

Future climate change

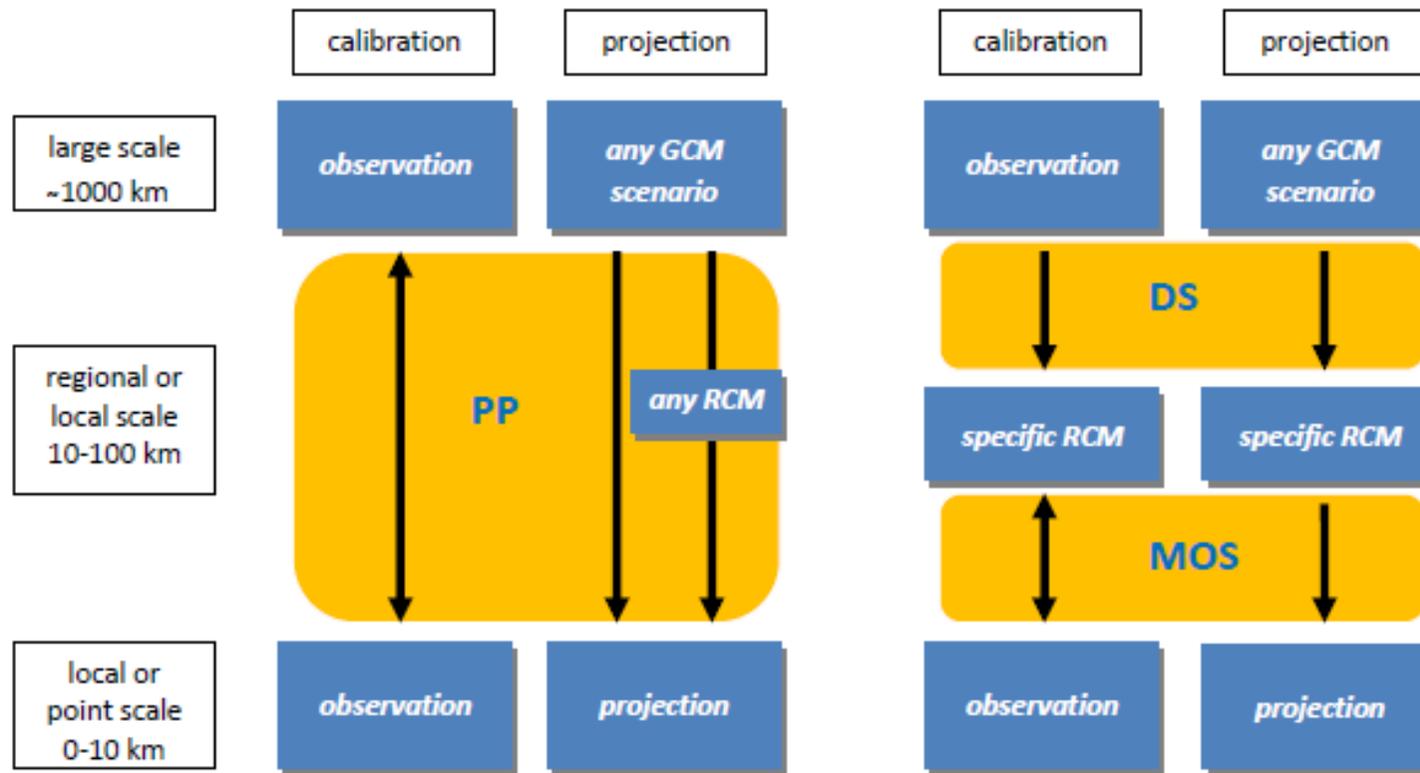
Skill of methods for describing
regional climate futures

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Erik Kjellström, Philip Lorenz



Tallin, 6-7 September 2012

TYPES OF DOWNSCALING METHODOLOG



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SKILL OF DOWNSCALING

The quality of a downscaling product stands and falls with the ability of the forcing GCM to provide meaningful large scale boundary conditions

The main shortcomings of GCMs in Europe:

Circulation in many GCMs is too zonal in winter (van Ulden et al., 2007)

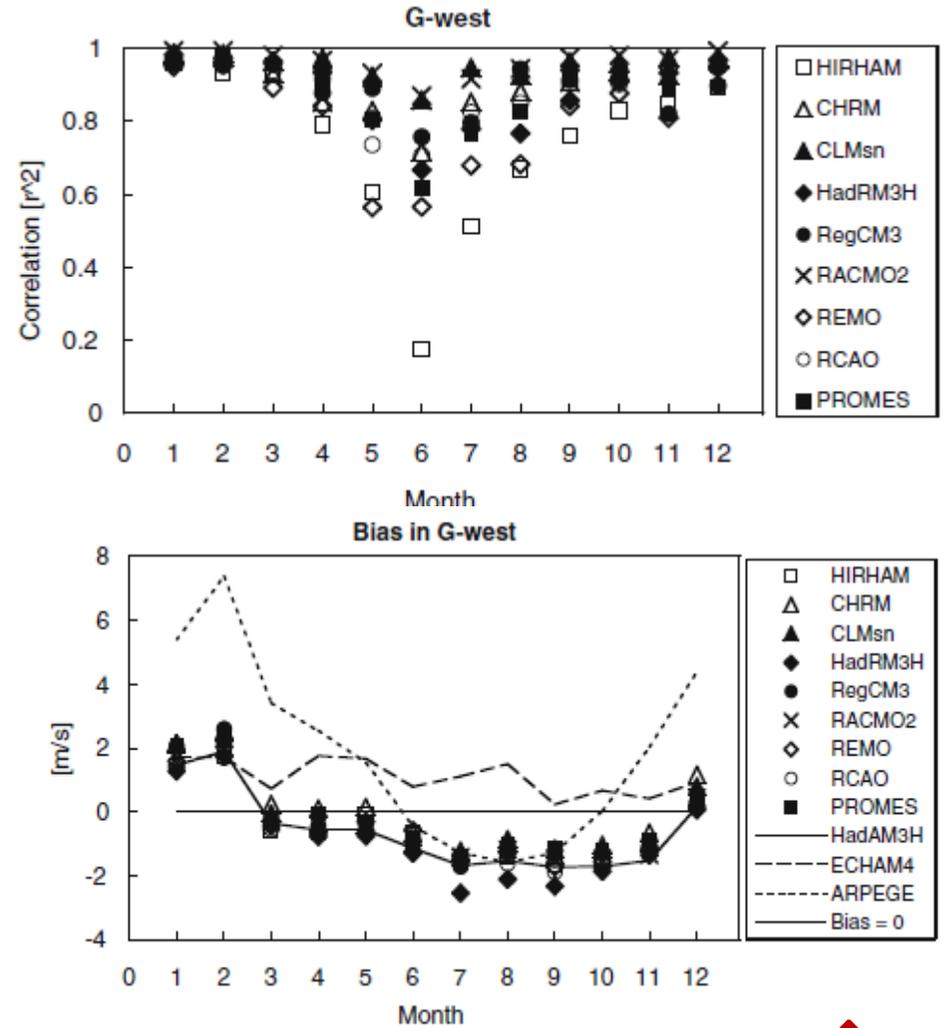
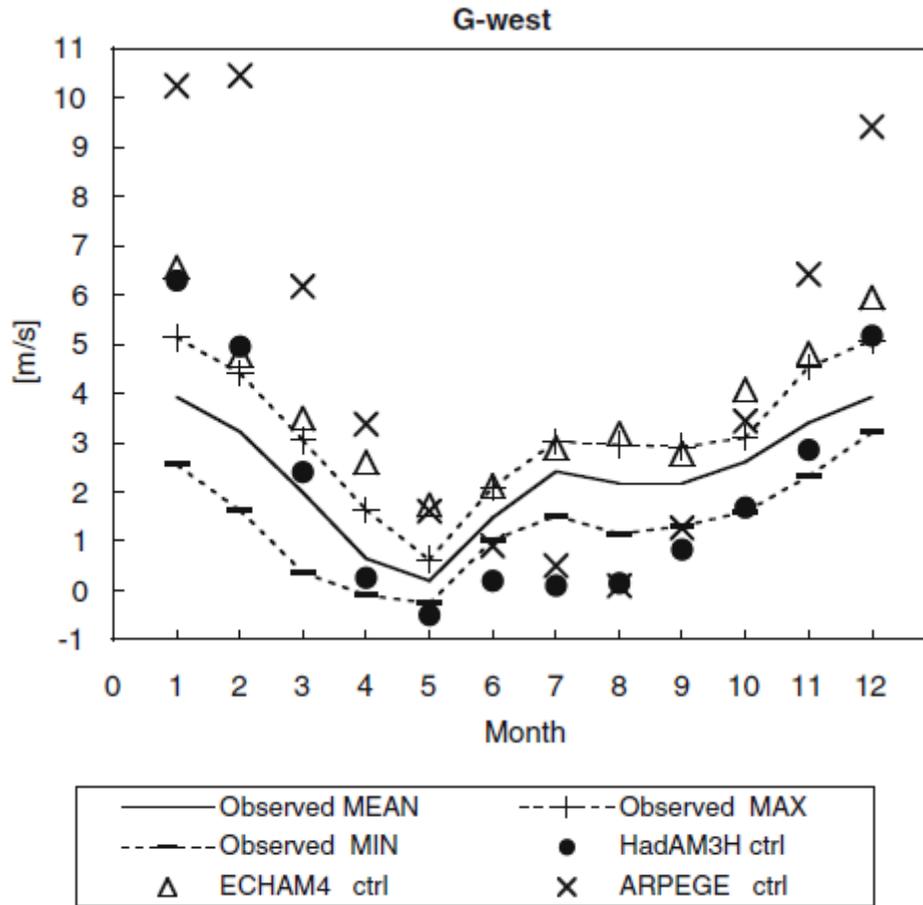


Large part of uncertainty in Northern and Central European temperature and precipitation stems from driving GCM (Déqué et al., 2007)

A large blue double-headed arrow pointing both left and right, spanning most of the width of the slide. It has a white outline and a blue fill.

