Non-local MOS and spatial representativity

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with large contributions from

J.M. Eden and D. Maraun,

VALUE training school, ICTP Trieste, 4. November 2014

Downscaling classification (used in VALUE COST action)

1. Dynamical Downscaling

1. Perfect Prog(nosis) (PP)

2.1 deterministic

2.2 probabilistic (PDFs but no time series)

2.3 stochastic, time series / weather generator

3. Model Output Statistics (MOS)

3.1 deterministic (this talk: pair-wise, non-local)

3.2 probabilistic

3.3 stochastic, timeseries / weather generator

Perfect Prog downscaling - estimating precip from pressure

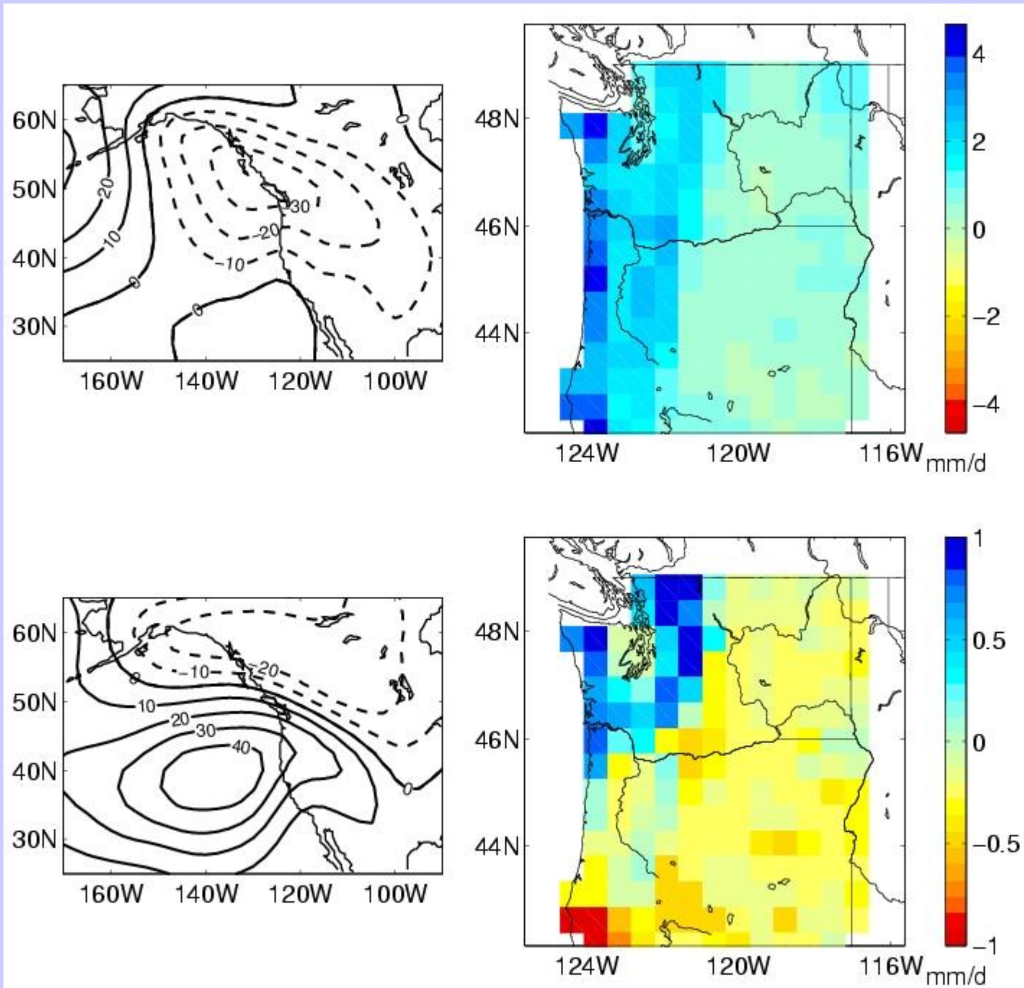
Coupled anomaly patterns (SVD) between DJF 1000 hPa geopotential height (NCEP) and daily preciptation

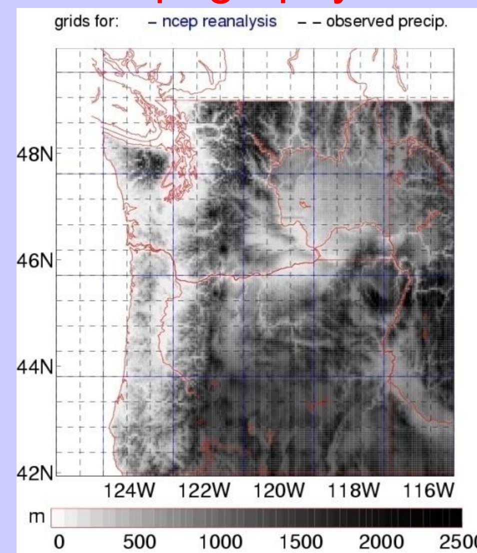
geopot. height (Z1000) precipitation

topography

pair 1

pair 2



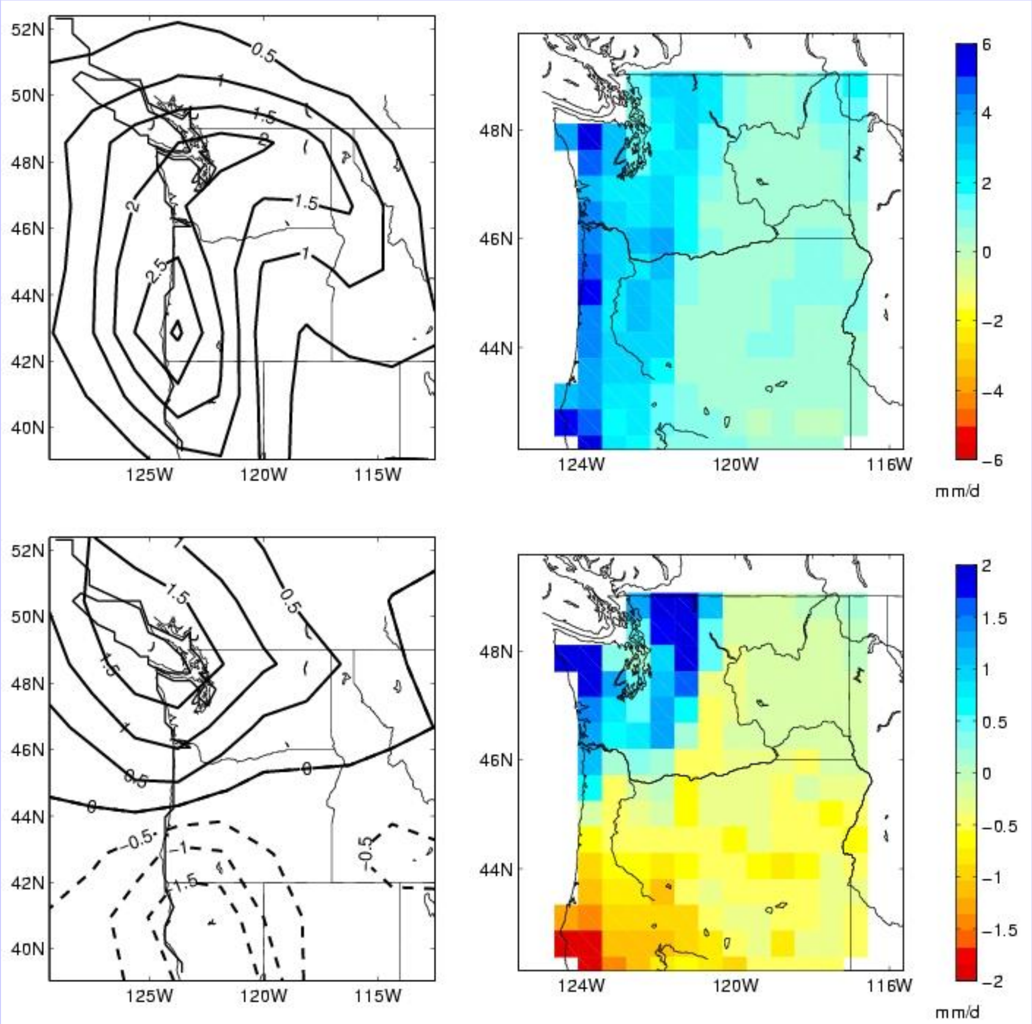


(Widmann and Bretherton, J. Climate 2000; Widmann et al., J. Climate, 2003)

