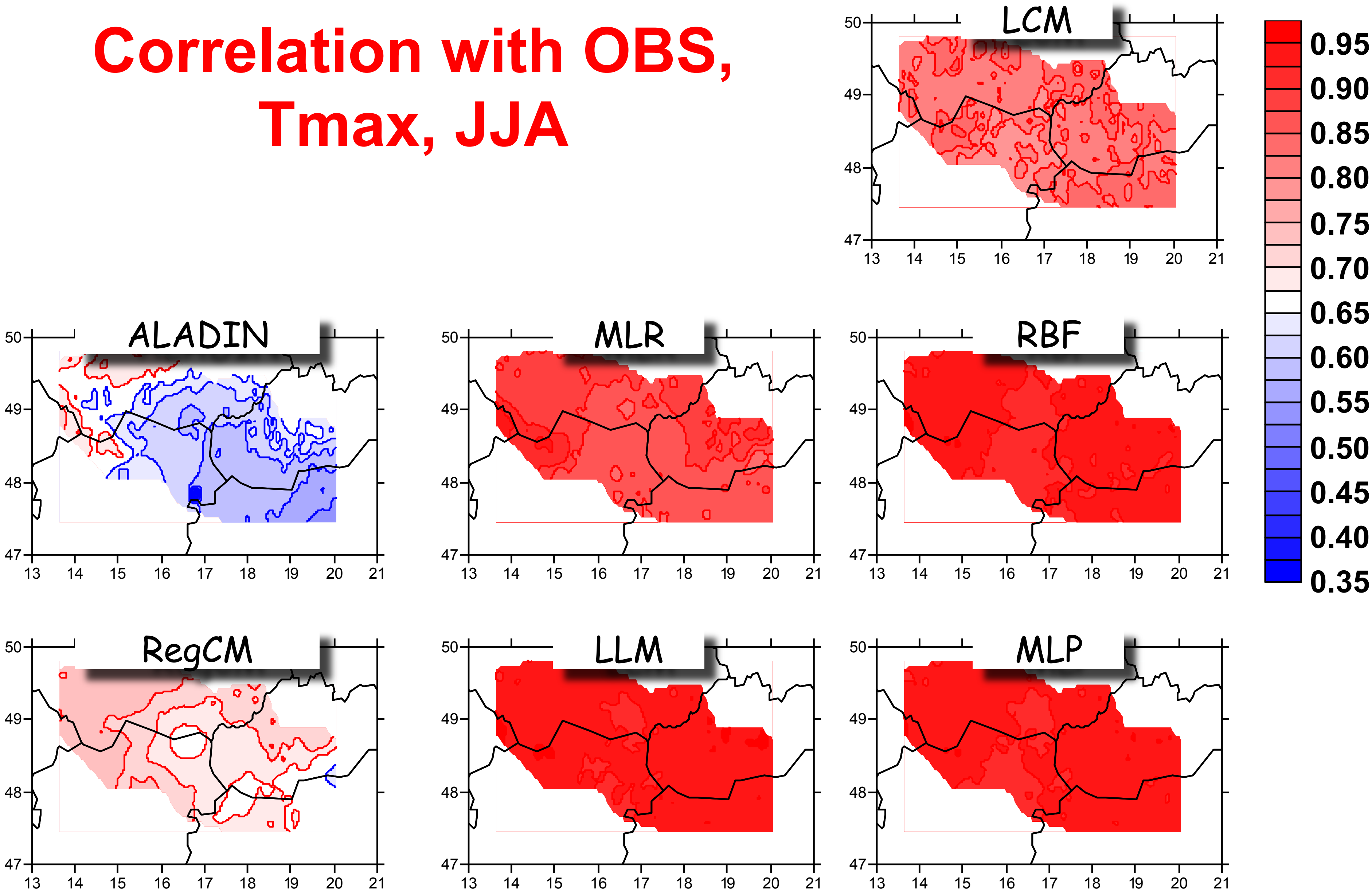
Example: reproduction of observed time series

- RCMs nested in reanalysis
- SDS models driven by reanalysis
- what would you expect to be better?

