# Introduction to downscaling

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with large contributions from

J..M. Eden and D. Maraun,

3rd VALUE training school, ICTP Trieste3. November 2014

# Content

## Conceptual basis and method classification

- Perfect Prog (PP) downscaling and Model Output Statistics (MOS)
- deterministic vs. probabilistic

## Examples for precipitation (heavily biased towards on work)

### GCM-MOS

- test with NCEP reanalysis precipitation
- assessment of precipitation skill and development of corrections (MOS) for ECHAM5 precipitation

### RCM-MOS

- precipitation biases and corrections
- deterministic and probabilistic MOS

## The VALUE validation framework

# Recent review paper on downscaling

## PRECIPITATION DOWNSCALING UNDER CLIMATE CHANGE: RECENT DEVELOPMENTS TO BRIDGE THE GAP BETWEEN DYNAMICAL MODELS AND THE END USER

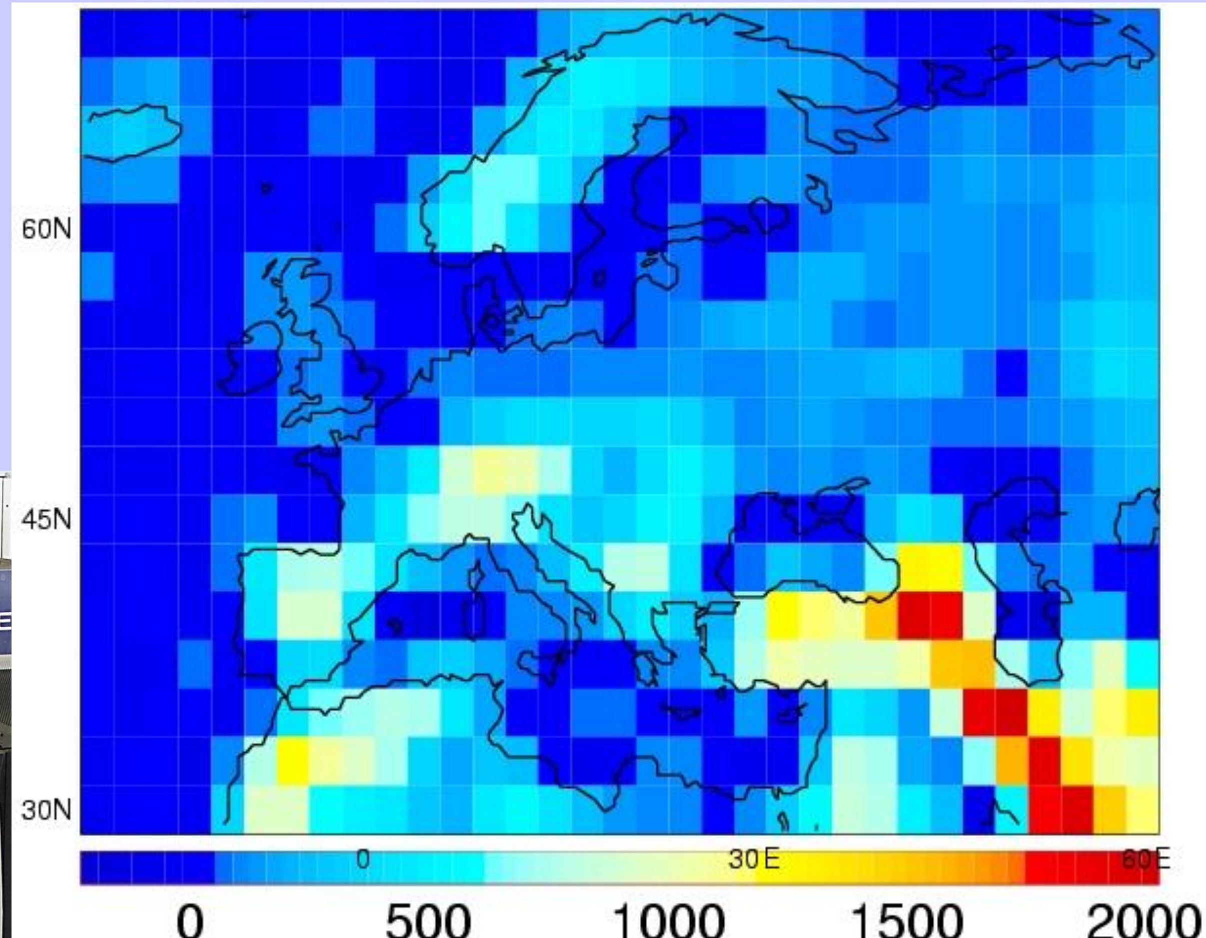
D. Maraun,[1,2] F. Wetterhall,[3] A. M. Ireson,[4] R. E. Chandler,[5] E. J. Kendon,[6] M. Widmann,[7] S. Brienen,[8,9] H. W. Rust,[10] T. Sauter,[11] M. Themeßl,[12] V. K. C. Venema,[8] K. P. Chun,[4] C. M. Goodess,[2] R. G. Jones,[6] C. Onof,[4] M. Vrac,[10] and I. Thiele-Eich[8]

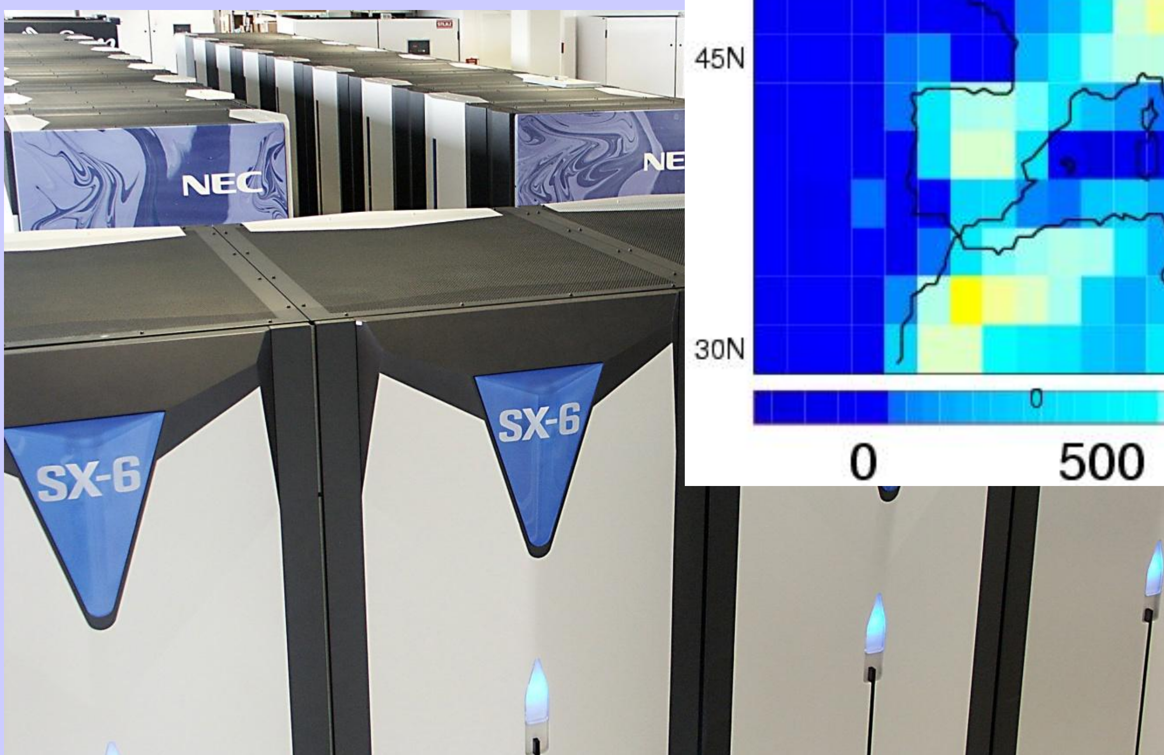
Received 19 October 2009; revised 26 March 2010; accepted 5 April 2010; published 24 September 2010.

[1] Precipitation downscaling improves the coarse resolution and poor representation of precipitation in global climate models and helps end users to assess the likely hydrological impacts of climate change. This paper integrates perspectives from meteorologists, climatologists, statisticians, and hydrologists to identify generic end user (in particular, impact modeler) needs and to discuss downscaling capabilities and gaps. End users need a reliable representation of precipitation intensities and temporal and spatial variability, as well as physical consistency, independent of region and season. In addition to presenting dynamical downscaling, we review perfect prognosis statistical downscaling, model output statistics, and weather generators, focusing on recent developments to improve the representation of space-time variability. Furthermore, evaluation techniques to assess downscaling skill are presented. Downscaling adds considerable value to projections from global climate models. Remaining gaps are uncertainties arising from sparse data; representation of extreme summer precipitation, subdaily precipitation, and full precipitation fields on fine scales; capturing changes in small-scale processes and their feedback on large scales; and errors inherited from the driving global climate model.

**Citation:** Maraun, D., et al. (2010), Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user, *Rev. Geophys.*, *48*, RG3003, doi:10.1029/2009RG000314.

# Topography in a global climate model

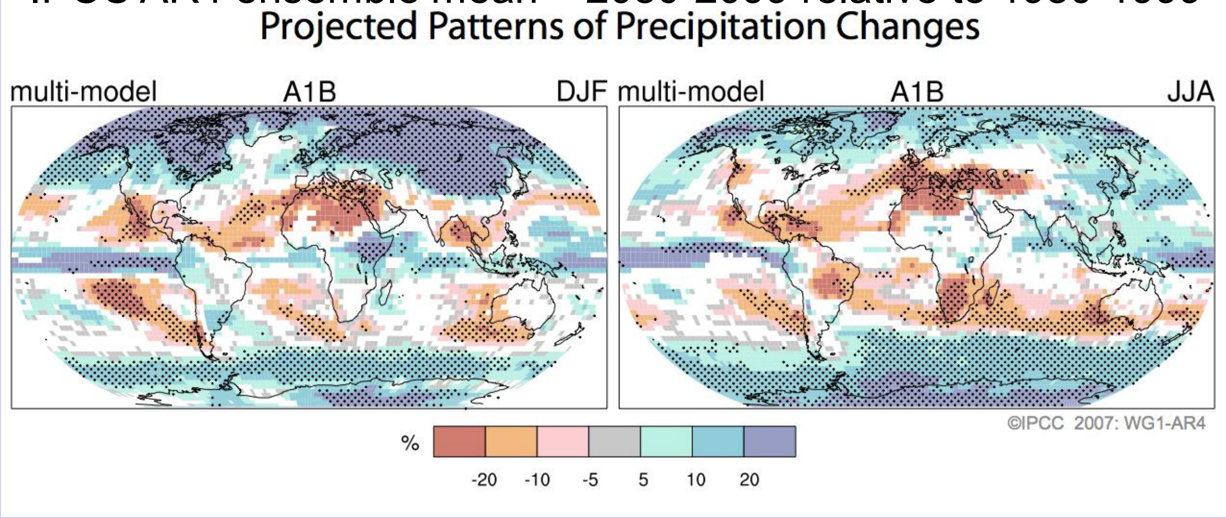



NCEP Reanalysis Model
same resolution as
IPCC AR4 models

# Problems with GCM-simulated precipitation

IPCC AR4 ensemble mean – 2080-2099 relative to 1980-1999




**Coarse resolution**

**Biases**

**internal variability vs. true model differences?**

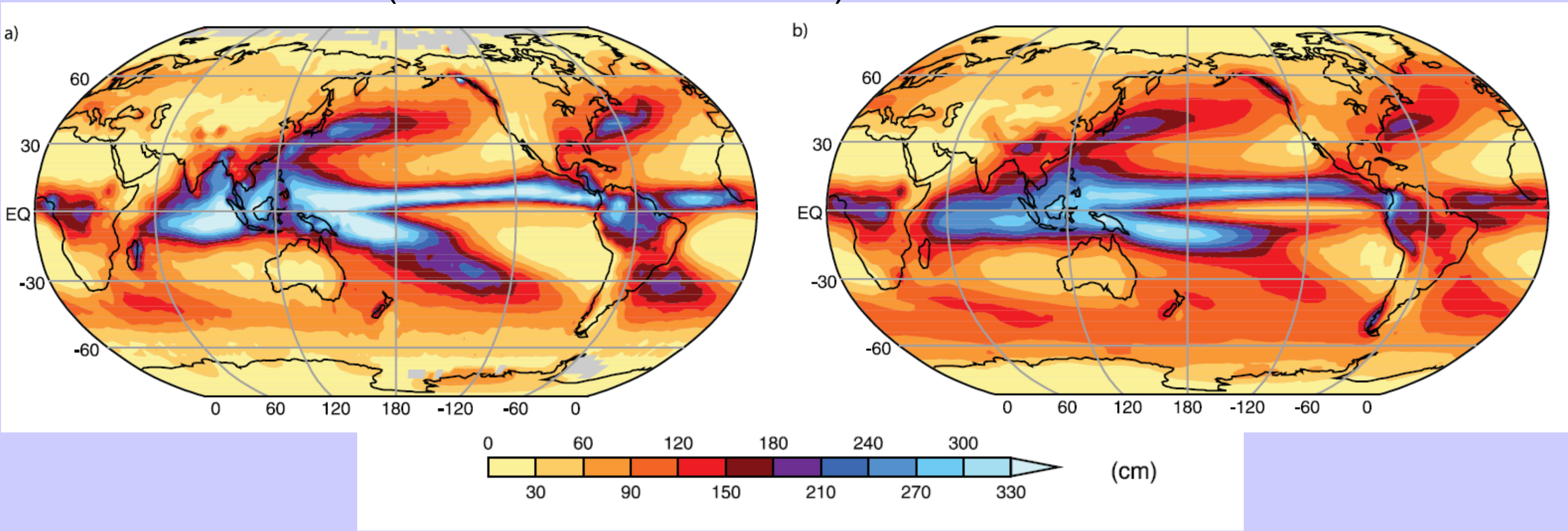
**large-scale circulation vs. parametrisation errors?**

**representation of temporal variability?**

**GCM precip can often not be directly used**

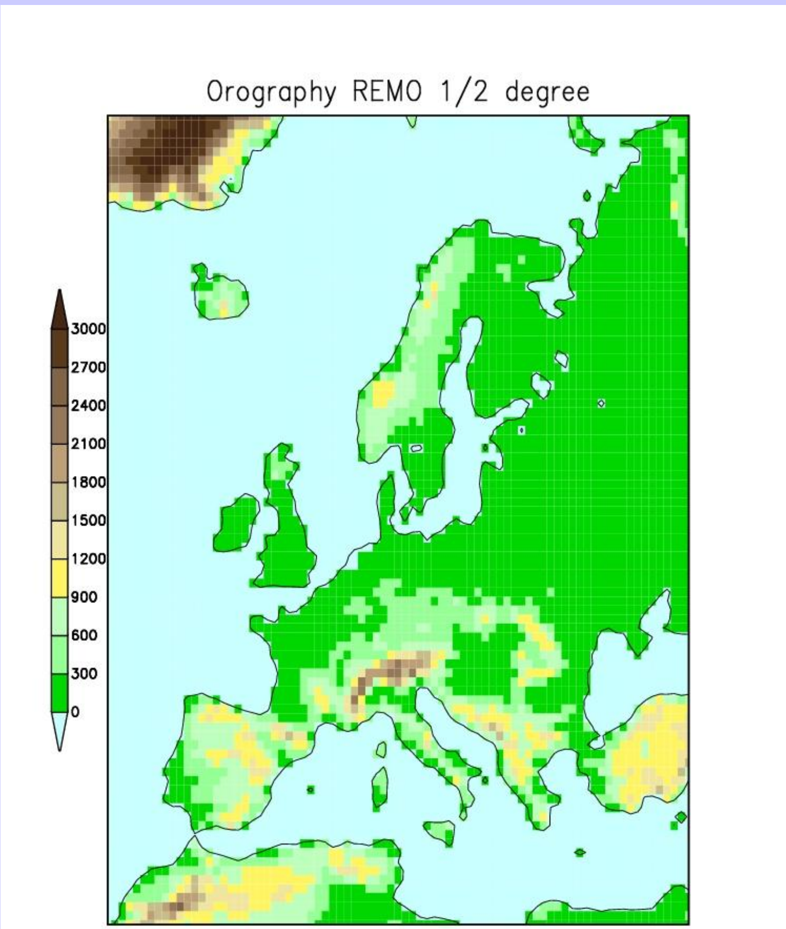
CMAP observations (annual mean 1980-1999)

IPCC AR4 ensemble mean

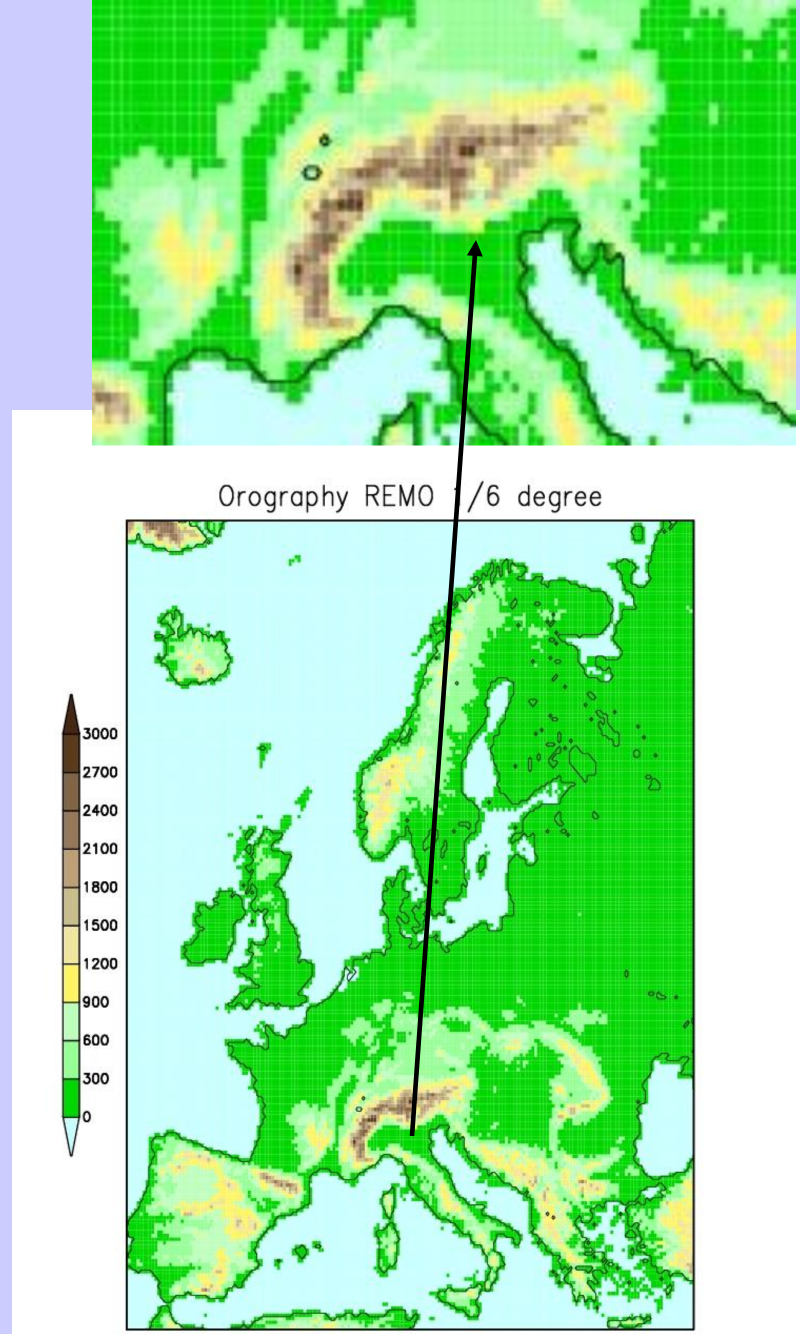


# Topography in a regional model (REMO)

(courtesy F. Feser)