Model Output Statistics - estimating true precipitation from simulated precipitation

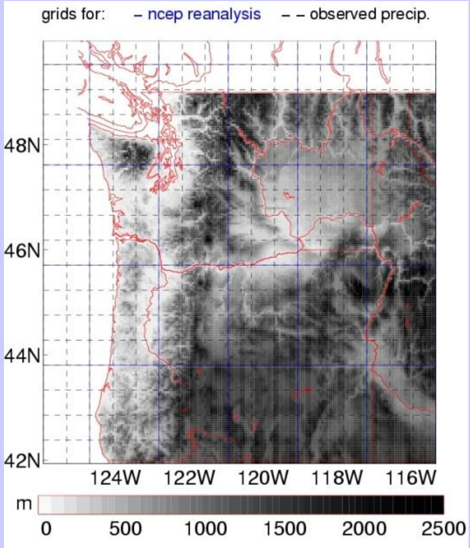
simulated precipitation (NCEP reanalysis)

observations

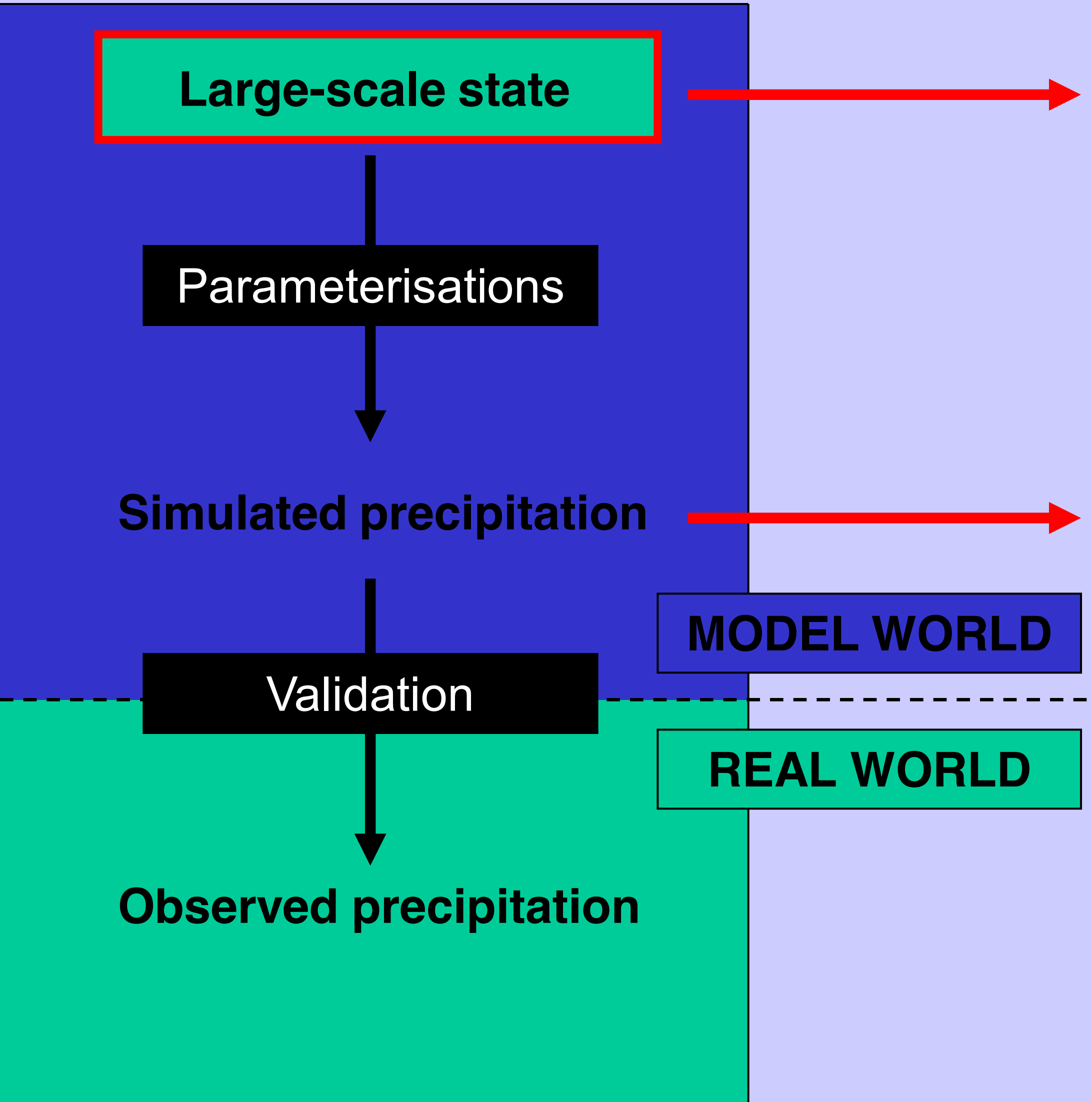


Coupled anomaly patterns (SVD) between DJF daily simulated (NCEP) and observed preciptation

topography



Nudging of ECHAM5 towards ERA40 reanalysis



Variables nudged towards ERA40 reanalysis (entire troposphere):

- circulation (div, vort.)
- temperature

SST as in ERA40

Skill assessment and MOS based on parametrisation errors

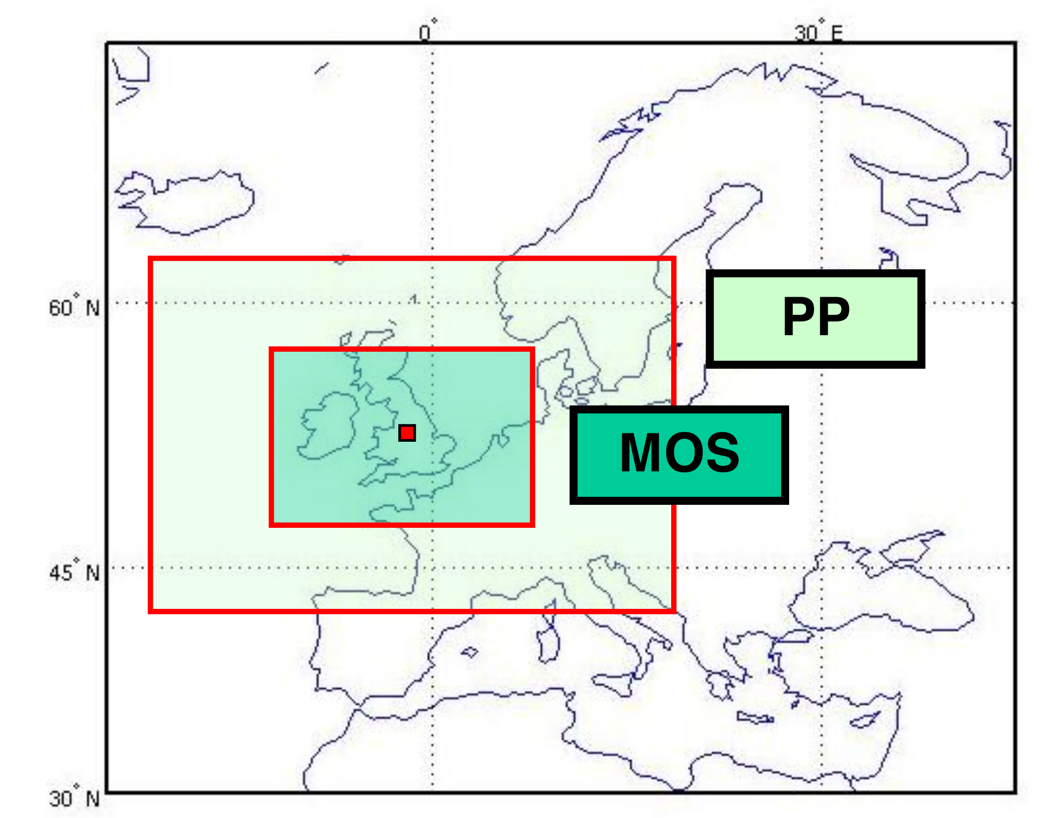
(Eden et al. 2012)

PerfectProg and event-wise, non-local MOS downscaling

We estimate precip for each observation gridcell using

- PC-MLR and 1D-MCA (regression maps, Widmann, J. Clim. 2005)

- PP and MOS



MOS: ECHAM5 simulated precipitation is used as the predictor field.