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Too zonal in winter



van Ulden et al., 2007

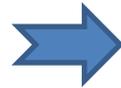


SKILL OF DOWNSCALING

RCMS

The parametrisations are developed and tuned for specific climates and might be at least slightly misspecified under future climate conditions.

RCMs have been shown to adequately simulate European daily temperature and precipitation intensities , although considerable biases have to be expected (e.g. Jacob et al., 2007)

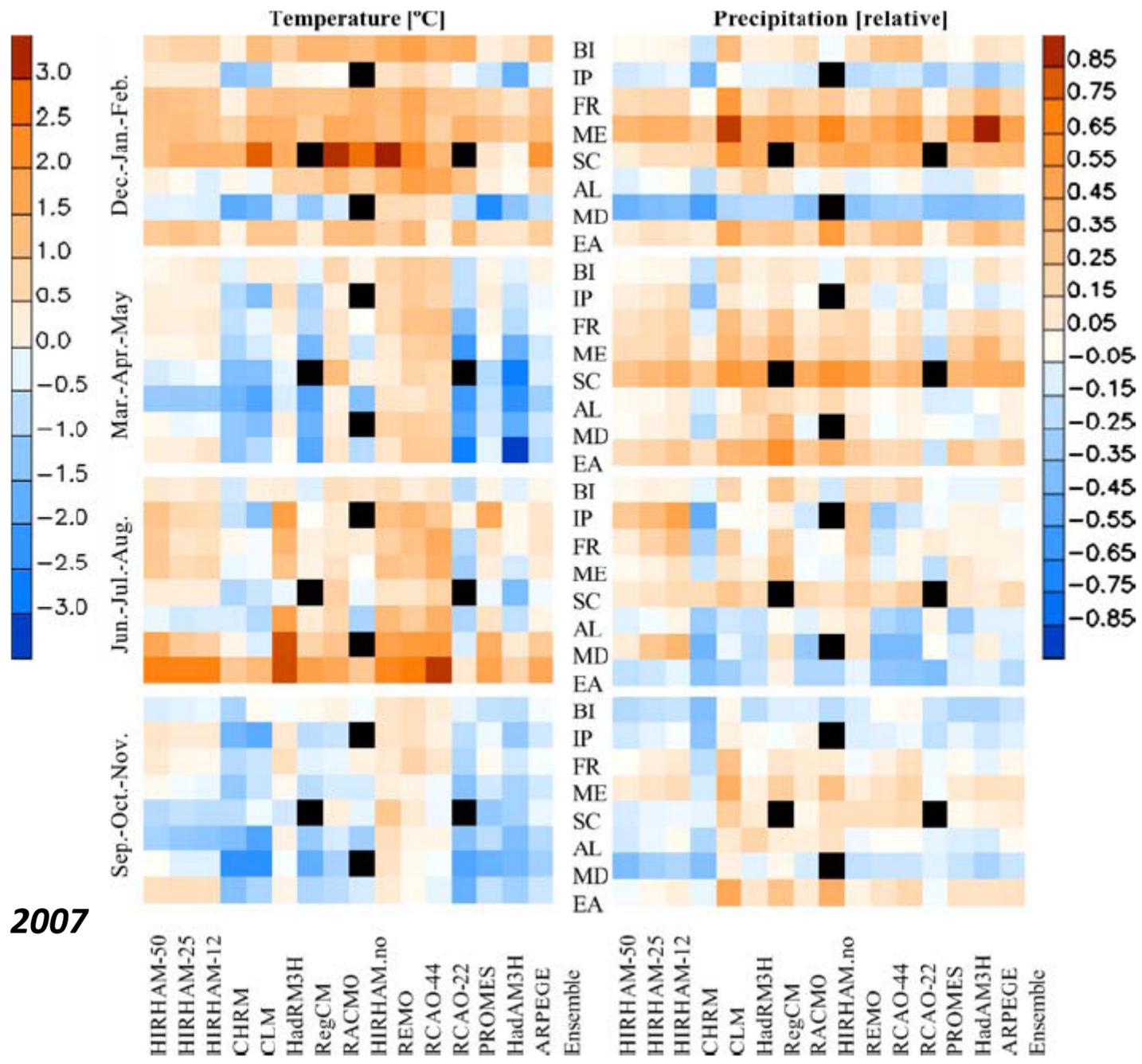


RCMs are able to simulate spatially coherent fields.

The biases in one variable may propagate into strong biases in dependent variables (e.g. Yang et al. 2010).



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Jacob et al. 2007

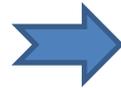


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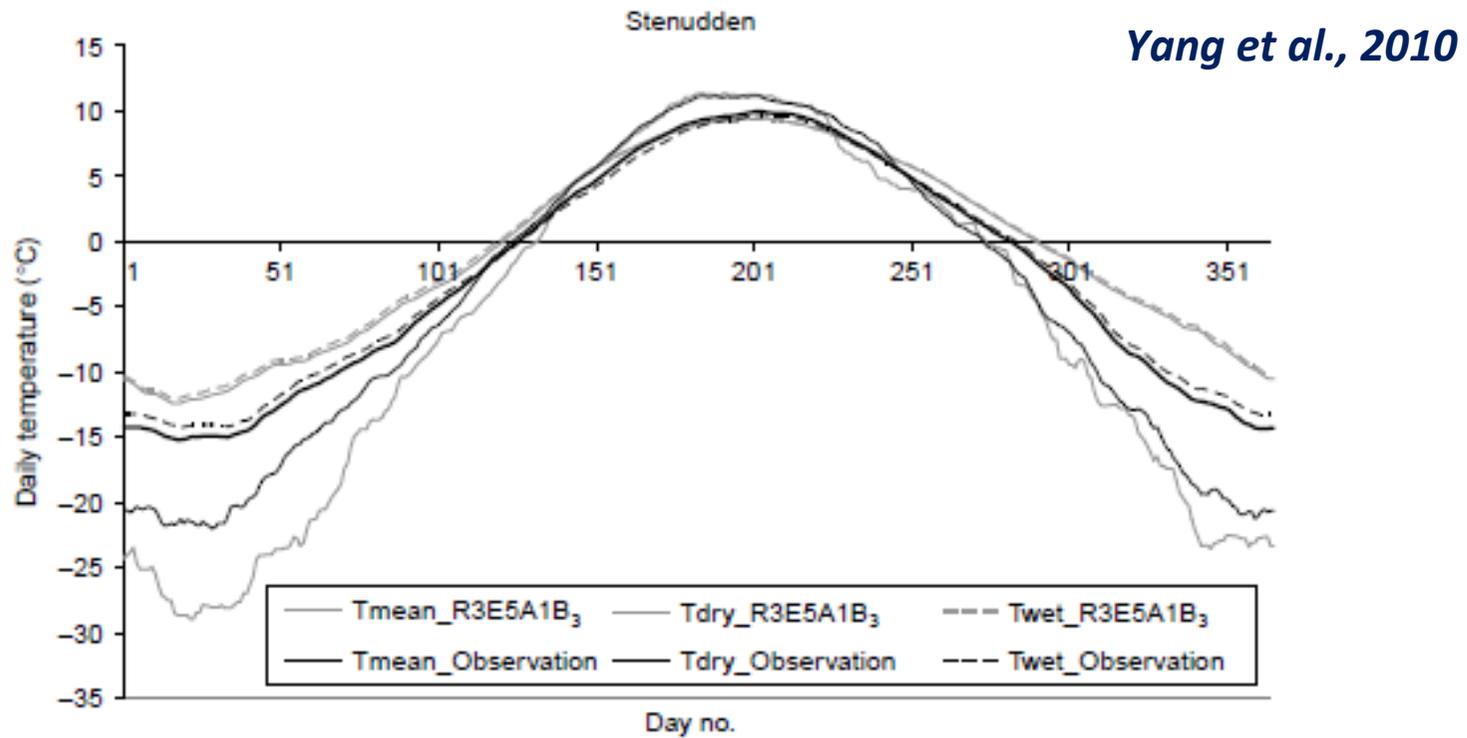
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SKILL OF DOWNSCALING