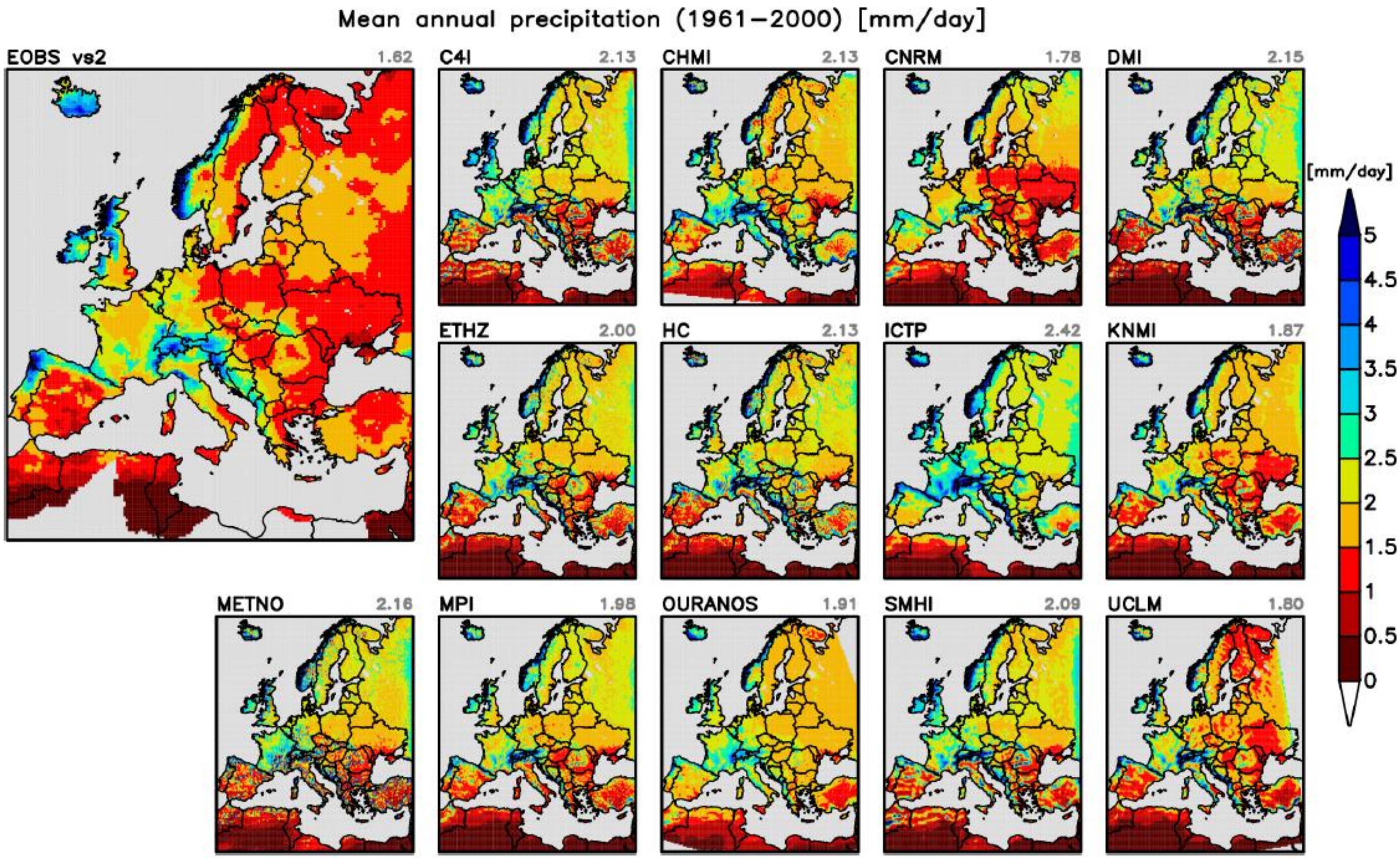

50 km resolution




17 km resolution

# RCMs are biased

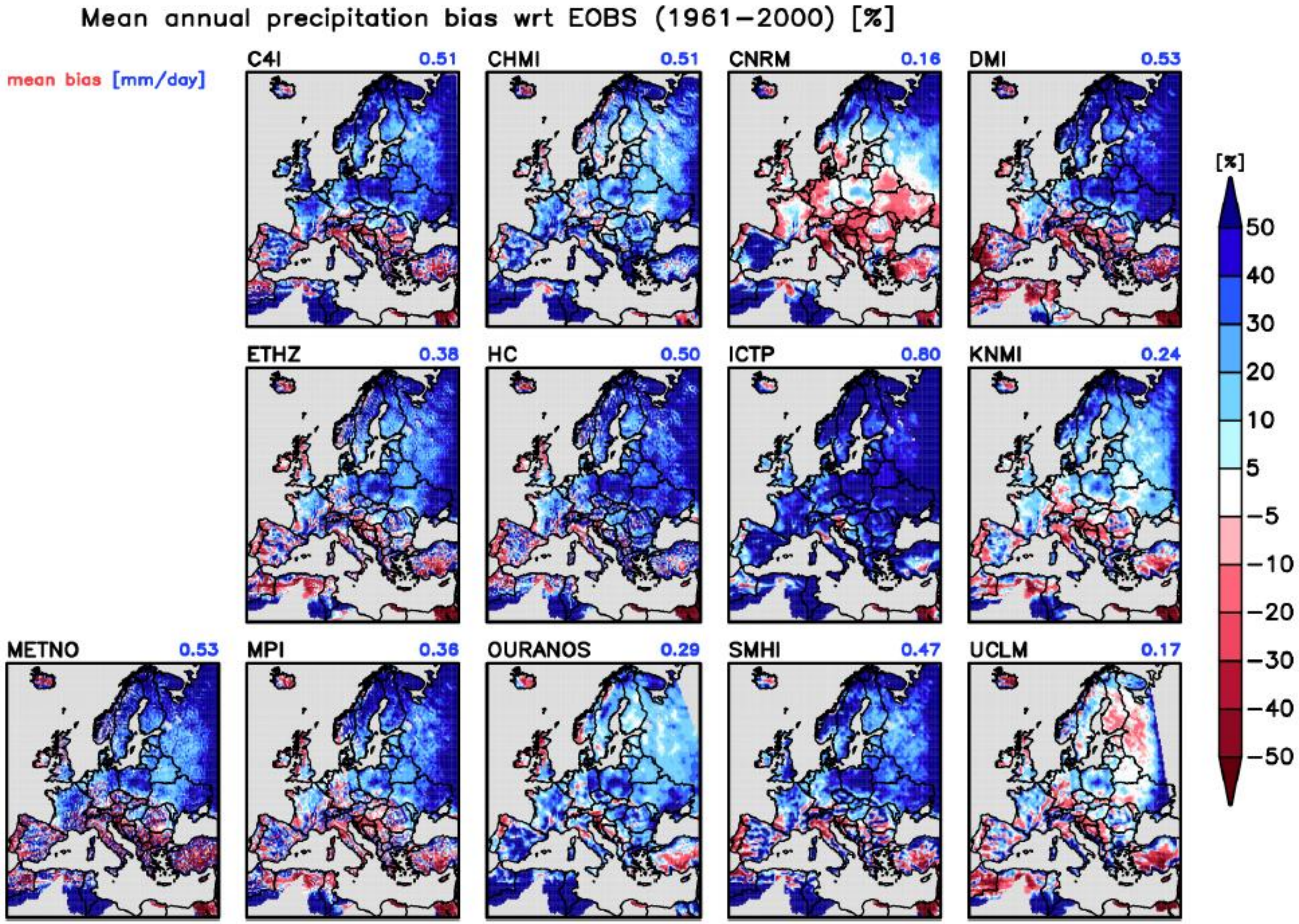
## mean precipitation in ERA40-driven RCMs (from ENSEMBLES)




*Kotlarski, unpublished*

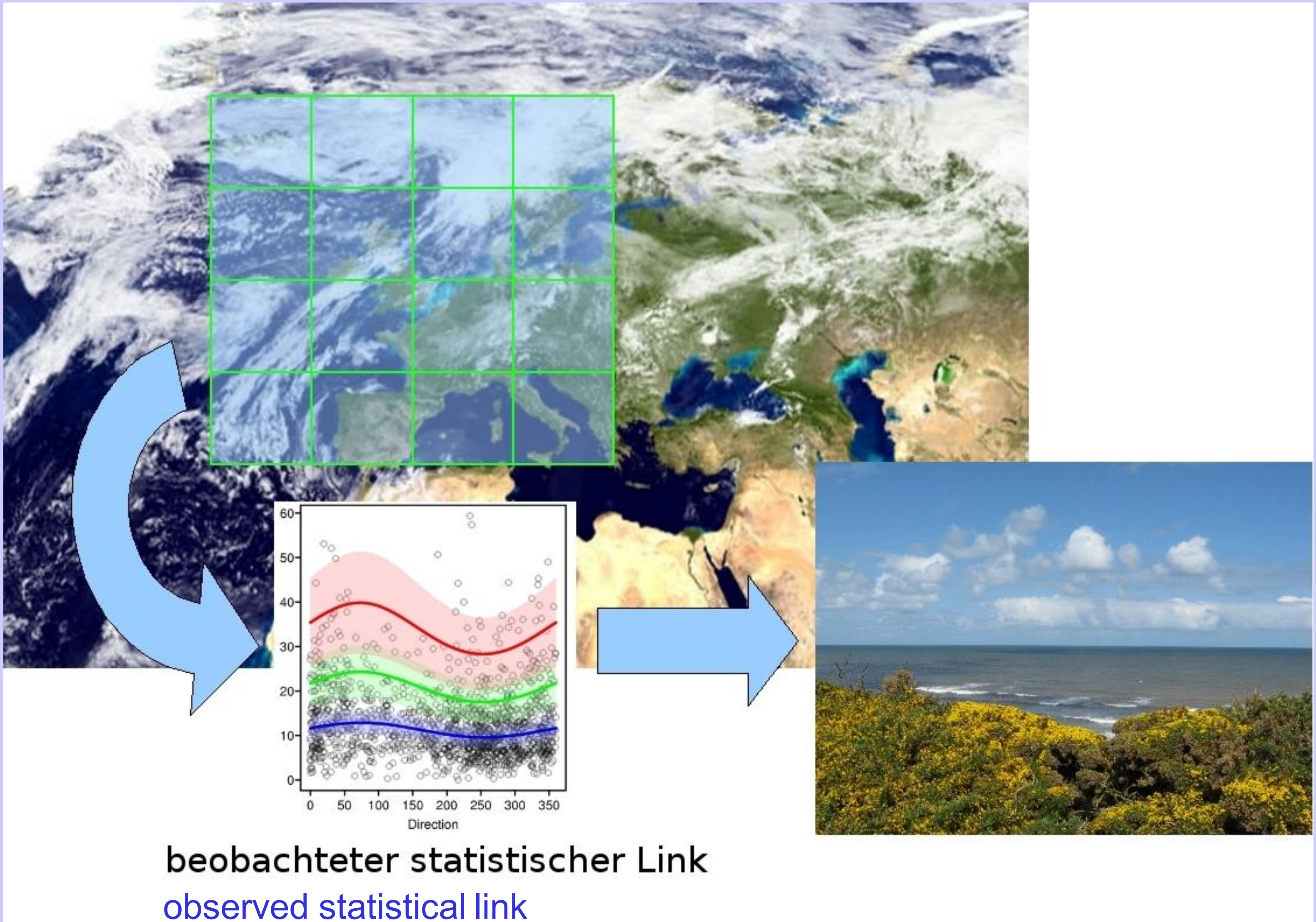
# RCMs are biased

## precipitation bias in ERA40-driven RCMs (from ENSEMBLES)



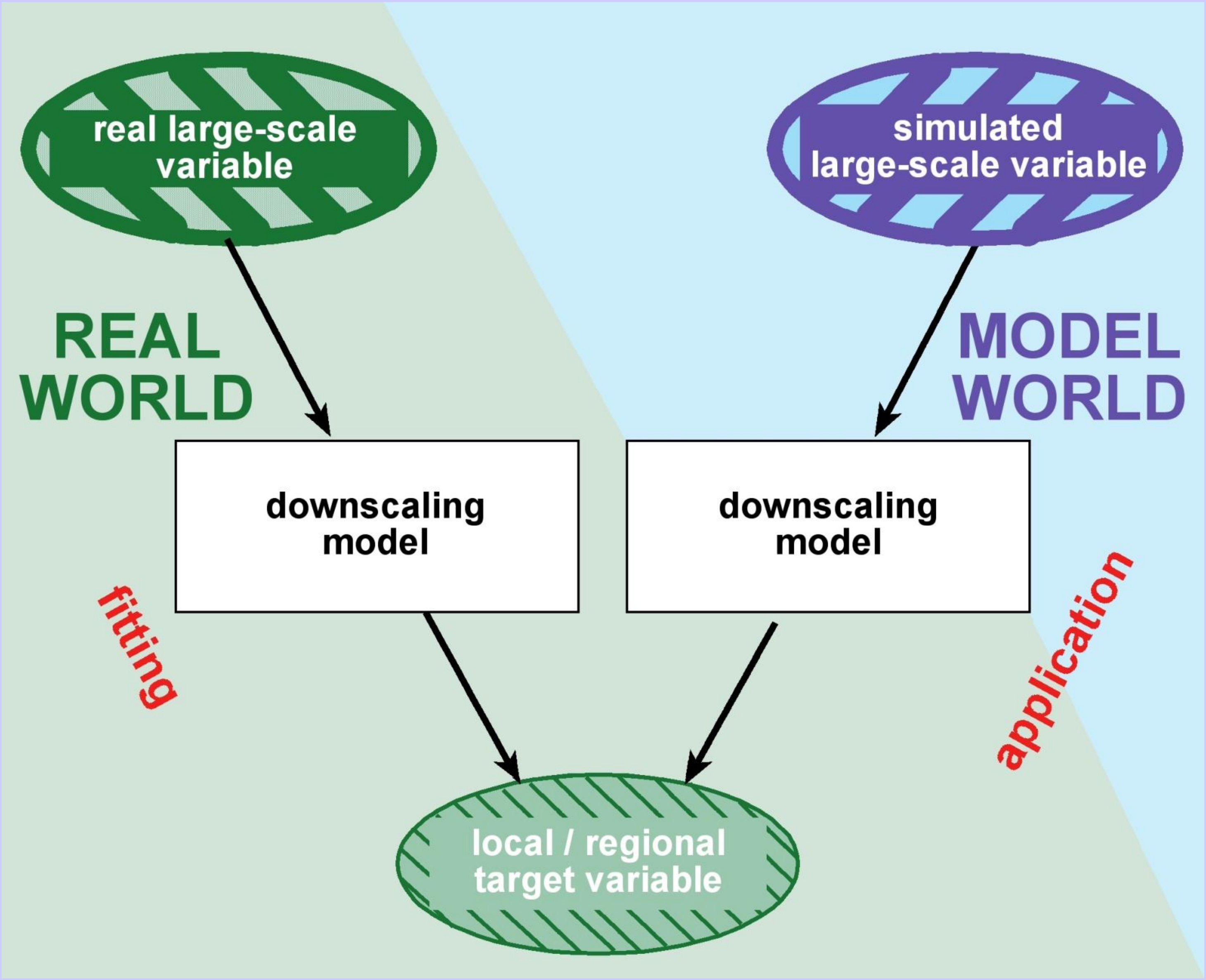

*Kotlarski, unpublished*

# Statistical downscaling (Perfect Prog)




(courtesy Douglas Maraun)