PP: geopotential height, temperature and humidity at various pressure levels used as predictor fields.

One-dimensional MCA and CCA

If one of the two fields is only 1-D, i.e. a time series:

- **CCA is identical to MLR (with or without PCA-prefiltering**

- **MCA is identical to using time expansion coefficients of the regression map as predictor**

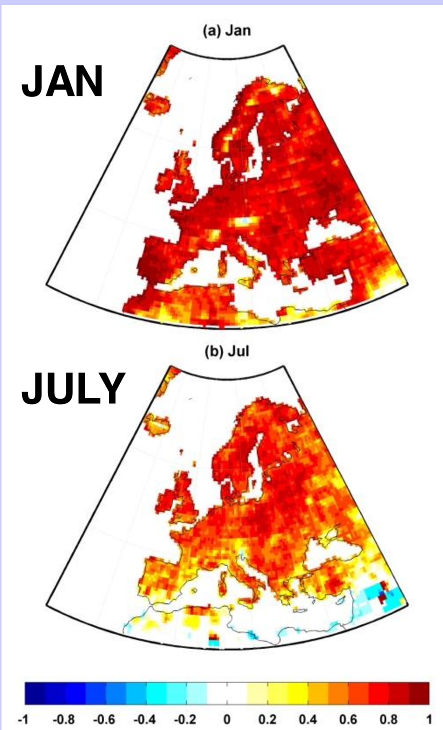
**Although MLR maximises explained variance in the fitting period, it is not clear which method performs better on independent data.
(i.e. in a cross-validation setting)**

PCA-prefiltering for CCA requires subjective decisions, MCA does not

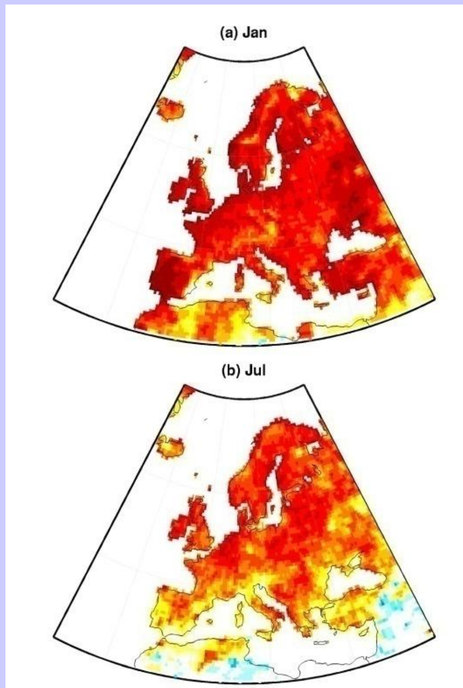
(Widmann, J. Climate, 2005)

Cross-validated skill of different MOS methods: correlations of estimated and observed monthly means (1958-2001)

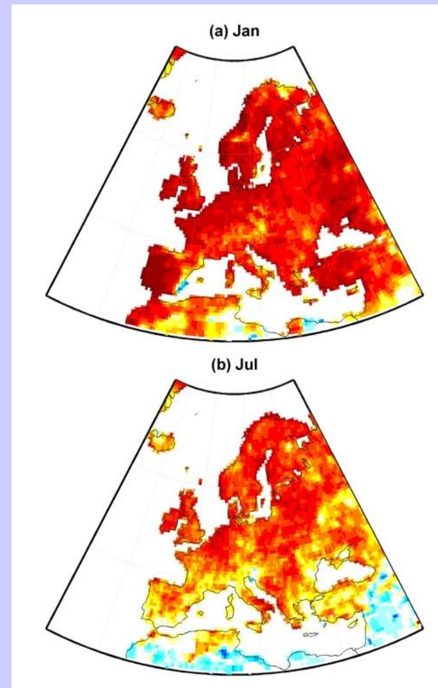
Local scaling



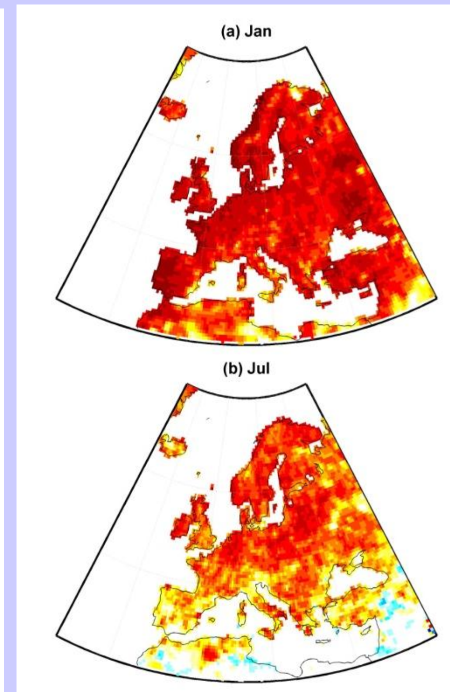
1D-MCA

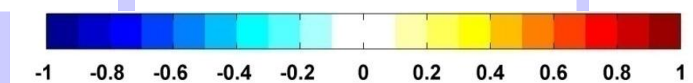


MLR; 2 PCs

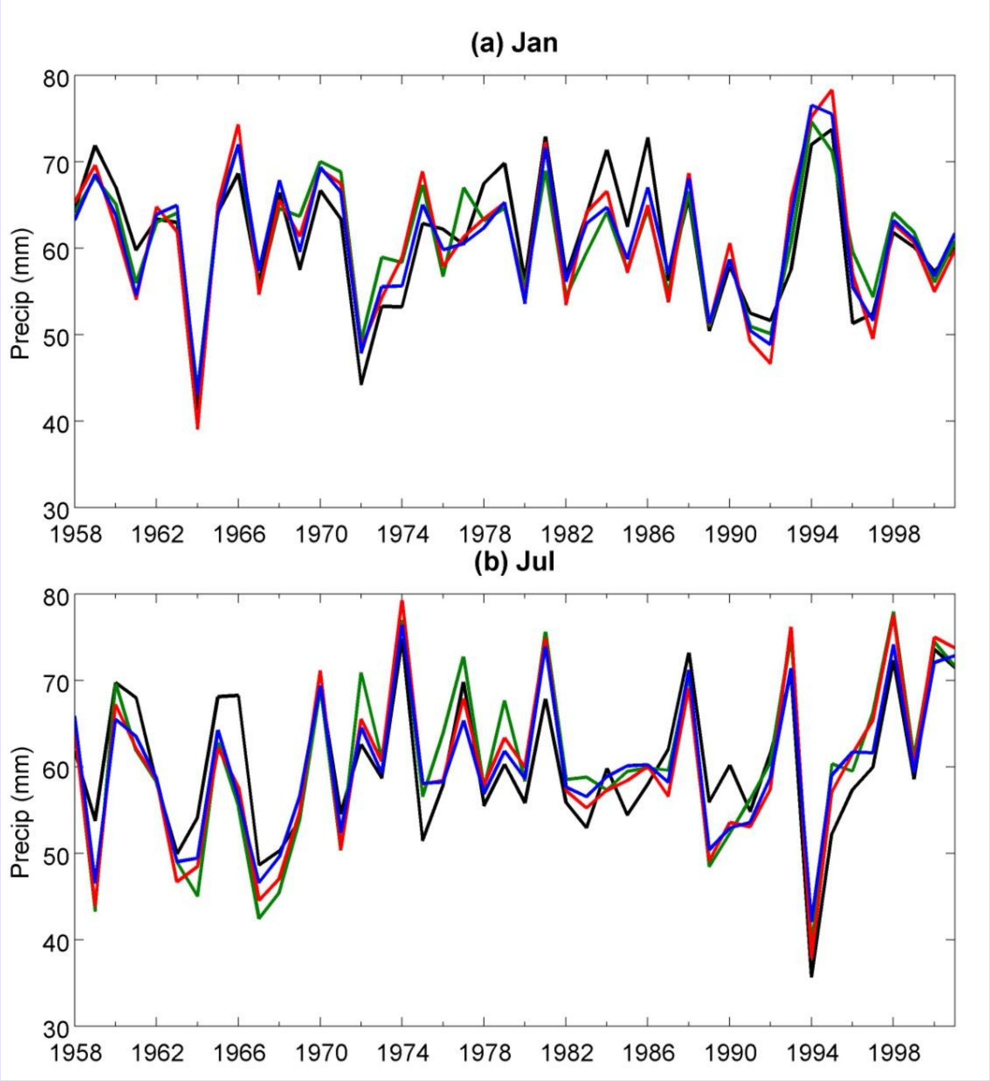


MLR; 10 PCs





Observed and MOS-estimated European mean precipitation (using cross validation)