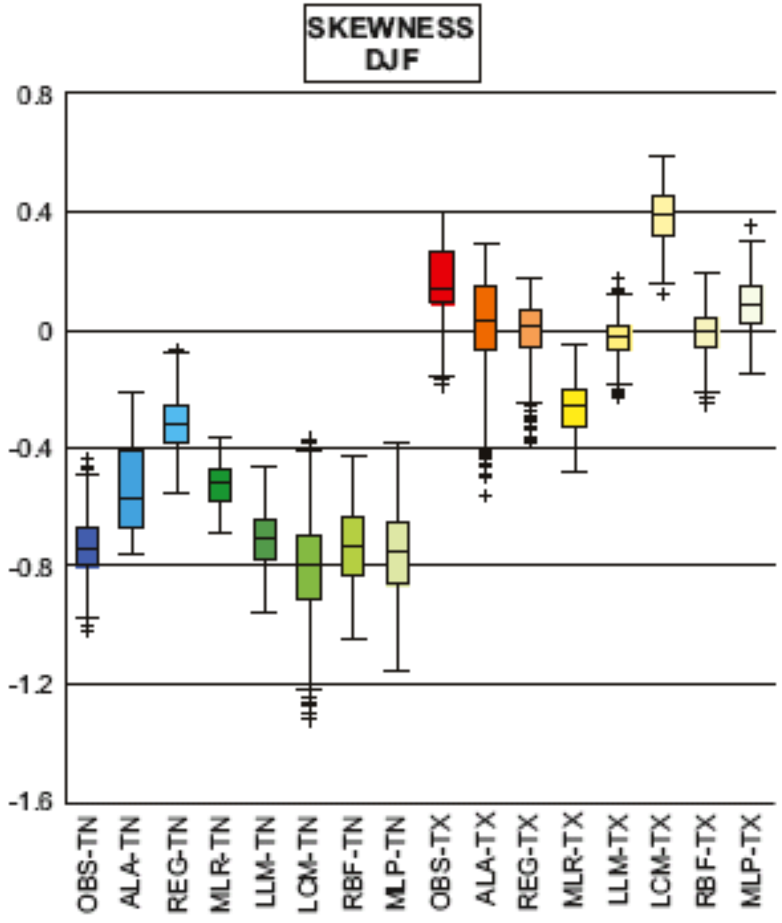
Correlation with OBS, Tmin, DJF

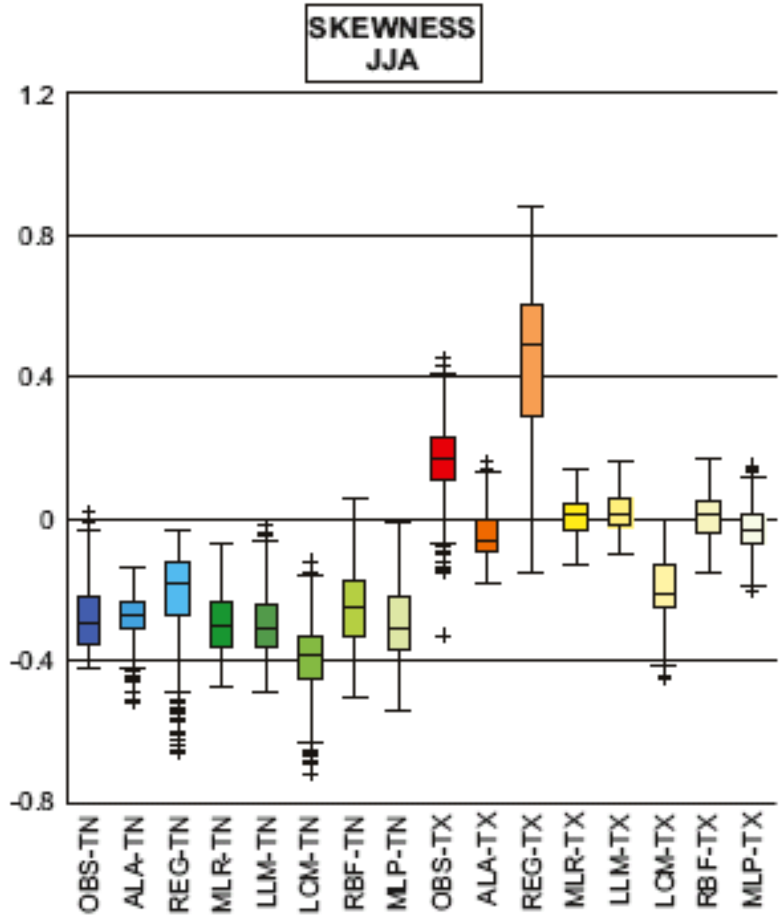


Correlation with OBS, Tmax, JJA

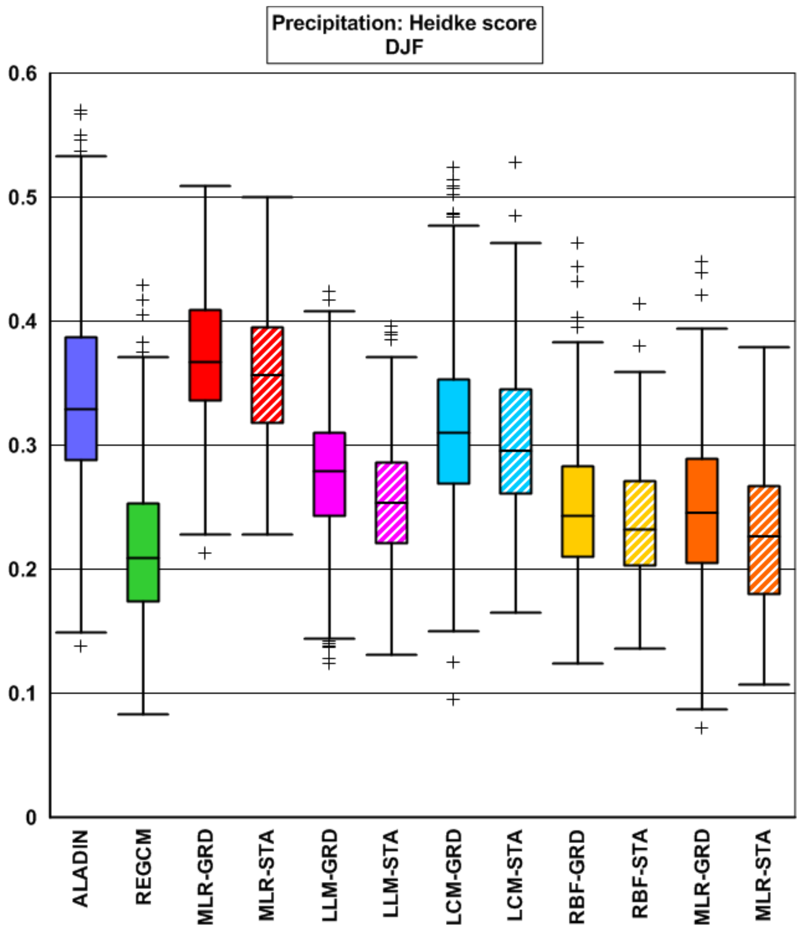


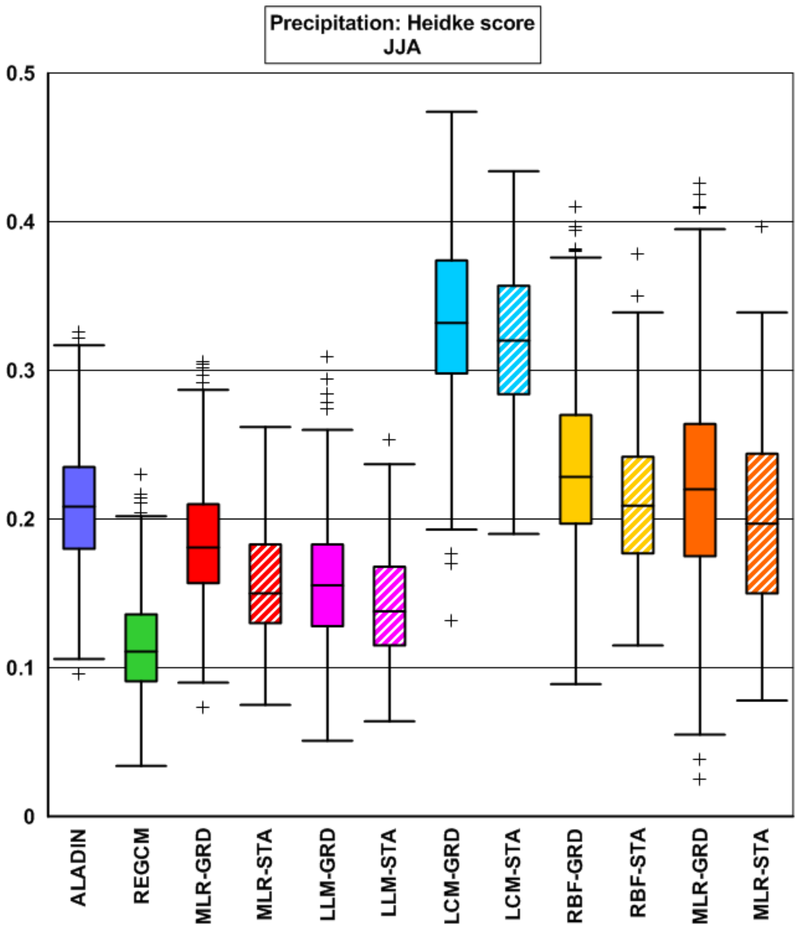
Temperature skewness