# **Perfect Prog**(nosis) **Downscaling**



# Perfect Prog downscaling

Challenging predictor requirements

- informative: high predictive power on timescale of interest

- effective: non-redundant, smallest set

- physically motivated

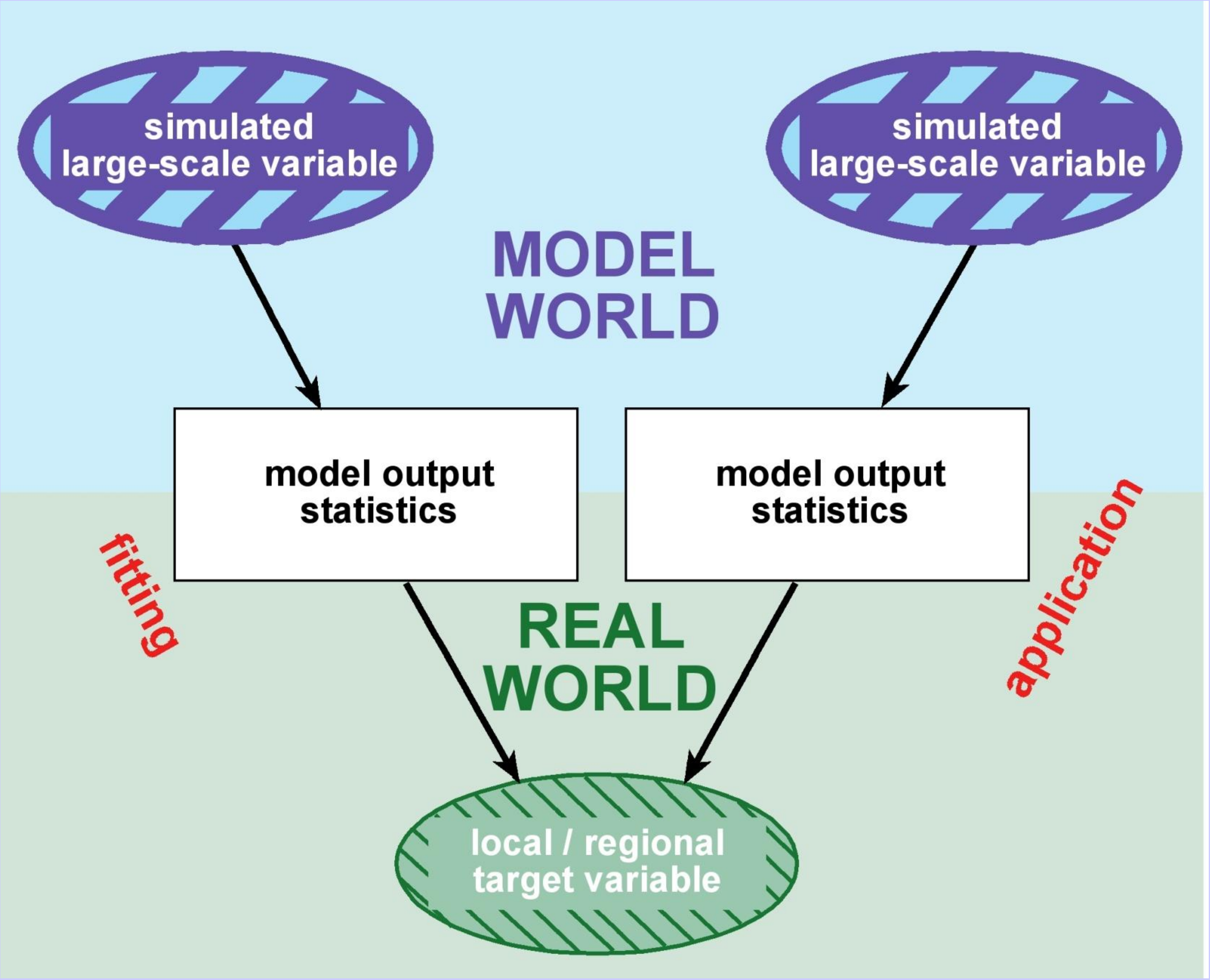
- ‘perfectly’ simulated
  in a climate change context this means predictors must be a plausible realisation of future climate (no systematic model errors)

- candidates include circulation, temperature, humidity

Statistical relationships need to be stable over time

Bypasses complex synoptic- and mesoscale processes that may be successfully simulated and tries to describe them with simple statistical models

# Model Output Statistics (MOS), aka bias correction



# Downscaling classification (used in VALUE COST action)

1. Dynamical Downscaling (E. Coppola, S. Kotlarski)

1. Perfect Prog(nosis) (PP)

2.1 deterministic

2.2 probabilistic (PDFs but no time series)

2.3 stochastic, time series / weather generator (R. Chandler)

3. Model Output Statistics (MOS)

3.1 deterministic

3.2 probabilistic

3.3 stochastic, timeseries / weather generator

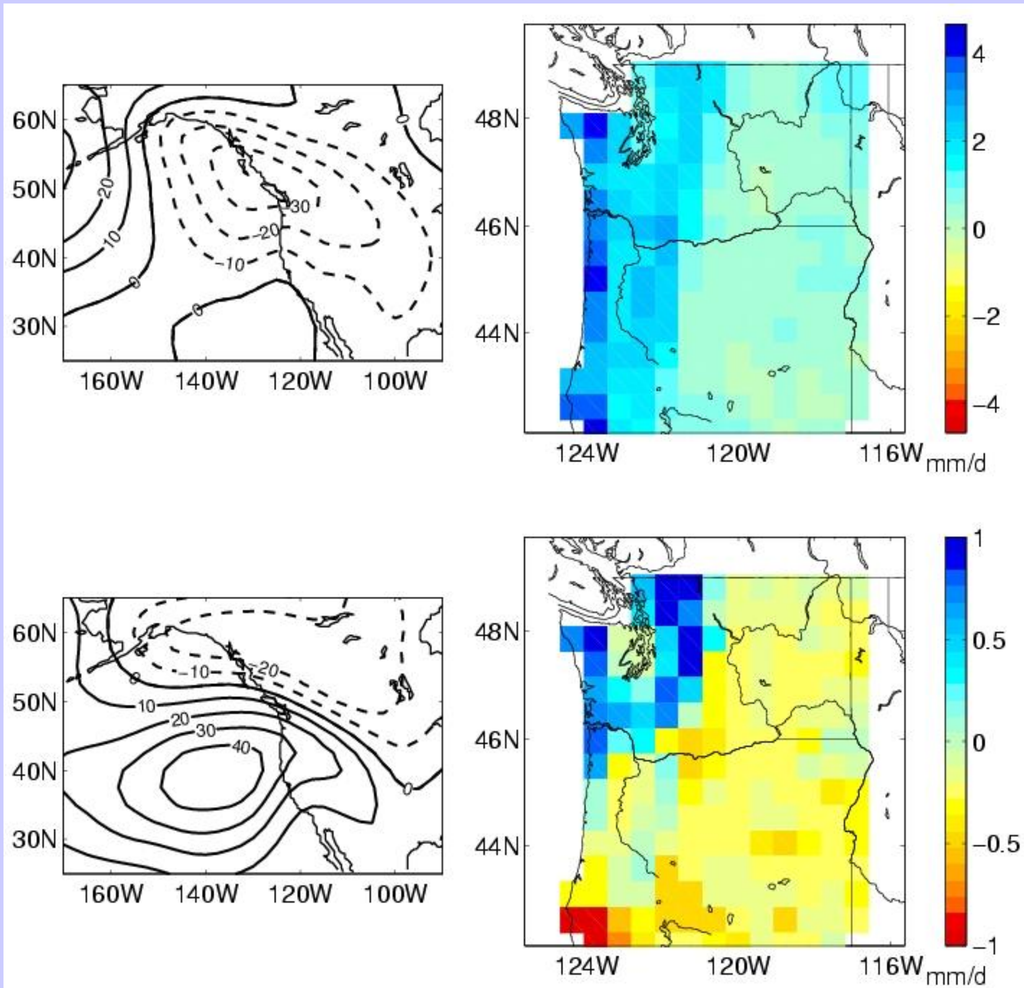
# Perfect Prog downscaling - estimating precip from pressure

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

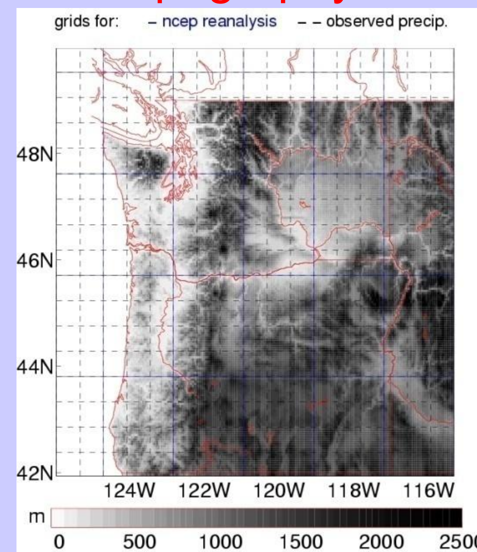
geopot. height (Z1000) precipitation

pair 1

pair 2




topography

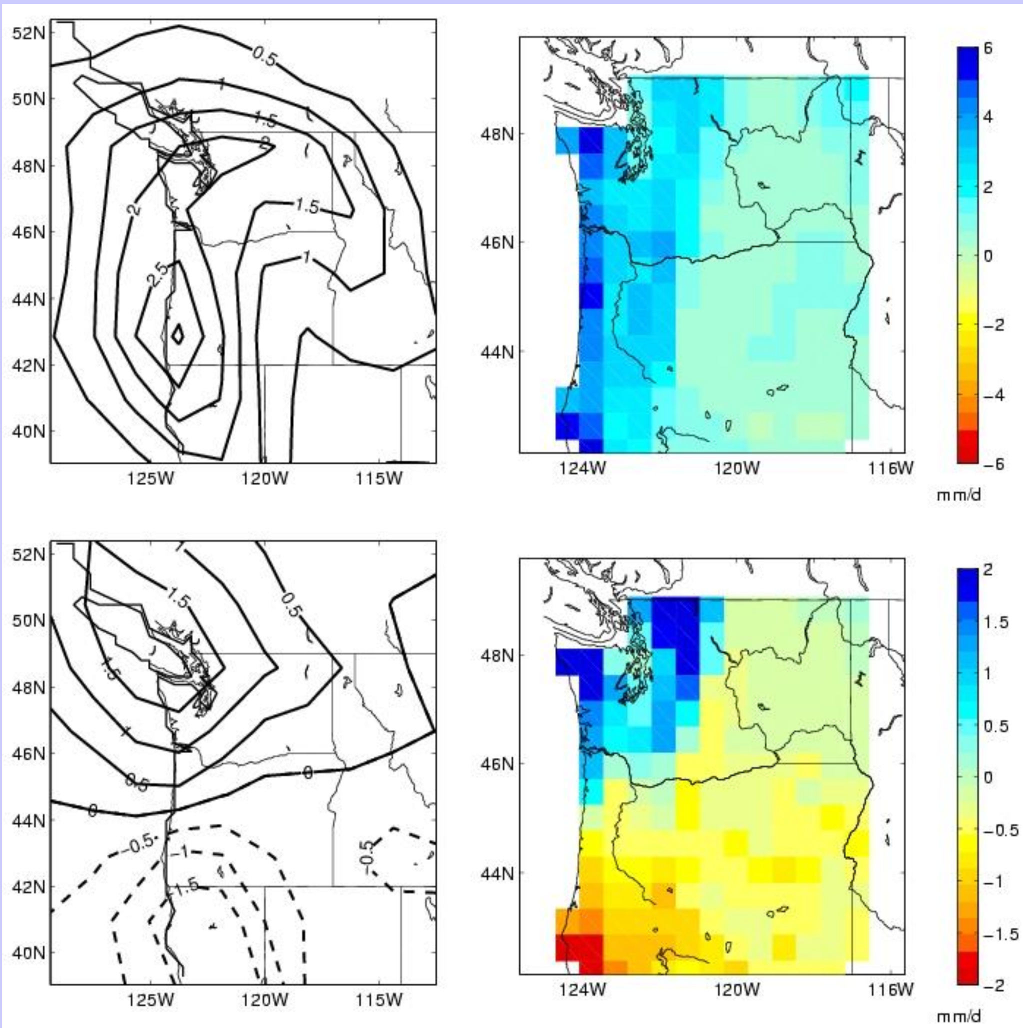



**(Widmann and Bretherton, J. Climate 2000; Widmann et al., J. Climate, 2003)**

# Model Output Statistics - estimating true precipitation from simulated precipitation

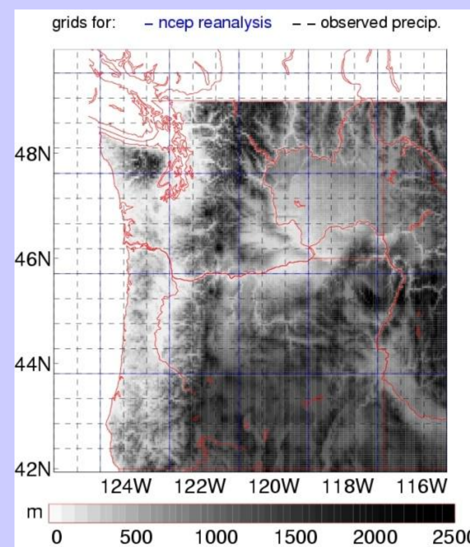
simulated precipitation (NCEP reanalysis)

observations




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

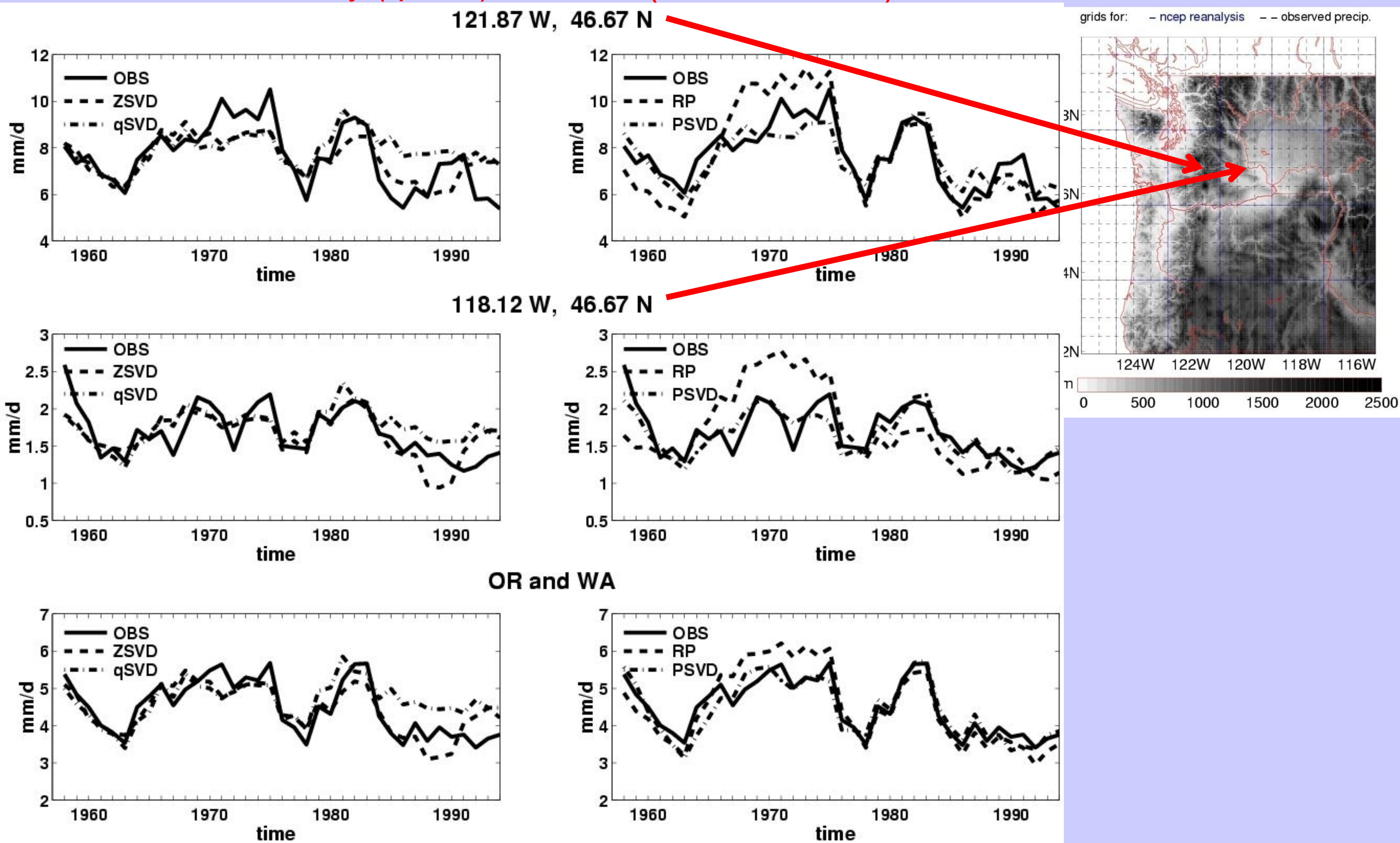
topography



# precipitation (3 y mean, DJF 1958-1998)

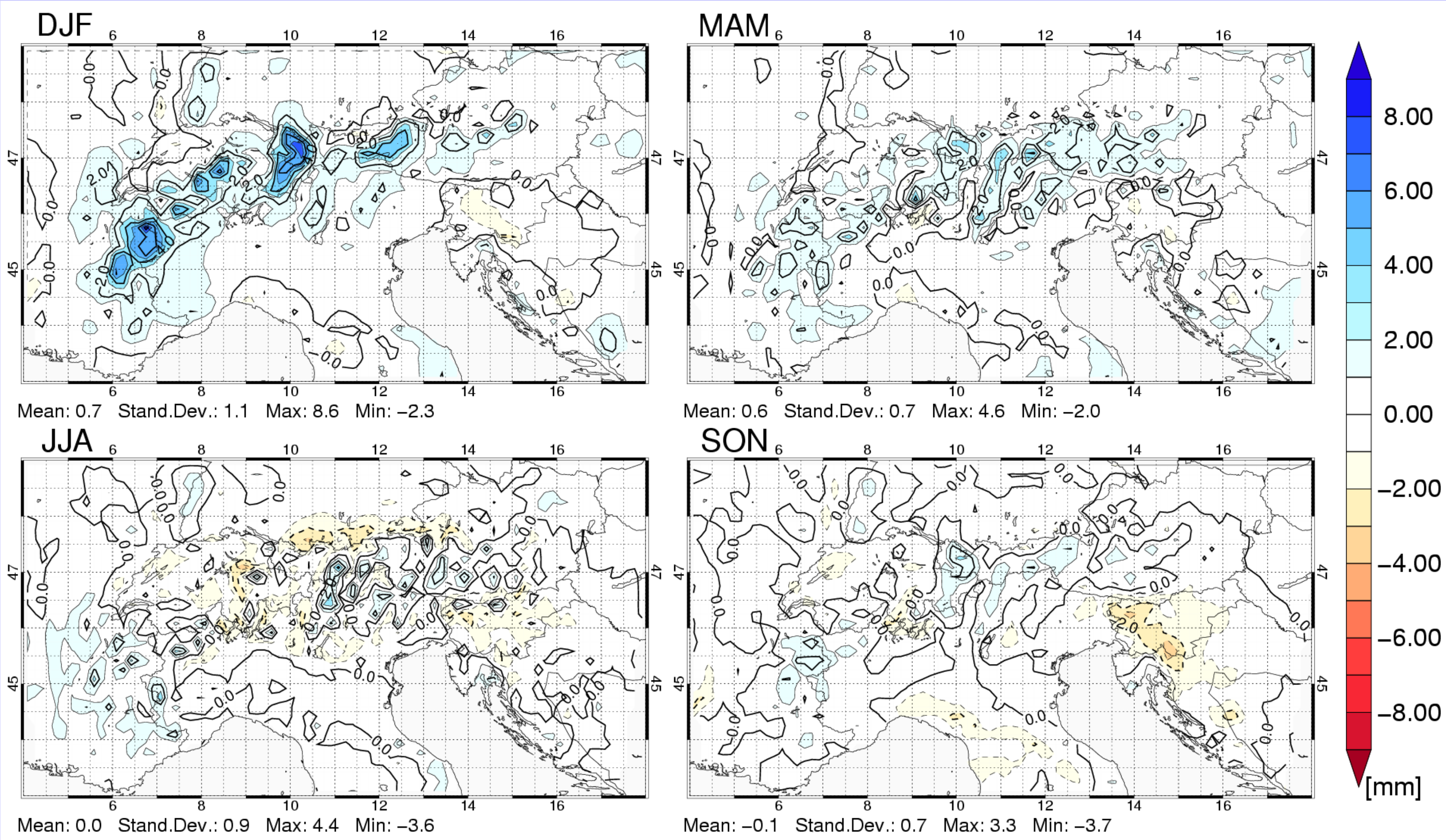
predictors: geopot. height (ZSVD) or humidity (qSVD)

simulated precipitation (RP and PSVD)