OBS

local scaling
r = 0.777 RMSE = 3.86

1D-MCA

r = 0.746 RMSE = 3.75

MLR with 5 PCs

r = 0.786 RMSE = 2.94

local scaling
r = 0.600 RMSE = 5.17

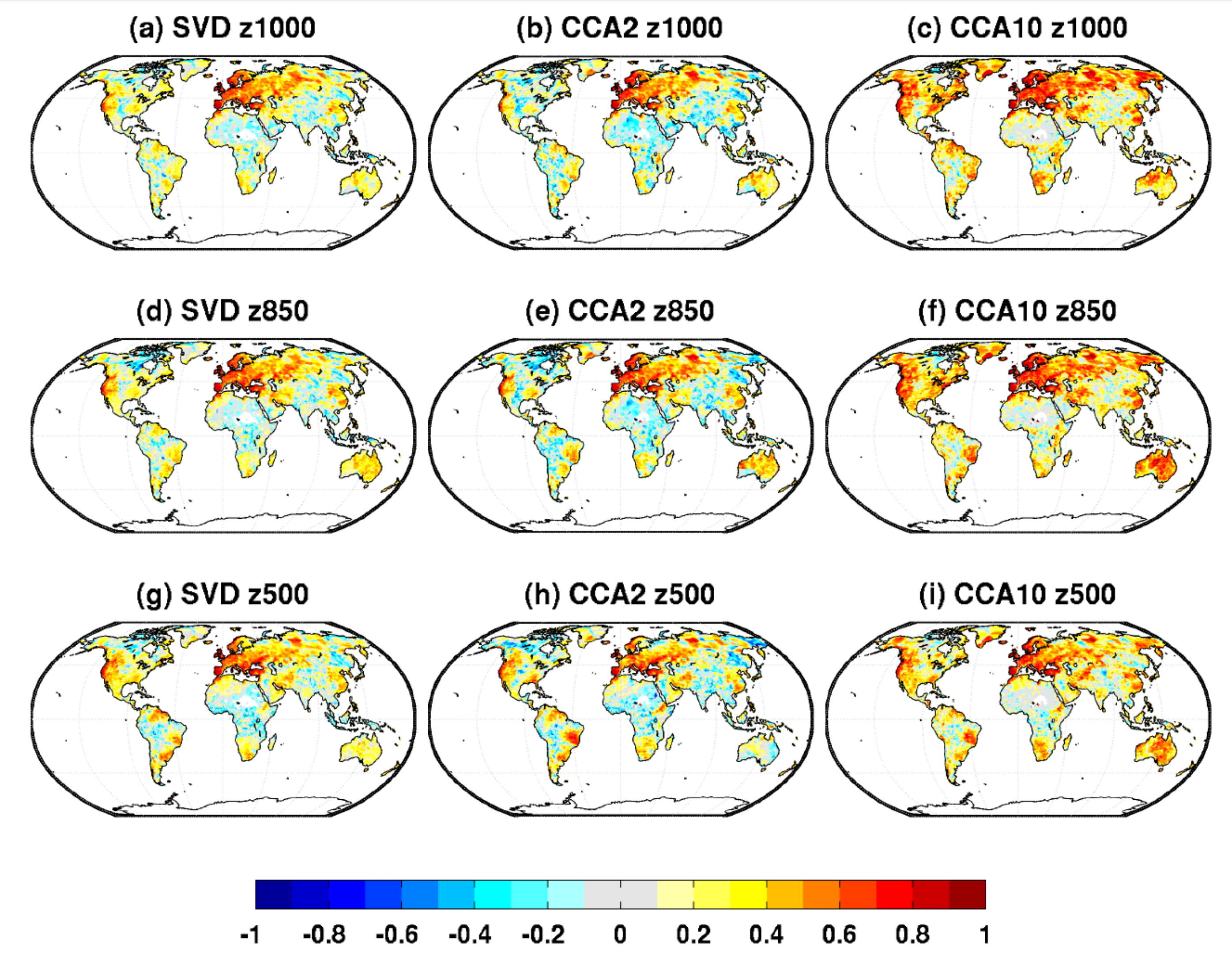
1D-MCA

r = 0.573 RMSE = 4.46

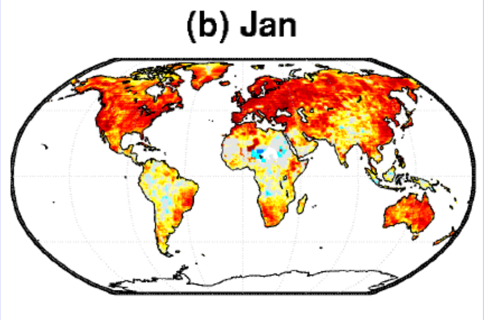
MLR with 5 PCs

r = 0.569 RMSE = 4.01

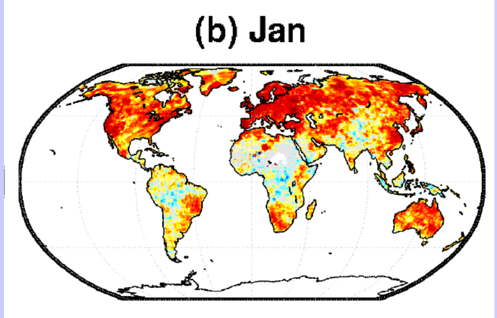
Correlations of January precipitation from PP and MOS downscaling with observations