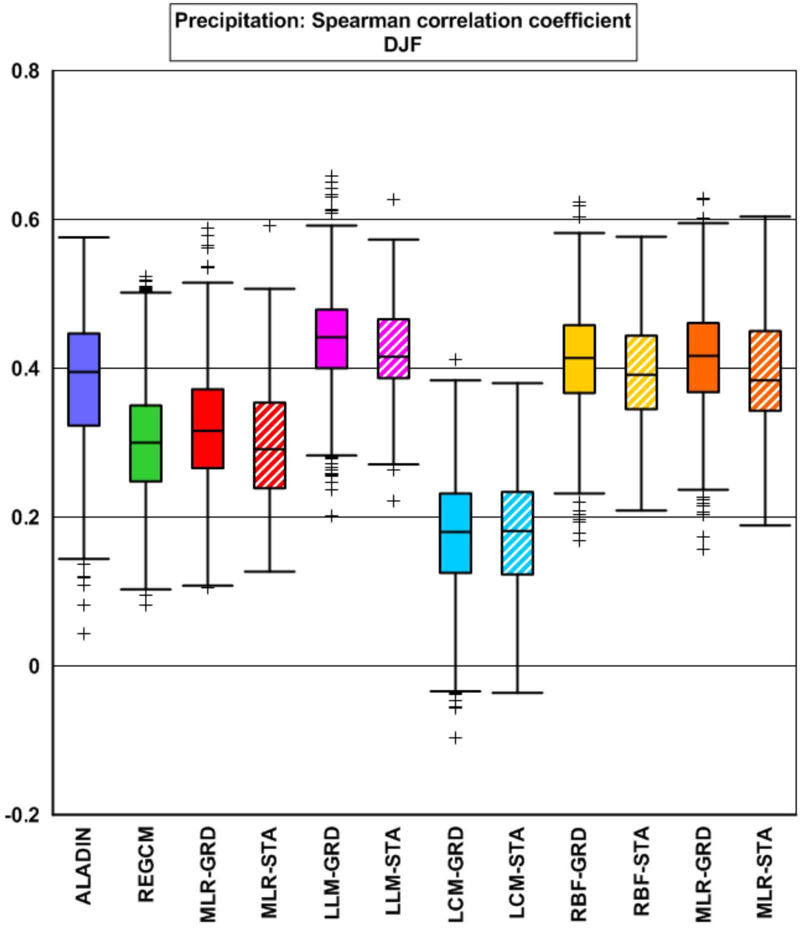


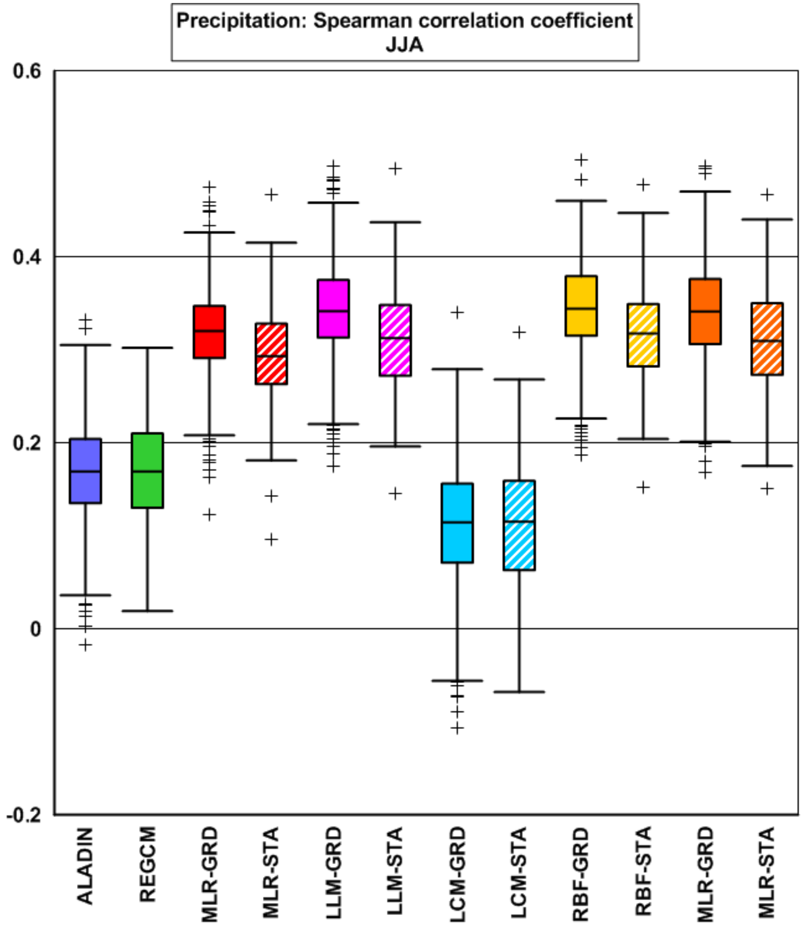
Reproduction of time series of precip occurrence: Heidke skill score





Reproduction of time series of precip amount: Spearman correl





Statistical vs. dynamical downscaling

- **+** of downscaling:
  - computationally simple
  - provides local information
- **+** of RCMs:
  - physical consistency among variables

Statistical vs. dynamical downscaling

- not competing, but complementary techniques
- both have weak points that are frequently
  - not admitted
  - not reconciled