# Bias of RCM (MM5, ERA40 driven) over the Alps

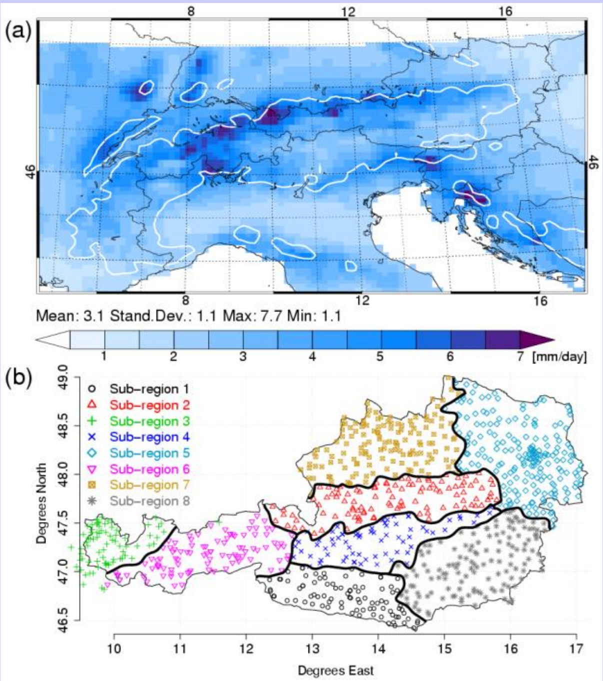
## Difference to observations (HISTALP) in mm/wetday

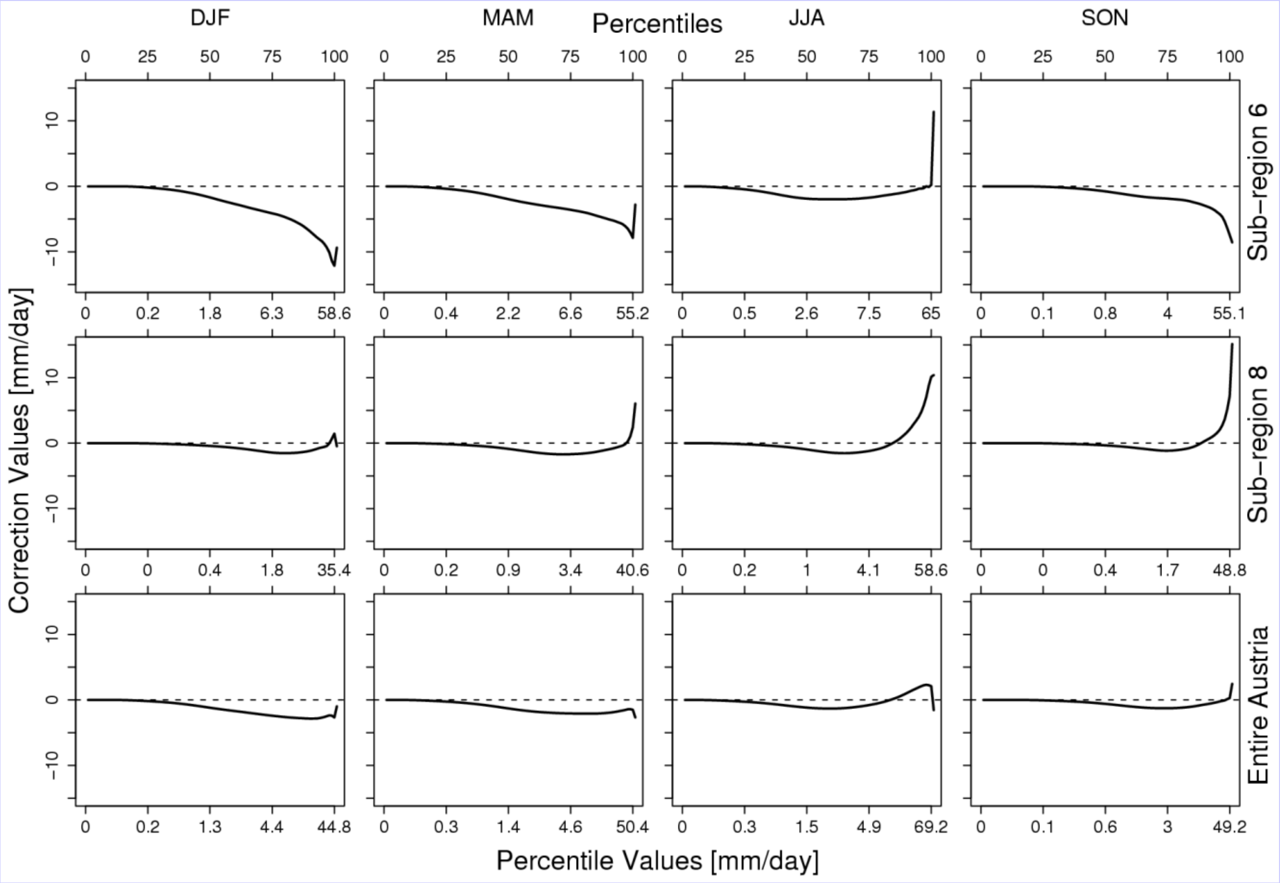



(courtesy Matthias Themeßl, Uni Graz)

# Correction of RCM-simulated daily precipitation distribution

## MM5 driven by ERA40




**substantial improvement over raw RCM output**

**works better than MLR**

**(Themeßl et al., IJC 2011)**

# Model Output Statistics (aka bias correction)

Model Output Statistics (MOS) is standard in weather forecasting and is preferred to Perfect Prog (PP). It is also used to correct RCMs

MOS in weather forecasting and in the reanalysis example are based on (generalised) regression equations and thus require representation of true circulation variability in model (known as ‚pair-wise MOS‘).

If only climatologies or standard simulations are available:

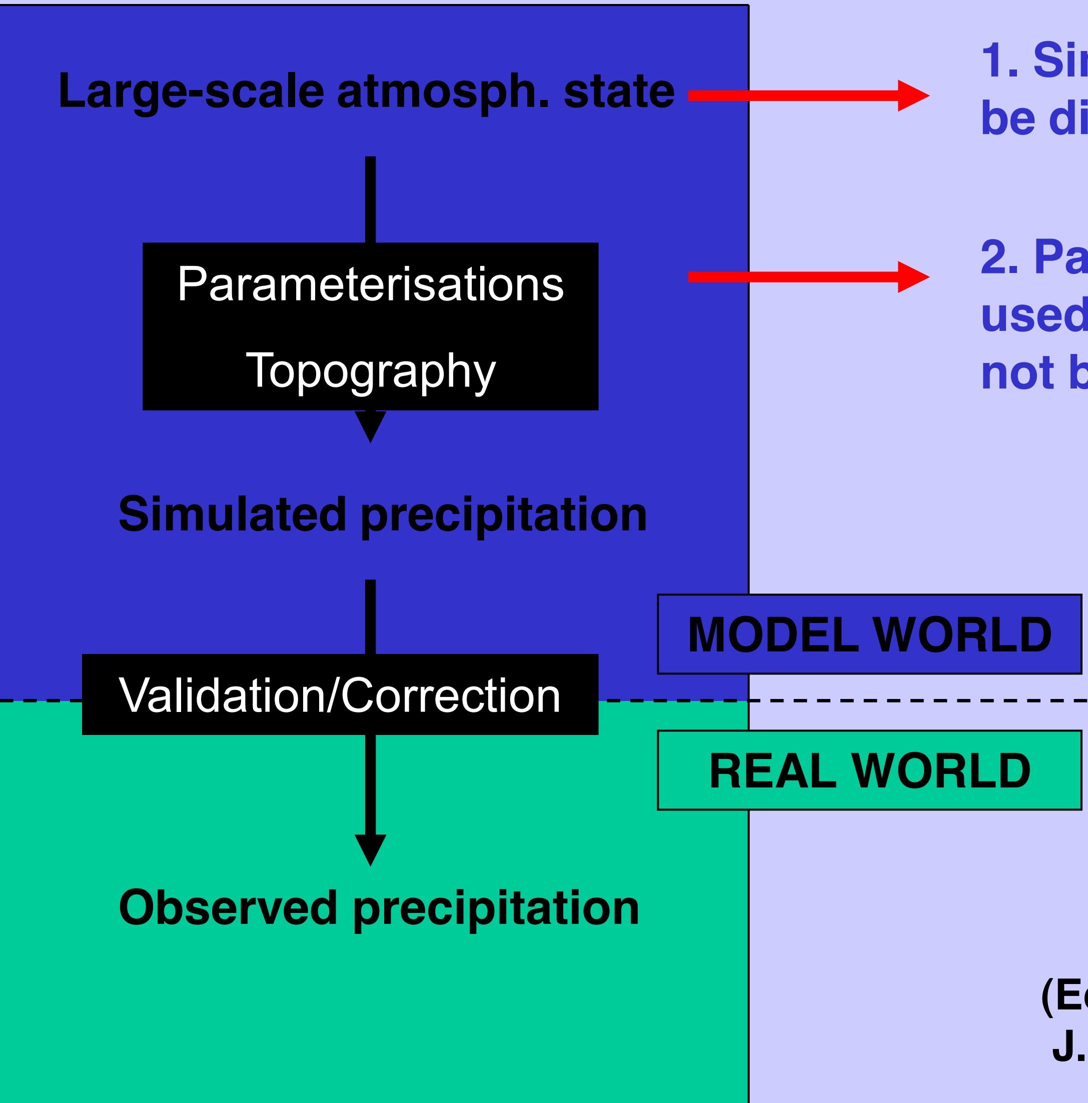
- only simple MOS models can be fitted (scaling and correction of PDFs) and it is unclear to what extent these are biased by different circulation (known as distribution-wise MOS);

- it is not clear whether temporal variability is reasonably simulated and the MOS correction makes any sense.

Full MOS has not been possible yet with GCMs as only standard forced simulations were available (random circulation variability). For RCMs reanalysis-driven simulations provide the necessary set-up.

# Contributions to error in simulated precipitation

**For skill assessment and correction two types of error should be separated.**
**MOS is conceptually consistent with PP if only error 2 is corrected.**




**1. Simulated large-scale fields can be different from true values**

**2. Parameterisations and topography used to simulate precipitation may not be accurate**

**(Eden, Widmann, Grawe and Rast, 2012, J. Climate)**

## What is the purpose of downscaling?

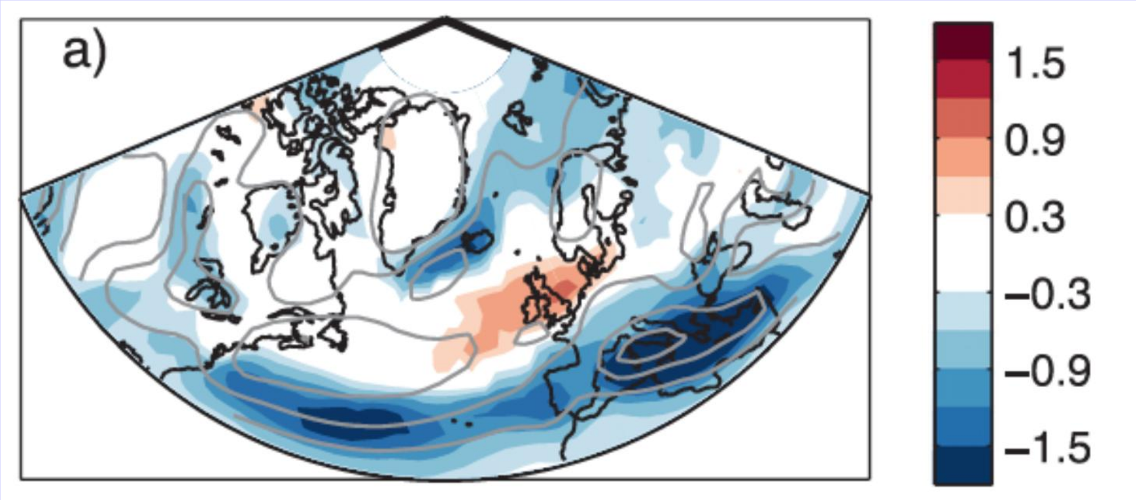
- provide regional climate consistent with large-scale GCM states?

- provide ‘best’ estimate for climate change, i.e. also correct for large-scale GCM errors?

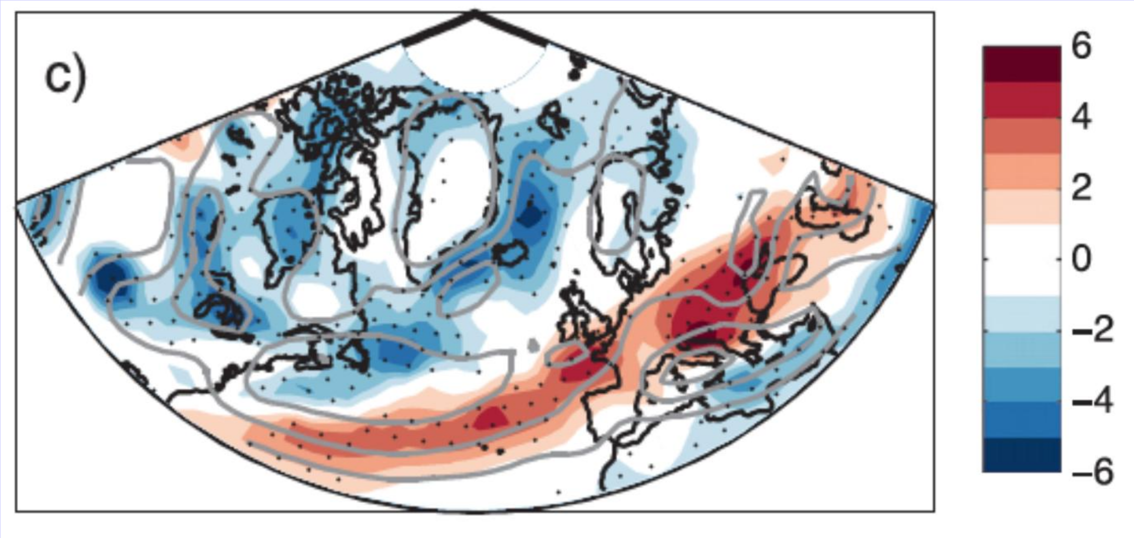
**Can’t have both !**

First case is consistent with many cases of Perfect Prog downscaling

# Storm track density, climate change and bias



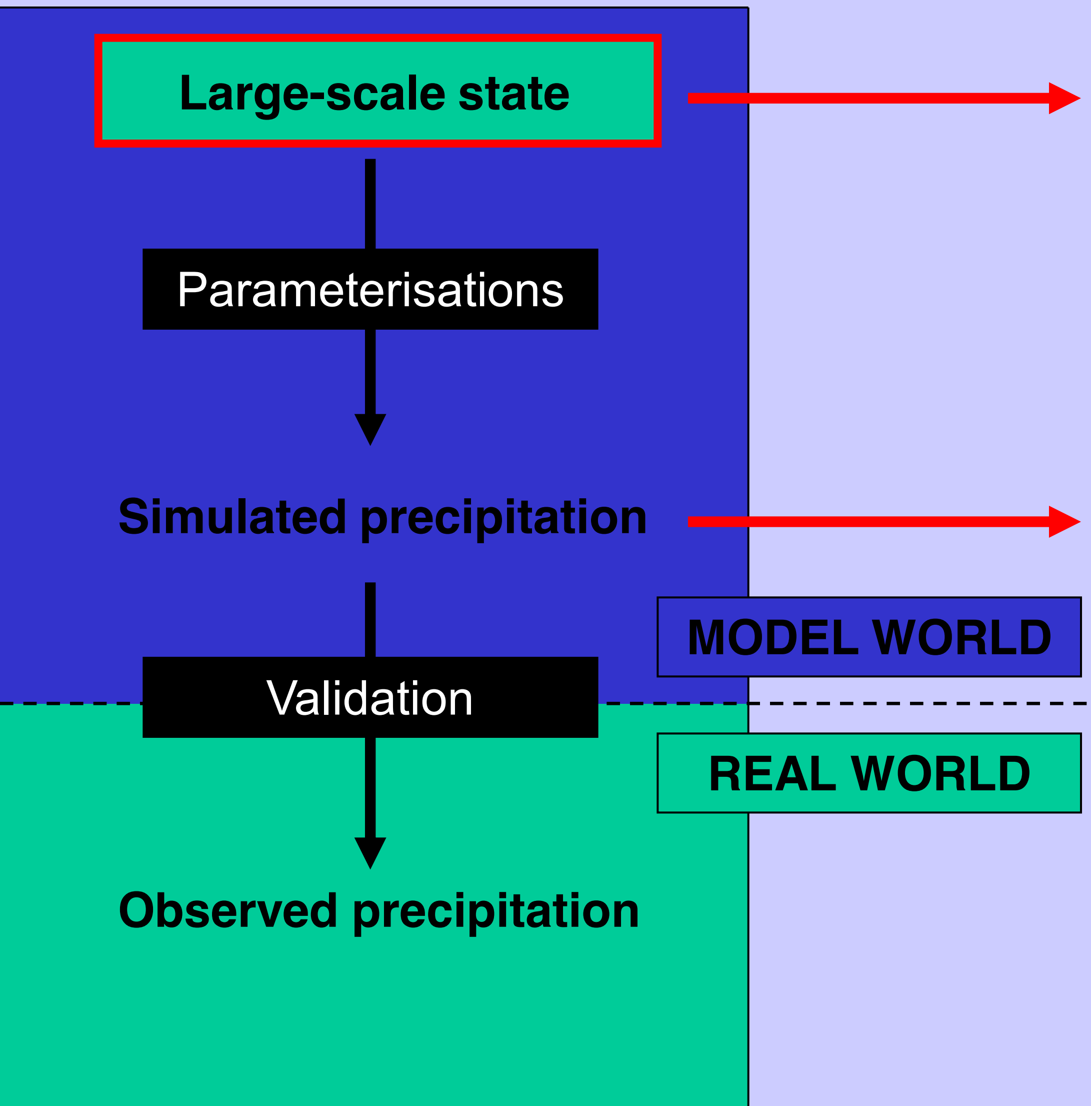

Mean CMIP5 response of wintertime storm track density to RCP 8.5 in late 21st century




Mean CMIP5 bias

Zappa et al. (2013 J. Clim.)