Local scaling



MLR; 10 PCs

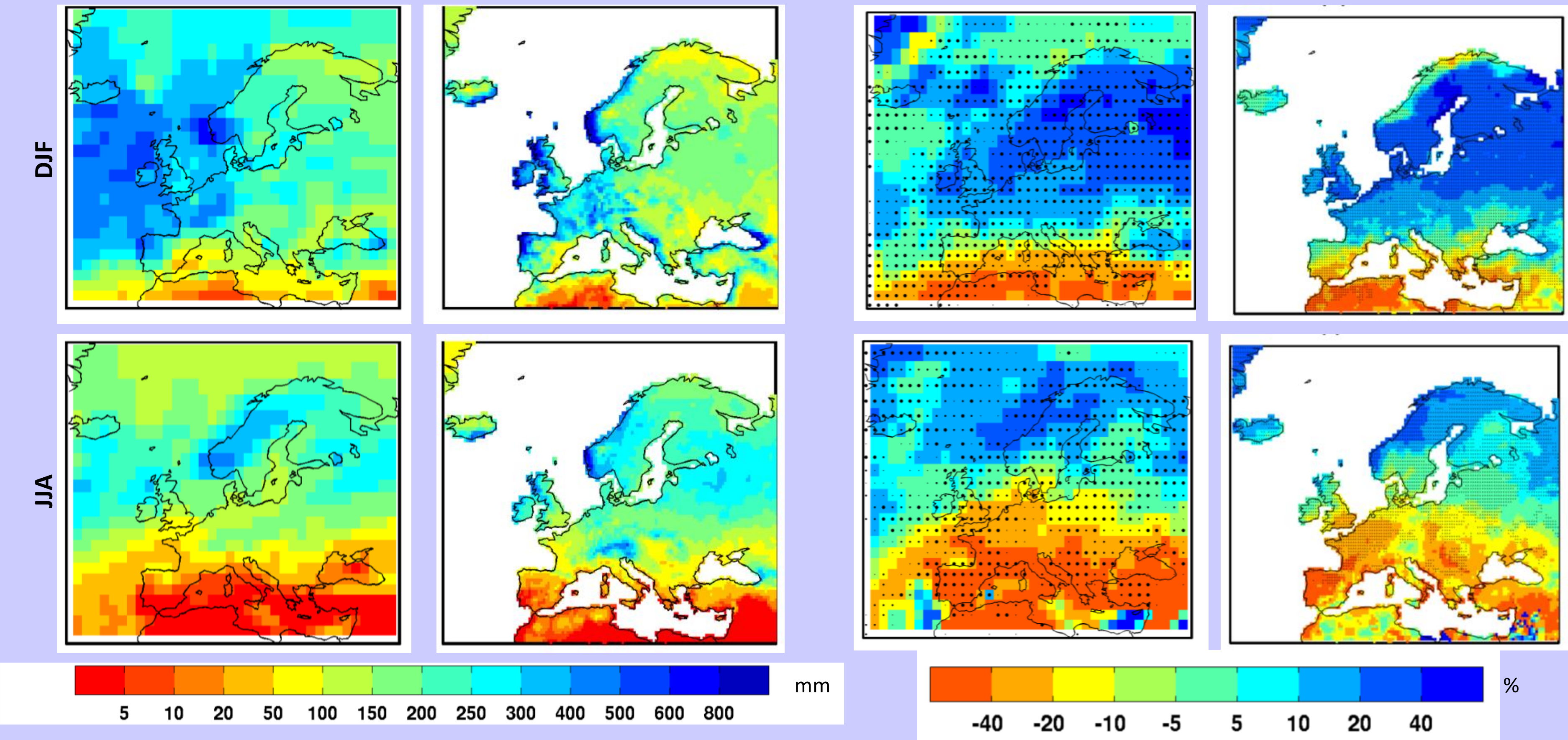


(Eden and Widmann, J. Climate, 2014)

Absolute precipitation 2080-2099 and relative change (raw and downscaled)

Seasonal precipitation (A1B SRES; 2080-2099) **% Difference between 2080-2099 and 1980-1999**

Raw ECHAM5 | Downscaled using PC-MLR | Raw ECHAM5 | Downscaled using PC-MLR



Spatial representativity

in RCMs

Principal options for comparing spatial variability in simulations and observations

- calculate characteristic measures

Spatial dependence

Index	Distributionwise	Eventwise
distribution of daily relative areas of threshold excesses	qs/bias	mse
EOFs	?	
eigenvalues of EOFs	?	
d.o.f.s	?	
structure, amplitude, location	SAL	
range of variogram		
madogram		

one-point correlation maps

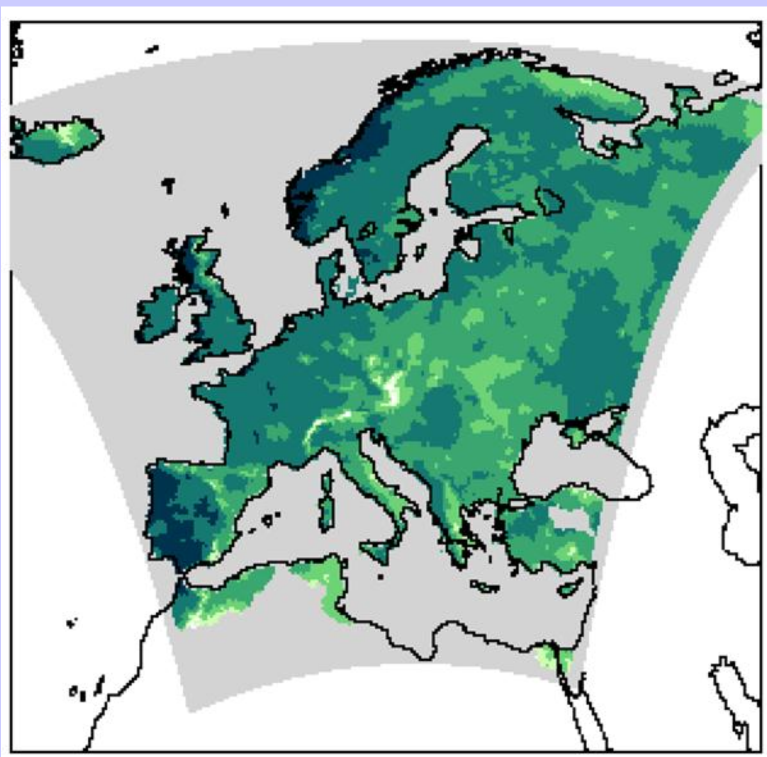
- calculate links between simulated and observed variables (approach taken here)

Local correlations between observed and RCM-simulated precipitation

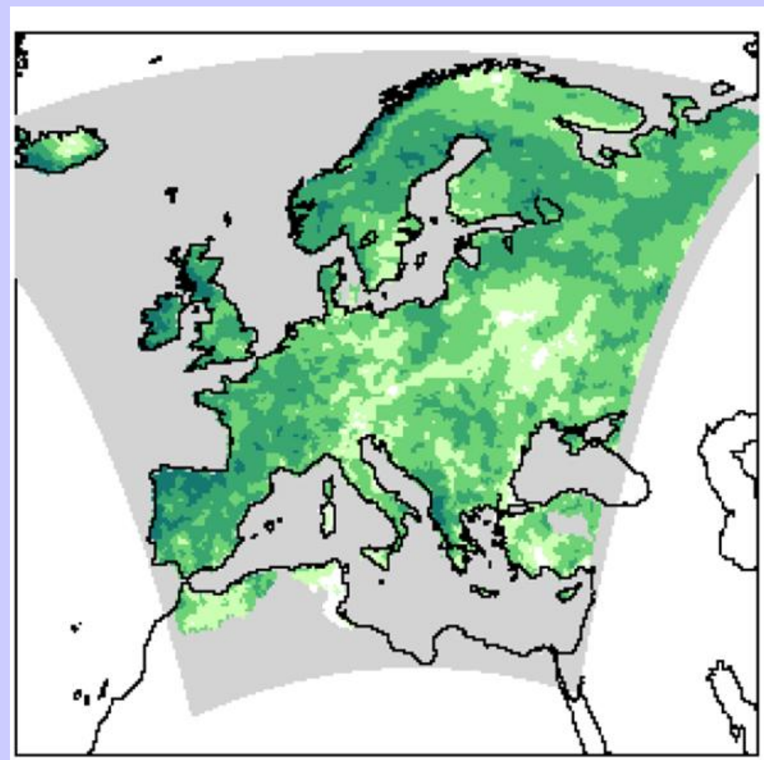
Simulation: seasonal precipitation means RACMO2 (KNMI, 0.22 deg) driven by ERA40, 1961-2000

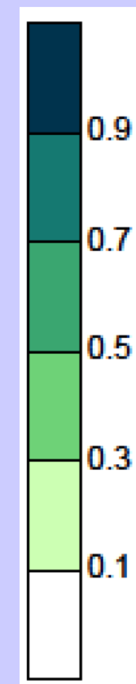
Observations: E-OBS

DJF



JJA





(Maraun and Widmann, submitted)

Spatial representativity issues

Scale mismatch

- PDFs for area means are different from the PDFs for local variables.
  This can be addressed by PDF mapping.

- area mean does not explain all of the local variance.
  This can be addressed by probabilistic MOS.

Location representativity

- the model grid cell that included the target location might not be the best predictor for several reasons

  * systematic bias in large-scale atmospheric circulation
  * unrealistic topography
  * small-scale processes linked to topography that are not captured by the local grid cell (e.g. local winds)

  This can be addressed by non-local MOS.