RCMS



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SKILL OF DOWNSCALING

RCMS

Distribution based bias

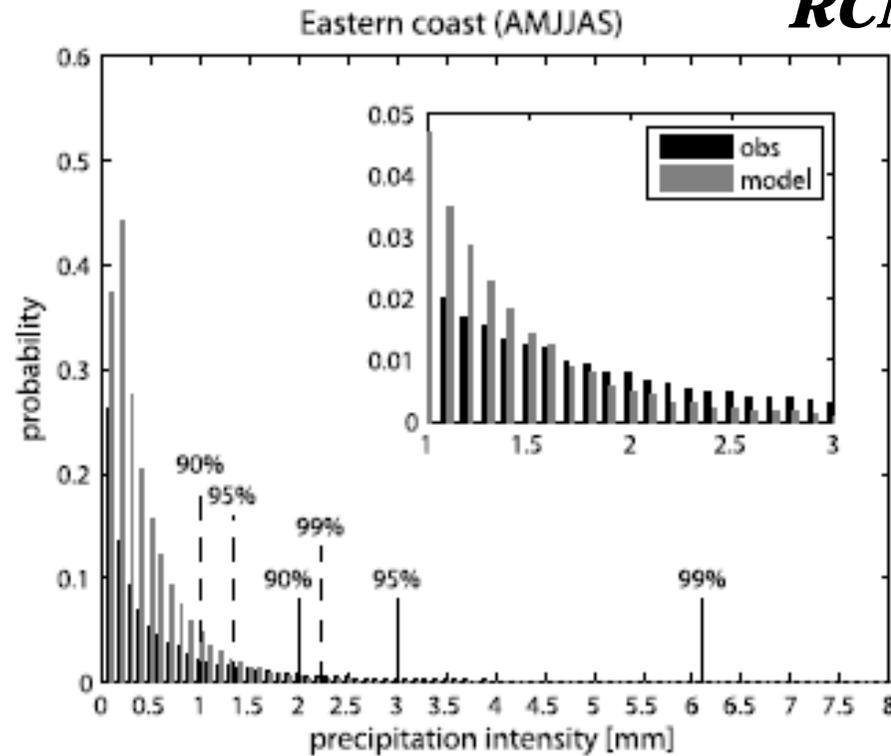


Fig. 8. Probability density of precipitation intensity over the three representative regions: northern mountains (upper panel), southern plains (middle panel) and Eastern coast (bottom panel). Inner boxes highlight the probability of precipitation intensity from 0.1–1 mm h⁻¹. The 90th, 95th and 99th percentiles are marked for the observations (solid vertical lines) and the RCA3 simulation (dashed vertical lines).

JH Jeong et al., 2011

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SKILL OF DOWNSCALING

ENSEMBLES

A way of filtering the occasional errors and an indicator of uncertainty

Sharing codes – are the models independent?



Ensemble design

multi-model ensembles

perturbed physics ensembles

Is it possible to distinguish between uncertainty related to model formulation and that related to initial conditions?

Ensemble projections or single climate projections?

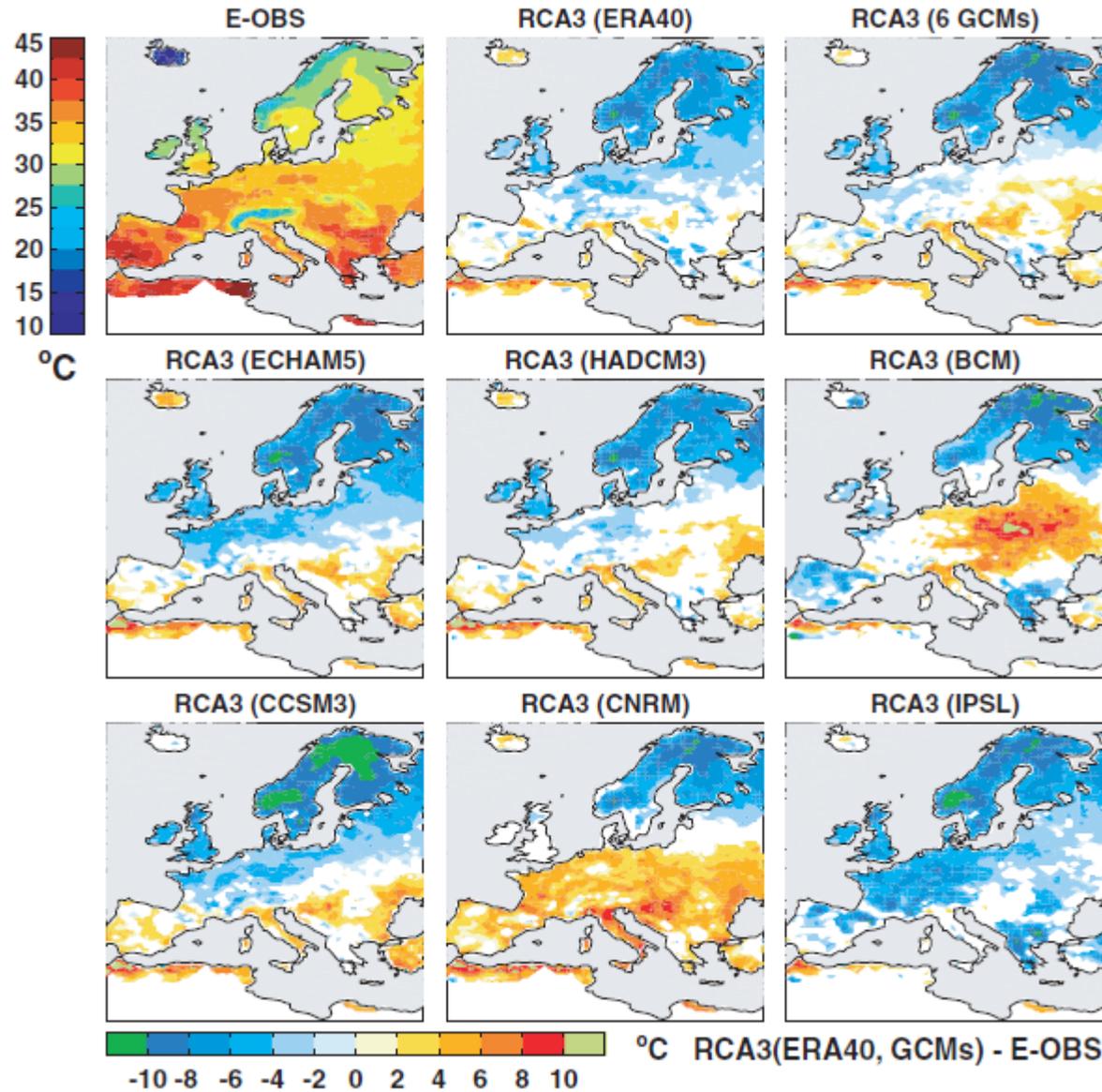
To weight or not to weight?



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SKILL OF DOWNSCALING

20-yr ret. values of T_{max} (1961-1990)

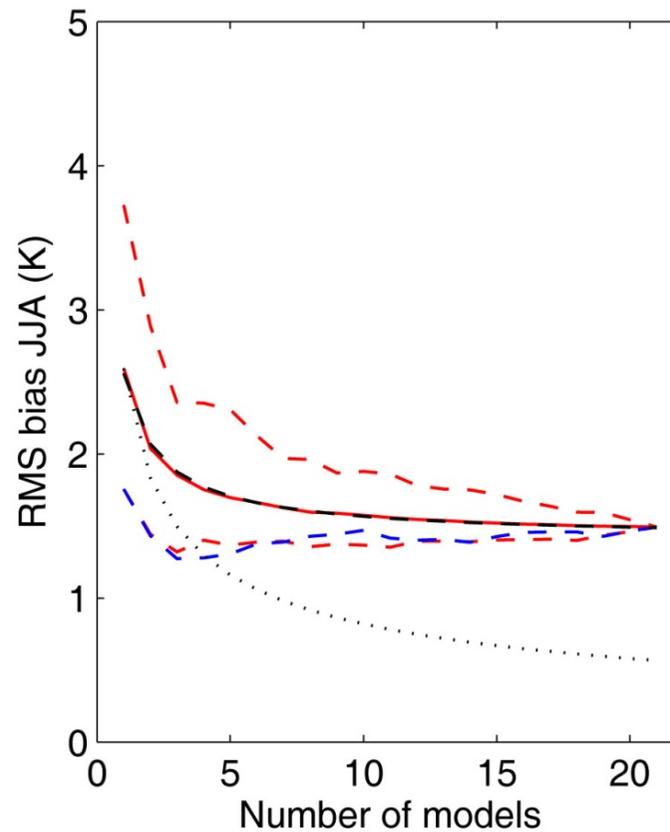
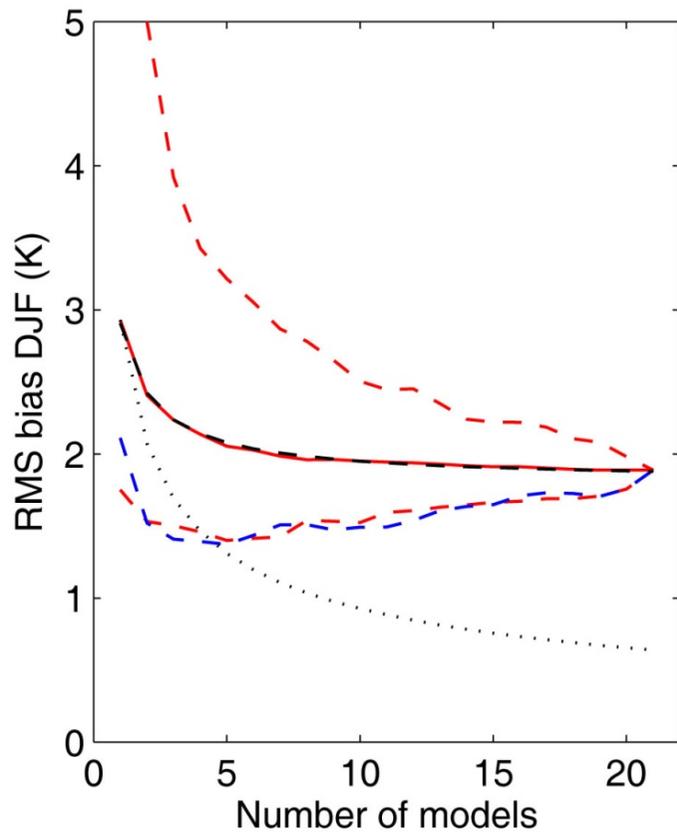