# Nudging of ECHAM5 towards ERA40 reanalysis




**Variables nudged towards ERA40 reanalysis (entire troposphere):**

- circulation (div, vort.)

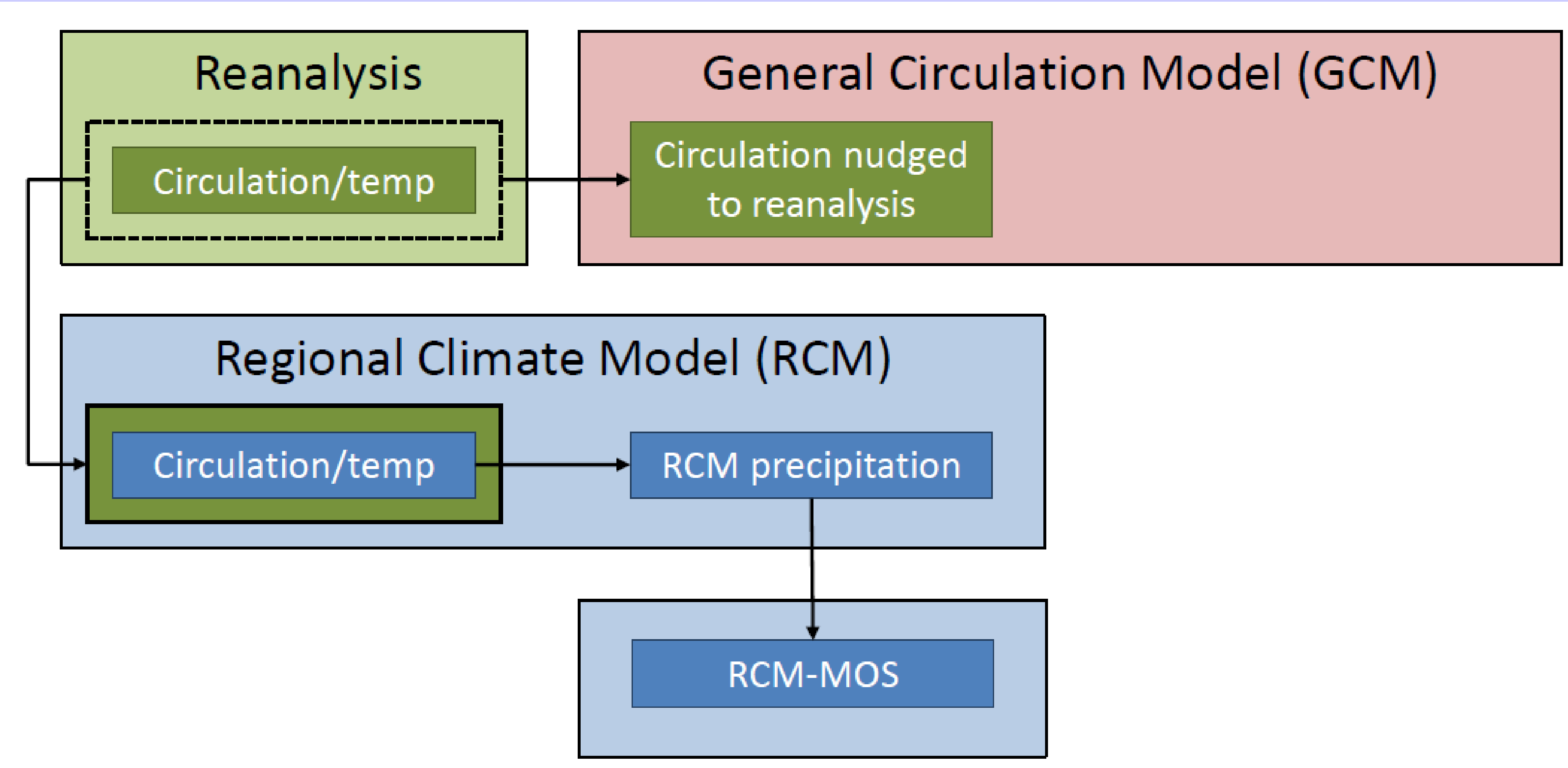
- temperature

**SST as in ERA40**

**Skill assessment and MOS based on parametrisation errors**

(Eden et al. 2012)

# RCM and GCM setup for pairwise Model Output Statistics




**Pairwise GCM MOS has been applied already for monthly mean precipitation (Eden and Widmann, J. Clim 2014)**

# Distributionwise vs pairwise Model Output Statistics

If only climatologies or standard simulations are available only ‚distributionwise' MOS is possible:

- scaling, bias correction, correction of PDFs

- it is not clear whether temporal variability is reasonably simulated and the MOS correction makes any sense.

If simulations are available in which the simulated and real weather situations match (generalised) regression equations can be used. We call this ‚pairwise' MOS. Examples:

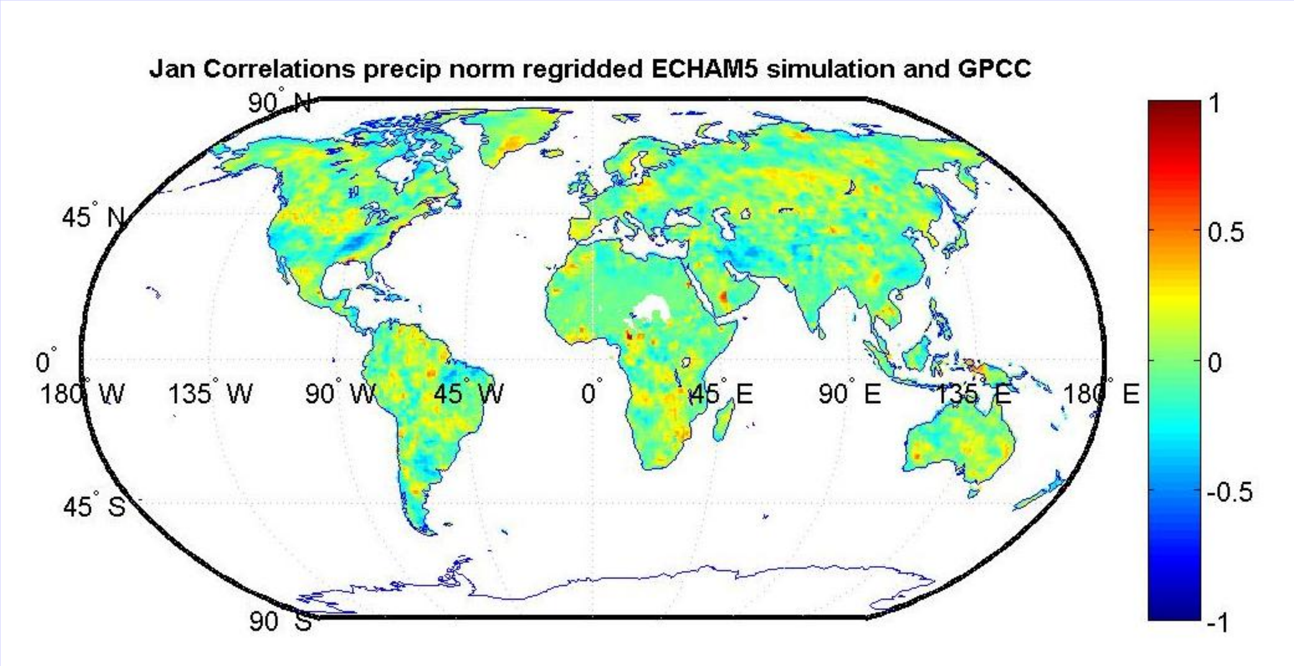
- RCMs driven by reanalysis (perfect boundary)

- GCMs nudged towards reanalysis

# Correlation ECHAM5 precipitation and GPCC observations

# January 1958-2002

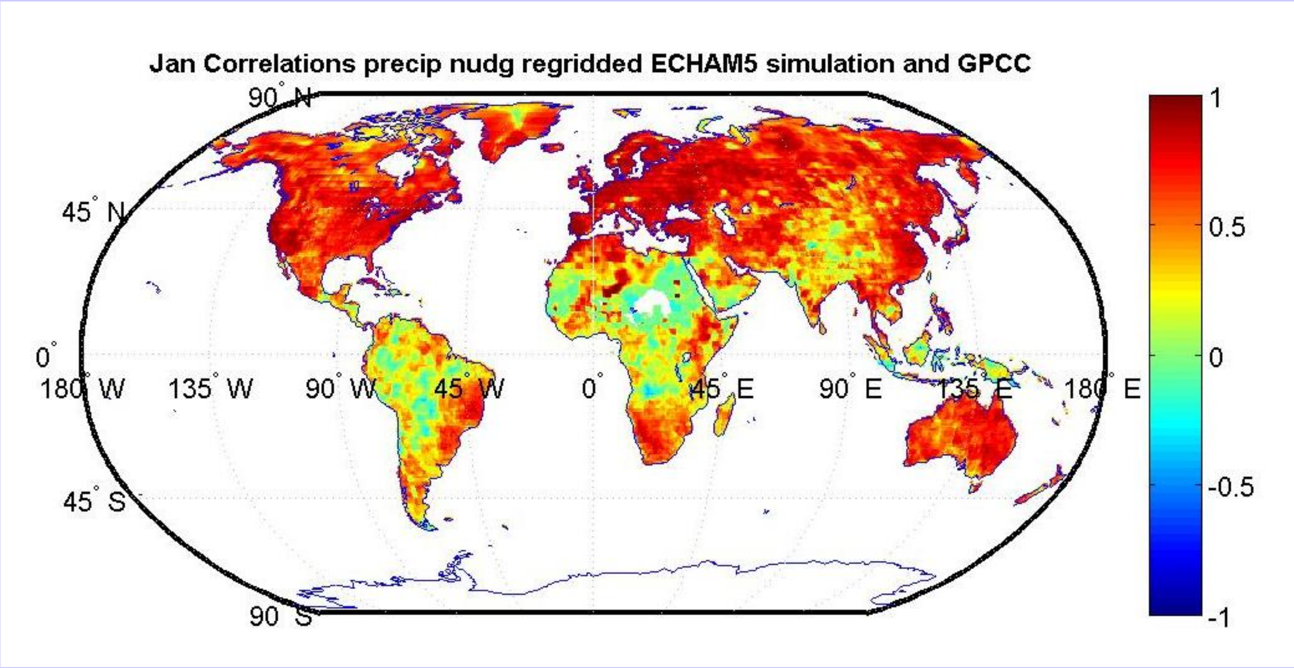
Normal (non-nudged)




**first quantification of GCM skill in simulating temporal precipitation variability given correct synoptic circulation**