Assessment of location representativity (operational definition)

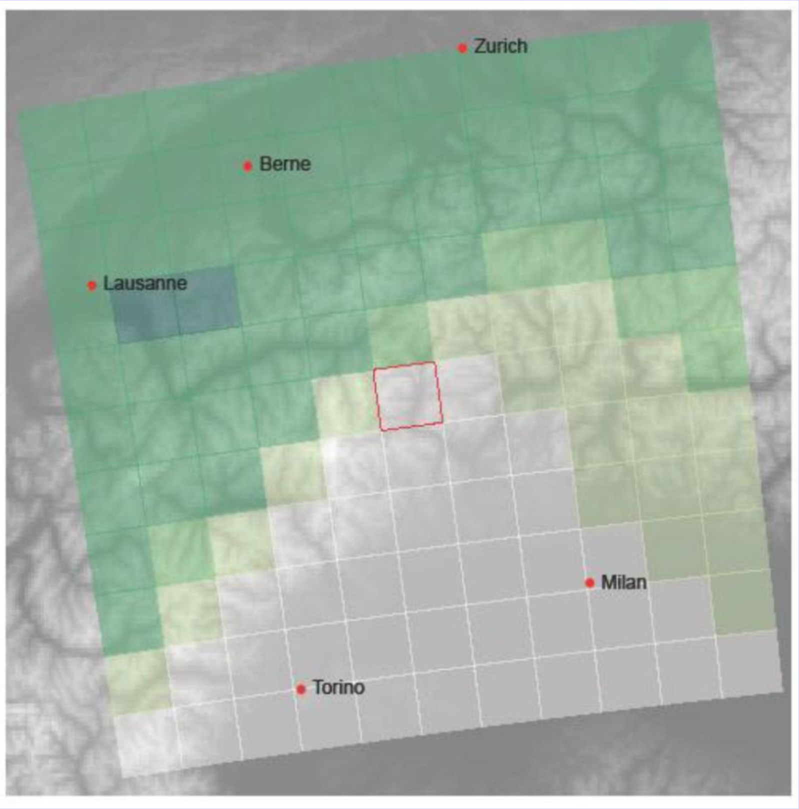
In a perfect boundary setup the grid cell with the best location representativity is the one with the highest correlation with the local time series.

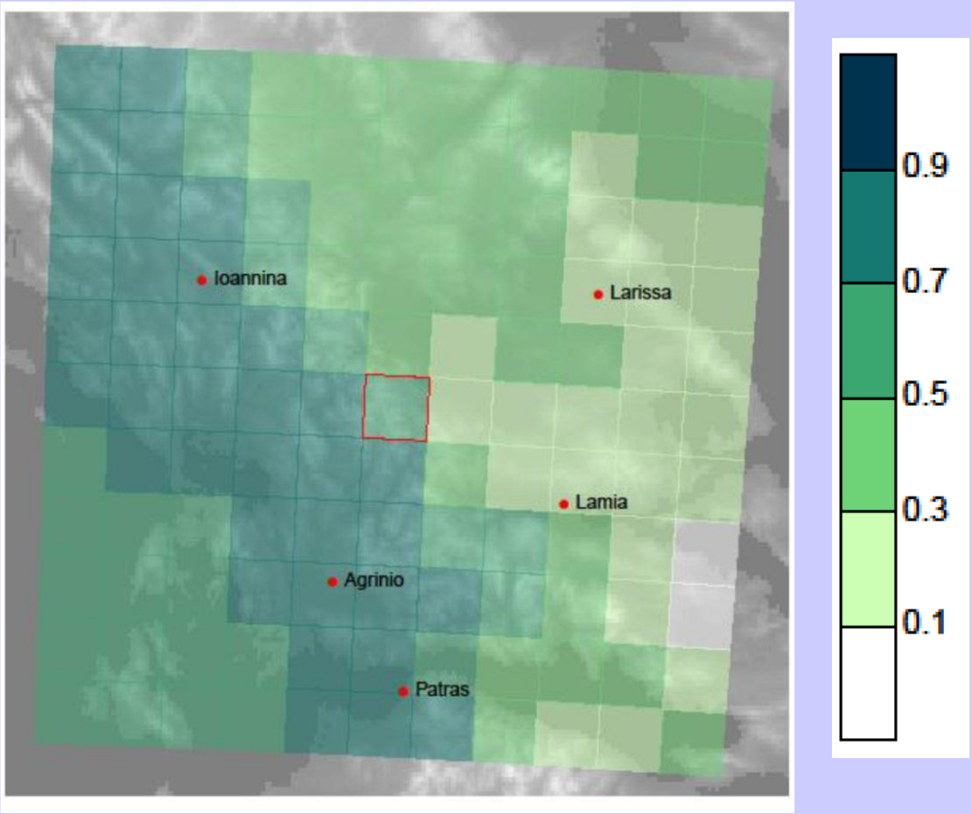
Because of internally generated variability in RCMs we consider correlations for seasonal means.

Correlations between observed (at central grid box) and RCM-simulated precipitation