Nikulin et al. 2011

March, 6-7 September 2012

SKILL OF DOWNSCALING

RCMS



Knutti et al, 2010



SKILL OF DOWNSCALING

ENSEMBLES

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Ensemble design

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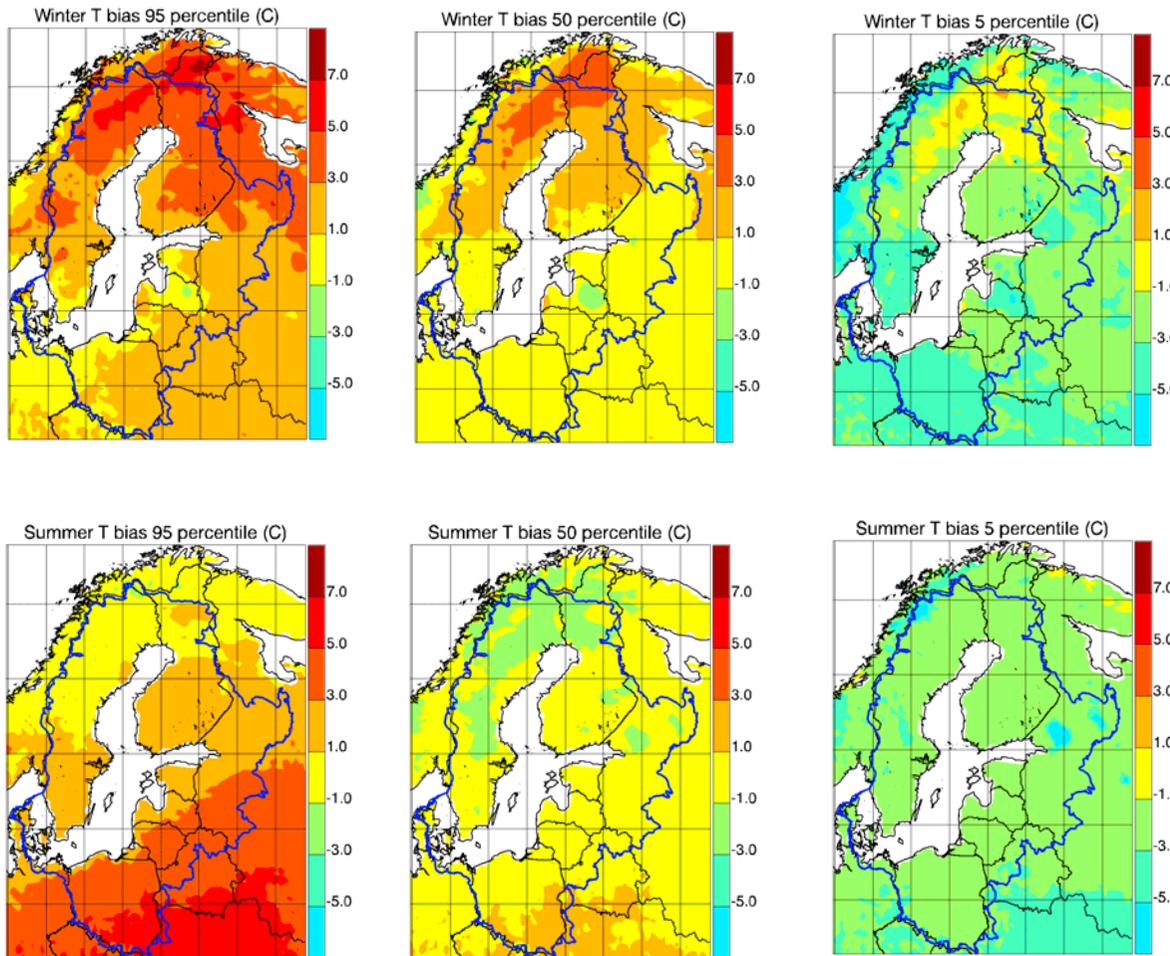
Ensemble projections or single climate projections?

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PERFORMANCE OF RCMS IN REPRODUCING THE CLIMATE

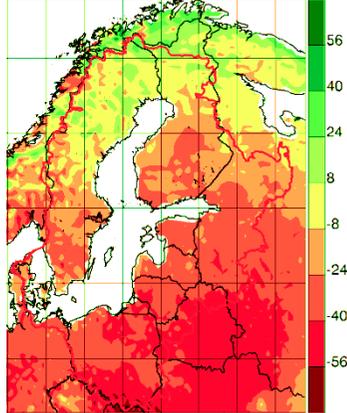


Simulated temperature bias ($^{\circ}\text{C}$) w.r.t. E-OBS for 1961-2000. The maps show the pointwise smallest (left), median (middle) and largest (right) bias taken from an ensemble of 10 RCMs with lateral boundary conditions taken from ERA40

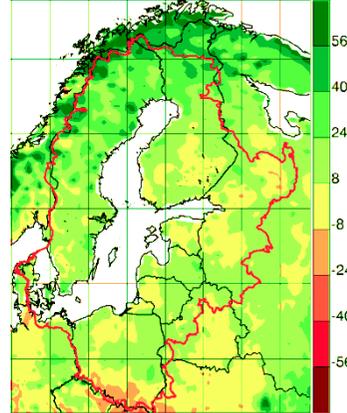
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PERFORMANCE OF RCMs IN REPRODUCING THE CLIMATE

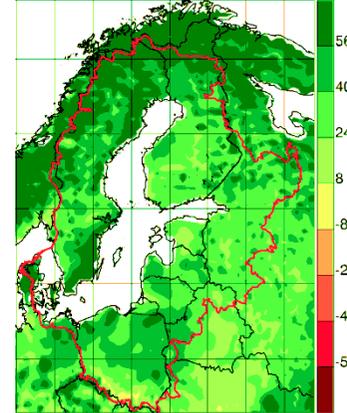
Summer precip bias 5 percentile (%)



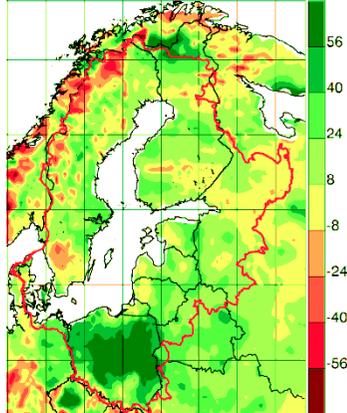
Summer precip bias 50 percentile (%)



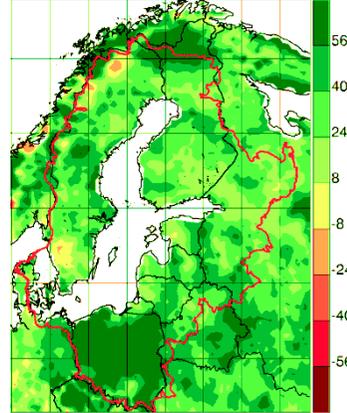
Summer precip bias 95 percentile (%)



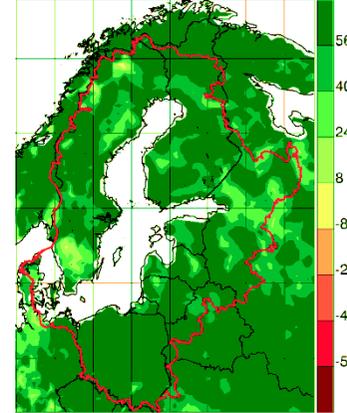
Winter precip bias 5 percentile (%)



Winter precip bias 50 percentile (%)



Winter precip bias 95 percentile (%)



Simulated precipitation bias (%) w.r.t. E-OBS for 1961-2000. The maps show the pointwise smallest (left), median (middle) and largest (right) bias taken from an ensemble of 10 RCMs with lateral boundary conditions taken from ERA40.