**correction in low-skill regions makes no sense (aka 'the Mars problem')**

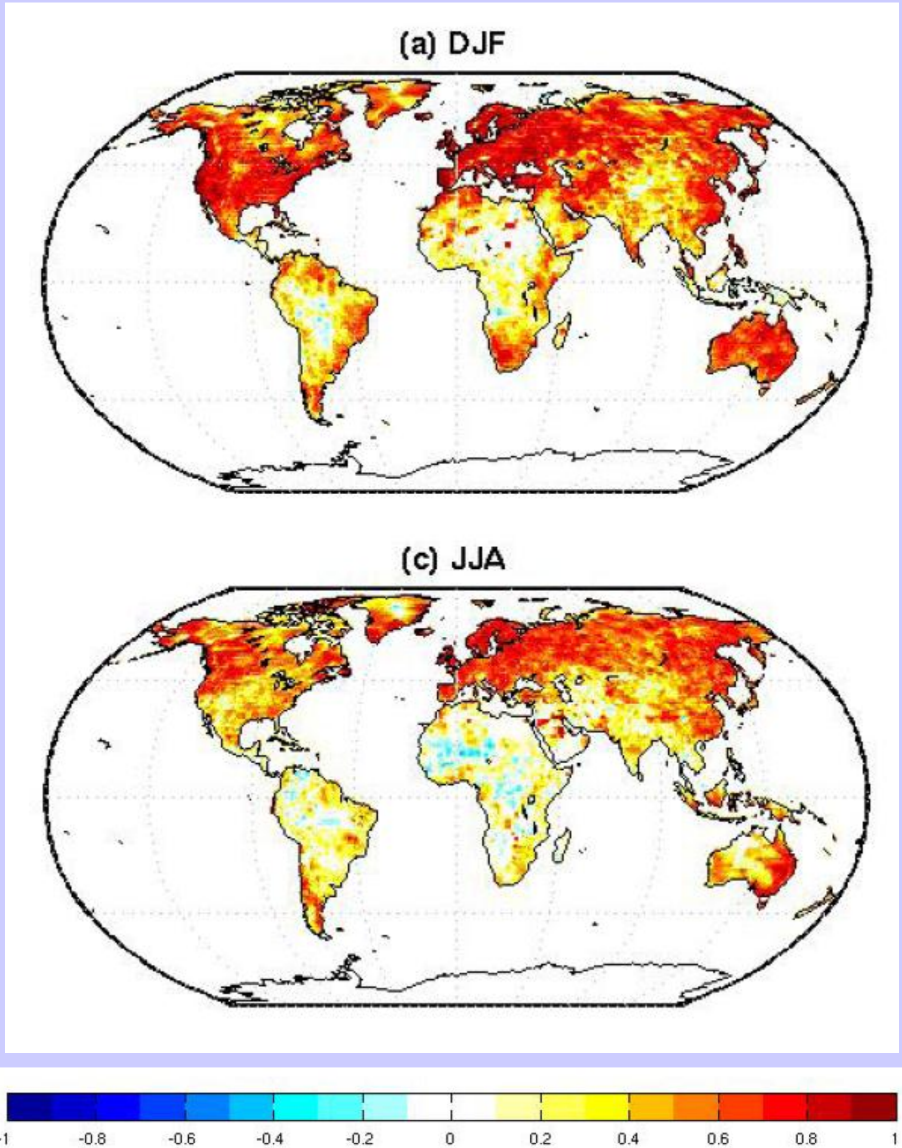
Nudged to ERA-40



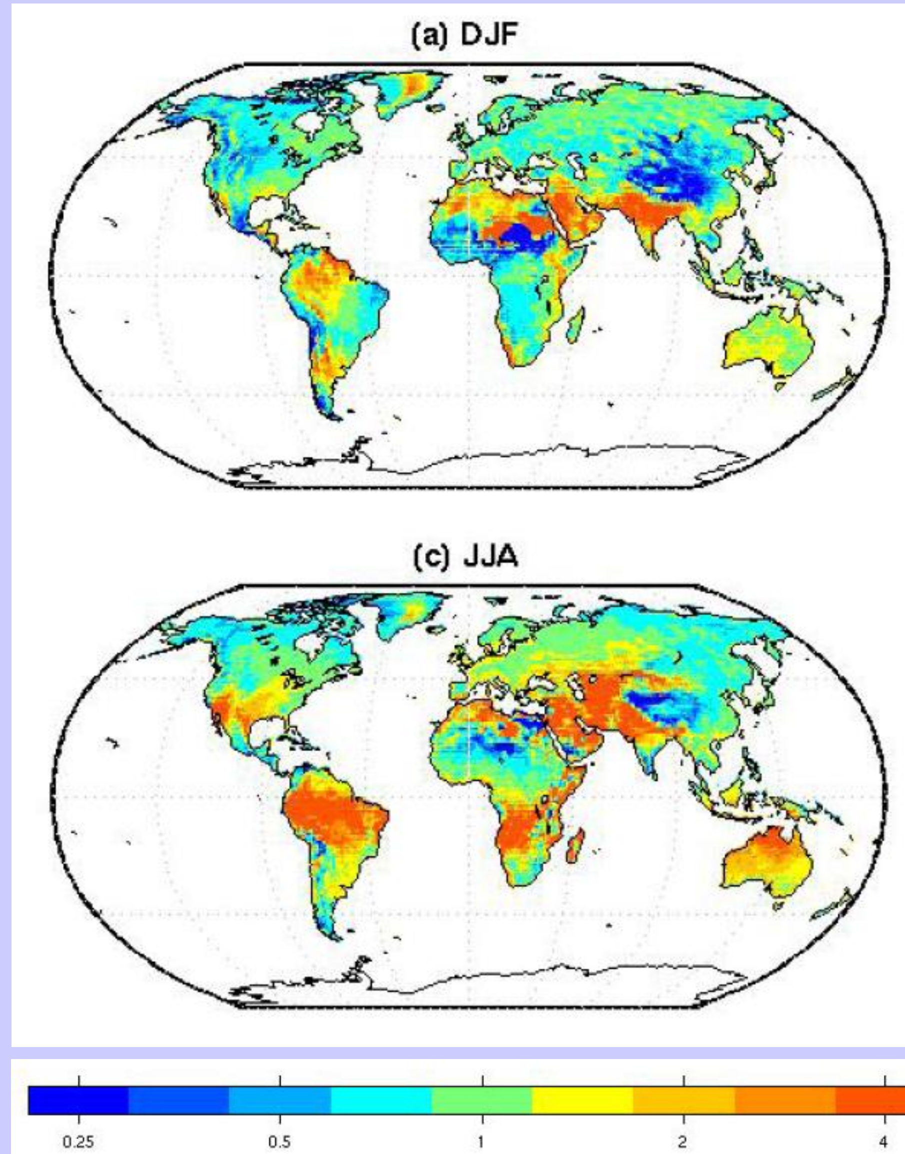

**(Eden, Widmann, Grawe, and Rast, J. Climate 2012)**

# Correlations of ECHAM5 with observed seasonal precipitation means and scaling factors

## correlations




## scaling factors



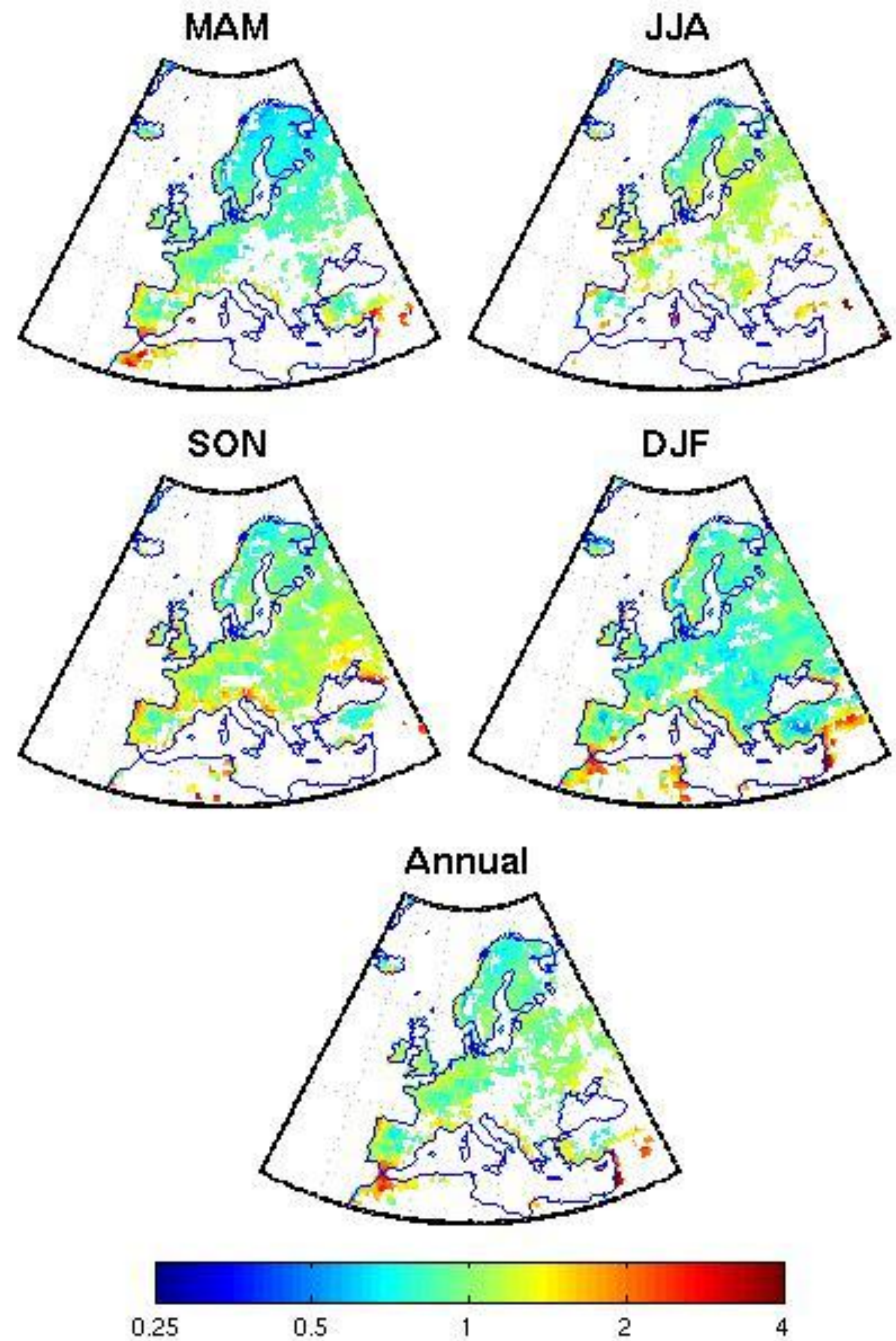
# ECHAM5 scaling factors using GPCC obs (0.5 deg)

scaling factors shown only for gridcells where interannual variability is well-captured (i.e. correlation coefficient > 0.7)

ECHAM5:

- good agreement with observations over large parts of Europe
- too wet over Scandinavia
- too dry over parts of the Mediterranean coast
- some differences between nudged and non-nudged simulation

(Eden et al. 2012)



# Probabilistic MOS

# for RCMs and GCMs

# Deterministic downscaling

One predictor in --> one predictand out

Does not account for unexplained small-scale variability (local noise)

Local, deterministic MOS

- bias correction
- PDF matching
- can be applied to RCMs and GCMs
- can be used with reanalysis-driven RCMs or nudged GCMs for fitting, or with standard GCM (and nested RCM) runs: different errors are corrected

Non-local MOS (and PP) (tomorrow‘s lecture)

- predictors from a domain
- PC-MLR, 1D MCA ...

# Probabilistic MOS for downscaling daily precipitation

- probabilistic: account for non-explained local variability by predicting distributions

- use mixture of Gamma and Generalised Pareto distribution

- make distribution parameters dependent on simulated precipitation

PLEIADES

**P**rojections and predictions of **L**ocal pr**E**cipitation **I**ntensities: **A**dvanced **D**ownscaling using **E**xtreme value **S**tatistics

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UNIVERSITY OF BIRMINGHAM

LSCE

VolkswagenStiftung

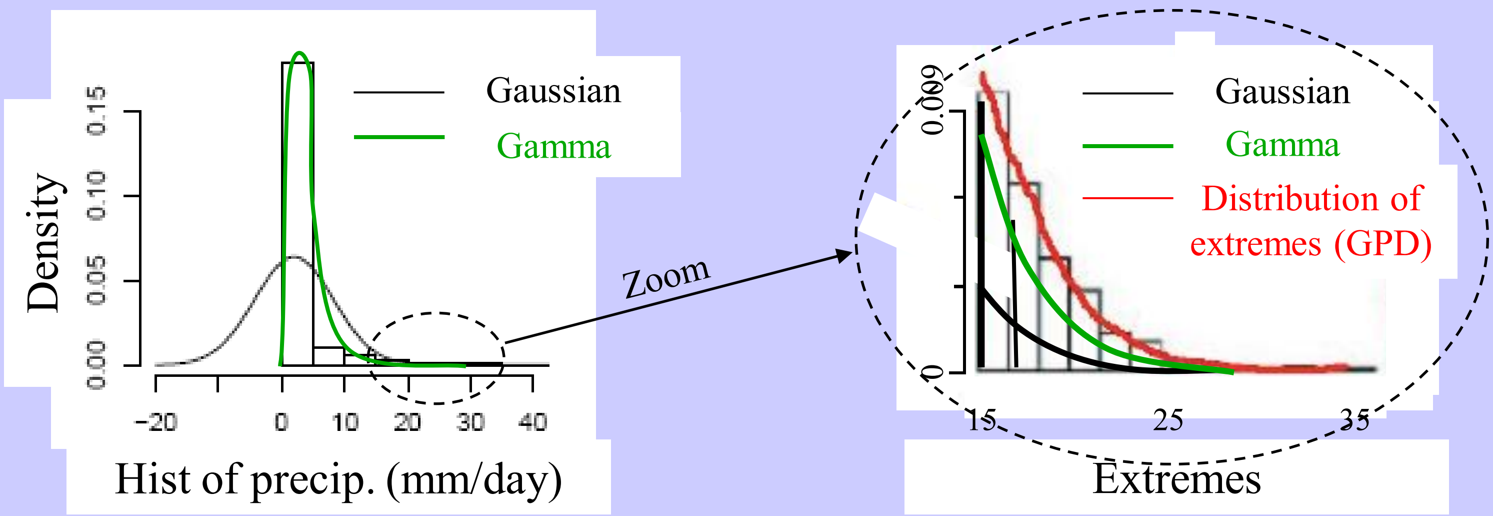
# Stationary mixture model

# (i.e. no downscaling)

# Modelling daily precipitation distributions

**distributions for bulk of precipitation values**

- Gamma or log-normal distribution
- bad representation of extremes




(M. Vrac, 2009)

**extreme value distributions for the extremes**

- Generalized Extreme Value Distribution  for block maxima
- Generalized Pareto Distribution for peaks over threshold

# Stationary mixture model

- From Frigressi et. al. (2002) – merge classical and EV distributions

$$P(R > r \mid R > u) = \left(1 + \xi \frac{r-u}{\sigma}\right)^{-1/\xi}$$

$$\boxed{G(r_t \mid \beta) = c_\beta \left[ \left(1 - \underbrace{w(r_t \mid m, \tau)}_{\text{weight}}\right) \overbrace{\Gamma(r_t \mid \gamma, \lambda)}^{\text{Gamma pdf}} + \underbrace{w(r_t \mid m, \tau)}_{\text{weight}} \underbrace{GPD(r_t \mid \xi, \sigma, u = 0)}_{\text{Generalized Pareto Distribution (GPD) pdf}} \right]}$$

$$\beta = (m, \tau, \gamma, \lambda, \xi, \sigma)$$

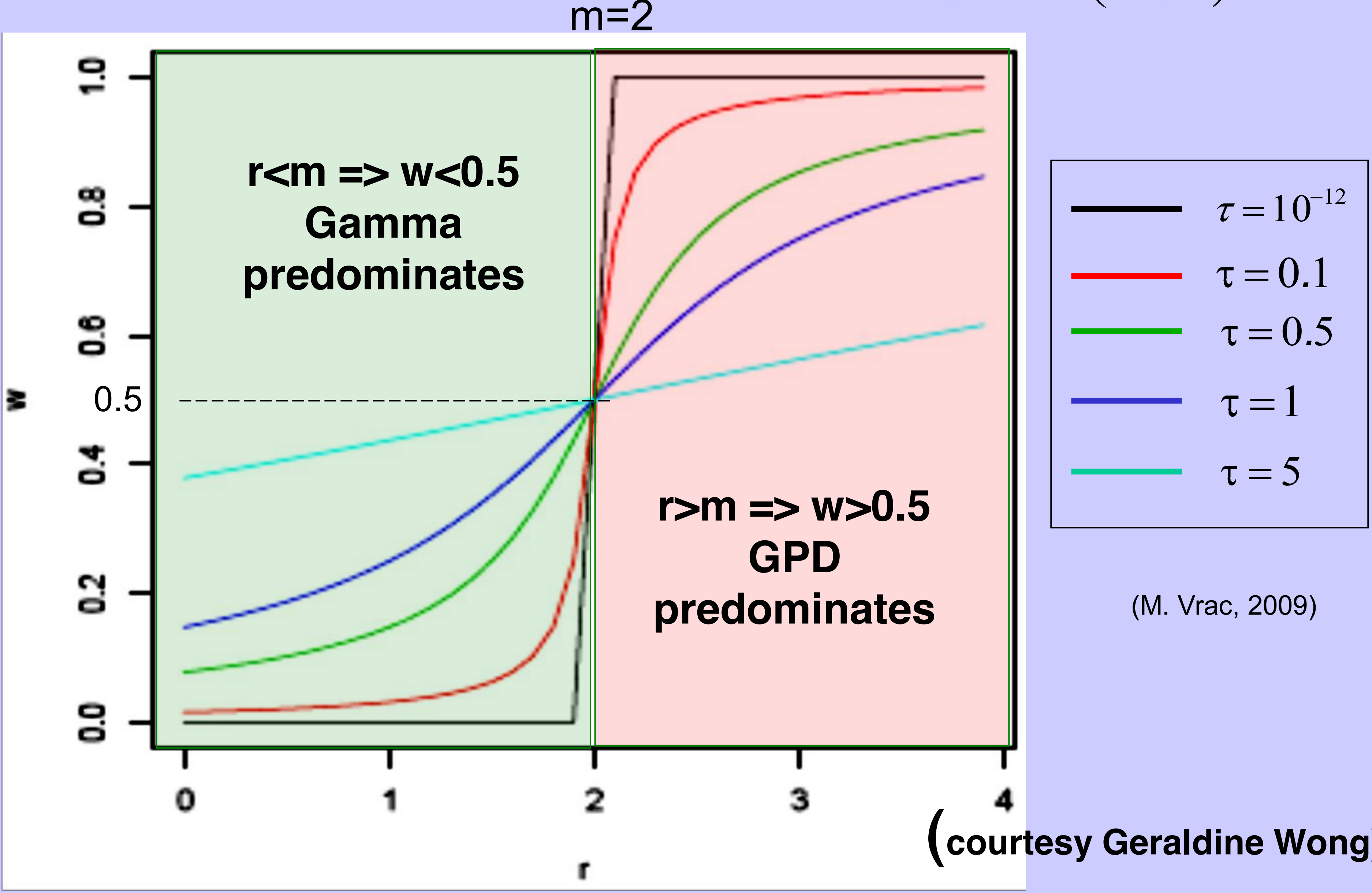
where $w(r_t \mid m, \tau) = \frac{1}{2} + \frac{1}{\pi} \arctan\left(\frac{r_t - m}{\tau}\right)$

Location where transition from Gamma to GPD

Rate of transition

PLEIADES

$$w(r_t|m,\tau) = \frac{1}{2} + \frac{1}{\pi}\arctan\left(\frac{r_t - m}{\tau}\right)$$




(M. Vrac, 2009)

(courtesy Geraldine Wong)

# Non-stationary mixture model

# (MOS downscaling)

# Probabilistic MOS (non-stationary mixture model)

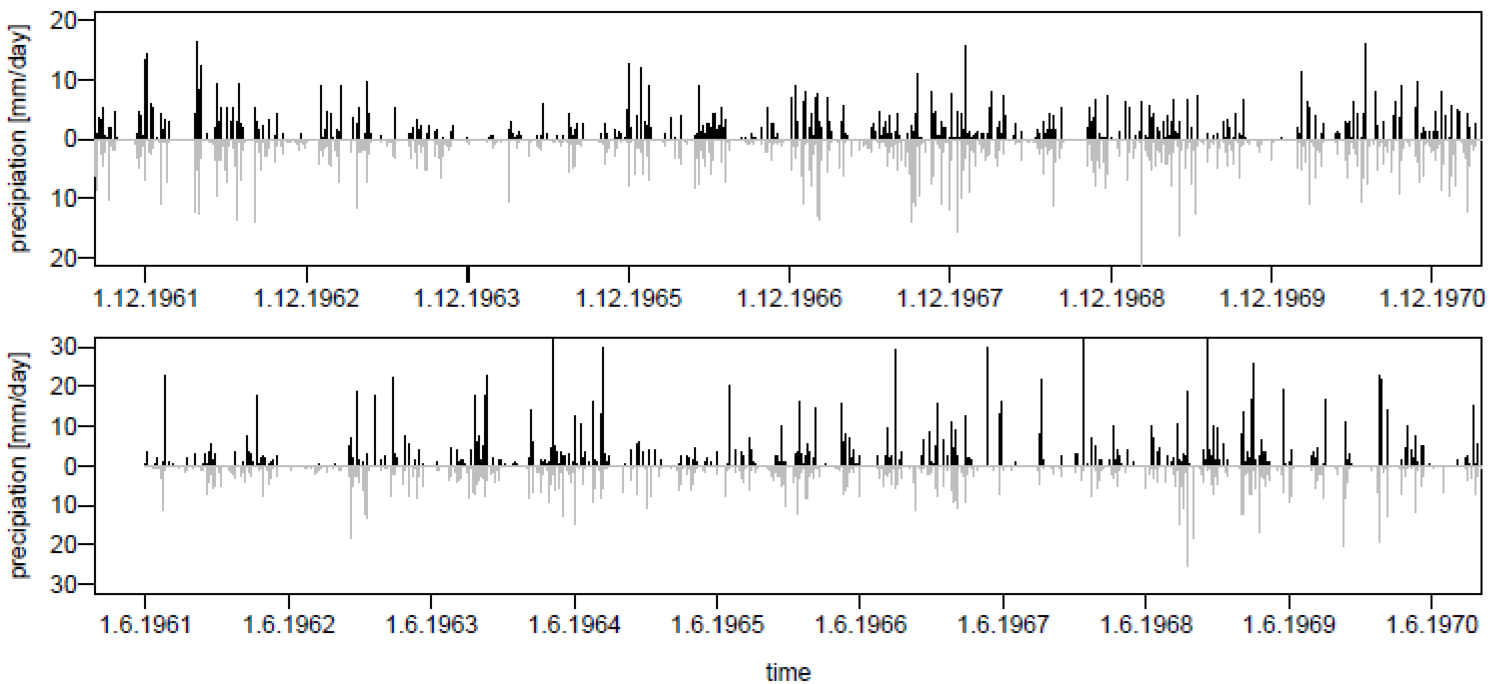



Figure 4: Daily precipitation time series (section) for Cambridge. Top: DJF; bottom: JJA. Black: observed; grey: raw RCM, averaged across 3x3 grid boxes

(Wong, Maraun, Vrac, Widmann and Eden, J. Clim. 2014)

# Probabilistic MOS (non-stationary mixture model)

$$
\begin{aligned}
\lambda_i &= \lambda_0 + \lambda_1 x_i \\
\gamma_i &= \gamma_0 + \gamma_1 x_i \\
\sigma_i &= \sigma_0 + \sigma_1 x_i \\
\xi_i &= \xi_0 \\
m_i &= m_0 + m_1 x_i \\
\tau_i &= \tau_0
\end{aligned}
$$

x_i is simulated precipitation on day i

Example for ‘vector generalised linear model’ (VGLM)

model parameters are fitted using Maximum Likelihood Estimation

(Wong, Maraun, Vrac, Widmann and Eden, in revision)