Simulation: DJF precipitation means RACMO2 (KNMI, 0.22 deg) driven by ERA40

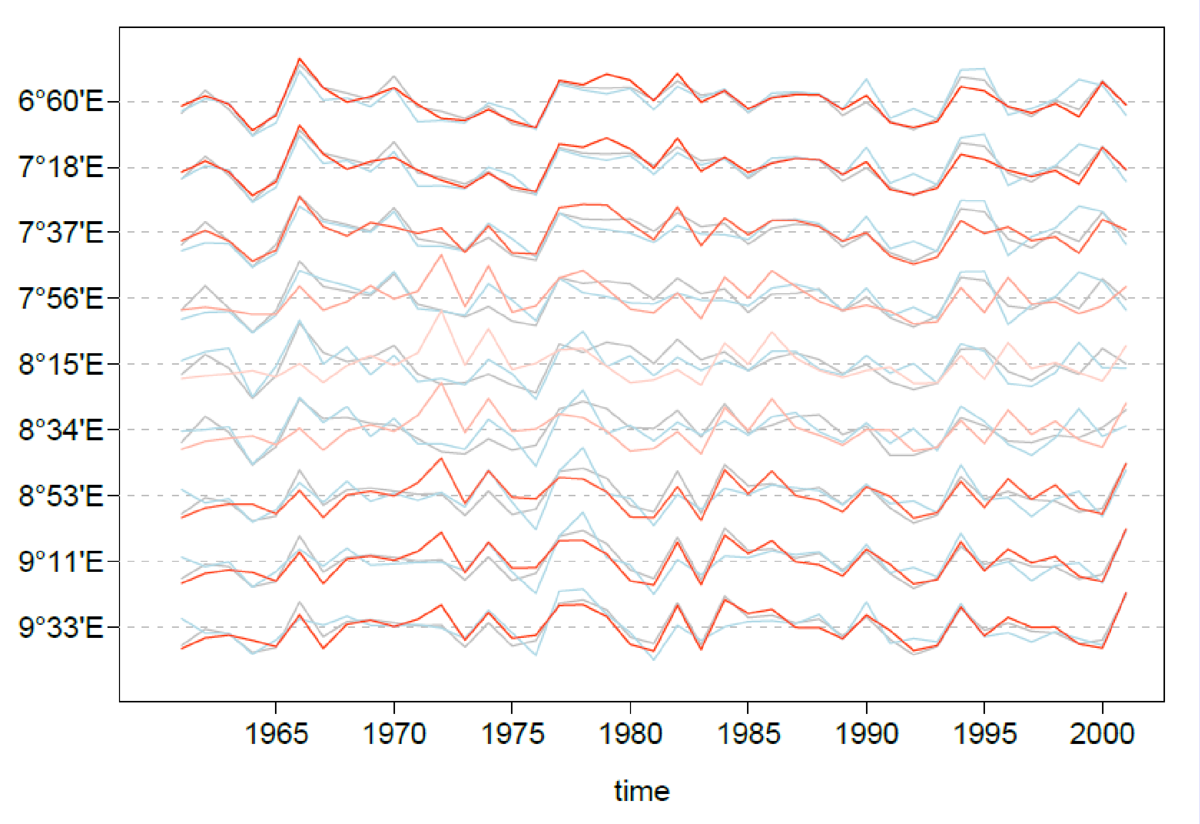
Observations: E-OBS

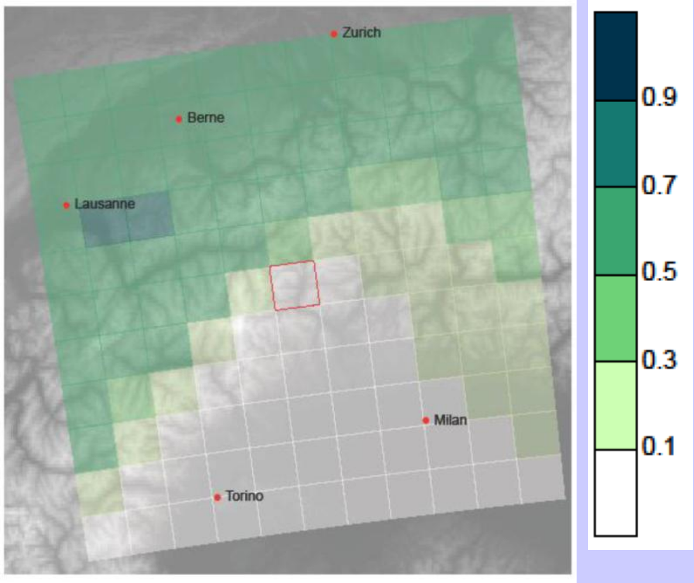




Time series, zonal cross section through central grid cell

observed
simulated

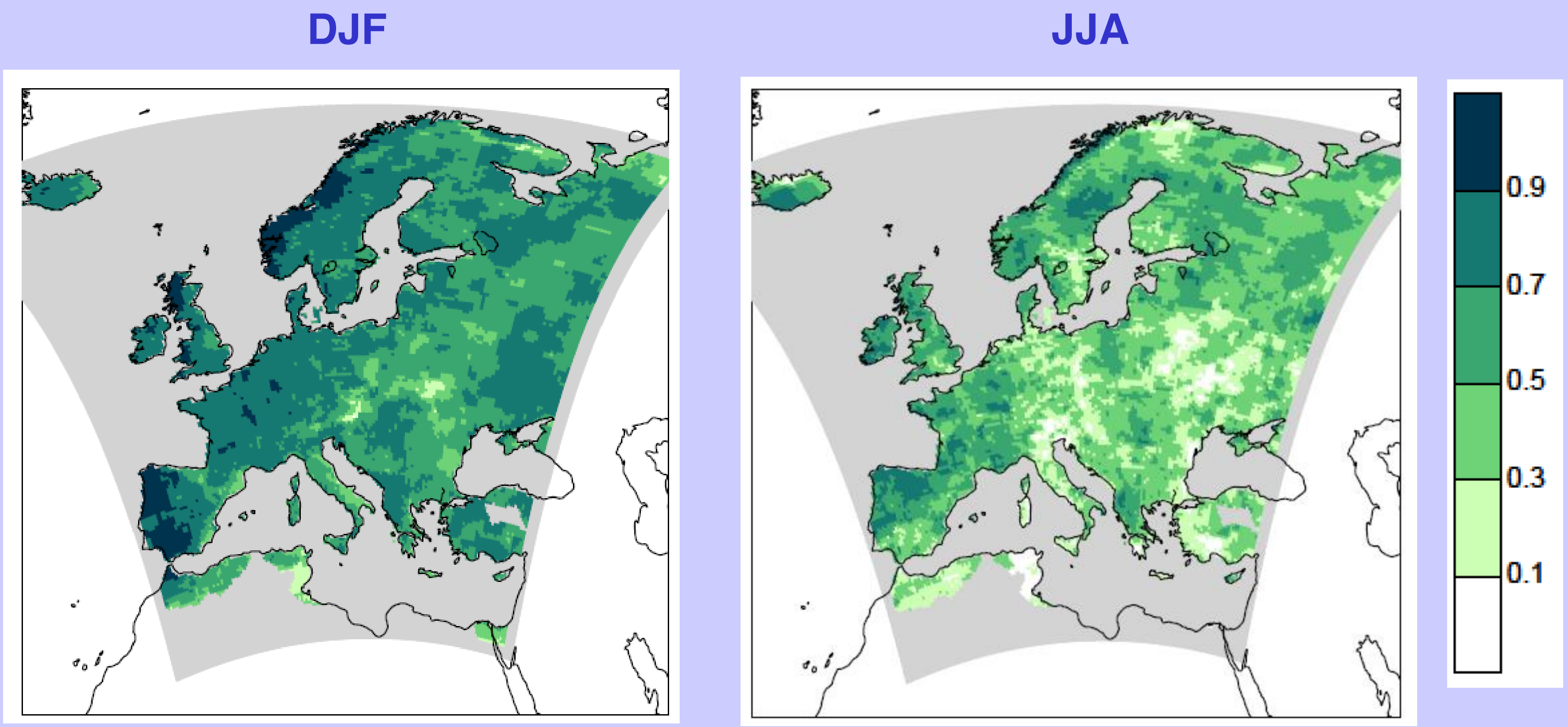




Non-local correlations between observed and RCM-simulated precipitation (best grid box

Simulation: seasonal precipitation means RACMO2 (KNMI, 0.22 deg) driven by ERA40

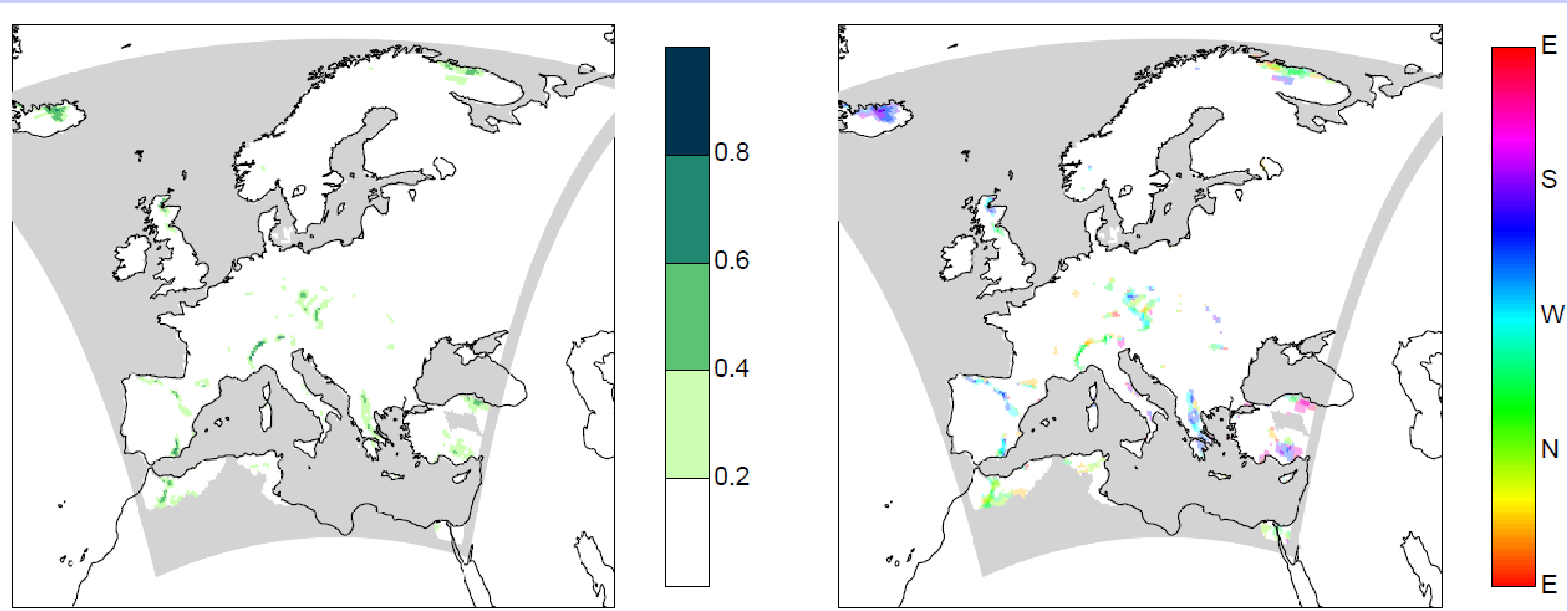
Observations: E-OBS



(Maraun and Widmann, submitted)