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SKILL OF DOWNSCALING

RCMS

A few RCM validation studies consider sub-daily scales. Jeong et al. 2011 have shown that diurnal precipitation cycle in Sweden is reasonably captured by RCM at SMHI, but afternoon peak occurs too early and is spatially too uniform.

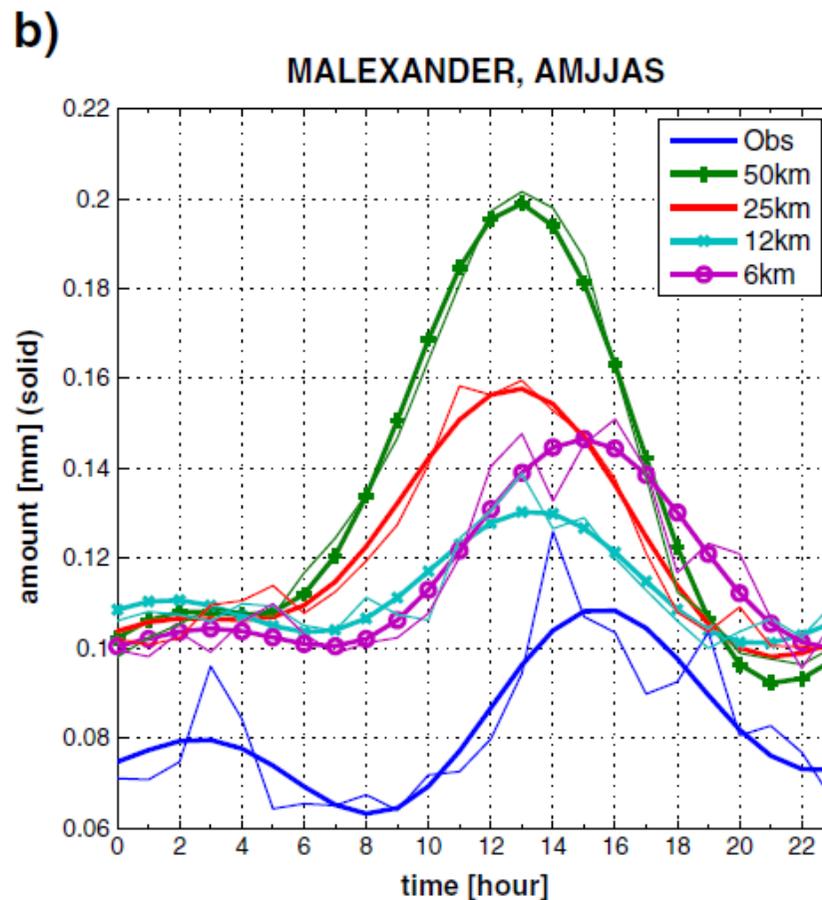
Increasing model resolution in general improve model simulations, in particular precipitation in complex terrain (Salathé et al., 2003)



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Fig. 4.2-7: An example of the estimated diurnal cycle of precipitation amount [hourly precipitation amount] from observation and from the RCA3 (RCM developed by the Rossby Centre of SMHI) simulations with 4 different resolutions for the station 'Malexander' in central southern Sweden (picture taken from Walther et al, 2011).



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RECENT DEVELOPMENTS AND EXTENSION OF RCMs

Oceans - the aspect of boundary conditions in RCMs

Nudging procedure

Hydrostatic and nonhydrostatic solutions

Lakes in the RCMs

Dynamics of vegetation

Biogeochemistry



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MOS

MOS has been shown to successfully correct temperature biases as well as biases in precipitation intensities and the number of wet days (Piani et al. 2010)

Widmann et al. 2003 developed a non-local MOS that corrects systematic spatial displacements of precipitation.

Yang et al. 2010 applied MOS to improve correlation between simulated temperature and precipitation.

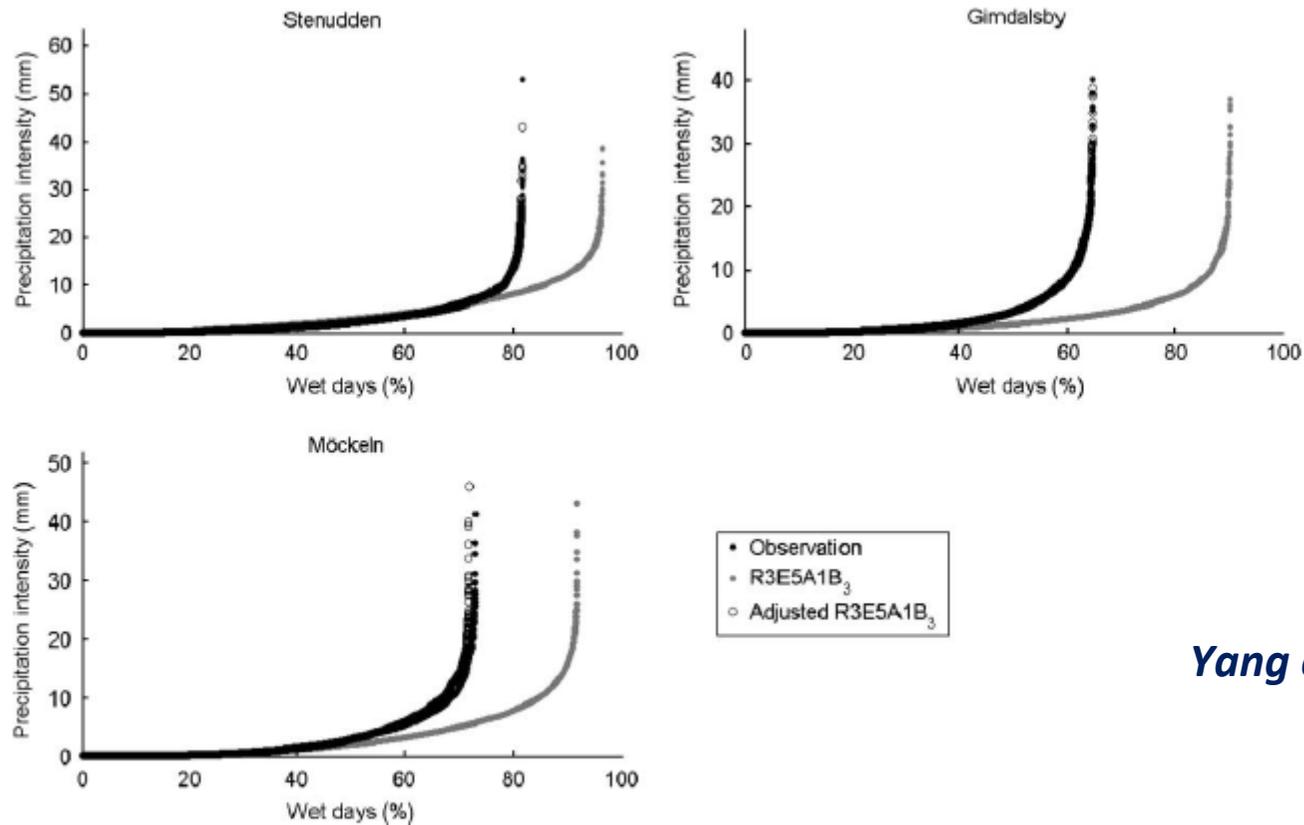
MOS is not capable of correcting the misrepresentation of temporal structure of a simulated variable (cannot correct errors in the length of dry, wet or hot spells).