# Stochastic MOS: VGLM mixture model

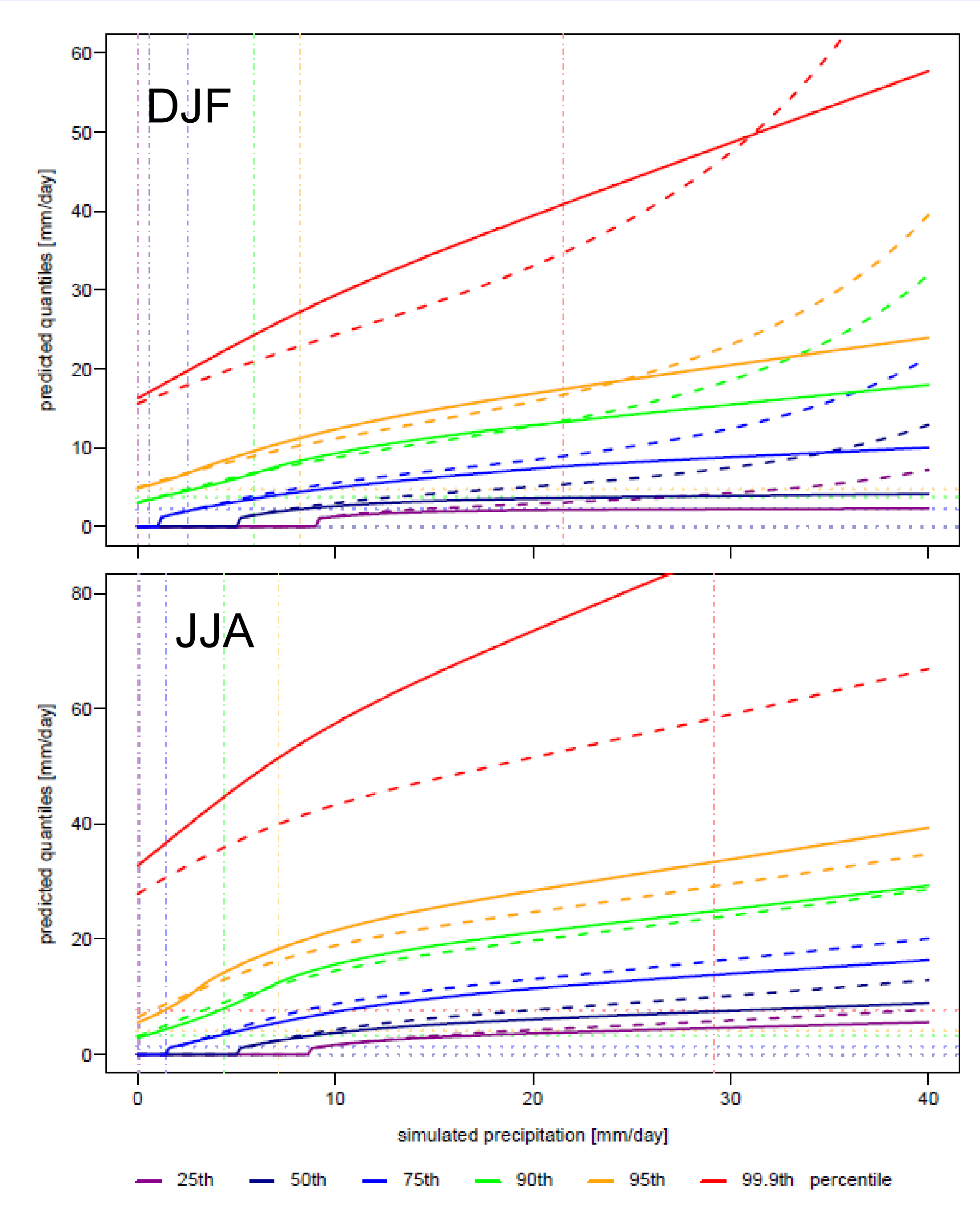
Daily precipitation in Cambridge

Simulation:
CLM driven by ERA40 with nudging of upper-level winds

Solid: VGLM mixture

Dashed: VGLM Gamma

(Wong et al., J. Clim. 2014)



# Stochastic MOS: VGLM mixture model

Daily precipitation
in Cambridge

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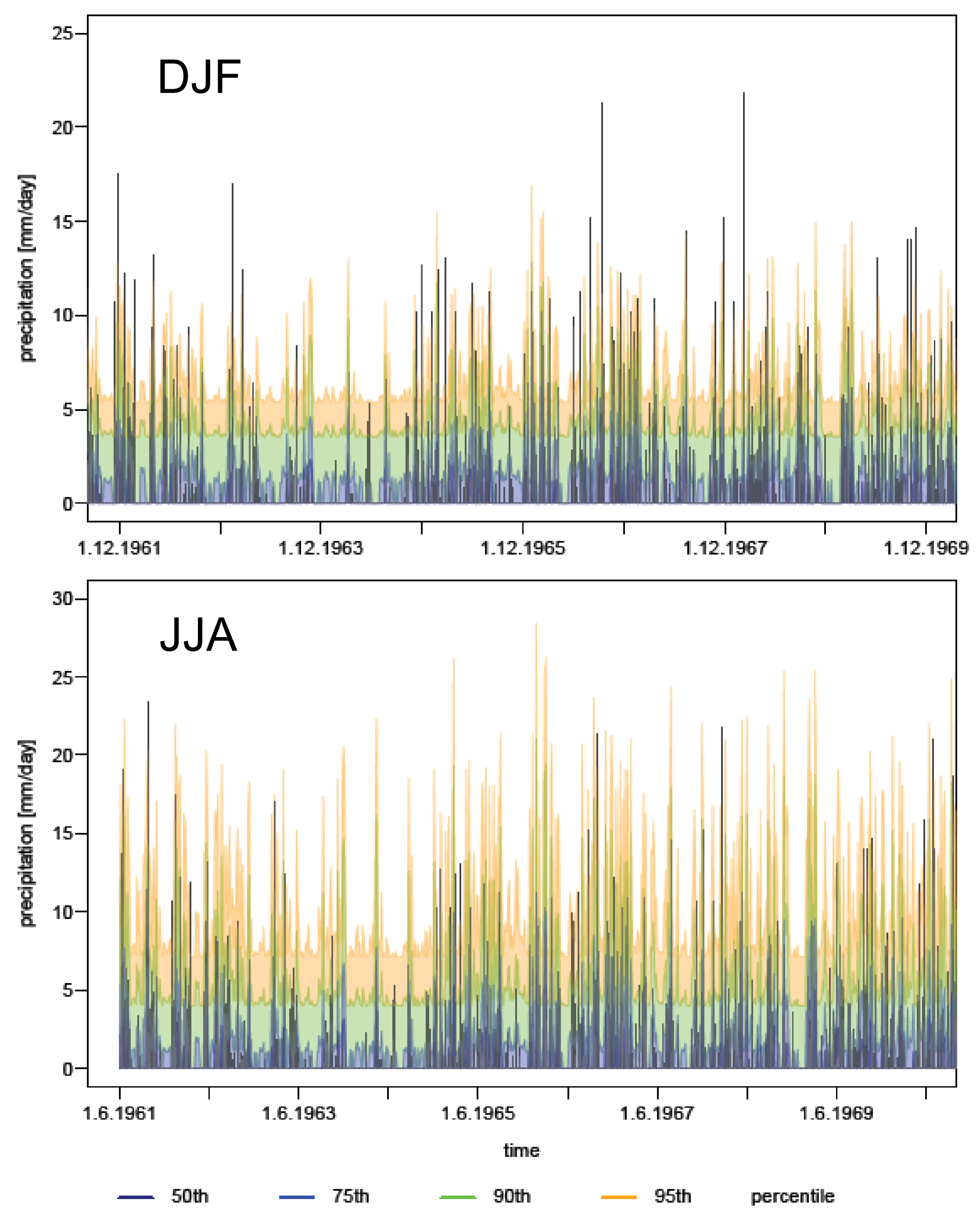
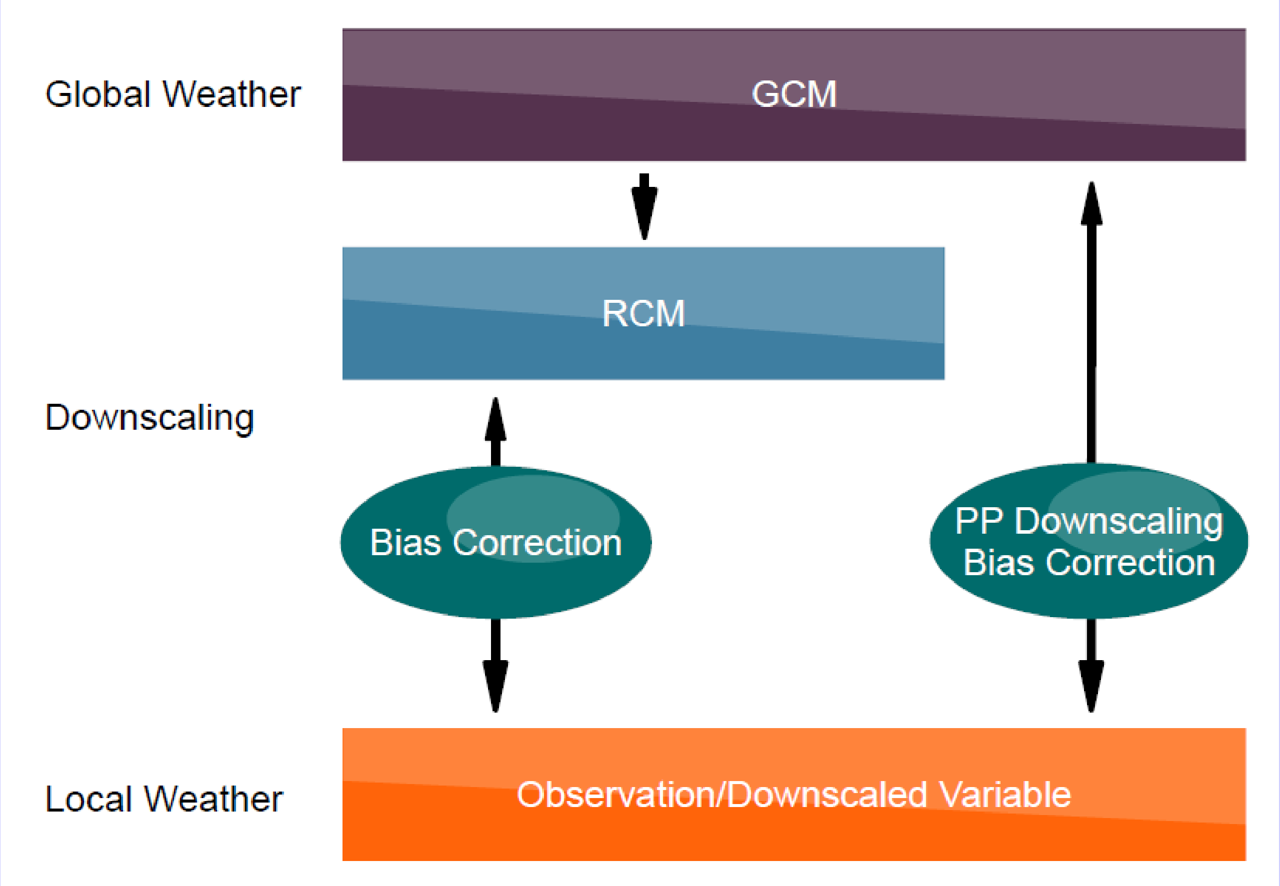



**(Wong et al., J. Clim. 2014)**

# RCM-MOS
# vs GCM-MOS




**Does the RCM provide added value?**

**Aspects:**

- **fit between estimated distributions and past observations (this talk)**
- **spatial coherence**
- **magnitude of climate change signal**
- **pattern of climate change signal**

# Validation of RCM and GCM MOS: wet day occurrence from logistic regression

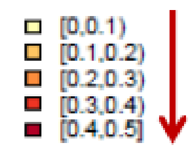
UNIVERSITY OF BIRMINGHAM

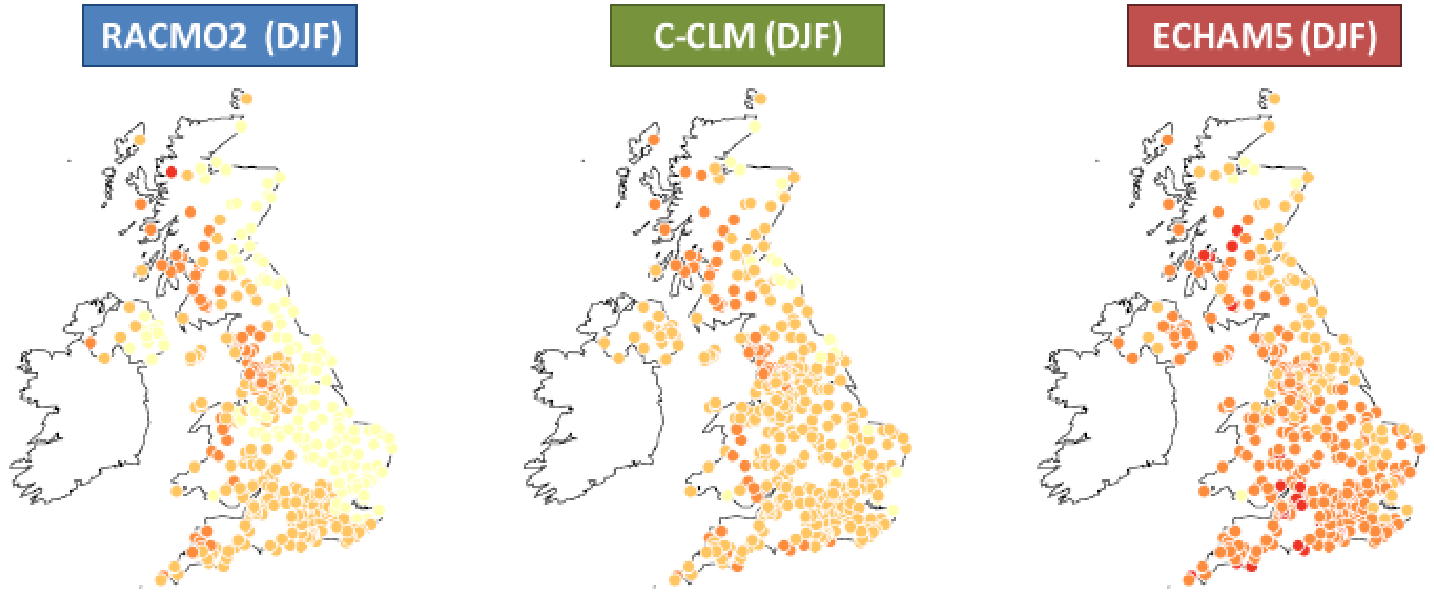
Reference:

stationary Gamma

- Brier skill score quantifies the capability of our model to predict wet and dry days.
- Wet day: precipitation > 1mm.

$$\boxed{\begin{aligned} BS &= \frac{1}{n}\sum_{i=1}^{2}(f_i - o_i)^2 \\ BSS &= 1 - \frac{BS_{VGLM}}{BS_{ref}} \end{aligned}}$$




**(Eden et al., JGR 2014)**

# Validation of RCM and GCM MOS VGLM Gamma model

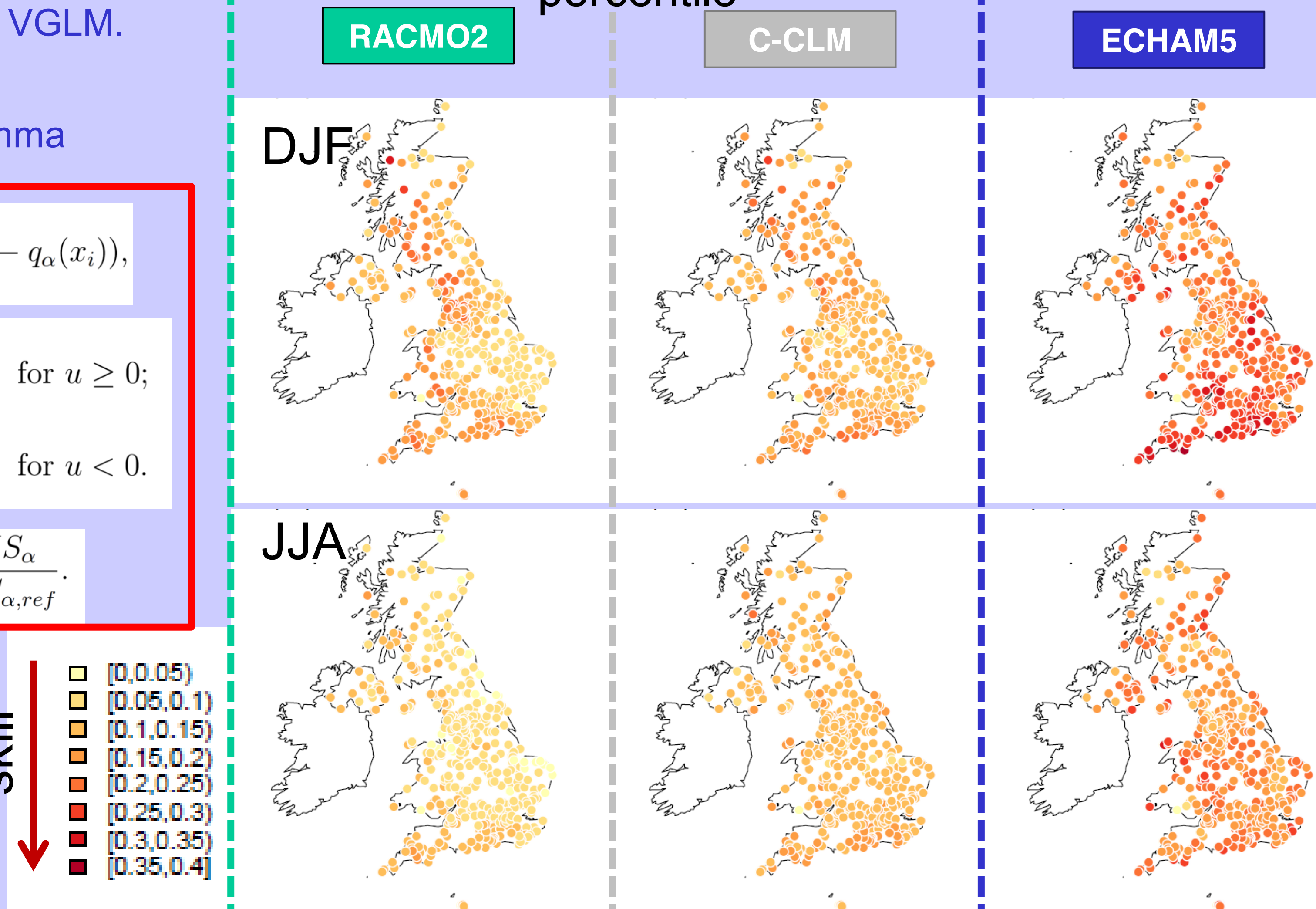
- Quantile verification skill score (QVSS) measures the relative performance success of the VGLM.
- Reference: stationary Gamma