Difference between non-local and local correlations (DJF)

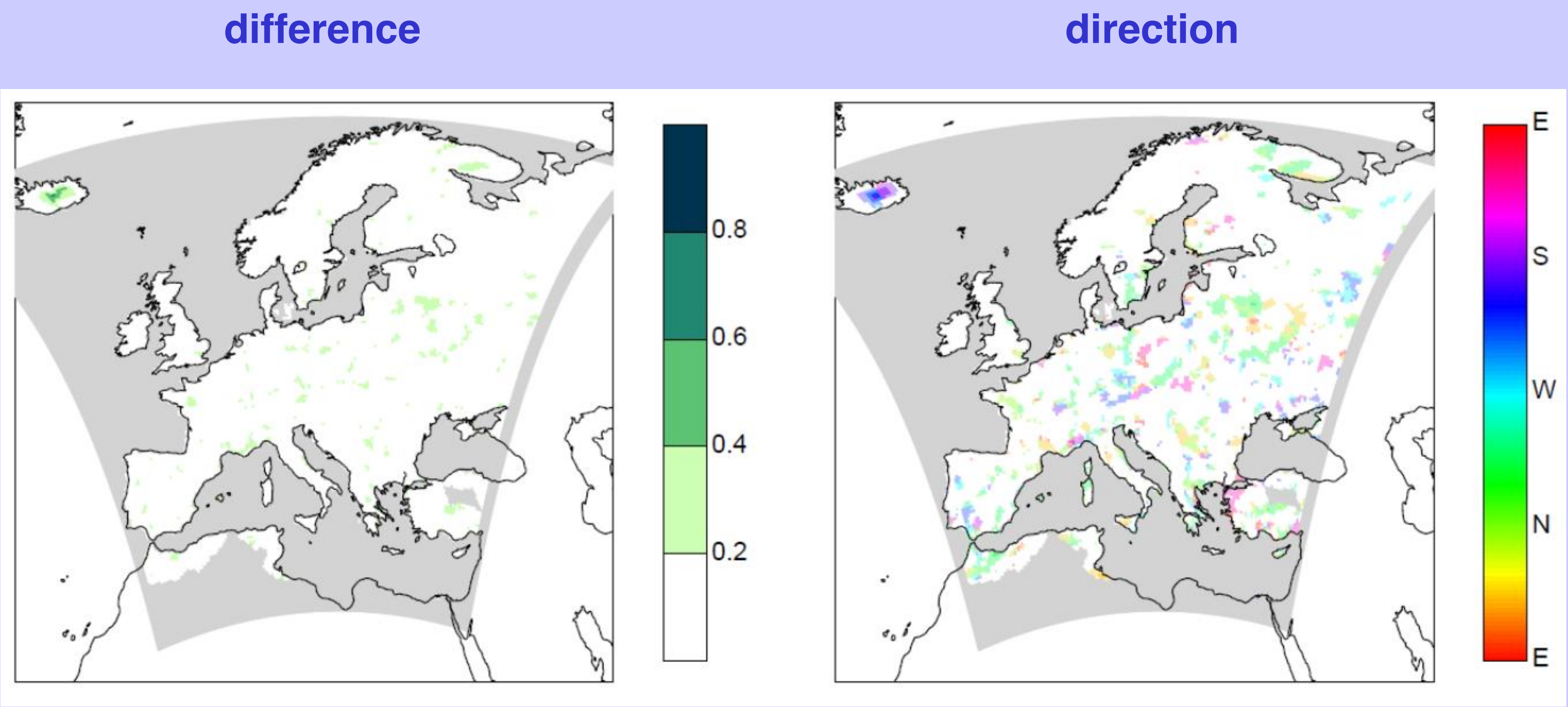
difference **direction**



Some systematic improvement over areas with complex topography

Local grid cell is in some areas not location representative, which leads to low local correlations.

Difference between non-local and local correlations (DJF)



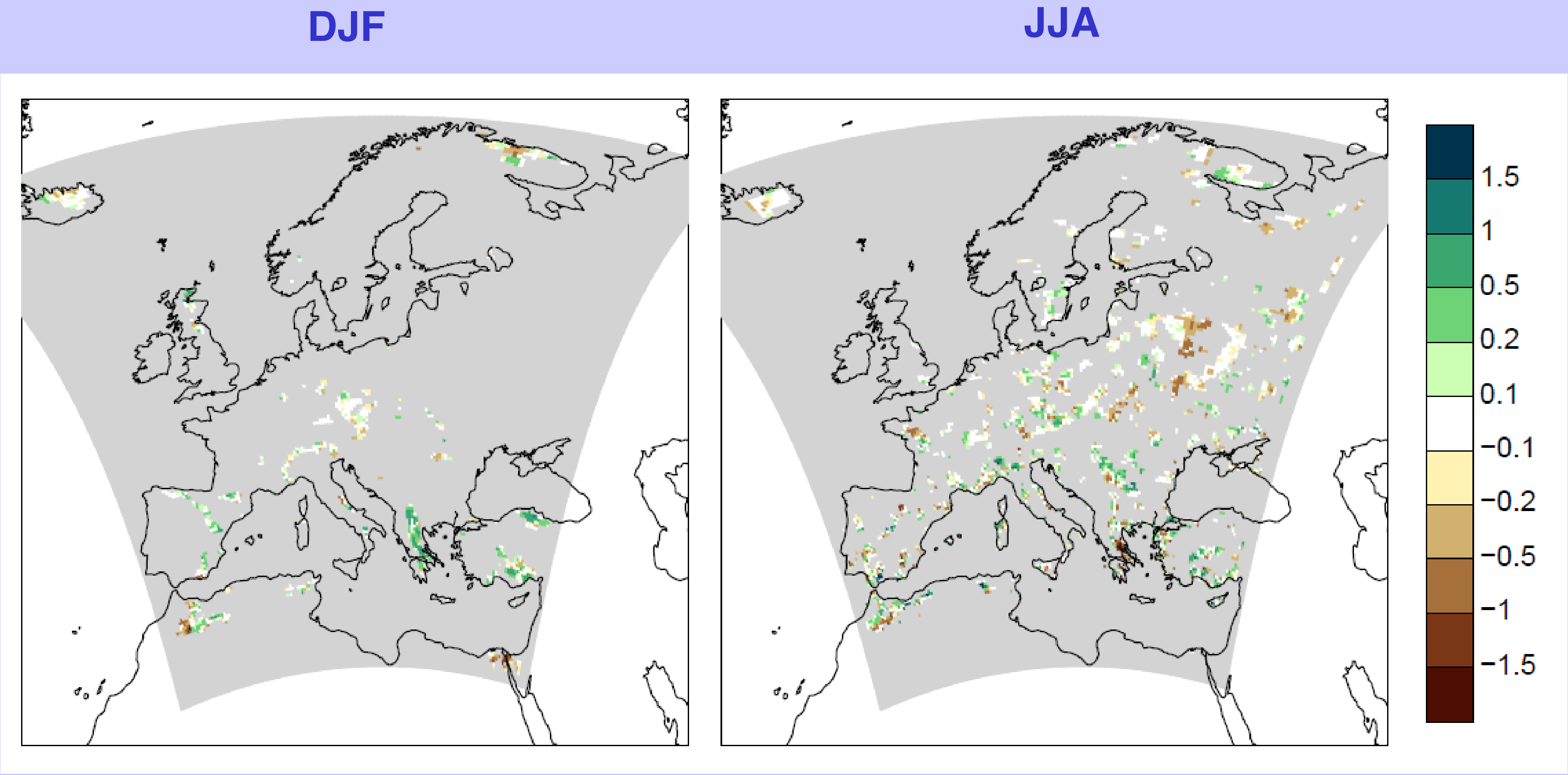
No systematic improvement

Low local correlations not due to local representativity problems

Change in trends using non-local grid cells

Closer to observed trends

Less close to observed trends



Summary

In areas of complex topography the local model grid cells may not be representative for the local target variable.
(even after a PDF mapping or probabilistic MOS)

Pattern-based methods or using simulated predictors from nearby locations can improve downscaling performance.