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MOS



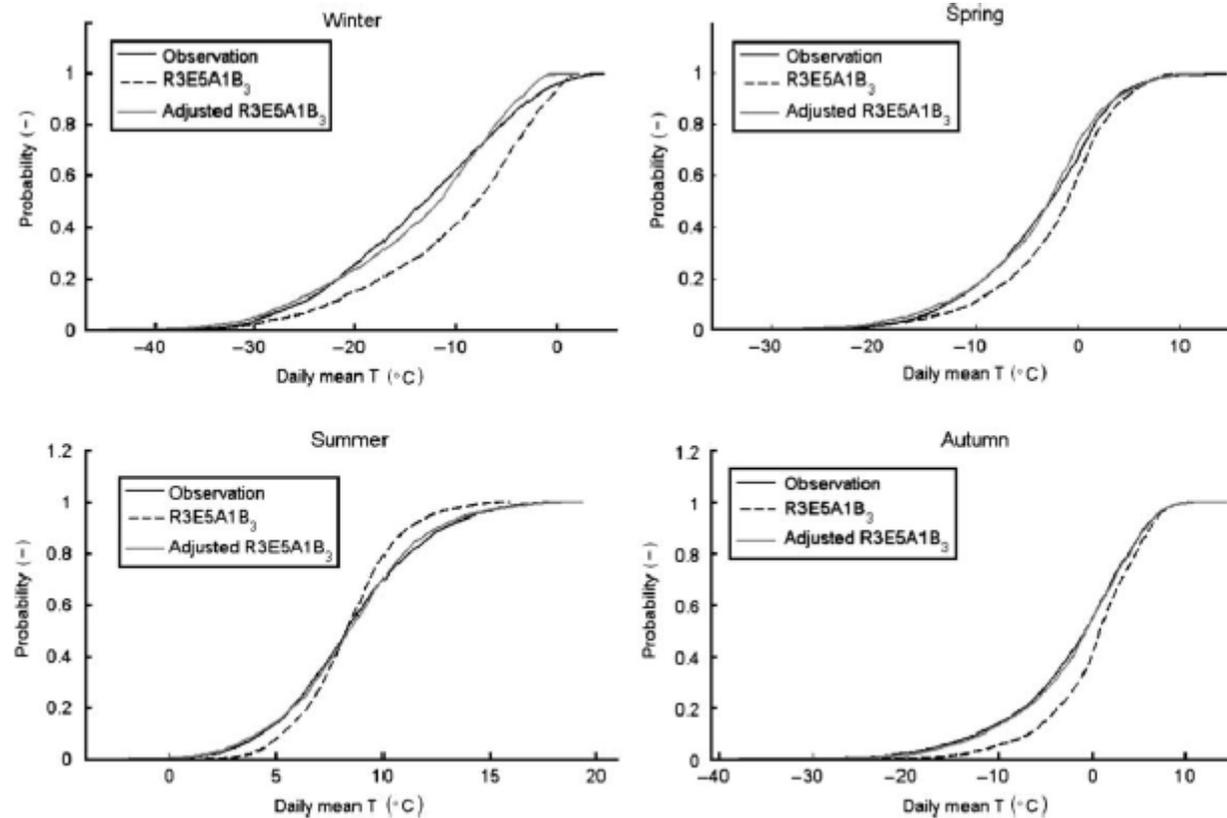
Yang et al., 2010

Figure 4 | Distribution of precipitation intensities for all three study basins calculated from observations (1961–1990) and raw R3E5A1B₃ output and DBS-adjusted R3E5A1B₃ output for the control period. Note that the observations are difficult to see as the DBS-adjusted values closely overlie them.

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SKILL OF DOWNSCALING

MOS



Yang et al., 2010

Figure 7 | Distribution of daily temperature from observations (1961–1990) and raw R3E5A1B₃ and DBS-adjusted R3E5A1B₃ projection outputs for the control period for each season in the Stenudden basin.



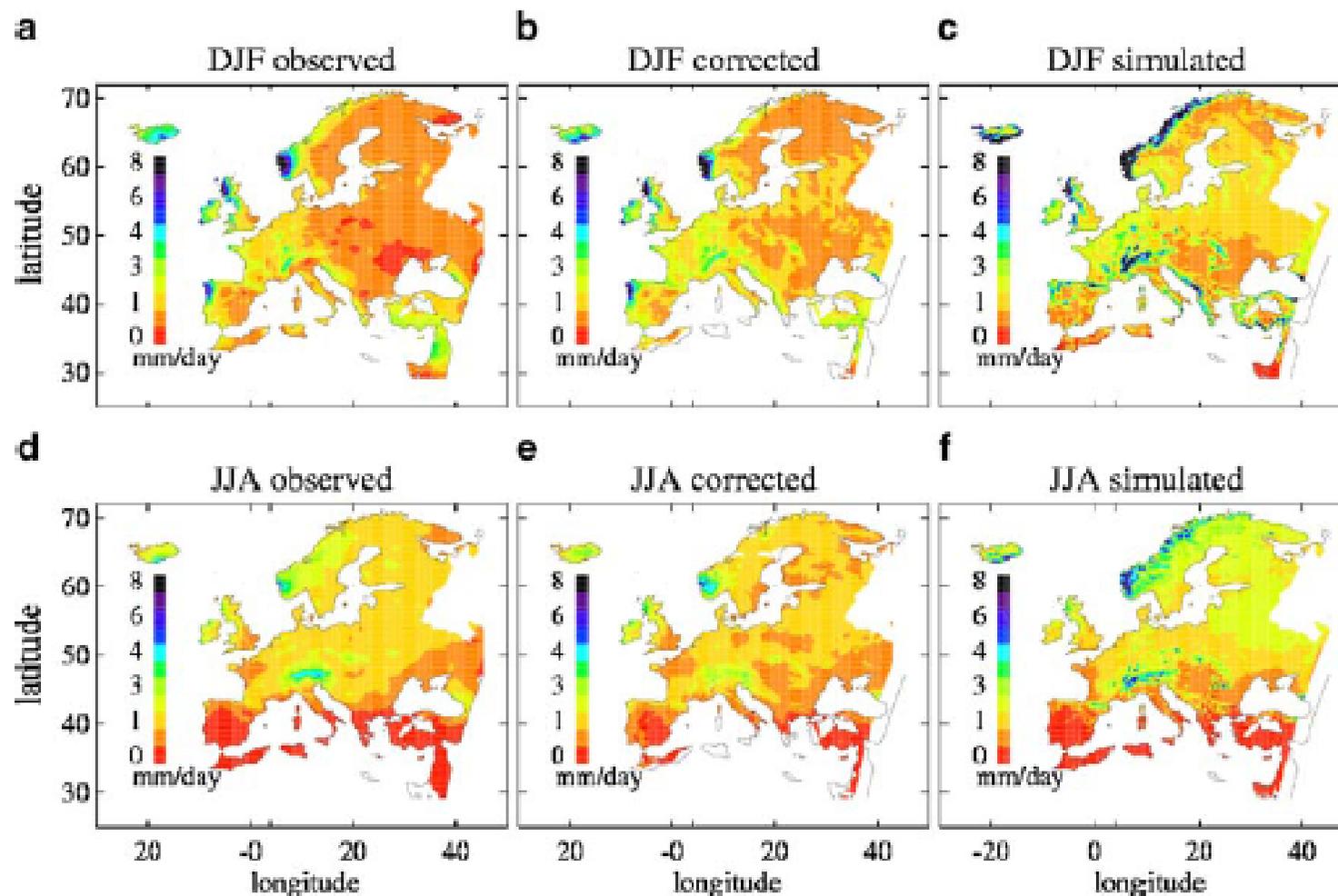


Fig. 4.2-5. Application of bias correction, derived from simulated and observed data from 1961 to 1970, to model data from 1991 to 2000. a Mean observed daily precipitation for winter (DJF) 1991 to 2000, b same as a but for corrected simulated data, c same as a but for uncorrected simulated data. d–f Same as a–c but for summer (JJA) (Piani et al., 2010, Fig.2)

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PP

PP explicitly uses an empirical knowledge by inclusion of observational data into statistical models. A simulated predictands are bias free.

If the predictors do not capture the climate change signal, nonstationarities may arise.

Underrepresentation of temporal variability

Problems with variability around the mean. There are methods to deal with it: inflation or randomisation, but it is impossible to evaluate their quality in the scenarios for future.



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PP

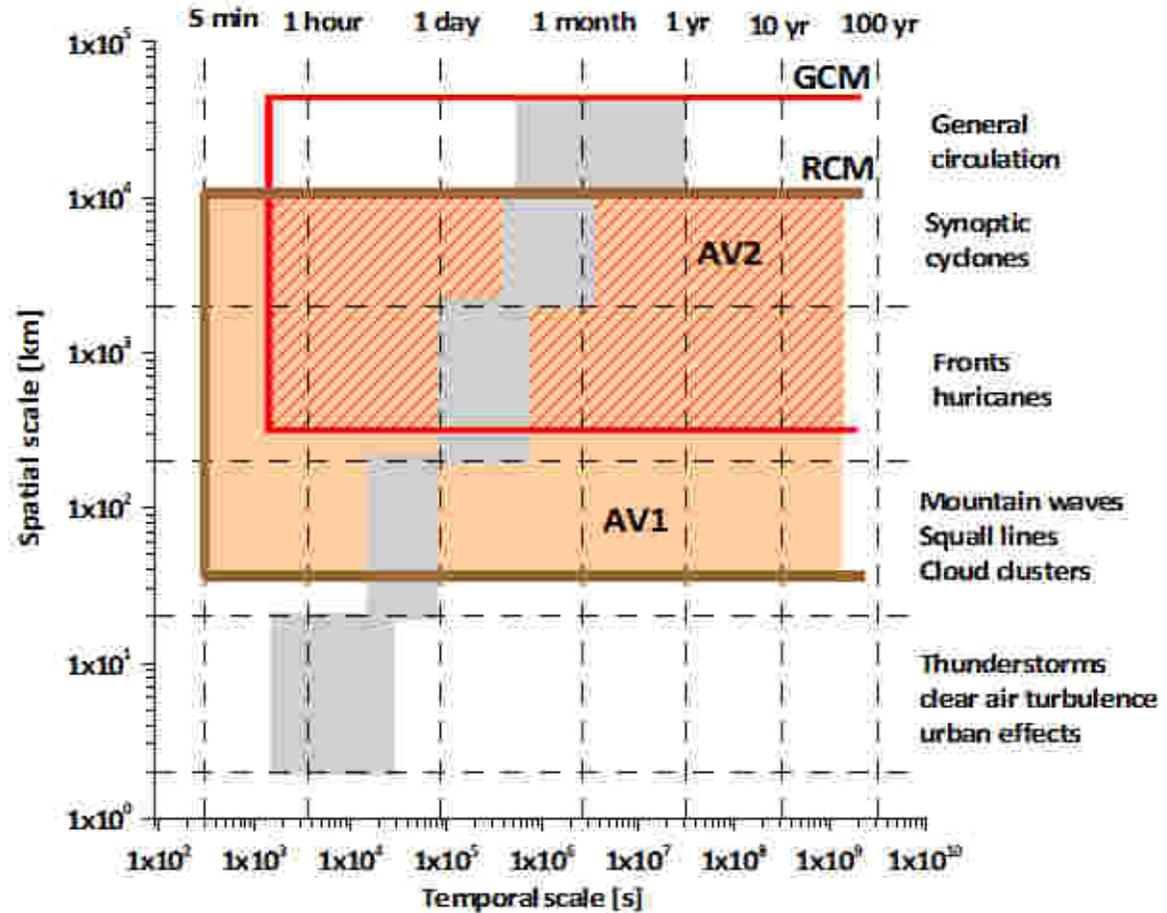
A main disadvantage of PP is a handling of spatial coherence.