$$QVS_\alpha = \sum_{i=1}^{M} \rho_\alpha(y_i - q_\alpha(x_i)),$$

$$\rho_\alpha(u) = \begin{cases} \alpha u & \text{for } u \geq 0; \\ (\alpha - 1)u & \text{for } u < 0. \end{cases}$$

$$S_\alpha = 1 - \frac{QVS_\alpha}{QVS_{\alpha,ref}}.$$

QVSS for 90th percentile




**(Eden et al., JGR 2014)**

# UKCP09
# probabilistic climate change projections: precipitation

2080s, medium emissions scenario

Based on

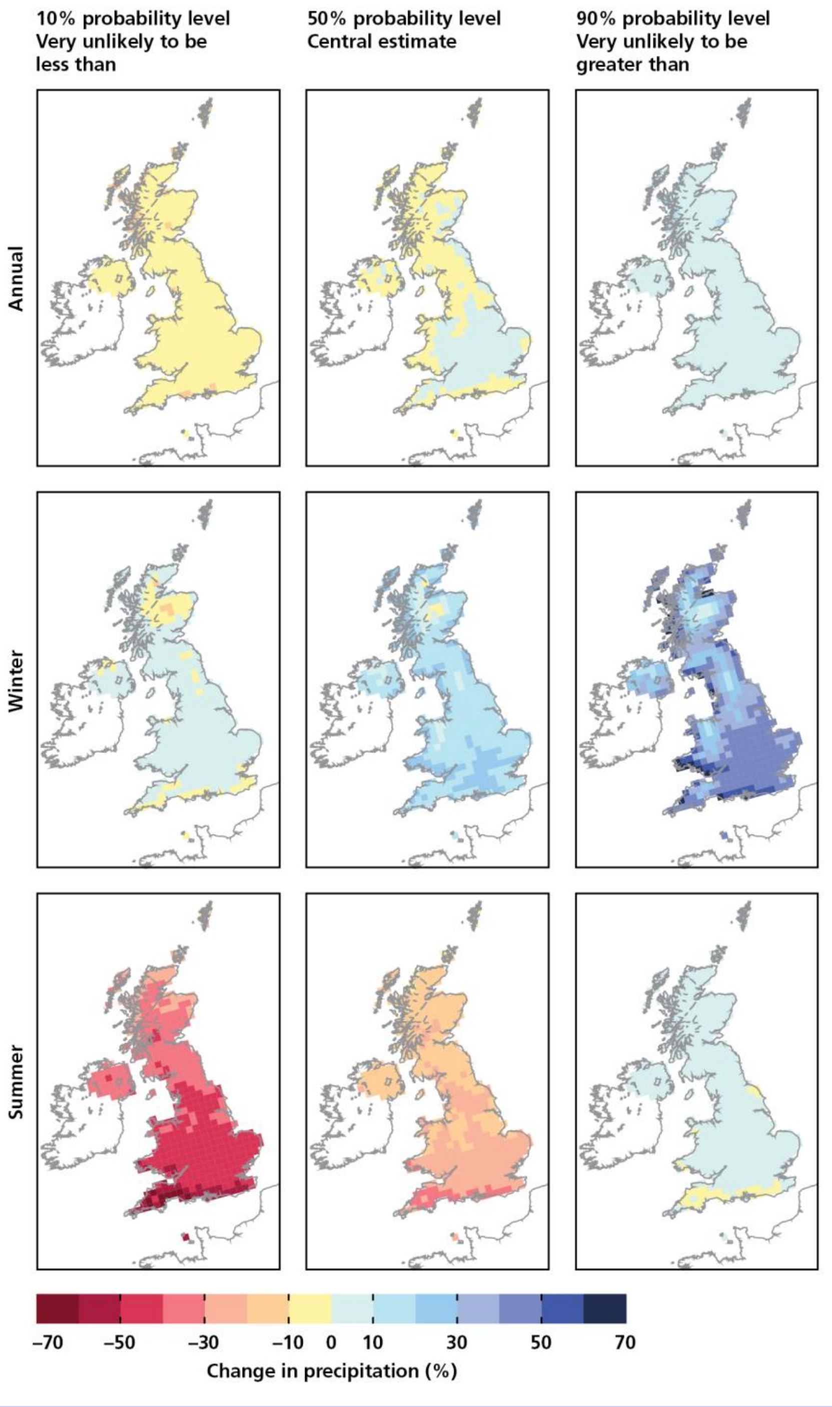
- weather generator fitted to current climate

- modified by (additive) change factors for mean and variance, derived from RCMs

- perturbed physics RCMs and GCMs from Hadley Center/Met Office

- also 12 other GCMs

(UK Climate Projections: briefing report http://ukcp09.defra.gov.uk )



UKCP09
probabilistic climate change projections:
daily average temperature

2080s

medium emissions scenario

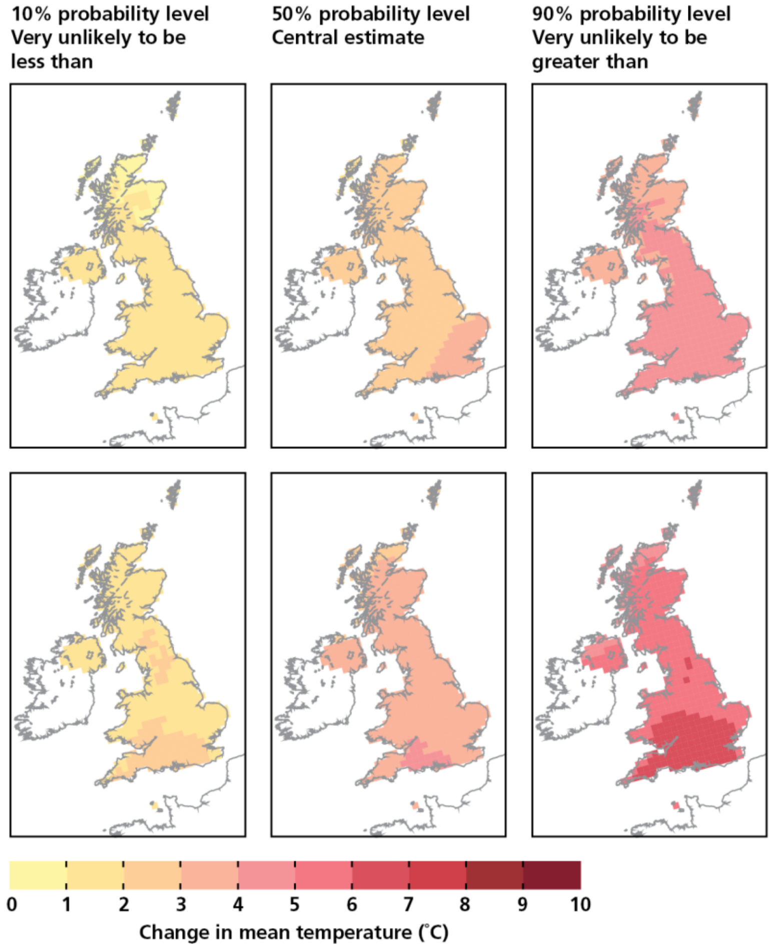
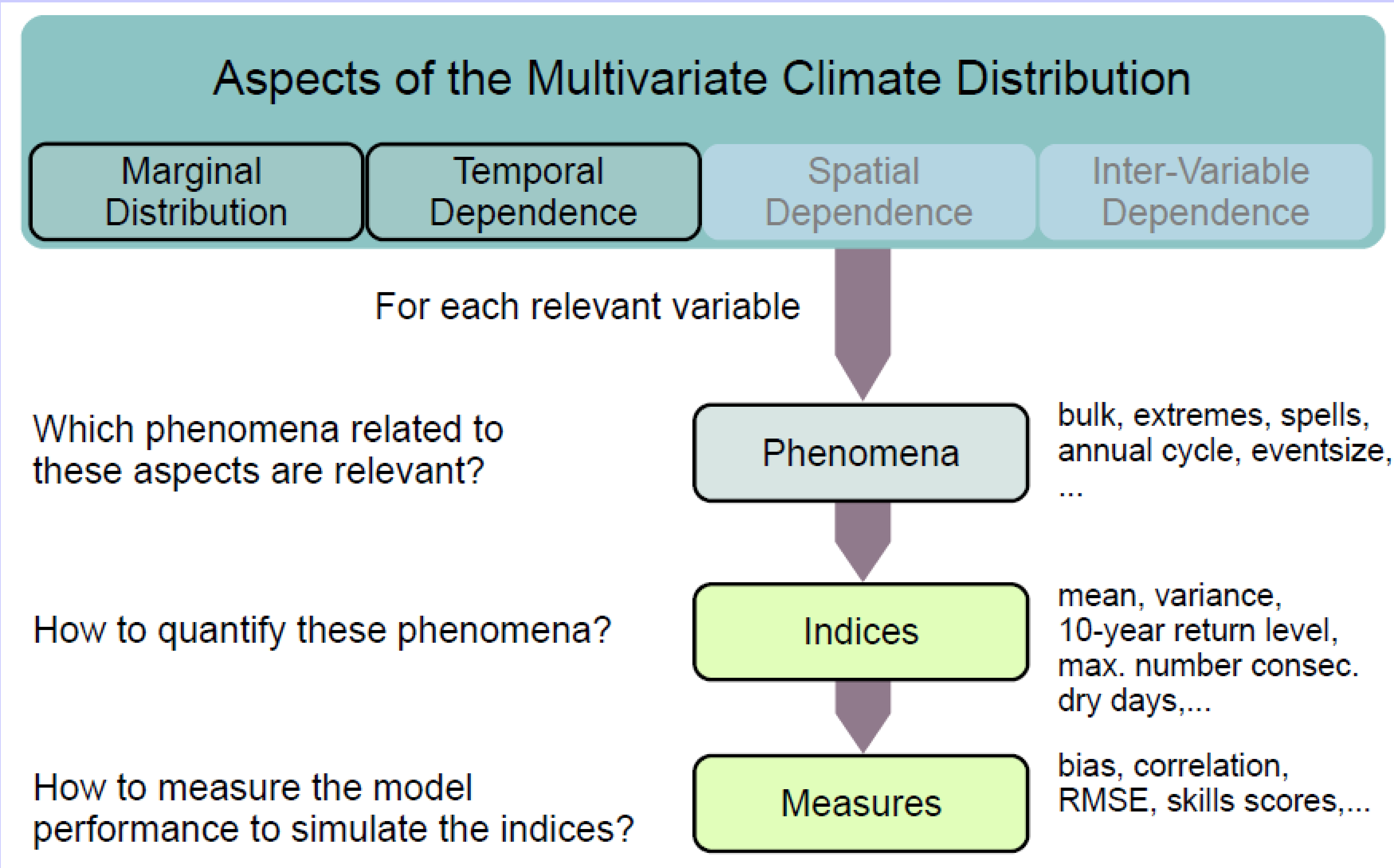



Figure 9: 10, 50 and 90% probability levels of changes to the average daily mean temperature (°C) of the winter (upper) and summer (lower) by the 2080s, under the Medium emissions scenario.

(UK Climate Projections: briefing report)

# The science of VALUE: Validation



## The science of VALUE:   Validation

- Distributionwise

  How is the climate distribution represented?

- Eventwise

  How well are events represented?

  Essential, even though we are not interested in forecasting.

# The science of VALUE: Validation Indices and performance measures

## Marginal distribution

| Index | Distributionwise | Eventwise |
|---|---|---|
| mean | bias/mean percentage error (mpe) | |
| variance | mpe | |
| skewness | bias | |
| full distribution | distance measure | |

## Temporal dependence / Extremes

| Index | Distributionwise | Eventwise |
|---|---|---|
| time series | | mse |
| acf lag 1,2,3 | just indices | |
| quantiles/return values | quantile score (QS), bias | QS |
| threshold exceedance | | Brier score |
| number of threshold exceedances | bias | |
| amount above threshold | bias | |
| shape parameter of GEV | bias | |
| quantiles of spell length distribution | QS, bias | |
| transition probabilities | just indices | |
| time of maximum/minimum of annual cycle | bias | |
| amplitude of annual cycle | mpe | |
| proportion of variance in low frequency band | just indices | |
| sign of the low pass filtered series | | Brier score |

# The science of VALUE:
# Validation indices and performance 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 | | |

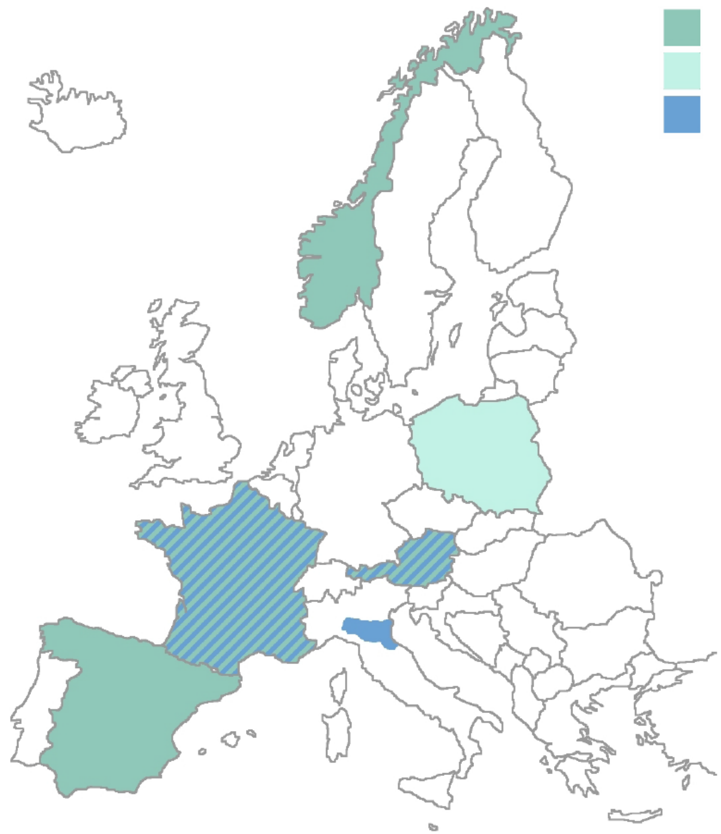
**One-point correlation maps**

## Inter-variable dependence

| Index | Distributionwise | Eventwise |
|---|---|---|
| correlation | just indices | |
| variable conditional on (no) exceedance | as marginals | |
| joint exceedances | as exceedances | |

# The science of VALUE: Validation in present climate

## Predictands (observations) 1980-2010




### Different settings/data

- high quality gridded data for large scale comparisons;
- ECA-D station data for specific example catchments;
- hourly station data for selected regions.

### Variables

- temperature, precipitation, wind, humidity, radiation.

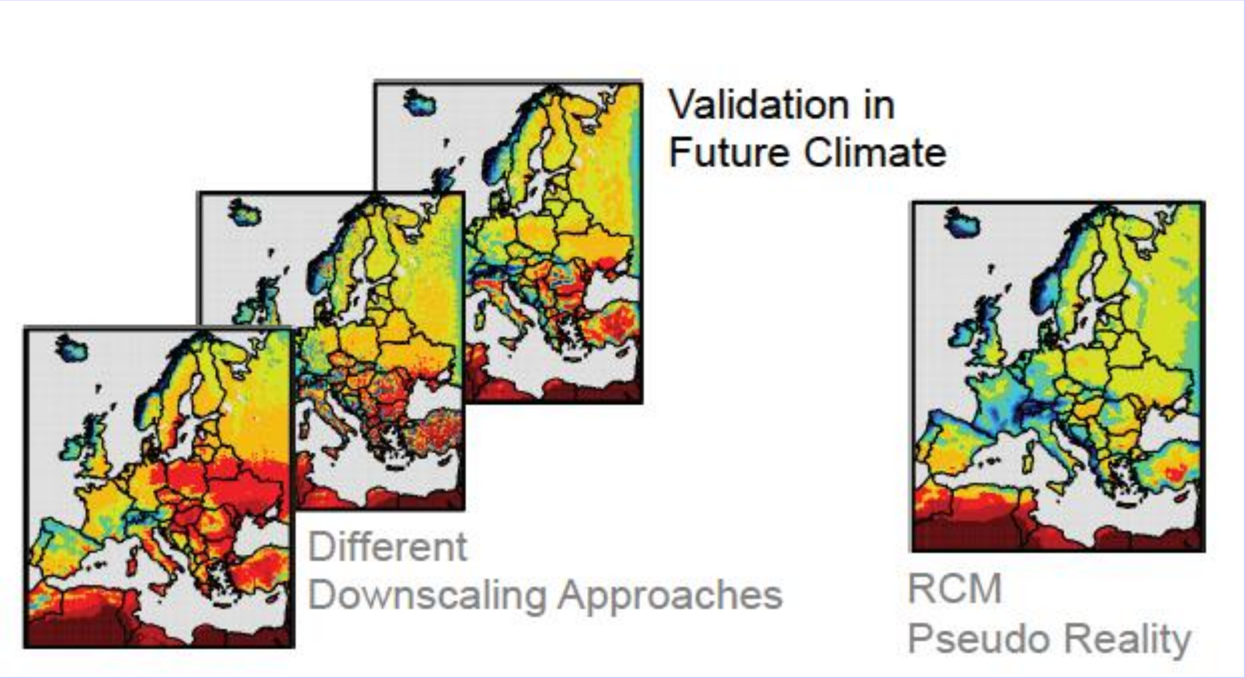
## Predictors (stat. DS) and boundary conditions (dyn. DS) : ERA interim

## The science of VALUE: Validation in future climate

### RCM-simulated pseudoreality

- fit DS models using GCM-driven RCMs as predictands

- validate how well RCM-simulated climate for the second half of the 21$^{th}$ century is estimated



# Summary and final comments

VALUE has provided a systematic classification of methods
(used also in NCPP controled vocabulary).

A systematic validation and method comparison is needed. VALUE has defined a systematic framework, which is currently being implemented on a web-portal.

The ranking of methods will most likely depend on which aspects are validated.

Errors introduced by the large-scale GCM forcing are a big problem and there is no concensus whether and if so how to deal with the in downscaling

END