The development of downscaling methods to full spatial fields for climate change studies is still in its early stages (Onibon et al. 2004 disggregation of areal rainfall by the Gaussian process).



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Concept of *added value*



Orlanski, 1975
Laprise, 2004
von Storch, 2005
Feser, 2006
Di Luca, 2012

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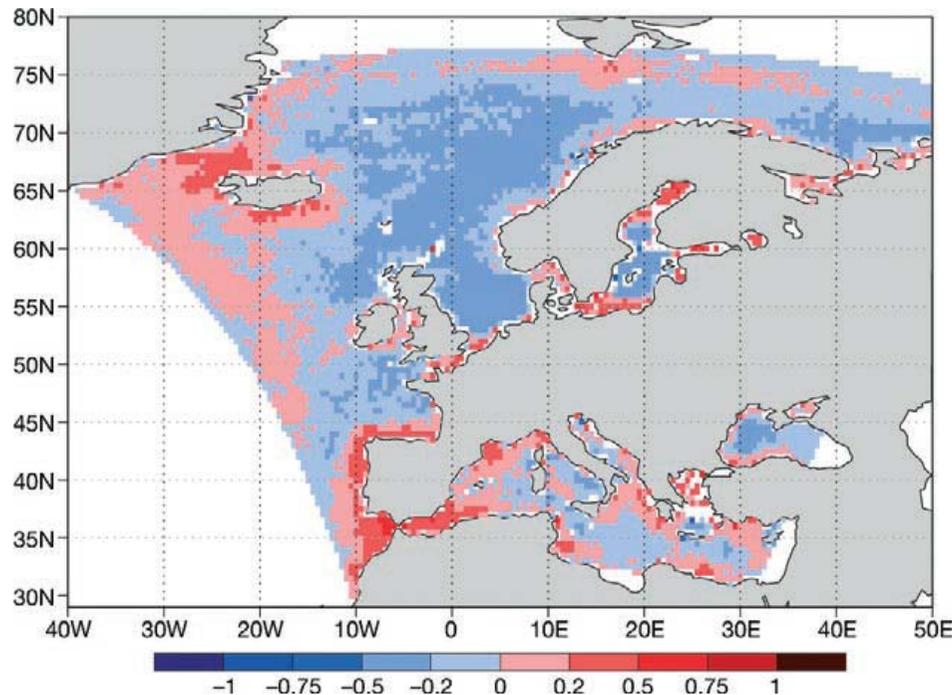


Fig. 4.2-8. Brier skill score using QuikSCAT level 2B12 as the truth, global reanalysis (NCEP reanalysis) as the reference forecast, and a regional model (SN-REMO) as the forecast, after Winterfeldt et al. (2010).

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SUMMARY

RCMs are able to improve quality and precision of GCMs, but with some limitations.

RCMs simulations are biased and these biases are partly common to all models (they are not excluded by ensembles)

MOS is able to correct a considerable part of biases, the distribution based corrections should be implemented in majority of cases.

PP explicit uses an empirical knowledge by inclusion of observational data into statistical models. A simulated predictands are bias free.

If the predictors do not capture the climate change signal, nonstationarities may arise.



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STATISTICAL-EMPIRICAL DOWNSCALING METHODS

Model Output Statistics

bias correction

delta change or scaling

Perfect Prognosis

regression methods

weather classification methods

Weather Generators



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VALIDATION TECHNICS

Errors of driving global climate model

Errors inherent in the downscaling approach

Perfect Boundary Condition

Big Brother Experiments



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VALIDATION INDICES

Mean, variation, extremes, spatial and temporal structure

Perfect Boundary Condition

Big Brother Experiments

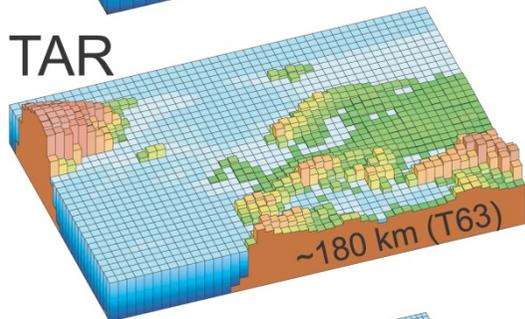
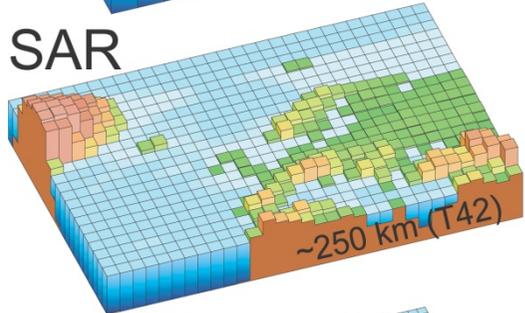
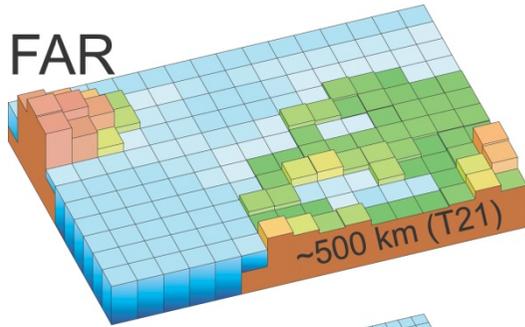
Should the validation use the data directly with grid box resolution or should data be smoothed in advance?

Distribution-wise and event –wise validation

Validation in climate change context (nonstationarity of skill and/or biases)



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INTRODUCTION

Grid scale: 100-300 km

Skillful scale: 100-2500 km

***Downscaling:
a process linking large
scale variables with small
scale variables***

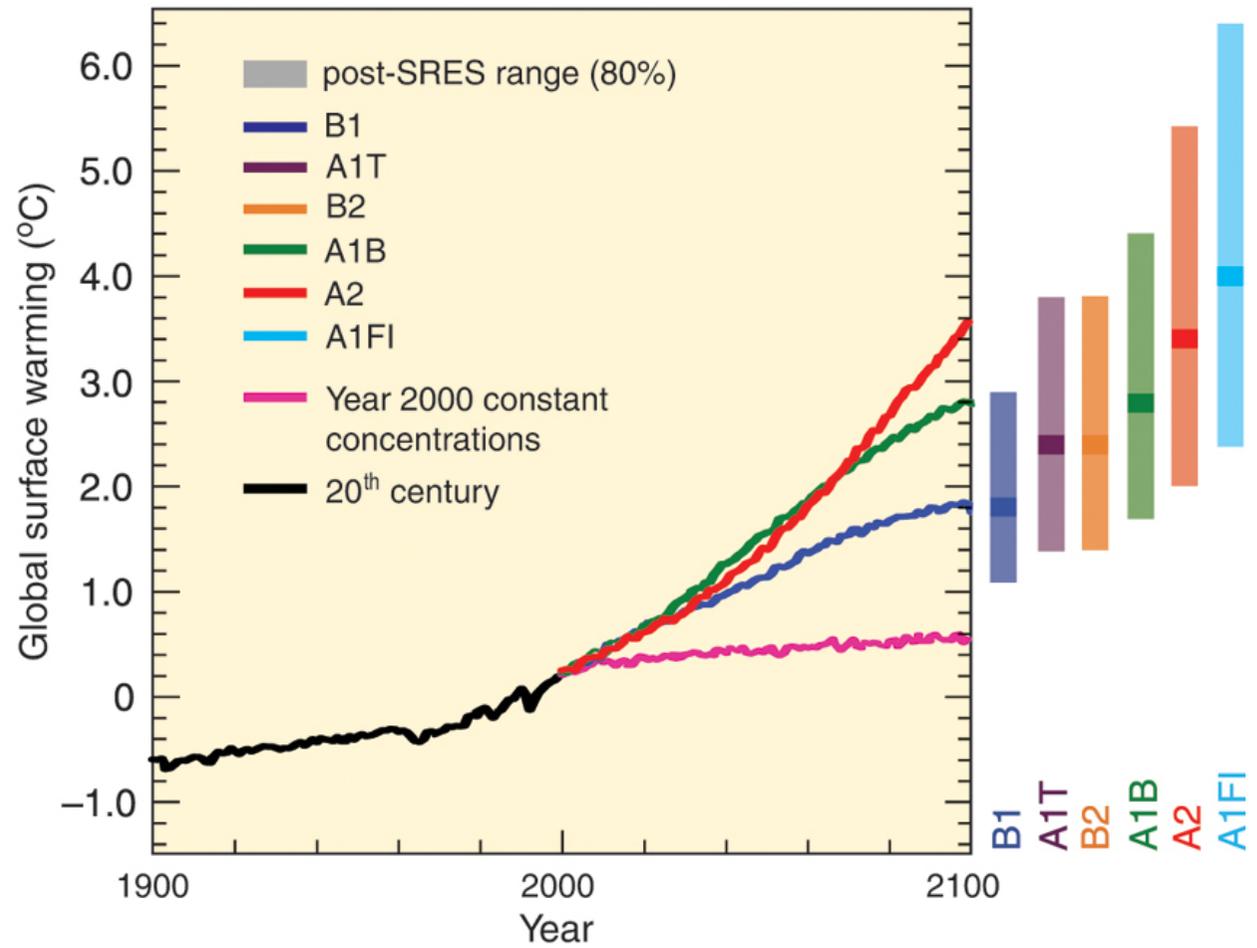
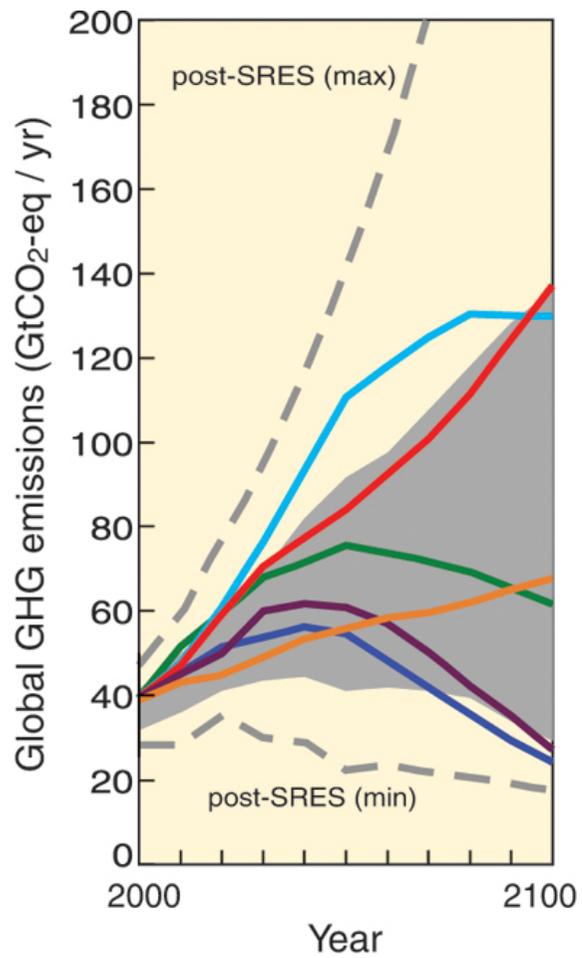
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DRIVERS OF CLIMATE VARIABILITY AND CHANGE

- ***Solar radiance***
- ***Oceanic processes***
- ***Biosphere with its annual cycle and long-term changes***
- ***Criosphere with its annual cycle and long-term changes***
- ***Volcanic processes***
- ***Biogeochemical cycles and their long-term changes***
- ❑ ***GHG concentration***
- ❑ ***Aerosols***
- ❑ ***Sulphur compounds***



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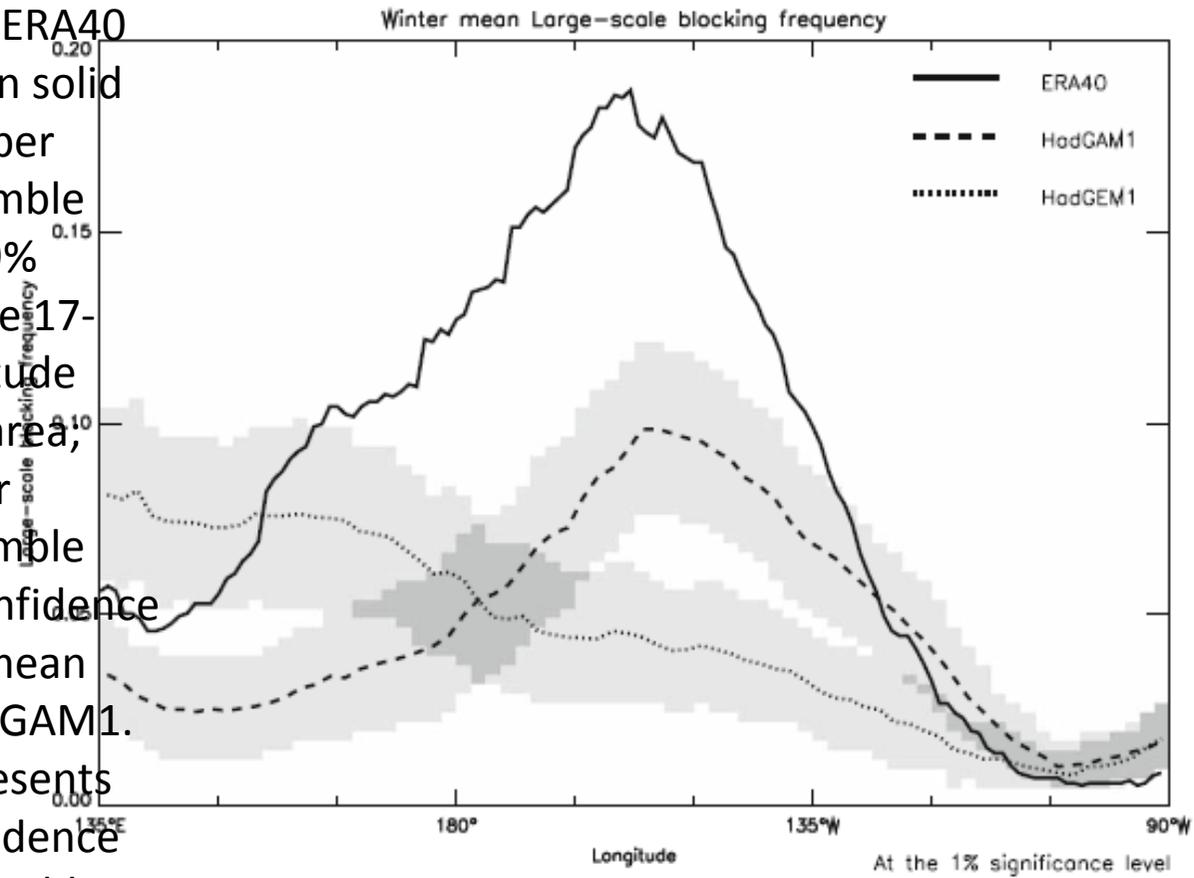


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SKILL OF DOWNSCALING

Hinton et al., 2009

Winter (DJF) mean blocking frequencies for ERA40 (Dec 1978 to Feb 1995) in solid line; HadGAM1 six member ensemble with the ensemble mean dashed and the 99% confidence interval of the 17-year mean at each longitude denoted by the shaded area; HadGEM1 three member ensemble with the ensemble mean dotted and the confidence interval on the 17-year mean represented as with HadGAM1. The darker shading represents the area where the confidence intervals of the two ensembles overlap



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SELECTED SOURCES OF UNCERTAINTY

Effects of low spatial resolution	Results of methodological assumption	Sources of uncertainty
<p>Sub-grid processes like cloud formation, convection, precipitation and many others are not explicitly simulated</p> <p>Real coastline and land cover can significantly differ from that in the model.</p> <p>Low resolution flattens the orography influencing not only local climate conditions predicted by the model but also the atmospheric circulation which has an impact on climate in wider spatial scale.</p>	<p>Effects of nonstationarity of empirical and statistical relationships between large scale predictors and local or point scale predictands.</p> <p>Effects of nonstationarity of biases.</p> <p>Effects of systematic errors in climate models or their groups on ensembles statistics</p>	<p>Uncertainty according to natural drivers of climate variability like solar or volcanic activity.</p> <p>Uncertainty according to anthropogenic drivers of climate change like emissions and concentrations of aerosols and greenhouse gases and changes in land use.</p> <p>Input data to climate models - their quality, precision and limited temporal and spatial distribution.</p>